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APPLICATION OF THE R METHOD IN SOLVING MATERIAL HANDLING EQUIPMENT SELECTION PROBLEMS

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Abstract: *In manufacturing industries, material handling equipment plays a vital role and is considered as one of the important pillars to increase production efficiency. Hence, the selection of appropriate material handling equipment for a specific task is well acknowledged, but the complexity of this selection process drastically increases with the rise in the number of alternative equipment available in the market and a set of conflicting evaluation criteria. To resolve this problem, several multi-criteria decision-making (MCDM) techniques have been proposed by past researchers. In this paper, the application potentiality of a newly developed MCDM technique, i.e. R method is explored while solving five material handling equipment selection problems, i.e. conveyor, automated guided vehicle (AGV), stacker, wheel loader and excavator. The derived ranking results are contrasted with other popular MCDM techniques to validate its potentiality in shortlisting the candidate alternatives from the best to the worst, which would ultimately help in improving the overall efficiency of the manufacturing processes.*

Key words: *Material handling equipment; Selection; MCDM; R method; Ranking*

1. Introduction

The growth of a manufacturing unit largely depends on the resources procured and utilized as monitored by the decision-makers. The material handling systems can increase the profitability of a manufacturing organization at a lower cost of production. Selection of suitable equipment for material handling requires knowledge of the complete production process, flow of material etc. Since material handling equipment cost shares a substantial amount of the total production cost, its proper selection becomes an important step in facility layout planning and design. Moreover,

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due to the existence of global competitors, quicker delivery of products is most desired requiring optimal use of available time and space in the production facilities. It is believed that material handling increases the cost of the product without adding any value, but proper use of time and space can increase the value of the complete process. To develop a robust material handling system based on available facilities, principles, like ergonomics, unit load concept, space utilization and automation etc. need to be addressed. These require a decision on the selection of various handling equipment for the movement of materials available in different forms from one place to another. The competitive nature of the market forces the manufacturers to reduce - costs and enhance the quality of their products. Benefits of good selection decision include less workforce and associated cost, and a decline in fuel cost, production and delivery times, thus increase in productivity. This complete material handling system mainly consists of activities and deployment of related equipment which constitute a major portion of the factory space, workforce and production time. Size, shape, weight and other characteristics of the material considerably affect the decision on handling system for any industrial application. The major categories of material handling equipment, such as transport equipment that are found in industries are positioning equipment, unit load formation equipment, storage equipment, identification and control equipment etc. (Chakraborty & Banik, 2006). Transport equipment help in shifting material to different locations and positioning equipment is utilized to operate at a single location. Transport equipment includes conveyors, cranes and industrial trucks. Unit load formation equipment confines materials so that they uphold their structure while movement. Storage equipment, like automatic storage and retrieval systems, helps to hold excess materials over a period of time. Identification and control equipment aid in collecting the information required to maintain the flow of materials. Figure 1 provides a list of commonly employed material handling equipment in a typical manufacturing industry. The selection decision of the most apposite material handling equipment to perform a given handing task has now become more complex due to the availability of a wide range of candidate alternatives with varying specifications to serve the same purpose. It compels the deployment of suitable mathematical tools to identify the appropriate material handling equipment in the presence of a set of conflicting criteria, like cost, safety, flexibility, serviceability, speed etc. (Saputro et al. 2015). Most of small manufacturing organizations usually prefer conventional material handling equipment due to compatibility issues with the existing facilities. The varying flow of materials and design principles of facility layout along with too many choices under various categories of material handling equipment pose a challenging task to the decision-makers. Further, the technical and economic feasibility of the application of material handling equipment requires expertise. To resolve a material handling equipment selection problem, the concerned decision-makers primarily rely on handbooks/catalogues, articles, manuals, experience, opinions and expertise, which is often time-consuming having poor reliability. Limited applications of different mathematical models, mainly in the form of multi-criteria decision-making (MCDM) techniques for solving material handling equipment selection problems are available in the literature. Although, these methods are quite effective in identifying the most suitable material handling equipment for varying tasks, they have their limitations in solving complex high-dimensional decision-making problems.

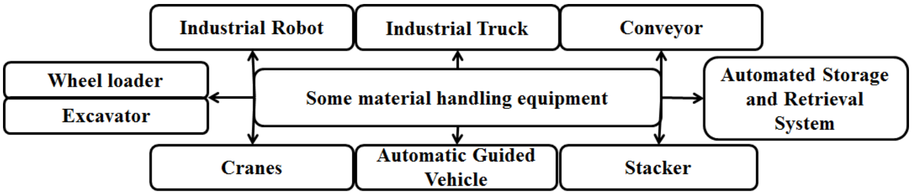

Figure 1. Commonly used material handling equipment in a typical manufacturing setup

