ESTIMATION OF FORCE AND ROUGHNESS IN MACHINING OPERATIONS BY USING NEURAL NETWORKS FOR EDUCATIONAL APPLICATION

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Abstract. *This paper reports the development of a module for force and surface roughness estimation as a part of educational software which is able to simulate the most common machining process, based on CNC technology. It targets becoming an auxiliary tool on professional labor training (engineers or technicians) in optimized machining process planning. Besides the conventional theoretical models, the software will implement an artificial neural network, an AI technique which is largely used in empiric problems to make prediction. The first results shows that the ANN model is very accurate and can approximate with reasonable confidence the experimental and theoretical results.*

Key words: artificial neural networks, machining, force and roughness, simulation, CNC

1. INTRODUCTION

The machining processes in general are responsible for a significant share of the total component cost as well as they affect its functionality. Especially in good making companies, the machining processes are extensively time consuming and use a lot of tools/machine resources, and thus requires attention in planning.

The process planner which normally formats the operation sheets, prior to CNC programming, do not have reliable tools which can simulate the machining processes and help them to select those adequate parameters to some task .Even the existing CAD/CAM software focus usually on the geometrical definition of tool paths, and don't take into consideration fundamental machining physical boundaries such as machine power, acting forces, surface roughness and tool life.

This work attempts to generate a reliable tool which can help the students to better understand those conditions, by using a modern computational method relying on neural networks.

2. BACKGROUND RESEARCH

2.1. Machining Processes

2.1.1. Turning

The turning can be considered a type of machining process which produces cylindrical parts, generating revolved surfaces, both internally and externally. This can be done by rotating the work piece and displacing the unique cutting edge tool in a plane that contains the rotation axis of the part.

Figure 1 – Examples of external and internal turning operations

The cutting force in turning (F_c) can be expressed in several ways, however the most simple establishes:

$$F_c = K_s.A \quad \text{(N)} \tag{1}$$

Where: K_s is the specific cutting pressure in MPa e A is the chip area in mm^2, which can be obtained by the product of feed and depth of cut.

Or a estimation of Ks, Kienzle had present a simple and precise experimental equation, relating the chip width h

$$K_s = K_{s1}.h^{-z} \quad \text{(MPa)} \tag{2}$$

Where: K_{s1} e z are material and tool constants
The chip width can be related to the feed through the main cutting edge positiong angle (χ) by:

$$h = f.sen\chi \quad \text{(mm)} \tag{3}$$

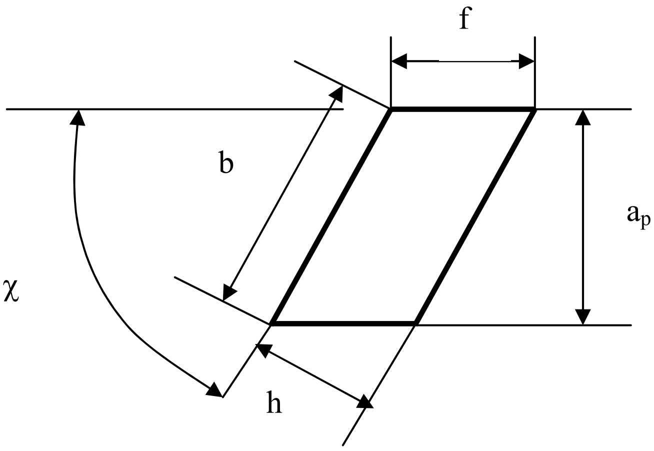

Figure 2 – Relation between chip width and feed

2.1.1. Milling

The milling process is a machining process that produces pieces of several features. The tool is normally provided of more than one cutting edge, and moves and rotates simultaneously. The process is able to generate plan, angular and circular surfaces [11].

The milling operation can be classified, following the position of the tool teeth regarding the machined surface, in:*Peripheral Milling*: where the tool's acting teeth are placed in the cylindrical portion of the body and produce a machined surface which is parallel to its rotation axis.; *Face Milling*: where the tool's acting teeth are placed in the top portion of the body and produce a machined surface which is perpendicular to its rotation axis and *End Milling*: where the tool's acting teeth are placed in the cylindrical and top portion of the body and produce a machined surfaces which are both parallel and perpendicular to the its rotation axis.

