Development and application of an Intelligent System to predict and optimize the surface roughness of 1018 and 4140 Steel

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Abstract

The aim of this research is to present a new methodology for predicting and optimizing the surface roughness during machining of 1018 and 4140 Steel. There is particular interest in finding the best machining value parameters that should be used to achieve good surface roughness. These parameter values can be found by this neural intelligent approach. This methodology analyzes and identifies the parameters involved in the machining process; with this information the model is able to predict the surface roughness value in different conditions and then optimize the results with different intelligent heuristics. The experimental results show that we may conclude that this intelligent system is a suitable methodology for predicting and optimizing surface roughness during the machining of 1018 and 4140 Steel.

Key words*: neural network, machining parameters, surface roughness, random search, hill climbing.*

1. Introduction

Determining and optimizing the parameters involved in a machining process is a critical 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 when determining and improving the machinability of materials.

Nowadays greater attention is given to accuracy and surface roughness of products by the industry [1]. The machining process is a dynamical system with many variables. Predicting and optimizing these variables are two important strategies in the manufacturing process.

Surface roughness and dimensional accuracy are critical factors in predicting machining performance in any machining operation. The predictive modelings of machining operations require detailed prediction of all boundary conditions. Surface roughness prediction models are generally based on experiments in the laboratory because it 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 made up of Neural Networks, Fuzzy Logic and Evolutionary Computation, sometimes alone and other times in combination, have been applied in manufacturing and have been the subject of extensive research. This technology has become an important computing tool for solving engineering problems [4], [13]. 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 as state of art using intelligent systems to control and optimize machining, giving support in the prediction and improvement of surface roughness in different materials [5].

Artificial Neural Networks (ANN's) 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. ANN's have been extensively applied in modeling many metal-cutting operations such as turning, milling, and drilling [8].

An Intelligent System is proposed in this research to predict the surface roughness during machining of 1018 and 4140 Steel. A neural network back propagation was used in the first step and the results were optimized by two intelligent algorithms, Random Search and Hill Climbing.

The results show that this Intelligent System could serve as support in decision making to improve the machining process and productivity and to save on costs 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 of 1018 and 4140 Steel. The basic research tools, Neural Network and Optimization Algorithms, are shown in section 3. Experimentation and results are shown in

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section 4, and the research conclusions and future work are given in sections 5 and 6.

2. Literature Review

The use of Fuzzy Logic, evolutionary computation and neural networks for parametric design of products has proven to be highly useful. In these designs a great number of variables and interrelations are involved generating a great quantity of completely unknown parameters [6], [7]. Fuzzy Logic technology has the ability to handle lexical uncertainties that are imprecise. It is very common in most human words used to evaluate concepts and to reach conclusions. These knowledge systems have been proposed in order to reach better design processes and to improve product design quality [8] [3].

Rico [8] used Response Surface Methodology and neural networks for predicting surface roughness. Models have been developed to predict the surface roughness and the temperature of the tool during machining of the 1018 steel. Pawadea [4] showed, in his article "Effect of Machining Parameters and Cutting Edge Geometry on Surface Integrity of High-speed Turned Inconel 718", that the highest cutting speed, the lowest feedrate, and a moderate depth of cut coupled with the use of a honed cutting edge can ensure induction of compressive residual stresses in the machined surfaces.

Krain [9] evaluated the effect of varying feed rate/chip thickness, immersion ratio (radial depth of cut), tool material and geometry on tool life, tool wear and productivity obtained when end milling Inconel 718. The study showed that no single tool material or geometry gave the best overall performance. Kopac et al. [10] utilized a Taguchi experimental design to determine the optimal machining parameters for a desired surface roughness for traditional turning. The Taguchi designed method was used to identify the impact of various parameters on output and determine the combination of parameters for controlling them to reduce the variability in that output. They found that the surface roughness increased with an increase in cutting speed.

Ocktem [11] developed a model to determine the best cutting parameters leading to minimum surface roughness in end milling mold surfaces of an ortez part used in biomedical applications by coupling neural networks and genetic algorithms.

It appears that a considerable amount of work is going on in the area of machining parameters optimization, based on different criteria such as tool wear, vibration, surface roughness, unit cost, etc [4] [9] [10]. Nowadays artificial intelligence (AI) based on modeling is a new trend in modeling for machining operations [2]. found that the use of heuristic methods to predictions of surface roughness was very limit emphasis was laid on the development of a s roughness prediction model.

New research using Neural Networks has appea improve and optimize the assembly and disassem products [6]. All the components of the product to be functional and easy to maintain, therefo these restrictions should be analyzed and solved d product design and the machining process shou analyzed and optimized before sending the pa production.

2.1 Artificial Neural Networks.

Neural networks are computational paradigms simulate some of the human brain properties, suc some rational capacities like association, recognitic shapes and even behavior patterns. Prediction i important property of neural networks.

