A new Neural Predictor for ELF Magnetic Field Strength

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***Abstract*—A new Neural Predictor (NP) is presented for the evaluation of the extremely low frequency (ELF) magnetic field distribution in indoor or outdoor environment. The NP uses a reduced number of measurements and performs the evaluation of the magnetic field strength in the environment under analysis, by achieving a high degree of immunity to the noise present in the measurements. In order to achieve good performance, ad hoc strategies have been adopted in the set up and training of the Neural Network. The NP has been tested on a real environment and the results obtained exhibit a close agreement between predicted and measured field values.**

***Index Terms*— Artificial neural networks, Magnetic field measurement, Magnetic shielding.**

I. Introduction

In the last years, the wide spread use of electric energy has generated increasing interest in studying possible interactions between electromagnetic fields and human beings. In particular, attention has focused on extremely low frequencies (ELF) fields, to protect the users of electric devices against non-ionizing low-frequency magnetic fields. Even if currently available research has not established a clear and well defined association between electromagnetic fields exposures and biological effects, guidelines and standards describing exposure limits have been set up by international standards institutions [1][2][3]. To estimate the possible exposure hazards, it is necessary to accurately evaluate the ELF magnetic field in the interesting region. The analytically evaluation of magnetic field is a very complex task for the lack of a complete knowledge of the different sources, in terms of their shapes, nature and driving circuits. For this reason in order to predict the field distribution, the set up of equivalent source models (ESMs) have been widely investigated (see for example [4-5] and references within). Indeed for the numerical evaluation of the magnetic field level ESMs [4], obtained by exploiting a certain number of measurements, are often used in such a way that the magnetic field strengths originated by such sources give field distributions similar to those actually measured around real appliances. Unfortunately the ESMs are not able to characterize the field strength in complex environment. This is due to the impossibility to find a precise ESM for large environment starting from a reduced number of measurements, also affected by a certain amount of noise, due both to the instrument and to its collocation, which should be extremely precise to be used to solve the inverse problem connected to the search of ESM.

In this paper the authors present a novel Neural Predictor (NP) for the evaluation of the ELF magnetic distribution. The NP uses a number of measures taken in correspondence of suitable accessible points into the environment, and performs the evaluation of the magnetic field strength in the environment under analysis, by achieving a high degree of immunity to the noise present in the measurements. In order to achieve good performance, *ad hoc* strategies have been adopted in the set up and training of the Neural Network. The NP has been tested on a real environment and the results obtained exhibit a close agreement between predicted and measured field values.

II. The Neural Predictor

The Neural Predictor is based on a Multi Layer Perceptron (MLP) Neural Network (NN), having as input the coordinates of the prediction point. The outputs are the three components of the magnetic field in correspondence of prediction points (see fig. 1).

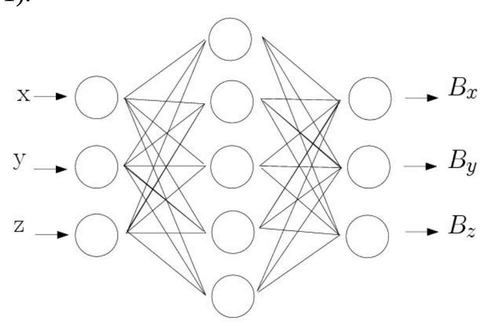

Fig. 1. Neural Predictor input/output schematization.

The approach is analogous to that used in [6] and no further information about the source is required by the neural predictor. Since the aim of this NP is to have good performance in prediction when a reduce number of measurements is available and also to reduce the effects of noise on these measurements, some strategies *ad hoc* have been adopted in the set up and training of the NN. In particular for this kind of problem, which involves small data set, different solutions have been investigated:

1) the use of bootstrap/aggregated neural networks
2) the expansion of training data set by adding white noise to measurement
3) the combination of the two above techniques 1) and 2).

