DOI: 10.31534/engmod.2018.3.ri.02f
Original scientific paper
Received: 28.02.2018.

Surface roughness modelling in super duplex stainless steel turning

Mario Veić, Sonja Jozić, Dražen Bajić

University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, 21000 Split, CROATIA
e-mail: mario.veic@fesb.hr

SUMMARY

Super duplex stainless steels are alloys that have good corrosion resistance properties and are intended for applications in corrosive environments. Due to their chemical composition and microstructure providing high strength and thermal resistance as well as high ductility, the machinability of these alloys is difficult, resulting in longer production cycles and higher costs in terms of more frequent replacement of tools. In this paper, the machinability of the super duplex EN 1.4410 was investigated under environmentally friendly machining process by using cold compressed air as a coolant. Experimental data were generated using the range of selected input parameters and correspondingly analysed surface roughness as output data. Predictive models were developed in order to make a comparison of their prediction performance. In addition, this paper also describes the methodology for optimised development of a particular predictive model. Finally, comparative analysis of the accuracy of predictive models was performed in order to define which model represents the best fit for the analysed experimental data, and also to show validity of the optimisation process.

KEY WORDS: *ANFIS; response surface method; super duplex stainless steel; surface roughness; vortex tube.*

1. INTRODUCTION

Stainless steel or corrosion-resistant steel is an iron alloy containing at least *10.5%* of chromium (modern stainless steels contain up to *30%* of chromium), unlike the ordinary steel that is rapidly oxidised to the air if it is not in some way corrosion-protected. Unlike other materials that are mainly classified by their chemical composition, corrosion-resistant steels are more often classified according to their microstructure. The microstructure of stainless steel can be ferrite, martensite and austenitic, so it is characterised as either ferrite, martensite or austenitic stainless steel. There is also a group with a structure composed of approximately *50%* of austenite and *50%* of ferrite. These are duplex stainless steels which have better properties than austenitic and ferrite steels.

Today, duplex steels are applied in many places due to their superior corrosion resistance and very good mechanical properties. Due to their high ferrite content, they are ferromagnetic, and they also have higher thermal conductivity and lower thermal expansion than austenitic steels. In places where high resistance to puncture corrosion is required, the choice of austenitic steel is more appropriate. Because of the relatively high strength, duplex steels are the optimal choice for structures exposed to corrosion, where their remarkable combination of corrosion resistance and mechanical properties are highlighted. Duplex steels have a much larger stretching limit (about *425 MPa*) versus austenitic (about 210 *MPa*) steels. Their hardness is also higher and their abrasion wear resistance accordingly. A lot of new duplex steels have good toughness and ductility. Because of the large fraction of the ferritic phase, the temperature drops rapidly from a tough to a fragile area, similarly to ferrite stainless steels. The temperature range of their application is limited to *-40°C* or *315°C* due to numerous microstructure precipitates that can be isolated at a relatively low temperature, which have a poor influence on corrosion resistance and mechanical properties. The first stainless duplex steel was manufactured in Sweden in 1930 and has been successfully applied in the paper industry as a replacement for austenitic stainless steel that is sensitive to inter-crystalline corrosion. At the same time, the first duplex cast was manufactured in Finland. The period after the Second World War marked the beginning of a more intensive application of crushed and cast duplex alloys in the process industry. The first duplex steels (duplexes of the first generation) do not have a well-balanced chemical composition and generally do not contain nitrogen. Such steels are difficult to weld and have poorer mechanical properties and corrosion resistance compared to later developed duplex steels in which nitrogen is an indispensable legal supplement. The division of the second-generation duplex steels was based on the resistance of the duplex steel to perforated corrosion by the Pitting Resistance Equivalent Number *(PREN),* which can be calculated as follows:

$$PREN = \%Cr + 3.3\ (\%Mo + 0.5W) + 16\%N \qquad \textbf{(1)}$$

1.1. LITERATURE OVERVIEW

Super and hyper duplex steels contain more elements which provide them with the *PREN* value over 40. The basic elements in duplex steel are chromium and nickel, but nitrogen, molybdenum, copper, manganese, silicon and tungsten also play a very important role in the formation of microstructures. An increased percentage of molybdenum increased their corrosion resistance. They have great application as construction materials. Super duplex stainless steels are extremely corrosion-resistant alloys intended for applications in corrosive environments such as saltwater. Because of their chemical composition and microstructure which ensures high strength and thermal resistance as well as high ductility, the machinability of these alloys is poor, resulting in longer production cycles and higher costs in terms of more frequent tool replacement.

Oliveira Junior [1] investigated the turning process of SAF 2507 alloy in order to analyse the influence of the machining process on corrosion resistance in practical applications. The results of the experiments show that using PVD coated tools at high pressure cooling achieves a longer tool life, a satisfactory surface finish quality, and high corrosion resistance of machined material after the machining process.

Rajaguru [2] investigated the machining of super duplex steel by using tools with different types of coatings. Process characteristics such as tool wear, cutting force, cutting temperature, and integrity of the machined surface were analysed. Tool wear analysis has shown that the [MT-TiCN]Al_2O_3 coating tool provides a relatively good wear resistance due to high MT-TiCN hardness and Al_2O_3 oxidation stability. TiN-[MT-TiCN]Al_2O_3 coatings are exposed to relatively high cutting force values. TiOCN-Al_2O_3-TiCN-[MT-TiCN]-TiN coating provides lower cutting forces due to high TiOCN hardness and their lower friction coefficient, AlTiN coating generates the highest temperature due to high friction and low thermal conductivity. [MT-TiCN]-Al_2O_3 coating provides lower surface roughness due to increased resistance to abrasion wear of the cutting edges. Finally, it can be concluded that [MT-TiCN]-Al_2O_3 coating provides a relatively good performance in terms of tool wear, cutting force, cutting temperature and surface integrity compared to other used coatings.