Neural networks are non-linear mapping systems consist of simple processors called neurons, linke weighted connections. Each neuron has inputs generates an output that is the result of the informa that was stored and of the processes in the hid layers. The output signal of a neuron is fed to o neurons as input signals via interconnections. Since capability of a single neuron is limited, comp functions can be needed through the connection many neurons. It is widely reported that the struct of neural network, the representation of data, normalization of inputs outputs and the appropri selection of activation functions have a str influence on the effectiveness and performance of trained neural network [5], [12].

Some merits of ANN applications can be summarize as follows:

(1) Fault tolerance and adaptability;
(2) Data-driven nature;
(3) Noise suppression capabilities

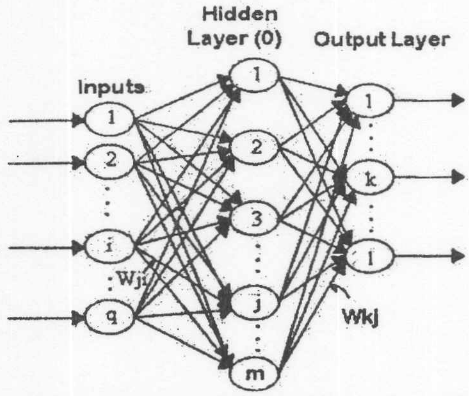

Figure 1. Typical multi-layered feed-forward ANN.

There are several neural networks [2], [5], [4], [9], This research shows that the perceptron with a back propagation learning rule is the one most used to predict parameters. To develop this research a multilayer perceptron with a back propagation learning rule was used.

2.2 Intelligent Algorithms

The Random Search randomly generates a large number of solutions for an optimization problem. Usually the numbers are generated through uniform distribution, selecting the best. According to Shi [14], the random search almost always converges on the optimal solution and it applies it to almost all of the problems of optimization. The main disadvantage in the method is that finding an optimal solution or one very close to optimal can be a slow process. This disadvantage is mitigated by the important developments in computer systems at present.

The method of generating random solutions can vary considerably for each problem. However, it generally uses pseudo numbers with uniform distribution to get these solutions, since this ensures that the solutions evaluated come from different areas within the space of solution, and that this is not giving preference to any particular information.

Hill climbing is an optimization technique which belongs to the family of local search. It is a relatively simple technique to implement, making it a popular first choice. Although more advanced algorithms may give better results, there are situations where hill climbing works well. [15]

Hill climbing can be used to solve problems that have many solutions but where some of the solutions are better than others. The algorithm is started with a random solution to the problem. It sequentially makes small changes in the solution, each time improving it a little bit. At some point the algorithm arrives at a point where it cannot see any further improvement, and at this point the algorithm terminates. Ideally, at that point a solution is found that is close to optimal, but it is not guaranteed that hill climbing will ever come close to the optimal solution Hill climbing attempts to maximize (or minimize) a function f(x), where x is a discrete state, locally increasing (or decreasing) the value of f, until a local maximum (or local minimum) x_m is reached. Hill climbing can also operate in a continuous space: in that case, the algorithm is called gradient ascent [13], (or gradient descent if the function is minimized).

3. Development of the Intelligent System

3.1. Methodology

The methodology followed in this study is shown below

- Testing and data collection
- Classification
- Intelligent Systems Analysis
  - Roughness prediction by Neural Network
  - Optimization by
    - Random Search Algorithm
    - Hill Climbing Algorithm
  - Comparison of results and selection of the best

The identification and optimization of variables involved in the process of manufacturing a product is not an easy task. New research using intelligent systems in manufacturing processes show that integrating the knowledge of experts into these tasks is accomplished by having good results. 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.

3.2. Problem Description

The main focus of this research is to determine the optimal parameters of the machining process to improve the surface quality of 1018 and 4140 steel using a vertical machining center.

The pieces used in the experimentation were of 130x75x25 mm. Tests were carried out in a vertical machining center PCMill 125 (figure 2) and the arguments that were used in the testing are shown in table 1.

Material	1018	4140
Speed (RPM)	800	1000
Feed (mm/min)	50,60,70,80,90,100,110	

Table 1. Machining parameters used in the test

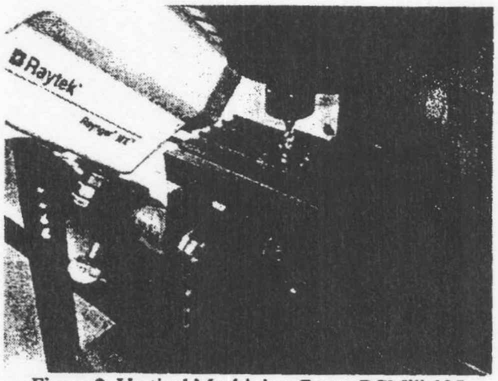

Figure 2. Vertical Machining Center PCMill 125

The thickness of each cut was 1mm and during the process an infrared thermometer "RAYMX4PE" show in the Figure 3 was used, for measuring temperature.

