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ORIGINAL ARTICLE

Study of optimization for material processing parameters by means of probabilistic methodology for multi-objective optimization

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Abstract
Optimization for material processing parameters is a typical problem of multi-objective optimization, therefore selection and use of proper multi-objective optimization approach is indispensible. The inherent characteristic of newly proposed probabilistic methodology for multi-objective optimization is that it is with the feature of optimization of multiple objectives at the same time in viewpoint of system theory and in spirit of probability theory. In the present paper, the probabilistic methodology is employed to perform the designs of materials processing for improving quality and cost saving at the same time. The laser welding process of ANSI 304 austenitic stainless steel by using a pulsed Nd: YAG laser welding system and thin-wall machining of milling aluminum alloy 2024-T351 are taken as two examples. The quantitative optimum design of materials processing is performed equitably by conducting the assessment of preferable probability of each alternative. The studies indicate that: (1). the optimized parametric combination for the laser welding process of 2 mm thickness ANSI 304 austenitic stainless steel by using a pulsed Nd: YAG laser welding system is at laser parameters of 2.7 kW peak power, welding speed of 2 cm/min and pulse duration of 4 ms; (2). the optimized combination parameter for the thin-wall machining of milling aluminum alloy 2024-T351 is at tool diameter of 8 mm, feed per tooth of 0.06 mm/z, axial cut depth of 24 mm and radial cut depth of 0.625 mm. The optimal configurations guarantee the comprehensive quality of product and reducing energy consumption.

Keywords Material processing · Multi-objective optimization · Probability theory · Preferable probability · Optimum design

Abbrevations

MOO	Multi-objective optimization
MCDM	Multi-criteria decision–making
VIKOR	VIšekriterijumsko KOmpromisno Rangiranje
TOPSIS	Technique of ranking Preferences by Similarity to the Ideal Solution
AHP	Analytical Hierarchy Process
MOORA	Multi-Objective Optimization on the basis of Ratio Analysis
PMOO	Probabilistic methodology for multi-objective optimization

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1 Introduction

Presently, with the rapid development of high technology, it has more requirements for the performance of processed products, therefore the pursuit of product performance optimization has become one of the key things for modern product design and manufacturing. Thus increasing studies focused on optimization of multi-objective process parameters of product manufacturing rapidly. The aim of multi-objective optimization was to find a vector set composed of decision variables that can satisfy the constraints of decision variables and meet the requirements of the target to be optimized. The objective functions to be optimized that describe the performance evaluation indexes are often contradictory, which makes the optimization of the objective functions operate under the condition of incommensurability. Optimization of one objective makes others increase at the expense of some target values in multi-objective optimization usually. At the same time, multi-objective optimization involves the selection of decision variables in high-dimensional space, so it is difficult to objectively judge the advantages and disadvantages of the optimal solution in common view. It indicates the great importance of a rational evaluation approach. For example, in the processing of ceramic materials, the performance of machine tools, processing environment and processing cost should be considered, and then the processing parameters of machine tools should be designed to achieve ideal processing quality, it is a typical multi-objective optimization problem. In machining, in order to achieve multiple machining goals, choice of machining parameters is always made relying on the experience of predecessors or some common-sense laws. This often leads to high processing cost, waste of manpower and material resources and low processing quality, which does not meet the requirements of sustainable development. Especially, in nowadays, it is strongly required to realize the coordinated and unified development of environmental protection and economic development through the evaluation of resources, replacement products and services, which jointly promotes the environment-friend design worldwide. In order to meet the needs of coordinated and unified development, it is necessary to optimize the initial processing parameters for the traditional mechanical processing industry, so as to reduce the consumption of resources and improve product quality. Undoubtedly, the application of multi-objective optimization in all aspects of manufacturing reduces the waste of resources and ensures the reliability of processing quality. Generally speaking, the benefit of optimizing the process parameters of machining is to conform to the requirements of high quality of product, cost saving and reducing waste of machining resources, it brings new development momentum to enterprises and increase the market share of enterprises as well.

