A case study of using radial basis function neural networks for predicting material properties from Barkhausen noise signal

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Abstract: Radial basis function neural networks are used to predict residual stress of case-hardened steel samples in this study. The predictions are carried out based on the non-destructive Barkhausen noise measurement which is a potential method applicable to quality control. Neural network models are identified with the algorithm proposed in the literature and thus another aim of the study is to evaluate the applicability of the algorithm. The developed models perform well in the predictions and thus the algorithm applied is applicable. When compared with linear models, neural networks produce better prediction results.

Keywords: Barkhausen noise, neural networks, residual stress, quality control.

1. INTRODUCTION

Quality control of manufactured components requires that their fitness for use can be measured. The fitness is typically evaluated through mechanical properties such as hardness, yield and tensile strength and residual lifetime (Dobmann et al. 2006). The mechanical properties can be measured directly but unfortunately the methods that can be used are destructive. Destructive methods only provide statistical information of the components but obviously leave the measured component useless and therefore they are not applicable to quality control purposes. Thus non-destructive methods must be used. The drawback of non-destructive methods is that usually they do not measure the property of interest directly. Instead, they measure some property that is related to the desired property. Models are then needed to evaluate the desired material property indirectly.

Barkhausen noise (BN) measurement is a potential non-destructive testing method suitable for ferromagnetic materials. It can be used, for example, to evaluate the case-depth of a hardened component (Santa-aho et al. 2012a) or to detect grinding burns from a ground component (Santa-aho et al. 2012b). The measurement is based on the stochastic movements of magnetic domain walls within the material when it is placed in a varying external magnetic field (Jiles 2000). The domain wall movements cause rapid changes to the magnetisation of the sample. These changes can be captured and they form the noise-like BN signal. A typical BN signal with the sinusoidal excitation magnetic field is presented in Fig. 1.

For quality control purposes, prediction models are needed to evaluate the desired material properties quantitatively. The earlier studies of the present authors have used multivariable linear regression (MLR) models in predictions (Sorsa et al. 2012a, Sorsa et al. 2012b). Linear models have been used to capture the major interactions between BN and the material properties. In this study, the aim is to test if it is beneficial to use nonlinear models in predictions. Radial basis function (RBF) neural network models are used for the task.

The predicted material property is the residual stress state which is an essential property considering the lifetime of a component. Residual stresses are the stresses remaining in the material without external loads. They are caused, for example, by inhomogeneous plastic deformation or temperature gradients during processing (Withers and Badeshia 2001). Tensile residual stresses may be detrimental to material but deliberate compressive stresses may increase the lifetime of a component (Withers and Badeshia 2001). BN has been shown to be sensitive to changes in residual stresses (Lindgren and Lepistö 2002, Mierczak et al. 2011). It is generally shown that compressive stresses decrease Barkhausen activity while tensile stresses increase it. The relationship has been evaluated through certain features calculated from the BN signal. These features are, for example, the root-mean-square (RMS) value (Lindgren and Lepistö 2002) and the maximum amplitude (Mierczak et al. 2011) of the signal. Among these many other BN properties has been shown to vary depending on the stress state.

The relationship between BN and material properties is complex and case-dependent. Thus it is challenging to identify the most significant features to be used in predictions. Many methods can be used in selection such as simple deterministic forward-selection or backward-elimination or more complex stochastic methods such as genetic algorithms (Guyon and Elisseeff 2003). The aim of this study is not to evaluate different selection methods and thus the selection is carried out through two simple steps. First, a set of eight potential features is selected based on the literature and the earlier results and then this set is exhaustively searched to find the most suitable subset.

As mentioned above, the RBF neural network model is identified with the algorithm given in (Sarimveis et al. 2002). The second goal of this study is to evaluate the applicability of this algorithm. It is based on the fuzzy partitioning of the input variables. Even though the algorithm greatly simplifies the identification of the RBF network it still has a tuneable parameter. This parameter defines the number of cluster centres obtained from the fuzzy partitioning. In this study, this parameter is gradually increased and its influence to the obtained prediction model is evaluated.

