OPTIMIZAITON OF PROCESS PARAMETERS IN WEDM ON AISI D2 STEEL USING FULL FACTORIAL DESIGN METHOD

[1]Malek Mahir, [2]Brambhatt Dhaval, [3]Khalasi Milan, [4]Prajapati Jignesh, [5]Jadav Jayprit
[1]B.E, [2]B.E, [3]B.E. [4]B.E, [5]B.E
Mechanical Engineering
Ipcowala Institute of Engineering & Technology, Dharmaj, Petlad, India

Abstract : Wire Electrical Discharge Machine (WEDM) is an advanced machine tool, extensively used to machine hard to cut materials like nickel, titanium and other super alloys. Selection of WEDM process parameters to yield the desired level of performance measures like Material removal Rate (MRR) and Surface Roughness (SR) is crucial from quality and economic viewpoints. In the present work an attempt has been made to investigate the effect of WEDM process parameters such as pulse on time, pulse off time and peak current in machining of AISI D2 steel. A 2-level factorial of full factorial design has been used for experimental plan. The significance of process parameters are estimated by ANOVA analysis. Mathematical prediction models are developed for MRR and SR by FFD. Using optimization process of TLBO and also Grey Relation Analysis optimize the calculation.

Keyword : Grey relational analysis; Teaching Learning Based Optimization; Multi-objective optimization; Full Factorial Design; Wire electrical discharge machining.

Introduction

Wire Electrical Discharge Machining (WEDM) is a non- traditional process of material removal from electrically conductive materials to produce parts with intricate shape and profiles. WEDM is revolutionized the tool and die, mold, punch, and metalworking and aerospace industries. It is considered as a unique adaptation of the conventional EDM process, which uses an electrode to initialize the sparking process. However, WEDM utilizes a continuously travelling wire electrode made of thin copper, brass or tungsten of diameter 0.05–0.3 mm, which is capable of achieving very small corner radii. The wire is kept in tension using a mechanical tensioning device reducing the tendency of producing inaccurate parts. The wire work-piece gap usually ranges from 0.025 to 0.05 mm and is constantly maintained by a computer controlled positioning system. In setting the machining parameters, the main goal is the minimum surface roughness. The setting of machining parameters relies strongly on the experience of operators and machining parameters tables provided by machine tool builders. It is difficult to utilize the optimal functions of a machine owing to their being too many adjustable machining parameters.

Literature Review

Wire Electric Discharge Machining (WEDM) is an essential operation in several manufacturing in some industries, which gives importance to variety, precision and accuracy. Several researchers have attempted to improve the performance characteristics namely the material removal rate, dimensional accuracy, cutting speed, surface roughness, spark gap and kerf width. But the full potential utilization of this process is not completely solved because of its complex and stochastic nature and more number of variables involved in this operation.

Several researchers have attempted to improve the performance characteristics namely the surface roughness, cutting speed, dimensional accuracy and material removal rate etc. but the full potential utilization of this process is not completely solved because of its complex and stochastic nature and more number of variables involved in this operation.

In order to predict the surface finish and material removal rate while machining D2 tool steel, Scott et al. [2] developed the empirical models. It was observed that there was no single combination of levels of the different factors that could be optimal under all situations. To locate the optimal machining parameters, the non-dominated point approach was applied, using explicit enumeration of all possible combinations and the dynamic programming method. Miller et al. [3] made an investigation to study the effects of spark cycle and pulse on-time on wire EDM of metal foams, metal bond grinding wheels, sintered Nd-Fe-B magnet, and carbon–carbon bipolar plate. Although results presented are machine-dependent, this research provides the guidelines and procedures for the development of wire EDM process for machining new engineering materials to achieve different manufacturing objectives, either the high MRR, miniature features, or a compromise between the two. This study also demonstrated the capability of wire EDM process to machine different advanced materials. Sarkar et al. [4] optimized the trim cutting operation of WEDM of γ- TiAl alloy for a given machining conditions by desirability function approach and pareto-optimization algorithm and superior performance as compared to desirability function approach. Response Surface Methodology (RSM) was used to develop a prediction model of surface roughness for machining mild steel. The experiments was carried out with TiN-coated tungsten carbide (CNMG) cutting tool, for machining mild steel work-piece covering a wide range of machining conditions.

Mahapatra and Patnaik [5] made an attempt was made to determine the important machining parameters for performance measures like MRR, SF, and kerf separately in the WEDM process. Taguchi's experimental design method is used to obtain optimum parameter combination for maximization of MRR, SF as well as minimization of kerf. In order to optimize for all the three objectives, mathematical models are developed using the non-linear regression method. This study evaluates the performance measures with equal importance to weighting factors since higher MRR, SF and low kerf are equally important objectives in WEDM application. In future, the study can be extended using different work materials, and hybrid optimization techniques.

