A Novel Framework Based on Integration of Simulation Modelling and MCDM Methods for Solving FMS Scheduling Problems

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Scheduling in Flexible Manufacturing Systems (FMSs) is an important area of research as it significantly affects performance of the systems. In scheduling problems, determination of an appropriate order for jobs to be processed on a machine is a difficult task and to solve such problems, job priority rules (JPRs) are used. Several JPRs have been developed with an aim to obtain better performance, measured in terms of one or more scheduling performance measures (SPMs). However, selection of an appropriate rule is still an area of research as no single rule provides better results for all SPMs considered simultaneously. This work proposes a framework which is based on an integration of simulation and multi criteria decision making (MCDM) methods for the selection of an appropriate JPR yielding optimum results for multiple SPMs taken together. The proposed framework includes development of a simulation model to collect values of the SPMs corresponding to different JPRs. Further, five MCDM methods have been used to determine rank of the JPRs. Since different MCDM methods produce different ranking result therefore, the final rank of the JPRs has been determined by comparing the rank derived from these methods using membership degree method. To exemplify the probable application of the proposed framework, it has been implemented on a specific FMS taken from the literature in order to select the best JPR.

Povzetek: Razvit je okvir za reševanje problemov razporejanja v fleksibilnih proizvodnih sistemih, ki združuje simulacijsko modeliranje in metode MCDM.

1 Introduction

High system throughput and customer satisfaction are considered as the most important performance metrics required from a manufacturing system. However, due to conflicting nature of these performance metrics, the concept of flexible manufacturing system (FMS) was evolved which provides flexibility as well as high productivity at the same time. FMS is a centrally or distributed computer control system consisting of automated machines viz. CNC, material handling system (MHS), automatic storage and retrieval system (AS/RS) and other auxiliary devices. Various studies have suggested that a significant amount of improvement in performance can be obtained with installation of FMS over conventional manufacturing systems [1], [2]. Further, the performance of these systems can be additionally enhanced if effective and efficient operational decisions are made [3]. Despite the fact that small setup times, variability of parts, high machine utilization etc. are some of the advantages, there are various operational problems associated with FMSs. The three major operational problems of FMS are classified as scheduling, control problems, and pre-release planning [4].

The focus of this study is to scrutinize scheduling problem associated with FMS. Scheduling is an extensively researched area and it is considered to be an important concern in the management and planning of manufacturing processes [3], [5]. It is the process of assigning available resources to the concerned job so as to enhance productivity, flexibility, profitability, and production of the system [6]. Scheduling in FMS environment is more complex as compared to conventional manufacturing environment due to its versatile capabilities [7]. The FMS scheduling problem consists of two sub-problems [8]. The first one is related to the allocation of the requisite operation to a suitable machine and the second one pertains to the job sequencing of operations on each machine. Over the years, Job Priority Rules (JPRs) are found to be the simplest and most widely accepted means to resolve the second sub problem i.e., sequencing of jobs on each machine. These rules provide precedence to one job over other jobs, based on their performance on a predefined priority function, for processing on the machine. Further, the scheduling problem is described as dynamic or static based on the availability of jobs [9]. A scheduling problem is classified as dynamic if jobs arrive into the system during the scheduling process i.e. all jobs are not available at the beginning and it is categorized as static if they are available at the starting of the scheduling process [10]. To solve static scheduling problem, many optimization algorithms and heuristics have been developed [11], [12]. However, JPRs are found to be the most appropriate means to resolve the dynamic scheduling problems [13], [14].

JPRs are classified on the basis of processing time, due date, rules neither based on processing time and due date, combinatory rules and rules based on shop floor conditions [9]. The processing time based rules are found to perform well under tight load conditions whereas for light load conditions, due date based rules are preferred [15]. Several JPRs have been developed and proposed in the literature and it has been established that the performance of the FMS is significantly affected by the chosen JPR. Further, selection of an appropriate JPR among the available one is a complex task as no single rule can provide best results for all the performance measures taken together. With this intention, this work attempts to provide an effective framework using a combined approach of simulation modelling and MCDM methods to select the best JPR resulting in the optimum performance of FMSs with dynamic scheduling of parts.

Selection of an appropriate JPR requires various performance measures to be satisfied simultaneously and therefore, the selection problem resembles an MCDM problem. Several MCDM methods such as WSM, WPM, AHP, VIKOR, ELECTRE, TOPSIS etc. are available which can be used to select the best JPR among the available ones [16]. However, due to inherent characteristics of these and many other MCDM methods, the best JPR produced by them may be different. Therefore, the framework proposed in this work examines the priorities of the JPRs on the basis of rank obtained from five MCDM methods viz. Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS), Proximity Index Value (PIV), Multi-Attribute Border Approximation Area Comparison (MABAC), Evaluation based on Distance from Average Solution (EDAS) and Technique of Order Preference Similarity to the Ideal Solution (TOPSIS). Subsequently, it determines the final rank of the JPRs by comparing the rank produced by these methods using membership degree method. To demonstrate the potential application of the proposed framework, it has been employed to select the best JPR for a specific FMS taken from the literature. Rest of the paper is structured as follows: Section 2 discusses the various JPRs, SPMs, simulation modelling, and the MCDM methods employed in the present study. Section 3 describes the steps involved in the development of the proposed framework. Section 4 explains working of the proposed framework through an illustrative example taken from the literature. Finally, section 5 presents conclusion of the present study.

2 JPRs, SPMs, simulation modelling and MCDM methods

2.1. Job priority rules (JPRs) in FMSs

Job priority rules are used to select the next job to be processed on a machine from a set of jobs that are waiting in the queue for processing. Since, these rules are simple and easy to implement, they are most commonly used in FMSs for job sequencing. Consider an FMS with m machines designated as Mi (i=1, 2, m) processing n parts say Pj (j = 1,2, ..., n). If t = Current time of the system, ATj = Time of arrival of part j in the system, Tij = Time of arrival of part j on machine i, PTij = Processing time of part j on machine i, DDj = Due date of part j, TTj = Total time required to perform all operations on part j, RTj = Remaining processing time for part j and NRj= Number of remaining operations to be performed on part j. Some of the most commonly used JPRs along with their priority functions and reference are shown in Table 1.

