Artificial Neural Networks Used in Forms Recognition of the Properties of Ancient Copper Based Alloys

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Abstract. The study presents correlation between physical and mechanical properties of ancient copper based alloys and chemical compositions. Such dependencies have been assessed by using neural networks approaches. Neural networks are capable of recognizing complex non-linear relationships between variables without needing a prior specification of the nature of the relationship, thus they are particularly useful when applied to complex systems. The choice between arsenic and tin bronzes has been analyzed on the basis of arsenic content in each sample. Mechanical properties have been assessed for tin bronzes and the influence of the variation of tin in composition has been monitored by trained neural networks. Radial basis function network (RBFN) was selected in addition to feed-forward networks and a clustering algorithm was used to group input vectors. The input data is represented by chemical compositions and micro-hardness analyses carried out on samples belonging to Early Bronze Age and Middle Bronze Age artifacts Transylvania.
Keywords: neural networks, mechanical properties, ancient copper, alloys

1. Archaeological Background

Beginning in the late fifth and the first half of the fourth millennia BC, communities in the Near East and Europe worked with arsenic bronze for almost two millennia before tin bronze became a significant competitor. During the Middle Bronze Age (ca.2200–1600 BC) arsenic bronze remained the most common of the two bronze alloys throughout Europe and western Asia. Only in the Late Bronze Age did tin bronze displace the arsenic variety in most of the area.

Three explanations for the reasons behind the abandon of arsenic bronzes and its replacement by tin bronze have been offered by scholars:

1 Tin bronze is a superior alloy, it is harder and stronger, and has better mechanical properties than arsenic bronzes;

2 Tin bronze is an intentional or deliberate alloy, while arsenic bronze is not. There is a fundamental difference in the way these alloys are prepared. As a consequence, the composition of tin bronze alloys can be controlled carefully whilst it is difficult to control the composition of arsenic bronze alloys.

3 Smelting ores containing arsenic produces arsenic trioxide fumes which create a health hazard.

2. Study Goals

In this study we aimed to:

- To establish the dependency between the chemical composition and the micro-hardness of several tin bronzes in comparison with arsenic bronzes.
- To monitor the influence of the variation of tin and arsenic in bronze composition for various techniques of fabrication.
- To train neural networks to recognize the type of fabrication techniques when the chemical composition is known. In this respect, 84 bronze samples belonging to the Bronze Age in Transylvania have been studied in order to establish the dependency between the hardness and the fabrication technique.

The main techniques used for obtaining bronze products that have been taken into consideration were:

- Casting
- Cold hammering with reduction of 10%, 20%, 30%, 40%, 50% in thickness (Fig. 1).

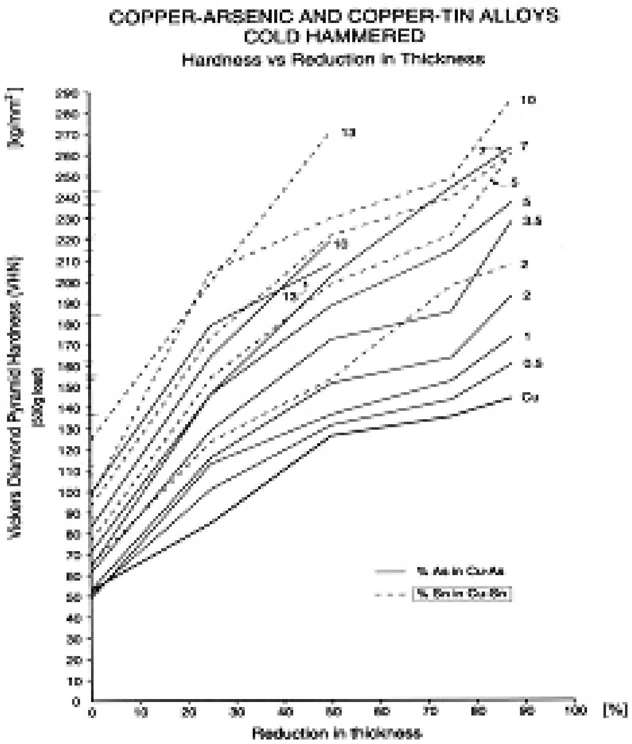

Fig. 1. Comparison of the work hardening behaviour (after Lechtman 1996).

3. Methodology

Neural networks are at their simplest level a mathematical mimic of human learning. Individual processing elements (PE) act analogously to nerve cells in that inputs are received, weights attached and an output value passed to connect PEs.
Each processing element consists two parts, the first in which input values are multiplied by individual weighting factors and summed, the second in which the summed value is passed on to a transfer or "squashing" function that constrains the value of the output (Bell and Croson 1998:140). No desired outputs are used to train the pattern unit. The algorithm is unsupervised and self-organizing. Once this phase of training is completed a back propagation algorithm is used to train desired outputs. Additional hidden units may be added in effect merging a back propagation layer with Radial Basis Function Network (RBFN).
Preliminary clustering algorithm was used to group input vectors into clusters. (Kadar 2004:441). By using t84 cases have been classified in clusters, the best cut at 6 clusters computed with Clustan Graphics can be seen in Figure 2.

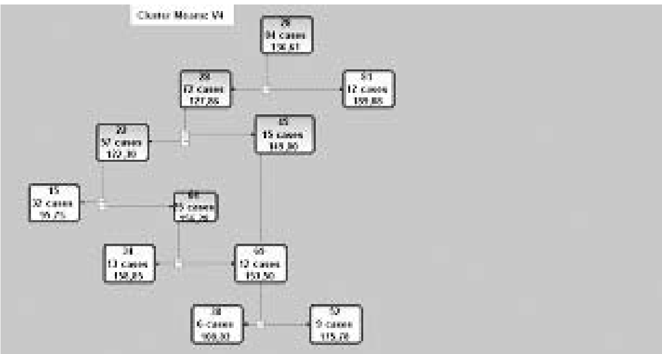

Fig. 2. Classification by Clustan Graphics.

