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The prediction of mechanical behavior for steel wires and cord materials using neural networks

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Abstract

The tensile strength of the steel wire material is required to be sufficiently high for better performance. Steel with a high cleanness will prevent problems during drawing and the heat treatment. The studies show that among many defects the most important ones are the non-metallic inclusions and undesirable phases encountered during improper heat treatment. Especially different non-metallic inclusions will play an important role during crack propagation due to their weak matrix bond. In this study typical wire and cord failures due to non-metallic inclusions are examined. A generalized regression neural network was developed to predict the tensile strength as a function of experimental conditions. The predicted values of the tensile strength estimated by neural network are found to be in good agreement with the actual values from the experiments.

Keywords: Steel wire; Tensile strength; Microstructure; Image analysis; Generalized regression neural networks (GRNN)

1. Introduction

The steel wire materials are semi-products that are suitable for cold drawing processes. Although steel wire can be produced by stainless steel and other alloyed steels, it is mostly produced in industry using plain carbon steels. Steel containing up to 1% C is usually used for steel wire production. However, the largest part of steel wire production constitutes low carbon steels that have less than 0.1% C [1].

Modern steel production technology is mostly aimed towards producing clean steel. On the other hand, the quality of steel wires depends on the methods during the production. The cleaner the steel wire microstructure is, the higher the quality of the steel wire obtained is. Therefore, all techniques applied from raw material inputs to solidification stage aim to increase the cleanness of the composition and the microstructure of the produced steel.

The required microstructure for the production of high strength steels such as the wire used for the production of rope, various spring wires, cord wires or prestressed concrete wires is a sorbite microstructure having severe deformation such that the distance between lamelars is very short. Since fine cementite lamelars that constitute the fine structured pearlite have more resistance against fracture during the deformation than that of coarse pearlite, the cold drawability of fine pearlite microstructure is good. Because fine carbide plates are bending without fracture during the deformation and so this causes to prevent crack formation. The distance between lamelars for the fine pearlite microstructure providing high strength is around 20 nm and this microstructure includes elastic deformation [2,3]. In addition, there must not be similar phases such as

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Nomenclature

a	actual/experimental values in the data set	μ	mean value of a set
b	scalar bias value of a neuron	ANN	artificial neural networks
f	activation function	$\mathrm{Cov}(a,p)=\sigma_{ap}$	covariance between a and p data sets
n	the sum of the weighted inputs and the bias	E	expected value
p	predicted values in the data set	G_k	Gaussian functions
w_i	weighting coefficients	GRNN	generalized regression neural network
x	input vector of a neural network	$R(a,p)$	correlation between a and p data sets
y	output of a neuron		

pre eutectoid ferrite, cementite, bainite and martensite in the microstructure. Moreover, the microstructure should be clean as mentioned earlier, i.e., they must not contain non-metallic inclusions.

Another important issue with steel wire production is the determination of the tensile strength based on the production parameters. This paper presents the prediction of tensile strength using a generalized regression neural network (GRNN). The inputs of the network are the diameter, carbon, ferrite and inclusion quantities in the steel. The neural network developed in this study has become very successful to predict tensile strength from the process properties. As stated in [4], artificial neural networks are very effective modern analytical tools to develop models for predicting mechanical properties of materials. In this study, general information about artificial neural networks is given first in the next section; then a brief theoretical background of generalized regression neural networks is presented. In the third section, a short summary of steel wire failures is provided. Experimental work and results are discussed in the last section.

2. A brief background of neural networks

Artificial neural networks (ANN) have emerged as a result of simulation of biological nervous system, such as the brain, on a computer. On the other hand, biological neural networks are much more complicated than the mathematical models used for ANNs. ANN was founded by McCulloch and co-workers beginning in the early 1940s [5]. They built simple neural networks to model simple logic functions. Since it is customary to drop the "A" or the "artificial", NN and ANN will be used interchangeably throughout the rest of the paper to refer to an artificial neural network.

Nowadays, neural networks can be applied to problems that do not have algorithmic solutions or problems for which algorithmic solutions are too complex to be found. In other words, it is not easy to formulate a mathematical model that does not have a clear relationship between inputs and outputs for some systems. To overcome this problem, ANN uses the samples to obtain the models of such systems. Their ability to learn by example makes neural networks (NN) very flexible and powerful. Therefore, neural networks have been intensively used for solving regression and classification problems in many fields. In short, neural networks are nonlinear processes that perform learning and classification. Recently neural networks have been used in many areas that require computational techniques such as pattern recognition, optical character recognition, outcome prediction and problem classification. In materials science and engineering fields, the researchers have used neural network techniques to develop prediction models for mechanical properties of materials [4]. For instance, Haque and Sudhakar [4] published many papers for the prediction of fracture toughness in microalloy steel, corrosion fatigue behavior and fatigue crack growth in dual-phase (DP) steel, mechanical behavior of powder metallurgy steel, dry sliding wear in Fe2%Ni based PM alloy and the effect of heat treatment on mechanical properties in MIM alloy.

