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SHORT COMMUNICATION

Application of preference selection index method for decision making over the design stage of production system life cycle

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Abstract The life cycle of production system shows the progress of production system from the inception to the termination of the system. During each stage, mainly in the design stage, certain strategic decisions have to be taken. These decisions are more complex as the decision makers have to assess a wide range of alternatives based on a set of conflicting criteria. As the decision making process is found to be unstructured, characterized by domain dependent knowledge, there is a need to apply an efficient multi-criteria decision making (MCDM) tool to help the decision makers in making correct decisions. This paper explores the application of a novel MCDM method i.e. Preference selection index (PSI) method to solve various decision-making problems that are generally encountered in the design stage of production system life cycle. To prove the potentiality, applicability and accuracy of PSI method in solving decision making problem during the design stage of production system life cycle, five examples are cited from the literature and are compared with the results obtained by the past researchers.

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1. Introduction

The production system is the collection of people, equipment, and procedures organized to accomplish the manufacturing operations of an organization (Groover, 2001; Cochran et al., 2000; Attri and Grover, 2012). The above requirement of a production system depends on the type of the product that the organization offers and the strategy that it employs to serve its customers (Panneerselvam, 2010).

Like the product life cycle, the production system has its own cycle. Chase and Aquilano (1977) have described that the production/productive system life cycle (Fig. 1) has four general phases: design, start-up, steady state, and termination.

Besides this, Chase and Aquilano (1977) have also discussed the effect of product life cycle on the production system life cycle. Moreover, Attri and Grover (2012) have differentiated between product life cycle and production system life cycle. Several researchers e.g., Chase and Aquilano (1977),

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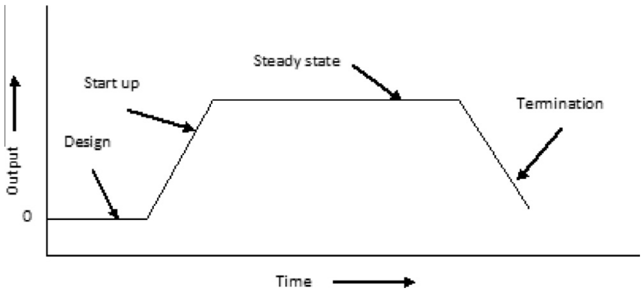

Figure 1 Production system life cycle (Chase and Aquilano, 1977).

Table 1 Decision to be taken during each stage of production system life cycle.

S. No.	Stage name	Decision to be taken
1.	Design stage	• Product design selection • Facility location selection • Facility layout selection • Process selection • Technology selection • Machine selection • Material selection • Material handling selection • Inspection/Measuring equipment selection
2.	Start-up stage	• Personnel selection • Vendor/supplier selection
3.	Steady state stage	• Failure cause analysis of machine tool • Technology selection in light of environmental change
4.	Termination stage	• Decision on salvage of resources

Nakano et al. (2008), Bellgran et al. (2002), Wiktorsson (2000), Bellgran and Säfsten (2010), Kosturiak and Gregor (1999), Preiss et al. (2001), Attri and Grover (2012) have documented different life cycle models of production system.

During each stage of the production life cycle different decisions (generally strategic in nature) have to be taken. Table 1 shows the brief view of decisions to be taken during different stages of production system life cycle.

A lot of applications of MCDM methods in various fields of design stage can be found in the literature such as, material selection by preferential ranking method (Chatterjee and Chakraborty, 2012), non-traditional machining process selection using analytic network process (Das and Chakraborty, 2011), selection of industrial robots using compromise ranking and outranking method (Chatterjee et al., 2010), design of material handling equipment selection model using analytic hierarchy process (Chakraborty and Banik, 2006), evaluation of flexible manufacturing system using digraph and matrix methods (Rao, 2006), rapid prototyping process selection using graph theory and matrix approach (Rao and Padmanabhan, 2007), facility layout design selection using weighted euclidean distance based approach (Rao and Singh, 2012), evaluation of product design using TOPSIS approach (Rao, 2007), selection of manufacturing process for manufacturing a product using graph theoretic approach (Singh et al., 2011), selection of facility layout using graph theoretic approach (Rao, 2007), selection of machine tool using data envelopment analysis (Sun, 2002) and automated inspection system selection using PROMETHEE method (Pandey and Kengpol, 1995).

The selection decisions in design stage of production system life-cycle are complex, as decision making has become more challenging now a days. Moreover, decision makers have to assess a wide range of alternatives based on a set of conflicting criteria. Thus, there is a need for simple, systematic, and logical methods or mathematical tools to guide decision makers in considering a number of selection attributes and their interrelationships. Although, a number of multi-criteria decision making (MCDM) techniques are available in the literature to assist the decision makers in making good judgments. It is observed that in all these methods, the ranking of alternatives is affected by the weight of criteria. Moreover, some of these methods are quite difficult to understand and complex to implement requiring extensive mathematical knowledge. Thus, there is still requirement of a simple, logical and systematic approach to solve the decision making problems without taking the criteria of weight into consideration. This paper endeavors to explore the applicability of a novel MCDM method, i.e. Preference selection index (PSI) method to deal with the decision making problems in the design stage of the production system life cycle.