Karande & Chakraborty (2013) explored the application potentiality of the WUTA method to identify the best equipment for a given handling task. Khandekar & Chakraborty (2015) proposed the application of FAD principles to identify the most appropriate loading, handling and hauling equipment for surface mines. The derived ranking results were later compared with those of the past researchers to prove the robustness of the adopted approach. Hadi-Vencheh & Mohamadghasemi (2015) first applied the voting approach to determine the corresponding criteria weights which were subsequently converted into a single fuzzy weight based on linguistic variables. F-VIKOR method was later applied to select the most suitable handling equipment, and the ranking results were finally compared with those derived using F-TOPSIS. Bairagi et al. (2015) applied the technique of precise order preference to address rank reversal problems while solving material handling equipment selection problems. Nguyen et al. (2016) integrated F-AHP and F-ARAS methods to select the best conveyor for a specific handling task. Saputro & Rouyendegh (2016) integrated entropy-based TOPSIS with MOMILP to solve material handling equipment selection problems. The subjective and objective criteria weights were measured using F-AHP and entropy methods respectively. Agarwal & Bharti (2018) attempted to solve the AGV selection problem using AHP, DEMATEL, TOPSIS, F-AHP, F-DEMATEL and F-TOPSIS methods. Rahimdel & Bagherpour (2018) applied DEMATEL and TOPSIS methods in the fuzzy environment to select the best haulage system from a set of fixed crushers and trucks, semi-mobile crushers and mobile crushers for an open-pits mine. Ulutaş et al. (2020) integrated correlation coefficient and standard deviation values with indifference threshold-based attribute ratio analysis to determine the corresponding criteria weights for a material handling equipment selection problem. MARCOS method was later employed to rank the candidate alternatives. Goswami & Behera (2021) investigated the applicability of ARAS and COPRAS methods to select three material handling equipment for industrial use. Horňáková et al. (2021) utilized AHP to evaluate the best material handling technology based on the entry conditions and type of the material. Satoglu & Turkekul (2021) applied AHP to estimate the corresponding criteria weights and later employed the MOORA method to rank the pallet truck alternatives. Bozanic et al. (2021) presented neuro-fuzzy system to select loader for construction purposes. Some recent research work includes the selection of passenger vehicles (Biswas et al., 2020); location for emergency medical services (Alosta et al., 2021); green supplier (Fazlollahtabar & Kazemitash, 2021) and appropriate training models (Feng, 2021). Table 1 presents the expansions of the abbreviations used in this article.

This brief literature review indicates the application of MCDM techniques, sometimes integrated with criteria weighting methods based on subjective (depends on decision-maker) or objective (does not depend on the decision-maker; relies on the established procedure) approaches, along with fuzzy set theory in solving diverse material handling equipment selection problems. The above techniques require quantitative, qualitative, or imprecise performance values to work upon. Thus, the objective of the present work is to utilize a simple approach to solve complex decision-making problems. Although validating the applicability and feasibility of many of the newly developed MCDM techniques in solving material handling equipment selection problems is limited, this paper explores and proposes the application of the R method for the first time in solving five material handling equipment selection problems in a real-time manufacturing environment and calculates the number of computations required to solve the selection problem. Being a new approach, the application of the R method in solving MCDM problems is itself very limited and there is a huge opportunity in exploring its application potentiality in dealing with high-dimensional MCDM problems.

The rest of this paper is structured as follows: Section 2 presents the mathematical steps of the R method along with weight calculations. Section 3 demonstrates the application of the R method in solving five real-time material handling equipment selection problems. Results and discussions are presented in Section 4, sensitivity analysis in Section 5 and conclusions are drawn in Section 6.

Table 1. Abbreviated terms with elaboration

Abbreviation	Elaboration
ARAS	Additive Ratio Assessment
AHP	Analytic Hierarchy Process
COPRAS	Complex Proportional Assessment
CRITIC	Criteria Importance Through Intercriteria Correlation
DEMATEL	Decision Making Trial and Evaluation Laboratory
ELECTRE	ELimination and Choice Expressing the REality
FANMA	Abbreviation derived from name of authors
F	Fuzzy
FAD	Fuzzy Axiomatic Design
MARCOS	Measurement of Alternatives and Ranking according to the Compromise Solution
MOMILP	Multi-Objective Mixed Integer Linear Programming
MOORA	Multi-Objective Optimization on The Basis of Ratio Analysis
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VIse Kriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted Aggregates Sum Product Assessment
WUTA	Weighted Utility Additive

2. R method

The R method is a recently developed MCDM technique (Rao & Lakshmi, 2021), which ranks the alternatives based on their performance scores with respect to each of the evaluation criteria. Furthermore, it also ranks the considered criteria based on the opinion of the concerned decision-maker. These assigned ranks are subsequently converted into corresponding weights and composite scores are evaluated using these weights, leading to the final ranking of the alternatives. The procedural steps of the R method are presented below (Rao & Lakshmi, 2021, 2021a).

Step 1: Construct the decision matrix based on the performance scores of the alternatives against each criterion.

Step 2: Assign ranks (1, 2, 3,…, etc.) to the criteria based on their significance and perception of the decision-maker. Assign average rank to equally significant criteria.

Step 3: Assign ranks (1, 2, 3,…, etc.) to the candidate alternatives based on their performance scores against each criterion. Allocate average rank to those alternatives having equal performance scores against a specific criterion.

Step 4: Transform the ranks assigned to both the alternatives and criteria into corresponding weights using the information provided in Table 2. However, to compute weights from the assigned ranks, Eq. (1) can be employed.

$$w_j = \frac{[1 / \sum_{k=1}^{j} (1/r_k)]}{\sum_{j=1}^{n} [1 / \sum_{k=1}^{j} (1/r_k)]} \tag{1}$$

where w_j is the weight of j^{th} alternative or criterion (j = 1,2,...,n), r_k is the ranked assigned to k^{th} alternative or criterion (k = 1,2,...,j) and n is the number of alternatives or criteria.

Step 5: Calculate the composite scores of the candidate alternatives by adding up the products of the criteria weights and the corresponding weights of the alternatives.

Step 6: Award ranks to the alternatives based on their composite scores. The alternative with the maximum composite score is the best option.

