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Research Article

Parameter Optimization Design of Plasma Arc Machining SS 304 Alloy by Means of Probabilistic Multi – objective Approach

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Abstract: Plasma arc machining is an unconventional machining process, which is widely used to machine intricate part profiles of alloys with difficulty in general machine. In general, the surface roughness, kerf ratio, and material removal rate (MRR) are used as evaluation targets of the production process and quality of the machining samples; the plasma arc cutting parameters, such as arc voltage, standoff distance, cutting speed, and plasma offset, are employed as the input parameters for the cutting of SS 304 alloy machined at two different types of nozzles (130 A and 200 A). The parameter optimization design of plasma arc machining is a typical of optimal problem with multiple objectives. The employment of a rational multi – objective approach is quite important to the designers for the parameter optimization design of plasma arc machining. In this article, the probabilistic multi – objective optimization is utilized to conduct the parameter optimization design of plasma arc machining SS 304 alloy of thickness 6 mm, which is designed according to a mixed Taguchi design of L18 orthogonal array. The optimal parameters of plasma arc machining SS 304 alloy from the designed experiment for Nozzle 1 (130 A) are arc voltage at 136V, cutting speed of 2000mm/min, standoff distance of 2mm, and plasma offset of 2.25mm; the optimized parameters of plasma arc in machining SS 304 alloy from the designed experiment for Nozzle 2 (200 A) are arc voltage at 133V, cutting speed of 2000 mm/min, standoff distance of 2 mm, and plasma offset of 1.25mm. The results indicate the reasonability of the approach.

***Keywords*:** plasma arc cutting, SS 304 alloy, DOE, parameter optimization, probabilistic multi – objective

1. Introduction

Stainless steel (SS) 304 alloy is widely used in the manufacturing industries, such as manufacturing of automotive, aerospace structures, architectural paneling, and marine environment due to its higher strength and wear resistance. But the difficulty of this material is the machining by using common processes. Plasma arc cutting (PAC) is one of the unconventional machining processes most commonly used in the process [1].

The advantages of PAC process are the abilities of cutting all electrically conductive materials and high alloy steel materials with medium and large thicknesses at high cutting speed.

The design of experiment (DOE) is conducted to study the selection of suitable process variables and their influence in evaluating the part quality commonly [1–13].

Rouniyar et al. analyzed and optimized their experiment results by using the grey relational analysis [13]; Singh et al. carried out the multi-response optimization of electro-discharge machining (EDM) process on basis of experimental analysis of machining superalloy Inconel-718 [14].

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Tsiolikas et al conducted the optimization of neural network parameters of plasma arc cutting process by using Taguchi Robust Design [15]. Kechagias et al performed the parameter design of CNC plasma - arc cutting of carbon steel plates using robust design [16].

The parameter optimization design of plasma arc in cutting SS 304 alloy is a typical optimal problem with multiple objectives, thus multi – objective optimization could be employed to deal with it reasonably.

Many multi-objective optimizations have been proposed, e.g., VIšekriterijumsko KOmpromisno Rangiranje (VIKOR), Technique of ranking Preferences by Similarity to the Ideal Solution (TOPSIS), Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), and Analytical Hierarchy Process (AHP), etc. [17–21].

In fact, the essence of multi-objective optimization is the issue of "simultaneous optimization of multiple objectives" inevitably. However, the above approaches of multi- objective optimization (MOO) took the "additive" algorithm as the actual operation with weighting factors to measure the differences of significance of different objectives [17–21]. Therefore, the "additive" algorithm of multiple evaluation indexes has actually a big distance from the essence of "simultaneous optimization of multiple indexes" actually, but seems to be "union" in viewpoint of set theory and probability theory instead [22]. The grey relational analysis also introduced artificial factors, which has unclear meaning [12,13].

Contrarily, in the spirit of probability theory, the "simultaneous optimization of multiple indexes" should appropriately take the form of "joint probability" of the multiple independent objectives.

Besides, since the introduction of artificial factors in some previous methods, the relevant algorithms could be considered as a semi-quantitative approach in some sense. Additionally, the choice of scaled factor (denominator) in the normalization process is a puzzled problem, different normalization factors usually result in considerable differences [22].

