Kovove Mater. 60 2022 45–53
DOI: 10.31577/km.2022.1.45

A novel method based on probability theory for simultaneous optimization of multi-object orthogonal test design in material engineering

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Received 7 August 2021, received in revised form 13 December 2021, accepted 17 February 2022

Abstract

A probability theory-based method for simultaneous optimization of multi-object orthogonal test design is addressed in the present paper, which employs the concept of preferable probability to represent the preferable degree of the candidate alternative in the optimization. The utility indexes of all the performance indicators of alternative are divided into beneficial and unbeneficial types according to the preference in the optimization, and each utility index contributes to a partial preferable probability in positively or negatively correlative manners linearly according to its type; the total preferable probability of a candidate alternative is the product of all partial preferable probabilities, which thus transfers the multi-objective problem into a single objective problem. Finally, all candidate alternatives are ranked upon their total preferable probability to complete the optimization. As to multi-objective orthogonal test design, the optimization is conducted by applying range analysis to the total preferable probabilities of candidate alternatives.

Key words: orthogonal test design, multi-object optimization, probability-based method, overall consideration, preferable probability

1. Introduction

Usually, in many industrial processes and experiments, several quality characteristics are involved in the analysis for quality improvement or optimization. The overall quality improvement or optimization of an experiment involves the simultaneous optimization of these several controlling indexes (objects). Optimization for one individual object separately could not give the proper result of the simultaneous optimization of several objects integrally, i.e., the optimization of the multiple objects simultaneously does not equal any individual object optimization.

Up to now, though several multi-objective optimization methods have been developed [1–5], such as Multi-Objective Optimization based on Ratio Analysis (MOORA), Analytical Hierarchy Process (AHP), Vlšekriterijumsko KOmpromisno Rangiranje (VIKOR), Technique of Ranking Preferences by Similarity to the Ideal Solution (TOPSIS), etc., the general mathematical treatment in the above approaches is an "additive" algorithm for the normalized evaluation indexes, and some approaches even contain artificial factors, such as VIKOR, TOPSIS, and MOORA [3, 4], etc. From the perspective of "simultaneous optimization of multiple indexes," the above approaches have their inherent defects since the "additive" algorithm is equivalent to taking the form of "union" in probability theory [6]. In fact, in the viewpoint of probability theory, "simultaneous optimization of multiple indexes" must take the form of a "multiplication" algorithm for the partial probability of each independent event appropriately [6]. So, we have to obtain the partial probability for each object as an independent event in the multi-objective optimization process first. In addition, it is troublesome because of the introduction of artificial factors in the previous approaches. Yang et al. pointed out that if different normalization methods are applied, it may produce considerable differences in the results [7]. So, the above approaches are at most

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semi-quantitative methods in some sense.

As to optimization of multi-object orthogonal test design, in Taguchi's method, both "analysis of the signal to noise ratio (SNR)" and "grey relational analysis (GRA)" are combined to solve the problem [8]. The normalization factors, the nonequivalence of SNR assessments for beneficial and unbeneficial indicators, the "additive" algorithm, and the artificial factor (grey relational coefficient) are all involved in the assessment, which inevitably induces the inherent shortcomings.

Derringer et al. and Jorge et al. once proposed desirability function to transfer each response variable into a desirability value [1, 2], then all the desirability values are combined by using the geometric means to get a single desirability value to represent the overall assessment for the combined responses. But this approach is not consistent with the essence of probability theory for simultaneous optimization of multi-objects at all.

Therefore, comprehensively quantitative assessment for simultaneous optimization of multi-object is still needed.

In this paper, a probability theory-based method for simultaneous optimization of multi-object is addressed first, which employs the concept of preferable probability to represent the preferable degree of the candidate material or alternative in the optimization. The total (overall) preferable probability of a candidate alternative is the product of all partial preferable probabilities. The total preferable probability of a candidate alternative is the unique decisive index for the alternative selection quantitatively. Thus, the final index to be optimized is the total preferable probability of a candidate alternative, and then the optimization of multi-object orthogonal test design is conducted by using range analysis to the total preferable probabilities comprehensively.

