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Applications of WASPAS Method in Manufacturing Decision Making

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Abstract. In order to survive in the present day global competitive environment, it now becomes essential for the manufacturing organizations to take prompt and correct decisions regarding effective use of their scarce resources. Various multi-criteria decision-making (MCDM) methods are now available to help those organizations in choosing the best decisive course of actions. In this paper, the applicability of weighted aggregated sum product assessment (WASPAS) method is explored as an effective MCDM tool while solving eight manufacturing decision making problems, such as selection of cutting fluid, electroplating system, forging condition, arc welding process, industrial robot, milling condition, machinability of materials, and electro-discharge micro-machining process parameters. It is observed that this method has the capability of accurately ranking the alternatives in all the considered selection problems. The effect of the parameter λ on the ranking performance of WASPAS method is also studied.
Key words: manufacturing, decision making, WSM, WPM, WASPAS.

1. Introduction

Manufacturing can be defined as the application of mechanical, physical and chemical processes to modify the geometry, properties and/or appearance of a given input material while making a new finished part/product. The type of manufacturing performed by an organization largely depends on the end product it produces. In the modern sense, manufacturing includes various interrelated activities, like product design, material selection, process planning, machine selection, maintenance planning and documentation, quality assurance, management and marketing of products (Rao, 2007). Today's manufacturing processes are caught between the growing needs for quality, high process safety, minimal manufacturing costs and short manufacturing times. In order to meet these demands, manufacturing processes need to be chosen in the best possible way. Selection of the manufacturing processes and optimal process parameter settings plays a pivotal role to ensure

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high quality of products, reduce manufacturing costs, trim down lead times and inventory levels, and increase the overall productivity of the manufacturing organizations.

Decision makers in the manufacturing sector frequently face the problem of assessing a wide range of alternative options and selecting the best one based on a set of conflicting criteria. It must be noted that in choosing the most appropriate alternative, there is not always a single definite criterion of selection, and the decision makers have to take into account a large number of criteria. Thus, there is a need for some simple, systematic and logical methods or mathematical tools to guide the decision makers in considering a number of conflicting selection criteria and their interrelations. The objective of any selection procedure is to identify the suitable evaluation criteria and obtain the most appropriate combination of criteria in conjunction with the real requirement. Thus, efforts need to be extended to identify those criteria that influence the best alternative selection for a given problem, using simple and logical methods, to eliminate the unsuitable alternatives, and select the most appropriate one to strengthen the existing selection procedures.

In order to deal with those complex selection problems arising in the modern day manufacturing environment, various multi-criteria decision-making (MCDM) methods have already been proposed and augmented by the earlier researchers. Each selection problem basically consists of four main components, i.e. (a) alternatives, (b) attributes/criteria, (c) relative importance (weight) of each attribute, and (d) measures of performance of alternatives with respect to different attributes. These types of selection problems having the desired structure are quite suitable to be solved using the MCDM techniques. Thus, the main aim of any MCDM approach is choose the best option from a set of feasible alternatives in the presence of various conflicting criteria. In this paper, an endeavor is taken to justify the applicability and solution accuracy of an almost new MCDM approach, i.e. weighted aggregated sum product assessment (WASPAS) method while solving eight real time selection problems as being encountered in present day manufacturing environment.

2. WASPAS Method

Every MCDM problem starts with the following decision/evaluation matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

where m is the number of candidate alternatives, n is the number of evaluation criteria and x_{ij} is the performance of ith alternative with respect to jth criterion.

The application of WASPAS method, which is a unique combination of two well known MCDM approaches, i.e. weighted sum model (WSM) and weighted product model (WPM) at first requires linear normalization of the decision matrix elements using the following two equations:

For beneficial criteria,

$$\bar{x}_{ij} = \frac{x_{ij}}{\max_i x_{ij}}. \tag{2}$$

For non-beneficial criteria,

$$\bar{x}_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \tag{3}$$

where $\bar{x}_{ij}$ is the normalized value of x_{ij}.

In WASPAS method, a joint criterion of optimality is sought based on two criteria of optimality. The first criterion of optimality, i.e. criterion of a mean weighted success is similar to WSM method. It is a popular and well accepted MCDM approach applied for evaluating a number of alternatives in terms of a number of decision criteria. Based on WSM method (MacCrimon, 1968; Triantaphyllou and Mann, 1989), the total relative importance of ith alternative is calculated as follows:

$$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij} w_j \tag{4}$$

where w_j is weight (relative importance) of significance (weight) of jth criterion.

On the other hand, according to WPM method (Miller and Starr, 1969; Triantaphyllou and Mann, 1989), the total relative importance of ith alternative is computed using the following expression:

$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j}. \tag{5}$$

A joint generalized criterion of weighted aggregation of additive and multiplicative methods is then proposed as follows (Zavadskas *et al.*, 2013a, 2013b):

$$Q_i = 0.5 Q_i^{(1)} + 0.5 Q_i^{(2)} = 0.5 \sum_{j=1}^{n} \bar{x}_{ij} w_j + 0.5 \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j}. \tag{6}$$

In order to have increased ranking accuracy and effectiveness of the decision making process, in WASPAS method, a more generalized equation for determining the total relative importance of ith alternative is developed as below (Šaparauskas *et al.*, 2011; Zavadskas *et al.*, 2012):

$$Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)} = \lambda \sum_{j=1}^{n} \bar{x}_{ij} w_j + (1-\lambda) \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \quad (\lambda = 0, 0.1, \ldots, 1). \tag{7}$$

Now, the candidate alternatives are ranked based on the Q values, i.e. the best alternative would be that one having the highest Q value. When the value of λ is 0, WASPAS method is transformed to WPM, and when λ is 1, it becomes WSM method. Till date, WASPAS method has very few successful applications, only in location selection problems (Zolfani *et al.*, 2013) and civil engineering domain (Dėjus and Antuchevičienė, 2013; Staniūnas *et al.*, 2013).

3. Decision Making in Manufacturing Environment

In this paper, an attempt is made to prove and validate the applicability of WASPAS method while considering the following eight real time selection problems arising in manufacturing environment:

(a) cutting fluid selection,
(b) electroplating system selection,
(c) selection of forging condition,
(d) arc welding process selection,
(e) selection of industrial robot,
(f) milling condition selection,
(g) machinability of materials, and
(h) electro-discharge micro-machining process parameter selection.

3.1. *Cutting Fluid Selection*

Use of a cutting fluid during a machining operation is essential to have increased tool life and enhanced productivity. The performance of a cutting fluid is often judged by the machining process output variables, like tool life, cutting force, power consumption, surface finish etc. Utmost importance needs to be provided while selecting the most appropriate cutting fluid in a given machining application. The cutting fluid selection problems have already been solved by the past researchers adopting different mathematical approaches, like analytic hierarchy process (AHP) (Sun *et al.*, 2001), digraph theory and matrix approach (GTMA) (Rao and Gandhi, 2001), multi-objective decision making model (Tan *et al.*, 2002), a combined multiple attribute decision making method (Rao, 2004) and preference ranking organisation method for enrichment evaluation (PROMETHEE) (Rao and Patel, 2010).

