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A Comparison of Single of Decision Tree, Decision Tree Forest and Group Method of Data Handling to Evaluate the Surface Roughness in Machining Process

S. Ghorbani, N. I. Polushin

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Abstract**—**The machinability of workpieces (AISI 1045 Steel, AA2024 aluminum alloy, A48-class30 gray cast iron) in turning operation has been carried out using different types of cutting tool (conventional, cutting tool with holes in toolholder and cutting tool filled up with composite material) under dry conditions on a turning machine at different stages of spindle speed (630-1000 rpm), feed rate (0.05-0.075 mm/rev), depth of cut (0.05-0.15 mm) and tool overhang (41-65 mm). Experimentation was performed as per Taguchi's orthogonal array. To evaluate the relative importance of factors affecting surface roughness the single decision tree (SDT), Decision tree forest (DTF) and Group method of data handling (GMDH) were applied.

Keywords**—**Decision Tree Forest, GMDH, surface roughness, taguchi method, turning process.

I. Introduction

AMONG several industrial machining processes, turning operation is a fundamental machining operation used to generate cylindrical surface. To obtain the required surface, typically, the workpiece rotates on a spindle, while the fixed tool cuts the workpiece. The main challenge for the manufacturing industry is to increase the productivity and the quality of the machined parts as an optimum surface finish would influence performance of mechanical parts and cost of manufacture [1]. Also, the quality of the machined surface is useful for diagnosing the stability of the machining process, where a deteriorating surface finish may cause progressive tool wear, workpiece material non-homogeneity, cutting tool chatter, etc. [2].

To get good surface quality, the optimization technique is required to find optimal cutting parameters and theoretical models to do predictions. In actual practice, there are many factors affecting the surface roughness, such as cutting conditions (cutting speed, feed rate and depth of cut), tool variables (tool material, tool vibration, tool overhang, nose radius, rake angle, cutting edge geometry, tool point angle, etc.), and workpiece hardness [3], [4]. A large number of theoretical and experimental studies have been done by researchers to establish the quantitative relations between the surface roughness and the cutting condition and the tool variables to improve cutting parameter, tool geometry, and cutting tool material to optimize the machining process. Reference [5] studied the effects of the cutting parameters and tool materials on surface roughness in machining of high-alloy white cast iron (Ni-Hard) at two different hardness levels (50 HRC and 62 HRC) using Taguchi approach and the analysis of variance. Reference [4] investigated the surface roughness of AISI 1050 steel during turning operation using cubic boron nitride (CBN) and ceramic cutting tools. Reference [6] optimized the cutting parameters in machining tool steel with 55 HRC. Reference [7] evaluated the surface roughness and cutting tool wear in machining of AISI 4140 (63 HRC) steel applying Taguchi's L_{27} orthogonal array design of experiment. Reference [8] studied the influence of tool geometry on the surface roughness obtained during machining of AISI 1040 steel with Al2O3/TiC tool. Kacal and Gulesin [9] focused on the optimization of the machining parameters in finish turning of austempered cast iron (GJS-400-15).

Vibration occurred during a machining process is a frequent problem affecting the tool life and the surface finish. In addition, severe chatter vibration during turning operation is caused by a dynamic motion between the cutting tool and the work piece in the feed and cutting speed directions [10]-[13]. Therefore, a better management of the machining system is required to correspond to the cutting tool and machine tool-workpiece combination in order to move toward a more rapid metal removal rate. Exploring higher cutting speeds depends to a great extent on the cutting tool material. The proper selection of cutting conditions and tool material is also important in order to avoid vibration during machining, to increase the productivity of machining operation and to obtain a desirable surface finished of machined part [14]. The analysis of tool vibration on surface roughness is also investigated by several authors. Vibration between cutting tool and workpiece (machine tool structure and workpiece/spindle) is the response of the system to the cutting force distribution [15]. This vibration also can be reduced using some passive vibrational absorbers. To improve a surface finish in machining operation, [16] and [17] used a passive damping pad of viscoelastic material of neoprene and a passive vibration damping, respectively, for predicting and suppressing the vibration level of cutting tool. Reference [18]

S. Ghorbani and N. I. Polushin are with the Department of Functional Nanosystems and High-temperature Materials, National University of Science and Technology "MISiS", Russia, Moscow, No. 4, Leninsky Prospect, Moscow, Russia (phone: +79269801269, e-mail: siamak.ghorbani@yahoo.com).

suggested an impact damper with different materials (such as brass, aluminum, cast iron, phosphor, copper, bronze, and structured steel) in order to suppress the chatter by improving stiffness and damping capability of the tool. Reference [19] proposed a new tool design with an increased vibration damping ability, which includes special elements made of damping materials. An optimal control method for controlling the tool position in orthogonal cutting in both feed and radial directions has been presented by [20].

