Hannah Wiedner
hannah.wiedner@bev.gv.at

Application of an Artificial Neural Network for evaluation of activity concentration exemption limits in NORM industry by gamma-ray spectrometry

Hannah Wiedner[1,*], Virginia Peyrés[2], Teresa Crespo[2], Marcos Mejuto[2], Eduardo García-Toraño[2], Franz Josef Maringer[1]

[1]BEV – Federal Office of Metrology and Surveying, Arltgasse 35, 1160 Vienna, Austria
[2]CIEMAT – Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas, Avda. Complutense 40, 28040 Madrid, Spain

INTRODUCTION

Naturally occurring radionuclides such ^{40}K and the decay products of the primordial radionuclides ^{232}Th, ^{235}U and ^{238}U are present in many natural resources.

Naturally occurring radioactive materials (NORM) containing these radionuclides
- are exploited by industrial endeavors
- often exceed the exemption limits of the activity concentration for radionuclides in the U and Th series, depending on the mineral composition and geological origin

Industrial activities are generating a significant portion of waste
- this can enhance the potential of exposure of workers and the public
- management and deposition of material above the exemption limit is very costly

The European Metrology Research Project MetroNORM focuses on creating traceable, accurate, and standardized measurement methods, reference materials and systems for (in-situ) application in the concerned industries.

The main problem with measuring NORM is
- the variety of densities and compositions of the materials
- the many (interfering) gamma-rays of different energies
- that the sample activity often barely exceeds the background and therefore long measuring times are required
- that analysis requires an expert

Alternative: Artificial Neural Networks (ANNs)
In this work an ANN was created that is able to decide from the input data of a raw gamma-ray spectrum if the activity concentrations in a sample are above or below the exemption limits.

ARTIFICIAL NEURAL NETWORKS (ANNS)

ANNs are mathematical software tools that
- emulate the way the human brain works (see Figure 1)
- are trained, tested and validated with sample datasets and capable of "learning by doing"
- can generalize the "knowledge" gained by the content of the training set and apply it to new problems. This can be viewed as a **new calibration tool** where **no expert knowledge** of gamma-ray spectrometry is needed by the **end user** (see Figure 2)

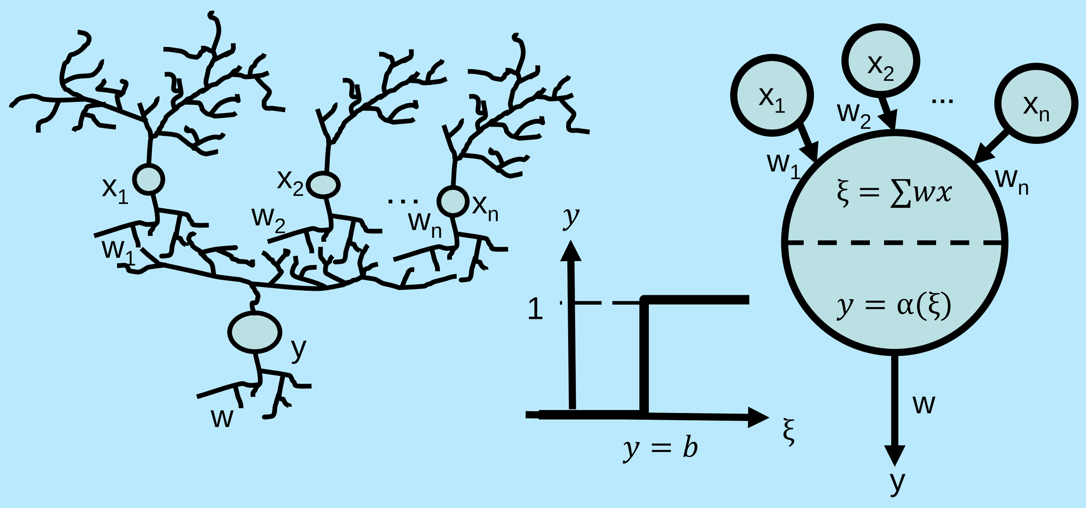

Figure 1 – Basic processes in the human brain

As shown in Figure 3, an ANN consists of a number of nodes that represent the computing units (or neurons), connections (axons and dendrites) between those nodes, connection weights (synapses) and thresholds (activity in the soma). A non-linear transfer function, often a sigmoidal function, is applied to the weighted sums of each neuron. Generally speaking, an ANN consists of an input and an output layer and can also contain hidden layers.