Ruma Sen et. Al. [6] are examine the influence of the machining parameters on the performance measures and also evaluate optimum setting of the process parameters through ANN-Fuzzy-TLBO hybrid technique. From study it is cleared that, with increasing Pulse on time and drop in pulse off time, cutting speed and surface roughness increases significantly whereas wire consumption decreases. The trends of the influence of the process parameters on the performance however have not been found to be conclusive. The relationships between the machining parameters with the machining characteristics have been modelled using ANN. The result obtained based on MPCI value for the optimal parametric condition following TLBO technique has been found to be better than the result achieved by following GA. The confirmatory experiment confirms the applicability of this evolutionary computational technique. Thus, it can be also concluded that BPNN-Fuzzy-TLBO methodology may present a better alternative for parametric optimization Maraging steel 300 in WEDM.

Experimentation

3.1 Material

D2 steel is an air hardening, high-carbon, high-chromium tool steel. It has high wear and abrasion resistant properties. D2 steel's high chromium content gives it mild corrosion resisting properties in the hardened condition. D2 Steel of: 150mm length, 50mm height and 16mm thickness we are used for our experiment.

Table 1:
Chemical composition of D2 Steel

Element	**Content (%)**
Carbon	1.40-1.60
Manganese	0.60
Silicon	0.60
Cobalt	1.00
Chromium	11.00-13.00
Sulphur	0.03

Table 2:
Mechanical and Physical properties of D2 Steel

Properties	Metric	Imperial
Poisson's Ratio	0.27-.30	0.27-0.30
Elastic Modulus	190-210 GPa	27557-30457 ksi
Density	7.7*1000 Kg/m^3	0.278 lb/m^3
Melting Point	1421˚C	2590 ˚F

3.2Experimental Details

In this paper, the experiments were performed on 5-axis Steer CNC WEDM machine of table size 500 × 400 × 300 (Fig.1). A 0.18 mm diameter molybdenum wire were preferred as the tool electrode. Deionized water was used as the dielectric fluid in this research. Furthermore, the discharge pulse time (factor A), the discharge stop time (factor B), the peak current (factor C) were selected the input process parameters for the WEDM process and the ranges for each of input process parameters were identified. The input process parameters and their levels are shown in Table 3. A level 2 Full Factorial Design was used for the experimental design. At each experiment, Eight (8) specimens of size 20mm × 20mm × 16mm from original job dimension (150mm × 50mm × 16mm) was made to cut by the WEDM process.

Table 3:

Machining parameters and their levels

Machining Parameter	Symbol	Unit	Level 1	Level 2
Pulse ON Time (T_{on})	A	µs	105	125
Pulse OFF Time(T_{off})	B	µs	22	32
Peak Current(Ip)	C	A	4	6

(**fig. 1**: machining of material in wedm)

3.3Experimental Setup

During WEDM process, the electrode (wire) diameter remains constant and the variation in amount of width of cut is negligible as compared to other parameters such as cutting speed and material thickness. Mean cutting speed was observed directly from the WEDM machine monitor. Hence, the MRR for WEDM operation was evaluated using Eq. (1), which is shown below:

MRR = KTV (mm^3/min)

Where, T = Thickness = 16mm
K = Kerf = D+2G (mm)
G = Spark Gap (mm)
V = Cutting Speed (mm/min)

Eight (8) samples are machined according to Level 2 Full Factorial Design using different process parameters and machining time is noted down. The arithmetic mean surface roughness (Ra) of the machined surface is measured by using Mitutoyo Surftest SJ-301 stylus type surface texture-measuring instrument. The experimental assignment for three variable parameters with their levels by Level 2 Full Factorial Design and the mean measurement results for material removal rate (MRR), machining time and surface roughness (Ra) are shown in Table 4.

Table 4:
Experimental design and results by Level 2 Full Factorial Design

Experiment No.	A	B	C	Machining Time (min)	MRR (mm^3/min)	Ra (µm)
1	125	22	6	13.59	12.3578	7.1
2	105	32	4	20.21	8.4914	5.2
3	125	32	4	22.19	7.7432	5.8
4	105	22	4	15.13	11.3556	6.6
5	125	22	4	16.27	10.5045	5.3
6	105	22	6	12.57	13.3436	7.8
7	125	32	6	18.34	9.3070	6.0
8	105	32	6	18.12	9.4948	5.8

Analysis of Variance (ANOVA)

4.1Analysis of Material Removal Rate

The fit summary Suggest that the quadratic model is statistically significant for analysis of MRR. The reduced ANOVA for quadratic model is shown in the table 5. F-value is utilized to rank the significant factors. As for the experimentation of MRR quadratic model is suggested, non-significant terms are removed by backward elimination of keeping alpha out 0.1 (i.e. confidence level 95%). After selecting quadratic model with backward elimination it is found that the model is not hierarchical and so the wire tension (WT or in coded form 'E') is added to form the model hierarchical. The model is significant as probability >F is less than 0.0001) and the F- value is large. The predicted R-Squared and adjusted R-squared has a close agreement with values 0.9852 and 0.9740 respectively, as difference between these two are less than 0.0112. Normality of residuals was checked using Normal probability plot. Most of the residuals fall on a straight line, which indicates that errors are normally distributed.