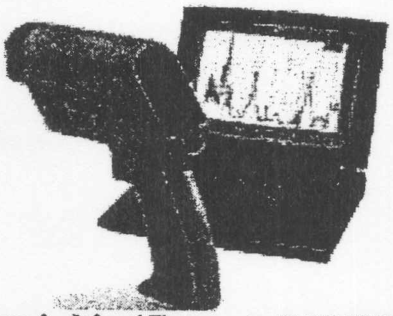

Figure 3. Infrared Thermometer "RAYMX4PE"

In the case of roughness we used a Mitutoyo SJ-301 roughness meter shown in Figure 4, which was on a granite table and we used block pattern to help us level it. Hence there was a relationship between the parameters and the roughness generated; this is the information to be analyzed.

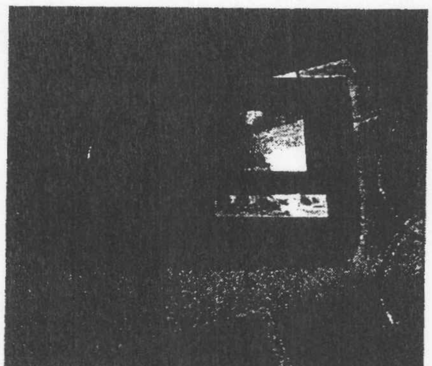

Figure 4. Mitutoyo SJ-301 roughness meter

The data obtained in the experimentation was used to train and validate the Neural Network as show in table 2.

Material	Feed	Speed	Ra	Material	Feed	Spee
Steel 1018	50	800	2.04	Steel 4140	80	800
Steel 1018	50	1000	2.02	Steel 4140	80	1000
Steel 4140	50	800	3.52	Steel 1018	90	800
Steel 4140	50	1000	3.07	Steel 1018	90	1000
Steel 1018	60	800	2.54	Steel 4140	90	800
Steel 1018	60	1000	3.01	Steel 4140	90	1000
Steel 4140	60	800	3.15	Steel 1018	100	800
Steel 4140	60	1000	2.05	Steel 1018	100	1000
Steel 1018	70	800	5.49	Steel 4140	100	800
Steel 1018	70	1000	3.66	Steel 4140	100	1000
Steel 4140	70	800	2.92	Steel 1018	110	800
Steel 4140	70	1000	3.23	Steel 1018	110	1000
Steel 1018	80	800	4.5	Steel 4140	110	800
Steel 1018	80	1000	2.9	Steel 4140	110	1000

Table 2. Data for the test

3.2.1. Neural Network.

To build the network it is important to identify following parameters: (1) The set of training patter input and target (2) A learning rate value (3) criterion that terminates the algorithm (4) methodology to update weights (5) The nonlinear function (6) Initial weight values (7) Learni moments. To develop this research a multilay perceptron with a back propagation learning rule w used. Some of variables used are:

Tinp = Neurons of the input layer plus polarization
Tmid = Neurons of the hidden layer
Tout = Neurons of the outer layer
eta = Learning constant
alpha = Moment

The parameter values were obtained by an experime design. Table 3 shows the best results obtained in tl tests for network training.

Tinp	Tmid	Tout	eta	alpha	Nepochs	error
3+1	[illegible]	[illegible]	0.600	0.250	[illegible]	0.0039

Table 3. Results with the best values for the variables used in the Neural Network

The Input parameters used were: Material, feed an speed. For Output value we used the surfac roughness value.
The Figure 5 shows the Neural Network result compared with real data on roughness.

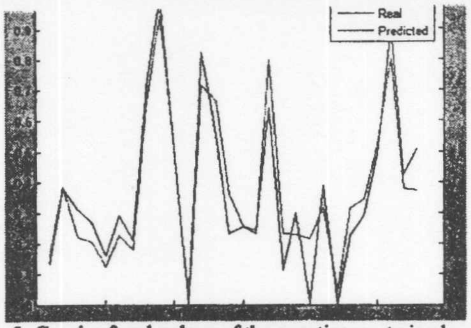

Figure 5. Graph of real values of the equation vs. trained network

The results show that the network output data is reliable and close to the real data.

3.2.2. Optimization Algorithms.

Once the network is trained, the next step is to use heuristics and algorithms to optimize the data. The random search is a program that tries random numbers in the work range to minimize the result of the roughness and finds the lowest value as an answer for the vector, indicating the parameters to be used to obtain this value. MatLab 7.0 software was used to elaborate the program. Figure 6 shows the results after the random search for program optimization was implemented.

