Application of new robust design by means of probability-based multi-objective optimization to machining process parameters

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Abstract:

Introduction/purpose: New robust design by means of probability-based multi-objective optimization takes the arithmetic mean value of the performance indicator and its deviation as twin independent responses of the performance indicator. The aim of this article is to check the applicability of new robust design in optimizing machining process parameters. To conduct the examination in detail, the robust design for optimal cutting parameters to minimize energy consumption during the turning of AISI 1018 steel at a constant material removal rate is applied as well as the concurrent optimization of the machining process parameters and the tolerance allocation of a spheroidal graphite cast iron piston.

Methods: In the spirit of the probability-based method for multi-objective optimization, the arithmetic mean value of the performance indicator and its deviation are taken as two independent responses of the performance indicator to implement robust design. Each of the above twin responses contributes one part of the partial preferable probabilities to the performance indicator of the alternatives in the treatment. The arithmetic mean value of the performance indicator should be assessed as a representative of the performance indicator according to the function or the preference of the performance indicator, and the deviation is the other *index of the performance indicator, which has the characteristic of the smaller-the-better in general. Furthermore, the square root of the product of the above two parts of the partial preferable probability forms the actual preferable probability of the performance indicator. Moreover, the product of partial preferable probabilities gives the total preferable probability of each alternative, which is the overall and unique index of each alternative in the robust optimum.*

Results: The paper gives the rational optimum cutting parameters for minimizing energy consumption during the turning of AISI 1018 steel at a constant material removal rate and the concurrent optimization of the machining process parameters and the tolerance allocation of a spheroidal graphite cast iron piston.

Conclusion: The application study indicates its rationality and convenience of new robust optimization in the optimization of machining process parameters.

Key words: preferable probability; probability-based method; multi-objective optimization; robust design; simultaneous optimization.

Introduction

The importance of quality improvement through reducing the effect of noise on response was recognized early in 1950s by Taguchi - Taguchi's method (Roy, 2010; Mori & Tsai, 2011). Designed experiments could be performed to study the effects of both controllable and uncontrollable factors on product or process response. Uncontrollable factors are called noise factors by Taguchi (Roy, 2010; Mori & Tsai, 2011). The idea of robust design corresponds to a design of a set of controllable factors which make the quality of a product insensitive to so-called noise factors or sensitive as little as possible i.e. with a minimum effect of noise (Roy, 2010; Mori & Tsai, 2011).

In Taguchi's method (Roy, 2010; Mori & Tsai, 2011), it was further assumed that **controllable factors** include factors that can be easily controlled by an experimenter or a product designer, such as design of a prescription or a melting temperature in an alloy melting process, while **uncontrollable factors (noise factors)** are those impossible or not easily possible to control. So, robust design is a concept seeking a set of controllable factors which make product and processes with minimum sensitivity to the variations of uncontrollable factors without removing uncontrollable factors.

Moreover, signal-to-noise ratio (SNR) was introduced by Taguchi as a specific term to characterize robust design (Roy, 2010; Mori & Tsai, 2011). Optimum factors correspond to a set of controllable factors which guarantee an appropriate SNR maximum. There are three types of standard types of SNRs which were suggested by Taguchi:

- Nominal-the-best

$$SNR_T = 10\log\left(\frac{\overline{y}^2}{\sigma^2}\right), \tag{1}$$

- Smaller-the-better

$$SNR_s = -10\log\left(\frac{1}{l}\sum_{i=1}^{l} y_i^{\ 2}\right), \quad \text{and} \tag{2}$$

- Larger-the-better

$$SNR_L = -10\log\left(\frac{1}{l}\sum_{i=1}^{l}\frac{1}{y_i^{\ 2}}\right). \tag{3}$$

In the above Eqs. (1) - (3), l stands for the number of each experimental test, $\overline{y}$ is the arithmetic mean value of the l data of experimental tests, and σ is the standard deviation.

The mean value $\overline{y}$ of the tests and the standard error σ are inherently independent responses for a set of actual experiments or processes in general, which was pointed out by many statisticians - scientists (Box, 1988; Box & Meyer, 1986; Welch et al, 1990; Welch et al, 1992; Nair et al, 1992).