2. Preference selection index (PSI) method

Preference selection index method was developed by Maniya and Bhatt (2010) for solving the multi-criteria decision making (MCDM) problems. In the proposed method it is not necessary to assign a relative importance between attributes. Moreover, there is no requirement of computing the weights of attributes involved in decision making problems in this method. This method is useful when there is a conflict in deciding the relative importance among attributes.

In the literature, a number of MCDM approaches are available such as graph theoretic approach (GTA), data envelopment analysis (DEA), grey relational analysis (GRA), compromise ranking method (VIKOR), analytic hierarchy process (AHP), analytic network process (ANP), multi-objective optimization by ratio analysis (MOORA), preference ranking organization method for enrichment evaluation method (PROMETHEE), technique for order preferences by similarity to ideal solution (TOPSIS), weighted euclidean distance based approach (WEDBA) etc.

In the graph theoretic approach, the decision making problem is solved by computing the determinant, which requires a lot of calculations. In the data envelopment analysis, it becomes necessary to discriminate the input and output attributes. Moreover, the decision maker must have the knowledge of linear programming (Maniya and Bhatt, 2011). In case of GRA and VIKOR Method, value of distinguishing coefficient (ξ) and weight of the strategy of the majority of attributes (v) play an important role on the final ranking of the alternative. This has necessitated the decision makers to perform the sensitivity analysis to evaluate the effect of ξ and v on the ranking of the alternative. But in the case of our proposed PSI method, there is no need to perform the sensitivity analysis. In the AHP method, relative importance of each factor is determined with respect to objective in order to calculate the weight. Moreover, the decision maker has to check the consistency in making judgements taken to assign relative importance between attributes and alternatives. This process becomes difficult when numbers of attributes and alternatives are larger in selection process (Maniya and Bhatt, 2010). The ANP method is a generic form of the AHP which allows for complex interdependence relationships among different elements or attributes.

It may be noted that all these existing methods require the assignment of relative importance between attributes or computation of weights of attributes involved in a problem. The weights of attributes are generally computed by the AHP method. Moreover, all these methods require intricate and cumbersome calculations. However, in the PSI method, results are obtained with minimum and simple calculations as it is based on the concept of statistics without the necessity of weights of attributes. This method can be used for any number of attributes.

The steps involved in the PSI method are as follows (Maniya and Bhatt, 2010, 2011; Vahdani et al., 2011):

Step: 1. Define the problem: Determine the objective and identify the pertinent attributes and alternatives involved in the decision-making problem under consideration.

Step: 2. Formulate the decision matrix: This step involves construction of a matrix based on all the information available that describes the problem attributes. Each row of decision matrix is allocated to one alternative, and each column to one attribute. Therefore, an element X_{ij} of the decision matrix X gives the value of the jth attribute in original real values; that is a non-normalized form and units for the ith alternative. Thus, if the number of alternatives is M and the number of attributes is N, then the decision matrix as an $N \times M$ matrix can be represented as follows:

$$X_{ij} = \begin{array}{cc} \begin{array}{cccccc} 1 & 2 & 3 & .. & .. & N \end{array} & \textit{Attribute} \\ \begin{bmatrix} X_{11} & X_{12} & X_{13} & .. & .. & X_{1N} \\ X_{21} & X_{22} & X_{23} & .. & .. & X_{2N} \\ X_{31} & X_{32} & X_{33} & .. & .. & X_{3N} \\ .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. \\ X_{M1} & X_{M2} & X_{M3} & .. & .. & X_{MN} \end{bmatrix} & \begin{array}{c} 1 \\ 2 \\ 3 \\ .. \\ .. \\ M \end{array} \end{array} \quad (1)$$

Step: 3. Normalize the data: In the multi-attribute decision making methods it is required to make the attribute value dimensionless. For this purpose the attribute values are transformed into 0 and 1. This process of transforming is known as normalization, which is done on the basis of the type of the attribute.

If the attribute is beneficial type, then larger values are desired, which can be normalized as:

$$N_{ij} = \frac{X_{ij}}{X_j^{\max}} \quad (2)$$

If the attribute is non-beneficial type, then smaller values are desired, which can be normalized as:

$$N_{ij} = \frac{X_j^{\min}}{X_{ij}} \quad (3)$$

Where X_{ij} is the attribute measure ($i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, M$).

Step: 4. Compute the mean value of the normalized data: In this step, mean value of the normalized data of every attribute is computed by the following equation:

$$\mathbb{N} = \frac{1}{n}\sum\nolimits_{i=1}^{n} N_{ij} \quad (4)$$

Step: 5. Compute the preference variation value: In this step, a preference variation value between the values of every attribute is computed using the following equation:

$$\phi_j = \sum\nolimits_{i-1}^{n} [N_{ij} - \mathbb{N}]^2 \quad (5)$$

Step: 6. Determine the deviation in preference value: In this step, deviation in the preference value is computed for every attribute using the following equation:

$$\Omega_j = [1 - \phi_j] \quad (6)$$

Step: 7. Compute the overall preference value: In this step of PSI method, overall preference value is determined for every attribute using the following equation:

$$\omega_j = \frac{\Omega_j}{\sum_{j=1}^{m} \Omega_j} \quad (7)$$

Moreover, the total overall preference value of all the attributes should be one i.e. $\sum_{j=1}^{m} \Omega_j = 1$.