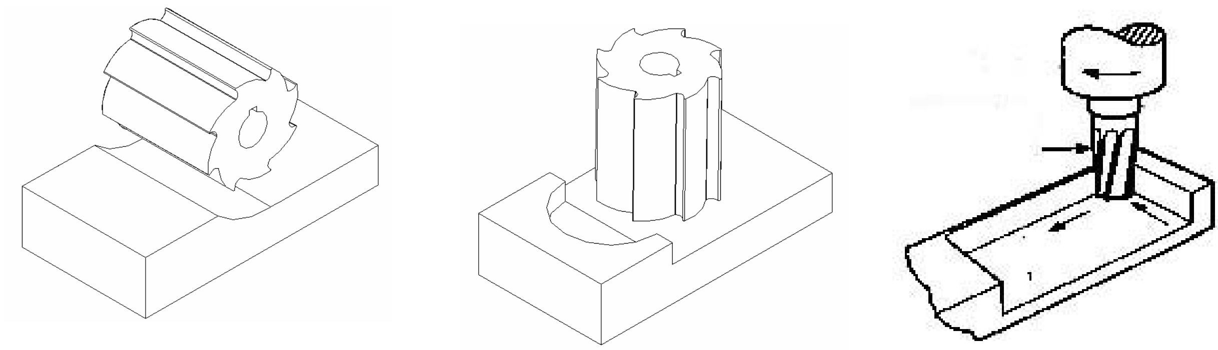

Figure 3 – Examples of typical milling operations

Additionally, it can be mentioned two different methods of milling: up and down milling. In the first, the feed movement takes place on the opposite direction of the cutting movement; on the other hand, in the second, these movements occur in the same direction. Other milling operations can be performed depending upon the kind of the cutter in question, such as gear teeth, slopes, angular profiles etc.

Both in face and peripheral milling, the mean cutting power can be calculated using the mean pressure coefficient K_{sm}, following the equation:

$$P_c = \frac{K_{sm} a_e a_p v_f}{60.10^6} (kW) \qquad (4)$$

Where K_{sm} can be estimated by the well know Kienzle relation for $h = h_m$; a_e is the work depth and a_p is the cutting depth.

The bibliography presents some formulation to determine the average roughness in milling. One of them which is often used can be found in tooling manufactures catalogs, such as in [7]. The equation is:

Face and End milling: $$R_{\max} = \frac{f_z^{\,2}}{8r_\varepsilon}.1000(\mu m) \qquad (5)$$

Where: $R_{máx}$ is the theoretical roughness, f_z is the cutting feed per tooth in mm and $r\varepsilon$ is the tool nose radius.

Peripheral milling: $$R_{\max} = \frac{f_z^{\,2}}{4D}.1000(\mu m) \qquad (6)$$

Where: D is the cutter diameter in mm.

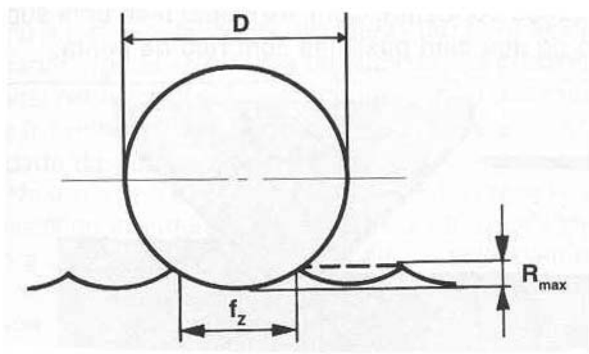

Figure 4 - Theoretical roughness in peripheral milling

2.2. Neural networks

An artificial neural network (ANN) can be classified as a mathematical model, which tries to imitate the biological nervous systems, consisted of processing units, called neurons that are logically interconnected in layers. There are several references to ANN applications in machining area as per [7], [8] and [9], mainly regarding function approximation of some critical phenomena as tool wear, force or roughness. The general purpose is to obtain a model that relates certain inputs (supposed to be relevant) to desired outputs in order to take some decision.