Sustainable development of manufacturing technology with automation has gained more attention these years. Therefore, in order to solve the optimal problem of materials processing with multiple objectives, it is of great significance to study multi-objective optimization in material processing. The interactive and automatic evaluation of producibility of welding components in a multidisciplinary optimization design environment was conducted, which involves multiple requirements of functions in one single welded component structure [1, 2]. However, in the early design and analysis, the producibility evaluation of welding part relies on physical testing and expert judgment instead of rational assessment, which is usually empirical and expensive especially under condition of a component with complex geometry. The successive approach was to follow the rule of "product performance first" and "producibility second", which might lead to a result of well optimum designed performance and problematic producibility within a system; and finally, the various problems occur due to manufacturing defects and quality varying. The manufacturing defects and quality variation undoubtedly result in problems of safety and satisfaction of customer in practical applications of these welded components. Therefore, it is quite necessary to use a rational assessment to guarantee the automatic and interactive welding-producibility [1–7]. In the past, the producibility assessment of welding part concerned welding simulation, metamodel methods and weighting factors [1–7]. And finally, the optimization analysis still involves either adding all weighting responses into a single objective or Pareto solution set or grey relational analysis for Taguchi orthogonal array. However, the reliability of these kind of algorithms is problematic with uncertainty [8, 9].

The optimization of thin-wall machining was once performed by using Pareto-optimal solution with crucial requirements of enhanced energy efficiency, product quality, and productivity as objectives [10]. However, the result is problematic due to the uncertainty of Pareto-optimal solution set, which could not give a definitive consequence [8].

In fact, the inherent essence of optimization of multiple objectives is the "simultaneous optimization of multiple objectives" in a system inevitably. However, the previous methods of multi-objective optimization (MOO) and multi-criteria decision - making (MCDM) in the past took the "additive" algorithm as the actual algorithm for indexes in parameterization with weighting factors, or Pareto solution set with uncertainty, or grey relational analysis, etc. [5–10]. Till now, the commonly used methods include, VIKOR (VIšekriterijumsko KOmpromisno Rangiranje), TOPSIS (Technique of ranking Preferences by Similarity to the Ideal Solution), MOORA (Multi-Objective Optimization on the basis of Ratio Analysis), and AHP (Analytical Hierarchy Process), etc., are not be considered as fully quantitative, which all include uncertainties actually [10–15].

In fact, the "additive" algorithm for evaluating multiple indexes is equivalent to the "union" in the spirits of probability theory and set theory, which is definitely inconsistent with the essence of "simultaneous optimization of multiple indexes" [8]. Appropriately, in the respect of probability theory, "simultaneous optimization of multiple indexes" is to take the form of "joint probability" of the corresponding multiple events actually.

Additionally, in the additive algorithm there is a problem of choosing the scaled factor (denominator) of the normalization procedure of different objective, different scaled factors could often lead to quite different consequences [8, 16–18]. Therefore, the previous algorithms could not be considered as rational approaches in some sense due to their uncertainty and misusing of "union" in the spirits of probability theory and set theory.

Considering above situation, a probabilistic methodology was proposed [8]. In the new methodology, each attribute/objective of the multi-objective optimization problem was taken as an independent event from the perspective of probability theory, furthermore the entire thing of the multi-objective optimization was taken as a "joint event" of all individual events, thus the overall/total probability of "joint event" was the product of each individual event in the entire thing [8]. This methodology has the advantages of taking the simultaneous optimization of multiple objectives in the spirit of probability theory, which results in a definitive solution and an overall planning approach entirely.

