A Comparison between Back Propagation and the Maximum Sensibility Neural Network to Surface Roughness Prediction in Machining of Titanium (Ti 6Al 4V) Alloy

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Abstract. Titanium alloys are attractive materials due to their unique high strength, excellent performance at elevated temperatures and exceptional resistance to corrosion. The aerospace and military industries are the main users of this material. Titanium alloys are classified as materials difficult to machine. The correct parameters for machining are a hard to determine, and today researches are looking to develop new models to predict and optimize these parameters. The surface roughness (Ra) in turning of a titanium alloy machining Ti 6Al 4V predicted using neural and maximum sensitivity network is shown. The machining tests were carried out using PVD (TiAIN) coated carbide inserts under different cutting conditions. Confidence intervals were estimated in the model to get correct results. There are various machining parameters and they have an effect on the surface roughness. A set of initial parameters in finished turning of Ti 6Al 4V obtained from literature have been used. These parameters are cutting speed, feed rate and depth of cut. This paper shows the results obtained using these neural networks approaches to analyze the variables to model the machining process.

Keywords: Neural Network, Machining parameters, Surface Roughness, Maximum Sensibility, Back Propagation.

1 Introduction

Determining and optimizing the parameters involve in a machining process is a critical and very important task. The surface quality is one of the most specified customer requirements. It is a characteristic that could influence the performance of mechanical parts and production costs. The final surface is one of the most important considerations to determine and improve the machinability of materials. Nowadays greater attention is paid to accuracy and surface roughness of product by industry [1]. The

machining process is a dynamical system where many variables interact, due to this, predicting and optimizing these variables are two important strategies in manufacturing. Surface roughness and dimensional accuracy are critical factors in predicting machining performance of any machining operation. The predictive modeling of machining operations requires detailed prediction of all boundary conditions. Surface roughness prediction models generally are based on laboratory experiments because is very difficult, in practice, to keep all factors under control as required to obtain reproducible results [2]. In the last two decades, the intelligent systems composed by Neural Networks, Fuzzy Logic, Evolution Computation, sometimes alone and others times in combination have been applied in manufacturing have been the subject of extensive research. This technology has become an important computing tool to solve engineering problems [3], [6]. It has led to increased research on a wide variety of industrial applications, such as product manufacturability control, process planning, etc. New research and developments are appearing en the state of art use of intelligent systems to control and optimize the machining giving support to predictions and improvement of the surface roughness at different materials [4]. The Artificial neural networks (ANNs) are one of the most powerful computer modeling techniques, based on statistical approach, currently being used in many fields of engineering to simulate the complex relationships which are difficult to describe with physical models. ANNs have been extensively applied in modeling many metal-cutting operations such as turning, milling, and drilling [5]. An Intelligent System is proposed in this research to predict and compare *back propagation and the maximum sensibility neural network to surface roughness prediction in machining of Titanium (Ti 6Al 4V) alloy.* The results shown that, this Intelligent System could serve as support in decision making to improve the machining process and productivity and to save on the cost of new products.

   This research is organized in the following way: In section 1 a brief introduction will be given and section 2 has a short summary of previous research using intelligent systems in the *machining process.* The basis for research tools, Neural Network and Optimization Algorithms are shown in section 3, experimentation and results are shown in section 4, the research conclusions and future work are given in sections 5 and 6.

2   Literature Review

Ramesh in his article "Modeling for prediction of surface roughness in machining of Ti64 alloy using response surface methodology" [7] proposes a prediction model in which he includes parameters such as progress, speed and depth of cut to see their effects turning the titanium and getting the surface quality parameters response. On the other hand Che-Haron [8] worked on an investigation that determined the impact machining of Ti64 on the surface finish, checked alterations obtained in machining analyzed material characterizations in the material piece and diverse types of tooling used in the study. Rico [5] uses the Surface Response methodology and neural networks to predict the roughness. The author develops a model for predicting temperature and roughness of the cutting tool for machining steel 1018. Pawadea [4] shows in

