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Parametric Analysis and Multi Objective Optimization of Cutting Parameters in Turning Operation of EN353 – With CVD Cutting Tool Using Taguchi Method

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***Abstract*— Modern manufacturers, seeking to remain competitive in the market, rely on their manufacturing engineers and production personnel to set up manufacturing processes for new products. Achieving a desired level of surface quality on turned parts requires practical knowledge and skill to set up this type of operation with the given specifications and conditions. They often rely on past experience, published guidelines from hand books for determining the machining parameters to achieve a specified level of surface roughness. This paper discusses an investigation into the use of Taguchi parameter Design and Regression analysis to predict and optimize the surface roughness and metal removal rate in turning operations using CVD cutting tool.**

***Index Terms*— ANOVA, CVD, MRR, Regression Analysis.**

I. INTRODUCTION

Turning is the machining operation that produces cylindrical parts. It can be defined as machining of an external surface such that, there is a relative movement between work piece and single- point cutting tool. Cutting tool is being fed parallel to the axis of the work piece. In the present work a set of experiments are conducted on the work piece EN353 with CVD and PVD cutting tools to evaluate the effect of machining parameters such as speed, feed, depth of cut on surface roughness and metal removal rate. Regression model is able to predict values for responses in comparison with experimental values within reasonable limits and Taguchi approach is used to obtain the optimal settings of these process parameters, finally ANOVA is used to analyze the influence of these cutting parameters during machining.

II . LITERATURE REVIEW

In order to develop and optimize a surface roughness model, it is essential to understand the current status of work in this area. The need for selecting and implementing optimal machining conditions and most suitable cutting tools has been felt over few decades. Sahin et al. (2004)[1] proposed a surface roughness model in the turning of AISI 1040 carbon steel was developed in terms of cutting speed, feed rate and depth of cut using response surface methodology. Machining tests were carried out using PVD-coated ceramic tools under different cutting conditions. The established equation showed that the feed rate was found to be main influencing factor on the surface roughness. Tozu et al. (2006)[2] optimized the machining characteristics of Inconel 718 bars using tungsten carbide and cermet cutting tools based on Taguchi method, the signal-to-noise (S/N) ratio and the analysis of variance (ANOVA). The roundness and flank wear of the ultrasonically and conventionally machined work pieces were measured and compared & the optimal cutting parameters for turning operations were obtained.

Sardinas et al. (2006)[3] presented a multi-objective optimization technique, based on genetic algorithms, to optimize the cutting parameters in turning processes: cutting depth, feed and speed. Two conflicting objectives, tool life and operation time, were simultaneously optimized. The proposed model used a micro genetic algorithm in order to obtain the non-dominated points and build the Pareto front graph. An application sample was developed and its results were analyzed for several different production conditions. Doniavi et al. (2007) [4] attempted to develop an imperial model with the use of response surface methodology, a widely adopted tool for the quality engineering field. The model showed that the feed rate was found to be main influencing factor on the surface roughness. The results for analysis of variance showed that the first order term of depth of cut was not significant. But the first order term of cutting speed and feed rate were significant. Ozel et al. (2007)[5] investigated surface finishing and tool flank wear in finish turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts. Multiple linear regression models and neural network models were developed for predicting surface roughness and tool flank wear. In neural network modeling, measured forces, power and specific forces were utilized in training algorithm. Neural network based predictions of surface roughness and tool flank wear were carried out and compared with a non-training experimental data. These results showed that neural network models are suitable to predict tool wear and surface roughness patterns for a range of cutting conditions.

Thamma (2008)[6] constructed the regression model to find out the optimal combination of process parameters in turning operation for Aluminium 6061 work pieces. The study highlighted that cutting speed, feed rate, and nose radius had a major impact on surface roughness. Smoother surfaces could be produced when machined with a higher cutting speed,

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smaller feed rate, and smaller nose radius. Gusri et al. (2008) [7] applied Taguchi optimization methodology to optimize cutting parameters in turning Ti-6Al-4V ELI with coated and uncoated cemented carbide tools.