Step: 8. Compute the preference selection index: Now, the preference selection index is calculated for each alternative using the following equation:

$$\theta_i = \sum_{j=1}^{M} X_{ij} \text{ x } \omega_j \quad (8)$$

Step: 9. Select the appropriate alternative for the given application: At last, each alternative is ranked according to descending or ascending order to facilitate the managerial interpretation of the results. The alternative having the highest preference selection index will be ranked first and so on.

In the current paper, main objective is to compare the performance of the PSI method with the other known MCDM techniques in solving decision making problems.

3. Illustrative examples

In this section, five examples from the literature are cited to demonstrate the application of the PSI methodology in making the accurate decisions during the design stage of the production system life cycle.

3.1. Example 1: Facility layout design selection

This problem deals with the selection of plant layout design for a chemical packaging industry (Rao and Singh, 2012). Rao and Singh (2012) considered four alternative plant layout designs and five attributes i.e. interaction with existing facility distance (IEFD), area available for each assembly group (AAG), material quantity flow (MQF), accessibility for fire fighting (AFF) and comfort of crew (COC), as shown in Table 2. Among these three attributes interaction with the existing facility distance (IEFD) is a beneficial attribute and remaining ones are non-beneficial attributes.

To solve this facility layout design problem following procedural steps are carried out:

Step: 1. In this problem, objective is to select the optimal facility layout design problem for a chemical packaging industry. Here, four alternative plant layout designs and five attributes are considered which are same as that of Rao and Singh (2012).

Step: 2. The decision matrix for the problem is shown in Table 2.

Step: 3. The decision matrix is normalized using Eqs. (2) and (3) depending upon the type of data. Normalized decision matrix is shown in Table 3.

Step: 4. The mean values of normalized data of every facility layout design attribute computed by Eq. (4) are $\mathbb{N}_{\text{IEFD}} = 0.7204$, $\mathbb{N}_{\text{AAG}} = 0.7917$, $\mathbb{N}_{\text{MQF}} = 0.8152$, $\mathbb{N}_{\text{AFF}} = 0.8418$, $\mathbb{N}_{\text{COC}} = 0.6136$.

Table 3 Normalized decision matrix for example 1.

Layout alternatives	IEFD	AAG	MQF	AFF	COC
1	0.8235	1.0000	0.8696	0.9592	0.2046
2	1.0000	0.6000	0.6087	0.8367	1.0000
3	0.6829	0.7333	1.0000	0.5714	0.7500
4	0.3750	0.8333	0.7826	1.0000	0.4999

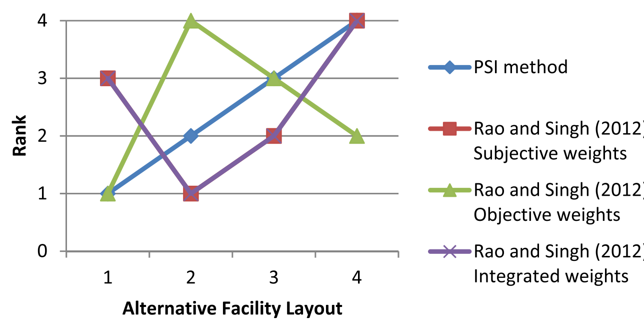

Figure 2 Comparative Ranking for example 1.

Step: 5. In this step preference variation value for every facility layout design attribute is computed using Eq. (5) and its values are $\phi_{\text{IEFD}} = 0.295$, $\phi_{\text{AAG}} = 0.0853$, $\phi_{\text{MQF}} = 0.0808$, $\phi_{\text{AFF}} = 0.1119$, $\phi_{\text{COC}} = 0.3481$.

Step: 6. Now, the deviation in a preference value which is calculated for every facility layout design attribute is computed using Eq. (6) and its values are $\Omega_{\text{IEFD}} = 0.7905$, $\Omega_{\text{AAG}} = 0.9147$, $\Omega_{\text{MQF}} = 0.9192$, $\Omega_{\text{AFF}} = 0.8881$, $\Omega_{\text{COC}} = 0.6519$.

Step: 7. The overall preference values of every facility layout design attribute computed by Eq. (7) are $\omega_{\text{IEFD}} = 0.1898$, $\omega_{\text{AAG}} = 0.2197$, $\omega_{\text{MQF}} = 0.2207$, $\omega_{\text{AFF}} = 0.2133$, $\omega_{\text{COC}} = 0.1565$.

Step: 8. Facility layout design indexes for every facility layout design alternative by Eq. (8) are $\theta_1 = 0.8124$, $\theta_2 = 0.7909$, $\theta_3 = 0.7597$, $\theta_4 = 0.7185$.

Step: 9. Now, the facility layout design alternatives are arranged in descending order according to the facility layout design index value as $\theta_1 > \theta_2 > \theta_3 > \theta_4$.

