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A Machine Learning Method for Cutting Parameter Selection in Rotary Ultrasonic-Assisted End Grinding

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ABSTRACT

Recently, rotary ultrasonic-assisted end grinding (RUAEG) has been utilised since it can increment the pace of material elimination and reduce the thrust force. Assigning ultrasonic vibration to the tools was more significant than the other grinding parameters. However, there is no systematic way to choose the cutting parameters to reach efficient outcomes (lower surface roughness and thrust force). The present research employs an adaptive network-based fuzzy inference method to model the RUAEG outcomes, including surface roughness and thrust force, based on the cutting parameters. Moreover, a single objective genetic algorithm is employed to calculate the optimum hyperparameters of the developed adaptive network-based fuzzy inference to reach the highest efficiency. At the end of the process, the multi-objective genetic algorithm is applied to find the optimal machining parameters of RUAEG to achieve the lowest surface roughness and thrust force. The approach is developed using MATLAB with the practically extracted dataset by RUAEG and conventional end-grinding processes of silicon nitride. The optimal cutting parameters are recommended to reach the lowest surface roughness and thrust force. The recommended optimal cutting parameters were able to reach 0.5177 (μm) and 11.8103 (N) for surface roughness and thrust force using the RUAEG method.

Keywords: Ultrasonic Grinding, Silica, Fuzzy Neural Network, Genetic Algorithm, Thrust Forces, Surface Roughness.

NOMENCLATURE

AHP	analytic hierarchy process
ANFIS	adaptive network-based fuzzy inference system
CEG	conventional end grinding
DoC	depths of cuts
FIS	fuzzy inference system
FS	feeding speed
GA	genetic algorithm
MSE	mean square error
RMSE	root mean square error
RNN	recurrent neural network
RS	rotational speed
RUAEG	rotary ultrasonic-assisted end grinding
SR	surface roughness
SVR	support vector regression
TF	thrust force
TOPSIS	technique for order preference by similarity to ideal situation
VMM	Visual Measurement Machine

I. INTRODUCTION

Ultrasonic machining is a subtractive and non-conventional mechanical material removal process generally associated with low amplitude vibrations and a higher frequency of a tool against the material surface. It is employed in machining non-metallic and conductive materials [1-4]. The preferable materials are low

ductility and more than 40 HRC hardness, such as silicon nitride, inorganic glasses, nickel/titanium alloys, etc. [5, 6]. A transducer/booster combination is employed to convert the high-frequency electrical energy to mechanical vibrations in amplitudes of 0.05 to 0.125 (mm) and vertical frequencies of 18 to 40 (kHz) [7]. Ultrasonic machining does not cause residual stress or thermally destroy the workpiece. These are critical points for the survival of brittle materials in service.

Owing to the brittle nature of Silicon nitride (Si_3N_4), it is not possible to absorb higher stresses through plastic deformation. Thus, cracks and subsurface damage are induced by machining and mainly grinding processes in the workpiece [8]. Furthermore, the workpiece fails under periodic mechanical loadings [9]. Novel machining methods are also limited because engineering ceramics are used mostly as electrical insulators. The reason is that the approaches like electro-discharge or electrochemical machining need a conductive component [10].

Moreover, higher surface quality is needed owing to the use of Si_3N_4 in sensitive locations like turbine blades. The laser-machining method has been presented to solve the machining problem of ceramic parts [11, 12]. However, it also has disadvantages like the complexity of material machining with a greater than 6 (mm) thickness, high price, needs for a professional operator, and lower productivity [13]. Therefore, other methods are utilised, such as ultrasonic vibration on the tool, via instruments with different materials like diamond grinding and SiC to machine Si_3N_4 .

Kumabe and Masuko [14] proposed the principle of utilising vibration-assisted machining approaches for the first time. Adding up to 40 (kHz) frequency with a 2–30 (μm) ultrasonic vibration amplitude on the workpiece tool is the principle of the designated method [15]. According to Kato and Takeyama [16], chip size and machining forces are reduced in ultrasonic-assisted drilling compared to conventional drilling. Barani *et al.* [17] also confirmed this phenomenon. The creation of the built-up edge is decreased by decreasing the force. Hence, using ultrasonic vibration assistance enhances the hole quality. The ultrasonic-assisted machining has been modelled using different methods, including analytical [2, 3], numerical [1], and artificial intelligence-based [18] methods. As one of the most accurate models, Jamshidi and Nategh [2] proposed the precious

analytical model of the ultrasonic-assisted machining model to calculate the frictional behaviour of the process.

There are three ultrasonic-assisted grinding parameters, including feeding speed (FS), rotational speed (RS), and depths of cuts (DoC), that has direct effects on the output of the process as thrust force (TF) and surface roughness (SR). Jamshidi and Budak [19] investigated surface burn as the disadvantage of the grinding process using a different range of grinding selection parameters. Later, Jamshidi and Budak [20] proposed the framework for the selection of the grinding conditions. Their proposed method can be used in integrated digital twins to enhance productivity and part quality with respect to the constraints.

The rotary ultrasonic-assisted machining procedure is an operation oriented by exerting ultrasonic vibration on the instrument [21]. Uhlmann *et al.* [22] used rotary ultrasonic-assisted surface machining for the first time. They examined the effect of various tools in different DoC and RS on the material removal rate and surface quality. Moreover, TF, chip, and burr in vibration-assisted drilling and conventional drilling were studied by Amini *et al.* [23]. The ultrasonic-assisted rotary cutting of ceramic matrix composites was studied by Li *et al.* [24]. They found a significant effect of FS on the machining force. Liu *et al.* [25] investigated the Longitudinal torsional coupled rotary ultrasonic-assisted drilling of carbon fibre-reinforced polymers drilling to eliminate the burr, delamination and tear. They decreased the damage factors by 69.67% compared with conventional drilling. The SR and TF in rotary ultrasonic-assisted end grinding (RUAEG) were studied by Baraheni and Amini [26, 27]. RUAEG caused surface and subsurface damage. Thus, further studies are required in this regard. Then, to achieve the desired quality, ceramic grinding parameters should be correctly adjusted, including RS, cutting velocity, grain size, and type of adhesive.

Researchers used the multi-objective genetic algorithm (GA) in different domains of the manufacturing fields to extract the optimal process parameters whenever there are different collaborating objectives simultaneously [28]. Shen *et al.* [29] developed a hybrid model with a support vector machine and a fuzzy adaptive network for estimating the material removal process in rotary ultrasonic machining. The results prove the model's efficiency compared to a single support vector machine and fuzzy adaptive network.

Norouzi *et al.* [30] modelled and optimised the ultrasonic welding process using feedforward neural network, GA and particle swarm optimisation. They were able to increase the strength of the final product by 10% in comparison with a non-optimised method. The extraction of optimal process parameters of the grinding process using a fuzzy inference system (FIS) is investigated by Virivinti and Mitra [31]. Fuse *et al.* [32] proposed the hybrid model with the combination of FIS and analytic hierarchy process (AHP) or technique for order preference by similarity to the ideal situation (TOPSIS) to predict the machinability of titanium alloys. Inapakurthi *et al.* [33] used a recurrent neural network (RNN) to model the industrial grinding operation based on selecting different hyperparameters, such as hidden layers, number of nodes, etc. Miriyala and Mitra [34] used the deep learning method to identify integrated grinding circuits. Sharma *et al.* [35] optimised the integrated grinding circuit considering chance-constrained programming. The improved process compared with conventional box and budget sampling techniques. Sauter *et al.* [36] detected the grinding burn using unsupervised machine learning methods. Safarzadeh *et al.* [37] estimated the roundness of the product in the centerless grinding process using support vector regression (SVR) and gaussian process regression models. Miriyala *et al.* [38] proposed the evolutionary-based neural network model in a surrogate model to optimise the continuous crystallization process in industrial applications. Their proposed methodology improved the magnitude speed by five orders compared with a high-fidelity physics-driven model. Recently, Inapakurthi and Mitra [39] proposed the optimal surrogate method in the industrial grinding process using SVR. Using their proposed method, they reached 99.88% and 71.40% of the least root mean square error (RMSE) and correlation value.