In his research, Paiva [3] used three types of PVD coatings: Al50Cr50N, Al60Cr40N, and Al50Cr50N/Ti95Si5N, which were applied to a carbide tool. Analysing the wear mechanisms of the used tools, it resulted that adhesive wear is dominant in all types of coatings. Due to the more favourable chemical composition, the Al50Cr50N/Ti95Si5N coating provides less friction and consequently less tool wear.

Kumar [4] analysed the impact of machining parameters on the tool wear during the turning experiment of super duplex stainless steel SAF 2507 with uncoated carbide tool. The process was carried out under dry conditions, wet machining and by using gaseous carbon dioxide as a coolant. Carbon dioxide has a beneficial effect as a coolant, which ensures less tool wear.

Ahmed [5] studied the wear mechanisms of uncoated and coated carbide tools during the turning experiment of SAF 2507 alloy. The results of the experiments show that the dominant mechanism of tool wear is adhesive wear for all the used tools and that AlTiN coating provides better process characteristics compared to CVD TiCN + Al_2O_3 coatings and uncoated tools in the sense of a significant reduction in the formation of the built-up edge. Dhanachezian [6] investigated the machinability of the austenitic stainless steel AISI 316L and super duplex 2507 by using tools coated with Ti-AlN PVD coatings. The results of the experiments show that higher cutting forces, poor quality of the treated surface and higher tool wear occur during the machining of super duplex stainless steel. It is also concluded that more preferred forms of separate particles occur during the machining of austenitic stainless steel. Finally, it can be concluded that the super duplex stainless steel 2507 is an extremely difficult material for machining. Kadam [7] conducted the turning experiments of super duplex stainless steel with uncoated and Physical Vapor Deposition (PVD) coated carbide inserts under dry cutting condition. The parametric influence of cutting speed, feed and depth of the cut on the surface finish and machinability aspects, such as cutting force and tool wear, were analysed. Tool wear was analysed by using an optical microscope and scanning electron microscope. The study includes the identification of tool wear mechanism occurring on the flank face. The characterisation of the coating was made by the Calo test for the measurement of coating thickness and nanoindentation for hardness. Comparison of performance of PVD coatings TiAlSiN ($3.3\ \mu m$), AlTiN ($3\ \mu m$) and AlTiN ($7\ \mu m$) has been made in terms of tool life. The coatings were produced on P-grade tungsten carbide inserts by using High Power Impulse Magnetron Sputtering (HiPIMS) technology. The findings of the study also provide the economic solution in case of dry turning of super duplex stainless steels. There have also been only a few papers on mathematical modelling of machining processes of super duplex stainless steel. Airao [8] investigated the surface roughness of super duplex 2507 stainless steel in dry and wet machining condition. Dry and wet milling experiments were conducted with three levels of cutting speed, feed rate and constant axial depth of the cut. The multiple regression analysis has been applied to discover the relationship between surface roughness and cutting parameters. The regression equation revealed that the feed rate is the most dominant factor that influences the surface roughness followed by the cutting speed. It is also concluded that surface finish obtained in wet machining is much better compared to dry machining. In his experimental study, Thiyagu [9] analysed the turning process of super duplex stainless steel with the objective of minimising surface roughness and cutting force. The design of experiments and optimisation were done using Box–Behnken design (BBD) and Response surface methodology (RSM). The factors and levels considered for experimentation include cutting speed, feed rate, depth of the cut, and tool nose radius on three levels. A second-order response surface models developed for surface roughness and cutting force were used in predicting the response in the design space. The Analysis of variance (ANOVA) and R-Squared value reveal that the developed models were significant. Surface roughness increases with the increase in the feed rate and cutting speed. In addition, the models` adequacy was validated using confirmation experiments. The prediction error accounts from *-4.07* to *0.55%* for surface roughness and *-2.47* to *2.52%* for cutting force. Koyee [10] coupled Taguchi approach with fuzzy-multiple attribute decision-making methods for achieving better surface quality in constant cutting speed face turning of EN 1.4404 austenitic, EN 1.4462 standard duplex and EN 1.4410 super duplex stainless steels. Two typical multiple attribute decision making techniques were simultaneously adopted to determine multi-surface quality characteristics indices. Additionally, the results of analyses of the means and the validation experiments confirm that the optimum cutting conditions derived by this method produce far better surface finish than the best finish obtained in the course of experimentation. The analyses of variance results have shown the predominant effect of feed rate on the surface quality. Finally, the collected chip at the constant cutting speed and varying feed rates and depth of cuts has shown that friendlier-to-machine chips are obtained when machining the austenitic stainless steels compared to duplex stainless steel grades. Kumar [11] conducted the analysis and optimisation of surface roughness and tool flank wear during machining of super duplex stainless steel with uncoated carbide inserts as cutting tool. The experiments were repeated under three different cutting conditions, namely dry, wet and gas cooled machining. Cutting speed, feed rate and depth of the cut were the input turning process parameters. Taguchi method was used to analyse and optimise the output response parameters. Validation experiments were carried out to compare the experimental results with the predicted optimal values.

It is evident from the abovementioned papers that all literatures in general studied dry and conventional wet machining process of super duplex stainless steel. Only a few researchers applied gaseous cooling with liquid CO_2. The application of cold compressed air as coolant by using vortex tube in the machining of super duplex stainless steel represents a new approach to reduce the surface roughness and the tool flank wear. Furthermore, the development and optimisation of the surface roughness predictive model based on neuro-fuzzy inference systems for the super duplex stainless steel turning at various cutting environments have not been applied. In this paper, the machinability of the super duplex stainless steel EN 1.4410 will be investigated in terms of obtaining the satisfactory quality of the treated surface by using cold compressed air as a coolant. By performing the turning experiments with the chosen range of input parameter limits, we will develop mathematical models and optimised predictive models. The comparative analysis will determine the accuracy of each developed predictive method.