The ranking order shows that the facility layout design 1 is the right choice. Rao and Singh (2012) also calculated layout design 1 as the first choice using the objective weights by using the weighted euclidean distance based approach (WEDBA). The ranking performance of PSI method with respect to those derived by Rao and Singh (2012) are exhibited in Fig. 2.

Table 2 Qualitative data for example 1 (Rao and Singh, 2012).

Layout alternatives	IEFD	AAG	MQF	AFF	COC
1	102	3000	200	94	Very low (0.1364)
2	84	1800	140	82	High (0.6667)
3	123	2200	230	56	Average (0.5)
4	224	2500	180	98	Low (0.3333)

Attributes: IEFD (interaction with existing facility distance in meters); AAG (area available for each assembly group in m^2); MQF (material quantity flow in kg/hr); AFF (accessibility for firefighting in %); COC (comfort of crew).

Table 4 Qualitative data for example 2 (Byun and Lee, 2004).

RP system	A	R	S	E	C	B
SLA3500	120	6.5	6.5	5	0.745	0.5
SLS2500	150	12.5	40	8.5	0.745	0.5
FDM8000	125	21	30	10	0.665	0.745
LOM1015	185	20	25	10	0.59	0.41
Quadra	95	3.5	30	6	0.745	0.41
Z402	600	15.5	5	1	0.135	0.255

Attributes: A (accuracy); R (surface roughness); S (tensile strength); E (elongation); C (cost of the part); B (build time).

3.2. Example 2: Rapid prototyping process selection

Byun and Lee (2004) developed a decision support system for selection of a rapid prototyping (RP) process using the modified TOPSIS method. Byun and Lee (2004) designed a case study of a designed test part comprising of six RP systems. They considered six attributes i.e. accuracy (A), surface roughness (R), tensile strength (S), elongation (E), cost of the part (C), and build time (B). Among these six attributes S and E are the beneficial attributes, and A, R, C, and B are the non-beneficial attributes.

To solve this rapid prototyping (RP) process selection problem following procedural steps are carried out:

Step: 1. In this problem, the objective is to select the rapid prototyping (RP). Here, six alternative RP processes and six attributes are considered which are same as that of Byun and Lee (2004).

Step: 2. The decision matrix for the problem is shown in Table 4.

Step: 3. The decision matrix is normalized using Eqs. (2) and (3) depending upon the type of data. Normalized decision matrix for the problem is shown in Table 5.

Table 5 Normalized decision matrix for example 2.

RP system	A	R	S	E	C	B
SLA3500	0.7917	0.5385	0.1625	0.5000	0.1812	0.5100
SLS2500	0.6333	0.2800	1.0000	0.8500	0.1812	0.5100
FDM8000	0.7600	0.1667	0.7500	1.0000	0.2030	0.3423
LOM1015	0.5135	0.1750	0.6250	1.0000	0.2288	0.6220
Quadra	1.0000	1.0000	0.7500	0.6000	0.1812	0.6220
Z402	0.1583	0.2258	0.1250	0.1000	1.0000	1.0000

Step: 4. The mean values of normalized data of every RP process selection attribute computed by Eq. (4) are $\mathbb{N}_A = 0.6428$, $\mathbb{N}_R = 0.3977$, $\mathbb{N}_S = 0.5688$, $\mathbb{N}_E = 0.6750$, $\mathbb{N}_C = 0.3292$, $\mathbb{N}_B = 0.6010$.

Step: 5. In this step preference variation value for every RP process selection attribute is computed using Eq. (5) and its values are $\phi_A = 0.4150$, $\phi_R = 0.5290$, $\phi_S = 0.6168$, $\phi_E = 0.6088$, $\phi_C = 0.5417$, $\phi_B = 0.2436$.

Step: 6. Now, the deviation in a preference value which is calculated for every RP process selection attribute is computed using Eq. (6) and its values are $\Omega_A = 0.5850$, $\Omega_R = 0.4710$, $\Omega_S = 0.3832$, $\Omega_E = 0.3913$, $\Omega_C = 0.4583$, $\Omega_B = 0.7564$.

Step: 7. The overall preference values of every RP process selection attribute computed by Eq. (7) are $\omega_A = 0.1921$, $\omega_R = 0.1547$, $\omega_S = 0.1258$, $\omega_E = 0.1285$, $\omega_C = 0.1505$, $\omega_B = 0.2484$.

Step: 8. RP process selection indexes for every RP process alternative by Eq. (8) are $\theta_{\mathrm{SLA3500}} = 0.4740$, $\theta_{\mathrm{SLS2500}} = 0.5540$, $\theta_{\mathrm{FDM8000}} = 0.5102$, $\theta_{\mathrm{LOM1015}} = 0.5218$, $\theta_{\mathrm{Quadra}} = 0.7000$, $\theta_{\mathrm{Z402}} = 0.4928$.

Step: 9. Now, the RP process alternatives are arranged in descending order according to the RP process selection index value as $\theta_{\mathrm{Quadra}} > \theta_{\mathrm{SLS2500}} > \theta_{\mathrm{LOM1015}} > \theta_{\mathrm{FDM8000}} > \theta_{\mathrm{Z402}} > \theta_{\mathrm{SLA3500}}$.

