ARTIFICIAL INTELLIGENCE CONTROLLED SYSTEM FOR THE MONITORING OF ELECTROMAGNETIC POLLUTION

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***Abstract* – The article presents some possibilities to monitoring, by an artificial intelligence controlled system, of the electromagnetic pollution into Equipment Test Laboratory. Practical results, obtained by direct measuring on site, they are presented too.**

Keywords: *electromagnetic pollution, monitoring, artificial intelligence*

1. INTRODUCTION

Starting from the definition elaborated by the 77 Comity of the International Electrotechnical Commission (IEC), CEM represents the capability of an apparatus, equipment or system to performing its individually designed function in a common electromagnetic environment without causing or suffering unacceptable degradation due to unintentional electromagnetic interference to or from other equipment in the same environment, including the human factor, [1], [2].
International scientifically and technical organisations very prestigious like as CIGRE (International Council on Large Electric System), CIRED (International Research Centre for Environment and Development), UNIPEDE (International Union of Producers and Distributors of Electrical Energy), IEEE, IEE etc., periodically notes their research in the EMC field. For example, in CIGRE activates GT (workgroup) 36, dedicated to EMC in power and electric systems. This workgroup has six technical directions, specialised in EMC: corona lighting, electric and magnetic field of the apparatus, equipment and installations, EMC in power plants, transport and distribution of electrical energy etc.
The measuring, assessment and quantification of the human bean expose in the professional and residential environment at the electric and magnetic fields of industrial of high frequency, made by the electrical grids constitute, in presently, one of the high priority concerning of the CIGRE-GT 36, [2], [3].
Following the decreasing of the electromagnetic pollution emission and the increasing of the reliability factors, performability and security of the installations and systems [4], in the European Union is realised a certification of the electrical apparatus and equipment in accordance with EMC conditions, which it carry on in conformity with EU directives, applied from years 1995-1997.

The electromagnetic pollution control and ambient monitoring of the electromagnetic pollution emissions made by electrical apparatus, equipment and installations represents actual concerns in the study and the EMC and environment applications problems.
Through this it follows:

- the human factor's exposes at electromagnetic field, considered as being ambient pollution;
- the parameter increasing of quality, reliability, performability and security, specific of the equipment and installations controlled, analysed and monitoring;
- database making necessary in technical state diagnostic of equipment, apparatus and installations, using "electromagnetic finger print" of its.

A special direction is the monitoring of the existing electromagnetic pollution emissions in electrical teaching schools, to avoid more correctly the expose of students, pupils, auxiliary and teaching personal, respectively.
Data and database obtained through monitoring can be used successfully in technical state diagnostic of equipment and also, in abnormal operating detection occurred in installations, [5], [6].
The monitoring and diagnostic control is possible applying some adequate artificial intelligence techniques, the new designed system allowing the increasing of versatility for a simple monitoring of expose in electromagnetic field.

Figure 1: Measuring in Equipment Test Laboratory

This paper contains the research results made by authors in order to design, realisation and application of a system, artificial intelligence controlled, for electromagnetic pollution monitoring in Equipment Test Laboratories from the Faculty of Electrical Engineering from Iasi, Figure 1.

2. THE ANN MODEL FOR THE ANALYSIS OF MAGNETIC FIELDS

An ANN can be defined as a network that resembles the functional architecture of the brain. It consists of a highly connected array of elementary processors called neurones. In this paper, the multilayer perceptron (MLP) type ANN is considered.

The MLP consists of several layers: one input layer, one or more hidden layers and one output layer. Neurones in a layer are generally interconnected to all the neurones in the adjacent layer with different weights as shown in Figure 2. Each neurone receives its inputs from the neurones in the higher layer through interconnections and propagates its activation to the neurones in the next lower layer. Except for the input layer, each neurone receives a signal, which is a linearly weighted sum of all outputs from neurons of the former layer, [7].

