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Advances in Production Engineering & Management (*APEM journal*) is an interdisciplinary refereed international academic journal published quarterly by the *Production Engineering Institute* at the *University of Maribor*. The main goal of the *APEM journal* is to present original, high quality, theoretical and application-oriented research developments in all areas of production engineering and production management to a broad audience of academics and practitioners. In order to bridge the gap between theory and practice, applications based on advanced theory and case studies are particularly welcome. For theoretical papers, their originality and research contributions are the main factors in the evaluation process. General approaches, formalisms, algorithms or techniques should be illustrated with significant applications that demonstrate their applicability to real-world problems. Although the *APEM journal* main goal is to publish original research papers, review articles and professional papers are occasionally published.

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A comparative study of preference dominance-based approaches for selection of industrial robots

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A B S T R A C T

In the modern era of highly mechanized technologies, manufacturing organizations are now extensively using different kinds of industrial robots for performing complicated and perilous tasks with superior levels of accuracy. The major role of robotic technology within manufacturing organizations is to amalgamate design, manufacturing and management planning activities into a flexible system for improving production lines with minimum manufacturing cost involvement. However, the pre-implementation, implementation, and post-implementation phases of robotic technologies are the foremost issues associated with the selection and rationalization of robotic investments, which is based on a thorough review and exploration of various alternative robots and their mutually conflicting performance measures. Evaluating alternative robots in the presence of multiple conflicting attributes often makes the selection task very complex. This paper focuses on the application feasibilities of two preference dominance-based multi-attribute decision-making (MADM) approaches, namely evaluation of mixed data (EVAMIX) and extended preference ranking organization method for enrichment evaluation II (EXPROM2) whilst selecting the best alternative robots within given manufacturing environments. Using these two methods, a list of all the feasible alternatives from the best to the worst suitable robot is obtained by taking into account different robot selection attributes. The ranking performances of these methods are also compared with those of the past researchers, using four performance tests.

A R T I C L E   I N F O

Keywords:
Industrial robot selection
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1. Introduction

Advanced manufacturing technologies (AMTs) play a major role in improving quality and flexibility of small, medium and large scale manufacturing organizations. AMTs have an immense potential in enhancing manufacturing performance to compete in the global market. Today's highly competitive global market requirements can only be fulfilled by implementing computer integrated manufacturing (CIM) technologies, like robots. Recent growths in information technology and computer science have been the key reason for increased utilization of robots in different advanced manufacturing systems. The principal role of robotic technology in manufacturing organizations is to integrate design, manufacturing, management and planning functions into a flexible system. Proper decision-making in pre-implementation, implementation and post-implementation phases of robotic technology is one of major issues associated with the selection and justification of advanced manufacturing technologies which needs a thorough assessment and analysis of various performance measures based on a number of key decisive factors. An industrial robot is commonly defined as a mechanical device that sometimes resembles a human and is capable of performing a variety of complex human tasks on command or by being programmed in advance. In a wider perspective, robot is a reprogrammable multifunctional manipulator which is designed to move materials, parts, tool or other devices by means of variable programmed motions and perform a variety of other tasks. Robots can work under menial conditions, like excessive heat and noise, heavy load, toxic gases etc. The application domains of robots include welding, spray painting, material handling, component assembling, surface treatment etc. If robots are properly deployed, they can improve quality and productivity of a manufacturing organization radically. The important features, like its decision-making capability, capability of responding to various sensory inputs and communicating with other machines make it an essential tool for different industrial applications. Since, a huge amount of initial investment is required for robot acquisition and installation, the investment in robot systems needs a strong decision-making and evaluation process for the manufacturing organizations. Many organizations are now using robots as an integrated part of CIM technology. So, improper selection of robots may adversely affect an organization's competitiveness in terms of productivity of its facilities and quality of its products [1]. Robotic system selection is an important and a crucial task in today's highly competitive environment. Selecting robot technologies for specific industrial applications requires careful scrutiny and assessment of robot alternatives based on industry-specific requirements as well as characteristics of the alternative robots [2]. Different types and categories of robot technologies with diverse capabilities, features, facilities and specifications, as available in today's market, make it more difficult to select the best one among several alternatives. So the main objective of a robot selection process is to identify the predominant attributes and obtain the most appropriate combination of those attributes in combination with the real time requirements of the industrial application. A robot selection attribute is defined as a factor that influences the selection of an industrial robot. To properly evaluate and select a robot for a particular industrial application, several subjective and objective attributes, including accuracy, repeatability, degrees of freedom, control resolution, maximum tip speed, memory capacity, load carrying capacity, programming flexibility, man-machine interfacing ability and vendor's service quality are usually taken into consideration. Also manufacturing environment, product design, production system and cost involvement are some other influencing factors that directly affect the robot selection process. Cost and load capacity of a robot are objective attributes that can be numerically defined, on the other hand, programming flexibility, man-machine interfacing ability and vendor's service quality are subjective attributes. These attributes can be further classified as beneficial and non-beneficial. Beneficial attributes are those whose higher values are desirable (e.g., load carrying capacity, programming flexibility) and non-beneficial attributes are those whose lower values are preferable (e.g., cost, repeatability error). Many of these attributes are conflicting in nature and have different units, which cannot be unified and compared as they are. Thus, while selecting the most suitable robot for a given application, the decision makers (DMs) generally face difficulties due to involvement of such a huge number of conflicting and non-commensurate robot performance characteristics, making the selection process an MADM problem.

Several MADM-based approaches for robot selection have already been proposed and developed by the past investigators to help the manufacturing organizations for making good robot selection decisions. To provide an overview of these various approaches, the literature on robot selection is briefly reviewed here. Bhangale et al. [3] developed a three-stage robot selection procedure for some pick-n-place operation, including elimination stage, evaluation stage, and ranking and selection stage. TOPSIS and a graphical approach were used to rank and select the best robot alternative, and the relative rankings of the alternative robots were compared with those as obtained using the other methods. Rao and Padmanabhan [4] employed diagraph and matrix approach (GTMA) for evaluating and ranking a set of alternative robots for a given industrial application, using the similarity and dissimilarity coefficient values. A robot selection index was also proposed to evaluate and rank the alternative robots. Shih [5] suggested an incremental analysis method with group Technique for Order of Preference by Similarity to Ideal Solution

(TOPSIS) for selection of industrial robots. Chatterjee et al. [6] applied 'VIsekriterijumsko KOmpromisno Rangiranje' (VIKOR) and 'ELimination and Et Choice Translating Reality' (ELECTRE) methods for the selection of robots for some industrial applications. Kumar and Garg [7] developed a distance-based approach for evaluation, selection and ranking of robots, and compared its ranking performance with other techniques. Athawale and Chakraborty [8] compared the ranking performances of ten most popular MADM methods while selecting the best robot for some industrial pick-n-place operation. Rao et al. [9] proposed a novel decision-making method for optimal robot selection by integrating the objective weights of criteria and subjective preferences of the DM in conjunction with fuzzy logic which would convert the qualitative attributes into quantitative attributes. Koulouriotis and Ketipi [10] developed a digraph-based model for evaluation and selection of industrial robots from a feasible set of alternatives. Devi [11] extended VIKOR method in intuitionistic fuzzy environment for solving MADM problems in the area of robot selection. Athawale et al. [12] solved two industrial robot selection problems using solving VIKOR method and validated the results. İç [13] explored the applicability of an integrated TOPSIS and design of experiments (DoE) methodology to identify critical selection attributes and their interactions while solving different real time CIM selection problems, including industrial robots. İç et al. [14] developed a two-phase robot selection decision support system (DSS), i.e., ROBSEL, to help the DMs in robot selection. In that DSS, at first, the user would obtain a feasible set of robots by providing the values of 15 predefined requirements, and then it would use fuzzy analytic hieararchy process (FAHP) to rank the alternative robots. Bahadir and Satoglu [15] developed a DSS for robot selection based on axiomatic design principles (ADP). Datta et al. [16] explored the use of interval-valued grey numbers (IVGN) to tackle subjective evaluation information collected from a group of expert and multiplicative multi-objective optimization by ratio analysis (MULTIMOORA) method in order to aggregate individual criterion scores into an equivalent evaluation index towards evaluating feasible ranking order of candidate alternative robots. Liu et al. [17] proposed an interval 2-tuple linguistic TOPSIS (ITL-TOPSIS) method to handle the robot selection problem under uncertain and incomplete information environment. Ketipi and Koulouriotis [18] presented an extensive review of robot selection models with their advantages and disadvantages considering the flexibility and the other utility parameters. Ketipi et al. [19] presented an integrated comparative analysis of a representative sample of methodologies which have been implemented for two real-world problems and also used a generator of random example cases in conjunction with rank correlation coefficients along with dendrograms and bar graphs tools in order to detect similarities and differences between the selection methods as well as to evaluate qualitatively their overall behavior.

From the literature survey as presented above, it is understood that numerous research works have already been reported by the past researchers on solving the industrial robot selection problems using different mathematical and MADM-based approaches. But till date, very less effort has been made to compare the relative performances of several MADM methods employed simultaneously. In this paper, an effort is made to compare the relative performances of two almost unrevealed, yet very potential preference dominance-based MADM methods, namely EVAMIX and EXPROM2, while solving two industrial robot selection problems in discrete manufacturing environments. The illustrative examples are used to demonstrate the application aptness of the two MADM methods. It is observed that both the considered methods have huge potentials to deal with such complex decision-making problems in conflicting real time manufacturing environments. The computational details of these methods are presented in Section 2 and 3, respectively.

2. EVAMIX method

The EVAMIX method was primarily established by Voogd in 1983, and later advocated by Martel and Matarazzo [20]. This method is a generalization of concordance analysis for those decision matrices which consist of both ordinal and cardinal data. The basic concept of this method is based on the computation of the dominance score of an alternative over another alternatives on criterion-by-criterion basis. As an initial step, the ordinal and cardinal information is dealt separately through two separate overviews. Alternatives are compared two-by-two for each overview. The outcome is displayed in two dominance matrices, which display the respective dominance scores, thereby indicating to which extent one alternative is dominant over the other. Through standardization of these two matrices, a mutual comparison of quantitative and qualitative information becomes possible. Summation of the standardized dominance scores, including the weights of the quantitative and qualitative attributes results in a total score of each pair of alternatives. The attribute weights can be obtained applying AHP [21] or entropy method [22]. These standardized dominance scores are further utilized to compute the appraisal scores for each of the alternatives which are subsequently used to determine a complete ranking preorder of the alternatives. From a procedural point of view, EVAMIX method consists of the following steps as enlisted below [20, 23-25]:

Step 1: First separate the ordinal and cardinal criteria in the decision matrix.

Step 2: Normalize the beneficial attributes (where higher values are preferable) using the following equation:

$$r_{ij} = \left[x_{ij} - min(x_{ij})\right] / \left[max(x_{ij}) - min(x_{ij})\right] \ (i = 1,2,\ldots,m\ ;\ j = 1,2,\ldots,n) \tag{1}$$

where x_{ij} is the performance measure of i^{th} alternative with respect to j^{th} criterion, r_{ij} is the normalized value of x_{ij}, m is the number of alternatives and n is the number of criteria. For non-beneficial attributes (where lower values are preferable), Eq. 1 can be rewritten as follows:

$$r_{ij} = \left[max(x_{ij}) - x_{ij}\right] / \left[max(x_{ij}) - min(x_{ij})\right] \tag{2}$$

Step 3: Calculate the evaluative differences of i^{th} alternative on each ordinal and cardinal attributes with respect to other alternatives. This step involves the calculation of differences in criteria values between different alternatives pair-wise.

Step 4: Compute the dominance scores of each alternative pair, (i, i') for all the ordinal and cardinal criteria using the following equations:

$$\alpha_{ii'} = \left[\sum_{j \epsilon O} \{w_j sgn(r_{ij} - r_{i'j})\} c\right]^{1/c} \tag{3}$$

where

$$sgn(r_{ij} - r_{i'j}) = \begin{cases} +1 \text{ if } r_{ij} > r_{i'j} \\ 0 \text{ if } r_{ij} = r_{i'j} \\ -1 \text{ if } r_{ij} < r_{i'j} \end{cases}$$

$$\gamma_{ii'} = \left[\sum_{j \epsilon C} \{w_j sgn(r_{ij} - r_{i'j})\} c\right]^{1/c} \tag{4}$$

where the symbol c is a scaling parameter, for which any arbitrary positive odd number, like 1,3,5,... may be chosen, O and C are the sets of ordinal and cardinal criteria, respectively, $\alpha_{ii'}$ and $\gamma_{ii'}$ are the dominance scores for alternative pair, (i, i') with respect to ordinal and cardinal criteria, respectively, and w_j is the weight of j^{th} criterion.

Step 5: Calculate the standardized dominance scores. Martel and Matarazzo [20] proposed an additive interval method to derive the standardized ordinal dominance score $(\delta_{ii'})$ and cardinal dominance score $(d_{ii'})$ for the alternative pair, (i, i') as follows. Standardized ordinal dominance score:

$$(\delta_{ii'}) = \frac{(\alpha_{ii'} - \alpha^-)}{(\alpha^+ - \alpha^-)} \tag{5}$$

where α^+ (α^-) is the highest (lowest) ordinal dominance score for the alternative pair, (i, i'). Standardized cardinal dominance score:

$$(d_{ii'}) = \frac{(\gamma_{ii'} - \gamma^-)}{(\gamma^+ - \gamma^-)} \tag{6}$$

where γ^+ (γ^-) is the highest (lowest) cardinal dominance score for the alternative pair, *(i, i')*.

Step 6: Determine the overall dominance score. The overall dominance score, $D_{ii'}$ for each pair of alternatives, *(i, i')* is calculated to measure the degree by which alternative *i* dominates alternative *i'*.

$$D_{ii'} = w_O\delta_{ii'} + w_c d_{ii'} \tag{7}$$

where w_O is the sum of the weights for the ordinal criteria ($w_o = \sum_{j\epsilon o} w_j$) and w_C is the sum of the weights for the cardinal criteria ($w_c = \sum_{j\epsilon c} w_j$).

Step 7: Calculate the appraisal score.

$$(S_i) = \sum\nolimits_{i'} \left(\frac{D_{i'i}}{D_{ii'}}\right)^{-1} \tag{8}$$

The appraisal score for i^{th} alternative *(S_i)* is computed which gives the final preference of the alternatives. Higher the appraisal score, better is the performance of the alternative. The best alternative is the one which has the highest value of the appraisal score.

3. Extended PROMETHEE II method

The extended PROMETHEE II (EXPROM2) is a modifed version of PROMETHEE II method. Similar to PROMETHEE II, pair-wise comparison of alternatives considering the deviations with respect to each criterion is considered in EXPROM2 method. Basically, it is based on the concept of the ideal and anti-ideal solutions. The ideal and anti-ideal alternatives do not necessarily belong to the set of considered alternatives, although in most of situations, they are directly derived from the existing set of alternatives. Practically, the ideal and anti-ideal alternatives simply represent the extreme limits on the performances, set by the constraints of the problem under consideration. PROMETHEE II method derives a full ranking preorder of the alternatives by using a net flow value concept, but excludes the incomparability between two alternatives. This complete preorder expresses the preference of an alternative over another. This constitutes a limitation of the original PROMETHEE II method. To overcome this limitation, Diakoulaki and Koumoutsos [26] developed an extension of PROMETHEE II method which is popularly known as EXPROM2. In this method, the relative performance of one alternative over the other is defined by two preference indices. The first one is the weak preference index, based on the aggregated preference function considering the criteria weights, as determined in PROMETHEE II method. The second one is the strict preference index, based on the notion of the ideal and anti-ideal solutions. The ideal and anti-ideal values are directly derived from the decision matrix, and they reflect the extreme limits for a particular criterion. A total preference index is also computed by adding the strict and the weak preference indices which gives an accurate measure of the intensity of preference of one alternative over the other considering all the criteria. The procedural steps of EXPROM2 method are given as below [26-28]:

Step 1: Normalization of the decision matrix for beneficial and non-beneficial attributes using Eqs. 1 and 2, respectively.

Step 2: Calculation of the evaluative differences of i^{th} alternative with respect to other alternatives. This step involves the calculation of differences in criteria values *(d_j)* between different alternatives pair-wise.

