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Machining parameter optimization in turning process for sustainable manufacturing

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There is an increase in awareness about sustainable manufacturing process. Manufacturing industries are backbone of a country's economy. Although it is important but there is a great concern about consumption of resources and waste creation. The primary aim of this study was to explore sustainability concern in turning process in an Indian machining industry. The effect of cutting parameters, Speed/Feed/Depth of Cut, the machining environment, Dry/MQL/Wet, and the type of cutting tool on sustainability factors under study were observed. Analysis of Variance (ANOVA) was used to analyse the data obtained from experimentation in a small scale machining industry. The process is modelled mathematically using response surface methodology (RSM).The economic and environmental aspect like surface roughness, material removal rate and energy consumption were considered as sustainability factors. The model helps to understand the effect of the cutting parameters and conditions on surface finish, energy consumption, and material removal rate. The process was optimized for minimum power consumption considering environmental concern as prime importance. Studies suggest that the cutting environment and tool type influenced on the power consumption during turning process. Extended form of the proposed model could be useful to predict the environmental impact due to machining process, which would bring environmental concern into conventional machining.

1. Introduction

In recent era, manufacturing industry is focusing their capabilities towards achieving sustainable products through sustainable manufacturing. This is an effect of increased awareness amongst the manufacturer and the users (Averam et al., 2011). The associated countries are being compelled to reduce negative environmental impact due to manufacturing process. We must understand that the cost of environment is higher than any other objective (personal or of nation) for our better future (CPCB, 2010). Machining industry is the most energy consuming and waste generating industry. How a manufacturing process can be used so that the emissions would be on lower side and would provide high productivity is a question each industry is facing (Tan et al., 2011). Sustainability is no longer a choice but rather it has become a necessity.

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The sustianability approach is based on three pillars namely economic, environment and social aspects, well known as tripple bottom line approach. The factors involved in machining proceess can be categorized in three groups viz. Economic Indicator, Environmental Indicator and Social Indicator. Fig.1 illustrates the approach used in sustainable manufacturing. The US department of commerce defines the sustainable manufaturing as

Sustainable manufacturing is the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources. Sustainable manufacturing also enhances employee, community, and product safety.

Sustainability related aspects like quality of product, energy consumption, emissions and other environmental aspects are getting an integrated part at operational level and decision making in manufacturing (Shao et al., 2010). As the concept of product sustainability is getting important amongst organization, its assessment is becoming more challenging. There appears to be no universal methodology for sustainability assessment of products or processes. This is because of problems in quantifying the parameters commonly known as indicators of sustainability pertaining to manufacturing process or manufactured product (Jawahir et al., 2006).

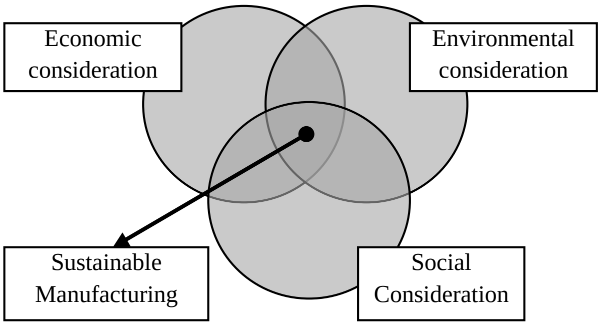

Fig. 1. Three pillers of sustianbility (Aurich et. al., 2013)

Machining process is one of the most used production processes to shape the products. It is the most power consuming and waste generating operations amogst all becuse of its profound use. The machining industries of all sizes have capability of saving money and improve their environmental performance (Kopac & Pusavec, 2009). Therefore, sustainability assessment of machining process is major area of focus for most researchers. First, it is important to define the parameters involved in machining process and categorize those in three aspects of sustainability. Fig. 2 shows the sustainability parametrs for a typical machining process and sustainability assessment model of a machining process.

The cause and response are considerded from a small scale industry point of view taking into account limitation in their measurement during operations. The input parameters identified from available literature include work piece material, work piece geometry, tool material, tool geometry, process parameters; namely speed, feed and depth of cut, and the machining environment dry, minimum quantity lubrication (MQL) and wet machining. The response parameters taken for assessment are catagorized into three aspects of sustainability. The machining cost, surface roughness, material removal rate, tool life were considered as economic aspect, energy consumption, tool temperature, CO_2 equivalant, water use, waste disposal as environmental aspect while noise, vibration, illness rate, absenteeism and job satisfaction were considered as social aspects.

2. Literature Review

Various methodologies have been used by researchers to understand the sustainability of a machining process. A three dimensional system approach (Yuan et al., 2012) highlighted sustainability issues of manufacturing from pollution prevention point of view. Three key components of process; namely technology, energy and material were considered for the study. Supported case study shows the effective use of methodology in a nano-scale manufacturing unit. Li et al.(2012) presented eco efficiency approach for evaluating energy consumption as well as the resource utilization in manufacturing process supported by a case study of grinding process. Munoz and Sheng(1995) focused on waste streams of machining process considering process mechanics, tool wear, metal working fluid loss, chip waste and energy consumption. Jiang et al.(2012) described a new method for environmental assessment of manufacturing process for entire process plan. The weights for process plan parameters were obtained using Analytical hierarchy processing (AHP) approach.

