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Robust parametric optimization of cyclone separator by means of probabilistic multi - objective optimization

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ABSTRACT

In this article, robust parametric optimization of cyclone separator is done by means of robust probabilistic multi - objective optimization (RPMOO). In RPMOO, the optimal attributes (objectives) are essentially divided into two types, i.e., both unbeneficial and beneficial types, which devote their partial preferable probabilities with equivalent manner quantitatively; especially the averaged value of the experimental data of each attribute and its dispersity are evaluated individually in accordance with its corresponding type. The total preferable probability of each scheme alternative is formed from the multiplication of all available partial preferable probabilities, which is the uniquely decisive indicator of an alternative in this assessment; the optimum scheme is with the highest total preferable probability. For the parametric optimization of cyclone separator, the inlet velocity, helical angle, and outlet diameter are as the variable parameters, while the pressure drop and separation efficiency are the evaluated responses of the cyclone separator to get optimization, the former is an unbeneficial type of attribute and the latter is a beneficial type of attribute. The orthogonal array $L_9(3^3)$ was employed to arrange the experimental scheme alternatives. The evaluated results indicate that the optimized experimental scheme is alternative 6, which yields the optimal responses of a pressure drop of 0.3 mba and a separation efficiency of 98.95 % at an optimum inlet velocity of 13 m/s, an outlet diameter of 72 mm, and a helical angle of 5. This work reveals the independent contributions of the averaged value of the experimental data and its dispersion to an attribute response in the optimization process, and the irrelevance of pressure drop and separation efficiency in the system.

1. Introduction

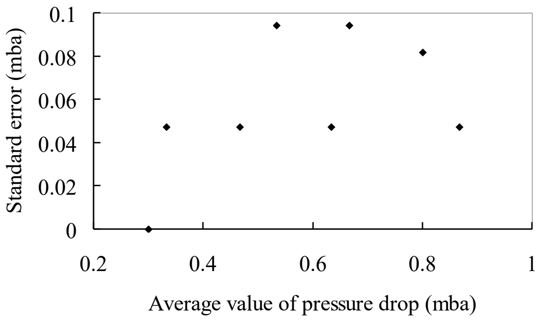
The Robust parametric optimization and determination in machine equipment could rapidly improve the productivity and social value in industry. In general, producing components with high accuracy could raise the performance of the mechanical parts [1], [2]. Cyclone separator is a typical mechanical part of a pollution control system, which has been widely used in many cases [3]. In general, performances of cyclone separator are measured by specific attribute indexes simultaneously, such as pressure drop, energy consumption, and particle separation efficiency, etc. These performance responses are usually affected by dimensions, flow velocity, particle size, and design, etc., parameters. Various studies aim to improve cyclone performance by adjusting the sizes of certain parts, the number of inlets, the inlet slope and the length of the cyclone cone, etc. Some mathematics methods are employed as well, such as statistical methods, artificial neural network, Taguchi method and response surface method [3].

As to robust assessment of Taguchi method, the performance response to be optimized is assessed with an indicator of SNR (Signal-to-Noise Ratio) usually, but it was questioned by statisticians [4]–[8]. The puzzled defects of SNR are as follows: (1) it is not sufficient to reflect the need of simultaneous optimizations of both averaged value and the dispersity of a response by using a sole *SNR* as the measurement, because both the averaged value and dispersity of a response are in fact dual independent performances; (2) it will be involve a large number of experiments in case of multiple variables in orthogonal array design; (3) it involves an irrational treatment of multiple attributes (objectives) to emerging into a quasi-single one, such as grey relation method.

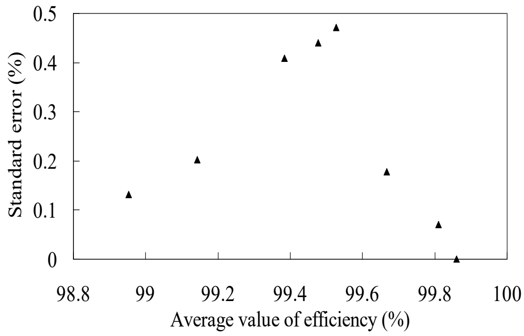
Besides, robust optimization of a mechanical part concerns many attributes in general, which even conflicts each other, such many attributes need to be simultaneously optimized in the system without any replacement. Therefore, robust parametric optimization of a mechanical part is an appropriate multi - objective optimization containing robustness inevitably.

