A new application of multi-criteria decision-making methods for the scheduling of flexible manufacturing systems: A case study

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Abstract. With the growing use of flexible manufacturing systems (FMSs), it became more important to optimize them. Scheduling is one of the critical problems in FMS optimization. This study presents a new application of multi-criterion decision-making (MCDM) methods for scheduling problems of automated guided vehicles (AGVs). Designation of AGVs to job shops is the major concern of this study. The research methodology consists of two steps. We first identify the criteria for finding the importance of jobs and then apply several MCDM methods (i.e., TOPSIS, VIKOR, and PROMRTHEE) to assign AGVs to the jobs. At last, we highlight the scheduling plan for AGVs using the mathematical formulation. This paper can bring some managerial insights not only for those who use an FMS but also for anyone who is working in the field of smart management. By the scrutiny, we highlight that the travel distance is significantly correlated with utilities. In other words, the more important are the jobs, the less distance is between jobs and AGVs. The findings support the minimization premise of the travel by AGVs and utility maximization of sending AGVs to the jobs simultaneously. This is achieved through assignment of two AGVs to seven jobs for multiple periods.

KEYWORDS: Flexible manufacturing systems; Scheduling; Mathematical programming; Automated guided vehicles; Multi-Criteria Decision-Making.

1. Introduction

Flexible manufacturing systems (FMSs) are one of the many blessings of Industry 4.0. Implanting them would lead the system to become more resilient. The main components of an FMS are job stations, automated material handling (AMH) and storage, and the computer control system. An FMS consists of several programmable machines interconnected by an AMH system and controlled by a computer network [1]. One of the FMS's principal objectives is to reduce wasted time and cost in the system which accelerates efficiency [2]. Therefore, the application of scheduling models in this field is getting increasing attention. Valuable studies have been proposed for FMS scheduling in recent years.

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Kumar et al. [3] proposed a genetic algorithm (GA) for FMS scheduling. Baruwa and Piera [4] proposed a methodology based on a combination of simulation-based Petri nets and search methods for the FMS scheduling scalability problem for increasing lot size jobs. Priore et al. [5] proposed a dynamic approach for the FMS scheduling problem. Rifai et al. [6] addressed an FMS scheduling problem with multi-loading/unloading and shortcuts benefitting from a non-dominated sorting biogeography-based optimization (BBO) algorithm to optimize the machine assignment and job sequencing constantly. With the help of reinforcement learning, Shiue et al. [7] proposed a multiple-dispatching rules-based methodology for the real-time scheduling of a smart factory. Gonzalez et al. [8] presented a semi-hierarchical architecture for controlling automated guided vehicles (AGV) as one of the FMSs. Their research aims to reduce FMS's perturbations and improve its performance.

Wikarek et al. [9] presented a mixed-integer linear programming (MILP) model for FMSs' decision support in configuration and reconfiguration systems. Akhtar et al. [10] proposed a mathematical model emphasizing batch sizing to minimize lateness in the FMS scheduling problem. Bouazza et al. [11] benefited from a hyper-heuristic algorithm to address the FMS dynamic scheduling problem. Aiming for optimization of material handling within the factory (AGV scheduling) and constant robotic assembly line balancing, Rahman et al. [12] proposed a metaheuristic-based approach. Hu et al. [13] addressed a dynamic real-time FMS scheduling problem solved by a deep Q-network and graph convolutional network. To model the FMS, they integrated timed-place Petri nets and S3PR. Zhong et al. [14] addressed a multi-AGV scheduling problem in an uncertain environment, referring to conflict-free AGV path planning. They designed a mixed-integer programming (MIP) model to minimize AGVs' delay. Their study uses the integration of hybrid GA-particle swarm optimization and fuzzy logic. Jahed and Tavakkoli-Moghaddam [15] presented a mathematical model for AGVs' scheduling, considering the possibilities of failure and breakdown and maintenance duration time in a production system.

In situations where several different objectives (or attributes) should be considered, it seems rational to use multi-criteria decision-making (MCDM) methods [16]. Countless studies have been done to evaluate the efficiency of MCDM in different aspects of management and various industries. Since MCDM makes it possible to use the knowledge of experts, it is a great way to avoid uncertainty. As a result of the advent of the fourth and fifth industrial revolutions, MCDM became more popular in management systems [17, 18].

In the past, few studies have been reported to select AGVs using MCDM methods [19]. MCDM is a popular tool to select the best alternative for given applications. The MCDM methods are as follows: simple additive weighted (SAW), weighted product method (WPM), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), VIKOR ("VIekriterijumsko KOmpromisno Rangiranje" in Serbian language that means "multi-criteria optimization and compromise solution"), analytical hierarchy process (AHP), graph theory, matrix representation approach (GTMA), and the like [20-22]. Various mathematical and systems modeling approaches have been proposed to address the issue of effective evaluation and justification of materials handling equipment. Park [23] proposed an intelligent consultant system for materials handling equipment selection, including 50 equipment types and 29 attributes (i.e., move attributes, material characteristics, operation requirements, and area constraints).

