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Modeling of Wire Electrical Discharge Machining of Alloy Steel (HCHCr)

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This study provides predictive models for the functional relationship between input and output variables of wire cut electrical discharge machine (WEDM) environment using alloy steel (HCHCr). Multi- objective optimization of the process parametric combinations is attempted by modeling WEDM process by use of artificial neural networks (ANN). This work provide an optimized input data set to WEDM system and the results show improvement with better productivity, reduced cutting time and product cost at the cutting speed and surface finish. At experimental result, the surface quality decreases as cutting speed increases and 1.371 mm/min becomes the maximum cutting speed obtained with good surface finish of 0.387 micron. The results show the potential to improve production efficiency and part quality.

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1. Introduction

Discrete part manufacturing using computer numerical controlled wire cut electrical discharge machine (CNC-WEDM) is common in modern manufacturing. Depending on accuracy and surface finish requirements, the machining parameters which have a significant contribution to part quality, need to be set properly. In the present scenario, due to the complexity of manufacturing environment, the ultimate goals of higher productivity, better quality and lower production costs create a tremendous challenge for manufacturers competing in the world market. The development of computer aided manufacturing (CAM) is evolving towards the phase of intelligent manufacturing (IM). The goal of IM is satisfying customer needs at the most efficient level for the lowest possible cost. The ability of a system to sense its environment, make decisions and control actions leads towards the factories of future, where products are manufactured in an artificial life environment. EDM is a process of converting the inside machining of hard material to outside machining of soft material. WEDM is an indispensible process for machining and shaping hard, fragile and difficult-cutting metals in the tool and die industry (Yuan et al., 2009). The objective of WEDM modeling (Abbas et al., 2007; Chung et al., 2011; Ho et al., 2004) is to provide a mapping model between machining performance for example, the material removal rate (MRR) and surface roughness (SR) and the machining parameters, such as, discharge current, pulse on and off-time etc. Many manufacturing processes are very complex, non-linear, stochastic and even ill defined. They require solutions in real time to solve unpredicted and unforeseen problems, even on the basis of incomplete and imprecise information. In fact, operation of many manufacturing processes still relies on the operator’s skill due to lack of robust models. A tremendous amount of manufacturing knowledge and decision logic is required to meet the challenges. Artificial Intelligence (AI) based techniques are designed for capturing, representing, organizing and utilizing knowledge by computer and hence will play an important role in the manufacturing (Huang et al., 1995).

In WEDM the erosive impact of electrical discharge is used for cutting the work piece. Discharges are generated in the gap between work piece and wire, which are both immersed in dielectric fluid (de-ionized water) (Rana et al., 1994; Snoeys et al., 1986). Also, WEDM is a spark erosion process used to produce two or three dimensional complex shapes through electrically conductive work pieces. It is a process where material removal is largely due to melting and vaporization. The process is controlled by several parameters like gap voltage, gap current, spark time, wire speed, wire tension, wire material and die-electric pressure etc., which have direct or interaction effect on material removal rate, surface finish and dimensional accuracy. It is difficult to optimize the process without adopting well defined strategies to analyze and determine various technological parameters. As the process of material removal by this method is relatively slow, the optimization strategy would result in considerable saving of time and lead to higher productivity. Many experimental approaches which establish quantitative equations between set- up parameters and results using multiple regression analysis and objective functions have been tried, but the findings indicates development of no unique solution (Deuw, 1989; Indarkhya et al., 1990; Kino, 1984; Scott et al., 1991). Some researchers have tried to find out the material removal rate through various thermal models (Rana et al., 1994; Snoeys et al., 1986). Attempts have been made to predict causes of wire rupture in WEDM process and to establish process parameters to avoid wire breakage and short-circuiting of wire due to improper input parameters (Singh et al., 1985). It is observed that most of the proposed equations with the restrictive assumptions are not fully sufficient for a practical use. When dealing with real world manufacturing applications, it is usually not an easy task to precisely define the set of input variables that potentially affect the output variables of a particular process. Many times, this is further complicated by the existence of interactions between the variables. Even if these variables can be identified, finding an analytical expression of the relationship may not always be possible. The process of selecting the analytical expression and estimating the parameters of the selected expression could be very time consuming. High degree of accuracy and the fine surface finish make WEDM valuable for applications in manufacturing of press tools, dies, moulds, prototype parts and fabrication of electrical discharge machine (EDM) electrodes. Although once considered a "nontraditional machining, the EDM process is replacing drilling, milling, grinding and other traditional machining operations in many industries throughout the world. Today's EDM uses advanced computer numerical control with up to six-axes simultaneous operation and state-of-the-art power supply technology, which can produce a mirror surface finish and "split-tenth" accuracy.