The figure below shows a typical topology of neural network. There is an input layer where no calculation occur and a output layer, where the results are shown. Usually one or more hidden layers exist to continue with the calculation, though weight lines and improve the network performance.

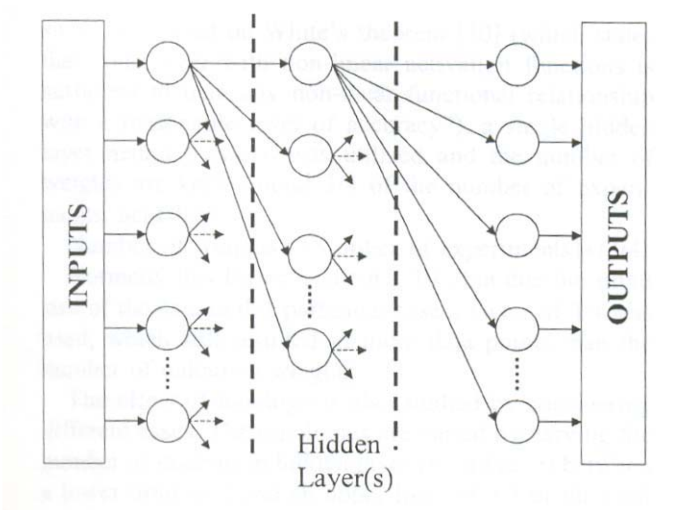

Figure 5 – Schematic Structure o an ANN

There are different types of ANN´s available, depending upon the specific problem attempted to be solved, such as classification, function approximation, prediction etc. In this work we will focus on two kinds: the Multilayer Perpectrons and the Radial Basis Function

2.2.1 Mutilayer Perceptrons

Multilayer perceptrons (MLPs) are layered feed-forward networks typically trained with static back-propagation. In this network, the input patterns are represented by the Input Processing Elements (or simple PE´s) where no calculation is made. The following sets of neurons are found in the hidden layer(s), and as soon as the i_{th} input PE is inputed, the information is conducted to the j_{th} PE in hidden layer through the weight W_{ij}. So, the incoming data, in such element, is represented by

$$a_j = \sum_{i=0}^{n} W_{ij} I_i \tag{7}$$

where a_j is the linear combination of each I_i multiplied by W_{ij} and will be the value used in the activation function (AF); to generate the output for the j_{th} PE belonging to the next layer(s). The output of this element is given by.

$$Y_j = AF(a_j) \tag{8}$$

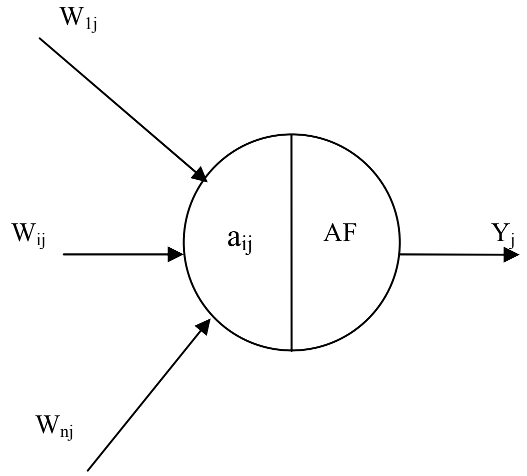

Figure 6 – Schematic Structure of a PE

The activation or transfer function is responsible to make the neuron more or less sensible to status changes on the network, and it can be linear, tangent, log etc.

The ANN are considered to be “intelligent” because of their ability to learn about the process being mapped. The learning process is conducted, in basic terms, though the implementation of the back-propagation procedure. It consists of updating the network weights in the direction in which the performance function decreases most rapidly. Once the output (Y_j) is calculated, it is compared with the target value (t_j). Then the following error is computed:

$$e_j = \frac{1}{2}(t_j - Y_j)^2 \tag{9}$$

This error e_j corresponds to just one output PE. There-fore the overall error (E vector) is expressed by:

$$E = (e_1, \ldots, e_j, \ldots, e_k) \tag{10}$$

Where k is the number of outputs.