1.2. ABOUT THE MOSE PROJECT

This paper has been composed within the workshop on machinability of super duplex stainless steel which was used for manufacturing bearing crowns at the Brodosplit Shipyard Company in Split, Croatia, Figure 1. The bearing crowns were used for the construction of the gates, as a vital part of the well-known MOSE project. The main objective of this project is the construction of the gates that will protect the city of Venice from flooding. The altitude of the city of Venice is very low and its proximity with the sea makes it vulnerable to the tides. When strong tides occur, the city is flooded by the sea, and even though people can swim in the streets, there are some negative points, such as the patrimony destruction. Global warming does not help in this process, because the temperature increase results in the dilatation of the ocean volume and the melting of the ice, which causes a higher level of the sea. It has then been decided, in the early 2000s, to build a giant structure that would prevent these floods. This structure is composed of different gates (*27 m* long, *20 m* wide and *5 m* each) that open and shut down vertically. In the machining part of the project, Brodosplit had a task of manufacturing the bearing crowns as a support for the bearings. These crowns had to be made in super duplex stainless steel because of its high resistance to corrosion (including seawater corrosion).

Fig. 1 *Bearing crown*

2. EXPERIMENTAL SETUP

The experimental work was performed at the Laboratory of Machine Tools at the Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture in Split. The aim was to obtain the measurement results that will enable the mathematical modelling of the selected output value of surface roughness Ra in the turning process. The experiments were carried out on the universal lathe machine by using cold compressed air as a coolant, Figure 2.

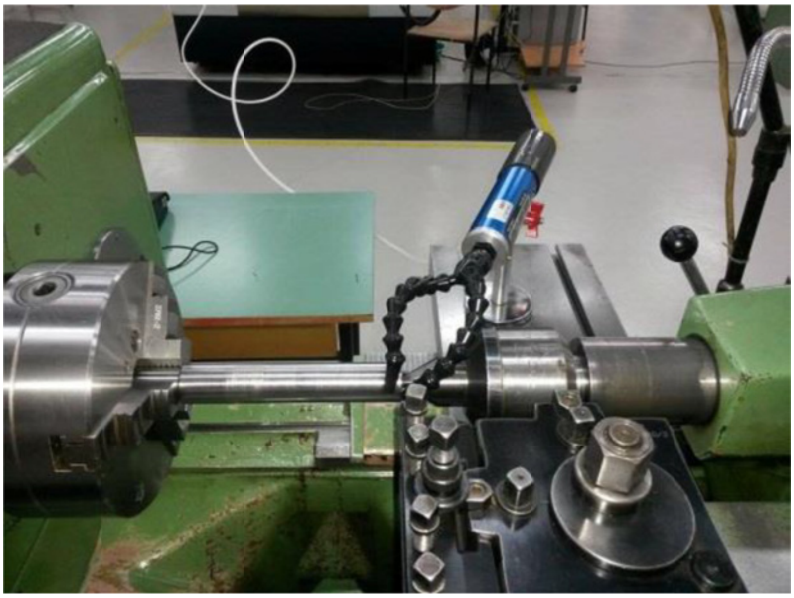

Fig. 2 *Turning experiment of super duplex stainless steel*

C5-CSRNR/L-27060-12-4 with hard metal cutting insert SNGN 12 07 08 was used as tool holder. The workpiece material was super duplex stainless steel 1.4410 according to EN 10028-7: 2007, with dimensions *ø50x250mm*. The chemical composition of workpiece material is presented in Table 1.

Table 1. *Chemical composition of workpiece material*

Element	*C*	*Mn*	*Si*	*S*	*P*	*Cr*	*Ni*	*Mo*	*Fe*	*N*	*Cu*
%	*0.012*	*0.786*	*0.415*	*0.0074*	*0.0181*	*24.36*	*6.755*	*3.69*	*63.5*	*0.07*	*0.165*

The measurements of surface roughness were obtained by using profilometer Mitutoyo Surftest 301. Cut-off length and the sampling length for surface measurements were selected to be *0.8mm* and *5.6mm*, respectively.

In this research, the cooling of the cutting zone is performed by means of Cold Air Guns which use vortex tube technology and filtered compressed air to produce sub-freezing air with the temperature of *-34 C*. With no moving parts to wear out, Cold Air Guns require no electricity at the target, just a compressed air source. The effective cooling from a Cold Air Gun can eliminate heat-related parts expansion while improving the parts` tolerance and surface finish quality. The air is a free available natural resource and compressed air is available on the regular basis at the shop floor for other purposes. It has no adverse effect on the health of the operator.

Employment of compressed cold air for cooling in the machining operations is a relatively new technique. Air that rotates around an axis is called vortex. The vortex tube, also known as the Ranque-Hilsch vortex tube, is a mechanical device that creates cold and hot air by forcing compressed air through a generation chamber, which spins the air at a high rate of speed into the vortex [12].

The vortex tube consists of an inlet nozzle, vortex chamber, cold-end orifice, hot-end control valve and a tube. It has no moving parts. High pressure air stream enters into the vortex tube tangentially, and there it splits into two lower pressure streams, one hot and one cold. Cold gas stream leaves the tube through the central orifice near the entrance nozzle, while the hot gas stream flows toward the control valve and leaves the tube there, Figure 3.