Table 2 provides values of the weights calculated from different ranks assigned to the alternatives or criteria based on Eq. (1). To illustrate the calculation steps involved in Table 2, the computation procedure of weights for four criteria or alternatives (column values under rank 4) is shown as below (Rao & Lakshmi, 2021, 2021a):

1/Reciprocal of rank 1: 1/(1/1) = 1.0000

1/Reciprocal of rank up to 2: 1/(1/1 + 1/2) = 0.6666

1/Reciprocal of rank up to 3: 1/(1/1 + 1/2 + 1/3) = 0.5454

1/Reciprocal of rank up to 4: 1/(1/1 + 1/2 + 1/3 + 1/4) = 0.4800

Total = 1.000 + 0.6666 + 0.5454+ 0.4800 = 2.6921

Therefore, weight is assigned to rank 1 = 1/2.6921 = 0.3714, similarly for rank 2 = 0.6666/2.6921 = 0.2476, for rank 3 = 0.5454/2.6921 = 0.2026 and for rank 4 = 0.4800/2.6921 = 0.1783.

Table 2. Weight calculations for different assigned ranks

Rank	Number of criteria or alternatives								
	2	3	4	5	6	7	8	9	10
	Calculated weights								
1	0.6	0.452	0.371	0.319	0.283	0.255	0.233	0.215	0.201
2	0.4	0.301	0.248	0.213	0.188	0.17	0.155	0.144	0.134
3	-	0.247	0.203	0.174	0.154	0.139	0.127	0.117	0.109
4	-	-	0.178	0.153	0.136	0.122	0.112	0.103	0.096
5	-	-	-	0.140	0.124	0.112	0.102	0.094	0.088
6	-	-	-	-	0.115	0.104	0.095	0.088	0.082
7	-	-	-	-	-	0.098	0.09	0.083	0.077
8	-	-	-	-	-	-	0.086	0.079	0.074
9	-	-	-	-	-	-	-	0.076	0.071

Rank	2	3	4	5	6	7	8	9	10
	Number of criteria or alternatives								
	Calculated weights								
10	-	-	-	-	-	-	-	-	0.068

3. Selection of material handling equipment

To check the application potentiality of the R method in solving material handling equipment selection problems, the following five demonstrative examples are considered.

3.1 Example 1: Conveyor selection

This example of conveyor selection (Kulak, 2005) is a classic and extensively adopted problem in the literature. Thus, it is well suited to validate the applicability of R method in accurately ranking the candidate alternatives and comparing the ranking performance with other popular MCDM techniques. This problem consists of four alternative conveyors to be evaluated based on six criteria. The corresponding decision matrix is provided in Table 3. Among the considered criteria, fixed cost per hour (FIC) and variable cost per hour (VAC) are non-beneficial attributes requiring their lower values. On the other hand, the higher values for the speed of conveyor (SPC), item width (ITWI), item weight (ITWEI) and flexibility (FLEX) are often preferred. Among the four beneficial criteria, FLEX is expressed subjectively and Rao (2007) adopted a linguistic scale to convert the subjective values of this criterion into quantitative measures. Now, following the procedural steps of the R method, it is first required to assign the corresponding ranks to the considered alternatives and evaluation criteria. Karande & Chakraborty (2013) applied AHP method to determine the weights of those six criteria as w_{FIC} = 0.1049, w_{VAC} = 0.1260, w_{SPC} = 0.1260, w_{ITWI} = 0.2402, w_{ITWEI} = 0.2245 and w_{FLEX} = 0.1782. Based on these weights, rank 1 is assigned to the ITWI criterion, followed by ITWEI, FLEX, SPC, VAC and FIC, as exhibited in Table 4. As VAC and SPC have the same priority weight, they are assigned their average rank of 4.5. When there is no prior information regarding the criteria weights, the opinion of a decision maker may be sought to assign the corresponding ranks to the set of evaluation criteria. In Table 4, based on the type of criterion (beneficial or non-beneficial), ranks are also assigned to the four alternative conveyors based on their performance against each criterion. For example, in Table 4, VAC being a non-beneficial criterion, its lowest value is always desirable. Thus, for this criterion, conveyor C_B is the best choice and is assigned a rank of 1. As the conveyor's C_A and C_C have the same value for VAC, they are assigned with an average rank of 2.5 (i.e. an average of 2 and 3). Conveyor C_D, having the highest VAC value, is allotted a rank of 4. Similarly, for beneficial criteria, the alternative conveyor with the highest value for the corresponding criterion is assigned with a rank of 1 and so on. Now, using Eq. (1) and Table 2, the corresponding weights for different assigned ranks are calculated for all the alternative conveyors and evaluation criteria, as exhibited in Table 5. Since, in this decision-making problem, there are four alternatives, the set of weights to be assigned to each alternative is {Rank 1 (0.371), Rank 2 (0.248), Rank 3 (0.203), Rank 4 (0.178)}. In the similar direction, for the six evaluation criteria, the set of weights to be assigned is {(Rank 1 (0.283), Rank 2 (0.188), Rank 3 (0.154), Rank 4.5 (0.130), Rank 6 (0.115)}. To estimate the weight for an average rank, the average of the weights for the corresponding ranks is considered. For example, conveyors C_A and C_C have the same average rank for the VAC criterion. Hence, both of them are assigned an average weight of 0.2251 (average of 0.248 and 0.203). The composite score for each of the alternative conveyors is finally calculated by adding the products of criteria weights and corresponding alternative weights, and the candidate conveyors are ranked based on the descending values of this composite score. Thus, conveyor C_C with the maximum composite score emerges as the best choice for the given handling task, followed by conveyors C_B, C_A and C_D. Thus, the complete ranking of the conveyors is derived as $C_C \rightarrow C_B \rightarrow C_A \rightarrow C_D$. Conveyor C_C also appeared to be the first choice when the same problem was solved using other MCDM techniques, like graph theory and matrix approach, WUTA, VIKOR, PROMETHEE, elimination et choice translating reality (ELECTRE), evaluation based on distance from average solution (EDAS), combinative distance-based assessment (CODAS), weighted aggregated sum product assessment (WASPAS), MOORA (Karande & Chakraborty, 2013; Rao, 2007; Mathew & Sahu, 2018) etc. Due to differences in the mathematical treatments in all the considered MCDM techniques, there are slight variations in the intermediate rankings of the conveyors, but, the top-ranked conveyor (C_C) exactly matches. It thus proves the potentiality of the R method in identifying the best alternative from a set of feasible options for a given decision-making problem.

