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Utilization of "Intersection" Methodology for Optimization with Many Objectives in Designed Experiments of Material Processing

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Abstract: Material processing involves many factors, and evaluation of final quality of a product also relates to many indexes from different respects. Thus the optimization of qualities and processing of a product is an optimization problem with many objectives (MOO) inevitably. Although there are some approaches proposed to deal with optimization problem with many objectives in nowadays, the inherent shortcomings in these approaches make them puzzled, which include their missing standpoint and use of additive algorithm containing subjective factors. Currently, an "intersection" methodology for optimization with many objectives is proposed by initiating a novel idea of favorable probability to depict the favorite degree of an alternative in optimal option impersonally, which aims to characterize the concurrent optimization of many objectives in a system in spirits of probability theory and set theory. In this article, some regulations are put forward for performing optimal option of material processing parameters in designed experiments of response surface methodology, orthogonal experiment design and uniform experiment design by means of the total / global favorable probability. In the treatment, the total / global favorable probability of an alternative is the decisive indicator in the optimal option uniquely, which transfers the optimization problem with many objectives into a mono-objective one. The result indicates that the novel approach can be employed to deal with the optimal problem of designed experiments for material processing rationally.

Keywords: favourable probability; "intersection"; material processing; optimization of many objectives; scheme selection

1 INTRODUCTION

Material processing involves many factors, and the final evaluation of a product quality also relates to many indexes from different respects. Thus the optimization of processing parameters and qualities of a product is an optimization problem with many objectives (MOO), which aims to seek a set of appropriate processing and machining technique that guarantees the multi-indexes of quality reaching to compromised optimum simultaneously [1-4].

Material processing and option have a long history since the early work [1-4], many approaches have been proposed to optimize and analyze the processing factors and parameters involved in material processing process [5, 6]. Usually, parametric optimization in material processing could be conducted with designed experiments which contain many objectives [5-8], and regression analysis as well [9-13]. However, there exist inherent shortcomings in the previous MOO approaches due to their use of additive algorithm containing personal factors, in addition to their fatal normalization or scaling processes, such as those in MADM, MOORA, AHP, VIKOR and TOPSIS, etc., which make them puzzled and problematic [5, 6]. In fact, above mentioned approaches attribute to have algorithms only but without any standpoint on optimization with many objectives, which do not give the essential target of optimization with many objectives, i.e., the previous approaches of MOO could not tell us what is the essence and target of MOO [5, 6].

Currently, an "intersection" methodology for optimization with many objectives was proposed to treat the MOO problem by creating a novel idea of favorable probability to depict the favorite degree of an alternative in optimal option impersonally [5, 6]. In the novel methodology, all objectives are taken as "events" within a system individually, thus the concurrent optimization problem of the many objectives is the optimization of the system, which is the overall/global optimization of the system from the viewpoint of system theory. Furthermore, all utility indexes of performances of candidate are classified into beneficial or unbeneficial type in the optimal process, each utility index of the performance quantitatively proffers a partial favourable probability in linear manner, and the product of all partial favourable probabilities results in the total/global favourable probability of a candidate in the spirits of probability theory and set theory, which is the total/global decisive index in the optimal option process uniquely. The novel methodology is a promised methodology that could be utilized to deal with various optimization problems concerning many objectives.

In this paper, some regulations are proposed for conducting optimal option of material processing parameters in designed experiments by means of the total/global favourable probability in respect of the novel approach.

2 FUNDAMENT OF THE NOVEL OPTIMIZATION METHODOLOGY WITH MULTIPLE OBJECTIVES

The core points of the "intersection" algorithm of optimization with many objectives are as follows:

A. All objectives/attributes in the optimization problem with many objectives are taken as "events" within a system, which leads to the concurrent optimization of many objectives as the optimization of the system.

B. The "concurrent optimization" of many objectives is treated by multiplication algorithm, which reflects the feature of "joint probability" and "intersection" in spirits of probability theory and set theory.

C. A novel idea of favourable probability is proposed to depict the favourite degree of an alternative in optimization option.

D. The treatment for utility indexes of performance of both beneficial and unbeneficial types is equivalent and conformable.

3 REGULATIONS OF OPTIMAL OPTION IN DESIGNED EXPERIENTS BY MEANS OF THE NOVEL OPTIMIZATION METHODOLOGY WITH MULTIPLE OBJECTIVES

As the global/total favourable probability of an alternative is the decisive index in the optimal option process uniquely, the global/overall optimization of the system could be focused on this index. Therefore, regulations are proposed for conducting optimal option of material processing parameters in designed experiments as follows.

