AN APPROACH OF PROBABILITY-BASED MULTI–OBJECTIVE OPTIMIZATION CONSIDERING ROBUSTNESS FOR MATERIAL ENGINEERING

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Abstract:

Introduction/purpose: The newly developed probability-based multi – objective optimization (MOO) has introduced a novel concept of preferable probability to represent a preferability degree of a candidate in optimization in order to overcome the inherent shortcomings of subjective and "additive" factors in the previous MOO methods. In this paper, the new method is extended to include robust optimization for material engineering. Furthermore, energy consumption in a melting process with orthogonal array design and the robust optimization of four different process schemes in machining an electric globe valve body are taken as examples.

Methods: The arithmetic mean value of each performance utility indicator of the candidate contributes to one part of the partial preferable probability, while the deviation of each performance utility indicator from its arithmetic mean value of the candidate contributes to the other part of the partial preferable probability quantitatively. Furthermore, following the procedures of the newly developed probability-based multi–objective optimization (PMOO), the total preferable probability of a candidate is obtained, which thus transfers a multi–objective optimization problem into a single–objective optimization problem.

Results: The optimal control factors of lower electric energy consumption with robustness are bundled steel, loose steel, and uncleaned steel of

12.5%, 50% and 37.5% by weight, respectively, in this steel melting process. This case is closely followed by the scenario of 50 wt% bundled steel, 50 wt% loose steel, and 0 wt% uncleaned steel. The robust optimization of four different process schemes for machining an electric globe valve body is scheme No. 1.

Conclusion: The extension of probability-based multi-objective optimization while considering robustness is successful, which can be easily used to deal with the optimal problem with dispersion of data to get objectively an optimal result with robustness in material engineering. The extension of probability-based multi-objective optimization while considering robustness will be beneficial to relevant research and process optimization.

Key words: multi-objective optimization, probability theory, preferable probability, material engineering, robustness.

Introduction

Recently, the probability-based multi–objective optimization (PMOO) method was developed (Zheng et al, 2021) in an attempt to solve the inherent problems of personal and subjective factors in previous multi–objective optimizations (MOOs). The new concept of preferable probability was introduced to represent a preferable degree of a candidate in optimization. In PMOO, all performance utility indicators of candidates are divided into two types, i.e., beneficial or unbeneficial types according to their functions in the selection; each performance utility indicator of the candidate makes its contribution to a partial preferable probability quantitatively, and furthermore, the product of all partial preferable probabilities makes the total preferable probability of a candidate in the viewpoint of probability theory, which is the unique decisive index in the selection process and thus transfers the multi – objective optimization problem into single–objective optimization. PMOO was also extended to the application of the multi-objective orthogonal test design method (OTDM) and the uniform design method (UDM) as well, where appropriate achievements have been obtained (Zheng et al, 2021; Zheng, 2022).

In general, quality improvement of products and optimization of processes are continuously demanded by manufacturers. In 1980s, Taguchi once contributed a discipline and structure to the design and assessment of experiments so as to raise the quality of products by means of design optimization with efficient cost (Roy, 2010). In Taguchi's method, a formal way is incorporated to include noise factors in the experiment layout, which aims to make products and processes insensitive to the influence of uncontrollable (noise) factors. He created an orthogonal experiment design to study the effects of noise factors with smaller size of experiments, which results in a favorable performance with the mean close to the target and reduced variation around the mean (Roy, 2010). The main point is to focus on the prechosen target for the output response with great extent and less variability. The controllable factors are called control factors. It is assumed that the majority of variability around the target is due to the existence of a second set of factors called noise factors or variables. Noise factors are uncontrollable in the product design or process operation (Myers et al, 2016). As a result, the term robust parameter design entails designing the system so as to get robustness (insensitivity) to inevitable changes in the noise variables. Taguchi suggested using a factor called "signal - to - noise ratio" (SNR) to characterize robustness. Taguchi suggested some primary SNRs. The three specific commonly used goals are: 1). the smaller the better; 2). the larger the better; 3). the target is the best.