Table 3. Decision matrix for conveyor selection problem (Kulak, 2005)

Alternative	Criteria					
	FIC	VAC	SPC	ITWI	ITWEI	FLEX
C_A	2	0.45	12	15	10	Very good (0.745)
C_B	2.3	0.44	13	20	10	Excellent (0.955)
C_C	2.25	0.45	11	30	20	Excellent (0.955)
C_D	2.4	0.46	10	25	15	Very good (0.745)

Table 4. Ranks assigned to the alternatives and criteria for the conveyor selection problem

Alternative	Criteria					
	FIC	VAC	SPC	ITWI	ITWEI	FLEX
C_A	1	2.5	2	4	3.5	2.5
C_B	3	1	1	3	3.5	1.5
C_C	2	2.5	3	1	1	1.5
C_D	4	4	4	2	2	2.5
Criteria rank	6	4.5	4.5	1	2	3

Table 5. Assigned weights to the alternatives and criteria for the conveyor selection problem

Alternative	Criteria						Composite score	Rank
	FIC	VAC	SPC	ITWI	ITWEI	FLEX		
C_A	0.3714	0.2251	0.2476	0.1783	0.1904	0.2251	0.2251	3
C_B	0.2026	0.3714	0.3714	0.2026	0.1904	0.3095	0.2607	2
C_C	0.2476	0.2251	0.2026	0.3714	0.3714	0.3095	0.3067	1
C_D	0.1783	0.1783	0.1783	0.2476	0.2476	0.2251	0.2182	4
Criteria weight	0.115	0.1300	0.1300	0.2830	0.188	0.154		

3.2 Example 2: AGV selection

This example deals with the selection of the most suitable AGV for a particular industrial application. Table 6 depicts the corresponding decision matrix having six criteria and eight alternatives. Among the six criteria, except cost (C), all the remaining criteria, i.e. controllability (CON), accuracy (ACC), range (R), reliability (REL) and flexibility (F) are beneficial. Based on a numerical scale provided by Rao (2007), all the subjective performance scores of the AGVs with respect to the evaluation criteria are first converted into their corresponding numerical values, as shown in Table 6.

Maniya & Bhatt (2011) adopted AHP method to calculate the corresponding criteria weights as w_{CON} = 0.346, w_{ACC} = 0.168, w_{C} = 0.0584, w_{R} = 0.073, w_{REL} = 0.063 and w_{F} = 0.293, and later applied modified grey relational analysis to rank the candidate AGVs. Based on the same set of criteria weights, Mathew & Sahu (2018) also solved this problem using EDAS, CODAS, WASPAS and MOORA methods. Using the procedural steps of the R method, the corresponding ranks are assigned to both the alternative AGVs and evaluation criteria, as exhibited in Table 7. Based on the AHP-based priority weights of the criteria, rank 1 is assigned to CON, rank 2 to F and so on. Ranks are also assigned to eight alternative AGVs based on their performance scores concerning each of the evaluation criteria. Applying Eq. (1) and the information provided in Table 2, the corresponding weights are now allotted to the ranks for both the alternative AGVs and criteria, as presented in Table 8. This table also provides the calculated values of the composite scores for the AGVs and their positions in the final ranking list. The ranking of the candidate AGVs is obtained as AG5→AG1→AG4→AG2→AG7→AG6→AG3→AG8. Thus, AG5 evolves as the most preferred solution for the specific industrial application, which exactly corroborates the observations of past researchers (Mathew & Sahu, 2018; Maniya & Bhatt, 2011).

Table 6. Decision matrix for AGV selection problem (Maniya and Bhatt, 2011)

Alternative	Criteria					
	CON	ACC	C	R	REL	F
AG1	High	Average	Above average	Average	High	Below average
AG2	Low	High	High	High	Average	Average
AG3	Low	Low	High	Low	Above average	High
AG4	Below average	High	Low	Average	Average	High
AG5	High	Average	Low	Above average	Below average	Average
AG6	Average	Average	High	Low	Above average	Above average
AG7	Low	Below average	High	Low	High	High
AG8	Low	Average	Above average	Average	Average	Above average

Low (0.115); Below average (0.295); Average (0.495); Above average (0.695); High (0.895)

Table 7. Ranks assigned to the alternatives and criteria for the AGV selection problem

