Modeling the Specific Energy in Turning Operations by Taguchi L32 Orthogonal Array Design

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ABSTRACT: This study considered Cutting Speed V, Feed rate F, Depth of cut D and Cutting Environment E as the input parameters for a Design of Experiment (DOE) based on a mixed-level Taguchi L32 orthogonal array. The test runs were conducted on a conventional lathe with spindle power of 3.75kW using TiN coated cutting tools and AISI 1040 carbon steel as workpiece. Signal-to-Noise (S/N) ratio analysis was applied to determine the optimum level for each parameter while analysis of variance (ANOVA) was employed to analyze the significant contributions of the control factors influencing the outcome - Specific Energy Consumption (SEC). Response surface methodology was used for developing a second order model for SEC as an energy efficiency indicator in Turning operations. Genetic Algorithm Solver was also used as optimization tool for the model. Results showed that for minimizing SEC, F was the most significant factor with a percentage contribution of 84.35% followed by V, E and D. The SEC model proved to be highly significant with p-value < 0.05 and was well fitted with the experimental value showing a high coefficient of determination (R2= 91.78%) value.

Keywords: Specific Energy Consumption, Taguchi Design of Experiments, Optimization.

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Nomenclature

Adj MS	-	*Adjusted Mean Squares*
%C	-	*Percentage Contribution*
E	-	*Cutting Environment*
D	-	*Cutting Depth*
DF	-	*Degree of freedom*
F	-	*Feed Rate*
GA	-	*Genetic Algorithm*
HB	-	*Higher-the-Better*
i	-	*Integer*
j	-	*Integer*
MRR	-	*Material Removal rate*
LB	-	*Lower-the-Better*
n	-	*Number of observations*
NB	-	*Nominal-the-Best*
P_C	-	*Cutting Power*
p-value	-	*Probability statistics*
S_{EC}	-	*Specific Energy Consumption*
Seq SS	-	*Sequential Sum of Squares*
S/N	-	*Signal-to-Noise ratio*
V	-	*Cutting Speed*
y	-	*Observed Response*
β_o	-	*Regression constant term*
β_i	-	*Main Effects Coefficient*
β_{ij}	-	*Interaction Effects Coefficient*
β_{ii}	-	*Quadratic Effects Coefficient*
ϵ	-	*Error*

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1. Introduction

Energy efficiency of production systems, especially of machining operations is becoming increasingly relevant and is a key focus of most developing nations [1]. The growing demands and continued rise in the value of energy serve to emphasize the importance of enhancing the energy and material-related efficiency of all manufacturing processes. Efficient energy

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management is therefore not only fundamental to, but an integral part towards sustainable production systems [2].

The energy required in machining process is drawn from the electrical grid and can be generated from different power sources such as thermal, nuclear, wind, ocean wave and tides, solar, biomass, rivers, geothermal, etc. Balogun and Mativenga [3] reported that the use of carbon rich electricity generation sources is of global concern, because these processes produce CO_2 emissions. Therefore, the higher the consumption of electricity in the manufacturing industries, the higher the carbon footprints related to the manufactured products. The industrial sector currently accounts for about half of the world's total energy consumption, and this sectoral consumption has almost doubled over the last 60 years [4]. Besides, global energy demand is expected to grow by 53% between 2008 and 2035 [5]. Also industrial energy consumption is projected to grow at 2.4-3.2% per year through 2030 in developing countries and 1.2% in developed countries [6].

Mativenga and Rajemi [7] reported that optimizing energy demand in manufacturing is important for reducing the energy intensity of products and their vulnerability to escalating energy prices in the future. Pusavec *et al* [8] reported that an estimated two- thirds of the electrical energy used by machining industry is meant for running motors and drives for cutting tools. The cost of energy used over a ten-year period is about 100 times higher than the initial purchase cost of the machine tools used to manufacture products [9]. Therefore, prior to machining of a part or component the optimum energy consumption per unit volume of the machined product should be determined in order to improve profitability, reduce operating cost and minimize environment impact generated from energy production of manufacturing firms. Specific energy in this study is considered as an energy efficiency indicator to minimize the energy intensity of a given machined product.