Artificial neural networks consist of a large number of interconnected processing elements known as neurons that act as microprocessors. Each neuron accepts a weighted set of inputs and responds with an output. Fig. 1 depicts a single neuron model. Such a neuron first forms weighted sum of the inputs

$$n = \left(\sum_{i=1}^{P} w_i x_i\right) + b,$$

where P and w_i are the number of elements and the interconnection weight of the input vector x_i, respectively, and b is the bias for the neuron. Note that the knowledge is stored as a set of connection weights and biases. The sum of the weighted inputs with a bias is processed through an activation function, represented by f, and the output that it computes is

$$f(n) = f\left[\left(\sum_{i=1}^{P} w_i x_i\right) + b\right].$$

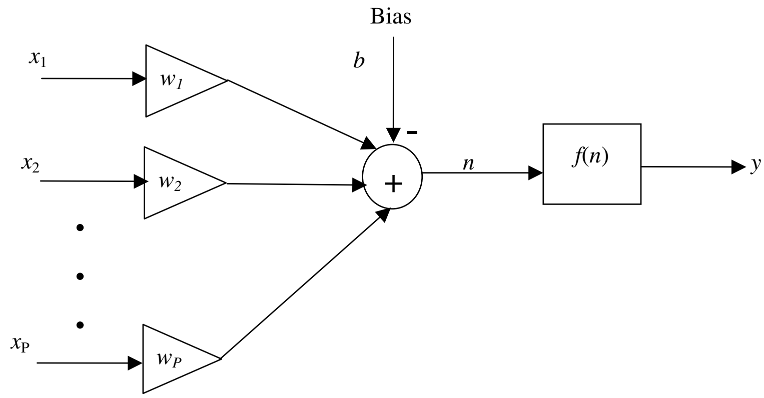

Fig. 1. Single neuron model.

Basically, the neuron model represents the biological neuron that fires when its inputs are significantly excited, i.e., n is big enough. There are many ways to define the activation function such as the threshold function, sigmoid function, and the hyperbolic tangent function. The type of activation function depends on the type of the neural network to be designed. For the threshold function, the output of the neuron is either 0, if the net input argument n is less than zero; or 1, if n is greater than or equal to 0. The sigmoid function takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0 and 1. The hyperbolic tangent function is one of the functions that take a sigmoid shape. By interconnecting neuron models, a neural network is formed.

A neural network can be trained to perform a particular function by adjusting the values of connections, i.e., weighting coefficients, between the processing elements. In general, neural networks are adjusted/trained to reach from a particular input to a specific target output until the network output matches the target. Hence the neural network can learn the system. This type of learning is known as supervised learning. The learning ability of a neural network depends on its architecture and applied algorithmic method during the training. Training procedure can be ceased if the difference between the network output and desired/actual output is less than a certain tolerance value. Thereafter, the network is ready to produce outputs based on the new input parameters that are not used during the learning procedure.

A neural network is usually divided into three parts: the input layer, the hidden layer and the output layer. The information contained in the input layer is mapped to the output layers through the hidden layers. Each unit can send its output to the units on the higher layer only and receive its input from the lower layer. This structure is known as multilayer perceptron and is shown in Fig. 2. This network is a three-layer perceptron since there are three stages of neural processing between the inputs and the outputs. More hidden layers can be added to obtain a quite powerful multilayer network.

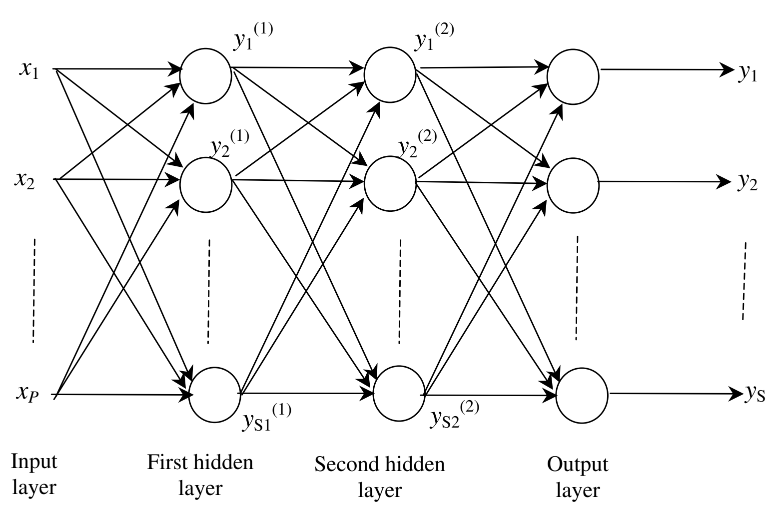

Fig. 2. Multilayer perceptron structure.

