Evaluation of a proposed neural network predictive model for grind-hardening

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This work describes the development of neural network model for grind-hardening process which utilizes the grinding heat to induce martensitic phase transformation in annealed or tempered steels. Neural networks have been shown to be versatile for performance prediction involving non-linear processes. Machining performance prediction involving various process variables is a non-linear problem.The developed neural network represents the obtained results from the developed network which are compared with experimental data achieved from surface grind-hardening process for temperd steels. The developed neural network attemps to use numerous variables involved in the grind-hardening process and develops a knowledge based system with the capabilities of utilising both existing and new grind data. The influence of different grinding parameters on the obtained temperature, surface roughness, cutting forces and hardness will be tested and predicted during the process. The comparison between the results shows a significant correlation which assure the benifites of using the proposed neural network in the machining field. It is believed that neural and adaptive systems should be considered other tools in the engineer's toolbox. However, today's measuring facilities and process technologies allow measuring the important process-related signals with high sampling rates. Consequently, it is possible to build up a database from the measured data and to produce appropriate process models by using novel technologies, such as artificial intelligence techniques.

يتناول هذا البحث تطوير نموذج الشبكة العصبية الاصطناعية ومحاولة تطبيقه على عملية التصلد التجليخى، كعملية قطع مستخدمة الحرارة الناتجة من التشغيل لتصليد سطح الشغلة المصنعة للحصول علي المواصفات المطلوبة. وتتميز هذه الدراسة بوضع تصور للتوقعات المنتظرة من عملية القطع هذه باستخدام هذه الشبكات الاصطناعية تحت تأثير ظروف القطع والتشغيل المختلفة. أظهرت النتائج من هذا النموذج الاصطناعي توقعات للتوزيع الحراري و خشونة السطح وقوى القطع ودرجة الصلادة السطحية و التي جاءت مطابقة لحد كبيرللنتائج المعملية السابق الحصول عليها من عملية التشغيل تحت نفس الظروف، مما يؤكد زيادة الثقة فى النتائج المتحصلة من النموذج المقترح لدراسة عمليات القطع والتشغيل ووضع التصورات المرتقبة للمعايير المختلفة المراد قياسها باستخدام الطرق التقليدية.

Keywords: Grinding, Grind-hardening, Neural networks, Multilayer perceptron

1. Grind-Hardening process

Grind-hardening is a special grinding process which utilizes the friction heat flux, in order to achieve high surface hardness of the ground part. This is achieved, as the dissipated heat induces martensitic phase transformation to the workpiece material, thus increasing its hardness. The main advantage of Grind-Hardening is that it is an integral heat treatment-machining process. This will lead to reduction of production cycle and consequently to reduction of time and cost (cost reduction is about 20 to 40 % relative to conventional hardening and heat treatment).

In Grind-Hardening, a certain intended amount of the machining energy is converted into thermal energy, penetrating the surface layer of the machined workpiece causing an increase of the temperature of workpiece surface over the critical temperature. Due to forced cooling or selfquenching mechanisms, phase transformation of the ground material is achieved [1].

The main parameters affecting this process are the workpiece material, the cutting speed, the depth of cut, the feed rate and the type of grinding wheel used. The surface hardness and the depth of hardened surface are the main results of this process.

The hardness penetration depth, which is defined as the depth beneath the surface where the hardness reaches a value of 80% of the surface hardness. According to Brinksmeier et al. [2] , the penetration depth amounts to 0.2 mm when Grind-Hardening tempered steel 42 Cr Mo 4 under the selected machining conditions.

Depending on these grinding conditions, a portion of the heat flux is transmitted to the workpart and leads to a large thermal loading leading to high temperature in the surface layer of the workpiece, fig. 1.

This thermal load is superimposed by a mechanical load, which can be characterized by the hertzian stress between abrasive grains and workpart surface.

