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Predictive Modeling of Surface Roughness for EN19 Alloy Steel Using Artificial Neural Networks

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Abstract -The utilization of the artificial neural network method (ANN) is widespread for both modeling and optimizing manufacturing processes.The determinationof optimum processing parameters assumes a pivotal role in addressing cost and time considerations within the manufacturing domain. Notably, the burnishing process presents a straight forward, uncomplicated, and cost-efficient technique, thereby frequently supplanting alternative surface finishing methodologies in the manufacturing sector. This research delves into the exploration of burnishing parameters, encompassing factors such as the count of passes, penetration depth, burnishing speed, and feed rate. These parameters are examined in relation to their impact on the surface roughness of EN 19 alloy steel. The outcome of this investigation underscore the viability of utilizing ANN models to accurately predict the results of surface roughness for the burnishing process [28]. Consequently, the optimal validation performance, coupled with high coefficient of determination (R) values, culminates in the accurate prediction of surface roughness outcomes for the burnishing process through the adept utilization of ANN models [27].

Keywords–Single Roller burnishing, Surface roughness, Modeling, Artificial Neural Network

INTRODUCTION

Surface quality holds significant importance in assessing both the effectiveness of machine tools and the quality of machined components. Consequently, attaining the intended surface quality stands as a crucial factor influencing the operational effectiveness of mechanical elements [2]. Particularly, surface roughness assumes a pivotal role as a key quality parameter for machined surfaces. This parameters impact extends to numerous attributes, including wear resistance, fatigue strength, coefficient of friction, lubrication, wear rate, and corrosion resistance of machined parts [7].In the contemporary landscape of manufacturing, paramount emphasis is placed on achieving precise dimensions and impeccable surface texture. This accentuates the significance of quantifying and characterizing surface finish as an anticipatory gauge for machining effectiveness. Among cold-working finishing techniques, burnishing emerges distinctively, setting it apart from counterparts like shot peening and sand blasting. Unlike others, burnishing yields both a refined surface finish and introduces residual compressive stresses within the metallic surface strata [3, 4]. This sets burnishing apart from chip-forming finishing methods such as grinding, honing, lapping, and super-finishing, which instead give rise to residual tensile stresses at the machined surface layers [2]. Additionally, burnishing offers economic appeal due to its simplicity and cost- effectiveness, demanding less time and skill while achieving a high calibre surface finish [2].

The burnishing procedure entails the application of substantial pressure using a meticulously polished, rigid ball, or roller onto a metallic surface. As illustrated in figure 1 [26], when the applied burnishing pressure surpasses the yield strength of the metal, the elevated pressure compels the surface's peaks to undergo a permanent spreading effectively filling in the troughs [4]. This results in the surface of the metallic material becoming more even, accompanied by the induction of plastic deformation that confers work hardening. Consequently, the material retains a residual stress distribution, characterized by compressive forces exerted on the surface [4].

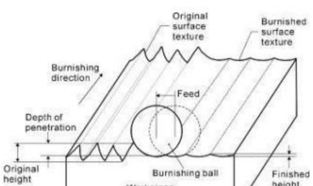

Fig. 1 Schematic diagram of Basic Principle of Roller Burnishing [26]

Numerous authors have contended that burnishing yields enhancements in various surface attributes, including surface hardness, wear resistance, fatigue resistance, yield and tensile strength, as well as corrosion resistance [10]. In light of this, the current study sought to delve into the impact of burnishing parameters, specifically depth of penetration, number of tool passes, feed rate and burnishing speed on the surface roughness of EN 19 alloy steel [29]. This investigation was conducted utilizing Artificial Neural Networks (ANN)[2].

MATERIAL AND EXPERIMENTAL PROCEDURE

Within the scope of this investigation, the chosen material for the work piece is 'EN-19 Grade Alloy Steel,' a prevalent selection in the realm of automobile manufacturing. The chemical composition details of this material are provided in Table I for reference[25].

TABLE I
Chemical Composition of EN 19 alloy steel used for experimental investigation [25].