The turning parameters evaluated was cutting speed, feed rate, depth of cut and type of cutting tool, each at three levels. The results of analysis showed that the cutting speed and type of tool had a very significant effect on the tool life, and the feed rate and type of tool had also a very significant effect on the surface roughness. Thamizhmanii et al. (2008)[8] analyzed the surface roughness produced by turning process on hard martensitic stainless steel by Cubic Boron Nitride cutting tool. The work piece material was hard AISI 440C martensitic stainless steel. The experiments were designed using various operating parameters like cutting speed, feed rate and depth of cut. It was found that low surface roughness was produced at cutting speed of 225 m/min with feed rate of 0.125 mm/rev and 0.50 mm depth of cut (doc). However, moderate cutting speed of 175 m/min under above feed rate and doc is an ideal operating parameters taking flank wear in to account. Srikanth et al. (2008)[9] proposed a real coded genetic algorithm (RCGA) to find optimum cutting parameters (speed, feed and depth of cut). This paper explained various issues of RCGA and its advantages over the approach of binary coded genetic algorithm. The results obtained, conclude that RCGA was reliable and accurate for solving the cutting parameter optimization. Mahdavinejad et al. (2009)[10] showed the precision of machine tools on one hand and the input setup parameters on the other hand, were strongly influenced in main output machining parameters such as stock removal, toll wear ratio and surface roughness. There were a lot of input parameters which were effective in the variations of these output parameters. In CNC machines, the optimization of machining process in order to predict surface roughness is very important. From this point of view, the combination of adaptive neural fuzzy intelligent system was used to predict the roughness of dried surface machined in turning process. Gopalsamy et al. (2009)[10] applied Taguchi method to find optimum process parameters for end milling while hard machining of hardened steel. A L16 array, signal-to-noise ratio and analysis of variance (ANOVA) were applied to study performance characteristics of machining parameters (cutting speed, feed, depth of cut and width of cut) with consideration of surface finish and tool life. Results obtained by Taguchi method match closely with ANOVA and cutting speed is most influencing parameter. Suhail et al. (2010)[11] presented experimental study to optimize the cutting parameters using two performance measures, work piece surface temperature and surface roughness. Optimal cutting parameters for each performance measure were obtained employing Taguchi techniques. The experimental results showed that the work piece surface temperature can be sensed and used effectively as an indicator to control the cutting performance and improves the optimization process. Thus, it is possible to increase machine utilization and decrease production cost in an automated manufacturing environment. Akhyar et al., 2008, Selvaraj and Chandramohan, 2010). [13] Robust design focuses on improving the fundamental function of the product or process, thus facilitating flexible designs and concurrent engineering.

Kaladhar et al., 2011 [14] presented a multi-characteristics response model for optimizing process parameter in turning on AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool with Taguchi robust design integrated with utility concept. K.Palanikumar and Karthikeyan, 2006 [15] revealed that maximization of MRR and minimization of surface roughness are important criteria and could be arrived significantly for composite turning operations. Suresh Dhiman et al.,2008 [16]presented various studies on machining and non machining characteristics of AISI 1018 steels .They studied the effect of cutting parameters (feed, depth of cut , speed) of AISI1018 steel on various factors(Temperature, surface roughness, cutting forces) that account for machining costs. Aman Aggarwal and H.Singh,2005[17**]** made an attempt to review the literature on optimizing machining parameters in turning process. Various conventional techniques were employed for machining include geometric programming, geometric plus linear programming, goal programming, sequential unconstrained minimization technique, dynamic programming etc. The latest techniques for optimization include fuzzy logic, scatter search technique, genetic algorithm, and Taguchi technique and response surface methodology. Indrajit Mukherjee and Pradip Kumar ray,2005 [18] presented the application potential of several modeling and optimization techniques in metal cutting processes, classified under several criteria ,has been critically appraised, and generic framework for parameter optimization in metal cutting process is suggested for the benefits of selection of an appropriate approach. It incorporates the use of one or more of the existing modeling and optimization techniques, making the frame work a unified and effective means.

III. EXPERIMENTAL SETUP AND CUTTING CONDITIONS

In this study EN353 work material, with 300 mm long and 50mm diameter was used for experimentation using a lathe machine. 50 mm was held in the chuck and 250 mm was turned in dry condition. During measuring 5mm was set as the cut of length.

Table: 1: Chemical composition of the alloy steel EN353 (63HRC)

Element	C	Si	Mn	S	P	Cr	Mo	Ni
Composition	0.2	0.2	0.6	0	0	0.9	0.1	1

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The cutting parameters of machining of EN353 are cutting speed, feed, and depth of cut are taken at three levels as shown below in the table

Table:2

Parameters	Level -1	Level-2	Level-3
Cutting Speed (rpm)	740	580	450
Feed rate (mm/rev)	0.09	0.07	0.05
Depth of Cut (mm)	0.25	0.2	0.1

Table 3: Experimental data and results for 3 parameters, corresponding Ra,and MRR for CVD tool.