Table 5:
ANOVA for MRR

Source	DF	Adj SS	Adj MS	F- Value	P- Value
Ton	1	0.9611	0.9611	9.92	0.035
Toff	1	19.6098	19.6098	202.47	0.000
Ip	1	5.1336	5.1336	53.00	0.002
Error	4	0.3874	0.0969		
Total	7	26.0919			

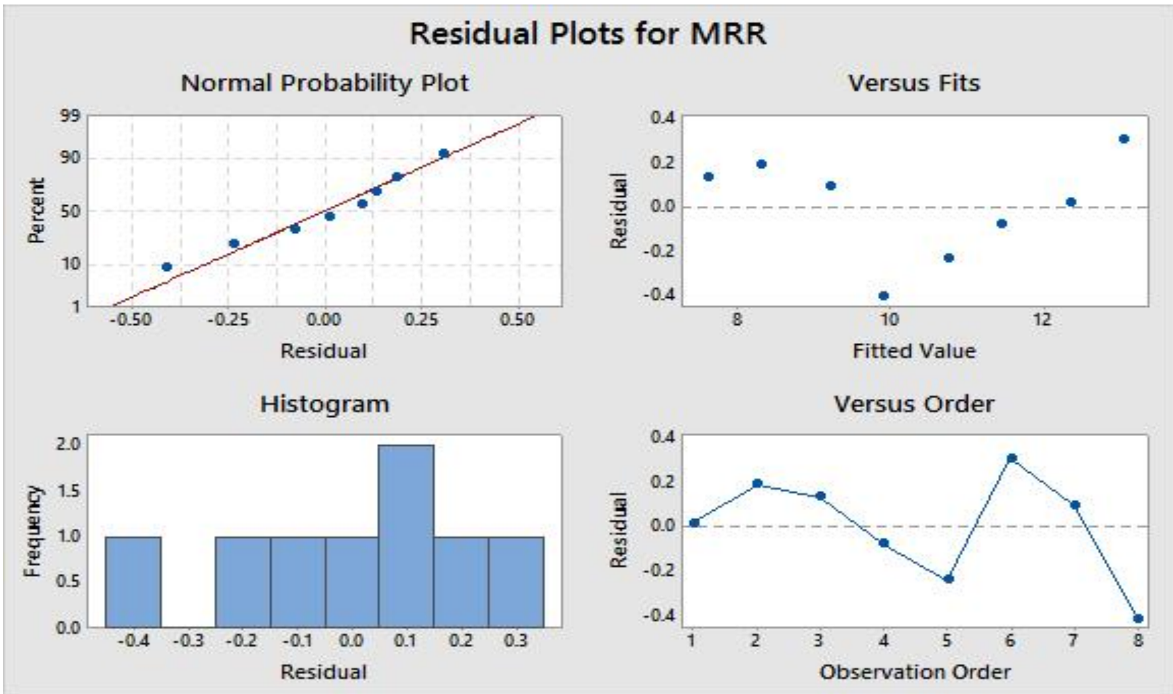
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.311214	98.52%	97.40%	94.06%

The empirical relation of MRR in terms of actual factors is obtained as follows. Final Equation in Terms of Actual Factors:

MRR = 10.325 + 0.347 Ton_105 - 0.347 Ton_125 + 1.566 Toff_22 - 1.566 Toff_32 - 0.801 Ip_4+ 0.801 Ip_6

And graph of Residual plot in Fig. 2



(**fig. 2** residual plot for mrr)

4.2Analysis of Surface Roughness

The fit summary Suggest that the quadratic model is statistically significant for analysis of SR. The reduced ANOVA table for quadratic model of SR is shown in the table 6. Because for the experimentation of SR quadratic model is suggested, non-significant terms are removed by backward elimination of keeping alpha out 0.1. The model is significant as probability >F is less than 0.0001.