Alternative	Criteria					
	CON	ACC	C	R	REL	F
AG1	1.5	4.5	3.5	4	1.5	8
AG2	6.5	1.5	6.5	1	6	6.5
AG3	6.5	8	6.5	7	3.5	2
AG4	4	1.5	1.5	4	6	2
AG5	1.5	4.5	1.5	2	8	6.5
AG6	3	4.5	6.5	7	3.5	4.5
AG7	6.5	7	6.5	7	1.5	2
AG8	6.5	4.5	3.5	4	6	4.5
Criteria rank	1	3	6	4	5	2

Table 8. Weights allocated to the alternatives and criteria for the AGV selection problem

Alternative	Criteria						Composite score	Rank
	CON	ACC	C	R	REL	F		
AG1	0.194	0.107	0.1195	0.112	0.194	0.086	0.1406	2
AG2	0.0925	0.194	0.0925	0.233	0.095	0.0925	0.1275	4
AG3	0.0925	0.086	0.0925	0.09	0.1195	0.155	0.1062	7
AG4	0.112	0.194	0.194	0.112	0.095	0.155	0.1400	3
AG5	0.194	0.107	0.194	0.155	0.086	0.0925	0.1428	1
AG6	0.127	0.107	0.0925	0.09	0.1195	0.107	0.1102	6
AG7	0.0925	0.09	0.0925	0.09	0.194	0.155	0.1161	5
AG8	0.0925	0.107	0.1195	0.112	0.095	0.107	0.1035	8
Criteria weight	0.283	0.154	0.115	0.136	0.124	0.188		

3.3 Example 3: Stacker selection

A manual stacker selection problem (Ulutas et al., 2020) for a small warehouse is considered in this demonstrative example, which consists of five evaluation criteria, such as the price of the stacker (P) (in USD), capacity (C) (in kg), lift height (H) (in mm), warranty period (W) (in month) and fork length (L) (in mm), and eight alternatives, as shown in Table 9. Ulutaş et al. (2020) applied indifference threshold-based attribute ratio analysis approach integrated with correlation coefficient and standard deviation values to determine the criteria weights as $w_P = 0.1061$, $w_C = 0.3476$, $w_H = 0.3330$, $w_W = 0.1185$ and $w_L = 0.0949$, which would be employed here for R method-based ranking of the candidate stackers. To rank those alternatives, Ulutaş et al. (2020) proposed the application of the MARCOS method. In Table 10, ranks are first assigned to the five evaluation criteria based on their importance in solving this material handling equipment selection problem. Similarly, alternative stackers are also ranked depending on their performance with respect to each of the criteria. In Table 11, these ranks assigned to both the criteria and alternative stackers are converted into their corresponding weights. Finally, while adding the products of the criteria and alternative weights, the composite scores for all the eight stackers are computed in Table 11, which are deployed for their subsequent ranking. Table 11 reveals the ranking of the alternative stackers as S8→S1→S3→S4→S5→S7→S2→S6. The emergence of S8 as the most suitable stacker for the considered manual handling task exactly matches the observation of the past researchers (Ulutas et al., 2020).

Table 9. Decision matrix for the stacker selection problem (Ulutas et al., 2020)

Alternative	Criteria				
	P	C	H	W	L
S1	660	1000	1600	18	1200
S2	800	1000	1600	24	900
S3	980	1000	2500	24	900
S4	920	1500	1600	24	900
S5	1380	1500	1500	24	1150
S6	1230	1000	1600	24	1150
S7	680	1500	1600	18	1100
S8	960	2000	1600	12	1150

Table 10. Ranks assigned to the alternative and criteria for the stacker selection problem

Alternative	Criteria				
	P	C	H	W	L
S1	1	6.5	4.5	6.5	1
S2	3	6.5	4.5	3	7
S3	6	6.5	1	3	7
S4	4	3	4.5	3	7
S5	8	3	8	3	3
S6	7	6.5	4.5	3	3
S7	2	3	4.5	6.5	5
S8	5	1	4.5	8	3
Criteria rank	4	1	2	3	5

Table 11. Weights assigned to the alternatives and criteria for the stacker selection problem

Alternative	Criteria					Composite score	Rank
	P	C	H	W	L		
S1	0.233	0.0925	0.107	0.0925	0.233	0.1367	2
S2	0.127	0.0925	0.107	0.127	0.09	0.1064	7
S3	0.095	0.0925	0.233	0.127	0.09	0.1284	3
S4	0.112	0.127	0.107	0.127	0.09	0.1151	4
S5	0.086	0.127	0.086	0.127	0.127	0.1119	5
S6	0.09	0.0925	0.107	0.127	0.127	0.1059	8
S7	0.086	0.127	0.107	0.0925	0.102	0.1068	6
S8	0.102	0.233	0.107	0.086	0.127	0.1455	1
Criteria weight	0.153	0.319	0.213	0.174	0.14		