3.1 Orthogonal Experimental Design

As to orthogonal experimental design, range analysis could be undoubtedly conducted for the total/global favourable probability. Furthermore, the optimal configuration with appropriate experimental parameters could be obtained correspondingly, which is the optimal option that might be in accordance with the maximum total/global favourable probability.

3.2 Uniform Experiment Design and Response Surface Methodology

As to uniform experiment design and response surface methodology, the total/global favourable probabilities of all candidates of the designed experiment are employed to conduct a regression analysis first, a regressed formula of the total/global favourable probability *vs* input variables could be established. Furthermore, maximizing the total/global preferable probability is performed to obtain its maximum value at specific values of input variables. Subsequently, further regression for each response is conducted to get its regressed expression. Afterwards, a properly compromised result of each response is obtained by entering the input variables as the specific values in each regressed expression.

4 ULTILIZATION OF THE NOVEL OPTIMIZATION METHODOLOGY WITH MANY OBJECTIVES IN MATERIAL PROCESSING

4.1 Optimal Design of Machinability Characteristics of Electrical Discharge Machining by Using Response Surface Methodology

Hosni et al conducted design experiments with responses of machinability features of electrical discharge machining by means of response surface methodology, the design is shown in Tab. 1 [14]. The concentration of Span-20 surfactant C_s, and concentration of chromium powder C_p were taken as two independent variables (parameters) for the study. The objective responses in the study included wear rate of electrode *EWR* (mm^3/min), surface roughness *Ra* (mm) and removal rate of material *MRR* (mm^3/min) [14]. The experimental results are cited and shown in Tab. 2.

In applying the newly developed "Intersection" methodology, the removal rate of material *MRR* (mm^3/min) is classified into beneficial performance index, while the wear rate *EWR* of electrode (mm^3/min) and surface roughness *Ra* (mm) belong to unbeneficial performance index. Tab. 3 shows the partial components of favorable probability of each evaluation response and the total / global favorable probability of each experimental option, as well as comparative rank.

Tab. 3 shows that the scheme 2 exhibits the optimal result, which is followed by schemes 11, 9 and 6, et al.

Table 1 Parameters and levels of electrical discharge machining

Parameter	Level		
	1	2	3
C_s (g/L)	0	5	10
C_p (g/L)	0	2	4

Table 2 Experimental design and results of electrical discharge machining

No.	C_s (g/L)	C_p (g/L)	*EWR* (mm^3/min)	*MRR* (mm^3/min)	*Ra* (mm)
1	5.00	4.00	0.0103	41.0399	5.0300
2	10.00	2.00	0.0000	44.0563	4.4367
3	10.00	0.00	0.0186	37.5628	4.4600
4	0.00	2.00	0.0211	43.1316	5.5600
5	10.00	4.00	0.0086	39.7328	4.9167
6	5.00	2.00	0.0040	40.4615	5.0333
7	0.00	4.00	0.0203	40.8241	5.2500
8	0.00	0.00	0.0343	32.5657	6.2500
9	5.00	2.00	0.0041	41.1986	4.6767
10	5.00	0.00	0.0283	37.9382	4.9300
11	5.00	2.00	0.0021	42.6777	4.5300

Table 3 Favorable probability and comparative rank

No.	Favorable probability				Rank
	MRR	*EWR*	*Ra*	*Global* P_i ×10^3	
1	0.0930	0.1063	0.0905	0.8953	6
2	0.0999	0.1520	0.1000	1.5183	1
3	0.0851	0.0696	0.0997	0.5903	7
4	0.0978	0.0587	0.0821	0.4710	8
5	0.0901	0.1140	0.0924	0.9477	5
6	0.0917	0.1343	0.0905	1.1147	4
7	0.0925	0.0621	0.0870	0.4998	9
8	0.0738	8.86E-07	0.0711	4.65E-06	11
9	0.0934	0.1338	0.0962	1.2023	3
10	0.0860	0.0266	0.0921	0.2108	10
11	0.0967	0.1426	0.0985	1.3596	2

4.2 Optimization Treatment with Many Objectives on Turning Process of Steel by Using Orthogonal Design Method

In general, the tool life will reduce with the increase of productivity in turning process [15]. Therefore, it is necessary to conduct optimal design of turning process parameters so as to ensure the coordination between goals in production process.

Trung [15] once used SKS3 steel to study the parametric optimization with orthogonal experimental design (OED) $L_9(3^4)$ in turning process. The tool used in the study was coated with TiN. The OED contains four input variables, each with three levels.