Zulkarnain once studied optimization problem of the cyclone separator by using multi-response TOPSIS - PCR with $L_9(3^3)$ experimental design [3], which employed pressure drop and separation efficiency as the optimal responses of the cyclone separator. TOPSIS and PCR ware utilized to generate the optimal combination of both levels and factors, CFD and verification tests methods were used to valid the study. As to the experimental results of the cyclone separator conducted by Zulkarnain [3], the variation of dispersity of pressure drop *vs* its averaged value is shown in Fig. 1 (a), while the variation of dispersity of article separation efficiency *vs* its averaged value is shown in Fig. 1 (b).

As seen in Fig. 1 clearly indicates the independence of mean values and dispersities of both pressure drops and separation efficiency, which confirms the judgment of the statisticians, and implies the necessity of separate treatment the averaged value and its dispersity of an attribute response in the optimization. Inevitably, this robust parametric optimization of cyclone separator is a double dual-objective optimization for both pressure drop and separation efficiency. Both averaged values and dispersities of pressure drop and separation efficiency make the optimal responses doubled automatically.



a) Dispersity *vs* averaged value of pressure drops



b) Dispersity *vs* averaged value of efficiency

Fig. 1. Variation of disparities vs averaged values of both pressure drop and separation efficiency of experimental results for cyclone separator

Detailed analysis indicates that the intrinsic connotation of "multi-objective optimization" has the meaning of "multi-objective optimization at the same time" [9], it is an "overall optimization of the system" from the point of view of system theory. Therefore, it is necessary to find "intersection" among the objectives to make them "coordinate" with each other, so as to realize the optimization of the overall function of the system. The concept of "intersection" comes from set theory, which refers to three sets A, B and C, and the set C consists of all elements belonging to both set A and set B, thus set C is called the intersection of set A and set B, it is recorded as AB. Mathematically in general probability theory, the probability *P(AB)* of two independent events "simultaneous appearance" is represented as the product of *P(A)* and *P(B)*, i.e., *P(AB) = P(A)·P(B)* [9], [10].

When each attribute (objective) is regarded as an "event" analogically, the "simultaneous optimization of multiple objectives" now becomes the "simultaneous occurrence of multiple events" in probability theory. Furthermore, their joint probability of "simultaneous appearance" of theses independent events can be expressed by using Equation (1),

$$P_t = P_1 \cdot P_2 \cdot \ldots \cdot P_\beta \cdot \ldots = \prod_{\beta=1}^{l} P_\beta \quad (1)$$

In Equation (1), P_β devotes the probability of the β-th attribute (objective), and l is the total number of attributes. In such way, the optimization problem with multiple objectives becomes an equivalent probability problem analogically. Based on above idea, the probabilistic multi - objective optimization (PMOO) approach was established [9]. In PMOO, the optimal attributes are essentially classified into two types, i.e., both unbeneficial type and beneficial type. Furthermore, all attributes devote individually their partial preferable probabilities quantitatively.

Furthermore, robust PMOO (RPMOO) was set up to meet the requirement of statisticians that both averaged value and dispersity of a response must be treated as two individual performances [9], [10], which could reveal the independence and irrelevance of the many optimal objective responses, as well as the proper simultaneity in the optimal problem. In particular, the averaged value of the test data for each attribute is representative of the objective of participating in the evaluation, and its type is the same as that of the corresponding attribute; while the dispersion of the test data for each attribute is assigned the unbeneficial type in general. Obviously, each optimal objective (attribute) contributes its strength individually to the optimization in the RPMOO, which avoids the shortcomings of *SNR* approach. Moreover, the total preferable probability of each scheme alternative is obtained by the product of all available partial preferable probabilities, which makes the uniquely decisive representative of the alternative to participate the competitive optimization. Finally, the optimum scheme is with the biggest total preferable probability [9], [10].

In this article, the robust parametric optimization problem of the cyclone separator is conducted by means of PMOO, which provides an example of dealing with such a robust parametric optimization problem and reveals the irrelevance and simultaneity of pressure drop and particle separation efficiency, and reflects the independence of both the averaged value and the dispersity of an attribute response in a system.

2. Method

2.1. Probabilistic multi – objective optimization

PMOO is concisely demonstrated here so as to use it conveniently [9], [10]. In general, in a multi - objective optimization (MOO) problem some attribute utility indexes are with the characteristics of “the higher the better” [9], [10], i.e., such attribute with higher utility value is more welcomed and could get more preference in the optimization, this type of attribute is called beneficial type of attribute.