2. Main treatment of the probability theory method

2.1. Concept of preferable probability for alternative selection

As a multi-objective optimization, several objects (controlling indexes) are involved undoubtedly. Some object indicators might be beneficial to the alternative selection, but other indicators are unbeneficial to it. An actual alternative is an integral body of both beneficial and unbeneficial indicators. In general, it is impossible for an alternative to have only full beneficial or unbeneficial indicators to the alternative selection. Therefore, an overall consideration is needed to simultaneously deal with both the beneficial and unbeneficial indicators for alternative selection. Thus, probability theory could be employed to conduct this issue quantitatively.

As a quantitative assessment to the term "the higher, the better" for the utility index of a response indicator of candidate alternative, a new concept of preferable probability is adopted, which reflects the preferable degree of the candidate alternative in the selection, i.e., the preferable probability represents the preferable degree of the utility index in the alternative selection quantitatively.

From the principle of simplicity, the preferable probability of a utility index with the character of "the higher, the better" (beneficial factor) in the alternative selection process is positively correlative to this utility index linearly, i.e.,

$$P_{ij} \propto U_{ij},\ P_{ij} = \alpha_j U_{ij},\quad i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m. \tag{1}$$

In Eq. (1), U_{ij} represents the j-th utility index of the i-th candidate alternative; P_{ij} is the partial preferable probability of the beneficial utility index U_{ij}; n is the total number of candidate alternatives in the alternative group involved; m is the total number of utility index of each candidate alternative in the group; α_j is the normalized factor of the j-th utility index.

Furthermore, according to the general principle of normalization in probability theory [6], the summation of each P_{ij} for the index i in j-th utility index is normalized and equal to 1, i.e., $\sum_{i=1}^{n} P_{ij} = 1$, thus, it obtains

$$\sum_{i=1}^{n} \alpha_i U_{ij} = \sum_{i=1}^{n} P_{ij} = 1,\ \alpha_j = 1/(n\overline{U_j}), \tag{2}$$

where $\overline{U}_j$ is the arithmetic average value of the j-th utility index in the alternative group involved.

Evenly, the partial preferable probability of the unbeneficial utility index U_{ij} to the candidate alternative is negatively correlative to its utility index linearly, i.e.,

$$P_{ij} \propto (U_{j\max} + U_{j\min} - U_{ij}),\quad P_{ij} = \beta_j (U_{j\max} + U_{j\min} - U_{ij}),\quad i = 1, 2, \ldots, n;\ j = 1, 2, ..., m. \tag{3}$$

In Eq. (3), $U_{j\max}$ and $U_{j\min}$ present the maximum and minimum values of the utility index U_j in the alternative group, respectively; β_j is the normalized indicator of the j-th utility index.

Correspondingly, by using the general principle of normalization in probability theory [6], it obtains

$$\beta_j = 1/[n(U_{j\max} + U_{j\min}) - n\overline{U_j}]. \tag{4}$$

Furthermore, in the viewpoint of "simultaneous optimization of multi-objects" of probability theory [6],

Table 1. Fundamental performance indicators of seven materials [5]

Steel No.	SH (Bhn)	CH (Bhn)	SFL (MPa)	BFL (MPa)	UTS (MPa)	C (USC/lb)
1	220	220	460	360	880	0.342
2	200	200	330	100	380	0.171
3	270	270	630	435	590	0.119
4	270	270	670	540	1190	1.283
5	585	240	1160	680	1580	3.128
6	700	315	1500	920	2300	2.315
7	750	315	1250	760	1250	4.732

Table 2. Assessed results of material selection for exhaust manifold of automobile