3.4 Example 4: Wheel loader selection

This problem deals with the selection of an appropriate wheel loader to transport bulk quantities of materials, like debris, gravels and sands at a shorter time on a construction site (Prasad et al., 2015). To solve this problem, Prasad et al. (2015) developed a software prototype in VBASIC based on the quality function deployment (QFD) technique while matching the customers' requirements with the technical specification of the considered wheel loaders. The performance of seven wheel loaders, i.e. ZW140a (WL1), ZW150b (WL2), ZW180e (WL3), ZW250e (WL4), ZW40d (WL5), ZW50C (WL6), ZW80d (WL7) were evaluated based on bucket capacity (BC) (in m^3), cost (C) (measured in a relative 1-9 scale), digging depth (DD) (in mm), operating weight (OW) (in ton) and travel speed (TS) (in km/h). Table 12 depicts the initial decision matrix for this problem. Prasad et al. (2015) estimated the corresponding criteria weights as w_{BC} = 0.1794, w_C = 0.1300, w_{DD} = 0.1525, w_{OW} = 0.3139 and w_{TS} = 0.2242 which would be employed for R method-based solution of this problem. Based on the criteria weights and performance scores of the alternative wheel loaders, ranks are assigned to both the criteria and alternatives, as shown in Table 13, which are subsequently converted into their related weights in Table 14. The composite scores of the candidate wheel loaders are now calculated and they are finally ranked based on descending values of this score in Table 14. The complete ranking of the wheel loaders is achieved as WL4→WL3→WL7→WL2→WL1 →WL6→WL5. Wheel loader 4 (WL4) evolves out as the best-suited alternative for the given handling task, which exactly matches with the observation of Prasad et al. (2015).

Table 12. Decision matrix for the wheel loader selection problem (Prasad et al., 2015)

Alternative	Criteria				
	BC	C	DD	OW	TS
WL1	2	5	110	10.29	20
WL2	2.2	5	110	11.8	20
WL3	2.2	6	110	14.71	24
WL4	2.9	8	120	19.89	23
WL5	0.5	3	50	3.375	15
WL6	0.9	3	55	3.66	15.2
WL7	1	4	65	5.27	34

Table 13. Ranks assigned to the alternative and criteria for the wheel loader selection problem

Alternative	Criteria				
	BC	C	DD	OW	TS
WL1	4	4.5	3	4	4.5
WL2	2.5	4.5	3	3	4.5
WL3	2.5	6	3	2	2
WL4	1	7	1	1	3
WL5	7	1.5	7	7	7
WL6	6	1.5	6	6	6
WL7	5	3	5	5	1
Criteria rank	3	5	4	1	2

Table 14. Weights assigned to the alternatives and criteria for the wheel loader selection problem

Alternative	Criteria					Composite scores	Rank
	BC	C	DD	OW	TS		
WL1	0.122	0.117	0.139	0.122	0.117	0.1227	5
WL2	0.1545	0.117	0.139	0.139	0.117	0.1338	4
WL3	0.1545	0.104	0.139	0.17	0.17	0.1531	2
WL4	0.255	0.098	0.255	0.255	0.139	0.2080	1
WL5	0.098	0.2125	0.098	0.098	0.098	0.1139	7
WL6	0.104	0.2125	0.104	0.104	0.104	0.1191	6
WL7	0.112	0.139	0.112	0.112	0.255	0.1461	3
Criteria weight	0.174	0.14	0.153	0.319	0.213		

3.5 Example 5: Excavator selection

The last demonstrative example considers an excavator selection problem (Prasad et al., 2015) for material handling which consists of four evaluation criteria, i.e. battery power (BP) (in Ah), cost (C) (in a relative 1-9 scale), operating weight (OW) (in ton) and rated power (RP) (in kW), and six alternative excavators, i.e. ZX200LC-3G (EX1), ZX225USR-3 (EX2), ZX240-3G (EX3), ZX350H-3G (EX4), ZX350LCH-3G (EX5) and ZX470LCH-3 (EX6). With the help of a software prototype and based on QFD technique, Prasad et al. (2015) solved this problem, while identifying ZX470LCH-3 (EX6) and ZX200LC-3G (EX1) as the best and the worst alternatives respectively, and also determined the corresponding criteria weights as w_{BP} = 0.2123, w_C = 0.0559, w_{OW} = 0.4972 and w_{RP} = 0.2346. Table 15 provides the decision matrix for this decision-making problem. Following the steps of the R method, the considered evaluation criteria and alternative excavators are first ranked depending on their weights and performances with respect to the criteria respectively in Table 16. In Table 17, these ranks assigned to the criteria and alternatives are transformed into their respective weights. Based on the computed composite scores, the alternative excavators are finally ranked from the best to the worst in Table 17. Like the observations of Prasad et al. (2015), ZX470LCH-3 (EX6) and ZX200LC-3G (EX1) emerge as the most and the least preferred alternatives respectively for the considered handling task. The complete ranking of the excavators is derived as EX6→EX5→ EX4→EX3→EX2→EX1.

Table 15. Decision matrix for excavator selection problem (Prasad et al., 2015)

Alternative	Criteria			
	BP	C	OW	RP
EX1	96	3	21.7	110
EX2	88	3	23.3	122
EX3	96	3	23.6	125
EX4	128	4	34.58	184
EX5	128	4	35	184
EX6	170	5	48.1	260

Table 16. Ranks assigned to the alternative and criteria for the excavator selection problem

Alternative	Criteria			
	BP	C	OW	RP
EX1	4.5	2	6	6
EX2	6	2	5	5
EX3	4.5	2	4	4
EX4	2.5	4.5	3	2.5
EX5	2.5	4.5	2	2.5
EX6	1	6	1	1
Criteria rank	3	4	1	2

Table 17. Assigned weights to alternatives and criteria for the excavator selection problem

Alternative	Criteria				Composite score	Rank
	BP	C	OW	RP		
EX1	0.13	0.188	0.115	0.115	0.1310	6
EX2	0.115	0.188	0.124	0.124	0.1336	5
EX3	0.13	0.188	0.136	0.136	0.1440	4
EX4	0.171	0.13	0.154	0.171	0.1574	3
EX5	0.171	0.13	0.188	0.171	0.1700	2
EX6	0.283	0.115	0.283	0.283	0.2531	1
Criteria weight	0.203	0.178	0.371	0.248		