In this case, a term “preferable probability” was introduced to reflect the “preference degree” of the objective (attribute) in the optimal competition rationally [9]. Furthermore, as a simple consideration, it supposes rationally that the partial preferable probability of this type of objective response is in linear dependence on its specific value of the attribute utility index positively, which is formulated by Equation (2),

$$P_{\alpha\beta} = A_\beta Y_{\alpha\beta}, \ \alpha = 1, 2 \ldots, k, \ \beta = 1, 2 \ldots, l. \quad (2)$$

In Equation (2), k is the total number of scheme alternatives in the relevant alternative system; l is the total number of attribute response indexes of each scheme; $Y_{\alpha\beta}$ is the utility value of the β-th attribute indicator of the α-th scheme; $P_{\alpha\beta}$ reflects the partial preferable probability of the beneficial type of response $Y_{\alpha\beta}$; A_β shows the normalization factor of the β-th beneficial response index. With the help of probability theory [11], for the β-th attribute response index, following regulation can be derived [9], [10],

$$A_\beta = 1/(k\overline{Y_\beta}). \tag{3}$$

In Equation (3), $\overline{Y_\beta}$ represents the averaged value of the utility of β-th attribute index involved with $\overline{Y}_\beta = (\sum_{\alpha=1}^{k} Y_{\alpha\beta})/k$.

Besides, some other attribute utility indexes in a MOO problem might be with the characteristic of "the lower the better" [9], [10], which is called unbeneficial type of attribute. In such case, the partial preferable probability *of* this type of objective response is in linear dependence on its specific value of the attribute utility index negatively, i.e.,

$$P_{\alpha\beta} = B_\beta\,(Y_{\beta max}+Y_{\beta min} - Y_{\alpha\beta}),\ \ \alpha = 1, 2..., k,\ \ \beta = 1, 2..., l. \tag{4}$$

In Equation (4), both $Y_{\beta max}$ and $Y_{\beta min}$ show the minimum and maximum utility values of the attribute indicators in the β-th attribute involved, individually; B_β is the normalization factor of the β-th unbeneficial type of response, following regulation can be derived [9], [12],

$$B_\beta = 1/[k(Y_{\beta\max} + Y_{\beta\min}) - k\overline{Y_\beta}]. \tag{5}$$

As seen in Equation (5), moreover, the total preferable probability of the α-th scheme alternative could be formulated as [9]–[11],

$$P_\alpha = P_{\alpha 1} \cdot P_{\alpha 2} \cdot ... \cdot P_{\alpha\beta} \cdot ... = \prod_{\beta=1}^{l} P_{\alpha\beta}. \tag{6}$$

Particularly, in this assessment, the total preferable probability is the uniquely decisive index of each scheme in the optimization process.

On the other hand, the multi-objective optimization problem is now converged into a "single-objective optimization one" in term of total preferable probability by using the procedures of Equation (2) through Equation (6) automatically. At last, the optimum scheme is the specific alternative with the biggest total preferable probability, which is actually the optimal consequence of the overall optimization. This is the essential principle of PMOO. Furthermore, when a weighting factor w_β for β-th attribute response is involved to depict its weighting, the total preferable probability of the α-th scheme could be formulated by following expression [9], [13],

$$P_\alpha = P_{\alpha 1}^{\ w_1} \cdot P_{\alpha 2}^{\ w_2} \cdot ... \cdot P_{\alpha\beta}^{\ w_\beta} \cdot ... = \prod_{\beta=1}^{l} P_{\alpha\beta}^{\ w_\beta}. \tag{7}$$

In general, weighting factor is used to stress the difference of the importance of objective response in the optimization, which is artificially designed usually. Many applications of above approach are performed [9], [11], [14]–[18], which gave acceptable consequences and are consistent

 10.12928/ijio.v7i1.12050

with the known. This indicates the reasonability of the approach. The diagram of PMOO procedure is shown in Fig. 2.

