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RESEARCH PAPER

Prediction of Surface Roughness Using a Novel Approach

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ABSTRACT
Surface quality is a technical prerequisite in the field of manufacturing industries and can be treated as a quality index for machined parts. Attainment of appropriate surface finish plays a key role during functional performance of machined part. The machining parameters typically influence it. Consequently, a highly focused task is to enumerate the good relation between surface roughness (Ra) and machining parameters. In the current work, response surface methodology (RSM) based regression models and flower pollination algorithm (FPA) based sparse data model were developed to predict the minimum value of surface roughness. The model is developed for hard turning of AISI 4340 steel (35 HRC) using a single nanolayer of TiSiN-TiAlN PVD-coated cutting insert. The results obtained from this approach had good harmony with experimental results, as the standard deviation of the estimated values was simply 0.0804 (for whole) and 0.0289 (for below 1 μm Ra). Compared with RSM models, the proposed FPA based model showed a minuscule percentage of mean absolute error. The model obtained asubstantial correlation coefficient value of 99.75% among the other model's values. The behavior of machining parameters and its interaction against surface roughness in the developed models were discussed with Pareto chart. It was observed that the feed rate was highly significant parameter in swaying machining surface roughness. In inference, the FPA sparse data model is better than the RSM-based regression models for prognosis of surface roughness in hard turning of AISI 4340 steel (35 HRC). The model developed using FPA based sparse data for surface roughness during hard turning operation in the current work is not reported to the best of author's knowledge. This model disclosed a more dependable estimation over the multiple regression models.

KEYWORDS: *Hard turning; Surface roughness; Regression; Flower pollination algorithm.*

1. Introduction

Hardening of steels frequently associates with medium and high carbon steels that undergo heat treatment and quenching processes to increase the hardness. Hardened steels have good wear, corrosion resistance and can also resist high pressure and shock. Components made form hardened steel are applied in various areas includes automobile, aerospace, transportation and energy. AISI 4340 is medium carbon steel with high strength used in various applications such as aircraft landing gear, power transmission gears and shafts, heavy duty shafts, spindles, pins, chucks, axles, etc. Machining of hardened steels has become cost-effective and prevalently used in manufacturing various components as stated above due to its advantages over the grinding process. For instance, provision of shorter lead times, eco-friendly nature and around 60% of reduction in machining time etc. made this popular[1-3]. Though it offers high accurate machine components, there certain obstacles such as tooling cost, unwanted residual stresses and formation of dark and white layer which further affects the surface quality of hardened

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components. Surface quality of a hard-turned component is the most common substantial outcome as it is the key factor to influence the machined part operational properties. Surface roughness is get affected by corrosion, wear, creep and fatigue resistance of machined part. As a result, customizing machined surface roughness is highly required to attain a high level of precision for various industrial applications[4-5]. Many researchers have used different soft computing techniques in hard turning to predict reliable surface roughness in advance. A number of soft computing techniques applied in the hard machining domain were reviewed in [6]. The paper focused on certain major techniques such as genetic algorithms, simulated annealing, ant colony optimization, fuzzy sets, artificial neural networks (ANN), particle swarm optimization (PSO) in related with four machining operations. The authors concluded that the future works must focus on the efficient and cost effective way of data acquisition. A rigorous review is done on applications of statistical methods to develop predictive models for surface roughness by Mital and Mehta[7] and concluded that the surface finish was strongly affected by the cutting speed, feed, and tool nose radius. Agrawal et al. [8]used a soft computing technique random forest regression for modeling of surface roughness which was not employed by any researcher earlier. Using CBN cutting insert, they developed three regression models to predict surface roughness when hard turn AISI 4340 (69 HRC). They conclude that the random forest regression model was more effective than the other two multiple and quantile regression models. Recently, Asutosh Panda et al. [9] developed surface roughness model using RSM for AISI 4340(49 HRC) steel. Further, desirability function was used to optimizing the process parameters to minimize the surface roughness. Suresh et al. [10]conducted hard turning experiments on AISI 4340 using coated carbide tool to optimize and develop prediction models for machinability issues. RSM based second order multiple regression models were developed for the response. Adequacy of these models was checked by analysis of variance (ANOVA) and observed a good correlation between experimental and predicted values. Nilrudra Mandal et al. [11] investigated surface quality of AISI 4340 steel using yttria stabilized zirconia toughened alumina (ZTA) cutting inserts at high speeds. A satisfactory multiple regression models for surface finish was developed using response surface methodology (RSM). Muhammad Azam et al. [12] also used RSM to develop the surface roughness model when machining AISI 4340 (31 HRC) hardened steel and found the average prediction error as 3.38%. Ashok KumarSahoo et al. [13] conducted experimental investigations using different types of cutting tools to study the machinability issues of AISI 4340 hardened steel. Later onfirst and second order multiple regression models for the machinability issues were developed. Apart from these previous works, most of the authors were also developed the prediction models using RSM for AISI 4340 steel [13-20]. Some other works have been reported on modeling developed using soft computing techniques such as ANN [21 & 22]. By studying the previous works on modeling surface roughness for AISI 4340 steel, it can be concluded that the majority of the works used multiple regression models using RSM to predict surface roughness. A few works were reported on predictive modeling using soft computing techniques. There is a necessity to apply the various soft computing techniques in the hard machining domain. It is diverse from conventional machining due to certain intricacies that lead to imprecision in outcome. Soft computing techniques can handle such a hostile environment of imprecision and uncertainty in hard machining effectively in performance prediction and optimization.

