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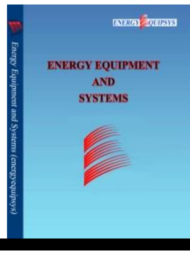

Using machine learning and optimization for controlling surface roughness in grinding of St37

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ABSTRACT

In the context of the industrial grinding process, the quality of products is often assessed by the final surface roughness, which is influenced by various parameters in the industrial environment. Previous studies lacked a feasible formulation based on a kinematical and statistical model to explain the uncertainty and non-linearity of grinding conditions, particularly concerning the cooling method, leading to significant discrepancies between the formulated and real results. This study introduces a novel strategy that combines deep learning and optimization to establish a suitable framework. It employs an artificial neural network to simulate and predict surface roughness, considering various dressing and cooling parameters in the industrial grinding of St37 steel alloy. Initially, an analysis of variance (ANOVA) is conducted to determine the correlation between input and output data. Subsequently, a neural network approach with one and two hidden layers, incorporating various activation functions, is employed. Therefore controlling and improving the accuracy of surface roughness predictions in industrial grinding processes can be automated. The mean squared error (MSE) metric is applied to each implementation to identify the best network architecture for the dataset. Upon selecting the network with the lowest MSE, the final algorithm predicts a set of randomly selected data from the dataset, achieving an overall accuracy of 80%. When compared to the accuracy of the formulated implementation, the neural network approach demonstrates a significantly higher accuracy of up to 30%, surpassing conventional analytical formulation in predicting final surface roughness. These results underscore the considerable potential and feasibility of deep learning approaches for industrial applications.

Keywords: Artificial Neural Networks, Grinding, Surface Roughness Control, Dressing, Sustainable Machining.

1. Introduction

State-of-the-art engineering materials have been extensively used in power plant and energy industrial applications during the last two decades [1]. Grinding is a displacement or position-controlled processing procedure where the excess material from the workpiece surface is removed by using an abrasive tool. The benefits include a high material removal rate, finer surface finishes, and more prolonged production runs [2]. Grinding is a widely used

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machining process for material removal roughing and high-quality finishing operations. Wheel preparation is a vital stage in this process: truing, dressing and conditioning [3]. The ground surface roughness is a prominent resultant of any grinding process depending on the interaction of multiple factors like grinding condition and wheel properties. The value prediction of surface roughness due to the complexity of the real-world procedure is more attention. The empirical and analytical methods find an applicable relationship between the number of active cutting edges and the surface roughness based on the grinding experiment. The traditional statistical analysis, for example, evaluates a distribution function of the grain protrusion heights considering the stochastic nature of the grinding wheel topology. However, the predicted value based on these methods is up to three orders of magnitude smaller than the measured value [4].

The manufacturing of industry 4.0 vision sets a set of special considerations [5], and any grinding process is regarded as one of the most important factors in evaluating the quality of final products due to these criteria; however, for example, wheel type and topography, wheel dressing and conditioning, sizes and wheel-workpiece speed ratio, cooling and lubricating conditions [6], which are interdependent and even non-linearly [7, 8]. The grinding wheel is an uncommon factor, among others, distinguishing the grinding process from other cutting processes. The wheel topography and prepared conditions broadly influence the grinding performance [9, 10]. Surface roughness also signifies the portion of energy and other resources swallowed during machining [11]. To minimize energy consumption and heat reduction dressing procedure should bring an appropriate suitable topography to the wheel-cutting surface [12]. Besides dresser topography, dressing depth, dressing lead/traverse rate, the type of dresser used, and the number of dressing passes [13], the cooling method is another demand that must be in the contraction of research. The thermal damage will produce undesired surface roughness and several cooling alternatives like minimum quantity lubrication (MQL) is a replacement for dry machining in which a minimum quantity of lubricant fluid is mixed up with compressed air and sprayed periodically on the machining area [14, 15]. Applying the MQL approach can decrease the grinding forces, energy consumption, wheel wear, and production costs and generate an adequate surface finish and improved surface integrity compared to dry and fluid conditions [16]. The application of green machining techniques for sustainable manufacturing becomes more and more attractive nowadays to reduce the consumption of energy and cutting tools and cutting fluids and consequently decrease the production costs and environmental effects due to this regard generate different grinding wheel topographies, depth of dressing and dressing speed has been changed during dressing and conditioning of vitrified Al_2O_3 wheels using a single point diamond dresser [17].

Furthermore, the drawbacks of conventional modeling like kinematics and statistics are strongly sensitive to parameter considerations. Besides, the statistical approach could not define qualitative parameters like cooling methods. In this regard, several examinations apply to alter the surface condition in front of parameters. However, besides analyzing experimental data with theoretical and statistical implementation, many studies use prediction methods like artificial neural network algorithms to find an association between parameters. In the literature review, an existing context in the field of machining and grinding processes involves the evaluation of neural networks to determine the relationships between various parameters.