Fisher et al. [24] introduced MATHES (material handling equipment selection expert systems) to select material handling equipment from 16 possible choices. MATHES incorporated 172 rules dealing with path, flow volume, units' sizes, and distance between departments as parameters. MATHES-II has been provided with the same procedure as MATHES. However, MATHES-II had a larger working scope and greater consultation functions. Chan et al. [25] described developing an intelligent material handling equipment selection system, called MHESA (material handling equipment selection advisor). In addition to the above approaches, Fonseca et al. [26] developed expert decision support systems to select the material handling equipment. One of the successful applications of expert systems was SEMH (selection of equipment for material handling), which searches its knowledge base to recommend the degree of mechanization, and the material handling equipment to be used, based on various characteristics (i.e., type, weight, and size). Kulak [27] developed a decision support system called FUMAHES (fuzzy multi-attribute material handling equipment selection), which consists of a database, a rule-based system, and multi-attribute decision-making modules.

The rest of this paper is organized as follows. In Section 2, the research problem is illuminated. Then, in Section 3, a new methodology is proposed to address the research problem. Section 4 is dedicated to our real-life case study. Also, Section 5 contains the results of applying the proposed method in the considered case study. This study ends with a comprehensive but succinct conclusion in Section 6.

2. Problem description

After the advent of Industry 4.0 and the inclusive usage of the FMS, companies experienced a higher velocity in their service flow with considerably lower costs and a shorter waiting time. One of the most common FMS is an AGV, which can transport materials (as well as parts, tools, products, etc.) between job stations. In a system running through Industry 4.0 principles, AGVs receive orders from job stations. The nearest AGV heads to the ordered job station to receive the goods and conveys them to the destination (warehouse or another job station).

Let us look at the issue from another prion. Consider a free AGV is receiving several orders from different job stations. Is it optimal to reach the nearest first? Is there any scientific way to prioritize the orders?

This study addresses the job selection problem for AGVs with an MCDM approach. It should be mentioned that any other FMS can benefit from the findings of this research. The assumptions of this research stabilized as follows. AGVs are homogeneous, their speed and cost are constant, and operation times are deterministic. AGVs run along a predefined route to deliver prescribed tasks without the involvement of an onboard operator. Much effort has been made to achieve an efficient AGV system and reduce operating costs. However, most efforts consider designing and optimizing the layout, control, and traffic management of single-load AGV systems. One of the most important decision-making problems regarding AGVs is their task scheduling. It has to be mentioned that according to the scheduling theory principles, it is essential to avoid wasting time and cost companies [28-30].

In summary, this paper investigates the job selection problem for AGVs when the various jobs on the AGV are dispatched. The objective is to prioritize them to reach the optimal job schedule. For this reason, an MCDM methodology is proposed to optimize the sequel. At first, we identify the criteria for finding the importance of each job. We rank the jobs using three MCDM methods by highlighting the most effective criteria in this stage. In the second stage, based on the presented methodology by Mohammadi and Rezaei [31], we obtain the importance of each job. Figure 1 shows the research methodology. Based on what is indicated in this figure (executive steps), we can state the research steps. In the first step, with the help of the existing literature review and interviews, we highlight criteria for finding jobs' importance. The criteria mentioned above are as follows: the AGV's distance from the job station, piled-up WIPs, the production rate of the job station, and the loading/unloading rate of the job station.

{Please insert Figure 1 about here.}

We identify four criteria due to reviewed papers and experts' interviews. In the second stage, we apply three MCDM methods (i.e., the main rationale behind choosing these three is that we try to have both compromising and non-compromising techniques while making decisions. Furthermore, among many MCDM methods, the methods mentioned above have proven validity). Applying several methods brings the challenge of aggregating them. Based on a novel methodology proposed by Mohammadi and Rezaei [31], we integrate the results of MCDM methods. At last, an optimal scheduling plan for AGVs is presented with the help of mathematical formulation.

3. Methodology

Organizations have used a centralized architecture to manage their production systems for many years. As decisions are made based on input from the entire system, one of the key benefits of centralized design is that it could offer the possibility for global optimization. However, centralized control systems have several significant limitations, particularly when dealing with stochastic and dynamic manufacturing environments. This design often requires lengthy computation times, which may not be practical for real-time systems, especially when dealing with unforeseen occurrences like express job orders or resource breakdowns. This is because it requires system-wide knowledge. Also, the central controller occasionally responds delicately to information updates. Therefore, little informational changes in system variables may have an impact on other entities' schedules, raising system anxiety. There is a growing tendency among researchers and practitioners to use the decentralized architecture to manage manufacturing operations to get around the drawbacks of a monolithic system. This is because centralized approaches have some disadvantages compared to decentralized control systems. The decentralized control design often involves less computing work, has many decision-making entities that eliminate the vulnerability of single-node system failure, and may process data in parallel. Numerous implementation strategies are put forth to achieve the decentralized industrial control system in order to realize the notion.

This section investigates the methodology applied in this research. As mentioned in the previous section, we employ the MCDM methods in the first stage. The criteria extracted based on the literature and interviews for the jobs' importance identification are summarized in Table 1. Based on the criteria, MCDM methods are applied, in which their description can be found in the appendix.