Tab. 1. Literature review of modeling studies on hard turning

Work material	Tool material	Modeling tools	Variables studied
AISI 4340[8]	CBN	Regression modeling, Random forest regression, Quantile regression	Cutting speed, feed and depth of cut
AISI 1060[9]	TiCN coated carbide insert	RSM based regression, Fuzzy and Simulated annealing (SA)	Cutting speed, feed and work material hardness
AISI 4340[16]	CVD multilayer (TiN/TiCN/Al_2O_3/TiN) coated carbide insert	Multiple regression	Cutting speed, feed and depth of cut
AISI 4340[22]	PVD coated insert	Linear regression , ANN	Cutting speed, feed
AISI 4340[23]	TiSiN-TiAlN	RSM based regression	Cutting speed, feed

	nanolaminated CVD coated tool		and depth of cut
AISI H13[24]	Mixed ceramic insert	RSM, ANN	Cutting speed, feed , depth of cut and work material hardness
AISI 4340[25]	Titanium Nitride-coated cutting tool	RSM, Johnson transformation and Boc-Cox transformation	Cutting speed, feed , depth of cut and nose radius
AISI 1050[26]	Uncoated carbide insert	Polynomial regression	Cutting speed, feed and depth of cut
AISI 1045[27]	TiSiN-TiAlN nano-laminated CVD coated tool	RSM based regression	Cutting speed, feed and depth of cut
AISI 52100[28]	PVD coated TiSiN–TiAlN nanolaminated tool	Multiple regression, ANN	Cutting speed, feed and depth of cut
C40 steel[29]	Tungsten coated carbide tool insert	ANN	Cutting speed, feed , depth of cut and nose radius

Some of the key studies found in the literature survey relating to the modeling of hard turning are tabulated in the Table. It can be noticed from the table that none of the studies has done to model the hard turning of AISI 4340 steel using FPA technique. In disparity to the literature survey, this paper points to modeling the experimental results using three RSM-based regression models and FPA modeling, which provides higher accuracy in predicting outcome. FPA is one of the new meta-heuristic algorithms, was developed in a simple form by Yang. From the literature studies on modeling surface roughness for hardened AISI 4340 steel, researchers were not paid attention to employ the FPA for predictive modeling. The novelty aspect of the present work is to develop the predictive model using FPA and comparing the outcome with the three RSM based regression models.

2. Experimental Details

AISI 4340 steel is high strength low alloy steel hardened up to 35 HRC using heat treatment processes (hardening & tempering). The initial diameter and length of the test samples were 40 mm and 120 mm respectively. The work pieces were supported by tail stock while machining. A four level L_{16} Taguchi's OA was chosen for the experimentation. The set of machining parameters and its attribution of the levels are listed in Table 2. Once the orthogonal array was chosen, the next one was to perform the experimental trials. For this, LOKESH TL250 model CNC lathe of 11 kW spindle power, 4000 rpm spindle speed was used to perform experiments.A single nanolayer of TiSiN-TiAlN PVD-coated, graded as SECO TH 1000, TNMG 120404 cutting tool was used. An ISO designated PCLNL 2020 K12 right hand side tool holder was employed for mounting the cutting tool to carry out the experiments. Mitutoyo measured the machined surface roughness make Talysurf SJ201P, having a diamond probe of 5µm radius, a cutoff length of 0.8 mm, and a measured range of surface roughness values -200µm to +150µm. The measurement was repeated three times along the work piece and their average was considered the resulting one. The machining parameters were under the control of CNC part program. In the ensuing section, the outcome of the experimental trials is presented and discussed.