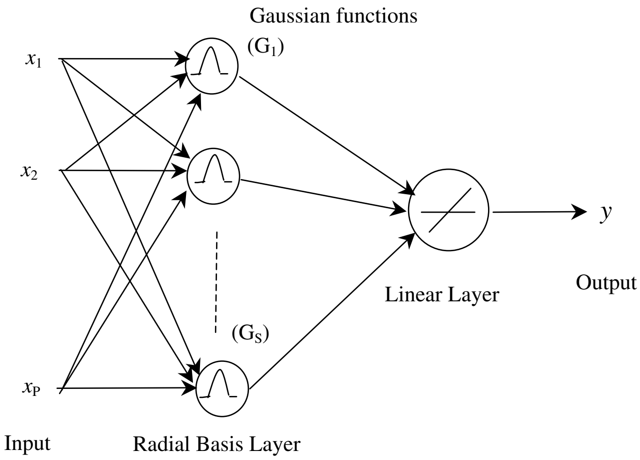

Fig. 3. Radial basis function neural network model.

2.1. Generalized regression neural network (GRNN)

In this study, a generalized regression neural network (GRNN) was developed in order to predict the tensile strength energy using Matlab® Neural Network Toolbox. GRNN is often used for function approximation, because this network provides several advantages over the multilayer networks in different applications such as approximation and generalization of the target function based on a relatively few data sets [6]. In the present study, the input parameters of the neural network are the diameter of steel wire, carbon, ferrite and inclusion percentages and the output is the tensile strength.

A generalized regression neural network (GRNN) has four layers as shown in Fig. 3: input layer, a layer of radial basis centers, a linear layer of regression unit and the output layer. The radial basis functions are commonly chosen to be a probability density function such as Gaussian functions (G_k) that compute the localized function of the input vector. The connecting lines between the inputs and Gaussian functions represent both the locations of the center (μ_k vector) and the width, i.e., the standard deviation of the Gaussian function (σ_k) in input space. The only weights that need to be learned in the GRNN are the widths that determine the smoothness or bandwidth of the radial basis functions. The lines connecting the Gaussian functions to the neuron in the linear layer represent the weighting coefficients ($\boldsymbol{w}$) of the neural network. Then the linear combinations of the weighted Gaussian functions generate the output.

3. Steel wire failures

Failures that occur during the wire drawing process and during the utilization of the finished product are due to several reasons. These failures can be classified according to the reasons as follows:

(a) Faults during steel production
- Craks
- Segregation
- Non-metallic inclusion
- Fused-in extraneous matters that are metallic or non-metallic objects

(b) Failures during heat training process
- Surface decarburisation
- Hard spots
- Coarse grain
- Grain boundary ferrite

(c) Failures during the production
- Martensite or bainite due to friction
- Rolled-in extraneous matters
- Scratches
- Oxide layer

The most common failures during the steel wire production and utilization are due to failures of raw materials, especially non-metallic inclusions inside the raw materials. Besides, grain boundary ferrite due to heat treatment may exist in the microstructure. Ferrite phase and inclusions are not desired in the steel wire, because they affect the mechanical properties. For instance, while ferrite phase decreases strength and hardness of the steel wire, inclusions decrease the strength of steel wire and this may lead to fracture during the wire drawing [7].

The non-metallic inclusions occur in the molten metals via metallurgical reactions or the erosion of refractory materials. These inclusions may not always be removed from the molten metals. The residual inclusions may be in considerable size, type and amount that can be intolerable for steel wires. The size, type, amount and distribution of inclusions substantially affect deformation, fracture behavior and strength of steel wire.

The non-metallic inclusions may be sulphides, oxides, silicates, etc. In general, these inclusions are not simple dual chemical compounds such as MnO and SiO_2, but rather more complex compounds or eutectic. That is why the determination of the compounds is difficult and time consuming. Therefore, it is usually sufficient to determine the quantity and distribution of the inclusions [7,8].

Wire production defects play important role in the wire drawing process and especially in the failures of the springs produced by cold drawn wire. Pre-microcracks occurred after the production defects result in fracture of the machine parts subjected to torsion and fatigue [8–11]. The size and the distribution of these pre-microcracks are very important for failures [8,9]. Using the strength intensity factor, steel wires can be modeled according to the maximum defects size. Thus, it is theoretically possible to determine the value of fatigue strength for steel wires [8].

4. Experimental work

4.1. Failure investigations

As stated in Section 3, the most important reason for failure is due to non-metallic inclusions. Fig. 4 shows prestressed concrete wire that is failed during the production process. The sample in this figure is a typical cup and cone typed fracture surface. When the longitude cross-section of the sample is polished, silicon-typed coarse inclusion lines sized up to 200–300 μm are observed as can be seen in Figs. 5–7. Because of its sorbitic structure, the microstructure that can be easily deformed under the stress is subjected to failure due to hard silicon-typed inclusions.