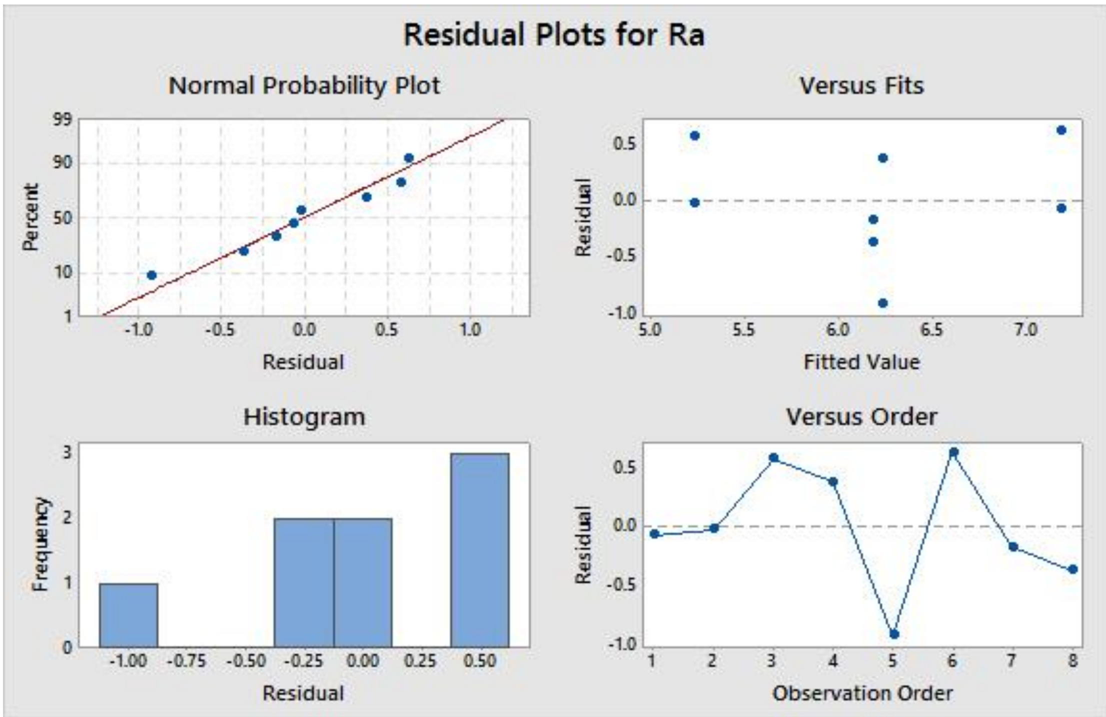
Table 6:
ANOVA for Surface Roughness

Source	DF	Adj SS	Adj MS	F- Value	P- Value
Toff	1	2.000	2.0000	5.28	0.070
Ip	1	1.805	1.8050	4.76	0.081
Error	5	1.895	0.3790		
Total	7	5.700			

Final Equation in Terms of Actual Factors:

Ra = 6.200 + 0.500 Toff_22 - 0.500 Toff_32 - 0.475 Ip_4 + 0.475 Ip_6

And graph of Residual plot in Fig. 3

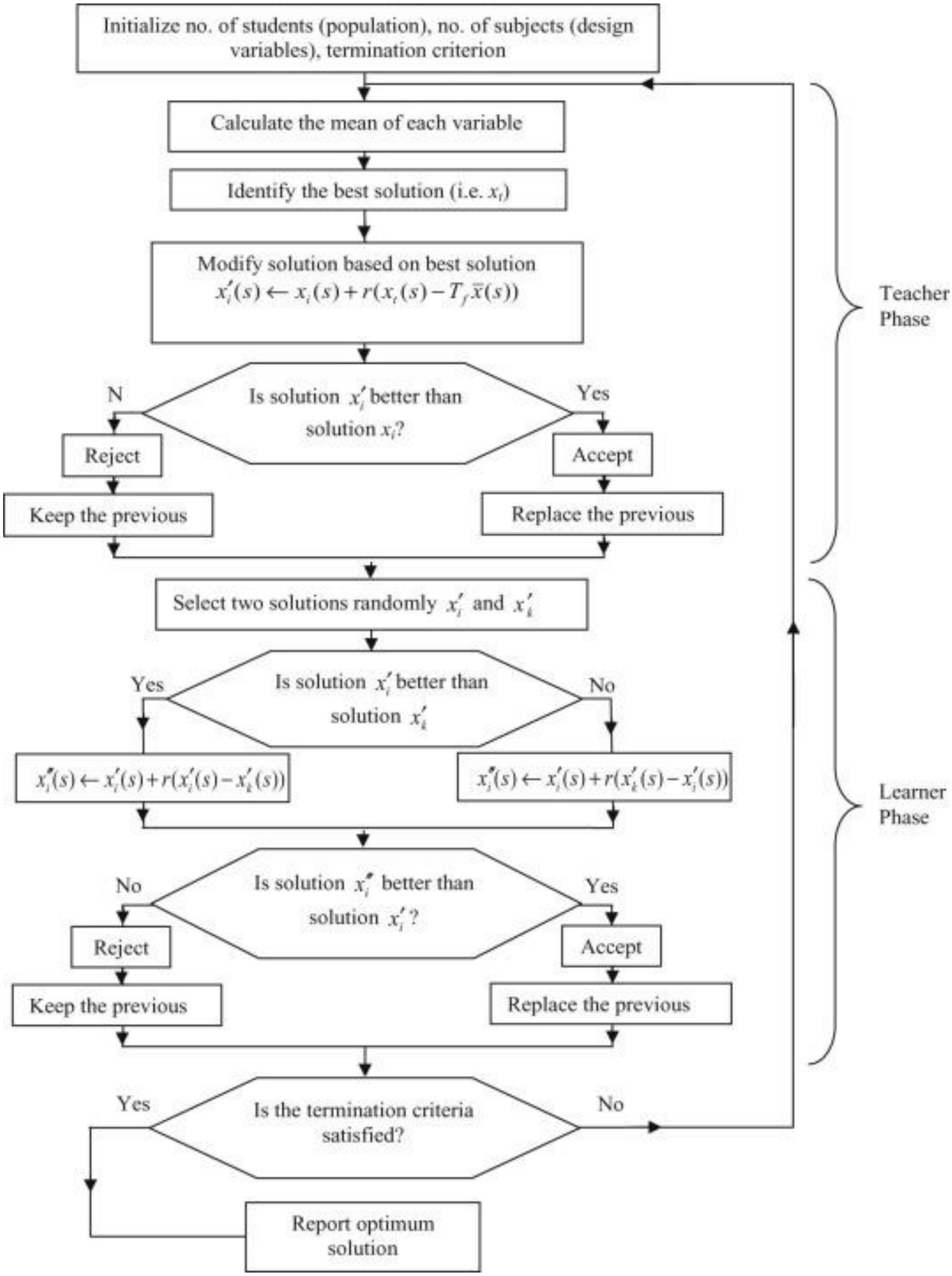


(fig. 3residual plot for ra**)**

Optimization using TLBO

5.1Teaching Learning Based Optimization (TLBO)

In TLBO Algorithm teacher and learners are the two vital components. This describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). Teacher is usually considered as a highly learned person who trains learners so that they can have better results in terms of their marks or grades. Moreover, learners also learn from the interaction among themselves, which also helps in improving their results. TLBO is population based method. In this optimization algorithm a group of learners is considered as population and different design variables are considered as different subjects offered to the learners and learners' result is analogous to the fitness value of the optimization problem. In the entire population the best solution is considered as the teacher. TLBO algorithm mainly working of two phases, namely teacher phase and learner phase. TLBO Algorithm is shown in figure.4



(**fig. 4** TLBO flow chart)

5.2Teacher Phase

A good teacher increases the level of learners' up to his or her level in terms of knowledge. But it is depending on the level of learners. This follows a random process depending on many factors. Now, Mi is the mean and Ti is the teacher at any iteration i. Ti will try to move Mi near its own level. Therefore new mean will be Ti labeled as Mnew. The solution is updated according to the difference among the existing and the new mean is

Difference_Meani = ri (Mnew – TFMi)

Here, TF = teaching factor that decides the value of mean to be changed
ri = random number in the range [0,1]

The value of TF can be either 1 or 2, which is again a heuristic step and decided randomly with same probability as, TF = round [1+ rand (0, 1) {2-1}]

Now, this difference modifies the existing result according to the below expression.
Xnew,i = Xold,i + Difference_Meani

5.3Learner Phase
In this phase, the knowledge of learners is increases by teacher and also by the interaction among themselves. A learner will gain knowledge if the other learner has more knowledge than him or her. The learners phase is expressed as below.

For i = 1:Pn
Randomly select two learners Xi and Xj, where, i ≠ j
If f (Xi) < f (Xj)
Xnew,i = Xold,i + ri(Xi − Xj)
Else
Xnew,i = Xold,i + ri(Xj − Xi)
End If
End For
Accept Xnew if it gives a better function value.

5.4Multi-objective Optimization

Optimization can be defined as process of selecting optimum values of variables which gives the best suitable values of objective function. Optimization can be of single objective or multi-objective type. The optimization process is can be of minimization type or maximization type.
In this research work there are three variables namely pulse on time, pulse off time, peak current. The outputs are Material Removal Rate and surface roughness. Weight method is used for the multi-objective optimization. Material Removal Rate and surface roughness are the two different sub-objectives. The function is normalized to solve multi-objective problem.

5.5Multi-objective Function and Limit of Variable
The first objective is to maximize the Material Removal Rate. The equation for the Material Removal Rate is

MRR = 10.325 - 0.347 Ton_125 - 1.566 Toff_32 - 0.801 Ip_4

The second objective is to minimize the surface roughness. The equation for the surface roughness is

Ra = 6.200 - 0.500 Toff_32 - 0.475 Ip_4

The above given single objective functions are mentioned together for multi-objective optimization. The normalized multi-objective function (Z) is formulated by giving weight factors in equation.