Several deep learning model implementations have been conducted in recent years [18] to provide a model to predict surface roughness in cylindrical grinding of Al-SiC work pieces by a standard aluminum oxide grinding wheel using a feedforward artificial neural network. The study includes a single hidden layer ANN with 12 neurons that runs on a small data set with 25 samples. The data set consists of four parameters wheel velocity, feed, workpiece velocity, and depth of cut as input. The simulation results bring a prediction accuracy of around 94%. Parameters optimization by neural network model is another interesting criterion that was implemented in various studies. Therefore, in

[19], an optimization model on ductile cast iron grinding with wet and minimum quantity lubrication (MQL)cooling conditions was developed by an artificial neural network based on the DOE method. At the continuation of the study, analyze variance with the ANN to investigate significant effects on the performance characteristics and the optimal cutting parameters of the grinding process. The surface roughness and material removal rate (MRR) were measured and used in the feedforward neural network for output. The grind wheel life directly affects the final performance of the CNC machining and grinding process. The results in [20] presented an experiment on actual historical data collected over five processes and optimization schemes using neural model-based to control strategies on the industrial grinding process. Optimizing cooling methods by the effects of nanofluids on machining steel-based tools using neural networks is another aspect of the study. In this way, the research done in [21] provides a small data set to evaluate and measure the performance of the network using R^2 metrics. Besides, the analysis of variance (ANOVA) finds the significant factors that affect the surface roughness in the process. Unlike conventionally available methods to predict a relation between grinding parameters and state-of-the-art surface roughness for an advanced industrial solution, the newly implemented method seems to overcome the complexity of prediction environments. Medical implants were manufactured on special materials like stainless steel, titanium, and CoCrMo alloys. These materials were presented earlier in high-demand construction like aircraft and satellites due to the high-temperature corrosion. The study by [22] provided that WPD and EEMD process signals were collected during the grinding using a hybrid and long short-term memory network model that uses RNN to predict various input signals. Composite materials like super alloys provide a sophisticated infrastructure for high-end production, and due to the wide range of the usage of these materials, it is common that many contexts available in the field machining process. In addition, the results of a study in [23] evaluate the influence of the axial depth of cut, feed per tooth, and cutting speed process parameters on the surface roughness. Therefore, developed statistical techniques to identify the relation between parameters as a prediction method, and then the ANN models were used to obtain a higher accuracy of prediction. Tables 1 and 2 illustrate a complete summary of available research in the industrial grinding and machining process that implements artificial neural networks as a ground truth approach to predict and find a relation between input parameters and surface roughness.

Table 1. The overall schema of available research that implements any neural network algorithms to predict grinding parameters

	Neural Network method	Input size	Measured target	output size	Cooling Type	Data set size	Developed platform
1	Cutting speed, Wheel speed Feed, Depth of cut	4	Surface roughness	1	N/A	25	MATLAB
2	Table speed Depth of cut	2	Surface Roughness, MRR	2	Wet MQL	27	MATLAB
3	N/A	N/A	lifetimes to gauge the performance, Removal rates	N/A	N/A	N/A	N/A
4	Cutting speed, Feed Depth of Cut	3	Surface Roughness	1	nanofluids	8	MATLAB
5	Grinding force, Vibration, Acoustic emission signals	N/A	Surface roughness	N/A	N/A	N/A	N/A
6	Axial Depth of Cut, Feed per Tooth, Cutting Speed	3	Surface roughness	1	Dry	15	LabView

Table 2. Implementing appropriate input and target parameters is necessary for a supervised neural network

	Grinding type	Simulation method	Alloy workpiece	Wheel type	Year	Reference
1	cylindrical grinding	ANN	LM25/SiC/4p metal matrix composites (MMC)	vitrified-bonded white aluminum oxide	2014	[18]
2	surface grinding	ANN	ductile cast iron	vitrified bond aluminum oxide PSA-60JBV	2015	[19]
3	disk grinding	ANN	aluminum	N/A	2005	[20]
4	CNC surface grinding	ANN	raw steel	10 um vitrified alumina grinding wheel	2014	[21]
5	surface grinding	LSTM (RNN)	C-250 maraging steel	CBN grinding wheel	2021	[22]
6	dry end-milling	ANN	Co–28Cr–6Mo Co–20Cr–15W–10Ni both biomedical alloys	AlTiCrSiN PVD-coated tool	2021	[23]

Literature review shows that it is necessary to conclude the most important aspects that did not appear in the previous research; such as:

- the effects of dresser parameters on surface roughness
- cooling method which is another crucial parameter that is negligible or just one method used as a default
- researchers use a small portion of the data set for studies and neural network implementation
- for a professional neural network implementation, different structures and architecture must be considered, like different neuron sizes and activation function

2. Materials and Methods

2.1 Neural network

The concept behind the neural network is to simulate human brain functionality like training and learning by mathematical and statistical formulation [24]. For emulation of a human neural network, an artificial neural network consists of simple computing units called neurons, each unit connects via weighted connectors, and the optimum computing weight related to specific inputs call learning [24, 25]. The artificial neural network is a part of a machine learning procedure that produces unique computational implements based on a statistical approach to solve real-world problems. The outstanding feature of this approach is the ability to overcome nonlinearity, parallelism, and noise tolerance [26]. The learning system comprises the relationships between the data. Data is input along with the consequences related to the data. The system training and the neural network algorithm relate the data to the results and create rules that become part of the system[27]. In the field of neural networks, there are several varieties based on architecture and data structures, but there are three primary majors that are distinguishable in this field Artificial Neural Networks (ANN), Convolution Neural Networks (CNN), and Recurrent Neural Networks (RNN). The Artificial Neural Network (ANN) is a group of multiple perceptrons (or neurons) at each layer. ANN is also known as a Feed-Forward Neural network because the inputs are processed only in the forward direction [28]. The ANN is capable of learning and solving any nonlinear function[26], and because of that, this network is popularly known as Universal Function Approximation. One of the main reasons behind this is to choose any appropriate transfer function for any neuron in the network. In general, the ANN is appropriate to overcome problems related to tabular data (regression methods), image data (classification), and text data. However, the ANN uses a backpropagation algorithm for finding gradient error and minimizing it. In some cases, due to the intense network (network with a large number of hidden layers), these algorithm leads to vanishing and exploding gradient. Also, the ANN cannot predict sequential information in the input stream [29]. The multilayer perceptron neural network (MLP) is a feedforward structure in which the nonlinear components (neurons and nonlinear transfer function inside) are connected in a straight layer style, and the calculation and data stream flow unidirectionally from inputs to output (Fig. 1). The number of input and output depends on the representations of problems and data sets available for prediction. The MLPs with an arbitrary number of hidden units are universal approximators for continuous maps to implement any function [30].