There is no systematic method to calculate the SR and TF during the RUAEG of Si_3N_4 considering the machining parameters, consisting of FS, RS and DoC. Here, an adaptive network-based fuzzy inference system (ANFIS) machine learning method is a candidate to be trained to calculate the Si_3N_4 grinding outcomes based on the cutting parameters. In addition, the single objective GA optimisation technique is employed to extract the ANFIS model's optimal hyperparameters. It can increase the efficiency of the machine learning method in predicting the RUAEG outcomes. At the final step of this study, multi-objective

GA is applied to find the optimal RUAEG parameters of Si_3N_4 to achieve the finest surface with the cooperation of low TF during the machining. In addition, the proposed method is also implemented in the conventional end grinding (CEG) process beside RUAEG to prove that the newly proposed method is efficient. Also, water and CO_2 gas are used as a coolant despite most previous research.

The next Section provides a detailed description of the proposed methods and experiments. A regenerated experimental dataset explains the proposed methodology in Section III. In this Section, multi-objective GA and ANFIS single objectives are explained. In Section IV, the proposed method is implemented in the MATLAB program. Also, the most suitable RUAEG parameters are extracted in this Section. Finally, the conclusion is presented in Section V.

II. MATERIALS AND METHODS

An ultrasonically vibrating machine has two significant components: a sonotrode and an electroacoustic transducer. An electronic control unit is connected to the machine components via a cable. The control unit produces the current oscillation using an electronic oscillator within the ultrasonic range of frequency. Then, the transducer is employed for conversion the oscillating current to mechanical vibration. There are two transducers in ultrasonic machining, including magnetostrictive and piezo-electric. Si_3N_4 is crucial in developing ceramic materials for advanced applications. This material has a lower final cost since Si_3N_4 is produced, and nitrogen and silicon are two common elements. In addition, Si_3N_4 is in the group of non-oxidising ceramic materials with high resistance power in oxidation, the same as silicon carbide (SiC). Lastly, It is easy to convert the Si_3N_4 to the complete density bodies to reach higher strength [40].

This study performed two types of experimental tests, including RUAEG and CEG. A CNC milling machine was used for the experiments. A unique fixture was designed for the Si_3N_4 workpieces. Using an ultrasonic vibration generator (by KIA Co.), the RUAEG process was performed. System vibration amplitude and resonance frequencies were 15 (μm) and 20.5 (kHz), respectively. PU-09 gap sensor (AEC Co.) was

employed to measure ultrasonic vibration amplitude. The pressure of the cooling gas (CO_2) was 5 bar. RUAEG operation was performed using a tool with horn, transducer, and diamond core tool components. Figure 1a shows the experiment's establishment. The diameter of the cutting tool is 6 (mm).

Kistler type 9257B dynamometer was used to obtain TFs, which were analysed then by Dynoware application. A Hommel Etamic roughness meter device was used to measure SR. That was measured by moving the workpiece's probe 4 (mm) in length. It measures 10-point valleys and peaks distance over a source line and gives the numbers' mean as SR. Three places were considered to perform SR measurements and report the average values. The vibration amplitude was measured by the PU-09 gap sensor (Figure 1c), which was manufactured by AEC company in Japan. That works based on eddy current. An electromagnetic zone was produced, and the tool displacement induced coil impedance. The resulting voltage change is converted into amplitude by the mechanism which was described in the device catalogue. Figure 1b shows the vibration amplitude measuring device.

The rectangular Si_3N_4 workpieces $3 \times 12 \times 50$ (mm) were prepared. The elasticity modulus, density, and Poisson's ratio of the utilised Si_3N_4 were 310 (GPa), 3.26 (g/cm^3), and 0.25. Based on the previous study of the RUAEG by Baraheni and Amini [26], the critical parameters for the process, including FS, RS, and DoC, are 8 (mm/min), 5440 (rpm), and 60 (μm). Then, two parameters are defined as fixed parameters, and the third parameter is defined variable. The variation range of these three parameters is defined based on the expert's knowledge in the field. Table 1 represents the design of experiments in RUAEG and CEG. It reduces the chance of overshooting the problem of the neural network part of the studies as the number of variables is more than the experiments. As shown in Table 1, there are 18 samples regarding three process parameters for CEG/RUAEG. The data is divided into three sets to bypass the overfitting problem of the proposed ANFIS model. Each data group has one variable parameter with two fixed parameters. Then during the optimisation, the task is to extract the optimal value of the variable parameter related to linking the dataset.

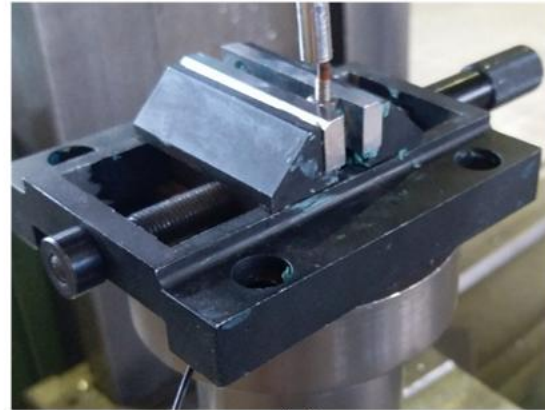
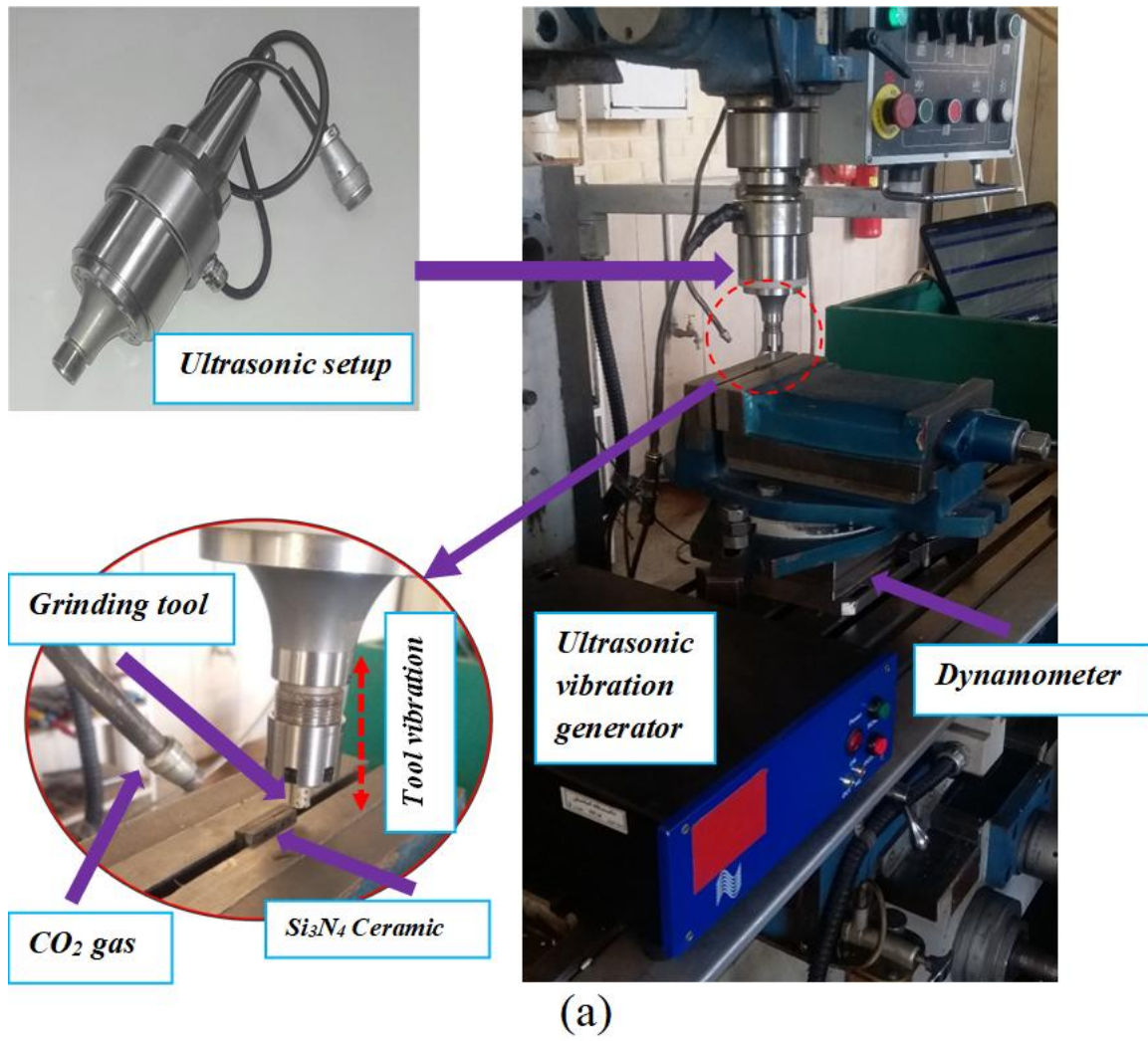


Figure 1. Experiments setup (a): components; (b): Vibration amplitude measuring device; (c): Gap sensor.