Table 1: JPRs and their priority functions

JPRs	**Symbol**	**Priority Function**	**Reference**
First Come, First Served	FCFS	$min\ (T_{ij})$	[14], [17]
Last Come, First Served	LCFS	$max\ (T_{ij})$	[14]
Shortest Processing Time	SPT	$min\ (PT_{ij})$	[14], [17]
Longest Processing Time	LPT	$max\ (PT_{ij})$	[14], [18]
Earliest Due Date	EDD	$min\ (DD_j)$	[18], [19]
First at shop, first out	FASFO	$min\ (AT_j)$	[20]
Least Slack Time	LST	$min\ (DD_j - t - RT_j)$	[19], [20]
Minimum Critical Ratio	MCR	$min\ ((DD_j - t)/RT_j)$	[19]
Maximum Balanced processing time	MBPT	$max\ (RT_j)$	[14], [21]
Least Balanced processing time	LBPT	$min\ (RT_j)$	[14], [19], [20]
Most Number of Operations Remaining	MNOR	$max\ (NR_j)$	[20]
Least Number of Operations Remaining	LNOR	$min\ (NR_j)$	[19], [20]

Greatest Total Work	GTW	$max\ (TT_j)$	[14]
Lowest Total Work	LTW	$min\ (TT_j)$	[14], [17], [19]
Modified due date	MDD	$min\ (DD_j - t)$	[19], [22]
Least processing time on Next machine	LPTNM	$min\ (PT_{(i+1)j})$	[23], [24]
Maximum processing time on Next machine	MPTNM	$max\ (PT_{(i+1)j})$	[23], [24]
Processing time and due date total	PDT	$min\ (PT_{ij}+DD_j)$	[25]

2.2. Scheduling performance measures (SPMs)

In a manufacturing system, scheduling performance measures (SPMs) are the attributes used to estimate the performance of a schedule. There are a number of different SPMs which can be used to evaluate the performance of a schedule. However, their consideration may vary depending upon the requirements of a specific industry. The frequently found SPMs are described as follows:

1. Makespan time (MT): It is the amount of time required to complete a set of jobs. It is desirable to schedule the parts in such a way that MT is the minimum. Considering to as the time at which first part enters into the system and tf as the time at which last part exits from the system, MT is defined by Eqn. (1).

$$MT = t_f - t_o \tag{1}$$

2. Average waiting time in the queue (AW): AW is the average waiting time spent by parts on a machine to get processed. Considering a system with m machines designated as MCi (i=1,2, ..., m) processing n parts labelled as Pj (j=1,2, ..., n). If Wji denotes the waiting time of part j on machine i, the Average waiting time in the queue (AW) on machine i is computed according to Eqn. (2).

$$AW_i = \sum_{j=1}^{n} W_{ji} \tag{2}$$

3. Machine utilization (MU): It refers to the extent to which the productive capacity of a machine is utilized. Mathematically, it is the ratio of the time a machine is working to the total time it is available for processing as given by Eqn. (3).

$$MU_i = \frac{Time\ the\ machine\ 'i'is\ working}{Total\ time\ the\ machine\ 'i'is\ available} \times 100 \tag{3}$$

4. Average lateness (AL): It is the difference between the completion time and the due date of a part. Since, each part has different completion time and may have different due date, the average of the lateness of all the parts is used to measure performance of the system. If DDj and Cj denote the due date and completion time of a part j respectively, then AL is given by Eqn. (4)

$$AL = \sum_{j=1}^{n} \left(DD_j - C_j\right) \tag{4}$$

5. Number of late parts (NL): Any part completed after its due date is regarded as late. An appropriate schedule is the one which does not result in any late part. Hence, total number of late parts is considered as a SPM and it should be minimized.

2.3. Simulation modelling

A simulation model is a replicate of a real process or system in a virtual space. It has gained importance in the past few years due to its exceptional ability to quantify and observe behavior of complex systems under different scenarios. It helps to examine how an existing system or process might perform if some or all the parameters are altered. In manufacturing environment, it is extensively used to study and compare performance of the system under different designs. Inventory management, scheduling, investigation of different control strategies, are some of the most common issues addressed by simulation modeling.

Simulation modeling finds a wide range application and consequently, several studies based on it have been conducted by researchers for examining and improving performance of the FMSs. For example, Chawla et al., (2018) performed a simulation based investigation to determine optimal utilization of the AGVs [26]. Amoako-Gyampah & Meredith, (1996) conducted a simulation based study and suggested different heuristics for tool allocations in FMS [27]. Mahmood et al., (2017) examined the performance of FMS with the help of modeling and simulation [28]. Hussain & Ali, (2019) examined the impact of control and design factors on different SPMs specifically AW, MU and MT with the help of simulation modeling [29]. A comprehensive review on FMS modeling reported that simulation modeling has been used by different authors to solve problems associated with FMSs [2]. Further, software-based simulation modeling has gained popularity over other methods due to its simplicity. Few examples of prominent software preferred for modeling of FMSs are WITNESS, ARENA, ProModel etc.

2.4. MCDM methods

MCDM methods are techniques that are used to solve decision making problems involving several conflicting attributes/criteria. Over the years, a large number of MCDM methods have been developed and employed to solve decision making problems pertaining to different knowledge domain. Among the several MCDM methods, TOPSIS is the most widely used [30] and MARCOS [31], PIV [32], MABAC [33] and EDAS [34] are recently developed methods. Therefore, these MCDM methods have been included in the proposed framework. The computational steps of these methods are discussed in the following subsections.

Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS) method

MARCOS is a recently developed MCDM method which can be used to rank alternatives [31]. In this method, rank of the alternatives is determined on the basis of their utility function value which is a connection between reference values and alternatives [35], [36]. The computational steps of this method are discussed as follows [31], [35]:

Step 1: Formulate decision matrix D = [aij]m×n , where the element aij represents the value of jth decision attributes for ith alternative and total number of decision attributes and alternatives varies from 1 to m and 1 to n respectively.

Step 2: Insert non-ideal NI = [aNj]1×n and ideal PI = [aPj]1×n alternative at the top and bottom of D to develop extended decision matrix (E). The values aPj and aNj for beneficial and non beneficial attributes are computed using Eqn. (5) and Eqn. (6) respectively.

$$a_{Pj} = \max_i (a_{ij}), \qquad a_{Nj} = \min_i (a_{ij}) \quad (5)$$

$$a_{Pj} = \min_i (a_{ij}), \qquad a_{Nj} = \max_i (a_{ij}) \quad (6)$$

Step 3: Develop normalized decision matrix N = [sij](m+2)×n where, sij = aij/aPj for beneficial attribute and sij = aPj/aij for non beneficial attribute.

Step 4: Determine weighted normalized matrix W = [vij](m+2)×n. If wj is the weight assigned to attribute j, then vij = sij×wj.

Step 5: Compute positive utility degree $PU_i = \sum_{j=1}^{n} v_{ij} / \sum_{j=1}^{n} v_{Pj}$ and negative utility degree $NU_i = \sum_{j=1}^{n} v_{ij} / \sum_{j=1}^{n} v_{Nj}$ of the alternatives.

Step 6: Determine the utility function (Ui) value of the alternatives using Eqn. (7).

$$U_i = \frac{PU_i + NU_i}{1 + \frac{1 - f(PU_i)}{f(PU_i)} + \frac{1 - f(NU_i)}{f(NU_i)}} \quad (7)$$

where, $f(PU_i) = \frac{PU_i}{PU_i + NU_i}$ and $f(NU_i) = \frac{NU_i}{PU_i + NU_i}$.

Step 7: Rank the alternatives on the basis of their Ui value. Higher the Ui value higher is the rank and vice-versa.