{Please insert Table 1 about here.}

In the second step, the following multi-objective mathematical model is presented to find the best allocation plan for AGVs to different job stations.

$$\text{Min } R^{*}_{ijt} X_{ijt} \tag{1}$$

$$\text{Min } dis_{ijt} X_{ijt} \tag{2}$$

s.t.

$$\sum_{i=1}^{n} X_{ijt} = 1 \qquad \forall j,t \tag{3}$$

$$X_{ijt} W_{ijt} \le C_i \qquad \forall i,j \tag{4}$$

$$S_j + P_j \le d_j \qquad \forall j \tag{5}$$

$$T - \sum_{j=1}^{m} \frac{V_i}{dis_{ijt}} X_{ijt} \le U_i \qquad \forall i,t \tag{6}$$

The objective function (1) minimizes the penalty for not assigning the best AGV to the different jobs. While the objective function (2) is related to minimizing the distance to be traveled. Parameter dis_{ijt} represents the distance between AGV i to the job station j in the period of t. It is worth mentioning that X_{ijt} is a binary variable that gets 1 if the i-th AGV is assigned to job station j at period t. The model is subject to a few constraints, starting with Constraint (3), which indicates that each job has to be an AGV to apply for the order in each period. Constraint (4) asserts that the weight of the burden order to transfer (W_{ijt}) should be less or equal to the capacity of AGV (C_i). Constraint (5) shows that the summation of setup time (S_j) and processing time (P_j) of each job has to be less or equal to the due date (d_j). The last constraint states that the idle time of AGVs has an upper limit and should be less than a specific amount.

4. Results and discussion

The application of the proposed methodology is delineated in this section using a real-life case study, and the results and managerial insight are explained after that. Since one of the automotive industries in Iran has got AGVs recently to facilitate the process of material handling, finding an appropriate plan for their assignments to the jobs is of high importance. Our implication of the methodology is related to one of the automotive companies in Iran (due to data security, we are not allowed to mention the company's name). The company had difficulty in its retrieval systems, seeking to solve it using AGVs. Since the managers are looking for ways to manage their AGV systems, the proposed methodology is of great help for them.

In this section, we first identify the importance of each job by several MCDM methods. Then, the Ensemble ranking model presented by Mohammadi and Rezaei [31] is applied to integrate the rankings and find the last optimal importance for each job. We use GAMS (general algebraic modeling system) software in a DELL Corei5 Laptop with 2.66 GHz and 4 GB RAM to solve the considered problem. The results of three MCDM methods (i.e., TOPSIS, VIKOR, and PROMETHEE (preference ranking organization method for enrichment evaluation) are shown in Table 2. Based on the obtained results for the first stage of the methodology, the integration process starts in the second stage. The final result of this stage is indicated in Table 3. The results of the aggregation method are presented in Tables 3 and 4. As Table 3 indicates, job 7 is important as the other three MCDM methods agree. It is also worth noting that the final ranking is very similar to the TOPSIS method. As evident based on Table 4, the weight of the TOPSIS method is more than the other two methods. The final results indicate that AGV first must go to job 7. Based on the scores of job 7 in the criteria, it is expected owing to the fact.

{Please insert Table 2 about here.}
{Please insert Table 3 about here.}
{Please insert Table 4 about here.}

We highlight two factors by applying the Ensemble ranking method (i.e., the confidence index and the trust level). These two factors are significant indications of the validity of the aggregation method. In this case study, the confidence level is 0.835, and the trust level is 0.958. Since the factors are high, we can conclude that the MCDM methods have analogous rankings. The second point, which can be derived from this, is that Ensemble ranking will get the average result in this case. This is all because, in this case, the HQ (headquarters) functions operate as the Euclidean norm. Another point that needs the readers to heed is related to the fact that the number of outliers (i.e., alternative rank) is less than in other cases, in which we may not observe a high degree of confidence index and trust level. We present a multi-objective programming model to find the best dedications of AGVs to the jobs. The notations and the model are described in the previous section. Hence, in this section, we scrutinize the amount of each parameter in our case study.

Using the mathematical formulation, we assign the AGVs to the jobs in three periods. As mentioned above, we have seven jobs waiting for AGVs, and we have two AGVs in the workshop. Based on the proposed mathematical formulation, we minimize the travel by AGVs and maximize the utility of sending AGVs to the jobs (it is worth noting that each job has a utility obtained using the Ensemble ranking method) or, in other words, to minimize the penalty of not assigning the best AGV to the different jobs. Tables 5 and 6 show the parameters used in the mathematical model.

In the following, the results of the mathematical formulation are presented to assign each AGV to a specific job in different periods. Table 7 shows the assignment of AGVs to the jobs in the first period, second, and third periods.

