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Prediction of multi performance characteristics of wire EDM process using grey ANFIS

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Abstract. Super alloys are used to fabricate components in ultra-supercritical power plants. These hard to machine materials are processed using non-traditional machining methods like Wire cut electrical discharge machining and needs attention. This paper details about multi performance optimization of wire EDM process using Grey ANFIS. Experiments are designed to establish the performance characteristics of wire EDM such as surface roughness, material removal rate, wire wear rate and geometric tolerances. The control parameters are pulse on time, pulse off time, current, voltage, flushing pressure, wire tension, table feed and wire speed. Grey relational analysis is employed to optimise the multi objectives. Analysis of variance of the grey grades is used to identify the critical parameters. A regression model is developed and used to generate datasets for the training of proposed adaptive neuro fuzzy inference system. The developed prediction model is tested for its prediction ability.

1. Introduction

Newer materials are continuously being developed to cater to the needs of ultra-supercritical power plants to withstand temperature up to 975K and pressure up to 26MPa. Some of these materials are Inconel 617, Nimonic 263, Inconel 740, Haynes 230, Haynes 282. Inconel 617 is the lead candidate material(1) falls into the Group D category of Nickel base Superalloys. The conventional machining of superalloys are limited due to high chemical reactivity, high hot hardness, rapid strain hardening, segmented chip formation, self-induced chatter, low thermal conductivity and poor heat dissipation at tool chip interface. Poor tool life, accelerated abrasion, high adhesion and higher diffusion wear are the productivity problems faced in the conventional machining of superalloys. The machining of nickel base super alloys needs attention as the wastage while machining becomes unaffordable(2). Non-conventional machining techniques such as EDM and wire EDM are effective alternatives. It has been reported that the first geometries can be effectively machined using wire EDM process(3). Wire EDM process has been suggested as a replacement for broaching for the development of fir tree slots in turbine blades(4). EDM process is the most competitive technology for turbine blisk finishing operation (5). In a product the dimensional deviation, form tolerances and orientation tolerances play a significant role(6). The effect of feed rate, current and pulse on time on the circularity deviation of a hot work tool steel was studied and regression analysis was applied to develop predictive models(7). Electrical discharge machining of conductive ceramics was investigated with focus on form and orientation tolerances using grey relational analysis(8). Grey Relational Analysis (GRA) (9) has been successfully employed to solve problems with high uncertainty, multi-inputs and discrete data. Optimization based on the grey relational technique is one of the commonly adopted methods in machining processes(10). Multiple regression Analysis (MRA) are used to get a second order non-linear equation and these equations are used to create a large dataset for the training and testing of the neuro fuzzy models. A neural network with fuzzy decision rules forms a hybrid intelligent system. ANFIS has been used by researchers to create prediction models for different welding(11) and machining processes (12). Prediction of white layer thickness and surface roughness using ANFIS model were reported in literature (13). The response features based on the form and orientation tolerances needs attention. This paper proposes the Multi performance optimization in wire EDM using grey ANFIS.

2. Proposed methodology

The proposed methodology of development of Grey ANFIS for predicting parameters with multi performance characteristic of wire EDM process is depicted in Figure 1. Parameters under consideration are pulse on time, T_{on} (µs), pulse off time, T_{off} (µs), discharge current (Ampere), peak voltage (Volts), flushing pressure (lpm), wire tension (kgf), table feed (mm/min) and wire speed (mm/min) which lead to an Taguchi L18 experimental design The performance characteristics are surface roughness (µm), material removal rate (mm^3/sec), Wire Wear Rate (gram/sec), and form and orientation tolerances. Accuracy measures such as MAD, MAD and RMSE are used to make the proposed neuro fuzzy model anetwork as a robust prediction model.