Maximize Z = w (MRR / MRR,max) – (1-w) (SR / SR,max)
Here w = weight factor for the equation. MRR,max and SR,max are the maximum and minimum values of the objective functions MRR and SR respectively.
The limits of the variable parameters are given as below,

$$105 \leq Ton \leq 125$$
$$22 \leq Toff \leq 32$$
$$4 \leq IP \leq 6$$

5.6Result after optimization TLBO algorithm
Optimum values after optimization.

Ton = 125.00 Toff = 32.00 IP = 4.00

Material Removal Rate MRR = 7.6185 (mm^3/min)
Surface Roughness Ra = 5.225 (µm)
The above given values are the final values for the multi-objective optimization of material removal rate and surface roughness for the given set of the input variables.

Optimization using GRA

6.1Grey Relation Analysis (GRA)
Now-a-days, multi criterion decision-making (MCDM) techniques are gaining significance for complex genuine issues because of their inalienable capacity to judge distinctive choices on different criteria for conceivable determination of the best. In this paper, a multi-criteria decision making model combining with grey relational analysis (GRA) has been proposed to study the optimization problem in WEDM process. The methodology consists of a number of steps as follows:

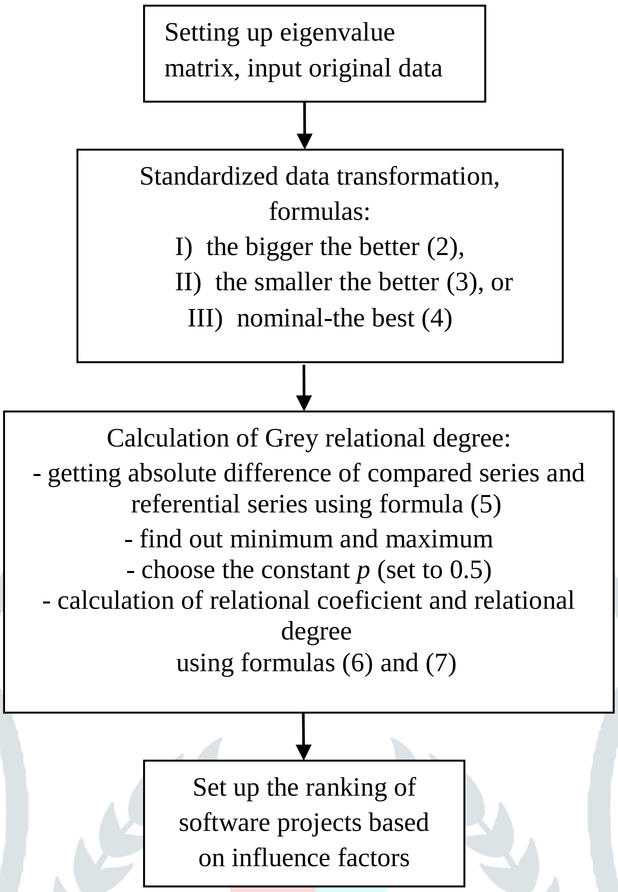
Let the number of the listed software projects be *m*, and the number of the influence factors be *n*. Then a *m* x *n* value matrix (called eigenvalue matrix) is set up.

$$X = \begin{bmatrix} x_1(1), x_1(2), ...x_1(n) \\ x_2(1), x_2(2), ...x_2(n) \\ .... \\ .... \\ x_m(1), x_m(2), ...x_m(n) \end{bmatrix} \quad (1),$$

where $x_i(k)$ is the value of the number *i* listed project and the number *k* influence factors.

Usually, three kinds of influence factors are included, they are:

1. Benefit – type factor (the bigger the better),
2. Defect – type (the smaller the better)
3. Medium – type, or nominal-the-best (the nearer to a certain standard value the better).



(fig. 5. the generation of grey relation degree for software projects**)**

It is difficult to compare between the different kinds of factors because they exert a different influence. Therefore, the standardized transformation of these factors must be done. Three formulas can be used for this purpose.

$$x_i(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (2).$$

The first standardized formula is suitable for the benefit – type factor.

$$x_i(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \quad (3).$$

The second standardized formula is suitable for defect – type factor.

$$x_i(k) = \frac{|x_i(k) - x_0(k)|}{\max x_i(k) - x_0(k)} \quad (4).$$

The third standardized formula is suitable for the medium – type factor.

The grey relation degree can be calculated by steps as follows:

a) The absolute difference of the compared series and the referential series should be obtained by using the following formula:

$$\Delta x_i(k) = |x_0(k) - x_i(k)| \quad (5),$$

and the maximum and the minimum difference should be found.

b) The distinguishing coefficient p is between 0 and 1. Generally, the distinguishing coefficient p is set to 0.5.
c) Calculation of the relational coefficient and relational degree by (6) as follows.