{Please insert Table 5 about here.}
{Please insert Table 6 about here.}
{Please insert Table 7 about here.}

By analyzing the results of our AGV task delegation, several final points come to emerge as the ultimate advantages of this application; the labor costs associated with installing automated guided vehicles will be reduced because we will not need to hire a new employee or replace an existing one. Finding, hiring, and keeping staff are difficult tasks. Employees anticipate that their pay will increase in line with their level of expertise and length of employment. The labor expenditures are likely to rise as time goes on, whether through annual wage increases, bonuses, more vacation time, and better insurance. This implies that labor costs rise annually. AGVs can take the place of employees, eliminating the increase in labor costs. In reality, as time goes on, the use of AGVs becomes more profitable rather than costlier. Any additional revenue generated by a machine after recovering the initial investment is pure profit (excluding the cost of maintenance, repair, and energy consumption). In many ways, using AGVs improves worker safety. They may accomplish activities that are hazardous for human employees, such as handling hazardous products, working in extreme temperatures, and moving large materials, in addition to removing the human factor, which is the cause of many mishaps. Personnel are finally moved out of harm's path as a result.

In contrast to manual forklift operators, who can race around a facility at high speeds and endanger personnel, AGVs operate in a regulated manner with smooth and constant acceleration/deceleration and monitored top speeds. AGVs frequently carry out identical tasks as fixed automation systems (like conveyors). Fixed automation systems require time and money to install, and they frequently disrupt production. In some cases, a facility cannot function while the systems are being installed. On the other hand, installing AGVs is less expensive and, more significantly, has no negative effects on business operations while it is being done. As a result, there is less downtime and more production. Also, facilities frequently need to change their layout and procedures to better meet demand. A permanent automation system that has already been installed is difficult and expensive to shift; however, AGVs can be readily reconfigured to follow different pathways.

5. Conclusion and managerial implication

A flexible manufacturing system (FMS) was a production method that could quickly adapt to the type and quantity changes of products. Computerized systems and automatic machines could be of great help in this system. This study presented a novel methodology for assigning jobs to AGVs. In this case, we applied three MCDM methods (i.e., TOPSIS, VIKOR, and PROMRTHEE). To rank the jobs using the forgoing method, we first highlighted several criteria for jobs' importance. By identifying the ranking for jobs' importance, we then used an aggregation method presented by Mohammadi and Rezaei [31]. Based on Ensemble ranking results, we could conclude that the TOPSIS method played a more important part in finding the final aggregated result among all methods.

It was also worth noting that a high degree of confidence and trust level was obtained from the results of the Ensemble ranking. In the next step, we applied the mathematical formulation to assign the jobs to the AGVs. Two objectives were considered in this regard. The first one was to minimize the traveled distance between AGVs and jobs. And the second one showed the maximization of the utility of sending the AGVs to the jobs (it was worth noting that each job had a utility obtained using the Ensemble ranking method). A real-life case study was presented to verify the proposed methodology, and the results were shown in Section 4. The results indicated that AGV 1 had a better capacity to transfer materials. This could be mainly because of the short distance between this AGV and the jobs. Furthermore, it could be derived from the results that most of the assignments were similar in all three periods. We highlighted that the travel distance significantly correlated with utilities by scrutinizing the parameters. In other words, the more important the jobs, the less distance was between jobs and AGVs.

In summary, the novelty of this research can be listed below:

- This research has benefited from three accurate MCDM methods, namely TOPSIS, VIKOR, and PROMRTHEE.
- The results of these three methods have been aggregated by one of the most recent methods, namely ensemble ranking.
- A multi-objective mathematical model has been applied to pave the way for job assignments.
- The proposed method has been used to manage FMS scheduling for the first time.
- A real-life case study has been investigated the application of this method.

Based on the findings we could summarize the key notes as followings:

The heart of the AGV system is the top control system. Its primary duties include managing tasks, vehicles, traffic, communications, and other aspects of the AGV system for multiple AGV machines. Similar to how a computer operating system manages processes, task management provides an explanation and execution environment for the AGV ground control program, scheduling operations based on task priority and start time, and performing various task-related operations like start, stop, and cancel. The main component of AGV management is vehicle management as we have monitored in this study. It assigns and deploys the AGV to complete duties in accordance with requests for material handling tasks.

The quickest AGV walking distances and paths are determined, and the AGV's walking motion is controlled and guided to ensure prompt loading and unloading. Traffic management is offered so that AGVs can automatically avoid one another and, at the same time, avoid traffic jams caused by vehicles waiting for one another, depending on the physical size, operational status, and path conditions of the individual AGV. The AGV ground control system, the AGV stand-alone ground monitoring system, the ground IO equipment, the vehicle simulation system, and the host computer can all communicate with one another thanks to communication management. Since the AGV communicates via radio, a wireless network must be set up. Although each AGV is in touch with the ground system, there is no inter-AGV communication. This study can carve the way researchers approach the optimization of AGV scheduling by considering the previously-mentioned factors.

This study can be applied in managing FMS scheduling and can pave the way for smart management in the fourth industrial revolution (i.e., Industry 4.0). Finally, we highly recommend that future researchers apply this method in other industries and report their results. Also, they can use different MCDM methods and compare the results.

Appendix A: TOPSIS

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method aims to rank the alternatives by calculating the distance of each alternative from the positive ideal solution and the negative ideal solution for problems in decision-making, thus determining the optimum alternative. The steps of this method presented by Chen [32] is as follows:

Step 1: Decision matrix R={r_{ij}}*s*, where r_{ij} (i=1, 2, …, m ; j=1,2, …, n) is the value of the j-th attribute in the i-th alternative will be identified in this step.