his article titled "Effect of machining and cutting edge geometry parameters on surface integrity of high-speed turned Inconel 718" high-speed cutting and low feed rate, as well as the moderate depth of cut through the use delicate angles of cut that can ensure the generation of residual compression efforts when machining. A. Molinari [9] were devoted to comprehensive studies of chip produced during the milling Ti-6Al-4V, analyzing the process of orthogonal cutting produced at different speeds and the transformation of adiabatic shear banding. He found that the lower speeds chip becomes rougher; this due to thermomechanical limitation, which generates adiabatic shear banding, and behaves differently at high speeds. Krain [10] evaluated the effects of the change in feed rate and the thickness of the chip by changing the radius of the cutting tool as well as material and geometry of this phenomenon and its impact on the life and wear of the tool in the milling of Inconel 718. He showed that not single material or geometry gives the best results. Kopac et al. [11] used an experimental Taguchi design to determine the optimal machining parameters for best surface finish in a traditional turning. The design of Taguchi method was used to identify the impact of various parameters and how a combination of them helped to control the variation. They found that the roughness increases with increasing cutting speed. Ocktem [12] developed a model for determining the best parameters for the optimum roughness in the milling of the faces of a mold to producing a piece by means of biomechanics application (Ortez) using neural networks and genetic algorithms. It appears that a considerable amount of work is being done in the optimization of machining parameters, based on different criteria such as tool wear, vibrations, surface roughness, unit cost, etc [3] [10] [11]. Nowadays artificial intelligence (AI) based on modeling is a new trend in modeling for machining operations [2]. It was found that use of heuristic methods to model prediction of surface roughness was very limited, so emphasis was laid on the development of a surface roughness prediction model.

3 Artificial Neural Networks

Neural networks are computational paradigms that simulate some of the human brain properties, such as some rational capacities, like association, recognition of shapes and behavior patterns. Prediction is an important property of neural networks. Neural networks are non-linear mapping systems that consist of simple processors called neurons, linked it by weighted connections. Each neuron has inputs and generates an output that is the result of the information that was stored and of the processes in the hidden layers. The output signal of a neuron is fed to other neurons as input signals via interconnections. Since the capability of a single neuron is limited, complex functions can be formed by connecting many neurons. It is widely reported that structure of neural network, representation of data, normalization of inputs/outputs and appropriate selection of activation functions have strong influence on the effectiveness and performance of the trained neural network [4], [13].

Some merits of ANN applications can be summarized as, Fault tolerance and adaptability; Data-driven nature; Noise suppression capabilities
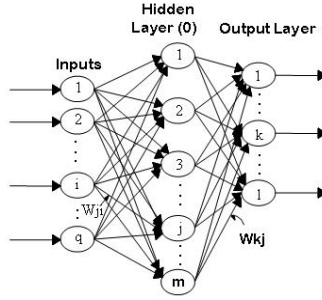
Fig. 1. Typical multi-layered feed-forward ANN

There are several neural networks [2], [4], [3], [10], This researches shown that a perceptron with back propagation learning rule is the most used to predict parameters. To develop this research a multilayer perceptron with back propagation learning rule was used. The Back Propagation Neural Network (BPNN) consists of three layers of neurons: input layer, hidden layer, and output layer Fig. 1. The input layer receives external information such as adjustable process parameters in Table 1. The output layer transmits the data and thus corresponds to various individual outputs. In this study, the number of neurons in the output layer was only one. The BPNN also incorporates hidden layers of neurons that do not interact with the outside world, but assists in performing a nonlinear feature extraction on the data provided by the input and output layers. Here, the number of the hidden layer was obtaining with design of experiment. [19]. Back propagation (BP) is based on searching a surface errors (error as a function of ANN weights) using gradient descent for points with minimum error. Each interaction BP constitutes 2 sweeps: forward activation to produce a solution and a backward propagation of the computed error to modify the weights. This starts at the input layer where each input node transmits the value received forward to each hidden node in the hidden layer. The collective effect on each of the hidden nodes is summed up by performing the dot product of all values of input nodes and their corresponding interconnection weights, as describe in the equation (1).

$$y = \begin{cases} 1, & if \sum_{i=1}^{n} w_i x_i \geq b, \\ 0, & if \sum_{i=1}^{n} w_i x_i < b, \end{cases} \tag{1}$$