Fig. 8 shows the cross-section of rope wire that has failed due to a brittle fracture at just near the fracture surface. The steps shown in this figure is an evidence of inclusion lines. In this case, the crack is progressed through the inclusion lines. The breadthways of the crack progression indicate that the material is subjected to bending and torsion. As a matter of fact, wires around the rope are exposed to torsion. Besides inclusion lines constitute a suitable media for crack progression. Also, Fig. 9 shows the crack progression from inclusion to inclusion. Although the main structure is deformable because of its sorbitic structure, the crack starting from the surface causes failure due to its easy and rapid progression.

A similar failure occurred at steel cord wire, as well. The reason for failure is silicate and complex inclusions (Fig. 10). The crack constitutes of saw tooth like steps by progressing along the inclusion lines as can be seen in Figs. 11 and 12.

The authors investigated another steel cord sample that has failed due to non-metallic inclusions. This

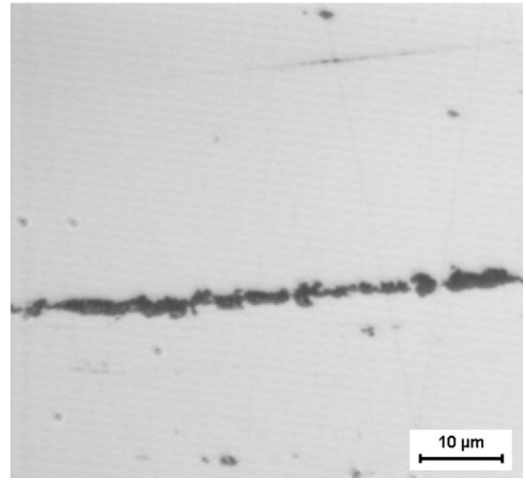

Fig. 5. Inclusion lines in the sample.

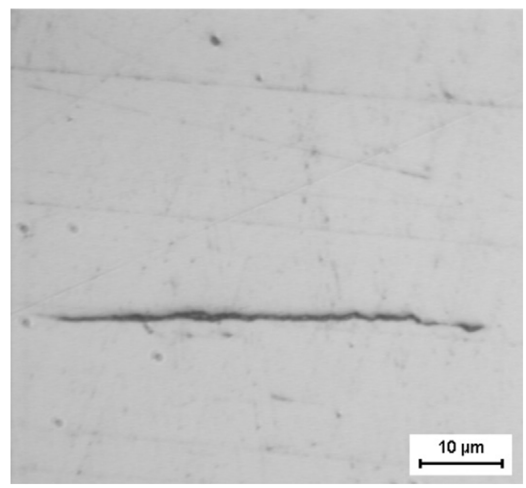

Fig. 6. Inclusion lines in the sample.

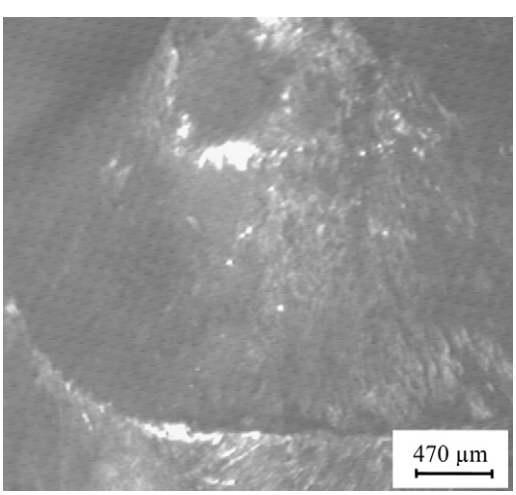

Fig. 4. Cup and cone type failure cross-section.

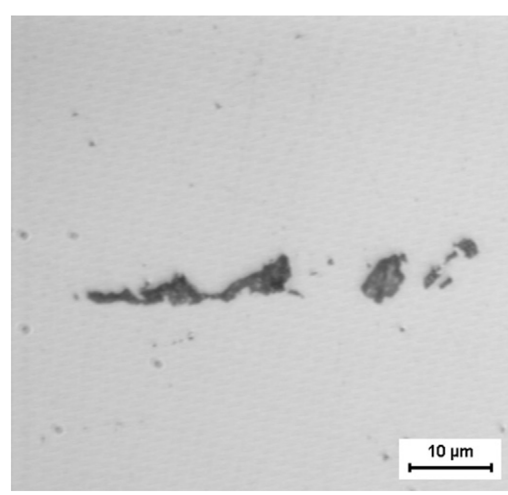

Fig. 7. Inclusion lines in the sample.