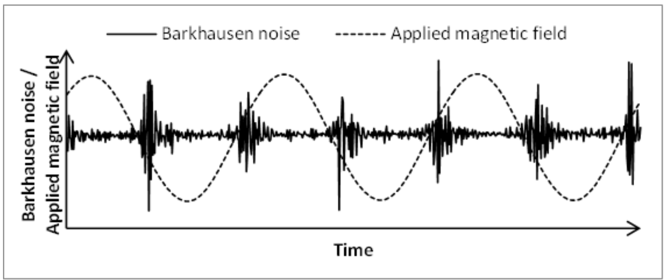

Fig. 1. A typical BN signal and the external magnetic field.

2. MATERIALS AND METHODS

2.1 Material Description

Two sets of case-hardened steel samples are used. The first set is manufactured from 18CrNiMo7-6 (EN 10084) steel. The same sample set is used earlier in (Sorsa et al. 2012a) and (Sorsa et al. 2012b). The other sample set is manufactured from RAEX400 low alloyed hot-rolled steel. This sample set is used earlier in (Santa-aho et al. 2012c) and (Sorsa et al. 2013). Different tempering times and temperatures are used in order to vary the final hardness and residual stress of the samples. Furthermore, the samples in the second set are subjected to external loading. A more thorough description of the materials and sample preparation can be found in the publications mentioned above.

2.2 Measurements

The residual stress measurements are carried out with the XStress 3000 X-ray diffractometer using CrKα radiation and the chi method with the tube voltage of 30 kV, current of 6.7 mA and the collimator diameter of 3 mm. Rollscan 300 instrument is used to capture the BN signals with the magnetizing frequencies of 45 and 125 Hz for the 18CrNiMo7-6 (EN 10084) and RAEX400 steel data sets, respectively. The measuring devices are manufactured by Stresstech Oy (Finland).

2.3 Identification of the RBF Neural Network Models

An artificial neural network is a set of parallel simple computational units, neurons. Radial basis function (RBF) neural networks used in this study utilise a radial basis function as an activation function in the hidden layer neurons. The radial basis function of the h:th neuron is given by (Ramuhalli et al. 2002)

$$f_h(x_i) = exp\left(-\frac{\|x_i - c_h\|^2}{\sigma_h^2}\right), \quad (1)$$

where σ_h and c_h are the width and the centre of the basis function, respectively, and $\|x_i - c_h\|$ is the Euclidean distance between the i:th input vector and the centre of the basis function. RBF networks include three layers. The input layer only distributes the input variables to all hidden layer neurons. The output of the hidden layer neurons is obtained by (1). These outputs are weighted and fed to the output layer neurons where the weighted values are summed to obtain the output of the network. The network output is thus given by (Ramuhalli et al. 2002)

$$y = \sum_{h=1}^{H} w_h f_h(x_i). \quad (2)$$

Above, H is the number of neurons and w_h are the weighting coefficients.

The usage of the RBF network needs the identification of the appropriate number of neurons and the centres and widths of the radial basis functions. This may be a complex and computationally expensive task. Two popular approaches for identifying these parameters are clustering and dynamic stepwise selection (Wang and Xiang 2007). Trial-and-error is obviously inefficient in finding the appropriate values especially because the parameters hold cross-correlations and thus need to be defined simultaneously.

The algorithm proposed in (Sarimveis et al. 2002) simplifies the identification of the RBF network significantly. The algorithm is based on the fuzzy partitioning of the input variables and only the number of partitions used needs to be set. Fig. 2 gives an illustration of the partitioning in a two variable case. Both variables are evenly partitioned into five triangular fuzzy sets leading to 25 overlapping subspaces. In the figure, the fuzzy sets of variable 1 are denoted by $A_{1,1}$, $A_{1,2}$ and so on. Similarly notation is used for variable 2. Fig. 2 also shows a fuzzy subspace A that is determined by the fuzzy sets $A_{1,3}$ and $A_{2,3}$. When there are more than two input variables, the partitioning presented in Fig. 2 is generalised to the multidimensional case.