Step 3: Determination of the preference function, $P_j(i, i')$. There are mainly six types of preference functions, e.g., usual criterion, U-shape criterion, *V*-shaped criterion, level criterion, *V*-shape with indifference criterion and Gaussian criterion. But most of these preference functions require the definition of some preferential parameters, like preference and indifference thresholds. However, in real time situations, it may be difficult for the DM to specify which specific form of preference function is suitable for each criterion and also to determine the parameters involved with them. To overcome these difficulties and make the related mathematical approach easier and faster, the simplest form of preference function (usual criterion) is adopted here, as given below:

$$P_j(i,i') = 0 \; if r_{ij} \leq r_{i'j} \tag{9}$$

$$P_j(i,i') = (r_{ij} - r_{i'j}) if \; r_{ij} > r_{i'j} \tag{10}$$

Step 4: Calculation the weak preference index considering the criteria weight values using the following equation:

$$WP(i,i') = \left[\sum_{j=1}^{n} w_j \, x P_j(i,i')\right] \Big/ \sum_{j=1}^{n} w_j \tag{11}$$

where w_j is the relative importance (weight) of j^{th} criterion.

Step 5: Defining the strict preference function, $SP_j(i, i')$. The strict preference function is based on the comparison of the difference values (dm_j) with the range of values as defined by the evaluation of the whole set of alternatives for a criterion.

$$SP_j(i,i') = \left[max(0, d_j - L_j)\right] / \left[dm_j - L_j\right] \tag{12}$$

where L_j is limit of preference (0 for usual criterion preference function, and indifference values for other five preference functions) and dm_j is difference between the ideal and anti-ideal values of j^{th} criterion.

Step 6: Computation of the strict preference index using the following equation:

$$SP(i,i') = \left[\sum_{j=1}^{n} w_j x SP_j(i,i')\right] \Big/ \sum_{j=1}^{n} w_j \tag{13}$$

Step 7: Calculation of the total preference index value as:

$$TP(i,i') = Min[1, WP(i,i') + SP(i,i')] \tag{14}$$

Step 8: Determination of the leaving and the entering outranking flows using the following equations. Leaving (positive) flow for i^{th} alternative:

$$\varphi^{+}(i) = \frac{1}{m-1} \sum_{i'=1}^{m} TP(i,i') \quad (i \neq i') \tag{15}$$

Entering (negative) flow for i^{th} alternative:

$$\varphi^{-}(i) = \frac{1}{m-1} \sum_{i'=1}^{m} TP(i',i) \quad (i \neq i') \tag{16}$$

The leaving flow expresses how much an alternative dominates the other alternatives, while the entering flow denotes how much an alternative is dominated by the other alternatives. Based on these flow values, EXPROM2 method can give the complete ranking preorder of the candidate alternatives by using a net flow.

Step 9: Computaion of the net outranking flow $\varphi(i)$ for each alternative as:

$$\varphi(i) = \varphi^{+}(i) - \varphi^{-}(i) \tag{17}$$

Step 10: Determination of the ranking of all the considered alternatives depending on the values of *φ(i)*. The higher the value of *φ(i)*, the better is the alternative. Thus, the best alternative is the one having the highest *φ(i)* value.

The EXPROM2 is a preference dominance approach designed to handle quantitative as well as qualitative attributes with discrete alternatives. In this method, pair-wise comparison of the alternatives is performed to compute a preference function for each criterion. Based on this preference function, a preference index for alternative i over i' is determined. This preference index is the measure to support the hypothesis that alternative i is preferred to i'.

4. Performance comparison tests for preference dominance-based methods

In order to establish the application suitability of the two preference dominance-based methods for solving industrial robot selection problems, their relative ranking performances are compared using the following four tests [29]:

(a) Determination of overall ranking aggrement among all the considered methods using Kendall's coefficient of concordance (Z) value employing Eq. 18.

$$Z = \frac{\sum_{i=1}^{m} \left(S_i - \frac{\sum_{i=1}^{m} S_i}{m} \right)^2}{\frac{1}{12} k^2 (m^3 - m)} \tag{18}$$

(b) Computation of pair-wise rank similarities among all the methods by Spearman's rank correlation coefficient (r_s) values accoprding to Eq. 19.

$$r_s = 1 - 6 \frac{\sum_{i=1}^{m} D_i^2}{m(m^2 - 1)} \tag{19}$$

(c) Agreement between the top three ranked alternatives, and
(d) Number of ranks matched, as the percentage of the total number of considered alternatives.

5. Illustrative examples

In order to reveal the computational precision and expediency of the two considered preference dominance-based MADM methods for solving industrial robot selection problems, the following two real time examples are illustrated.

5.1 Industrial robot selection example 1

This example deals with the selection of the most appropriate industrial robot to be used for some pick-andn-place operations to avoid certain obstacles. In this example, Bhangale et al. [3] considered five different robot selection attributes, such as load capacity (LC), repeatability (R), maximum tip speed (MTS), memory capacity (MC) and manipulator reach (MR). The minimum requirements with respect to different robot selection attributes for this application are presented in Table 1. Load capacity is defined as the maximum operating payload capacity of a robot without affecting its performance. It is basically related to robot acceleration and speed, and is a function of manipulator acceleration and wrist torque. Repeatability is the measure of the ability of a robot to return to a programmed position. Accuracy is the measure of closeness between the robot end effectors and the target point, and can usually be defined as the distance between the target point and the center of all points to which the robot goes on repeated trials.

Maximum tip speed is the speed at which a robot can move in an inertial reference frame. Memory capacity of a robot is measured in terms of number of points or steps that it can store in its memory while traversing along its pre-defined path. Manipulator reach is the maximum distance that can be covered by the robotic manipulator so as to grasp an object for the given pick-n-place operation.

Table 1 Minimum criteria requirements for example 1 [3]

Sl. No.	Attribute	Minimum requirement
1	Load capacity	2 kg
2	Repeatability	0.5 mm
3	Maximum tip speed	255 mm/s
4	Type of drives (actuators)	electrical only
5	Memory capacity	250 points/steps
6	Manipulator reach	500 mm
7	Degree of freedom	5

Among these robot selection attributes as considered in this problem, load capacity, maximum tip speed, memory capacity and manipulator reach are beneficial criteria, requiring higher values, whereas, repeatability is a non-beneficial attribute, requiring lower value.

Based on the predefined attribute requirements as presented in Table 1, Bhangale et al. [3] listed seven alternative robots with their relevant attribute values, Table 2. Bhangale et al. [3] also calculated the criteria weights as w_{LC} = 0.1761, w_R = 0.2042, w_{MTS} = 0.2668, w_{MC} = 0.243 and w_{MR} = 0.2286 using an eigen vector-based approach, but did a mistake while calculating the weights, as the summation of all the criteria weights exceeds one. So, in this research work, the criteria weights, as estimated by Rao [30] using AHP method, are used for all the preference ranking-based analyses, and these weights are w_{LC} = 0.036, w_{RE} = 0.192, w_{MTS} = 0.326, w_{MC} = 0.326 and w_{MR} = 0.120. Rao [30] solved the same robot selection problem using AHP method and obtained a ranking of the alternative robots as 3 > 2 > 7 > 1 > 4 > 6 > 5.

Table 2 Quantitative data for robot selection problem 1 [3]

Sl. No.	Robot	LC [kg]	R [mm]	MTS [mm/s]	MC [points]	MR [mm]
1	ASEA-IRB 60/2	60	0.4	2540	500	990
2	Cincinnati Milacrone T3-726	6.35	0.15	1016	3000	1041
3	Cybotech V15 Electric Robot	6.8	0.1	1727.2	1500	1676
4	Hitachi America Process Robot	10	0.2	1000	2000	965
5	Unimation PUMA 500/600	2.5	0.1	560	500	915
6	United States Robots Maker 110	4.5	0.08	1016	350	508
7	Yaskawa Electric Motoman L3C	3	0.1	177	1000	920

5.1.1 EVAMIX method

The problem of selecting the best suited industrial robot for the given pick-n-place operation is first solved using EVAMIX method. It begins with the separation of ordinal and cardinal criteria values in the decision matrix. In this example, as there is no ordinal criterion, this step is omitted here. Now, the decision matrix of Table 2 is normalized using Eqs. 1 and 2, respectively for beneficial and non-beneficial attributes, as shown in Table 3. After normalizing the decision matrix, the evaluative differences for each criterion with respect to all pair of alternative robots are calculated. Now, the dominance scores of each pair of alternative robots (i, i') with respect to each attribute are computed applying Eq. 4. While calculating the dominance scores, the value of c is taken as 1. Based on the additive interval technique, the standardized dominance scores for all the robot pairs are determined using Eq. 6. As the pick-n-place robot selection matrix has no ordinal criteria, so the ordinal dominance scores and standardized ordinal dominance scores need not to be calculated.

The overall dominance score for each pair of alternative robots is estimated using Eq. 7 which exemplifies the degree by which one robot dominates the others. These overall dominance scores for all pairs of alternative robots are given in Table 4. The appraisal score for each alternative is then calculated using Eq. 8 and based on the descending values of these appraisal scores, the final ranking of the alternative robots is obtained, as shown in Table 5.

Table 3 Normalized decision matrix

Robot	LC	RE	MTS	MC	MR
1	1.0000	0	1.0000	0.0566	0.4127
2	0.0670	0.7813	0.3551	1.0000	0.4563
3	0.0748	0.9375	0.6560	0.4340	1.0000
4	0.1304	0.6250	0.3483	0.6226	0.3913
5	0	0.9375	0.1621	0.0566	0.3485
6	0.0348	1.0000	0.3551	0	0
7	0.0087	0.9375	0	0.2453	0.3527

Table 4 Overall dominance scores for each robot pair

Robot pair	$D_{ii'}$	Robot pair	$D_{ii'}$	Robot pair	$D_{ii'}$
(1, 2)	0.3513	(3, 4)	0.8707	(5, 6)	0.2974
(1, 3)	0.3513	(3, 5)	0.8631	(5, 7)	0.4881
(1, 4)	0.5582	(3, 6)	0.6875	(6, 1)	0.3125
(1, 5)	0.6228	(3, 7)	0.8631	(6, 2)	0.4881
(1, 6)	0.6875	(4, 1)	0.4418	(6, 3)	0.3125
(1, 7)	0.5582	(4, 2)	0.0000	(6, 4)	0.6638
(2, 1)	0.6487	(4, 3)	0.1293	(6, 5)	0.7026
(2, 3)	0.0905	(4, 5)	0.6875	(6, 7)	0.7026
(2, 4)	1.0000	(4, 6)	0.3362	(7, 1)	0.4418
(2, 5)	0.6875	(4, 7)	0.6875	(7, 2)	0.3125
(2, 6)	0.5119	(5, 1)	0.3772	(7, 3)	0.1369
(2, 7)	0.6875	(5, 2)	0.3125	(7, 4)	0.3125
(3, 1)	0.6487	(5, 3)	0.1369	(7, 5)	0.5119
(3, 2)	0.9095	(5, 4)	0.3125	(7, 6)	0.2974

Table 5 Appraisal score and rank of each robot alternative

Robot	S_i additive interval technique	Rank
1	0.1578	2
2	0.0803	5
3	0.6405	1
4	0.0919	4
5	0.0634	7
6	0.1470	3
7	0.0654	6

The ranking of the alternative robots is observed as 3 > 1 > 6 > 4 > 2 > 7 > 5 which signifies that Robot 3 (Cybotech V15 Electric Robot) is the best choice for this given pick-n-place operation. Robot 1 (ASEA-IRB 60/2) is the second best choice and Robot 5 (Unimation PUMA 500/600) is the worst chosen alternative.

5.1.2 EXPROM2 method

In this method, at first, the decision matrix of Table 2 is normalized using Eqs. 1 and 2, respectively for beneficial and non-beneficial attributes and is shown in Table 6. Then employing Eqs. 9, 10 and 12 the corresponding weak and strict preference functions are computed for all pairs of robot alternatives. Although there are six different types of preference functions that may be adopted, but as most of these preference functions require the definition of some preferential parameters, like preference and indifference thresholds to be specified by the DM in real time situations, the usual criterion is adopted here for computing the weak preference function. After specifying these preference functions, weak preference index, strong preference index and total preference index values for the alternative pairs of robots are computed using Eqs. 11, 13 and 14 respectively, as shown in Table 7. As in this computation, usual criterion is chosen as the preferred preference function, both the values of weak and strong preference indices are observed to be same here.

Table 6 Normalized decision matrix

Robot	LC	RE	MTS	MC	MR
1	1.0000	0	1.0000	0.0566	0.4127
2	0.0670	0.7813	0.3551	1.0000	0.4563
3	0.0748	0.9375	0.6560	0.4340	1.0000
4	0.1304	0.6250	0.3483	0.6226	0.3913
5	0	0.9375	0.1621	0.0566	0.3485
6	0.0348	1.0000	0.3551	0	0
7	0.0087	0.9375	0	0.2453	0.3527

Table 7 Weak, strong and total preference index values for robot pairs

Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$	Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$
(1, 2)	0.2438	0.2438	0.4877	(4, 5)	0.2551	0.2551	0.5101
(1, 3)	0.1454	0.1454	0.2909	(4, 6)	0.2534	0.2534	0.5068
(1, 4)	0.2463	0.2463	0.4927	(4, 7)	0.2456	0.2456	0.4911
(1, 5)	0.3169	0.3169	0.6337	(5, 1)	0.1800	0.1800	0.3600
(1, 6)	0.3130	0.3130	0.6259	(5, 2)	0.0300	0.0300	0.0600
(1, 7)	0.3689	0.3689	0.7378	(5, 3)	0	0	0
(2, 1)	0.4628	0.4628	0.9256	(5, 4)	0.0600	0.0600	0.1200
(2, 3)	0.1845	0.1845	0.3691	(5, 6)	0.0603	0.0603	0.1205
(2, 4)	0.1630	0.1630	0.3261	(5, 7)	0.0528	0.0528	0.1057
(2, 5)	0.3858	0.3858	0.7716	(6, 1)	0.1920	0.1920	0.3840
(2, 6)	0.3819	0.3819	0.7638	(6, 2)	0.0420	0.0420	0.0840
(2, 7)	0.3763	0.3763	0.7526	(6, 3)	0.0120	0.0120	0.0240
(3, 1)	0.3735	0.3735	0.7470	(6, 4)	0.0742	0.0742	0.1484
(3, 2)	0.1936	0.1936	0.3873	(6, 5)	0.0762	0.0762	0.1523
(3, 4)	0.2334	0.2334	0.4667	(6, 7)	0.1287	0.1287	0.2574
(3, 5)	0.3649	0.3649	0.7298	(7, 1)	0.2415	0.2415	0.4830
(3, 6)	0.3610	0.3610	0.7221	(7, 2)	0.0300	0.0300	0.0600
(3, 7)	0.3554	0.3554	0.7109	(7, 3)	0	0	0
(4, 1)	0.3045	0.3045	0.6091	(7, 4)	0.0600	0.0600	0.1200
(4, 2)	0.0023	0.0023	0.0046	(7, 5)	0.0623	0.0623	0.1247
(4, 3)	0.0635	0.0635	0.1270	(7, 6)	0.1223	0.1223	0.2446

Now, based on the leaving and entering outranking flows as given in Table 8 and computed using Eqs. 15 and 16, respectively, the related net outranking flows are estimated for all the alternatives using Eq. 17. After arranging these net outranking flows in descending order, the final ranking of the alternative robots is obtained, as shown in Table 8. This table depicts that Robot 3 (Cybotech V15 Electric Robot) is the best choice, followed by Robot 3 (Cincinnati Milacrone T3-726). Robot 5 (Unimation PUMA 500/600) is the worst chosen robot among the considered alternatives.

Table 8 Ranking of alternative robots with leaving, entering and net flow values

Robot	$\varphi^+(i)$	$\varphi^-(i)$	$\varphi(i)$	Rank
1	0.5448	0.5848	-0.0400	4
2	0.6515	0.1806	0.4709	2
3	0.6273	0.1352	0.4921	1
4	0.3748	0.2790	0.0958	3
5	0.1277	0.4871	-0.3594	7
6	0.1750	0.4973	-0.3223	5
7	0.1720	0.5092	-0.3372	6

5.2 Performance analysis of preference dominance-based methods for example 1

Now, to examine the suitability and judge the rank conformities among the two preference dominance-based methods while solving this pick-n-place industrial robot selection problem, their ranking performances are compared using four different performance tests.