By Grind-Hardening of medium and high carbon steels, very fine grained martensitic structure is formed. Due to the carbon content of the material the structure consists of acicular martensite that appears in form of parallel needles within former austenite grains. These needles are a few micrometers in length and about 0.1 to 0.5 µm thickness [3].

2. Neural networks

Neural networks have been used in different areas of manufacturing such as modeling purposes tool wear monitoring and decision making on grinding. Grind-Hardening is a new process that should be handeled as highly non-linear problem.

Neural networks are collections of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. Neural networks composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses.

The performance feedback is utilized directly to change the parameters through systematic procedures called learning or training rules, so that the system output improves with respect to the desired goal. In neural networks the parameters are often modified in a selected set of data called the training set and are fixed during operation.

The problem of data fitting is one of the oldest in experimental science. The real world tends to be very complex and unpredictable, and the exact mechanisms that generate the data are often unknown. Moreover, when we collect physical variables, the sensors are not ideal (of finite precision, noisy, with constrained bandwidth, etc.), so the measurements do not represent the real phenomena exactly. One of the quests in science is to estimate the underlying data model.

The importance of inferring a model from the data is to apply mathematical reasoning to the problem. The major advantage of a mathematical model is the ability to understand, explain, predict, and control outcomes in the natural system. Fig. 2 illustrates the data-modeling process. The most important advantage of the existence of a formal equivalent model is the ability to predict the natural system's behavior at a future time and to control its outputs by applying appropriate inputs.

3. Multilayer perceptron

The Multi-Layer Perceptron (MLP) is one of the most widely implemented neural network

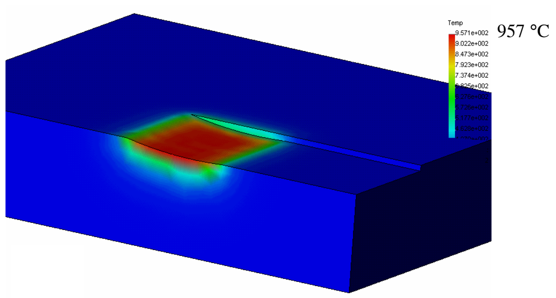

Fig.1. Temperature distribution during surface Grind-Hardening process.

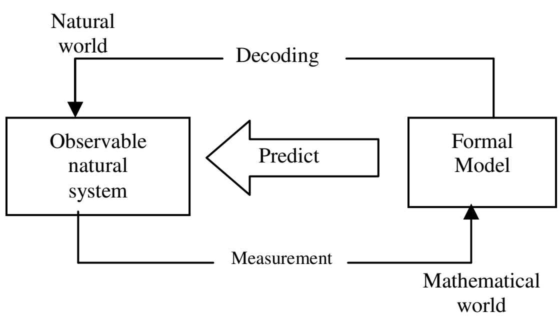

Fig. 2. Natural systems and formal models.

topologies. The MLP is capable of approximating arbitrary functions. This is important in the study of nonlinear dynamics, and other function mapping problems.

The MLP is trained with error correction learning, which means that the desired response for the system must be known. Error correction learning works in the following way: From the system response at Processing Element i (PEi) at iteration *n*, $yi(n)$, and the desired response $di(n)$ for a given input pattern an instantaneous error $ei(n)$ is defined by:

$$e_i(n) = d_i(n) - y_i(n).$$

Using the theory of gradient descent learning, each weight in the network $w_{ig}(n+1)$, can be adapted by correcting the present value of the weight with a term that is proportional to the present input and error at the weight, i.e.

$$w_{ij}(n+1) = w_{ij}(n) + \eta\delta_I(n)\,x_j(n)\,.$$

The local error $\delta i(n)$ can be directly computed from $ei(n)$ at the output Processing Element or can be computed as a weighted sum of errors at the internal PEs. The constant η is called the step size. This procedure is called the backpropagation algorithm.

The advantage of this procedure is that it can be implemented with local information and requires just a few multiplications per weight, which is very efficient. Another procedure called momentum learning which is an improvement to the straight gradient descent in the sense that a memory term (the past increment to the weight) is used to speed up and stabilize convergence [4].