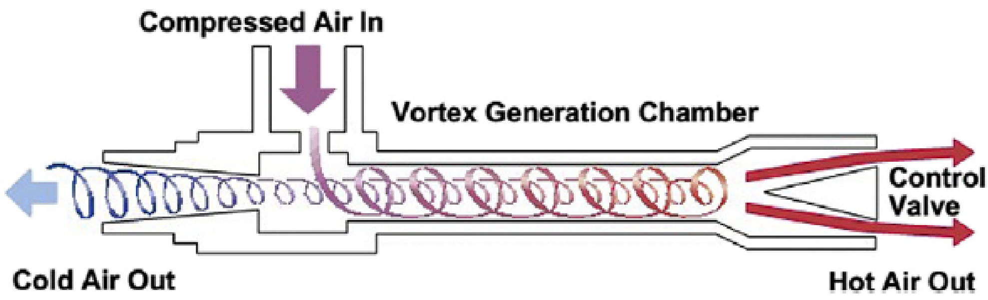

Fig. 3 *The schematic representation of vortex tube working principle [12]*

The aim of the experimental study of this paper is to obtain the measured results of surface roughness. In the next chapter, by processing all experimental data, we will develop predictive models in order to describe the dependence of the observed output value on a particular input processing parameter.

3. SURFACE ROUGHNESS PREDICTIVE MODELLING

3.1. MATHEMATICAL MODELLING OF SURFACE ROUGHNESS

The results of the experiments were used to develop a mathematical surface roughness model by using the regression analysis method. The surface roughness equation is modelled using the response surface method (RSM), which consists of a series of statistical techniques that are useful in analysing the problem in which the response depends on several variables to optimise the response itself. For the calculation of regression constants and parameters, the central composite (CCD) second-order design was used in the Design Expert software package. The number of experimental points required in the second-order trial plans is determined by the following expression:

$$N = 2^k + n_o + n_a \tag{2}$$

Where:

2^k – the number of experiments in the basic points,

n_o – number of repeated experiments at the middle level,

n_a – number of experiments on the central axes.

The points which provide equal precision in all directions are added to the central axes. These points are designated as alpha (α) and calculated by the following equation:

$$\alpha = (2^k)^{1/4} \tag{3}$$

where k is the number of input parameters.

Optimisation implementation in the Design Expert software requires the application of limit input parameters whose values have been adopted on the basis of the manufacturer's recommendation and physical limitations of the machine, as shown in Table 2.

Table 2. *Physical values of input parameters*

Input parameters	*Unit of measure*	*Lower bound*	*Upper bound*
Feed	*mm/rev*	*0.063*	*0.24*
Cutting speed	*m/min*	*28*	*45*
Cutting depth	*mm*	*1*	*2*

Table 3 in Chapter 4 shows all input parameters of the experiment and the corresponding response surface roughness. The impact of input parameter on response can be found by the variance analysis (ANOVA). The variance analysis is a comparison procedure of multiple samples, with each sample being the basic set. After examining the significance of the coefficients of the second-order model, the final mathematical model of surface roughness was obtained as follows:

$$\begin{aligned} R_a = & -0.62164 + 4.23948 \cdot f_n + 0.00561015 \cdot v_c + 1.29789 \cdot a_p - \\ & -0.036536 \cdot f_n \cdot v_c + 1.67702 \cdot f_n \cdot a_p - 0.012941 \cdot v_c \cdot a_p - \\ & -8.61849 \cdot f_n^2 + 0.000588806 \cdot v_c^2 - 0.33654 \cdot a_p^2 \end{aligned} \quad \textbf{(4)}$$

Where:

R_a – surface roughness,

v_c – cutting speed,

a_p – cutting depth,

f_n – feed.

Dependence diagrams of the mathematical model of surface roughness on the processing input parameters are shown in Figures 4, 5 and 6.

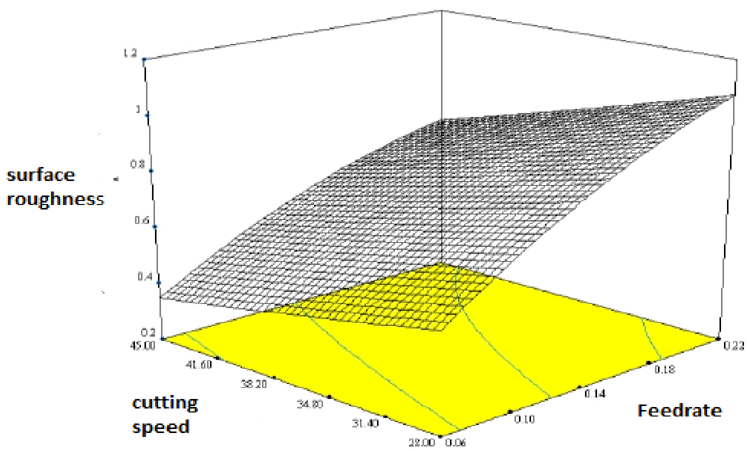

Fig. 4 *Surface roughness dependence on feedrate and cutting speed under constant cutting depth value 1.5 mm*

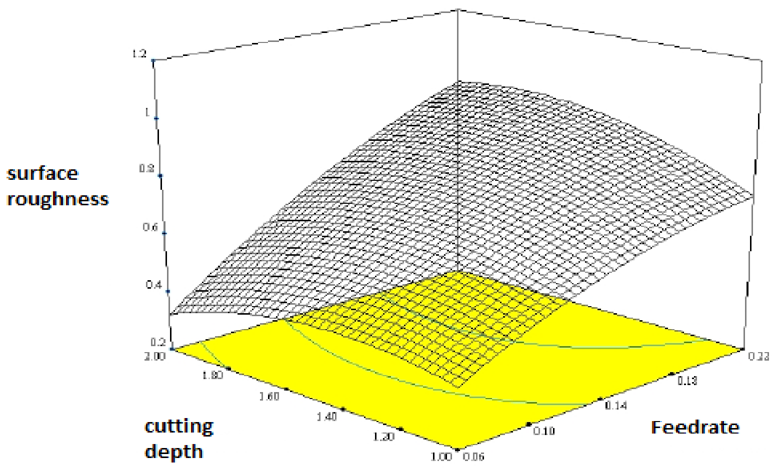

Fig. 5 *Surface roughness dependence on feedrate and cutting depth under constant cutting speed value 36.5 m/min*

