Sigma J Eng Nat Sci, Vol. 41, No. 1, pp. 178–193, February, 2023

Sigma Journal of Engineering and Natural Sciences
Web page info: https://sigma.yildiz.edu.tr
DOI: 10.14744/sigma.2023.00016

Research Article

Decision making in the manufacturing environment using the technique of precise order preference

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ARTICLE INFO

Article history
Received: 28 June 2021
Accepted: 13 November 2021

Keywords:
TPOP; Manufacturing; Decision-Making; Data Fusion

ABSTRACT

Wrong decisions in manufacturing systems can jeopardize the continuity of production and reduce productivity and efficiency. Therefore, it is essential to make the right decisions in solving the problems encountered in manufacturing environments. In the literature, there are many methods developed to be used in solving decision-making problems. The results of different methods used in solving the same problem are different from each other. Thus, the rankings obtained by the different methods to solve the same decision-making problem in the manufacturing environment are different. Different rankings obtained for the same problem cause inconsistencies and it is not easy to determine which sort of order is better. In this study, the use of the technique of precise order preference (TPOP) is proposed to solve the decision-making problems in manufacturing systems. Three case studies are presented to illustrate the use of the TPOP method to solve decision-making problems in manufacturing systems. The case studies show that the TPOP method can be used easily to solve decision-making problems in manufacturing systems. Furthermore, the consistencies of the multi-criteria decision-making methods used in this study are analyzed using Spearman's correlation coefficient values. TPOP method has the highest Spearman's correlation value for three case studies.

Cite this article as: Altuntaş S, Dereli T, Erdoğan Z. Decision making in the manufacturing environment using the technique of precise order preference. Sigma J Eng Nat Sci 2023;41(1):178–193.

INTRODUCTION

The manufacturing system is the complete set of equipment and human resources that can perform one or more process operations on raw materials, parts, or a set of parts [1]. There are many selection problems in manufacturing systems such as warehouse selection, facility layout selection, raw material selection, production program selection, supplier selection, selection of marketing strategies, machine selection. While the right

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This paper was recommended for publication in revised form by Regional Editor Abdelraheem Mahmoud Aly

Published by Yıldız Technical University Press, İstanbul, Turkey

Table 1. Decision-making difficulties in the production environment

Decision-making difficulties in the production environment	Authors
Making multi-objective decisions	Rasmi *et al.* [2], Su & Lin [3]
The need to handling uncertainty	Boral *et al.* [4], Vazifehdan & Darestani [5], Ervural *et al.* [6], Su & Lin [3]
To overcome disagreements within the group in the group decision environment.	Ervural *et al.* [6], Pagone *et al.* [7] Yu *et al.* [8]
To provide sustainability	Boral *et al.* [4], Ghenai *et al.* [9], Pagone *et al.* [7], Zhang [10], Sinha & Anand [11], Stoycheva *et al.* [12]
To make decisions in flexible manufacturing systems quickly and effectively.	Ervural *et al.* [6]
To determine the weights of selection criteria accurately	Ghenai *et al.* [9], Pagone *et al.* [7]
To combine data mining and digital technologies in decision-making processes for quick decision making	Guo *et al.* [13], Kunath & Winkler [14], Li *et al.* [15]
To combine information of different sources at various stages of decision-making problems using data fusion	Cheng *et al.* [16], De Vin *et al.* [17], Wu *et al.* [18], Yin *et al.* [19]

choices provide profit/benefit, wrong choices cause various losses/costs in manufacturing systems. When literature is reviewed, various difficulties have been identified in handling decision-making problems in the manufacturing environment. These difficulties are summarized in Table 1.

Multi-criteria decision-making (MCDM) methods are widely used in manufacturing systems where wrong decision-making will cause great losses. MCDM methods are extensively used to select the most suitable one among many alternatives in making complex decisions in human life. MCDM method is defined as the selection process made by the decision-maker by using two or more criteria in a set of alternatives consisting of many options [20]. It is a modeling and methodological tool to deal with complex engineering problems [21]. In the literature, various methods have been used to make multi-criteria decisions in the production systems. These methods are TOPSIS (technique for order preference by similarity to ideal solution) [22]–[29], VIKOR (multiple criteria optimization and compromise solution) [30]–[32], AHP (analytic hierarchy process) [22], [27], [32]–[35], ELECTRE (elimination and choice translating reality) [27], [36], GRA (gray relational analysis) [27], [37], [38], CODAS (combinative distance based assessment) [39], [40] etc. Various studies were carried out to improve the weaknesses of these methods. However, the most important problem of these methods is selecting the most appropriate method for the current problem. Each of the used decision-making methods gives a different order of preference. The most suitable ranking selection among these preference rankings is also a decision-making problem. Therefore, this situation reveals a paradox that selecting the most appropriate MCDM method for a decision problem leads to an MCDM problem [41]. In addition to this problem, a rank reversal problem can occur due to adding and removing alternative causes after the order of preference is obtained.

