ISSN 2176-5480

22nd International Congress of Mechanical Engineering (COBEM 2013)
November 3-7, 2013, Ribeirão Preto, SP, Brazil
Copyright © 2013 by ABCM

COMPARATIVE EVALUATION OF ARTIFICIAL NEURAL NETWORKS MODELS TO CLASSIFY WELD FLAWS USING PULSE-ECHO ULTRASONIC SIGNALS

Giovanni Alfredo Guarneri
UTFPR - Av. Sete de Setembro, 3165, Curitiba-PR, Brasil
giovanni@utfpr.edu.br

Flávio Neves Junior
UTFPR - Av. Sete de Setembro, 3165, Curitiba-PR, Brasil
neves@utfpr.edu.br

Lúcia Valéria Ramos de Arruda
UTFPR - Av. Sete de Setembro, 3165, Curitiba-PR, Brasil
lvrarruda@utfpr.edu.br

Abstract. *The present work evaluates several artificial neural networks models, based on Multilayer Perceptron, Radial Basis Function and Self-organizing Maps, to classify defects in the weld beads attaching metal plates of carbon steel. The database used for training models consists of pulse-echo (A-scan) ultrasonic signals. The artificial neural networks were designed to identify two classes of defects in welds, lack of fusion and longitudinal cracks. Moreover, they can identify defect-free welds. All artificial neural networks were trained and tested with no feature extraction from input signals. Subsequently, they were trained using the Principal Component Analysis technique to feature extraction thereof. The results show that defects classification has occurred with a success rate up to 91% for a Multilayer Perceptron, with two hidden layer model and using Principal Component Analysis technique to feature extraction.*

Keywords: *Nondestructive tests, ultrasonic technique, artificial neural network, and pattern recognition*

1. INTRODUCTION

The ultrasonic waves are used at nondestructive testing (NDT) method for welded structures since 1960's. It's the most widely NDT technique used on in-service inspection applications of large welded structures (Ditchburn *et al.*, 1996). There are many different techniques to ultrasonic NDT and the pulse-echo technique is the most commonly used for its simplicity and efficiency (Veiga *et al.*, 2005). In this technique, a piezoelectric ultrasonic transducer generates ultrasonic waves. These waves propagate through metal plate and they are reflected by defects (planar or volumetric) and back surface. The same ultrasonic transducer receives the reflected waves and converts them to electrical signals. These signals, called A-scan signals, contain information about the type, size and orientation of the defect (Sambath *et al.*, 2011).

The analysis of A-scan is to identify a defect is not a trivial task. This task must be done by experts and the results depend on the experience and knowledge (Seyedtabaii, 2012). Nevertheless, a human inspector is subject to mistake during identification task. Thus, an automatic signal classification system (ASCS) to assist the inspector in that analysis may improve the reliability of the inspection process (Veiga *et al.*, 2005).

Polikar *et al.* (1998) give an overall schematic of an ASCS and define three major tasks to such systems: preprocessing raw data, feature extraction and classification. The preprocessing task normalizes raw data signals values to a suitable range for other tasks. The feature extraction task is responsible to obtain attributes from normalized A-scan signals. These attributes must be able to characterize the flaws. Finally, the classification task aims to analyze the attributes from an A-scan signal and indicates one from a known set of flaws. The algorithm that implements a classification task is called *classifier*. There are several approaches to build a classifier, such as traditional statistical classifiers, rule-base classifiers and learning-base classifiers, which typical examples are artificial neural networks (ANN) (Song *et al.*, 2002).

This work aims to compare the performance of several ASCS architectures to classify defects in the weld beads attaching metal plates of carbon steel. All ASCS has the same preprocessing algorithm, but the feature extraction and classifier algorithms are different for each ASCS. The feature extraction algorithms used in this work were Principal Component Analysis (PCA) and none (every points of normalized A-scan signal are used as attributes). Only ANN classifiers algorithms were used. These classifiers are based on Multi-layer Perceptron (MLP), Radial Basis Function (RBF) and Self-organizing Maps (SOM). All ANN classifiers were trained with the same knowledge database. The knowledge database has A-scan signals of two flaw classes, lack of fusion (LF) and longitudinal cracks (LC). Moreover, it has also A-scan signals of defect-free welds (ND). This knowledge database has derived using a simulation software for ultrasonic testing called *simSUNDT*, developed at the Dept. of Mechanics at Chalmers University of Technology (Bovik and Bostrom, 1997; Wirdelius, 2004; Persson and Wirdelius, 2010).