Proximity Index Value (PIV) method

PIV method was developed in 2018 to prioritize different alternatives [32]. This method is popular among researchers due to its advantage of minimizing the rank reversal problem in situations when either more alternatives are added or a few are removed from the existing list of alternatives, as compared to other MCDM methods specifically, TOPSIS [37], [38]. This method comprises of the following steps [32], [38]:

Step 1: Formulate decision matrix as discussed in step 1 of MARCOS method.

Step 2: Develop normalized decision matrix N = [sij]m×n

where, $s_{ij} = \frac{a_{ij}}{\sqrt{\sum_i a_{ij}}}$.

Step 3: Determine weighted normalized matrix W = [vij]m×n. If wj is the weight assigned to attribute j, then vij = sij×wj.

Step 4: Compute proximity value ($PV_i = \sum_{j=1}^{n} u_i$) of each alternative, where ui values are determined using Eqn. (8).

$$u_i = \begin{Bmatrix} \max_i (v_{ij}) - v_{ij} ; & if\ j \in ben \\ v_{ij} - \min_i (v_{ij}) ; & if\ j \in non \end{Bmatrix} \quad (8)$$

Step 5: Rank the alternatives on the basis of their ui value. A lower ui value corresponds to higher rank and vice-versa.

Multi-Attribute Border Approximation area Comparison (MABAC) method

MABAC method, developed in 2015, has been effectively used to solve problems pertaining to different knowledge domain [33], [39], [40]. In this method, rank to the alternatives is assigned on the basis of their distance from the border approximation area (BAO). An alternative having highest distance from the BAO is ranked first and rank of other alternatives decreases as their distance from BAO decreases. The computational steps of this method are as under [33], [41]:

Step 1: Formulate decision matrix as discussed in step 1 of MARCOS method.

Step 2: Develop normalized decision matrix N = [sij]m×n where, sij is computed using Eqn. (9).

$$s_{ij} = \begin{Bmatrix} \frac{a_{ij} - \min_i (a_{ij})}{\max_i (a_{ij}) - \min_i (a_{ij})} ; & if\ j \in bene \\ \frac{\max_i (a_{ij}) - a_{ij}}{\max_i (a_{ij}) - \min_i (a_{ij})} ; & if\ j \in non\ b \end{Bmatrix} \quad (9)$$

Step 3: Determine weighted normalized matrix W = [vij]m×n. If wj is the weight assigned to attribute j, then vij = (sij+1)×wj.

Step 4: Determine the border approximation area matrix G = [gj]1×n where, $g_j = \left(\prod_{i=1}^{m} s_{ij}\right)^{1/m}$

Step 5: Compute total distance of each alternative from the border approximation area $S_i = \sum_{j=1}^{n} q_{ij}$ where, qij = vij – gj

Step 6: Rank the alternatives based on their Si value. An alternative with the maximum Si value gets rank 1 and rank decreases as Si value decreases.

Evaluation based on Distance from Average Solution (EDAS)

EDAS, developed in 2015, is a compensatory method in which the distance of an alternative from the optimal value is used to identify the best alternative [34]. This method has been used to solve air traffic problem [42], personnel selection problem [43], and evaluation of airlines services [44]. The computational steps involved in this method are as follows [34], [44]:

Step 1: Formulate decision matrix as discussed in step 1 of MARCOS method.

Step 2: Compute average solution (AV) corresponding to each attribute AV = [rj]1×n where, $r_j = \frac{1}{n}\left(\sum_{i=1}^{m} a_{ij}\right)$

Step 3: Determine positive (PD) and negative (ND) distances from the average solution as defined by Eqn. (10) and Eqn. (11) respectively.

$$PD_{ij} = \begin{Bmatrix} \dfrac{\max(0, a_{ij} - r_j)}{r_j} & if\ j \in ben \\ \dfrac{\max(0, r_j - a_{ij})}{r_j} & if\ j \in non\ ben \end{Bmatrix} \quad (10)$$

$$ND_{ij} = \begin{Bmatrix} \dfrac{max\ (0, r_j - a_{ij})}{r_j} & if\ j \in benef \\ \dfrac{max\ (0, a_{ij} - r_j)}{r_j} & if\ j \in non\ ben \end{Bmatrix} \quad (11)$$

Step 4: Compute weighted positive distance $WPD_i = \sum_{j=1}^{n}\left(PD_{ij} \times w_j\right)$ and $WND_i = \sum_{j=1}^{n}\left(ND_{ij} \times w_j\right)$ of each alternative. Where, wj is the weight assigned to attribute j.

Step 5: Determine appraisal score (A) using Eqn. (12).

$$A_i = \frac{PN_i + NN_i}{2} \quad (12)$$

where, $PN_i = \frac{WPD_i}{\max_i (WPD_i)}$ and $NN_i = \frac{WND_i}{\max_i (WND_i)}$.

Step 6: Rank the alternatives on the basis of their Ai value. Rank 1 is given to the alternative having maximum Ai value and the rank decreases with decreasing Ai value.

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is the most widely used MCDM method for solving varieties of decision problems belonging to different knowledge domain [45]. This method prioritizes the alternatives on the basis of their distance from positive and negative ideal alternatives. It suggests that an alternative closest to positive ideal alternative and farthest from negative ideal alternative should be ranked first [46]. The steps involved in finding the distances from positive and negative ideal alternatives and thus organizing them as per their performances are as follows [45]–[47]:

Step 1: Formulate decision matrix as discussed in step 1 of MARCOS method.

Step 2: Develop normalized decision matrix N = [sij]m×n where, $s_{ij} = \frac{a_{ij}}{\sqrt{\sum_i a_{ij}}}$.

Step 3: Determine weighted normalized matrix W = [vij]m×n. If wj is the weight assigned to attribute j, vij = sij×wj.

Step 4: Discover the positive PI = [aPj]1×n and negative NI = [aNj]1×n ideal alternatives. Elements aPj and aNj are determined using Eqn. (13) and Eqn. (14) respectively

$$a_{Pj} = \begin{Bmatrix} \max_i (a_{ij}) & if\ j \in benef \\ \min_i (a_{ij}) & if\ j \in non-\ bene \end{Bmatrix} \quad (13)$$

$$a_{Nj} = \begin{Bmatrix} \min_i (a_{ij}) & if\ j \in benef \\ \max_i (a_{ij}) & if\ j \in non-\ benef \end{Bmatrix} \quad (14)$$

Step 5: Compute positive distance $PD_i = \sqrt{\sum_{j=1}^{n}\left(a_{Pj} - a_{ij}\right)^2}$ and negative distance $ND_i = \sqrt{\sum_{j=1}^{n}\left(a_{Nj} - a_{ij}\right)^2}$ of alternatives from the ideal alternative.

Step 6: Compute relative closeness of alternative, $RC_i = \frac{ND_i}{PD_i + ND_i}$.

Step 7: Rank the alternatives based on their RCi value. A higher RCi value corresponds to higher rank and vice-versa..