These performance tests compare the ranking as provided by these two methods with respect to each other and also with respect to AHP method as applied by Rao [30] for solving this robot selection problem. Table 9 summarizes the ranking preorders of the robot alternatives, as obtained using these eight methods. The ranking performances of both the Evamix and EXPROM2 methods with respect to those derived by Rao [30] are exhibited in Fig. 1.

Table 9 Ranking preorders obtained using different methods

Robot	AHP [30]	EVAMIX	EXPROM2
1	4	2	4
2	2	5	2
3	1	1	1
4	5	4	3
5	7	7	7
6	6	3	5
7	3	6	6

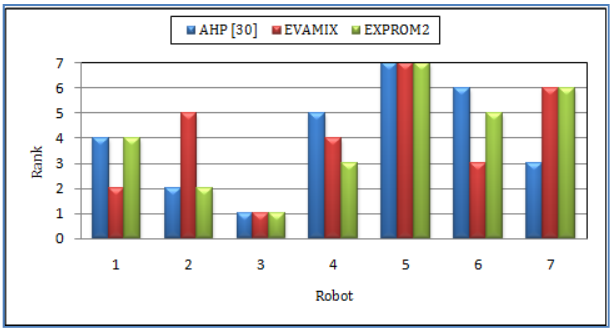

Fig. 1 Comparative rankings of alternative robots for example 1

a) Now, in order to determine the overall ranking agreement among all the considered methods, the Kendall's coefficient of concordance *(Z)* value is now computed. For this industrial robot selection problem, the *z* value is obtained as 0.7460, suggesting a high rank conformity among all these methods.
b) Table 10 shows the Spearman's rank correlation coefficient (r_s) values when the rankings of the robot alternatives as obtained using the two preference dominance-based methods are compared between themselves and also with respect to the rank ordering of Rao [30] as derived using AHP method. It is revealed that the r_s value ranges from 0.4285 to 0.7500. Table 10 also shows that there are good agreements between the two preference dominance-based methods and also with AHP method. The performances of EVAMIX in comparison to EXPROM2 method is relatively poor in terms of rank similarities.

c) Table 10 also shows the results of another test, performed to determine the agreement between the top three ranked robot alternatives as indicated by these methods. This table suggests that the ranks obtained applying EXPROM2 method perfectly match with those of Rao [30] for the best and the second best robot alternatives.
d) The last test is performed with respect to the number of total ranks matched, expressed as the percentage of the number of alternatives. These results are also shown in Table 10. It is again observed that EXPROM2 evolves out as the best method as compared to EVAMIX.

Table 10 Performance test table for preference dominance-based methods for robot selection problem 1

Method	EVAMIX	EXPROM2
AHP [30]	0.4285, (1,#,#), 28.57	0.7500, (1,2,#), 57.14
EVAMIX		0.6785, (1,#,#), 42.86

5.3 Industrial robot selection example 2

Now in order to further demonstrate and validate the efficiency of the two preference dominance-based methods while utilizing various robot selection attributes to achieve a comprehensive ranking of the alternative robots, another industrial example from Rao and Padmanabhan [4] is considered here.

In this example, four attributes were identified and five alternative robots were short-listed based on the threshold values set for those attributes. In the present research work, the considered attributes are load capacity (LC), repeatability error (RE), vertical reach (VR) in mm and degrees of freedom (DF). Among these attributes, LC, VR and DF are beneficial in nature requiring higher values. RE is a non-beneficial attribute where lower value is desirable. The relative normalized weights for the attributes were calculated by Rao and Padmanabhan [4] using AHP method as w_{LC} = 0.0963, w_{RE} = 0.5579, w_{VR} = 0.0963 and w_{DF} = 0.2495. The consistency ratio (CR) was computed as 0.0160, which is much less than its threshold value of 0.1 as used in AHP method, and hence, these weights are acceptable. Rao and Padmanabhan [4] solved this industrial robot selection problem using GTMA, and obtained a ranking of the alternative robots as 3 > 2 > 1 > 4 > 5, indicating robots 3 and 5 as the best and the worst choices for the given industrial application under the specified conditions. The decision matrix for this industrial robot selection problem is shown in Table 11.

Table 11 Quantitative data for robot selection problem 2 [4]

Robot	LC	RE	VR	DF
1	60	0.4	125	5
2	60	0.4	125	6
3	68	0.13	75	6
4	50	1	100	6
5	30	0.6	55	5

5.3.1 EVAMIX method

This robot selection problem is now solved using EVAMIX method. At first, the decision matrix of Table 11 is normalized, as shown in Table 12. After obtaining the normalized decision matrix, the evaluative differences of each robot for all the qualitative and quantitative criteria with respect to other robot alternatives are computed. Then, the dominance scores of each pair of alternative robots are calculated. Now, the standardized ordinal and cardinal dominance scores for all the robot pairs are determined using the additive interval technique. The overall dominance score for each pair of robots is calculated, representing the degree by which a particular robot dominates the others. These overall dominance scores for all the robot pairs are shown in Table 13. Finally, the appraisal score for each alternative robot is computed and based on the descending order of these appraisal scores, the final ranking is obtained, as shown in Table 14. The best choice of robot for this industrial example is Robot 3, followed by Robot 2 and the last choice is Robot 4.

Table 12 Normalized decision matrix

Robot	LC	RE	VR	DF
1	0.7895	0.6897	1.0000	0.0000
2	0.7895	0.6897	1.0000	1.0000
3	1.0000	1.0000	0.2857	1.0000
4	0.5263	0.0000	0.6429	1.0000
5	0.0000	0.4598	0.0000	0.0000

Table 13 Overall dominance scores for robot pairs

Robot pair	$D_{ii'}$	Robot pair	$D_{ii'}$
(1, 2)	0.3753	(3, 4)	0.7790
(1, 3)	0.0963	(3, 5)	1.0000
(1, 4)	0.7505	(4, 1)	0.2495
(1, 5)	0.8753	(4, 2)	0.1248
(2, 1)	0.6248	(4, 3)	0.2211
(2, 3)	0.2211	(4, 5)	0.4421
(2, 4)	0.8753	(5, 1)	0.1248
(2, 5)	1.0000	(5, 2)	0.0000
(3, 1)	0.9037	(5, 3)	0.0000
(3, 2)	0.7790	(5, 4)	0.5579

Table 14 Appraisal score and rank for each robot

Robot	S_i additive interval technique	Rank
1	0.0868	4
2	0.2344	2
3	1.4834	1
4	0.0675	5
5	0.1281	3

5.3.2. EXPROM2 method

In this method, first, the corresponding weak and strict preference functions are computed for all pairs of robot alternatives from the normalized decision matrix as shown in Table 12. After calculating these preference functions, weak preference index, strong preference index and total preference index are estimated, as shown in Table 15. After determining these three preference indices, the leaving and entering outranking flows for different robots are calculated, as given in Table 16. The related net outranking flows are then computed for all robots which are used to derive the final ranking order of the robot alternatives by arranging them in a descending order of preference, as also shown in Table 16. Robot 3 emerges out as the best choice, while Robot 5 becomes the last ranked alternative.

Table 15 Weak, strong and total preference index values for different robot pairs

Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$	Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$
(1, 2)	0	0	0	(3, 4)	0.6035	0.6035	1.0000
(1, 3)	0.0688	0.0688	0.1376	(3, 5)	0.6747	0.6747	1.0000
(1, 4)	0.4445	0.4445	0.8890	(4, 1)	0.2495	0.2495	0.4990
(1, 5)	0.3006	0.3006	0.6012	(4, 2)	0	0	0
(2, 1)	0.2495	0.2495	0.4990	(4, 3)	0.0344	0.0344	0.0688
(2, 3)	0.0688	0.0688	0.1376	(4, 5)	0.3621	0.3621	0.7242
(2, 4)	0.4445	0.4445	0.8890	(5, 1)	0	0	0
(2, 5)	0.5501	0.5501	1.0000	(5, 2)	0	0	0
(3, 1)	0.4429	0.4429	0.8858	(5, 3)	0	0	0
(3, 2)	0.1934	0.1934	0.3868	(5, 4)	0.2565	0.2565	0.5130

Table 16 Leaving, entering and net outranking flow values with robot ranks

Robot	$\varphi^{+}(i)$	$\varphi^{-}(i)$	$\varphi(i)$	Rank
1	0.4069	0.4710	-0.0640	3
2	0.6314	0.0967	0.5347	2
3	0.8182	0.0860	0.7322	1
4	0.3230	0.8227	-0.4998	4
5	0.1283	0.8313	-0.7031	5

5.4 Performance analysis of preference dominance-based methods for example 2

Now, to examine the rank similarities among the two preference dominance-based methods while solving this industrial robot selection problem, their ranking performances are compared using the four different performance tests. Table 17 summarizes the ranking preorders of the robot alternatives as obtained using different MADM methods. The ranking performances of both the Evamix and EXPROM2 methods with respect to those derived by Rao and Padmanabhan [4] are exhibited in Fig. 2.

Table 17 Ranking preorders of robot alternatives obtained using different methods

Robot	GTMA [4]	EVAMIX	EXPROM2
1	3	4	3
2	2	2	2
3	1	1	1
4	4	5	4
5	5	3	5

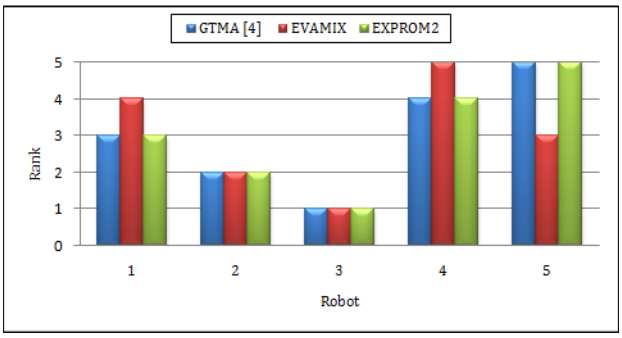

Fig. 2 Comparative rankings of alternative robots for example 2

a) At first for this industrial robot selection problem, the z value is computed as 0.8666, indicating a very strong rank similarities among these methods.
b) In the second test, the r_s values are calculated to compare the rankings of the alternative robots, as obtained using different preference dominance-based methods between themselves and also with respect to the rank ordering as derived by GTMA. It is revealed that the r_s value ranges from 0.7 to 1.0, and a perfect match exists for GTMA-EXPROM2 methods. Table 18 shows that the two preference dominance-based methods have very high rank agreement between themselves and also with respect to GTMA.
c) Table 18 shows the results of the next test, performed to evaluate the agreement between the top three ranked robot alternatives as indicated by these methods. This table confirms that EXPROM2 method produces the same rankings for the best, second best and third best robot alternatives with respect to GTMA.
d) The last test is conducted with respect to the number of total ranks matched, expressed as a percentage of the number of alternatives. These results are shown in Table 18. It is again observed that EXPROM2 method evolves out as the best performer as compared to EVAMIX method.

Table 18 Performance test table for preference dominance-based methods for robot selection problem 2

Method	EVAMIX	EXPROM2
GTMA [4]	0.70, (1,2,#), 40	1.00, (1,2,3), 100
EVAMIX		0.70, (1,2,#), 40

6. Conclusions

Although different MADM methods have already been proposed by the past researchers for economic evaluation and selection of industrial robots, it is not still clear which MADM method is the best for a given industrial robot selection problem. This paper considers two preference dominance-based methods and compares their relative ranking performances while selecting the best suited industrial robots for the given industrial applications. Four performance tests are also conducted. The cited industrial robot selection problems demonstrate the suitability and accuracy of EVAMIX and EXPROM2 methods which have very high prospects in solving complex robot selection decision-making problems. The rankings derived using these four preference ranking methods almost perfectly match with those as obtained by the past researchers. It is found that although EXPROM2 performs well, EVAMIX method can also be successfully applied for the robot selection problems as the change of the method does not produce any significant differences in the top-ranked robot alternatives. In EVAMIX method, a linear criteria transformation procedure converts all the criteria values into dimensionless numbers ranging from 0 to 1. The dominance scores for each pair of alternatives are calculated on the basis of criterion-by-criterion comparison and an additive interval model is then adopted. While in EXPROM2 method, alternatives are compared with respect to the deviations that the alternatives show to each other for each criterion. EXPROM2 method also allows the involvement of different preferential parameters set by the decision maker. The considered methods can give precise rankings of the considered alternatives irrespective of the complexity of the decision-making problem, which is validated by the performance comparison tests. For all the illustrative case studies, very high z and r_s values clearly justify the universal applicability of these methods for solving complex decision-making problems. As these two preference dominance-based methods can easily be implemented using EXCEL worksheet, any type of industrial robot selection problem can be solved employing these methods, thus reducing the cost, computational time and programming knowledge constraints as involved in most of the popular MADM tools like AHP, ELECTRE and GTMA methods. Both these methods can be efficiently applied to any type of real time robot selection problems involving any number of criteria, and any number of decision alternatives.

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Particle swarm optimization approach for modelling a turning process

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A B S T R A C T

This paper proposes the modelling of a turning process using particle swarm optimization (PSO). The independent input machining parameters for the modelling were cutting speed, feed rate, and cutting depth. The input parameters affected three dependent output parameters that were the main cutting force, surface roughness, and tool life. The values of the independent and dependent parameters were acquired by experimental work and served as knowledge base for the PSO process. By utilizing the knowledge base and the PSO approach, various models could be acquired for describing the cutting process. In our case, three different polynomial models were obtained: models a) for the main cutting force, b) for surface roughness, and c) for tool life. All the models had exactly the same basic polynomial form which was chosen similarly to that in the conventional regression analysis method. The PSO approach was used for optimization of the polynomials' coefficients. Several different randomly-selected data sets were used for the learning and testing phases. The accuracies of the developed models were analysed. It was discovered that the accuracies of the models for different learning and testing data sets were very good, having almost the same deviations. The least deviation was noted for the cutting force, whilst the most deviation, as expected was for tool life. The obtained models could then be used for later optimization of the turning process.

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1. Introduction

Since the advent of modern manufacturing technologies and up-to-date machine tool CNC systems, shorter manufacturing times and higher manufacturing capabilities have been achieved that have led to reductions in final production costs, thus increasing profit margins. As the modern production technologies were significantly improving, this directly affected the optimizing of machining parameters. Machining experts can usually work with a design team so that machining can be optimized in order to obtain the best combination of cutting force, surface roughness, and minimal tool wear. Should the machining experts be eliminated from the process for any reason (i.e., employment issues, no experts available), intelligent methods could be used instead. Naturally the results can have some deviation from the true optimal values, however even experts cannot always provide the most optimal parameters for various situations.

In general, the concept behind all optimization algorithm variants is the same, namely that optimal cutting conditions are desired in order to reduce manufacturing costs. This is the easiest to achieve by combining basic cutting parameters. During the turning process the definable parameters are typically cutting speed, feed rate, and cutting depth. As the cutting diameter becomes progressively smaller, the revolutions should increase in order to obtain the same cutting speed, which usually is higher the lower the roughness is. In regard to feed rate it is exactly the opposite. Should lower roughness be preferred a reduction of the feed rate is needed, exactly the same as with cutting depth, which provides lower surface roughness if it is smaller. These combinations are crucial especially for finish turning, which usually consists of only one fine cut finish.

It is of the essence to take into consideration essential equations for machining that serve for understanding the concept of turning process modelling using particle swarm optimization (PSO). A study of cutting basics is required for this purpose, which would include descriptions from turning, milling, drilling, and grinding. The literature is mainly oriented towards high speed cutting, and this is a good starting point for optimal and fast manufacturing processes. It is also wise to check experimental results using the integrated approach for machining parameters, which was done by Liang et. al. [1], and Jafarian et al. by applying neural networks to the same process [2]. After all the equations and variables are known, input and output information is needed based on experimental work [3]. Bharati and Baskar introduced particle swarm optimization into manufacturing systems, as did Chan and Tiwari, however their work was based mainly on optimizing a single parameter per cutting operation, and for optimization purposes these individual parameters were not linked together with other cutting parameters (i.e., roughness, cutting force, tool life) [4, 5]. Cus and Balic presented the optimization of a machining process via GA algorithms [6]. El-Mounayri et al. composed an optimization algorithm for predicting surface roughness [7], whilst Senveter et al. used the neural network approach for the same problem [8]. Zuperl and Cus used neural networks as well for the machining optimization purposes [9]. Bushan conducted similar parameters' optimization, however solely for minimizing power consumption during machining and also for maximizing the tool life [10]. Byrne et al. implemented tool condition monitoring within the system [11]. A similar procedure was also introduced by Choudhury and Appa [12], however it was done solely for minimizing tool wear. The importance of proper cutting parameters selection has also been pointed out by Lee and Tarng [13]. Billatos and Tseng paved the way for knowledge-based optimization for intelligent machining, which is essential for proper particle swarm optimization procedure if we wish to optimize using more than one input parameter [14]. Brezocnik et al. proposed and developed a genetic programming system [15], as well as a very efficient and highly integrated genetic programming and genetic algorithm system for the modelling of surface roughness for different machining processes [16]. Quiza et al. upgraded a whole procedure to multi-objective optimization in order to increase the versatility of an algorithm [17].