The test design and test results are cited in Tab. 4 [15]. Wherein, the input variables are: v_c cutting speed, f feeding speed, a_r cutting width, and a_p cutting depth; The objective responses include surface roughness of the sample *Ra*, and cutting removal rate *MRR*. *Ra* belongs to unbeneficial attribute index, while *MRR* belongs to beneficial attribute index. The evaluation results of PMOO are shown in Tab. 5.

Table 4 Results of the turning process of SKS3 steel by using OED [15]

No.	Input variable				Response	
	v_c (m/min)	f (mm/rev)	a_r (mm)	a_p (mm)	Ra (mm)	MRR (mm^3/min)
A1	80	0.05	4	0.1	0.970	25.465
A2	80	0.10	8	0.3	1.085	305.577
A3	80	0.15	12	0.5	2.032	1145.916
A4	100	0.05	8	0.5	0.746	318.310
A5	100	0.10	12	0.1	0.609	190.986
A6	100	0.15	4	0.3	1.001	286.479
A7	120	0.05	12	0.3	0.858	343.775
A8	120	0.10	4	0.5	0.326	381.972
A9	120	0.15	8	0.1	1.083	229.183

Tab. 5 shows the assessments of the partial and global favorable probabilities of Ra and MRR in the orthogonal test design.

Table 5 Evaluations of preferable probabilities under the orthogonal test design

No.	Favorable probability			Rank
	P_{Ra}	P_{MRR}	Global $P_i \times 10^2$	
A1	0.110934	0.00789	0.087522	9
A2	0.101742	0.094674	0.963239	4
A3	0.026055	0.355030	0.925029	6
A4	0.128836	0.098619	1.270575	3
A5	0.139786	0.059172	0.827135	7
A6	0.108456	0.088757	0.962626	5
A7	0.119885	0.106509	1.276882	2
A8	0.162404	0.118343	1.921942	1
A9	0.101902	0.071006	0.723565	8

From Tab. 5, the Test No. A8 is with the maximum value of the global favorable probability P_i, it could be directly chosen as the optimal scheme in orthogonal test design with many objectives at the first glance.

Furthermore, Tab. 6 shows the assessments of range analysis of the global favorable probabilities of the strengthened plate in drawing process by using OED.

Table 6 Evaluations of range analysis of the global preferable probabilities of turnin process

Level	v_c	f	a_r	a_p
Level 1	0.6586	0.8783	0.9907	0.5461
Level 2	1.0201	1.2374	0.9858	1.0676
Level 3	1.3075	0.8704	1.0097	1.3725
Range	0.6489	0.3670	0.0239	0.8264
Order	2	3	4	1

The range analysis in Tab. 6 shows that the impact order of input variables reduces from a_p, v_c, f to a_r. As a result, the optimal option is a_p3-v_c3-$f2$-a_r3, which only differs from experimental scheme A8 by the value of the weakest input parameter a_r, so the optimized configuration is really close to the experimental scheme A8 [15].

4.3 Multi-objective Uniform Experiment Design in Isoprene Rubber Formulation

Yao once studied the composition design of isoprene rubber [16]. In the test of isoprene rubber formulation, three input variables were investigated and their dosage ranges in parts are: x_1 (semi-reinforced carbon black): 20-40, x_2 (sulfur): 0.8-2.0, x_3 (TMTD): 0.8-2.2. The responses include tensile strength Y_1 (MPa), elongation at break Y_2 (%), tear strength Y_3 (kN/m) and permanent deformation at break Y_4 (%).The uniform design table $U_9(9^5)$ is chosen for uniform design of experiment (UDE) [16].

Tab. 7 shows the design and experimental results of responses, Y_1, Y_2, Y_3 and Y_4. In the optimal design, Y_1, Y_2 and Y_3 are beneficial performance utility indexes of the division in the new methodology [5, 6], while Y_4 is attributed to the unbeneficial performance utility index. The partial components of favorable probability of above utility indexes together with global favorable probabilities are shown in Tab. 8. The data in Tab. 8 shows that the test No. 4 indicates the maximum value of the global favorable probability P_{t1}, therefore it can be taken as the optimal option in the UDE with multi-response from the direct observation.