Step 2: The difference of attributes and the order of magnitude should be considered, then decision matrix R is normalized, and the normalized matrix is transformed to $' = \{r'_{IJ}\}$.

Step 3: The weighted normalized decision matrices are found: $v_{ij} = W_j r'_{IJ}$.

Step 4: D_{IS} and D_{NIS} are identified by:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{A1}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2}$$

Step 5: The relative closeness of each alternative is calculated as follows:

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-} \qquad \text{(A2)}$$

The value of relative closeness reflects the relative superiority of the alternatives. Larger RC_i indicates that alternative i is relatively better, whereas smaller RC_i indicates this alternative is relatively poorer.

Appendix B: VIKOR

The VIKOR ("VIekriterijumsko KOmpromisno Rangiranje" in Serbian language) suggested by Opricovic and Tzeng [33] is explained here. As briefly mentioned already, it focuses on ranking alternatives and determines compromise solutions for a problem with conflicting criteria.

Step 1. Construct the performance matrix and weight vector: $\tilde{D} = \begin{bmatrix} \tilde{f}_{11} & \cdots & \tilde{f}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{f}_{m1} & \cdots & \tilde{f}_{mn} \end{bmatrix}$

Also, $W = \left[w_1, w_2, ..., w_n \right]$ and $\sum_{j=1}^{n} w_j = 1$. Where A_i denotes the alternative i (i=1, 2, …, m); C_j represents the criterion (or attribute) j (j=1, 2, …, n); f_{ij} indicates the fuzzy performance rating of alternative A_i (a district in this study) for criterion C_j (indicator in this study); and w_j indicates the weight for each criterion. Here.

Step 2. Determine the ideal f_i^+ and the nadir f_i^- values of all criteria functions according to the benefit or cost functions. The set of criteria representing benefits (good effects) is denoted by I^b, and a set I^c represents costs. (Equations (B1-2)).

$$f_i^+ = \max f_{ij},\ f_i^- = \max f_{ij} \qquad \forall i \in I^b \qquad \text{(B1)}$$

$$f_i^+ = \max f_{ij},\ f_i^- = \max f_{ij} \qquad \forall i \in I^c \qquad \text{(B2)}$$

Step 3. Compute the normalized fuzzy difference $\tilde{d}_{ij}$: (Equations (B3) and (B4)).

$$d_{ij} = \frac{f_i^+ \theta f_{ij}}{r_i^+ - l_i^-} \qquad \forall i \in I^b \tag{B3}$$

$$d_{ij} = \frac{f_{ij} \theta f_i^+}{r_i^- - l_i^+} \qquad \forall i \in I^b \tag{B4}$$

Step 4. Compute the values S_j and R_j by the relations: (Equations (B5) and (B6)).

$$S_j = \sum_{i=1}^{n} w_j \otimes d_{ij} \tag{B5}$$

$$R_j = \max w_j \otimes d_{ij} \tag{B6}$$

Step 5. Compute the values Q_j by the relation: (Equation (B7)).

$$Q_j = \vartheta \frac{R_j \theta S^+}{S^{-r} - S^{+l}} \oplus (1-\vartheta) \frac{R_j \theta R^+}{R^{-r} - R^{+l}} \tag{B7}$$

where $S^+ = \min \tilde{S}_j, S^{-r} = \max S_j^r, R^+ = \min R_j, and R^{-r} = \max R_j^r$ Additionally, ϑ is introduced as a weight for the strategy of "the majority of criteria" S_j whereas $1-\vartheta$ is the weight of the individual regret R_j.

The weighting parameter ϑ is the maximum utility of a group whose value can be between 0 and 1, which is considered in this research 0.5.

Step 6. Rank the alternatives, sorting them in a decreasing order. The results are three ranking lists $\{A\}_s, \{A\}_R \; and \; \{A\}_Q$ according to crisp(S), crisp(R), and crisp(Q), respectively.

Step 7. Propose a compromise solution the alternative $A^{(1)}$, which is the best-ranked solution by the measure Q if the following two conditions are satisfied:

In this step, we decide according to the R, S, and Q values of the options sorted in descending order. The following two conditions are considered:

C1. "Acceptable advantage": $Ad\vartheta \geq DQ$

where $Ad\vartheta = \frac{\left[Q(A^{(2)}) - Q(A^{(1)})\right]}{\left[Q(A^{(m)}) - Q(A^{(1)})\right]}$ is the advantage rate of alternative $A^{(1)}$ ranked first compared with the alternative with the second position $A^{(2)}$ in $\{A\}_Q$ and the threshold $DQ = \frac{1}{(m-1)}$

C2. "Acceptable stability in decision making":

Alternative $A^{(1)}$ must also be the best ranked by S or R.

If one of the conditions is not satisfied, then a set of compromise solutions is proposed, which consists of:

CS1. Alternatives $A^{(1)}$ and $A^{(1)}$ if only condition (C2) is not satisfied, or

CS2. Alternatives $A^{(1)}$, $A^{(2)}$, …, $A^{(M)}$ if condition (C1) is not satisfied; $A^{(M)}$ is determined by the relation $\frac{\left[Q(A^{(M)})-Q(A^{(1)})\right]}{\left[Q(A^{(m)})-Q(A^{(1)})\right]} < DQ$ for maximum M. The positions of these alternatives are in closeness.