This paper proposes a modelling of the machining process using particle swarm optimization by which models for specific materials can be prepared by successfully combining independent and dependent variables. Such polynomial models would serve for the later optimizations of manufacturing processes. It is vital to use as much input information as possible at the same time, as only in this way is it assumable that the polynomial will be accurate, as this affects the quality of optimization.

2. Experimental work

2.1 Equipment, tools, and materials

The experimental work presented in this paper was based on the work of Jurkovic Z. [3], and was carried out at the Production Engineering Institute, Faculty of Mechanical Engineering, at the University of Maribor. The aim of this experiment was to obtain suitable dependent output values regarding machining parameters from independent input machining parameters' values.

CNC machine tool:

A CNC lathe Georg Fischer NDM-16 was used for our experiment. The machine characteristics are briefly as follows.

- main electric motor power / safety limited: P = 30 kW, maximum P = 40 kW,
- feed rate motor power: P = 1.8 kW,
- maximal feed rate: f = 5000 mm/min,
- maximal workpiece size: Ø 160 mm × 500 mm,
- revolution area stage I: P = 27 kW*;* T = 625 Nm at 410 min^{-1}, 15-1140 min^{-1},
- revolution area stage II: P = 30 kW*;* T = 220 Nm at 1320 min^{-1}, 40-4000 min^{-1},
- tool system: Block tool system (BTS) – BT32.

Tool holder and insert:

- tool holder 0-3225P15,
- insert Sandvik Coromant DNMG 150608-PM4025: manufactured by CVD technology, middle layer Al_2O_3, top layer TiN covered.

Manufacturers recommended cutting conditions:

- v_c = 265-405 m/min,
- f = 0.15-0.50 mm/rev,
- a_p = 0.5-6 mm.

Tested material:

Workpiece material was carbonised steel with standard markings C45E (EN 10083/1996). The material was hot-rolled into a 6 m long cylinder with diameter of Ø 100 mm, and mass of 61.7 kg/m. After the essential forming into cylinders, it was tempered. The material was later cut into cylinder lengths with dimensions of Ø 100 mm × 380 mm.

Measuring tools:

In order to obtain the measuring results, the measuring tools had to successfully acquire the following measurements as required: main cutting force F_C, surface roughness R_a, and maximal tool life T. The measurement equipment was:

- cutting force: Kistler 9257A dyanometer, which had a measuring area covering three axes $F_{x,y,z}$ = 5 kN, which sent the measured signal to the computer by utilizing LabVIEW™,
- surface roughness: SJ-201P Mitutoyo measuring unit with reference values 2.5 mm,
- tool wear: Carl Zeiss microscope with magnification of 30× and resolution of 0.0001 mm.

2.2 Experimental results

The measured values during the experiment were of the cutting force, surface roughness and tool life, whilst the given parameters were surface speed, feed rate, and cutting depth. Suitable equipment was used for obtaining correct parameters, and monitoring those tools that gave us proper results.

Input parameters:

- cutting speed – v_c [m/min],
- feed rate – f [mm/rev],
- cutting depth – a_p [mm].

Output parameters:

- main cutting force – F_C [N],
- surface roughness – R_a [μm],
- maximal tool life – T [min].

Using these parameters, including polynomial equations optimization, successful multiple regression analysis implementation can be achieved. However, the basis of this paper is a non-deterministic approach, so regression analysis will not be analytical but a stochastic method based on acquiring a particle swarm algorithm that does the computing of the coefficients of the prescribed mathematical model. The measured values essential for rough turning are presented in Table 1.

Cutting speed is a tangential component of the spindle speed, which is measured in min^{-1}. In general, for finish cutting it is of the essence that the cutting speed is noticeably higher than the one used for rough machining. In contrast the feed rate requires the finish machining to be lower than for the roughing. The same also applies for the cutting depth, which is also much smaller with the finish cutting. The input and output parameters are shown graphically in Fig. 1.

Table 1 Input and output values for rough turning

	Input values			Output values		
Nr.	V_c [m/min]	f [mm/rev]	a_p [mm]	F_c [N]	R_a [μm]	T [min]
1	300	0.30	1.50	879.2240	4.300	17.6
2	400	0.30	1.50	894.3270	3.880	4.73
3	300	0.50	1.50	1436.299	11.11	6.68
4	400	0.50	1.50	1408.114	11.48	1.88
5	300	0.30	3.00	1754.215	4.210	13.8
6	400	0.30	3.00	1726.937	4.500	3.80
7	300	0.50	3.00	2896.122	14.29	4.10
8	400	0.50	3.00	2860.663	13.71	1.16
9	350	0.40	2.25	1677.149	8.100	5.38
10	350	0.40	2.25	1672.771	8.130	5.10
11	350	0.40	2.25	1679.359	8.120	5.44
12	350	0.40	2.25	1678.825	8.120	5.28
13	350	0.40	2.25	1675.829	8.110	5.50
14	350	0.40	2.25	1678.223	8.100	5.22
15	266	0.40	2.25	1697.504	7.820	12.9
16	434	0.40	2.25	1683.361	8.150	1.81
17	350	0.23	2.25	1002.763	2.460	10.5
18	350	0.57	2.25	2609.254	17.95	0.75
19	350	0.40	1.00	765.9210	6.360	6.65
20	350	0.40	3.50	2746.389	9.070	3.58

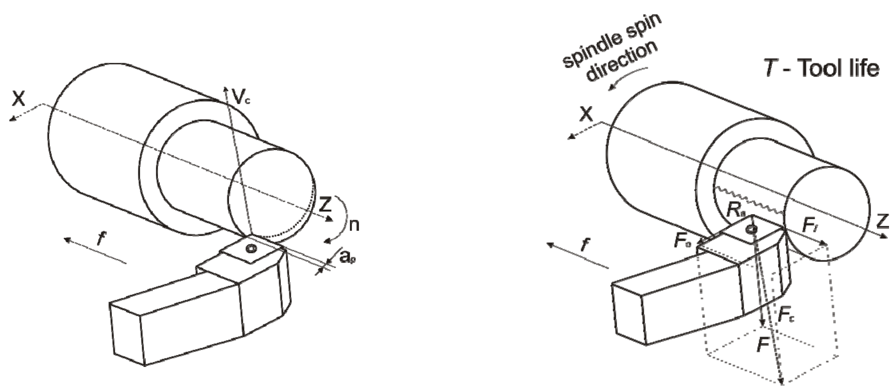

Fig. 1 Input values (left) and output values (right)

3. Used methods – PSO algorithm

Particle swarm optimization algorithm uses stochastic operations and is designed around a population of organisms/particles. This algorithm is based upon a living organism model, such as flocks of birds. These organisms then interact upon social-psychological correlations, the very same way as living organisms and have the possibility of adapting to various problems.

3.1 Basis information

Randomly generated initial organisms/particles are needed in order to determine the optimal solution. The algorithm works within a basic route, which is determined using solution particle position and particle velocity vectors as a guide, and where we can determine that a certain solution, within a certain optimization time, is currently determined by the velocity vector, which defines our best solution. This is determined as a fitness function for each organism which is also commonly known as the capability of finding a better solution. Such a vector marks the personal best values for each single organism within the system and is called the personal best solution – pBest. In contrast, each particle swarm within every singular moment has its best global position, which is called gBest. At each cycle the repetition values for pBest and gBest are updated.

3.2 Computational model

Initial locations for each organism within the search space are created randomly. After that the algorithm conducts optimizing cycles, where with each repetition the current personal best solution (pBest) and global best solution (gBest) are searched for. Eq. 1 shows the core of the optimization algorithm, whilst Eq. 2 stands for updating the particle location after each optimization cycle.

$$v_i = v_i + c_1 rand(\,)(p_i - x_i) + c_2 Rand(\,)(p_g - x_i) \tag{1}$$

Particle location update:

$$x_i = x_i + v_i \tag{2}$$

The variables in Eq. 1 and Eq. 2 represent:

- c_1 in c_2 – acceleration coefficients (acceleration coefficients),
- $rand(\,)$ and $Rand(\,)$ – random values within interval (0 1),
- x_i – i^{th} particle,
- p_i – pBest for i^{th} particle,
- p_g – gBest of all particles (global best particle),
- v_i – velocity update value for particle i.

The particle swarm optimization equation (Eq. 1) consists of three terms. The first term allows initialisation and it is not changed, however it does get us to the current velocity and initial solution location. The second term allows that a particle learns from its own experiences, and in the third term the particles interact with each other, exchanging valuable expertise for solving the problems. Therefore, the pseudocode of the PSO algorithm can be written as shown in Fig. 2.

```
Start PSO
    For each particle
        Initialize particle
    END
    Do
        For each particle
            Calculate particle fitness
            If fitness function > best particle fitness (pBest) then value becomes new pBest
            Choose particle with best fitness value (gBest)
        END
        For each particle
            Calculate particle velocity
            Update particle location
        END
    While maximal iterations N are reached, or maximal tolerated error is reached
END PSO
```

Fig. 2 Particle swarm optimization pseudocode

4. Modelling results and discussion of the prediction model

As previously stated, the optimization algorithm starts with the initialisation of particles with random velocity values. Manually adjustable acceleration coefficients c_1 and c_2 are required, which are directing the algorithm searching abilities in search space. The rest of the parameters (i.e., pBest, gBest) are manipulated and updated directly through the optimization algorithm. If a finish machining optimization model is desired, despite the similarity, two separate procedures have to be initiated in order to obtain results for both rough machining and finishing machining, regardless of the machining process type. According to Fig. 2, a knowledge-based table has to be included into the initial procedure. Basic prediction polynomial model has to be created at this point. On the basis of the preliminary results, the following polynomial model was chosen for the modelling of the turning process:

$$f(x_1, x_2, x_3) = k_1 + k_2 \cdot x_1 + k_3 \cdot x_2 + k_4 \cdot x_3 + k_5 \cdot x_1 \cdot x_2 + k_6 \cdot x_1 \cdot x_3 + k_7 \cdot x_2 \cdot x_3 + \\ + k_8 \cdot x_1 \cdot x_2 \cdot x_3 \tag{3}$$

Here $f(x_1, x_2, x_3)$ stand for any of the three resulting output machining parameters:

- main cutting force – F_c,
- surface roughness – R_a,
- maximal tool life – T.

Parameters x_1, x_2, x_3 in Eq. 3 are independent input parameters: cutting speed, feed rate, and cutting depth. Optimization polynomials for dependent machining parameters will be obtained by applying the PSO algorithm to the learning data set. These dependent values' polynomials (cutting force, surface roughness, and tool life) are then useable for processing and optimizing the turning process by means of multi-objective optimization, in order to determine the most optimal input data set for machining the surface to optimal roughness, with minimal cutting force and maximal tool life duration.

4.1 PSO parameters

The following results are representative values only for the material C45E (EN 10083/1996). Under different machining circumstances, the developed system still remains completely the same; the user only has to prepare the new knowledge-base.

In order to properly set a PSO algorithm, choosing certain essential additional parameters is in order, which in our case will be:

- number of iterations 500000,
- correction factor c_1 = 1.2,
- correction factor c_2 = 2.4,
- swarm size 35,
- particle size 8.

4.2 Modelling results

Modelling of the machining process was done by PSO, therefore the optimizing procedure was controlled by PSO parameters. On the basis of the particle swarm optimization algorithm's architecture, the display of the results had to be done in the form of coefficients k_1, k_2,..., k_8, which determined the specific combination and weight factor per independent machining parameter. The results of four PSO algorithm runs are shown in Tables 2, 3 and 4. Those polynomial coefficients, that were acquired using the PSO approach for cutting force, surface roughness, and tool life were representative and would serve for preparing the computing models according to Eq. 3.

Table 2 Coefficients for F_c

	Run No.			
Coefficients	1	2	3	4
k_1	-484.575	-494.739	-513.83	-551.681
k_2	1.76549	1.794344	1.848204	1.955626
k_3	1049.84	1074.501	1120.634	1212.698
k_4	190.7856	195.0709	203.0669	219.0319
k_5	-3.95561	-4.02566	-4.15588	-4.41687
k_6	-0.63984	-0.65201	-0.67457	-0.7199
k_7	1592.993	1582.59	1563.301	1524.522
k_8	1.185408	1.214965	1.26942	1.379419

Table 3 Coefficients for R_a

	Run No.			
Coefficients	1	2	3	4
$k1$	12.81179	4.868139	4.148009	5.390292
$k2$	-0.04611	-0.02361	-0.02159	-0.0251
$k3$	-17.3847	1.716672	3.550831	0.593602
$k4$	-9.44103	-6.05252	-5.78467	-6.3452
$k5$	0.117782	0.063638	0.058538	0.066865
$k6$	0.020514	0.010912	0.010171	0.011751
$k7$	26.79597	18.64592	17.96812	19.2813
$k8$	-0.05334	-0.03023	-0.02837	-0.03207

Table 4 Coefficients for T

	Run No.			
Coefficients	1	2	3	4
k_1	75.93721	47.00029	56.27326	58.90766
k_2	-0.14739	-0.06632	-0.09197	-0.09925
k_3	-71.3179	-2.12526	-23.9187	-29.7181
k_4	9.408307	21.41499	17.60706	16.57052
k_5	0.099249	-0.09507	-0.03459	-0.01866
k_6	-0.03268	-0.0664	-0.05579	-0.05294
k_7	-38.9424	-67.6777	-58.818	-56.505
k_8	0.116313	0.197149	0.172374	0.166003

4.3 The best models

Several different combinations of learning and testing data sets were applied during modelling of prediction models. Eight of the experimental results were applied for the learning phase and the remaining 12 for testing the prediction model. Different combinations of learning input data sets provided similar results in terms of accuracy. Note, it was possible to encounter slight differences between the initial polynomial (Eq. 3) and the final polynomials, due to certain coefficients' eliminations, hence the partial result was insignificant for the final result. The best models obtained by particle swarm optimization for the rough turning were:

$$F_c = -484.575 + 1.76549 \cdot x_1 + 1049.84 \cdot x_2 + 190.7856 \cdot x_3 - 3.95561 \cdot x_1 \cdot x_2 - 0.63984 \cdot x_1 \cdot x_3 + 1592.993 \cdot x_2 \cdot x_3 + 1.185408 \cdot x_1 \cdot x_2 \cdot x_3 \tag{4}$$

$$R_a = 12.81179 - 0.04611 \cdot x_1 - 17.3847 \cdot x_2 - 9.44103 \cdot x_3 + 0.117782 \cdot x_1 \cdot x_2 + 0.020514 \cdot x_1 \cdot x_3 + 26.79597 \cdot x_2 \cdot x_3 - 0.05334 \cdot x_1 \cdot x_2 \cdot x_3 \tag{5}$$

$$T = 75.93721 - 0.14739 \cdot x_1 - 71.3179 \cdot x_2 + 9.408307 \cdot x_3 + 0.099249 \cdot x_1 \cdot x_2 - 0.03268 \cdot x_1 \cdot x_3 - 38.9424 \cdot x_2 \cdot x_3 + 0.116313 \cdot x_1 \cdot x_2 \cdot x_3 \quad (6)$$

Although analytical multiple regression analysis seemed to be easier to calculate, however, per the results the PSO algorithm was superior to it in terms of the amount of work required to obtain the same, similar or even better results. The following results are representative results for the PSO algorithm for rough tuning with material C45E (EN 10083/1996.) The data set determined for main cutting force F_C (Eq. 4), surface roughness R_a (Eq. 5), and tool life T (Eq. 6) provide a full set of information for an elementary model of the turning process, where the predictions are presented in paragraph 4.4.