Rao and Patel (2010) considered a cutting fluid selection problem for a cylindrical grinding operation while taking into account four alternatives whose performance was evaluated based on eight criteria, i.e. wheel wear (WW) (in mm), tangential force (TF) (in N), grinding temperature (GT) (in °C), surface roughness (SR) (in μm), recyclability (R), toxic harm rate (TH), environment pollution tendency (EP) and stability (S). Four cutting fluid properties, i.e. R, TH, EP and S were expressed in linguistic terms which were converted to corresponding fuzzy scores (Rao, 2007). The data for this cutting fluid selection problem is exhibited in Table 1. Amongst the eight selection criteria, R and S are the only beneficial attributes requiring higher values. The related normalized decision matrix is given in Table 2. Applying AHP method, Rao and Patel (2010) determined the priority

Table 1
Data for cutting fluid selection problem (Rao and Patel, 2010).

Cutting fluid	WW	TF	GT	SR	R	TH	EP	S
1.	0.035	34.5	847	1.76	L (0.335)	A (0.500)	AA (0.590)	AA (0.590)
2.	0.027	36.8	834	1.68	L (0.335)	H (0.665)	H (0.665)	H (0.665)
3.	0.037	38.6	808	2.40	AA (0.590)	AA (0.590)	BA (0.410)	A (0.500)
4.	0.028	32.6	821	1.59	A (0.500.)	AA (0.590)	AA (0.590)	BA (0.410)

L: Low, BA: Below average, A: Average, AA: Above average, H: High.

Table 2
Normalized decision matrix for cutting fluid selection problem.

Cutting fluid	WW	TF	GT	SR	R	TH	EP	S	$Q^{(1)}$	$Q^{(2)}$	Q
1.	0.7714	0.9449	0.9539	0.9034	0.5678	1.0000	0.6949	0.8872	0.8417	0.8995	0.8706
2.	1.0000	0.8859	0.9688	0.9464	0.5678	0.7519	0.6165	1.0000	0.8830	0.8683	0.8756
3.	0.7297	0.8446	1.0000	0.6625	1.0000	0.8474	1.0000	0.7519	0.8444	0.9172	0.8808
4.	0.9643	1.0000	0.9842	1.0000	0.8474	0.8474	0.6949	0.6165	0.9027	0.9037	0.9032

Table 3
Effect of λ on ranking performance of WASPAS method for example 1.

$\lambda = 0$	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$	$\lambda = 0.6$	$\lambda = 0.7$	$\lambda = 0.8$	$\lambda = 0.9$	$\lambda = 1.0$
0.8995 (3)	0.8937 (3)	0.8879 (3)	0.8821 (3)	0.8764 (3)	0.8706 (4)	0.8648 (4)	0.8590 (4)	0.8533 (4)	0.8475 (4)	0.8417 (4)
0.8683 (4)	0.8698 (4)	0.8712 (4)	0.8727 (4)	0.8742 (4)	0.8756 (3)	0.8771 (2)	0.8786 (2)	0.8801 (2)	0.8815 (2)	0.8830 (2)
0.9172 (1)	0.9099 (1)	0.9026 (2)	0.8954 (2)	0.8881 (2)	0.8808 (2)	0.8735 (3)	0.8662 (3)	0.8590 (3)	0.8517 (3)	0.8444 (3)
0.9037 (2) (2)	0.9036 (2) (2)	0.9035 (1)	0.9034 (1)	0.9033 (1)	0.9032 (1)	0.9031 (1)	0.9030 (1)	0.9029 (1)	0.9028 (1)	0.9027 (1)

weights of the considered eight criteria as $w_{\mathrm{WW}} = 0.3306$, $w_{\mathrm{TF}} = 0.0718$, $w_{\mathrm{GT}} = 0.1808$, $w_{\mathrm{SR}} = 0.0718$, $w_{\mathrm{R}} = 0.0459$, $w_{\mathrm{TH}} = 0.1260$, $w_{\mathrm{EP}} = 0.1260$ and $w_{\mathrm{S}} = 0.0472$. This set of criteria weights is employed here for the WASPAS method-based analyses. Table 2 also provides the values of total relative importance (performance scores) for all the considered alternatives for a λ value of 0.5. It is observed that cutting fluid 4 is the best choice and the entire ranking order of the alternatives is 4-3-2-1. Applying PROMETHEE method, Rao and Patel (2010) derived a ranking list of the alternatives as 4-2-3-1. In both the cases, the best and the worst choices of the cutting fluids exactly match. Table 3 shows the effect of varying values of λ on the performance scores and rankings (in brackets) of the considered cutting fluids. It is clearly visible that the rankings of the best and the worst cutting fluid alternatives remain almost unaffected for different λ values, and a better ranking per-

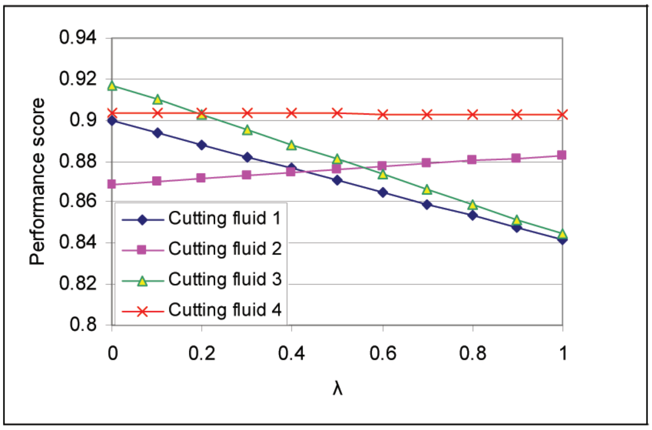

Fig. 1. Variations of performance scores of cutting fluids with respect to λ.

formance is achieved for the higher value of λ , i.e. when WASPAS method behaves like WSM method. This can also be verified in Fig. 1.