Taguchi suggested a SNR for cases in which the response standard deviation is related to the mean linearly. For this case, Taguchi's SNR for "the target is the best" condition is given by

$$SNR = -10\log(\bar{y}^2 / s^2) \tag{1}$$

where the SNR is to be maximized; $\bar{y}$ is the mean value of the test points, and s is the standard error.

In fact, for a set of actual experiments or processes, the mean value of the test points $\bar{y}$ and the standard error s are independent factors in general.

While, in Eq. (1), the SNR condenses the two factors into one factor, the optimization of the maximum of the SNR is not equivalent to the optimizations of the both minima of s and $\bar{y}$ closing to the target at the same time. What is worse is that in the cases of "the smaller the better" and "the larger the better', the expressions of SNRs suggested by Taguchi even excluded the factor of the standard error. This point was criticized by many statisticians (Box, 1988; Box & & Meyer, 1986; Welch et al, 1990, 1992; Nair et al, 1992) though the essence of the SNR in Taguchi's approach to robust parameter design is to propose an easy-to-use performance criterion which takes the process mean and variance into consideration. Statisticians further suggested taking both response mean and variance into account by using separate models. Therefore, for robust optimization, the optimization of the both minima of s and $\bar{y}$

closing to the target should be conducted with individual models at the same time.

In this paper, the new PMOO method is extended to include robust optimization of dispersion of data in material engineering due to the advantage of impersonality of the PMOO method, where both the response mean $\overline{y}$ and the variance s are taken into account by using separate models. Furthermore, energy consumption in the melting process with orthogonal array design and robust optimization of four different process schemes in the machining process of the electric globe valve body are studied as examples.

Extension of the probability-based multi–objective optimization method to include robustness

In PMOO, all performance utility indicators of candidates are divided into beneficial or unbeneficial types according to their functions in the selection where each performance utility indicator of the candidate makes its contribution to a partial preferable probability quantitatively, and furthermore, the product of all partial preferable probabilities makes the total preferable probability of a candidate in the viewpoint of the probability theory, which is the unique decisive index in the selection process and transfers the multi–objective optimization problem into a single–objective optimization problem (Zheng et al, 2021; Zheng, 2022).

In traditional MOO, the performance indexes of candidates are assumed to be well determined without any uncertainty. However, this is not always the case; for example, if we perform one experiment for ten times, we could get ten experimental data in general and both the arithmetic mean value of the ten data and the mean deviation can be taken as representatives for these experiments; In some other cases, the performance indexes and attributes are often vague, which results in un-exact numerical values instead of well determined data. In order to assess such problems containing uncertain elements, a proper approach is still needed. Taguchi created a formal way to include noise factors (Roy, 2010), but it is puzzling. Here we propose an extension for the newly developed PMOO to include the dispersion of data so as to establish probability-based multi–objective robust optimization.

In general, an uncertain element X_{ij} has the form of Eq. (2),

$$X_{ij} = \overline{X}_{ij} \pm \delta X_{ij} \tag{2}$$

In Eq. (2), $\overline{X}_{ij}$ represents the arithmetic mean value of the uncertain element X_{ij}, and δX_{ij} is the mean deviation of the performance index X_{ij}.

The arithmetic mean value $\overline{X}_{ij}$ represents the main function of the performance of a candidate, which quantitatively contributes one part of partial preferable probability according to its type of being either beneficial or unbeneficial relating to their functions in the selection.

For the beneficial type of performance, it contributes one part of partial preferable probability linearly in a positive manner; as to the unbeneficial type of performance, it contributes one part of partial preferable probability linearly in a negative manner (Zheng et al, 2021; Zheng, 2022).

Under condition of the uncertain element X_{ij}, the beneficial type of the arithmetic mean value $\overline{X}_{ij}$ of the uncertain element X_{ij} makes one part of the performance index according to

$$P_{ij1} = \alpha_{j1}\overline{X}_{ij}, \; i = 1,2,\ldots, n; \; j = 1, 2, \ldots, m. \quad (3)$$