Appendix C: PROMETHEE-II

PROMETHEE-II (preference ranking organization method for enrichment evaluation) method used in this research, ranks the options in detail. The preference function P compares the two options a_i and a_j in k index due to the distance between the two options. It depends on the distance between the two options, as shown in Equations (C1) and (C2).

$$P_k(a_i,a_j) = P\left[d_k(a_i,a_j)\right] \quad \text{(C1)}$$

Equation (C2) shows that the preference function p, for comparing the two options a_i and a_j in terms of index k, is the distance between the two options. It depends on the distance between options a_i and a_j. D in this respect represents the distance. The distance between the values of options a_i and a_j is stepwise. In general, this preference function is shown in Table C1.

{Please insert Table C1 about here.}

$$d_k(a_i,a_j) = f_k(a_i) - f_k(a_j) \quad \text{(C2)}$$

Suppose A and B are two hypothetical options, and we denote the performance of option A for criterion j by $g_j(a)$. Our dominance relationship between the two available options can be shown by one of the Equations (C3) to (C5):

$$aPb \Leftrightarrow \begin{cases} g_j(a) \geq g_j(b); \forall j \in J \\ g_k(a) \geq g_k(b); \exists k \in J \end{cases} \quad \text{(C3)}$$

where P means complete superiority or mastery. When one option has complete precedence or dominance over the other for each criterion option A is better than option B and there is a criterion called k, in which criterion option A is strictly superior to option B.

$$aIb \Leftrightarrow g_j(a) = g_j(b); \forall j \in J \tag{C4}$$

Equation (C5) says that two options are equal when they are the same for each number in different criteria.

$$aRb \Leftrightarrow \begin{cases} g_s(a) \geq g_s(b); \exists s \in J \\ g_r(a) \geq g_r(b); \exists r \in J \end{cases} \tag{C5}$$

In Relation (16), *R* indicates incomparability. When in a series of criteria option *A* has absolute superiority over option *B*, and in a series of criteria option *B* has absolute superiority over option *A*, we cannot decide which option is better.

When option *A* is superior to option *B*, the intensity of this superiority cannot be understood from the above relations. The Prometheus method uses preference functions to eliminate this shortcoming and affect the intensity of the superiority of the options. There are different preference functions according to which the greater the difference between the two options in one criterion, the higher the degree of preference. If the criterion is positive, the difference between the two options with $d_j(a, b)$ in the *j*-th criterion is shown by:

$$d_j(a,b) = g_j(a) - g_j(b) \tag{C6}$$

Figure C1 shows our preference function in this problem. Equation (C7) shows the relations of the preference function in this figure.

{Please insert Figure C1 about here.}

P or $p_j(a, b)$ is the degree of preference of *a* over *b* based on the criterion *j*.
d or $d_j(a, b)$ is the distance between *a* and *b* based on the criterion *j*.
q, *p*, and *s* represent the indifference threshold, the preference threshold, and the midpoint between *p* and *q*, respectively.

To solve this problem, we use the function with the indifference threshold. As shown in Figure C1, we have a threshold (e.g., *p* and *q*), which is a linear function.

$$p = \begin{cases} 0 & d \leq q \\ \dfrac{d-q}{p-q} & q < d < p \\ 1 & d > p \end{cases} \tag{C7}$$

Before using the PROMETHEE methods, three inputs must be specified, including the weight of criteria w_j, the performance of each option in $g_j(0)$, and the preference function for each criterion $p_j(0)$ according to the decision-maker (DM). Then, we can follow the steps listed below:

Step 1: Calculate the overall preference index of each relativity option to the other options. The overall preference index should be calculated for each pair of options according to Equations (C8) and (C9). The closer this index is to one, the stronger the overall preference of option a over b. Equation (C8) indicates the superiority of option *A* over option *B*.

$$\pi(a,b) = \frac{\sum_{j=1}^{n} p_j(a,b)w_j}{\sum_{j=1}^{n} w_j} \tag{C8}$$

$$\pi(b,a) = \frac{\sum_{j=1}^{n} p_j(b,a)w_j}{\sum_{j=1}^{n} w_j} \tag{C9}$$

Several points can be mentioned. Also, the advantage of option *A* over option *B* is usually zero because the distance is zero as shown in Equation (C10). The advantage of option *A* over option *B* is something between zero and one, depending on the amount of distance shown in Equation (C11). In the same way, the superiority of option *B* over option *A* is also displayed. Also, the sum of the superiority of option *A* over option *B* the superiority of option *B* over option *B* is between zero and one, which is shown in Equation (C12).

$$\pi(a,b) = 0 \tag{C10}$$

$$0 \le \pi(b,a) \le 1 \tag{C11}$$

$$0 \le \pi(a,b) + \pi(b,a) \le 1 \tag{C12}$$

Step 2: Calculate implicit dominance flows.