2.5. Method to determine final rank of the alternatives

It has been observed that the computational steps involved in different MCDM methods are different. Hence, it is much likely that rank of the alternatives produced by different MCDM methods may be different. Therefore, membership degree method developed by Yang et al., (2019) is used to determine final rank of the alternatives. Steps of this method are given below (Yang et al., 2019; Wakeel et al., 2020):

Step 1: Arrange alternatives in rows and their rank in columns resulting in the formulation of rank frequency matrix (R) as given by Eqn. (15). Each element c_{pq} of R denotes the frequency of rank q for alternative p over n different MCDM methods.

$$R = \begin{bmatrix} c_{11} & \cdots & c_{1q} \\ \cdots & \cdots & \cdots \\ c_{p1} & \cdots & c_{pq} \end{bmatrix} \quad (15)$$

where, p and q vary from 1 to m and m denotes total number of alternatives.

Step 2: Formulate membership degree matrix (MD) by dividing each element of R by total number of MCDM methods i.e. n as shown in Eqn. (16)

$$MD = \begin{bmatrix} l_{11} & \dots & l_{1q} \\ \dots & \dots & \dots \\ l_{p1} & \dots & l_{pq} \end{bmatrix} \quad (16)$$

where, $l_{pq} = \frac{c_{pq}}{n}$

Step 3: Determine rank index (RIp) using Eqn. (17).

$$RI_p = \sum_{q=1}^{N} (l_{pq}) \times q \quad (17)$$

Step 4: The rank index is used to determine final rank of the alternatives. An alternative with the minimum RIp value is ranked first and lower rank is assigned to the alternatives with higher RIp values.

3 Proposed research framework

The jobs received at a workstation undergo a wide range of operations. When job traffic is high, the sequence of job processing becomes very important due to high cost of waiting jobs and the cost of idle workstations. Inefficient scheduling results in the formation of job queues. This situation puts pressure on the managers to develop schedules which handle the job traffic effectively and efficiently. A number of JPRs have been laid for prioritizing the jobs at different workstations. As soon as a workstation finishes a task, the job priority rule decides the succeeding job that enters the workstation. Determining which JPR best suits a particular system is a difficult task as none of the suitable choices give any clear indication on managing a system in the best possible way. Thus, management should select the best option using a systematic approach. The approach must consider multiple contributing factors in order to get a deeper insight into the system and make better decisions. Multi Criteria Decision Making (MCDM) methods can accomplish the above said requirements. MCDM techniques can assist managers and decision-makers in making informed decisions by solving problems involving multiple criteria. This work proposes a simulation-based decision-making framework to select best JPR using MCDM methods. The step-by-step procedure for the proposed research framework is discussed as follows:

1. Identify the potential JPRs used in FMS and SPMs used to examine the performance of the concerned industry.
2. Develop the simulation model of the FMS using appropriate software such as ARENA, WITNESS etc. It is to be noted that while developing the simulation model the modules and corresponding attributes should be provided to collect SPM.
3. After developing the simulation model, collect the SPM values corresponding to each JPR.
4. Arrange JPRs and SPM in rows and columns respectively to formulate decision matrix to be used by the MCDM methods i.e. MARCOS, PIV, MABAC, EDAS and TOPSIS methods to rank the potential JPRs.
5. Determine the final rank of JPRs by comparing the ranking results of different MCDM methods using membership degree method.

The proposed research framework comprising of the above steps is shown in Figure 1.

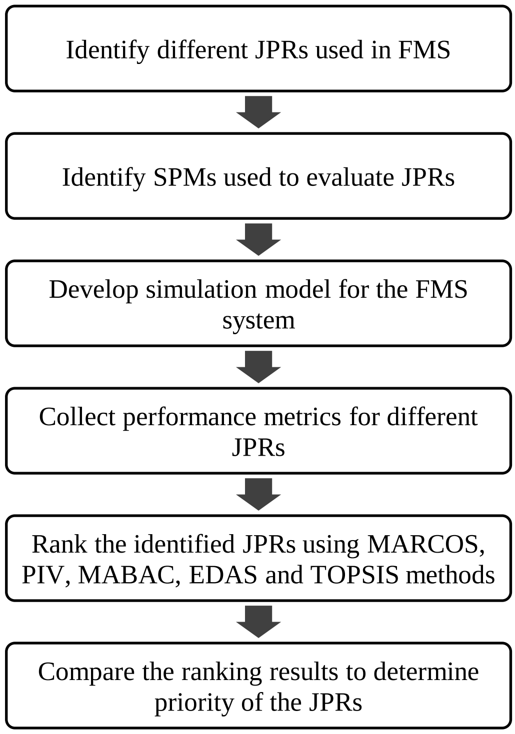

Figure 1: Proposed research framework.

4 Illustrative example

To demonstrate the potential application of the proposed research framework, it has been employed to select the best JPR for an FMS taken from literature [49]. The FMS consisted of five CNC machines named as FMC1, FMC2, FMC3, FMC4, and FMC5 for processing five different part types A2021, B2021, C2021, D2021, and E2021. All five machines had infinite input buffer capacity and three to four operations were essentially required for complete processing of a specific job type. The processing time of various parts was stochastic.

Since inter-arrival time and due date of jobs were not known for the FMS, they were determined using Eqn. (18) [50] and Eqn. (19) [10], [50] respectively.

$$\nu = \frac{1}{\lambda} = \frac{\mu_p \mu_g}{\eta \omega} \quad (18)$$

$$DD_i = A_i + K \times TT_j \quad (19)$$

where, v and λ are mean inter-arrival and job arrival time respectively, μ_p and μ_g are the mean processing time and number of operations per job respectively, η and ω are the utilization and number of machines in the shop floor respectively. Ai is the arrival time of job i, TTj is the total time required to perform of all operations on part j and K is the tightness factor which reflects the amount of expected delay a job will experience and it is taken as 3 in this study.

Further, simulation model for the FMS configuration shown in Table 2 was developed using the student's version of ARENA 16.0 simulation software. While developing the model, following assumptions were made:

(i) Part transfer, loading and unloading times were all included in the processing time,

(ii) No rework was allowed,

(iii) No order cancellation was allowed,

(iv) Machines never broke down, and

(v) Pre-emption was not allowed.

Since, the maximum number of parts that can be created in students' version of ARENA is limited to 150, the number of parts for part types A2021, B2021, C2021, D2021 and E2021 was considered as 45, 27, 27, 23 and 16 respectively. Initially, Create module was used to create 5 different parts with inter arrival time computed using Eqn. (18). Further, each part progressed to the Assign module where parameters such as arrival time, processing time, due date, number of operations, and sequence of operations were assigned. In accordance with the sequence of operations, each part was moved to its corresponding machine station. Before slotting a part in the machine for operation, it was passed through Assign Attribute module where parameters such as remaining processing time, remaining number of operations etc. were modified. Subsequently, the parts were processed according to the predefined JPR. The parts were further moved forward to the next corresponding station after passing through another Assign Attribute module. As soon as all the operations were completed on a part, it was moved to the Dispose station where it was checked whether the part was late or not. If the part was late, lateness was stored using the Record module. Finally, if the part under examination was the last part of the system, the current simulation time was collected to measure the make span time. The logic module for the simulation model so developed is shown in Figure A1 of Appendix.