Loading an initial value for each weight (normally a small random value) to start backpropagation, then proceed until one of these three stopping criterion is met, these are; To cap the number of iterations, to threshold the output mean square error, or to use cross validation. Cross validation is the more powerful of the three since it stops the training at the point of best generalization (i.e. the performance in the test set) is obtained. In our study cross validation is used, thus a small part of the training data is used to see how the trained network is working. Cross validation computes the error in a test set at the same time that the network is being trained with the training set, when the performance starts to degrade in the validation set, training should be stopped.

A learning curve is developed during the training procedure to show how the mean square error evolves with the training iteration. When the learning curve is flat, the step size is to be increased to speed up learning. While, when the learning curve moves up and down the step size should be decreased. An important point that should be considered in order to decrease the training times, and provides better performance, is the normalization of the training data [4].

In other words, the learning method of the developed neural network is performed as follow: the neural networks applys a specific weight for the different inputs and starts to calculate the output, then the mean sqaure error between the calculated output (response) and the actual output. Then the network applys another values of the weights and performs the same previous sequence; this is called backpropagation algorithm. During this process a learning curve representing the learning behaviour of the neural netwrok is provided.

4. Developed Grind-Hardening neural network

The developed neural network, fig. 3, consists of the following non-linear computational elements.

4.1. Input axon

This component simply accepts the inputs to the system and passes it on to the rest of the neural network, box A. It also contains the controllers which contain the global control parameters for the network. The first dials, part 5, are the static controllers. It contains parameters such as the number of epochs per run, the number of exemplars per epoch, the data sets to use, etc. The second dials, part 6, are the backprop controllers. It contains learning parameters like the learning mode (batch, online, etc.).

4.2. First hidden layer

The first hidden layer, box B, is made up of, the synapse, is the first component in the box and makes the connection between each input and each processing element (PE) in the hidden layer. The synapse contains the connections and the trainable weights for each connection, part 1. The second component is the tanh axon, part 4. This component has the processing elements for the hidden layer, each of which sums the weighted connections from the inputs. The GaussianAxon implements a radial basis function layer. The second part is the Gaussian Axon which responds significantly to a local area of the input space (where the peak of the Gaussian is located), part 8. It is therefore considered to be a local function approximator. The center of the Gaussian is controlled using the bias weight inherited from the BiasAxon.

The third part is the Tanh Axon which applies a bias and tanh function to each neuron in the layer. Such nonlinear elements provide a network with the ability to make soft decisions.

4.3. Output layer (classification)

The output layer, box C, is made up of the synapse and the tanh axon, the Bias Axon simply provides a bias term, which may be adapted, part 7.

4.4. Criterion

It accepts the output (s) of the network and the desired output(s) and compares them. It computes the error and passes this error to the backpropagation components which adjust the weights of the network for training. Because the criterion has the information about the performance of the network, it contains many access points for network performance, box D.

The developed neural network, fig. 3, is called a Multi-Layer Perceptron (MLP). It consists of multiple layers of Processing Elements (PEs) connected in a feedforward fashion. Backpropagation of errors is used to train the MLP, The backpropopagation components pass the error backwards from the end of the network to the beginning. The output axon generates the actual network outputs. A working neural network simulation requires the interaction of many different components. The learning algorithm adapts the weights of the system based on the error until the system produces the desired output.

The goal of the developed network is for the system output to be the same as the desired output, so it is required to minimize the mean squared error using Backpropagation method. This is done through three main steps, first, the input data is propagated forward through the network to compute the system output. Next the error is computed and propagated backward through the network, and then it is used to modify the weights [4].

Fig. 4 represents the structure of the developed Grind-Hardening neural network, in which the inputs for the developed neural networks are the different Grind-Hardening parameters, such as rotational speed, depth of cut, etc. The output of the network is the Grind-Hardening force.