However, the SNR in Eq. (1) unites the two factors $\overline{y}$ and σ into one factor SNR_T unreasonably - the optimization of the maximum of the SNR_T is not equivalent to the simultaneous optimizations of the both minima of σ and $\overline{y}$ closing to the target. More problematically, the expressions of Eq. (2) and Eq. (3) for "smaller-the-better" and "larger-the-better" imply more serious cases, i.e., these formulae even exclude the factor of the standard deviation σ. This point was frequently criticized by statisticians (Box, 1988; Box & Meyer, 1986; Welch et al, 1990; Welch et al, 1992; Nair et al, 1992). A kind advice from statisticians was to consider both responses of the mean and the variance by using two individual models.

Therefore, the optimization of the both minima of σ and $\overline{y}$ closing to the target should be treated with two individual models at the same time so as to perform rational robust optimization.

In recent years, a probability-based method for multi–objective optimization (PMOO) was developed to solve the inherent problems of the “additive algorithm” with personal and subjective factors in previous multi–objective optimizations (Zheng et al, 2022a; Zheng et al, 2022b; Zheng et al, 2023). A new concept of preferable probability was introduced to represent the preference degree of performance utility indicator of candidates in optimization. In this new methodology, all performance utility indicators of alternatives could be preliminarily divided into two types, i.e., beneficial or unbeneficial types according to their functions or pre-required preference in the optimization; every performance utility indicator of the alternative could quantitatively contribute to a partial preferable probability. Moreover, the product of all partial preferable probabilities leads to the total preferable probability of an alternative by means of the probability theory, which is the uniquely decisive index of a candidate in the optimization process, thus transfering a multi–objective optimization problem into a single–objective one.

This paper shows the application of new robust design by means of the probability theory with taking the arithmetic mean values of the performance indicators of the alternatives and their deviations as two independent factors rationally in order to deal with the problem of robust optimization of machining process parameters. Two examples - turning of AISI 1018 steel at a constant material removal rate and a concurrent optimization of the machining process parameters and the tolerance allocation of a spheroidal graphite cast iron piston - are given to show the rationality of robust design in manufacturing.

Rational process of robust design by means of probability-based multi-objective optimization

1) Fundamental principle of probability-based multi-objective optimization

In the methodology of the probability-based method for multi–objective optimization [8-10], a new concept of preferable probability was introduced to represent a preference degree of a performance utility indicator in optimization. All performance utility indicators of alternatives could be preliminarily divided into two types, i.e., beneficial or unbeneficial types according to their functions or pre-required preference in the optimization; every performance utility indicator of an alternative contributes to a partial preferable probability quantitatively; moreover, the product of all partial preferable probabilities leads to the total preferable probability of an alternative in the viewpoint of probability theory to reflect the essence of their simultaneous optimization, which is the unique decisive index in the optimization process, thus transfering a multi–objective optimization problem into a single–objective one (Zheng et al, 2022a; Zheng et al, 2022b; Zheng et al, 2023).

The formation of total preferable probability of an alternative by multiplying all partial preferable probabilities of their performance utility indicators reveals the spirit of simultaneous optimization of each performance utility indicator in the spirit of the probability theory explicitly, which undoubtedly solves the intrinsic problems of “additive algorithms” of subjective factors in previous multi–objective optimizations.

2) Process of new robust design by means of probability-based multi-objective optimization

In the light of the suggestion from statisticians that both responses of the mean and the variance could be taken into account by using two individual models, the process of rational robust design by means of probability-based multi-objective optimization is as follows.

A) The arithmetic mean value of the performance indicator of the alternatives and its deviation are taken as twin independent responses of the performance indicator to conduct robust design. Each of the above two responses contributes one part of the partial preferable probabilities to the performance indicator of the alternatives in the treatment of robust design.

B) The arithmetic mean value of the performance indicator should be assessed as a representative of the performance indicator according to its function and preference, and the deviation is the other index of the performance indicator which has the characteristic of the smaller-the-better in general.

C) The square root of the product of both parts of partial preferable probability of the performance indicator forms the actual preferable probability of the performance indicator.