3.2. *Electroplating System Selection*

The electroplating is generally carried out to alter characteristics of a surface to provide improved appearance, ability to withstand corrosive agents, resistance to abrasion or other desired properties (Kumar and Agrawal, 2009). Electroplating with various capabilities are available for a wide range of applications, like surface finishing, thickness maintaining, avoiding rusting, restoring dimension of under-size parts, aesthetic etc. The use of an appropriate coating in electroplating can increase the life expectancy of a given component. Selection of the electroplating system to suit a specific application of manufacturing environment, from the large number of available platings has now become a difficult task. Kumar and Agrawal (2009) considered an electroplating system selection problem, as given in Table 4, where the best coating material needs to be chosen amongst seven alternatives, i.e. silver, gold, lead, rhodium, nickel, chromium and platinum. There were five evaluation criteria, i.e. hardness (H) (in HV), thickness (T) (in µm), aesthetic (AE), adhesion (AD) and cost (C). Thus, this decision matrix consists of both quantitative and qualitative criteria values which are linear normalized in Table 5. Using AHP method, the weights of the five criteria were evaluated as $w_{\mathrm{H}} = 0.1761$, $w_{\mathrm{T}} = 0.2042$, $w_{\mathrm{AE}} = 0.2668$, $w_{\mathrm{AD}} = 0.1243$ and $w_{\mathrm{C}} = 0.2286$ (Singh and Rao, 2011). In the subsequent WASPAS method-based analyses, these criteria weights are also adopted. Applying an integrated AHP and GTMA technique, Singh and Rao (2011) obtained a rank ordering of the electroplating coating materials as 4-5-6-7-3-1-2, which identifies chromium and platinum as the two best choices. Rhodium became the worst chosen plating material. The results of WASPAS method-based analysis are provided in Table 5. Table 6 shows the effect of changing λ values on the ranking performance of WASPAS method. It is quite interesting to observe that for higher λ values, the rank orderings of the alternative electroplating

Table 4
Data for electroplating system selection problem (Kumar and Agrawal, 2009).

Alternative	H	T	AE	AD	C
Silver	350	20	Good (4)	Good (4)	Medium (2)
Gold	250	25	Excellent (5)	Average (3)	High (3)
Lead	150	30	Average (3)	Poor (1)	Low (1)
Rhodium	400	20	Fair (2)	Average (3)	Medium (2)
Nickel	550	30	Poor (1)	Fair (2)	Low (1)
Chromium	600	35	Poor (1)	Excellent (5)	Low (1)
Platinum	580	30	Good (4)	Good (4)	High (3)

Table 5
Normalized decision matrix for electroplating system selection problem.

Alternative	H	T	AE	AD	C	$Q^{(1)}$	$Q^{(2)}$	Q
Silver	0.5833	0.5714	0.8	0.8	0.5	0.6466	0.6345	0.6405
Gold	0.4167	0.7143	1	0.6	0.3333	0.6368	0.5842	0.6105
Lead	0.2500	0.8571	0.6	0.2	1	0.6326	0.5423	0.5874
Rhodium	0.6667	0.5714	0.4	0.6	0.5	0.5297	0.5209	0.5253
Nickel	0.9167	0.8571	0.2	0.4	1	0.6681	0.5543	0.6112
Chromium	1	1	0.2	1	1	0.7866	0.6509	0.7188
Platinum	0.9667	0.8571	0.8	0.8	0.3333	0.7343	0.6867	0.7105

Table 6
Effect of λ on ranking performance of WASPAS method for example 2.

$\lambda=0$	$\lambda=0.1$	$\lambda=0.2$	$\lambda=0.3$	$\lambda=0.4$	$\lambda=0.5$	$\lambda=0.6$	$\lambda=0.7$	$\lambda=0.8$	$\lambda=0.9$	$\lambda=1.0$
0.6345	0.6357	0.6369	0.6381	0.6393	0.6405	0.6417	0.6430	0.6442	0.6454	0.6466
(3)	(3)	(3)	(3)	(3)	(3)	(3)	(3)	(4)	(4)	(4)
0.5842	0.5894	0.5947	0.6000	0.6052	0.6105	0.6158	0.6210	0.6263	0.6315	0.6368
(4)	(4)	(4)	(4)	(4)	(5)	(5)	(5)	(5)	(5)	(5)
0.5423	0.5513	0.5603	0.5694	0.5784	0.5874	0.5965	0.6055	0.6145	0.6236	0.6326
(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)	(6)
0.5209	0.5218	0.5227	0.5236	0.5244	0.5253	0.5262	0.5271	0.5279	0.5288	0.5297
(7)	(7)	(7)	(7)	(7)	(7)	(7)	(7)	(7)	(7)	(7)
0.5543	0.5657	0.5770	0.5884	0.5998	0.6112	0.6226	0.6340	0.6454	0.6567	0.6681
(5)	(5)	(5)	(5)	(5)	(4)	(4)	(4)	(3)	(3)	(3)
0.6509	0.6645	0.6780	0.6916	0.7052	0.7188	0.7323	0.7459	0.7594	0.7730	0.7866
(2)	(2)	(2)	(2)	(2)	(1)	(1)	(1)	(1)	(1)	(1)
0.6867	0.6915	0.6962	0.7010	0.7057	0.7105	0.7153	0.7200	0.7248	0.7296	0.7343
(1)	(1)	(1)	(1)	(1)	(2)	(2)	(2)	(2)	(2)	(2)

coating materials exactly corroborate with those derived by Singh and Rao (2011). Figure 2 shows the change in the Spearman's rank correlation coefficients for different values of λ. It is also evident that better ranking performance of WASPAS method is achieved when it behaves like WSM method.

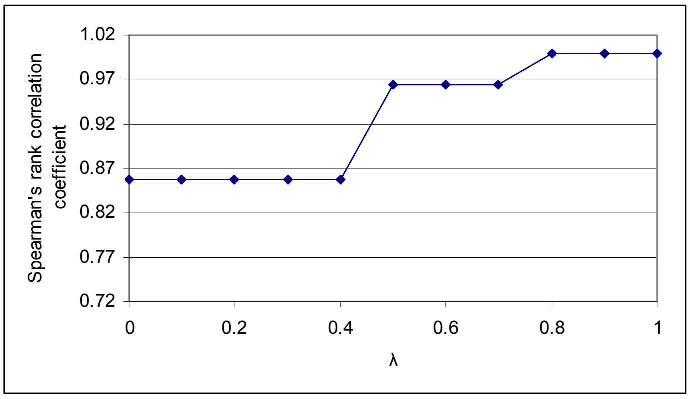

Fig. 2. Effect of λ on Spearman's rank correlation coefficient for example 2.