4.4 Testing phase and deviation analysis

The developed models had to be proved during testing phase. The results presentation has been simplified due to the extensive amount of data included within the analysis for all three output values: cutting force F_c, surface roughness R_a, and tool life T. Only results for surface roughness are presented here. Experimental and predicted values for surface roughness are presented in Table 5. In the same way as the results for surface roughness, identical tables have been prepared for cutting force and tool life. These results are described in detail in the next paragraph.

Table 5 Calculated values for surface roughness R_a, with the inclusion of deviation analysis

Experimental value R_a [µm]	Prediction 1 [µm]	Prediction 2 [µm]	Prediction 3 [µm]	Prediction 4 [µm]	Max. deviation [%]	Min. deviation [%]
4.30	4.289	4.169	4.159	4.173	3.264	0.232
3.88	3.888	3.994	4.005	3.988	3.235	0.231
11.11	11.118	11.204	11.219	11.202	0.986	0.075
11.48	11.472	11.395	11.385	11.392	0.825	0.062
4.21	4.217	4.310	4.315	4.291	2.514	0.174
4.50	4.493	4.412	4.410	4.425	1.978	0.150
14.29	14.284	14.218	14.213	14.218	0.536	0.041
13.71	13.715	13.779	13.777	13.766	0.504	0.038
8.10	8.435	8.435	8.435	8.432	4.147	4.101
8.13	8.435	8.435	8.435	8.432	3.763	3.716
8.12	8.435	8.435	8.435	8.432	3.890	3.844
8.12	8.435	8.435	8.435	8.432	3.890	3.844
8.11	8.435	8.435	8.435	8.432	4.019	3.972
8.10	8.435	8.435	8.435	8.432	4.147	4.101
7.82	8.506	8.503	8.505	8.497	8.776	8.663
8.15	8.363	8.367	8.366	8.366	2.673	2.622
2.46	1.273	1.272	1.273	1.270	48.345	48.213
17.95	15.59	15.599	15.597	15.593	13.127	13.097
6.36	7.197	7.194	7.196	7.193	13.169	13.106
9.07	9.672	9.676	9.675	9.671	6.690	6.624

The model for cutting force F_c, was the most accurate prediction model as the percentage deviation reached a minimum of 0.001 %, however, in certain cases the value of 6.3 % was exceeded. The reason for such a high percentage error is probably the single cutting force optimization procedure (i.e., only the main cutting force was taken into consideration), therefore error difference might be derived from incomplete model. The average deviation of the cutting force was marked at around 1.75 %, solely due to the fact of few higher percentage deviation values.

Data analysis for surface roughness R_a, is shown in detail in Table 5, however a few important facts are still in order for properly displaying the optimization model. The minimum deviation was at 0.04 %, whilst on the other hand the maximum remained at 48 %. Interestingly this value was for the same cut as the maximal deviation for the cutting force. By considering the maximal value to be correct, this provides us with an average error of 5.85 %, however, if we were to eliminate the possible incorrect measurement, this value would decrease significantly.

However, in regard to tool life values *T*, as the experimental values became drastically lower, the optimization analysis became harder. As with the preliminary results, as the minimal deviation approached 4.31 % and the maximal value remained at 60 %, the average for the tool-life values increased up to 24.5 %. One way to decrease such a high value of error is to increase the knowledge-base. As previously mentioned, we took only eight cuts (i.e., measurements) during the learning phase, and such a low amount of information in combination with the low output values, combine to create a higher error possibility. On the other hand, with the inclusion of all available twenty cuts within the knowledge-base for the learning phase, the average error decreased to a value of 17.54 %. Should we have had even more available experimental results, the error would have decreased even more.

5. Conclusion and future research

This article proposed a particle swarm optimization approach for predicting (i.e., modelling) of cutting force, surface roughness, and tool-life. The predictions are based on independent input parameters (cutting speed, feed rate, and cutting depth). Conclusions from the research are:

- The particle swarm optimization approach can be successfully used for the modelling of machining processes such as turning and similar cutting processes.
- The proposed approach provides comparable results to other well-known approaches, such as conventional regression analysis.
- If the dependent output values are of higher value (i.e., cutting force), a smaller knowledge base can be used but in contrast, if the dependent values are lower (i.e., tool life), the number of independent values (i.e., number of measurements) will at least be doubled.
- The obtained models have relatively simple polynomial forms and may be further optimized by various approaches, such as genetic algorithms. They may also serve as inputs to special system based on multi-objective optimization (e.g., by using NSGA-II algorithm).

During the research we decided to develop and implement a relatively new gravitational search algorithm (GSA), which is based on physical gravitational laws [18, 19]. Preliminary tests showed slight deviations of the results, however the data processing was very fast [20]. In addition, the models obtained by the PSO will be further optimized by multi-objective optimization approaches, such as NSGA-II, SPEA2, and DEMO.

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Optimization for sustainable manufacturing based on axiomatic design principles: a case study of machining processes

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A B S T R A C T

Despite being a wasteful process, machining is often regarded as an important manufacturing method due to the fact that it is a flexible and economic process. However, in order to gain more cost-saving and enhanced environmental performance, sustainability principles have to be incorporated into machining technologies. A step-wise optimization procedure is proposed based on axiomatic design (AD) principles for identifying an optimized sustainable manufacturing solution that comprises combinations of minimum and maximum levels obtainable within the constraints involved (cutting condition, performance and sustainability). A case study involving three alternative processes (namely conventional machining, high pressure jet-assisted machining, and cryogenic machining) is presented for demonstrating the application of the proposed approach, which indicated that the suggested procedure is able to facilitate an optimization process by varying the design parameters (DPs) within a particular sequence. In the case study, a hybrid model consisting of crisp and fuzzy AD analysis techniques was also used for analysing the sustainability performances of the processes being considered. The hybrid model is able to point out the most viable machining process that satisfies all the sustainable functional requirements (FRs) by using information content for indication purposes.

A R T I C L E I N F O

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1. Introduction

Machining is a material removal process that usually involves the cutting of metals using a variety of cutting tools. Therefore, being a process that removes material, machining is inherently wasteful owing to the use of raw materials and energy. Nonetheless, due to their high dimensional accuracy, process flexibility and cost-effectiveness in producing parts, machining processes can be particularly useful [1]. In the developed world, it is estimated that machining processes contribute about 5 % of the total GDP. Furthermore, the importance of machining is anticipated to increase even further due to shorter product cycle and more flexible manufacturing systems induced by economic factors [2].

Machining processes constitute a major manufacturing activity that contributes to the development of the worldwide economy [3]. By implementing sustainability principles in machining technologies, end-users can potentially save money and enhance environmental performance even if the production remains in the same range or reduces [4, 5]. To make a manufacturing process sustainable, the following six factors (together with their desired levels) as shown in Table 1 are generally regarded as significant [6]. These six factors can be divided into two broad categories i.e. sustainability factors for safety, health and environment (S_{SHE}) and operational sustainability factors (S_{OP}) which comprises machining costs, energy consumption and waste management [2]. Alongside sustainability measures, machining performance (in terms of surface roughness, part accuracy and so on) is also an important consideration in designing a product for machining and in subsequent process planning operations [7]. Hence, a general workflow of optimization method for process sustainability assessment of machining processes has been previously proposed. This proposed method (as shown in Fig. 1) aims to make a trade-off among performance and sustainability measures, and therefore to provide the optimal combinations of operating parameters and to propose ways of enhancing and improving sustainability level [6]. It requires a hybrid modelling technique that comprises both numerical analysis and nondeterministic means such as fuzzy logic to scientifically quantify the influence of each sustainability parameter. After that, the modelled production process can be optimized to attain desired level of sustainability with respect to constraints imposed by all involved variables. Although it serves as a comprehensive guideline, the proposed workflow does not provide a step-wise procedure that facilitates the optimization process.

Recently, research works have been carried out to address sustainability assessment / comparison on manufacturing processes. A macro-level (excludes impact of cutting tools and cutting fluids) environmental comparison has been done on flood machining and near-dry machining using gear milling as a case study. The conducted study has a disadvantage that the analysis performed is valid only for the machining process of the considered part. The problem can be solved by creating a general model of analysis to be valid for any machining process [8]. Lifecycle assessment approach was also used to compare alternative machining processes with the aim of convincing the industry of the merits of sustainable machining technologies [9]. Experimentally, conventional machining and its alternative processes (e.g., high pressure jet-assisted machining and cryogenic machining) have been examined based on their machining costs, cutting fluid usage and energy consumption [3]. Nonetheless, the last two approaches do not involve combination of numerical and fuzzy models that can deal with human thought and are therefore not adequate in supporting decision-making process.

This paper presents a case study that demonstrates the selection of optimized manufacturing process with the help of a hybrid model based on axiomatic design principles. Section 2 briefly covers the basic principles of axiomatic design, while Section 3 discusses the formation of design equation for the optimization problem. The subsequent section gives a detailed presentation about the case study and the results are discussed in Section 5. Lastly, Section 6 provides concluding remarks for this paper.

Table 1 Measurable sustainability factors in machining processes and their desired levels [6]

Measurement factor	Desired level
Energy consumption	Minimum
Environmental friendliness	Maximum
Machining costs	Minimum
Operational safety	Maximum
Personnel health	Maximum
Waste reduction	Maximum

2. Principles of axiomatic design

Axiomatic design (AD) system is a design model based on product attribute in which two axioms are utilized for design. The first axiom highlights the necessity to maintain independence of functional requirements (FR) while the second one is to minimize the information necessary to meet the FRs [10]. In other words, a good design should fulfil its various FRs independently and simply [11].

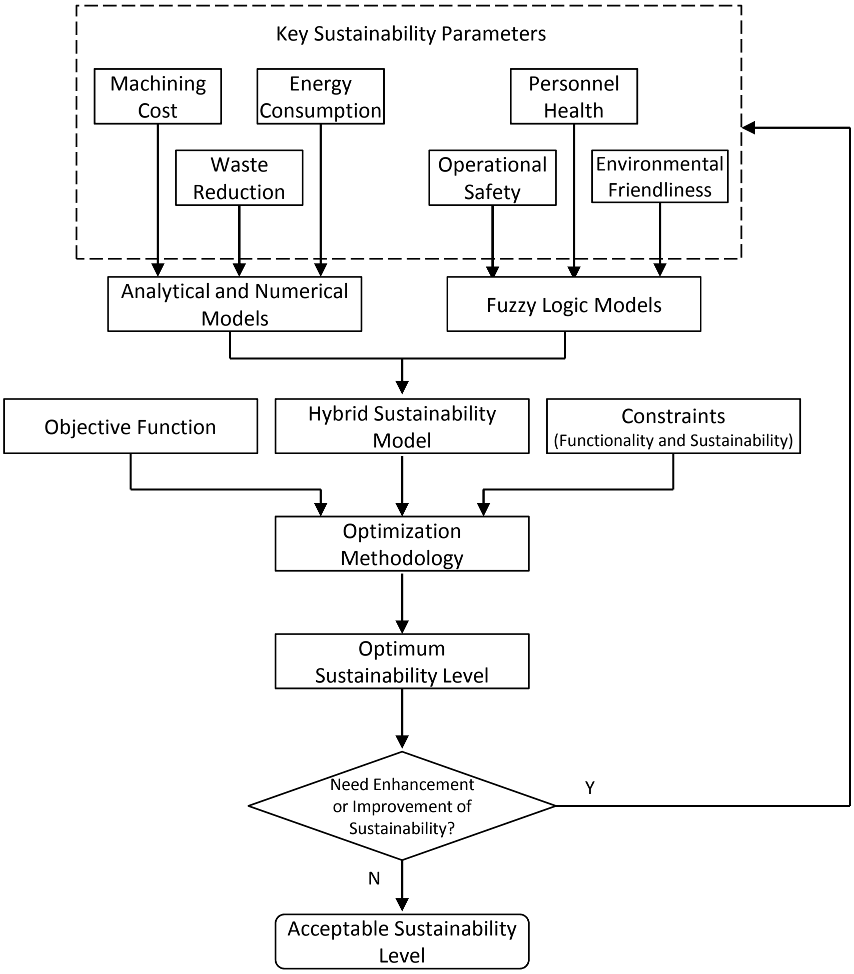

Fig. 1 Flowchart showing the proposed optimization method for process sustainability assessment of machining processes [6]

The relationship between functional requirements and design parameters (DPs) can be expressed mathematically as follows where {**FR**} is the functional requirement vector and {**DP**} signifies the design parameter vector:

$$\{\mathrm{FR}\}=|\mathrm{A}|\{\mathrm{DP}\} \tag{1}$$

The type of design being considered is defined by the structure of |**A**| matrix. To fulfil the independence axiom, |**A**| matrix of a design should be uncoupled or decoupled.

According to the information axiom, the best design among all design alternatives that satisfy independence axiom is the one that has the smallest information content (I_i). As represented by the following equation, I_i can be related to p_i, which is the probability of satisfying the given functional requirement FR_i, and the relationship between I_i and p_i is inversely proportional:

$$I_i = \log_2\left(\frac{1}{p_i}\right) \tag{2}$$

The probability of having a successful design is governed by "design range" and "system range". Design range is a designer-specified range of tolerance whereas system range means the capability of the system in delivering what the designer desires to achieve. Acceptable design solution exists in the region where design range and system range overlap as depicted in Fig. 2 [10]. Hence, p_i (in the case of uniform probability distribution function) can be formulated as:

$$p_i = \left(\frac{\text{Common range}}{\text{System range}}\right) \tag{3}$$

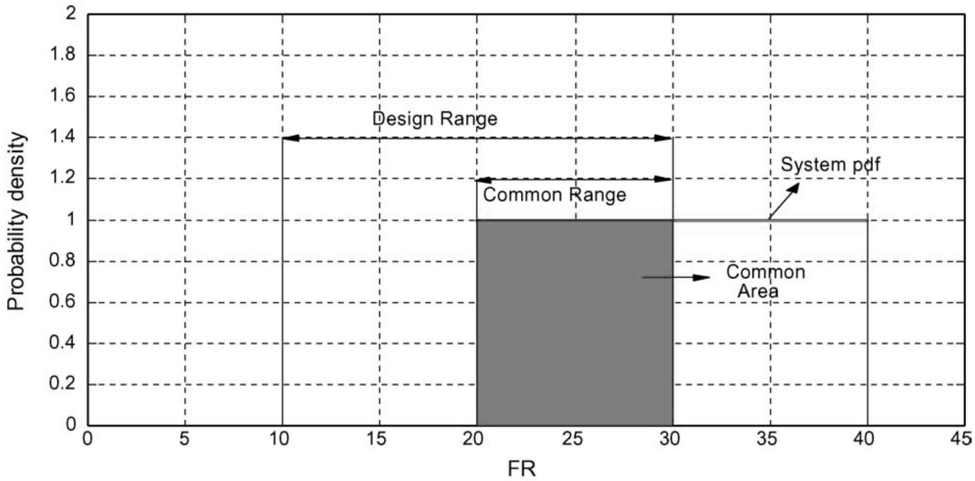

Fig. 2 Design range, system range, common range and probability density function of a FR [10]

The abovementioned crisp AD approach is suitable for solving decision-making problems under certainty. However, one needs to be aware that expressing decision variables in the form of crisp numbers would be ill defined [12]. While crisp AD approach cannot be utilized when available information is qualitative and linguistic, fuzzy set theory is particularly useful when dealing with imprecision of language and human thought in decision-making process [13].