Life cycle Assessment (LCA) is widely considered for understanding the environmental impact of a manufacturing process. It is an authoritative instrument to analyze the manufacturing process. Narita et al. (2006) developed a methodology to assess environmental burden of a machining process using LCA methodology. The model developed provides equivalent CO_2 for the process using the energy consumption, metal working fluid used, chip generated and tool used in the process. Branker et al.(2011) presented new economic model based on LCA methodology. Theoretical and experimental results were used to validate the model for carbon emission and cost sensitivity. Use of LCA methodology demands the knowledge of LCA study. Many of the industries may not have recourses available for the same. Also the availability of environmental data of the country is a major concern.

Large numbers of parameters namely economic, environmental and social need to be evaluated for sustainability assessment of a machining process (Weiser et al., 2008; Jiang et al., 2012). In any analysis it is important to define the boundary of the study first (Smith et al., 2012). Multi criteria decision making approaches like Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) etc. can be applied for the assessment. The outcome of such analysis will be based on the judgment of the decision maker, which in turn, depends on his/her experience and knowledge.

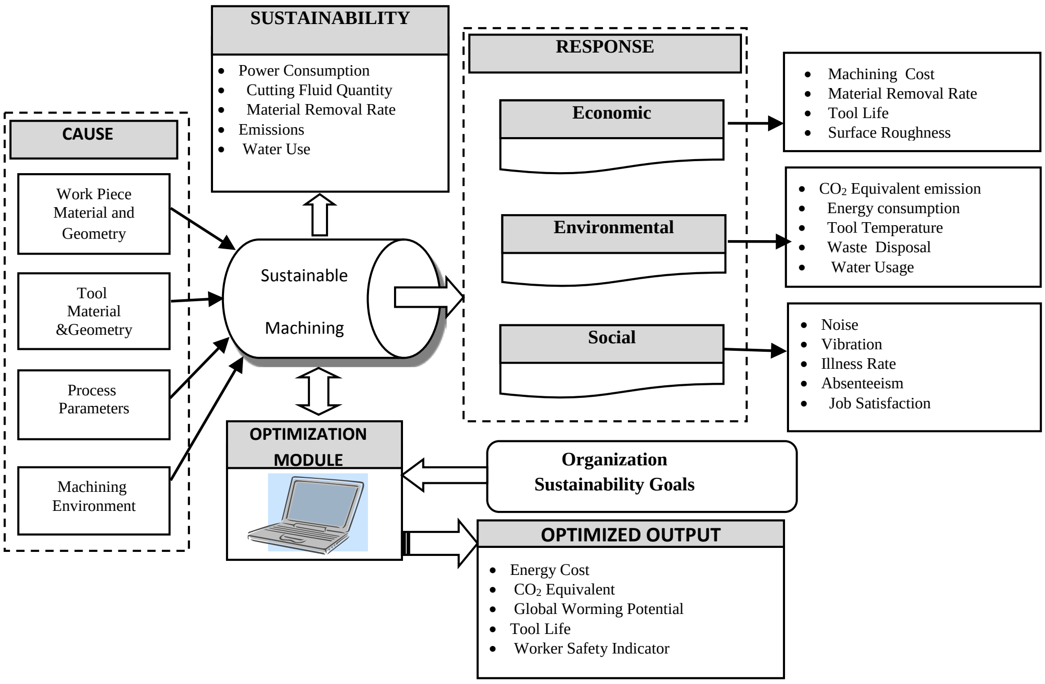

Fig. 2. Sustainability assessment model

Indian Machining industry scenario is slightly different from other developed countries. Because of profound availability of skilled manpower, conventional machining is still being used by large organizations. Majority of workers found in such small scale industry do not have proper training and hence it is very difficult to help them understand the concepts of mathematical model and outcomes. While most methods are being developed and applied for CNC machining, sustainability assessment of a conventional machining process at small scale industry is hardly sufficient attention. Thus there is a need of developing a simple model, which could be easy to understand and could be easily incorporated for small scale industries working on conventional machining (Smith et al., 2012).

Process parameter and cutting environment plays important role in end result of a machining process. Dahmus and Gutowski (2004) presented a system-level environmental analysis of machining process. They considered the environmental impact due to machining process and associated material preparation process and suggested that further focus in this area is needed. An economic and environmental impact aspect of machining highly depends on these parameters. Muthukrishnan and Davim(2009) studied the effect of machining parameters on surface roughness of Al-SiC using coarse grade Polycrystalline diamond (PCD) inserts. Artificial Neural Network (ANN) and Analysis of Variance (ANOVA) were used to validate the results. Rajemi et al. (2010) developed a model for optimizing energy footprint of machined product. They identified critical parameters in minimizing energy use and hence reducing energy cost and environmental impact. Table 1 shows the typical indicators used by various researchers for sustainability assessment purpose. The sustainability issues presented in this paper emphasises on economic and environmental aspect of machining process based on energy use, material removal rate, and surface finish of product manufactured. Here attempt has been made to avoid complexity in the model, which would allow any person working in the conventional machining industry to understand the process impacts easily.