Tab. 2. Experimental outcome

Trial no.	*v* m/min	*f* mm/rev	*d* mm	Ra (µm)
1.	75	0.05	0.10	0.240
2.	75	0.10	0.15	0.926
3.	75	0.15	0.20	1.800
4.	75	0.20	0.25	3.200
5.	105	0.05	0.15	0.340
6.	105	0.10	0.10	0.800

7.	105	0.15	0.25	1.800
8.	105	0.20	0.20	2.922
9.	145	0.05	0.20	0.300
10.	145	0.10	0.25	0.940
11.	145	0.15	0.10	1.966
12.	145	0.20	0.15	3.150
13.	180	0.05	0.25	0.378
14.	180	0.10	0.20	0.800
15.	180	0.15	0.25	1.008
16.	180	0.20	0.10	3.338

3. Predictive Modeling of Surface Roughness

Modeling represents the behavior of the input parameters during machining in a scientific manner. In order to know the product's surfacequality in advance, certain predictive models are to be developed before the machining. Despite the fact there are a number of theoretical models are available which are inaccurate as it is restricted to a limited range of machining conditions. The theoretical approach does not consider imperfections that occur during machining and overlook noise and other process factors. Therefore, prediction using a theoretical approach is unreliable and inaccurate at machining zones witha high intricacy. For example, the theoretical model for surface roughness (R_a = square of feed rate/32* tool nose radius) is not able to predict accurately, because it considers only feed rate and tool nose radius. In practical aspect, surface roughness depends upon various factors such as tool vibrations, built up edge formation. In this regard, the majority of researchers resorted to the empirical models [30 &31].

3.1. RSM based regression modeling

Due to the reasons stated in the above, majority of the researchers resort to the empirical approach. Multiple regression analysis is a potential and widely used multivariate model in empirical research as it provides more reliable prediction than theoretical models. Selection of suitable mathematic models is a key factor for the success of regression analysis. In the current work, multiple regression models were developed using RSM. Non-linearity is observed in predictive models for surface roughness during machining at which complexity occurs due to tribological and thermo dynamical aspects. In these situations, RSM can easily evaluate the non-linear problems and provide a reliable prediction for chosen responses.In order to apply RSM, process parameters, experimental design and output response is required. In the present work, cutting speed (*v*), feed rate (*f*) and depth of cut (*d*) were taken as process parameters. The surface roughness (Ra) of the machined work piece was taken as output response. The relationship between input and output response in the present work can be written as [32]:

$$Y = C\, v^{p} f^{q} d^{r} \tag{1}$$

Where *p*,*q*,*r*are the constants of corresponding input parameters and Y is proposed response using quadratic (non-linear) regression model which is an appropriate for studying the effects of second order terms of input parameters and its cross product terms on surface roughness. From the literature, models developed in terms of polynomials provide most effective estimation of the experimental output. They are [32]:

a) Linear regression model
b)

$$\text{Y} = a_0 + \sum_{i\ 1}^{l} a_i\, X_i + \varepsilon_{ij} \tag{1a}$$

c) Quasi-linear regression model
d)

$$\text{Y} = a_0 + \sum_{i\ 1}^{l} a_i\, X_i + \sum_{ij}^{l} a_{ij}\, X_i X_{ji} + \varepsilon_{ij} \tag{1b}$$

e) Non-linear (quadratic) regression model

$$\text{Y} = a_0 + \sum_{i\ 1}^{l} a_i\, X_i + \sum_{ij}^{l} a_{ij}\, X_i X_{ji} + \sum_{i\ 1}^{l} a_{ii}\, {X_i}^2 + \varepsilon_{ij} \tag{1c}$$

Here a_0, a_i, a_{ij}, a_{ii} are the regression coefficients.X_i , denotes process parameters and ε_{ij} represents error of fit of regression equation. A logarithmic transformation can be employed to deal situations where a non-linear association subsists between input and output response. Hence, the non-linear form of Eq. (1) can be transformed into the following logarithmic transformation form [32]:

$$\ln(Y) = lnC + p\ lnv + q\ lnf + r\ lnd \tag{1d}$$

Tab. 3. Expt. Ra vs. Predicted Ra and error

	Expt.	Predicted Ra(µm) using developed models							
Trials No	Ra (µm)	Eq.1(e) (Linear)	Error (%)	Eq.1(f) (Quadratic)	Error (%)	Eq.1(g) (Power)	Error (%)	Eq. (FPA)	Error (%)
1.	0.24	0.253	5.416	0.159	33.541	0.219	8.399	0.26	8.333
2.	0.926	1.109	19.762	0.899	2.875	0.890	3.803	0.938	1.295
3.	1.8	1.965	9.166	1.898	5.486	1.849	2.722	1.934	7.444
4.	3.2	2.821	11.843	3.157	1.324	2.918	8.808	3.249	1.531
5.	0.34	0.156	53.882	0.372	9.433	0.315	7.130	0.324	4.705
6.	0.8	1.166	45.850	0.885	10.712	0.821	2.706	0.761	4.875
7.	1.8	1.868	3.822	1.779	1.148	1.671	7.160	1.971	9.5
8.	2.922	2.878	1.478	2.974	1.812	2.774	5.042	2.972	1.711
9.	0.3	0.054	81.933	0.450	50.016	0.342	14.106	0.352	17.333
10.	0.94	0.910	3.170	0.816	13.172	0.803	14.543	0.991	5.425
11.	1.966	2.074	5.503	1.976	0.523	1.838	6.488	1.862	5.289
12.	3.15	2.930	6.977	3.024	3.986	2.746	12.797	3.067	2.634
13.	0.378	0.045	88.043	0.387	2.632	0.333	11.724	0.393	3.968
14.	0.8	0.964	20.6	0.660	17.475	0.677	15.317	0.8	0
15.	1.008	1.820	80.634	1.180	17.108	1.133	12.443	1.033	2.480
16.	3.338	2.984	10.581	3.396	1.743	3.247	2.713	3.548	6.291
The mean error (%)			28.04		10.81		8.49		5.17