In Grey relational analysis, Grey relational coefficient ξ can be expressed as follows:

$$\xi_i(k) = \frac{\Delta \min + p\Delta \max}{\Delta x_i(k) + p\Delta \max} \quad (6),$$

and then the relational degree follows as:

$$r_i = \sum [w(k)\xi(k)] \quad (7).$$

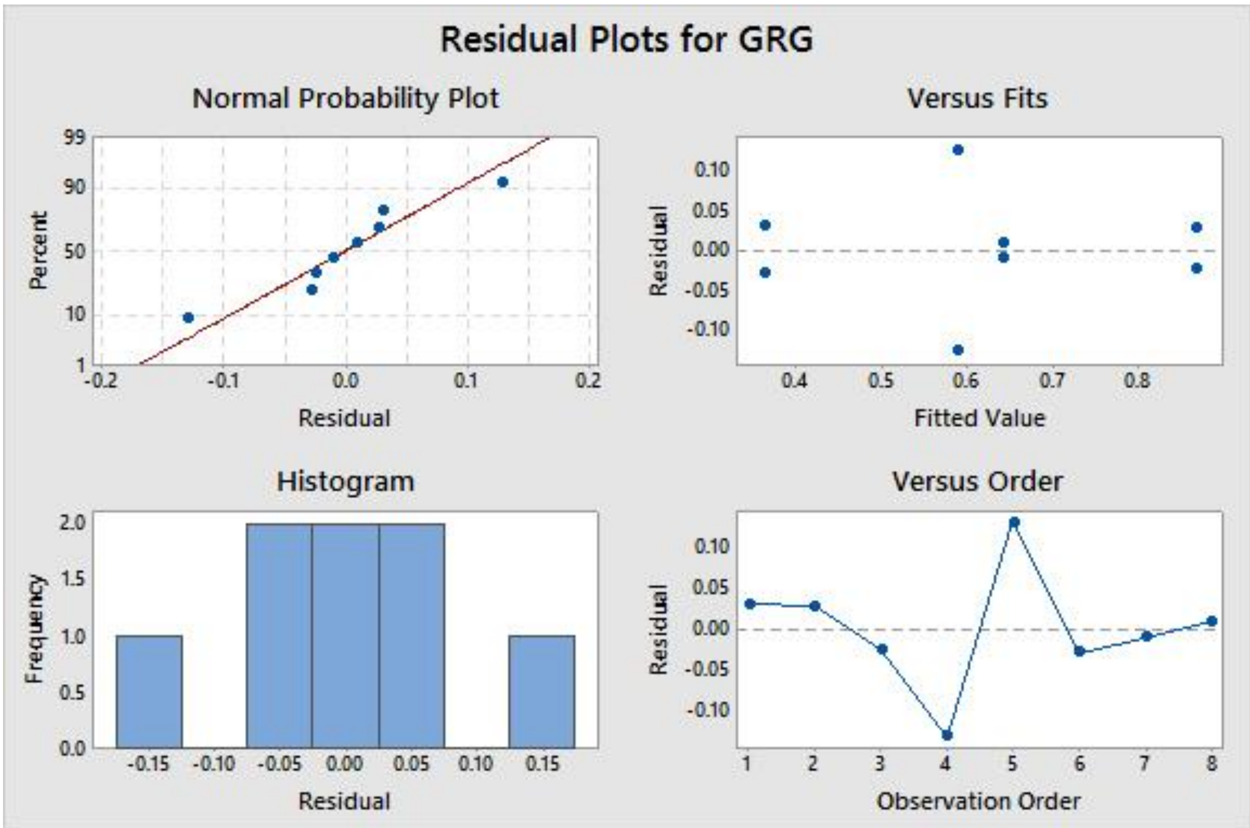
In equation (7), ξ is the Grey relational coefficient, *w (k)* is the proportion of the number *k* influence factor to the total influence indicators. The sum of *w (k)* is 100%. The result obtained when using (6) can be applied to measure the quality of the listed software projects.