Table 1

Typical Indicators used by various researchers for sustainability analysis

Economic Indicators	Environmental Indicators	Social Indicators
• Energy Cost	• Air quality	• Customer Satisfaction
• Investment	• Carbon Footprint	• Employee Health
• Labour Cost	• Chip mass	• Employment creation
• Machining cost	• Coolant usage	• Employee Safety
• Material consumption cost	• Coolant Mist Produced	• Health related absenteeism rate
• Machining time	• CO_2Emissions	• Human energy
• Productivity	• CO_2Equivalant	• Injury Rate
• Product quality	• Energy Use	• Job satisfaction
• Production quantity	• GHG Emissions	• Labour Turnover
• Profit	• Global warming potential	• Mist / dust level
• Rate of Return	• Heat generation	• Skill Improvement
• Surface roughness	• Land pollution	
• Tool wear	• Natural resource depletion	
• Tool life	• Noise level	
	• Tool Temperature	
	• Water quality	
	• Water Usage	

3. Selection of study parameters

There are literally a large number of variables involved in the sustainability analysis of a machining process and the model is targeted for the small scale industries. Therefore, it is necessary to reduce the number of input/output parameters to avoid complexity. The literature review suggested that major influencing parameters in a machining process are work piece material, cutting environment (Dry / Wet / MQL), Type of Tool, and the process parameters i.e. cutting speed, feed & depth of cut. But all the mentioned factors are hardly considered together for the study. In this paper three important output parameters; namely surface roughness, material removal rate and power consumption are considered. The system boundary for this study is depicted in Fig. 3.

4. Material and Method

4.1 Experimental Conditions

Three machines in different industries were selected to accomplish the experimentation work and gathering the necessary data. Workers having different skill sets and educational levels were chosen for absorbing the variation in the process modeling. Experimentation was performed on three conventional medium duty lathe machines with varying capacity and motor power. AISI 1040 carbon steel commonly known as EN-8 was selected for the case study because of its wide engineering applications. Three types of tools namely Brazed ceramic tool, Insert with Titanium Nitride (TiN) Coating and Insert with Titanium Aluminum Nitride (TiAlN) coating, which are most commonly used in machining industry were selected for study purpose. The details are listed in Table 2. The geometry of the component was kept constant throughout experimentation

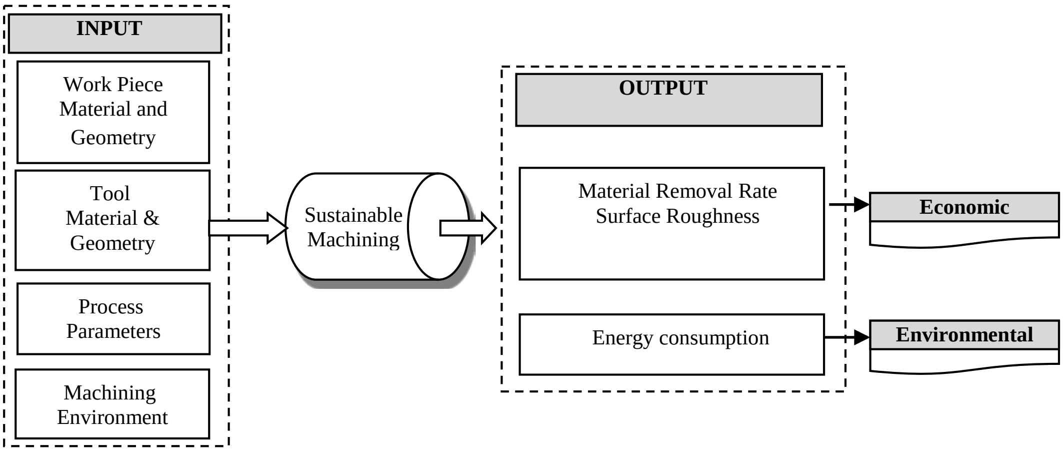

Fig. 3. System boundary for study

Experimental design is widely used in many engineering applications. In factorial design, as the number of input parameters increases, the experiment to be conducted rapidly increases. L27 orthogonal array is a systematic and effective method, which provides better results with reduced number of experiments when all factors are considered at three levels. To compensate for the measurement errors, each experiment is being replicated three times and average value of variable is considered for experimentation and analysis. Table 2 shows details of the machine, cutting tool, tool holder and cutting fluid used during the experimentation. The input parameters were varied at three levels. The variable values at various levels used during experimentation are listed in table 3. The experiments were carried out in accordance with 3 level L27 orthogonal array using design of experiment technique. Table 4 shows the material composition of AISI 1040 used for the study

Table 2
Details of the machine, tool , tool holder and cutting fluid

SN	Particular	1	2	3
1	Lathe Motor Power	1.5 HP	2.0 HP	3.0 HP
2	Cutting Tool Insert	CNMG 120412 TF (AlTiN coated) CNMG 120412 MP (TiN coated)		
3	Tool Holder	PCLNR/L 1616H 12-M SANDVIK		
4	Cutting fluid	Servocut-S (Manufactured by Indian Oil)		
5	Cutting Fluid flow rate (Wet)	5 % cutting fluid mixed with water and flow rate of 15 lit /hr.		
6	Compressor Air Pressure (MQL)	Air at 4 bar & 5% cutting fluid mixed with water & cutting fluid flow rate of 90 ml/ hr.		