Element	C	Mn	Si	S	P	Cr	Ni	Mo
Wt (%)	0.44	0.79	0.19	0.03	0.01	1.06	0.08	0.28

The ACE Designers CNC lathe (Junior Jobber), equipped with a Fanuc controller [25], and was employed to conduct all burnishing tests. The initial work pieces were cylindrical, featuring a diameter of 32 mm and a length of 200 mm. Subsequently, these work pieces underwent turning processes to achieve specific dimensions of 30mm in diameter and 183 mm in length. For the rough turning phase, the following machining parameters were employed: a rotational speed of 2000 rpm, a feed rate of 0.2 mm/rev, a 1 mm depth of cut, a cutting speed of 120 mm/min, and the utilization of a TNMG160408 tool insert. During the finishing turning phase, distinct parameters were applied: a speed of 2500 rpm, a feed rate of 0.1 mm/rev, and a depth of cut of 0.25 mm. Additionally, small grooves, each spanning 2 mm, were introduced at 40 mm intervals to partition the turned work piece into four segments. The complexity of the process necessitates a substantial number of experiments to comprehensively grasp its intricacies. Unfortunately, this approach is both time-intensive and costly. To mitigate these challenges, a more efficient strategy involving experimental layout planning based on design of experiments principles has been proposed. This approach entails varying levels of the process variables, with a focus on brushing speed, burnishing feed, depth of penetration, and the number of tool passes. These selections are informed by prior investigations in the field.[1] With the objective of exploring the impact of process parameters on the resultant performance output, an experiment was meticulously planned and executed. This endeavour focused on gauging surface roughness and surface hardness as the primary responses. The process parameters of interest were deliberately altered across a spectrum ranging from the lowest to the highest values for each factor, a concise overview of which is encapsulated in table II [4].

TABLE II
Factors and levels for CCD [25].

Coded levels	-2	-1	0	1	2
Burnishing Speed, rpm	1000	1100	1200	1300	1400
Burnishing Feed, mm/rev	0.04	0.05	0.06	0.07	0.08
Depth of Penetration, mm	0.1	0.2	0.3	0.4	0.5
Number of Passes	1	2	3	4	5

Figure 2 (a) provides a visual representation of the roller burnishing tool assembly, meticulously designed and fabricated [25]. The CNC turret served as the platform for affixing the burnishing tool, while the work piece was secured using the tailstock centre. The burnishing process was facilitated with the application of lubricant, as depicted in figure 2 (b). The challenge arises in selecting an appropriate amount of training and testing data due to diversity of available opinions for different applications.

Fig.2. (a) Photographic view of roller burnishing tool [25]

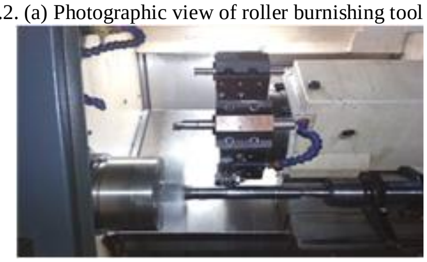

Fig.2 (b) Experiment setup of roller burnishing process [25]

The objective of this current study was to examine the influence of burnishing parameters- including Depth of Penetration (mm), number of tool passes (N), feed rate (f/(mm/min)), and burnishing speed (v/(r/min))- on the surface roughness (Ra/µm) of EN19 Alloy Steel. This investigation was conducted utilizing Artificial Neural Networks (ANN) [2].

UtilizingArtificial Neural Networks (ANN) for Modeling

Computers play an essential role in the daily operations of engineering design, aiding engineers in enhancing their designs through the use of diverse applications [12].

Artificial Neural Networks (ANNs) emulate fundamental elements of brain functions [13-15], drawing inspiration from the neural architecture of the human brain. This architecture processes information through intricate interactions between numerous neurons [13,16].

Over the recent years, there has been a consistent surge in the fascination with neural network modeling across various domains within materials science. The fundamental building block of an Artificial Neural Network (ANN) is the neuron, which is interconnected with other neurons through weight factors. The training of a network typically involves the utilization of a substantial amount of input data along with their corresponding output values [17]. The architecture of the ANN employed for modeling surface roughness is depicted in figure 3. This design encompasses numerous simple processing neurons organized sequentially into layers: the input layer, intermediate (hidden) layers, and the output layer. Simulation within this framework revolves around establishing a meaningful connection between a set of neurons representing input data and their corresponding established outputs, the thoughtful selection of input parameters emerges as a critically important aspect within the domain of neural network modeling [17].