6.2Result and Discussion

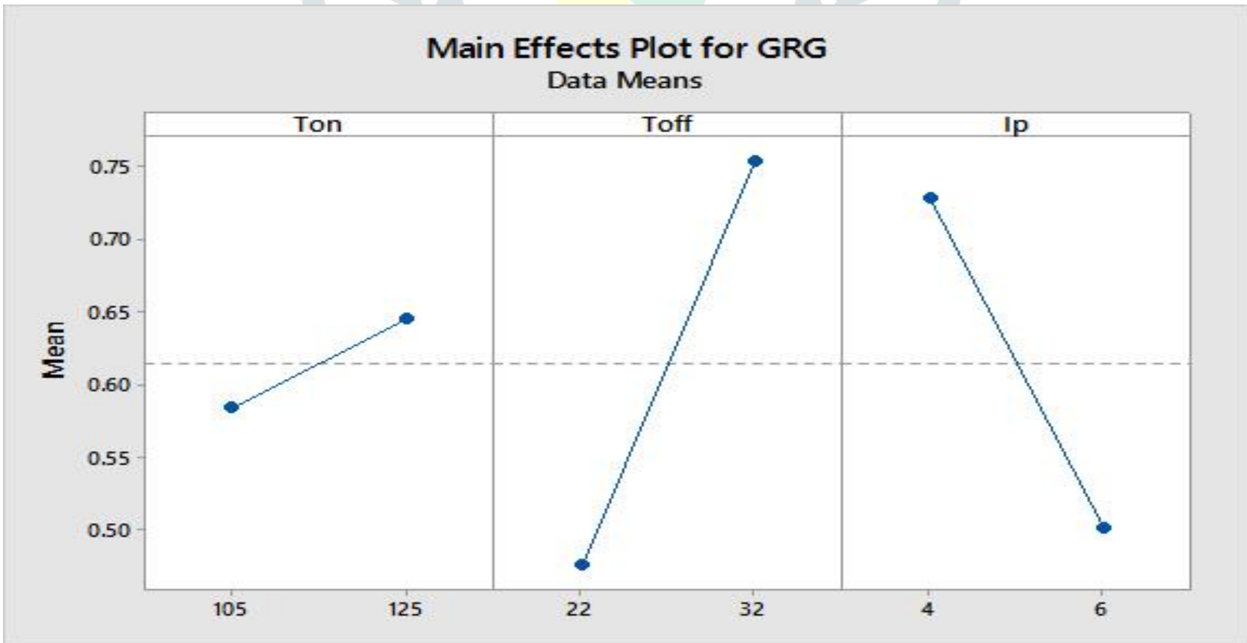
Exp. No.	MRR	Deviation (MRR)	Grey Relation Coefficient (MRR)	Ra	Deviation (Ra)	Grey Relation Coefficient (Ra)
1	12.3578	0.8240	0.3777	7.1	0.7308	0.4063
2	8.4914	0.1336	0.7891	5.2	0.0000	1.0000
3	7.7432	0.0000	1.0000	5.8	0.2308	0.6842
4	11.3556	0.6450	0.4367	6.6	0.5385	0.4815
5	10.5045	0.4931	0.5035	5.3	0.0385	0.9286
6	13.3436	1.0000	0.3333	7.8	1.0000	0.3333
7	9.3070	0.2792	0.6417	6.0	0.3077	0.6190
8	9.4948	0.3128	0.6152	5.8	0.2308	0.6842

MRR	Ra	Grey Relation Grade	Rank
12.3578	7.1	0.3920	7
8.4914	5.2	0.8946	1
7.7432	5.8	0.8421	2
11.3556	6.6	0.4591	6
10.5045	5.3	0.7160	3
13.3436	7.8	0.3333	8

9.3070	6.0	0.6304	5
9.4948	5.8	0.6497	4



(**fig. 6** residual plot for GRG)



(**Fig. 6** Main effect plot for GRG)

According to software the optimal parameter for experiment are
Ton = 125 μs Toff = 32μs Ip = 4A

Conclusion

- In our project we use ANOVA according to this Pulse off time Parameter are very much affected to the MRR. Percentage contribution of Pulse off time are 75.16% for MRR.
- And according to ANOVA method also Pulse off time are affected to Surface roughness. Percentage contribution of Pulse off time are 35.09% for Ra value.
- Based on the Teacher Learning Based, the best suited values of process parameters are Ton = 125 µs, Toff = 32 µs, IP = 4 A.
- The Analysis of Variance resulted that the pulse off has major influence on the surface roughness (µm) in the Full Factorial Design method and TLBO. Whereas the pulse off time has significant effect on the material removal rate.
- The objectives such as material removal rete, surface roughness are optimized using a single objective Full Factorial Design method and multi objective TLBO optimization and the same has been validated with the experimental results.
- Based on Grey relation Analysis, the best suited value of process parameters are Ton = 125 µs, Toff = 32 µs, IP = 4 A.

References

1. Sonu Dhiman, Ravinder Chaudhary, V.K. Pandey, "Analysis and study the effects of various control factors of CNC-wire cut EDM for S7 steel" MEIJ, Vol. 1, No. 1, May 2014, page no. 57-65
2. R. Venkata Rao, V. D. Kalyankar, "Parameter optimization of modern machining processes using teaching- learning-based optimization algorithm" Elsevier, Engineering applications of artificial intelligence 26, 2013, page no. 524 – 531
3. P.Raju et. Al. "Optimization of WEDM parameters for Surface roughness on 316L SS using Full Factorial Design" AMME 2014
4. Ho, K.H., Newman, S.T., Rahimifard, S and Allen R.D., "State of art in wire electric discharge machining", Int. J. Mach. Tools Manuf., 2004,Vol. 44, pp. 1247-1259.
5. Scott D, Bovina S, Rajurkar K P (1991) Analysis and optimization of parameter combinations in wire electrical discharge machining. Int J Prod Res 29(11):2189-2207.