Table 3
Machining parameters

SN	Parameter	Level 1	Level 2	Level 3
1	Cutting Speed (m/min)	21.93	33.73	50.55
2	Feed (mm/rev)	0.1658	0.1855	0.2107
3	Depth of Cut (mm)	0.5	0.75	1.0
4	Environment	Dry	MQL	Wet
5	Tool	Brazed tip	TiN coated Insert	TiAlN coated Insert

Table 4
Material Composition of AISI 1040 (EN-8)

C %	Si %	Mn %	S %	P %	Cr %	Mo %	Ni %
0.36 - 0.44	0.10 - 0.40	0.60 - 1.00	0.05 max	0.05max	-	-	-

4.2 Experimental procedure and measurements

The work piece geometry as shown in Fig.4 was provided to the worker. All the machines selected were having four spindle speeds available to use. The most suited and used speeds were selected for the experimentation. The depth of cut was selected as 0.5 mm, 0.75 mm and 1 mm. The worker was allowed to choose feed by their experience. They were asked to vary the feed as slow, medium and fast. Since the experimentation was carried out as a manual operation there was variation in the feed hence we decided to perform three replicates of each experiment and take average value to minimize the measurement errors. The orthogonal array L 27 was followed for the experimentations. The experimentations were carried out in three shifts i.e. Morning, afternoon and evening.

The raw work piece material of 30 mm diameter was cut into pieces of 43 mm length. All the pieces were weighed with the help of weighing scale and the dimensions were measured using digital Vernier caliper. This was necessary to find the amount of material removed during the machining accurately as it could be difficult to collect and measure the weight of the chips produced during operation. Each raw work piece was coded to facilitate the after analysis of finished product. To determine the spindle speed noncontact tachometer was used. To maintain constant flow rate of the cutting fluid coolant pump was set to deliver flow rate of 15 lit / hour. The flow rate was selected based on worker experience and was maintained constant throughout experimentation. To deliver air and cutting fluid mixture during minimal quantity lubrication condition spray gun and the compressor was used with a coolant flow rate of 90 ml /hr at 4 bar air pressure. The variation in current during operation and idle running was measured using the clamp meter and Power required was calculated using Eq. (1), where cosΦ represents power factor value. Lathe motor being inductive load, in this study it is considered as 0.7 (Bureau of Indian Standard IS:7752, 2007). The power consumed by the coolant pump during wet machining was also measured in the same way. The Power required by the compressor was measured for the amount of time the compressor was switched on for compressing the air. It was observed that the total cycle time of charging and discharging was approximately 34 minutes. Out of that the compressor was using the electricity for 5 minutes to get the required air pressure. Once the pressure was reached to 6 bar the power supply was cut off. The amount of electricity used during this cycle was distributed over the machining time of the work piece and added in total power consumption.

$$P = \sqrt{3}V_L \times I_L \times \cos \emptyset \qquad (1)$$

The surface roughness of the machined component was measured using Handy-surf E35-B surface roughness tester shown in Fig. 5 with a cut-off length of 0.8 mm and sampling length 5 mm. Average surface roughness(Ra) was calculated by taking average of three readings obtained at three different points of machined surface. After machining was over the finished component was measured for dimensional accuracy and weighed to determine the amount of material removed. The tolerance for dimensional accuracy was maintained at ± 0.05 mm. It could have been difficult to measure timings accurately during the process hence we decided to take video shooting of all experiments for later analysis.

4.3 Data Analysis

The experimentations were conducted on three machines to compensate for variation in data. Data was collected for 27 experiments with three replications on each machine. We recorded 243 data samples in all. For analysis purpose the similar experimental conditions on all machines were grouped and average value of input / output variable was used for the analysis. The data was analyzed using Minitab 16 software. This software provides excellent tools for statistical analysis of the data. MS-Excel was also used for calculation and plotting. Fig 6 depicts the finished components obtained from the experimentation.

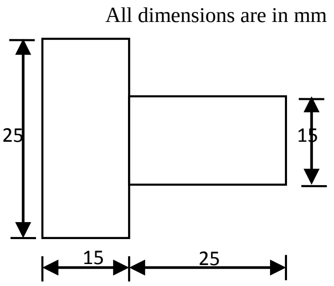

Fig. 4. Work piece geometry

Fig.5. Handy surf E35 B

Fig. 6. Manufactured Work piece (Dambhare et al., 2014)

5. Results and Discussion

5.1 Taguchi analysis

Most analysis presented in literature review section used Taguchi technique to find the value of response variable. Taguchi methodology provides results using fewer experimental runs than other techniques. A small number of experiments can be used to develop a model although a bigger number of experiments will provide more accurate results (Lakshminarayanan & Balasubramanian, 2009). The results obtained may be not optimal, but when these results are implemented, process is improved (Carmita Camposeco-Negrete, 2013). The purpose of this study was to investigate factors influencing sustainability issues in machining industries. The Taguchi analysis was performed using Minitab 16 software to understand the influencing parameters on responses.