Table 1. Experiments design.

	FS (mm/min)	RS (rpm)	DoC (μm)
1st test group	3, 6, 8, 12, 16, 24	5540	60
2nd test group	8	1110, 1750, 2220, 2720, 3500, 5440	60
3rd test group	8	5440	30, 40, 60, 80, 100, 120

They were analysed by transforming the TF data from Dynoware to Excel. Experiments were performed for the RUAEG process by turning an ultrasonic vibration generator in the beginning. Then, the generator is switched off to perform the CEG procedure by the tool reaching the middle of the workpiece. In TF measurement, three areas exist in each process: beginning, stable, and ending. The stable part consists of the measured TF. Figure 2a represents the measurement area of the TF in the procedures. SR plots were derived by the Hommel Etamic roughness meter tool. Thrust force values are acquired from Dynoware software and analysed. To carry out experiments, initially, the ultrasonic vibration generator is switched on in order to conduct the RUAEG process. Then, when the tool reaches the middle of the segment, the generator is switched off to conduct the CEG process. In each process, there are three zones in thrust force computation: beginning, stable and ending. The stable zone in Figure 2a occurs between two processes (ending of RUAEG and beginning of CEG). Computed thrust force belongs to a stable zone. The computing zone of thrust force in both processes is plotted in Figure 2a. TF is measured along the tool axis direction or z-direction. Figure 2b displays an SR plot in the RUAEG procedure using FS of 12 (mm/min), RS of 5440 (rpm), and DoC of 60 (μm). TURBO WAVE V7.20 software is used to extract the shown plot in Figure 2b. It should be noted that R_a , R_z , R_{max} and R_t of the shown result in Figure 2b are 0.4, 2.57, 3.98 and 3.98 (μm), respectively. The meaning of SR in the rest of the paper is R_z parameter unless it is mentioned something else by the author.

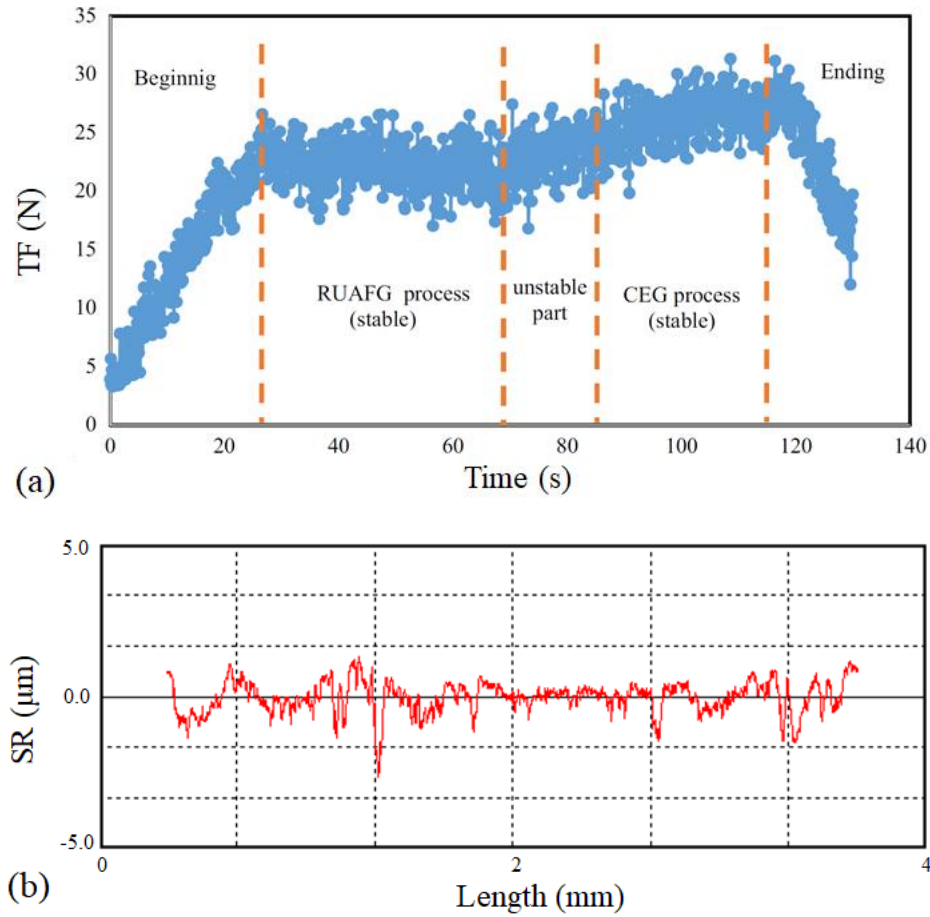


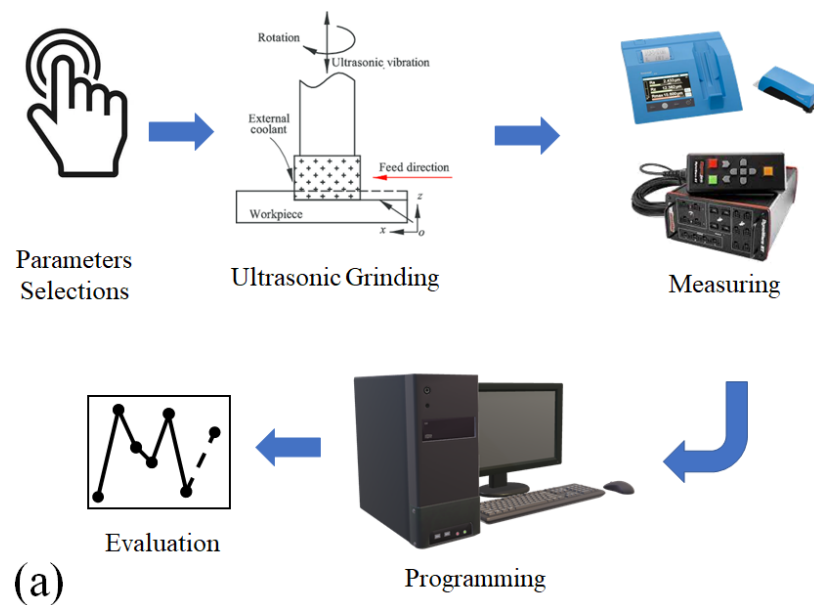
Figure 2. (a): The TF measurement in 5440 (rpm) RS; 60 (μm) DoC; 16 (mm/min) FS; (b): SR plot in RUAEG procedure using FS of 12 (mm/min), RS of 5440 (rpm), and DoC of 60 (μm).

III.METHODOLOGY

This paper aims to extract the optimum machining parameters of ultrasonic-assisted rotary end-grinding silicon nitride ceramics to reach the best SR via the lower machining forces. Then, ANFIS, one of the high-accuracy machine learning methods, is applied to develop the model to connect the machining parameters to SR and the machining force. The ANFIS hyperparameters are extracted using GA to achieve the best performance of the proposed model. As we have two different datasets in this study (CEG and RUAEG) with the addition of two different outputs (SR and TF), the model has been trained four times to develop the

optimal ANFIS model for each model with corresponding to the appropriate set of data. The recorded TF and SR are used to make the ANFIS model.