3.2. FPA based sparse data modeling

3.2.1. Structure of the FPA

The FPA is proposed by Xin She Yang [33].The algorithm mimics the natural pollination process in flowering plants. Pollination is the process by which a flowering plant produces its offspring and survives. The fertilized pollination process is treated as successful, leading to the generation of a new seed which is further responsible for the growth of a new plant. There are two types of natural pollination mechanisms known as cross and self-pollination. In self-pollination, the pollen source is the flower of the same plant or itself, while in cross pollination the pollen is obtained from another plant from farther distance. While mapping this scenario to the structure of the algorithm, these two processes are termed as local and global search strategies respectively. Typical pollination process is realized in the algorithm through several phases like initialization of population of flowers, and defining switch probability. The switch probability determines the type of search adopted. The search can be either local or global which is mentioned in terms of flower pollination terminology as biotic and abiotic pollination process respectively. After population initialization, every individual is updated in each iteration. Every individual is a potential solution which is updated in each iteration. Once the new weights are obtained the corresponding new solutions are evaluated with respect to the objective function. If the new solution is better, then update the population with these weights.

Every individual in the population is updated either with global or local pollination process as determined by the switching parameter through the eq. (1) & (2) respectively.

$$x_i^{t+1} = x_i^t + \gamma L(g_* - x_i^t) \qquad \textit{for } r > p \qquad (1)$$

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t - x_k^t) \qquad \textit{for } r < p \qquad (2)$$

Whereas the levy distribution (L) is given by

$$L = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{S^{1+\lambda}} \qquad (3)$$

Here, the i^th^ individual (pollen) in the t^th^ iteration is represented as x_i^t while the corresponding step factor is γ .

3.2.2. Implementation of FPA

The problem statement is to determine the set of these coefficients that predict surface roughness for the process parameters (v, f, d). In the search method using evolutionary computing tools, involves in generation or initialization ofthe population. Every individual is a possible solution bounded to the solution space. The dimension on of the solution space refers to the number if coefficients to be determined in the proposed mathematical model. The implementation of the FPA to the sparse data modeling problem in engineering starts with population initialization. Here, the initial population is given as

pop = $\{X_1, X_2, X_3 \ldots\ldots X_N\}$

Here, X_K refers to Kth individuals, and such 'N' individuals can be considered the size of the population. Every individual is a set of coefficients representing a potential solution. The K^{th} individuals is described as

$$X_K = [A_K, B_K, C_K, D_K, E_K, F_K, G_K, H_K, I_K, J_K, K_K]$$

Now the population matrix is given as,

pop =

$$\begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ . \\ . \\ . \\ X_N \end{bmatrix} = \begin{bmatrix} A_1 & B_1 & C_1 & D_1 & E_1 & F_1 & G_1 & H_1 & I_1 & J_1 & K_1 \\ A_2 & B_2 & C_2 & D_2 & E_2 & F_2 & G_2 & H_2 & I_2 & J_2 & K_2 \\ . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . \\ A_N & B_N & C_N & D_N & E_N & F_N & G_N & H_N & I_N & J_N & K_N \end{bmatrix}$$

The corresponding fitness vector is given as

$$c = [c_1, c_2, \ldots\ldots\ldots\ldots, c_N]$$

The final fitness is computed using this fitness value. Every member of the fitness vector computers the fitness of the individuals.

A nonlinear relationshipexits between the surface roughness and the corresponding machining process parameters. With reference to this it is possible to develop a mathematical model with the empirical data from the machining process the model typically takes the form of a multiple indeterminate polynomial. The number of variables depends on the input parameters of the experiments. The type of model considered in this work is given as

$$Ra = A*v + B*f + C*d + D*v^2 + E*f^2 + F*d^2 + G*(v*f) + H*(f*d) + I*(d*v) + J*(v*f*d) + K$$

Here *v*,*f* and*d* are speed, feed and depth of cut while the polynomial coefficient vector is

X= [A, B, C, D, E, F, G, H, I, J, K]

Hence the initial population is given as a vector of solutions represented by *pop*.