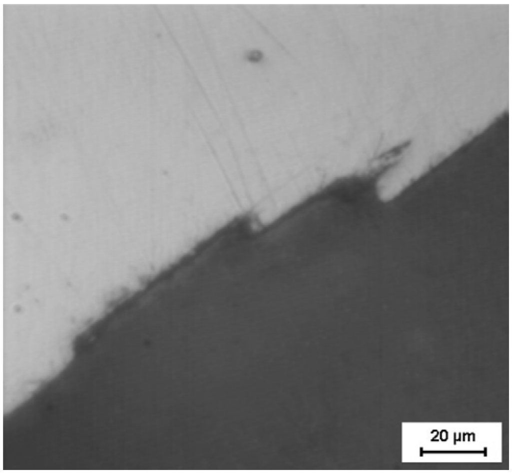

Fig. 8. Inclusion lines in the fracture surface.

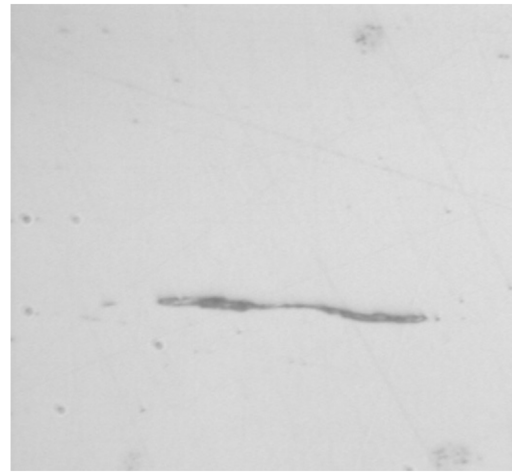

Fig. 10. Silicate type inclusion lines.

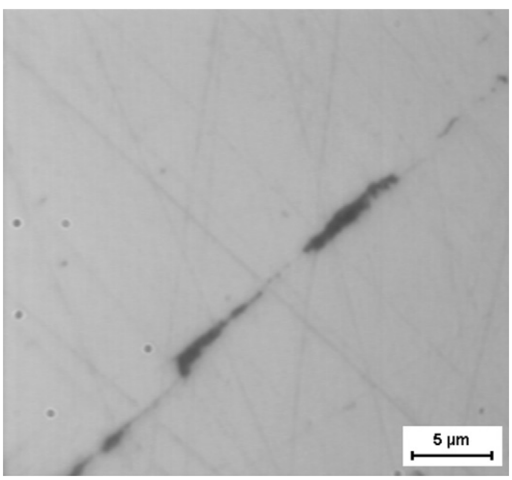

Fig. 9. Crack progression at the inclusions.

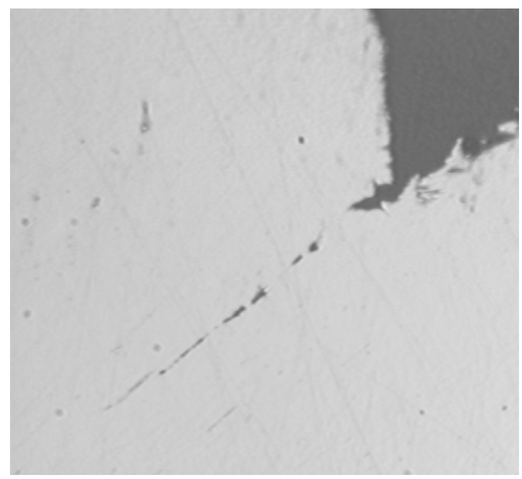

Fig. 11. Crack progression along the inclusion lines.

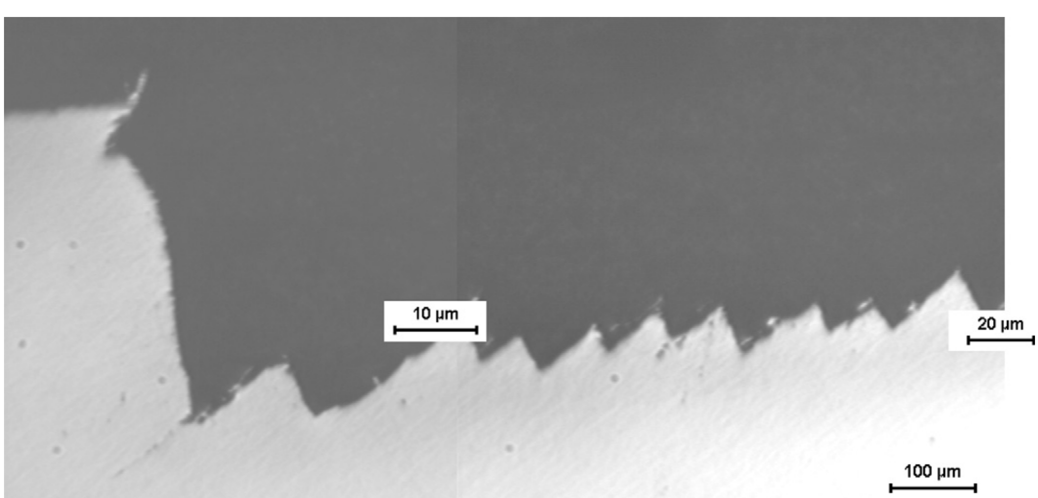

Fig. 12. The constitution of crack like saw tooth along the inclusion lines.

sample shows different failure mechanism. In the investigation of the polished cross-section of this sample, coarse inclusions that are not orientated along the rolling direction have been determined as seen in Fig. 13. Further, it has been observed that non-metallic inclusions have progressed towards surface with an acute angle in Fig. 14. During the wrapping of wire around the inside of tire, bend and torsion stresses are applied. The crack starting from the inclusions progresses towards to inner part of the wire along the inclusions. This crack causes fracture as it progresses along the coarse inclusions or MnS inclusions.