This paper is organized as follows. Section 2 discusses how the knowledge database was assembled by using *simSUNDT* software. Section 3 describes the methods for building ASCS architectures. Results obtained are presented in Section 4 and concluding remarks are presented in Section 5.

2. KNOWLEDGE DATABASE

2.1 Weld Flaws

According to American Welding Society (AWS, 2000), any interruption of a weldment typical structure is considered as weld discontinuity. A flaw is a weld discontinuity does not meet any requirement of a particular specification. AWS (2000) gives three general classification of weld discontinuities: (1) Procedures/Process, (2) Metallurgical and (3) Base Metal. This work was limited to the study of only two types of discontinuities lack of fusion and longitudinal cracks, both belonging to the class (1).

2.1.1 Lack of fusion

The lack of fusion (or incomplete fusion) is a discontinuity which appears when the weld metal does not melt properly with the base metal. It can occur at interface between weld metal and base metal (sidewall) or between adjoining weld beads (AWS, 2000). According AWS (2000), the main reasons that cause lack of fusion are insufficient welding current, lack of access to all faces of the weld joint and insufficient preweld cleaning. Figure 1 shows examples to lack of fusion flaws.

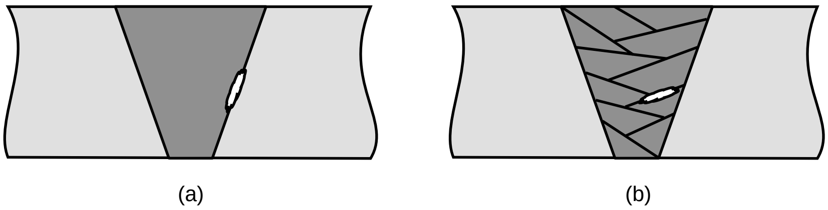

Figure 1. Lack of fusion examples (a) at sidewall and (b) between adjoining weld beads

2.1.2 Cracks

The AWS (2000) defines cracks of welded joints as a result of localized stresses that exceeds the material ultimate. Cracks can be divided into *hot cracks*, which occur during solidification, or *cold cracks* which occur in ambient temperature when the weldment has been placed in service.

The cracks can also be divided according to their location. They may occur in the weld metal and the base metal. Figure 2 shows examples of cracks.

There are three cracks types which occur in the weld metal (AWS, 2000):

- *Crater cracks*: they are often star shaped. They may occur when the welding operation is interrupted;
- *Longitudinal weld cracks*: they are parallel to axis of weld. They may occur as extension of crater cracks formed at the end of the weld;
- *Transverse weld cracks*: they are perpendicular to axis of weld. They may occur when is used a low-ductility weld metal;

The base metal cracks occur in the heat-affected zone (HAZ) and there are two types, according AWS (2000):

- *Transverse base metal cracks*: they are perpendicular to axis of weld. They are usually associated with welds on steels of high hardenability;
- *Longitudinal base metal cracks*: they are parallel to axis of weld. They may occur as extension of weld interface cracks. They can be subdivided into *toe cracks*, *root cracks* and *underbead cracks*.

2.2 Software *simSUNDT*

The software *simSUNDT* is a tool which simulates the whole ultrasonic NDT procedure, generating the A-scan signals for defects insert into a weld bead. The *simSUNDT* has three components: a preprocessor which the operator configures a

ISSN 2176-5480

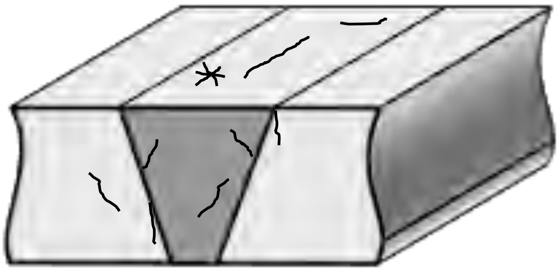

Figure 2. Cracks examples

simulation session; a kernel (UTDefect) which deals with the mathematical model (Bostrom and Wirdelius, 1995; Bovik and Bostrom, 1997); and a postprocessor which shows the simulation results.

The simulator's mathematical model is three dimensional one and the probe scans the object on a rectangular mesh. It can simulates tree types of planar defects, which two of them can be interpreted as lack of fusion (rectangular and circular cracks) and one is as longitudinal crack (strip-like crack). It can also simulate four volumetric defects: spherical cavity (pore), spherical inclusion (slag), spheroid cavity (pore) and cylindrical cavity (side drilled hole). The software *simSUNDT* can also simulate the weld and the corresponding back scattered grain noise that is superposed to the defect signal that correlates better to a real inspection situation (Persson and Wirdelius, 2010).