2. Design of experiment

In this work single pass cutting of alloy steel (HCHCr) was considered where cutting speed and surface finish were of prime importance (Azouzi et al., 1997). The WEDM process generally consists of several stages i.e. a rough-cut stage, a rough-cut with finishing stage and a finishing stage. During rough-cut and finishing phase, the cutting speed and surface finish both are of primary importance. This indicates that rough cut with finishing phase is the most challenging one because both have to be considered simultaneously (Scott et al. 1991). Hence, rough-cut with finishing phase machining environment was explored in this work. However, as pointed out (Tarang et al. 1995), the optimum criterion for achieving both (surface finish and cutting speed) is very difficult. There was an attempt to target multi-objective optimization problem through this work. To achieve this optimization, the WEDM process has been modeled initially. Based on literature survey, pilot studies and preliminary investigations, the following six parameters were selected as input (Tarang et al., 1995; Spedding et al., 1997):

Table 1 Levels of control parameters considering rough cut with finishing phase

Parameters	Levels		
	Level 1	Level 2	Level 3
T_{ON} (micron sec.)	2	6	10
T_{OFF} (micron sec.)	5	4	10
Ip (amp.)	3	3	8
W_T (gm.)	1000	1150	1300
Vg (volt)	30	40	30
W_F (mm/min.)	5	4	2

- Pulse on time (T_{ON})
- Pulse off time (T_{OFF})
- Peak current (Ip)
- Average gap voltage (Vg)
- Wire- tension (W_T)
- Wire feed setting (W_F)

During the experimentation, following factors were kept constant in order to eliminate their effect on the measure of process performance:

- Product shape (rectangular)
- Conductivity of the dielectric (20 mho)
- Work piece height (24 mm)
- Wire material (Brass alloy)
- Wire diameter (0.25 mm)
- Angle of cut (Vertical)
- Work piece material (HCHCr alloy steel)
- Work piece Hardness (56 HRC)
- Length of cut (10 mm)

In the present research work, machining performance of WEDM process was measured using following two responses (output) parameters (Verghese et al., 1994: Chien et al., 2001):

- Cutting speed (CS)
- Surface roughness (R_a)

Based on input parameters and their levels as given in Table 1, an experiment (considering factorial design) was performed and output data was recorded for modeling the WEDM process (as illustrated in Table 2). The design consists of 125 experimental runs. Table 2 indicates the actual experimental values of output parameters (cutting speed and surface roughness) at 125 input parameters (T_{ON}, T_{OFF}, Ip, Vg, W_T and W_F) combination.

The experiment was performed on Electra, Maxi-cut-e CNC Wire-cut EDM machine. The work-piece blocks were semi-finished with milling and later finished to accurate dimensions by grinding. The geometric and dimensional accuracies were maintained to meet the entire job setting conditions. For each run, the specified input parameters were set and the work piece was machined completely. Each time, the work piece was machined through 10 mm length in Y direction and the cutting speed was recorded. Start and finish time of machining operation was noted to determine the cutting time. Time delays due to wire breakage or power failure were automatically

Table 2 Experiment Matrix (actual 125 experimental data on WEDM)