3.3. *Selection of Forging Condition*

Forging is the process by which metal is heated and shaped by plastic deformation by suitably applying compressive force. Rao (2007) considered a problem for selection of the best forging condition for manufacturing Al-MMC automotive components, while taking into account three candidate alternatives, i.e. condition 1: initial billet temperature (IBT) = 400 °C, initial die temperature (IDT) = 350 °C and die speed (DS) = 3 mm/s; condition 2: IBT = 500 °C, IDT = 450 °C and DS = 2 mm/s; and condition 3: IBT = 425 °C, IDT = 350 °C and DS = 0.1 mm/s. Those forging conditions were evaluated based on five criteria, such as product quality (PQ) (in %), production rate (PR) (in pieces/h), die cost (DC), heating cost (HC) and forging load per unit length (FL) (in N). Among these five criteria, DC and HC are expressed qualitatively, and all attributes except PR are non-beneficial in nature. Rao (2007) determined the criteria weights as $w_{\mathrm{PQ}} = 0.236$, $w_{\mathrm{PR}} = 0.459$, $w_{\mathrm{DC}} = 0.179$, $w_{\mathrm{HC}} = 0.037$ and $w_{\mathrm{FL}} = 0.089$ which are used for the WASPAS method-based analyses. The detailed information for this forging condition selection problem is given in Table 7. This decision matrix is then linearly normalized, as given in Table 8. From this table, it is observed that alternative 1 (IBT = 400 °C, IDT = 350 °C and DS = 3 mm/s) is the best forging condition for the given application, which exactly matches with the observation of Rao (2007). The effect of the changing values of λ on the ranking performance of WASPAS method is given in Table 9, which ensures steady performance of this method over the given range of λ value without any significant rank reversal.

3.4. *Arc Welding Process Selection*

Welding is a process of joining two or more pieces of the same or dissimilar materials to achieve complete coalescence. The welding process is different from one material to another and choosing an appropriate method for welding is a difficult task (Ravisankar *et al.*, 2006; Singh and Rao, 2011). Rao (2007) considered a welding process selection

Table 7
Data for forging condition selection problem (Rao, 2007).

Alternative forging condition	PQ	PR	DC	HC	FL
1.	4.01	73.97	L (0.335)	VL (0.255.)	15773
2.	2.19	67.92	VH (0.745)	L (0.335)	9119
3.	1.46	12	L (0.335)	VH (0.745)	15110

VL: Very low, L: Low, VH: Very high.

Table 8
Normalized decision matrix for example 3.

Alternative forging condition	PQ	PR	DC	HC	FL	$Q^{(1)}$	$Q^{(2)}$	Q
1.	0.3641	1	1	1	0.5781	0.8035	0.7503	0.7770
2.	0.6667	0.9182	0.4497	0.7612	1	0.7609	0.7497	0.7553
3.	1	0.1622	1	0.3423	0.6035	0.5432	0.3987	0.4710

Table 9
Effect of λ on ranking performance of WASPAS method for example 3.

$\lambda=0$	$\lambda=0.1$	$\lambda=0.2$	$\lambda=0.3$	$\lambda=0.4$	$\lambda=0.5$	$\lambda=0.6$	$\lambda=0.7$	$\lambda=0.8$	$\lambda=0.9$	$\lambda=1.0$
0.7503 (1)	0.7557 (1)	0.7610 (1)	0.7663 (1)	0.7716 (1)	0.7769 (1)	0.7823 (1)	0.7876 (1)	0.7929 (1)	0.7982 (1)	0.8035 (1)
0.7497 (2)	0.7509 (2)	0.7520 (2)	0.7531 (2)	0.7542 (2)	0.7553 (2)	0.7565 (2)	0.7576 (2)	0.7587 (2)	0.7598 (2)	0.7609 (2)
0.3987 (3)	0.4132 (3)	0.4276 (3)	0.4421 (3)	0.4565 (3)	0.4710 (3)	0.4854 (3)	0.4998 (3)	0.5143 (3)	0.5287 (3)	0.5432 (3)

problem to join mild steel (0.2% C) of 6 mm thickness, known to be the best weldable metal in arc welding processes, i.e. shielded metal arc welding (SMAW), gas tungsten arc welding (GTAW) and gas metal arc welding (GMAW). The performance of those three arc welding processes was evaluated based on six qualitative criteria, i.e. weld quality (WQ), operator fatigue (OP), skill required (SR), cleaning required after welding (CR), availability of consumables (AC) and initial preparation required (IR). Among these six criteria, WQ and AC are beneficial attributes requiring higher values for the arc welding process selection. Using AHP method, Rao (2007) determined the priority weights of these six criteria as $w_{\text{WQ}} = 0.3534$, $w_{\text{OF}} = 0.2526$, $w_{\text{SR}} = 0.1669$, $w_{\text{CR}} = 0.1103$, $w_{\text{AC}} = 0.0695$ and $w_{\text{IP}} = 0.0473$ which are also used here for the subsequent analyses. The original and the corresponding normalized decision matrices for this arc welding process selection problem are respectively shown in Tables 10 and 11. Table 11 also exhibits the ranking of the alternative arc welding processes as SMAW-GTAW-GMAW for a λ value of 0.5 which exactly matches with that derived by Rao (2007) while employing GTMA method. In Table 12, the effect of varying values of λ on the ranking performance of WASPAS method is depicted and it is interesting to note that the rankings of all the three arc weld-

Table 10
Data for arc welding process selection problem (Rao, 2007).

Arc welding process	WQ	OF	SR	CR	AC	IR
SMAW	A (0.500)	A (0.500)	A (0.500)	H (0.665)	VH (0.745)	A (0.500)
GTAW	VH (0.745)	H (0.665)	VH (0.745)	A (0.500)	A (0.500)	H (0.665)
GMAW	AA (0.590)	VH (0.745)	H (0.665)	AA (0.590)	H (0.665)	VH (0.745)

Table 11
Normalized decision matrix for example 4.

Arc welding process	WQ	OF	SR	CR	AC	IR	$Q^{(1)}$	$Q^{(2)}$	Q
SMAW	0.6711	1	1	0.7519	1	1	0.8564	0.8416	0.8490
GTAW	1	0.7519	0.6711	1	0.6711	0.7519	0.8478	0.8354	0.8416
GMAW	0.7919	0.6711	0.7519	0.8474	0.8926	0.6711	0.7621	0.7590	0.7606

Table 12
Effect of λ on ranking performance of WASPAS method for example 4.

$\lambda=0$	$\lambda=0.1$	$\lambda=0.2$	$\lambda=0.3$	$\lambda=0.4$	$\lambda=0.5$	$\lambda=0.6$	$\lambda=0.7$	$\lambda=0.8$	$\lambda=0.9$	$\lambda=1.0$
0.8416 (1)	0.8431 (1)	0.8446 (1)	0.8461 (1)	0.8476 (1)	0.8490 (1)	0.8505 (1)	0.8520 (1)	0.8535 (1)	0.8549 (1)	0.8564 (1)
0.8354 (2)	0.8367 (2)	0.8379 (2)	0.8392 (2)	0.8404 (2)	0.8416 (2)	0.8429 (2)	0.8441 (2)	0.8454 (2)	0.8466 (2)	0.8478 (2)
0.7590 (3)	0.7593 (3)	0.7596 (3)	0.7599 (3)	0.7602 (3)	0.7606 (3)	0.7609 (3)	0.7612 (3)	0.7615 (3)	0.7618 (3)	0.7621 (3)

ing processes remain stable over the considered range of λ value for the given welding application.