2.3 Simulation parameters

It is necessary to define simulator parameters before starting a simulation session. All parameters definitions are described in Wirdelius (2004). First, it is necessary to specify the object and the ultrasonic NDT procedure. Here the material proprieties of base metal (*steel*) are defined, the calibration method parameters (*Side-drilled hole* with ⊘ 2.4 mm at depth 15 mm), the probe arrangement (*pulse-echo*), the time window (*All positions* from 0 μs to 50 μs, step 0.02 μs) and *accuracy index* 3. Furthermore, the measuring mesh (X dimension from -20 mm to 50 mm, step 5 mm; Y dimension not vary) and weld proprieties are specified. The geometry of weld, defined by five parameters are showed in Fig. 3. The weld metal are set to *steel*.

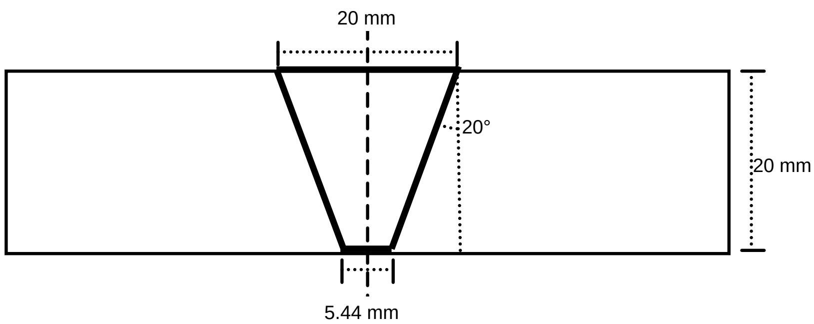

Figure 3. Weld geometry

The second step is to define the probe parameters. The wave type is set to *Transversal (vert. pol.)* with *No supression* of others wave components. The skew angle probe is set to 60°. The probe's shape is *elliptic* and its dimensions are 5 mm (*x-length*) by 5 mm (*y-length*), with only 1 element. The probe is unfocused and the frequency spectrum of electrical exciting pulse has *cossine square* shape, with central frequency set to 1.5 MHz and bandwidth set to 100% (1.5 MHz at -6 dB). Finally, the probe couplant constant (Bostrom and Wirdelius, 1995) is set to 0.4.

The last step in the simulation parameterization is to set defect parameters. The lack of fusion defects were parameterized as *circular cracks*. Position parameters on the mesh (X and Y positions), the geometric parameters (diameter, center depth, tilt and skew angles), depth of back surface and type parameters (*open*, *close* or *partly close*) must be a priori defined for all simulated defects. All lack of fusion defects were simulated as *open cracks*, with back surface at 20 mm, skew angle sets to 0° and Y-position at 0 mm. The tilt angle, depth center and X-position were adjusted so that the defect stay at the margin between the base metal and weld metal. The diameter was chosen randomly between 1.5 mm and 7.5 mm with uniform probability distribution.

The longitudinal cracks were parameterized as *strip-like cracks*. Position parameters on the mesh (X and Y positions), the geometric parameters (height, center depth and tilt angle), depth and tilt of back surface and roughness parameters on

ISSN 2176-5480

the crack surface must be a priori defined. All longitudinal defects were simulated with no roughness on the crack surface, with back surface at 20 mm (no tilt) and Y-position at 0 mm. The others parameters were chosen randomly with uniform probability distribution. The limits for each parameters were: -90° $\leq$ tilt angle $\leq$ 90°; 5 mm $\leq$ depth center $<$ 19.5 mm; 1.5 mm $\leq$ height $\leq$ 7.5 mm; and -17 mm $<$ X-position $<$ 17 mm.

The defect-free welds were parameterized as *side-drilled hole*. Position parameters on the mesh (X and Y positions) and the geometric parameters (diameter and center depth) must be a priori defined. All defect-free welds were simulated with a small diameter (0.1 mm) with center depth at 20 mm. The position were set out of scanning area, with Y-position at 0 mm and X-position at 50 mm.