S.No	Speed, S (rpm)	Feed,f (mm/rev)	Depth of cut, (mm)	Surface Roughness Ra(μm)	Material removal rate (mm^3/min)
1	740	0.05	0.25	3.7624	0.6233
2	740	0.05	0.2	2.5408	0.2564
3	740	0.05	0.1	2.6463	0.2684
4	740	0.07	0.25	4.0304	0.7792
5	740	0.07	0.2	2.2705	0.355
6	740	0.07	0.1	2.4472	0.356
7	740	0.09	0.25	4.3392	0.8727
8	740	0.09	0.2	2.3151	0.355
9	740	0.09	0.1	2.5792	0.4918
10	580	0.05	0.25	4.1644	0.5647
11	580	0.05	0.2	2.3815	0.5272
12	580	0.05	0.1	2.936	0.5366
13	580	0.07	0.25	4.3271	0.5647
14	580	0.07	0.2	2.6254	0.1411
15	580	0.07	0.1	2.8209	0.1411
16	580	0.09	0.25	4.2722	0.6593
17	580	0.09	0.2	1.9945	0.3846
18	580	0.09	0.1	1.9765	0.1948
19	450	0.05	0.25	3.1275	0.1699
20	450	0.05	0.2	1.9613	0.1687
21	450	0.05	0.1	2.2436	0.0881
22	450	0.07	0.25	3.5635	0.3108
23	450	0.07	0.2	2.0062	0.3422
24	450	0.07	0.1	2.8849	0.233
25	450	0.09	0.25	3.0145	0.1626
26	450	0.09	0.2	2.258	0.155
27	450	0.09	0.1	2.883	0.1608

Note: Highest S/N ratio yields the optimal quality with minimum variance. From the table:4 below it can be seen that the depth of cut (d) had the strongest influence on surface finish, followed by cutting speed(S) and then by feed(f).

Table: 4 Response table for signal to noise ratio for CVD tool [Ra]

Level	Speed(S)	Feed(f)	Depth of Cut(d)
1	-8.324	-8.902	-8.239
2	-9.325	-9.267	-7.045
3	-9.259	-8.739	-11.624
Delta(max-min)	1.001	0.528	4.579
Rank	2	3	1

Response Table for means for CVD tool [Ra]

Level	Speed(S)	Feed(f)	Depth of Cut(d)
1	2.660	2.863	2.602
2	3.055	2.997	2.261
3	2.992	2.848	3.845
Delta(max-min)	0.395	0.149	1.583
Rank	2	3	1

Table:5 Response Table for Signal to Noise Ratio for CVD tool [MRR]

Level	Speed(S)	Feed(f)	Depth of Cut(d)
1	-14.656	-10.58	-12.533
2	-9.003	-10.135	-11.293
3	-7.091	-10.034	-6.924
Delta(max-min)	7.564	0.546	5.609
Rank	1	3	2

Response Table for Means for CVD tool [MRR]

Level	Speed(S)	Feed(f)	Depth of Cut(d)
1	0.199	0.356	0.2746
2	0.4127	0.3582	0.2984
3	0.4842	0.3819	0.5231
Delta(max-min)	0.2852	0.0259	0.2485
Rank	1	3	2

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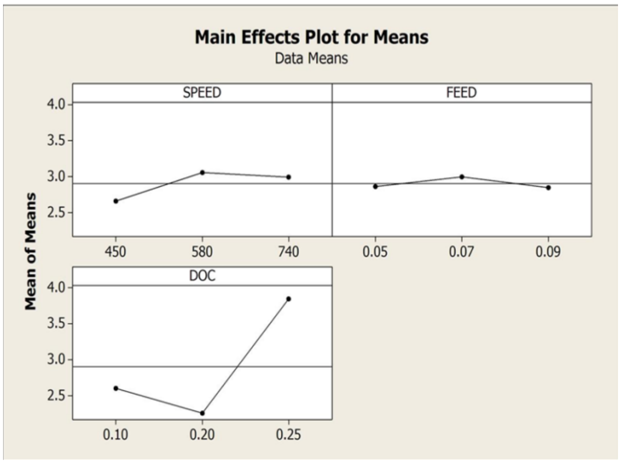