Table 5
Response Table for Signal to Noise Ratios for Surface Roughness (Smaller is better)

Level	Environment	Tool type	Cutting speed	Feed	Depth of cut
1	-14.08	-15.56	-13.48	-12.82	-12.61
2	-11.29	-11.03	-12.86	-12.12	-12.40
3	-12.57	-11.33	-11.59	-12.99	-12.93
Delta	2.79	4.53	1.88	0.87	0.53
Rank	2	1	3	4	5

Table 6
Response Table for Signal to Noise Ratios for Material Removal Rate (Larger is better)

Level	Environment	Tool type	Cutting speed	Feed	Depth of cut
1	30.61	29.93	30.21	30.04	29.84
2	30.46	31.52	30.24	30.84	31.33
3	31.67	31.29	32.29	31.86	31.57
Delta	1.20	1.59	2.08	1.82	1.73
Rank	5	4	1	2	3

Table 7
Response Table for Signal to Noise Ratios for Power required for machining (Smaller is better)

Level	Environment	Tool type	Cutting speed	Feed	Depth of cut
1	35.54	28.78	28.95	29.27	28.93
2	24.81	30.25	29.60	29.52	30.31
3	28.89	30.22	30.69	30.45	30.00
Delta	10.73	1.47	1.74	1.18	1.38
Rank	1	3	2	5	4

Table 5 shows the results for signal to noise ratio of surface roughness (Ra) verses the input parameters. Smaller is better criteria was selected for analysis. The ranking depict that tool type, machining environment and cutting speed are ranked 1, 2 & 3 as influencing parameters on surface finish. Table 6 suggests that material removal rate (MRR) depends on cutting speed, feed and depth of cut while tool type and machining environment also contributes to certain extent. Table 7 shows the signal to noise ratio for power required for machining (P). Cutting environment is significant parameter for power consumption compared to rest as during wet conditions the pump power and during MQL condition the compressor power is added while calculating total power. The S/N ratio shows close relationship of the Input parameters on the responses.

5.2 Response Surface Method

In this study all the variables are quantifiable hence we decided to use response surface methodology which is a statistical technique to analyze a number of independent variables influencing the response (Muthukrishnan & Davim, 2009). Response Surface Methodology (RSM) is a set of techniques used in the empirical study of relationships between one or more responses and a group of variables (Cornell, 1990). In RSM second order polynomial equation used to represent response Y is given as Eq. (2),

$$Y = b_0 + \sum b_i x_i + \sum b_{ii} x_i^2 + \sum b_{ij} x_i x_j + e_r \tag{2}$$

Here, the polynomial is being developed for five influencing variables on responses Ra, MRR and P.

5.2.1 RSM model for surface roughness Ra

Table 7 shows the ANOVA results of the model. The data was provided in coded form for input variables. The ‘p – value’ in the last column represents the influence of the terms. For 95% confidence level the p-value less than 0.05 we reject the null hypothesis that parameter does not affect the response in other words it indicates significant influence of the parameter. Lower p value of the regression model shows that the model is significant. It can be inferred from table 8 that machining Environment and Type of tool influences the surface roughness while feed contributes to certain extent. Eq. 3 represents the RSM model for surface roughness (Ra). The values R^2 = 93.63 % and R^2(adj) = 82 % obtained for model indicates high significance of the model.

$$\text{Surface Roughness (Ra)} = 24.2191 - 7.7294Env - 7.8198Tt + 1.1085V_c - 3.4217f - 1.7592a + 1.2396Env^2 + 1.4083Tt^2 - 0.5085 \times V_c^2 + 0.4096f^2 + 0.2773a^2 + 0.4118(Env \times Tt) + 0.4262(Env \times f) + 0.0760(Env \times a) + 0.0525(TT \times f) - 0.0052(Tt \times a) + 0.1317(V_c \times f) + 0.2659(f \times a) \tag{3}$$

Table 8

Analysis of Variance results for Surface Roughness Ra (Significant terms Only)

Source	DF	Seq SS	Adj SS	Adj MS	F	p
Regression	17	69.5398	69.5398	4.0906	7.78	0.002
Linear	5	41.0942	29.5827	5.9165	11.26	0.001
Env	1	4.2018	10.4528	10.452	19.89	0.002
Tt	1	28.9701	12.0953	12.095	23.02	0.001
Square	5	22.6427	23.1037	4.6207	8.79	0.003
Env × Env	1	9.2192	9.2192	9.2192	17.55	0.002
Tt × Tt	1	11.8994	11.8994	11.899	22.65	0.001
f×a	1	0.4241	0.4241	0.4241	0.81	0.392
Residual Error	9	4.7291	4.7291	0.5255		
Total	26	74.2689				
Std. Deviation		0.72488		R-Sq =		93.63%
Press		50.0944		R-Sq(adj) =		81.60%

Fig. 7 validates the model developed for surface roughness (Ra). Correlation factor between experimental and calculated value was found to be 0.9676 which indicates model holds good for predicting the Ra value.