2.2 Experimental Setup

The experimental data have been collected from the previous study [14], conducted by a vitrified bond Al_2O_3 grinding wheel. The workpiece was St37-soft steel (83±3 HRB) with a 65-mm length in grinding direction and 12 mm in width. A Single-point diamond dressing tool was used with an access angle α_d=10°. Three different cooling methods were utilized during the grinding process: dry, water-based, and MQL with compressed air and argon. The surface roughness measurements were performed after the tenth pass by a mobile roughness measurement (Surface Tester-TR200 with a cutoff length of 0.8 mm according to DIN EN ISO 3274:1998). At the end of each test, Ra across the grinding direction was measured at five different points on the ground surface. The evaluated grinding experiments consist of several fixed parameters, and a few parameters vary during the process to measure their effects on the surface roughness as an output parameter. Table 3 illustrates a complete description of all fixed parameters during the current experiment.

In case of monitoring the sensitivity of surface roughness to special grinding conditions, the study assumes that Ra has a direct correlation with the undeformed chip thickness ($h_{eq} = \frac{Q'_w}{V_c}$), depth of dressing ($a_d$), axial feed (pitch) of the dressing tool per wheel revolution is called the dressing lead (or axial dressing tool traverse across grinding wheel surface) - (s_d) and also different cooling methods. Besides the qualitative variable parameters like a_d and s_d, the cooling methods also directly affect surface roughness, but this is a qualitative parameter with no quantitive amount defined for them. All these variable parameters are depicted in the Table 4.

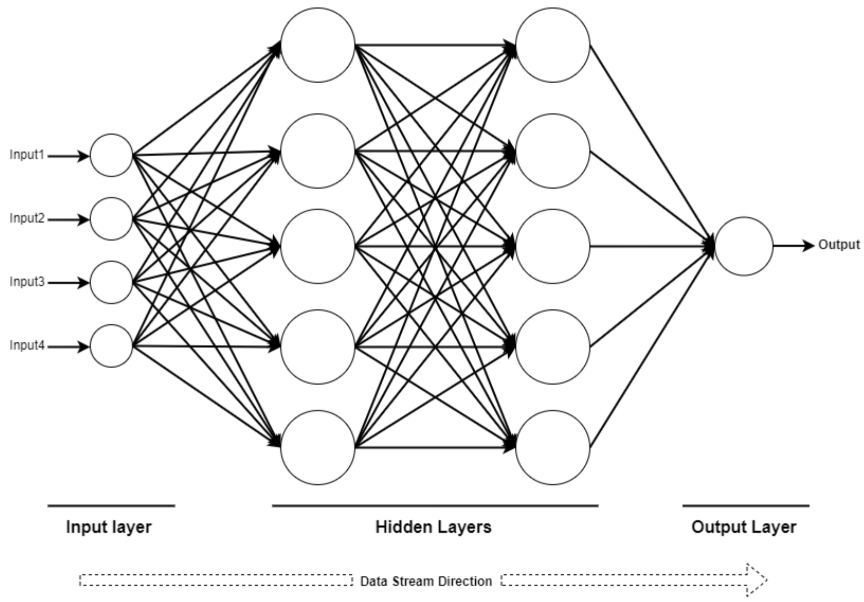

Fig.1. Any neural network architecture includes input and output layers in every case. The hidden layers define the complexity of the network

Table 3. Experimental setup and parameters

Grinding elements	Parameters
Mode	Plunge surface grinding, down cut
Machine	MST-300-1000 universal surface grinder
Wheel	Al_2O_3: AW60L5V28103 (ds=250 mm)
Wheel Speed ($\boldsymbol{V_c}$)	26 m/s
Feed Rate ($\boldsymbol{V_{ft}}$)	2500 mm/min
Depth of Cut ($\boldsymbol{a_e}$)	5 µm
Coolant-lubricant environments	Dry, Fluid (water-based), MQL with compressed air, MQL with compressed Argon
Conventional Coolant Wet	Water-miscible coolant lubricant at 5% concentration
Conventional Coolant Flow Rate	18 lit/hr
MQL Oil	Vegetable oil
MQL flow rate	150 ml/hr
MQL Viscosity (at 20°C)	84 cP
MQL Carrier Gas	Compressed air, Compressed Argon
MQL Gas Pressure	4bar
Workpiece Material	St37-soft steel with 83±3 HRB
Workpiece Dimensions	65mm×12mm×58mm
Dresser Material	Diamond
Dresser Type	Single point
Dresser Access Angle ($\boldsymbol{\alpha_d}$)	10°

Table 4. In the current implementation, several grinding parameters are assumed to be set and changed in five important parameters defined in the table, and each parameter has several quantities.