One of the processes widely used in manufacturing is Turning. Over the years, optimization of Turning processes with respect to machining performance based on machining cost, quality and productivity has received enormous attention unlike optimization based on Specific Energy consumption, despite recent emphasis on energy savings and conservation.

2 Materials and Methods

2.1 Experimental Setup and Procedure

Cutting performance tests were carried out on a lathe machine *(Master 2500, Colchester, UK)* with a 3.75kW spindle power and a maximum spindle speed of 2500 rpm. A cylindrical AISI 1040 carbon steel rod of diameter 35mm and overhang length 120mm was used as the workpiece per experimental run. The cutting tool used for the turning operation was Widia tool holder *(ANSI No. PCLNR2525M16, Widia, UK)* and diamond shaped Carbide inserts with TiN coating *(ISO CNMG120408)*. KOOLCUT-40 soluble oil was used to perform the experiment under wet cutting environment.

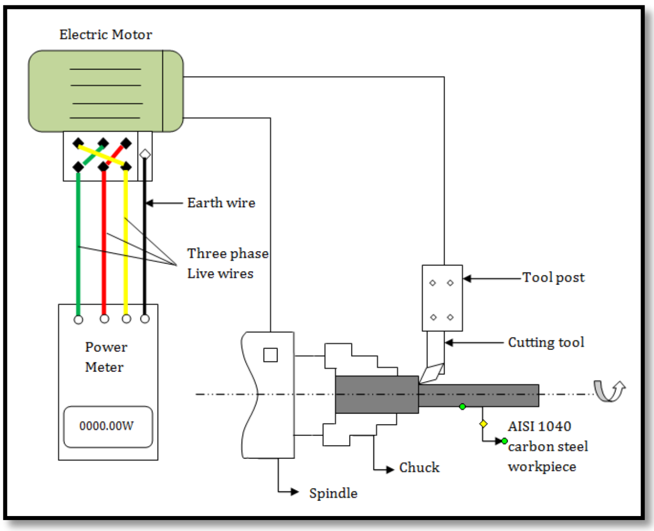

Figure 1, Experimental Setup for the Turning Operation

2.2 Experimental Design

Experimental design is an efficient procedure of planning experiments so that the data obtained can be analyzed to yield valid and objective conclusions [10]. The Taguchi experimental design technique was adopted to study the entire parameter space with only a minimum number of experiments. The advantages of Taguchi's method are the saving of effort in conducting experiments, saving experimental time, reducing the cost, and discovering significant factors quickly. The main thrust of the Taguchi's experimental design is to determine the parameter settings which produce the best level of performance characteristics with minimum variation [10]. The process parameters selected as the control factors include: Cutting Environment (E), Cutting Speed (V), Feed rate (F) and Depth of cut (D). The tests were carried out following Taguchi-L32 mixed level design of experiments (DOE) where factor E was varied at two levels (E_1- wet and E_2 - dry), while input factors V, F, and D were varied at four levels as: (V_1, V_2, V_3, V_4 = 50, 75, 100, 125m/min), (F_1, F_2, F_3, F_4 = 0.2, 0.3, 0.4, 0.5mm/rev), and (D_1, D_2, D_3, D_4 = 0.25, 0.50, 0.75, 1.00mm). The mixed-level Taguchi-L32 design was adopted because it is the best available design suitable to accommodate factors with varying levels having a one 2-level parameter and three 4-level parameters.

The DOE matrix consisting of 32 experimental runs was generated using MINITAB 16 software. The matrix was used for obtaining Cutting Power P_C [W], material removal rate (MRR) [mm^3/s] and specific energy S_{EC} consumption data for every experimental run.