In Eq. (3), P_{ij1} represents one part of the partial preferable probability of the beneficial utility index $\overline{X}_{ij}$; n is the total number of candidates in the candidate group involved; m is the total number of the performance utility indices of each candidate in the group; α_{ij1} is the normalized factor of the j-th utility index of the candidate performance indicator, $\alpha_{ij1} = 1/(n\bar{\bar{X}}_j)$, $\bar{\bar{X}}_j$ is the arithmetic mean value of the utility index of the performance indicator in the candidate group involved,

$$\overline{\overline{X}}_j = \frac{1}{n}\sum_{i=1}^{n}\overline{X}_{ij}. \quad (4)$$

For the unbeneficial type of performance, $\overline{X}_{ij}$ makes one part of its partial preferable probability of the performance according to

$$P_{ij1} = \beta_{j1}(\overline{X}_{j\max} + \overline{X}_{j\min} - \overline{X}_{ij}), \; i = 1,2,\ldots, n; \; j = 1, 2, \ldots, m. \quad (5)$$

In Eq. (5), $\bar{X}_{jmax}$ and $\bar{X}_{jmin}$ represent the maximum and minimum values of the performance utility indices $\bar{X}_{ij}$ of the candidate performance indicator in the group, respectively, and β_{j1} is the normalized factor of the j-th utility indices of the candidate performance indicator, $\beta_{j1} = 1/[n(\overline{X}_{j\min} + \overline{X}_{j\max}) - n\overline{\overline{X}}_j]$.

The mean deviation δX_{ij} is the unbeneficial type of the performance index in assessment in general, which has the characteristic of "the lower the better". The mean deviation δX_{ij} contributes the other part of the uncertain element X_{ij}, P_{ij2}, which is assessed according to Eq. (6),

$$P_{ij2} = \beta_{j2}(\delta X_{j\max} + \delta X_{j\min} - \delta X_{ij}),\ i = 1,2,\ldots,n;\ j = 1, 2, \ldots, m. \quad (6)$$

In Eq. (6), δX_{jmax} and δX_{jmin} represent the maximum and minimum values of the performance utility indices δX_{ij} of the candidate performance indicator in the group, respectively, and β_{j2} is the normalized factor of the j-th utility indices of candidate performance indicator, $\beta_{j2} = 1/[n(\delta X_{j\min} + \delta X_{j\max}) - n\overline{\delta X}_j]$.

The entire partial preferable probability of the uncertain element X_{ij} is the arithmetic mean of both parts, or square root of their product, i.e.,

$$P_{ij} = (P_{ij1} + P_{ij2})/2, \text{ or } P_{ij} = (P_{ij1} \times P_{ij2})^{0.5}. \quad (7)$$

The entire partial preferable probability P_{ij} includes all information of the uncertain element X_{ij} comprehensively, which is the overall representative of the uncertain element X_{ij} in the selection process competitively.

Moreover, the total / comprehensive preferable probability of the i^{th} candidate in a multi-objective optimization problem is the product of its partial preferable probability P_{ij} of each utility index of the candidate performance indicator in the overall selection due to the "simultaneous optimization" of multiple objectives in the viewpoint of probability theory (Zheng et al, 2021), i.e.,

$$P_i = P_{i1} \cdot P_{i2} \cdots P_{im} = \prod_{j=1}^{m} P_{ij}\ . \quad (8)$$

The total preferable probability of a candidate is the uniquely decisive index in the overall selection process competitively, which transfers a multi–objective optimization problem (MOOP) into a single – objective optimization one. The main characteristic of the new probability-based multi–objective optimization is that the treatment for both beneficial utility index and unbeneficial utility index is equivalent and conformable, which is without any artificial or subjective scaling factors involved in the process.

Application of the extended PMOO to assess an optimal problem with dispersion of data in material engineering

In the following study, the entire partial preferable probability of the uncertain element X_{ij} takes the arithmetic mean of both parts of Eq. (7).

1) Robust optimization for saving electric energy consumption of a foundry

Electric furnaces are generally used in foundries widely, including cupola furnaces, rotary furnaces, and induction furnaces. The induction furnace is usually utilized to melt a massive amount of steel. The electricity consumed for melting 1 ton of metal is in the range of 600–680 kWh/ton (Deshmukh & Hiremath, 2020). Deshmukh et al reported an orthogonal array experiment for the optimization of the process parameters in the melting process in the foundry with a "Signal to Noise Ratio" effect (Deshmukh & Hiremath, 2020). The study was focused on varying the process parameters so as to reduce consumption of electrical energy and get an optimization robust property (Deshmukh & Hiremath, 2020). An L9 orthogonal array was used to conduct the design experiment for control factors: bundled steel, loose steel and uncleaned steel in wt %, see Table 1.