The partitioning is the basis for determining the number of neurons and the centres of the radial basis functions (Sarimveis et al. 2012). For the partitioning, the number of partitions must be determined. This can be set to each variable individually but in this study the number of partitions is kept constant for all the variables. After partitioning, each data point is browsed and fuzzy subspace that is closest to each data point is determined. The centres of the subspaces obtained are then used as the centres of the radial basis functions (Sarimveis et al. 2002). Thus both the centres and the number of neurons are obtained through the steps described above.

The final parameter that needs to be set is the width of the radial basis functions. The width is obtained by (Leonard and Kramer 1991)

$$\sigma_h = \sqrt{\frac{1}{p}\sum_{j=1}^{p}\left\|c_h - c_j\right\|^2} \ , \tag{3}$$

where c_j are the p closest neighbours of c_h.

The procedure given above gives the parameters needed to train the RBF neural network. The training basically includes two steps where the neuron outputs are first calculated and the weighting coefficients are identified. The weighting coefficients are obtained as the least-squares solution of (2).

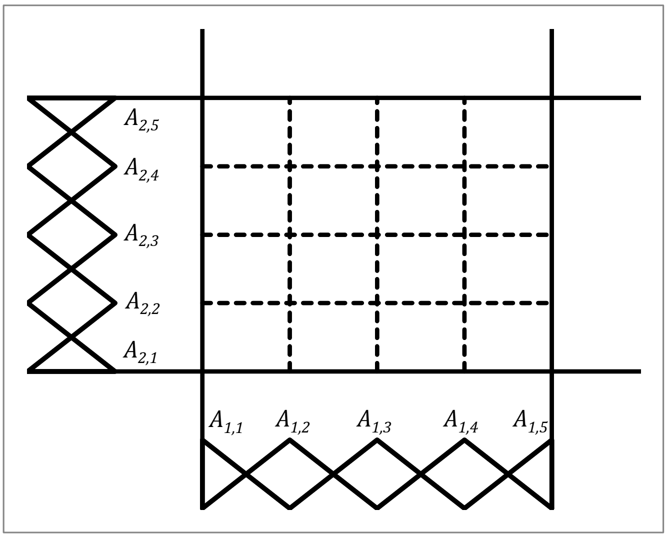

Fig. 2. Fuzzy partitioning of the input variables.

3. RESULTS AND DISCUSSION

3.1 Features Selected and Data Sets Used

As mentioned in the introduction, a pre-selected set of features calculated from the BN signal is used in this study. These features are selected based on the earlier results by the present authors and the literature. The RMS value is the most often used feature. It has been used, for example, in (Santa-aho et al. 2012b) and (Lindgren and Lepistö 2002). Peak position and width are obtained from the so called Barkhausen profile and are used in (Stewart et al. 2004) and (Sorsa et al. 2012b). Coercivity has also been shown to be significant in (Davut and Gür 2007) and (Sorsa et al. 2012b). Entropy is found significant in (Sorsa et al. 2010) and peak amplitude in (Mierczak et al 2011) and (Sorsa et al. 2013). The power spectral density (PSD) is used, for example, in (Piotrowski et al. 2010). The features used are given in Table 1.

Data set 1 is obtained from the set of case-hardened samples manufactured from 18CrNiMo7-6 (EN 10084) steel. Data set 2 is obtained from the case-hardened samples that are bent to vary the stress states. The data sets include 60 and 98 data points, respectively. They are divided into training and testing data sets so that the testing set includes 10% of the data points and the extreme data points are included in the training set.