In this paper, the probabilistic methodology for multi-objective optimization (PMOO) is used to perform the optimal designs of materials processing of quality improvement and cost saving. The laser welding process of ANSI 304 austenitic stainless steel by using a pulsed Nd: YAG laser welding system and thin-wall machining of milling aluminum alloy 2024-T351 are taken as two examples. By performing the assessment of preferable probability of each scheme, the quantitative optimum designs of materials processing are thus completed equitably.

The importance of this paper is to present a reasonable approach which enables the influence of the process variables on the producibility, product quality and energy efficiency, and the evaluations of these responses in industrial environment to be conducted properly. The innovation of the work is the assessment of these process parameters and responses are using the probabilistic multi-objective methodology.

2 Brief statement of the probabilistic methodology for multi-objective optimization

2.1 The characterization of preference in optimization

A new concept of preferable probability was put forward in the probabilistic methodology for multi-objective optimization to represent the preference degree of an attribute (objective) in the assessment [8]. In the treatment, all attributes (objectives) are classified into two types preliminarily, i.e., beneficial and unbeneficial kinds, and furthermore the quantitative assessment of the partial preferable probability of each performance index is conducted according to its type individually [8]. Moreover, the simultaneous optimization of multiple objectives could be done by taking the product of entire "partial preferable probability" of all objectives to form an overall/total preferable probability. It implies that each objective is analogically an "individual event". Thereafter, the total preferable probability is the unique index of the overall "joint event" (alternative), thus the optimization problem of these multiple objectives is transferred into a single objective one, finally the total preferable probability of each scheme/alternative is the decisive indicator for the optimization.

2.2 Quantitative assessment of preferable probability

The partial preferable probability is as a quantitative indicator of preference degree of the performance utility value of an attribute.

As to the characterization of the partial preferable probability of a beneficial type of attribute, for simplicity the partial preferable probability is assumed to be proportional to the performance utility value of the attribute index directly [8],

$$P_{ij} = \gamma_j \chi_{ij},\ i = 1, 2, \ldots, n; j = 1, 2, \ldots, m. \tag{1}$$

In Eq. (1), χ_{ij} expresses the utility value of the index of the j-th attribute of the i-th scheme [8]; P_{ij} indicates the corresponding partial preferable probability of χ_{ij}; n reflects the total number of the schemes; m is the number of attributes; γ_j is the coefficient of the j-th attribute in the preferable probability assessment.

Equivalently, the partial preferable probability of an unbeneficial attribute was assumed to be negatively linear correlated to the corresponding performance utility value of the attribute index,

$$P_{ij} = \eta_j(\chi_{j\max} + \chi_{j\min} - \chi_{ij}),\ i = 1, 2, \ldots, n; j = 1, 2, \ldots, m. \tag{2}$$

where η_j indicates the coefficient of the j-th attribute in the preferable probability assessment, χ_{jmax} and χ_{jmin} present the maximum and minimum values of the j-th attribute performance utility index within the involved scheme group, individually [8].

Furthermore, in accordance with the normalization of probability, it derives the expressions of coefficients of γ_j and η_j as [8],

$$\gamma_j = \frac{1}{n\overline{\chi}_j}, \eta_j = \frac{1}{n(\chi_{j\max} + \chi_{j\min} - n\overline{\chi}_j)}, \tag{3}$$

where $\overline{\chi}_j$ is the arithmetic mean value of the j-th performance utility index within the involved scheme group [8].

Moreover, according to probability theory, the product of all partial preferable probabilities P_{ij} results in the total preferable probability (joint probability) of the i-th scheme, i.e.,

$$P_i = P_{i1} \cdot P_{i2} \cdots P_{im} = \prod_{j=1}^{m} P_{ij}. \tag{4}$$

Subsequently, the total preferable probability P_i is the unique and decisive indicator to determine the status of the scheme of the optimization comparatively. In general, the winner is the alternative scheme which has the highest value of total preferable probability among all schemes [8].

3 Utilization of the probabilistic methodology of multi–objective optimization in material processing

3.1 Utilization in material laser welding

Laser welding is superior to other welding methods such as friction stir welding and arc welding, etc. [1, 2, 9].

