The Iraqi Journal For Mechanical And Material Engineering, Vol.17, No2,July 2017

MULTI-OBJECTIVE OPTIMIZATION OF WIRE EDM PARAMETERS BY APPLYING MOORA TECHNIQUE

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ABSTRACT:

The application of optimization techniques is essential for a manufacturing unit to respond effectively to ruthless competitiveness and increasing demand of quality product in the market. In this study, multi-objective optimization on the basis of ratio analysis (MOORA) technique was used to solve different decision-making problems and optimize the machining parameters in the wire electrical discharge machining processes for different materials. Five decision making problems requiring determination of optimum machining parameters using different techniques are considered in this paper. In all these cases, the obtained results using the MOORA technique compared with those suggested by the past investigators and the results demonstrate the simplicity, suitability, possibility, and flexibility of this technique when finding the solution for different complex decision-making problems during machining setting.

KEYWORDS: Machining, WEDM, MOORA, Multi-Optimization

الامثلية لمتغيرات التشغيل بالتفريغ الكهربائي باستخدام تقنية التحليل النسبي

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ملخص البحث :-

ان تطبيق التقنيات الخاصة للحصول على الاختيار الامثل تعتبر من الاساسيات لوحدة التصنيع وذلك لتعزيز القدرة التنافسية والحصول على جودة عالية للمنتج. يتضمن موضوع البحث استخدام تقنية التحليل النسبي(MOORA) لحل المشاكل اتخاذ القرار خلال الانتاج وللحصول على الاختيارالامثل لعدد من المتغيرات والعوامل في ان واحد خلال عمليات التشغيل باستخدام التفريغ الكهربائي ولمواد مختلفة. حيث تم تطبيق تقنية (MOORA) على خمس بحوث سابقة لعمليات التشغيل باستخدام التفريغ الكهربائي والتي اعتمد فيها الباحثين على طرق اخرى في ايجاد الاختيار الامثل لمتغيرات التشغيل. وبعد مقارنة النتائج التي تم الحصول عليها باستخدام تقنية التحليل النسبي مع نتائج البحوث المذكورة تبين ان استخدام هذه التقنية هي الابسط والاكثر ملائمة في تحديد الامثلية لعدد من متغيرات عمليات التشغيل المعقدة وكذلك الافضل من بين طرق التحليل الاخرى في ايجاد الحلول لمشاكل اتخاذ القرار خلال عملية التشغيل .

Received:4-6-2016
Accepted:5-3-2017

INTRODUCTION :-

Electrical discharge machining (EDM) is a potential process of developing complex geometrical shapes and integral angles in mold, die, aerospace, surgical components, etc. (Aich and Banerjee, 2014). EDM is considered a competitive machining technology due to its contact-free removal mechanisms where by using this process no deformation occurs even for thin component (Liu et al., 2014). Selecting appropriate wire electrical discharge machining WEDM parameters is significant to determine the quality of the manufactured parts, productivity and the cost. The multi-objective optimization requires quantitative determination of the relationship between responses with combination of machine setting parameters. This paper investigates the applicability of MOORA technique to select the optimum parameters of WEDM. MOORA technique is to be uncomplicated and easy to use during the calculation in order to reach to the optimum solutions. In addition, this technique helps the decision makers to exclude the inappropriate alternatives, though choosing the most appropriate alternative to reinforce the existing selection procedures (Brauers, 2004; Brauers et al., 2008).

DEFINITION OF THE MOORA METHOD :-

The MOORA technique is a multi-objective optimization, as well known as multi-criteria or multi attribute optimization technique. It can be used to solve various types of complex decision making problems in the manufacturing environment (Kivak, 2014; Maiyar et al., 2013; Kuram and Ozcelik, 2013) where the requirement is to simultaneously optimize two or more often conflicting objectives which are subjected to certain constraints. First step of the MOORA method is the formulation of the decision matrix, as represented in Eq. (1), to illustrate representation of the different alternatives with respect to a different objectives (Brauers et al., 2008; Kalibatas and Turskis, 2008; Brauers and Zavadskas, 2010)

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots\ \cdots\ \cdots\ \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots\ \cdots\ \cdots\ \cdots & X_{2n} \\ \cdots & \cdots & \cdots\ \cdots\ \cdots\ \cdots & \cdots \\ \cdots & \cdots & \cdots\ \cdots\ \cdots\ \cdots & \cdots \\ X_{m1} & X_{m2} & \cdots\ \cdots\ \cdots\ \cdots & X_{mn} \end{bmatrix} \tag{1}$$