4.2. Implementation of neural network

Sixty-seven plain carbon steel wires within the range of 5–8 mm diameter and containing 0.45–0.83% C have been examined. First, tensile strength of the steel wires was determined by tension test. Then, some of the steel wire specimens are polished in the direction of cross-section and etched using nital. Using Quantimet 500 image analysis system, a quantitative-metallographic analysis is done on the polished and etched specimens to determine the amount of inclusions, grain-boundary ferrite and sorbite.

Fig. 13. Coarse inclusions in the sample.

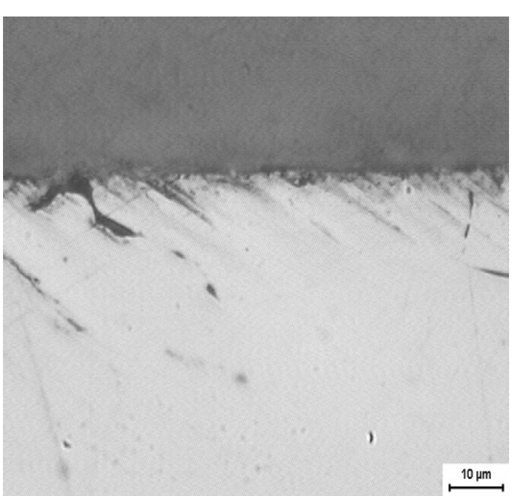

Fig. 14. Coarse inclusions towards surface.

Because of the difficulties in the determination of the final tensile strength properties during the production, a generalized regression neural network (GRNN) model was developed to predict the tensile strength using all the production parameters (the amount of carbon, ferrite and inclusions) and the diameter of steel wires. To develop the prediction model, a dataset was constructed having 67 input and output pairs from the experiments. The dataset consists of five parameters, namely, the diameter of steel wires, carbon, ferrit and inclusion percentages and tensile strength. The four input parameters that are the diameter (d), carbon, ferrite and inclusion percentages and the output parameter that is tensile strength (Rm) were used for generalized regression neural network application. Approximately two thirds (2/3) of the input and output pairs, which makes 45 pairs, were selected randomly for the training set and the remaining one third (1/3) of the pairs, which makes 22 pairs, were assigned for the test set that was used to validate the accuracy of the trained network. The weights interconnecting artificial neurons were adjusted during a training procedure to obtain the output parameter from the input parameters. The result of the training procedure is shown in Fig. 15. After the training procedure, the network was tested as shown in Fig. 16 in which the network outputs, i.e., predicted values, are represented by '×' and corresponding targets, i.e., actual/experimental output, are represented by '○' for each run. It can be concluded that the neural network predicted the actual impact energy, the target, successfully. In order to evaluate the system performance from the statistical point of view, Fig. 17 shows the correlation between the actual/experimental and the network predicted data. The generalized regression neural network demonstrated a very good statistical performance with a correlation coefficient of $R = 0.96$ that is very close to 1. In other words, there is a very good agreement between the experimental/actual and the neural network predicted results. The correlation coefficient used in this study to assess the strength of the relationship between the actual versus the predicted outputs is defined as follows:

$$R(a,p) = \frac{\mathrm{Cov}(a,p)}{\sqrt{\mathrm{Cov}(a,a)\mathrm{Cov}(p,p)}},$$

where $\mathrm{Cov}(a,p)$ is covariance between a and p sets that refer the actual output and the predicted output sets, respectively. Likewise, $\mathrm{Cov}(a,a)$ and $\mathrm{Cov}(p,p)$ are the autocovariance of a and p sets, correspondingly.