In order to achieve a high quality at low costs, optimization of process parameters is the necessary step. The welding geometry of the laser welding process of ANSI 304 austenitic stainless steel by using a pulsed Nd: YAG laser welding system (Han's Laser WF300) was studied [9]. Taguchi orthogonal array based grey relational analysis was employed to conduct the optimization of laser welding process parameters [9]. However, the intrinsic defects of grey analysis of subjective factor and "additive" algorithm in evaluation of multiple indexes made the evaluation results short of rationality [8, 9].

In the study, a 2 mm thick ANSI 304 stainless steel was employed at three different levels of three variables, i.e., peak power (A), welding speed (B) and pulse duration (C). The weld bead geometry with full penetration (P), narrow bead width (W) and minimum crater (H) are taken as the multiple responses of the optimization [9].

Table 1 Parametric designs of welding ANSI 304 austenitic stainless steel with a pulsed Nd: YAG

Process parameter	Notation	Level		
Peak power (kW)	A	2	2.7	3
Welding speed (cm/min)	B	1	2	4
Pulse duration (ms)	C	4	7	10

In the welding process, shielding was conducted by using argon gas with a flow rate of 20 l/min [9]. Table 1 shows the parametric design of the experiment.

Table 2 cites the experimental results with Taguchi array $L_9(3^4)$.

According to the aim of preference of the optimal design, the response penetration (P) belongs to beneficial type of index, while the responses bead width (W) and crater (H) attribute to unbeneficial type of indexes in the assessment. The results of assessment for this welding problem by means of probabilistic multi-objective optimization are shown in Table 3.

It can be seen that the scheme No. 5 is with the highest total preferable probability at first glance, therefore the preliminary optimum parameters of variables for this welding problem are corresponding to those of the scheme No. 5, which is with the parametric combination of $A_2B_2C_3$ at this stage.

Furthermore, range analysis of the total preferable probability can be conducted, of which the result is shown in Table 4. The impact order of parametric effect is $B > A > C$,

Table 3 Assessment results by means of probabilistic approach

Run no	Partial preferable probability			Total preferable probability	Rank
	P_P	P_H	P_W	$P_i \times 10^3$	
1	0.0654	0.1109	0.1123	0.8155	7
2	0.0777	0.1448	0.1187	1.3358	6
3	0.0731	0.1451	0.1284	1.3609	5
4	0.1306	0.0850	0.0594	0.6598	8
5	0.1306	0.1277	0.1405	2.3441	1
6	0.1306	0.1361	0.1160	2.0625	2
7	0.1306	7.25×10^{-6}	0.1116	0.0001	9
8	0.1306	0.1078	0.1285	1.8086	3
9	0.1306	0.1427	0.0846	1.5763	4

Table 2 Experimental design and results with Taguchi array $L_9(3^4)$

Run No	Parametric design			Result		
	A (kW)	B (cm/ min)	C (ms)	Penetration, P (μm)	Crater, H (μm)	Width, W (μm)
1	2	1	4	1002	470.5	1599
2	2	2	7	1190	3.33	1483
3	2	4	10	1119	0.1	1306
4	2.7	1	7	2000	828.2	2564.34
5	2.7	2	10	2000	239.2	1084.5
6	2.7	4	4	2000	124.12	1531
7	3	1	10	2000	2000	1613
8	3	2	4	2000	514.28	1304
9	3	4	7	2000	32.89	2105.26

Table 4 Result of range analysis of total preferable probability

	A	B	C
Level 1	1.1707	0.4918	1.5622
Level 2	1.6888	1.8295	1.1906
Level 3	1.1283	1.6666	1.2351
Range	0.5604	1.3377	0.3716
Impact order	2	1	3
Optimum conf	2	2	1

and the final optimal parametric combination predicted for this laser welding problem is $A_2B_2C_1$, which is closely accompanied by scheme No. 5.