For each of the twenty JPRs defined in section 2.1.1, the simulation model was run to collect the performance values for the five SPM. It needs to be mentioned here that 30 replications of each simulation run were performed and the results of the five SPM for each of the JPRs were collected which are shown in Table A1 of Appendix.

It is observed that MT is minimum (2794.59 minutes) when jobs are processed according to the LBPT rule. Whereas, number of late jobs and average lateness are minimum (75.033 and 664.17 minutes) when SPT and EDD rule are used respectively. Further, mean of AW for all machines is minimum (192.30 minutes) for SPT rule and average MU is maximum (63.73 %) for LTW rule as evident from Table 2.

Table 2: Mean AW and MU

JPR	**Mean AW (min)**	**Mean MU (%)**
FCFS	256.78	63.47
LCFS	273.09	63.18
SPT	192.30	62.75
LPT	303.41	62.28
EDD	204.37	63.55
FASFO	203.95	63.30
LST	226.11	63.48
MCR	241.53	63.21
MBPT	272.26	63.53
LBPT	228.62	63.70
MNOR	307.75	63.62
LNOR	270.21	63.25
GTW	268.88	63.00
LTW	210.37	63.73
MDD	216.02	63.35
LPTNM	380.75	60.03
MPTNM	250.10	63.02

Thus, based on the results, it is observed that no single JPR provides optimum results for all the SPMs. Hence, MCDM methods were used to find the best JPR that produced the optimal results for all SPMs. Considering Table A1 as the decision matrix, five MCDM methods were employed to determine rank of the JPRs. Equal weight was assigned to the SPMs as they were considered to be equally important. The performance value and corresponding rank of the JPRs derived from different MCDM methods used in this study is shown in Table A2 of the Appendix.

It is found that LTW is ranked first by three MCDM methods i.e. MARCOS, MABAC, and EDAS. However, it ranked second and sixth by PIV and TOPSIS methods. Whereas, PDT and MDD is ranked first by PIV and TOPSIS methods respectively. Thus, it is difficult to suggests which among the considered JPR is should be used as none among them is ranked first by all the methods. Therefore, membership degree method was employed to determine the rank index and final rank of the JPRs which are shown in Table 3.

Table 3: Rank index and final ranks of the JPRs

JPR	**Rank Index, RI_p**	**Final Rank**
FCFS	9.6	9
LCFS	11.6	11
SPT	6.8	8
LPT	15.2	16
EDD	3.8	3
FASFO	5.8	6
LST	6.4	7
MCR	13.2	13
MBPT	16	17
LBPT	4.2	4
MNOR	14	14
LNOR	9.6	10
GTW	15	15
LTW	2.2	1
MDD	4.6	5
LPTNM	17.6	18
MPTNM	12.8	12

It is evident from Table 3 that among the considered JPRs, LTW is the top ranked rule and therefore, it is the best one for producing optimum performance of the five SPMs. Further, the next preferred rule is PDT followed by EDD, LBPT, MDD, FASFO, LST, SPT, FCFS, LNOR, LCFS, MPTNM, MCR, MNOR, GTW, LPT, MBPT and LPTNM. Hamidi (2016) proposed the PDT rule to utilize benefits of both SPT and EDD rules and showed that this is an effective and promising rule as compared to FCFS, SPT, EDD, MCR and LST rules [25]. Similar results have been obtained in this study where SPT is found better than other rules except LTW.

5 Conclusion

Flexible manufacturing systems (FMSs) are preferred over conventional manufacturing systems due to their ability to provide flexibility as well as high throughput at the same time. However, there are various operational problems associated with FMSs which need to be resolved to enhance productivity of these systems. Scheduling is one of the operational problems which have attracted attention of the researchers as it significantly affects performance of the FMS. This work intended to provide an effective decision-making framework to resolve one of the scheduling problems i.e. sequencing of jobs on each machine. Job priority rules (JPRs) are used to determine sequence of the jobs to be processed on a machine. These rules provide precedence to a job over other jobs based on a predefined priority function. Several JPRs have been proposed so far to obtain better results for one or two performance measures. However, it is difficult to judge which rule is the best one to produce optimal values for all the performance measures considered simultaneously. The current era of production systems requires better results for more than one performance measures taken together. Hence, selection of an appropriate JPR becomes more difficult as more than one performance measures need to be justified simultaneously. MCDM methods are one of the most powerful decision-making methods used to select the best alternative from among the existing ones on the basis of multiple attributes. Hence, the decision-making framework proposed in this work was based on selection of JPR using MCDM methods combined with simulation modeling. In the proposed framework, initially the potential JPRs and scheduling performance measures (SPM) for the concerned industry were identified. Further, a simulation model of the FMS was developed to collect the performance value for the various SPMs for different JPRs. The SPMs values corresponding to JPRs acted as a decision matrix for MCDM methods. Five MCDM methods were employed to rank the JPRs which produced their different ranks and therefore, it was difficult to decide which JPR is the best one. Consequently, the ranks obtained from different MCDM methods were compared to determine the final rank of the JPRs using membership degree method. The proposed framework was implemented to select the best JPR for a specific FMS taken from the literature. It has been found that for the considered FMS system, LTW rule provides optimum results for the five SPMs.

The proposed framework can be used by the FMS based industries to solve problem related to selection of the best JPR so as to obtain optimum values of their specific SPMs. It needs to be mentioned here that industries may not necessarily employ the same MCDM methods that have been used in the present study to determine rank of JPRs, instead other MCDM methods can also be used. However, steps of the proposed framework listed in the paper are essentially required to be followed for selection of the best JPR leading to the optimal performance of the system.

References

[1] R. El-Khalil and Z. Darwish, “Flexible manufacturing systems performance in U.S. automotive manufacturing plants: a case study,” *Production Planning & Control*, vol. 30, no. 1, pp. 48–59, Jan. 2019, doi: 10.1080/09537287.2018.1520318.

[2] A. Yadav and S. C. Jayswal, “Modelling of flexible manufacturing system: a review,” *International Journal of Production Research*, vol. 56, no. 7, pp. 2464–2487, Apr. 2018, doi: 10.1080/00207543.2017.1387302.

[3] D.-K. Lee, J.-H. Shin, and D.-H. Lee, “Operations scheduling for an advanced flexible manufacturing system with multi-fixturing pallets,” *Computers & Industrial Engineering*, vol. 144, p. 106496, Jun. 2020, doi: 10.1016/j.cie.2020.106496.

[4] H. Tempelmeier and H. Kuhn, *Flexible manufacturing systems: decision support for design and operation*, vol. 12. John Wiley & Sons, 1993.