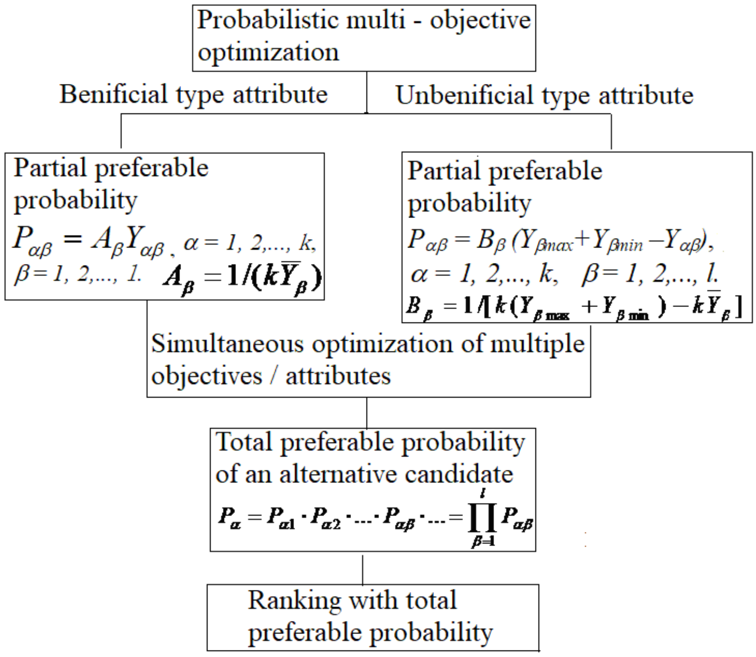


Fig. 2 Diagram of PMOO procedure

2.2. Robust probabilistic multi – objective optimization (RPMOO)

As was declared by statisticians that both averaged value and dispersity of a response are dual separate performances and should be seen as twin independent sub-responses [4]–[8], therefore, both averaged value and dispersity of a response could be taken as twin independent sub responses into assessment of MOO. Robust probabilistic multi - objective optimization (RPMOO) was proposed to address the statisticians' fundamental problem of both mean value and dispersion of a response as twin independent sub responses in robust design [9], [10].

In the RPMOO, the averaged value of the test data of each attribute is the representative of the objective to join the evaluation, its type is the same as that of the role of the attribute to contribute its partial preferable probability; besides, the dispersity of the test data of each attribute response is assigned to the unbeneficial type of attribute in general to contribute its partial preferable probability, respectively [9], [10]. In the next section, robust parametric optimization of the cyclone separator is conducted to demonstrate the utility of RPMOO in design processes and to show the simultaneity of pressure drop and particle separation efficiency in the optimal system, and their irreversibility.

3. Results and Discussion

Back to the optimal experiment of cyclone separator, Taguchi orthogonal array design $L_9(3^3)$ was employed in the experiment by Zulkarnain [3]. The inlet velocity, the helical angle, and the outlet diameter are used as the variable parameters, the pressure drop and particle separation efficiency are optimized responses and objectives of the cyclone separator system [3].

In the assessment of RPMOO for cyclone separator, the pressure drop is an unbeneficial type of response, and the separation efficiency is assigned to the beneficial type of response. In the experiment, 9 trial runs completed [3], which is cited in Table 1. In Table 2 response represents pressure drop, and response 2 indicates separation efficiency. The assessment result of this issue by using RPMOO is presented in Table 3. In Table 3, the columns 2, 3, 4, 5 and 6 give the evaluation consequences of part of partial preferable probability P1a and P1s.d. of averaged value and dispersity (standard difference) for response 1, part of partial preferable probability P2a and P2s.d. for response 2, and total preferable probability $P_t \times 10^4$ for every scheme alternative, respectively. The column 7 gives the ranking value according to the total preferable probability of each alternative.

From Table 3, it can be seen that the experimental scheme 6 is with the highest total preferable probability and is at rank 1 position in the assessment by means of robust probabilistic multi - objective optimization, thus the optimized experimental scheme is alternative 6 with the optimum responses of pressure drop of 0.3 mba and separation efficiency of 98.95 % at the corresponding optimum experimental parameters of inlet velocity of 13 m/s, the outlet diameter of 72 mm, and the helical angle of 5, i.e., the configuration of A2B3C1, respectively.

Furthermore, Table 4 gives the consequences of range analysis for total preferable probability, which also shows that the optimized experimental scheme is alternative 6, and the corresponding parameters of alternative 6 is the optimized ones. Therefore, the input variable parameters of the cyclone separator for industrial process can be adjusted at the corresponding parameters of alternative 6 to achieve the appropriate separation efficiency of 98.95 % and pressure drop of 0.3 mba, which improves the energy efficiency and system reliability with robustness coordinately. So, the alternative 6 is the best configuration for the system to get its overall optimum status comprehensively. Obviously, robust probabilistic multi - objective optimization takes both mean value and standard for pressure drop and separation efficiency into account at the same time in equivalent manner, which is a systemic approach in the viewpoint of systems theory [9], [10].

Comparatively, the optimization for this cyclone separator with robustness conducted by A. Zulkarnain et al by using SNR method together with PCR and TOPSIS obtained other optimal configuration, A1B3C3 [3], which leads to a consequence of average values of 0.34 mba for pressure drop and 99.50 % for separation efficiency, respectively. Obviously, though the relative increase of their separation efficiency respect to our results is by about 0.556 %, the relative increase of their pressure drop to our result reaches to over 13.333 %.