3.2 Utilization in material machining

The machining of milling aluminum alloy 2024-T351 specimens on a computer numerical control (CNC) vertical machining center (MC-3/400) was performed [10]. The wall thickness was reduced from 2.5 mm to 1.25 mm. End mills of solid carbide flat-bottom were used to conduct the machining experiments. The dry mode of cutting was employed to perform the machining study. It aimed to simultaneously improve the productivity of the thin-wall cutting process, and reduce the power consumption, surface roughness, and in-process wall deflection.

The tool diameter d_i, feed per tooth f_z, axial cut depth a_d and radial cut depth r_d, were used as input parameters, which were controllable with 3 levels. The measurement of surface roughness (Ra) is conducted with a non-contact profilometer (Taylor Hobson Talysurf CCI Lite). The in-process wall deflection (D_f) was detected with linear variable differential transformer (Solartron AX/5/S) in-process.

The design of the experiments is shown in Table 5 with 81 tests [10]. The 81 tests were conducted to perform the optimization of the thin-wall machining, which was once analyzed by using Pareto-optimal solution with crucial requirements of enhanced energy efficiency, product quality, and productivity [10].

Furthermore, a specific parameter Q_i was introduced to characterize the quality of product, which was defined by using the weighting additive algorithm of surface roughness and wall deflection [10]. A higher Q_i value indicates superior surface finish and dimensional accuracy; the removal rate P_y was defined using the volume of material removed V_m (mm^3) divided by the machining time t_m (s), $P_y = V_m/t_m$, which was used to characterize the rate of cutting amount. The cutting power P_c was used to reflect the power consumption in the machining. As a result, the removal rate P_y and specific parameter Q_i are beneficial type of performance indexes, and the cutting power P_c is unbeneficial type of performance index.

In the experiment, there appeared 3 abnormal samples, says No. 17, No. 66 and No. 78, which gave no experimental results due to the tool failure, here they are excluded in our analysis.

The effective experimental data of this machining problem is shown in Tables 6 and 7. The assessment results are shown in Tables 8 and 9 by means of probabilistic methodology for multi-objective optimization.

It can be seen that the experimental scheme No. 62 is with the highest total preferable probability, the corresponding P_y, P_c and Q_i are *6640.63* mm^3/min, *275.76* W, and *0.679*, respectively, see Tables 8 and 9. Therefore the optimum input parameters of variables for this machining problem are corresponding to those of the scheme No. 62, i.e., $d_i = 8$ mm, $f_z = 0.06$ mm/z, $a_d = 24$ mm and $r_d = 0.625$ mm from Table 5.

4 Conclusions

By using the probabilistic methodology for multi-objective optimization, two examples of materials processing are conducted. By performing the assessment of preferable probability of each alternative scheme, the optimal design is thus completed. The studies indicates that,

(1) for the laser welding process of 2 mm thickness ANSI 304 austenitic stainless steel with a pulsed Nd: YAG laser welding system, the optimized parametric combination is at laser parameters of 2.7 kW peak power, welding speed of 2 cm/min and a pulse duration of 4 ms;

(2) for the thin-wall machining of milling aluminum alloy 2024-T351, the experimental scheme No. 62 is with the highest total preferable probability, the corresponding removal rate, cutting power and specific parameter are *6640.63* mm^3/min, *275.76* W, and *0.679*, respectively. The optimum input parameters (factors) for this machining problem are at tool diameter of 8 mm, feed per tooth of 0.06 mm/z, axial cut depth of 24 mm and radial cut depth of 0.625 mm correspondingly.

The optimization results exhibit the superiority of the probabilistic methodology for multi-objective optimization to guarantee the comprehensive quality of product and reducing energy consumption.