Steel No.	Partial preferable probability						Total		
	SH	CH	SFL	BFL	UTS	C	Pi × 10^5	Rank here	Rank Kumar
1	0.0735	0.1202	0.0767	0.0949	0.1077	0.2062	0.1426	6	6
2	0.0668	0.1093	0.0550	0.0264	0.0465	0.2140	0.0105	7	7
3	0.0902	0.1475	0.1050	0.1146	0.0722	0.2164	0.2502	4	5
4	0.0902	0.1475	0.1117	0.1423	0.1457	0.1632	0.5023	3	4
5	0.1953	0.1311	0.1933	0.1792	0.1934	0.0788	1.3522	2	3
6	0.2337	0.1721	0.2500	0.2424	0.2815	0.1160	7.9605	1	2
7	0.2504	0.1721	0.2083	0.2003	0.1530	0.0054	0.1497	5	1

the product of all the partial preferable probability P_{ij} of each candidate alternative results in the total (overall) preferable probability of the i-th candidate alternative, i.e.,

$$P_i = P_{i1} \cdot P_{i2} \cdots P_{im} = \prod_{j=1}^{m} P_{ij}. \tag{5}$$

Till now, the multi-objective problem is transferred into a single objective problem by the total preferable probability of a candidate alternative quantitatively, which is the unique decisive index for the alternative selection. Thus the total preferable probability can be used to conduct the ranking of all the candidate alternatives comparatively to complete the optimization.

2.2. Procedure of probability theory-based method for simultaneous optimization of multi-object orthogonal test design

As the multi-objective problem is transferred into a single objective problem by using the total preferable probability of a candidate alternative, which is the unique and overall decisive index for the simultaneous optimization of multi-object orthogonal test design in respect of probability theory, the range analysis in the popular orthogonal test design for a single object can be conducted for the total preferable probability naturally.

The probability theory-based method for simultaneous optimization of multi-object orthogonal test design is well developed.

2.3. Application of the probability theory-based method in material selection

2.3.1. Material selection for exhaust manifold of automobile

Kumar et al. [5] conducted material selection for the exhaust manifold of an automobile; seven alternative materials and six criteria for material selection are employed to perform the optimal design. The seven materials include ductile iron (1), cast iron (2), cast alloy steel (3), hardened alloy steel (4), surface hardened alloy steel (5), carburized steels (6), and nitride steels (7); the optimal criteria involve surface hardness (SH), core hardness (CH), bending fatigue limit (BFL), surface fatigue limit (SFL), ultimate tensile strength (UTS), and relative cost (C) [5]. Kumar et al. conducted material selection by using the TOPSIS method. The fundamental performance indicators of the above materials from [5] are cited in Table 1.

In this selection, the relative cost belongs to the unbeneficial type index, and all other indexes belong to the beneficial type index. Table 2 shows the assessed results together with the result of Kumar for comparison. From Table 2, it can be seen the best selection is material (6), i.e., carburized steel, which is different from that obtained by Kumar with the use of TOPSIS; this is attributed to Kumar's normalization and the inherent defects of TOPSIS with "additive" algorithm [7].

Table 3. Test results of gas metal arc welding process parameters [9]

Test No.	UTS (MPa)	CVN (J)	BP (mm)	BH (mm)	BW (mm)
1	420	110	2.04	2.25	10.82
2	500	100	1.12	2.85	5.14
3	380	80	2.58	3.1	7.22
4	320	90	1.03	2.51	11.42
5	410	60	1.45	3.72	5.35
6	220	100	1.05	2.05	8.83
7	280	55	2.01	2.15	10.72
8	510	115	3.5	3.88	4.5
9	480	85	3.78	2.85	6.85
10	320	60	2.15	2.15	11.2
11	250	95	1.9	2.98	12.4
12	310	83	2.42	2.06	9.8
13	520	100	3.82	2.97	4.18
14	430	70	2.25	3.08	8.32
15	270	60	1.65	2.15	10.74
16	290	80	1.88	2.7	12.88

Table 4. Partial and total preferable probabilities of the optimization of gas metal arc welding process parameters