2.4 A-scan signal database

The A-scan signal database was built with results of many simulation sessions. A hundred simulation sessions were carried out for each LF and LC class flaws. So, were taken the signs of A-scan with the largest gain of each simulation. For defect-free welds were taken all A-scan signals with gain greater than -30 dB (0 dB is the gain of A-scan signal generated by simulator calibration process). This procedure gives an A-scan signal database with 100 A-scan signals for lack of fusion defects, 100 A-scan signals for longitudinal cracks defects and 73 A-scan signals for defect-free welds. All these signals have 2501 samples. Figure 4 shows an A-scan example for each defect.

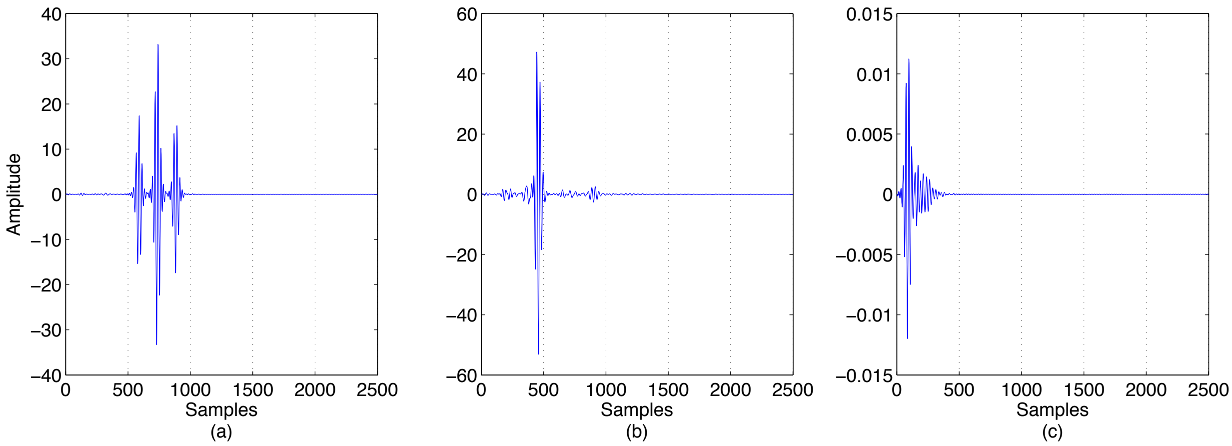

Figure 4. A-scan signals examples: (a) LF, (b) LC and (c) defect-free weld

3. METHOD

As previously mentioned in Sect. 1, an ASCS executes three main tasks (Polikar *et al.*, 1998): data preprocessing, feature extraction and classification. This section describes the methods applied in these three tasks to build the ASCS used in this comparative evaluation.

3.1 Preprocessing raw data

The knowledge database described in Sect. 2 is formed by a set of raw A-scan signals. These signals have a high frequency component (probe central frequency) whose amplitude is modulated according to echoes which are reflected by defects and returned back to surface. These amplitudes determine the envelope of the A-scan signal. Therefore, only the envelope of the A-scan signal has information about defects. Thus, the raw A-scan signals may be simplified if the envelope signal was extracted. A method for envelope extraction is calculating the absolute value of the analytic signal. The analytic signal of a real discrete signal is obtain with `hilbert` function of MATLAB®. Figure 5 shows the envelope signal of the A-scan signal for Fig. 4a (a) and the its frequency spectrum (b).

As can be seen in Fig. 5b, the bandwidth of envelope signal is approximately 5 MHz. All A-scan envelope signals were sampled at 50 MHz. Thus, these signals can be downsampling to 5 MHz without loss information. With this procedure, the A-scan envelope signal decreases its size to 251 samples.

Once extracted the A-scan envelope signal and performed downsampling procedure, the resulting signals still show large amplitude variations (see Tab. 1). Therefore, the last procedure to be performed as preprocessing of the A-scan signals is the normalization by maximum and minimum amplitude value. All signals are normalized by assuming the highest amplitude value as 1 and the lowest value as 0.