Input							Output	
S. No.	T_{ON} (μs)	T_{OFF} (μs)	W_F (mm/min)	W_T (gm.)	Vg (Volt)	Ip (Amp.)	Cutting Speed (CS) (mm/min)	Ra (microns)
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	2	4	6	1000	60	2	0.6	3.05
2	2	5	4	1150	40	5	0.65	2.92
3	2	6	3	1300	30	6	0.72	2.68
4	3	10	5	1300	50	5	0.9	2.06
5	3	8	3	1150	60	4	0.9	1.98
6	3	6	3	1300	30	3	0.7	2.60
7	4	8	4	1300	60	8	1.0	2.80
8	4	6	5	1150	40	7	0.9	2.99
9	4	3	3	1000	35	6	0.8	3.00
10	5	2	6	1100	65	3	1.2	1.98
11	5	3	8	1000	40	5	0.4	2.40
12	5	3	4	1150	45	5	1.0	2.87
13	5	4	7	1000	60	5	0.6	2.40
14	6	3	5	1300	70	8	0.6	1.56
15	6	2	7	1000	70	4	0.3	3.20
16	6	4	3	1150	40	4	1.1	1.98
17	7	1	3	1000	40	5	0.35	2.25
18	7	5	4	1150	50	5	1.1	1.88
19	7	5	4	1000	50	3	1.2	1.96
20	8	6	4	1150	50	4	1.0	2.60
21	8	5	5	1300	50	5	1.2	2.57
22	8	6	3	1000	40	6	1.4	2.96
23	9	6	4	1300	60	8	1.2	2.57
24	9	6	4	1150	50	4	1.2	2.38
25	9	4	2	1300	40	7	1.2	3.40
26	10	4	4	1000	50	5	1.1	3.22
27	10	4	6	1000	45	4	1.1	2.18
28	10	10	5	1300	30	8	1.2	1.52
29	4	3	4	1000	60	5	0.5	3.04
30	4	3	4	1000	70	5	0.4	2.98
31	4	3	4	1000	80	5	0.3	2.96
32	4	4	5	1000	40	5	0.6	2.94
33	4	4	5	1000	60	5	0.4	2.85
34	6	5	6	1000	50	7	0.6	2.56
35	6	5	6	1000	70	5	0.4	2.78
36	7	6	7	1000	50	6	0.6	2.66
37	7	6	7	1000	70	6	0.3	2.82
38	9	8	8	1000	40	6	0.7	2.26
39	9	8	9	1000	60	8	0.5	2.67
40	8	9	9	1000	80	8	0.6	2.32
41	7	6	7	1000	60	5	0.5	2.56
42	8	7	8	1000	40	6	0.7	2.20
43	9	5	4	1000	30	9	1.2	2.06
44	9	4	4	1000	30	9	0.9	2.58
45	9	3	4	1000	30	9	0.9	2.60
46	10	2	4	1000	30	9	1.0	2.80
47	10	5	5	1000	30	8	0.9	2.99
48	10	4	5	1000	30	8	0.9	3.00
49	10	3	5	1000	30	8	1.0	2.68
50	5	4	7	1000	30	5	0.7	2.40
51	5	3	4	1000	30	5	0.7	2.87
52	5	2	4	1000	30	5	0.9	1.56
53	6	4	5	1000	30	7	0.6	3.20
54	7	3	5	1000	30	7	1.0	1.98
55	7	2	6	1000	30	7	0.8	2.25
56	7	7	6	1000	30	7	0.8	1.88
57	5	4	7	1000	35	5	1.0	1.96
58	5	3	4	1000	35	5	0.7	2.60
59	6	4	5	1000	30	7	0.9	2.57
60	7	3	5	1000	30	7	0.9	3.06
61	7	2	6	1000	30	7	0.9	2.98
62	7	7	6	1000	30	7	0.8	2.60

Table 2 (Continued)