Once the net effect at one hidden node is determined, the activation at that node is calculated using a transfer function (e.g. sigmoidal function) to yield an output between 0 and +1. The amount of activation obtained represents the new signal that is to be transferred forward to the subsequent layer. The same procedure of calculating the net effect is repeated for each hidden node and for all hidden layer. The net effects calculated at the output nodes are consequently transformed into activations using a transfer function. The activations are just calculated at the output node [20]. The Neural Network Maximum Sensibility (NNMS) has three layers. Every layer has a specific function. The first layer is composed by a set of source nodes and these neurons detect and distribute the input signal to the first inner layer of neurons. These

inner neurons can become active with any input signal and send a fired signal to the second inner layer. Every neuron of the first inner layer has a Gaussian activation function (2). The objective is to determine the magnitude of the distance between the weights of the inner neurons and the input signals. The input signal is recognized when there is little distance; however, the level of activation must be high.

$$G(x, \lambda, cm) = e^{-((x-cm)/\lambda)^2} \tag{2}$$

NNMS works with normalized real numbers; that means, a number in a range between 0 and 1, so weight initialization at zero value and a value is avoided and a value of -1 is used instead. The best neuron is determined using *maxp* procedure where the maximum value and its position are calculated by means of an input vector (*SN*). [17]. In the learning procedure, the maximum sensibility state establishes the type of learning required. Use activation algorithm first. Here, a winning neuron *wn* is determined along with its activation value *v*. Locate a useless neuron, position nn. The value *vnn* is not considered: $(nn, vnn) = \text{minp}(UW)$. If $v > ms$ then for each i input assign (3): All the neurons of the first inner layer can be activated. The best neuron is determined by selecting the most active neuron. This neuron must surpass a threshold called margin of sensibility (ms).

$$W_{wn,i} = \frac{(W_{wn,i} + X_i)}{2}. \tag{3}$$

3.1 Surface Roughness

In everyday life as well as in industry, the degree of roughness of a surface is very important. Sometimes it is necessary to have very high values of roughness, other times it is undesirable because the surface of the product requires a better appearance, or it requires the lowest surface friction because it is in contact with another surface, in this manner minimizing the phenomenon of wear materials. Surface roughness is the set of irregularities on the actual surface, conventionally defined within a section where the shape and undulation errors have been eliminated. [18] To measure the roughness of the parts an electronic instruments sensitivity micrometer called roughness meter is used to quickly determine the roughness of surfaces. There are several parameters that reflect the measurement of roughness, such as Ra, Ry, Rz. The most common is that Ra is the arithmetic mean [18] of the absolute values of the distance profile roughness of the line of the length measurement see Figure 2.
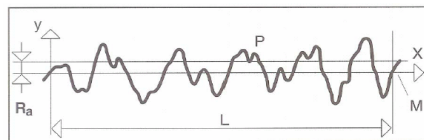

Fig. 2. Graphic Ra for measuring the roughness

4   Development of the Intelligent System

The methodology followed in this study is shown below

- Performance of the test or data extraction
- Classification of the data
- Intelligent Systems Analysis
  - Neural Network for predict
  - Maximum Sensibility Network to predict
  - Compare the results and select the best of them

The identification and optimization of variables involved in a manufacturing process is not an easy task. New research using intelligent systems in manufacturing process show that integrating the knowledge of experts into these tasks is accomplished by having good results, and to achieve this difficult feat, the global trend has been to adapt intelligent systems that are able to develop the ability to learn from these experts and their improvements.

4.1   Description Problem

The main purpose of this study is to identify the parameters that we are going to use in machining, predict the roughness produced by them, in a process of machining of titanium 64 and ensure appropriate values in the machining to guarantee the desired roughness when machining this alloy. The parameters used to carry out this analysis are shown in the table 1.