Table 5 Design of the experiment

No	Input variable				No	Input variable			
	d_i (mm)	f_Z (mm/Z)	a_d (mm)	r_d (mm)		d_i (mm)	f_Z (mm/Z)	a_d (mm)	r_d (mm)
1	12	0.06	8	0.3125	42	4	0.04	12	0.625
2	12	0.02	8	0.3125	43	4	0.04	24	0.3125
3	12	0.04	12	0.625	44	12	0.06	24	1.25
4	12	0.02	12	0.625	45	12	0.02	8	0.625
5	8	0.06	24	0.3125	46	8	0.02	12	0.3125
6	8	0.06	8	1.25	47	8	0.06	24	1.25
7	8	0.02	8	1.25	48	8	0.02	8	0.625
8	4	0.06	8	0.3125	49	12	0.04	8	1.25
9	4	0.02	8	1.25	50	4	0.04	8	1.25
10	8	0.02	12	1.25	51	8	0.02	24	0.3125
11	12	0.04	8	0.3125	52	8	0.06	12	0.3125
12	12	0.06	24	0.3125	53	12	0.04	24	0.3125
13	12	0.02	8	1.25	54	4	0.02	12	0.625
14	12	0.04	12	1.25	55	8	0.04	24	1.25
15	12	0.04	24	0.625	56	4	0.02	24	0.3125
16	8	0.02	24	1.25	57	8	0.04	12	0.625
17	4	0.04	24	1.25	58	4	0.06	24	0.625
18	12	0.02	24	1.25	59	8	0.02	8	0.3125
19	12	0.02	12	0.3125	60	4	0.04	24	0.625
20	8	0.04	24	0.625	61	4	0.06	8	1.25
21	4	0.06	8	0.625	62	8	0.06	24	0.625
22	4	0.02	24	1.25	63	12	0.06	12	1.25
23	8	0.04	24	0.3125	64	8	0.06	8	0.3125
24	4	0.06	24	0.3125	65	12	0.02	12	1.25
25	4	0.06	12	0.3125	66	4	0.06	12	1.25
26	4	0.02	8	0.625	67	12	0.06	12	0.625
27	4	0.02	12	1.25	68	4	0.04	12	0.3125
28	12	0.06	8	1.25	69	12	0.04	8	0.625
29	4	0.04	8	0.3125	70	12	0.04	24	1.25
30	8	0.04	12	0.3125	71	8	0.04	8	0.3125
31	4	0.02	8	0.3125	72	8	0.04	8	0.625
32	8	0.02	24	0.625	73	4	0.04	12	1.25
33	12	0.04	12	0.3125	74	12	0.02	24	0.625
34	4	0.04	8	0.625	75	8	0.02	12	0.625
35	8	0.06	8	0.625	76	8	0.06	12	0.625
36	12	0.06	8	0.625	77	8	0.06	12	1.25
37	12	0.06	24	0.625	78	4	0.06	24	1.25
38	12	0.02	24	0.3125	79	8	0.04	12	1.25
39	4	0.02	12	0.3125	80	8	0.04	8	1.25
40	4	0.06	12	0.625	81	12	0.06	12	0.3125
41	4	0.02	24	0.625					