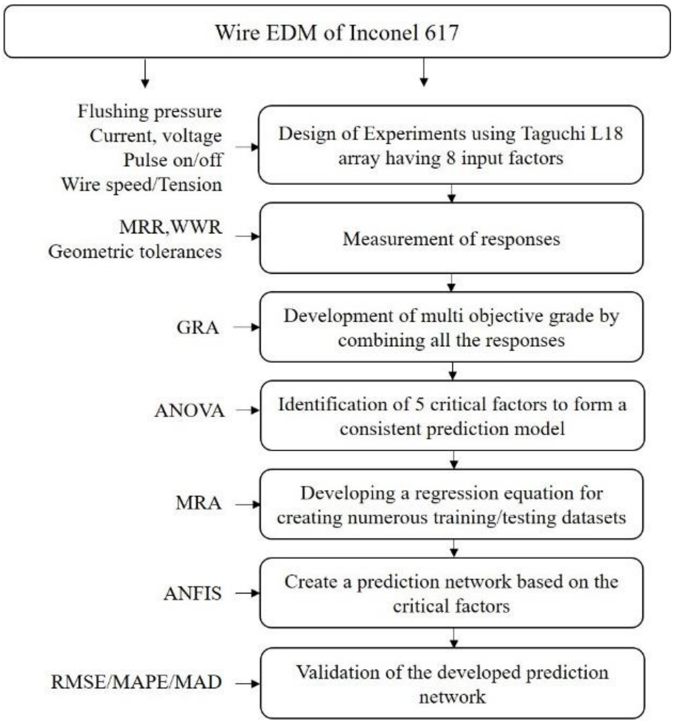

Figure 1. Methodology for the development of a neuro fuzzy prediction model for wire EDM.

3. Experimentation

The proposed experiments are carried out in wire cut EDM machine 'Electronica Sprintcut'. The wire is brass alloy of 0.25mm diameter and the dielectric is deionized water. A semicircular profile comprising of two parallel edges is cut into the 10mm thick Inconel 617 workpiece. The wire EDM machining set up is shown in the Figure 2. The Taguchi L_{18} mixed level orthogonal array is planned as per the principles of design of experiments. Flushing pressure has been set at two levels and the rest of the parameters are set at three levels each as show in the Table 1. The experiments are conducted and the various results obtained are shown in Table 2.

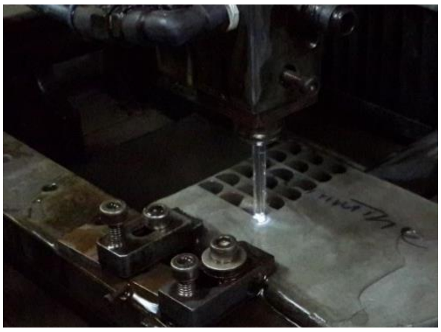

Figure 2. Machining of the profile in Electronica Sprintcut.

Table 1. Experimental design-L18 array for wire EDM of Inconel 617.

S.No.	Input Parameters							
	Flushing (lpm)	Table feed (mm/min)	T_{on} (μs)	T_{off} (μs)	Current (A)	Voltage (Volts)	Tension (kgf)	Wire Speed (mm/min)
1	6	2.70	110	50	150	10	3	3
2	6	2.70	125	55	200	15	8	4
3	6	2.70	131	63	230	20	14	5
4	6	3.83	110	50	200	15	14	5
5	6	3.83	125	55	230	20	3	3
6	6	3.83	131	63	150	10	8	4
7	6	5.18	110	55	150	20	8	5
8	6	5.18	125	63	200	10	14	3
9	6	5.18	131	50	230	15	3	4
10	12	2.70	110	63	230	15	8	3
11	12	2.70	125	50	150	20	14	4
12	12	2.70	131	55	200	10	3	5
13	12	3.83	110	55	230	10	14	4
14	12	3.83	125	63	150	15	3	5
15	12	3.83	131	50	200	20	8	3
16	12	5.18	110	63	200	20	3	4
17	12	5.18	125	50	230	10	8	5
18	12	5.18	131	55	150	15	14	3

Material removal rate is estimated based on the kerf width, which is an outcome of the machining. The kerf width is measured using an Olympus make optical microscope. MRR is obtained from the calculated kerf width values and the cutting speed which is calculated during the machining process as shown in Eq.(1) (14),

$$MRR = K h CS \tag{1}$$

K is the Kerf width, h is the thickness of the workpiece, CS is the cutting speed. The wire wear rate is calculated by the weight loss method. The difference in weight between the fresh wire and the used wire is found out. The rate at which the wire erodes can be calculated from the machining time recorded for each cycle of measurement. The wire wear rate is a direct index of the productivity of the process. The wire images are obtained using the Olympus optical microscope. Surface roughness (R_a) values are measured using the Talysurf Surfcorder probe type tester. R_a values indicate the peak and valleys in a particular line where the probe moves. The surface roughness measurements are made with a cut off value of 0.08mm and are made against the direction in which the wire travels and hence leading to higher values of surface roughness. The circularity error, perpendicularity error, cylindricity error and parallelism error are measured using the HELMEL make coordinate measuring machine. These errors are a direct index of the dimensional deviation which occur during the electrical discharge machining process.