Five criteria are considered for the evaluation of rank reversal problems [42]. These criteria are irrelevant alternatives [43], [44], alteration of the indication of the best alternative, decomposition of the decision problem [45], the non-discriminating criterion [46], [47] and the transitivity property [45]. In the literature, the various studies are carried out by considering these criteria. In addition to this problem, another problem at hand in the literature is inconsistent ranking order. Decreasing inconsistency of the alternatives within sort order obtained using different solution approaches is essential for optimum decision making. Applying different decision-making methods to solve the same problem reveals rank reversal and inconsistent ranking order problems. Various methods such as rank position [48], [49], Borda count [50]–[52], and Condorcet method [53], [54] have been proposed to overcome these problems. However, these methods are not sufficient to reveal the benefits of decision-making methods. Bairagi et al.[55] proposed the technique of precise order preference (TPOP) that overcoming these problems and effectively combined order of preference obtained using the different decision-making methods. This method is based on combining information of the different sources, as in other data fusion methods. The distinguishing attribute of the TPOP is obtaining an accurate and precise selection value using the final selection values of the different MCDM methods. In this study, facility layout design selection and storage location selection problems are handled among essential decision problems of manufacturing systems. Making the right decisions related to these two problems is essential for both time and cost. Therefore, the TPOP [55] which revealed the benefits of the methods using the last selection values of different decision-making problems and obtained

Table 2. The studies on decision-making problems in manufacturing systems

Authors	Method	Aim
Besbes *et al.* [22]	TOPSIS and AHP	Addressing the problem of choosing a new workshop layout to meet demand changes
Kumar *et al.* [24]	TOPSIS method	Addressing the uncertain issue of supplier selection
Liao & Kao [25]	TOPSIS, multi-choice goal programming	Determining the most appropriate supplier and order quantity
Ma *et al.* [26]	TOPSIS	Selecting the most appropriate project for a paper manufacturing company
Ozcan *et al.* [27]	AHP, TOPSIS, ELECTRE, and Gray theory	Selecting the most appropriate warehouse
Peng *et al.* [28]	TOPSIS method	Developing a decision support system to select the best cutting parameters in manufacturing systems
Yuvaraj & Pradeep Kumar [29]	TOPSIS method and the ANOVA (one-way analysis of variance) technique	Determining the parameters of the abrasive water jet cutting process
Singh *et al.* [32]	Fuzzy AHP and VIKOR	Ranking sustainable production strategies.
Sasananan *et al.* [33]	AHP	Proposing a third-party logistics vendor selection model for a cement manufacturing industry
Yadav & Sharma [34]	AHP	Selecting the most appropriate supplier
Kluczek [35]	AHP	Evaluating the sustainability of production processes
Mathew & Sahu [40]	CODAS, evaluation based on distance from average solution (EDAS), weighted aggregated sum product assessment (WASPAS) and multi-objective optimization based on ratio analysis (MOORA)	Selecting suitable material handling equipment
Saad *et al.* [56]	Fuzzy-AHP method	Evaluating supply performance in the automotive industry
Memari *et al.* [57]	Fuzzy-TOPSIS	Selecting the most appropriate supplier for the automotive spare parts manufacturer

a sensitive order of preference, was preferred to overcome these problems.

The rest of this paper is organized as follows. The literature review is provided in Section 2. In Section 3, the TPOP method is applied to three case studies to show how the TPOP method works for decision-making in the manufacturing environment. Later, Spearman's correlation coefficient values are calculated for these case studies. In Section 3, information about case analysis is given, and the method's results are explained in detail. Future research directions are provided in the last Section.

LITERATURE REVIEW

Many methods have been proposed in the literature for the solution of decision-making problems in manufacturing systems. The studies using multi-criteria decision-making methods for decision-making problems in manufacturing systems are given in Table 2.

The participation of decision makers or experts is important to assess sustainable manufacturing effectively. Fuzzy group decision-making methods have been developed to make sensitive and accurate decisions in group decision-making [58], [59]. The performance of the decision-making process must bring together individuals who can handle the problem from different perspectives. However, a co-decision may not be made in the group decision-making process due to collisions within the group [8]. In the literature, various studies [6], [8], [58]–[61] have been carried out to solve this problem. Obtaining a precise and correct order of preference in the decision-making process in production systems is another critical problem. In the literature, there are various problems related to the order of preference. After the order of preference is obtained, adding or removing an alternative causes a rank reversal problem [42], [62]–[65]. Furthermore, the application of different methods to the problem with the same alternatives causes inconsistent ranking order problem [45], [66], [67].

Various methods may/could produce different rankings. This situation causes inconsistencies in the decision-making process. It is essential to offer decision-makers a precise and single alternative ranking covering complete information. Therefore, the aggregation methods in the literature have been proposed to obtain the best order of preference within input orders [55], [68]–[71]

The stage of the different preference sequences obtained from different decision-making methods is also a decision-making problem. Decision-makers with sufficient knowledge in the field under concern can choose the most suitable ranking among different rankings. However, it may be the case that the process is not objective. Nowadays, it is getting harder to compete and companies need to make optimum decisions to survive in a competitive environment. However, optimal decisions depend on the information that decision-makers have. This information should be as complete as possible. Data fusion methods can obtain complete information. Data fusion is the process of merging data from multiple sources into a single compound with higher information quality [72]. In the literature, data fusion methods are widely used in many fields such as security, robotics, medicine, environment, military applications, financial, and so on [73]–[78]. Some methods hybridize data fusion with decision problems [72], [73], [75], [78]–[82]. This approach also applies to multi-criteria decision-making methods.

The purpose of this study is to provide a useful method for overcoming uncertainty and making objective decisions in the final decision-making phase where decision makers do not have sufficient knowledge. Each of MCDM methods has different advantages from each other. Therefore, the TPOP method, which combines information obtained from different methods, helps get complete information. TPOP obtains an accurate and precise selection value using the final selection values of the different MCDM methods. TPOP method are used due to this advantage in the study. The consistencies of the MCDM methods are analyzed to show that TPOP method is the most reliable. The consistencies of the MCDM methods used in this study are analyzed using Spearman's rank correlation coefficient values. TPOP method has the highest Spearman's rank correlation coefficient values among MCDM methods used in the three case studies. Therefore, in this study, TPOP method is proposed to solve manufacturing systems' decision-making problems. Making the right decisions in manufacturing systems is quite important. In this study, three significant decision problems, namely facility layout design selection, warehouse selection, environmentally conscious manufacturing program selection in manufacturing systems, are solved using the TPOP approach. The application of the TPOP method in manufacturing systems is infrequent in the literature. This study extends the current literature on decision-making in the manufacturing environment with the TPOP method.