Table 1. The pre-selected set of features calculated from the BN signals

Feature	Abbreviation
the RMS value	x_1
peak position	x_2
the FWHM value	x_3
coercivity	x_4
entropy	x_5
peak amplitude	x_6
crest factor	x_7
power spectral density	x_8

3.2 Procedure Applied

The procedure used includes basically two steps. They are feature selection and model identification. The feature set given in Table 1 is exhaustively searched to find the appropriate subset. For each candidate subset the models are identified. The MLR models are identified with the least-squares method and the RBF neural network models with the algorithm described in Section 2.3. The number of neighbours in (3) is set to 2. The number of partitions used is gradually increased. The feature selections and model performance are evaluated through the root-mean-squared error (RMSE) of prediction which is obtained from

$$\text{RMSE} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2 \ , \tag{4}$$

where N is the number of data points, $\hat{y}$ and y are the predicted and measured residual stresses, respectively. It should be noticed that when the performance of feature selection is evaluated the predicted residual stress values are obtained through the leave-one-out (LOO) cross-validation procedure. Cross-validation is applied to avoid overfitting. After finding the most suitable feature subsets, the actual models are identified with the whole training data set. The testing data set is then used to evaluate the goodness of the models.

Even though LOO cross-validation is used the algorithm used for identifying the neural network model may lead to overfitting. Overfitting may be a problem when the number of fitting parameters relative to the number of data points increases. In this case, the number of fitting parameters increases as the number of input features and partitions are increased. This is shown in Fig. 3. The figure shows that the number of fitting parameters saturates with the maximum value being equal to the number of data points in the training set. The training sets of data sets 1 and 2 hold 54 and 81 data points, respectively.

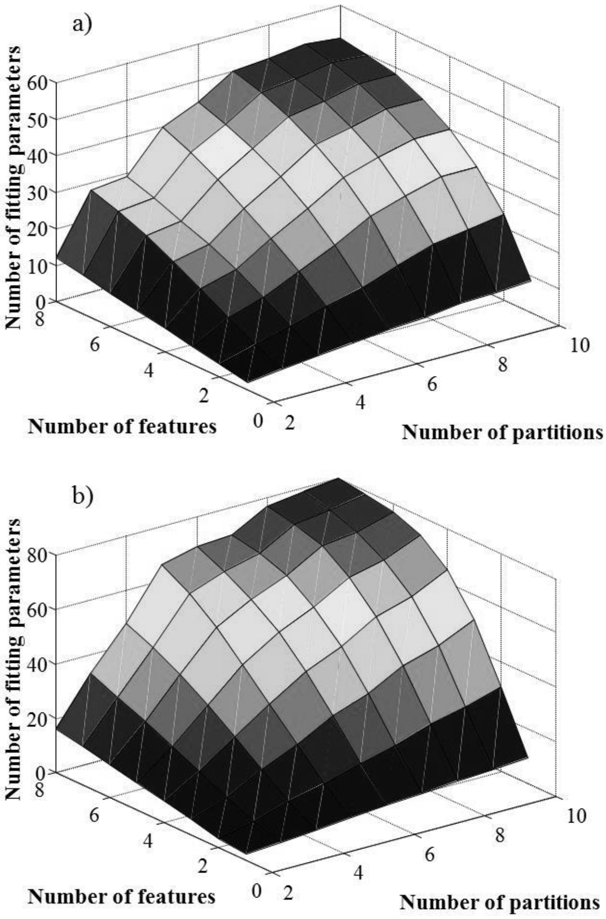

Fig. 3. The average number of fitting parameters as a function of the number of features and partitions a) for data set 1 and b) for data set 2.

3.3 Feature Selection Results

As mentioned above, the suitable feature subset is exhaustively searched from the set of candidate features given in Table 1. The search is carried out separately for different data sets with different number of partitions. Fig. 4 shows the minimum RMSE values as a function of the number of partitions. The figure indicates that the best solutions are found generally when the number of partitions is between 3 and 6. When the number of partitions is lower the model structure is too simple for the case. On the other hand, the number of parameters increases with the higher number of partitions as shown in Fig. 3 and thus the deterioration of model performance is assumingly due to overfitting. The very best solution for data set 1 includes features x_3 and x_6 with 4 partitions. The best feature subset for data set 2 includes features x_2, x_5 and x_8 with 5 partitions. When MLR models are used, the found subset for data set 1 includes only features x_2 and x_3. For data set 2, features x_1, x_2, x_3, x_4 and x_7 are to be used.