Where X*ij* is the representation measure of *i*th alternative on *j*th attribute, *m* symbolizes to the number of alternatives, and *n* symbolizes to the number of attributes.
Second step, a ratio system is evolved in which every representation of an alternative on an attribute is compared to a denominator which is a representative for all the alternatives as regard with that attribute. Brauers et al. (2008) took into consideration different ratio systems, like total ratio, Schärlig ratio, Körth ratio etc. and determined that for this denominator, the square root of the sum of squares of each alternative per attribute is the best option. The following Eq. (2) represents the ratio:

$$x_{ij}^{a} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \left(j = 1,2,\ldots\ldots\ldots n \right) \tag{2}$$

where x_{ij} denotes *i*th alternative of *j*th objective. Usually these numbers belong to the term [0, 1] which refers to the normalized performance of *i*th alternative on *j*th attribute. In case of that there are different responses and require to optimize these responses in the same time this called multi-response optimization and the normalized performances are added in case of maximization (for valuable attributes), while subtracted in case of minimization (for non valuable attributes) (Balezentis et al., 2012; Gadakh et al., 2013; Balezentis and Zeng, 2013). Then the optimization problem becomes as Eq. (3):

$$y_i = \sum_{j=1}^{g} x_{ij}^{a} - \sum_{j=g+1}^{n} x_{ij}^{a} \tag{3}$$

where g represents the maximum number of attributes, (n-g) represents the minimum number of attributes, and y_i represents the normalized estimate value of *i*th alternative with respect to all the attributes. Predominantly, it is noticed that some attributes are more significant than others. The attribute is multiplied with its corresponding weight so as to obtain more significance to this attribute i.e. significance coefficient. (Brauers and Zavadskas, 2009). Then, considering this attribute weight to obtain on the Eq.(4):

$$y_i = \sum_{j=1}^{g} w_i x_{ij}^{a} - \sum_{j=g+1}^{n} w_i x_{ij}^{a} \, (j = 1,2,..........n) \tag{4}$$

where w_j defines as a weight of *j*th attribute, this weight can be limited by using analytic hierarchy method or entropy procedure. The maximization (for valuable attributes) in the decision matrix resulted in positive value of y_i while the minimization (for non valuable attributes) resulted in negative value of y_i. An ordinal ranking of y_i reveals to the final priority. Therefore, the desirable or best alternative possesses the maximum value of y_i, while the undesirable or worst alternative possesses the minimum value y_i.

RESULTS AND DISCUSSION :-

The MOORA method has the capability in solving multi-objective decision making problems in machining process and to explain that the following five examples of wire electrical discharge machining (WEDM) are considered in this research.

WEDM of EN-31 Tool Steel

Gajjar and Desai (2015) applied Taguchi design and grey relation analysis to evaluate the performance of WEDM using molybdenum wire during machining of EN-31 tool steel. In this study, the machining parameters of EDM i.e. pulse on time (T_{on}), pulse off time (T_{off}), and servo voltage (SV) were selected as input parameters. While the output parameters were material removal rate (MRR), Kerf width (KW) and surface roughness (R_a) which are the main parameters affecting on the performance of WEDM. The-higher-the-better criterion was considered for the MRR while the-lower-the-better criterion was considered for KW and R_a. Table 1 shows the attribute values for input and output parameters. Table 2 illustrates the normalized performance of the alternatives with take into account the values of attributes, as obtained from Eq. (2). Subsequently, the normalized estimate values (y_i) of all the alternatives with considered characteristics are calculated by applying Eq. (4). Table 2 also demonstrates the results of the MOORA technique based solution for the machining parameters selection problem which provides relative ranking of the alternative during setting according to the descending sort of their estimate values. It can be seen from Table 2 that experiment no.4 possesses the first rank which includes the optimum machining parameters i.e. pulse on time (120 µs), pulse off time (40 µs), and servo voltage (30 V). The results were agreed to those referenced by Gajjar and Desai (2015).