Figure 3 presents the proposed method's scheme as the main contribution that combines GA and ANFIS. Considering Figure 3a, the procedure is begun by choosing the proper machining parameters. Then the ultrasonic grinding of the Si_3N_4 workpieces is done with the plantation of the dynamometer to calculate the TF and SR after grinding. The developed algorithm consists of pre-processing to remove the out-of-range data to improve the algorithm's accuracy. The single objective GA is utilized to select the ANFIS optimal hyperparameters to reach the lowest mean square error (MSE) between the actual and predicted data (Figure 3b). This algorithm is initiated two times to develop the models ANFIS1 and ANFIS2, which are used to obtain the workpiece's TF and SR in ultrasonic grinding of Si_3N_4 . Based on Figure 3b, the multi-objective GA is used to find the optimal machining parameters of the ultrasonic grinding of Si_3N_4 to reach the most appropriate outcomes, including low SR and TF. Table 2 shows the employed dataset in this research, including cutting parameters with associated SR and TF using both CEG and RUAEG methods.



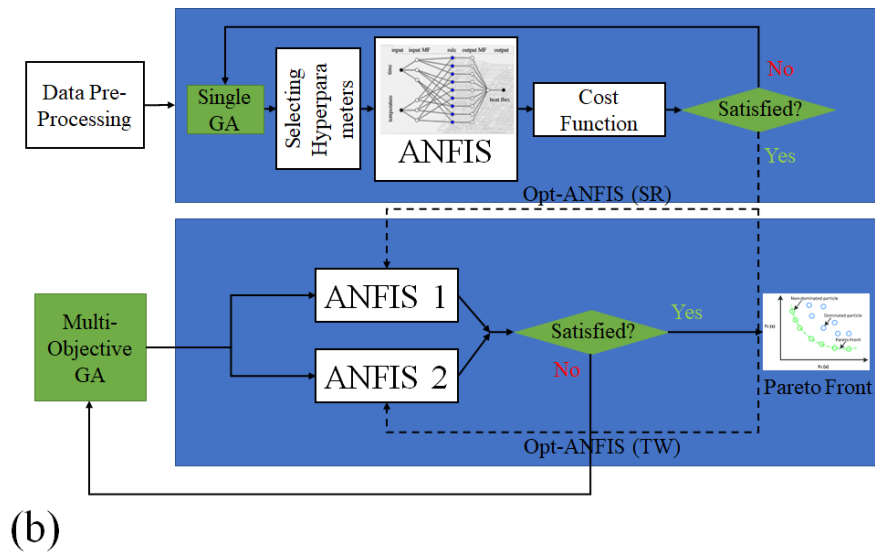


Figure 3. (a): The structure scheme for the approach; (b): The artificial intelligent part of the study.

Table 2. Datasets were used in this study.

No.	DoC (μm)	FS (mm/min)	RS (rpm)	SR or R_z (μm)		TF (N)	
				CEG	RUAEG	CEG	RUAEG
1	60	3	5440	3.02	1.56	20.82	4.484
2	60	6	5440	3.84	1.92	30.02	4.308
3	60	8	5440	4.17	1.82	18.99	8.4
4	60	12	5440	4.77	2.18	34.25	8.72
5	60	16	5440	5.14	2.65	27.82	21.19
6	60	24	5440	5.85	3.74	65.6	41.72
7	60	8	1110	5.42	5.12	138.5	46.28
8	60	8	1750	4.5	3.7	99.1	34.52
9	60	8	2220	4.6	3.39	90.24	34.4
10	60	8	2720	4.31	2.97	88.32	31.2
11	60	8	3500	4.3	2.72	34.25	6.98

12	60	8	5440	4.17	1.82	18.99	8.4
13	30	8	5440	3.98	1.03	22.97	5
14	40	8	5440	4.16	1.11	38.6	6.4
15	60	8	5440	4.17	1.82	18.99	4.308
16	80	8	5440	4.53	2.31	93.5	18.76
17	100	8	5440	5.16	3.95	128	46
18	120	8	5440	7.48	5.02	147	54.8

1.Data Pre-processing

Three tasks must be considered in the dataset before extracting the model. First of all, the out-of-range data must be eliminated. There are produced as a result of the malfunction of the system. Because of the sensor's fault, the out-of-range data should also be eliminated before applying it to the model. The second stage is system normalisation or standardisation to reduce the complexity of the data before training. Here, each method decreases the network's input data's complexity and enhances the system's efficiency.

The data standardisation can be obtained as the following:

$$\sigma_{x_i} = \frac{x_i - \bar{x}}{\sigma_x} \quad (1)$$

In this equation, x_i , represent the i th raw input data while σ_{x_i} represent the standardized input data. In addition, σ_x and $\bar{x}$ are the functions that are applied to determine the standard deviation as well as the average deviation of data, respectively. The following equation can be used to normalize the data:

$$n_{x_i} = \frac{x_i - \underline{x}}{\bar{x} - \underline{x}} \quad (2)$$

in which n_{x_i} represents the i th normalized input data. Moreover, $\bar{x}$ and $\underline{x}$ represent the functions to find the maximum and minimum values.

In addition, 16 samples of data are used for the training purpose of the model. Also, 2 samples of data are used for testing the model. The test data is not applied to the system before the network testing step to achieve realistic outcomes by the developed models. ANFIS is utilized here to predict the TF during grinding and the workpiece SR considering the cutting process parameters (FS, RS and DoC).

2.Adaptive Network-based Fuzzy Inference System

ANFIS is a combined system consisting of FIS and an artificial neural network. ANFIS is employed to solve complicated and nonlinear problems. It proves that ANFIS can cover reasoning operations and self-learning. The fuzzy rules for ANFIS are:

Rule 1: if t is O_1 , and x is P_1 then $z_1 = a_1t + a_2x + a_3$.

Rule 2: if t is O_2 , and x is P_2 then $z_2 = b_1t + b_2x + b_3$.

In both the rules, t and x are inputs. z_1 and z_2 are the outputs determined by the discussed rules. During the learning procedure, a_1, a_2, a_3, b_1, b_2 , and b_3 are acquired. According to Figure 4, the ANFIS structure has five levels, each with two inputs and one output. The following is the meaning of each layer:

Layer 1 is a defuzzification layer that uses the function membership to compute fuzzy clusters based on the input training data. a_i and b_i are used to generate the membership function and estimate the membership degree as:

$$Q_i^1 = \mu_{A_i}(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}}; i = 1,2 \quad (3)$$

$$Q_i^1 = \mu_{B_i}(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}}; i = 1,2 \quad (4)$$

where are μ_x and μ_y are the membership degrees. A_i and B_i are fuzzy sets, and x is the input; when Q_i^1 is the i th node in the j th layer output.

Layer 2 stands for the rule which is utilized to double the firing power, and the output will be as follows:

$$Q_i^2 = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), i = 1, 2 \quad (5)$$

Layer 3 is for normalising the last layer's firing intensity. Dividing the firing strength of the i th rule by the all firing strengths summation, the normalised values can be generated as:

$$Q_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2 + w_3 + w_4}, i = 1, \dots, 4 \quad (6)$$

The defuzzification layer is layer 4. The outcome is calculated as the normalised firing strength and the parameter set inner product (p_i, q_i and r_i) as:

$$Q_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (7)$$

The last result of the fifth layer is generated by adding the defuzzification results of every rule:

$$Q_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

Using the gradient descent method's backpropagation algorithm, error signals are calculated from the output layers to the input layers. Using the customizable parameters, this algorithm aims to minimize training errors.