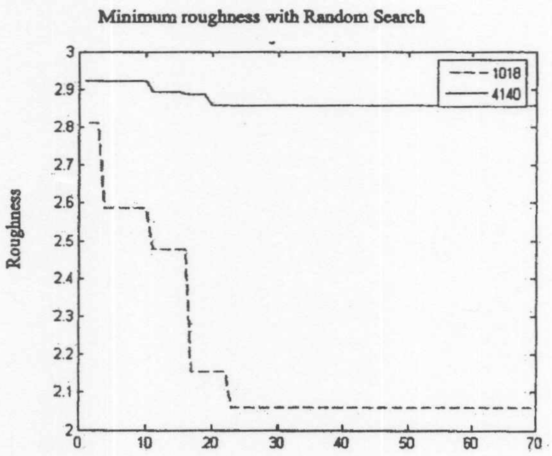

Figure 6. Results of roughness optimization with Random Search

Another way of finding the optimal machining parameters, is through the use of an algorithm called Hill Climbing, which starts from a point of search and in each interaction selects a new point in the vicinity, if the new item is better than the previous one, it becomes the current point. If you do not select another point the evaluation ends with no improvement. Figure 7 shows the results obtained using this algorithm.

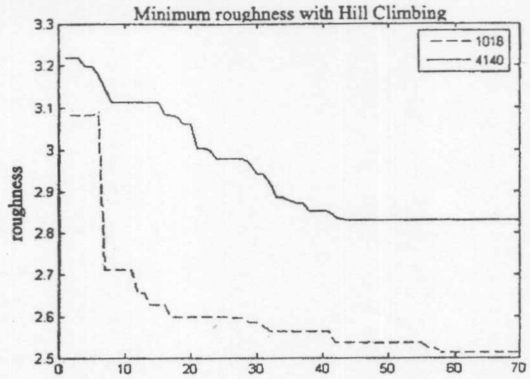

Figure 7. Results of roughness optimization with Hill Climbing

The result of the optimization is shown in Table 4. It was obtained thorugh an average of the values generated by algorithms doing tests 10 times.

Type of algorithm	[illegible]	[illegible]		
	Roughness	Material	Speed	Feed
[illegible]	2.0287	1018	841	52
[illegible]	2.8100	4140	982	55
[illegible]	3.0729	1018	846	79
[illegible]	2.7910	4140	1000	56

Table 4. Results of optimization

3.3. Discussion

The Neural Network fits exactly with the data allowing a prediction that is close to reality. Figure 8 shows the compared results of the parameters obtained with the ANN and the real parameters.

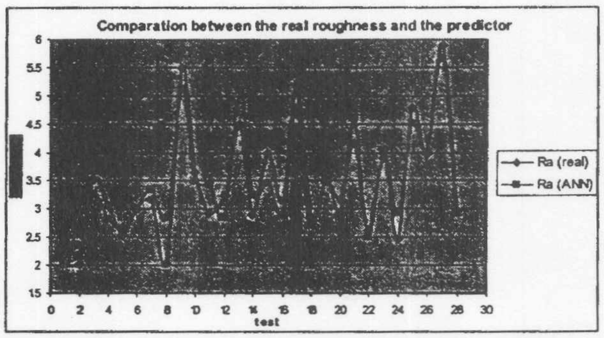

Figure 8. Comparison between real roughness and the predictions

The results are very similar, using the hill climbing algorithm. The results were not constant and ranged from 4.5 to 2.0236 for 1018 steel. In the case of 4140 there was not much problem due to the fact that this algorithm is typically local, taking into account only the immediate consequences of the choices, sometimes resulting in a point outside the best region

4. Conclusions

1. We have shown how a neural network can help us to predict surface roughness and how it could be used as a complementary technique to improve the machining process and parts. The following are the main advantages found when using the neural network:
   - Ability to take incomplete or corrupt data and provide approximate results.
   - Inherent parallelism gives for fault-tolerance – loss of a few interconnections or nodes leaves the system relatively unaffected.
   - The neural networks are fast and efficient for handling large amounts of data.
2. It is very important to know the conditions that a piece must have in order to achieve reduced machining time. These conditions can be easily found by an intelligent system.
3. Within optimization algorithms we can see that the Random Search converges faster and more accurately, unlike Hill Climbing, since the latter may never find a solution if it is caught somewhere that is not in the target area, rendering you unable to find better results through examples, maximums or plateaus or ridges.

5. Future work

It is convenient to keep working on techniques to improve these methodologies (using evolutionary computation). Research is being done to integrate multi-objective algorithms, taking into account the different combinations of variables and constraints involved in the machining of parts.

We should analyze different types of materials in different conditions in the process, like super alloys, because this type of material has poor machinability and the process is very expensive.

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