The error is then transmitted backwards fron the output layes to the input layer. The connection weights are updated by each PE, leading the network to converge.

These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data (typically three times more training samples than network weights).

2.2.2 Radial Basis Function

Radial basis function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses gaussian transfer functions, rather than the standard sigmoidal functions employed by MLPs. The centers and widths of the gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPs.

A typical RBF network is shown in Fig 7.

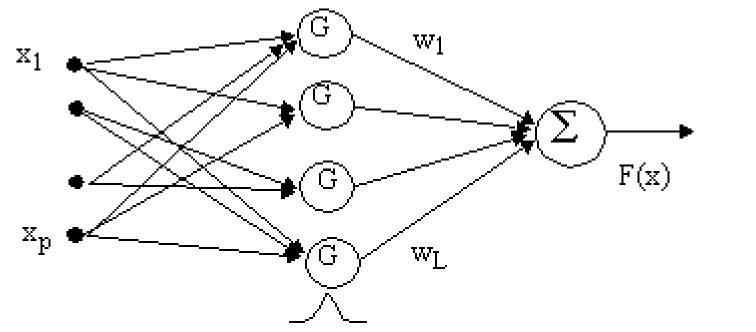

Figure 7 – RBF network topology

The network has p inputs and y outputs. The first layer is connected with the second or internal layer by weights that come from the inputs elements and the bias element. Weights from internal layer to outputs are also defined. Each element in the internal layer receives an input pattern vector and compares it with the mean weight vector that connects the input with second layer. The weight vector determines the position of the center of the radial hidden element in the input space. Here, the activation function is similar to a Gaussian density function. This function is defined as follows:

$$G(x;x_i) = \exp\left(\frac{-1}{2\sigma_i^2} \sum_{k=1}^{p} (x_k - x_{ik})^2 \right) \tag{11}$$

where x_i is the mean and σ_i^2 is the variance, which needed to be calculated previously.

The output F(x) is then obtained by linearization the Gaussian function outputs, using the network weights, as follow:

$$F(x) = \sum_{i=1}^{L} W_i (G(x;x_i)) \tag{12}$$

In short, we may say that Radial basis network is a very efficient network when function approximation is needed. This artificial neural network has the following characteristics:

1. It is very fast in comparison to back-propagation;
2. it has the ability of the representing nonlinear functions;
3. It does not experience local minima problems of back-propagation.

3. METHODOLOGY

The methodology was based in applying a software package which can implement with confidence the ANN technique. It was used the NS package due to its easy of use and possibility to migrate the certified ANN to any application though a DLL implementation.

We have generated 2 configurations of networks, one MLP and other RBF, and submitted to them both experimental and theoretical data for cutting force and roughness as per table 1, 2, 3 and 4. The MLP net had 3-10-1 (input, hidden, output) configuration using tanh activation function, and the RBF the had the same configuration, however using the Gaussian functions. We have used 20% of the samples for cross validation.

Table 1. Experimental data for Cutting Force based on machining parameters, turning system of mild steel (according to [13])

Vc (m/min)	f (mm/r)	ap (mm)	Fc (N)
29	0.212	1	457.1
22	0.107	1	276.2
17	0.107	1	238.1
13	0.212	1	333.3
29	0.212	1.2	571.4
22	0.212	1.2	457.4
17	0.212	1.2	476.2
13	0.107	1.2	323.8
29	0.212	1.5	523.8
22	0.212	1.5	619.1
17	0.212	1.5	523.8
13	0.212	1.5	428.5

Table 2. Theoretical data for Cutting Force based on machining parameters

Vc (m/min)	f (mm/r)	ap (mm)	Fc (N)
29	1	0,212	445,2
22	1	0,107	224,7
17	1	0,107	224,7
13	1	0,212	445,2
29	1,2	0,212	534,24
22	1,2	0,212	534,24
17	1,2	0,212	534,24
13	1,2	0,107	269,64
29	1,5	0,212	667,8
22	1,5	0,212	667,8
17	1,5	0,212	667,8
13	1,5	0,212	667,8