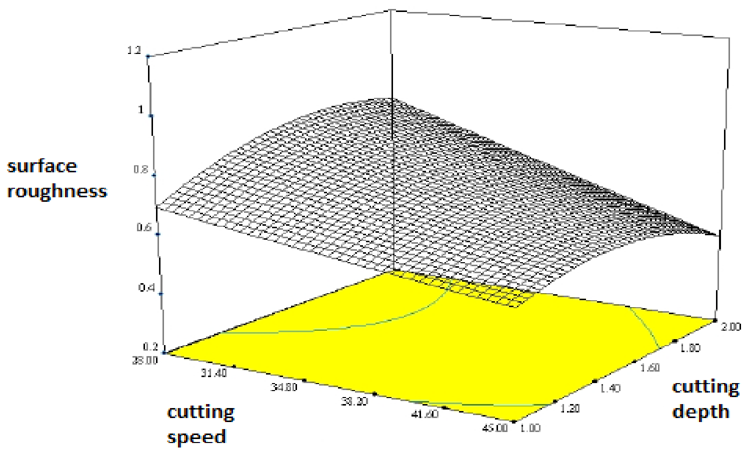

Fig. 6 *Surface roughness dependence on cutting depth and cutting speed under constant feedrate value 0.14 mm/rev*

3.2. ADAPTIVE NEURO-FUZZY PREDICTIVE MODEL

An adaptive neuro-fuzzy inference system (ANFIS) is a hybrid predictive model which uses both the neural network and the fuzzy logic to generate mapping relationship between inputs and outputs.

The structure of this model consists of five layers in which each layer is constructed by several nodes. Same as in the neural network, the inputs of each layer are gained by the nodes from the previous layer, as shown in Figure 7. Moreover, a layer with fuzzy rules and an output layer are contributed to the construction of this model.

Description of each layer in the ANFIS model is as follows [13]:

1. Layer 1: Every node *i* in this layer is a square node with the node function:

$$O_i^1 = \mu_{A_i}(x) \tag{5}$$

where $\mu_{A_i}(x)$ is a membership function for the input *x*.

In this study, we selected the Gauss2mf linear membership function because it generates the lowest value of mean squared error.

2. Layer 2: Every node in this layer is a circle node which multiplies the incoming inputs and sends the product out. Each node output represents the firing strength of a rule.

$$w_i = \mu_{A_i}(x) x \mu_{B_i}(y) \quad (6)$$

3. Layer 3: Every node in this layer is a circle node labelled *N*. The *i-th* node calculates the ratio of the i-*th* rule's firing strength to the sum of all rules' firing strengths:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \quad (7)$$

4. Layer 4: In this layer, Takagi-Sugeno fuzzy type rules (if–then rules) are applied in the weighted output of each node.

$$O_i^4 = \bar{w}_i f_i \quad (8)$$

where f_i represents the output of *i-th* Takagi-Sugeno-type fuzzy rules.

5. Layer 5: This layer represents the modelled output by the ANFIS network.

$$O_i^5 = output = \sum_{i=1}^{n} \bar{w}_i f_i \quad (9)$$

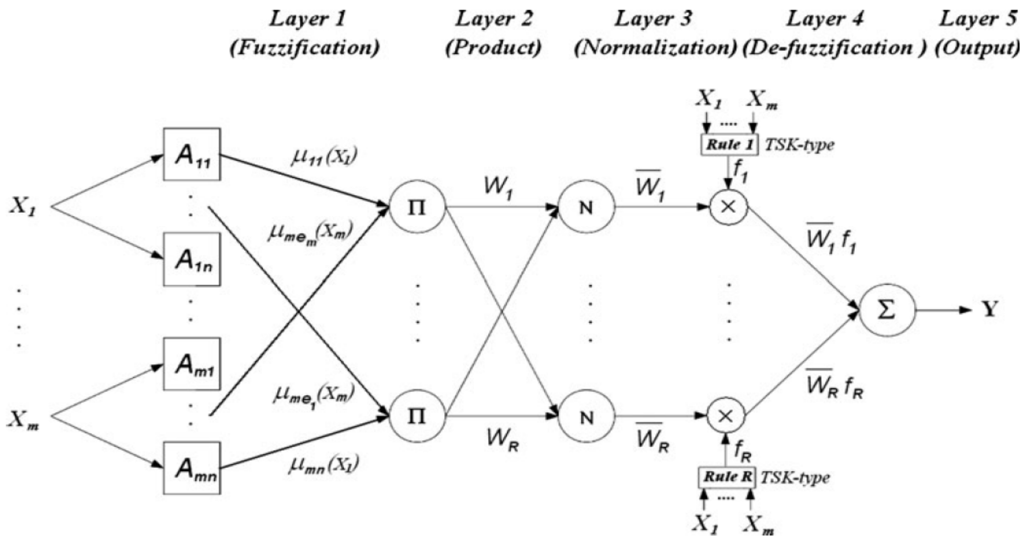

Fig. 7 *Structure of ANFIS model [13]*

ANFIS DESIGN

ANFIS modelling of the machining processes was mainly used for the prediction of surface roughness, tool life and cutting forces [14, 15, 16]. Prior to implementing this method, it is necessary to execute experimental data sharing on learning, testing, and validation sets. It is followed by its implementation in the MATLAB software package. Creating a fuzzy system provides an automatic structure of the ANFIS network. ANFIS networks are generated with differences in fuzzy logic systems, generated by differences in membership functions, by the number of affiliation functions for each input variable and the value type for the output variable. ANFIS architecture is composed of three input variables and one output variable. Each input value generates three linear Gauss2mf membership functions, and the output value is also generated by the linear Gauss2mf function. After generating the fuzzy logic system and structure of the ANFIS network, the if-then rule follows the train of the ANFIS network hybrid algorithm, which takes place over 100 cycles (epochs). The obtained ANFIS training network mean squared error is *0.0075593*. After training the ANFIS network, we proceed with the procedure for testing the network. An error of *0.058022* was found when testing the ANFIS network. After testing the ANFIS network, the validation of the trained ANFIS network is provided. During the validation of the ANFIS network, *0.051512* validation error was obtained.