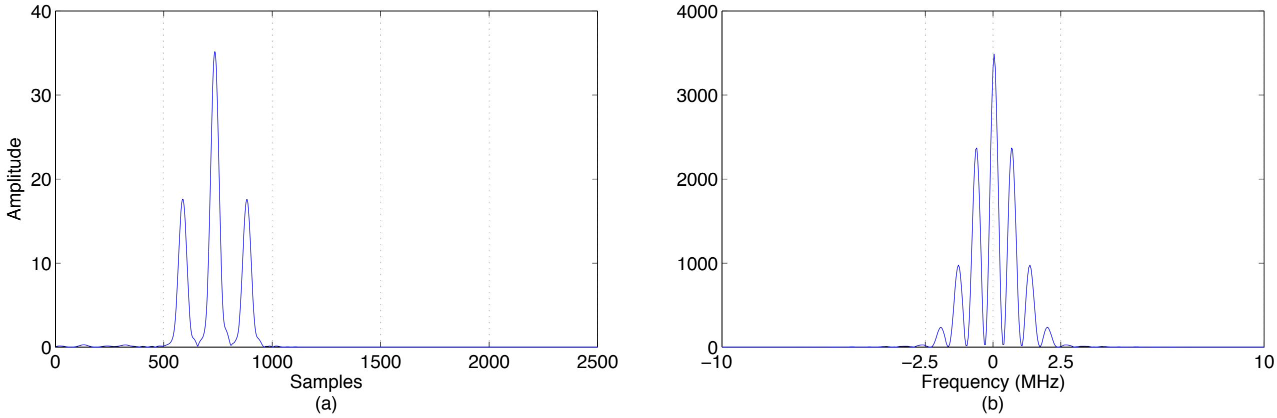

Figure 5. (a) A-scan envelope signal and (b) the envelope signal frequency spectrum

Table 1. Maximum and minimum amplitude values of raw A-scan envelope signal database per weld defect class.

Value	LF	LC	ND
Maximum	17.3190	26.5519	0.0238
Minimum	5.8650e-08	-8.7143e-06	1.3786e-09

3.2 Feature extraction

According to Haykin (1998), feature extraction is a process which a *input space* is mapped to a *feature space*. This mapping is carried out such that the *feature space* has a dimension smaller than the *input space*, but it still keep data information contents. The input data set can have also reduced dimensionality. There are many techniques for extracting features, some specific for use in ultrasonic A-scan signals (Case and Waag, 1996; Dunlop and McNab, 1997; Song *et al.*, 2002; Miao *et al.*, 2008) and other generic for any type of signal, such as Wavelet Transforms (WT) (Polikar *et al.*, 1998; Lee and Estivill-Castro, 2007; Zhan and Jin, 2009; Li *et al.*, 2010; Sambath *et al.*, 2011) and Principal Component Analysis (PCA) (Sophian *et al.*, 2003; Miao *et al.*, 2008).

From an statistical point of view, the PCA is an effective technique in pattern recognition application for reducing dimensionality. In fact, PCA is an invertible linear transformation, maximizing the rate of decrease of variance and the components of the resulting vectors are orthogonal (Haykin, 1998).

In this work, all classifiers were trained and tested with two input data sets. The first input data set is the normalized A-scan envelope signals database, processed as described in Sect. 3.1. In this set, each input data vector has 251 dimensions. The second input data set is the result of PCA processing on the first input data set. This PCA processing was performed by `processpca` function of MATLAB®. The `processpca` takes two arguments. The first argument is a matrix where each column is a input data vector. The second argument is the maximum fraction of variance for removed rows (`maxfrac`). We used `maxfrac=0.01` to eliminates those principal components that contribute less than 1% to the total variation in the data set. This reduced the dimension of input data vectors to 19.

3.3 Classifiers

The ANN-based classifiers are widely used to identify defects in welded structures. There are several published studies that demonstrate the good performance of these classifiers using ultrasonic signals as input data. Some of these works are: Lorenz and Wielinga (1993); ter Brugge *et al.* (1995); Polikar *et al.* (1998); Veiga *et al.* (2005); Martín *et al.* (2007); Sambath *et al.* (2011); Zhang *et al.* (2011); Seyedtabaii (2012).

All of these cited works use a Multilayer Perceptron neural network classifier. However, Zhang *et al.* (2011) propose a Probabilistic Neural Network (PNN) classifier to flaw classification and compare its performance with a MLP classifier. Likewise, Seyedtabaii (2012) gives a comparative performance evaluation of several ANN classifiers, including MLP, RBF, SOM, PNN and GRNN classifiers. As Seyedtabaii (2012), the present work shows a comparative evaluation among ANN-based classifiers, specifically MLP, RBF and SOM classifiers. Despite the overall goal of both works are the same, the methods used are different.

3.3.1 Multilayer Perceptron classifiers

The MLP are the most widely studied and used ANN classifiers (Zhang, 2000). In general multilayer feedforward neural network classifiers have an input layer, at least one hidden layer and an output layer. All their neurons have a sigmoid function transfer. The MLP are trained with a back-propagation training algorithm, which uses mean squared normalized error as performance function.

