Jurnal
Teknologi

Full Paper

PREDICTION OF SHIELDING EFFECTIVENESS OF CEMENT-GRAPHITE POWDER USING ARTIFICIAL NEURAL NETWORK

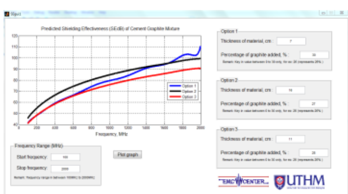
See Khee Yee*, Samsul Haimi Dahlan, Mohd Zarar Mohd Jenu, Chee Kiong Sia

Research Center for Applied Electromagnetic, Faculty of Electrical and Electronic Engineering, Faculty of Mechanical and Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia

Article history
Received
12 July 2015
Received in revised form
28 November 2015
Accepted
02 January 2016

*Corresponding author
skyee@uthm.edu.my

Graphical abstract



Abstract

This paper presents the method to predict the shielding effectiveness of cement powder mixed with different amount of graphite powder. Cement mixed with different percentage of graphite is prepared. Their dielectric constant and loss tangent are measured based on the transmission/reflection technique using APC7 connector. The measured data is fed into Artificial Neural Network (ANN) for training. When the training process is completed the neural network is used to predict the dielectric constant and loss tangent of cement-graphite mixture that contains different amount of graphite. The comparison shows that the trained neural network is very successful to predict the dielectric constant and loss tangent of cement-graphite mixture. The proposed graphical user interface has made the process of shielding effectiveness prediction becomes more user friendly especially for those designers who are not familiar with the analytical calculation of shielding effectiveness and dielectric measurement.

Keywords: Dielectric constant, loss tangent, cement powder, graphite powder

1.0 INTRODUCTION

The proliferation of mobile phone, mobile phone based stations; television and radio transmitter, radar, and many other electronic devices and systems that are operating in high frequencies have generated electromagnetic environment explicitly. Shielding technique which is conventionally used to reduce the emission from printed circuit board (PCB) has shifted its application to building construction in order to protect the human and the sensitive devices inside the building from the exposure to additional electromagnetic (EM) wave. The inherent shielding provided by the building material such as concrete, plasterboard, bricks are very limited [1]. There are numerous literatures concerned the ways to improve the shielding effectiveness (SE) of the building material [2][3][4][5]. Essentially, researches show that shielding materials and absorbing materials in the form of powder, fibre, or filament are efficient to enhance the SE of the building material.

In order to analytically calculate the SE of a material, it is necessary to identify the dielectric properties of the material. These parameters can be obtained by dielectric measurements. Most of the researches [5][6] only report the dielectric properties of the building material when a certain percentage of additives are added into the building material and for every change of the material composition and percentage, dielectric measurement must be repeated. Hence, it is necessary to have a prediction that is able to indicate the relationship between the percentages of the additive to the dielectric properties of building materials.

In this work, prediction tool which is based on the artificial neural network (ANN) is proposed where based on this tool, the dielectric properties of cement powder added with different percentages of graphite powder can be estimated. The ANN is embedded into a Graphical User Interface (GUI). Based on it, the building construction designers are able to estimate the total SE of the cement powder with different percentages of graphite powder and thickness without repeating the dielectric measurement.

2.0 SHIELDING EFFECTIVENESS (SE)

Shielding Effectiveness (SE) is a parameter which is used to describe how good a material or barrier is in reducing the EM wave. It is represented as the ratio of incident electric field, E_i and transmitted electric field, E_t, as represented by Equation (1) in unit dB. Based on the plane wave theory [7], the SE can be represented by Equation (2). The definitions of the parameters in Equation (2) are listed in Table 1. The SE can be analytical calculated once the relative permeability, dielectric constant, loss tangent and thickness of the material are defined. The ANN proposed in this work only predict the dielectric constant and loss tangent of the cement-graphite mixtures because they are non-magnetic material, their relative permeability are unity. The predicted dielectric constant and loss tangent will be replaced into Equation (2) to determine the SE.