Grinding variable parameter	Value
Depth of each dressing pass ($\boldsymbol{a_d}$)	3,15,30,45 µm
dressing lead; axial dressing tool traverse across grinding wheel surface ($\boldsymbol{s_d}$)	0.06041, 0.1762, 0.3021 mm
Cooling Type	Dry, Wet, MQL with air, MQL with Argon

2.3 Cooling and Dressing Methods

Excessive heat generated during the grinding process can damage the work material's surface and flaws due to inadequate removal rates and wheel wear [31]. Power consumed by the process flows into the wheel, work, chip, and coolant. The heat entering the workpiece must be removed quickly to prevent high local temperatures and phase transformations from developing and prevent high residual temperatures after the wheel has passed [32]. For this reason, an appropriate cooling method like dry or lubricating fluid and process parameters can help reduce heat generation. The application of an appropriate cooling method performs a significant role in the quality of grinding surface roughness [33]. In dry grinding conducted in standard machining processes like milling, drilling, and turning because of saving a large number of resources such as cooling lubricant, pump system, and also air pressure system made the whole dimensions of the system quite compact and there it is common in the most grinding process [34]. Dry grinding provides a perfect optical view, direct cutting force measurements, and the simplified determination of process heat flows, but the main demand is excessive heat generation. The application of water-based cutting fluids due to less environmental threat in addition to high thermal conductivity and supreme cooling/lubricating efficiency is sufficient [35]. Coolants and lubricants have an important place in the industry in terms of both environmental, health, and economic aspects [32]. The minimum quantity lubrication (MQL) originally has been developed primarily to reduce the cost of production by utilizing a less amount of lubricant (Table 5). The MQL method, where oil is utilized as cutting fluid, is found to improve the lubrication to a considerable extent and the specific energy requirement becomes less compared to the conventional jet cooling method. However, the tool's and work surface's cooling capacity are poor [33]. This technique is a recognized opportunity to eliminate environmental concerns [32].

The dressing is the key factor determining the grinding wheel surface condition (topography) in micro/macro conditions, which determines the grinding wheel performance [40]. The conventional mechanical dressing process is nowadays the most widely used dresser tools in industry, including stationary dressers and rotary dressing wheels [41]. For this reason, mechanical dressing with diamond tools has become a popular method for retrieving the grinding capabilities and wheel geometry. The stationary type consists of a single-grain diamond that is embedded in one shank and a multi-point tool that has many small diamonds embedded into the one diamond section [42] (Fig. 2).

Table 5. Mineral-based cutting fluids are common practice in the industry; however, they are hazardous to our ecology and health. There is a need to implement a sustainable cooling/lubrication system that helps the environment and improves the machinability of alloys [39]. The current table illustrates three main categories of cooling methods in the industry.

Coolant Category	Materials	Symbol	description
Dry	Air	Dry	Air jet [34], sometimes steam contained in the air [36]
	Cold air guns	CAG	A method to obtaining cold air using the phenomenon occurring in the centrifugal tube [36]
Water Base	Water with Oil	Wet	A mixture of water and soluble oil [38, 39]
	Water, Surfactant, Graphene	Wet, W-S W-G	A mixture of Water with Surfactant or Graphene or both (Ni et al., 2019)
Minimum quantity lubrication (MQL)	Oil Base	MQL	A mixture of oil and compressed air sprayed on the grinding wheel [32]
	Water Soluble Oil and Air	MQC	A mixture of water and compressed air. this method is more efficient than MQL in terms of cooling but lubrication lower than MQL [36]
	Oil and Air	MQCL	A unique method consists of certain oil with low viscosity and compressed air with a temperature of around -30, which increase the efficiency of cooling besides lubrication [32, 36]
	Oil and Cold Air	CAMQL	Oil transported by a stream of compressed cooled air [36]
	Oil and Cold Air	CAOM	A cold air and oil mist method, oil transported by compressed air stream using MQL method and an additional cold compressed air stream delivered simultaneously by the cold air gun [36]

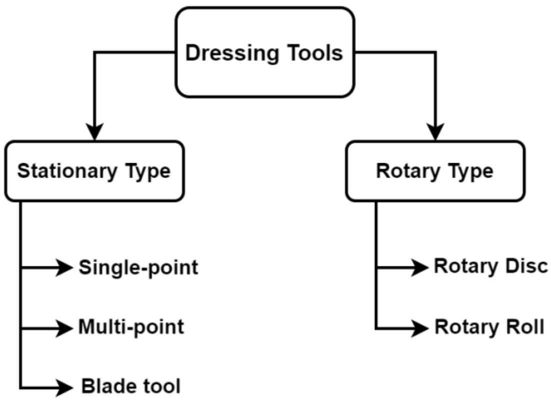

Fig. 2. The diagram of available industrial diamond dresser tools in the market

3. Results and discussion

3.1 Implementing Data-set

Machine learning and deep learning models are very powerful in predicting various phenomena. Those models require a particular amount of data to train on to achieve reasonable predictions, whereas this amount is generally limited and challenging to obtain [43]. It is common knowledge that few training data results in a poor approximation. In other words, too little test data will result in an optimistic and high variance estimation of model performance [44], regardless of other publications that did not consider any attention to the effect of data size on simulation purity. The current study provides sufficient data, including 57 different conditions in the industrial grinding process. The data set includes five different parameters. Three of them are input measured before the setup experiments procedure, and one of them is the mean surface roughness that was measured three times from three different points by a standard calibrated device. The last row of data is calculated surface roughness by the experimental formula conducted in the previous study. The most sophisticated part of data-set implementation is to describe qualitative parameters as a part of quantitive ones to be processable in any prediction algorithms. For this reason, assigning a non-zero positive real number for each type of qualitative input parameter is necessary. The cooling methods implemented in the study were Dry, Wet, MQL with Air, and MQL with Argon; therefore, four numbers like 1 to 4 were assigned to them. All the parameters and assignments are tabulated in Table 6 and the random data for the primary data set are illustrated in the Table 7.