The MLP classifiers used in this work were implemented using the Neural Network Toolbox™ of MATLAB®. To obtain a suitable number of neurons from the hidden layer, the cross-validation method for model selection proposed by Haykin (1998, p.236) was used. The A-scan envelope signal database and the PCA processed database were randomly partitioned into a training set (182 input vectors) and a test set (91 input vectors). A set of MLP classifiers with similar architecture were created and configured, varying the number of neurons on the hidden layer. These similar architecture have the following parameters: log-sigmoid transfer function, Scaled Conjugate Gradient back-propagation training algorithm (`trainscg`) and performance goal was set to 0.01. All MLP classifiers were trained with the training set and tested with the test set. The MLP classifier with the best success classification rate was choose.

3.3.2 Radial Base Function classifiers

The RBF classifier is another kind of multilayer feedforward neural network. According to Cover's theorem, a pattern classification problem cast in a high-dimensional space nonlinearly (*feature space*) is more likely to be linearly separable than in an low-dimensional space (*input space*) (Haykin, 1998). In a RBF classifier, the neurons at hidden layer provide a set of nonlinear functions that are a basis for input vectors when they are mapped from the *input space* into the *feature space*. The learning of RBF classifier is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data (Haykin, 1998). A RBF classifier have always an input layer, one *hidden layer* and an output layer.

A RBF classifier was implemented using the function `newrb` from the Neural Network Toolbox™ of MATLAB®. This function requires four parameters: a matrix with the training input data as column vectors, a matrix with the target class data as column vectors, a mean squared error goal and a spread value of radial basis functions. The training and target set were same used to MLP classifiers. The mean square error goal was set to 0.01. The selection of the best spread value was done with cross-validation method.

3.3.3 Self-organizing Maps classifiers

The SOM classifiers are based on *competitive learning* (Haykin, 1998). They have only an output layer, where the neurons compete among themselves and only one is activated at any time. These neurons are placed at the nodes of an one- or two-dimensional *lattice*.

The Neural Network Toolbox™ of MATLAB® provides the `selforgmap` function to create a SOM classifier. This function needs the dimension of map as parameter. To select the best dimension was used the cross-validation method.

4. RESULTS

The cross-validation method for model selection of MLP classifiers provided the results presented in Tab. 2. From this table it is clear that MLP classifiers with two hidden layers had slightly higher performance MLP classifiers with only one hidden layer. Apparently MLP classifiers with one hidden layer have a simpler structure than the classifiers with two hidden layers. However, when are calculated the quantity of synaptic weights for each model (Tab. 3), the MLP classifiers with two hidden layers contain fewer synaptic weights. So, they are computationally simpler than the MLP classifiers with one hidden layer.

Table 2. Best MLP classifiers models chosen by cross-validation method.

Classifier Model	Test success classification rate (%)			
	LF	ND	LC	Over All
251-10-3	86.90	99.60	78.33	87.19
251-9-8-3	86.93	100.0	79.61	87.72
19-7-3 (PCA)	91.40	95.00	86.51	90.55
19-6-4-3 (PCA)	87.23	99.80	87.34	90.64

The MLP classifiers trained with the database processed by PCA have improved performance around 3%. However, the most notable result was the reduction in the number of synaptic weights around 15 times, which make them more computationally simpler. There was no evaluation of the computational complexity of PCA feature extraction process.

Thus, it is not possible to determine whether there was an improvement in computational complexity.

Table 3. Quantity of synaptic weights of MLP classifiers.

Classifier Model	Synaptic weight
251-10-3	$(251+1)10+(10+1)3=2553$
251-9-8-3	$(251+1)9+(9+1)8+(8+1)3=2375$
19-7-3	$(19+1)7+(7+1)3=164$
19-6-4-3	$(19+1)6+(6+1)4+(4+1)3=163$

The RBF classifiers had similar performance to the MLP classifiers without PCA feature extraction. The values obtained are shown in Tab. 4. There was no improvement in performance to the RBF classifier trained with the database processed by PCA. The Tab. 5 confirms the assertion in Haykin (1998) that MLP classifiers may require a smaller number of parameters than RBF classifiers for the same degree of accuracy.

Table 4. Best RBF classifiers models chosen by cross-validation method.