Nine experiments were performed five times to reflect the variations that might be caused by noise factors. Table 2 shows the tested data of electric energy consumption from these designed experiments.

Table 1 –Control factors in experiment design
Таблица 1 – Контрольные факторы при проектировании эксперимента
Табела 1 – Контролни фактори при пројектовању експеримента

Scheme	Bundled steel (% by weight)	Loose steel (% by weight)	Uncleaned steel (% by weight)
1	12.5	37.5	50
2	33	33	33
3	37.5	12.5	50
4	50	0	50
5	12.5	50	37.5
6	50	12.5	37.5
7	50	50	0
8	33	33	33
9	37.5	50	12.5

Table 2 – Test data of electric energy consumption from these experiments

Таблица 2 – Данные о потреблении электроэнергии в результате экспериментов

Табела 2 – Подаци о утрошку електричне енергије из наведених експеримената

	Test data (kWh)					Representative data	
Scheme	1	2	3	4	5	Mean	Deviation
1	110	112	131	108	104	113	9.3808
2	109	111	120	121	114	115	4.7749
3	112	120	115	118	110	115	3.6878
4	98	102	106	112	104	104.4	4.6303
5	117	112	109	113	108	111.8	3.1875
6	121	116	109	107	113	113.2	4.9960
7	114	118	108	110	112	112.4	3.4409
8	116	112	110	104	109	110.2	3.9192
9	110	118	112	109	107	111.2	3.7630

Since the optimization of this problem is intended for saving electric energy consumption, the mean value of the electric energy consumption in Table 2 belongs to an unbeneficial performance index, thus Eq. (5) is employed to assess its portial preferable probability. Besides, Eq. (6) is used to assess the deviation contribution to the partial preferable probability. Finally, the entire partial preferable probability of each scheme is assessed by Eq. (7). Table 3 shows the results of the assessments. P_{mean}, and $P_{deviation}$ in Table 3 indicate one part of partial preferable probability of the mean value and the deviation value of electric energy consumption, respectively; P_{entire} is the entire partial preferable probability of electric energy consumption, which determines the ranking of each scheme in Table 3.

From Table 3, it can be seen that scheme 5 is the optimal one, since it consumes lower electric energy with less deviation, i.e., it is robust. The optimal control factors of bundled steel, loose steel and uncleaned steel are 12.5%, 50%and 37.5% by weight in this steel melting process, respectively; scheme 7 is No. 2, being close to scheme 5 with the control factors of bundled steel, loose steel and uncleaned steel at 50%, 50% and 0 % by weight, respectively.

Table 3 – Results of the assessments for the preferable probability of all schemes and their ranking

Таблица 3 – Результаты оценивания предпочтительной вероятности всех схем и их ранжирования

Табела 3 – Резултати оцењивања пожељних вероватноћа свих схема и њихово рангирање

Scheme	P_{mean}	$P_{deviation}$	P_{entire}	Rank
1	0.1099	0.0447	0.0773	9
2	0.1078	0.1093	0.1085	7
3	0.1078	0.1245	0.1161	5
4	0.1188	0.1113	0.1150	6
5	0.1111	0.1315	0.1213	1
6	0.1097	0.1062	0.1079	8
7	0.1105	0.1280	0.1192	2
8	0.1128	0.1212	0.1170	4
9	0.1117	0.1234	0.1176	3

2) Robust optimization for multi-objective decision making of mechanical processing plans based on the interval number

Han et al conducted multi-objective robust decision making of a mechanical processing plan based on the interval number (Han et al, 2020); four different process schemes for machining process of the electric globe valve body are comparetively studied, which is taken as an example here as well.

Table 4 shows the technical parameters of the four schemes. In this optimization process, only the rate of the qualified product is the beneficial type of the performance index, others belong to the unbeneficial type. Table 5 lists the partial preferable probability and the total preferable probability of each plan, as well as the overall ranking comparatively.