Steel No.	Partial preferable probability					Total		
	UTS	CVN	BP	BH	BW	Pi × 10^5	Rank here	Rank Kumar
1	0.0711	0.0819	0.0589	0.0716	0.0471	1.1547	5	5
2	0.0846	0.0745	0.0323	0.0599	0.0899	1.0969	6	4
3	0.0643	0.0596	0.0745	0.0550	0.0742	1.1653	4	6
4	0.0541	0.0670	0.0297	0.0665	0.0425	0.3053	16	13
5	0.0694	0.0447	0.0419	0.0430	0.0883	0.4925	9	9
6	0.0372	0.0745	0.0303	0.0754	0.0620	0.3936	12	10
7	0.0474	0.0410	0.0580	0.0735	0.0478	0.3958	11	12
8	0.0863	0.0856	0.1011	0.0399	0.0947	2.8199	2	2
9	0.0812	0.0633	0.1092	0.0599	0.0770	2.5875	3	3
10	0.0541	0.0447	0.0621	0.0735	0.0442	0.4878	10	11
11	0.0423	0.0707	0.0549	0.0574	0.0351	0.3310	14	15
12	0.0525	0.0618	0.0699	0.0752	0.0548	0.9334	7	7
13	0.0880	0.0745	0.1103	0.0576	0.0971	4.0405	1	1
14	0.0728	0.0521	0.0650	0.0554	0.0659	0.9000	8	8
15	0.0457	0.0447	0.0477	0.0735	0.0477	0.3407	13	14
16	0.0491	0.0596	0.0543	0.0628	0.0315	0.3142	15	16

2.3.2. Optimization of gas metal arc welding process parameters

Achebo et al. performed the optimal issue of gas metal arc welding process parameters by using multi-objective optimization based on ratio analysis (MOORA) and standard deviation (SDV) [9]. The evaluation indicators include ultimate tensile strength (UTS), Charpy V-notch impact energy (CVN), bead penetration (BP), the bead height (BH) and bead width (BW), and the adjusted variables are welding current, voltage, electrode diameter, and welding speed [9]. Table 3 shows the test results [9].

Table 4 presents the assessed results of partial preferable probabilities and the total preferable probability for each alternative of the 16 tests together with the result of Achebo for comparison.

From Table 4, it can be seen that the appropriate alternative is test No. 13, which agrees with that of Achebo accidentally [9], but the sequences of other alternatives are not the same as those given by Achebo.

2.3.3. Application of the probability theory-based method in multi-objective orthogonal test design

In general, the multi-objective orthogonal test design is conducted by using the approaches of the so-called "comprehensive balance method" or "comprehensive scoring method," "grey relational analysis," or

T a b l e 5. Input variables and levels of the orthogonal test design for molding plastics [11]

Levels	Input test variables				
	Mold temperature A (℃)	Melt temperature B (℃)	Pressurizing time C (s)	Packing pressure D (MPa)	Injection time E (s)
1	30	230	8	50	3.5
2	40	240	10	60	4.0
3	50	250	12	70	4.5
4	60	260	14	80	5.0

T a b l e 6. Results of orthogonal test design for molding plastics process of storage box

Test No.	Input test variables					Performance indicator		Partial preferable probability		Total preferable probability	
	A	B	C	D	E	W (mm)	S (%)	P_{ij} for W	P_{ij} for S	Pi × 10^3	Rank
1	1	1	1	1	1	4.177	2.009	0.0552	0.0498	2.7469	12
2	1	2	2	2	2	3.701	1.732	0.0606	0.0587	3.5541	8
3	1	3	3	3	3	1.560	0.765	0.0847	0.0898	7.6099	2
4	1	4	4	4	4	0.807	0.637	0.0932	0.0939	8.7566	1
5	2	1	2	3	4	3.432	1.348	0.0636	0.0710	4.5181	7
6	2	2	1	4	3	4.449	1.590	0.0521	0.0633	3.2966	10
7	2	3	4	1	2	1.857	1.200	0.0814	0.0758	6.1689	3
8	2	4	3	2	1	3.639	2.178	0.0613	0.0443	2.7161	13
9	3	1	3	4	2	2.882	1.042	0.0698	0.0809	5.6466	4
10	3	2	4	3	1	2.546	1.225	0.0736	0.0750	5.5201	6
11	3	3	1	2	4	4.468	2.193	0.0519	0.0439	2.2761	14
12	3	4	2	1	3	3.864	2.919	0.0587	0.0205	1.2035	15
13	4	1	4	2	3	2.506	1.170	0.0741	0.0768	5.6850	5
14	4	2	3	1	4	3.475	1.930	0.0631	0.0523	3.3018	9
15	4	3	2	4	1	4.850	2.065	0.0476	0.0480	2.2829	11
16	4	4	1	3	2	8.258	1.812	0.0091	0.0561	0.5112	16

"analysis of the signal to noise ratio" [8, 10, 11], which are not fully quantitative, but empirical ones instead.

