Artificial neural networks applied to prediction of surface roughness in dry drilling of some polymers

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Abstract. Polymers become more and more attractive for automotive and aerospace industries due to their remarkable mechanical, thermal and electrical properties that make these materials suitable for many industrial applications. Machining of polymers is of a great interest among researchers and engineers due to the possibility of replacing expensive materials with plastics that have similar mechanical characteristics, but of a lower cost. Drilling is the most common mechanical machining operation in manufacturing of parts. Within this context, it is essential to analyze this cutting process and find the best solution for controlling the output parameters of the process, such as surface roughness and cutting forces. The present work concerns the developing of an artificial neural model for the prediction of surface roughness in dry drilling of some polymeric materials: high density polyethylene (grade HDPE 1000), polyamide (grade PA6) and polyacetale (grade POM-C). The neural model was built based on trial-and-error method, by modifying the number of hidden layers and the number of hidden neurons on each layer. The experimental plan was designed to be suitable for artificial neural network prediction. The aim of experimental work was to study the effect of cutting parameters (spindle speed, feed rate and drill diameter) on the quality of machined surface (surface roughness). This paper proposes a neural model that is able to predict the surface roughness considering not only the cutting parameters, but the type of material. Moreover, a study concerning the accuracy of the neural model depending on the number of hidden layers and the number of hidden neurons on each hidden layer was carried out. The predicted values of roughness were compared with experimental data in order to determine the precision of the neural model.

1. Introduction
During the last 30 years polymers replaced many metallic components in a variety of industries, such as aircraft, automotive and spacecraft [1] due to an increased demand for high performance and, at the same time, lightweight components [2].

As mechanical joining of polymers and other material components could not be avoided, the assembly quality strongly depends on the machined quality of drilled holes.

Drilling is a final mechanical machining operation used to manufacture holes that often need to be very accurate in order to enable a precise mounting of mechanical parts.

Although the cutting fluid are used not only as lubricants, but also for alleviating the temperature effects [3], due to environmental regulations and cost reduction, there is a significant interest among researchers and engineers for dry machining, especially for dry drilling.
For this reason, researchers and engineers have to deal with a high influence not only of cutting parameters [4], but surface integrity [5,6], cutting forces [7-9] or dimensional accuracy [8,10].

The hole surface roughness is influenced by many process variables, such as feed rate or rotational speed. But many other factors have a direct influence on machined surface roughness. For example, drill geometry [11,12] and type of material have a great influence on hole quality [13].

In order to investigate how these factors are influencing the quality of hole surface and, at the same time, to optimize the drilling process, scientists use modern techniques and methods, such as analysis of variance (ANOVA) [4,13,14], Taguchi method, artificial neural networks (ANN) [13] or response surface methodology (RSM) [15].

Among all these methods, artificial neural networks become more and more appreciated due to neural model capability to offer a very accurate prediction of data [16]. The artificial neural network method can be used as an alternative to experimental work, whose mathematical model is not possible to be performed [17]. It is important to point that, even if the accuracy of ANN predicted data is remarkable, some limitations of this method still exist.

Artificial neural networks are mathematical tools that connect inputs to outputs, by interconnecting artificial neurons. The most used ANN is the network in which every layer is directly connected to immediately previous layer (back propagation network) [18]. The model is learnt how to solve the problem and, in the end, can predict output data without performing long and time consuming experiments or numerical simulations.

It was previously shown that any non-linear problem can be solved by ANN models with no more than two hidden layers, if the number of hidden neurons is correctly set.

The aim of this research is to obtain a neural network model that is able to predict reliable values of surface roughness in dry drilling of simple polymers, depending on both the cutting parameters and material type, in terms of material hardness.

2. Materials and methods

2.1. Workpiece materials and drilling experiments

The materials used in this study are: polyethylene (grade HDPE 1000), polyamide (grade PA6), polyacetale (grade POM-C). Due to their properties, these materials have many industrial applications.

Material HDPE 1000, due to its wear and shock resistance, can mainly be used for toothed and chain wheels. Polyamide PA6, due to its wear resistance, is used for bushes, wear plates or pinions. Finally, POM-C has important application in manufacturing parts with good dimensional stability, due to its low water absorption property. All these 3 materials have an excellent machinability.