The ranking order shows that the Quadra is the best RP process system. Byun and Lee (2004) found Quadra as the best RP system by using the modified TOPSIS method. Moreover, Rao and Patel (2009), Chakraborty (2011) obtained the Quadra as the best RP process system using the PROMETHEE and MOORA method. The ranking performance of the PSI method with respect to those derived by Rao and Patel (2009), Chakraborty (2011) are exhibited in Fig. 3.

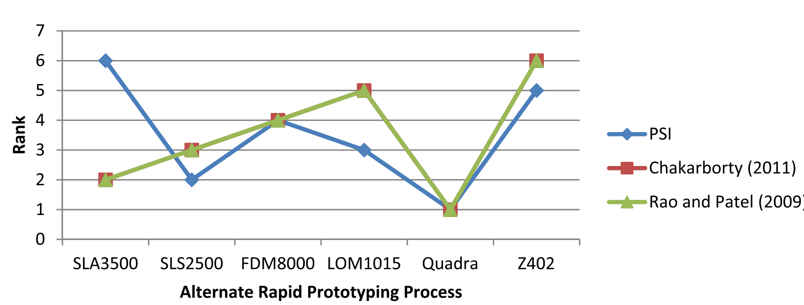

Figure 3 Comparative Ranking for example 2.

Table 6 Qualitative data for example 3 (Rao, 2007).

Cutting fluids	WW	TF	GT	SR	R	TH	EP	S
1	0.035	34.5	847	1.76	0.335	0.5	0.59	0.59
2	0.027	36.8	834	1.68	0.335	0.665	0.665	0.665
3	0.037	38.6	808	2.4	0.59	0.59	0.41	0.5
4	0.028	32.6	821	1.59	0.5	0.59	0.59	0.41

Attributes: WW (wheel wear); TF (tangential force); GT (grinding temperature); SR (surface roughness); R (recyclability); TH (toxic harm rate); EP (environment pollution tendency); S (stability).

Table 7 Normalized decision matrix for example 3.

Cutting fluids	WW	TF	GT	SR	R	TH	EP	S
1	0.7714	0.9449	0.9540	0.9034	0.5678	1.0000	0.6949	0.8872
2	1.0000	0.8859	0.9688	0.9464	0.5678	0.7519	0.6165	1.0000
3	0.7297	0.8446	1.0000	0.6625	1.0000	0.8475	1.0000	0.7519
4	0.9643	1.0000	0.9842	1.0000	0.8475	0.8475	0.6949	0.6165

3.3. Example 3: Cutting fluid selection

This problem deals with the selection of cutting fluid for cylindrical grinding (Rao, 2007). In this, Rao (2007) considered four grinding fluids and eight cutting fluid attributes i.e. wheel wear (WW), tangential force (TF), grinding temperature (GT), surface roughness (SR), recyclability (R), toxic harm rate (TH), environment pollution tendency (EP), and stability (S). Among these, R and S are beneficial attributes while WW, TF, GT, SR, TH, and EP are non-beneficial attributes.

To solve this cutting fluid selection problem following procedural steps are carried out:

Step: 1. In this problem, objective is to select the cutting fluid. Here, four alternative cutting fluids and eight attributes are considered which are same as that of Rao (2007).

Step: 2. The decision matrix for the problem is shown in Table 6.

Step: 3. The decision matrix is normalized using Eqs. (2) and (3) depending upon the type of data. Normalized decision matrix for this problem is shown in Table 7.

Step: 4. The mean value of normalized data of every cutting fluid selection attribute computed by Eq. (4) are $\mathbb{N}_{WW} = 0.8664$, $\mathbb{N}_{TF} = 0.9188$, $\mathbb{N}_{GT} = 0.9767$, $\mathbb{N}_{SR} = 0.8781$, $\mathbb{N}_{R} = 0.7458$, $\mathbb{N}_{TH} = 0.8617$, $\mathbb{N}_{EP} = 0.7516$, $\mathbb{N}_{S} = 0.8139$.

Step: 5. In this step preference variation value for every cutting fluid selection attribute is computed using Eq. (5) and its values are $\phi_{WW} = 0.0467$, $\phi_{TF} = 0.0139$, $\phi_{GT} = 0.0012$, $\phi_{SR} = 0.0667$, $\phi_{R} = 0.1383$, $\phi_{TH} = 0.0316$, $\phi_{EP} = 0.0864$, $\phi_{S} = 0.0828$.

Step: 6. Now, the deviation in a preference value which is calculated for every cutting fluid selection attribute is computed using Eq. (6) and its values are $\Omega_{WW} = 0.9533$, $\Omega_{TF} = 0.9861$, $\Omega_{GT} = 0.9988$, $\Omega_{SR} = 0.9333$, $\Omega_{R} = 0.8617$, $\Omega_{TH} = 0.9684$, $\Omega_{EP} = 0.9136$, $\Omega_{S} = 0.9172$.