2.3 Experimental Determination of Specific Energy Consumption S_{EC}

In this study, the electrical Power was measured by a 3-phase digital power meter *(MS2203, MASTECH, China)* which was connected to the lathe machine motor in a delta-mode as in Figure 1. Cutting Power P_C in each run was recorded and converted to S_{EC} using Equation 1.

$$S_{EC} = \frac{P_C}{MRR} = \frac{P_C}{VFD*10^3} \qquad - \qquad (1)$$

2.4 Response Surface Methodology

The relationship between the process parameters and output response was determined using multiple regression analysis of the data obtained from the DOE to develop a second order polynomial model. Similar functional relationship between the desired response and the process parameters had been expressed by Palanikumar [11] and Raj [12] as:

$$S_{EC} = f(V, F, D) + \epsilon \qquad - \qquad (2)$$

For better correlation and approximation of the response surface, the study utilized the second order response surface model which involves linear terms, two-way interactions terms and quadratic terms. Therefore, the specified model for the study showing the relationship between response, S_{EC} and the turning parameters $X_{i,j}$ was estimated using Equations 3 and 4.

$$y = \beta_o + \sum_{i=1}^{n} \beta_i X_i + \sum_i \sum_j \beta_{ij} X_i X_j + \sum_{i=1}^{n} \beta_{ii} X_i^2 \qquad (3)$$

$$S_{EC} = \beta_o + \beta_1 V + \beta_2 F + \beta_3 D + \beta_{12} VF + \beta_{23} FD + \beta_{31} DV + \beta_{11} V^2 + \beta_{22} F^2 + \beta_{33} D^2 \qquad (4)$$

MINITAB-16 software was used to determine the regression coefficients of the model based on the response, specific energy consumption.

2.5 OPTIMIZATION METHODS

2.5.1 Taguchi S/N Ratios

Taguchi S/N ratio is a statistical measure of performance or quality for data analysis and prediction of optimal parameter setting [13]. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). It depends on the quality characteristics of the process to be optimized. The standard S/N ratios generally used include: Nominal-is-Best (NB), "lower-the-better" (LB) and Higher-the-Better (HB).

In this study, MINITAB 16 was used to solve the optimization problem. Specific energy consumption was taken as LB characteristics, aimed at minimizing the response, with an ideal target being zero. This LB - S/N ratio was computed as equation (5) following Ross [13].

$$S/N = -10log\frac{1}{n}\sum_{i=1}^{n} y_i^2 \qquad - \qquad (5)$$

2.5.2 Genetic Algorithm (GA)

Genetic algorithms (GA) are computational models inspired based on Darwin's survival of the fittest principle of evolution, natural selection and genetics using a search procedure to find the best and fittest design solutions [14]. These algorithms encode a potential solution to a specific problem on a simple chromosome–like data structure. The objective of the GA optimization approach is to achieve minimum S_{EC} by adjusting the cutting conditions by numerical optimization using the GA Toolbox in MATLAB *(R2007b)*. The optimization problem was solved by coupling the S_{EC} model from response surface methodology with the GA. The optimization was formulated in the standard mathematical format as:

- Find: *V* (Cutting speed, m/min), *F* (Feed rate, mm/rev), and *D* (Depth of cut)
- Minimize: S_{EC} (*V, F, D*)
- Subject to constraints: $\begin{cases} V_{min} \le V \le V_{max} \\ F_{min} \le F \le F_{max} \\ D_{min} \le D \le D_{max} \end{cases}$

The following options were selected in the GA Solver Toolbox for formulating the optimization problem: Number of Variables = 3; Lower bound [50 0.20 0.25]; Upper bound [125 0.50 1.00]; Population type = Double vector; Population = 100; Crossover Fraction: 0.80; Mutation rate: 0.20; Number of generations = 100. The algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to the fitness limit.

3. RESULTS AND DISCUSSION

3.1 Data Presentation

The results obtained from the experimental runs following the DOE are shown in Table 1.

Table 1 Experimental results for S_{EC} and S/N ratios.