The results obtained show that the prediction of material properties from BN signals is very case-dependent. All the selected features can be considered meaningful because they are used in the literature as mentioned in Section 3.1. However, the results clearly show that it is not desired to include all the features into the model but to select the most suitable ones for the case. Thus an automated solution for feature selection is essential when building prediction models between BN and material properties.

Fig. 4. The RMSE value as a function of the number of partitions.

3.4 Prediction Results

As mentioned in Section 3.1, the actual prediction models are identified with the selected feature subsets using the whole training data set. The performance indices of the identified models are given in Table 2. The table shows the RMSE values and also the correlation coefficients (R) between the measured and predicted residual stresses. The table shows that with both data sets, the RBF model gives significantly better results. The RMSE value of the testing set decreases over 10 MPa with both data sets when neural networks are applied. Also the correlations increase.

Fig. 5 shows the measured and predicted residual stresses for data set 1. The earlier experiences indicate that the prediction of residual stress is challenging especially with data set 1. That is also seen in Fig. 5. However, a careful examination of the figure shows that the RBF neural network model behaves better as already indicated by Table 2. Fig. 6 shows the measured and predicted residual stresses for data set 2.The figure clearly shows that the performance of the RBF neural network model is better than the performance of the MLR model. Comparison of Fig. 5 and Fig. 6 further shows that the prediction of residual stress is an easier task with data set 2. That is due to the fact that the major variation in the samples of data set 2 is due to the applied load and thus due to the stress changes. With data set 1, other sources of variation, such as hardness and microstructure changes, are also important which makes the prediction of residual stress a more difficult task.

3.5 Applicability of the Procedure

The results given above give two conclusions. Firstly, it is shown that it is beneficial to use nonlinear model structures when material properties are predicted based on the BN measurement. Secondly, the procedure applied for identifying the RBF neural network model performs well and can be used. The main benefit of the algorithm proposed in (Sarimveis et al. 2002) is that the identification of the neural network structure simplifies greatly. With this simplification, the RBF neural network model can be better used in the computationally expensive feature selection step. Considering feature selection algorithms, the number of partitions must still be defined. In this study, different values were used which may be impractical in some cases. It is however possible to include the number of partitions in the optimisation algorithm that tries to find the most suitable feature subset (Alexandridis et al. 2005).

Table 2. The performance indices of the obtained MLR and RBF neural network models

		Data set 1		Data set 2	
		Training	Testing	Training	Testing
MLR	RMSE	66.9	57.6	77.4	59.3
	R	0.78	0.88	0.93	0.96
RBF	RMSE	51.1	45.8	53.1	46.9
	R	0.88	0.93	0.97	0.98