Researchers attempt to develop models which are able to predict surface roughness for a variety of machining conditions, cutting tools, and workpiece materials. A reliable model would simplify manufacturing process planning and control and also would assist in optimizing machinability of materials. Therefore, the purpose of this work is (1) to study the effect of machining parameters, cutting tool and workpiece material on the surface roughness of machined parts, (2) to develop a surface roughness prediction technique which is termed the Single decision tree (SDT), Decision tree forest (DTF) and Group method of data handling (GMDH) and (3) to describe the results and statistical error analysis.

II. Materials and Turning Tests

The workpiece materials employed in this study are AISI 1045 steel, AA2024 aluminum alloy, and A48-class30 gray cast iron with 200 mm length and 65 mm diameter. A set of experiments has been carried out to study the effect of cutting conditions and tool structure on the machined parts. For these tests, machining experiments were performed at lathe machine model 16K20VF1 (Russia) with a maximum power of 5.5 kW and maximum spindle speed of 1600 rpm. The tools employed have been PCLNR 2525M12 Sandvik Coromant tool made of AISI 5140 with Carbide rhombic cutting insert with a general specification of CT35M coated with TiC. As it is shown in Fig. 1, the conventional cutting tool, cutting tool with horizontal holes (Ø 7 mm) in toolholder arranged in a chess-board pattern, and cutting tool with horizontal holes (Ø 7 mm) filled up with epoxy-granite were used to perform turning operations using three different level of spindle speeds (630-800-100 rpm), feed rate (0.05-0.06-0.075 mm/rev), depth of cut (0.05-0.1-0.15 mm), and tool overhang (41-50-65 mm) without using cooling fluid. Table I shows the physical and mechanical characteristics of epoxy-granite used in the holes of the toolholder in Fig. 1 (c) in order to suppress the chatter vibration between cutting tool and workpiece as it possesses a good vibration damping capacity in comparison with steel and cast iron [21], [22]. During turning operation, in each trial, the rust layers were removed by using a new cutting insert in order to reduce the effect of homogeneity of the workpiece material on the experimental result and a new cutting insert CT35M coated with TiC was used to minimize the effect of tool wear on the experimental results. In this work, the average surface roughness (R_a), as one of the most important criteria for a machining process, was measured. Measurement of the R_a was performed using a profile meter model 130 (Russia) with a sampling length of 12.50 mm and measurement speed of 0.5 mm/s. The values of the R_a were calculated by averaging four roughness values obtained from four different points of machined surface in 900 increments around the circumference.

Design of experiment (DOE) is a procedure of determining the objective of an experiment and selecting the number of trials and a condition running them. DOE is an essential and sufficient systematic approach for solving an engineering problem that has been set with the required precision. DOE applies the principles and technique at the data collection to generate valid and supportable engineering conclusions. The use of design of experiment makes behavior of an investigator purposeful, organized appreciably facilitates an increase in productivity of his/her work and reliability of a result obtained [23]. The Taguchi technique, owing to its efficiency and systematic approach, has been extensively applied in parameter design and experimental planning. Taguchi method is one of the important tools used in the industry to shortage product design, develop time and produce lower product cost. This method also takes into consideration the effect of uncontrollable factors on the response. In addition, Taguchi method is highly flexible and can allocate different levels of factors, even when the numbers of the levels of factors are not the same [24]. In this study to design the experiments, the orthogonal array of Taguchi method was used. The experimental results of surface roughness (Ra), performed according to the Taguchi method, are illustrated in Table II. In Table II: A represents conventional cutting tool, B – cutting tool with holes, C – cutting tool filled up with epoxy-granite, a – AISI 1045 steel, b – AA2024 aluminum alloy, c – A48-class30 gray cast iron, V – spindle sped (rpm), F – feed rate (mm/rev), D – depth of cut (mm), L – overhang (mm) and R_a – surface roughness (µm).