APPLICATION OF THE TPOP METHOD TO DECISION MAKING IN THE MANUFACTURING ENVIRONMENT

In this section, the TPOP method is applied to two case studies for decision-making in the manufacturing environment. Basic definitions related to the TPOP are given in the following. Figure 1 shows the steps of the TPOP method.

A_i into S matrix in Fig.1 is the ith alternative, $i = 1,2, \ldots m$ and $j = 1,2, \ldots t$. f_{ij} is the final selection value of A_i obtained by jth conventional approach. e_j at Step 4 in Fig.1 is the entropy of the final selection value for the jth approach. s_j at Step 4 in Fig.1 is the apparent weight of the jth approach ($1 \le s_j' < 2$). w_j at Step 7 in Fig.1 is the precise weight of the final selection value for the jth approach $\left(\frac{1}{t+\sqrt{t}} \le w_j \le \frac{2}{t+1}\right)$. $f_{ij} \in H$ implies that a higher value of f_{ij} is desirable. $f_{ij} \in L$ implies that a lower value of f_{ij} is desirable. In this study, the VIKOR method is involved in the L cluster, and Improved OWA, Improved AHP, Improved GRA, Improved UTA, WEBDA, and CMBA methods are involved in the H cluster. EWNFSW at Step 9 in Fig.1 is the exponentially weighted normalized final selection values. PSI at Step 10 in Fig.1 is a precise selection index.

In the multi-criteria decision-making process, correct expression of the problem and determining the importance level of each criterion on decision making is essential in making the right decisions. Another critical step is to determine the final order of preference. In multi-criteria decision-making problems, different ranking results force decision-makers to make the final decision. To overcome this situation, the TPOP method, a data fusion method, was proposed by Bairagi et al. [55]. The TPOP method can measure the performance of alternatives more precisely than other data fusion methods. This method provides ease of application to the user with its operational simplicity. The TPOP method takes the final scores of traditional decision-making methods and prevents unnecessary calculations in the data processing. The method examines inconsistencies within various alternative rankings. It is necessary for weighting the final selection values of each decision-making method. Because each method has a different functional calculation ability to sort the alternatives. The TPOP method uses an advanced entropy weighting method to obtain more accurate and reliable weights. Next, the TPOP method calculates precise selection indices that determine the correct sort order for the alternatives, using the advanced entropy weighting method obtained with the advanced entropy method and the last selection values obtained with traditional decision-making methods [55], [84] The ranking order obtained from using the TPOP method can be considered the most precise one because the TPOP uses final selection values obtained by the conventional approaches. A comparison of the TPOP method with existing data fusion methods is given in Table 3. Details on the TPOP method can be found in Bairagi et al. [55].

The first case study is related to facility layout design selection. The second case study is a warehouse selection. The third case study is an environmentally conscious manufacturing program selection. The first case study aims