Here $I_1, I_2 \ldots I_N$ are individuals while the number of individuals is N. However, each individual is again a polynomial coefficient vector.

3.2.3. Fitness formulation

The method of calculating an individual's fitness involves evaluating its performance collectivity over the entire data. The error between the measured Ra and predicated Ra is initially calculated for all the experiments for an individual. These errors form a vector of errors concerning an individual. The fitness of this individual now evaluated by a statistical quantity like average (mean) or maximum if the errors [33]. This is demonstrated as follows:

Let the sparse data of the machining process is represented as matrix as follows,

$$\begin{bmatrix} E_1 \\ . \\ . \\ . \\ E_T \end{bmatrix} = \begin{bmatrix} v_1 & f_1 & d_1 \\ . & . & \\ . & . & \\ . & . & \\ v_T & f_T & d_T \end{bmatrix}$$

E_1, E_2... $E_T$represent T number of experiments. Each experiment is again a vector of machining parameters (*v*, *f*, *d*)

Similarly, $\{Ra_{1R}, Ra_{2R} \ldots Ra_{TR}\}$ and$SR_R' = [\ Ra_{1R}', Ra_{2R}' \ldots\ldots\ldots Ra_{TR}']$

Accordingly, the difference vector is computed and given as,

$\Delta_R = \{\Delta_{1R}, \Delta_{2R}, \Delta_{3R} .. \Delta_{TR}\}$

Here, for example, the Δ_{1R} is referred as the difference between the Ra_{1R} measured and Ra_{1R} with respect to R^{th}individual. The same is given as,

$\Delta_{1R} = Ra_{1R} – Ra'_{1R}$

As there are N individuals in the population, initially their individual fitness is calculated as follows:

$F_1 = \max(\Delta_{11}, \Delta_{12} \ldots \Delta_{1T})$
$F_2 = \max(\Delta_{21}, \Delta_{22} \ldots \Delta_{2T})$
So on $F_N = \max(\Delta_{N1}, \Delta_{N2} \ldots \Delta_{NT})$
However, the above set of fitness values of every individual is calculated by choosing the maximum error (or difference) as that individual's fitness. Similarly, the individual fitness value is calculated by taking average of all the Δ's as follows,

$$fitness: c = \frac{\sum_{i=1}^{T} \Delta_{iR}}{T}$$ Where i= 1, 2...T.

The computation process is demonstrated in Fig.1

$$\begin{bmatrix} X_1 \\ X_2 \\ | \\ | \\ X_N \end{bmatrix} \begin{matrix} \begin{bmatrix} E_1 \\ | \\ | \\ E_2 \end{bmatrix} \Rightarrow \begin{bmatrix} \Delta_{11} \\ | \\ | \\ \Delta_{1T} \end{bmatrix} \Rightarrow C_1 = \left[\frac{\sum_{R=1}^{T} \Delta_{1R}}{\mathrm{T}}\right] \\ \begin{bmatrix} E_1 \\ | \\ | \\ E_2 \end{bmatrix} \Rightarrow \begin{bmatrix} \Delta_{21} \\ | \\ | \\ \Delta_{2T} \end{bmatrix} \Rightarrow C_2 = \left[\frac{\sum_{R=1}^{T} \Delta_{2R}}{\mathrm{T}}\right] \end{matrix}$$

Fig. 1. Demonstration of fitness calculation.

However, the computation of final fitness is common to both the techniques of individual fitness evaluation and is given as,

Fitness = min (c1, c2 …cN)

In this way, the best individual is the one with minimum individual fitness in either fitness evaluation technique.

4. Results and Discussions on Experimental Results

In this section, the aforementioned (sections 2.1 & 2.2) methodologies were applied to the experimental results to predict surface roughness and discussion was carried out on the outcome. In addition to that, Pareto chart was used to find the most dominating machining parameter that affects the machined surface's surface quality.
RSM based multiple regression models were developed for surface roughness using the linear Eq. 1(a), the quadratic (second order) Eq. 1(c) and the logarithmic transformed (non-linear) Eq. 1(d) models. The models were established using Minitab-19 software and the obtained models are:

Linear regression model
Ra = -0.478-0.00064**v*+18.66**f*-1.54**d*[R-sq=92.11%; R-sq(adj)=90.13%] (1e)

Non-linear (quadratic) regression model

Ra=-1.288+0.01069**v*+6.94**f*+7.15*d-0.000000**v***v*+83.6**f***f*+15.4**d***d*-0.0220**v***f*-0.0615**v***d*-47.1**f***d*
[R-sq=99.28%; R-sq (adj)=98.21%] (1f)