Figure – 1 Plots of main effects for means for Surface roughness (Ra) on CVD tool

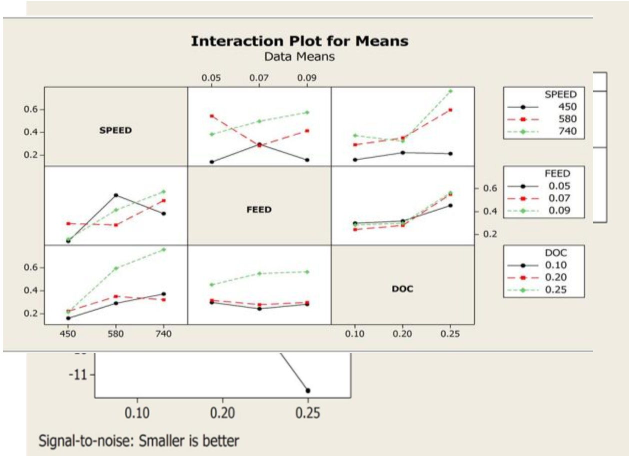

Figure - 2 S/N ratio for Surface roughness (Ra) on CVD tool

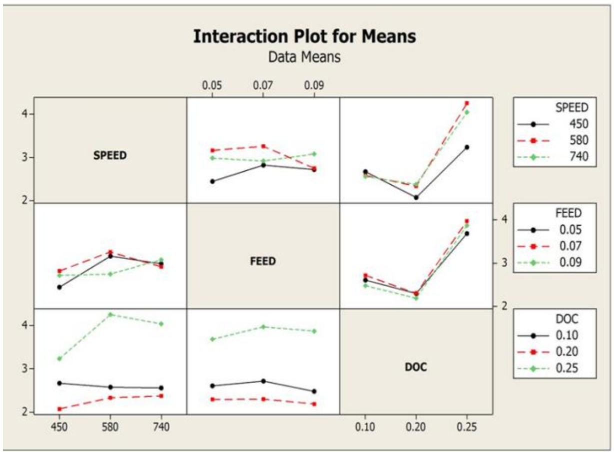

Figure 3 Interaction data means for Surface roughness (Ra) on CVD tool

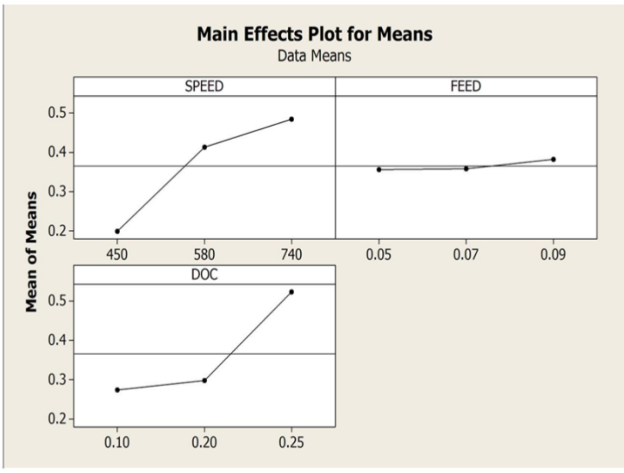

Figure 4 Plots of main effects for means for Material removal rate on CVD tool

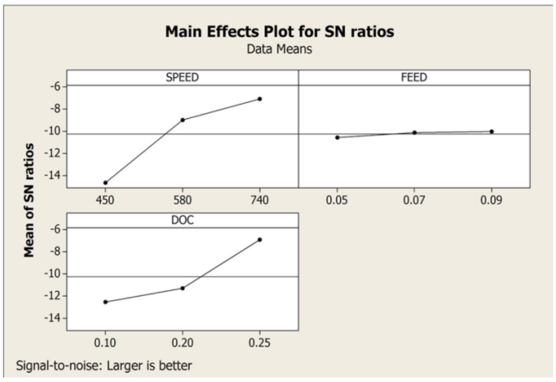

Figure 5 S/N ratio for Material removal rate on CVD tool

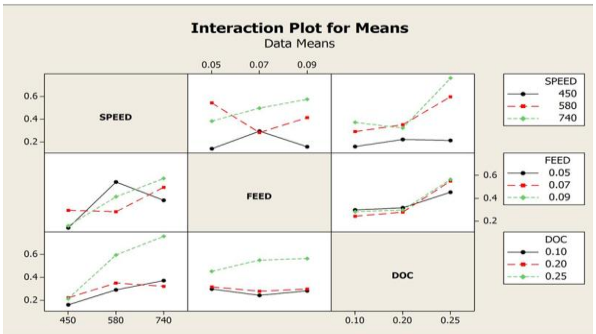

Figure 6 Interaction data means for Material removal rate on CVD tool

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Table. 6: Optimized table obtained on CVD tool