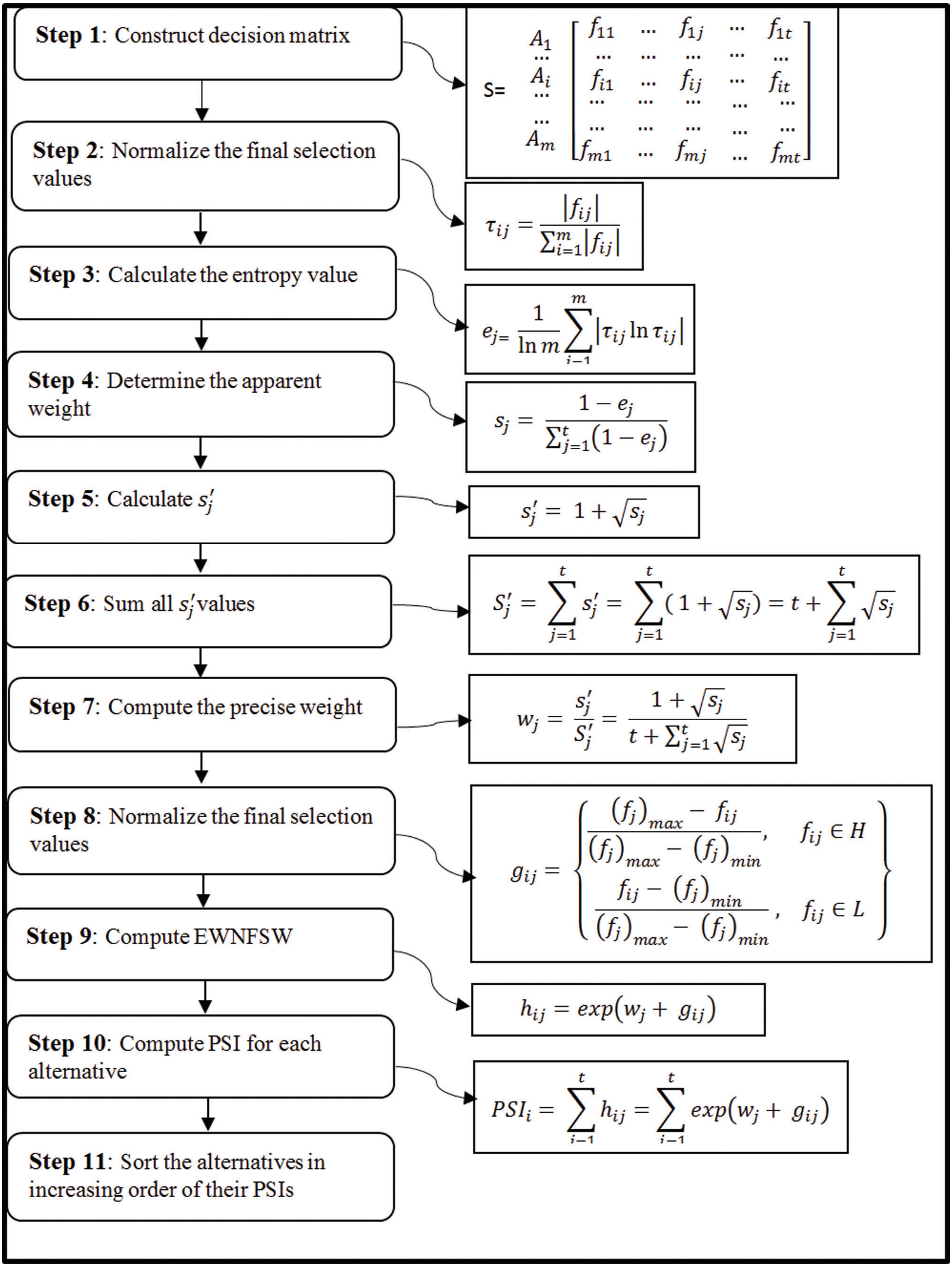

Figure 1. Steps of the TPOP [83], adapted from [55].

Table 3. Comparison of the TPOP method with existing data fusion methods [55]

	Conventional/current techniques	Technique of precise order preference
Difference	Each current method is multi-criteria, multi-alternatives decision-making technique	The proposed method is multi-approaches multi-criteria, multi-alternatives decision-making technique
	Inputs are the decision matrix consisting of performance scores of alternatives and weight matrix consisting of weights of criteria	Inputs are the matrix consisting of final selection values obtained using different current/conventional techniques
	Final selection values are different for different techniques (such as closeness coefficients of TOPSIS, composite score of SAW, net score of MOORA and so on)	Precise selection index is the final selection value that is unique
	Initial decision matrices used as input may be multiple in numbers	Initial input matrix is always single
	Decision makers' personal opinion, discretion, experience may play important role in estimating weights of criteria	Decision makers' do not play any role in determination of weights of the initial techniques
	Primary technique of first order	Primary technique of second order with advanced weight determination approach
Similarity	Ranking order of alternatives is the output	Ranking order of alternatives is the output
	Normalization of input data (performance score) is required	Normalization of input data is required
	Alternatives are explicit	Alternatives are explicit
	Alternatives are finite	Alternative are finite
Advantage	Prior application of other technique is not required	Easy and simple in application Removes rank reversal Determine the precise ranking order
Disadvantage	Individual application may give rise to rank reversal	Prior application of current techniques is required

to select the most suitable facility layout design considering 5 criteria. The second case study aims to list alternative warehouses based on 13 criteria. The third case study aims to select the environmentally conscious manufacturing program considering 6 criteria. 7 Multi-Criteria Decision Making Methods (MCDM), namely Improved OWA (ordered weighted averaging), Improved VIKOR (Compromise ranking method), Improved AHP (analytic hierarchy process), Improved GRA (gray relational analysis), Improved UTA (utility additive), WEDBA (The Weighted Euclidean Distance-Based Approach) and CMBA (Combinatorial Mathematics-Based Approach) are used for ranking in these case studies.

The flowchart of the study is given in Figure 2.

CASE STUDY-1

The first case study concerns the choice of facility layout design for selecting plant layout design for a chemical packaging industry situated in the western part of India. There are four alternative plant layout designs available in this case study. This case study is obtained from Venkata' [85] study.

There are five attributes, namely interaction with existing facility distance (m), area available for each assembly group (m2), material quantity flow (kg/h), accessibility for firefighting (%), and comfort of the crew for the selection of plant layout designs. The final selection values of Improved OWA, improved AHP, improved GRA, improved UTA, and improved VIKOR are used to implement the TPOP. The final selection values for the plant layout design selection problem are given in Table 4.

As can be seen in Table 4, the alternative rakings obtained by MCDM methods are different. These methods can't propose a single ranking of facility layout design alternatives. Weights of various MCDM methods for this case study are given in Table 5. The exponentially weighted normalized final selection values are given in Table 6.

The TPOP method finds a ranking based on the results of the previously known methods. A comparison of the ranking of facility layout design alternatives is given in Table 7. Finally, the precise ranking order of facility layout design alternatives is given in Fig. 2. As shown in Fig. 3, alternative 1 (P1) ranked first among facility layout designs by the TPOP. It should be noted that alternative 1 (P1) was