In this section, the probability theory-based method is used to conduct the multi-objective orthogonal test design problem quantitatively.

2.3.3.1. Orthogonal test multi-object optimization design for molding plastics process of storage box

In this section, the probability theory-based method is used to deal with the multi-object orthogonal test design for the molding plastics process of a storage box.

Zhu et al. [11] performed the multi-object optimization of the molding plastics process of storage box with CAE software; it involves five input variables, i.e., mold temperature, melt temperature, pressurizing time, packing pressure, and injection time; in addition, orthogonal test design with moldflow and four levels are used. The volume shrink mark index (S) and the buckling deformation (W) are taken as indicators of the multi targets optimization problem [11].

The volume shrink mark index and the buckling deformation are all unbeneficial performance indicators to the technique optimization; therefore, Eqs. (3) and (4) are applied to conduct the assessment for their partial preferable probability.

Table 5 shows the results of the orthogonal test design for the molding plastics process of the storage box [11]. Table 6 represents the test results, the partial preferable probabilities, and the total preferable probabilities of the orthogonal test design for the molding plastics process of the storage box.

Table 6 indicates the maximum of the total preferable probability Pi attributes to Test 4, so Test 4 could be chosen as the optimal combination at first glance from the multi-objective orthogonal test design directly.

Furthermore, Table 7 shows the assessed results of range analysis of the total preferable probabilities

Table 7. Assessed results of range analysis of the total preferable probabilities for the orthogonal test design of molding plastics process for storage box

Variable	A	B	C	D	E
Level 1	5.6669	4.6492	2.2077	3.3553	3.3165
Level 2	4.1749	3.9182	2.8897	3.5578	3.9702
Level 3	3.6616	4.5845	4.8186	4.5398	4.4488
Level 4	2.9452	3.2969	6.5327	4.9957	4.7132
Range	2.7217	1.3523	4.3250	1.6404	1.3967
Order	2	5	1	3	4

Table 8. Results of orthogonal test design for molding plastics process of storage box

Factor	A (℃)	B (s)	C (s)	D (s)	E (s)	F) (MPa)	G (MPa)	Residual stress (MPa)	Volume shrinkage rate (%)	Buckling deformation (mm)
Test 1	220	1.0	5	10	3	100	50	54.24	13.85	1.460
Test 2	220	1.3	10	15	4	110	55	53.97	11.48	1.378
Test 3	220	1.6	15	20	5	120	60	53.71	9.968	1.322
Test 4	230	1.0	5	15	4	120	60	54.02	14.36	1.353
Test 5	230	1.3	10	20	5	100	50	53.39	11.96	1.409
Test 6	230	1.6	15	10	3	110	55	53.93	10.49	1.392
Test 7	240	1.0	10	10	5	110	60	53.95	12.79	1.341
Test 8	240	1.3	15	15	3	120	50	53.58	10.91	1.419
Test 9	240	1.6	5	20	4	100	55	54.01	14.77	1.330
Test 10	220	1.0	15	20	4	110	50	53.22	10.73	1.448
Test 11	220	1.3	5	10	5	120	55	54.35	13.69	1.395
Test 12	220	1.6	10	15	3	100	60	54.40	11.45	1.293
Test 13	230	1.0	10	20	3	120	55	53.72	12.01	1.390
Test 14	230	1.3	15	10	4	100	60	53.97	10.49	1.383
Test 15	230	1.6	5	15	5	110	50	53.63	14.11	1.421
Test 16	240	1.0	15	15	5	100	55	53.59	10.89	1.354
Test 17	240	1.3	5	20	3	110	60	53.97	14.82	1.385
Test 18	240	1.6	10	10	4	120	50	53.90	12.71	1.349

Notice: A, melt temperature; B, injection time; C, holding pressure time; D, cooling time; E, mold opening time; F, injection pressure; G, holding pressure.

for the orthogonal test design of the molding plastics process for the storage box.