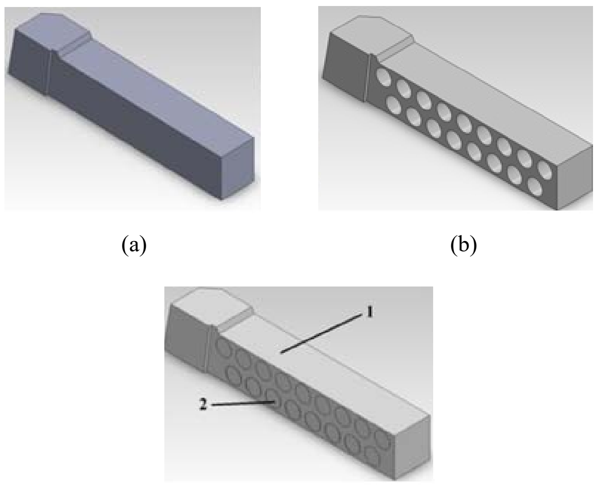

Fig. 1 3D- model of cutting tools in SolidWorks: (a) conventional cutting tool; (b) cutting tool with horizontal holes arranged in a chess-board pattern (Ø 7 mm) and (c) cutting tool filled up with epoxy granite: 1 — toolholder and 2 — epoxy granite

TABLE I
PHYSICAL AND MECHANICAL CHARACTERISTICS OF EPOXY GRANITE

Parameter	Epoxy-granite
Density (kg/m^3)	2400–2600
Strength stress (MPa)	
Compression	150-160
Tensile	15-20
Elasticity module (MPa*10^{-4})	3.5–4.0
Poisson's ratio	0.25–0.40
Thermal conductivity (W/(m*K))	1.7–1.75
Linear expansion coefficient (1/°C)	(12–16)*10^{-6}
Damping ratio	0.6

TABLE II
DESIGN OF EXPERIMENT AND EXPERIMENTAL RESULTS OF SURFACE ROUGHNESS

No. Exp.	Cutting tool	Workpiece material	V(rpm)	F(mm/rev)	D(mm)	L(mm)	R_a(μm)
1	A	a	630	0.050	0.05	41	2.072
2	A	a	630	0.060	0.10	50	2.490
3	A	a	630	0.075	0.15	65	1.831
4	A	a	800	0.050	0.10	65	1.384
5	A	a	800	0.060	0.15	41	1.081
6	A	a	800	0.075	0.05	50	1.219
7	A	a	1000	0.050	0.15	50	1.033
8	A	a	1000	0.060	0.05	65	1.320
9	A	a	1000	0.075	0.10	41	1.397
10	A	b	630	0.050	0.05	41	1.231
11	A	b	630	0.060	0.10	50	1.090
12	A	b	630	0.075	0.15	65	1.006
13	A	b	800	0.050	0.10	65	0.814
14	A	b	800	0.060	0.15	41	0.820
15	A	b	800	0.075	0.05	50	0.831
16	A	b	1000	0.050	0.15	50	0.986
17	A	b	1000	0.060	0.05	65	1.055
18	A	b	1000	0.075	0.10	41	0.983
19	A	c	630	0.050	0.05	41	2.452
20	A	c	630	0.060	0.10	50	2.602
21	A	c	630	0.075	0.15	65	2.490
22	A	c	800	0.050	0.10	65	2.260
23	A	c	800	0.060	0.15	41	2.390
24	A	c	800	0.075	0.05	50	2.200
25	A	c	1000	0.050	0.15	50	2.110
26	A	c	1000	0.060	0.05	65	2.290
27	A	c	1000	0.075	0.10	41	2.260
28	B	a	630	0.050	0.05	41	2.390
29	B	a	630	0.060	0.10	50	1.920
30	B	a	630	0.075	0.15	65	2.670
31	B	a	800	0.050	0.10	65	0.974
32	B	a	800	0.060	0.15	41	0.860
33	B	a	800	0.075	0.05	50	1.200
34	B	a	1000	0.050	0.15	50	0.588
35	B	a	1000	0.060	0.05	65	0.569
36	B	a	1000	0.075	0.10	41	1.640
37	B	b	630	0.050	0.05	41	0.640
38	B	b	630	0.060	0.10	50	1.218
39	B	b	630	0.075	0.15	65	1.285
40	B	b	800	0.050	0.10	65	0.893
41	B	b	800	0.060	0.15	41	0.864
42	B	b	800	0.075	0.05	50	1.260
43	B	b	1000	0.050	0.15	50	0.961
44	B	b	1000	0.060	0.05	65	0.957
45	B	b	1000	0.075	0.10	41	0.960
46	B	c	630	0.050	0.05	65	1.867
47	B	c	630	0.060	0.10	50	1.900
48	B	c	630	0.075	0.15	65	2.560
49	B	c	800	0.050	0.10	65	2.200
50	B	c	800	0.060	0.15	41	2.290
51	B	c	800	0.075	0.05	50	2.300
52	B	c	1000	0.050	0.15	50	1.990
53	B	c	1000	0.060	0.05	65	2.120
54	B	c	1000	0.075	0.10	41	2.360
55	C	a	630	0.050	0.05	41	2.740
56	C	a	630	0.060	0.10	50	2.490
57	C	a	630	0.075	0.15	65	2.450
58	C	a	800	0.050	0.10	65	2.110
59	C	a	800	0,060	0.15	41	1.520
60	C	a	800	0.075	0.05	50	1.380
61	C	a	1000	0.050	0.15	50	0.742
62	C	a	1000	0.060	0.05	65	0.753
63	C	a	1000	0.075	0.10	41	0.745
64	C	b	630	0.050	0.05	41	0.583
65	C	b	630	0.060	0.10	50	0.598
66	C	b	630	0.075	0.15	65	0.640
67	C	b	800	0.050	0.10	65	0.614
68	C	b	800	0.060	0.15	41	0.597
69	C	b	800	0.075	0.05	50	0.575
70	C	b	1000	0.050	0.15	50	0.578
71	C	b	1000	0.060	0.05	65	0.647
72	C	b	1000	0.075	0.10	41	0.693
73	C	c	630	0.050	0.05	41	2.320
74	C	c	630	0.060	0.10	50	2.050
75	C	c	630	0.075	0.15	65	2.120
76	C	c	800	0.050	0.10	65	1.934
77	C	c	800	0.060	0.15	41	2.220
78	C	c	800	0.075	0.05	50	1.770
79	C	c	1000	0.050	0.15	50	1.560
80	C	c	1000	0.060	0.05	65	1.690
81	C	c	1000	0.075	0.10	41	1.760