Table 2. Measured responses in the wire EDM of Inconel 617.

No.	MRR	WWR	Ra	Circularity	Cylindricity	Perpendicularity	Parallelism
1	3.7812	0.0150	5.5290	0.0069	0.0120	0.0676	0.0070
2	10.1033	0.1252	7.9310	0.0068	0.0127	0.0955	0.0050
3	10.9371	0.2044	8.6320	0.0154	0.0109	0.0738	0.0096
4	4.7666	0.0306	5.7550	0.0159	0.0134	0.0758	0.0068
5	10.5225	0.1192	8.6670	0.0121	0.0124	0.0837	0.0016
6	8.6970	0.0991	9.0570	0.0099	0.0157	0.0557	0.0062
7	3.1506	0.0206	5.9540	0.0118	0.0177	0.0706	0.0045
8	9.2167	0.1419	8.9430	0.0102	0.0117	0.0905	0.0092
9	12.7500	0.1216	9.6880	0.0127	0.0099	0.0940	0.0106
10	2.3563	0.0082	6.6980	0.0318	0.0140	0.0784	0.0156
11	8.7055	0.1081	7.5160	0.0126	0.0154	0.0841	0.0100
12	9.9794	0.1070	10.3300	0.0204	0.0140	0.0730	0.0097
13	6.5413	0.0604	8.2290	0.0127	0.0110	0.0647	0.0084
14	7.1534	0.0659	7.3570	0.0235	0.0188	0.0533	0.0134
15	14.5051	0.2964	10.7650	0.0115	0.0159	0.0619	0.0101
16	2.2694	0.0027	7.3130	0.0246	0.0178	0.0377	0.0253
17	14.7037	0.2327	10.4760	0.0083	0.0116	0.0630	0.0138
18	11.4241	0.2401	9.3520	0.0170	0.0177	0.0569	0.0195

4. Adaptive neuro fuzzy inference system

4.1. Grey grade development

The normalization of the responses is carried out in order to minimize the variability in the data range. After the normalization process the grey relational coefficients are calculated using the Eq. (4) where Δ_{min} is the smallest value of $\Delta_{0i}(k)$, Δ_{max} is the largest value of $\Delta_{0i}(k)$. The absolute difference between $x_o^*(k)$ and $x_i^*(k)$ is $\Delta_{0i}(k)$. $x_o^*(k)$ is the ideal or reference sequence.

The grey relational coefficient is given by the following formulae,

$$x_i = \left(x_i\left(1\right), x_i\left(2\right), ..., x_i\left(n\right)\right), x_i \in X, i = 1, 2, ..., m \tag{2}$$

x_i be the compared series and x_0 be the reference series

$$x_0 = \left(x_0\left(1\right), x_0\left(2\right), ..., x_0\left(n\right)\right), x_0 \in X \tag{3}$$

The grey relational coefficient is given by,

$$\gamma\left(x_0\left(k\right), x_i\left(k\right)\right) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}\left(k\right) + \zeta\Delta_{\max}} \tag{4}$$

The grey relational grade is obtained from the following formula,

$$\gamma\left(x_0, x_i\right) = \frac{1}{n}\sum_{k=1}^{n}\gamma\left(x_0(k), x_i(k)\right) \tag{5}$$

The grey relational coefficients are combined into a grey relation grade by giving equal weightage to all the responses. Eq. (5) is used for calculating the grey relational grade. The developed grades are shown in Table 3.

4.2. Analysis of Variance

Analysis of variance of the grey grade is carried out with respect to the eight factors and the results are as tabulated in Table 4. Flushing speed has the highest contribution on the responses followed by pulse on time and pulse off time.