Another assumption in the previous study was a direct correlation between ground surface roughness and grinding parameters like undeformed chip thickness, depth of dressing, and axial dressing tool traversing across grinding wheel surface and also cooling method. The relation was described in (Eq.1), where Q'_w is the volumetric removal rate per unit width and R_1 is an experimentally determined constant for different cooling conditions. Table 8 shows different values of R_1 for four coolant-lubricant conditions used in the study.

$$R_a = R_1 s_d^{0.5} a_d^{0.25} \left(\frac{Q_w^{'}}{V_c} \right)^{0.25} \tag{1}$$

Table 6. As mentioned in table 5, the current implementation contains three parameters as input, each of which has several values illustrated in this table.

Grinding variable parameter	Value
Depth of each dressing pass ($\boldsymbol{a_d}$)	3,15,30,45 um
axial dressing tool traverse across grinding wheel surface ($\boldsymbol{s_d}$)	0.06041, 0.1762, 0.3021 um
Cooling Type	Dry = 1, Wet = 2, MQL Air = 3, MQL Argon = 4

Table 7. A set of 12 random data from the main dataset. The current dataset includes 57 sets of data for the grinding process.

	Input Parameters			Output Parameters	
	a_d; (μm)	s_d; (mm)	Cooling Type	R_a $(Experiment)$; (μm)	R_a $(Formula)$; (μm)
1	3	0.1762	1	0.357	0.4525
2	15	0.06041	1	0.535	0.471
3	10	0.157	1	0.46	0.869
4	3	0.3021	2	0.57	0.4837
5	30	0.1762	2	0.42	0.6569
6	45	0.06041	2	0.53	0.4256
7	15	0.06041	3	0.454	0.3898
8	30	0.3021	3	0.843	1.037
9	45	0.1762	3	0.74	0.8763
10	3	0.3021	4	0.45	0.4695
11	10	0.157	4	1.47	1.02
12	30	0.1762	4	0.498	0.6376

Table 8. R_1 Values for different coolant-lubricant conditions

Grinding condition	Dry	Wet	MQL with Air	MQL with Argon
R_1	0.0864	0.07054	0.085025	0.06847

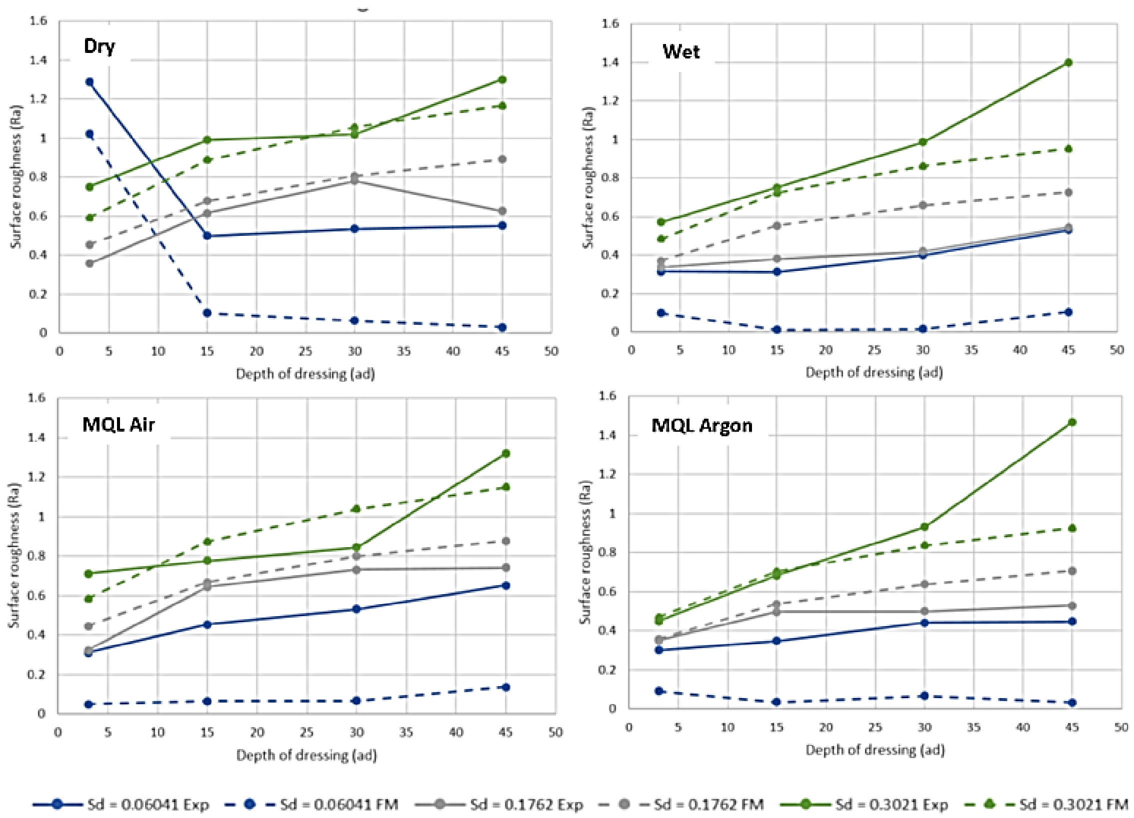

Fig. 3. The effects of depth of dressing on final surface roughness at the different cooling methods and also different axial dressing tools traversing across grinding wheel surface. The plot includes experimental data (Exp) and formula-based calculated data (FM)

3.2 The effects of Cooling and Dresser

In the first steps, to investigate the effects of different factors on the surface roughness as target parameters plotting software is employed. The data set includes 57 different points on various conditions from surface grinding St73-soft steel. It is worth mentioning that due to the influence of dresser parameters and cooling conditions on the final results. Before each test, the health of tools (especially the grinding wheel and dresser) was examined, and also, after each dressing procedure, the examination rehappened. As a result, shown in Fig.3, four different plots are available, and all of them investigate the effect of depth of dressing pass on the final surface roughness. For each cooling method, each plot includes all the axial dressing tools traversing across the grinding wheel surface (s_d) as the second effective parameter on the final condition. It is clear that surface roughness can be worse by the increasing depth of pass and dressing traverse.