4. Results and discussion

In order to validate the performance of the R method, rankings of the alternative material handling equipment for all the five illustrative examples are contrasted with those derived using other popular MCDM methods, i.e. VIKOR, WASPAS, MOORA, COPRAS and TOPSIS. To maintain uniformity of calculations in all these methods, criteria weights as considered in the R method are employed for solving those examples. It can be interestingly noticed that in all these MCDM techniques, the position of the top-ranked material handling equipment exactly matches. There are marginal deviations in the intermediate rankings of the alternatives which may be attributed to the differences in the mathematical treatments involved in the MCDM techniques. Figure 2 plots the Spearman's rank correlation coefficients between R method and other considered MCDM techniques for example 2 (AGV selection problem). It can be unveiled from this figure that the R method has high a degree of similarity with the other MCDM technique with respect to the ranking pattern of the alternatives. The correlation coefficient of R with VIKOR, WASPAS, MOORA, COPRAS and TOPSIS is 0.9, 0.81, 0.88, 0.81 and 0.90 respectively. This indicates more similarity in rank with VIKOR and TOPSIS followed by MOORA, WASPAS and COPRAS. Similar observations are also noticed for the remaining material handling equipment selection problems (not shown here due to paucity of space).

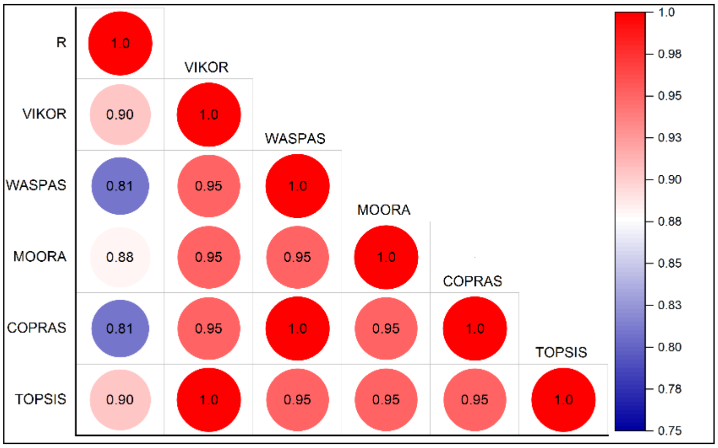

Figure 2. Rank correlation plot for different MCDM techniques for AGV selection problem

To prove the simplicity of the R method, numbers of computations involved in different MCDM methods are calculated with respect to computational complexity considering a decision-making problem with M alternatives and N criteria (Ghaleb et al., 2020; Chatterjee & Chakraborty, 2022). Table 18 shows the number of computations required for each of the MCDM techniques. On the other hand, Table 19 exhibits the actual numbers of computations required by these MCDM techniques while solving the five illustrative material handling equipment selection problems. It becomes clear from Table 19 that except for MOORA, the R method outperforms others with respect to the number of computation steps.

Table 18. Number of computation steps involved in different MCDM methods

R		VIKOR		WASPAS	
Step	Computation	Step	Computation	Step	Computation
Assigning ranks to the criteria	N	Determining the best and the worst values	$2N$	Calculation of the normalized matrix	$M \times N$
Assigning ranks to the alternatives based on each criterion	$M \times N$	Calculation of the normalized matrix	$M \times N$	Weighted sum matrix and performance score	$M \times N + M$
Assigning weights to the criteria	N	Calculation of the weighted normalized matrix	$M \times N$	Weighted product matrix and performance score	$M \times N + M$

Assigning weights to the alternatives	$M \times N$	Computation of S, R and Q values	$3M$	Generalized weighted aggregation	M
Composite score evaluation	M	Computation of S^*, R^*, S^-, and R^- values	4	-	-
Total computations required	$2MN+2N+M$	Total computations required	$2MN+3M+2N+4$	Total computations required	$3MN+3M$

Table 18. Number of computation steps involved in different MCDM methods (Continued)

MOORA		COPRAS		TOPSIS	
Step	Computation	Step	Computation	Step	Computation
Calculation of the normalized matrix	$M \times N$	Calculation of the normalized matrix	$M \times N$	Evaluation of the normalized matrix	$M \times N$
Calculation of the weighted normalized matrix	$M \times N$	Calculation of the weighted normalized matrix	$M \times N$	Evaluation of the weighted normalized matrix	$M \times N$
Calculation of weighted normalized assessment value	M	Computation of sums of beneficial criteria and non-beneficial criteria	$2M$	Computation of positive distances	$(M \times N)+M$
-	-	Determining minimum value of non-beneficial sums	1	Evaluation of negative distances	$(M \times N)+M$
-	-	Determining relative significance and quantitative utility	$2M$	Determination of relative closeness with respect to the ideal solution	M

Total computations required	$2MN+M$	Total computations required	$2MN+4M+1$	Total computations required	$4MN+3M$

Table 19. Actual number of computations for different examples

Method	R	VIKOR	WASPAS	MOORA	COPRAS	TOPSIS
Example 1	54	66	72	44	57	92
Example 2	116	136	168	104	129	216
Example 3	98	118	144	88	113	184
Example 4	87	112	126	77	99	161
Example 5	62	78	90	54	73	108