The theoretical data were calculated though equation (1), using a constant value of K_s = 2100 N/mm^2

Table 3. Experimental data for Roughness based on machining parameters, turning system of hard steel (according to [11])

Vc (m/min)	f (mm/r)	ap (mm)	rε (mm)	Rmax (μm)
150	0.2	1	0.8	8,0
200	0.2	1	0.8	17,0
300	0.2	1	0.8	10,0
300	0.2	1	0.8	8,0
350	0.2	1	0.8	12,0
200	0.2	0.4	0.8	9,0
200	0.2	0.5	0.8	9,0
200	0.2	1	0.8	9,0
200	0.2	1.2	0.8	7,0
200	0.2	1.5	0.8	7,0
200	0.1	0.7	0.8	3,0
200	0.14	0.7	0.8	9,0
200	0.2	0.7	0.8	9,0
200	0.24	0.7	0.8	13,0
200	0.28	0.7	0.8	16,0
200	0.07	0.8	0.4	7.5
200	0.095	0.9	0.4	7,0
200	0.14	0.10	0.4	9,0
200	0.17	0.11	0.4	12,0
200	0.2	0.12	0.4	14,0

Table 4. Theoretical data for Roughness based on machining parameters, eq. [5]

Vc (m/min)	f (mm/r)	ap (mm)	rε (mm)	Rmax (μm)
150	0.2	1	0.8	4.0
200	0.2	1	0.8	4.0
300	0.2	1	0.8	4.0
300	0.2	1	0.8	4.0
350	0.2	1	0.8	4.0
200	0.2	0.4	0.8	4.0
200	0.2	0.5	0.8	4.0
200	0.2	1	0.8	4.0
200	0.2	1.2	0.8	4.0
200	0.2	1.5	0.8	4.0
200	0.1	0.7	0.8	1.0
200	0.14	0.7	0.8	2.0
200	0.2	0.7	0.8	4.0
200	0.24	0.7	0.8	5.8
200	0.28	0.7	0.8	7.8
200	0.07	0.8	0.4	0.2
200	0.095	0.9	0.4	0.5
200	0.14	0.1	0.4	1.0
200	0.17	0.11	0.4	1.4
200	0.2	0.12	0.4	2.0

4. RESULTS

4.1 Force Analysis

Below, we placed the main results in graphic form (Fc x Desired Fc).

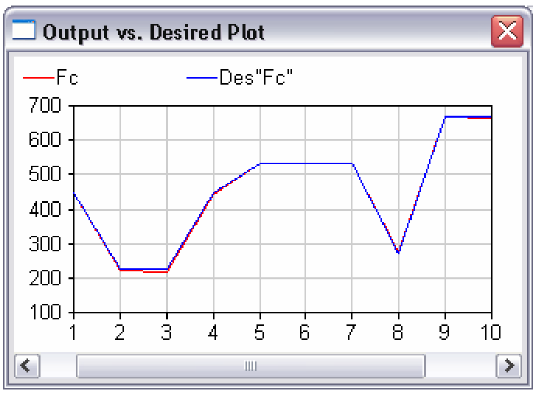

Figure 8 – Training results for the theoretical equation – MLP topology (force vs sample number)

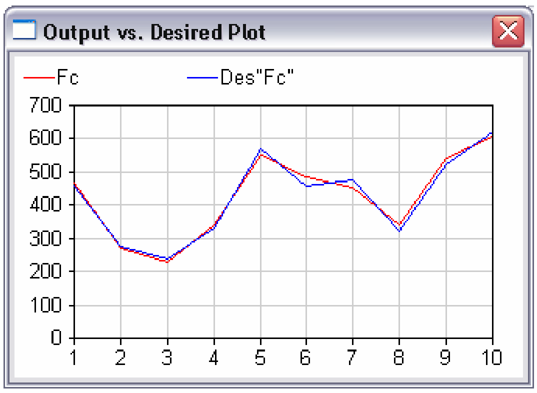

Figure 9 – Training results for the experimental data – RBF topology (force vs sample number)

The mean squared error calculated for this case was MSE = 0,0027.