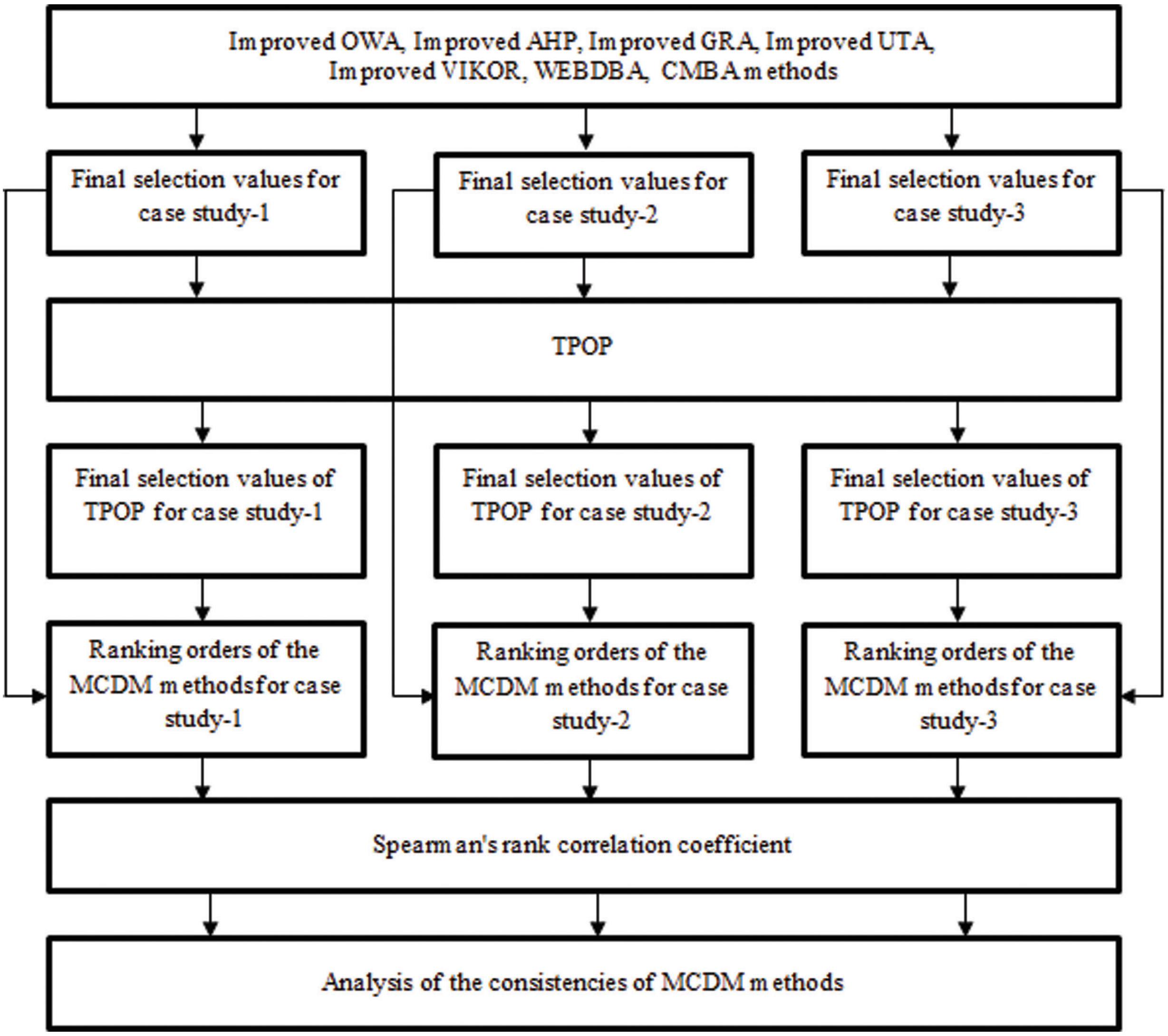

Figure 2. The flowchart of the study.

Table 4. Final selection values for plant layout design selection problem for case study-1 [85]

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEBDBA	CMBA
P1	0.9102	0.8583	0.7613	0.1924	0*	0.7512	124.1070
P2	0.8701	0.7669	0.5536	0.1053	0.8023	0.4189	125.7824
P3	0.7652	0.7389	0.5774	0.0673	0.9446	0.4319	120.6495
P4	0.7687	0.7927	0.6480	0.1755	0.3252	0.6344	115.1523

*The value is taken as 10-55 due to very close to 0.

also ranked first with respect to previously used MCDM methods.

CASE STUDY-2

This case study is about an automatic warehouse selection for the products of a firm located in India. The 4 existing warehouses will be evaluated for the storage of petrochemical products. Warehouses are evaluated, considering 13 criteria. They are power consumption, cycle time, material flow rate tonnage, total crew members, rea of setup, maintenance calls, wear and tear of the final pallet, scope for expansion, operability/skill required, firefighting reachability, operator safety, material flow rate, and the

Table 5. Weights of various MCDM methods for case study-1

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
e_i	0.9979	0.9989	0.9943	0.9457	0.7330	0.9776	0.9996
$1 - e_i$	0.0021	0.0011	0.0057	0.0543	0.2670	0.0224	0.0004
s_i	0.0059	0.0032	0.0162	0.1538	0.7562	0.0636	0.0011
$\sqrt{s_i}$	0.0770	0.0563	0.1271	0.3922	0.8696	0.2521	0.0340
$1 + \sqrt{s_i}$	1.0770	1.0563	1.1271	1.3922	1.8696	1.2521	1.0340
w_j	0.1222	0.1199	0.1280	0.1581	0.2123	0.1422	0.1174

Table 6. The exponentially weighted normalized final selection values for case study-1

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA	TPOP
P1	1.1301	1.1274	1.1365	1.1712	1.2365	1.1528	1.3165	8.2709
P2	1.4900	2.4240	3.0893	2.3497	2.8910	3.1335	1.1246	16.5022
P3	3.0718	3.0646	2.7549	3.1837	3.3610	3.0133	1.8226	20.2720
P4	2.9986	1.9530	1.9610	1.3406	1.7446	1.6383	3.0568	14.6929

Table 7. The exponentially weighted normalized final selection values for case study-1

Alternative	TPOP	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
P1	8.2709	1	1	1	1	1	1	2
P2	16.5022	2	3	4	2	3	4	1
P3	20.2720	4	4	3	3	4	3	3
P4	14.6929	3	2	2	4	2	2	4

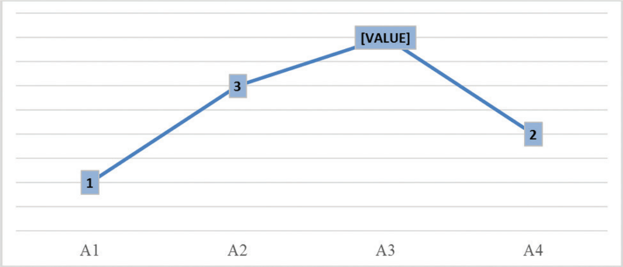

Figure 3. Precise ranking order of facility layout design alternatives for Case study-1.

number of forklifts. In this study, the results of five different methods (improved OWA, improved AHP, improved GRA, improved UTA, improved VIKOR, WEDBA, and CMBA) are used to conduct the TPOP method. The final selection values for warehouse selection are given in Table 8. Table 8 can be considered as a decision matrix for the TPOP method. Weights of the five methods (MCDM) based on Table 8 are given in Table 9. The exponentially weighted normalized final selection values obtained from the TPOP method are given in Table 10. Furthermore, a comparison of ranking order for Case study-2 based on the exponentially weighted normalized final selection values is given in Table 11.