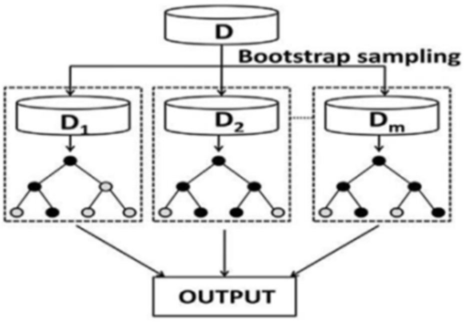

Fig. 2 Conceptual diagram DTF

III. METHOD

A. Decision Tree Forest (DTF)

A DTF can be used to evaluate the sensitivity of parameters or parameter combinations. A DTF is an ensemble of SDTs, which can be formed by various methods, by different sub-samples of observations over one and the same phenomenon, by use of different characteristics whose predictions are combined to make the overall prediction for the forest (Fig. 2). In DTF, laws of the researched phenomenon and the improvement of a large number of independent trees are grown in parallel, and consideration of a problem gives a better understanding about the fact that they do not interact until after all of them have been built [25]. Bootstrap resampling method and aggregating are the basis of bagging which is incorporated in DTF [26]. Different training sub-sets are drawn at random with replacement from the training data set. Separate models are produced and used to predict the entire data from aforesaid sub-sets. Then, various estimated models are aggregated by using the mean for regression problems or majority voting for classification problems. Theoretically, in bagging, first a bootstrapped sample is constructed as [27]:

$$\mathrm{D}_{\mathrm{i}}^{*} = (Y_i^*, X_i^*) \tag{1}$$

where $\mathrm{D}_{\mathrm{i}}^{*}$ is a bootstrapped sample according to the empirical distribution of the pairs Di = (Xi,Yi), where (i=1, 2, . . . ; n). Secondly, the bootstrapped predictor is estimated by the plug-in principle.

$$\mathrm{C}_{\mathrm{n}}^{*}(x) = h_n(D_i^*, \dots, D_n^*)(x) \tag{2}$$

where $C_n(x)=h_n(D_1,...,D_n)(x)$ and h_n is the *n*-th hypothesis. Finally, the bagged predictor is:

$$\mathrm{C}_{\mathrm{nB}}(x) = E^*[D_n^*(x)] \tag{3}$$

Bagging can reduce variance when combined with the base learner generation with a good performance [28]. The DTFs gaining strength from bagging technique use the out of bag data rows for model validation. This provides an independent test set without requiring a separate data set or holding back rows from the tree construction. The stochastic element in DTF algorithm makes it highly resistant to over-fitting.