Table 7 Design and experimental results of optimization with the responses of Y_1, Y_2, Y_3 and Y_4

Variable				Response			
No.	x_1	x_2	x_3	Y_1 (MPa)	Y_2 (%)	Y_3 (kN/m)	Y_4 (%)
1	20	1.25	1.85	13.920	690.64	42.91	32.72
2	22	1.85	1.50	13.704	703.29	45.36	32.96
3	25	1.10	1.15	14.921	751.36	54.60	31.30
4	27	1.70	0.80	15.193	763.43	57.80	34.10
5	30	0.95	2.025	14.242	729.44	47.85	35.51
6	32	1.55	1.675	13.531	700.58	47.78	35.93
7	35	0.80	1.325	13.504	746.66	50.02	33.85
8	37	1.40	0.975	13.281	726.30	50.71	36.83
9	40	2.00	2.20	12.431	606.54	39.96	43.70

Table 8 Partial components of preferable probability of Y_1, Y_2, Y_3 and Y_4 and global preferable probabilities

Exp. run	P_{Y1}	P_{Y2}	P_{Y3}	P_{Y4}	$P_{t1} \times 10^4$
1	0.1116	0.1076	0.0982	0.1181	1.3927
2	0.1099	0.1096	0.1038	0.1174	1.4675
3	0.1196	0.1171	0.1249	0.1221	2.1363
4	0.1218	0.1189	0.1323	0.1142	2.1891
5	0.1142	0.1137	0.1095	0.1103	1.5670
6	0.1085	0.1092	0.1093	0.1091	1.4125
7	0.1087	0.1163	0.1145	0.1149	1.6570
8	0.1065	0.1132	0.1160	0.1066	1.4901
9	0.0997	0.0945	0.0914	0.0873	0.7518

Furthermore, regression analysis of total favorable probably *vs* input variables is conducted, which results in a regressed function,

$$P_{t_1} \times 10^4 = 3.5448 + 0.1626x_1 - 4.5063x_2 - 0.0049x_1^2 + \\ +0.9701x_2^2 - 0.0961x_3^2 + 0.0696x_1x_2 - 0.3133x_2x_3, \quad (1) \\ R^2 = 0.999992.$$

The function P_{t1} reaches to its maximum value of $P_{t1} \times 10^4 = 2.7147$ at specific values of input variables $x_1 = 22.12$, $x_2 = 0.80$ and $x_3 = 0.8$, which is much higher than the values of the total favorable probability P_i in Tab. 8.

While, the regression function of response Y_1 is,

$$f_{Y_1} = 18.7356 + 0.2916x_1 - 9.6921x_2 - 0.0108x_1^2 + \\ +2.1053x_2^2 + 0.2473x_3^2 + 0.1839x_1x_2 - 1.268x_2x_3, \quad (2) \\ R^2 = 1.$$

The predicted value for f_{Y1} is 16.0807 at above specific values of input variables $x_1 = 22.12$, $x_2 = 0.80$ and $x_3 = 0.8$.

The regression function of response Y_2 is,

$$f_{Y_2} = 576.9396 + 18.972x_1 - 70.9024x_2 - 0.3377x_1^2 + \\ +36.7414x_2^2 + 2.2947x_3^2 - 0.1002x_1x_2 - 44.8255x_2x_3, \quad (3) \\ R^2 = 0.9994.$$

The predicted value for f_{Y2} is 769.1696 at the specific values of input variables $x_1 = 22.12$, $x_2 = 0.80$ and $x_3 = 0.8$.

The regression function of response Y_3 is,

$$f_{Y_3} = 53.8523 + 2.722x_1 - 48.2493x_2 - 0.0694x_1^2 + \\ +10.1200x_2^2 - 0.9884x_3^2 + 0.9111x_1x_2 - 5.4124x_2x_3, \quad (4) \\ R^2 = 1.$$

The predicted value for f_{Y3} is 60.0092 at the specific values of input variables $x_1 = 22.12$, $x_2 = 0.80$ and $x_3 = 0.8$.

The regression function of response Y_4 is,

$$f_{Y_4} = 34.05144 - 0.5809x_1 - 0.6335x_2 + 0.0120x_1^2 + \\ +1.0011x_2^2 + 2.0612x_3^2 + 0.1679x_1x_2 - 2.8228x_2x_3, \quad (5) \\ R^2 = 1.$$

The predicted value for f_{Y4} is 29.6786 at the specific values of input variables $x_1 = 22.12$, $x_2 = 0.80$ and $x_3 = 0.8$.

4.4 Multi-objective Optimization for Cleaning Device Design with Uniform Design Method

Sun et al. conducted cleaning device design and optimization with many objectives by means of uniform design, here it is reanalyzed by using the newly proposed method quantitatively.