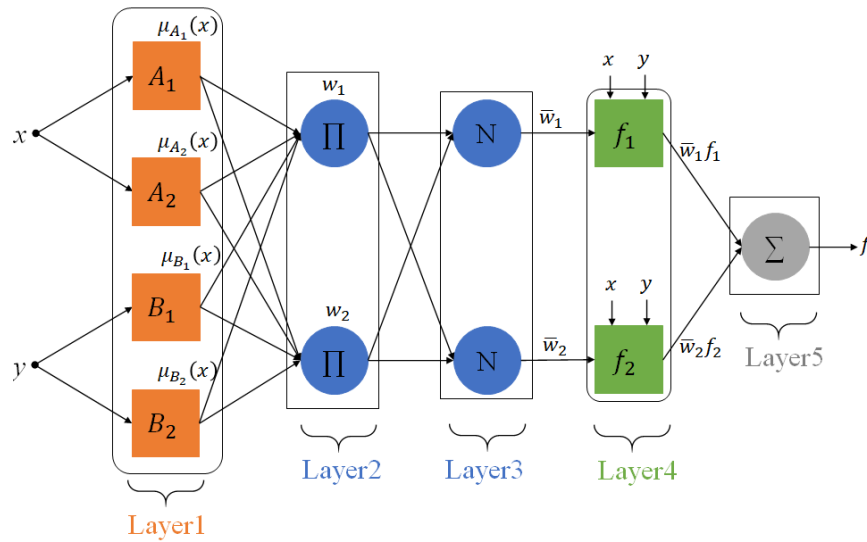


Figure 4. The structure of ANFIS.

After establishing the ANFIS architecture, it is necessary to get the model's hyperparameters using optimisation techniques. To extract the ANFIS hyperparameters, the RMSE is employed as the objective function.

3. Genetic Algorithm

GA is a search tool based on the population that mimics genetics [41]. It is appropriate for the ample and not perfectly unimodal and smooth solution space. Therefore, it is utilised for optimising complex design problems with combinational difficulty. It decreases the adherence to the human designer's expertise in selecting the grinding cutting parameters. This study employs GA twice as a single and multi-objective objective function. Initially, the single objective GA is used to calculate the optimum hyperparameters of the developed ANFIS model in the previous Section.

Single Objective GA: GA parameters must be carefully selected to maximise convergence speed and accuracy. For the GA to be successful and achieve the desired output, it is essential to correctly adjust the crossover and mutation parameters. It is possible to miss a solution close to the current state due to the high mutation rate. Moreover, the probability of becoming trapped in an optimal local increases when the mutation parameter is set to a small number. Additionally, crossover means that kids don't become identical copies of their parents. According to Mitchel's suggestion, the mutation parameter should have a fair value, while the crossover parameter should have a considerable value.

The population size of GA in this paper is 80. There is a limit to the GA's exploration capabilities when a small population size is considered. In addition, the large population size increases the optimization length without improving the results significantly. GA outcomes will indicate that the current study's population, crossover, mutation, and generation parameters have been chosen properly. It should be noted that using the suggested hybrid soft computing approach, the objective function of the GA under consideration is the recalculated elastic deformation of the workpiece during machining. The cost function J_{single} is defined

below to extract the optimal number of FIS θ_1 , epoch number θ_2 , initial step size θ_3 , decrease in the step size rate θ_4 , and increase in the step size rate θ_5 :

$$J_{\text{single}}(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5) = \sum_{i=1}^n |T_i - O_i| \quad (9)$$

where T_i and O_i are the i th experimentally measured and calculated output via ANFIS during the testing process, respectively. As there are four different models, including ANFIS-TF-CEG (ANFIS using CEG dataset for calculation of TF), ANFIS-SR-CEG (ANFIS using CEG dataset for calculation of SR), ANFIS-TF-RUAEG (ANFIS using RUAEG dataset for calculation of TF), and ANFIS-SR-RUAEG (ANFIS using RUAEG dataset for calculation of SR), then single objective GA is employed four times to extract the optimal hyperparameters of each model.

Multi-Objective GA: In 1995, Deb *et al.* [42] proposed the GA algorithm, which combines GAs with Pareto optimisation to solve multi-objective optimisation problems. In 2002, the multi-objective GA was introduced as an improvement to the single-objective GA to reduce the system's complexity and increase the calculation pace of the solution via individual stratification. One of the advantages of the multi-objective GA is the ability to find the Pareto front solutions to non-convex problems. The Pareto front distribution of the solution can be extracted by running the multi-objective GA once, which is computationally effective. In the first step, the penalty values are calculated using the estimated SR or TF via the proposed ANFIS in the previous subsection via random weight selections. In the next step, the mutation and crossover of the genetic operator are used to calculate the new population. As the most important part of the multi-objective GA, the Elitist strategy is used to find the best solution for a newly generated population every cycle. This process is repeated until the number of iterations is satisfied. In the multi-objective GA, there is no goal to terminate the optimisation since there is no single objective function. Two functions, crowding distance and non-domain sorting, are used to achieve this task. The non-dominated sorting is used for the cyclic grading purpose of the algorithm. The methodology of the cyclic grading using non-dominated sorting is described as follows:

The first non-dominated layer is identified based on the non-dominated set in the group.

The non-dominated set is removed from the group.

The search is continued in the remaining group.

The solutions are sorted based on the dominance relationship.

The crowding distance technique extracts the distance between every solution and calculates the surrounding solutions' density. It is calculated via summation of the distance between individuals for each objective function. Also, normalisation is employed to prevent the problem that the objectives are on different scales. There is a need for two different cost functions in multi-objective GA to extract the Pareto front distribution of the data. These cost functions are defined below:

$$J_1(DoC, FS, RS) = \sum_{i=1}^n |T_i^{SR} - O_i^{SR}| \quad (10)$$

$$J_2(DoC, FS, RS) = \sum_{i=1}^n |T_i^{TF} - O_i^{TF}| \quad (11)$$

where J_1 and J_2 are the cost functions related to the SR and TF model of the CEG/RUAEG process. Also, T_i^{SR} , T_i^{TF} , O_i^{SR} , and O_i^{TF} are the i th of testing dataset experimentally measured SR, experimentally measured TF, calculate SR of CEG/RUAEG via proposed ANFIS and calculate TF of CEG/RUAEG via proposed ANFIS, respectively.

IV. RESULTS AND DISCUSSIONS

Four investigated models, including ANFIS-CEG-TF, ANFIS-CEG-SR, ANFIS-RUAEG-TF and ANFIS-RUAEG-SR, have been modelled in MATLAB to regenerate the appropriate model for calculation of the SR and TF based on cutting parameters in the RUAEG and CEG grinding process. Afterwards, the MATLAB multi-objective GA function is utilized to find the optimum machining parameters of the procedure for both CEG and RUAEG. In addition, it should be noted that there are three different datasets based on Table 1. Each set of data has two fixed and one variable parameters. It prevents the proposed machine learning model from overshooting problems as the number of variables is more than the experiments. Then, using the

proposed methodology, the number of variables reduces from three to one while not harming the accuracy and efficiency of the proposed method. It also should note that the fixed values and the range of variables for each set are defined based on the best knowledge of experts. In addition, the proposed methodology is investigated in the first dataset in Table 1. The rest can be followed for the second and third sets of data using the same methodology.

The represented model in Section III with the GA optimisation method is modelled in MATLAB. ANFIS is developed based on the model explained in Section III.2. The model is optimised according to the GA optimisation method in Section III.3.