Therefore, comprehensive consideration indicates that the probability-based robust optimization here in this article is reasonable. Besides, the applications of PMOO approach concern many fields and departments, which includes portfolio investment, mechanical design, materials selection, manufacturing process, and transportation [9]–[17], [19], other fields, such as greenhouse gas emissions, technology transfer, vendor selection, location determination of new supermarket branches, and risk management, etc. could get its utilization as well [18], [20], [29]–[38], [21], [39], [40], [22]–[28].

Table 1. Experimental results of robust parametric optimization of cyclone separator with $L_9\,(3^3)$

Run	Factor			Response 1 (mbar)			Response 2 (%)		
	A (m/s)	B (mm)	C°	1	2	3	1	2	3
1	10	45	5	0.4	0.6	0.6	99.71	99.43	99.86
2	10	57	10	0.7	0.6	0.6	99.86	99.86	99.86
3	10	72	15	0.8	0.6	0.6	99.86	99.86	99.71
4	13	45	10	0.5	0.4	0.5	99.00	99.43	99.00
5	13	57	15	0.7	0.8	0.9	99.86	99.86	99.86
6	13	72	5	0.3	0.3	0.3	99.14	98.86	98.86
7	16	45	15	0.9	0.8	0.9	99.86	99.86	98.86
8	16	57	5	0.3	0.4	0.3	99.71	99.86	98.86
9	16	72	10	0.3	0.3	0.3	99.43	99.86	98.86

10.12928/ijio.v7i1.12050

Table 2. Response

	Response 1 (mbar)		Response 2 (%)	
Run	**Avg.**	**s. d.**	**Avg.**	**s. d.**
1	0.5333	0.0943	99.6667	0.1782
2	0.6333	0.0471	99.8600	0
3	0.6667	0.0943	99.8100	0.0707
4	0.4667	0.0471	99.1433	0.2027
5	0.8	0.0817	99.8600	0
6	0.3	0	98.9533	0.1320
7	0.8667	0.0471	99.5267	0.4714
8	0.3333	0.0471	99.4767	0.4403
9	0.3	0	99.3833	0.4096

Table 3. Assessment result of robust parametric optimization of cyclone separator with $L_9\,(3^3)$

	P_1		P_2		P_t	
Run	P_{1a}	$P_{1s.d.}$	P_{2a}	$P_{2s.d.}$	$P_t\times10^4$	**Rank**
1	0.1131	2.4590×10^{-7}	0.1113	0.1254	3.8813×10^{-6}	8
2	0.0952	0.1209	0.1115	0.2017	2.5897	2
3	0.0893	2.4590×10^{-7}	0.1114	0.1714	4.1936×10^{-6}	7
4	0.125	0.1209	0.1107	0.1149	1.9235	3
5	0.0655	0.0324	0.1115	0.2017	0.4771	5
6	**0.1548**	**0.2419**	**0.1105**	**0.1452**	**6.0049**	**1**
7	0.0536	0.1209	0.1111	2.05×10^{-7}	1.4759×10^{-6}	9
8	0.1488	0.1209	0.1111	0.0133	0.2657	6
9	0.1548	0.2419	0.1110	0.0264	1.0986	4

Table 4. Consequences of range analysis for total preferable probability

Level	**A**	**B**	**C**
1	0.8632	0.6412	2.0902
2	2.8018	1.1108	1.8706
3	0.4548	2.3678	0.1590
Range	2.3471	1.7267	1.9312
Order	1	3	2
Opt. conf.	A_2	B_3	C_1

4. Conclusion

The robust probabilistic multi - objective optimization is an effective methodology to deal with the parametric optimization and determination in cyclone separator design. In the RPMOO 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 approach could reveal the independence of mean value and dispersion of an objective response and reflect the replacement of multiple objectives in the optimal system. The achievement of the present article indicates the validity of the corresponding approach.

For future studies, the application of the robust probabilistic multi-objective optimization (RPMOO) approach can be extended by incorporating additional performance indicators of cyclone separators, such as energy consumption, particle size distribution, and erosion rate, in order to achieve a more comprehensive system-level optimization. Moreover, the integration of RPMOO with computational fluid dynamics (CFD) simulations and real industrial operating conditions is recommended to further validate the robustness and generalizability of the proposed methodology. Future research may also explore the use of RPMOO in optimizing other separation devices or complex engineering systems with higher-dimensional parameter spaces and uncertain operating environments.

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