Input							Output	
S. No.	T_{ON} (μs)	T_{OFF} (μs)	W_F (mm/min)	W_T (gm.)	Vg (Volt)	Ip (Amp.)	Cutting Speed (CS) (mm/min)	Ra (microns)
63	2	5	5	1000	30	3	0.8	2.90
64	5	8	4	1000	50	6	0.9	2.99
65	2	5	5	1000	30	4	0.7	3.00
66	3	10	6	1000	40	4	0.6	2.98
67	4	5	7	1000	50	5	0.6	2.40
68	9	6	3	1000	60	9	0.5	2.67
69	8	2	3	1000	60	8	0.7	2.56
70	8	4	3	1000	60	8	0.6	2.20
71	8	3	3	1000	60	8	0.5	2.36
72	2	9	6	1000	40	7	0.4	2.78
73	2	8	6	1000	40	7	0.6	2.90
74	4	8	6	1000	40	4	0.5	2.80
75	4	6	7	1000	60	5	0.4	2.99
76	2	3	5	1000	40	3	0.5	2.50
77	4	7	7	1000	20	4	0.6	2.98
78	6	5	5	1000	60	6	0.5	2.60
79	8	5	6	1000	60	8	0.5	2.87
80	5	7	6	1000	60	4	0.5	2.56
81	5	7	6	1000	40	4	0.5	2.70
82	5	9	6	1000	40	4	0.7	2.98
83	5	9	6	1000	50	4	0.5	2.25
84	5	9	6	1000	60	4	0.4	2.88
85	5	9	6	1000	70	4	0.4	2.06
86	7	8	6	1000	70	6	0.7	1.98
87	7	8	6	1000	60	6	0.5	2.60
88	7	8	6	1000	30	6	0.8	2.80
89	7	8	6	1000	40	6	0.5	2.99
90	7	8	6	1000	50	7	0.5	3.00
91	7	8	6	1000	60	7	0.6	1.98
92	7	8	6	1000	60	7	0.7	2.40
93	8	7	6	1000	60	8	0.8	2.87
94	8	7	6	1000	50	8	1.0	1.56
95	8	7	6	1000	40	8	0.7	3.20
96	8	7	6	1000	50	8	1.0	1.98
97	8	7	6	1000	60	5	1.0	2.25
98	8	7	6	1000	70	5	1.0	1.88
99	9	6	6	1000	60	5	1.3	1.96
100	9	6	6	1000	70	5	1.0	2.98
101	9	6	6	1000	40	6	0.6	3.05
102	9	6	6	1000	50	6	0.6	2.87
103	9	6	6	1000	60	6	0.7	2.58
104	9	6	6	1000	70	6	0.6	2.88
105	5	6	6	1000	60	4	0.5	2.56
106	5	6	6	1000	40	4	0.5	2.68
107	5	5	6	1000	40	4	0.5	2.60
108	5	5	6	1000	50	4	0.6	2.80
109	5	5	6	1000	60	4	0.7	2.99
110	5	5	6	1000	70	4	0.7	2.50
111	4	5	6	1000	70	5	0.9	2.58
112	4	5	6	1000	60	5	1.1	2.70
113	4	5	6	1000	50	5	0.9	2.87
114	10	7	7	1000	50	4	0.6	2.56
115	10	7	7	1000	60	4	0.6	2.80
116	5	7	7	1000	70	4	0.5	1.98
117	5	7	6	1000	80	4	0.4	2.85
118	5	7	6	1000	40	4	0.3	2.88
119	5	9	6	1000	40	4	0.5	2.86
120	10	4	9	1000	60	4	0.5	2.60
121	10	4	4	1000	30	4	0.5	2.87
122	10	6	5	1000	40	4	0.9	2.66
123	10	6	6	1000	60	4	0.7	2.37
124	10	7	2	1000	30	4	0.9	2.46
125	4	10	3	1000	40	5	0.8	2.78

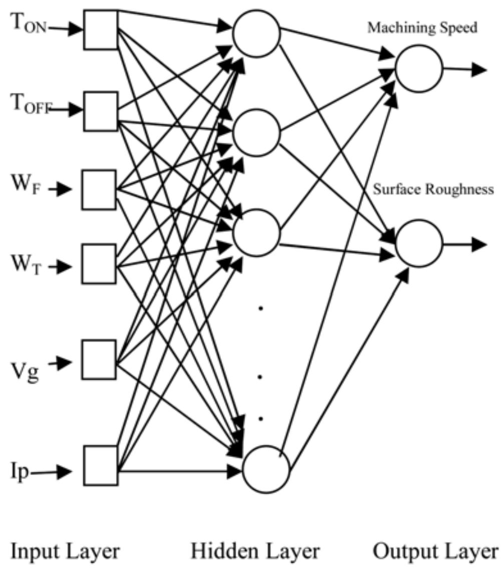

Fig. 1 Configuration of the neural network

compensated by the control system. After machining, each output was cleaned and numbered for reference and the surface roughness (Ra) was measured using a handy surf make surface texture measuring instrument with accuracy 1 mm for travel length 5 mm. The roughness (surface finish as $1/R_a$) was measured at four different locations and perpendicular to the direction of cut and finally the average roughness was determined. This procedure was repeated for other sizes of the work piece.