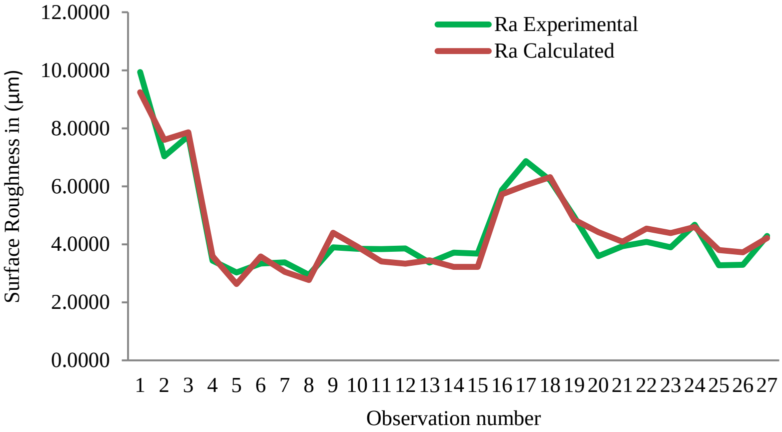

Fig. 7. Validation of Model for Surface Roughness

5.2.2 RSM model for material removal rate (MRR)

Table 9 shows ANOVA results for MRR model. The p-value for almost all input parameters except cutting environment is less than 0.05 which indicates that the terms Tool Type, and Process parameters speed, feed and depth of cut have strong influence on the MRR . The model is also significant as per the results shown. The values of R^2 = 97.22 % and R^2(adj) = 92 % demonstrate close significance of the model. Eq. 4 represents the model obtained for MRR using RSM.

Table 9

Analysis of Variance results for Material Removal Rate (MRR) (Significant terms Only)

Source	DF	Seq SS	Adj SS	Adj MS	F	p
Regression	17	1463.0	1463.0	86.061	18.52	0.000
Linear	5	949.74	439.28	87.856	18.90	0.000
Tt	1	103.84	236.54	236.54	50.90	0.000
Vc	1	343.26	232.33	232.33	49.99	0.000
f	1	241.34	36.65	36.645	7.89	0.020
a	1	198.85	71.74	71.737	15.44	0.003
Square	5	309.86	386.88	77.377	16.65	0.000
Env × Env	1	52.35	52.35	52.347	11.26	0.008
Tt × Tt	1	75.27	75.27	75.269	16.20	0.003
Vc × Vc	1	141.60	218.63	218.62	47.04	0.000
a×a	1	38.56	38.56	38.560	8.30	0.018
Interaction	7	203.44	203.44	29.063	6.25	0.007
Env×Tt	1	54.81	93.99	93.991	20.22	0.001
Env×f	1	2.42	30.92	30.916	6.65	0.030
Env×a	1	11.87	40.97	40.969	8.82	0.016
Tt×a	1	1.76	47.44	47.442	10.21	0.011
Vc×f	1	70.79	70.79	70.795	15.23	0.004
f×a	1	39.78	39.78	39.784	8.56	0.017
Residual Error	9	41.83	41.83	4.647		
Total	26	1504.8				
Std. Deviation		2.15579		R-Sq =		97.22%
Press		359.963		R-Sq(adj) =		91.97%

$$MRR = 18.4114 + 3.1327Env + 34.5809Tt - 45.8682V_c - 16.0796f + 20.8425a + 2.9537Env^2 - 3.5419Tt^2 + 10.4553V_c^2 + 0.5890f^2 - 2.5351a^2 - 5.5973(Env\times Tt) + 2.0722(Env\times f) - 3.0173(Env\times) - 0.1615(Tt\times f) - 3.2469(Tt\times a) + 4.2070(V_c\times f) + 2.5750(f\times a) \quad (4)$$

Fig. 8 justifies the trueness of the model with correlation coefficient of 0.9860. The experimental and calculated values are closely matching which proves soundness of the model.

5.2.3 RSM model for power required during machining (P)

Table 10 indicates the ANOVA results for power required during machining. Small p-value for the regression suggest model is significant. Power required for machining by large depends on machining environment, tool type and cutting speed while feed and depth of cut has no significance. Eq. 5

represents the RSM model for power required during machining. The values of R^2 = 98.05% and R^2(adj) = 94.36 % reveal significance of the model.