[5] K. E. Stecke, “Design, planning, scheduling, and control problems of flexible manufacturing systems,” *Ann Oper Res*, vol. 3, no. 1, pp. 1–12, Jan. 1985, doi: 10.1007/BF02023765.

[6] A. Prakash, F. T. S. Chan, and S. G. Deshmukh, “FMS scheduling with knowledge based genetic algorithm approach,” *Expert Systems with Applications*, vol. 38, no. 4, pp. 3161–3171, Apr. 2011, doi: 10.1016/j.eswa.2010.09.002.

[7] C. Low, Y. Yip, and T.-H. Wu, “Modelling and heuristics of FMS scheduling with multiple objectives,” *Computers & Operations Research*, vol. 33, no. 3, pp. 674–694, Mar. 2006, doi: 10.1016/j.cor.2004.07.013.

[8] P. Sharma and A. Jain, “Effect of routing flexibility and sequencing rules on performance of stochastic flexible job shop manufacturing system with setup times: Simulation approach,” *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 231, no. 2, pp. 329–345, Jan. 2017, doi: 10.1177/0954405415576060.

[9] M. S. Jayamohan and C. Rajendran, “New dispatching rules for shop scheduling: A step forward,” *International Journal of Production Research*, vol. 38, no. 3, pp. 563–586, Feb. 2000, doi: 10.1080/002075400189301.

[10] O. Holthaus and C. Rajendran, "New dispatching rules for scheduling in a job shop — An experimental study," *Int J Adv Manuf Technol*, vol. 13, no. 2, pp. 148–153, Feb. 1997, doi: 10.1007/BF01225761.

[11] C. Blum and M. Sampels, "An Ant Colony Optimization Algorithm for Shop Scheduling Problems," *Journal of Mathematical Modelling and Algorithms*, vol. 3, no. 3, pp. 285–308, Sep. 2004, doi: 10.1023/B:JMMA.0000038614.39977.6f.

[12] M. K. Marichelvam, M. Geetha, and Ö. Tosun, "An improved particle swarm optimization algorithm to solve hybrid flowshop scheduling problems with the effect of human factors – A case study," *Computers & Operations Research*, vol. 114, p. 104812, Feb. 2020, doi: 10.1016/j.cor.2019.104812.

[13] F. T. S. Chan, H. K. Chan, H. C. W. Lau, and R. W. L. Ip, "Analysis of dynamic dispatching rules for a flexible manufacturing system," *Journal of Materials Processing Technology*, vol. 138, no. 1, pp. 325–331, Jul. 2003, doi: 10.1016/S0924-0136(03)00093-1.

[14] P. D. D. Dominic, S. Kaliyamoorthy, and M. S. Kumar, "Efficient dispatching rules for dynamic job shop scheduling," *Int J Adv Manuf Technol*, vol. 24, no. 1, pp. 70–75, Jul. 2004, doi: 10.1007/s00170-002-1534-5.

[15] M.Krishnan, T. R. Chinnusamy, and T. Karthikeyan, "Performance Study of Flexible Manufacturing System Scheduling Using Dispatching Rules in Dynamic Environment," *Procedia Engineering*, vol. 38, pp. 2793–2798, Jan. 2012, doi: 10.1016/j.proeng.2012.06.327.

[16] G.-H. Tzeng and J.-J. Huang, *Multiple Attribute Decision Making: Methods and Applications*. CRC Press, 2011.

[17] M. Thürer, M. Stevenson, and T. Qu, "Job sequencing and selection within workload control order release: an assessment by simulation," *International Journal of Production Research*, vol. 54, no. 4, pp. 1061–1075, Feb. 2016, doi: 10.1080/00207543.2015.1047978.

[18] M. Z. Baharom, W. Nazdah, and W. Hussin, "Scheduling Analysis for Job Sequencing in Veneer Lamination Line," *Journal of Industrial and Intelligent Information*, vol. 3, no. 3, 2015.

[19] H.-H. Doh, J.-M. Yu, J.-S. Kim, D.-H. Lee, and S.-H. Nam, "A priority scheduling approach for flexible job shops with multiple process plans," *International Journal of Production Research*, vol. 51, no. 12, pp. 3748–3764, Jun. 2013, doi: 10.1080/00207543.2013.765074.

[20] M. Montazeri and L. N. Van Wassenhove, "Analysis of scheduling rules for an FMS," *The International Journal of Production Research*, vol. 28, no. 4, pp. 785–802, 1990.

[21] S. Wadhwa, Y. Ducq, M. Ali, and A. Prakash, "Performance analysis of a flexible manufacturing system," *Global Journal of Flexible Systems Management*, vol. 10, no. 3, pp. 23–34, 2009.

[22] V. Vinod and R. Sridharan, "Dynamic job-shop scheduling with sequence-dependent setup times: simulation modeling and analysis," *Int J Adv Manuf Technol*, vol. 36, no. 3, pp. 355–372, Mar. 2008, doi: 10.1007/s00170-006-0836-4.

[23] R. Haupt, "A survey of priority rule-based scheduling," *Operations-Research-Spektrum*, vol. 11, no. 1, pp. 3–16, 1989.

[24] S. S. Panwalkar and W. Iskander, "A Survey of Scheduling Rules," *Operations Research*, vol. 25, no. 1, pp. 45–61, Feb. 1977, doi: 10.1287/opre.25.1.45.

[25] M. Hamidi, "Two new sequencing rules for the non-preemptive single machine scheduling problem," *The Journal of Business Inquiry*, vol. 15, no. 2, pp. 116–127, 2016.

[26] V. K. Chawla, A. K. Chanda, S. Angra, and S. Rani, "Simultaneous Dispatching and Scheduling of Multi-Load AGVs in FMS-A Simulation Study," *Materials Today: Proceedings*, vol. 5, no. 11, Part 3, pp. 25358–25367, Jan. 2018, doi: 10.1016/j.matpr.2018.10.339.

[27] K. Amoako-Gyampah and J. R. Meredith, "A simulation study of FMS tool allocation procedures," *Journal of Manufacturing Systems*, vol. 15, no. 6, pp. 419–431, Jan. 1996, doi: 10.1016/S0278-6125(97)83055-5.

[28] K. Mahmood, T. Karaulova, T. Otto, and E. Shevtshenko, "Performance Analysis of a Flexible Manufacturing System (FMS)," *Procedia CIRP*, vol. 63, pp. 424–429, Jan. 2017, doi: 10.1016/j.procir.2017.03.123.

[29] Mohd. S. Hussain and M. Ali, "A Multi-agent Based Dynamic Scheduling of Flexible Manufacturing Systems," *Glob J Flex Syst Manag*, vol. 20, no. 3, pp. 267–290, Sep. 2019, doi: 10.1007/s40171-019-00214-9.

[30] S. K. Yadav, D. Joseph, and N. Jigeesh, "A review on industrial applications of TOPSIS approach," *International Journal of Services and Operations Management*, vol. 30, no. 1, pp. 23–28, Jan. 2018, doi: 10.1504/IJSOM.2018.091438.