Statistical measures such as the Maximum error, the Normalized mean square error (NMSE), the Correlation between actual and predicted, Root Mean Squared Error (RMSE), Mean absolute percentage error (MAPE) and Mean Squared Error (MSE) were employed for qualitative evaluation of the models.

B. Group Method of Data Handling (GMDH)

One of the active areas of research is modeling of systems based on their input and an output pattern used for system analysis in order to predict and simulate the system's behavior. System models are also required for designing new processes, analyzing existing processes, designing controllers, optimizations, supervision, and fault detection and diagnosis. Many methods for identifying and modeling non-linear systems were proposed including fuzzy inference, neural networks, polynomial classifiers, and genetic algorithm. These methods require large amount of data to estimate the parameters of the model in higher order systems [29].

The GMDH is a modeling technique that provides an effective approach for data mining, forecasting and systems modeling, optimization and pattern recognition in order to identify a high-order input-output non-linear relationship. GMDH was firstly introduced by Ivakhnenko in 1966 as an inductive learning algorithm for extremely high-order regression-type polynomial. GMDH is an inductive self-organizing algebraic model since it is able to model complex systems without having specific knowledge of the systems [30]. The GMDH algorithm provides an optimal structure, obtained in an iterative procedure of partial descriptions of the data by adding new layers [31]. By means of GMDH, the dominant relations on system variables during the training process can be determined. GMDH automatically determines the optimal network structure (the number of neurons in each layer, the number of layers and the input variables) in a way that minimizes the difference between the network output and the desired output. The unnecessary nodes from the network are also eliminated by GMDH [31]. Therefore, GMDH has good generalization ability and can fit the complexity of non-linear systems with a relatively simple network that is numerically stable.

The formal definition of system identification problem is to find a function $\hat{f}$ that can be approximately used instead of actual function *f*, in order to predict the output $\hat{y}$ for a given input vector $X = (x_1, x_2, \dots, x_n)$ as close as possible to its actual output *y*. Therefore, given *n* observation of multi input single-output data pairs so that:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \;\; (i = 1,2, \dots. M) \tag{4}$$

It is now possible to train a GMDH network to predict the output values $\hat{y}_i$ for any given input vector $X = (x_{i1}, x_{i2}, \dots, x_{in})$ that is:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots \dots, x_{in}) \;\;\; (i = 1,2, \dots, M) \tag{5}$$

In order to solve this problem, GMDH builds the general relationship between output and input variables in the form of mathematical description, which is also called reference. The problem is now to determine a GMDH network so that the square of difference between the actual output and the predicted one is minimized, that is:

$$\sum_{i=1}^{M} \left[\hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots \dots, x_{in}) - y_i\right]^2 \to \min \tag{6}$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra function a series in the form of:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i\, x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k \tag{7}$$

which is known as the Kolmogorov–Gabor polynomial [32]. The polynomial order of PDs is the same in each layer of the network. In this scenario, the order of the polynomial of each neuron (PN) is maintained the same across the entire network. For example, assume that the polynomials of the PNs located at the first layer are those of the second order (quadratic):

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \quad (8)$$

Here, all polynomials of the neurons of each layer of the network are the same, and the design of the network is based on the same procedure. The second-order polynomial is fundamental structure of the GMDH network that has been proposed by Ivakhnenko. Generally, different types of polynomial such as bilinear, quadratic, triquadratic, and third order are used to design self-organized systems. The use of tri-quadratic and third-order polynomial can generate more complicated network in comparison with quadratic polynomial. Bilinear polynomial produces lower complicated structure in comparison with quadratic polynomial. Quadratic polynomial has six weighting coefficients that generated good results in engineering problems. Based on the previous investigations, selection of polynomials could depend on minimum error of objective function and complexity of polynomial type. In this study, quadratic polynomial was utilized for modeling of scour depth around different types of bridge pier. The weighting coefficients in (7) were calculated using regression techniques so that the difference between actual output, y, and the calculated one, $\hat{y}$, for each pair of xi; xj as input variables was minimized. In this way, the weighting coefficients of quadratic function Gi were obtained to optimally fit the output in the whole set of input–output data pair, that is:

$$E = \left(\sum_{i=1}^{M} (y_i - G_i)^2 / M \right) \rightarrow min \quad (9)$$

III. Results and Discussion

In this study, first of all, the experiments were performed according to the Taguchi's orthogonal array, and the results were obtained for surface roughness (Table II). Secondly, a SDT was used to develop model for predicting the related factors using the classification and regression tree (CART) algorithm (Fig. 3). The CART is an algorithm that performs a binary split, where only two child nodes are formed from the parent node, where the alpha value for the criteria of splitting and merging was set at 0.05. Besides, the weights for misclassification costs were set asymmetrically in order to make up for the imbalance in data distribution. At the end of a training process, the model with the lowest error was selected as the final model. In addition, for qualitative evaluation of the models, the statistical measures such as the correlation between actual and predicted, maximum error, root mean squared error, mean squared error, mean absolute percentage error, and the normalized mean square error were used. The relative importance of variables on estimated surface roughness and the results of the error statistics calculated surface roughness have been assessed using SDT and the DTF methods, which are shown in Tables III and IV. In decision tree, the relative importance of input parameters can be found by algorithm itself determining the important parameters through branching of inputs, and knowledge of decision tree can help us choose parameters and assess the dependencies between related attributes. As can be seen from Fig. 3, the greatest number of branching was performed using workpiece material, spindle speed, and cutting tool. Therefore, using Fig. 3, Tables III and IV, workpiece material, spindle speed and cutting tool are the most important parameters affecting surface roughness.

TABLE III
Relative Importance of Variables on Estimated Surface Roughness

Variable	Importance	
	SDT	DTF
Workpiece material	100.0	100.0
Spindle speed (rpm)	21.50	23.31
Cutting tool	20.08	13.90
Feed rate (mm/rev)	20.04	8.450
Depth of cut	15.58	7.330
Overhang (mm)	11.82	6.270

TABLE IV
Results of the Error Statics Calculated Surface Roughness

Error	SDT	DTF
Correlation between actual and predicted values	0.9165	0.8633
Maximum error	1.0459	0.9471
RMSE (Root mean squared error)	0.2748	0.3884
MSE (Mean squared error)	0.0755	0.1508
MAPE (Mean absolute percentage error)	16.141	27.916
NMSE (Normalized mean square error)	0.3377	0.3231

In the next step, the GMDH network was improved using back propagation algorithm. This method included two main steps. First, the weighting coefficients of quadratic polynomial were determined using least square method from input layer to output layer in form of forward path. Second, weighting coefficients were updated using back propagation algorithm in a backward path. Again, this mechanism could be continued until the error of training network (E) was minimized. Two sets of input data are used during the training process: (1) the primary training data, and (2) the control data which are used to stop the building process when overfitting occurs. The control data typically have about 20% as many rows as the training data. Two hidden layers were considered for each model. To genetically design such networks, a population of 10 individuals with a crossover probability of 0.7, mutation probability of 0.07, and 600 generations was used; it appeared that no further improvement could be achieved for such a population size. Based on Table III, the parameters of interest in this model, which affect the estimated surface roughness, are workpiece material, spindle speed, cutting tool, depth of cut, feed rate, and tool overhang. Equations (10) to (12) show the results from this method to predict the estimated surface roughness for each workpiece material.

Estimated surface roughness (μm) for AISI 1045 steel is:

$$Ra = 10.08 + V * (-0.0164) + V * L * (-0.0002) + V^2 * (1.28E-5) + F * L * (-0.1675) + D^2 * (-25.37) + L^2 * (0.0012) \quad (10)$$

Estimated surface roughness (µm) for AA2024 aluminum alloy is:

$$R_a = V * (-0.0023) + V * D + S^2 * (2.171E-6) + D * 11.24 + L * (0.053) + L^2 * (-0.0005) \quad (11)$$

Estimated surface roughness (µm) for A48-class30 gray cast iron is:

$$R_a = 4.426 + V * D + V * L + D^2 * (19.67) + L * (-0.071) + L^2 * (-0.0007) \quad (12)$$

where R_a represents surface roughness (µm), V-spindle speed (rpm), F-feed rate (mm/rev), D-depth of cut (mm) and L-tool overhang (mm). Moreover, using GMDH method, the correlation between actual and predicted values of the surface roughness are; $R^2 = 0.8855$, $R^2 = 0.7743$ and $R^2 = 0.8457$ for AISI 1045 steel, AA2024 aluminum alloy and A48-class30 gray cast iron, respectively. The results indicate that regression analysis performed on actual and GMDH values resulted in a positive correlation with a R2 around of 0.8.