Step: 7. The overall preference values of every cutting fluid selection attribute computed by Eq. (7) are $\omega_{WW} = 0.1266$, $\omega_{TF} = 0.1309$, $\omega_{GT} = 0.1326$, $\omega_{SR} = 0.1239$, $\omega_{R} = 0.1144$, $\omega_{TH} = 0.1286$, $\omega_{EP} = 0.1213$, $\omega_{S} = 0.1218$.

Step: 8. Cutting fluid selection indexes for every alternative cutting fluid by Eq. (8) are $\theta_1 = 0.8457$, $\theta_2 = 0.8465$, $\theta_3 = 0.8539$, $\theta_4 = 0.8727$.

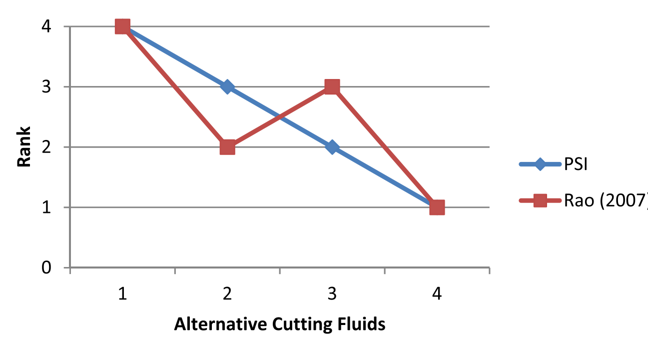

Figure 4 Comparative Ranking for example 3.

Step: 9. Now, the cutting fluid alternatives are arranged in descending order according to the cutting fluid selection index value as $\theta_4 > \theta_3 > \theta_2 > \theta_1$.

The ranking order shows that cutting fluid 4 is the best cutting fluid for the given cylindrical grinding operation. Rao (2007) found cutting fluid 4 as the best cutting fluid for given application by using the graph theoretic approach. The ranking performances of PSI method with respect to those derived by Rao (2007) are exhibited in Fig. 4.

3.4. Example 4: Welding process selection

This example is related with the selection of an arc welding process to join mild steel job of 6 mm thickness (Rao, 2007). This welding process selection problem consists of three alternate arc welding processes i.e. shielded metal arc welding (SMAW), gas tungsten arc welding (GTAW), and gas metal arc welding (GMAW). The attributes considered are: weld quality (WQ), operator fatigue (OF), skill required (SR), cleaning required after welding (CR), availability of consumables (AC) and initial preparation required (IP). Among these attributes OF, SR, CR, and IP are non-beneficial, while WQ and AC are considered as beneficial attributes.

To solve this welding selection problem following procedural steps are carried out:

Table 8 Qualitative data for example 4 (Rao, 2007).

Welding process	WQ	OF	SR	CR	AC	IP
SMAW	0.5	0.5	0.5	0.665	0.745	0.5
GTAW	0.745	0.665	0.745	0.5	0.5	0.665
GMAW	0.59	0.745	0.665	0.59	0.665	0.745

Attributes: WQ (weld quality); OF (operator fatigue); SR (skill required); CR (cleaning required after welding); AC (availability of consumables); IP (initial preparation required).

Table 9 Normalized decision matrix for example 4.

Welding process	WQ	OF	SR	CR	AC	IP
SMAW	0.6711	1.0000	1.0000	0.7519	1.0000	1.0000
GTAW	1.0000	0.7519	0.6711	1.0000	0.6711	0.7519
GMAW	0.7919	0.6711	0.7519	0.8475	0.8926	0.6711

Step: 1. In this problem, objective is to select welding process. Here, four alternative arc welding processes and six attributes are considered which are same as that of Rao (2007).

Step: 2. The decision matrix for the problem is shown in Table 8.

Step: 3. The decision matrix is normalized using Eqs. (2) and (3) depending upon the type of data. Normalized decision matrix for the problem is shown in Table 9.

Step: 4. The mean values of normalized data of every welding process selection attribute computed by equation (4) are $\mathbb{N}_{\mathrm{WQ}} = 0.8210$, $\mathbb{N}_{\mathrm{OF}} = 0.8077$, $\mathbb{N}_{\mathrm{SR}} = 0.8077$, $\mathbb{N}_{\mathrm{CR}} = 0.8664$, $\mathbb{N}_{\mathrm{AC}} = 0.8546$, $\mathbb{N}_{\mathrm{IP}} = 0.8077$.

Step: 5. In this step preference variation value for every welding process selection attribute is computed using Eq. (5) and its values are $\phi_{\mathrm{WQ}} = 0.0553$, $\phi_{\mathrm{OF}} = 0.0587$, $\phi_{\mathrm{SR}} = 0.0587$, $\phi_{\mathrm{CR}} = 0.0313$, $\phi_{\mathrm{AC}} = 0.0562$, $\phi_{\mathrm{IP}} = 0.0587$.

Step: 6. Now, the deviation in a preference value which is calculated for every welding process selection attribute is computed using Eq. (6) and its values are $\Omega_{\mathrm{WQ}} = 0.9447$, $\Omega_{\mathrm{OF}} = 0.9413$, $\Omega_{\mathrm{SR}} = 0.9413$, $\Omega_{\mathrm{CR}} = 0.9687$, $\Omega_{\mathrm{AC}} = 0.9438$, $\Omega_{\mathrm{IP}} = 0.9413$.