Power regression model

Ra = -0.7+ 2.50**v*+ 1.48**f*+ 1.07**d* - 0.413* *v***v*+ 0.260**f***f*+ 0.083**d***d*-0.051**v***f*-0.540**v***d* - 0.844**f* **d*
[R-sq=99.04%; R-sq (adj) = 97.59%] (1g)

Further, using FPA based sparse data an effective model was developed to predict surface roughness.
FPA based sparse data model

Ra=-0.02264**v*-40.305**f*-11.889*d-0.0001**v***v*+9.4**f***f*-47.13**d***d*+0.480**v***f*+292.80**f***d*-0.264**d***v*-2.55**v***f***d*+2.16 [R-sq=99.75%; R-sq(adj) = 99.50%] - (1h)

To test the adequacy of the developed models, the coefficient of determination(R-sq) is used, envisages the strength of correlation between experimentally measured and estimated values. In the current work, the linear model (Eq.1e) can explain 92.11% of variation in surface roughness by the machining parameters. The quadratic model (Eq.1f) is an expanded model where the interaction and square terms of machining parameters are included to check their significance on the surface roughness. Further, the log transformation (Eq.1g) was used to transform the skewed data set into more normalized one. The R-sq value of quadratic model (Eq.1g) is little higher (0.24%) than the value of power model. The quadratic model is able to explain 99.28% of variation in surface roughness by the machining parameters. As far as concern the developed RSM based regression models, all the models showed good accuracy for the prediction of surface roughness. Among which, the quadratic model is relatively better when compared to the remaining two. In case of FPA based model, the obtained value of R-sq was 99.75% which is higher than the RSM-based models. It represents excellent correlation between actual and predicted values of surface roughness than the other models. A normal probability plot is an effective wayto investigate the adequacy of fit of the developed models. All the residuals in the drawn plots were very close to the straight lines indicates that the error distribution was normal. Hence the developed models were adequate. The normal plots for all the models (Fig.2) were correlated with Anderson-Darling test for surface roughness, where most of the residuals were very close to the straight line that indicates the errors are normally as well as independently distributed and postulations were not infringed, and also obviously approximates the predicted and experimental values. With P-values for all the models (0.248, 0.060, 0.086 and 0.137) attained from Anderson-Darling test was larger than significance level value (α-value of 0.05) which agree the normal distribution of data and adequacy of the models.