As for fuzzy information axiom approach, triangular fuzzy number (TFN, as shown in Fig. 3) can be used to express data in linguistic terms when system and design ranges happen to be stated linguistically. The notation of TFN and information content are formulated by Eq. 4 and Eq. 5 respectively. In this case, the common area is the intersection between TFNs of design range and system range as illustrated in Fig. 4 [14].

$$\mu(x) = \left\{\begin{array}{ll} \dfrac{x - c}{a - c}, & c \leq x \leq a \\ \dfrac{b - x}{b - a}, & a \leq x \leq b \\ 0, & \text{otherwise} \end{array}\right\} \tag{4}$$

$$I_i = \log_2\left(\frac{\text{TFN of system range}}{\text{Common area}}\right) \tag{5}$$

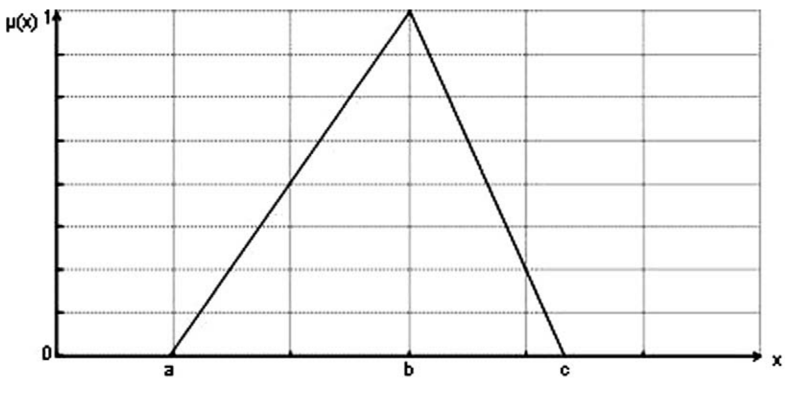

Fig. 3 Triangular fuzzy number [13]

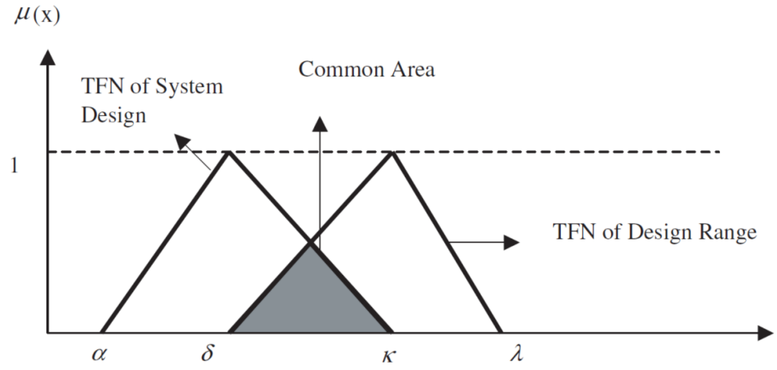

Fig. 4 The common area of system and design ranges [14]

Both crisp and fuzzy AD approaches have been applied extensively for design and decision-making purposes. A review of literature indicates that AD principles have been utilized in five major areas of applications namely (1) product design, (2) system design, (3) manufacturing system design, (4) software design and (5) decision-making [13]. For instance, Shin et al. [15] employed the crisp approach in designing a nuclear fuel spacer grid. Apart from that, Gumus et al. [16] developed a product development lifecycle model based on the independence axiom and design domains. As for fuzzy AD, the approach is utilized in a multi-attribute transportation company selection problem by Kulak and Kahraman [14]. Also, it has been used in manufacturing system selection by Kulak et al. [12]. The authors applied fuzzy AD approach to identify suitable punching machine among a number of alternatives. Besides that, Celik et al. [17] also employed the information axiom to select the best docking facilities of shipyards. Nonetheless, the application of AD principles for sustainable manufacturing system can be considered being in its infancy stage.

3. Optimization methodology: the design equation

The optimization problem of sustainable manufacturing involves parameters (according to categories, together with desired levels) as shown in Table 2 [7]. To provide a simpler visualization on the cause-effect relationship, the mathematical model can be derived into the following FRs to be satisfied by an optimized manufacturing system in general and a set of DPs as the corresponding solutions to fulfil the FRs:

FR_1: To maintain cutting condition within manageable range
FR_2: To attain satisfactory machining performance
FR_3: To achieve process sustainability at desired level

DP_1: Parameters of cutting condition must be set within constraints
DP_2: Employ adequate cooling method
DP_3: All sustainability factors to satisfy respective requirement

The relationship between the FRs and DPs can be stated in terms of design equation (see Eq. 6). Note that both DP_1 and DP_2 have to be considered in order to achieve FR_2. Previous research has proven that machining performance (e.g., surface roughness and material removal rate) differs with cooling methods and cutting conditions utilized for the machining process [3, 7]. Besides that, it can be seen that all three DPs are involved when it comes to satisfying FR_3. This is due to the dependency of sustainability parameters on cutting condition and cooling method set by the user as experiments have shown that machining cost and energy consumption vary with cutting speed and coolant delivery systems [3]. In this case, the design matrix obtained is a triangular matrix which signifies that the design being considered is a decoupled design. Under this circumstance, with the purpose of satisfying the independence axiom, DPs should be adjusted in a particular sequence. DP_1 should be varied first to meet FR_1, followed by adjusting DP_2 to fulfil

FR_2. Lastly, DP_3 can be determined to achieve FR_3 [10]. In other words, parameters of cutting condition such as cutting speed and feed rate must first be decided before proceeding to select cooling method to fulfil required machining performance. Finally, for each selected cooling method (with given cutting conditions), sustainability parameters can be analyzed and compared against the requirement.

$$\begin{bmatrix} \mathrm{FR}_1 \\ \mathrm{FR}_2 \\ \mathrm{FR}_3 \end{bmatrix} = \begin{bmatrix} \mathrm{X} & 0 & 0 \\ \mathrm{X} & \mathrm{X} & 0 \\ \mathrm{X} & \mathrm{X} & \mathrm{X} \end{bmatrix} \begin{bmatrix} \mathrm{DP}_1 \\ \mathrm{DP}_2 \\ \mathrm{DP}_3 \end{bmatrix} \tag{6}$$

Table 2 Parameters involved in optimization problem

Category	Parameter	Desired level
Cutting condition	Cutting speed (V)	$V_{\min} \leq V \leq V_{\max}$
	Feed rate (f)	$f_{\min} \leq f \leq f_{\max}$
	Depth of cut (d)	$d_{\min} \leq d \leq d_{\max}$
Sustainability	Machining cost (MC)	$\mathrm{MC} \leq \mathrm{MC}'$
	Energy consumption (EC)	$\mathrm{EC} \leq \mathrm{EC}'$
	Waste reduction (WR)	$\mathrm{WR} \geq \mathrm{WR}'$
	Personnel health (PH)	$\mathrm{PH} \geq \mathrm{PH}'$
	Operational safety (OS)	$\mathrm{OS} \geq \mathrm{OS}'$
	Environmental friendliness (EF)	$\mathrm{EF} \geq \mathrm{EF}'$
Functional/Performance	Surface roughness (R_a)	$R_a \leq R_a'$
	Cutting force (F)	$F \leq F'$
	Tool life (T)	$T \geq T'$
	Material removal rate (M_R)	$M_R \geq M_R'$
	Chip breakability (CB)	$\mathrm{CB} \geq \mathrm{CB}'$

4. Case study

In this section, a case study is presented to demonstrate the application of AD principles for the purpose of optimizing the process sustainability. The three alternative processes to be considered in this study are namely (1) conventional machining, (2) high pressure jet assisted machining (HPJAM) and (3) cryogenic machining (cryo). Knowing that the use of cooling/lubrication fluid (CLF) is the main factor that impacts the environment and sustainability, HPJAM and cryogenic machining are considered as alternatives to conventional flood machining in this study due to their innovative methods of reducing/eliminating the consumption of CLF [1, 9].

HPJAM exhibits an innovative way of cooling and/or lubricating the cutting zone by having an extremely high-pressure CLF delivery system at a relatively lower flow rate. This enables a comparatively small amount of CLF to penetrate closer to the share zone (region which undergoes highest temperature during machining) and cools it [9]. Earlier research has proven that HPJAM can provide a more sustainable process and improve machining performance in terms of chip breakability and material removal rate [18, 19].

Cryogenic machining is another innovative manner of cooling the cutting tool and/or part during machining. Instead of oil-based CLF, it delivers a cryogenic CLF to the cutting region. Usually, liquid nitrogen is used as coolant in this process. The fluid eventually evaporates and returns to the atmosphere. This eliminates the need to clean part, chips and machine tool, and thus leads to lower disposal cost [9]. Other than that, cryogenic machining is able to bring better part surface quality, increased material removal rate and hence higher productivity [4].

Recently, experiments have been conducted to evaluate the sustainability performance of the abovementioned processes by using 100 mm centerless-ground Inconel 718 round bars with a diameter of 40 mm as work piece [3]. To show a more realistic application, empirical data collected from the experiments are adopted in this study and will be used in subsequent sections.

4.1 Determining the cutting condition

In this study, machining parameters employed are presented in Table 3. These parameters were chosen according to previously published research work on cryogenic machining and HPJAM [20-22]. For more detailed setup of experiments (such as tool type and CLF flow rate), readers are directed to earlier research work [3].

Table 3 Cutting condition being considered

Parameter	Value
Cutting speed, V [m/min]	30, 60
Feed rate, f [mm]	0.25
Depth of cut, d [mm]	1.2

4.2 Selection of adequate cooling method

Cooling method can be selected from a series of available processes in order to achieve necessary machining performance (FR_2). For instance, by using cryogenic machining, the surface roughness of the produced part can be enhanced as compared to conventional machining [4]. This study assumes that all three processes (conventional machining, HPJAM and cryogenic machining) are capable of meeting the required machining performance with cutting conditions given in the last section and shall proceed for further analysis.

4.3 Comparison of sustainability performance against desired level

As mentioned in earlier section, FR_3 dictates the requirement to achieve process sustainability at desired level. This FR can be further decomposed to specify requirement for each of the sustainability factors. An example of decomposed FR_3 is shown as follows:

$FR_{31,MC}$: Machining cost per part must be in the range of 0 to 1.85 €.
$FR_{32,EC}$: Energy consumption per part must be in the range of 0 to 0.15 kWh.
$FR_{33,WR}$: Part cleaning cost must be in the range of 0 to 0.08 €.
$FR_{34,EF}$: Environmental friendliness must be at least 5 (5,20,20).
$FR_{35,OS}$: Operational safety must be at least 5 (5,20,20).
$FR_{36,PH}$: Personnel health must be at least 5 (5,20,20).

The selection of cutting condition with cutting speed of 30 m/min, feed rate of 0.25 mm, and depth of cut of 1.2 mm yields the corresponding machining costs (include cutting tool and CLF costs), energy consumption rate and waste processing cost as shown in Table 4 [3]. Table 4 also shows sustainability performances such as environmental friendliness and personnel health which are graded qualitatively. The information axiom can be used to construct a hybrid model that facilitates the analysis of sustainability performance.

For operational sustainability factors (S_{OP}) such as machining costs, energy consumption and waste management cost, crisp AD approach can be used to translate the evaluation results into performance scores in terms of information content using Eq. 2 and Eq. 3. From Table 4, it can be seen that the evaluation results for quantitative factors are given in individual values instead of a range that consists of upper and lower limits. This makes calculation of common range impossible as system range is not provided. To overcome this difficulty, an acceptance threshold can be introduced. It can be deemed as maximum allowable variation for each parameter and serves as an imaginary upper limit for each system range. An illustrative example is given in Fig. 5 to show the computation of common range for machining costs of HPJAM. In the figure, the intersection between design range and system range is crosshatched. Note that the upper limit of system range is obtained by introducing a 20 % variation in machining costs. Detailed computation of information content for machining costs of HPJAM is presented as follows:

Area of system range is: $[(1.794 + 0.2 \times 1.794) - 1.794] \times 1 = 0.3588$

Area of common range is: $(1.850 - 1.794) \times 1 = 0.056$

$$I_i = \log_2\left(\frac{\text{System range}}{\text{Common range}}\right) = \log_2\left(\frac{0.3588}{0.056}\right) = 2.6797$$

Table 4 Sustainability performance corresponding to cutting condition of V = 30 m/min, d = 1.2 mm, and f = 0.25 mm

Machining process	Machining costs (€/part)	Energy consumption (kWh/part)	Waste management (€/part)	Environmental friendliness	Operational safety	Personnel health
Conventional machining	1.811	0.148	0.078	Poor	Poor	Poor
Cryogenic machining	2.016	0.147	0.004	Excellent	Excellent	Excellent
HPJAM	1.794	0.202	0.074	Fair	Good	Good

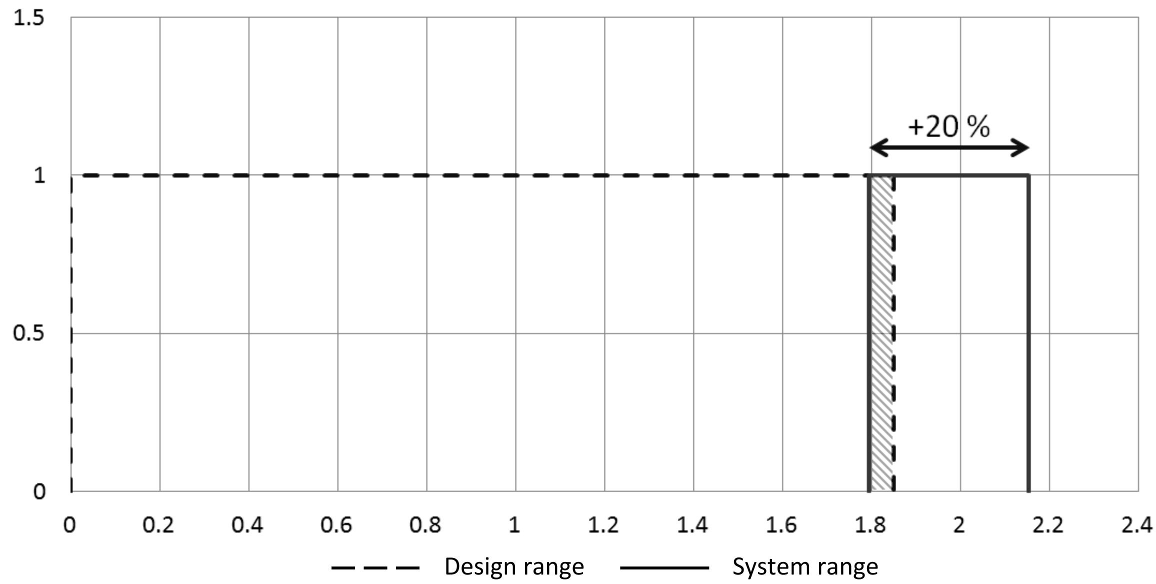

Fig. 5 Machining costs of HPJAM: intersection of design range and system range

Fuzzy AD approach has been applied extensively when dealing with linguistic terms. In this scenario, it is particularly helpful for analyzing sustainability performance for environmental friendliness, personnel health and operational safety (S_{SHE}) by converting qualitative terms like "poor", "fair" and "good" into information content. As shown in Fig. 6, the stakeholder subjectively evaluates the alternatives with the linguistic term "poor" if these criteria are assigned a score of (0, 0, 6) over 20; "fair" with a score of (4, 7, 10) over 20; "good" with a score of (8, 11, 14) over 20; "very good" with a score of (12, 15, 18) over 20; "excellent" with a score of (16, 20, 20) over 20 [14]. With the design and system ranges determined, Eq. 4 and Eq. 5 can be applied to compute the information content for each FR in each alternative. With the aid of Fig. 7, a detailed calculation of information content for environmental friendliness of HPJAM is given as follows:

Area of system range is: 0.5 × (10 – 4) × 1 = 3

Area of common range is: 0.5 × (10 – 5) × 0.2778 = 0.6945

$$I_i = \log_2\left(\frac{\text{System range}}{\text{Common range}}\right) = \log_2\left(\frac{3}{0.6945}\right) = 2.111$$

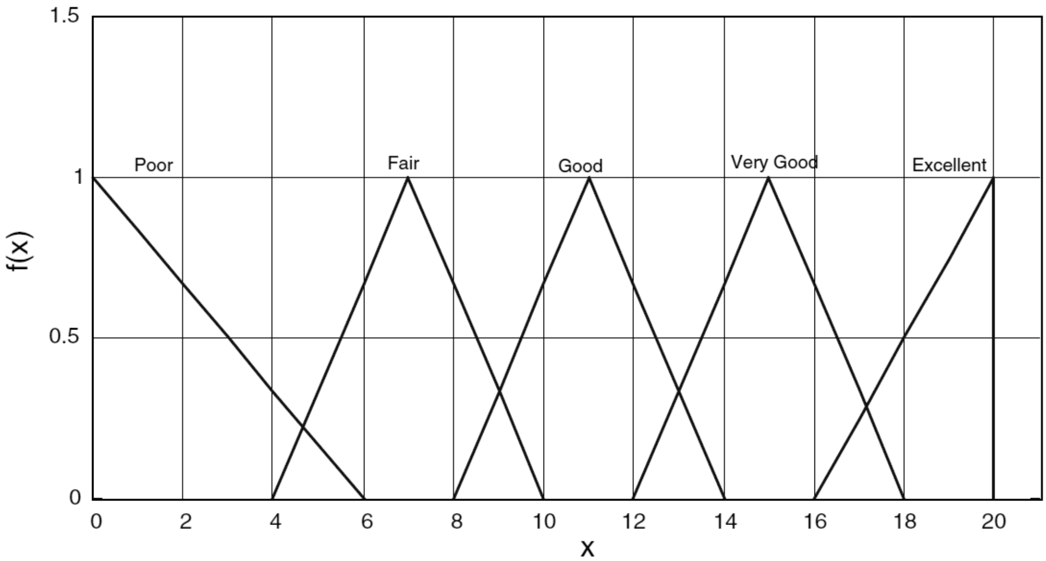

Fig. 6 TFNs for intangible factors [14]