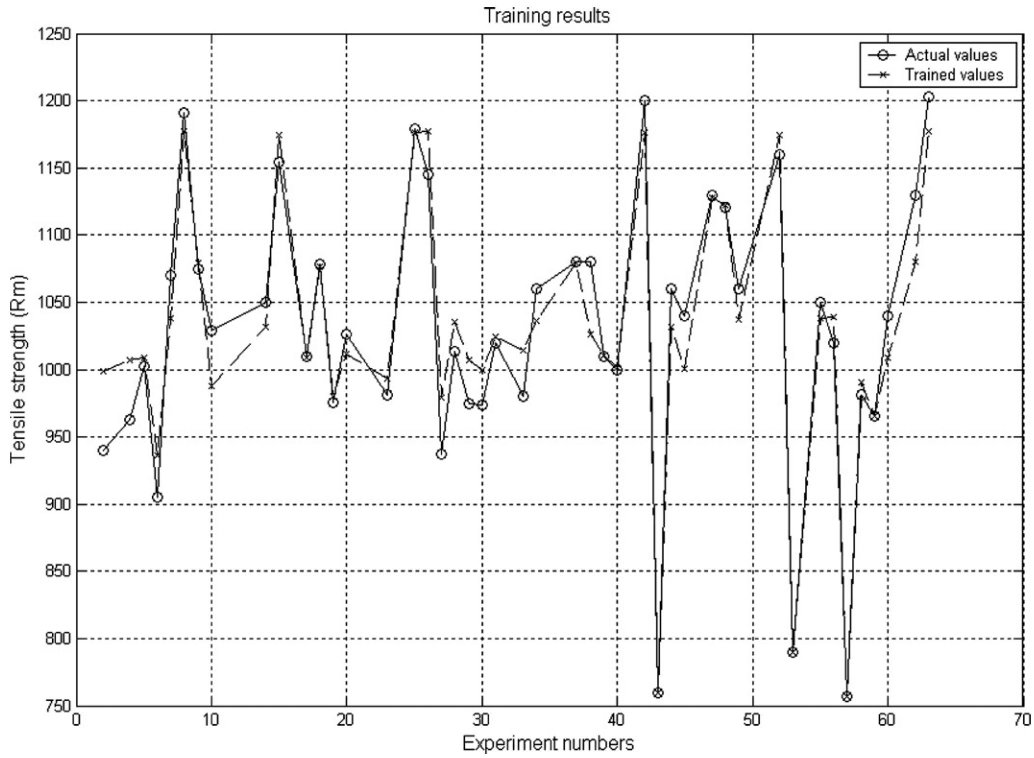

Fig. 15. Training results of GRNN model.

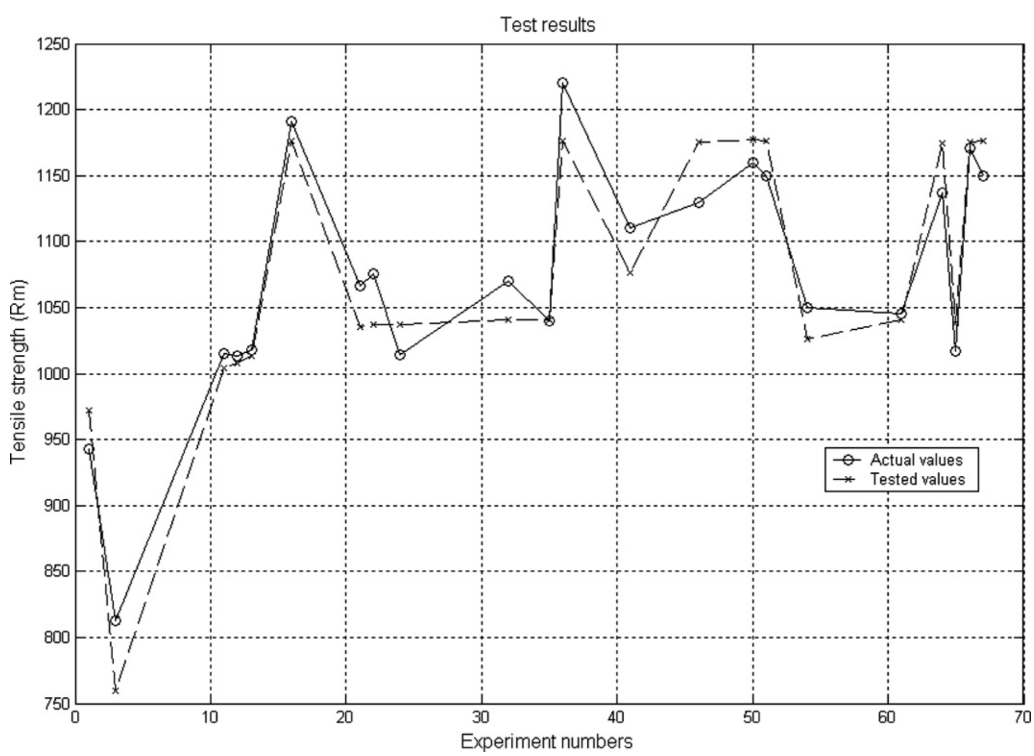

Fig. 16. Actual experimental output and neural network predictions.