WEDM of D3 Tool Steel

Shivade and Shinde (2014) investigated the influence of pulse-on time (T_{on}), pulse-off time (T_{off}), peak current (I_p) and wire speed (W_S) on the material removal rate (MRR), dimensional deviation (DD), gap current (GC) and machining time (T) during machining of D3 tool steel. Grey Relational Analysis (GRA) is utilized with Taguchi method in order to optimize all four process parameters. The higher-the-better quality characteristic has been employed to obtain the signal to noise (S/N) ratio of MRR and Gap current, whereas lower-the-better quality characteristic used for dimensional deviation and machining time. Table 3 shows the data of input and output parameters. Table 4 reveals the results of the MOORA technique for selected machining parameters problem which offers a proportional ranking of the alternative when sorted according to the descending order of their estimate values. It can be seen from Table 4 that experiment no.7 possesses the highest rank, and the corresponding machining parameters which indicated the optimum parameters are pulse-on time (9µs), pulse-off time (2 µs), peak current (3 A) and wire speed (5 m/min). This result was quite corresponded to those indicated by Shivade and Shinde (2014).

WEDM of Incoloy800 Super alloy

Muthu Kumar et al. (2010) used Taguchi method combined with grey relational analysis to enhance the multi-response characteristics of material removal rate (MRR), kurf width (KW), and surface roughness (R_a) in the wire EDM of Incoloy 800. Gap voltage (A), pulse-on time (B), Pulse-off-time (C) and wire feed (D) used as input machining parameters. Table 5 reveals to the data of input and output parameters. The-higher-the-better criterion was considered for MRR while the-lower-the-better criterion was considered for KW width and R_a. Table 6 reveals the normalized vector and identical ranking of every experiment. In Table 6 shows that experiment no.2 has the highest rank and the optimum machining parameters are gap voltage (50 volts), pulse-on time (8µs), Pulse-off-time (6µs) and wire feed (8 mm/min). The results were agreed with those referenced by Muthu Kumar et al. (2010).

WEDM of AISI 304 Stainless Steel

J Patel and P Patel (2013) determined the various WEDM process parameters i.e. for obtaining optimal values of these parameters during machining of AISI 304 stainless steel. They considered four different process parameters i.e. pulse on time (T_{on}), pulse off time (T_{off}), wire tension (T), and wire feed (f) which effect on the material removal rate (MRR) and surface roughness (R_a). Table 7 reveals to the data of input and output parameters. The-higher-the-better criterion was considered for MRR while the-lower-the-better criterion was considered for Ra. Table 8 reveals the results of the MOORA technique which provides a relative ranking of the alternative. It can be seen from Table 8 that experiment no.7 has the highest rank, and the corresponding process parameters for the optimum values are pulse on time (130µs), pulse off time (50µs), wire tension (11), and wire feed (160). This results agreed with the results that suggested by J Patel and P Patel (2013).

WEDM of Monel K-500

Kumar et al. (2015) performed the parameters optimization of WEDM process of nickel-copper alloy (Monel K-500) with multi-response criteria based on the Taguchi orthogonal array with the grey relational analysis. They considered pulse on time (T_{on}), pulse off time (T_{off}), peak current (I_p), Servo voltage (SV) as the input parameters. While material removal rate (MRR) and surface roughness (R_a) were considered as output parameters. Table 9 shows the data of input and output parameters. Table 10 reveals to the MOORA technique based solution for process parameter chosen problem which provides a relative ranking of the alternative when organized according to the descending order of their estimated values. It can be seen from Table 10 that experiment no. 20 has the maximum rank, and the corresponding optimum process parameters are pulse on time (120µs), pulse off time (50µs), peak current (12), and Servo voltage (50). This results was matched to the one suggested by Kumar et al. (2015) .

Table 1: Experimental results of example 3.1 (Gajjar and Desai (2015)

Expt No.	T_{on} (µs)	T_{off} (µs)	SV (V)	MRR	KW	R_a
1	110	40	20	0.039	0.2561	3.3433
2	110	50	30	0.0325	0.2769	3.071
3	110	60	40	0.0164	0.273	2.3967
4	120	40	30	0.0613	0.2531	3.2255
5	120	50	40	0.0409	0.282	3.0883
6	120	60	20	0.0256	0.2598	3.265
7	130	40	40	0.0465	0.2611	2.6817
8	130	50	20	0.0494	0.2907	3.4817
9	130	60	30	0.0492	0.3182	3.2767
SumX_{ij}Sq				0.015955	0.6818	87.00505
SqrtX_{ij}Sq				0.126314	0.825712	9.32765

Table 2: Normalized Matrix and results of analysis of example 3.1(Gajjar and Desai (2015)