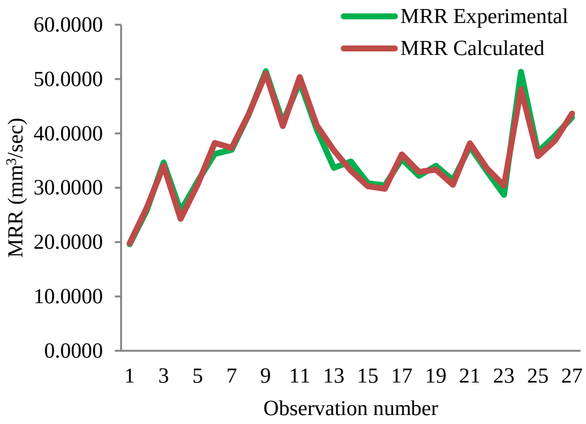

Fig. 8. Validation of Model for MRR

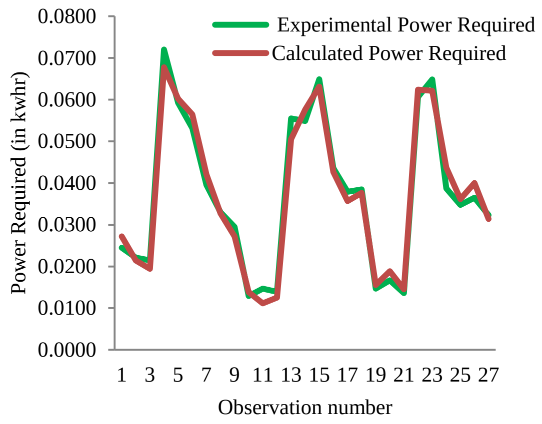

Fig. 9. Validation of Model for Power Required for Machining (P**)**

Table 10
Analysis of Variance results for Power Required (P) (Significant terms Only)

Source	DF	Seq SS	Adj SS	Adj MS	F	p
Regression	17	0.008437	0.008437	0.000496	26.60	0.000
Linear	5	0.002049	0.005179	0.001036	55.52	0.000
Env	1	0.001625	0.003381	0.003381	181.24	0.000
Tt	1	0.000050	0.000098	0.000098	5.27	0.047
Vc	1	0.000085	0.000122	0.000122	6.56	0.031
a	1	0.000137	0.000066	0.000066	3.54	0.093
Square	5	0.006110	0.006170	0.001234	66.15	0.000
Env × Env	1	0.005971	0.005971	0.005971	320.09	0.000
Vc × Vc	1	0.000036	0.000096	0.000096	5.16	0.049
Residual Error	9	0.000168	0.000168	0.000019		
Total	26	0.008605				
Std. Deviation		2.15579		R-Sq = 97.22 %		
Press		359.963		R-Sq(adj) = 91.97 %		

$$P = -0.071746 + 0.130744Env - 0.022287Tt + 0.033281Vc + 0.010216f - 0.020002a - 0.31457\,Env^2 + 0.000806\,Tt^2 - 0.006936Vc^2 - 0.000858f^2 + 0.003954a^2 + 0.004491(Env\times Tt) - 0.002110(Env\times f) + 0.000092(Env\times a) + 0.002302(Tt\times f) + 0.001798(Tt\times a) - 0.003856(Vc\times f) - 0.001179(f\times a) \quad (5)$$

Fig.9 reveals the close relationship between experimental and calculated values with correlation factor of 0.9901.

5.2.4 Response optimization for sustainability

The objective was to optimize the influencing parameters to improve sustainability of a machining process. The goal was set to keep power consumption to minimum, surface roughness to minimum and to maximize material removal rate. Relative importance was provided accordingly as shown in Table 11.

Table 11
Parameter conditions for Optimization

	Goal	Lower	Target	Upper	Weight	Importance
Ra	Min	2.9500	2.9500	6.4500	1	2
MRR	Max	35.5000	51.4500	51.450	1	3
P	Min	0.0129	0.0129	0.0424	1	1

Table 12
Global Solution

Parameter	Opt. Value
Environment	1
Tool type	2.57576
Cutting Speed	3
Feed	3
Depth of cut	1.67016

Table 13
Predicted Responses

Parameter	Output	Desirability
Ra	2.7623	1.000000
MRR	53.6737	1.000000
P	0.0040	1.000000

Table 12 shows the global solution obtained by performing the RSM optimization using Minitab 16. Dry environment with TiAlN coated tool, cutting speed = 50.55 m/min, feed=0.2107 mm/rev and depth of cut =1 are the optimized values for given conditions. The values in fraction are rounded off to next higher level. Table 13 shows the predicted values of the responses for the optimized solution.

6. Conclusion

Conventional machining was selected for the study purpose. Sustainability issues related to Economic and Environmental aspect in the form of surface roughness, material removal rate and power consumption were studied. Experiments were conducted with varying conditions for speed feed, depth of cut, machining environment and cutting tool type. Taguchi analysis was performed to understand the ranking of factors affecting the response. The process was modelled using Response surface methodology (RSM). ANOVA results were obtained to understand the significance of the model developed.

Study has revealed that surface roughness by large is influenced by cutting environment and tool used. Material removal rate is influenced by tool type, cutting velocity, feed and depth of cut while power required for machining depends on cutting environment, tool type cutting velocity and depth of cut. The experimental and the results obtained from model are closely related. The results found are in line with the previous studies by various researchers.