[31] Ž. Stević, D. Pamučar, A. Puška, and P. Chatterjee, "Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS)," *Computers & Industrial Engineering*, vol. 140, p. 106231, Feb. 2020, doi: 10.1016/j.cie.2019.106231.

[32] S. Mufazzal and S. M. Muzakkir, "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, May 2018, doi: 10.1016/j.cie.2018.03.045.

[33] D. Pamučar and G. Ćirović, "The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC)," *Expert Systems with Applications*, vol. 42, no. 6, pp. 3016–3028, Apr. 2015, doi: 10.1016/j.eswa.2014.11.057.

[34] M. Keshavarz Ghorabaee, E. K. Zavadskas, L. Olfat, and Z. Turskis, “Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS),” *Informatica*, vol. 26, no. 3, pp. 435–451, 2015.

[35] Ž. Stević and N. Brković, “A Novel Integrated FUCOM-MARCOS Model for Evaluation of Human Resources in a Transport Company,” *Logistics*, vol. 4, no. 1, Art. no. 1, Mar. 2020, doi: 10.3390/logistics4010004.

[36] A. Ulutaş, D. Karabasevic, G. Popovic, D. Stanujkic, P. T. Nguyen, and Ç. Karaköy, “Development of a Novel Integrated CCSD-ITARA-MARCOS Decision-Making Approach for Stackers Selection in a Logistics System,” *Mathematics*, vol. 8, no. 10, Art. no. 10, Oct. 2020, doi: 10.3390/math8101672.

[37] N. Z. Khan, T. S. A. Ansari, A. N. Siddiquee, and Z. A. Khan, “Selection of E-learning websites using a novel Proximity Indexed Value (PIV) MCDM method,” *J. Comput. Educ.*, vol. 6, no. 2, pp. 241–256, Jun. 2019, doi: 10.1007/s40692-019-00135-7.

[38] S. Wakeel, S. Bingol, M. N. Bashir, and S. Ahmad, “Selection of sustainable material for the manufacturing of complex automotive products using a new hybrid Goal Programming Model for Best Worst Method–Proximity Indexed Value method,” *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications*, p. 1464420720966347, Oct. 2020, doi: 10.1177/1464420720966347.

[39] D. Pamučar, Ž. Stević, and E. K. Zavadskas, “Integration of interval rough AHP and interval rough MABAC methods for evaluating university web pages,” *Applied Soft Computing*, vol. 67, pp. 141–163, 2018.

[40] D. I. Božanić, D. S. Pamučar, and S. M. Karović, “Application the MABAC method in support of decision-making on the use of force in a defensive operation,” *Tehnika*, vol. 71, no. 1, pp. 129–136, 2016.

[41] D. Bozanic, D. Tešić, and J. Kočić, “Multi-criteria FUCOM – Fuzzy MABAC model for the selection of location for construction of single-span bailey bridge,” *Decision Making: Applications in Management and Engineering*, vol. 2, no. 1, Art. no. 1, Mar. 2019.

[42] M. Keshavarz Ghorabaee, M. Amiri, E. K. Zavadskas, Z. Turskis, and J. Antucheviciene, “Stochastic EDAS method for multi-criteria decision-making with normally distributed data,” *Journal of Intelligent & Fuzzy Systems*, vol. 33, no. 3, pp. 1627–1638, Jan. 2017, doi: 10.3233/JIFS-17184.

[43] M. K. Kikomba, R. M. Mabela, and D. I. Ntantu, “Applying EDAS method to solve air traffic problems,” *International Journal of Scientific and Innovative Mathematical Research (IJSIMR)*, vol. 4, no. 8, pp. 15–23, 2016.

[44] D. Stanujkic, G. Popovic, and M. Brzakovic, “An approach to personnel selection in the IT industry based on the EDAS method,” *Transformations in Business & Economics*, vol. 17, no. 2, p. 44, 2018.

[45] M. Behzadian, S. Khanmohammadi Otaghsara, M. Yazdani, and J. Ignatius, “A state-of the-art survey of TOPSIS applications,” *Expert Systems with Applications*, vol. 39, no. 17, pp. 13051–13069, Dec. 2012, doi: 10.1016/j.eswa.2012.05.056.

[46] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications A State-of-the-Art Survey*. Berlin Heidelberg: Springer-Verlag, 1981.

[47] Y.-J. Lai, T.-Y. Liu, and C.-L. Hwang, “TOPSIS for MODM,” *European Journal of Operational Research*, vol. 76, no. 3, pp. 486–500, Aug. 1994, doi: 10.1016/0377-2217(94)90282-8.

[48] W.-C. Yang, S.-H. Chon, C.-M. Choe, and K. Un-Ha, “Materials Selection Method Combined with Different MADM Methods,” *Journal of Artificial Intelligence*, vol. 1, no. 2, p. 89, 2019.

[49] G. A. Chang and W. R. Peterson, “Modeling and analysis of flexible manufacturing systems: a simulation study,” in *Proceedings of the 2015 ASEE Annual Conference & Exposition, Seattle, WA, USA*, 2015, pp. 14–17.

[50] R. Rangsaritratsamee, W. G. Ferrell Jr, and M. B. Kurz, “Dynamic rescheduling that simultaneously considers efficiency and stability,” *Computers & Industrial Engineering*, vol. 46, no. 1, pp. 1–15, 2004.