The workpiece was supply as plates with dimensions of 150x60x30 mm. The general properties of these materials are shown in table 1.

| Properties                | HDPE 1000 | PA 6 | POM-C |
|---------------------------|-----------|------|-------|
| Young modulus [MPa]       | 750       | 3250 | 2800  |
| Brinell Hardness          | 45        | 150  | 140   |
| Density [kg/dm³]          | 0.96      | 1.14 | 1.41  |
| Melting temperature [°C]  | 135       | 220  | 165   |

Drilling experiments were performed with an industrial used cobalt steel drill (HSS Co). The drilling experiments were conducted on a CNC drilling and milling machine (EMCO MILL 55...
CNC, EMCO MAIER Ges. M.b.H. Austria). For each drill diameter, hour holes were drilled with each combination of cutting parameters in attempt to analyse the surface roughness of the fourth hole in line, when high temperature exist. A schematic view of the drilling experiments is shown in figure 1.

![Image of drilling experiment](image)

**Figure 1.** Drilling experiment: (a) Physical experiment; (b) Schematic view of drilling experiments.

To study the effect of cutting parameters on the hole surface roughness an experimental plan with three factors (drill diameter, spindle speed and feed rate) was designed, with two factors at three level and one factor at two level. The experimental plan is shown in table 2.

| Factors                  | Levels |
|--------------------------|--------|
| Drill diameter [mm]      | 8 10  - |
| Spindle speed [rev/min]  | 500 1000 1250 |
| Feed rate [mm/rev]      | 25 50  75 |

The surface roughness was measured with a 2D profilometer (Mitutoyo Surftest SJ-210, Japan) that uses as software Surftest SJ Communication Tool. In order to result reliable values, the Ra surface roughness was measured five times and the average value of the measurements was reported. The experimental results are shown in table 3.

The effect of drilling parameters on the surface roughness was studied and presented in a previous work [13]. For each material, analysis of variance was conducted in order to investigate the importance coefficient of each process parameter or combination of parameters on the surface quality of the holes, in terms of surface roughness Ra.

It was reported that low values of roughness result if drill holes of 10 mm diameter with low spindle speed (500 rev/min) and high feed rate (75 mm/rev) for HDPE 1000. The best cutting regime for low surface roughness, when drilling 8 mm holes in PA6 and POM-C is low spindle speed (500 rev/min) and high feed rate (75 mm/rev).

The final conclusion was that POM-C has the best machinability of all studied materials, followed by HDPE 1000 and PA6.
Table 3. Average experimental values of surface roughness Ra.

| Exp. no. | Drill diameter [mm] | Spindle speed [rev/min] | Feed rate [mm/rev] | Surface roughness Ra of the 4th hole [μm] |
|----------|---------------------|-------------------------|--------------------|------------------------------------------|
|          | HDPE 1000           | PA 6                    | POM-C              |
| 1        | 8                   | 500                     | 25                 | 1.225                                    |
| 2        | 8                   | 500                     | 50                 | 1.176                                    |
| 3        | 8                   | 500                     | 75                 | 1.305                                    |
| 4        | 8                   | 1000                    | 25                 | 3.194                                    |
| 5        | 8                   | 1000                    | 50                 | 1.176                                    |
| 6        | 8                   | 1000                    | 75                 | 1.305                                    |
| 7        | 8                   | 1250                    | 25                 | 3.055                                    |
| 8        | 8                   | 1250                    | 50                 | 3.869                                    |
| 9        | 8                   | 1250                    | 75                 | 4.044                                    |
| 10       | 10                  | 500                     | 25                 | 2.465                                    |
| 11       | 10                  | 500                     | 50                 | 2.170                                    |
| 12       | 10                  | 500                     | 75                 | 1.139                                    |
| 13       | 10                  | 1000                    | 25                 | 4.529                                    |
| 14       | 10                  | 1000                    | 50                 | 2.392                                    |
| 15       | 10                  | 1000                    | 75                 | 1.807                                    |
| 16       | 10                  | 1250                    | 25                 | 5.503                                    |
| 17       | 10                  | 1250                    | 50                 | 2.672                                    |
| 18       | 10                  | 1250                    | 75                 | 3.102                                    |

2.2. Artificial neural network model for roughness prediction

The prediction of surface roughness Ra in strong relation to cutting parameters (drill diameter, spindle speed and feed rate) was carried out using artificial neural network method (ANN). In this regard, EasyNN-plus software was used to generate a neural model, as it is shown in figure 2.