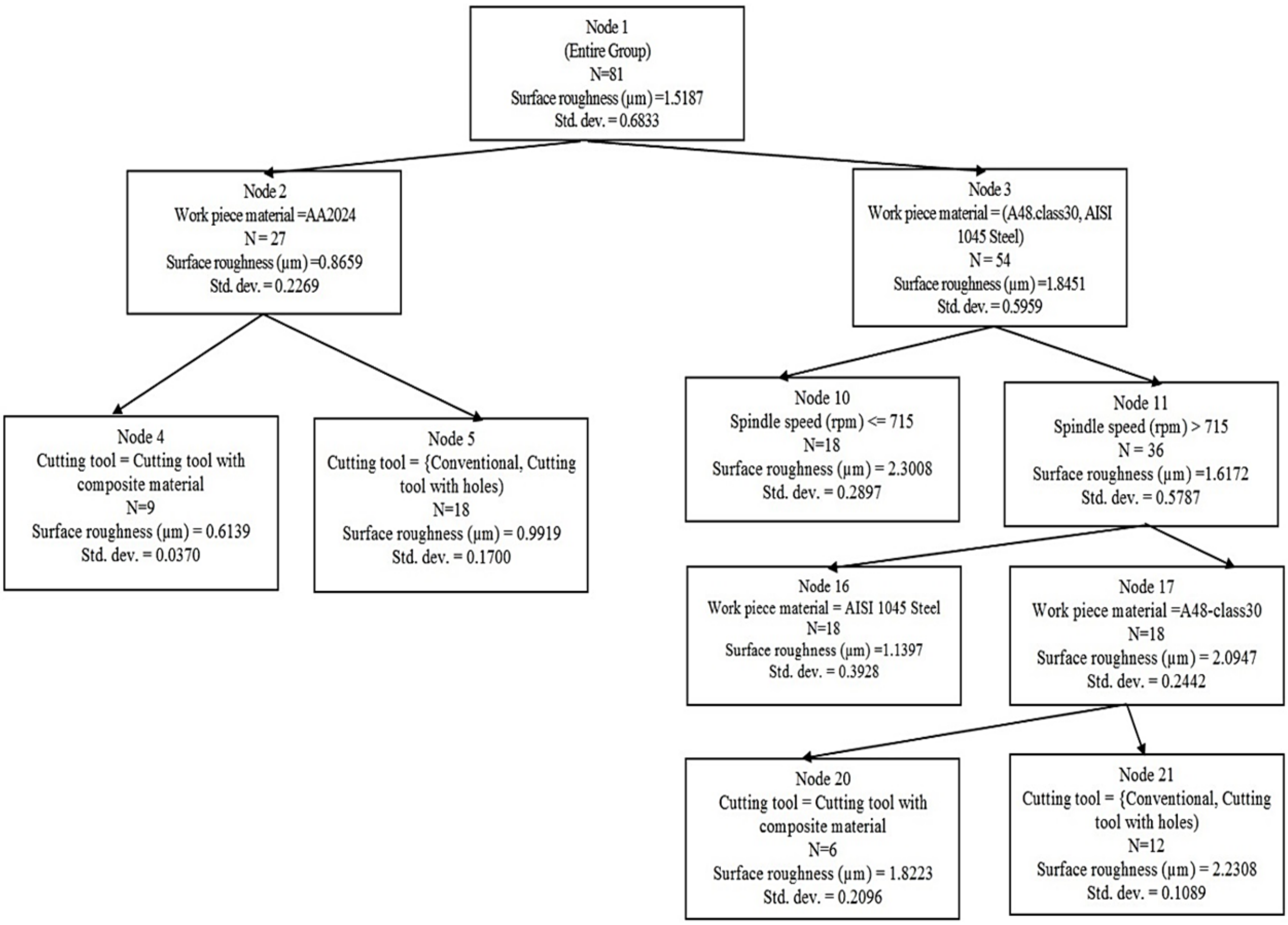

Fig. 3 Result of SDT to predict the estimated surface roughness generated by CART algorithm

SDT, DTF, and GMDH have been used to estimate surface roughness in turning of different workpiece materials (AISI 1045 Steel, AA2024 aluminum alloy, A48-class30 gray cast iron). All the methods have been found to estimate surface roughness well as discussed above. However, from the standpoint of identifying a better method among the tree, the obtained results from the tree methods were compared. Therefore, a comparison between results obtained by SDT, DTF, and GMDH shows that the SDT model with $R^2 = 0.9165$ provides a more effective means to model and predict the estimated surface roughness in comparison with DTF and GMDH models.