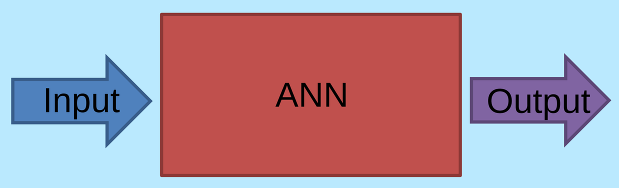

Figure 2 – Blackbox as seen by end user

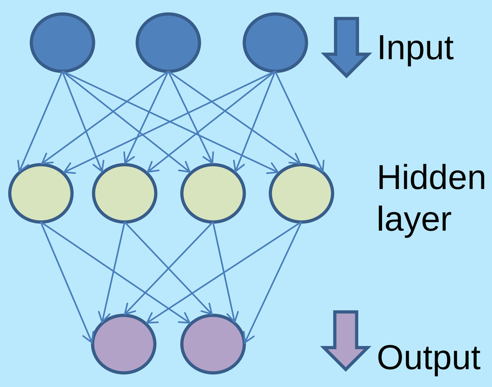

Figure 3 – ANN schematic

For all kinds of ANNs there are three major steps to follow (Figure 4). The training phase consists of designing and building the neural network as well as providing it the relevant training data. The validation phase is used to evaluate if the network is correctly trained and working properly. The testing phase is to check if the output is correct and to evaluate predictive power of the ANN.

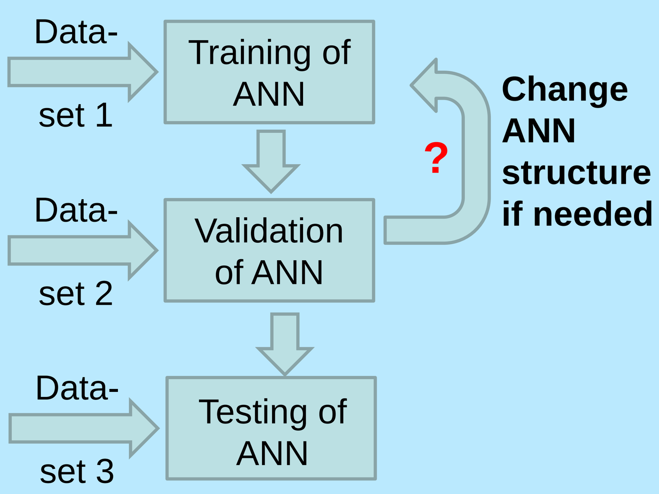

Figure 4 – ANN system realization

MATERIALS AND METHODS

The ANN has been designed using Matlab's nntool suite.

The "knowledge" of the ANN is stored in the connection weights. The ANN is trained by providing input and target values and changing the connection weights until the ANN's output best fits the target values. The connection weights define how "important" a certain input parameter is and have been calculated using a backpropagation algorithm and a sigmoidal transfer function. After each cycle the connection weights are adapted and the training data is presented again, as long as it takes to reach a minimum.

Table 1 – List of NORM reference materials used to create the sample materials

CIEMAT	MetroNORM
Phosphogypsum Huelva	Phosphogypsum (D1.2.2)
Ilmenite Huelva	Tuff 1 (D1.2.2)
	Tuff 2 (D1.3.2)
	Sand (D1.3.2)
	TiO_2 (D1.3.2)

Table 2 – List of nuclides and gamma energies analysed and used as input for the ANN

Nuclide	γ-ray energies (in keV)		
^{210}Pb	46,65		
^{234}Th	63,31	92,59 *	
^{235}U	143,77	163,36	
^{212}Pb	238,63	300,09	
^{214}Pb	242,00	295,22	351,93
^{228}Ac	911,20	968,96	

*combination of 2 lines that are not well seperated: 92.38 keV and 92.80 keV

Only a small number of real sample material was available to complete this work. To solve this problem and widen the applicability of the algorithm, a set of artificial gamma-ray spectra with varying density and activity concentration and material composition have been created by Monte Carlo simulation and used in the training, testing and validation of the ANN. The spectra have been simulated using PENELOPE 2014 and PENNUC.
A total number of 635 samples has been generated as training material for the ANN, creating a 635 x 15 matrix (see Figure 5).

For testing, six NORM reference materials (see Table 1) have been measured and analysed (see Table 2), manually assigning activity categories (Table 3). The samples (see Figure 6) were measured on an extended-range coaxial detector with 45.5 % efficiency for 200000 s.