![Figure 2. Neural model for surface roughness Ra prediction.](image)

The input layer has four neurons: drill diameter, spindle speed, feed rate and material hardness. The output layer has one neuron (surface roughness Ra). In order to generate the optimum configuration of the neural model, trial-and-error method was used. The performance of different combination of layers and neurons was tested. Then, the average relative error, mean square error and root mean square error were reported.
Even from the beginning, it is important to present the limitations of this neural model. The values of Ra can be predicted only within the limits of minimum and maximum values of input parameters. An extrapolation may be carried out, but the accuracy of the predicted data strongly depends on the high number of training data. If the number of the training data is low, when extrapolating, there are many chances to obtain unreliable or even aberrant values from the neural network.

3. Results and discussion
Due to the complexity of the prediction problem, trial and error method was considered to be the best option in the development of the neural model. The goal was to identify the simplest neural model that accurately predicts surface roughness. At the beginning, training and learning were carried out on a single hidden layer neural network, by increasing each time the number of neurons on the hidden layer.

After training ended, the performance of the neural model was tested and the percentage relative error, mean square error and root mean square error were calculated. Since the beginning, it was considered that reliable neural model should assure an average percentage relative error up to 5%. At the same time, hidden layer should have no more than 7 hidden neurons in order to obtain reliable results and avoid overfitting. Therefore, the maximum number of neurons on hidden layer was set to 7 neurons.

After testing several combinations of neural models with a single hidden layer, it was found that neural model 4-8-1 gives the best relative error, meaning 7.80%. But this value of the relative error exceeded the target error of 5% and, for this reason, it was decided to build neural models with two hidden layers. The neural model combinations that have their performance tested and the values of the prediction error are presented in table 4.

| Pair of variables | Percentage Relative Error (RE) | Mean Square Error (MSE) | Root Mean Square Error (RMSE) |
|-------------------|--------------------------------|-------------------------|------------------------------|
| 4-2-1             | 41.79                          | 5.05                    | 2.25                         |
| 4-4-1             | 29.71                          | 0.94                    | 0.97                         |
| 4-6-1             | 15.09                          | 0.36                    | 0.60                         |
| 4-8-1             | 7.80                           | 0.05                    | 0.23                         |
| 4-4-4-1           | 16.63                          | 0.36                    | 0.60                         |
| 4-6-6-1           | 1.62                           | 0.00                    | 0.05                         |
| 4-7-7-1           | 0.49                           | 0.00                    | 0.01                         |
| 4-8-8-1           | 1.49                           | 0.01                    | 0.09                         |

In case of a single hidden layer neural model, it can be concluded that increasing the number of hidden neurons on the hidden layer leads to decreasing of percentage relative error value, meaning an improvement in prediction capability of the neural model. As the maximum number of the neurons on the hidden layer was set to 7 and RE of 4-8-1 neural model is 7.80%, it was concluded that this problem cannot be solved with a single layer neural network.

Therefore, several combinations of two hidden neural models were learnt and trained and their performances were tested. Although, the neural model 4-6-6-1 gave 1.62% RE, which is less than the target error, two other combinations were trained and tested. It was found that 4-7-7-1 gave the best results in prediction of surface roughness Ra. Model 4-8-8-1 gives a higher RE than the previous model tested (4-7-7-1), but it is not recommended due to the number of neurons on the hidden layer.

Considering these results, the optimum combination of neurons and layers in prediction of surface roughness Ra of simple polymers depending on spindle speed, feed rate, drill diameter and material hardness is considered to be 4-7-7-1, which gives a RE of 0.49%, an MSE of 0.00 and RMSE of 0.01.
4. Conclusions
In this study, an artificial neural model for the prediction of surface roughness in dry drilling of some polymeric materials: high density polyethylene (grade HDPE 1000), polyamide (grade PA6) and polyacetal (grade POM-C) was developed. The neural model was built based on trial-and-error method, by modifying the number of hidden layers and the number of hidden neurons on each layer.

The proposed neural model is able to predict the surface roughness Ra, by considering not only the cutting parameters, but the type of material, if using the material Brinell hardness as an input parameter.

The following conclusions can be drawn:
(i) Artificial neural network is a proper tool in prediction and optimisation of process parameters due to its flexibility in modifying the network configuration.
(ii) Artificial neural network with 4-7-7-1 configuration provided the most accurate and reliable results in prediction of surface roughness Ra (output parameter) as a response to a combination of input process parameters (drill diameter, feed rate and spindle speed) and materials hardness.
(iii) Considering the prediction outputs, it can be concluded that the relation between input and output parameters of the dry drilling process of studied polymers is very complex and the neural network configuration needs to be built with 2 hidden layers.

5. References
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