ANNs as chemometric toolbox
Two advantages of ANNs:
1 The ability to deal with sparse data
2 Non-linearity which allows creation of complex decision surfaces within the input space.

Artificial neural networks(ANNs) present advantages such as:
- The ability to deal with sparse data
- Non-linearity which allows creation of complex decision surfaces within the input space.Learning from examples , the solution algorithm being printed in synaptic connections. The general model of ANNs is presented in figure 3

In Figure 3, x_1, x_2,... x_n are neuron inputs, w_1, w_2, ...w_n are the interconnection weights, f is the neuron threshold, $f()$ is the activation function and y is neuron output
We note: $x = [x_1, x^2, ..., x_n]^T$ the input vector and $w = [w_1, w_2, ..., w_n]^T$ synaptic weights vector.

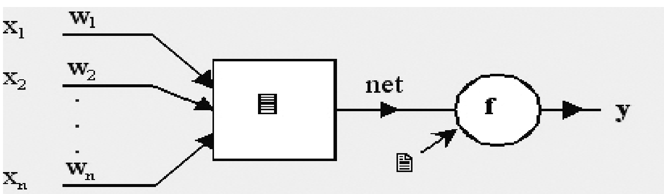

Fig. 3. Model of ANN.

A. Feed-Forward network topology. Generally the activation functions are monotone, but non-monotone functions can be used as well. In complex applications one has to use neural networks built by two or many layers, each containing a number of neurons depending of the application.
B. RBF network. Radial Basis Functions are similar to back propagation networks with one important addition. The hidden layer in a RBFN consists of radial symmetric pattern units' coupled to an output payer.

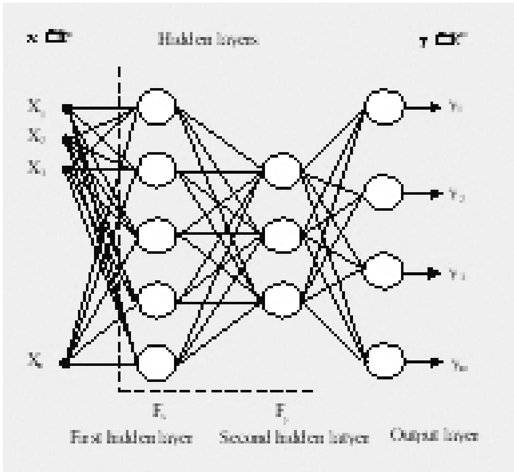

Fig. 4. Feed-forward network topology.

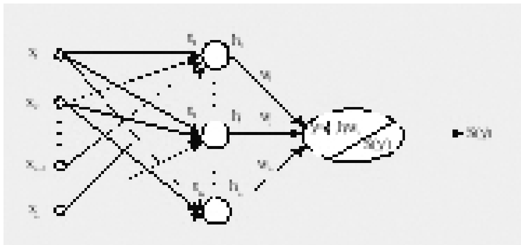

Fig. 4. RBF network topology.

The network was trained and tested with the same data sets as in case of feed forward network. The correct answer of the classifier was achieved in only 50% of the total cases. A possible explanation of this behavior is that the distribution of data to be classified is not suited for this type of networks.

4. Results

In this study we used Matlab 6.5 for implementing and testing the network and the main results are shown bellow:
A Feed forward neural network:
Seven data sets were used from the representative classified alloys. The resulted network was then tested with other seven sets of data.
Several network structures were tested and the best results were given by 4:9:6 structure. For this structure the training process was very fast and the error diminish quickly under 10–3 (Fig. 7).
Hundred trials conducted to correct classification in 84% cases.

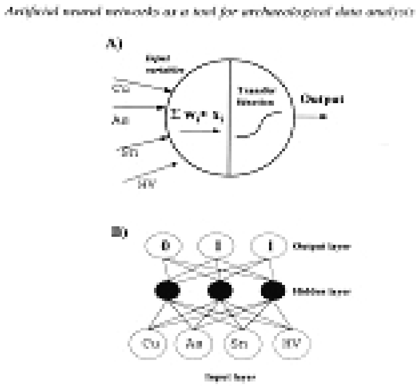

Fig. 6. Feed-forward network topology used for the study of chemical composition and hardness.

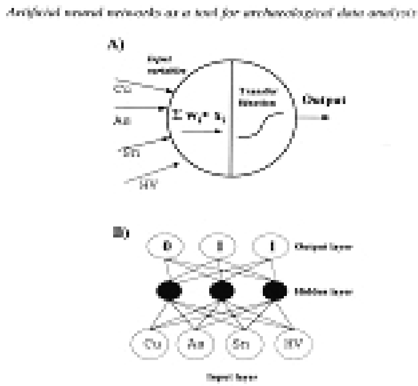

Fig. 7. Typical error evolution during training.

5. Conclusions

Neural networks are a valuable addition to multivariate techniques used to classify archaeological artifacts. We have to also say that they have limitations as any other classification technique. Feed-forward networks are susceptible to over-training or "memorialization" of the training set. In such cases the network fails to generalize and can not identify unknowns outside the confines of the training set. We should also mention that network topologies must be determined empirically, meaning that the best combination of settings has to be optimized for each case and problem to be solved.Feed forward networks were the most suited to this type of application, where the input vector was consisted of 4 variables representing values of Cu, As, Sn and hardness and the output were 6 variables representing processing techniques such as: casting, cold-hammering with reduction in thickness of 10, 20, 30, 40 and 50 %.

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