Table 4 – Technical parameters of the four plans
Таблица 4 – Технические параметры четырех планов
Табела 4 – Технички параметри четири плана

Plan	Time for product A (min)	Rate of qualified products B (%)	Total cost C (RMB Yuan)	Material consump. D (yuan)	Electric energy consump. E (°)	Solid waste F (kg)	Waste liquid discharge G (L)
1	[40, 51]	[96, 98]	[238, 285]	[82.6, 114.5]	[18.6, 21.5]	[0.86, 0.97]	[2.8, 3.1]
2	[48, 59]	[91, 95]	[254, 303]	[92.4, 123.3]	[19.8, 23.2]	[0.95, 1.22]	[2.9, 3.5]
3	[50, 62]	[89, 92]	[258, 310]	[94.2, 126.1]	[20.3, 25.2]	[1.07, 1.28]	[3.1, 3.9]
4	[42, 56]	[92, 96]	[245, 292]	[86.8, 116.9]	[19.1, 22.3]	[0.92, 1.15]	[2.9, 3.3]

Table 5 – Partial preferable probability and the total preferable probability of each plan, as well as their ranking.
Таблица 5 – Частичная предпочтительная вероятность и общая предпочтительная вероятность каждого плана, а также их ранжирование
Табела 5 – Делимичне пожељне вероватноће и укупна пожељна вероватноћа сваког плана и њихово рангирање

	Partial preferable probability							Total	
Plan	A	B	C	D	E	F	G	$P_t \times 10^4$	Rank
1	0.2732	0.3113	0.2597	0.2544	0.2778	0.3344	0.3080	1.6082	1
2	0.2534	0.2151	0.2469	0.2473	0.2545	0.1997	0.2332	0.3944	3
3	0.2376	0.2572	0.2369	0.2405	0.2026	0.2317	0.1782	0.2913	4
4	0.2357	0.2164	0.2565	0.2578	0.2651	0.2343	0.2805	0.5875	2

Table 5 shows that scheme No. 1 is the optimal one with a robust property.

Conclusion

The extension of the probability-based multi-objective optimization considering robustness is successful, which can be easily used to deal with an optimization problem with dispersion of data to get objectively an optimal result with robustness in material engineering.

Robust optimization design is a very important technology to improve quality of products and optimize processes for manufacturers. The extension of the probability-based multi-objective optimization considering robustness will be beneficial to relevant research and process optimization.

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ПРИМЕНЯЕМЫЙ В МАТЕРИАЛОВЕДЕНИИ ПОДХОД МНОГОКРИТЕРИАЛЬНОЙ ОПТИМИЗАЦИИ, ОСНОВАННОЙ НА ВЕРОЯТНОСТИ С УЧЕТОМ РОБАСТНОСТИ

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РУБРИКА ГРНТИ: 27.00.00 МАТЕМАТИКА:
27.47.00 Математическая кибернетика;
27.47.19 Исследование операций
81.00.00 ОБЩИЕ И КОМПЛЕКСНЫЕ ПРОБЛЕМЫ ТЕХНИЧЕСКИХ И ПРИКЛАДНЫХ НАУК И ОТРАСЛЕЙ НАРОДНОГО ХОЗЯЙСТВА:
81.09.00 Материаловедение
45.00.00 ЭЛЕКТРОТЕХНИКА:
45.09.00 Электротехнические материалы
ВИД СТАТЬИ: оригинальная научная статья

Резюме:

Введение/цель: Недавно разработанный подход многокритериальной оптимизации, основанной на вероятности (МОО) ввел новую концепцию предпочтительной вероятности для представления степени предпочтительности кандидатов в оптимизации, с целью преодоления существующих в предыдущих методах МОО недостатков, касающихся субъективных и "аддитивных" факторов. В данной статье представлен новый расширенный метод, включающий робастную оптимизацию применяемую в области материаловедения. Кроме того, приведены примеры энергопотребления в процессе плавки с ортогональной конструкцией решетки и робастной оптимизации четырех различных схем при машинном изготовлении корпуса электрического шарового крана.