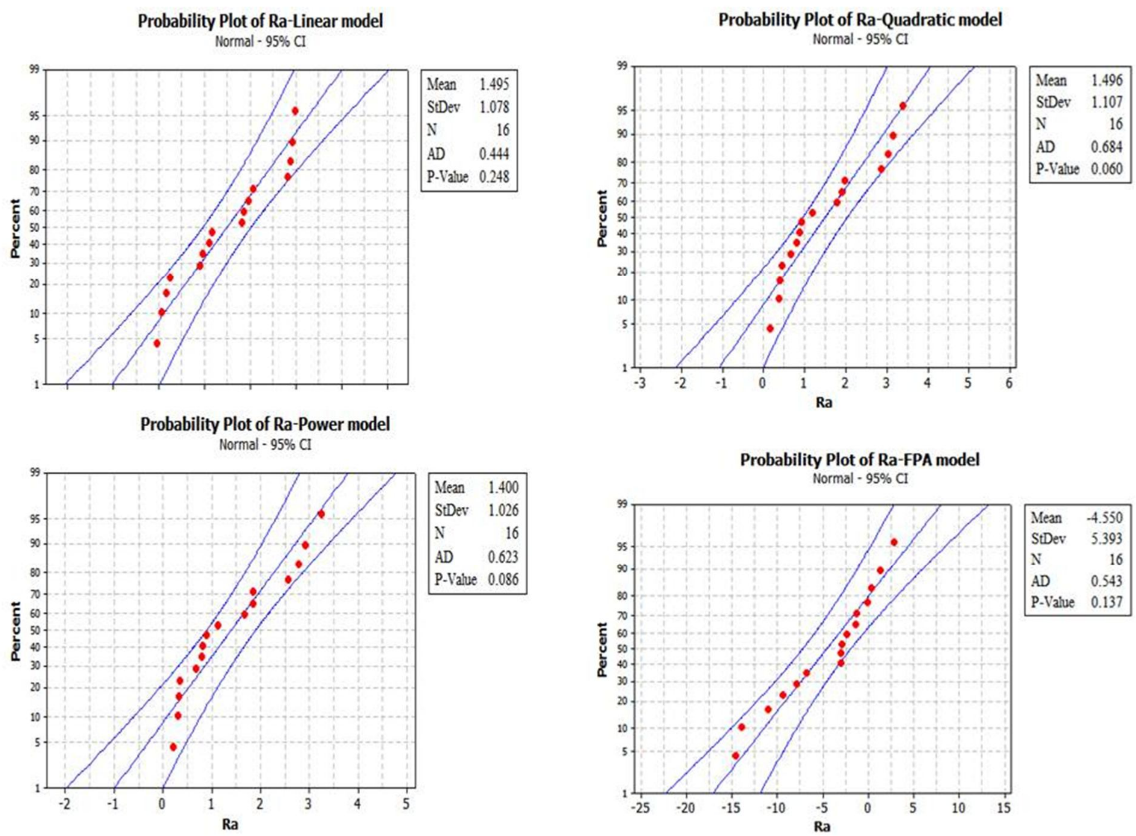


Fig. 2. Normal plots for all the models

To test the efficiency and accuracy of the developed RSM based and FPA based predictive models for the estimated average surface roughness, the percentage of mean absolute error($|\delta_i|$) could be used, which is described by equation:

$$|\delta_i| = \left|(R_{pr.} - R_{exp.})/R_{exp.}\right| * 100\% \qquad (2)$$

The predicted values of surface roughness are summarized in Table 3which is calculated by the equations (1e)-(1h). Further, experimental and predicted values of Ra are compared and plots related to this i.e experimental Ra vs. predicted Ra are shown in Fig 3. The percentage of error$|\delta_i|$ is calculated by Eq.2 and it was found to be 28.04% (linear), 10.81% (quadratic), 8.49% (power)and 5.17% (FPA) for surface roughness. Among these, FPA based model showed the least percentage of mean absolute error followed by power regression model.

This paragraph concerns with the additional check for the developed RSM and FPA based models to weigh up their relative prediction capability of surface roughness. The values of Ra which was obtained after conducting 16 experiments and the estimated values obtained from the developed models were plotted in Fig.3. From the graphical representation, all the models were potent in the prediction of surface roughness.However, when the attention is focused on more accuracy (below 1 µm), basic linear model performance was inferior to the remaining as they were considered the pairing of input parameters in their respective models. In particular, FPA model performance was relatively good. The standard deviation also confirmed the results of graphical representation. In the Table 4, the standard deviations of the differences of experimental values of Ra and the predicted values from four models were tabulated. The FPA based model shows the least standard deviation (0.0804) compared to the other models and this value also validates the model's prediction capability. When it comes to the more accurate values i.e. below 1 µm surface roughness, the FPA model shows least standard deviation. Other models (except linear model) can also reliably be applied for the prediction of Ra.

Tab. 4. Standard deviation of the developed models against to experimental

	Linear model	Quadratic model	Power model	FPA based model
Standard deviation for whole (*Expt. values* vs. *Pred.values*)	0.3053	0.0922	0.1258	0.0804
Standard deviation for below 1 µm Ra (*Expt. values* vs. *Pred.values*)	0.1908	0.0948	0.0585	0.0289

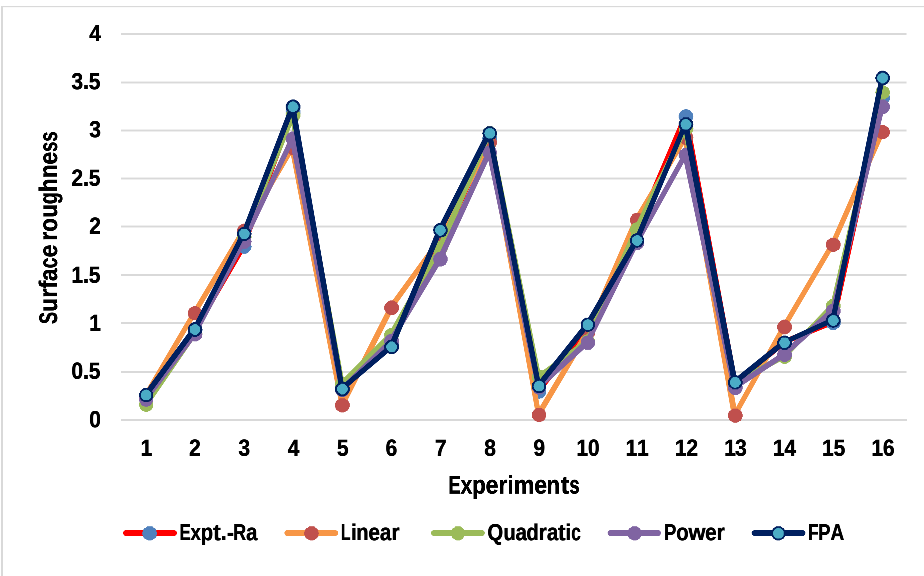
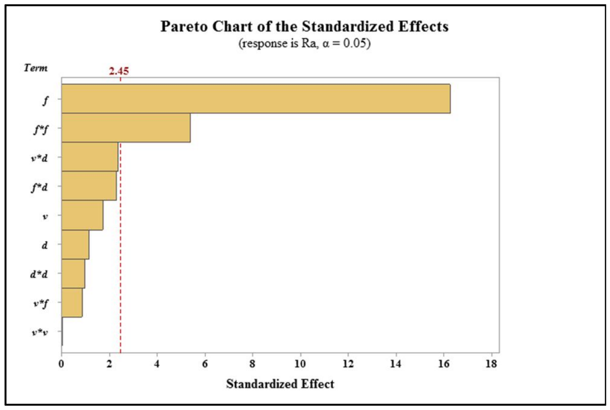