All relevant input parameters need to be included in the neural network's input data representation. In this specific investigation, the inputs consisted of burnishing force, number of passes, feed rate, and burnishing speed. These inputs were used to characterize the output, which was the surface roughness measurement. The architecture utilized for the ANN model follows a multilayer configuration of 4:5:5:1, as visually depicted in figure 3. The outputs of the hidden neurons are labelled as Y_j (j=1, 2,…, 5) and Y_i (i= 1,2,….,5). To ensure optimal print quality of results, the incorporation of high-resolution figures, plots, drawings, and photographs is essential, ideally exceeding 300 dpi.

The Training of the Network [30]

In general, three distinct learning strategies are employed [31]. Firstly, in supervised learning, the trainer imparts what the network should comprehend. Secondly, in reinforcement learning, the trainer indicates the correctness of outputs without explicitly instructing what should be learned. Lastly, unsupervised learning involves the network learning autonomously without the trainer's intervention. The learning set comprises inputs and outputs employed for network training. In supervised learning, the required outputs are included in this set, whereas they are absent in other scenarios [17, 18]. For this particular investigation, the approach of supervised learning was adopted. The development of the computer program was executed using MATLAB [19]

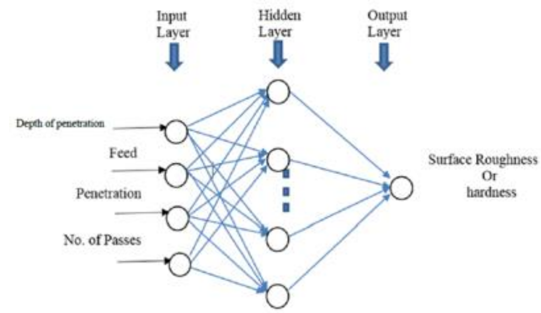

Fig. 3 ANN model for burnishing process

TABLE III
Experimental result and training set of ANN modeling

Run	Speed (rpm)	Feed (mm/rev)	Depth of Penetration (mm)	Number of Passes	Surface Roughness (um)
1	1100	0.05	0.2	4	0.45
2	1200	0.06	0.3	3	0.323
3	1100	0.07	0.2	4	0.704
4	1200	0.08	0.3	3	0.391
5	1200	0.06	0.3	3	0.49
6	1200	0.04	0.3	3	0.545
7	1000	0.06	0.3	3	0.359
8	1100	0.07	0.4	2	0.345
9	1300	0.05	0.2	2	0.39
10	1300	0.07	0.2	4	0.25
11	1200	0.06	0.3	3	0.429
12	1200	0.06	0.1	3	0.478
13	1100	0.05	0.2	2	0.49
14	1100	0.07	0.4	4	0.512
15	1200	0.06	0.5	3	0.362
16	1400	0.06	0.3	3	0.231
17	1100	0.05	0.4	4	0.515
18	1200	0.06	0.3	1	0.349
19	1300	0.05	0.2	4	0.454
20	1300	0.07	0.4	2	0.212
21	1300	0.05	0.4	4	0.394
22	1200	0.06	0.3	5	0.391
23	1200	0.06	0.3	3	0.324
24	1300	0.05	0.4	2	0.412
25	1200	0.06	0.3	3	0.622
26	1100	0.07	0.2	2	0.389

27	1300	0.07	0.2	2	0.44
28	1300	0.07	0.4	4	0.378
29	1100	0.05	0.4	2	0.442
30	1200	0.06	0.3	3	0.545

Training data results

[0.45356 0.32084 0.69277 0.3877 0.49063 0.55287 0.3628 0.34671 0.3877 0.254 0.43108 0.40956 0.55665 0.61056 0.3877 0.24169 0.51979 0.34727 0.3877 0.23458 0.39591 0.39163 0.26096 0.41128 0.66189]

Test results

[0.37766 0.3877 0.3877 0.29364 0.61119]

Weights

[1.272 0.84821 -2.1748 0.22988;
0.89496 0.026345 1.486 -1.9895;
1.1583 1.6042 1.4419 0.25007;
0.043371 -0.64975 1.5251 -1.8005;
-1.5124 -1.4079 -1.1812 -1.3767;
0.73312 1.2909 -0.070903 1.9588;
-1.5882 -1.9661 0.37362 -1.1777;
-0.96274 2.6188 0.46789 -0.032456;
-1.1578 1.0947 0.98721 1.6094;
-1.8576 -0.50732 0.63837 -1.7685]

Input ranges

[1100 1300;
0.04 0.08;
0.1 0.5;
1 5]

Testing Stage

To evaluate the quality of predictions made by an ANN, previously unseen test data is employed, and its outcomes are assessed at this phase. Statistical techniques such as root mean square error (RMSE) and coefficient of determination (R2) values have been utilized for comparative analysis [17, 20-23].