Runs	CE	Cutting speed (m/min)	Feed Rate (mm/rev)	DOC mm	CUTTING POWER (Watts)	MRR (mm^3/s)	SEC (J/mm^3)	S/N Ratios (dB)
1	WET	50	0.2	0.25	161.5	41.667	3.87500	-11.7654
2	WET	50	0.3	0.5	425.0	125	3.40000	-10.6296
3	WET	50	0.4	0.75	781.3	250	3.12500	-9.89700
4	WET	50	0.5	1	1187.5	416.67	2.85000	-9.09690
5	WET	75	0.2	0.25	242.2	62.5	3.87500	-11.7654
6	WET	75	0.3	0.5	637.5	187.5	3.40000	-10.6296
7	WET	75	0.4	0.75	1171.9	375	3.12500	-9.897
8	WET	75	0.5	1	1781.3	625	2.85000	-9.0969
9	WET	100	0.2	0.5	625.8	166.67	3.75500	-11.4922
10	WET	100	0.3	0.25	410.0	125	3.28000	-10.3175
11	WET	100	0.4	1	2073.2	666.67	3.11000	-9.85521
12	WET	100	0.5	0.75	1781.3	625	2.85000	-9.0969
13	WET	125	0.2	0.5	783.3	208.33	3.75980	-11.5033
14	WET	125	0.3	0.25	531.3	156.25	3.40000	-10.6296
15	WET	125	0.4	1	2604.2	833.33	3.12500	-9.897
16	WET	125	0.5	0.75	2226.6	781.25	2.85000	-9.0969
17	DRY	50	0.2	1	690.0	166.67	4.14000	-12.34
18	DRY	50	0.3	0.75	670.1	187.5	3.57333	-11.0615
19	DRY	50	0.4	0.5	583.3	166.67	3.49800	-10.8764
20	DRY	50	0.5	0.25	350.0	104.17	3.36000	-10.5268
21	DRY	75	0.2	1	981.0	250	3.92400	-11.8746
22	DRY	75	0.3	0.75	970.0	281.25	3.44889	-10.7536
23	DRY	75	0.4	0.5	810.2	250	3.24000	-10.2109
24	DRY	75	0.5	0.25	480.3	156.25	3.07200	-9.74842
25	DRY	100	0.2	0.75	955.2	250	3.82000	-11.6413
26	DRY	100	0.3	1	1690.0	500	3.38000	-10.5783
27	DRY	100	0.4	0.25	542.4	166.67	3.25440	-10.2494
28	DRY	100	0.5	0.5	1235.4	416.67	2.96496	-9.44038
29	DRY	125	0.2	0.75	1210.0	312.5	3.87200	-11.7587
30	DRY	125	0.3	1	2120.6	625	3.39200	-10.6091
31	DRY	125	0.4	0.25	665.0	208.33	3.19200	-10.0813
32	DRY	125	0.5	0.5	1548.0	520.83	2.97216	-9.46144

3.2 Data Analysis and Discussions

3.2.1 Regression Analysis

The Minitab software utilized the specified data to develop the S_{EC} model under wet and dry cutting environment. Equation 6 represents the specific energy consumption (S_{EC}) model in terms of the machining parameters such as cutting speed, feed rate and depth of cut under the influence of two cutting environment.

$$S_{EC} = 5.27391 - 0.01254V - 5.44568F + 0.32166D + 0.00005\,V^2 + 0.00025VF + 0.002VD + 5.76968F^2 - 2.45548FD + 0.21263D^2 \qquad - \qquad (6)$$

3.2.2 Analysis of Variance (ANOVA) for the S_{EC} Model

The experimental results were analyzed with ANOVA to identify the factors that significantly affect the performance measures on the total variance of the results. The ANOVA, carried out at $\alpha = 0.05$ significance level (95% confidence level) gave results for S_{EC} shown in Table 2. The sources with P-value < 0.05 are considered as high statistically significant.