Therefore, the appropriate expression of "simultaneous optimization of multiple objectives" in quantitative form is still on the way.

In view of above situation, each objective in the multi-objective optimization is analogical as an independent event from the perspective of probability theory, and the entire multi-objective optimization as a "joint event" of all individual events, thus the total / overall probability of "joint event" is the product of each individual event in whole thing [22]. While each independent event could be evaluated according to its preference degree in the assessment by introducing a quantified new index "partial preferable probability", and therefore simultaneous optimization of multiple objectives can be reasonably evaluated by the total / overall preferable probability of "joint event". This treatment has the advantage of considering simultaneous optimizations of multiple objectives in the spirit of probability theory, which is an overall planning approach entirely.

In this paper, the probabilistic multi – objective optimization is employed to study the parameter optimization design of plasma arc machining SS 304 alloy of thickness 6 mm, which is designed according to a mixed Taguchi design of L18 orthogonal array. The aim is to provide a rational optimal approach to conduct parameter optimization of material machining with multiple objectives, which conforms to the essence of "simultaneous optimization of multiple objectives".

2. Probabilistic Multi – objective Optimization

The main detail of the new approach of probabilistic multi – objective optimization is briefly illuminated in the following sections.

2.1 Brief illumination of the probabilistic multi-objective optimization

The idea of preferable probability was introduced to reflect the preference degree of the objectives (attributes) in the assessment in the probabilistic method for multi - objective optimization [22]. In the methodology, the objectives (attributes) are preliminarily classified into both beneficial and unbeneficial types; Moreover, the assessment of the partial preferable probability for each type of performance index is established corresponding to its type quantitatively, respectively. Subsequently, each objective is analogical as an independent event in probability theory, thus the simultaneous optimization of multiple objectives could be taken as the product of "partial preferable probability" of each objective event, which form a total / overall preferable probability. Finally, the total / overall preferable probability is used to participate the competition for a candidate in the optimization, which is decisive and unique / overall index of "joint event" (candidate). Through this way, the multi – objective optimization problem is transferred into a single objective one reasonably. Clearly, this treatment is attributed to the overall planning method.

2.2 Quantitative expression of the probabilistic multi - objective optimization

As the value of performance utility of an attribute could reflect the feature of the corresponding attribute in one aspect, therefore the corresponding preferable probability could be naturally correlated to the value of this performance utility inevitably [22].

For the simplicity, the partial preferable probability of a beneficial type of attribute was directly assumed to be proportional to the value of performance utility of the attribute index [22], i.e.,

$$P_{ij} \propto X_{ij},\ P_{ij} = \alpha_j X_{ij},\ i = 1,2,\ldots,n;\ j = 1,2,\ldots,m. \tag{1}$$

In Eq. (1), X_{ij} reflects the utility value of the index of the j-th attribute in the i-th scheme; P_{ij} indicates the partial preferable probability of the beneficial attribute X_{ij}; n represents the total number of candidate in scheme; m is the number of attributes for each scheme; α_j is the normalized coefficient of preferable probability of the j-th attribute.

While as to the unbeneficial attribute, its partial preferable probability could be assumed to be negatively linear correlated to the corresponding performance utility value of the attribute index,

$$P_{ij} \propto -X_{ij},\ P_{ij} = \beta_j (X_{j\max} + X_{j\min} - X_{ij}),\ i = 1,2,\ldots,n;\ j = 1,2,\ldots,m. \tag{2}$$

where β_j is the normalized coefficient of preferable probability of the j-th unbeneficial attribute, X_{jmin} and X_{jmax} are the minimum and maximum values of the j-th unbeneficial attribute performance utility index, respectively.

Furthermore, according to the normalization of probability, i.e.,

$$\sum_{i=1}^{n} P_{ij} = 1, \tag{3}$$

it results in the normalized coefficient of preferable probability α_j and β_j as,

$$\alpha_j = \frac{1}{n\overline{X_j}},\ \beta_j = \frac{1}{n(X_{j\min} + X_{j\max} - n\overline{X_j})} \tag{4}$$

where $\overline{X_j}$ is the arithmetic mean value of the j-th performance utility index.