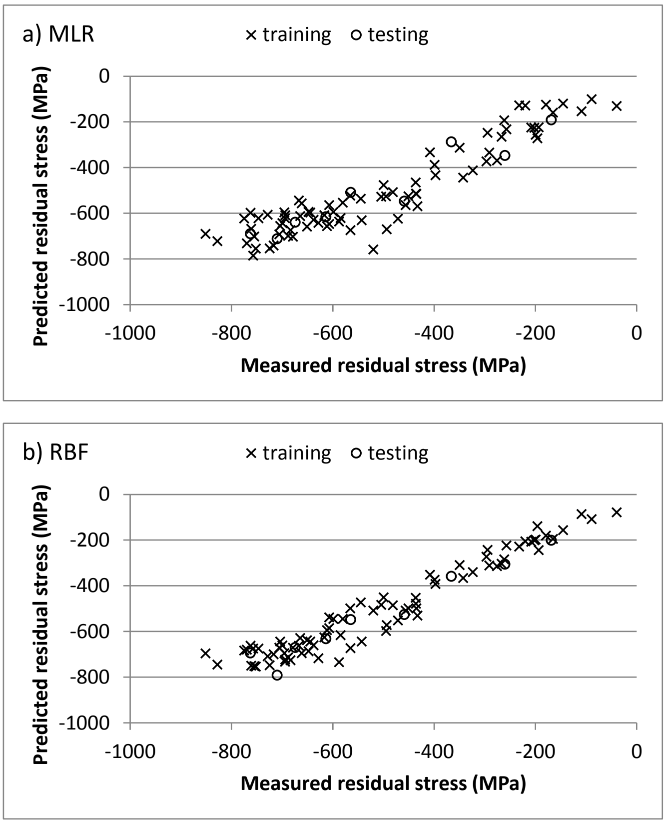

Fig. 5. The predicted residual stress as a function of the measured residual stress for data set 1. a) prediction with the MLR model and b) prediction with the RBF neural network model.

4. CONCLUSIONS

Barkhausen noise (BN) measurement is a potential non-destructive testing method that can be used in quality control. The method can be used to indirectly measure material properties such as residual stress and hardness. The indirect measurement needs models that predict the material properties based on the measured BN signal. The development of the prediction models is a complex task including feature selection and model identification steps. The task is even more complex if nonlinear model structures such as neural networks are used.

In this paper, the applicability of radial basis function (RBF) neural network models for predicting residual stress is studied. The RBF neural network model is identified with an algorithm proposed in (Sarimveis et al. 2002). The results show that the prediction accuracy of identified neural network models is significantly better than the prediction accuracy of multivariable linear regression (MLR) models. The results also show that the tested algorithm performs well in identification of the neural network model. This algorithm greatly simplifies the structure identification which is beneficial if RBF neural network models are used in prediction of material properties based on the BN measurement.

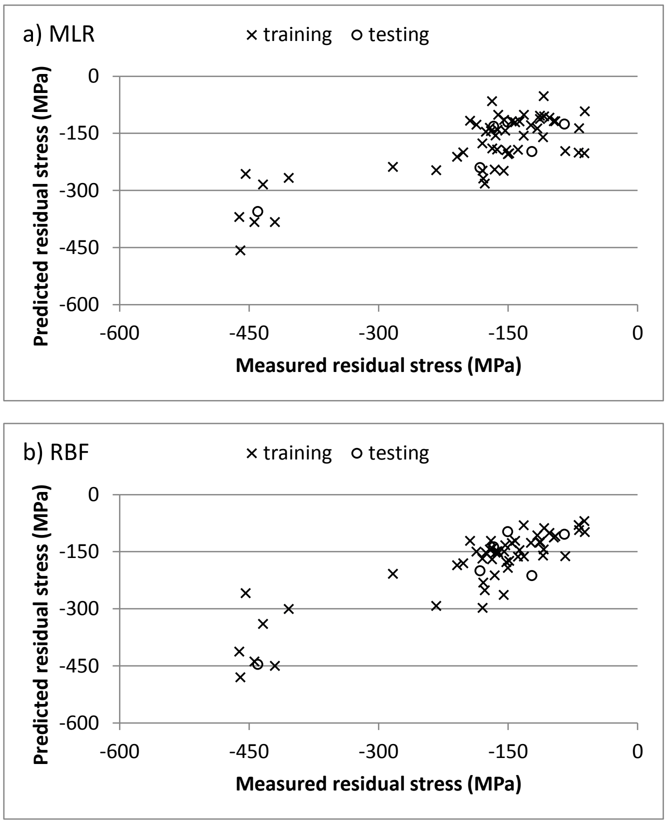

Fig. 6. The predicted residual stress as a function of the measured residual stress for data set 2. a) prediction with the MLR model and b) prediction with the RBF neural network model.

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