Table 1. Machining parameters used in the test

Conditions	Units	Level 1	Level 2	Level 3
Cutting Speed	m/min	40	60	80
Feed Rate	mm/rev	0.130	0.179	0.220
Depth of Cut	mm	0.500	0.750	1.000

The machining tests were extracted from Ramesh´s article [7]. The machining processes are carried out on a NAGMATI-175 lathe, Figure 3. The insert tool used was carbide cover-PVD TiAlN. The piece of work was a bar 38mm in diameter with 125mm length made of a titanium alloy (Ti-6Al-4V) Annelead. The turning took place over a length of 110mm for each experiment. The roughness was measure with a "Taylor Hobson Surtronic 3 +"surface roughness meter, shown in Figure 4. The measurements were made on a granite table, and using pattern blocks to level the pieces.
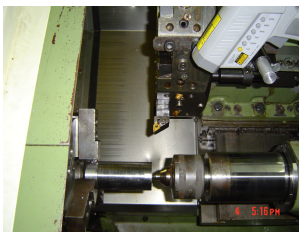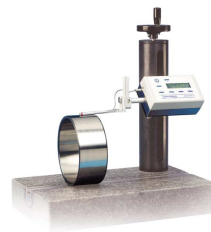

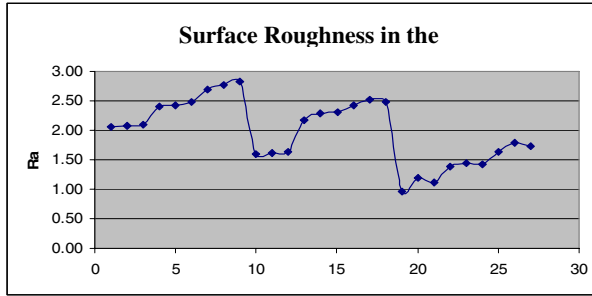**Fig. 3.** Lathe NAGMATI-175

Fig. 4. Surface roughness meter

Fig. 5. Surface roughness during machining

The information used to train the neural network and maximum sensibility are showed in the figure 5.

4.1.1 Neural Network Back Propagation

To build the network is important to identify the following parameters: (1) The set of training patterns, input and target (2) A value for learning rate (3) A criterion that terminates the algorithm (4) A methodology to update weights (5) The nonlinearity function (6) Initial weight values (7) Learning moments. To develop this research a multilayer perceptron with back propagation learning rule was used. Some of variables used were: Tinp = Neurons of the input layer and bias; Tmid = Neurons of the hidden layer; Tout = Neurons of the output layer; eta = Constant learning; alpha = Moment

The parameters values were obtained by a design of experiment. The following Table 2 shows the best results obtained in the tests to train the network.

Table 2. Results with the best values for the variables used in the Neural Network

Tinp	Tmid	Tout	eta	alpha	Ntepochs	error4
3+1	25	1	0.600	0.250	5000	0.0025

Input parameters: Speed, feed and depth cut; Output value: Surface roughness value.

After make different test to train the network, the best configuration graphic, the results between experimental data and training data using the best neural network parameters are shown in Fig. 6. The results show that the network output data is reliable and close to the real data.

4.1.2 Neural Network of Maximum Sensibility (NNMS)

The neural network of maximum sensibility is motivated by the theory of functional systems where by neurons depend on the maximum sensibility generated by a specific stimulus. Only one neuron provides its response. Otherwise, when the stimulus is unknown, the activation of all neurons is required to set a response. This Network was inspired by the biological theory of functional systems. This theory was proposed and
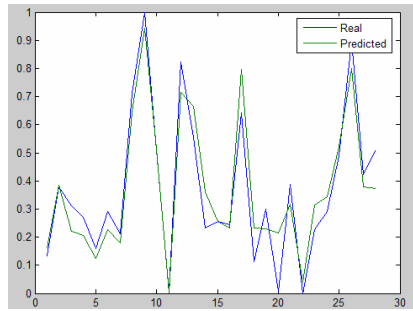
Fig. 6. Graphic real values of the experimentation vs. trained obtain of Neural Network Back Propagation

developed by neurophysiologist Pior K. Anokhin [13], [14], [15]. The functional system promotes the integration of neural information by an afferent synthesis from a dominant motivation, the environment and the memory. This afferent synthesis makes a decision to select a particular action taking into account the maximum sensibility of a dedicated structure to represent a motivation, one aspect of the environment or the memory [16], [17]. Some of variables used are: NTI = Input Neurons; NTO = Output Neurons; lambda = Neuron Sensibility; NTN = Total Neurons; ms= margin of sensibility. "NTI" and "NTO" depend on the data. They can be considered constant because the input parameters are speed, feed and depth cut. For output value the surface roughness was evaluated. With "lambda", "NTN" and "ms" we made a design of experiment to find the best results taking into account 2 levels in each factor and obtaining a model and optimizing it. The results for the best parameters for training the maximum sensibility neural network shows in the table # 3, and figure 7 shows the network output data evaluated against the real data.