Finally, the precise ranking order of automatic warehouse alternatives is given in Fig. 3. As shown in Figure 4, alternative 4 (P4) ranked first among alternatives by the TPOP method. Alternative 4 was also ranked first with respect to Improved AHP, Improved GRA, WEDBA, and CMBA, while it was ranked second with respect to Improved OWA, Improved UTA, and Improved VIKOR.

CASE STUDY-3

This case study is about an environmentally conscious manufacturing program selection. Warehouses are evaluated, considering 6 criteria. They are costs ($), quality (% defects), recyclability (% recyclable material), process waste reduction (%), packaging waste reduction (%), and regulatory compliance (% reduction in violations).

The results of five different methods (improved OWA, improved AHP, improved GRA, improved UTA, improved

Table 8. Final selection values for warehouse selection problem for case study-2 [85]

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
P1	0.4785	0.5664	0.5063	0.0111	0.5324	0.4539	4715069369.3921
P2	0.8000	0.7111	0.6343	0.0450	0.7097	0.4563	6020052114.9601
P3	0.7060	0.6559	0.5314	0.0313	0.2891	0.4051	5763369998.3237
P4	0.7867	0.7625	0.7170	0.0440	0.5000	0.5412	6358148982.8452

Table 9. Weights of various MCDM methods for case study-2

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
e_i	0.9866	0.9957	0.9929	0.9261	0.9673	0.9960	0.9957
$1 - e_i$	0.0134	0.0043	0.0071	0.0739	0.0327	0.0040	0.0043
s_i	0.0957	0.0305	0.0508	0.5295	0.2345	0.0283	0.0308
$\sqrt{s_i}$	0.3094	0.1746	0.2253	0.7276	0.4842	0.1683	0.1755
$1 + \sqrt{s_i}$	1.3094	1.1746	1.2253	1.7276	1.4842	1.1683	1.1755
w_j	0.1892	0.1697	0.1770	0.2496	0.2144	0.1688	0.1698

Table 10. The exponentially weighted normalized final selection values for case study-2

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA	TPOP
P1	3.2844	3.2211	3.2448	3.4890	2.2098	2.2484	3.2215	20.9190
P2	1.2083	1.5401	1.7675	1.2835	3.3684	2.2091	1.4559	12.8328
P3	1.6186	2.0407	2.8804	1.9227	1.2392	3.2181	1.7020	14.6218
P4	1.2593	1.1850	1.1937	1.3220	2.0460	1.1839	1.1851	9.3749

Table 11. Comparison of ranking order for case study-2

Alternative	TPOP		Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
P1	20.9190	4	4	4	4	3	3	4
P2	12.8328	1	2	2	1	4	2	2
P3	14.6218	3	3	3	3	1	4	3
P4	9.3749	2	1	1	2	2	1	1

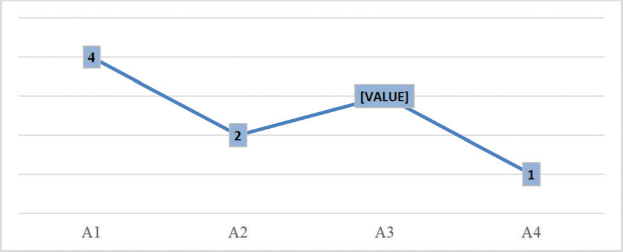

Figure 4. Precise ranking order of warehouse for case study-2.

VIKOR, WEDBA, and CMBA) are used for this case study. The final selection values of these methods are given in Table 12. Table 12 can be considered as a decision matrix for the TPOP method. The weights of the five methods used in this case study are given in Table 13. The exponentially weighted normalized final selection values obtained used the TPOP method are given in Table 14. Also, a comparison of ranking order for Case study-3 based on the exponentially weighted normalized final selection values is given in Table 15.

Table 12. Final selection values for environmentally conscious selection problem for case study-3 [85]

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
P1	0.6763	0.5788	0.6875	0.1079	0.4099	0.468	541.0829
P2	0.6052	0.6552	0.6712	0.1168	0.2288	0.6964	532.9109
P3	0.3412	0.3171	0.4641	0.042	0.8655	0.2226	449.6507
P4	0.5670	0.5154	0.5170	0.0918	0.7281	0.3693	512.641
P5	0.3412	0.3197	0.4349	0.0505	0.6951	0.2323	420.6097
P6	0.3975	0.4298	0.5144	0.0673	0.6732	0.3192	449.9200
P7	0.6250	0.5532	0.6665	0.1071	0.3663	0.5036	525.2307
P8	0.7125	0.7239	0.7297	0.1336	0*	0.6308	571.338
P9	0.7365	0.6901	0.7271	0.1233	0.4592	0.4944	580.2651
P10	0.5372	0.5674	0.6100	0.1017	0.3474	0.4648	514.6767
P11	0.6427	0.5897	0.6317	0.1087	0.2789	0.5612	532.6148
P12	0.2029	0.1905	0.3810	0.0178	0.9559	0.0752	374.1169
P13	0.6952	0.6336	0.6257	0.1121	0.4687	0.4586	573.0647
P14	0.4798	0.3939	0.4832	0.057	0.7217	0.2644	493.0809
P15	0.5797	0.4361	0.5154	0.0705	0.6709	0.2894	519.2702

*The value is taken as 10-55 due to very close to 0.