Table 6 Experimental results of the former 40 samples

No	Evaluation performance index			No	Evaluation performance index		
	P_y, *A*, (mm^3/min)	P_c, *B*, (W)	Q_i, *C*		P_y, *A*, (mm^3/min)	P_c, *B*, (W)	Q_i, *C*
1	1119.4	139.48	0.779	22	6181.82	170.95	0.338
2	426.231	112.28	0.929	23	2623.46	148.39	0.847
3	2063.11	235.51	0.717	24	4039.07	123.74	0.532
4	1093.8	204.48	0.801	25	2013.16	122.40	0.527
5	3692.09	195.56	0.789	26	964.691	88.02	0.760
6	4854.06	217.67	0.595	27	3086.54	107.96	0.503
7	1855.67	114.25	0.799	28	4447.67	299.32	0.608
8	1340.69	117.31	0.636	29	957.447	104.90	0.698
9	2057.01	81.11	0.634	30	1305.91	86.63	0.849
10	2785.87	163.54	0.708	31	515.429	70.30	0.834
11	795.88	122.46	0.815	32	2492.67	129.72	0.869
12	3396.98	504.59	0.669	33	1196.06	183.34	0.731
13	1693.04	220.40	0.659	34	1799.15	125.63	0.621
14	4753.03	377.12	0.527	35	2194.49	99.47	0.713
15	4148.59	329.30	0.690	36	1946.57	176.32	0.733
16	5585.98	235.21	0.624	37	5902.78	593.80	0.635
18	5101.7	614.99	0.476	38	1284.42	244.71	0.842
19	640.06	136.28	0.868	39	773.509	80.045	0.752
20	4690.37	208.79	0.745	40	3796.53	145.94	0.341
21	2528.09	135.48	0.534	41	2898.83	102.47	0.553

Table 7 Experimental results of the latter 38 samples

No	Evaluation performance index			No	Evaluation performance index		
	P_y, *A*, (mm^3/min)	P_c, *B*, (W)	Q_i, *C*		P_y, *A*, (mm^3/min)	P_c, *B*, (W)	Q_i, *C*
42	2701.27	133.51	0.418	61	5351.52	125.44	0.379
43	2882.44	119.18	0.632	**62**	**6640.63**	**275.76**	**0.679**
44	13,515.9	1049.16	0.238	63	6692.91	444.32	0.489
45	728.571	138.97	0.859	64	1220.10	71.19	0.824
46	700.678	65.49	0.933	65	2542.37	305.00	0.585
47	14,683.3	505.15	0.265	67	2927.67	277.44	0.661
48	828.281	59.69	0.934	68	1437.43	110.99	0.602
49	3161.81	267.37	0.615	69	1372.69	166.39	0.757
50	3821.18	109.93	0.558	70	9568.48	985.51	0.289
51	1404.7	99.71	0.954	71	869.516	60.07	0.898
52	1834.53	117.71	0.783	72	1553.93	93.03	0.786
53	2407.17	408.18	0.730	73	5736.78	143.52	0.461
54	1447.77	90.72	0.539	74	2193.86	308.06	0.793
55	10,436.6	391.94	0.396	75	1243.50	92.90	0.872
56	1549.21	82.01	0.768	76	3298.84	152.88	0.628
57	2334.45	122.92	0.760	77	7299.62	310.31	0.383
58	7619.52	153.99	0.350	79	5193.48	227.31	0.552
59	466.691	38.59	0.988	80	3456.85	165.43	0.665
60	5414.01	151.42	0.437	81	1683.54	185.53	0.692

Bold values show the status with highest total preferable probability from the evaluation

Table 8 Assessment results by means of probabilistic approach of the former 40 samples