Table 2 Analysis of variance (ANOVA) for S_{EC} Model

Source	DF	Seq SS	Adj SS	Adj MS	F	p-value	%C
Model	9	3.89123	3.89123	0.432359	63.10	0.0000	
V	1	0.11533	0.05103	0.051034	16.83	0.0005	2.85
F	1	3.41052	0.15395	0.153954	497.72	0.0000	84.38
D	1	0.02347	0.00499	0.004989	3.43	0.0777	0.58
V^2	1	0.03348	0.03348	0.033479	4.89	0.0378	0.83
F^2	1	0.10653	0.10653	0.106525	15.55	0.0007	2.64
D^2	1	0.00565	0.00565	0.005651	0.82	0.3736	0.14
VF	1	0.00002	0.00002	0.000019	0.00	0.9584	0.00
VD	1	0.00782	0.00782	0.007819	1.14	0.2970	0.19
FD	1	0.18842	0.18842	0.188418	27.50	0.0000	4.66
Resid. Error	22	0.15075	0.15075	0.006852			3.73
Total	31	4.04198					100

3.2.3 Summary of the Model

The statistical properties obtained for the model include: Sample Standard Deviation S = 0.0827784, Coefficient of determination (R-Sq) = 96.27%, Adjusted coefficient of determination (R-Sq, adj) = 94.74%, Predicted residual sum of squares (PRESS) = 0.332412; Predicted Coefficient of determination (R-Sq, pred) = 91.78%.

From Table 2, the p-value < 0.05 for the model implying that this model is highly statistically significant. It was observed that among the main (linear) factors, the feed rate was the most predominant with a percentage contribution to S_{EC} of %C = 84.38%, followed by cutting speed (%C = 2.85) and depth of cut (%C = 0.58). The depth of cut is rather insignificant due to its p-value > 0.05. The quadratic terms V^2 and F^2 are significant except for D^2. The interaction between feed rate and depth of cut (FD) was found to be the only significant interaction term in the model because its p-value < 0.05. Finally, the output coefficient of determination, R-squared value of 96.27% indicates the accuracy of the model and the predicted R-squared for the model is equal to 91.78% which indicates a good correlation with experimental data.

3.2.4 Adequacy Tests

Residual plots for response parameter S_{EC} in Figure 2 were utilized to check any model inadequacy or unusual problem with normality assumptions. Inspection of some diagnostic plots of the model was done to test the statistical validity of the model.

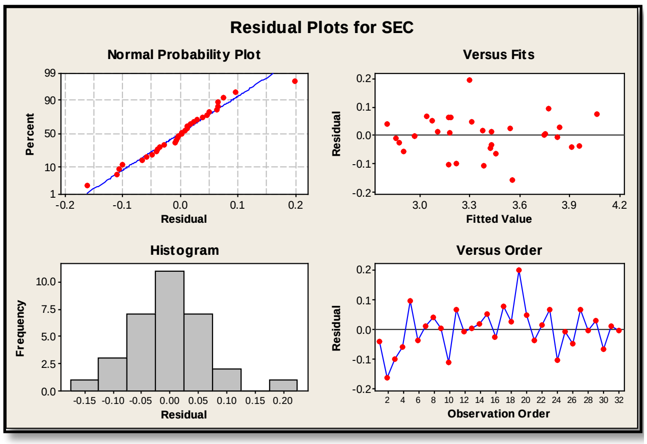

Figure 2, Residual Plots of S_{EC}

From Figure 2a, nearly all the points on the normal probability plot are said to spread approximately in a straight line implying that the errors were distributed normally and a little deviation from normality was observed. This shows the effectiveness of the model. From Figure 2c, the histogram showed an approximate symmetric nature indicating that the residuals are normally distributed. Figures 2b showed that the residuals were randomly scattered within constant variance across the residuals versus the predicted plot as they are scattered randomly around zero in residuals versus the fitted values. The residuals observed were from -0.20 to 0.20, which corroborates the earlier observation of high correlation between the model and experimental values. Figure 2d shows that there is no obvious pattern and unusual structure present in the data which implies that the residual structure analysis does not indicate any model inadequacy or no error due to time or data collection order.