3.5. *Selection of Industrial Robot*

An industrial robot is a general purpose, reprogrammable machine with certain anthropometrical features. Its mechanical arm is the most important and vital anthropometrical component. Other less but still important features, like its decision making capability, capacity of responding to various sensory inputs and communicating with other machines make it an important tool for diverse industrial applications, including material handling, assembly, finishing, machine loading, spray painting and welding (Rao and Padmanabhan, 2006).

This problem (Bhangale *et al.*, 2004) deals with the selection of the most appropriate industrial robot for some pick-n-place operations where it has to avoid certain obstacles. Five different robot selection attributes are considered as load capacity (LC) (in kg), maximum tip speed (MTS) (in mm/s), repeatability (RE) (in mm), memory capacity (MC) (in number of steps or points) and manipulator reach (MR) (in mm), among which LC, MTS, MC and MR are the beneficial attributes (where higher values are desirable), whereas,

Table 13
Quantitative data for industrial robot selection problem (Bhangale *et al.*, 2004).

Sl. No.	Robot	LC	RE	MPS	MC	MR
1.	ASEA-IRB 60/2	60	0.40	2540	500	990
2.	Cincinnati Milacrone T3-726	6.35	0.15	1016	3000	1041
3.	Cybotech V15 Electric Robot	6.8	0.10	1727.2	1500	1676
4.	Hitachi America Process Robot	10	0.20	1000	2000	965
5.	Unimation PUMA 500/600	2.5	0.10	560	500	915
6.	United States Robots Maker 110	4.5	0.08	1016	350	508
7.	Yaskawa Electric Motoman L3C	3	0.10	1778	1000	920

Table 14
Normalized decision matrix for example 5.

Sl. No.	LC	RE	MPS	MC	MR	$Q^{(1)}$	$Q^{(2)}$	Q
1.	1	0.2	1	0.1667	0.5907	0.5256	0.3843	0.4550
2.	0.1058	0.5333	0.4	1	0.6211	0.6371	0.5727	0.6049
3.	0.1133	0.8	0.68	0.5	1	0.6624	0.6232	0.6428
4.	0.1667	0.4	0.3937	0.6667	0.5758	0.4976	0.4758	0.4867
5.	0.0417	0.8	0.2205	0.1667	0.5459	0.3468	0.2706	0.3087
6.	0.0750	1	0.4	0.1167	0.3031	0.3995	0.2907	0.3451
7.	0.0500	0.8	0.7	0.3333	0.5489	0.5581	0.4980	0.5281

RE is a non-beneficial attribute (where lower value is preferable). Thus, this industrial robot selection problem consists of five criteria and seven alternative robots, as given in Table 13. Rao (2007) estimated the criteria weights as $w_{\mathrm{LC}} = 0.036$, $w_{\mathrm{RE}} = 0.192$, $w_{\mathrm{MTS}} = 0.326$, $w_{\mathrm{MC}} = 0.326$ and $w_{\mathrm{MR}} = 0.120$ using AHP method, and these weights are used here for the subsequent analyses. The corresponding linearly normalized decision matrix is shown in Table 14. In this table, the alternative industrial robots are ranked based on their performance scores as 5-2-1-4-7-6-3. It indicates that Cybotech V15 Electric Robot is the best choice for the given industrial application, whereas, Unimation PUMA 500/600 is the worst chosen alternative for a λ value of 0.5. On the other hand, for the same problem, using GTMA technique, Rao (2007) derived the ranking of the alternative industrial robots as 4-2-1-5-7-6-3, whereas, Chatterjee *et al.* (2010) determined these robot rankings as 5-2-1-4-7-6-3 and 3-2-1-5-7-6-4 while applying VIKOR (VIsekriterijumsko KOmpromisno Rangiranje) and ELECTRE (ELimination and Et Choice Translating REality) methods respectively. It is observed that in all the adopted MCDM techniques, the positions of the best two and the worst robot alternatives remain the same which strongly validate the potentiality of WASPAS method to provide almost accurate rank orderings. In Table 15, the effects of varying values of λ on the performance scores and rank orderings of the considered industrial robot alternatives are exhibited, which are also verified in Fig. 3.

3.6. *Milling Condition Selection*

Ching-Kao and Lu (2007) carried out an experiment on milling operations on a Papers B8 CNC machining center taking SUS304 stainless steel test pieces. The end mill which

Table 15
Effect of λ on ranking performance of WASPAS method for example 5.

$\lambda = 0$	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$	$\lambda = 0.6$	$\lambda = 0.7$	$\lambda = 0.8$	$\lambda = 0.9$	$\lambda = 1.0$
0.3843 (5)	0.3984 (5)	0.4126 (5)	0.4267 (5)	0.4408 (5)	0.4550 (5)	0.4691 (5)	0.4832 (5)	0.4973 (4)	0.5115 (4)	0.5256 (4)
0.5727 (2)	0.5791 (2)	0.5856 (2)	0.5920 (2)	0.5985 (2)	0.6049 (2)	0.6114 (2)	0.6178 (2)	0.6242 (2)	0.6307 (2)	0.6371 (2)
0.6232 (1)	0.6271 (1)	0.6310 (1)	0.6349 (1)	0.6388 (1)	0.6428 (1)	0.6469 (1)	0.6506 (1)	0.6545 (1)	0.6584 (1)	0.6624 (1)
0.4758 (4)	0.4780 (4)	0.4802 (4)	0.4823 (4)	0.4845 (4)	0.4867 (4)	0.4889 (4)	0.4910 (4)	0.4932 (5)	0.4954 (5)	0.4976 (5)
0.2706 (7)	0.2783 (7)	0.2859 (7)	0.2935 (7)	0.3011 (7)	0.3087 (7)	0.3163 (7)	0.3240 (7)	0.3316 (7)	0.3392 (7)	0.3468 (7)
0.2907 (6)	0.3015 (6)	0.3124 (6)	0.3233 (6)	0.3342 (6)	0.3451 (6)	0.3560 (6)	0.3668 (6)	0.3778 (6)	0.3886 (6)	0.3995 (6)
0.4980 (3)	0.5040 (3)	0.5100 (3)	0.5161 (3)	0.5221 (3)	0.5281 (3)	0.5341 (3)	0.5401 (3)	0.5461 (3)	0.5521 (3)	0.5581 (3)