No	Partial preferable probability			Total preferable probability	No	Partial preferable probability			Total preferable probability
	P_A	P_B	P_C	$P_t \times 10^6$		P_A	P_B	P_C	$P_i \times 10^6$
1	0.0044	0.0138	0.0151	0.9258	22	0.0244	0.0134	0.0066	2.1448
2	0.0017	0.0142	0.0181	0.4325	23	0.0104	0.0137	0.0165	2.337
3	0.0081	0.0124	0.0139	1.4115	24	0.0159	0.0141	0.0103	2.3192
4	0.0043	0.0129	0.0156	0.8664	25	0.0079	0.0141	0.0102	1.1467
5	0.0146	0.013	0.0153	2.9099	26	0.0038	0.0146	0.0148	0.8206
6	0.0192	0.0127	0.0116	2.8135	27	0.0122	0.0143	0.0098	1.7031
7	0.0073	0.0142	0.0155	1.6161	28	0.0176	0.0115	0.0118	2.3871
8	0.0053	0.0142	0.0124	0.9265	29	0.0038	0.0143	0.0136	0.7354
9	0.0081	0.0147	0.0123	1.4698	30	0.0052	0.0146	0.0165	1.2427
10	0.011	0.0135	0.0138	2.041	31	0.002	0.0148	0.0162	0.4897
11	0.0031	0.0141	0.0158	0.701	32	0.0098	0.014	0.0169	2.3235
12	0.0134	0.0085	0.013	1.4838	33	0.0047	0.0132	0.0142	0.8853
13	0.0067	0.0126	0.0128	1.0835	34	0.0071	0.014	0.0121	1.2035
14	0.0188	0.0104	0.0102	1.993	35	0.0087	0.0144	0.0139	1.7313
15	0.0164	0.0111	0.0134	2.4308	36	0.0077	0.0133	0.0143	1.456
16	0.0221	0.0124	0.0121	3.3271	37	0.0233	0.0072	0.0123	2.0729
18	0.0201	0.0069	0.0093	1.2854	38	0.0051	0.0123	0.0164	1.0208
19	0.0025	0.0139	0.0169	0.5918	39	0.0031	0.0147	0.0146	0.6563
20	0.0185	0.0128	0.0145	3.4388	40	0.015	0.0137	0.0066	1.3651
21	0.01	0.0139	0.0104	1.4394	41	0.0114	0.0144	0.0108	1.7684

Table 9 Assessment results by means of probabilistic approach of the latter 38 samples

No	Partial preferable probability			Total preferable probability	No	Partial preferable probability			Total preferable probability
	P_A	P_B	P_C	$P_t \times 10^6$		P_A	P_B	P_C	$P_i \times 10^6$
42	0.0107	0.0139	0.0081	1.2064	61	0.0211	0.014	0.0074	2.1853
43	0.0114	0.0141	0.0123	1.9755	**62**	**0.0262**	**0.0118**	**0.0132**	**4.0992**
44	0.0534	0.0006	0.0046	0.139	63	0.0264	0.0094	0.0095	2.3578
45	0.0029	0.0138	0.0167	0.6648	64	0.0048	0.0148	0.016	1.1443
46	0.0028	0.0149	0.0181	0.7482	65	0.01	0.0114	0.0114	1.3034
47	0.058	0.0085	0.0052	2.5381	67	0.0116	0.0118	0.0129	1.7557
48	0.0033	0.015	0.0182	0.8905	68	0.0057	0.0142	0.0117	0.9463
49	0.0125	0.012	0.012	1.7861	69	0.0054	0.0134	0.0147	1.0719
50	0.0151	0.0143	0.0108	2.3343	70	0.0378	0.0015	0.0056	0.3165
51	0.0055	0.0144	0.0185	1.4824	71	0.0034	0.015	0.0175	0.8984
52	0.0072	0.0141	0.0152	1.5601	72	0.0061	0.0145	0.0153	1.3603
53	0.0095	0.0099	0.0142	1.337	73	0.0227	0.0138	0.009	2.7959
54	0.0057	0.0145	0.0105	0.8711	74	0.0087	0.0114	0.0154	1.5187
55	0.0412	0.0101	0.0077	3.2197	75	0.0049	0.0145	0.017	1.2078
56	0.0061	0.0147	0.0149	1.3398	76	0.013	0.0136	0.0122	2.1684
57	0.0092	0.0141	0.0148	1.9166	77	0.0288	0.0113	0.0074	2.4335
58	0.0301	0.0136	0.0068	2.7881	79	0.0205	0.0125	0.0107	2.7618
59	0.0018	0.0153	0.0192	0.5416	80	0.0136	0.0135	0.0129	2.3739
60	0.0214	0.0137	0.0085	2.4803	81	0.0066	0.0132	0.0135	1.1768

Bold values show the status with highest total preferable probability from the evaluation

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