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Perspective

Parametric optimization and determination in machining processes by means of probabilistic multi-objective optimization

Maosheng Zheng[1,*], Jie Yu[2]

[1] School of Chem. Eng., Northwest University, Xi'an 710069, China
[2] College of Life Sci., Northwest University, Xi'an 710069, China
*** Corresponding author:** Maosheng Zheng, mszhengok@aliyun.com

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Abstract: In the present article, it attempts to present the determination of optimal parameters of machining processes by means of probabilistic multi-objective optimization (PMOO), in which the optimal objectives (attributes) are fundamentally divided into beneficial type and unbeneficial type, moreover all attributes of both beneficial type and unbeneficial type are evaluated separately with equivalent manner to get their partial preferable probability. Finally, the total preferable probability of each alternative is obtained by the product of all partial preferable probabilities, which is the unique and decisive representative of the alternative to join the competitive optimization, the optimum alternative is with the highest total preferable probability. An example of parametric optimization and determination of aerospace component with Electro Chemical Machining (ECM) is taken to illuminate the procedure. In the case of ECM, the current, voltage, and feed rate are as the optimal parameters to be investigated, while Material Removal Rate (MRR), and Surface Roughness (SR) are the optimal objective responses to be measured. The experimental runs were designed using an L_{27} Taguchi orthogonal array. In the assessment of PMOO for ECM, the objective MRR belongs to the beneficial attribute, and the objective SR is as the unbeneficial attribute. The novelty of this work is to reflect the simultaneity and the irreplacement of optimization of objectives MRR and SR in the optimal system. The evaluated results reveal that the optimized experimental scheme is the alternative 8, which is with the optimal responses of MRR of 280.112 g/min and SR of 0.45 μm, the corresponding optimum experimental parameters are voltage of 12 V, electrolyte flow rate of 12 m/s and tool feed rate of 0.4 mm/min, respectively. The achievement of the present article indicates the validity of the corresponding approach and algorithm.

Keywords: optimal parameters; machining processes; probabilistic multi-objective optimization; simultaneity; systems theory

1. Introduction

Parametric optimization and determination in machining processes could improve the productivity of the aerospace industry. In general, the machining performance could be measured in terms of Material Removal Rate (MRR), Surface Roughness (SR) and Tool Wear Rate (TWR) [1]. Producing components with high accuracy increases the performance of the mechanical parts [2].

In order to meet the requirements for aero-components, there appears some significant and essentially Unconventional Machining Process for production technologies, such as Electro Chemical Machining (ECM), Plasma Arc Machining (PAM), Electric Beam Machining (EBM), Electric Discharge Machining (EDM) and Ultra Sonic Machining (USM), which avoids the direct contact of metal to tool [3–5].

Electrochemical machining (ECM) is one of the most appropriate approaches for machining of aero-components since it has distinctive benefits, including negligible tool wear, excellent machining efficiency, autonomy, and low cost in accordance with the exact physical properties of the corresponding material [6,7].

However, the optimization of a machining system with many objective responses simultaneously is still a problem, though some so called "multi criteria decision making methods" were frequently used to deal with the relevant problems [8], such as Grey Rational Analysis (GRA), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), Vlse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Multi- Objective Optimization on the Basis of Ratio Analysis (MOORA), ELimination and Choice Expressing Reality (ELECTRE), Preference Ranking for Organization Method for Enrichment Evaluation (PROMETHEE), etc. The intrinsic drawback of above methods is the lack of revealing the simultaneity and the irreplacement of many optimal objectives in the system. The fatal shortcoming of these methods is not aware.

Recently, probabilistic multi-objective optimization (PMOO) was proposed [8], which could reveal the simultaneity and the irreplacement of many optimal objective responses in the system properly, in which the optimal objectives (attributes) are basically divided into both beneficial type and unbeneficial type, furthermore all attributes of above two types are evaluated separately with equivalent manner to obtain their partial preferable probability. Finally, the total preferable probability of each alternative is gained by the product of all partial preferable probabilities, which is the unique and decisive representative of the alternative to join the optimization competitively. The optimum alternative with the highest total preferable probability wins the competition at last [8].

In the present article, the parametric optimization and determination of aerospace component with Electro Chemical Machining (ECM) is taken as an example to illuminate the successful utility of probabilistic multi-objective optimization (PMOO) in machining processes.

2. Brief introduction of methodology of probabilistic multi-objective optimization

The probabilistic multi-objective optimization (PMOO) is concisely demonstrated here [8].