3. Modeling of WEDM process using artificial neural networks (ANN)

A feed-forward back-propagation neural network was developed to model the WEDM process using alloy steel (HCHCr). Results were obtained for various input settings and finally they were compared with ANN results to determine the optimal combination of machining parameters.

The experimental results as listed in Table 2 were used to train the neural network with types ranging between 6-10-2 to 6-25-2. Sigmoidal transfer function was considered for the training of neural network. In cumulative learning, the delta weights are accumulated, and the weights are adjusted until a complete set of input / output pairs is presented to the network. A learning rate of 0.25 (Sarkar et al., 2003) was considered in this study. After several trial and errors, it was found that the most appropriate layers size is 6-15-2 as shown in figures 1, 4 and 5.

Once the training of the neural network is complete, it provides results for arbitrary values of input data set ($3^6 = 729$).

4. Model verification

Developed ANN model was tested using training data ($3^6 = 729$ values). Table 3 presents the statistical measures of difference between actual outputs and the ANN model outputs, which ultimately compare the performance of the model. Table 3 indicates that the ANN model

Table 3 ANN model (residual analysis)

Statistical measures	Cutting speed (CS) (mm/min.)	Roughness average (Ra) (microns)
Mean	90.42/125 = 0.724	319.96/125 = 2.56
Standard deviation	0.173	0.2565
Variance	0.019	0.065
Minimum	0.30	1.52
Maximum	1.40	3.40
Range	1.10	1.88

Table 4 Prediction of cutting speed and surface roughness using ANN model

S. No.	Actual		Predicted (ANN)		Error %	
	Vc (CS) (mm/min)	Ra (microns)	Vc (CS) (mm/min)	Ra (microns)	Vc (CS) (mm/min)	Ra (microns)
1	0.70	3.00	0.694	3.062	0.87	2.10
2	1.1	1.98	1.024	2.017	6.90	1.87
3	1.2	1.52	1.182	1.532	1.15	0.80

provides better results in Wire-cut EDM process using alloy steel (HCHCr) environment. Based on the results, it can be said emphatically that the application of ANN model in WEDM process is successful.

Furthermore, a verification experiment was carried out. Table 4 lists the result of the verification experiment. It was concluded that the prediction based on ANN model was very close to actual experimental results.

5. Optimization strategy

The trained ANN model is capable to predict the response (output) parameters as function of six different control (input) parameters i.e. Pulse on time (T_{ON}), Pulse off time (T_{OFF}), Peak current (Ip), Average gap voltage (Vg), Wire- tension (W_T) and Wire feed setting (W_F). An attempt was made to generate higher number of input output parameter combinations to get more number of optimum points. The input parameters (six in numbers) were divided into 3 levels, as illustrated in Table 1. These considerations resulted in 3^6 (729) possible input combinations. The developed ANN model was used to predict the cutting speed and surface roughness for all possible levels of the 729 combinations (Laszio 1993). Finally, the results of this study proposed best of these combinations.

6. Experimental results and analysis

The experimental results in Table 2 were used to train the neural network with types ranging between 6-10-2 to 6-25-2. In the present work, six input and two output neurons were considered and the data was trained considering hidden neurons as 10, 15, 20 and 25 (Sarkar et al., 2003). The network was trained at 50000 epochs by considering layer-1 with six input parameters and layer-2 with two output parameters. With hidden neurons 10, 15, 20 and 25 and learning rate 0.25, various comparisons of cutting speed and surface roughness are presented in Figures 2 to 9.