The crank speed X_1, crank length X_2, airflow speed X_3, wind direction angle (installation angle of fan) X_4 and lower screen surface installation angle X_5, are chosen as the five input variables in the test design, and each variable takes ten levels. The sieve time Y_1 and the falling horizontal displacement Y_2 are used as the evaluation responses, which have the performance characters of the smaller the better for the optimization [17], so Y_1 and Y_2 are classified into the unbeneficial type of utility indexes of performance according to the novel method [5, 6]. The $U_{10}(10^{10})$ of the uniform design table is chosen for experiment design [17]. The experimental design and test results are cited in Tab. 9 [17]. The partial components of favorable probability of above performances together with global favorable probabilities are shown in Tab. 9. The data in Tab. 9 shows that the test option 7 indicates the maximum value of the global favorable probability P_{t2}, therefore it can be taken as one of the optimal combination in the UED with many objectives from the direct observation.

Similarly, the regression analysis of the total favorable probably *vs* input variables is conducted, which results in a regressed function,

$$P_{t2} \times 10^2 = -28.5651 + 0.1998X_1 + 0.5245X_2 + \\ +0.1347X_3 - 0.0435X_4 - 0.0083X_5 - 0.0004X_1^2 - \\ -0.0219X_2^2 - 0.0149X_3^2 + 0.0003X_4^2, \quad (6) \\ R^2 = 1.$$

Table 9 Test design test results, partial components of favorable probability and global favorable probability

No.	X_1 (r/min)	X_2 (mm)	X_3 (m/s)	X_4 (°)	X_5 (°)	Y_1 (s)	Y_2 (mm)	P_{Y1}	P_{Y2}	$P_{t2} \times 10^2$
1	260	13.5	4	35	11.34	0.4258	579	0.1325	0.0911	1.2063
2	265	14.5	5.5	60	7.34	0.863	536.5	0.0862	0.0992	0.8552
3	270	15.5	7	30	14.34	0.637	542.6	0.1101	0.0980	1.0793
4	275	16.5	3	55	10.34	1.082	562.8	0.0631	0.0942	0.5941
5	280	17.5	4.5	25	6.34	0.799	497.2	0.0930	0.1066	0.9919
6	285	13	6	50	13.34	0.666	554.9	0.1071	0.0957	1.0242
7	290	14	7.5	20	9.34	0.382	482.9	0.1371	0.1094	1.4993
8	295	15	3.5	45	5.34	0.795	546	0.0934	0.0974	0.9096
9	300	16	5	15	12.34	0.354	540.9	0.1400	0.0983	1.3770
10	305	17	6.5	40	8.34	1.325	478.2	0.0374	0.1103	0.4126

The function P_{t2} reaches its maximum value of $P_{t2}\times10^2 = 1.9737$ at specific values of input variables $X_1 = 277.5626$ r/min, $X_2 = 13.0$ mm, $X_3 = 4.6073$ m/s, $X_4 = 15°$ and $X_5 = 5.34°$, which is obviously higher than the values of the total preferable probability P_{t2} in Tab. 9.

The regression function of response Y_1 is,

$$f_{Y_1} = 48.1641 - 0.2717X_1 - 1.3349X_2 - 0.4256X_3 + \\ +0.0180X_4 - 0.1015X_5 + 0.0005X_1^2 + 0.0485X_2^2 + \\ +0.0453X_3^2 + 0.0049X_5^2, \quad (7) \\ R^2 = 1.$$

The predicted value for f_{Y1} is 0.0508 at the specific values of input variables $X_1 = 277.5626$ r/min, $X_2 = 13.0$ mm, $X_3 = 4.6073$ m/s, $X_4 = 15°$ and $X_5 = 5.34°$.

The regression function of response Y_2 is,

$$f_{Y_2} = -2076.83 + 9.5923X_1 + 164.4545X_2 + \\ +24.8636X_3 + 2.3195X_4 + 6.3X_5 - 0.0176X_1^2 - \\ -5.6364X_2^2 - 4X_3^2 - 0.027X_4^2, \quad (8) \\ R^2 = 1.$$

The predicted value for f_{Y2} is 510.9258 at the specific values of input variables X_1 = 277.5626r/min, X_2 = 13.0 mm, X_3 = 4.6073 m/s, X_4 = 15° and X_5 = 5.34°.

5 CONCLUSION

Through analyzing optimal scheme of material processing with designed experiments of response surface methodology, orthogonal experiment design and uniform experiment design in this paper, it can be seen that that the novel "intersection" methodology optimization with many objectives might be easily combined with designed experiments to treat optimal problem of designed experiments. The global favorable probability of an alternative is the decisive indicator in the optimal option uniquely, which could transfer the optimization problem with many objectives into an optimization problem with mono-objective. The subsequent analysis is focused on total favorable probability in the experimental designs.

Conflict Statement

There is not any conflict of interest in this article.

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