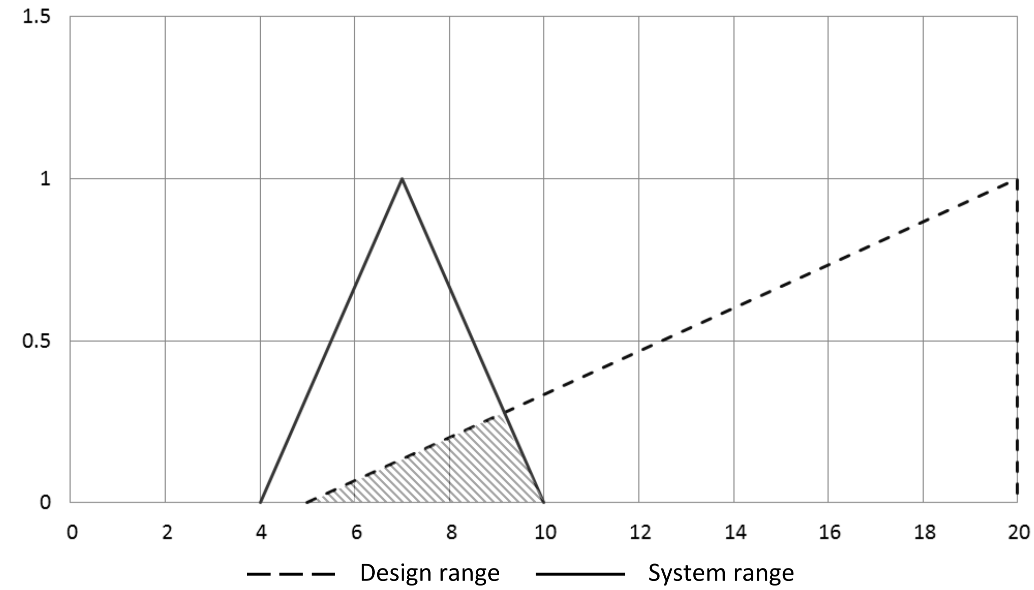

Fig. 7 Environmental friendliness of HPJAM: crosshatched area denotes intersection of design range and system range

Information content for each alternative machining process is tabulated in Table 5 according to respective sustainability factors. One should be aware that these calculated values are not subjected to criteria weight. Respective weighting factors can be imposed on S_{SHE} and S_{OP} [2] and it can be done by applying Eq. 7 to the values tabulated in Table 5. I_{ij} denotes information content of the alternative i for the criterion j; w_j represents the weight of the criterion j; p_{ij} symbolizes the probability of achieving the functional requirement FR$_j$ (criterion j) for the alternative i [14]. In this case, criteria weight of 0.5 is used for both S_{SHE} and S_{OP}. As a result, weighted information contents are obtained as shown in Table 6. After that, unit index of each category are calculated by dividing the total information contents in Table 6 by the number of sub-criteria of category. For instance, the category of operational sustainability factor has three sub-criteria namely machining costs, energy consumption and waste management. The total information content for these factors should be divided by three in order to obtain the unit index for operational sustainability. This step is essential because each criterion consists of different numbers of sub-criteria which may affect the sum of information content [12]. Calculated unit indexes are organized and shown in Table 7. Table 7 indicates that conventional machining is the only viable process that satisfies all required sustainability performance. Both cryogenic machining and HPJAM have infinite information content due to unsatisfying machining costs and energy consumption respectively.

$$I_{ij} = \begin{Bmatrix} \left[\log_2\left(\frac{1}{p_{ij}}\right)\right]^{1/w_j}, & 0 \leq I_{ij} < 1 \\ \left[\log_2\left(\frac{1}{p_{ij}}\right)\right]^{w_j}, & I_{ij} > 1 \\ w_j, & I_{ij} = 1 \end{Bmatrix} \tag{7}$$

Table 5 Unweighted information contents

Machining process	Machining costs	Energy consumption	Waste management	Environmental friendliness	Operational safety	Personnel health
Conventional machining	3.2152	3.8875	2.9635	6.9773	6.9773	6.9773
Cryogenic machining	Infinite	3.2928	0.0000	0.0000	0.0000	0.0000
HPJAM	2.6797	Infinite	1.3026	2.1110	0.6781	0.6781

Table 6 Weighted information contents

Machining process	Machining costs	Energy consumption	Waste management	Environmental friendliness	Operational safety	Personnel health
Conventional machining	1.7931	1.9717	1.7215	2.6415	2.6415	2.6415
Cryogenic machining	Infinite	1.8146	0.0000	0.0000	0.0000	0.0000
HPJAM	1.6370	Infinite	1.1413	1.4529	0.4598	0.4598

In the event when analysis results show infinite unit index for all processes, the procedure mentioned in sections 4.1 and 4.2 should be repeated to alter the parameters. As an example, cutting speed can be altered from 30 m/min to 60 m/min which in turn varies the machining costs and energy consumption (with other machining parameters unchanged and corresponding machining performance unaffected).

Table 7 Unit indexes for weighted information content (* denotes viable process that satisfies all FRs with minimum information content)

Manufacturing process	Operational sustainability	Safety, health and environment	Sum
Conventional machining	1.8288	2.6415	4.4702*
Cryogenic machining	Infinite	0.0000	Infinite
HPJAM	Infinite	0.7909	Infinite

Table 8 shows the revised sustainability performance when cutting speed of 60 m/min is used. This set of sustainability performances can eventually be converted to unit indexes when procedure stated in section 4.3 is repeated (see Table 9). It can be seen that both cryogenic machining and HPJAM are viable processes as they fulfil the required sustainability performance. Nevertheless, cryogenic machining should be selected since it has the smallest information content.

Table 8 Sustainability performance corresponding to cutting condition of V = 60 m/min, d = 1.2 mm, and f = 0.25 mm

Machining process	Machining costs (€/part)	Energy consumption (kWh/part)	Waste management (€/part)	Environmental friendliness	Operational safety	Personnel health
Conventional machining	2.049	0.082	0.078	Poor	Poor	Poor
Cryogenic machining	1.461	0.077	0.004	Excellent	Excellent	Excellent
HPJAM	1.319	0.105	0.074	Fair	Good	Good

Table 9 Unit indexes for weighted information content (* denotes viable process that satisfies all FRs with minimum information content)

Manufacturing process	Operational sustainability	Safety, health and environment	Sum
Conventional machining	Infinite	2.6415	Infinite
Cryogenic machining	0.0000	0.0000	0.0000*
HPJAM	0.3804	0.7909	1.1713

5. Discussion

Based on empirical data, when the cutting speed is set at 30 m/min, both cryogenic machining and HPJAM are being ruled out because of excessive machining costs and energy consumption respectively. Eventually, conventional machining is the remaining process to be selected as optimized manufacturing process. This is clearly indicated in Table 6 as information contents for machining costs of cryogenic machining and energy consumption of HPJAM show infinite values. Subsequently it leads to infinite unit indexes for both the processes as shown in Table 7 and conventional machining (having the smallest sum of unit indexes) is preferred as optimized process. When the cutting condition is altered, the optimization procedure is iterated and a new set of information content and unit indexes is yielded. In contrast, machining costs of conventional machining is too costly when higher cutting speed is used, causing the process to be excluded. As tabulated in Table 9, both cryogenic machining and HPJAM are acceptable but according to the information axiom, cryogenic machining should be the optimized process since it carries the smallest sum of unit indexes. The approach presented in Section 4 is able to point out the most viable process with the consideration of sustainability performances. After that, decision-maker can either decide to accept the sustainability level of the selected process or iterate the optimization procedure by adjusting the cutting condition and/or reselecting cooling method to obtain improved sustainability performance. As demonstrated in Section 4, adjustment in cutting condition may lead to changes in operational sustainability and thus a different outcome in terms of viable processes.

One should notice that criteria weights used in Section 4 are equally set as 0.5 for both S_{SHE} and S_{OP}. In this case, setting different weight factors for the criteria does not affect the outcome significantly. For instance, if the weight factors are set as 0.2 for S_{SHE} and 0.8 for S_{OP} (V = 60 m/min), the calculated unit indexes will be as shown in Table 10.

The result is unchanged as compared to the previous configuration that uses equal weight factors as cryogenic machining is still having the smallest total unit indexes. The performance of cryogenic machining in terms of S_{SHE} is simply overwhelming comparatively to other processes. Nevertheless, criteria weight can potentially be a helpful feature when a bigger number of competitive processes are being considered.

Table 10 Unit indexes for weighted information content, with adjusted criteria weight (* denotes viable process that satisfies all FRs with minimum information content)

Manufacturing process	Operational sustainability	Safety, health and environment	Sum
Conventional machining	Infinite	1.4748	Infinite
Cryogenic machining	0.0000	0.0000	0.0000*
HPJAM	0.4118	0.4826	0.8945

Acceptance threshold of 20 % is used throughout the analysis of S_{OP} in Section 4.3. This value signifies variation in sustainability performance that a decision-maker/stakeholder can allow and may be adjusted to other value should the stakeholder deems appropriate (e.g., 50 %). To understand the effect of altering the acceptance threshold, calculation of information content for machining costs of HPJAM is repeated as follows:

Area of system range is: $[(1.794 + 0.5 \times 1.794) - 1.794] \times 1 = 0.8970$

Area of common range is: $(1.850 - 1.794) \times 1 = 0.056$

$$I_i = \log_2\left(\frac{\text{System range}}{\text{Common range}}\right) = \log_2\left(\frac{0.8970}{0.056}\right) = 4.0016$$

It can be seen that the newly calculated information content differs from the previous value of 2.6797. When the value of acceptance threshold is increased, the system range widens accordingly, leading to a smaller possibility of satisfying the requirement of machining costs and thus an increased value of information content. Therefore, it is plausible to have individual acceptance threshold values for each of the sustainability performance under S_{OP} category. For example, decision-maker/stakeholder may decide that a 50 % variation is allowed for machining costs but the variation in energy consumption must not exceed 20 %. This may imply the stringency of a decision-maker/stakeholder in controlling the variation of a certain performance in the long run.

6. Conclusion

To gain economic advantage and enhanced environmental performance, sustainability principles have to be integrated into machining processes. One of the engineering challenges is to attain an optimized solution which involves combinations of minimum and maximum levels achievable within the constraints imposed. From the design equation presented in Section 3, a step-wise approach is proposed with the help of AD principles. A case study that involves three alternative processes is presented to demonstrate the application of the proposed approach and it can be concluded that an optimized manufacturing solution can be obtained by following a step-by-step procedure namely (1) setting the cutting condition, (2) selecting adequate cooling method and (3) analysis of sustainability performance. Subsequently, analysis results may be reviewed and accepted if desired level of sustainability is attained. Should the product require enhanced sustainability, the optimization procedure can be iterated to achieve satisfying performance.

The case study also includes a hybrid model (consists of crisp and fuzzy AD approaches) that facilitates analysis of sustainability performance. The proposed model is able to point out the most viable machining process (that satisfies all sustainability FRs) by using weighted information content as indication. For example, conventional machining has been identified as the most viable/sustainable machining process when cutting speed is set as 30 m/min. However, in the case where the cutting speed is altered to 60 m/min (with other cutting parameters unchanged), cryogenic machining is in turn indicated as the most sustainable machining process. The ability of the proposed approach in discriminating incompetent processes based on empirical data (in the aspect of sustainability) is expected to benefit product development and manufacturing companies in practicing environmentally conscious manufacturing as part of sustainable product realization. Potentially, it can facilitate decision-making process from a sustainable manufacturing standpoint and thus lead to a greener and cleaner production as well as an enhanced environmental policy for the company. Criteria weight does not affect the outcome of the analysis to a significant extent but it may be a useful feature if a greater amount of comparable processes are involved in the study. The effect of acceptance threshold (allowable variation in S_{OP} performance) is also discussed. Having separate acceptance threshold value for each of the criteria under the category of S_{OP} is possible and these individual values suggest the stringency of decision-maker/stakeholder in managing the variation of certain operational performance.

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Performance metrics for testing statistical calculations in interlaboratory comparisons

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A B S T R A C T

Interlaboratory comparisons are the most powerful tools for determining the competences of laboratories performing calibrations and testing. Performance metrics is based on statistical analysis, which can be very complex in certain cases, especially for testing where transfer standards (samples) are prepared by the pilot laboratory. Statistical quantities are calculated using different kinds of software, from simple Excel applications to universal or specific commercial programmes. In order to ensure proper quality of such calculations, it is very important that all computational links are recognized explicitly and known to be operating correctly. In order to introduce a traceability chain into metrology computation, the European project EMRP NEW 06 TraCIM was agreed between the EC and the European Metrology Association (EURAMET). One of the tasks of the project was also to establish random datasets and validation algorithms for verifying software applications in regard to evaluating interlaboratory comparison results. The statistical backgrounds for resolving this task, and the basic concept of the data generator are presented in this paper. Background normative documents, calculated statistical parameters, boundary conditions for generating reference data sets are described, as well as customer interface.

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1. Introduction

Interlaboratory comparisons are used to determine the performance of individual laboratories for specific calibrations, tests or measurements, and to monitor the continuing performance of laboratories [1-3]. In statistical language, the performance of laboratories can be described by three properties: laboratory bias, stability and repeatability [3]. In calibrations, stability and repeatability are normally substituted by the measurement uncertainty, estimated and reported by participating laboratories [1, 2]. In testing, laboratory bias may be assessed by tests on reference materials, when these are available. Otherwise, interlaboratory comparisons provide a generally available means of obtaining information about laboratory bias. However, stability and repeatability will affect data obtained in comparison, so that it is possible for a laboratory to obtain data in a round of a proficiency test which indicate bias that is actually caused by poor stability or poor repeatability [3].

One of the tasks of the European research project EMRP NEW 06 TraCIM [4] is to establish random datasets and validation algorithms for verifying software applications for evaluating interlaboratory comparison results. This task is shared between the Laboratory for Production Measurement at University in Maribor and the German national metrology institute PTB. The article aims to present general ideas and approaches on establishing an internet-based application, which will serve organizers of different kinds of interlaboratory comparisons to check correctness of their evaluation algorithms based on standardized and other internationally recognized statistical procedures.

2. Statistical quantities in interlaboratory comparisons

2.1 Goals of interlaboratory comparisons

An interlaboratory comparison is a computationally-intensive metrological tool for evaluating performance of different kinds of metrological laboratories, from national metrology institutes to market-oriented calibration and testing laboratories. Approaches in organization and statistical evaluation of the results can be very different and depend on the aim of an interlaboratory comparison, number of participants, their quality, form of results, etc. [5, 6]. Special approaches are used for international key comparisons for evaluating performance quality of national metrology institutes. The application of the procedures to a specific set of key comparison data provides a key comparison reference value (KCRV) and the associated uncertainty, the degree of equivalence of the measurement made by each participating national institute and the degrees of equivalence between measurements made by all pairs of participating institutes [1, 2, 5, 6]. On the other hand, interlaboratory comparisons applied in proficiency testing of testing laboratories follow standardized procedures [3, 7, 8] recommending different statistical evaluations of results for different types of interlaboratory comparison and for different ways of reporting measurement results.