4.3. Multiple regression analysis

The accuracy of a neuro fuzzy model depends on the number of data from which it is created. Since the experimental values here are limited MRA is used for obtaining the training and testing datasets. Using MRA a second order non-linear regression model is developed which relates the grey grades with the five input factors. This model is further used to develop a huge dataset which is further given as input to the neuro fuzzy model. Figure 5 shows the normal residual plot of the regression equation and from the plot it can be seen that deviation from the normal line is uniform indicating a good fit for the values.

$$\text{Regression equation for grey grade} = 2.19 - 0.01528\times A + 0.0082\times C - 0.0296\times D - 0.1372\times F + 0.0399\times G - 0.000056\times C^2 + 0.000270\times D^2 + 0.001330\times F^2 - 0.000897\times G^2 - 0.000083\times C\times D + 0.000477\times C\times F + 0.000116\times C\times G + 0.000691\times D\times F - 0.000628\times D\times G - 0.000414\times F\times G$$

4.4. Neuro fuzzy inference system

Inputs considered for modelling the ANFIS structure are flushing speed, T_{on}, T_{off}, voltage and tension of the wire. The developed grey grade is the output for the ANFIS model. The membership functions are assigned by dividing the input space into fuzzy regions. In this present investigation bell membership function is used. The training data set is used to find the initial premise parameters for the membership functions equally spacing each of the membership functions. The fuzzy rules are generated based on the input and output data pairs attained by experimentation. The conflicting rules are resolved by assigning a degree to each rule. After the conflicting rules are resolved a combined rule base is formed. The final stage is defuzzification process to get the output value. The centroid method is used for defuzzification. The ANFIS structure shown in Figure 4 consists of five layers. The nodes in the layers 1 and 4 are adaptive nodes. Nodes in layers 2, 3 and 5 are fixed nodes

Table 3. Obtained grey grade from the combination of responses.

No.	Flushing speed (lpm)	Table Feed (mm/min)	T_{on} (μs)	T_{off} (μs)	Current (A)	Voltage (Volts)	Tension (kgf)	Wire Speed (mm/min)	Grey Grade
1	0.3627	0.9227	1.0000	0.9921	0.6794	0.4915	0.6870	0.3627	0.7344
2	0.5747	0.5452	0.5215	1.0000	0.6138	0.3333	0.7770	0.5747	0.6243
3	0.6227	0.4213	0.4576	0.5924	0.8165	0.4446	0.5970	0.6227	0.5652
4	0.3849	0.8403	0.9205	0.5787	0.5597	0.4313	0.6950	0.3849	0.6307
5	0.5979	0.5576	0.4548	0.7022	0.6403	0.3858	1.0000	0.5979	0.6204
6	0.5086	0.6037	0.4260	0.8013	0.4341	0.6162	0.7204	0.5086	0.5878
7	0.3499	0.8914	0.8603	0.7143	0.3633	0.4676	0.8034	0.3499	0.6364
8	0.5312	0.5134	0.4340	0.7862	0.7120	0.3537	0.6093	0.5312	0.5634
9	0.7609	0.5526	0.3863	0.6793	1.0000	0.3392	0.5683	0.7609	0.6130
10	0.3349	0.9639	0.6913	0.3333	0.5205	0.4152	0.4584	0.3349	0.5316
11	0.5090	0.5822	0.5685	0.6831	0.4472	0.3838	0.5852	0.5090	0.5375
12	0.5682	0.5847	0.3529	0.4789	0.5205	0.4502	0.5940	0.5682	0.5076
13	0.4324	0.7179	0.4923	0.6793	0.8018	0.5170	0.6354	0.4324	0.6115
14	0.4516	0.6991	0.5888	0.4281	0.3333	0.6494	0.5011	0.4516	0.5222
15	0.9690	0.3333	0.3333	0.7267	0.4258	0.5443	0.5823	0.9690	0.5598
16	0.3333	1.0000	0.5947	0.4125	0.3603	1.0000	0.3333	0.3333	0.5769
17	1.0000	0.3897	0.3461	0.8929	0.7236	0.5332	0.4927	1.0000	0.6261
18	0.6547	0.3822	0.4065	0.5507	0.3633	0.6008	0.3983	0.6547	0.4800

Table 4. Analysis of variance.