Методы: Среднее арифметическое показателя эффективности кандидата способствует одной стороне частичной предпочтительной вероятности, в то время как отклонения показателя эффективности каждого кандидата от среднего арифметического количественно способствует другой стороне частичной предпочтительной вероятности. Также следует отметить, что при применении новоразработанной многокритериальной оптимизации, основанной на вероятности (МОО) вычисляется суммарная предпочтительная вероятность кандидата, что переводит задачу многокритериальной оптимизации в задачу однокритериальной оптимизации.

Результаты: Оптимальными контрольными факторами снижения потребления электроэнергии за счет робастности являются: импортная сталь, свободная сталь и сталь с примесями 12,5, 50 и 37,5 весовых процентов в соответствии с данным процессом плавки стали. Затем следует сценарий 50, 50 и 0 весовых процентов. Из четырех схем различных процессов машинного изготовления корпуса электрического шарового крана робастная оптимизация является схемой номер один.

Выводы: Многокритериальная оптимизация, основанная на вероятности, дополненная фактором робастности, оказалась более успешной, следовательно ее безусловно можно использовать при решении задач оптимальности с дисперсией данных для получения объективно оптимального результата с робастностью в области материаловедения. Расширение многокритериальной оптимизации, основанной на вероятности, учитывая робастность существенно поможет в релевантных исследованиях и оптимизации процессов.

Ключевые слова: многокритериальная оптимизация, теория вероятности, предпочтительная вероятность, материаловедение, робастность.

ПРИСТУП ВИШЕКРИТЕРИЈУМСКЕ ОПТИМИЗАЦИЈЕ ЗАСНОВАНЕ НА ВЕРОВАТНОЋИ, КОЈИ УЗИМА У ОБЗИР РОБУСТНОСТ, ПРИМЕЊЕН У ТЕХНОЛОГИЈИ МАТЕРИЈАЛА

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ОБЛАСТ: математика, материјали
ВРСТА ЧЛАНКА: оригинални научни рад

Сажетак:

Увод/циљ: Новоразвијени метод вишекритеријумске оптимизације заснован на вероватноћи (МОО) увео је концепт пожељне вероватноће да представи степен пожељности кандидата при оптимизацији као покушај да се превазиђу инхерентни недостаци субјективних и адитивних фактора у претходним методама МОО. У овом раду нова метода се проширује и укључује робустну оптимизацију приликом примене у области технологије материјала. Наведени су примери утрошка електричне енергије у процесу топљења са дизајном ортогоналног низа, као и робустне оптимизације четири различите шеме процеса машинске израде тела електричног лоптастог вентила.

Методе: Аритметичка средња вредност показатеља перформанси корисности кандидата доприноси једној страни делимичне пожељне вероватноће, док девијација сваког показатеља перформанси корисности кандидата од аритметичке средње вредности доприноси квантитативно другој страни делимичне пожељне вероватноће. Такође, применом поступка новоразвијене вишекритеријумске оптимизације, засноване на вароватноћи (МОО), добија се укупна пожељна вероватноћа кандидата, чиме се проблем вишекритеријумске оптимизације преводи у проблем једнокритеријумске оптимизације.

Резултати: Оптимални контролни фактори смањене потрошње електричне енергије помоћу робустности јесу увезани челик, слободни челик и челик с нечистоћама од 12,5, 50 и 37,5 тежинских процената, респективно, у овом процесу топљења челика. Одмах затим следи сценарио од 50, 50 и 0 тежинских процената, респективно. Од схема четири ратличита процеса машинске израде тела електричног лоптастог вентила, робустна оптимизација је схема број један.

Закључак:. Вишекритеријумска оптимизација заснована на вероватноћи проширена је помоћу робустности, што се показало успешним, тако да се може лако користити при решавању проблема оптималности са дисперзијом података како би се добио објективно оптимални резултат са робустношћу у технологији материјала. Проширивање вишекритеријумске оптимизације засноване на вероватноћи узимајући у обзир робустност биће од користи за релевантна истраживања и оптимизације процеса.

Кључне речи: вишекритеријумска оптимизација, теорија вероватноће, пожељна вероватноћа. технологија материјала, робустност.

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