On the other side, the effects of the cooling method on the final surface condition show that the MQL with Argon gas can bring the best result in the small depth of dressing and feed, but in harsh conditions, none of the cooling methods can stand aside exceeding the temperature and final surface roughness get worse and also in some situation workpiece surface got burned. Besides experimental data, the formulated situation is plotted and illustrates that formulation cannot accurately calculate the fine results and especially the bias between real data and formulated one in the harsh condition is so high.

It is crucial that finding an appropriate solution to predict or calculate surface roughness can help industries for less activity in many aspects; to improve the machining process, a surface roughness prediction model is developed. There are three common techniques for the development of a prediction model: multiple regressions that use machine learning algorithms for prediction, physics-based modeling that implements mathematical formulation to investigate results from available grinding parameters, and ANN technics. The ANN is one of the most widely used artificial intelligence techniques and has been successfully employed by researchers. It has the ability to learn the mapping between a set of input and output values.

3.3 ANOVA Analysis

The Analysis of Variance (ANOVA) test has long been a vital mechanism for researchers performing studies on multiple experimental classes. However, it cannot provide precise information on differences among the various study groups between them or on complex combinations of groups [45]. ANOVA is used to disintegrate the entire variability to quantify the effect of input parameters on output ones [46]. The percentage contribution of inputs was estimated based on the sum of squares of responses. This method of portioning variability into identifiable sources of variation and the associated degree of freedom in the model [18]. The current study considers three parameters as control (input) parameters, and surface roughness for this data set was evaluated from the experimental value of the data set. Table 9 illustrates the response surface; quadratic models summarize the ANOVA of each response and show the significant model terms of analysis on the current data set.

3.4 Network configuration

The multilayer perceptron neural network (MLP) is a feedforward structure neural network in which the nonlinear elements (neurons and nonlinear transfer function inside) are connected in a successive layer manner [30]. The number of input and output depends on the representations of problems and data sets available for prediction [47]. As mentioned before, for the current study, both neural network with one hidden layer (Fig. 4a) and two hidden layers (Fig.4b) was implemented to enrich a proper configuration for the data set. In Fig.4, suppose that there are m input series in the input layer (for the current study, m is 3), and for each data series x_i $(i = 1,2,\ldots,m)$ represents the inputs to hidden layer neurons. In the same way, defining the output of neurons in the hidden layer, j represents the number of neurons, and y_j represents the output of neurons in the hidden layer. The network has just one neuron as the output layer, and therefore z represents the output layer's final result. For the hidden layer, the bias value is γ, and ω is the connection weight from the input layer to the hidden layer. Consequently, for the output layer, θ represents bias, and ν represents the connection weight from the hidden layer to the output layer. The overall simplified relation between input and output for one hidden layer network is defined by

$$y_j = f\left(\sum_{i=1}^{m} \omega x_i - \gamma\right). \tag{2}$$

$$z = \sum_{i=1}^{s} \nu y_j - \theta \tag{3}$$

Table 9. The final solution of the ANOVA implementation on the current data set

Parameter	Sum Sq.	dF	Mean Sq.	F	P-Value
Cooling Type	0.316	3	0.105	2.77	0.055
a_d	0.763	3	0.254	6.68	0.001
s_d	1.936	2	0.968	25.39	0
Error	1.486	39	0.038	-	-
Total	4.502	47	-	-	-

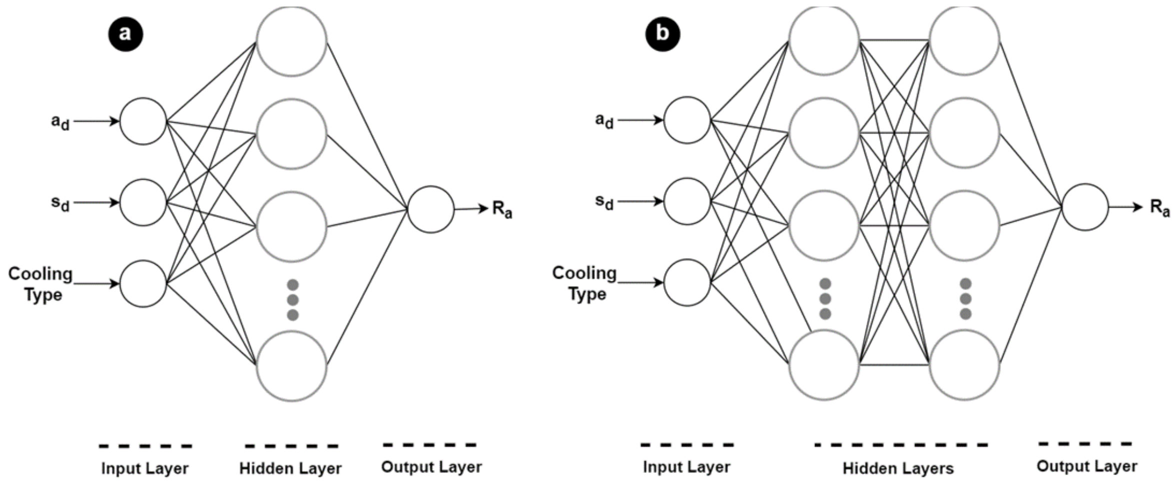

Fig. 4. The feedforward neural network with one hidden layer (a) and two hidden layers (b), also known as the deep-learning network, implies something profound. This system uses a deep thinker algorithm to reach a reasonable answer. Both architectures were implemented in an intelligence coding algorithm to reach the best structure with a reasonable solution.