The range analysis results of Table 7 show that the order of the input variables in impact decreasing is from C, A, D, E to B. The optimal combination is $C_4A_1D_4E_4B_1$, the CAE modeling test indicates that the corresponding buckling deformation and the volume shrink mark index are 0.7323 mm and 0.4241 % [11], respectively, which are much less than the minimum values of 0.8069 mm and 0.6370 % in the orthogonal test design for molding plastics process of the storage box, see Table 6.

2.3.3.2. Multi-objective optimization of the molding plastics process of storage box

Lei et al. conducted the multi-objective optimization of the molding plastics process of storage box with seven input variables [12], i.e., melt temperature, injection time, pressurizing time, cooling time, molding time, injection pressure, and packing pressure. The residual stress, the volume shrinkage rate, and the buckling deformation are taken as the factors (indicators) of the multi targets by using orthogonal test design with moldflow [12].

The residual stress, the volume shrinkage rate, and the buckling deformation are all unbeneficial indicators to the technique optimization; therefore, Eqs. (3) and (4) are employed to perform the assessment for their partial preferable probability.

Table 8 cites the results of the orthogonal test design for the molding plastics process of the storage box [12].

Table 9 presents the assessed results of the partial and total preferable probabilities for the residual stress, the volume shrinkage rate, and the buckling deformation assessment in the orthogonal test design of the molding plastics process for the storage box.

In Table 9, Test 3 exhibits the maximum of the total preferable probability Pi; it could be chosen as the

Table 9. Assessed results of partial and total preferable probabilities for the residual stress, volume shrinkage rate, and buckling deformation in the orthogonal test design

Alternative No.	Partial preferable probabilities			Total	
	Residual stress	Volume shrinkage rate	Buckling deformation	Pi × 10^4	Rank
Test 1	0.0552	0.0487	0.0523	1.4040	17
Test 2	0.0554	0.0592	0.0556	1.8256	8
Test 3	0.0557	0.0660	0.0579	2.1261	1
Test 4	0.0554	0.0464	0.0566	1.4552	14
Test 5	0.0560	0.0571	0.0544	1.7387	10
Test 6	0.0555	0.0636	0.0550	1.9430	4
Test 7	0.0555	0.0534	0.0571	1.6908	12
Test 8	0.0559	0.0618	0.0540	1.8605	6
Test 9	0.0554	0.0446	0.0575	1.4212	16
Test 10	0.0563	0.0626	0.0528	1.8559	7
Test 11	0.0551	0.0494	0.0549	1.4930	13
Test 12	0.0550	0.0594	0.0590	1.9273	5
Test 13	0.0557	0.0569	0.0551	1.7457	9
Test 14	0.0554	0.0636	0.0554	1.9543	2
Test 15	0.0560	0.0475	0.0539	1.4280	15
Test 16	0.0558	0.0619	0.0566	1.9536	3
Test 17	0.0554	0.0444	0.0553	1.3605	18
Test 18	0.0555	0.0538	0.0568	1.6940	11

Table 10. Assessed results of range analysis of the total preferable probabilities for the orthogonal test design of molding plastics process for storage box

Level	A	B	C	D	E	F	G
Level 1	1.7720	1.6842	1.4270	1.6965	1.7068	1.7332	1.6635
Level 2	1.7108	1.7054	1.7704	1.7420	1.7010	1.6840	1.7303
Level 3	1.6634	1.7566	1.9489	1.7080	1.7384	1.7291	1.7524
Range	0.1085	0.0724	0.5219	0.0452	0.0373	0.0492	0.0889
Order	2	4	1	6	7	5	3

optimal combination in the multi-objective orthogonal test design directly.

Table 10 presents the assessed results of range analysis of the total preferable probabilities for the orthogonal test design of the molding plastics process for the storage box.

The range analysis of the data in Table 7 shows that the order of the input variables for impact decreasing is from C, A, G, B, F, D, to E. The optimal combination is $C_3A_1G_3B_3F_1D_2E_3$, which coincides with the result of the complex comprehensive balance method in the multi-objective orthogonal test design accidentally [12].