5. Experimental work

A sufficient number of experiments of Grind-Hardening process were performed in IWF institute, Bremen University for flat specimens 100X150X30 mm, of SAE 4140 (42 Cr Mo 4) [5]. These Grind-Hardening experiments were performed to study the effect of the dressing procedure of grinding wheel on the produced hardened layer.

Because of the great sharpness of the grinding wheel abrasive the first contact area between the grinding wheel and the workpart doesn't possess enough friction energy, due to the small wear flat area at the first contact zone, fig. 1.

The process parameters used during the experiments are summarized in table 1.

Cutting forces, hardness, surface roughness and temperature were measured. Previous experiments were performed until a uniform hardened area on the workpiece surface was obtained. The final dressing conditions used are summerized in table 2.

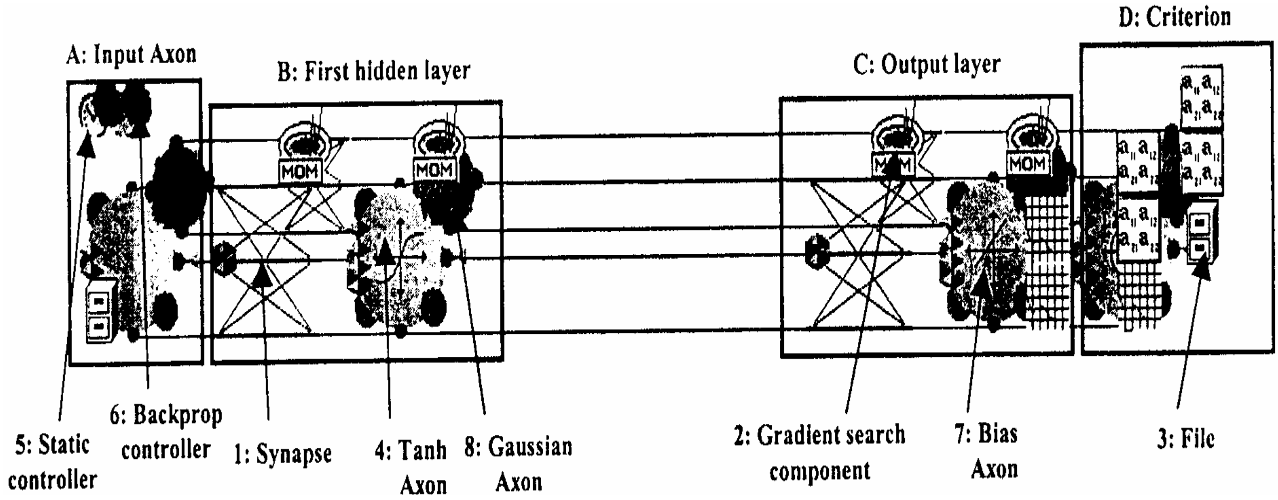

Fig. 3. Layout of Grind-Hardening neural network.

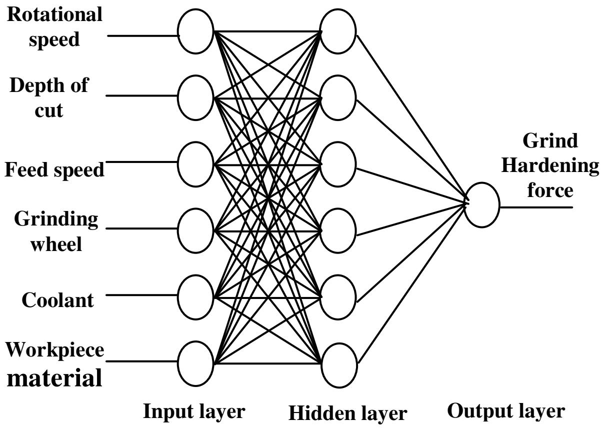

Fig.4. Grind-Hardening neural network structure.