Appendix

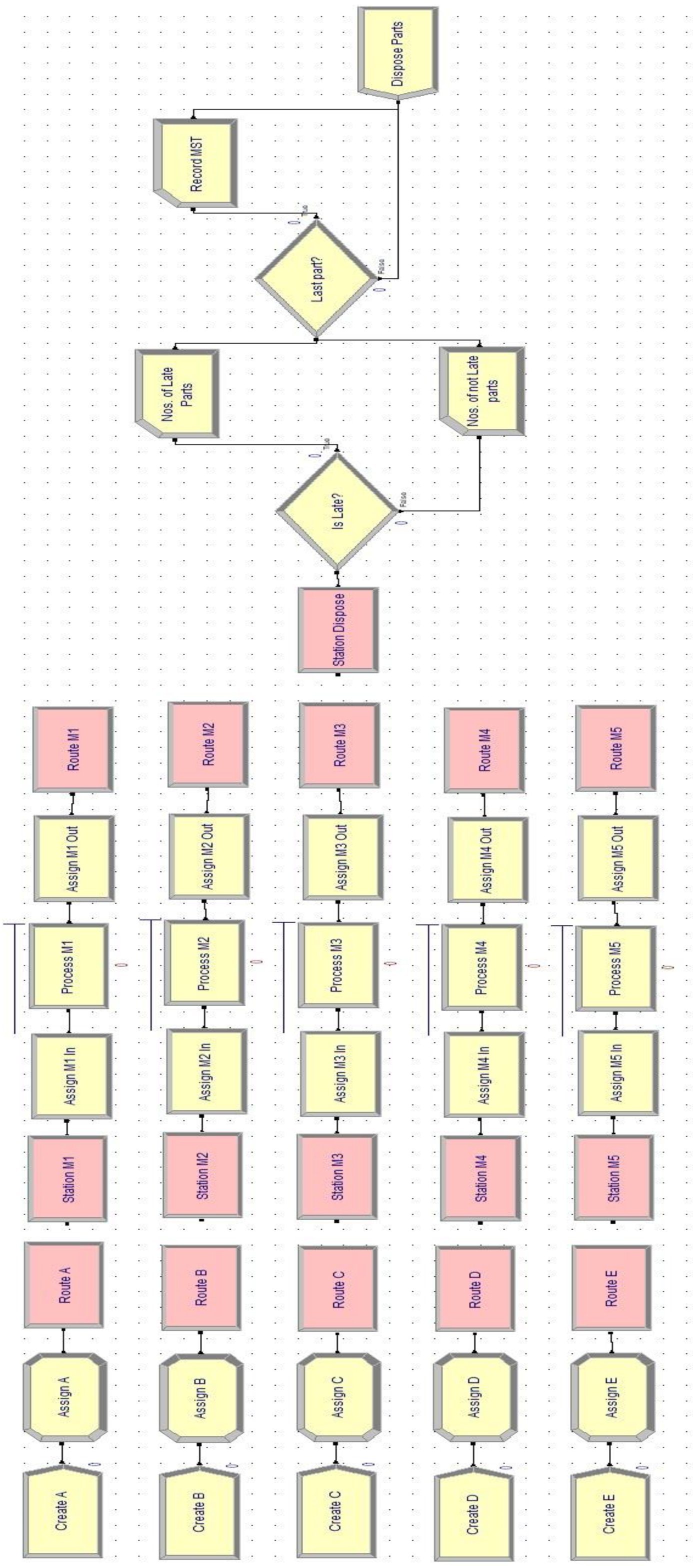

Figure A1: Logic module

Table A1 : Simulation results for SPMs

JPR	MT (min)	Machine Utilization, MU (%)					Average Waiting Time in Queue, AW (min)					Average Lateness (min)	Number of Late Jobs (Nos.)
		FMC5	FMC4	FMC3	FMC2	FMC1	FMC5	FMC4	FMC3	FMC2	FMC1		
FCFS	2837.45	78.62	86.88	99.83	24.6	27.42	199.35	809.98	261.32	8.3953	4.8601	944.94	121.43
LCFS	3050.49	78.58	86.67	99.1	24.36	27.18	158.46	646.99	548.07	8.06	3.883	1630.13	88.133
SPT	2815	78.07	85.81	98.68	24.33	26.88	98.7772	669.79	179.34	4.2176	9.3673	1160.07	75.0333
LPT	3198.25	77.97	85.91	96.44	24.08	26.99	90.2238	554.64	854.89	13.5061	3.7742	1614.5	98.8
EDD	2828.63	79.01	87.09	99.66	24.72	27.29	202.48	512.98	297.58	5.725	3.0891	664.17	115.27
FASFO	2828.17	78.76	86.65	99.41	24.47	27.22	85.7427	587.07	333.54	8.3443	5.0413	750.77	111.23
LST	2937.54	78.88	87.12	99.69	24.55	27.18	141.25	484.55	495.32	5.5276	3.8864	873.77	108.27
MCR	3050.88	78.8	86.6	99.11	24.43	27.12	42.3093	577.36	566.65	12.2729	9.0709	1195.62	98.133
MBPT	2881.25	78.94	86.8	99.99	24.61	27.29	104.33	699.64	534.74	15.8439	6.7646	1849.98	84.5667
LBPT	2794.59	79.39	87.21	99.99	24.54	27.38	233.62	431.28	471.62	4.2936	2.3071	942.12	101.43
MNOR	2908.18	79.1	87.16	99.99	24.53	27.31	126.45	1050.65	345.27	4.0419	12.3513	1748.76	93.7333
LNOR	3070.09	78.56	86.87	99.18	24.45	27.19	280.36	280.54	781.24	6.6853	2.2393	1059.94	115.07
GTW	3184.03	78.5	86.26	98.89	24.34	27.02	27.5716	532.23	760.75	16.4246	7.4244	1840.53	84.4
LTW	2795.86	79.18	87.55	99.99	24.64	27.31	242.76	519.86	281.83	5.4066	1.9688	763.92	108.07
MDD	2918.71	78.7	87.01	99.51	24.55	26.99	165.25	426.85	479.87	5.096	3.0327	813.85	112.1
LPTNM	3018.57	74.63	82.28	94.37	23.03	25.86	466.11	1093.47	336.12	5.7365	2.3219	1396.3	137.4
MPTNM	3089.06	78.41	86.47	98.94	24.29	26.97	99.19	459.92	676.07	9.6503	5.671	1607.35	84.0333
PDT	2832.29	79.08	86.93	99.85	24.76	27.47	208.55	509.68	299.08	4.8158	3.1614	670.79	114.93

Table A2 : Rank of JPRs derived from different MCDM methods

JPR	MARCOS		PIV		MABAC		EDAS		TOPSIS	
	U_i	Rank	u_i	Rank	S_i	Rank	A_i	Rank	RC_i	Rank
FCFS	0.5951	10	0.0649	9	0.0769	9	0.5815	10	0.6305	10
LCFS	0.5777	14	0.0687	11	-0.0036	12	0.5134	12	0.6339	9
SPT	0.6593	4	0.0502	8	0.0792	8	0.8282	6	0.6590	8
LPT	0.5590	17	0.0851	14	-0.1700	17	0.4206	14	0.5726	14
EDD	0.6532	5	0.0419	3	0.1637	4	0.8921	3	0.7291	4
FASFO	0.6193	9	0.0467	6	0.1134	5	0.7989	7	0.7425	2
LST	0.6212	8	0.0471	7	0.1101	6	0.7890	8	0.7365	3
MCR	0.5854	13	0.0769	13	-0.0247	14	0.4857	13	0.5853	13
MBPT	0.5569	18	0.0906	16	-0.0086	13	0.3379	17	0.5277	16
LBPT	0.6612	2	0.0446	5	0.1750	3	0.8561	4	0.6971	7
MNOR	0.5917	12	0.0897	15	0.0031	11	0.4032	15	0.5079	17
LNOR	0.6344	7	0.0665	10	0.0120	10	0.6350	9	0.5934	12
GTW	0.5948	11	0.0924	17	-0.1254	16	0.3858	16	0.5369	15
LTW	0.6749	1	0.0407	2	0.1881	1	0.9238	1	0.7076	6
MDD	0.6398	6	0.0434	4	0.1089	7	0.8455	5	0.7426	1
LPTNM	0.5765	16	0.1027	18	-0.4040	18	0.2867	18	0.4624	18
MPTNM	0.5774	15	0.0707	12	-0.0350	15	0.5401	11	0.6238	11
PDT	0.6605	3	0.0403	1	0.1789	2	0.9140	2	0.7285	5