Table 3. The best values for the variables used in the Neural Network of Maxim Sensibility

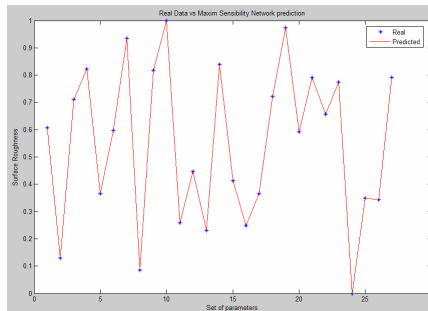| NTI	NTO	lambda	NTN	ms
3	1	0.39	27	0.92

Fig. 7. Real values of the experimentation vs. trained obtain of Neural Network of Maxim Sensibility

The next step was to calculate the values from each network and match up the results to the original values. This evaluation is shown in figure # 8. The result is that both networks give results very near the real values, but the Maximum Sensibility is more accurate.
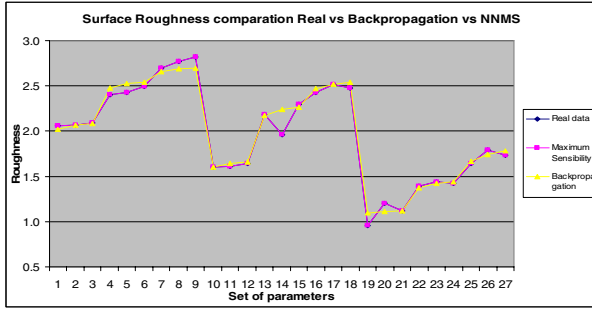

Fig. 8. Compare between Real Value vs. Backpropagation and NNMS results

4.2 Discussion

After that confidence intervals are calculated using the following formula $\bar{x} \pm \left(\left(t_{r-1,\alpha/2} \right) * \left(\frac{\sigma}{\sqrt{r}} \right) \right)$ to predict surface roughness with different parameters to use in the experiment, in the ranges in which the tests were run, in order to obtain improved parameters. Some examples are shown the Table 4 for both networks.

Table 4. Some prediction of roughness with confidence intervals to backpropagation and NNMS

Back propagation						Maxim Sensibility				
cutting speed	feed rate	depth cut	roughness	confidence intervals		cutting speed	feed rate	depth cut	roughness	confidence intervals
40.000	0.130	0.500	2.066	2.075-2.050		40.000	0.130	0.500	2.060	2.096-2.048
40.000	0.130	0.600	2.062	2.071-2.047		40.000	0.130	0.600	2.017	2.053-2.004
40.000	0.130	0.700	2.060	2.069-2.045		40.000	0.130	0.700	2.059	2.095-2.047
40.000	0.130	0.800	2.066	2.075-2.051		40.000	0.130	0.800	2.059	2.095-2.047
40.000	0.130	0.900	2.081	2.090-2.065		40.000	0.130	0.900	2.046	2.082-2.033
40.000	0.130	1.000	2.099	2.109-2.084		40.000	0.130	1.000	2.090	2.126-2.078
40.000	0.140	0.500	2.125	2.135-2.110		40.000	0.140	0.500	2.047	2.083-2.034

5 Conclusions

The advantage with this method is that once the results obtained were optimized to reduce the roughness and these values are sent to the machine, the result is a roughness very close to the limits shown in the table above, in the Table 5 shows the optimization values obtained for both neural networks. With these parameters, the next step is to bring the machine and carry out tests to verify the results generated by the network, although we can see that the results are very similar, so one can conclude that both are good, with the results of maximum sensitivity being obtained much faster.

Table 5. Predicted values with backpropagation and NNMS

Neural Network	cutting speed	feed rate	depth cut	roughness
Backpropagation	80	0.13	0.5	1.0584
NNMS	71	0.13	0.5	0.96

This shows that the neural network can help us predict the roughness, and this can be used as a complement when designing parts. It is very important to find the ideal conditions to permit machining optimization and reduce costs and the same time, which can be simple using an intelligent system.