3.3. OPTIMISATION OF ADAPTIVE NEURO-FUZZY PREDICTIVE MODEL

In order to reduce mean square error of the previously developed ANFIS model, in this section we will describe the implementation of evolutionary training of the ANFIS model by using the genetic algorithm source code. Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. This method combines Darwinian style survival of the fittest among binary string "artificial creatures" with a structured, yet randomized information exchange. Genetic algorithms consist of a population of binary bit strings. Initial values are determined randomly and evaluated. Each combination of ones and zeros is a possibility in the complex space that can be searched and the relation between them is found in the evaluation function that will return a "fitness" or ranking for that particular bit string [17].

Genetic algorithm consists of three main operations:

- Reproduction (Selection) - process in which individual strings are copied according to their fitness. Ones with higher fitness value have a better chance to survive in the next generation.
- Crossover - process that can be divided into two steps. First, pairs of bit strings will be mated randomly to become the parents of two new bit strings. The second part consists of choosing a place (crossover site) in the bit string and exchanging all characters of the parents after that point. The process tries to artificially reproduce the mating process where the DNA of two parents determines the DNA for the newly born.
- Mutation - included, not because the previous process of reproduction and recombination are not sufficient, but because of the probability that a certain bit cannot be changed by the previous operations due to its absence from the generation, either by a random chance or because it has been discarded. It only implies the change of 0 for 1 and vice versa.
- Genetic algorithm and neural networks are both inspired by computation in the biological system. In a genetic algorithm, only items of data that have value in predicting the outputs are retained as inputs to the system. A neural network, on the other hand, does not exclude irrelevant data inputs from the final system. It nullifies the effects of such data inputs by assigning a low weight to them in the decision process.

In this part of the paper, the genetic algorithm will be used for evolutionary training of the artificial neural network, which is part of the structure of the proposed ANFIS predictive model. Combining artificial neural networks with evolutionary algorithms leads to evolutionary artificial neural networks. The genetic algorithms are more appropriately said to be an optimisation technique based on natural evolution.

They include the survival of the fittest idea algorithm. The idea is to first 'guess' the solutions and then combine the fittest solution to create a new generation of solutions which should be better than the previous generation, Figure 8.

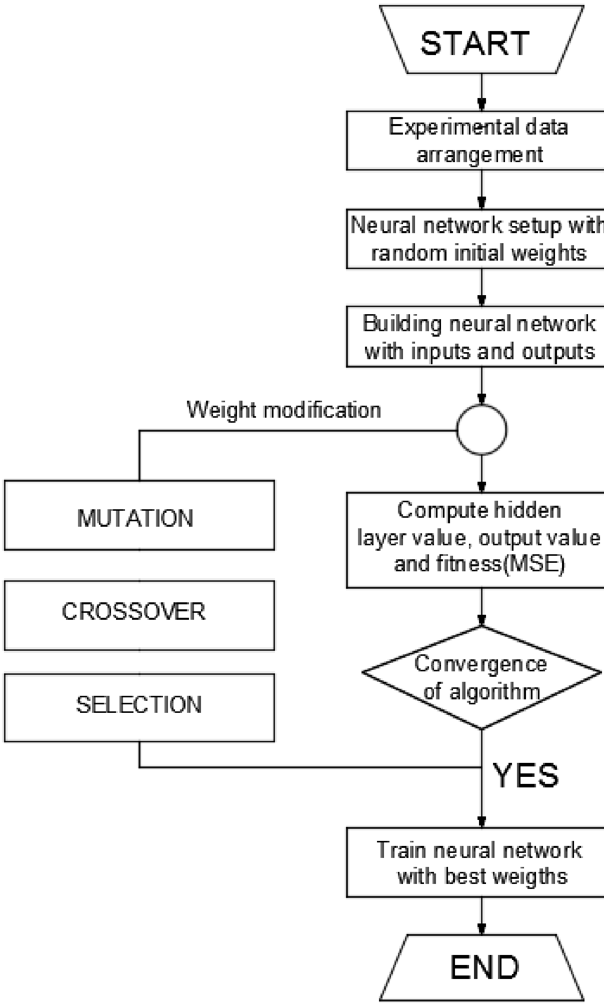

Fig. 8 *Flowchart of the evolutionary training of neural network*

4. ANALYSIS OF PREDICTIVE MODELS

In order to evaluate the performance index of the learning algorithm in solving the selected task, it is necessary to define the accuracy unit of measure. By using a measure of accuracy for the typical learning tasks, it is possible to compare the applied algorithm with other learning algorithms. In order to compare the predicted and measured surface roughness values, a statistical approach will be used to determine the root mean square error according to the expression:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(M_i - P_i\right)^2} \quad \textbf{(10)}$$

Where:

M_i – measured value

P_i – predicted value

N – number of measurements

The statistical error of surface roughness values predicted by the response surface method and ANFIS-based learning database method are shown in Table 3, and a graphical comparison of the accuracy of developed predictive models in Figure 9.