Table 1 The definition of parameters of Equation (2)

Symbols	Definition of parameters
η_o	Intrinsic impedance of free space, which is $\eta_o = \sqrt{\varepsilon_o \mu_o}$
η	Intrinsic impedance of material, which is $\eta = \sqrt{\dfrac{j\mu_o\mu_r}{\varepsilon_o\varepsilon_r(LT+j)}}$
γ	Propagation constant of the material, which is $\gamma = \sqrt{j\omega^2\mu_o\mu_r\varepsilon_o\varepsilon_r(LT+j)}$
t	Thickness of material in meter
μ_o	Permeability of air, which is 1.256 x 10^{-6}
ε_o	Permittivity of air, which is 8.854 x 10^{-12}
ε_r	Dielectric constant of material
μ_r	Relative permeability of material
LT	Loss tangent of material, which is $LT = \dfrac{\varepsilon_i}{\varepsilon_r}$
ε_i	Imaginary part of relative permittivity

$$SE_{dB} = 20\log\left(\left|\frac{E_i}{E_t}\right|\right) \tag{1}$$

$$SE_{dB} = 20\log\left|\frac{(\eta_o+\eta)^2}{4\eta_o\eta}\left(1-\left(\frac{(\eta_o-\eta)}{(\eta_o+\eta)}\right)^2 e^{-\gamma t}\right)e^{-j\beta_o t}e^{\gamma t}\right| \tag{2}$$

3.0 ARTIFICIAL NEURAL NETWORK (ANN)

The Artificial Neural Network (ANN) is capable in modelling complex nonlinear systems, which are not easily modelled by using a closed-form equation. It has been stated that ANN is a feasible method in prediction [8]. The required time for the ANN is much shorter when compared with the numerical approach as they need to generate a large number of grid cells and require several hours [9][10] [8]. Due to this, it is believed that by using ANN, the process to obtain the SE of cement-graphite mixture will become simpler. Although the time consumed in the training of ANN increases with the size of ANN model, this can be completed in advance. The biggest advantage of using the ANN method is that it is almost an accurate real time in prediction.

Basically, neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. The network can be trained by adjusting the values of the connections (weights), w between elements so that a particular input leads to a specific target output as shown in Figure 1. Here, the weights are adjusted based on the comparison of the output, a and the target until the network output matches the target. Typically, many input or target pairs are needed to train a network.

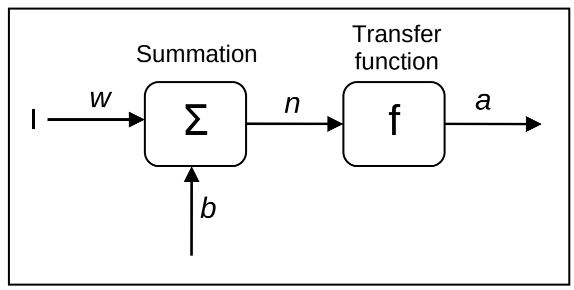


Figure 1 Single input neuron

In this work the principle of training multilayer neural network is based on backpropagation (BP) algorithm as illustrated in Figure 2. The input data X_1 and X_2 are multiplied with the weight coefficient. Symbols $w_{m,n}$ represent the weights of the connections between the network input X_m and neuron n in input layer. The summation of the product from both inputs will be fed to the transfer function f_k. Where the k represents the number of the transfer function. The output from each of the transfer function, namely y_1, y_2 and y_3 are fed to the f_4 in order to produce y_4. y_4 and y_5 is fed to the f_6 to produce y_6. y_6 is the predicted output [11].

Next, the predicted output y_6 is compared with the desired output value, z, which is provided by the user and can be found in the training data set. The difference is referred to as the error signal. The error signal is multiplied with the weight coefficient of each layer.