The results were optimized from sustainability point of view providing importance to power consumption and to keep it to minimum. The outcome of the model facilitate for setting machining parameters to accomplish the objective. Future work will cover more critical analysis of input parameters from overall sustainability point of view and to assess sustainability of conventional turning process.

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References

Aurich, J. C., Linke, B., Hauschild, M., Carrella, M., & Kirsch, B. (2013). Sustainability of abrasive processes. *CIRP Annals-Manufacturing Technology*,*62*(2), 653-672.

Avram, O., Stroud, I., & Xirouchakis, P. (2011). A multi-criteria decision method for sustainability assessment of the use phase of machine tool systems. *The International Journal of Advanced Manufacturing Technology*, *53*(5-8), 811-828.

Bureau of Indian Standards. (2007), Indian standard guide for improvement of power factor in consumers' installation part I low and medium supply voltages, retrived from https://law.resource.org/pub/in/bis/S05/is.7752.1.1975.html

Branker, K., Jeswiet, J., & Kim, I. Y. (2011). Greenhouse gases emitted in manufacturing a product—a new economic model. *CIRP Annals-Manufacturing Technology*, *60*(1), 53-56.

Camposeco-Negrete, C. (2013). Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA. *Journal of Cleaner Production*, *53*, 195-203.

CPCB. (2010), Evaluation of Central Pollution Control Board, Report submitted to Ministry of Environment and Forest Government of India, by Indian Institute of Management, Lucknow February 2010.

Dahmus, J. B. and Gutowski, T. G. (2004). An environmental analysis of machining, *Proceedings of IMECE2004*, November 13-19, 2004, Anaheim, California USA, 01 -10.

Dambhare, S.G., Deshmukh, S.J., Digalwar, A.K., Borade, A.B. and Phate, M.R. (2014) Sustainability issues in turning process: A study in Indian machining Industry, *Procedia CIRP*, 12th GCSM held at Johor Bahru, Malaysia during 22-24 Sept 2014.

Jawahir, I. S., Wanigarathne, P. C., & Wang, X. (2006). Product design and manufacturing processes for sustainability. *Chapter 12 Mechanical Engineers' Handbook*, 414-443.

Jiang, Z., Zhang, H., & Sutherland, J. W. (2012). Development of an environmental performance assessment method for manufacturing process plans. *The International Journal of Advanced Manufacturing Technology*, *58*(5-8), 783-790.

Jiang, Z., Zhang, H., Yan, W., Zhou, M., & Li, G. (2012). A method for evaluating environmental performance of machining systems. *International Journal of Computer Integrated Manufacturing*, *25*(6), 488-495.

Kopac, J., & Pusavec, F. Concepts of sustainable machining processes. In*Proceedings of the 13th international research/expert conference 'Trends in the Development of Machinery and Associated Technology'TMT 2009*.

Lakshminarayanan, A.K. and Balasubramanian, V. (2009). Comparison of RSM with ANN in predicting tensile strength of friction stir welded AA7039 aluminium alloy joints, *Transactions of Met. Soc. China*, 19, 9 – 18.

Li, W., Winter, M., Kara, S., & Herrmann, C. (2012). Eco-efficiency of manufacturing processes: A grinding case. *CIRP Annals-Manufacturing Technology*, *61*(1), 59-62.

Munoz, A. A., & Sheng, P. (1995). An analytical approach for determining the environmental impact of machining processes. *Journal of Materials Processing Technology*, *53*(3), 736-758.

Muthukrishnan, N., & Davim, J. P. (2009). Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis. *Journal of materials processing technology*, *209*(1), 225-232.

Narita, H., Kawamura, H., Norihisa, T., Chen, L. Y., Fujimoto, H., & Hasebe, T. (2006). Development of prediction system for environmental burden for machine tool operation. *JSME International Journal Series C*, *49*(4), 1188-1195.

Rajemi, M. F., Mativenga, P. T., & Aramcharoen, A. (2010). Sustainable machining: selection of optimum turning conditions based on minimum energy considerations. *Journal of Cleaner Production*, *18*(10), 1059-1065.

Shao, G., Kibira, D., & Lyons, K. (2010, January). A virtual machining model for sustainability analysis. In *ASME 2010 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. 875-883). American Society of Mechanical Engineers.

Smith, L., & Ball, P. (2012). Steps towards sustainable manufacturing through modelling material, energy and waste flows. *International Journal of Production Economics*, *140*(1), 227-238.

Tan, X. C., Wang, Y. Y., Gu, B. H., Mu, Z. K., & Yang, C. (2011). Improved methods for production manufacturing processes in environmentally benign manufacturing. *Energies*, *4*(9), 1391-1409.

Reich-Weiser, C., Vijayaraghavan, A., & Dornfeld, D. A. (2008, January). Metrics for sustainable manufacturing. In *ASME 2008 International Manufacturing Science and Engineering Conference collocated with the 3rd JSME/ASME International Conference on Materials and Processing* (pp. 327-335). American Society of Mechanical Engineers.

Yuan, C., Zhai, Q., & Dornfeld, D. (2012). A three dimensional system approach for environmentally sustainable manufacturing. *CIRP Annals-Manufacturing Technology*, *61*(1), 39-42.