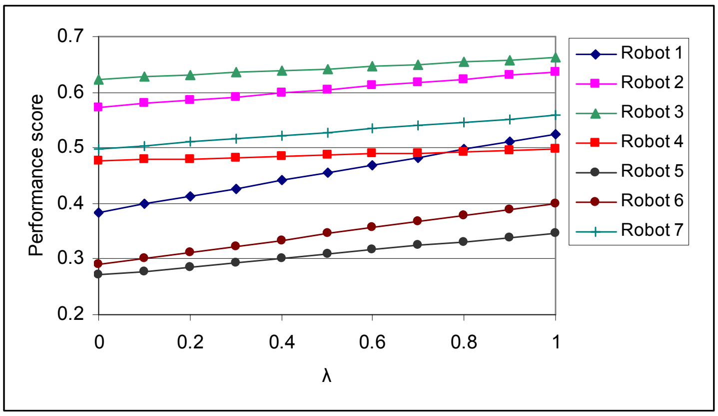

Fig. 3. Variations of performance scores for alternative robots for changing λ values.

served as cutting tools was made of tungsten carbide and coated with Al-Tin. The experiment was conducted based on L_9 orthogonal array, as shown Table 16. In that experiment, five important milling process parameters, like spindle speed (V) (in rpm), feed per tooth (F) (in mm/t), axial depth of cut (Da) (in mm), radial depth of cut (Dr) (in mm) and cutting time (CT) (in min) were considered along with two machining responses, i.e. tool wear rate (TWR) (in mm/min) and material removal rate (MRR) (in mm^3/s).

Gadakh and Shinde (2011) also solved this milling condition selection problem applying different MCDM methods, and determined the corresponding rankings of the alternative milling conditions. Rao (2012) identified some of the major calculation mistakes related to the findings of Gadakh and Shinde (2011), and determined the most preferred ranking of the milling conditions as 9-4-1-2-3-7-8-5-6 using GTMA method. The same experimental data of Ching-Kao and Lu (2007) is considered here for the WASPAS method-based analyses and the corresponding linearly normalized decision matrix is shown in

Table 16
Experimental plan along with observations (Ching-Kao and Lu, 2007).

Expt. No.	V	F	Da	Dr	CT	TWR	MRR
1.	1500	0.0592	7	0.4	281.53	1.2574×10^{-4}	16.58
2.	1500	0.0740	11	0.7	225.23	1.7760×10^{-4}	56.98
3.	1500	0.0888	15	1.0	187.69	1.7582×10^{-4}	133.20
4.	2000	0.0592	15	0.7	211.15	2.2022×10^{-4}	77.35
5.	2000	0.0740	7	1.0	168.92	2.0070×10^{-4}	69.07
6.	2000	0.0888	11	0.4	140.77	2.7918×10^{-4}	48.54
7.	2500	0.0592	11	1.0	78.04	5.8431×10^{-4}	108.53
8.	2500	0.0740	15	0.4	135.14	3.0412×10^{-4}	74.00
9.	2500	0.0888	7	0.7	112.61	3.1436×10^{-4}	72.52

Table 17
Normalized decision matrix for example 6.

Expt. No.	TWR	MRR	$Q^{(1)}$	$Q^{(2)}$	Q
1.	1	0.1245	0.5622	0.3528	0.4575
2.	0.7080	0.4278	0.5679	0.5503	0.5591
3.	0.7152	1	0.8576	0.8457	0.8516
4.	0.5710	0.5807	0.5758	0.5758	0.5758
5.	0.6265	0.5185	0.5725	0.5699	0.5712
6.	0.4504	0.3644	0.4074	0.4051	0.40626
7.	0.2152	0.8148	0.5150	0.4187	0.4669
8.	0.4134	0.5555	0.4845	0.4793	0.4819
9.	0.3999	0.5444	0.4722	0.4667	0.4694

Table 17. For a λ value of 0.5, machining condition 3 (V = 1500 rpm, F = 0.0888 mm/t, Da = 15 mm, Dr = 1.0 mm and CT = 187.69 min) is identified as the best condition to operate which exactly matches with the observation of Rao (2012). In this case, equal importance is assigned to both the responses (i.e. TWR and MRR). Table 18 exhibits the consistency of ranking performance of WASPAS method over the considered range of λ values. It is interesting to observe that the top three and the worst milling conditions remain almost unaffected over the entire range of λ values.

3.7. *Machinability of Materials*

Machinability is a measure of ease with which a workpiece material can be satisfactorily machined. It is of considerable importance to production engineers so that the processing can be planned more efficiently. The study of machinability of materials can be a basis for cutting tool and cutting fluid performance evaluation and machining parameter optimization. Machinability is influenced by various parameters, like inherent properties or characteristics of workpiece materials, cutting tool material, tool geometry, nature of tool engagement with workpiece, cutting conditions, type of cutting, cutting fluid, and machine tool rigidity and its capacity (Rao, 2006). Enache *et al.* (1995) conducted turning experiments on titanium alloys using different cutting tools of varying geometries. The machin-

Table 18
Ranking performance of WASPAS method with respect to λ for example 6.

$\lambda = 0$	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$	$\lambda = 0.6$	$\lambda = 0.7$	$\lambda = 0.8$	$\lambda = 0.9$	$\lambda = 1.0$
0.3528 (9)	0.3737 (9)	0.3947 (9)	0.4156 (9)	0.4366 (8)	0.4575 (8)	0.4785 (6)	0.4994 (5)	0.5203 (5)	0.5413 (5)	0.5622 (5)
0.5503 (4)	0.5521 (4)	0.5538 (4)	0.5556 (4)	0.5573 (4)	0.5591 (4)	0.5609 (4)	0.5626 (4)	0.5644 (4)	0.5661 (4)	0.5679 (4)
0.8457 (1)	0.8469 (1)	0.8480 (1)	0.8492 (1)	0.8504 (1)	0.8516 (1)	0.8528 (1)	0.8540 (1)	0.8552 (1)	0.8564 (1)	0.8576 (1)
0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)	0.5758 (2)
0.5699 (3)	0.5702 (3)	0.5705 (3)	0.5707 (3)	0.5710 (3)	0.5712 (3)	0.5715 (3)	0.5718 (3)	0.5720 (3)	0.5723 (3)	0.5725 (3)
0.4051 (8)	0.4053 (8)	0.4056 (8)	0.4058 (8)	0.4060 (9)	0.4063 (9)	0.4065 (9)	0.4067 (9)	0.4069 (9)	0.4072 (9)	0.4074 (9)
0.4187 (7)	0.4283 (7)	0.4380 (7)	0.4476 (7)	0.4572 (7)	0.4669 (7)	0.4765 (7)	0.4861 (6)	0.4957 (6)	0.5054 (6)	0.5150 (6)
0.4793 (5)	0.4798 (5)	0.4803 (5)	0.4808 (5)	0.4814 (5)	0.4819 (5)	0.4824 (5)	0.4829 (7)	0.4834 (7)	0.4840 (7)	0.4845 (7)
0.4667 (6)	0.4672 (6)	0.4678 (6)	0.4683 (6)	0.4689 (6)	0.4694 (6)	0.4700 (8)	0.4705 (8)	0.4711 (8)	0.4717 (8)	0.4722 (8)

Table 19
Quantitative data of machinability attributes (Enache *et al.*, 1995).