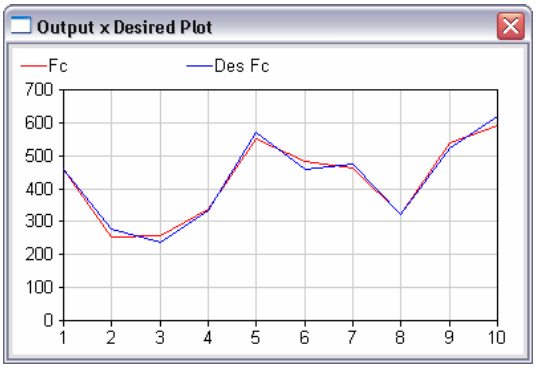

Figure 10 – Training results for the experimental data – MLP topology (force vs sample number)

4.2 Roughness Analysis

Below, we placed the main results in graphic form ($R_{máx}$ x Desired $R_{máx}$).

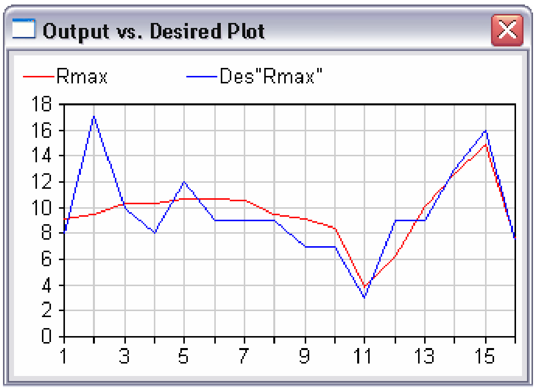

Figure 11 – Training results for the experimental data – MLP topology

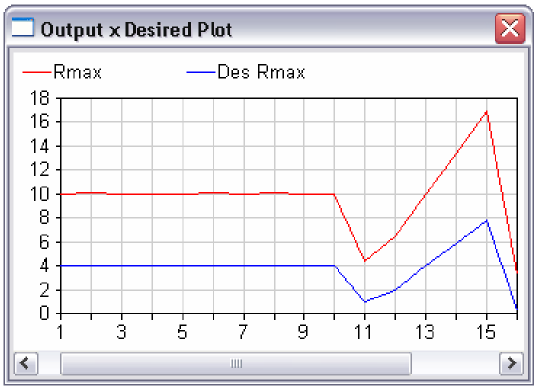

Figure 13 – Training results for the theoretical data – RBF topology

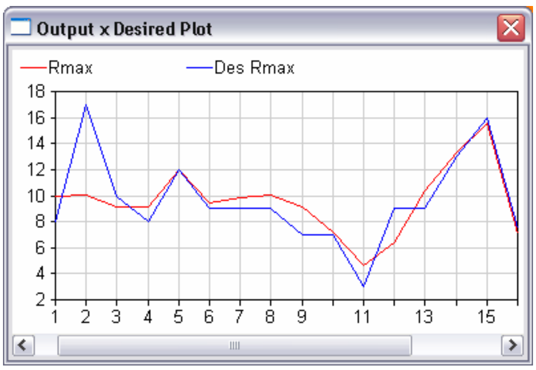

Figure 12 – Training results for the experimental data – RBF topology

5. CONCLUSIONS

Although the training data were too small, we have noticed that the neural net approach on both configuration (MLP and RBF) could reach to very close values, especially to the experimental data were no formula behavior exists. Also, in terms of performance we could verify that the RBF configuration had converged quite fast when compared to MLP similar net. When around 1000 iterations were need in MLP net to calculate the final weights, only 50 iterations were done by the RBF one.

The next step is to create an ANN library and embed in an Educational CNC Programming Software in order to make predictions about force and roughness, in rough or finishing operations, respectively.

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