Table 1
Grind-Hardening process parameters

Grinding wheel Tyrolit	10 A90 Q3 B H52 400 mm diameter.
Depth of cut, *ae*	0.100 mm
Cutting speed, *Vc*	35 m/s
Feed speed, *Vf*	0.5 m/min
Coolant	Dry

The value *Ud* = 5, means that each 1mm of the grinding wheel surface will pass over the diamond dresser 5 times per one revolution of the wheel.

Table 2
Summarized values of the final dressing conditions

Dresser	Diamond dresser.
Width of dresser, *bd*	0.7 mm
Cutting speed in dressing, *Vcd*	35 m/s
Feed speed, *Vf*	0.235 m/min (Ud=5)
Depth of cut, *ae*	30 μm (for 15 passes)

6. Evaluation of the proposed Grind-Hardening neural network

The collected results obtained at selected working dressing conditions are then used for training, cross validation and verification of the developed neural network.

The final learning curve during the training phase is shown in fig. 5.

This learning curve represents the behaviour of the neural network during the learning phase, as shown form the figure that the network keep trying to minimize the mean square error, this learning phase is performed using a part of the obtained Grind-Hardening results. Another part of the collected data were used for verification purpose, fig. 6 represents the comparison between the measured values of the normal and tangential cutting forces and the values of these components obtained by the developed neural network. A sample of these values are summerized in table 3; from which it can be noticed that a difference between the predected and the measured force componenets of about 10 %.

Fig. 7 shows the percentage differences between the measured and predicted normal and tangential force components. The percentage deviation of the predicted Fn from its measured values ranges from –4.7 to + 2.5%, whereas the deviation of Ft ranges from -1.1 to –10.5 %. This means, that the proposed neural network gives an under estimation with respect to the measured values in case of the tangential force component.

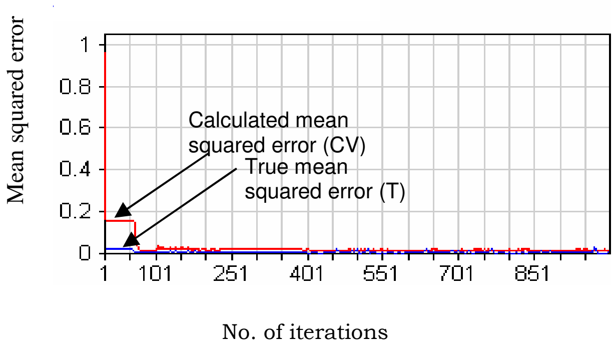

Fig. 5. The learning curve of the developed Grind-Hardening neural network.

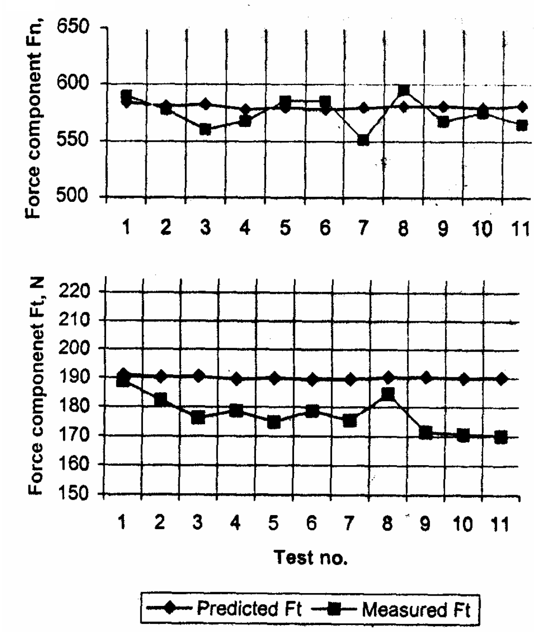

Fig. 6. The measured and developed values of the normal and tangential force components.