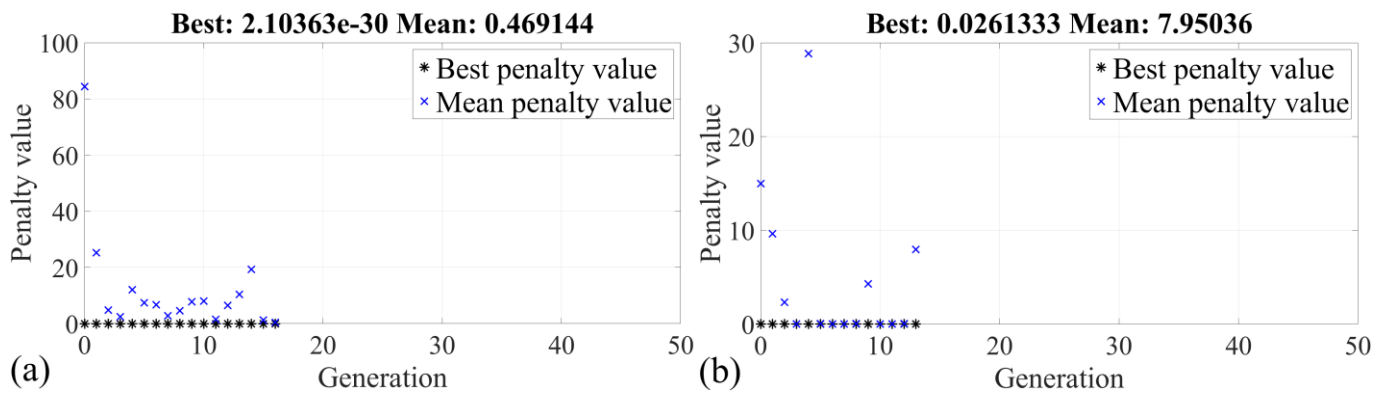
The "anfis" function in MATLAB is utilized for the ANFIS model design. In Section III, the proposed algorithms have been developed and coded. The function "plot" has been used to extract the visual version of the results. Furthermore, GA is developed by the function "ga" in MATLAB. Multi-objective GA is also applied by the MATLAB function "gamultiobj". The single objective GA optimisation method extracts the optimal hyperparameters of the developed ANFIS, including ANFIS-TF and ANFIS-SR. Table 3 lists the optimised hyperparameters of the proposed ANFIS-SR and ANFIS-TF in the RUAEG and CEG grinding process to predict the SR and TF, respectively.

Table 3. The selected hyperparameters of the ANFIS model using GA optimisation.

ITEM	Initial FIS	Epoch Number	Initial Step Size	Step Size Decrease Rate	Step Size Increase Rate
ANFIS-TF- CEG	9	3057	0.0830	0.8857	1.2963
ANFIS-SR- CEG	8	1485	0.0027	0.5848	1.1463

ANFIS-TF- RUAEG	8	3520	0.0214	0.8429	1.2308
ANFIS-SR- RUAEG	14	2037	0.0556	0.8848	1.0223

Figure 5a-d shows the convergence process of GA for four investigated models, including ANFIS models for the prediction of TF in CEG, SR in CED, TF in RUAEG and SR in RUAEG, respectively. It should be noted that the maximum generations, population size, maximum stall generations, maximum processing time, and maximum tolerance are set to 50, 20, 15, 2 (hours) and 10^{-14} , respectively. Based on the represented results in Figure 5a-d, the optimisation process is terminated at 16, 13, 16, and 11 generations because of violating the maximum stall generation, respectively. Based on the represented results in Figure 5a-d, the minimum best penalty value is reached by ANFIS-SR-RUAEG with 2.19128×10^{-32} . Also, ANFIS-SR-RUAEG reached the minimum mean penalty value of 2.12211×10^{-3} based on the represented results in Figure 5d. The fast convergence with higher accuracy proves the appropriate selection of GA's hyperparameters based on the knowledge of an expert in this field.



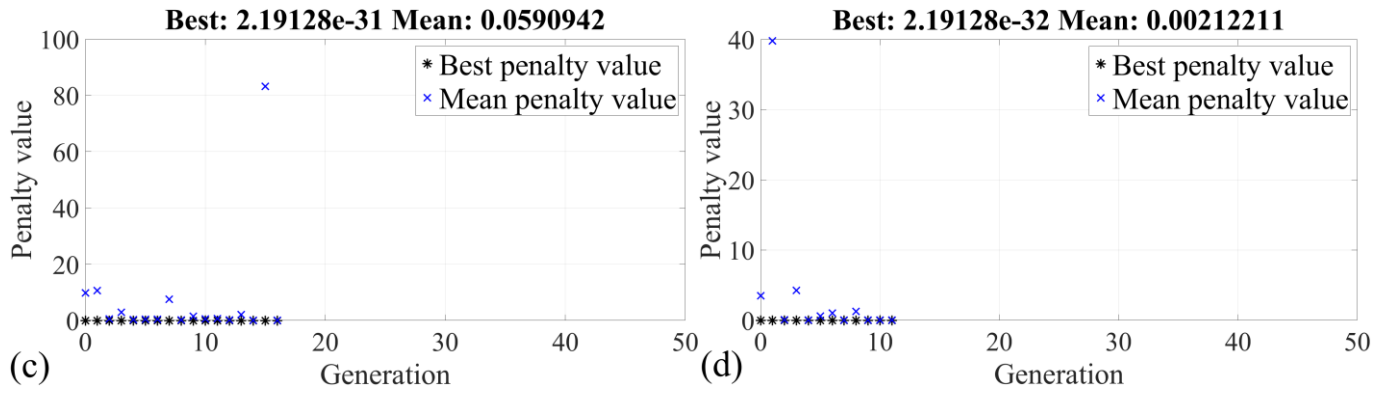
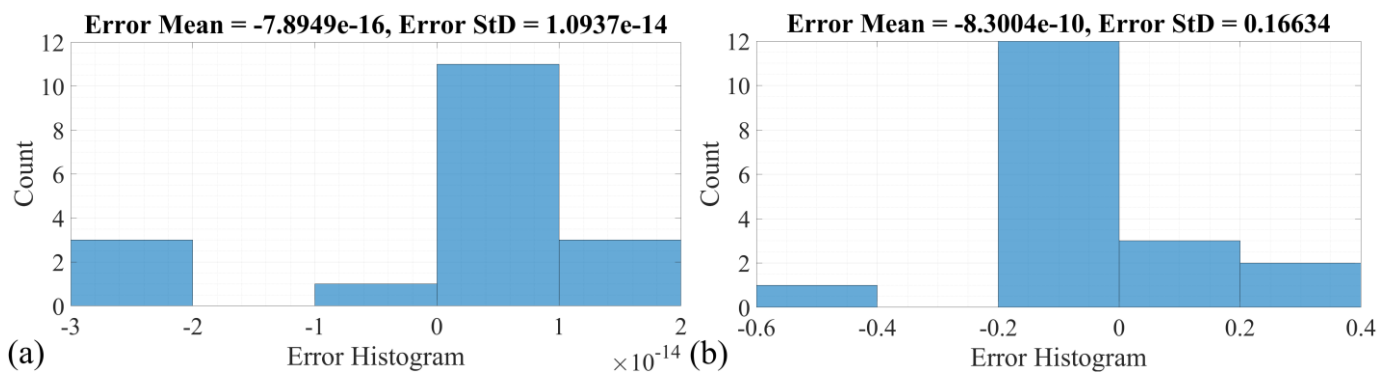


Figure 5. The convergence of GA optimisation method for (a): ANFIS-TF-CEG; (b): ANFIS-SR-CEG; (c): ANFIS-TF-RUAEG; (d): ANFIS-SR-RUAEG.

Figure 6a-d shows the error histogram of all data (test and train data) for ANFIS-TF-CEG, ANFIS-SR-CEG, ANFIS-TF-RUAEG and ANFIS-SR-RUAEG, respectively. The error rates are calculated based on the predicted outputs and target difference. Based on the represented results in Figure 6a-c, the error histogram of ANFIS-TF-CEG, ANFIS-SR-CEG and ANFIS-TF-RUAEG have right-skewed distribution. The error distribution of ANFIS-SR-RUAEG is normally based on represented results in Figure 6d. The average of the error between the predicted and actual values among all data for ANFIS-TF-CEG, ANFIS-SR-CEG, ANFIS-TF-RUAEG and ANFIS-SR-RUAEG are -7.8949×10^{-16} , -8.3004×10^{-10} , -2.9113×10^{-15} and 2.9606×10^{-16} , respectively. In addition, based on the represented results in Figure 6a-d, the standard deviation of the error for ANFIS-TF-CEG, ANFIS-SR-CEG, ANFIS-TF-RUAEG and ANFIS-SR-RUAEG are 1.0937×10^{-14} , 1.6634×10^{-1} , 8.196×10^{-15} and 7.501×10^{-16} , respectively.