Expt No.	Ton	Toff	SV	MRR	KW	R_a	ybar	Rank
1	110	40	20	0.308753	0.310157	0.358429	-0.35983	6
2	110	50	30	0.257295	0.335347	0.329236	-0.40729	7
3	110	60	40	0.129835	0.330624	0.256946	-0.45773	8
4	***120***	***40***	***30***	***0.485297***	***0.306523***	***0.3458***	***-0.16703***	***1***
5	120	50	40	0.323795	0.341523	0.331091	-0.34882	5
6	120	60	20	0.202669	0.314638	0.350035	-0.462	9
7	130	40	40	0.368129	0.316212	0.2875	-0.23558	2
8	130	50	20	0.391088	0.35206	0.373267	-0.33424	3
9	130	60	30	0.389504	0.385364	0.351289	-0.34715	4

Table 3: Experimental results of example 3.2 (Shivade and Shinde, 2014)

Expt No.	T_{on}	T_{off}	I_p	W_S	MRR	DD	GC	T
1	3	2	1	3	17.7	1.655	0.5	135.62
2	3	4	2	5	28.6	1.667	1.3	83.98
3	3	6	3	7	29.5	1.825	1.4	81.37
4	6	2	2	7	38.4	1.742	1.7	62.51
5	6	4	3	3	40.1	1.697	2	59.86
6	6	6	1	5	21.1	1.595	0.6	113.84
7	9	2	3	5	59.5	1.708	2.2	40.34
8	9	4	1	7	22.2	1.672	0.7	108.12
9	9	6	2	3	36.4	1.702	1.7	65.94

Table 4: Normalized Matrix and results of analysis of example 3.2 (Shivade and Shinde, 2014)

Expt No.	T_{on}	T_{off}	I_p	W_S	MRR	DD	GC	T	ybar	Rank
1	3	2	1	3	0.169634	0.325094	0.113607	0.51193	-0.55378	9
2	3	4	2	5	0.274098	0.327451	0.295378	0.317003	-0.07498	6
3	3	6	3	7	0.282723	0.358487	0.3181	0.30715	-0.06482	5
4	6	2	2	7	0.368019	0.342184	0.386264	0.235959	0.176141	3
5	6	4	3	3	0.384312	0.333344	0.454428	0.225956	0.27944	2
6	6	6	1	5	0.202219	0.313308	0.136328	0.429716	-0.40448	8
7	***9***	***2***	***3***	***5***	***0.570238***	***0.335505***	***0.499871***	***0.152273***	***0.582331***	***1***
8	9	4	1	7	0.212761	0.328433	0.15905	0.408125	-0.36475	7
9	9	6	2	3	0.348852	0.334326	0.386264	0.248906	0.151883	4

Table 5: Experimental results of example 3.3 (Muthu Kumar et al., 2010)

Expt No.	A	B	C	D	MRR (g/min)	KW (mm)	R_a (μm)
1	1	1	1	1	0.04833	0.317	3.11
2	1	2	2	2	0.05351	0.324	3.31
3	1	3	3	3	0.05128	0.299	3.6
4	2	1	2	3	0.04192	0.33	3.67
5	2	2	3	1	0.04295	0.322	3.97
6	2	3	1	2	0.05011	0.343	4.04
7	3	1	3	2	0.03844	0.356	4.11
8	3	2	1	3	0.03974	0.368	4.26
9	3	3	2	1	0.04538	0.376	4.4

Table 6: Normalized Matrix and results of analysis of example 3.3 (Muthu Kumar et al., 2010)

Expt. No.	MRR (g/min)	K (mm)	Ra (µm)	ybar	Rank
1	0.350089	0.312557	0.269126	-0.231594	2
2	***0.387611***	***0.319458***	***0.286433***	***-0.21828***	***1***
3	0.371458	0.294809	0.311529	-0.23488	3
4	0.303657	0.325374	0.317586	-0.339304	5
5	0.311118	0.317486	0.343547	-0.349916	6
6	0.362983	0.338192	0.349604	-0.324814	4
7	0.278448	0.35101	0.355662	-0.428223	8
8	0.287865	0.362842	0.368642	-0.443619	9
9	0.328720	0.37073	0.380757	-0.422767	7

Table 7: Experimental results of example 3.4 (J Patel and P Patel, 2013)

Expt No.	T_{on}	T_{off}	T	f	MRR	R_a
1	110	50	3	80	24.57	1.52
2	110	55	7	160	30	2.13
3	110	60	11	230	30.89	1.85
4	120	50	7	230	40.96	2.67
5	120	55	11	80	31.8	2.52
6	120	60	3	160	40.68	2.55
7	130	50	11	160	50.05	2.91
8	130	55	3	230	47.6	2.98
9	130	60	7	80	34.95	2.57