D) The product of all partial preferable probabilities forms the total preferable probability of each alternative, which is the overall and unique index of each alternative in the robust optimum.

E) The total preferable probability of the alternatives is the unique index which is used as the decisive indicator of every alternative to complete the robust optimum.

Applications of robust design by means of probability-based multi-objective optimization

The application examples of new robust design by means of probability-based multi-objective optimization in robust design of products are given here to illustrate the new approach in detail.

1) Optimization of cutting parameters to minimize energy consumption during the turning of AISI 1018 steel at a constant material removal rate

Camposeco-Negrete et al. conducted an optimization of cutting parameters to minimize energy consumption during the turning of AISI 1018 steel at a constant material removal rate. There are three control factors: the cutting speed (Factor A), the feed rate (Factor B), and the cut depth (Factor C) with three levels for each factor, as shown in Table 1 by means of the Taguchi $L_9(3^4)$ design with four test results (Camposeco-Negrete et al, 2016). The aim of this experimental design is to apply robust design for the optimization of energy consumption. The values of the cutting parameters shown in Table 1 were calculated in order to obtain a constant material removal rate of 1333.33 mm^3/s (Camposeco-Negrete et al, 2016).

Table 1 – Values and levels of the cutting parameters of AISI 1018 steel at a constant material removal rate by means of $L_9(3^4)$
Таблица 1 – Значения и уровни параметров резки стали AISI 1018 при постоянной скорости съема материала с помощью $L_9(3^4)$
Табела 1 – Вредности и нивои параметара сечења челика АИСИ 1018 при константној брзини уклањања материјала помоћу $L_9(3^4)$

Exp. no	Factor values			Energy consumed (kJ)			
	A (m/min)	B (mm/rev)	C (mm)	1	2	3	4
1	350	0.10	2.29	71.47	74.2	121.04	133.14
2	350	0.15	1.52	51.64	54.28	88.85	97.22
3	350	0.20	1.14	42.93	43.63	73.07	80.75
4	375	0.10	2.13	68.97	71.10	123.99	135.69
5	375	0.15	1.42	51.67	52.49	91.19	100.17
6	375	0.20	1.07	42.00	43.04	76.29	82.66
7	400	0.10	2.00	67.94	69.47	130.63	141.77
8	400	0.15	1.33	50.41	52.17	97.35	105.91
9	400	0.20	1.00	41.08	42.05	81.44	86.75

Table 2 shows the assessed results of the preferable probability and the ranks of this problem.

The mean value of energy consumption is shown by *μ*, and the standard deviation is represented by *s*.

According to the requirement of robust optimization, the performances of *μ* and *s* have the characteristic of the unbeneficial indexes in Table 2.

Table 2 – Assessed results of the preferable probability and the rank of AISI 1018 steel at a constant material removal rate by means of $L_9(3^4)$

Таблица 2 – *Результаты оценки предпочтительной вероятности и ранга стали AISI 1018 при постоянной скорости съема материала с помощью* $L_9(3^4)$

Табела 2 – Анализирани резултати пожељне вероватноће и ранга челика АИСИ 1018 при константној брзини уклањања материјала помоћу $L_9(3^4)$

Exp. no	Mean value of energy consumption *μ* (kJ)	S. D. of energy consumption *s* (kJ)	Preferable probability			
			P_μ	P_s	$P_t=(P_\mu \cdot P_s)^{0.5}$	Rank
1	99.9625	31.7308	0.0831	0.0946	0.0887	7
2	72.9975	23.4131	0.1189	0.1291	0.1239	4
3	**60.0950**	**19.6699**	**0.1360**	**0.1447**	**0.1403**	**1**
4	99.9375	34.8681	0.0831	0.0816	0.0823	8
5	73.8800	25.4402	0.1177	0.1207	0.1192	5
6	60.9975	21.4981	0.1348	0.1371	0.1359	2
7	102.4525	39.2377	0.0798	0.0635	0.0712	9
8	76.4600	29.2820	0.1143	0.1048	0.1094	6
9	62.8300	24.6534	0.1324	0.1240	0.1281	3

The assessed results in Table 2 indicate that test No. 3 has the highest value of the total preferable probability P_t at the first glance. Therefore, the robust configuration is around tests No. 3.