Step: 7. The overall preference values of every welding process selection attribute computed by Eq. (7) are $\omega_{\mathrm{WQ}} = 0.1633$, $\omega_{\mathrm{OF}} = 0.1657$, $\omega_{\mathrm{SR}} = 0.1657$, $\omega_{\mathrm{CR}} = 0.1705$, $\omega_{\mathrm{AC}} = 0.1661$, $\omega_{\mathrm{IP}} = 0.1657$.

Step: 8. Welding process selection indexes for every alternative welding process by Eq. (8) are $\theta_{\mathrm{SMAW}} = 0.9030$, $\theta_{\mathrm{GTAW}} = 0.8087$, $\theta_{\mathrm{GMAW}} = 0.7715$.

Step: 9. Now, the alternative welding processes are arranged in descending order according to the welding process selection index value as $\theta_{\mathrm{SMAW}} > \theta_{\mathrm{GTAW}} > \theta_{\mathrm{GMAW}}$.

The ranking order shows that SMAW process is the best arc welding process for the given conditions. Rao (2007) also found SMAW process as the best arc welding process by using GTA and AHP method.

3.5. Example 5: Material handling equipment selection

This problem is related to determination of the most appropriate conveyor (Kulak, 2005). The problem consists of four alternative conveyors and six attributes i.e. fixed cost per hour (FC), variable cost per hour (VC), speed of conveyor (SC), item width (IW), item weight (W) and flexibility (F). Among these six attributes, SC, IW, W and F are beneficial attributes while FC and VC are non-beneficial attributes.

To solve this conveyor selection problem following procedural steps are carried out:

Step: 1. In this problem, objective is to select conveyor. Here, four alternative conveyors and six attributes are considered which are same as that of Kulak (2005).

Step: 2. The decision matrix for the problem is shown in Table 10.

Step: 3. The decision matrix is normalized using Eqs. (2) and (3) depending upon the attribute type. Normalized decision matrix for the problem is shown in Table 11.

Step: 4. The mean values of normalized data of every conveyor selection attribute computed by Eq. (4) are $\mathbb{N}_{\mathrm{FC}} = 0.8979$, $\mathbb{N}_{\mathrm{VC}} = 0.9780$, $\mathbb{N}_{\mathrm{SC}} = 0.8846$, $\mathbb{N}_{\mathrm{IW}} = 0.7500$, $\mathbb{N}_{W} = 0.6875$, $\mathbb{N}_{F} = 0.8901$.

Step: 5. In this step preference variation value for every conveyor selection attribute is computed using Eq. (5) and its values are $\phi_{\mathrm{FC}} = 0.0155$, $\phi_{\mathrm{VC}} = 0.0009$, $\phi_{\mathrm{SC}} = 0.0296$, $\phi_{\mathrm{IW}} = 0.1389$, $\phi_{\mathrm{W}} = 0.1719$, $\phi_{\mathrm{F}} = 0.0484$.

Table 10 Qualitative data for example 5 (Kulak, 2005).

Conveyors	FC	VC	SC	IW	W	F
A1	2	0.45	12	15	10	Very good (0.745)
A2	2.3	0.44	13	20	10	Excellent (0.955)
A3	2.25	0.45	11	30	20	Excellent (0.955)
A4	2.4	0.46	10	25	15	Very good (0.745)

Attributes: FC (fixed cost per hour); VC (variable cost per hour); SC (speed of conveyor); IW (item width); W (item weight); F (flexibility).

Table 11 Normalized decision matrix for example 5.

Conveyors	FC	VC	SC	IW	W	F
A1	1.0000	0.9778	0.9231	0.5000	0.5000	0.7801
A2	0.8696	1.0000	1.0000	0.6667	0.5000	1.0000
A3	0.8889	0.9778	0.8462	1.0000	1.0000	1.0000
A4	0.8333	0.9565	0.7692	0.8333	0.7500	0.7801

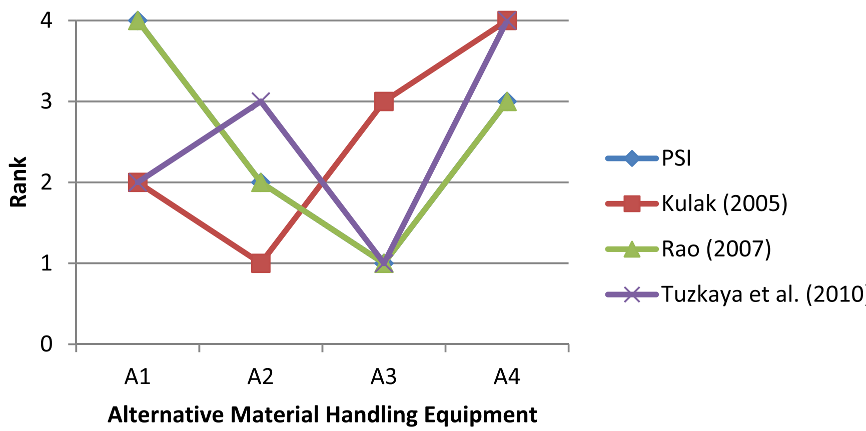

Figure 5 Comparative Ranking for example 5.