Classifier Model	Spread	Success classification rate (%)			
		LF	ND	LC	Over All
251-81-3	0.0971	79.25	100.0	85.22	87.00
19-76-3 (PCA)	4.3669	82.96	100.0	81.89	87.12

Table 5. Quantity of synaptic weights of RBF classifiers.

Classifier Model	Synaptic weight
251-81-3	$(251+1)81+(81+1)3=20658$
19-76-3	$(19+1)76+(76+1)3=1751$

The results in Tab. 6 indicate that the SOM are not suitable as classifiers in this particular problem. The successful performance in classification was below the other classifiers. However, according to Haykin (1998), the SOM is more suitable for the task of feature extraction.

Table 6. Best SOM classifiers models chosen by cross-validation method.

Classifier Model	Success classification rate (%)			
	LF	ND	LC	Over All
15x15	52.67	87.07	44.82	58.94
15x15 (PCA)	62.66	100.0	54.88	69.80

5. CONCLUSIONS

In this study the performance of several ASCS were compared during the identification of lack of fusion, longitudinal cracks and defect-free welds through pulse-echo ultrasonic signals. All these ASCS have used the following preprocessing techniques: envelope signal extraction from A-scan signal, downsampling from 50MHz to 5 MHz and normalization of amplitude values between 0 and 1. Regarding the feature extraction method, there were two groups of ACSC. In the first group, the normalized envelope A-scan signals were directly used as input of the classifiers and the second group used the PCA method for feature extraction. The artificial neural networks, of the types MLP, RBF and SOM, were used as classifiers. All ANN were trained and tested with the same A-scan signal database. This database was built using a simulation software for ultrasonic testing (*simSUNDT*).

The results are consistent with those presented in other similar works (Veiga *et al.*, 2005; Sambath *et al.*, 2011; Seyedtabaii, 2012). Note that the A-scan signals of the knowledge database were generated by a software simulator, and therefore, the results may be different for a knowledge database built by ultrasonic NDT equipments, mainly by the existence of measuring noise.

This study demonstrates (like similar work cited above) that the use of ANN-based classifiers leads to fair results of performance. However, these results may be improved by modification of used techniques in the three elements of ASCS. This became clear when comparing the ASCS systems that used MLP classifiers. A simple change in the feature extraction method has led to different results.

6. ACKNOWLEDGMENT

We would like to thank Professor Håkan Wirdelius, Ph. D, director of Scientific Centre of Non-Destructive Testing (SCENDT), for providing us the software *simSUNDT*, plus information about it which allowed to read the results of the simulations in MATLAB®.

7. REFERENCES

AWS, 2000. *Welding Inspection Handbook (3rd Edition)*. American Welding Society (AWS). ISBN 978-0-87171-560-9.

Bostrom, A. and Wirdelius, H., 1995. "Ultrasonic probe modeling and nondestructive crack detection". *The Journal of the Acoustical Society of America*, Vol. 97, No. 5, pp. 2836–2848. doi:10.1121/1.411850.

Bovik, P. and Bostrom, A., 1997. "A model of ultrasonic nondestructive testing for internal and subsurface cracks". *The Journal of the Acoustical Society of America*, Vol. 102, No. 5, pp. 2723–2733. doi:10.1121/1.420326.

Case, T. and Waag, R., 1996. "Flaw identification from time and frequency features of ultrasonic waveforms". *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on*, Vol. 43, No. 4, pp. 592 –600. ISSN 0885-3010. doi: 10.1109/58.503719.

Ditchburn, R., Burke, S. and Scala, C., 1996. "Ndt of welds: state of the art". *NDT & E International*, Vol. 29, No. 2, pp. 111 – 117. ISSN 0963-8695. doi:10.1016/0963-8695(96)00010-2.

Dunlop, I. and McNab, A., 1997. "Automated parameter extraction for ultrasonic flaw analysis". *Science, Measurement and Technology, IEE Proceedings* -, Vol. 144, No. 2, pp. 93 –99. ISSN 1350-2344. doi:10.1049/ip-smt:19970857.

Haykin, S., 1998. *Neural Networks: A Comprehensive Foundation*. Prentice Hall PTR, Upper Saddle River, NJ, USA, 2nd edition. ISBN 0132733501.

Lee, K. and Estivill-Castro, V., 2007. "Feature extraction and gating techniques for ultrasonic shaft signal classification". *Applied Soft Computing*, Vol. 7, No. 1, pp. 156 – 165. ISSN 1568-4946. doi:10.1016/j.asoc.2005.05.003.