Moreover, Table 3 shows the results of the range analysis for the total preferable probability shown in Table 2, which shows that the optimum configuration is A1B3C1, which is test No. 3 exactly.

Table 3 – Range analysis of the total preferable probability of AISI 1018 steel at a constant material removal rate by means of $L_9(3^4)$

Таблица 3 – Анализ ранжирования общей предпочтительной вероятности стали AISI 1018 при постоянной скорости съема материала с помощью $L_9(3^4)$

Табела 3 – Анализа рангирања укупне пожељне вероватноће челика АИСИ 1018 при константној брзини уклањања материјала помоћу $L_9(3^4)$

Level	A	B	C
1	0.1176	0.0807	0.1348
2	0.1125	0.1175	0.1175
3	0.1029	0.1348	0.0807
Range	0.0147	0.0540	0.0540
Order	3	1	2
Optimal configuration	A1	B3	C1

2) Concurrent optimization of the machining process parameters and the tolerance allocation of a spheroidal graphite cast iron piston

Janakiraman & Saravanan conducted a concurrent optimization of the machining process parameters and the tolerance allocation of a spheroidal graphite cast iron piston (2010) as an example of conducting a restudy with robust design of probability-based multi-objective optimization.

There are 3 control factors: cutting speed (A), feed rate (B), and depth of cut (C) with five levels in the experiments with response surface methodology design and the test results, as shown in Table 4.

The mean value of energy consumption is shown by μ, and the standard deviation is represented by s. As the target value is the input diameter (Janakiraman & Saravanan, 2010), a factor ε is introduced to present the deviation of the mean value from the target value of the input diameter, i.e., $\varepsilon = |\mu - \text{input diameter}|$.

Furthermore, according to the requirement of robust design, the performance of ε and s has the characteristic of unbeneficial indexes. All the assessed results are shown in Table 5 together with their preferable probability values and ranks.

Table 4 – Response surface central composite rotatable design matrix and the test results

Таблица 4 – Поверхность отклика матрицы центральной композитной вращающейся конструкции и результаты испытаний

Табела 4 – Површина одговора матрице централног композитног ротационог дизајна и резултати испитивања

Expt. no.	Cutting speed (A) (m/min)	Feed rate (B) (mm/rev)	Depth of cut (C) (mm)
1	24.05	2.01	0.014
2	35.95	2.05	0.014
3	24.05	4.99	0.014
4	35.95	4.99	0.014
5	24.05	2.01	0.041
6	35.95	2.01	0.041
7	24.05	4.99	0.041
8	35.95	4.99	0.041
9	20	3.5	0.028
10	40	3.5	0.028
11	30	1	0.028
12	30	6	0.028
13	30	3.5	0.005
14	30	3.5	0.05
15	30	3.5	0.028
16	30	3.5	0.028
17	30	3.5	0.028
18	30	3.5	0.028
19	30	3.5	0.028
20	30	3.5	0.028

Continued

Expt. no.	Input diameter (mm)	Output diameter measured (mm)				
		1	2	3	4	5
1	51.003	50.992	50.986	50.99	50.993	50.982
2	51.24	51.222	51.221	51.224	51.225	51.225
3	51.24	51.221	51.221	51.222	51.221	51.22
4	51.237	51.21	51.219	51.211	51.215	51.218
5	51.22	51.17	51.175	51.18	51.173	51.171
6	51.17	51.129	51.13	51.129	51.128	51.13
7	51.235	51.198	51.199	51.195	51.196	51.2
8	51.1	51.059	51.066	51.05	51.056	51.054
9	51.23	51.205	51.2	51.205	51.203	51.202
10	51.2	51.176	51.172	51.174	51.171	51.172
11	51.245	51.205	51.21	51.208	51.205	51.203
12	51.215	51.181	51.188	51.186	51.187	51.179
13	**51.245**	**51.244**	**51.24**	**51.245**	**51.240**	**51.242**
14	51.22	51.18	51.185	51.178	51.18	51.18
15	51.235	51.21	51.215	51.21	51.212	51.218
16	51.24	51.212	51.22	51.219	51.218	51.215
17	51.21	51.17	51.168	51.165	51.164	51.162
18	51.23	51.19	51.195	51.185	51.188	51.19
19	51.17	51.135	51.141	51.141	51.142	51.136
20	51.21	51.185	51.18	51.18	51.182	51.173

The assessed results in Table 5 indicate that test No. 13 has the highest value of the total preferable probability P_t that is closely followed by test No. 3.