Moreover, according to probability theory, the joint probability of the i-th scheme is the product of all the partial preferable probability P_{ij} as a whole,

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

Finally, the joint probability of the i-th scheme is actually the overall / total preferable probability of the scheme, which is the unique and decisive indicator to determine status of the scheme in the corresponding optimization [22]. The scheme with the largest overall / total preferable probability among all schemes corresponds to the unique optimum status under the consideration of simultaneous optimization of multiple objectives.

3. Applications in Parameter Optimization Design of Plasma Arc Machining SS 304 Alloy

Hema et al conducted experimental investigations on SS 304 alloy using plasma arc cutting [1], the surface roughness, kerf ratio, and material removal rate (MRR) are evaluated as the optimal goals which affect the production process and quality of the machining surfaces. The input variables include the plasma arc cutting parameters, such as arc voltage, standoff distance, cutting speed, and plasma offset for the cutting of SS 304 alloy machined, the cutting sample are nozzles at two different types of (130 A and 200 A).

Table 1 shows the designed input experimental factors and responses using nozzles 1 (130 A) and 2 (200 A) of the experiments with a mixed Taguchi design of L18 orthogonal array. For the two nozzles, a total of 36 experiments were conducted according to the L18 orthogonal array design.

The machining of the SS 304 alloy material is done by fixing the workpiece on the worktable of the plasma arc machine permanently. The dimension of the workpiece was 817 × 210 mm and thickness of it 6 mm. For more details of these PAC experiments, see reference [1].

Table 1. Factors and responses using nozzles 1 (130 A) and 2 (200 A)

Sl. no.	Arc voltage (V)	Cutting speed (mm/min)	Standoff distance (mm)	Plasma offset (mm)	Nozzle 1 (130 A)			Nozzle 2 (200 A)		
					Surface roughness (mm)	Kerf ratio	MRR (g/s)	Surface roughness (mm)	Kerf ratio	MRR (g/s)

1	133	1000	2	1.05	1.30	0.60	1.63	1.87	0.60	1.72
2	133	1000	3.5	1.25	1.45	0.55	1.59	2.82	0.55	1.62
3	133	1000	5	2.25	1.78	0.54	1.98	1.61	0.56	1.81
4	133	1500	2	1.05	1.28	0.54	2.95	1.85	0.52	2.92
5	133	1500	3.5	1.25	1.52	0.65	2.78	1.70	0.48	2.92
6	133	1500	5	2.25	1.42	0.66	2.79	1.60	0.52	2.33
7	133	2000	2	1.25	1.62	0.57	3.36	1.38	0.50	3.05
8	133	2000	3.5	2.25	1.79	0.60	2.91	1.66	0.52	3.10
9	133	2000	5	1.05	1.71	0.62	2.93	2.04	0.48	2.59
10	136	1000	2	1.25	2.01	0.61	2.49	1.88	0.56	1.80
11	136	1000	3.5	2.25	1.59	0.55	2.07	1.34	0.57	1.78
12	136	1000	5	1.05	1.59	0.63	1.93	1.30	0.63	2.10
13	136	1500	2	2.25	1.49	0.62	2.98	1.75	0.52	2.63
14	136	1500	3.5	1.05	1.77	0.53	2.73	2.09	0.53	2.22
15	136	1500	5	1.25	1.58	0.57	2.66	1.49	0.52	2.45
16	136	2000	2	2.25	1.16	0.51	3.42	1.78	0.48	3.07
17	136	2000	3.5	1.05	1.31	0.60	3.19	1.68	0.51	3.27
18	136	2000	5	1.25	1.62	0.57	2.87	2.12	0.53	2.77

Table 2 shows the evaluated consequences for the designed experiments with a mixed Taguchi design of L18 orthogonal array.

In the evaluation, the MRR has the characteristic of "larger the better", which belongs to the beneficial index, while kerf ratio and surface roughness have the characteristic of "smaller the better", which are attributed to the unbeneficial index.

By using probabilistic multi – objective optimization, the final optimum target is the total preferable probability uniquely, the scheme that has the maximum total preferable probability will be the optimal selection of the design comparatively in viewpoint of system theory.