In the next step, after analyzing the prediction model of surface roughness, the obtained results were compared with traditional regression models. Several mathematical models based on statistical regression techniques have been proposed to establish cause and effect relationship between cutting parameters and surface roughness [33]-[37]. These regression equations and correlation between actual and predicted values are:

$$R_a = 12.942 - 014.02f - 0.038V - 0.00445H, R^2 = 0.672 \quad (13)$$

$$R_a = 8.6 - 0.00017V + 28.2f + 3.74d + 0.688r + 1.244f * a,\ R^2 = 0.867 \quad (14)$$

$$R_a = 2.74 - 0.011V + 0.00117 * frequency + 261 * duty\ cycle,\ R^2 = 0.776 \quad (15)$$

$$R_a = 2.1066 - 0.0011V + 0.004f - 0.00976a, R^2 = 0.867 \quad (16)$$

$$R_a = 1.481 - 4.727 * 10^{-3}V + 9.817f + 0.1276a, R^2 = 0.504 \quad (17)$$

$$R_a = 1.9596 - 5.582 * 10^{-3}V - 2.706f + 0.071a + +0.025V * f + 1.244f * a,\ R^2 = 0.47 \quad (18)$$

where V represents the cutting speed, f - feed rate, a - depth of cut, r - nose radius, and H - material hardness. It is clearly seen that the results generated by SDT are more accurate in comparison with regression models with higher recognition rate, forecast accuracy, and strong practical value. In predicting the surface roughness, correlation between actual and predicted values is $R^2 = 0.9165$ for SDT and $R^2 = 0.6802$ for traditional regression models in average. Besides, the traditional regression techniques, as a method to estimate surface roughness, have difficulties in showing the significant parameters affecting surface roughness. Additionally, linear regression techniques need assumptions to be made, including assumptions about the normality, linearity and homoscedasticity of the data among others, and it is likely that the assumptions that are made in a regression technique may be violated.

Finally, in these works, experiments were conducted by machining three different workpiece materials (AISI 1045 steel, AA2024 aluminum alloy, A48-class30 gray cast iron). The results indicate that workpiece material has a significant effect on surface roughness as different material has different chemical composition, hardness, wear, heat and corrosion resistance and other specifications, which affect the machinability of the material. In addition, the significant influence of spindle speed on surface roughness can be explained by the fact that as spindle speed increases, the interaction between cutting tool and workpiece decreases, which leads to less vibration and consequently, to better surface roughness (R_a). Moreover, general evaluation is also made in terms of tool structure; the surface roughness (R_a) values in turning of AISI 1045 steel, AA2024 aluminum alloy, A48-class30 gray cast iron obtained by using cutting tool filled up with composite material are less than those of obtained by using conventional cutting tool and cutting tool with holes in toolholder. This can be explained by the fact that the cutting tool filled up with epoxy-granite has a heterogeneous structure. Vibration waves pass through the mediums: metal — composite material — metal — composite material. Vibration suppression, their partial reflection, and the change of direction occur because of the heterogeneous structure of the cutting tool and high damping capability of epoxy-granite filled up in toolholder. As a result, vibrations are damped, which stabilizes the cutting tool position leading to improve the surface quality. Therefore, it is possible to say that cutting tool design is of important factor affecting surface roughness (R_a) in a machining process.

IV. Conclusion

In this study, SDT, DTF, and GMDH are applied to evaluate the effect of different workpiece materials, cutting tools and cutting condition on surface roughness in machining process and to find the optimal model for better surface roughness prediction. It was found that each factor affects the surface roughness to a different extent. It has been shown that all the methods have been found to estimate surface roughness well. The SDT makes a more precise prediction compared with DTF and GMDH methods and traditional regression technique. In addition, the important parameters, in the estimated surface roughness, have been obtained using SDT and DTF model, and then they have been proposed basing on GMDH model. Furthermore, in contrast to traditional methods to predict the surface roughness, SDT, DTF and GMDH provide good performance and can be employed as effective decision support tools to assist in quality control.

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