For a network structure with two hidden layers (Fig.4b), Eqs. (2) and (3) do not change. Where upper right index 1 refers to the first hidden layer and upper right index 2 refers to the second hidden layer. However, the final result of the second hidden layer is the input of the output layer and does not change on objective function definition, but it is clear that partial calculation for a deep network, as given by

$$y_j^{(1)} = f^{(1)}\left(\sum_{i=1}^{m_1}\omega^{(1)}x_i - \gamma^{(1)}\right) \tag{4}$$

$$y_j^{(2)} = f^{(2)}\left(\sum_{i=1}^{m_2}\omega^{(2)}y_j^{(1)} - \gamma^{(2)}\right) \tag{5}$$

is more difficult. The Training network aimed to determine the optimum network parameters, including the number of hidden layers, hidden neurons, transfer function layers, and weight values for achieving the best network of modeling. Parameters were usually changed to minimize network errors in training and testing mode to obtain the optimum model. To reach an optimum model, several parameters are defined as the fixed structure of the network and shown in Table 10, then implement both one hidden layer and two hidden layers structures separately with neuron size change and to verify the network accuracy of the MSE parameters evaluated, the results of the trained network illustrated in Fig. 5.

Table 10. The overall ANN properties of the current implementation

Network Configuration		Learning Condition	
Object model	R_a	Learning Scheme	Supervised Learning
Input neurons	a_d S_d $Cooling\ Type$	Learning rule	Gradient descent
		Hidden neurons	6 ~ 20
		Output neuron	1
Output neuron	R_a	Sample pattern	80% train 10% validation 10% test
Transfer Functions	Purelin Tansig Logsig	Learning rate	0.01
		Marquart adjustment	Mu = 0.05
Training Function	TRAINBR	Max. epoch	1000
Learning Function	LEARNGDM	Goal	0.001

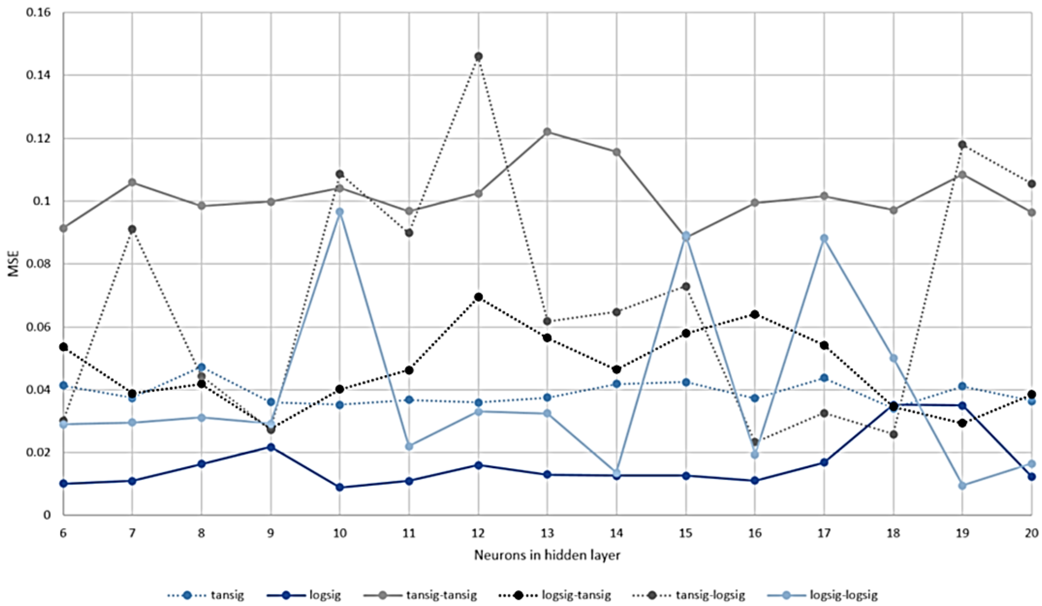

Fig. 5. The final results of different network implementations are depicted in the above figure. As mentioned, two network structure with one hidden layer and two hidden layers was implemented. Each hidden layer contains activation functions like tansig and logsig and several neuron sizes. This figure illustrates the number of neurons size versus MSE for accuracy metrics of implemented network.

Accuracy metrics refer to the procedure used to evaluate machine learning predictions' validity. However, selecting an appropriate accuracy metric for assessing a specific prediction has not yet been specified [47]. The correlation coefficient (R) and coefficient of determination (R^2) are widely used for the evaluation of the goodness of linear fit of regression models in ANNs [48]. The R value represents the degree of correlation between the actual and predicted variables and can vary from −1 to +1. The value of +1 (or −1) indicates the perfect correlation between two variables. The R^2 value is the ratio of the predicted variable that explains the regression model. In other words, it is the ratio of the explained variable to the total variable. R^2 is the square of correlation between the actual variable and predicted, which is calculated using

$$R = \frac{\frac{1}{n}\sum_1^n\left(D_{act}-\bar{D}_{act}\right)\left(D_{pre}-\bar{D}_{pre}\right)}{\sqrt{\frac{1}{n}\sum_1^n\left(D_{act}-\bar{D}_{act}\right)^2}\sqrt{\frac{1}{n}\sum_1^n\left(D_{pre}-\bar{D}_{pre}\right)^2}} \quad (6)$$

$$R^2 = 1-\frac{\sum_1^n\left(D_{pre}-\bar{D}_{pre}\right)^2}{\sum_1^n\left(D_{act}-\bar{D}_{act}\right)^2} \quad (7)$$