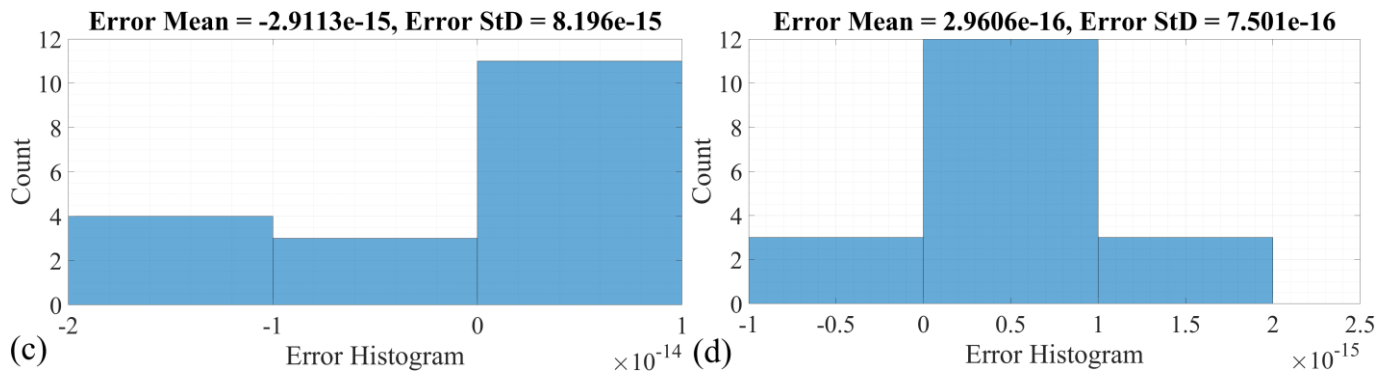
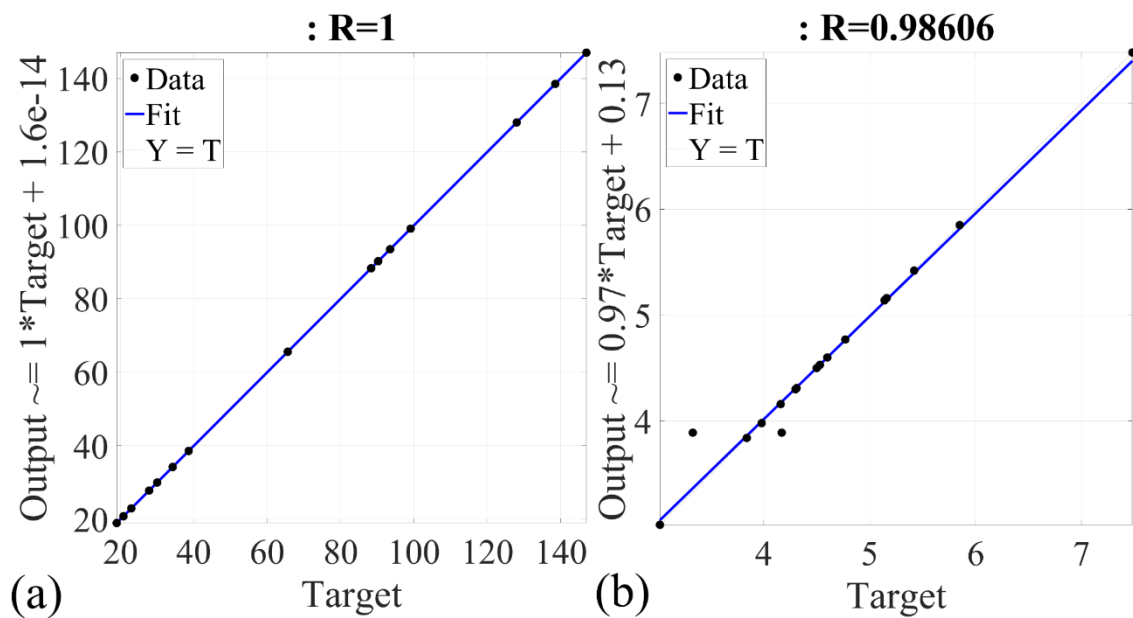


Figure 6. The error histogram for the data during the testing and training procedures for (a): ANFIS-TF-CEG; (b): ANFIS-SR-CEG; (c): ANFIS-TF-RUAEG; (d): ANFIS-SR-RUAEG.

Figure 7a-d shows the regression of the proposed models during the training and testing stages for ANFIS-TF-CEG, ANFIS-SR-CEG, ANFIS-TF-RUAEG and ANFIS-SR-RUAEG, respectively. The vertical and horizontal axes in Figure 7 represent the actual and predicted TF or SR based on the cutting parameters. Based on the represented results in Figure 7a-d, only ANFIS-SR-CEG was not able to reach the highest accuracy as R^2 is equal to one.



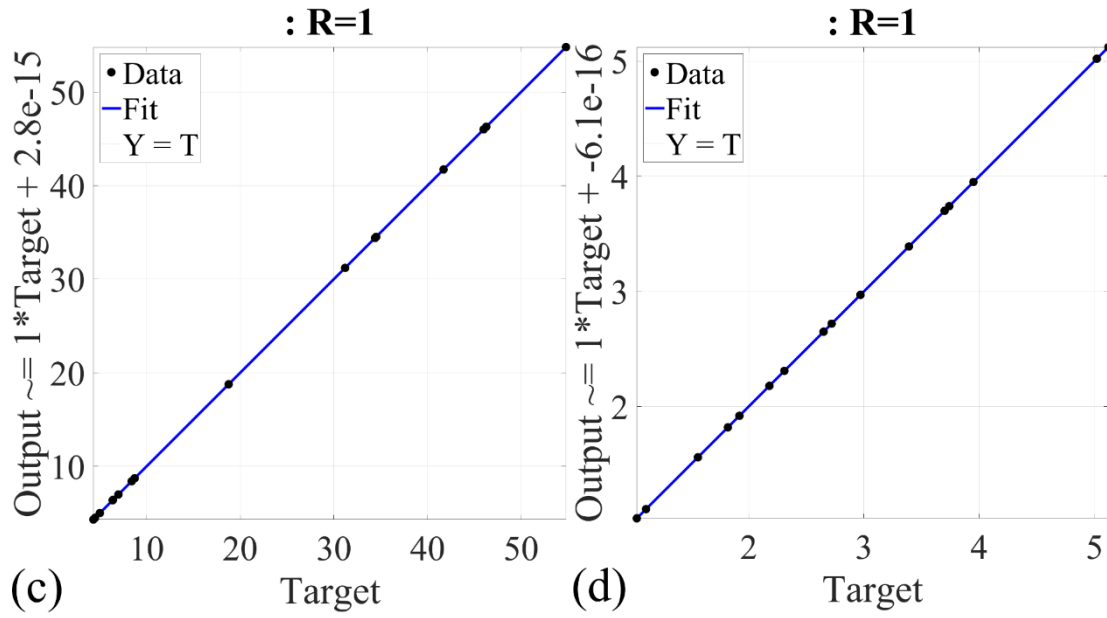


Figure 7. The regression of the data during the testing and training procedures for (a): ANFIS-TF-CEG; (b): ANFIS-SR-CEG; (c): ANFIS-TF-RUAEG; (d): ANFIS-SR-RUAEG.

Figure 8a-d shows the experimental and predicted TF and SR during CEG and RUAEG processes. 16 datasets are chosen for training, and two for testing the proposed methods. It should be noted that MSE calculated for the actual and predicted TF using ANFIS-TF-CEG and ANFIS-TF-RUAEG are 1.1360×10^{-28} and 7.1918×10^{-29} , respectively. Also, the MSE of the actual and predicted SR using ANFIS-SR-CEG and ANFIS-SR-RUAEG are 2.613×10^{-2} and 6.1904×10^{-31} . Moreover, the RMSE between the predicted and actual value among all data using ANFIS-TF-CEG, ANFIS-SR-CEG, ANFIS-TF-RUAEG and ANFIS-SR-RUAEG are 1.066×10^{-14} , 1.6166×10^{-1} , 8.4804×10^{-15} and 7.8679×10^{-16} , respectively. The results of this Section prove that our newly proposed GA-based ANFIS model in predicting TF and SR based on cutting parameters in CEG and RUAEG processes is efficient.