The bootstrap/aggregated method is based on the training of a prefixed number of neural networks with the same randomly re-sampled data set and on the combination of the prediction results by using a linear or non-linear function, for example just by averaging the results [7]. The expansion of the training data set by using white additive noise was used in literature to enhance Neural Network prediction performance [8]: starting from K original samples **x**, M*K samples are generated by using M random Gaussian noise vectors with fixed variance σ^2, $N_i(\sigma^2)$ i=1...M, and adding these to the original samples **x**. In the next section the comparison of these different solutions will be discussed in the prediction of magnetic field in a typical indoor environment application.

III. VALIDATION

In order to highlight the capabilities of the proposed method and the possibility to extend it to a large region hereafter the prediction of the magnetic field distribution in a classroom inside a building of the University of Catania has been carried out. The problem we address is to predict the ELF magnetic field distribution in the neighborhood of an electric plant, from a few measures taken along the walls and the soil surrounding the apparatus. Indeed the analyzed classroom is in close proximity of electrical equipments for the distribution and transmission of electricity. Measures had been carried out in correspondence of a regular grid on two surfaces parallel to the wall between the investigated areas and the room containing the electrical equipments. Starting from few data measured the bootstrap/aggregated NN and the noise expanded data set have been used for the training of the NN. For all the following experiments the same configuration for the NN has been employed: a single hidden layer network containing 10 neurons with "tansig" activation function has been adopted. The improvement obtainable by changing the NN configuration will be presented in the full paper. The training data set is made of the measured data: the number of the points that have been used for the training set was 140 for the reduced training and 1400 for the extended, while 40 points have been used for the test set in both cases; 5000 epochs have been set for the training, and the mean square error (MSE) threshold on the training has been fixed to 1e-4.

A. TEST #1: Bootstrap/aggregated

The bootstrap has been made by 30 different permutations of the same training-set (i.e. 30 different NNs has been trained, each referred to a different permutated pattern). The training of each NN has been stopped when the error threshold on the training-set was achieved. In table I the results of the tests performed have been reported. How it is possible to see from Table I, by the adoption of the bootstrap method the performances are improved: indeed, even if each NNs shows errors in several points during predictions, these errors are not collocated in the same points for all NNs. Then the average error is globally reduced and it is possible to achieve a MSE equal to 0.3074, while the best result in term of MSE obtained by using standard training method is 0.4106.

B. TEST #2: Noise added data set

The expansion of the training data set was made by using white additive noise with variance σ^2 = 1e-4. In this case the expanded training set consists of 1400 pattern. Unfortunately the NN, as previous configured, is not able to achieve the desired threshold on the training-set (1e-4) and all the epochs have been executed during the training. However, the MSE value on test set, 0.1381, is significantly improved respect to the previous case. This demonstrates that adding noise allows us to improve the performance of NP when small dataset for training are used.

C. TEST #3: Noise added data set + Bootstrap

The combination of the two previous employed strategies has been tested. The bootstrap has been made by 30 different permutations of the noisy expanded training-set. None of the 30 trained NN was able to achieve the training-set-error threshold (1e-4): this leads to high training-times for 30 NNs (about 3 hours). In order to reduce this time we adopt a parallel training, by using 20 PCs dual-core at 2.5 GHz. In this way we have obtained a 30 NNs training-time equals to 10 minutes. Also in this case, when we average the results, we can observe a better generalization. Indeed, the MSE of the bootstrap/aggregated NNs trained by using the noisy expanded training set is better than Test#1 and Test#2 approaches. Consequently the synergy between the two proposed methods allows us to reach the better prediction results.

TABLE I

COMPARISON OF THE TRAINING APPROACHES PROPOSED

Approach	MSE on test set
Standard training	0.4106
Bootstrap Method	0.3074
Noise added	0.1381
Noise added and Bootstrap	0.0769

IV. CONCLUSIONS

The NP has been successfully tested in practical problems, regarding the prediction of magnetic fields in the neighborhood of electrical devices. In particular, several different ways to design NNs have been proposed and compared with the aim to detect the best approach among them.

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