Work-tool combination	TW	SE	SR
Nr1	0.061	219.74	5.8
Nr2	0.093	3523.72	6.3
Nr3	0.064	2693.21	6.8
Nr4	0.028	761.46	5.8
Nr5	0.034	1593.48	5.8
Nr6	0.013	2849.15	6.2

Nr1: TiAl6V4-P20, Nr2: TiMo32-P20, Nr3: TiAl5Fe2.5-P20, Nr4: TiAl6V4-P20 (TiN), Nr5: TiAl6V4-K20, Nr6: TiAl6V4-K20. Cutting condition: dry, cutting speed – 150 m/min, feed – 0.15 mm/rev and depth of cut – 0.5 mm.

ability of six titanium alloys was evaluated with respect to three machining criteria, i.e. tool wear rate (TW) (in m/min), specific energy consumed (SE) (in N) and surface roughness (SR) (in μm), as given in Table 19. The normalized decision matrix for this problem is given in Table 20. The weights for the three criteria as used for the WASPAS method-based analyses are $w_{\mathrm{TW}} = 0.730645$, $w_{\mathrm{SE}} = 0.188394$ and $w_{\mathrm{SR}} = 0.0809612$ (Rao, 2007). In this case, all the three criteria are non-beneficial in nature. The performance scores as shown in Table 20 identifies that workpiece material TiAl6V4 has the better machinability than the other work materials while turning with a K20 cutting tool. Based on the descending values of performance scores, the six workpiece materials are ranked as 3-6-5-2-4-1 according to their machinability characteristics for a λ value of 0.5. For a λ value of 1.0, the derived ranking also remains the same, as given in Table 21 and Fig. 4. On the other hand, applying a combined technique for order performance by similarity to ideal

Table 20
Normalized decision matrix for example 7.

Work-tool combination	TW	SE	SR	$Q^{(1)}$	$Q^{(2)}$	Q
Nr1	0.2131	1	1	0.4251	0.3232	0.3741
Nr2	0.1398	0.0624	0.9206	0.1884	0.1399	0.1641
Nr3	0.2031	0.0816	0.8529	0.2328	0.1921	0.2125
Nr4	0.4643	0.2886	1	0.4745	0.4517	0.4631
Nr5	0.3823	0.1379	1	0.3863	0.3410	0.3637
Nr6	1	0.0771	0.9355	0.8209	0.6138	0.7173

Table 21
Ranking performance of WASPAS method with respect to λ for example 7.

$\lambda = 0$	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$	$\lambda = 0.6$	$\lambda = 0.7$	$\lambda = 0.8$	$\lambda = 0.9$	$\lambda = 1.0$
0.3232 (4)	0.3334 (4)	0.3435 (4)	0.3537 (4)	0.3640 (3)	0.3741 (3)	0.3843 (3)	0.3945 (3)	0.4047 (3)	0.4149 (3)	0.4251 (3)
0.1399 (6)	0.1447 (6)	0.1496 (6)	0.1544 (6)	0.1593 (6)	0.1641 (6)	0.1690 (6)	0.1738 (6)	0.1788 (6)	0.1835 (6)	0.1884 (6)
0.1921 (5)	0.1962 (5)	0.2003 (5)	0.2043 (5)	0.2084 (5)	0.2125 (5)	0.2165 (5)	0.2206 (5)	0.2247 (5)	0.2288 (5)	0.2328 (5)
0.4517 (2)	0.4540 (2)	0.4563 (2)	0.4585 (2)	0.4608 (2)	0.4631 (2)	0.4654 (2)	0.4677 (2)	0.4700 (2)	0.4723 (2)	0.4745 (2)
0.3410 (3)	0.3456 (3)	0.3501 (3)	0.3546 (3)	0.3591 (4)	0.3637 (4)	0.3682 (4)	0.3727 (4)	0.3773 (4)	0.3818 (4)	0.3863 (4)
0.6138 (1)	0.6345 (1)	0.6552 (1)	0.6759 (1)	0.6967 (1)	0.7173 (1)	0.7380 (1)	0.7588 (1)	0.7798 (1)	0.8002 (1)	0.8209 (1)

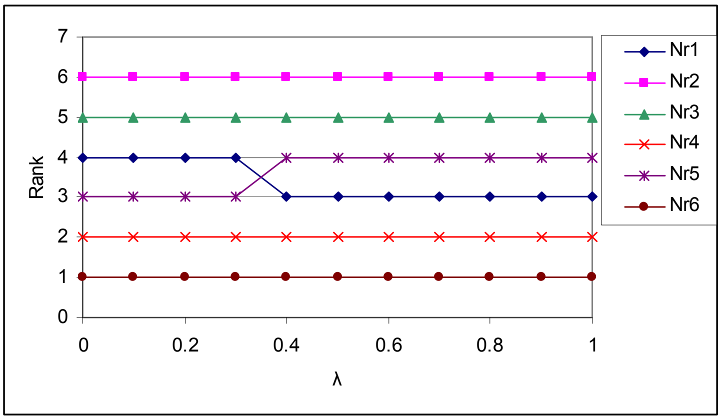

Fig. 4. Ranking performance of WASPAS method for example 7.

solution (TOPSIS) and AHP approach, Rao (2006) obtained the ranking of machinability of titanium alloy-based work materials as 4-6-5-2-3-1, and Rao and Gandhi (2002) also determined almost the same rank ordering for those materials while using GTMA method.

Table 22
RExperimental plan and observed results for the micro-EDM process (Pradhan *et al.*, 2009).

Expt. No.	Ip	Ton	Pr	t	MRR	TWR	OC	Taper
1.	0.5	1	0.1	60	0.006260	0.01198	36.50	0.08620
2.	0.5	10	0.3	80	0.012820	0.01542	48.50	0.02786
3.	0.5	20	0.5	95	0.024540	0.03140	65.00	0.01531
4.	1.0	1	0.3	95	0.012560	0.01359	47.00	0.03320
5.	1.0	10	0.5	60	0.069560	0.02099	50.00	0.00712
6.	1.0	20	0.1	80	0.017965	0.04156	57.08	0.01934
7.	1.5	1	0.5	80	0.013760	0.02889	55.03	0.04188
8.	1.5	10	0.1	95	0.036620	0.09154	65.05	0.00410
9.	1.5	20	0.3	60	0.033080	0.06368	78.05	0.01275

Table 23
Normalized decision matrix for example 8.