CVD	Speed(v)	Feed(f)	DOC(d)
Ra	580	0.07	0.2
MRR	740	0.09	0.25

Table 7: ANOVA for the response surface roughness (Ra) on CVD tool

Source	DOF	Sum of Squares	Mean of Squares	F Ratio	% of Contribution
Speed(S)	2	0.3963	0.198	0.9272	48.037
Feed(F)	2	0.0037	0.002	0.0087	0.4501
DOC(D)	2	0.3384	0.169	0.7917	41.018
SXF	4	0.0203	0.01	0.0475	2.461
SXD	4	0.0561	0.028	0.1313	6.802
FXD	4	0.0102	0.005	0.0238	1.2322
ERROR	8	0.3611	0.045		
TOTAL	26	0.825			100

Table 8: ANOVA for the response Material removal rate (MRR) on CVD tool

Source	DOF	Sum of Squares	Mean of Squares	F Ratio	% of Contribution
Speed(S)	2	0.3963	0.198	0.9272	48.037
Feed(F)	2	0.0037	0.002	0.0087	0.4501
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ERROR	8	0.3611	0.045		
TOTAL	26	0.825			100

IV. CONCLUSION

The results obtained in this study lead to conclusions for turning of EN353 after conducting the experiments and analyzing the resulting data.

(1) From the results obtained by experiment, the influence of surface roughness (Ra), and Material Removal Rate (MRR) by the cutting parameters like speed, feed, DOC is

(a) The feed rate has the variable effect on surface roughness, cutting speed and depth of cut an approximate decreasing trend.

(b) Cutting speed, feed rate and depth of cut for Material Removal Rate have increasing trend.

(2) The design of experiments (DOE), Taguchi method is applied for optimization of cutting parameters and Analysis of Variance (ANOVA) is done and found that

(a) The optimal combination of process parameters for minimum surface roughness is obtained at 580 m/min cutting speed, 0.07 mm/rev feed, 0.20 mm of depth of cut.

(b) The optimal combination of process parameters for maximum material removal rate is obtained at 740 m/min cutting speed, 0.09 mm/rev feed, 0.25 mm of depth of cut.

(3) ANOVA shows that the depth of cut has great influence for the response surface roughness (Ra), cutting speed has great influence for the response Material removal rate (MRR) .The percentage contribution values for the responses Ra, and MRR are as follows:

(a) In case of Ra response the depth of cut 87.68% is significant one followed by cutting speed.

(b) In case of MRR response the cutting speed 48.03% is significant one followed by depth of cut.

(4) The interaction of cutting parameters is also studied for the three responses Ra, and MRR as follows :

(a) The interaction for the cutting parameters is found that speed and depth of cut have great influence on the response Ra and the percentage contribution of speed and depth of cut is 4.84% followed by feed and depth of cut with 0.66%, speed and feed with 0.26%.

(b) The interaction for the cutting parameters is found that speed and depth of cut have great influence on the response MRR and the percentage contribution of speed and depth of cut is 6.80% followed by speed and feed with 2.46%, feed and depth of cut with 1.23%.

(5) Using the experimental data, a multi linear regression model is developed and the values obtained for the responses Ra and MRR are compared with measured values. A graph was plotted between Regression predicted values and experimentally measured values and shows that the models are adequate without any violation of independence or constant assumption.