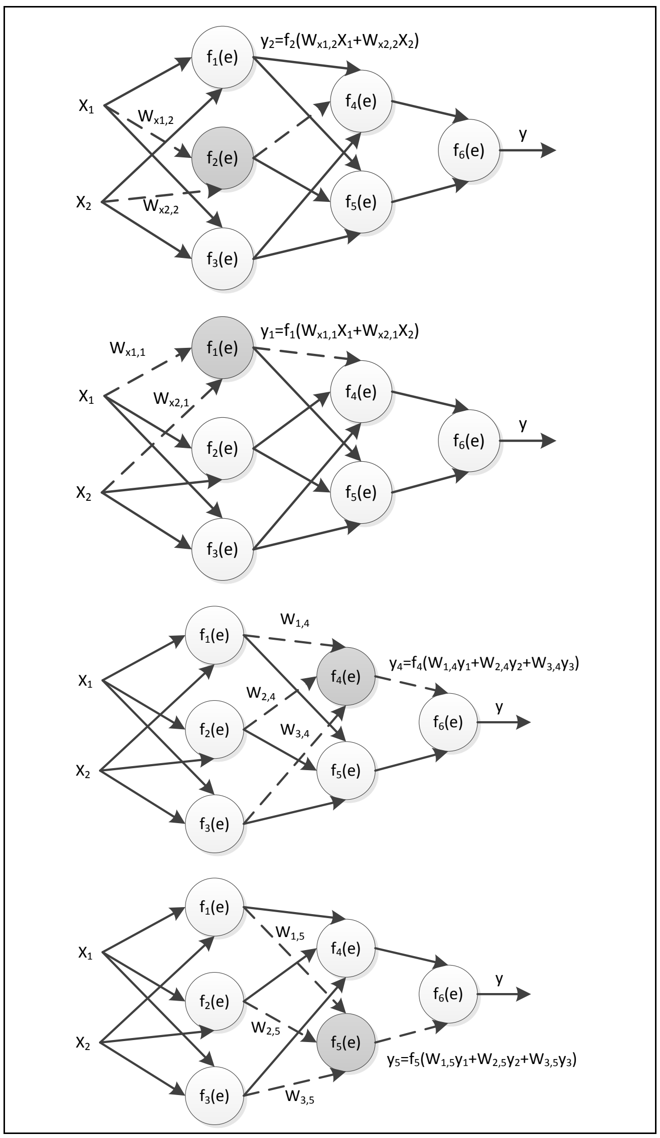
The performance of the ANN can be evaluated by the mean square error (MSE) as shown in Equation (4), where z is authentic values already known, such as the simulated or measured data (target data), and y is the predicted data. The training process stops once the criteria fixed by the users are met.

$$MSE = z - y \tag{4}$$

Neural network toolbox in Matlab is used for SE prediction. 500 layers of BP neural network is created. The input data is the frequency and percentages of graphite, while the output data is the dielectric constant and loss tangent of the cement-graphite mixture. The default network for function fitting is a feed-forward network with tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer.

The user input data is divided into three categories used for testing, validation and training purpose. By default, the toolbox divides 15% of data for validation and testing, respectively, and 70% of data for the training purpose. This ratio can be adjusted if necessary. The work uses the default Levenberg-Marquardt as training algorithm. After the ANN has been trained, it is used for prediction.

In order to validate the prediction results, dielectric measurements are carried out for new sample that contains 26 % of graphite.



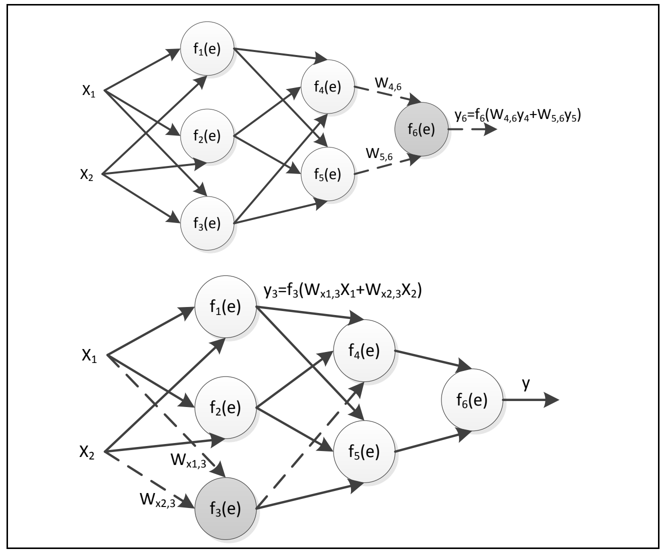


Figure 2 How the signal flow in a neural network [11]

4.0 DATA PREPARATION OF ANN

7 samples which contains different amount of graphite are prepared as prescribed in Table 2. The cement-graphite mixtures are blended evenly before the dielectric measurements are conducted. The dielectric measurement which is based on the transmission/reflection technique, using the APC7 connectors is carried out in order to obtain the dielectric constant and loss tangent of the sample in the frequency range from 100 MHz to 2 GHz. The dielectric measurement setup is explained in [12]. All data is collected and used in the ANN for the training, testing and validation process.

Table 2 Samples which contains different amount of graphite

Samples	Amount of graphite fine powder (g)	Amount of cement powder (g)
1	0	10
2	0.7	9.3
3	1.1	8.9
4	1.5	8.5
5	1.9	8.1
6	2.3	7.7
7	3	7

5.0 RESULT AND DISCUSSION

The comparisons of the predicted and actual dielectric constant and loss factor are discussed in this section at 200 MHz, 900 MHz and 1800 MHz as shown in Table 3, Table 4 and Table 5. These frequencies are chosen to represent the lower, intermediate, and higher frequency in the frequency range from 100 MHz to 2 GHz.