Therefore, the robust configuration is around tests No. 13, while test No. 13 clearly shows simultaneous smaller values of both ε and s from Table 5.

Table 5 – Assessed results together with the preferable probabilities and ranks
Таблица 5 – Результаты анализа с предпочтительными вероятностями и ранжированием
Табела 5 – Анализирани резултати са пожељним вероватно-ћама и рангирањем

Expt. no.	μ	ε	s	Preferable probability			Rank
				P_ε	P_s	$P_t=(P_\mu \cdot Ps)^{0.5}$	
1	50.9886	0.0144	0.0046	0.0750	0.0293	0.0469	12
2	51.2234	0.0166	0.0018	0.0715	0.0668	0.0691	3
3	51.2210	0.019	0.0007	0.0676	0.0820	0.0744	2
4	51.2146	0.0224	0.0040	0.0621	0.0365	0.0476	11
5	51.1738	0.0462	0.0040	0.0234	0.0375	0.0296	19
6	51.1292	0.0408	0.0008	0.0322	0.0802	0.0508	8
7	51.1976	0.0374	0.0021	0.0377	0.0633	0.0489	9
8	51.0570	0.0430	0.0060	0.0286	0.0097	0.0166	20
9	51.2030	0.0270	0.0021	0.0546	0.0627	0.0585	5
10	51.1730	0.0270	0.0020	0.0546	0.0643	0.0593	4
11	51.2062	0.0388	0.0028	0.0354	0.0537	0.0436	14
12	51.1842	0.0308	0.0040	0.0484	0.0375	0.0426	15
13	**51.2422**	**0.0028**	**0.0023**	**0.0939**	**0.0605**	**0.0754**	**1**
14	51.1806	0.0394	0.0026	0.0344	0.0560	0.0439	13
15	51.2130	0.0220	0.0035	0.0627	0.0443	0.0527	7
16	51.2168	0.0232	0.0033	0.0608	0.0470	0.0534	6
17	51.1658	0.0442	0.0032	0.0266	0.0480	0.0358	18
18	51.1896	0.0404	0.0036	0.0328	0.0418	0.0370	17
19	51.1390	0.0310	0.0032	0.0481	0.0474	0.0477	10
20	51.1800	0.0300	0.0044	0.0497	0.0313	0.0395	16

Conclusion

The above discussion indicates that new robust design by means of probability-based multi-objective optimization can be reasonably used to deal with the problem of optimizing machining process parameters. The arithmetic mean value of the performance indicator and its deviation are taken as twin independent responses of the performance indicator in the treatment, which contributes their parts of partial preferable probability of the performance indicator respectively. The arithmetic mean value of the performance indicator is assessed as a representative of the performance indicator according to its function and preference, and the deviation is the unbeneficial index in the assessment. The total preferable probability of each alternative is the uniquely overall index of each alternative in the robust optimum.

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Многокритериальная оптимизация, основанная на вероятности в качестве основы для применения новой робастной конструкции с параметрами механической обработки

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ВИД СТАТЬИ: оригинальная научная статья

Резюме:

Введение/цель: Новая робастная конструкция, разработанная с помощью многокритериальной оптимизации, основанной на вероятности, использует среднее арифметическое значение показателя эффективности и его отклонение как две независимые реакции показателей эффективности. Цель этой статьи − проверить применимость новой робастной конструкции для оптимизации параметров при механической обработке. При детальных испытаниях была использована робастная конструкция для определения оптимальных параметров резки и минимизации энергопотребления при токарной обработке стали AISI 1018, с учетом постоянной скорости съема материала, а также одновременной оптимизации параметров обработки и распределения допусков поршня из чугуна с шаровидным графитом.