2.3.3.3. Multi-objective optimization on strengthening plate of automobile body during drawing process based on orthogonal test

Gou et al. dealt with the problems of crack and wrinkle of the strengthening steel B280VK plate with the thickness of 1.2 mm in automobile body during drawing process by using orthogonal test design for the multi-objective optimization issue [13]. The crack evaluation function Φ_1 and wrinkle evaluation function Φ_2 were taken as the objective factors, and the blank holding force F (A), friction coefficient μ (B), resistance coefficients C and D for draw beads loads P_1 and P_2 were taken as input variables, then the orthogonal test design was conducted.

Table 11 presents the results of the strengthening plate of the automobile body during the drawing process based on the orthogonal test [13].

Since the crack evaluation function Φ_1 and wrinkle evaluation function Φ_2 are unbeneficial type factors to the technique optimization, Eqs. (3) and (4) are employed to perform the assessment for their partial favorable probability.

Table 12 presents the assessed results of the partial and total preferable probabilities for the crack evaluation function Φ_1 and wrinkle evaluation function Φ_2 in the orthogonal test design.

In Table 12, Test 5 exhibits the maximum of the to-

Table 11. Results of the strengthening plate of automobile body during drawing process based on orthogonal test [13]

No.	Input variable				Object	
	A	B	C	D	Φ_1	Φ_2
1	160	0.15	0.05	0.40	0.943	0.132
2	150	0.15	0.15	0.30	0.898	0.120
3	140	0.18	0.15	0.40	1.103	0.138
4	160	0.12	0.15	0.35	0.824	0.129
5	140	0.12	0.05	0.30	0.833	0.114
6	160	0.18	0.10	0.30	3.420	0.131
7	140	0.15	0.10	0.35	0.887	0.134
8	150	0.12	0.10	0.40	0.794	0.142
9	150	0.18	0.05	0.35	1.202	0.122

Notice: A, blank holding force F; B, friction coefficient μ; C, resistance coefficient for P_1; D, resistance coefficient for P_2.

Table 12. Assessed results of the partial and total preferable probabilities for the crack evaluation function Φ_1 and wrinkle evaluation function Φ_2 in the orthogonal test design

No.	Partial preferable probability		Total	
	Φ_1	Φ_2	Pi $\times 10^2$	Rank
1	0.1210	0.1086	1.3144	6
2	0.1227	0.1191	1.4614	2
3	0.1151	0.1033	1.1896	9
4	0.1255	0.1112	1.3952	3
5	0.1251	0.1243	1.5558	1
6	0.0294	0.1095	0.3217	4
7	0.1231	0.1068	1.3154	5
8	0.1266	0.0998	1.2635	8
9	0.1115	0.1173	1.3080	7

Table 13. Assessed results of range analysis of the total preferable probabilities of the strengthening plate during drawing process based on orthogonal test

Level	A	B	C	D
Level 1	1.3536	1.4048	1.3927	1.1129
Level 2	1.3442	1.3637	0.9668	1.3395
Level 3	1.0104	0.9397	1.3487	1.2559
Range	0.3432	0.4651	0.4259	0.2265
Order	3	1	2	4

tal preferable probability Pi; it could be chosen as the optimal combination in the multi-objective orthogonal test design directly.

Table 13 presents the assessed results of range analysis of the preferable probabilities of the strengthening plate during the drawing process based on the orthogonal test.

From the range analysis data in Table 13, it can be seen that the order of the input variables for impact decreasing is from B, C, A to D. The optimal combination is $B_1C_1A_1D_2$, which coincides with the result of the complex comprehensive balance method in the multi-objective orthogonal test design by chance [13].

4. Conclusions

The probability theory-based method for simultaneous optimization of multi-object orthogonal test design in material engineering is developed from the above discussion. Each utility index contributes to a partial preferable probability in the assessment quantitatively; the total preferable probability of a candidate alternative is the product of all partial preferable probabilities, which thus naturally transfers the multi-objective problem into a single objective problem. Finally, the total preferable probabilities of all alternatives are used to comprehensively complete range analysis and thus the multi-object orthogonal test design.

The assessed results of the typical examples indicate the validity.

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