Generally, in a multi-objective optimization (MOO) problem some attribute utility indexes are with the characteristics of "the higher the better" [8], i.e., the attribute with higher value is inevitably more welcomed and could get more preference, this type of attribute is called beneficial index. In this case, a term "preferable probability" could be introduced to reflect the "preference degree" of the attribute in the optimization process reasonably [8]. Furthermore, for the simplicity, it assumes that the partial preferable probability of such kind of attribute responses is proportional to the specific value of its attribute utility index positively, i.e.,

$$P_{ij} = A_j U_{ij},\ i = 1, 2, ..., n, j = 1, 2, ..., m. \tag{1}$$

In Equation (1), n is the total number of alternatives in the relevant candidate system; m represents the total number of objective response indicators of each alternative; U_{ij} is the utility value of the j-th objective indicator of the i-th alternative; P_{ij} represents the partial preferable probability of the beneficial attribute index U_{ij}; A_j represents the normalization factor of the j-th beneficial attribute (objective) indicator.

In the light of general principle of probability theory [9], for the j-th material objective response index, it derives following expression for the normalization factor [8],

$$A_j = 1/(n\overline{U_j}) \tag{2}$$

In Equation (2), $\overline{U_j}$ is the average utility value of the j-th attribute index in the attribute group involved.

On the other hand, in a MOO problem some attribute utility indexes are with the characteristics of "the lower the better" [8], i.e., the attribute with lower value is more welcomed and could get more preference, this type of objective responses is called unbeneficial index. In this case, the partial preferable probability of the unbeneficial attribute is assumed to be linearly related to its attribute utility index value negatively in the optimization process equivalently,

$$P_{ij} = B_j(U_{jmax}+U_{jmin}-U_{ij}),\ i = 1, 2, ..., n, j = 1, 2, ..., m. \tag{3}$$

In Equation (3), both U_{jmin} and U_{jmax} represent the minimum and maximum utility values of the attribute indicators in the j-th objective (attribute) group, respectively; B_j is the normalization factor of the j-th unbeneficial attribute index, which can be expressed as [8],

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

In Equation (4), the symbols $\overline{U_j}$, U_{jmin} and U_{jmax} are with the same meanings as in the previous paragraphs.

Furthermore, according to the fundamentals of probability theory [9], the total preferable probability of the i-th alternative can be written as the product of all partial preferable probabilities,

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

Obviously, in this assessment, the total preferable probability of each alternative is the unique and decisive index in the optimization process. This is the probabilistic multi-objective optimization (PMOO). Besides, through above procedures with Equations (1)–(5), the multi-objective optimization problem is now transformed into a single-objective optimization one in term of total preferable probability naturally. At last, the optimum alternative corresponds to the specific candidate that is with the highest total preferable probability, which is the optimal result of this overall optimization.

Moreover, if there is a weighting factor w_j for j-th objective response, the total preferable probability of the i-th alternative can be expressed in following form [8],

$$P_i = {P_{i1}}^{w_1} \cdot {P_{i2}}^{w_2} \cdot \ldots \cdot {P_{ij}}^{w_j} \cdot \ldots = \prod_{j=1}^{m} {P_{ij}}^{w_j}. \tag{6}$$

Many applications of above approach are performed [8], which gave acceptable consequences and are consistent with known. This indicates the reasonability of the approach.

In next section, the parametric optimization and determination of aerospace component with Electro Chemical Machining (ECM) is taken as an example to illuminate the utility of probabilistic multi-objective optimization in machining processes.

3. Application example and results

Parametric optimization and determination of aerospace component with Electro Chemical Machining (ECM) is illuminated as an example here [7]. In the case of ECM, the current, voltage, and feed rate are used as the optimal parameters to be investigated, while the Material Removal Rate (MRR), and Surface Roughness (SR) are the optimal objective responses to be measured and assessed. The experimental runs were designed using an L_{27} Taguchi orthogonal array.

In the experiment, 27 trial runs completed [7], which is cited in **Table 1**. In the assessment of PMOO for this issue, the objective MRR is as the beneficial attribute, and the objective SR is as the unbeneficial attribute.

The assessment result of this issue is presented in **Table 2**. In **Table 2**, the columns 4, 5, and 6 give the assessed results of partial preferable probability P_{MRR} for Material Removal Rate (MRR), partial preferable probability P_{SR} for Surface Roughness (SR), and total preferable probability $P_t \times 10^3$ for each alternative, respectively. The column 7 gives the ranking value according to the total preferable probability of each alternative.

From **Table 2**, it can be seen that the experimental scheme 8 is with the highest total preferable probability and at rank 1 position in the assessment by means of probabilistic multi-objective optimization, thus the optimized experimental scheme is alternative 8 with the optimum responses of MRR of 280.112 g/min and SR of 0.45 μm, which is with the optimum experimental parameters of voltage of 12 V, electrolyte flow rate of 12 m/s and tool feed rate of 0.4 mm/min. However, Animesh Kumar Sharma et al got the alternative 3 as their optimized the experimental scheme by means of using VIKOR and TOPSIS [7], the latter is with the responses of MRR of 117.824 g/min and SR of 0.89 μm. Obviously the responses of MRR and SR of alternative 8 are much superior to those of alternative 3.