Методы: Придерживаясь метода, основанного на вероятности многокритериальной оптимизации, среднее арифметическое значение показателя эффективности и его отклонений используются в качестве двух независимых откликов показателя эффективности для ввода в эксплуатацию робастной конструкции. Каждый из вышеописанных двойных откликов частичными предпочтительными вероятностями способствует улучшению показателей эффективности *альтернатив в процессе испытаний. Среднее арифметическое значение показателя эффективности следует оценивать, как репрезентативное значение показателя эффективности в соответствии с функцией или преимуществом показателя эффективности, а отклонение является вторым показателем индикатора эффективности, который в целом характеризуется как «меньше−лучше». Кроме того, квадратный корень произведения двух вышеуказанных частей частичной предпочтительной вероятности формирует фактическую предпочтительную вероятность показателя эффективности. Более того, произведение частичных предпочтительных вероятностей дает общую предпочтительную вероятность по каждой альтернативе, которая является общим и уникальным индексом каждой из альтернатив в робастном оптимуме.*

Результаты: В статье приведены рациональные оптимальные параметры резки для минимизации энергопотребления во время токарной обработки стали AISI 1018 при постоянном съеме материала, а также одновременной оптимизации параметров обработки и распределения допусков поршня из чугуна с шаровидным графитом.

Выводы: Исследование показало, что применение новой робастной оптимизации является рациональным и удобным способом оптимизации параметров механической обработки.

Ключевые слова: предпочтительная вероятность; вероятностный метод; многокритериальная оптимизация; робастная конструкция; одновременная оптимизация.

Вишекритеријумска оптимизација заснована на вероватноћи као основа за примену новог робустног дизајна на параметре машинске обраде

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ОБЛАСТ: математика, материјали
КАТЕГОРИЈА (ТИП) ЧЛАНКА: оригинални научни рад

Сажетак:

Увод/циљ: Нови робустни дизајн настао помоћу вишекритеријумске оптимизације засноване на вероватноћи узима аритметичку средњу вредност индикатора перформанси, као и њену девијацију, за двојне независне одговоре индикатора *перформанси. Циљ овог рада јесте да се провери применљивост новог робустног дизајна на оптимизацију параметара машинске обраде. За детаљно испитивање коришћен је робустни дизајн за одређивање оптималних параметара сечења како би се потрошња енергије током окретања челика АИСИ 1018, при константној брзини уклањања материјала, свела на најмању могућу меру. Поред тога, истовремено је примењена и оптимизација параметара машинске обраде и алокација толеранције клипа од сфероидног графитног ливеног гвожђа.*

Методе: У складу с методом заснованом на вероватноћи за вишекритеријумску оптимизацију, аритметичка средња вредност индикатора перформанси. као и њена девијација, узете су за двојне независне одговоре индикатора перформанси при примени робустног дизајна. Сваки од ова два поменута одговора доприноси једним делом парцијалних пожељних вероватноћа индикатору перформанси алтернатива у испитивању. Аритметичка средња вредност индикатора перформанси треба да се процењује као представник индикатора перформанси према функцији или преференцији индикатора перформанси, док је девијација други њихов показатељ кога, уопштено говорећи, каракактерише принцип „мање је боље”.Поред тога, квадратни корен производа два поменута дела парцијалне пожељне вероватноће формира стварну пожељну вероватноћу индикатора перформанси. Штавише, производ парцијалних пожељних вероватноћа даје укупну пожељну вероватноћу сваке алтернативе, што представља укупни и јединствени индекс сваке алтернативе у робустном оптимуму.

Резултати: У раду су представљени рационални оптимални параметри сечења за минимизирање потрошње енергије током окретања челика АИСИ 1018 при константној брзини уклањања материјала, као и истовремена оптимизација параметара машинске обраде и алокација толеранције клипа од сфероидног графитног ливеног гвожђа.

Закључак: Студија указује да је примена нове робустне оптимизације рационална и погодна за оптимизацију параметара машинске обраде.

Кључне речи: пожељна вероватноћа, метод заснован на вероватноћи, вишекритеријумска оптимизација, робустни дизајн, истовремена оптимизација.

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