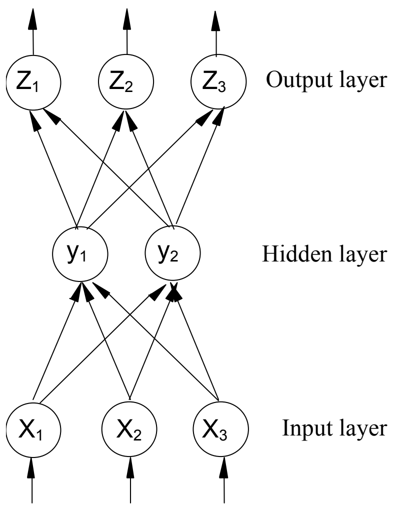

Figure 2: Typical ANN architecture

When h hidden layers exist, the layer 0 and layer (h+1) denote the input and the output layers, respectively. Then, the activation of a neurone j in the layer k, is defined as:

$$u_k^{(k)} = f_j\left(\sum_i w_{ji} u_i^{(k-1)}\right) \quad (1)$$

where:

$$f_j(x) = \begin{cases} \dfrac{1}{1+\exp^{-x}} & \text{if neuron j is a hidden neuron} \\ x & \text{otherwise} \end{cases} \quad (2)$$

and i covers all the neurones in the layer (k-1). Note that the activation of the j^k neurone in k^{th} layer, $u_j^{(k)}$ in (1), is only a function of the activations of the neurones in the $(k-1)^{th}$ layer and weights which connect the j^k neurone in k^{th} layer and the neurones in the $(k-1)^{th}$ layer. The nonlinearity $f_j(x)$ does not necessary to be the signoid function $(1/(1+\exp^{-x}))$. Other monotonic function which are differentiable in the domain of x can also be used for $f_j(x)$.

In the study the backpropagation learning algorithm is employed for training the ANN. This algorithm is classified as a supervised learning algorithm since it requires a target value for a given set of input parameters. Basic concept of this algorithm is the use of the gradient descendent algorithm to get the best estimates of the interconnected weights and for the given input to make the output of the network as close to the target value as possible. A well-trained ANN can produce proper outputs not only for the inputs in the training data set, but also for the inputs similar to the ones of this set. This property of ANN is often referred to as generalisation.

3. BACKPROPAGATION LEARNING

The backpropagation (BP) network can be thought of as a converter having many inputs and outputs. The learning process begins with feeding the input data into the ANN input layer, and assigning the ANN target for the output layer. Then, the initial connection weights and bias nodes at the hidden layers and the outputs layer are set randomly. The maximum error, the learning rate and the momentum are set for the ANN, respectively. The network coverts the input data according to connection weights. The calculated output in each hidden node is converted to output layer using signoid function (2). The summation of each signoid function in the hidden layer is the calculated output node. The calculated result from the output layer is converted to the output data and used for comparing with the ANN target using the linear activation function and the threshold function, respectively. From this point, the sum-square error is obtained and used for stopping the learning process.

The BP process begins when the sum-square error is greater than the maximum error. The output data in the output node is back propagated to the hidden layer and the input layer, respectively. During propagation, connection weights are adjusted until the network sum-square error is less than the maximum error.

When the learning process is finished, the weights are obtained and the ANN architecture is defined. The trained ANN is ready to identify or predict outputs related to the input data.

4. RESULTS AND DISCUSSIONS

To realises the necessary database for the ANN learning and test, its have done on site measuring in different points from the Equipment Test Laboratory from the Faculty of Electrical Engineering from Iasi using the Precision Digital Multimeter Metrahit 28S together with Field Measurement Adapter Metrahit FMA-1, Figure 3.