Table 13. Weights of various MCDM methods for case study-3

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
e_i	0.9836	0.9830	0.9935	0.9695	0.9461	0.9663	0.9976
$1 - e_i$	0.0164	0.0174	0.0065	0.0305	0.0539	0.0337	0.0024
s_i	0.1020	0.1082	0.0406	0.1896	0.3348	0.2097	0.0151
$\sqrt{s_i}$	0.3194	0.3289	0.2014	0.4354	0.5786	0.4580	0.1229
$1 + \sqrt{s_i}$	1.3194	1.3290	1.2014	1.4354	1.5786	1.4580	1.1229
w_j	0.1397	0.1407	0.1272	0.1520	0.1671	0.1544	0.1189

Table 14. The exponentially weighted normalized final selection values for case study-3

Alternative	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA	TPOP
P1	1.2873	1.5109	1.2818	1.4534	1.8148	1.6855	1.3620	10.3956
P2	1.4707	1.3093	1.3431	1.3459	1.5016	1.1669	1.4171	9.55459
P3	2.4121	2.4679	2.4324	2.5677	2.9229	2.5019	2.1222	17.4272
P4	1.5799	1.7016	2.0900	1.6702	2.5316	1.9757	1.5635	13.1125
P5	2.4121	2.4559	2.6449	2.38597	2.4457	2.4632	2.4433	17.2510
P6	2.1706	1.9979	2.1057	2.06377	2.3903	2.1417	2.1195	14.9893
P7	1.4172	1.5852	1.3613	1.4635	1.7339	1.5916	1.4709	10.6235
P8	1.2028	1.1511	1.1357	1.16417	1.1819	1.2969	1.1761	8.3086
P9	1.1499	1.2264	1.1442	1.27247	1.9108	1.6153	1.1263	9.4453
P10	1.6706	1.5436	1.6008	1.53337	1.6999	1.6942	1.5481	11.2905
P11	1.3709	1.4804	1.5042	1.44347	1.5824	1.4507	1.4191	10.2510
P12	3.1258	3.1290	3.0870	3.1644	3.2128	3.1720	3.0615	21.9526
P13	1.2425	1.3634	1.5303	1.4016	1.9299	1.7112	1.1663	10.3451
P14	1.8604	2.1369	2.3028	2.2557	2.5147	2.3392	1.7191	15.1287
P15	1.5427	1.9744	2.0997	2.0075	2.3845	2.2469	1.5140	13.7697

Table 15. Comparison of ranking order for case study-3

Alternative	TPOP	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
P1	10.3956	4	6	4	6	6	6	4
P2	9.55459	7	3	3	3	2	1	5
P3	17.4272	14	14	13	14	15	14	13
P4	13.1125	9	9	9	9	13	9	10
P5	17.2510	13	13	14	13	7	13	14
P6	14.9893	12	11	11	11	9	10	12
P7	10.6235	6	8	5	7	5	4	7
P8	8.3086	2	1	1	1	1	2	3
P9	9.4453	1	2	2	2	11	5	1
P10	11.2905	10	7	8	8	4	7	9
P11	10.2510	5	5	6	5	3	3	6
P12	21.9526	15	15	15	15	14	15	15
P13	10.3451	3	4	7	4	8	8	2
P14	15.1287	11	12	12	12	12	12	11
P15	13.7697	8	10	10	10	10	11	8

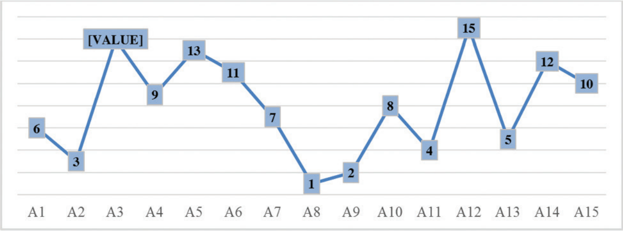

Figure 5. Precise ranking order of warehouse for case study-3.

Finally, precise ranking order of environmentally conscious manufacturing program alternatives is given in Fig. 5. As shown in Figure 4, alternative 8 (P8) ranked first among alternatives by the TPOP method. Alternative 8 was also ranked first for Improved AHP, Improved GRA, Improved UTA, and Improved VIKOR.

ANALYSIS OF THE CONSISTENCIES OF MCDM METHODS

The consistencies of MCDM methods are analyzed using Spearman's correlation coefficient values. Spearman correlation coefficient is calculated using Eq. (1) [86]

$$p = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \tag{1}$$

where, n is the number of sequences and d is the difference between the sequences.

Spearman's correlation coefficient is calculated for three case studies using the SPSS (Statistical Package for the Social Sciences) software [87]. Spearman's rank correlation coefficients are used to defect the similarity in the rankings of the different methods. This similarity value represents the consistency of the related method. Spearman's rank correlation analysis tests the direction and strength of the relationship between two ranked variables, or one ranked variable and one measurement variable. Also, it analyses one set of numbers affects another set of numbers [88].

Spearman's rank correlation coefficients between MCDM methods used in the case studies are given in Table 16-18.

TPOP and Improved AHP methods have the highest total correlation coefficient value. The order of the total correlation coefficient values of the methods is as below. $CC_{\text{TPOP, Improved AHP}} > CC_{\text{Improved OWA}} > CC_{\text{Improved GRA, WEBDBA}} > CC_{\text{Improved UTA}} > CC_{\text{Improved VIKOR}} > CC_{\text{CMBA}}$.

TPOP and Improved AHP, Improved GRA, CMBA methods have the highest total correlation coefficient value. The order of the total correlation coefficient values of the methods is as below. $CC_{\text{TPOP, Improved AHP, Improved GRA, CMBA}} > CC_{\text{Improved OWA, Improved UTA}} > CC_{\text{WEBDBA}} > CC_{\text{Improved VIKOR}}$.