Source		DF	SS	MS	F-Value	% contribution
Flushing (lpm)	A	1	0.0215	0.0215	8.7900	52.375
Table feed (mm/min)	B	2	0.0001	0.0001	0.0300	0.161
T_{on} (µs)	C	2	0.0139	0.0070	2.8500	16.968
T_{off} (µs)	D	2	0.0107	0.0053	2.1800	13.006
Current (A)	E	2	0.0010	0.0005	0.1900	1.158
Voltage (Volts)	F	2	0.0044	0.0022	0.9000	5.367
Tension (kgf)	G	2	0.0037	0.0018	0.7500	4.483
Wire Speed (mm/min)	H	2	0.0004	0.0002	0.0900	0.523

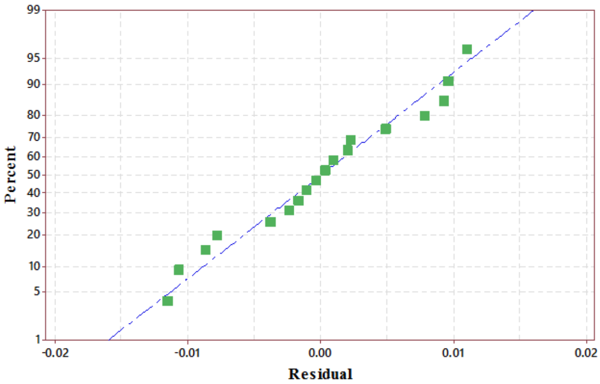

Figure 3. Normal residual plot for the obtained regression equation.

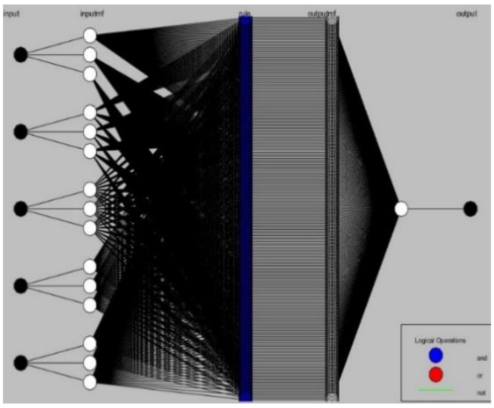

Figure 4. Neuro fuzzy structure for the development of prediction model.

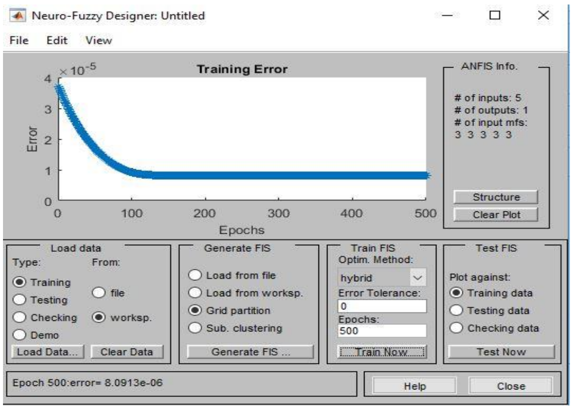

Figure 5. Typical ANFIS editor for the multi performance analysis.

The model is developed with five input neurons and a single output neuron with respective membership functions of Sugeno type FIS. The developed ANFIS model with five inputs and a single output parameter is trained and training details are presented. The ANFIS architecture employed with ‘gbellmf’ membership function consists of 243 rules which are generated based on the given input data set. Figure 5 shows the ANFIS editor for the wire EDM of Inconel 617. Figure 6 shows the ANFIS rule viewer with various membership functions used for this investigation. Figure 7 shows the effect of pulse on and pulse off time on the grey grades. Figure 8 shows the effect of pulse on time and flushing pressure on grey grade. It is conspicuous from the illustration that grey grade increases as the pulse on time increases whereas grey grade reduces at lower flushing pressures. Figure 9 shows the effect of pulse off time and flushing pressure on grey grades. It is clearly illustrated that a combination of higher pulse off time and lower flushing pressure leads to maximum grey grade.

Figure 6. ANFIS rule viewer depicting the rules created.

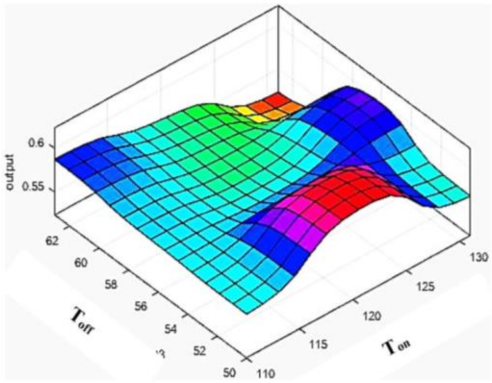

Figure 7. Influence of T_{off} and T_{on} on the grey grade.