The correlation coefficient, R, can range from -1 to $+1$. When R is closer to $+1$, this indicates a stronger positive linear relationship; when R is closer to -1, a stronger negative linear relationship is present. On the other hand, covariance of a and p is defined by

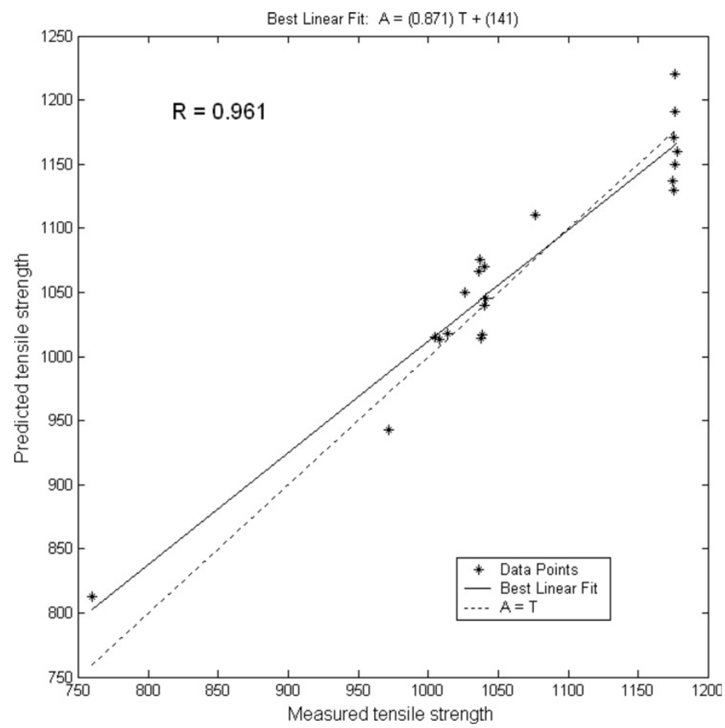

Fig. 17. The correlation between the actual experimental data and the network predicted.

$$\mathrm{Cov}(a,p) = \sigma_{ap} = \mathrm{E}\left[(a-\mu_a)(p-\mu_p)\right],$$

where E is the expected value, μ_a mean value of a set and μ_p mean value of p set. If $\mathrm{Cov}(a, p) = 0$, then a and p are said to be uncorrelated.

5. Conclusions

The tensile strength of steel wires must be as high as possible for a better performance of steel drawing process. To provide this goal, the steel must be produced with high quality and the problems that may happen during the steel wire production must be removed. Furthermore, any production error during the heat treatment must not be allowed.

The steel is required to be as clean as possible during the production for the quality of steel wires. On the other hand, the steel with sorbitic structure subjected to intensive deformation possesses the highest strength. Hence the percentages of inclusion, ferrite and carbon inside the steel are the main parameters that determine the strength of the steel. This affects the drawability limit of the steel, as well. Therefore, before the drawing process, statistical analysis of these parameters may expose the strength and drawability. Because the steel production is affected by many parameters, artificial neural network techniques are superior over the classical regression analysis.

In this study, a generalized regression neural network (GRNN) model has been developed to predict the tensile strength (Rm) of the steel from input parameters, namely, the diameter (d), carbon, ferrite and inclusion percentages, obtained from the process. The presented prediction model demonstrated a very good statistical performance with a 0.96 correlation coefficient between the actual/experimental data and the network predicted output. Hence the neural network based prediction model developed in this study can be used with a high degree of accuracy and reliability for determining the tensile strength of steel.

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References

[1] Taylan A, Oh S, Gegel HL. Metal forming. New York: ASM; 1983.
[2] Gasterich HJ, Hagedorn KE, Kaspar R, Pawelski O. Influence of the microstructure of higher carbon steels on fracture mechanical properties. Steel Res 1993;12:125–34.
[3] Languillaume J, Kapelski G, Baudelet B. Cementite dissolution in heavily cold drawn pearlitic steel wires. Acta Mater 1996;45:1201–12.
[4] Haque ME, Sudhakar KV. ANN back propagation prediction model for fracture toughness in microalloy steel. Int J Fatique 2002;24:1003–10.
[5] Perlovsky LI. Neural networks and intellect. Oxford University Press; 2001.

[6] Demuth H, Beale M. Radial basis networks. In: Neural network toolbox for use with Matlab. The Mathworks Inc., 2000 [chapter 7].
[7] Wire Rod Defects, Verlag Stahleisen M.B.H., Dusseldorf, 1973.
[8] Beretta S, Boniardi M. Fatigue strength and surface quality of eutectoid steel wires. Int J Fatigue 1999;21:329–35.
[9] Goes B. Fragmentation of as-drawn pearlitic steel wires during torsion tests. Eng Fract Mech 1998;60:255–72.
[10] Beretta S, Boniatdi M, Matteazzi S. Fatigue behaviour of rope eutectoid. Int J Fatigue 1996;18:63–9.
[11] Beretta S, Matteazzi A. Short crack propagation in eutectoid. Int J Fatigue 1996;18:451–6.