Table 8: Normalized Matrix and results of analysis of example 3.4 (J Patel and P Patel, 2013)

Expt. No.	MRR	SR	ybar	Rank
1	0.217221	0.206454	0.010767	5
2	0.265228	0.289308	-0.024080	7
3	0.273096	0.251277	0.021819	2
4	0.362124	0.362653	-0.000529	6
5	0.281141	0.342279	-0.061138	9
6	0.359649	0.346354	0.013294	4
7	***0.442488***	***0.395251***	***0.047237***	***1***
8	0.420828	0.404759	0.016069	3
9	0.308990	0.349071	-0.040081	8

Table 9: Experimental results of example 3.5 (Kumar et al., 2015)

Expt No.	T_{on}	T_{off}	I_p	SV	MRR	R_a
1	110	50	11	40	32.676	2.48733
2	110	50	12	50	28.8867	2.44567
3	110	50	13	60	43.8747	2.56867
4	110	55	11	50	20.927	2.197
5	110	55	12	60	17.656	1.74567
6	110	55	13	40	52.1453	2.784
7	110	60	11	60	13.243	1.638
8	110	60	12	40	23.0527	2.28467
9	110	60	13	50	37.0023	2.95633
10	115	50	11	40	53.4763	2.76567
11	115	50	12	50	48.266	2.77467
12	115	50	13	60	45.445	2.941
13	115	55	11	50	36.9663	2.66067
14	115	55	12	60	31.119	2.493
15	115	55	13	40	50.1157	2.97533
16	115	60	11	60	24.9557	2.42233
17	115	60	12	40	36.555	2.74267
18	115	60	13	50	36.936	2.904
19	120	50	11	40	54.5967	3.14733
20	120	50	12	50	63.3757	2.953
21	120	50	13	60	53.877	3.002
22	120	55	11	50	38.5617	2.959
23	120	55	12	60	44.9133	3.078
24	120	55	13	40	58.8947	3.263
25	120	60	11	60	26.7133	2.64867
26	120	60	12	40	51.525	3.19333
27	120	60	13	50	44.5737	2.79533
SumXijSq					47024.35	200.5423
SqrtXijSq					216.851	14.1613

Table 10: Normalized Matrix and results of analysis of example 3.5 (Kumar et al., 2015)

Expt. No.	MRR	R_a	ybar	Rank
1	0.150684	0.175643	-0.024959	15
2	0.133210	0.172701	-0.039491	21
3	0.202326	0.181387	0.020940	9
4	0.096504	0.155141	-0.058637	26
5	0.081420	0.123270	-0.041851	22
6	0.240466	0.196592	0.043874	3
7	0.061070	0.115667	-0.054598	23
8	0.106307	0.161332	-0.055025	24
9	0.170635	0.208761	-0.038127	20
10	0.246604	0.195298	0.051306	2
11	0.222577	0.195933	0.026643	7
12	0.209568	0.207679	0.001889	12
13	0.170469	0.187883	-0.017415	14
14	0.143504	0.176043	-0.032539	18
15	0.231107	0.210103	0.021004	8
16	0.115082	0.171053	-0.055971	25
17	0.168572	0.193674	-0.025102	16
18	0.170329	0.205066	-0.034737	19
19	0.251771	0.222249	0.029522	6
20	***0.292255***	***0.208526***	***0.083728***	***1***
21	0.248452	0.211986	0.036465	5
22	0.177826	0.208950	-0.031124	17
23	0.207116	0.217353	-0.010237	13
24	0.271591	0.230417	0.041174	4
25	0.123187	0.187036	-0.063848	27
26	0.237606	0.225497	0.012109	10
27	0.205550	0.197392	0.008158	11

CONCLUSIONS :-

The implementation of the MOORA technique is proposed in order to ability of making decision in the machining problems which assists in choosing the most appropriate alternative from among a considerable number of candidate alternatives for a presented problem. In this research, five clarifying examples are considered to demonstrate the application of this technique. It has been observed in all the cases the following:

1. Using MOORA technique is efficient in order to select the optimum process parameters in wire electrical discharge machining processes.
2. The highest rank of alternatives has almost matched with those derived by past researchers.
3. This technique is computationally very simple, easily comprehendible, and robust which can simultaneously consider any number of quantitative and qualitative selection of attributes, while offering a more objective and logical selection approach.
4. This technique can be used to solve several multi objective optimization problems pertaining to a wide range of manufacturing environment.

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