This section calculates the positive and negative implicit dominance currents for each option. The positive implicit dominance current is shown as Equation (C13).It should be noted that *A* represents the sum of all options. $\phi^{+}(a)$. Also, we represent the average degree of mastery of *A* over other options.

$$\phi^{+}(a) = \frac{1}{m-1} \sum_{\substack{x \in A \\ x \ne a}} \pi(a,x) \tag{C13}$$

The negative implicit dominance flow equation is shown in Equation (C14). $\phi^{-}(a)$ indicates the average degree of mastery of the other options over A.

$$\phi^{-}(a)=\frac{1}{m-1}\sum_{\substack{x\in A\\ x\neq a}}\pi(x,a) \tag{C14}$$

The lower $\phi^{+}(a)$ is, and the higher $\phi^{-}(a)$ is, the better the choice.

Step 3: Ranking with PROMETHEE-II**.**

In the Prometheus-2 method, using the I^{I}, and P^{II} interface and the results obtained from the first and second steps, a complete ranking is in the form of Equations (C15) and (C16).

$$aP^{II}b \Leftrightarrow \phi(a)>\phi(b) \tag{C15}$$

$$aI^{II}b \Leftrightarrow \phi(a)=\phi(b) \tag{C16}$$

where ϕ (a) or net flow is the implicit dominance of option A, which is represented by:

$$\phi(a)=\phi^{+}(a)-\phi^{-}(a) \tag{C17}$$

In general, PROMETHEE-II says to calculate ϕ for each of the options. Then, subtract the advantage from the failure to achieve net dominance. The higher this ϕ, the better. In this method, we have a final and complete ranking and can determine the posit.

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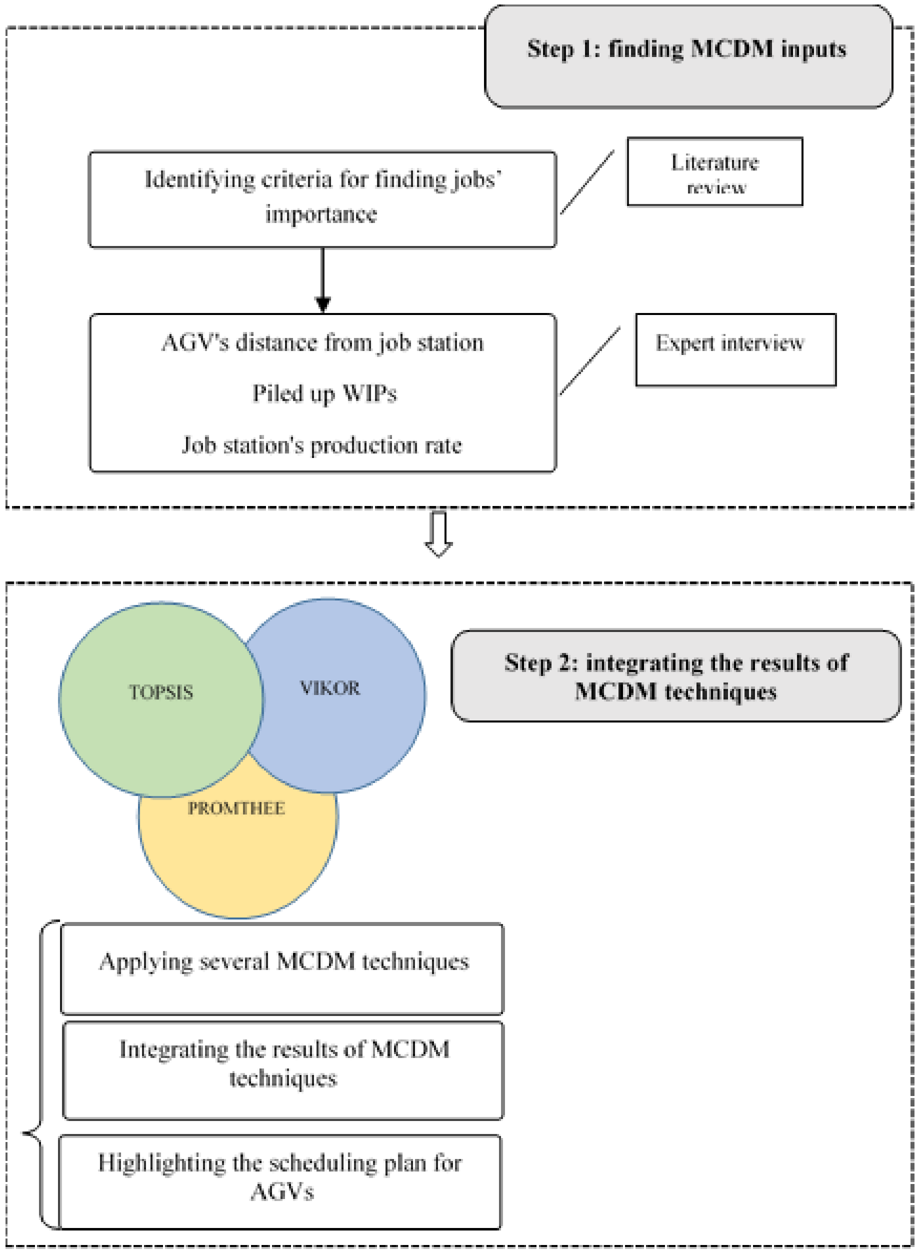

Figure 1. Main steps of the proposed MCDM method.