Expt. No.	MRR	TWR	OC	Taper	$Q^{(1)}$	$Q^{(2)}$	Q
1.	0.0899	1	1	0.0476	0.5344	0.2558	0.3951
2.	0.1843	0.7769	0.7528	0.1472	0.4652	0.3549	0.4100
3.	0.3528	0.3815	0.5615	0.2678	0.3909	0.3772	0.3840
4.	0.1806	0.8815	0.7766	0.1235	0.4905	0.3515	0.4210
5.	1	0.5707	0.7300	0.5758	0.7191	0.6999	0.7095
6.	0.2583	0.2882	0.6394	0.2120	0.3495	0.3169	0.3332
7.	0.1978	0.4147	0.6633	0.0979	0.3434	0.2701	0.3068
8.	0.5264	0.1309	0.5611	1	0.5546	0.4434	0.4990
9.	0.4756	0.1881	0.4676	0.3216	0.3632	0.3406	0.3519

3.8. *Electro-Discharge Micro-Machining Process Parameter Selection*

Based on L_9 orthogonal array of Taguchi technique, Pradhan *et al.* (2009) conducted some experiments to machine through micro-holes on titanium alloy (Ti-6Al-4V) to find the effects of major influencing parameters of electro-discharge micro-machining (micro-EDM) process, i.e. peak current (Ip) (in amp), pulse-on-time (Ton) (in μ-s), flushing pressure (Pr) (in kg/cm^2) and duty factor (t) (in %) on four performance measures of the machined micro-holes, i.e. MRR (in mg/min), TWR (in mg/min), overcut (OC) (in μm) and taper. Table 22 shows the experimental plan and the observed results for the considered micro-EDM process. In this experimental study, MRR needs to be maximized (beneficial criterion), and on the other hand, minimum values of the other three responses are desired (TWR, OC and taper are non-beneficial criteria). For this micro-EDM process parameter selection problem, equal weights are assigned to all the four responses (i.e. $w_1 = 0.25$, $w_2 = 0.25$, $w_3 = 0.25$ and $w_4 = 0.25$, where w_j is the weight allotted to jth response) which lead to simultaneous or multi-response optimization of the micro-EDM process. The normalized matrix is exhibited in Table 23 and it is observed from this table that experiment trial number 5 is the best machining condition for simultaneous optimization of all the four responses for a λ value of 0.5. It means that Ip $= 1.0$ amp, Ton $= 10$ μ-s, Pr $= 0.5$ kg/cm^2 and $t = 60\%$ would be the optimal settings of the parameters for this

Table 24
Results of single response optimization for micro-EDM process.

Expt. No.	$w_1 = 1$, $w_2 = 0$, $w_3 = 0$, $w_4 = 0$	$w_1 = 0$, $w_2 = 1$, $w_3 = 0$, $w_4 = 0$	$w_1 = 0$, $w_2 = 0$, $w_3 = 1$, $w_4 = 0$	$w_1 = 0$, $w_2 = 0$, $w_3 = 0$, $w_4 = 1$
1.	0.0900	1	1	0.0476
2.	0.1843	0.7769	0.7526	0.1472
3.	0.3528	0.3815	0.5615	0.2678
4.	0.1806	0.8815	0.7766	0.1235
5.	1	0.5707	0.7300	0.5758
6.	0.2583	0.2882	0.6394	0.2120
7.	0.1978	0.4147	0.6633	0.0979
8.	0.5264	0.1309	0.5611	1
9.	0.4756	0.1881	0.4676	0.3216

micro-EDM operation. These parametric combinations almost corroborate with the observations derived by Pradhan *et al.* (2009) while employing Taguchi technique.

It is quite interesting to observe that WASPAS method also has the ability to perform single response optimization of the responses when all the four responses of the micro-EDM process are separately optimized. The results of the single response optimization of the micro-EDM process are shown in Table 24. From this table, the optimal micro-EDM process parameter settings (Ip, Ton, Pr, t) for higher MRR, lower TWR, OC and taper are obtained at 1.0 amp/10 μ-s/0.5 kg/cm^2/60%; 0.5 amp/1 μ-s/0.1 kg/cm^2/60%; 0.5 amp/1 μ-s/0.1 kg/cm^2/60%; and 1.5 amp/10 μ-s/0.3 kg/cm^2/60% respectively. For the same responses, using Taguchi technique, Pradhan *et al.* (2009) determined the optimal parametric settings for the micro-EDM process as 1.5 amp/10 μs/0.5 kg/cm^2/95%; 0.5 amp/1 μs/0.3 kg/cm^2/60%; 0.5 amp/1 μs/0.1 kg/cm^2/60%; and 1.5 amp/10 μs/0.5 kg/cm^2/95% respectively. Thus, the WASPAS method-based results for parametric optimization of the micro-EDM process almost agree with those attained by Pradhan *et al.* (2009) proving its capability as an effective single and multi-response optimization tool.

4. Conclusions

In this paper, eight illustrative examples from real time manufacturing environment are solved using WASPAS method, which is a combination of two popular MCDM methods, i.e. WSM and WPM techniques. It has already been proved that the accuracy of an aggregated method would always be better than that of the single methods. For all the eight considered selection problems, it is observed that WASPAS method provides almost accurate rankings of the candidate alternatives as compared to those obtained by the earlier researchers. The effect of parameter λ on the ranking performance of WASPAS method is also studied, revealing the fact that better performance is attained at higher λ values. When the value of λ is set at 0, WASPAS method behaves like a WPM method, and when λ is 1, it is transformed into WSM method. The main advantage of this method is identified as its strong resistance against rank reversal of the considered alternatives. It is also found that this method has the unique capability of dealing with both single and multi-response optimization problems in various machining operations. As this method involves simple and sound mathematics, and is quite comprehensive in nature, it can be successfully applied to any manufacturing related decision making situation.

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WASPAS metodo taikymas priimant sprendimus gamyboje

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Organizacijoms siekiančioms išlikti konkurencingoje aplinkoje svarbu priimti teisingus sprendimus dėl veiksmingo išteklių panaudojimo gamyboje. Daugiakriteriniai metodai (MCDM) gali padėti organizacijoms sudaryti geriausią veiksmų planą. Šiame straipsnyje WASPAS metodas taikomas kaip veiksminga priemonė sprendžiant aštuonias sprendimų priėmimo problemas: pjovimo skysčio pasirinkimas, galvanizavimo sistemos parinkimas, kalimo sąlygų parinkimas, lauko suvirinimo procesų parinkimas, pramoninių robotų bei frezavimo sąlygų atranka, medžiagų bei elektros išlydžio mikro perdirbimo procesų parametrų parinkimas. Pastebėta, kad WASPAS metodas gali tiksliai įvertinti alternatyvas visoms nagrinėjamoms problemoms spręsti. Taip pat ištirtas parametro λ poveikis reitinguojant alternatyvas WASPAS metodu.