Table 3
Summarized values of measured and developed normal and tangential cutting forces

Measured Fn (N)	Predicted normal force Fn (N)	Difference (%)
583.1	589.9	1.1
580.8	577.8	-0.5
582.2	561	-3.6
578.4	567.2	-1.9
579.3	585.1	1
578.4	584.9	1.1
578.7	551.3	-4.7
581.1	596	2.5
581.4	567	-2.4
579.9	575.1	-0.8
580.4	565.2	-2.6
Measured Ft (N)	Predicted Tangential force, Ft (N)	Difference (%)
190.8	188.7	-1.1
190.2	182.3	-4.1
190.5	176.2	-7.5
189.5	178.6	-5.7
189.8	174.8	-7.9
189.5	178.6	-5.7
189.6	175.4	-7.4
190.2	184.5	-2.9
190.3	171.4	-9.9
189.9	170.6	-10.1
190.1	170.1	-10.5

The developed neural network was also used to predict the surface roughness of the produced workpiece surface. A sample of the measured and the predicted values of the produced surface roughness, using the developed neural network are summerized in table 4, and visualized in fig. 8.

According to table 4 the percentage deviation between the predicted and measured values of the mean surface roughness ranges from 6.3 to –10 %.

7. Conclusions

This work presents a proposed application of developed neural networks in Grind-Hardening process, in order to predict different machining features such as cutting forces and surface roughness. The experiments are performed on flat workpieces made of SAE 4140 (42 Cr Mo 4). It is shown

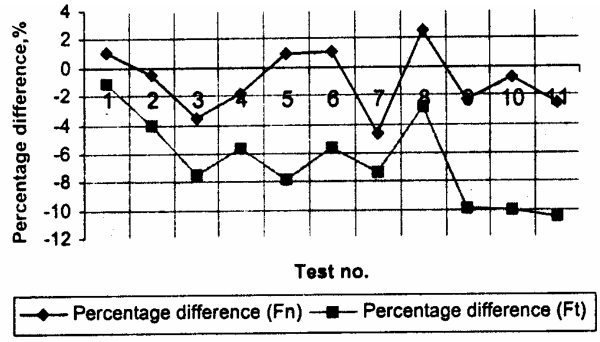

Fig. 7. The percentage differences for both normal and tangential force components.

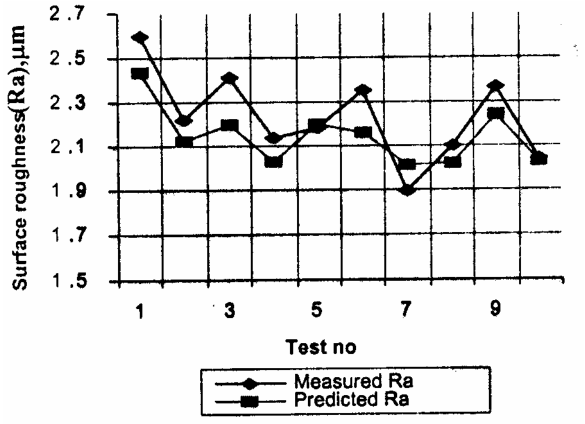

Fig. 8. The measured and predicted values of the surface roughness, *Ra.*

Table4 *
Values of measured and predicted surface roughness, Ra.

Measuredsurface roughness, *Ra* (µm)	Predicted surfaceroughness, *Ra* (µm)	Difference (%)
2.60	2.43	-6.5
2.22	2.12	-10
2.41	2.2	-8.7
2.14	2.02	-5.6
2.18	2.2	0.9
2.35	2.16	-8
1.89	2.01	6.3
2.10	2.02	-3.8
2.37	2.24	-5.4
2.04	2.02	-0.9

that the predicted values from the developed neural network are very close to the measured values, which indicates high confidence level for the developed network to support the prediction of the produced surface roughness and cutting forces in Gind-Hardening process.

The fact, that the neural network model verifies the experimental observations, indicates the reliability of the developed model, so it can be used in investigating the influence of machining parameters of Grind-Hardening on the investigated quantities.

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