where D_{act} is the actual variable, D_{pre} is the predicted variable, $\bar{D}_{act}$ is the mean value of the actual variable, $\bar{D}_{pre}$ is the mean value of the predicted variable, and n is the amount of collected data. Metrics based on absolute errors or squared errors are called scale-dependent metrics [49]. The scale-dependent metrics have the same scale as the original data and provide errors in the same units [39]. However, the scale-dependent metrics can be difficult to compare for series on different scales or with different units. Although the scale-dependent metrics are not unit-free, they are favored in machine learning evaluation. The commonly used scale-dependent metrics is MSE [47] given as

$$MSE = \frac{1}{n}\sum_1^n\left(D_{pre}-D_{act}\right)^2 \quad (8)$$

As shown in Fig.5, the best structure for neural network implementation with stable behavior is related to the logsig transfer function; furthermore, this transfer function provided better results for both single-layer and dual layers neural networks. In this conclusion, the final results for a single-layer neural network with 16 neurons and dual-layers with eight neurons in each layer are shown in Table 11 and Fig.6.

Table 11. The final results of the dual and single-layer neural network on a random set of data set a test bench

Dual hidden layers neural network					Single hidden layer neural network				
Cooling	a_d	S_d	Ra (Exp.)	Ra (Pred.)	Cooling	a_d	S_d	Ra (Exp.)	Ra (Pred.)
1	3	0.3021	0.75	0.9495	1	15	0.1762	0.615	0.5546
1	15	0.06041	0.498	0.8761	1	15	0.3021	0.99	0.8239
1	30	0.3021	1.02	1.0699	1	45	0.3021	1.3	1.2385
2	3	0.3021	0.57	0.6284	2	45	0.1762	0.545	0.7345
3	3	0.1762	0.323	0.354	3	15	0.06041	0.454	0.3823
3	15	0.06041	0.454	0.4264	4	3	0.1762	0.35	0.3807
3	30	0.1762	0.731	0.664	4	3	0.3021	0.45	0.6786
3	45	0.3021	1.32	1.4297	4	15	0.06041	0.349	0.3968
4	30	0.06041	0.441	0.3867	4	15	0.3021	0.683	0.8425
4	45	0.06041	0.447	0.4352	4	30	0.06041	0.441	0.436

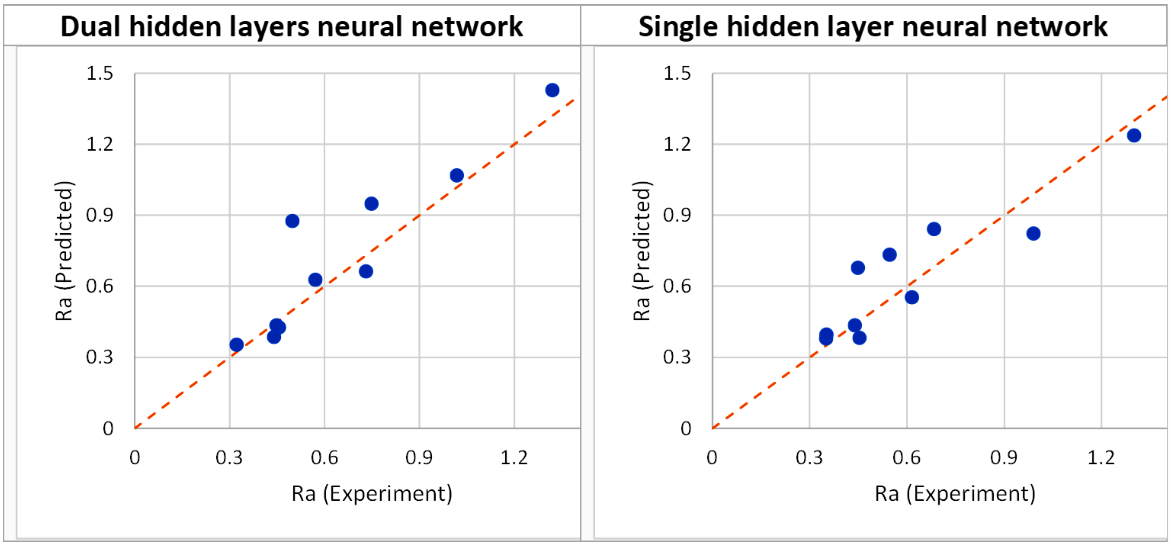

Fig. 6. Results demonstration and comparison for both dual and single-layer neural network

The test data set is a small portion of random data from the main data set. The results of the implemented neural network provided an accuracy of around 80%, illustrated in Table 11 and Fig. 6. However, from the final results, the dual-layer neural network provided a more accurate prediction than the single layer.

4. Conclusion

The present study investigates the impact of industrial dressing process parameters and grinding cooling-lubricating methods on surface roughness, considering dressing depths of 3, 15, 30, and 45 μm, dressing leads of 0.06041, 0.1762, and 0.3021 mm, and four cooling methods: dry, water-based grinding fluid, MQL with compressed air, and MQL with Argon. The study uses St37 soft alloy as the workpiece material. The key findings of this research are as follows:

1. Increasing the depth of cut and axial traverse rate of the dresser leads to a higher number of cutting micro-edges and increased heat generation in the grinding zone. Water-based and MQL-based methods effectively dissipate heat, with MQL using Argon being particularly efficient due to its superior heat transfer coefficient. However, at higher cut depths and traverse rates, the generated heat can surpass the coolant's

heat transfer capacity, potentially resulting in workpiece burning and inadequate surface roughness.

2. The ANN-based predictive model demonstrates promising performance in predicting surface roughness, achieving an average percentage error of approximately 20% on the existing dataset. The model is used to analyze the influence of process parameters on surface roughness.

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