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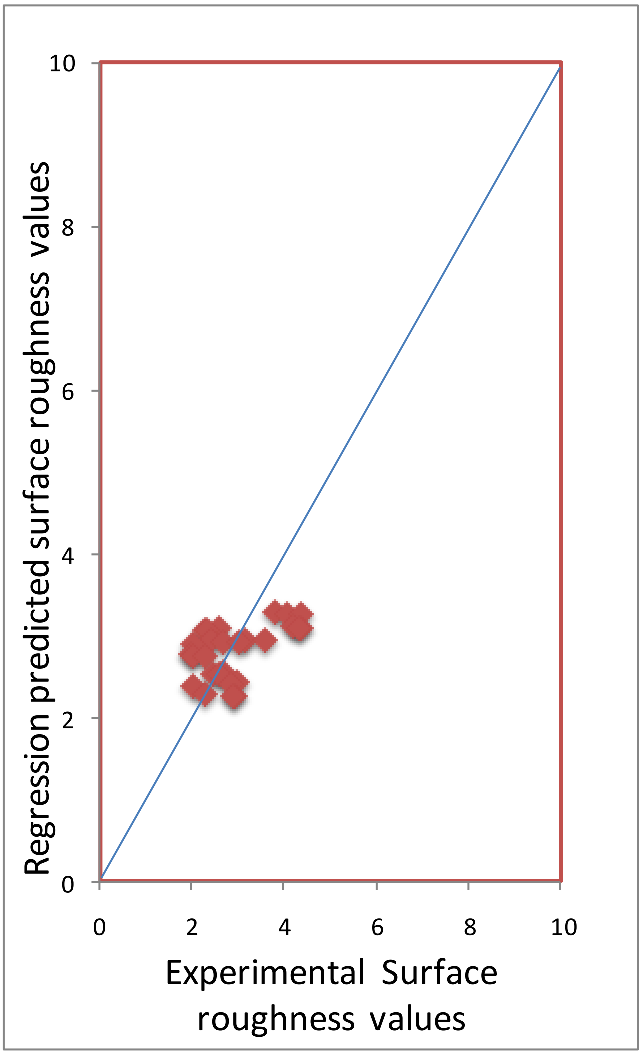

Figure – 7

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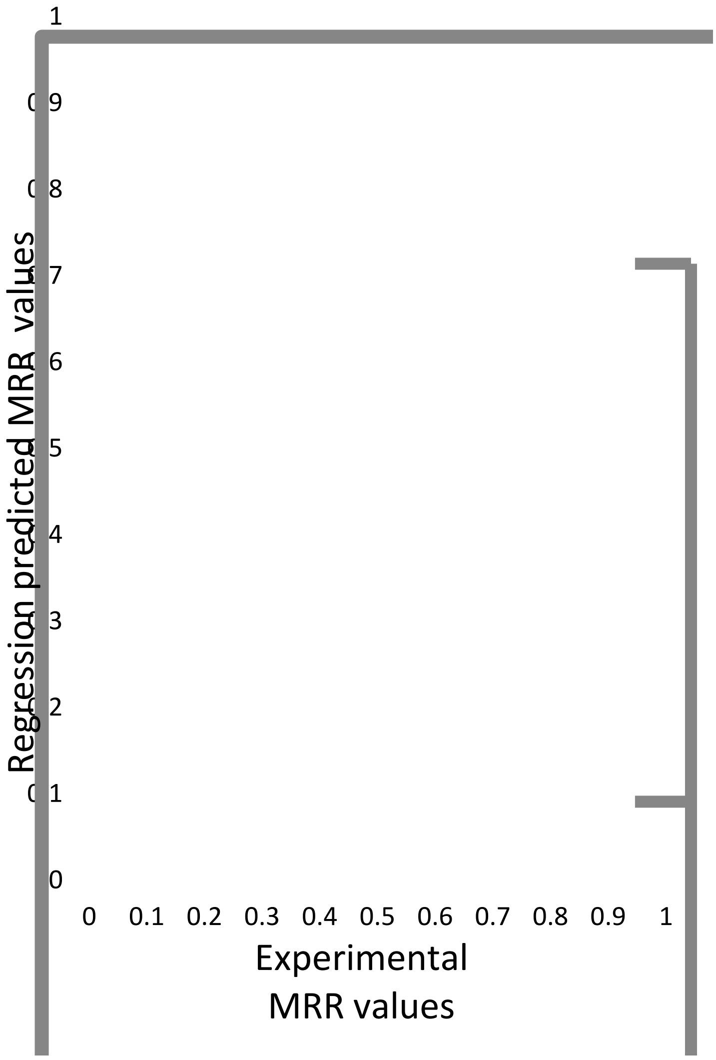

Figure – 8

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