3.2.5 Trend Analysis of Process Parameters on S_{EC} using Surface Plot

Figures 3a and 3b show the response surface plots of S_{EC} based on the DOE parameters. Figure 3a shows S_{EC} variation with respect to cutting speed and feed rate indicating that S_{EC} decreases with increase in feed rate. Figure 3b shows the influence of cutting speed and depth of cut on S_{EC}. The increase in depth of cut and cutting speed decreases the S_{EC} in the turning operations. Therefore, it can be deduced from Figures 3a and 3b that the minimum S_{EC} can be achieved by increasing the feed rate, cutting speed and depth of cut. This is due to the fact that when feed rate, cutting speed and depth of cut are increased, MRR increases thereby reducing S_{EC}.

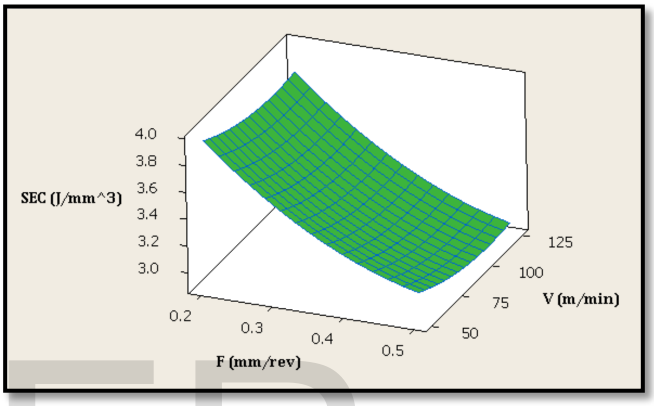

Figure 3a, Response surface of S_{EC} versus Cutting Speed V and Feed Rate F

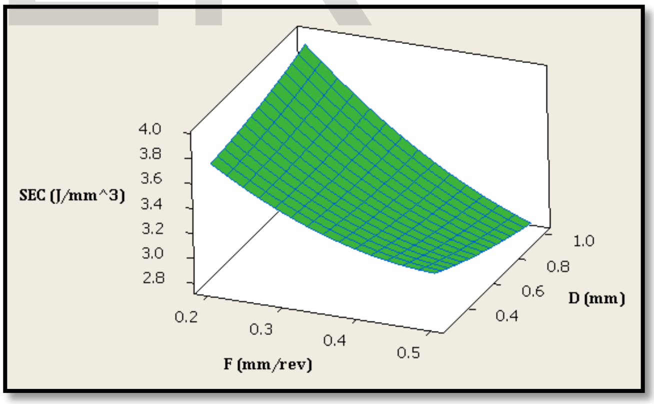

Figure 3b, Response surface of S_{EC} versus Feed Rate F and Depth of cut D

3.2.6 S/N Ratios Analysis for Optimum Settings

The MINITAB16 software was used to analyze the main effect of S/N ratio on the optimization analysis for S_{EC}. Figure 4 shows the main effect plots and the corresponding S/N response for S_{EC}. The overall mean response is represented by the horizontal line at the centre of the curves.

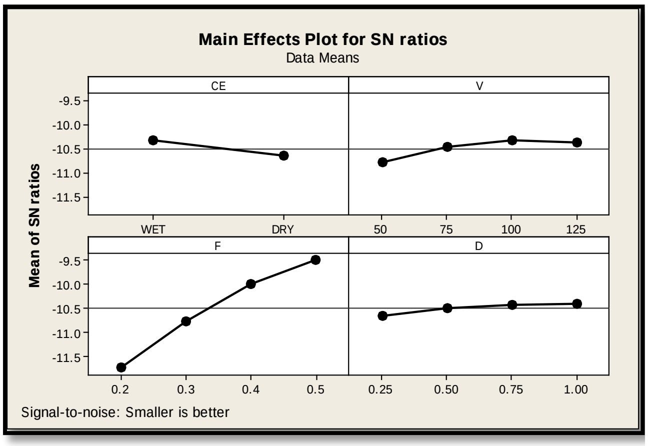

Figure 4, Main effect plot (SEC) for S/N ratios

a) Optimum settings

From the S/N ratio analysis in Figure 4, the level of the factors with the highest S/N ratio was taken as the optimum level for the response, therefore the optimal machining conditions are Wet Cutting Environment (E1), 100 m/min cutting speed (V3), 0.50 mm/rev feed rate (F4) and 1 mm depth of cut (D4) to minimize S_{EC}, that is, an optimal settings coded E1V3F4D4.