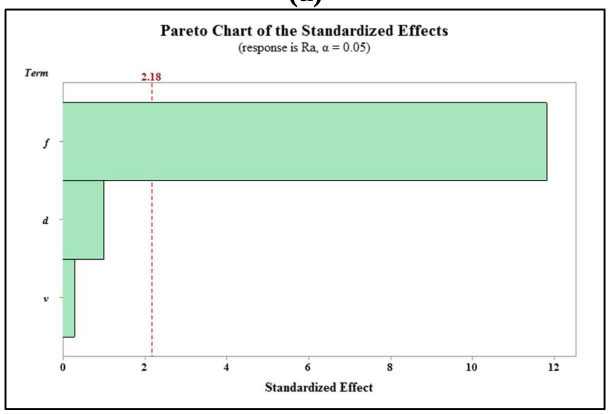
Fig. 3. Performance comparison of developed models

4.1. Pareto chart

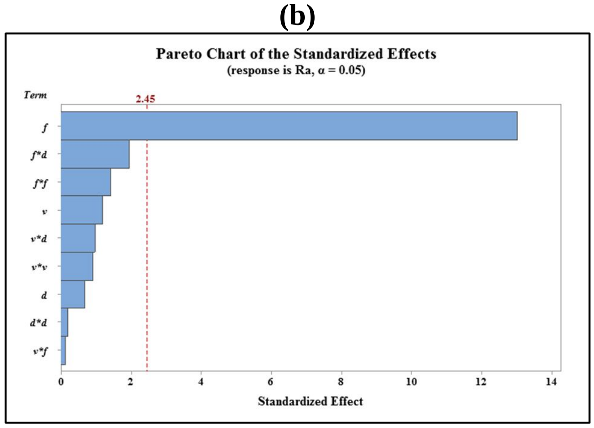
The Pareto chart (Fig.4) visually spots the significant effects and compare the relative magnitude of the various effects of the machining parameters on surface roughness. The machining parameters and its interactions are arranged in descending order according to its corresponding Fisher's test (F-value) at 95% (α = 0.05) confidence level. Fig.4 illustrates and confirms that the feed rate has the highest influence on surface roughness irrespective of the model used. Because of better comparison among the influence of machining parameters and their interactions on the surface roughness, their corresponding mean square values are divided by its error to obtain standardized values called F-values. In the Fig.4, the values of machining factors and its interaction beyond the F-value 2.45 (for quadratic and power models) & 2.18 (for linear model) which is represented as a red color breaking line are significant. The values of *v, d, v*v, d*d, v*f, f*d* are below the F-value 2.45 & 2.18 and are considered as insignificant.



(a)



(b)



(c)

Fig. 3. Pareto chart results: (a) Quadratic (b) Linear (c) Power

5. Conclusions

This paper applies a new modeling approach to predict the surface roughness in turning of AISI 4340 steel hardened at 35 HRC using a single nanolayer of TiSiN-TiAlN PVD-coated cutting insert. This could be the first paper that applies FPA for modeling in the field of machining. The results obtained from this approach had good harmony with experimental results, as the standard deviation of the estimated values was simply 0.0804(for whole) and 0.0289 (for below 1 µm Ra).The best value of surface quality obtained from all the 16 experimental was 0.24 µm at cutting parameters of 75 m/min, 0.05 mm/rev, and 0.1 mm.Based onthe discussions mentioned above, the subsequent conclusions can be drawn:

i. The proposed novel approach,i.eFPA performance, was better than the RSM-based regression models for surface roughness prediction.
ii. The predicted efficiency and accuracy of the developed models for the estimated average surface roughness was found by the percentage of error are: 28.04% (linear), 10.81% (quadratic), 8.49%

(power) and 5.17% (FPA). Among these, FPA based model showed the least percentage of mean absolute error followed by power regression model, indicates its reliability.

iii. The surface roughness was mostly affected by the feed rate which was confirmed by Pareto chart

iv. To check the adequacy of the developed modelscoefficient of determination(R-sq) were determined and all represents strong correlation with given data. The FPA based sparse data model obtained the strongest correlation coefficient value of 99.75% among the other models values.

v. Using the proposed FPA based sparse data model, an effective surface roughness prediction can be achieved before carrying out hard turning. The outcome of the work and the model would be helpful for the manufacturing industries in quality and economic aspects.

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