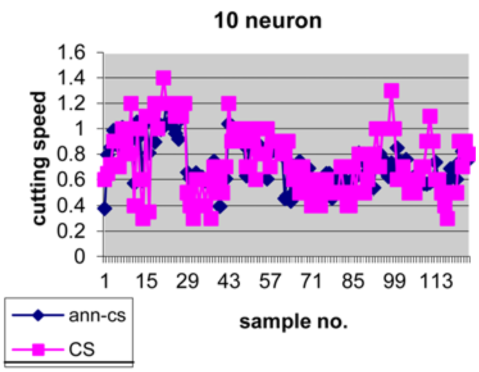

Fig. 2 Comparison of cutting speed (actual Vs ANN)

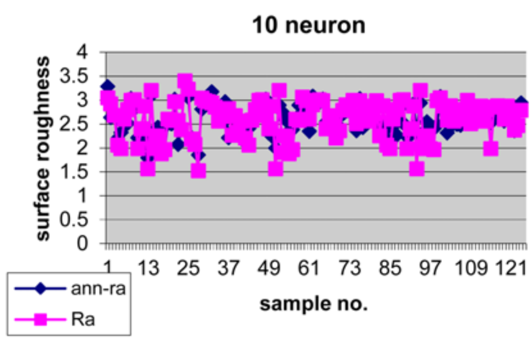

Fig. 3 Comparison of surface roughness (actual Vs ANN)

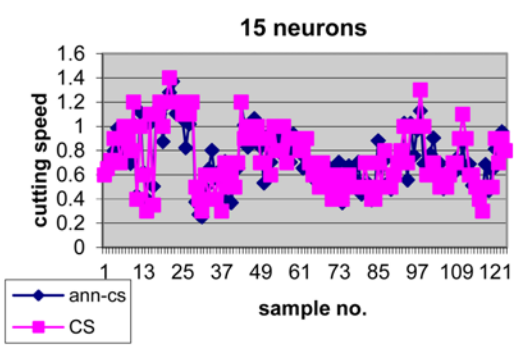

Fig. 4 Comparison of cutting speed (actual Vs ANN)

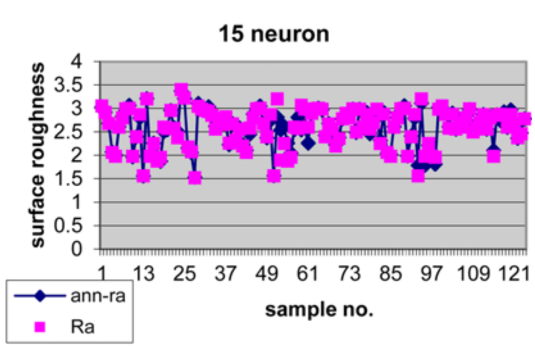

Fig. 5 Comparison of surface roughness (actual Vs ANN)

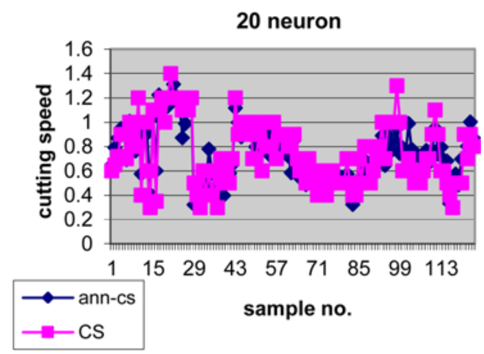

Fig. 6 Comparison of cutting speed (actual Vs ANN)

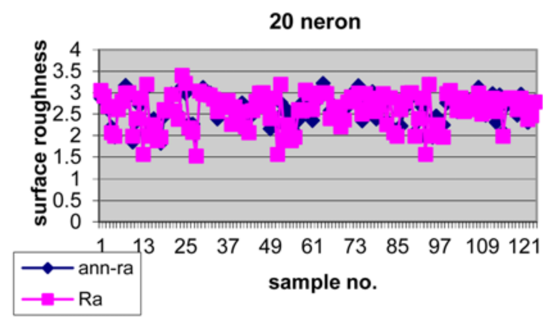

Fig. 7 Comparison of surface roughness (actual Vs ANN)