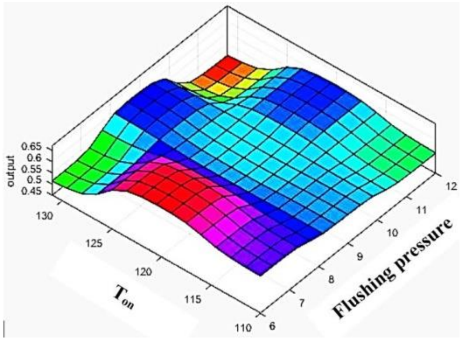

Figure 8. Influence of T_{on} and Flushing pressure on the grey grade.

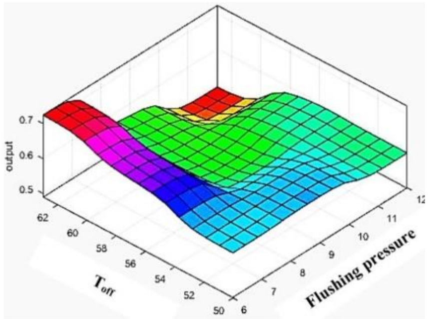

Figure 9. Influence of T_{off} and flushing pressure on the grey grade.

4.5. Performance analysis of the developed neuro fuzzy model

After training the model, it is validated and the results are presented as shown in Figure 10. The values predicted by the developed model are compared with the experimental values and it is revealed that there is a close relationship among the experimental values and the predicted values which are from the developed ANFIS model.

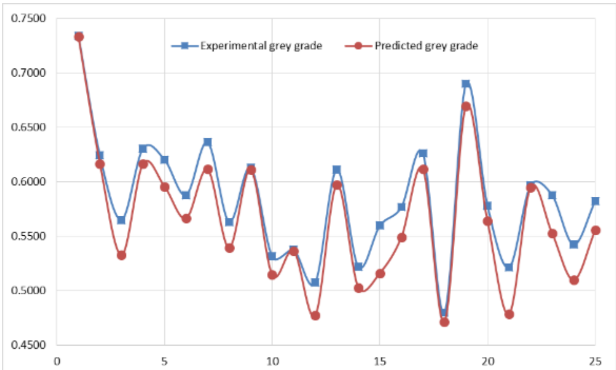

Figure 10. Comparison of the experimental and the predicted grey grades.

The absolute percentage error obtained between the predicted values and the calculated values of Grey relational grade value shows that the developed model is accurate for prediction of desired performance characteristics. The mean absolute deviation value was obtained as 0.0152. Root mean square error is 0.0216 and the Mean absolute percentage error is 2.91. Hence it can be observed that a robust prediction model has been obtained.

5. Conclusion

Limited research has been reported in the wire EDM of Inconel 617 which is a candidate material for ultra-supercritical boiler components. Form and orientation tolerances such as circularity deviation, cylindricity deviation have not been studied extensively and needs attention. The paper investigated the wire EDM process for establishing the control parameters in order to develop an artificial neuro fuzzy Inference model for prediction. Parameters under consideration are pulse on time, T_{on} (μs), pulse off time, T_{off} (μs), discharge current (Ampere), peak voltage (Volts), flushing pressure (lpm), wire tension (kgf), table feed (mm/min) and wire speed (mm/min) which lead to an Taguchi L18 experimental design The performance characteristics are surface roughness (μm), material removal rate (mm^3/sec), Wire Wear Rate (gram/sec), and form and orientation tolerances. The model was successfully developed such that the changes in the input parameter reflects the output. Accuracy measures such as Mean Absolute Deviation, Root Mean Square Error and Mean Absolute Percentage Error were calculated for the neuro fuzzy network indicating a robust prediction model. The mean absolute deviation value was obtained as 0.0152. Root mean square error is 0.0216 and the Mean absolute percentage error is 2.91. Further studies can be carried out in development of multi objective prediction models to reduce the dependence on grey techniques and the results can be compared.

6. References

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