2.2 Performance metrics

In order to evaluate performance of the participants in an interlaboratory comparison, measurement data (with or without associated measurement uncertainties) shall be collected from all the participants and evaluated by means of an agreed statistical approach [1-10]. Single measurement values reported by participants are compared with an agreed assigned (reference) value by considering reported measurement uncertainties and the uncertainty of the assigned value. The basic principle of evaluating performance of participants in an interlaboratory comparison is shown in Fig. 1 [7]. Different cases of reporting measurement results shall be considered. In BIPM key or supplementary comparisons and other calibration comparisons, one result and the assigned measurement uncertainty are reported [1, 2, 9, 10], while in some cases of comparisons in testing participants report more results without uncertainty. The assigned (reference) value can be calculated from the reported measurement values or simply defined as a value of the reference material or as a measurement value of the reference laboratory. The performance metrics depends on the way of reporting results and defining the assigned value. The uncertainty of the assigned value shall be considered in all cases. This value might be substituted by a standard deviation of the intercomparison scheme [3]. Uncertainties or other forms of dispersions of reported results shall be considered as well. These values are declaring quality of performance of participating laboratories in the scheme. In most cases participating laboratories declare their quality by themselves by reporting standard or expanded uncertainty or by reporting more results of the same measurand. However, in some cases in testing area pilot laboratory defines allowed deviation of reported results from the assigned value. In such cases participants don't report uncertainty of measurement [3].

Interlaboratory comparisons are statistically evaluated by using diverse software, which might produce errors in final results. Error sources could be computational malfunctions, typing mistakes, mistakes in statistical formulae, etc. In order to detect such errors, reference data sets and algorithms for all possible statistical approaches should be produced and made available to the pilots of interlaboratory comparisons, who are responsible to perform reliable performance metrics. Such reference data sets and calculations shall be cross-checked by using different software packages and by comparisons in different institutes [4].

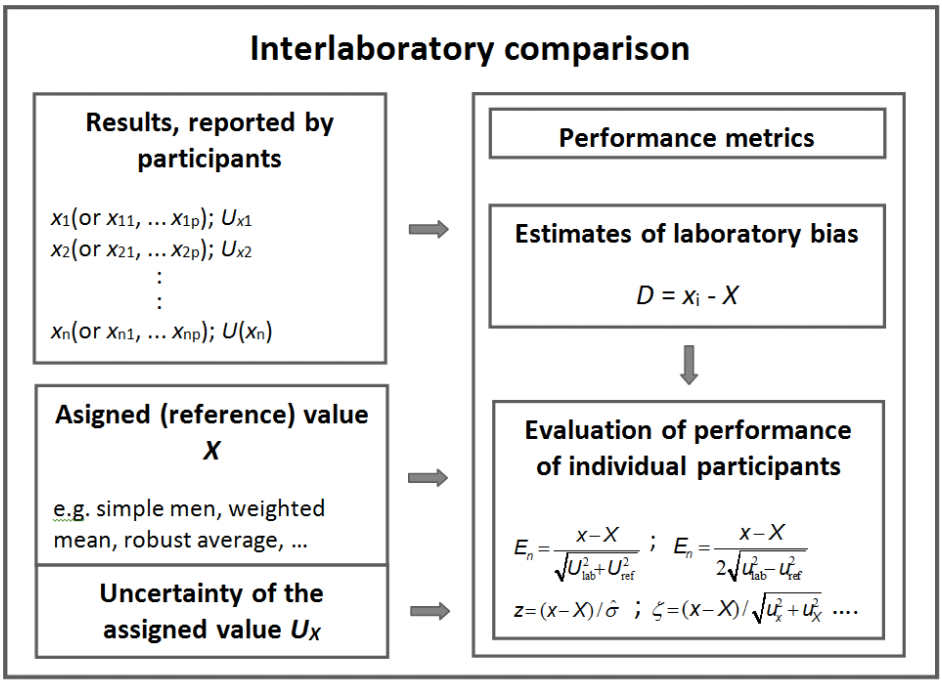

Fig. 1 Evaluation of interlaboratory comparison results

2.3 Reported values

Input values into the evaluating software are measurement results reported by participants and corresponding measurement uncertainties, as well as boundary conditions and evaluation strategy. Participants can report one or more results for the measurement quantity [2, 3, 7]:

- $x_1, x_2, \ldots, x_n$

  or

- $x_{11}, x_{12}, \ldots, x_{1n}$
  $x_{21}, x_{22}, \ldots, x_{2n}$
  $\vdots$
  $x_{p1}, x_{n2}, \ldots, x_{pn}$

The results can be reported with or without measurement uncertainties. The uncertainties can be reported as standard uncertainties (u_{x1}, u_{x2},..., u_{xn}) or expanded uncertainties at certain level of confidence (U_{x1}, U_{x2},..., U_{xn}) [11]. Uncertainties are not reported in some cases of comparisons in testing, especially when more than one result is reported per participant [3, 7].

Output values are calculated in accordance with the users' needs. User can select the set of output values through an intelligent interface. Generated input values are also considering user's boundary conditions. Most common output values in accordance with international standards and recommendations are presented in the following chapters [7].

2.4 Assigned value

The way of determining an assigned (reference) value should be defined prior to the interlaboratory comparison. The value can be determined in advance as a "certified reference value" X_{CRM} (when the material used in a proficiency test is a certified reference material) [3, 7] or a "reference value" X_{RM} (a value of the prepared reference material derived from a calibration against the certified reference values of the CRMs) [3, 7] or a "consensus value from expert laboratories" [3]. However, the most common way of determining the assigned value in calibration interlaboratory comparisons is to calculate it from the reported results x_i as a simple mean [1, 2, 9]:

$$X = \bar{x} \tag{1}$$

or a weighted simple mean [1, 2, 9]:

$$X = \frac{\sum_{i=1}^{p} u^{-2}(x_i) \cdot x_i}{\sum_{i=1}^{p}(x_i)} \tag{2}$$

where:

x_i – measured results reported by participants

$u(x_i)$ – uncertainties of the measured results reported by participants

When the participating laboratories report more than one measured value without stating uncertainty of measurement (in proficiency tests of testing laboratories), the reference value is calculated as a "robust" average [3, 7]:

$$X = \sum x_i^* / p \tag{3}$$

where:

$$x_i^* = \begin{cases} x^* - \delta, & \text{if } x_i < x^* - \delta \\ x^* + \delta, & \text{if } x_i < x^* + \delta \\ x_i \quad , & \text{otherwise} \end{cases}$$

x^* – median of x_i $(i = 1, 2, \ldots, p)$

$\delta = 1.5 s^*$

$x_1, x_2, \ldots, x_p$ – items of data, sorted in ascending order

2.5 Uncertainty of the assigned value

The assigned value is always determined experimentally with certain uncertainty. The uncertainty depends on the way of determining the assigned value and is calculated by following standardized or internationally recognized procedures [1, 2]. If the assigned value is calculated as a simple mean, its standard uncertainty is [1, 2, 9]:

$$u(X) = \sqrt{\frac{\sum u^2(x_i)}{p}} \tag{4}$$

where:

$u(x_i)$ – uncertainties of the measured results reported by participants

p – number of participants

Standard uncertainty of the weighted mean is [1, 2, 9]:

$$u(X) = \frac{1}{\sqrt{\sum_{i=1}^{n} u^{-2}(x_i)}} \tag{5}$$

where:

$u(x_i)$ – uncertainties of the measured results reported by participants

p – number of participants

The robust average has the following standard uncertainty assigned to it [3, 7]:

$$u(X) = 1.25 \cdot \frac{s^*}{\sqrt{p}}\ ;\ \ u(x_i)\ \text{not reported} \tag{6}$$

$$u(X) = \frac{1.25}{p}\sqrt{\sum_{i=1}^{p} u(x_i)^2}\ ;\ \ u(x_i)\ \text{reported} \tag{7}$$

where:

$$x_i^* = \begin{Bmatrix} x^* - \delta, & if\ x_i < x^* - \delta \\ x^* + \delta, & if\ x_i < x^* + \delta \\ x_i \quad\ , & otherwise \end{Bmatrix}$$

x^* – median of x_i ($i = 1, 2, \dots, p$)

$\delta = 1.5s^*$

$x_1, x_2, \dots, x_p$ – items of data, sorted into increasing order

$$s^* = 1.134\sqrt{\sum (x_i^* - x^*)/(p-1)}$$

If the assigned value is defined by perception, the following standard deviation is assigned to it [3, 7]:

$$\hat{\sigma} = \sqrt{(\emptyset \times \sigma_L)^2 + (\sigma_r^2/n)} \tag{8}$$

where:

$$\sigma_L = \sqrt{\sigma_R^2 - \sigma_r^2}$$

σ_R – reproducibility standard deviation

σ_r – repeatability standard deviation

n – number of replicate measurements each laboratory is to perform

$\sigma_R = 0{,}02c^{0.8495}$

c – concentration of chemical species to be determined in percent (mass fraction)

In the case of defining the assigned value from the results of a precision experiment, the standard deviation is expressed as [3, 7]:

$$\hat{\sigma} = \sqrt{\sigma_L^2 + (\sigma_r^2/n)} \tag{9}$$

where:

$$\sigma_L = \sqrt{\sigma_R^2 - \sigma_r^2}$$

σ_R – reproducibility standard deviation

σ_r – repeatability standard deviation

n – number of replicate measurements each laboratory is to perform

2.6 Performance statistics

Performance statistics is used for evaluating performance of participating laboratories. The final result for single laboratory is most usually "passed" or "failed". Corrective actions shall be taken by the laboratory, which fails the interlaboratory comparison. The first step in the performance statistics is to evaluate estimates of laboratory bias. An estimate could be evaluated as an absolute difference [3, 6, 7]:

$$D = x - X \tag{10}$$

where:

x – result reported by a participant

X – assigned value

or as a percentage difference [3, 7]:

$$D_{\%} = 100 \cdot (x - X)/X \tag{11}$$

The laboratory bias is tan used in different types of evaluation parameters, which should be in certainty limits in order to pass the comparison.

z-score is used in proficiency testing, where no uncertainties are reported by participating laboratories. The z-score is calculated by the following equation [3, 7]:

$$z = (x - X)/\hat{\sigma} \tag{12}$$

where:

x – result reported by a participant

X – assigned value

$\hat{\sigma}$ – standard deviation for proficiency assessment

When a participant reports a result that gives rise to a z-score above 3.0 or below −3.0, then the result shall be considered to give an "action signal". Likewise, a z-score above 2.0 or below −2.0 shall be considered to give a "warning signal". A single "action signal", or "warning signals" in two successive rounds, shall be taken as evidence that an anomaly has occurred that requires investigation.

E_n numbers are used in the comparisons, in which participating laboratories report measurement uncertainties in accordance with the Guide to the expression of uncertainty in measurement (GUM). If the reference value X is calculated as a simple mean, the following equation is used [1, 2, 9, 10]:

$$E_n = \frac{x - X}{\sqrt{U_{lab}^2 + U_{ref}^2}} \tag{13}$$

where:

U_{ref} – expanded uncertainty of the reference value X

U_{lab} – expanded uncertainty of a participant's result x

If the reference value X is calculated as a weighted mean, the E_n value is calculated as follows [1, 2, 9, 10]:

$$E_n = \frac{x - X}{2 \cdot \sqrt{u_{lab}^2 - u_{ref}^2}} \tag{14}$$

where:

u_{ref} – standard uncertainty of the reference value X

u_{lab} – standard uncertainty of a participant's result x

When uncertainties are estimated in a way consistent with the Guide to the expression of uncertainty in measurement (GUM), E_n numbers express the validity of the expanded uncertainty estimate associated with each result. A value of $|E_n| < 1$ provides objective evidence that the estimate of uncertainty is consistent with the definition of expanded uncertainty given in the GUM.

z'-scores are used when the assigned value is not calculated using the results reported by the participants and when the participants don't report uncertainties of their results. The z'-score is calculated by the following equation [3, 7]:

$$z' = (x - X)/\sqrt{\hat{\sigma}^2 + u(X)^2} \tag{15}$$

where:

x – result reported by a participant

X – assigned value

$\hat{\sigma}$ – standard deviation for proficiency assessment

$u(X)$ – standard uncertainty of the assigned value X

z'-scores shall be interpreted in the same way as z-scores using the same critical values of 2.0 and 3.0.

ζ-scores are used when the assigned value is not calculated using the results reported by the participants and when the participants report uncertainties of their results. The ζ-score is calculated by the following equation [3, 7]:

$$\zeta = (x - X)/\sqrt{u(x)^2 + u(X)^2} \tag{16}$$

where:

$u(x)$ – laboratory own estimate of the standard uncertainty of the result x

$u(X)$ – standard uncertainty of the assigned value X

When there is an effective system in operation for validating laboratories' own estimates of the standard uncertainties of their results, ζ-scores may be used instead of z-scores, and shall be interpreted in the same way as z-scores, using the same critical values of 2.0 and 3.0.

Another criteria are E_z-score [3]. Both values E_{z-} and E_{z+} shall be between -1 and 1 in order to be able to claim that the participating laboratory performance is satisfactory.

$$E_{z-} = \frac{x - (X - U(x))}{U(X)} \quad \text{and} \quad E_{z+} = \frac{x - (X + U(x))}{U(X)} \tag{17}$$

where:

x – result reported by a participant

X – assigned value

$U(x)$ – expanded uncertainty of the result x

$U(X)$ – expanded uncertainty of the assigned value X

2.7 Additional parameters

Additional parameters to be evaluated by the interlaboratory comparison evaluation software are different kinds of significance tests (χ^2-test, Birge criterion, etc.), confidence ellipse, rank correlation test, repeatability standard deviations [3, 9, 10].

3. Software validation application

The interlaboratory comparison software validation application allows the user to define boundary conditions for generating random data sets, for which selected reference statistical quantities are calculated. The user's software is then validated by comparing reference quantities with those calculated by the user's software [7].

The software validation application was developed in the environment Microsoft Visual Studio.Net 2012. Rounding of calculated data is defined based on the data type, declaration and other data properties. Uncertainty of calculated data will be defined by comparing calculation results with results created in other environments (e.g., Mathematica) and with results gained by other project partners.

3.1 User's interface

The user's interface consists of three modules [7]:

- selection of boundary conditions for generating data sets,
- selection of statistical quantities to be calculated,
- computation of statistical quantities and graphical presentation.

The first module is allowing the customer to define the following interlaboratory comparison characteristics [7]:

- number of participants, which is not limited,
- information about reporting uncertainty of measurement,
- number of results reported by single participant (this value is automatically set to 1, if "yes" is selected in the previous row),
- target value for the reported result (normally nominal value of the measurand or predefined assigned value),
- variation of results (this value can be extracted from real intercomparison results),
- accuracy of results (number of decimal places is selected based on the knowledge about real interlaboratory comparison results),
- type of measurement uncertainty (standard or expanded; the coverage factor can be selected in the case of expanded uncertainty),
- variation of the measurement uncertainty (this value can be extracted from real interlaboratory comparison results),
- accuracy of measurement uncertainty (number of decimal places is selected based on the knowledge about real interlaboratory comparison results).

3.2 Data generator

The data generator generates a random set of data after all boundary conditions are defined. This data set contains all numerical characteristics of real interlaboratory comparison results. Generation of random data sets can be repeated unlimited number of times. Generated data are real numbers with selectable number of decimal places. Uncertainty of generated data is u = 0, since the data is not rounded and since single values are independent from each other.

In order to reflect real interlaboratory conditions, generation of data sets is not completely randomly within boundary conditions selected by the user. The data is approximately normally distributed around the selected target value. Furthermore, one or more outliers can be incorporated into the data set.

After the data set is generated, the user can select statistical quantities (Section 2) to be verified. In the final module, the customer can see reference results and their graphical presentation [7].

4. Conclusion

The application consisting of data set generator and calculator of statistical quantities for interlaboratory comparisons is still being developed in the frame of running EMRP TraCIM project. The first module for selecting boundary conditions for creating data sets has already been finished and agreed among the participants in the corresponding project work package. Some modifications still need to done in the data generator. Generation of normally distributed values with incorporated outliers is still under consideration. After finishing the second and the third module, the calculation results will be validated by means of using different kinds of software and by comparison among the project participants.

The universal on-line application for validating different software packages for interlaboratory comparison data calculation is planned to be a free accessible internet application, which will be aimed to serve organizers of all interlaboratory comparisons, who are following standardized or internationally recognized rules. The main purpose of using the presented application will be to avoid misinterpretations of interlaboratory comparison results that might lead to wrong evaluation of the participants' performance capability. Therefore, the application will help to improve international comparability and traceability of measurement results in all types of proficiency testing.

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