Li, J., Zhan, X. and Jin, S., 2010. "New flaw feature extraction method for ultrasonic phased array nondestructive testing". In *Intelligent Control and Automation (WCICA), 2010 8th World Congress on*. pp. 6998 –7003. doi: 10.1109/WCICA.2010.5554254.

Lorenz, M. and Wielinga, T., 1993. "Ultrasonic characterization of defects in steel using multi-saft imaging and neural networks". *NDT & E International*, Vol. 26, No. 3, pp. 127 – 133. ISSN 0963-8695. doi:10.1016/0963-8695(93)90598-O.

Martín, Ó., López, M. and Martín, F., 2007. "Artificial neural networks for quality control by ultrasonic testing in resistance spot welding". *Journal of Materials Processing Technology*, Vol. 183, No. 2–3, pp. 226 – 233. ISSN 0924-0136. doi:10.1016/j.jmatprotec.2006.10.011.

Miao, C., Wang, Y., Zhang, Y., Qu, J., Zuo, M. and Wang, X., 2008. "A svm classifier combined with pca for ultrasonic crack size classification". In *Electrical and Computer Engineering, 2008. CCECE 2008. Canadian Conference on*. pp. 001627 –001630. ISSN 0840-7789. doi:10.1109/CCECE.2008.4564817.

Persson, G. and Wirdelius, H., 2010. "Recent survey and application of the *simSUNDT* software". *AIP Conference Proceedings*, Vol. 1211, No. 1, pp. 2125–2132. doi:10.1063/1.3362392.

Polikar, R., Udpa, L., Udpa, S. and Taylor, T., 1998. "Frequency invariant classification of ultrasonic weld inspection signals". *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on*, Vol. 45, No. 3, pp. 614 –625. ISSN 0885-3010. doi:10.1109/58.677606.

Sambath, S., Nagaraj, P. and Selvakumar, N., 2011. "Automatic defect classification in ultrasonic NDT using artificial intelligence". *Journal of Nondestructive Evaluation*, Vol. 30, pp. 20–28.

Seyedtabaii, S., 2012. "Performance evaluation of neural network based pulse-echo weld defect classifiers". *Measurement Science Review*, Vol. 12, No. 5, pp. 168–174.

Song, S.J., Kim, H.J. and Cho, H., 2002. "Development of an intelligent system for ultrasonic flaw classification in weldments". *Nuclear Engineering and Design*, Vol. 212, No. 1-3, pp. 307 – 320. ISSN 0029-5493. doi:10.1016/S0029-5493(01)00495-2.

Sophian, A., Tian, G.Y., Taylor, D. and Rudlin, J., 2003. "A feature extraction technique based on principal component analysis for pulsed eddy current ndt". *NDT & E International*, Vol. 36, No. 1, pp. 37 – 41. ISSN 0963-8695. doi: 10.1016/S0963-8695(02)00069-5.

ter Brugge, M., Nijhuis, J., Jansen, W., Drenth, H. and Spaanenburg, L., 1995. "On the representation of data for optimal learning". In *Neural Networks, 1995. Proceedings., IEEE International Conference on*. Vol. 6, pp. 3180 –3185 vol.6.

ISSN 2176-5480

doi:10.1109/ICNN.1995.487294.

Veiga, J.L.B.C., Carvalho, A.A.d., Silva, I.C.d. and Rebello, J.M.A., 2005. "The use of artificial neural network in the classification of pulse-echo and TOFD ultra-sonic signals". *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 27, pp. 394 – 398. ISSN 1678-5878.

Wirdelius, H., 2004. *User Guide to simSUNDT*. CHALMERS LINDHOLMEN HÖGSKOLA AB.

Zhan, X. and Jin, S., 2009. "A fractal-based flaw feature extraction method for ultrasonic phased array nondestructive testing". In *Mechatronics and Automation, 2009. ICMA 2009. International Conference on*. pp. 1606 –1611. doi: 10.1109/ICMA.2009.5246076.

Zhang, G., 2000. "Neural networks for classification: a survey". *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, Vol. 30, No. 4, pp. 451–462. ISSN 1094-6977. doi:10.1109/5326.897072.

Zhang, X., Sun, G., Liu, H. and Wang, Q., 2011. "Flaw classification in ultrasonic guided waves signal using wavelet transform and pnn classifier". In *Wireless Communications and Signal Processing (WCSP), 2011 International Conference on*. pp. 1 –5. doi:10.1109/WCSP.2011.6096901.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.