TPOP method has the highest total correlation coefficient value. The order of the total correlation coefficient values of the methods is as below. $CC_{\text{TPOP}} > CC_{\text{Improved UTA}} > CC_{\text{Improved AHP}} > CC_{\text{Improved GRA}} > CC_{\text{WEBDBA}} > CC_{\text{CMBA}} > CC_{\text{Improved OWA}} > CC_{\text{Improved VIKOR}}$.

TPOP method has the highest total correlation coefficient value for three case studies. Thus, the TPOP method is the most consistent.

Table 16. Spearman's rank correlation coefficients between MCDM methods for the case study-1

	TPOP	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
TPOP	1	0.8	1	0.8	0.4	0.4	0.8	0
Improved OWA	0.8	1	0.8	0.4	0.8	0.2	0.4	0.6
Improved AHP	1	0.8	1	0.8	0.4	0.4	0.8	0
Improved GRA	0.8	0.4	0.8	1	0.2	0.8	1	-0.4
Improved UTA	0.4	0.8	0.4	0.2	1	0.4	0.2	0.8
Improved VIKOR	0.4	0.2	0.4	0.8	0.4	1	0.8	-0.2
WEDBA	0.8	0.4	0.8	1	0.2	0.8	1	-0.4
CMBA	0	0.6	0	-0.4	0.8	-0.2	-0.4	1

Table 17. Spearman's rank correlation coefficients between MCDM methods for the case study-2

	TPOP	Improved OWA	Improved AHP	Improved GRA	Improved UTA	Improved VIKOR	WEDBA	CMBA
TPOP	1	0.8	1	1	0.8	0	0.8	1
Improved OWA	0.8	1	0.8	0.8	1	-0.4	0.6	0.8
Improved AHP	1	0.8	1	1	0.8	0	0.8	1
Improved GRA	1	0.8	1	1	0.8	0	0.8	1
Improved UTA	0.8	1	0.8	0.8	1	-0.4	0.6	0.8
Improved VIKOR	0	-0.4	0	0	-0.4	1	-0.4	0
WEDBA	0.8	0.6	0.8	0.8	0.6	-0.4	1	0.8
CMBA	1	0.8	1	1	0.8	0	0.8	1

Table 18. Spearman's rank correlation coefficients between MCDM methods for the case study-3

	TPOP	Improved OWA	AHP	Improved GRA	Improved UTA	Improved VIKOR	WEBDA	CMBA
TPOP	1	0.932	0.993	0.968	0.996	0.696	0.936	0.936
Improved OWA	0.932	1	0.925	0.914	0.939	0.529	0.800	0.979
AHP	0.993	0.925	1	0.954	0.996	0.682	0.907	0.943
Improved GRA	0.968	0.914	0.954	1	0.964	0.668	0.939	0.918
Improved UTA	0.996	0.939	0.996	0.964	1	0.679	0.918	0.950
Improved VIKOR	0,696	0,529	0.682	0.668	0.679	1	0.814	0.521
WEBDA	0,936	0,800	0,907	0.939	0.918	0.814	1	0.800
CMBA	0,936	0,979	0.943	0.918	0.950	0.521	0.800	1

CONCLUSION

Making the right decisions in manufacturing systems is quite important. The company may be stuck in financial difficulty due to chose the wrong alternative or made the wrong decisions. Provide a competitive advantage for firms in the market depends on making the right decisions in practice. For this reason, the alternative order to be proposed to the decision-maker is extremely important.

Multi-criteria decision-making methods are among the most widely used decision methods in science, economy, security, and engineering. It is aimed to take into account the decision-making process more clearly and rationally with the use of these methods. Thus, the level of accuracy of the decisions taken is also increased. With the TPOP method, it is ensured that the decision problems are taken by considering all the results of the methods used in the final decision. The TPOP is applied in the paper for a manufacturing environment, but its application is context-independent. Its application is not limited to the manufacturing environment. Furthermore, the value of TPOP does not lie in its application to a manufacturing environment but rather in the enhanced decision-making quality it provides in general.

In this study, three important decision-making problems related to the manufacturing system are solved using the TPOP method. These are warehouse selection, facility layout design selection, and environmentally conscious manufacturing program selection. Many methods for solving such decision problems have been proposed in the literature. However, the application of the TPOP method in manufacturing systems is infrequent in the literature. This study extends the current literature on decision-making in the manufacturing environment with the TPOP method. Spearman's correlation coefficients values are detected for three case studies. Spearman's rank correlation coefficients are used to defect the similarity in the rankings of the different methods. TPOP method has the highest total correlation coefficient value for three case studies. TPOP method gave the most consistent ranking results among the MCDM methods used. Therefore, in this study, the TPOP method is proposed to solve the decision-making problems in manufacturing systems.

Fuzzy logic approach is not used in the study. In future research, fuzzy logic can be integrated with the TPOP method to handle uncertainty during decision-making in the manufacturing environment. In addition, in the study, the TPOP method is compared with the OWA, AHP, GRA, UTA, and VIKOR methods, but not with other data fusion methods. In future studies TPOP method can be compare with other data fusion methods used for decision making in the literature. Different methods can be used to compare the consistency of the methods or expert opinion can be received. In addition, in the study, the TPOP method is compared with the OWA, AHP, GRA, UTA, and VIKOR methods, but not with other data fusion methods. In future studies TPOP method can be compare with other data fusion methods used for decision making in the literature. Different methods can be used to compare the consistency of the methods or expert opinion can be received. In addition, inconsistent ranking order problems that occurred in other decision-making problems in the manufacturing environments, such as supplier selection and material selection, can also be solved using the TPOP method.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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