6 Future Work

It is convenient to keep working on techniques to improve these methodologies (using evolution computation). Research is being done to integrate multi-objective algorithms considering the different variable combinations and constraints involved in the parts being machined. Analysis of different types of materials in different conditions within the process, such as super alloys, is needed because this type of material has poor machinability and the process is very expensive.

References

[1] Meziane, F., Vadera, S.: Intelligent systems in manufacturing: current developments and future Integrated manufacturing Systems, vol. 11, pp. 218–238 (2000)

[2] Morales, R., Vallejo, A., Avellan, J.: AI approaches for cutting tool diagnosis in machining processes. In: Proceedings of the 25th IASTED 978-0-88986-629-4, pp. 186–191 (2007)

[3] Pawadea, R.S., Suhas, S., Brahmankar, P.K.: Effect of machining parameters and cutting edge geometry on surface integrity of high-speed turned Inconel 718. International Journal of Machine Tools and Manufacture (2007), doi:10.1016/j.ijmachtools.2007.08.004

[4] He, W., Zhang, Y.F., Lee, K.S., Liu, T.I.: Development of a fuzzy-neuro system for parameter resetting injection molding. Transactions of the ASME 123 (February 2001)

[5] Rico, L., Díaz, J.: Surface roughness prediction at 1018 cold rolled steel using Response Surface Methodology and neural networks. Culcyt Research Year 2(10) (2005)

[6] Russell, S.J., Norvig, P.: Artificial Intelligence: A Modern Approach, 2nd edn., pp. 111–114. Prentice Hall, Upper Saddle River (2003)

[7] Ramesh, S., Karunamoorthy, L., Ramakrishnan, R.: Modeling for prediction of surface roughness in machining of Ti64 alloy using response surface methodology. Journal of Materials Processing Technology (2007), doi:10.1016/j.jmatprotec.2007.11.031

[8] Che-Haron, C.H., Jawaid, A.: The effect of machining on surface integrity of titanium alloy Ti–6% Al–4% V. Journal of Materials Processing Technology 166, 188–192 (2005)

[9] Molinari, A., Musquar, C., Sutter, G.: Adiabatic shear banding in high speed machining of Ti–6Al–4V: experiments and modeling. International Journal of Plasticity 18, 443–459 (2002)

[10] Krain, H., Sharman, A., Ridgway, K.: Optimization of tool life and productivity when end milling Inconel 718 M. Journal of materials processing technology 189, 153–161 (2007)

[11] Kopac, J., Bahor, M., Sokovic, M.: Optimal machining parameters for achieving the desired surface roughness in fine turning of cold preformed steel workpieces. International Journal of Machine Tools and Manufacture, 42707–42716 (2002)

[12] Oktem, H., Erzurumlu, F.: Prediction of minimum surface roughness in end milling mold parts using neural network and genetic algorithm Materials and Design. Journal 27, 735–744 (2006)

[13] Egiazaryan, S.K., G.G.: Theory of functional systems in the scientific school of p.k. anokhin. Journal of the History of the Neurosciences 16(1-2), 194–205 (2007)

[14] Anokhin, P.: Biology and Neurophysiology of the Conditioned Reflex and Its Role in Adaptive Behavior. Pergamon, Oxford (1974)

[15] Anojin, P.K.: Psicología y la filosofía de la ciencia: Metodología del sistema funcional. editorial Trillas, México (1985)

[16] Red'ko, V.G., Prokhorov, D.V., Burtsev, M.S.: Theory of functional systems, adaptive critics and neural networks. In: Proceedings of IJCNN, pp. 1787–1792 (2004)

[17] Torres-Treviño, L.M.: Controladores dinámicos con la red neuronal de máxima sensibilidad. Master's thesis, Autonomous University of san Luis Potosi, San Luis Potosí, México (1998)

[18] Carlos González González y Ramon Zeleny, Metrología Dimensional. Mc Graw Hill

[19] Kim, B., Kim, S.: GA-optimized back propagation neural network with multi-parameterized gradients and applications to predicting plasma etch data. Chemometrics and Intelligent Laboratory Systems 79, 123–128 (2005)

[20] Basheer, I.A., Hajmeer, M.: Artificial neural networks: fundamentals, computing, design, and application. Journal of Microbiological Methods 43, 3–31 (2000)