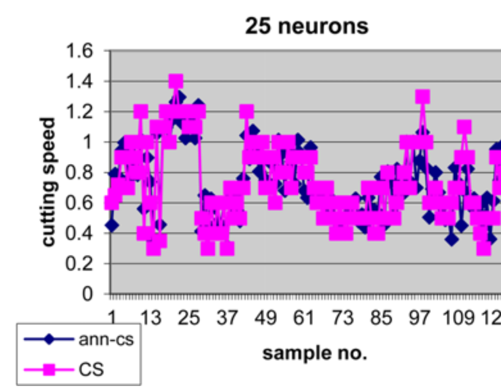

Fig. 8 Comparison of cutting speed (actual Vs ANN)

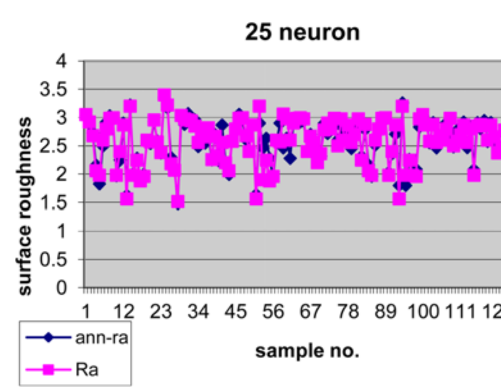

Fig. 9 Comparison of surface roughness (actual Vs ANN)

For this study, the input parameters (six in numbers) were divided into three levels within their working range as illustrated in Table 1. The ANN model was developed to predict the cutting speed and surface roughness for all combination levels of the input parameters ($3^6 = 729$). After data training through combinations 6-10-2, 6-15-2, 6-20-2 and 6-25-2 respectively, the comparison results of actual versus ANN were obtained. The error as difference between actual and ANN was determined for each cutting speed and surface roughness value. Finally, the graphs at hidden neurons 10, 15, 20 and 25 were plotted for comparison of cutting speeds (actual Vs ANN) and surface roughness (actual Vs ANN). These graphs are presented in Figures 2 to 9.

Figures 2 and 3 indicates the variation in ANN model values and it

Table 5 Sorted out list of optimum input-output parameter combinations

	Input						Output	
S. No.	T_{ON} (μs)	T_{OFF} (μs)	WF (mm/min)	WT (gm)	Vg (Volt)	Ip (Amp)	Cutting Speed (mm/min)	Ra (microns)
1	9	6	4	1300	60	8	1.371	2.582
2	8	6	3	1000	40	6	1.281	2.956
3	9	3	4	1000	20	9	1.233	2.236
4	10	2	4	1000	20	9	1.233	2.236
5	10	5	5	1000	20	8	1.233	2.236
6	10	4	5	1000	20	8	1.233	2.236
7	9	4	4	1000	20	9	1.233	2.236
8	9	5	4	1000	30	9	1.188	2.103
9	8	5	5	1300	50	5	1.184	2.546
10	10	10	5	1300	30	8	1.182	1.532
11	9	4	2	1300	40	7	1.157	3.360
12	7	3	5	1300	30	7	1.154	2.458
13	7	2	6	1300	30	7	1.154	2.458
14	5	4	7	1150	20	5	1.154	2.458
15	5	4	7	1150	20	5	1.154	2.458
16	5	3	4	1150	20	5	1.154	2.458
17	5	2	4	1150	20	5	1.154	2.458
18	7	7	6	1300	30	7	1.154	2.458
19	7	3	5	1300	30	7	1.154	2.458
20	7	2	6	1300	30	7	1.154	2.458
21	6	4	5	1300	30	7	1.154	2.458
22	6	4	5	1300	30	7	1.154	2.458
23	7	5	4	1150	50	5	1.137	1.958
24	5	3	4	1150	45	5	1.118	2.547
25	7	5	4	1000	50	3	1.103	1.873
26	5	8	4	1150	50	6	1.059	2.269
27	2	5	5	1000	30	3	1.053	1.981
28	10	4	5	1000	30	8	1.065	3.052
29	10	4	4	1000	50	5	1.061	3.210
30	9	6	6	1000	60	5	1.127	1.809
31	8	7	6	1000	50	8	1.025	1.783
32	10	2	4	1000	30	9	1.025	1.783
33	10	3	5	1000	30	8	1.025	1.783
34	10	4	3	1150	60	6	1.017	2.058
35	5	2	6	1100	65	3	1.018	1.968
36	9	4	4	1000	30	9	1.011	2.444
37	5	2	6	1100	65	3	1.018	1.968
38	6	4	3	1150	40	4	1.023	2.0176
39	2	5	5	1000	30	3	1.053	1.981
40	9	6	4	1150	50	4	1.106	2.503
41	8	7	6	1000	70	5	0.970	1.975
42	10	3	5	1000	30	8	0.973	2.678
43	4	8	4	1300	60	8	0.955	2.827
44	4	5	7	1150	20	5	0.978	2.338
45	10	7	2	1000	30	4	0.955	2.460
46	3	10	6	1150	40	4	0.984	1.906
47	10	7	2	1000	30	4	0.955	2.475
48	7	3	5	1000	30	7	0.935	2.535
49	7	3	5	1000	30	7	0.933	2.536
50	10	5	5	1000	30	8	0.900	2.990