Figure 3: Metrahit 28S with Field Measurement Adapter Metrahit FMA1

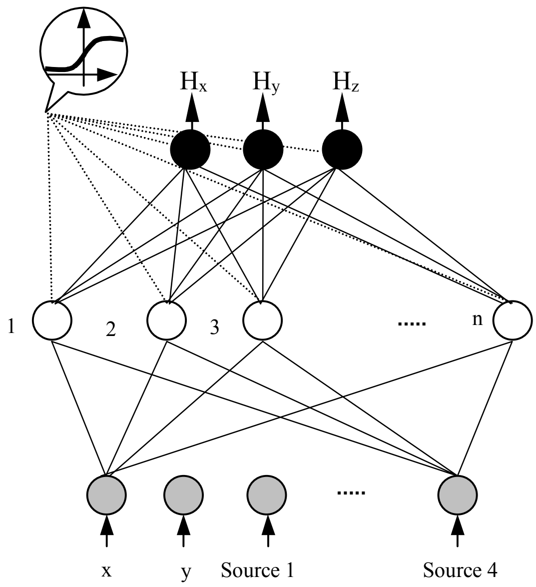

Figure 4: Proposed ANN architecture

ANN with the architecture from Figure 4 has six input neurones: x, y represents the measuring co-ordinates, but sources 1 ÷ 4 indicates the operating of High Voltage Laboratory, Equipment Test Laboratory from the other side of the building and two workstations, respectively. At the outputs the ANN produces the magnetic field on three directions: H_x, H_y, H_z, respectively.

Many topologies with different number of neurones on the hidden layer have been tested, its being shown in Table 1.

Topology	Training time [h]	Relative error on test data [%]
6-18-3	5	24.14
6-24-3	6.5	22.85
6-30-3	8.3	22.01

Table 1: Tested topologies

The optimum topology adopted is that with 24 neurones on the hidden layer for which the relative error on the test data is around of 22% and the training time is smaller.
Figure 5 presents the relative error on the test data corresponding to the 6-24-3 topology.

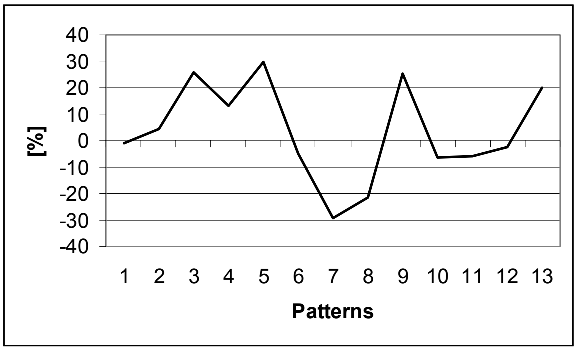

Figure 5: The errors obtained on test set for the 6-24-3 topology

Figure 6 shows the magnetic field values measured on a direction with Field Measurement Adapter Metrahit FMA-1 and ANN estimation.

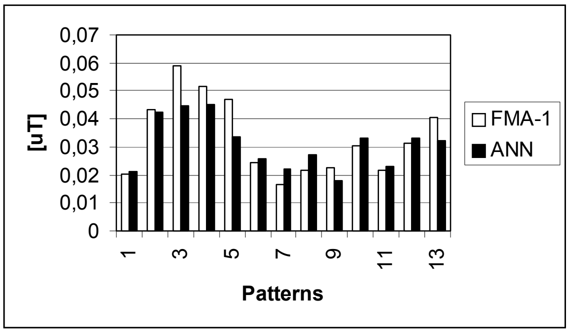

Figure 6: Magnetic field measured with FMA-1 and ANN estimated

The error is explained through a big dispersion of the electromagnetic sources and through a big difference between minimum and maximum measured values.

This error can be decreased using a database with more patterns covering all possible situations that can influence the measuring. Starting from this aim, new database has been completed with new measuring.
Figure 7 shows the magnetic field values using the new database. It consists an improving of the estimation, in this case some situations being good estimated, but another not yet.

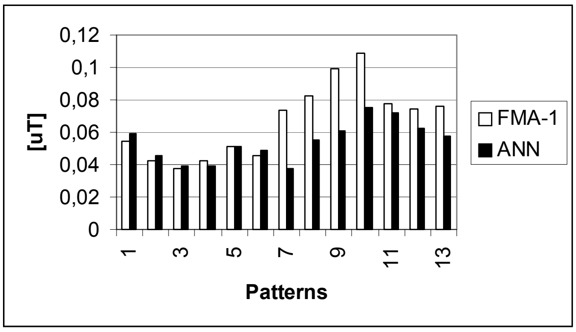

Figure 7: Magnetic field measured with FMA-1 and ANN estimation, using extended database

5. CONCLUSIONS

The monitoring and diagnostic control is possible applying some adequate artificial intelligence techniques, the new designed system allowing the increasing of versatility for a simple monitoring of expose in electromagnetic field.
Proposed ANN can estimate the magnetic field intensity, being a powerful tool to solving this kind of monitoring.
The error decreasing is possible using an extended database which take in consideration all possible electromagnetic sources.

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