AGV: Automated guided vehicle; MCDM: Multi-criterion decision-making

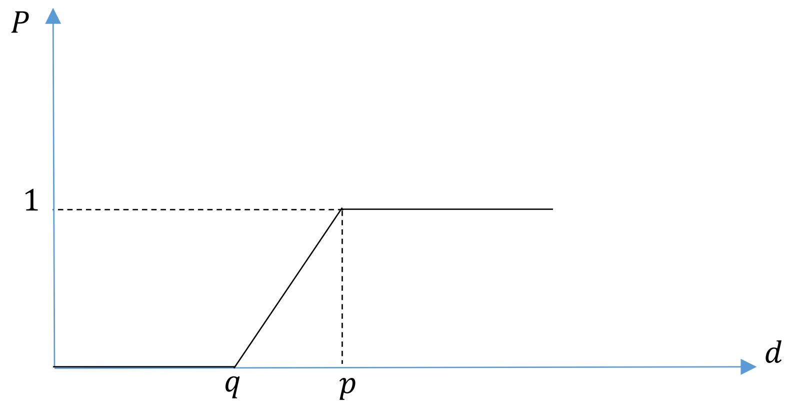

Figure C1. Preference function in the Prometheus method.

Tables

Table 1. Criteria for finding jobs' importance.

Criteria	Notation	Description
AGV's distance from job station (minute)	C1	The distance that AGVs should travel to reach each job station
Piled up work-in-process (WIP) items	C2	The amount of WIP items, which are in each job station, the more WIP is piled up, the more important that job station
Job station's production rate (1-10)	C3	The number of products that go out of the production line
Job station's loading/unloading rate (1-10)	C4	How fast is the job station for products loading and unloading

AGV: Automated guided vehicle; WIP: work-in-process

Table 2. Result of the proposed methods.

TOPSIS		VIKOR		PROMRTHEE	
Alternative	Rank	Alternative	Rank	Alternative	Rank
A7	1	A7	1	A1	1
A6	2	A4	2	A7	2
A1	3	A6	3	A6	3
A3	4	A3	4	A5	4
A4	5	A1	5	A3	5
A2	6	A5	6	A2	6
A5	7	A2	7	A4	7

Table 3. Rank of the proposed methods.

Rank	1	2	3	4	5	6	7
Alternative	A7	A6	A1	A3	A4	A2	A5

Table 4. Weights of each MCDM method and a total aggregated score.

Alternatives	**TOPSIS**	**VIKOR**	**PROMRTHEE**	**R***
A1	3	5	1	3.178
A2	6	7	6	6.131
A3	4	4	5	4.042
A4	5	2	7	4.690
A5	7	6	4	6.742
A6	2	3	3	2.174
A7	1	1	2	1.042
Weights	0.826	0.131	0.042	

Table 5. Parameters of the case study.

Job	Setup time of job *j* (minute)	Processing time of job *j* (minute)	Due date of job *j* (minute)	Transportation capacity of each AGV (kilograms)	Velocity of AGV *i* (m/min)	Upper limit for idle time of AGV *i* (minute)
1	10	15	60	25	100	15
2	26	17	53	25	100	15
3	17	15	45	25	100	15
4	24	14	48	25	100	15
5	28	16	35	25	100	15
6	12	16	57	25	100	15
7	14	15	43	25	100	15

AGV: Automated guided vehicle

Table 6. Transported material from job *j* by the *i*-th AGV and their distance.

Job	**Transported materials from job *j* by AGV *i* (kilogram)**		**Distance between AGV *i* and job *j* (meter)**	
	AGV 1	AGV 2	AGV 1	AGV 2
1	15	13	370	400
2	17	15	460	450
3	17.5	16	380	370
4	16	15	400	420
5	18	16	450	455
6	18	14	320	415
7	16	14	310	435

AGV: Automated guided vehicle

Table 7. Assignment of AGVs to the jobs in each period.

Jobs	First period		Second period		Third period	
	AGV 1	AGV 2	AGV 1	AGV 2	AGV 1	AGV 2
1	*			*		
2		*	*		*	
3	*			*		*
4	*		*		*	
5		*	*			*
6	*			*		*
7	*		*		*	

AGV: Automated guided vehicle

Table C1. Preference function.

	$f_1(0)$	$f_2(0)$	…	$f_j(0)$	…	$f_q(0)$
a_1	$f_1(a_1)$	$f_2(a_1)$	…	$f_j(a_1)$	…	$f_q(a_1)$
a_2	$f_1(a_2)$	$f_2(a_2)$	…	$f_j(a_2)$	…	$f_q(a_2)$
…	…	…	…	…	…	…
a_i	$f_1(a_i)$	$f_2(a_i)$	…	$f_j(a_i)$	…	$f_q(a_i)$
…	…	…	…	…	…	…
a_n	$f_1(a_n)$	$f_2(a_n)$	…	$f_j(a_n)$	…	$f_q(a_n)$