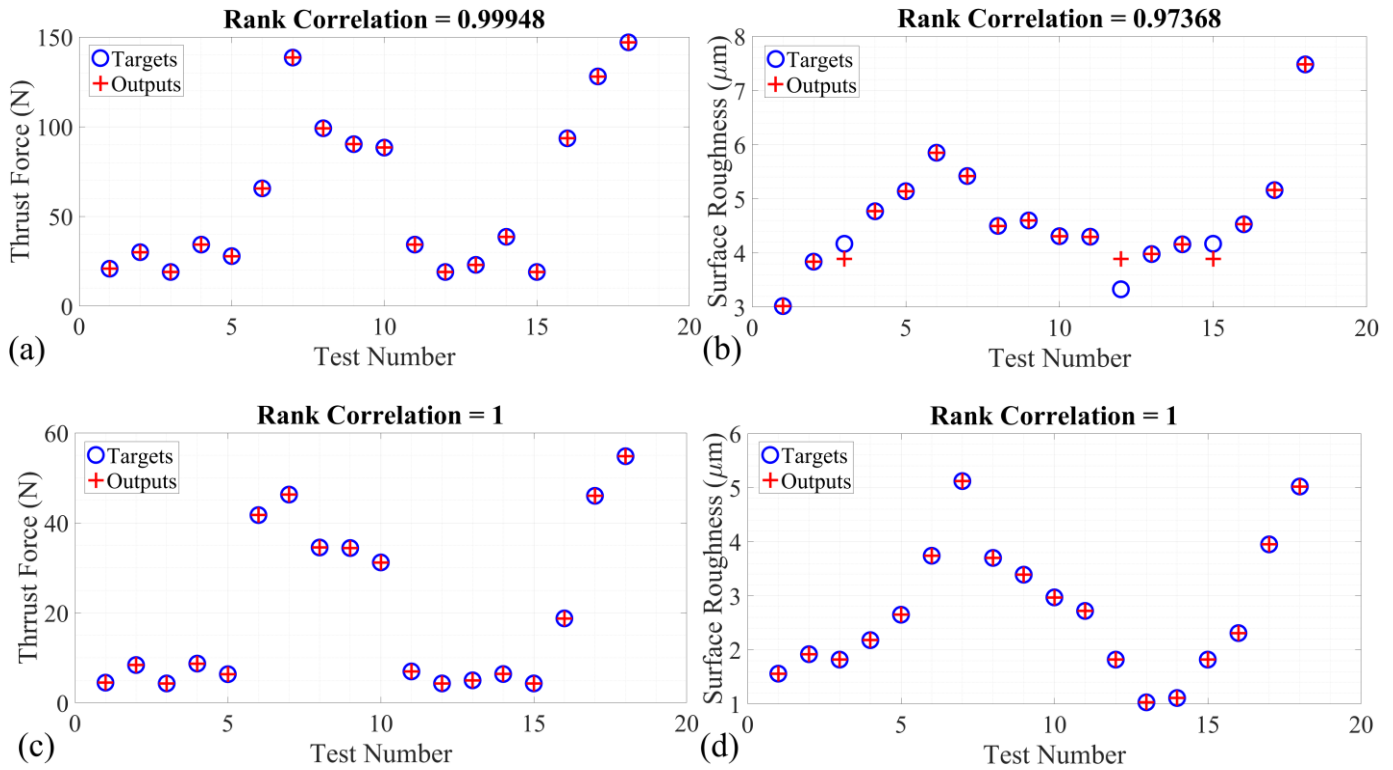


Figure 8. The actual and predicted results for all data consisting of test and train datasets using (a): ANFIS-TF-CEG; (b): ANFIS-SR-CEG; (c): ANFIS-TF-RUAEG; (d): ANFIS-SR-RUAEG.

Based on the extracted results from Figures 6-8, increasing feeding speed increases thrust force in both processes. According to the mechanics of cutting metals, by increasing feeding speed, the workpiece-tool engagement surface will be extended and result in a thrust force increment. As presented in Figure 8a and Figure 8c, the thrust force in CEG increases more as compared to RUAEG. Also, in both CEG and RUAEG, the thrust force is minimized by the rotational speed increment. By cutting velocity increment, cutting plate zone or initial deformation zone volume shortens. Therefore, lower energy is needed to separate the material and enhances cutting efficiency. According to Figure 8a and Figure 8c, as cutting depth increases, material deformation will be switched from ductile to brittle. Therefore, a larger force will be applied to the tool. Besides, in RUAEG, intermittent workpiece-tool contact causes less average thrust force compared to CEG. In the second step of the research, the proposed models for CEG and RUAEG process are used inside the multi-objective GA to calculate the optimised parameters of the process. It is based on the represented model

in Section III.3. The models related to the first dataset are selected to be used inside the multi-objective GA to find the optimum solution. As shown in Table 1, DoC and RS are the fixed parameters equal to 60 (μm) and 5440 (rpm), respectively. Also, the variation of FS in the first set of data is from 3 to 24 (mm/min). The multi-objective GA can find the four and two optimum solutions for the dataset relating to CEG and RUAEG methods. Table 4 shows these extracted solutions for CEG and RUAEG with the corresponding SR and TF. Then, in a massive production line, these extracted values can be chosen to increase the process's efficiency by increasing the final product's quality in smaller SR and lower energy in smaller TF. Based on the represented results in Table 4, SR in the RUAEG process using the proposed method is able to reach 0.5177 (μm), while using the experimental investigation, the lowest SR was 1.03 (μm). Also, SR in the CEG process using the proposed method reduces from 3.02 to 1.5864 (μm) in comparison with the experimental investigation.

Table 4. The results were obtained using multi-objective GA in CEG and RUAEG for the first dataset.

Method	DoC (μm)	FS (mm/min)	RS (rpm)	ANFIS SR (μm)	Exp SR (μm)	ANFIS TF (N)	Exp TF (N)
RUAEG	60	18.4738	5440	0.8511	0.9226	15.3588	11.8103
		19.6444		0.5423	0.6065	17.2637	20.0398
		18.6564		0.7482	0.8078	15.3987	14.8677
		19.4141		0.5513	0.5177	16.5192	16.4399
CEG	60	9.0511	5440	3.8560	2.8655	16.5732	19.4117
		10.5704		1.4953	1.5864	27.3853	28.8894

The extracted optimal process parameters are employed inside the experimental setups in the final research step. Then, the extracted SR and TF using the extracted optimal process parameters are captured and compared with the machine learning extracted results to prove that the proposed method is efficient. It shows

that the margin error between the experimental results and machine learning calculated optimal solution for SR is 12.08%. Also, the margin error for TF between the extracted optimal solution and the experimentally captured results is 12.29%. It proves the efficiency of the proposed method in terms of efficiency and accuracy.

V. CONCLUSION

Ultrasonic vibration-assisted machining is a process that makes use of a micro-scale high-frequency vibration applied to a cutting tool to improve the material removal effectiveness. RUAEG is used as non-traditional processing to machine ceramic materials. There are three RUAEG parameters, including FS, RS, and DoC, that have direct effects on the output of the process as TF and SR. Unfortunately, there is no systematic method to calculate the SR and TF during the RUAEG of silicon nitride ceramics considering the machining parameters, consisting of FS, RS and DoC. This paper studied a new ANFIS model to estimate the TF during grinding and SR of silicon nitride ceramics for two processes, including CEG and RUAEG. The single objective GA is utilized to extract the ANFIS optimal hyperparameters for both models. The proposed method was modelled in MATLAB. The outcomes were then extracted according to the data division for 11% testing and 89% training. The extracted results prove that the ANFIS can reach better outcomes during the test and training processes. The accuracy of the proposed ANFIS model for prediction of the SR using CEG and RUAEG methods were 0.98609 and 1.0 R^2 . In addition, the accuracy of the proposed ANFIS model for prediction of the TF using CEG and RUAEG methods were 1.0 and 1.0 R^2 . Afterwards, the models for calculating TF and SR are used inside the multi-objective GA to find the optimal parameters to achieve the best solution, which is the least TF and SR. The experimental investigation using the extracted optimal cutting parameters proves the efficiency of the proposed method with 12.08% and 11.30% margin error for SR and TF, respectively.

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DECLARATIONS

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