Table 3. *Results of performed experiments and comparison of accuracy of predictive models*

f_n [mm/rev]	V_c [m/min]	a_p [mm]	Ra [µm] Measured	RSM Predicted Ra	RMSE (%) RSM	ANFIS Predicted Ra	RMSE (%) ANFIS	Optimised ANFIS Ra	RMSE (%) Optimised ANFIS
0.063	28	1	0.32	0.8702	12.3	0.2981	0.49	0.3150	0.11
0.224	28	1	0.66	1.2598	13.4	0.7051	1.01	0.6841	0.54
0.063	45	1	0.39	1.4371	23.41	0.3888	0.03	0.3895	0.01
0.224	45	1	0.61	1.7267	24.97	0.6226	0.28	0.6381	0.63
0.063	28	2	0.41	0.9017	10.99	0.3984	0.26	0.4052	0.11
0.224	28	2	1.00	1.5613	12.55	0.9460	1.21	1.0162	0.36
0.063	45	2	0.24	1.2487	22.56	0.3212	1.82	0.2431	0.07
0.224	45	2	0.75	1.8083	23.66	0.6857	1.44	0.7492	0.02
0.045	36.5	1.5	0.20	1.0752	19.57	0.3791	**4.01**	0.2295	0.66
0.280	36.5	1.5	1.14	1.6910	12.32	1.2065	1.49	1.1457	0.13
0.144	22.2	1.5	1.23	1.2290	0.02	1.0687	3.61	1.1853	0.99
0.144	50.8	1.5	0.45	1.9131	**32.72**	0.3752	1.67	0.4241	0.58
0.144	36.5	0.66	0.60	1.1650	12.63	0.6162	0.36	0.6084	0.19
0.144	36.5	2.34	0.58	1.2614	15.24	0.6471	1.50	0.6152	**0.79**
0.144	36.5	1.5	0.75	1.4506	15.66	0.7761	0.58	0.7484	0.04
0.144	36.5	1.5	0.74	1.4506	15.89	0.7761	0.81	0.7484	0.19
0.144	36.5	1.5	0.75	1.4506	15.67	0.7761	0.58	0.7484	0.04
0.144	36.5	1.5	0.73	1.4506	16.11	0.7761	1.03	0.7484	0.41
0.144	36.5	1.5	0.73	1.4506	16.11	0.7761	1.03	0.7484	0.41
0.144	36.5	1.5	0.73	1.4506	16.11	0.7761	1.03	0.7484	0.41

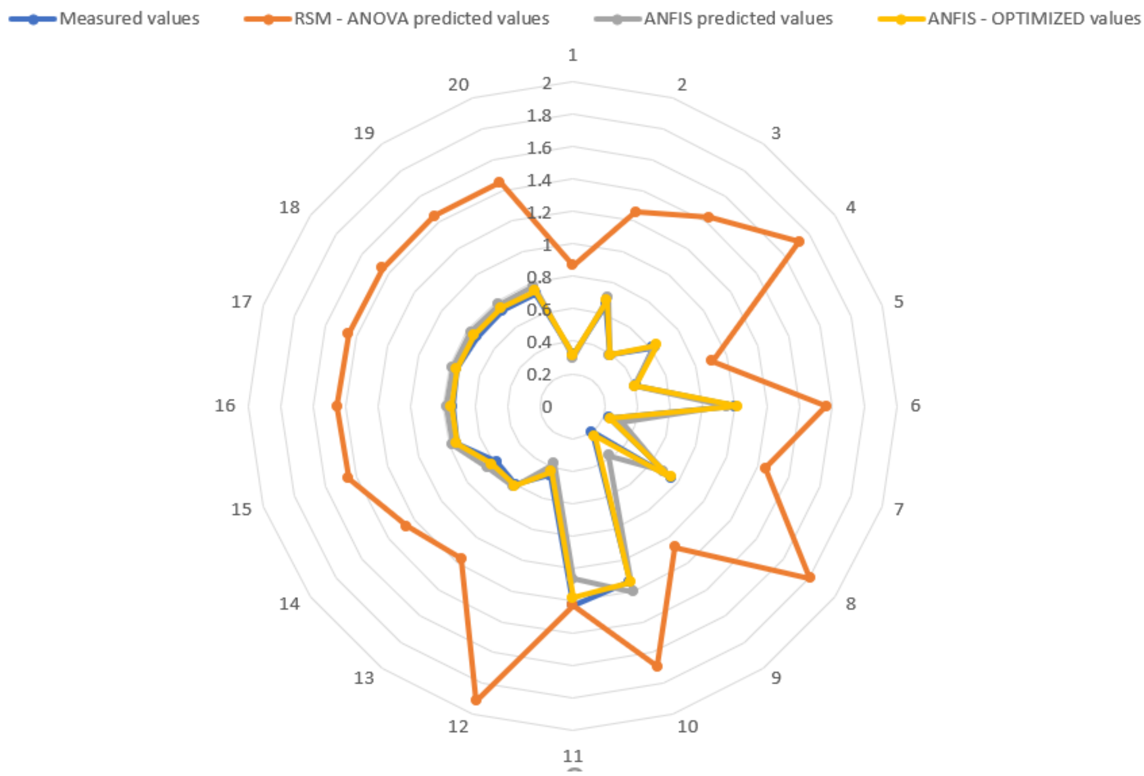

Fig. 9 *Comparison of the accuracy of developed predictive models*

5. CONCLUSION

This paper presents the development of surface roughness predictive models in the turning process of super duplex stainless steel under environmentally friendly conditions. Input parameters are feed, cutting speed and cutting depth. Based on the total of 20 obtained experiments, surface roughness prediction models were developed using the response surface method, variance analysis and optimised ANFIS predictive method, and the following conclusions were obtained as follows:

- By analysing the diagrams obtained by the regression analysis, it can be concluded that the feed has the greatest influence on the roughness of the treated surface. The determination coefficient of the mathematical model is $R^2 = 0.85$. It can be concluded that the model is representative because it explains *85%* of the deviations resulting from the processing parameters.
- 15 sets of experimental data were used for the training of the ANFIS network, while 3 sets of data were used to test the developed network. Two sets of data were used for the validation of the ANFIS network. The average accuracy of the ANFIS model validation is *95%*, indicating the possibility of applying this model when predicting surface roughness for other sets of input data.
- By analysing Figure 9, it can be concluded that all predictive models adequately describe the observed process, given the small differences in predicted and measured surface roughness values. By analysing the accuracy of the developed models, it can be concluded that the optimised ANFIS model is more accurate since it achieves a

maximum root mean square error value of *0.79%* compared to the value of *4.01%* for the ordinary ANFIS model and *32.72%* for the variance analysis, as illustrated in Table 3.