can be observed that all the cutting speed and surface roughness values through ANN model are coinciding with actual experimental values. Further, no abnormality in actual Vs ANN data comparison is apparent in Figures 2 and 3. Figures 4 and 5 show that the performance of ANN model is very close to the actual cutting speed and surface roughness, which on comparison indicates that the ANN model results are more close to actual outputs. Here it can be concluded that the ANN model provides better results in WEDM process using alloy steel (HCHCr) environment. The Figures 6, 7, 8 and 9 explores that the cutting speed and surface roughness through ANN model differs from the actual outputs at 20 and 25 hidden neurons. In these cases, the performance is away from goal, which is undesirable. Analysis of graphs 2 to 9 indicates that the best results of cutting speed and surface finish of WEDM process using alloy steel (HCHCr), are obtained through the combination 6-15-2 (as presented in Figures 4 and 5).

The neural network was trained with 729 (3^6) data set. After training, a list of 50 optimized inputs–output parameter combinations were obtained through computer program and is presented in Table 5. Table 5 indicates output parameter, the cutting speed in decreasing order and corresponding surface roughness at 50 optimized input parameters combination. Table 5 also helps to select the input parameters combination at the required cutting speed.

7. Discussion

This work has proposed a methodology to determine the optimal combination of control parameters in WEDM process using alloy steel (HCHCr). The ANN model was applied to predict the process performance. A feed forward neural network was developed to model the process parameters.

Optimal process parameter combinations corresponding to different cutting speed and surface finish were determined out of 729 possible combinations. The presented list of 50 optimum parameter combinations can act as guidelines for effective and efficient machining of alloy steel (HCHCr) using WEDM process. Through optimized input data set, the improved output results will enhance the productivity with better machining surface quality. Furthermore, the production cost and machining time will be saved through optimum machining speed in every run. This work in the area of machining alloy steel through WEDM process and ANN application will solve various challenging problems faced by the engineers and technocrats in the field of modern manufacturing systems. Present manufacturing industries can achieve the ultimate goals of higher productivity (higher cutting speed), better quality (required surface finish) and lower production cost (reduced cutting time), which would help manufacturers to compete in the world market.

8. Conclusions

This study has presented an effective approach for Multi- objective optimization of the process parametric combinations by modeling WEDM process by use of artificial neural networks (ANN). Based on the results of the present study, the following conclusions are drawn:

1. The surface quality of Alloy Steel (HCHCr) machining with WEDM process decreases as cutting speed increases.
2. This work provide an optimized input data set to WEDM system and

the results show improvement with better productivity, reduced cutting time and product cost at the cutting speed and surface finish.

3. For machining of Alloy steel (HCHCr) with WEDM process environment, 1.371 mm/min becomes the maximum cutting speed obtained with good surface finish of 0.387 micron.

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