Step: 6. Now, the deviation in a preference value which is calculated for every conveyor selection attribute is computed using Eq. (6) and its values are $\Omega_{FC} = 0.9845$, $\Omega_{VC} = 0.9991$, $\Omega_{SC} = 0.9704$, $\Omega_{IW} = 0.8611$, $\Omega_{W} = 0.8281$, $\Omega_{F} = 0.9516$.

Step: 7. The overall preference values of every conveyor selection attribute computed by Eq. (7) are $\omega_{FC} = 0.1760$, $\omega_{VC} = 0.1786$, $\omega_{SC} = 0.1734$, $\omega_{IW} = 0.1539$, $\omega_{W} = 0.1480$, $\omega_{F} = 0.1701$.

Step: 8. Material handling equipment selection index for every alternative conveyor by Eq. (8) are $\theta_{A1} = 0.7943$, $\theta_{A2} = 0.8517$, $\theta_{A3} = 0.9498$, $\theta_{A4} = 0.8228$.

Step: 9. Now, the alternative conveyors are arranged in descending order according to the conveyor selection index value as $\theta_{A3} > \theta_{A2} > \theta_{A4} > \theta_{A1}$.

The ranking order shows that conveyor 3 is the best conveyor for the given conditions. Tuzkaya et al. (2010) and Rao (2007) found conveyor 3 as the best conveyor while solving the same problem by fuzzy ANP, fuzzy PROMETHEE and TOPSIS method. The ranking performances of PSI method with respect to those derived by Tuzkaya et al. (2010) and Rao (2007), Kulak (2005) are exhibited in Fig. 5.

4. Discussion

It is observed that in comparison with other MCDM methods like AHP, ANP, TOPSIS, VIKOR, GTA, WEDBA, MOORA, PROMETHEE, GRA etc., the proposed PSI method is very simple to understand and easy to implement. In a literature review on these existing MCDM methods, it is revealed that it is necessary to assign the relative importance between attributes or weights of attributes are required. For this task, generally AHP or entropy method is used for computing the weights. But in case of PSI method, there is no such requirement. This method uses the concept of statistics, which

Table 12 Comparative performance of MCDM methods.

MCDM method	Computational time	Simplicity	Mathematical calculations required	Requirement of weights or assignment of importance between attributes	Introduction of extra parameters
PSI	Very less	Very simple	Minimum	Not required	Not required
GTA	Very high	Moderately critical	Maximum	Required	Not required
AHP	High	Very critical	Maximum	Required	Not required
ANP	Very high	Moderately critical	Moderate	Required	Not required
GRA	High	Simple	Maximum	Not required	Required
VIKOR	Less	Simple	Moderate	Required	Required
PROMETHEE	High	Moderately critical	Moderate	Required	Not required
WEDBA	High	Moderately critical	Moderate	Required	Not required
TOPSIS	Moderate	Moderately critical	Moderate	Required	Not required
MOORA	Less	Simple	Maximum	Required	Not required
DEA	Very high	Moderately critical	Moderate	Not required	Not required

may be helpful to the decision makers having weak mathematics background. The computational time requirement of the PSI method is very much less as compared to other MCDM methods.

Besides this, in PSI method, there is no requirement of introducing the extra parameters as in the case of other MCDM methods (ν in case of VIKOR method and ξ in case of GRA method). All these reasons have made the PSI method as a highly stable method for solving the decision making problems.

Table 12 shows the comparative performance of the PSI method with other well-known MCDM methods with respect to computational time, simplicity, mathematical calculations involved, weights or assignment of importance between the attributes and extra parameter requirement.

From this table, it is revealed that PSI method outperforms the other MCDM methods in all aspects which proves its applicability as the effective MCDM tool for solving decision making problems.

5. Conclusion

A methodology based on a preference selection index (PSI) method is suggested for decision making over the design stage of the production system life cycle. This proposed methodology helps in selection of a suitable alternative from among a large number of available alternatives for a given decision making problem. Five decision making problems from different areas of manufacturing environment are included to illustrate the application of the PSI method. The proposed PSI method does not consider any relative importance between attributes. The result obtained from considered decision making problems by the PSI method is compared with the results derived by the past researchers. In all the cases, it is observed that best alternative exactly matches with those derived by the past researchers.

PSI method can be effectively used by the decision makers to make accurate decisions in different areas of manufacturing environment such as material, product design, process design, facility location, facility layout, material handling, and manufacturing system in an efficient and timely manner. However, this method is based on the statistical calculations, which has necessitated the development of computer program which will result in the reduction of computational time. In future, computer program may be developed for expediting the computation process. Moreover, this approach can be extended to the other stages of the production system life cycle.

Finally it is concluded that the PSI method is most appropriate and competent for the decision making problems having a large number of conflicting attributes. As compared to other MCDM approaches, PSI method is easier to understand as it involves less numerical computations. Therefore PSI method can be considered as a novel method for solving the decision making problems.

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