- Based on the developed predictive models and knowing the advantages and limitations of these processes, it is possible to finally achieve a more productive process based on the further development and application of the artificial intelligence methods and development of a more intelligent production system.

6. REFERENCES

[1] Carlos Ancelmo de Oliveira Junior, Anselmo Eduardo Diniz, Rodnei Bertazzoli, Corelating tool wear, surface roughness and corrosion resistance in the turning process of super duplex stainless steel, Journal of Brazilian Society of Mechanical Sciences and Engineering, Vol. 36, No. 4, pp. 775-785, 2014.

https://doi.org/10.1007/s40430-013-0119-6

[2] J. Rajaguru and N. Arunachalam, Coated tool performance in dry turning of super duplex stainless steel, *Procedia Manufacturing*, Vol. 10, pp. 601-611, 2017.

https://doi.org/10.1016/j.promfg.2017.07.061

[3] J. Paiva, F. Amorim, P. Soares, S. Veldhuis, L. Mendes and R. Torres, Tribological Behaviour of superduplex stainless steel against PVD hard coatings on cemented carbide, *International Journal of Advanced Manufacturing*, Vol. 90, No. 5-8, pp. 1649-1658, Springer-Verlag, London, 2017.

https://doi.org/10.1007/s00170-016-9514-3

[4] K. Kumar and J. Senthilkumaar, Analysis of flank wear and chip morphology when machining super duplex stainless steel in gas cooled environment, *International Journal of Engineering and Technology* (IJET), Vol. 5, No. 6, pp. 5045-5056, India, 2013.

[5] Y. Ahmed, J. Paiva, D. Covelli and S. Veldhuis, Investigation of coated cutting tool performance during machining of superduplex stainless steels through 3D wear evaluations, *Coatings*, Vol. 7, No. 8, 127, 2017.

https://doi.org/10.3390/coatings7080127

[6] M. Dhanachezian, T. Tinesh, S.N. Paul and Inian Roy, Study of machinability characteristics for turning austenitic (316L) and super duplex (2505) stainless stell using PVD-TiAlN nano-multilayer inserts, ARPN *Journal of Engineering and Applied Sciences*, Vol. 11, No. 2, pp. 1262-1268, 2016.

[7] S. Kadam, R. Khake and S. Mudigonda, Experimental investigations on surface roughness, cutting forces and tool wear in turnining of super duplex stainless steel with coated carbide inserts, *Proceedings of the ASME 2017 12th International Manufacturing Science and Engineering Conference*, Vol. 2, 2017.

https://doi.org/10.1115/MSEC2017-3008

[8] J. Airao, C. Bhavesh, B. Vivek and K. Navneet, An experimental study of surface roughness variation in end milling of super duplex 2507 stainless steel, ICMPC, Vol. 5, No. 2, pp. 3682-3689, 2018.

[9] M. Thiyagu, L. Karunamoorthy and N. Arunkumar, Experimental studies in machining duplex stainless steel using response surface methodology, *International Journal of Mechanical & Mechatronics Engineering* IJMME-IJENS, Vol. 14, No. 3, pp. 48-61, 2014.

[10] R. Koyee, R. Eisseler and S. Schmauder, Application of Taguchi coupled Fuzzy Multi attribute Decision Making(FMADM) for optimizing surface quality in turning austenitic and duplex stainless steels, *Measurement*, Vol. 58, pp. 375-386, 2014.

https://doi.org/10.1016/j.measurement.2014.09.015

[11] K. Kumar and J.S. Senthilkumaar, Analysis and optimization of output parameters using Taguchi Design Analysis, Recent Patents on Mechanical Engineering, Vol. 7, No. 2, pp. 169-182, 2014.

https://doi.org/10.2174/2212797607666140620003400

[12] S. Jozić, D. Bajić and L. Celent, Application of compressed cold air cooling: achieving multiple performance characteristics in end milling process, *Journal of Cleaner Production*, Vol. 100, pp. 325-332, 2015. https://doi.org/10.1016/j.jclepro.2015.03.095

[13] J. Shing and R. Jang, ANFIS: Adaptive network-based fuzzy interference system, *IEE Transactions on Systems, Manufacturing and Cybernetics*, Vol. 23, No. 3, pp. 665-685, California, 1993.

[14] M. Shirdar, M. Nilashi, B. Karamollah, I. Othman, S. Izman, H. Moradifard, N. Janahmadi abd M. Barisamy, Application of ANFIS system in prediction of machining parameters, *Journal of Theoretical and Applied Information Technology*, Vol. 33, No. 1, pp. 83-93, 2011.

[15] H. Sohrabpoor, P.S. Khanghah and R. Teimouri, Investigation of lubricant condition and machining parameters while turning of AISI 4340, *International Journal of Advanced Manufacturing Technology*, Vol. 76, No. 9-12, pp. 2099-2116, 2014.

[16] I. Maher, M.E.H. Eltaib, A. Sarhan and R.M. El-Zahry, Investigation of the effect of machining parameters on the surface quality of machined brass (60/40) in CNC end milling – ANFIS modelling, *International Journal of Advanced Manufacturing Technology*, Vol. 74, No. 1-4, pp. 531-537, 2014.

https://doi.org/10.1007/s00170-014-6016-z

[17] D. Arjona, R.K. Lay and R.J. Harrington, A hybrid artificial neural network/genetic algorithm approach to on-line switching operations for the optimization of electrical power systems, Energy Conversion Engineering Conference, Aug. 1996.

https://doi.org/10.1109/IECEC.1996.561174