The R method has also several advantages over the other MCDM techniques. It does not require normalization of the decision matrix having simple and easy-to-understand calculation steps. The application of the R method, being unaffected by any extraneous tuning parameter, results in quick decision-making with minimum involvement of the decision-maker. It can deal with both qualitative and quantitative information in the decision matrix and has the ability to solve high-dimensional MCDM problems with any number of alternatives or criteria. Based on the calculated criteria weights and their importance, it assigns ranks to those criteria. When criteria weights are not available, judgments of the concerned decision-makers may be sought to provide relative importance to the considered criteria. In a similar direction, alternatives are also ranked based on their performance values against each of the criteria. Using simple mathematical steps, these ranks allotted to both the criteria and alternatives are subsequently converted into their corresponding weights. After adding the products of the criteria and alternative weights, the candidate alternatives are finally ranked based on their computed composite scores. For its application, the experience and knowledge of the participating decision- makers are not so much important.

5. Sensitivity Analysis

In-depth sensitivity analysis studies are carried out here to show the ranking stability and robustness of the R technique.

Figure 3 displays the ranking positions of the options under various scenarios. Each scenario considers a new set of weights for the criteria that were determined using the ENTROPY (Zou et al., 2006), FANMA (Srdjevic et al., 2003) and CRITIC (Diakoulaki et al., 1995) weighting methods. Equal weights, proportionate reduction and rise of the top three and bottom three weighted criteria, and a method of gradual elimination of the least significant criterion are all taken into account in this sensitivity analysis. Thus, scenario 1, 2 and 3 shows the rank of the alternatives which considers ENTROPY, CRITIC and FANMA weighting methods. The weights are evaluated using these weighting methods and then the R method is applied to rank the criteria based on the computed weights and the rank of the alternatives is determined using these new weights as computed by the R method. In scenario 4, equal weights are considered, and in scenario 5, the top three criteria weights are reduced by 5 % each, and the bottom 3 criteria are increased by 5% each. In scenario 6, eliminating the least important criterion having the minimum weight, i.e. C as previously identified from the original set of weights, utilized by the previous researcher, and then applying R method weight sets for the remaining criteria using the R method. Similarly, in scenario 7, reliability REL is successively eliminated from the evaluation process and a new rank set using the R method is utilized based on the remaining criteria. Further, in scenario 8 and 9, R and ACC are eliminated and a new rank set is again developed. This procedure continues till only two criteria remain in the evaluation process. For each scenario, the corresponding ranking order of the AGV alternatives is derived. It can be observed from Figure 3 that these scenarios in the R method-based analysis do not influence the rankings of the top alternative AGV; however, minor changes are observed in the intermediate rankings of the other AGVs. Thus, the position of the best AGV (AGV5) remains unaffected as they are insensitive to changes in the criteria weights, which proves the consistency and ranking stability of the adopted approach.

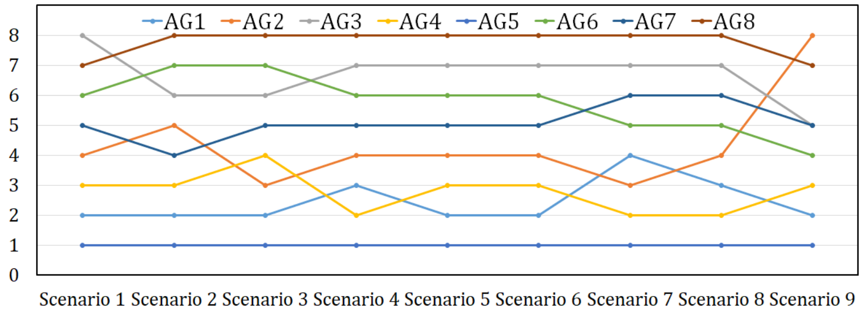

Figure 3. Ranking performance of R method at different scenarios

6. Conclusions

Due to the availability of a large set of equally potential alternatives and conflicting evaluation criteria, the selection of the most apposite material handling equipment for a specific handling task is a complicated problem. This paper demonstrates the application of the R method in solving five material handling equipment selection problems taken from the literature. Based on the analysis, the following conclusions can be drawn:

a) This approach seems to be an effective MCDM strategy for solving problems involving the selection of material handling equipment, resulting in the achievement of the most desirable option.
b) The R technique selects conveyor CC as the best equipment for the conveyor selection problem, which is consistent with previous findings.
c) This approach produces the automatic guided vehicle AGV5, which is consistent with earlier results and the top-ranked alternative.
d) This method ranks stacker S8 as the top choice, which is consistent with previous outcomes.
e) (e)Wheel loader 4 is the top-ranked alternative, according to this methodology, which is consistent with the previous findings.
f) This method determines excavator 6 as the top-ranked alternative, which is similar to the results of the past.
g) The results from the R approach are compared to those from the VIKOR, WASPAS, MOORA, COPRAS, and TOPSIS methods in this work. There is excellent agreement between the rankings obtained using the R method and other well-liked MCDM strategies for all of the challenges.
h) This method offers the most straightforward way to calculate the weights of the criterion.

There are minor differences in the intermediate rankings of the alternatives due to differences in the mathematical treatments of the other MCDM methods. The R method can process both quantitative and qualitative criteria, requires few computational steps, is unaffected by tuning parameters, and does not require data normalization. As a result, it can be successfully used to solve both low and high-dimensional MCDM problems in a real-time manufacturing environment. In the future, the effectiveness of this method in solving problems associated with parametric optimization can be investigated. Decision problems involving too many criteria and alternatives can be problematic.

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