Table 2 indicates that the 16th scheme exhibit the maximum total preferable probability for the designed experiments for Nozzle 1 (130 A), while the 7th scheme exhibit the maximum total preferable probability for the designed experiments for Nozzle 2 (200 A) in the designed experiments. Therefore, the optimized parameters of plasma arc machining SS 304 alloy from the designed experiment for Nozzle 1 (130 A) are arc voltage at 136V, cutting speed of 2000mm/min, standoff distance of 2mm, and plasma offset of 2.25mm; the optimized parameters of plasma arc in machining SS 304 alloy from the designed experiment for Nozzle 2 (200 A) are arc voltage at 133V, cutting speed of 2000 mm/min, standoff distance of 2 mm, and plasma offset of 1.25mm.

Although the final results of the optimized parameters of plasma arc machining SS 304 alloy from the designed experiment for Nozzles 1 (130 A) and 2 (200A) are the same as those by using grey relational analysis by chance, the analysis procedures are intrinsically different, there is a uncertain factor grey relational analysis, which is the selected subjectively without any rationality [1].

Table 2. Evaluated consequences for the designed experiments with a mixed Taguchi design of L18 orthogonal array

	130A					200A				
Sl. no.	Partial preferable probability			Total preferable probability		Partial preferable probability			Total preferable probability	
	P_{SR}	P_{kf}	P_{MRR}	$P_t \times 10^4$	Rank	P_{SR}	P_{kf}	P_{MRR}	$P_t \times 10^4$	Rank
1	0.0636	0.0541	0.0345	1.1868	15	0.0533	0.0490	0.0390	1.0186	17
2	0.0589	0.0588	0.0336	1.1652	16	0.0308	0.0538	0.0367	0.6087	18
3	0.0484	0.0598	0.0419	1.2129	14	0.0595	0.0529	0.0410	1.2896	15
4	0.0643	0.0598	0.0624	2.3976	2	0.0538	0.0567	0.0661	2.0183	6
5	0.0567	0.0493	0.0588	1.6444	10	0.0573	0.0606	0.0661	2.2975	5
6	0.0598	0.0484	0.0590	1.7090	9	0.0597	0.0567	0.0528	1.7879	9
7	0.0535	0.0569	0.0711	2.1652	4	**0.0649**	**0.0587**	**0.0691**	**2.6309**	**1**
8	0.0481	0.0541	0.0616	1.6022	12	0.0583	0.0567	0.0702	2.3221	4

9	0.0506	0.0522	0.0620	1.6386	11	0.0493	0.0606	0.0587	1.7516	10
10	0.0412	0.0531	0.0527	1.1520	17	0.0531	0.0529	0.0408	1.1445	16
11	0.0544	0.0588	0.0438	1.4028	13	0.0659	0.0519	0.0403	1.3791	13
12	0.0544	0.0512	0.0408	1.1392	18	0.0668	0.0462	0.0476	1.4670	12
13	0.0576	0.0522	0.0631	1.8957	5	0.0562	0.0567	0.0596	1.8979	8
14	0.0488	0.0607	0.0578	1.7099	8	0.0481	0.0558	0.0503	1.3490	14
15	0.0548	0.0569	0.0563	1.7547	7	0.0623	0.0567	0.0555	1.9620	7
16	**0.0681**	**0.0626**	**0.0724**	**3.0841**	**1**	0.0555	0.0606	0.0695	2.3357	3
17	0.0633	0.0541	0.0675	2.3111	3	0.0578	0.0577	0.0741	2.4707	2
18	0.0535	0.0569	0.0607	1.8494	6	0.0474	0.0558	0.0627	1.6583	11

4. Conclusion

Through this study, it following conclusions can be obtained:

1. The probabilistic multi-objective optimization conforms to the essence of "simultaneous optimization of multiple objectives";
2. The probabilistic multi-objective optimization is rational to be used to conduct the parameter optimization design of plasma arc cutting of SS 304 alloy;
3. The consequences signify the practical significance of the approach to the industrial production process;
4. The potential avenues of future research is to grasp the essence of "simultaneous optimization of multiple objectives" to explore more rational approach.

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