RESULTS AND DISCUSSION

The performance plot displays how the performance function value changes in relation to the iteration number specifically concerning surface roughness. It encompasses the graphical representation of training validation, and test performances. Upon observing the graph, it becomes evident that the error consistently diminishes with the increase in training epochs. Remarkably, the optimal validation performance is 0.0015 attained at the 0^{th} epoch for surface roughness, as visually indicated in figure 4.

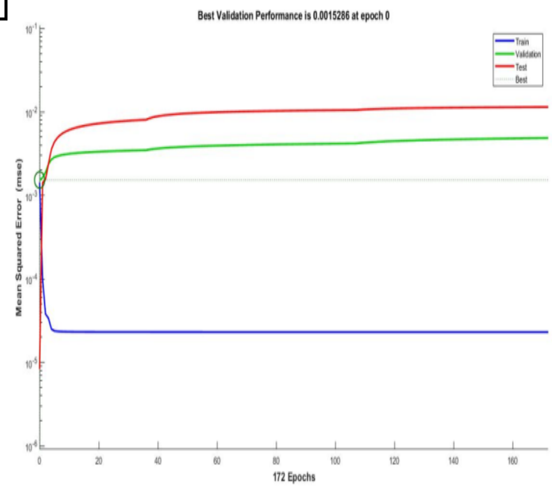

Fig. 4Performance ANN for surface roughness model

Figure 5 illustrates a regression analysis showcasing the correlation between network outputs and network targets. In an ideal training scenario, both the network outputs and targets would align perfectly; however real-world relationship tends to deviate from perfection. The three axes correspond to training, validation, and testing data. On each axis, a dashed line represents the ideal scenario where outputs match targets. In contrast, the solid line indicates the linear regression line that best fits the relationship between outputs and targets.

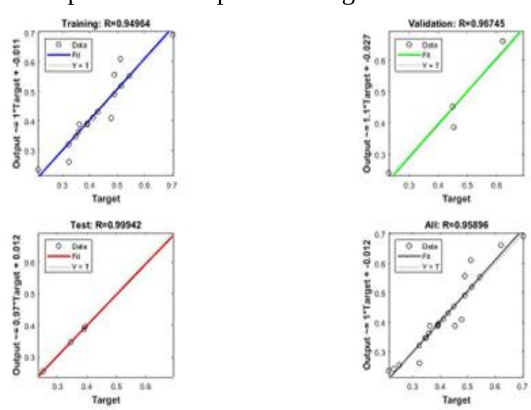

Fig.5 Regression ANN for surface roughness model

The R-value serves as a gauge for the linkage between outputs and targets. An R-value of 1 signifies an exact linear correlation, while an R-value near zero indicates a lack of linear association. In the context of this study [32], the R-value for surface roughness stands at 0.95, validating the accuracy of the ANN model's predictions.

TABLE IV
Comparison of ANN model with experiment results

Speed	feed	Depth	Passes	ANN Model Roughness	Experimental Results Roughness
1300	0.07	0.4	4	0.37766	0.378
1300	0.05	0.2	2	0.3877	0.39
1200	0.06	0.3	3	0.6119	0.622

CONCLUSION

This study introduces an ANN-based approach for modeling the impacts of roller burnishing parameters (depth of penetration, number of passes, feed rate, and burnishing speed) on the surface roughness of EN 19 alloy steel, considering diverse processing parameters. The successful implementation of this approach is evident. As depicted in fig.5, the predictions made by the ANN align closely with experimental outcomes for each average surface roughness value. This congruence implies that the ANN proves to be a valuable alternative [33] for analyzing the influence of burnishing parameters on average surface roughness.

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