Activity	Category
0,1 Bq/g	1
0,7 Bq/g	2
1 Bq/g	3
1,2 Bq/g	4
20 Bq/g	5

Table 3 – Activity categories

The result is a 1 x 12 matrix corresponding to the lines in Table 2.

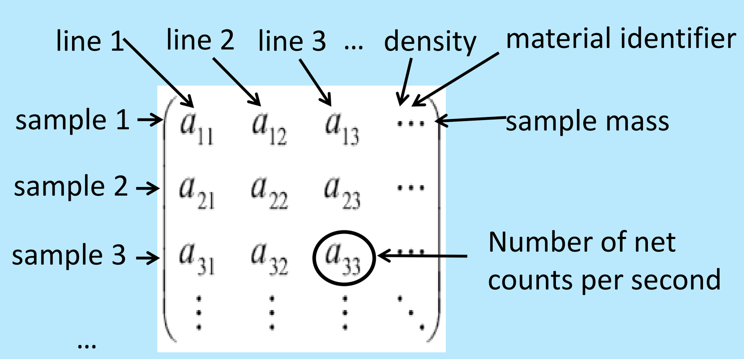

Figure 5 – Schematic of ANN input structure

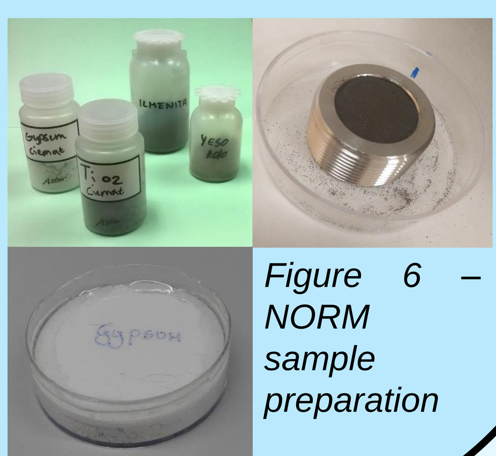

Figure 6 – NORM sample preparation

RESULTS AND CONCLUSION

Over the course of this work a functioning ANN has been created. The results show, that the ANN was able to successfully classify all of the testing data sets (see Figure 7 for results).

ANN features
- 15 input parameters (15 neurons)
- 1 hidden layer
- 31 hidden neurons
- 12 output parameters
- Regression factor of 99.75 % (Figures 8 and 9)
- Backpropagation algorithm
- Sigmoidal transfer function

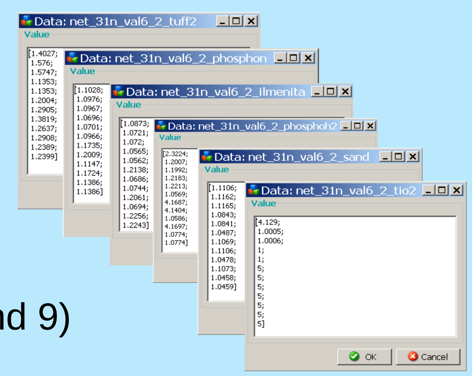

Figure 7 – ANN results for testing materials

The biggest limiting factor for the use of ANNs is the availability of real sample material. In the course of this work this problem has been sidestepped by calculating artificial spectra from Monte Carlo simulations but this, in turn, necessitates the complicated and time-consuming study of disequilibrium situations. It is necessary to note that this constraint only applies to the creation of training material and of the ANN itself, not the usability of the ANN.

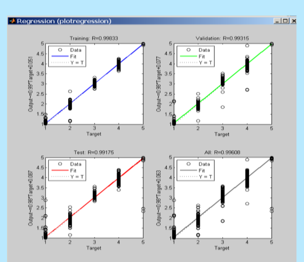

Figure 8 – Regression plot

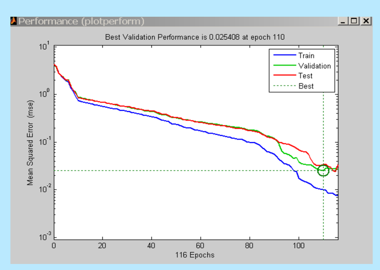

Figure 9 – A typical performance plot

FINANCIAL SUPPORT

This work is supported by the European Metrology Research Programme (EMRP), JRP-Contract IND57 MetroNORM (www.emrponline.eu). The EMRP is jointly funded by the EMRP participating countries within EURAMET and the European Union.
Hannah Wiedner received an Early Stage Researcher Mobility Grant associated to MetroNORM to complete this work.