Table 1. Experimental results of the aerospace component with ECM.

No.	Voltage (V)	Electrolyte flow rate (m/s)	Tool feed rate (mm/min)	MRR (g/min)	SR (μm)
1	12	8	0.2	288.176	1.23
2	12	8	0.4	208.656	0.91
3	12	8	0.6	117.824	0.89
4	12	10	0.2	235.424	0.57
5	12	10	0.4	330.512	1.22
6	12	10	0.6	311.472	1.87
7	12	12	0.2	235.424	1.12

Table 1. (*Continued*).

No.	Voltage (V)	Electrolyte flow rate (m/s)	Tool feed rate (mm/min)	MRR (g/min)	SR (μm)
8	12	12	0.4	280.112	0.45
9	12	12	0.6	140.896	1.46
10	15	8	0.2	344.960	1.21
11	15	8	0.4	205.744	1.32
12	15	8	0.6	328.608	0.78
13	15	10	0.2	160.720	1.93
14	15	10	0.4	228.032	0.81
15	15	10	0.6	114.016	0.90
16	15	12	0.2	205.520	1.36
17	15	12	0.4	219.072	1.72
18	15	12	0.6	177.744	1.78
19	18	8	0.2	202.272	0.85
20	18	8	0.4	339.472	1.97
21	18	8	0.6	271.264	1.58
22	18	10	0.2	308.112	1.49
23	18	10	0.4	302.848	1.18
24	18	10	0.6	314.048	1.27
25	18	12	0.2	268.912	1.48
26	18	12	0.4	132.384	1.61
27	18	12	0.6	134.848	2.01

Table 2. Assessment result of the aerospace component with ECM.

No.	MRR (g/min)	SR (μm)	Partial preferable probability for MRR, P_{MRR}	Partial preferable probability for SR, P_{SR}	Total preferable probability, $P_t \times 10^3$	Rank
1	288.176	1.23	0.0450	0.0391	1.7591	9
2	208.656	0.91	0.0326	0.0493	1.6050	11
3	117.824	0.89	0.0184	0.0499	0.9180	18
4	235.424	0.57	0.0367	0.0601	2.2082	3
5	330.512	1.22	0.0516	0.0394	2.0339	5
6	311.472	1.87	0.0486	0.0188	0.9120	19
7	235.424	1.12	0.0367	0.0426	1.5656	12
8	280.112	0.45	0.0437	0.0639	2.7941	1
9	140.896	1.46	0.0220	0.0318	0.6992	23
10	344.960	1.21	0.0538	0.0397	2.1399	4
11	205.744	1.32	0.0321	0.0362	1.1640	16
12	328.608	0.78	0.0513	0.0534	2.7397	2
13	160.720	1.93	0.0251	0.0169	0.4227	26
14	228.032	0.81	0.0356	0.0525	1.8672	7
15	114.016	0.90	0.0178	0.0496	0.8827	20
16	205.520	1.36	0.0321	0.0350	1.1219	17
17	219.072	1.72	0.0342	0.0235	0.8045	22

Table 2. (*Continued*).

No.	MRR (g/min)	SR (μm)	Partial preferable probability for MRR, P_{MRR}	Partial preferable probability for SR, P_{SR}	Total preferable probability, $P_t \times 10^3$	Rank
18	177.744	1.78	0.0277	0.0216	0.5998	24
19	202.272	0.85	0.0316	0.0512	1.6161	10
20	339.472	1.97	0.0530	0.0156	0.8255	21
21	271.264	1.58	0.0423	0.0280	1.1847	15
22	308.112	1.49	0.0481	0.0308	1.4832	13
23	302.848	1.18	0.0473	0.0407	1.9238	6
24	314.048	1.27	0.0490	0.0378	1.8547	8
25	268.912	1.48	0.0420	0.0312	1.3078	14
26	132.384	1.61	0.0207	0.0270	0.5584	25
27	134.848	2.01	0.0210	0.0143	0.3011	27

4. Conclusion

The probabilistic multi-objective optimization is an effective methodology to deal with the parametric optimization and determination in machining processes. In the PMOO assessment, the optimal objectives (attributes) are basically divided into both beneficial type and unbeneficial type; all objective responses of either beneficial type or unbeneficial type are evaluated separately with equivalent manner simultaneously. The achievement of the present article reflects the validity of the corresponding approach and algorithm for the utilization of multi-objective optimization in machining processes.

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