b) Ranking Effect of parameters

The ranks and delta-values also indicate the relative importance of each factor to the response. The values obtained for the various factors show that feed rate had the greatest effect on S_{EC} with rank and delta values of 1 and 2.243 respectively, followed by cutting speed with 2 and 0.440, cutting environment with 3 and 0.328, and depth of cut with 4 and 0.235 rank and delta values, respectively.

3.2.7 Optimization Results for Genetic Algorithm

GA optimization was based on the fitness function for specific energy S_{EC} equation (6) above.

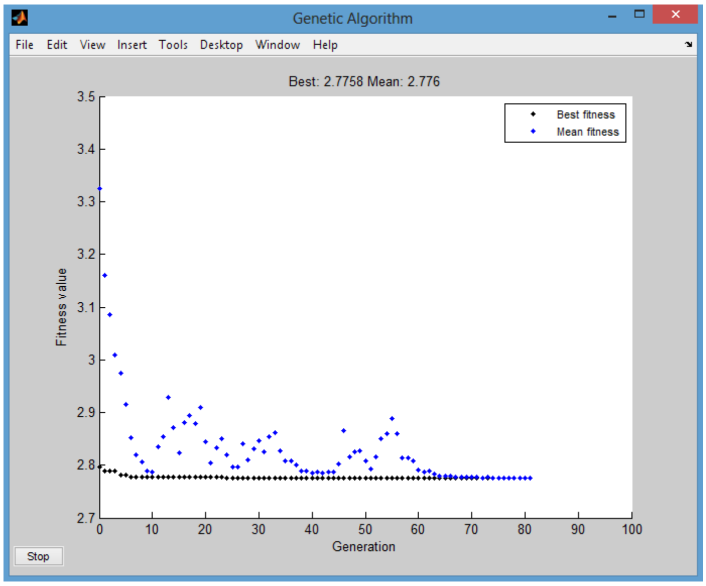

Figure 5, Performance of fitness value with generation.

Figure 5 showed that the optimal S_{EC} value = 2.7758J/mm^3 and accompanying optimal control factors of cutting speed V = 100.645 m/min, feed rate F = 0.5mm/rev and Depth of cut D = 1mm. Optimal solution was obtained at 81st generation (iteration) of the Genetic Algorithm.

4. CONCLUSION

- Taguchi DOE, Genetic Algorithm and Desirability function analyses are effective means of determining the optimal specific energy consumption S_{EC} in machining (Turning) operations.
- ANOVA for the S_{EC} - model revealed that feed rate F is the most significant factor with a percentage contribution (%C) of 84.38% on S_{EC}, followed by cutting speed V with %C = 2.85%. Depth of cut D had the least influence on S_{EC} with a %C = 0.58%.
- The main effect plots of S/N ratio and response indicates that F is the most dominant or ranked parameter on S_{EC} followed by V, E and depth of cut D, in that order.

- The factors interactions plots for S_{EC} indicated strong interactions between feed rate F and depth of cut D on S_{EC}.
- The residual plots for S_{EC} model were generated and showed that S_{EC}-model was well fitted with the experimental-values giving a high correlation between the fitted values and observed values (R^2= 91.78%).
- The 3D response surface plots of S_{EC} decreased with increasing cutting speed V, feed rate F and depth of cut D. The optimal parameter settings to minimize S_{EC} and reduce the deviation from target are: Wet cutting environment (Level 1), 100m/min cutting speed (Level 3), 0.5mm/rev feed rate (Level 4) and 1mm depth of cut (Level 4).

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