Based on these tables, it is found that the MSE between the predicted and actual dielectric constant is less than 0.09 for all frequencies. The discrepancy for the loss tangent is even smaller, which is 0.07. The ANN tends to produce greater MSE for sample with higher percentage of graphite. Among the three frequencies, it is found that the ANN is more reliable in predicting the dielectric constant and loss tangent at 1800 MHz and 900 MHz respectively.

In order to validate the performance of the ANN, the predicted results for samples that contain 26% of graphite are compared to the dielectric measurements results. The comparisons at 200 MHz, 900 MHz and 1800 MHz are presented in Table 6. It is found that the ANN can perform very well in predicting the dielectric constant and loss tangent of the cement-graphite mixture. The difference is less than 0.08 and 0.02 for dielectric constant and loss tangent respectively. The comparison shows that this ANN is reliable in predicting the dielectric constant and loss tangent of cement mixed with different percentage of graphite.

Table 3 Comparison of actual and predicted dielectric constant and loss tangent at 200 MHz

Percentages	Dielectric constant		
	Actual	**Predicted**	**MSE**
0	2.834	2.833	0.001
7	3.448	3.443	0.004
11	4.563	4.541	0.022
15	6.174	6.169	0.005
19	8.405	8.360	0.046
23	16.028	16.038	0.010
30	41.337	41.309	0.028
Percentages	**Loss tangent**		
	Actual	**Predicted**	**MSE**
0	0.012	0.009	0.003
7	0.020	0.018	0.001
11	0.029	0.033	0.003
15	0.070	0.066	0.004
19	0.152	0.148	0.004
23	0.470	0.467	0.003
30	9.390	9.452	0.062

Table 4 Comparison of actual and predicted dielectric constant and loss tangent at 900 MHz

Percentages	Dielectric constant		
	Actual	**Predicted**	**MSE**
0	2.809	2.829	0.019
7	3.392	3.381	0.011
11	4.439	4.443	0.004
15	5.744	5.749	0.005
19	7.248	7.226	0.023
23	11.669	11.686	0.018
30	30.274	30.363	0.089
Percentages	**Loss tangent**		
	Actual	**Predicted**	**MSE**
0	0.002	0.006	0.004
7	0.003	0.005	0.002
11	0.017	0.020	0.002
15	0.066	0.067	0.001
19	0.135	0.131	0.005
23	0.346	0.341	0.005
30	3.160	3.158	0.002

Table 5 Comparison of actual and predicted dielectric constant and loss tangent at 1800 MHz

Percentages	Dielectric constant		
	Actual	**Predicted**	**MSE**
0	2.7878	2.7916	0.004
7	3.3704	3.3681	0.002
11	4.3725	4.3663	0.006
15	5.5661	5.5511	0.015
19	6.7906	6.7788	0.012
23	10.2955	10.2890	0.006
30	25.3463	25.3323	0.014
Percentages	**Loss tangent**		
	Actual	**Predicted**	**MSE**
0	0.0052	0.0049	0.0002
7	0.0176	0.0185	0.001
11	0.0047	0.0093	0.005
15	0.0555	0.0553	0.0002
19	0.1113	0.1114	0.0001
23	0.2896	0.2978	0.008
30	2.1184	2.0778	0.041

Table 6 Comparison of actual and predicted dielectric constant and loss tangent at 200 MHz, 900 MHz and 1800 MHz for sample contains 26% of graphite

Frequencies	Dielectric constant		
	Actual	**Predicted**	**MSE**
200	38.882	38.961	0.079
900	25.372	25.415	0.0433
1800	21.091	21.064	0.0271
Frequencies	**Loss tangent**		
	Actual	**Predicted**	**MSE**
200	2.770	2.788	0.018
900	1.275	1.265	0.011
1800	0.951	0.953	0.001

6.0 APPLICATION OF ANN

In this work the ANN is used to predict the dielectric constant and loss tangent of cement-graphite mixtures. The ultimate purpose is to calculate the SE of the mixture. So it is embedded into a graphical user interface (GUI) to ensure the process of SE prediction becomes more user friendly especially for the building designers who are not familiar with those analytical calculation and dielectric measurement.

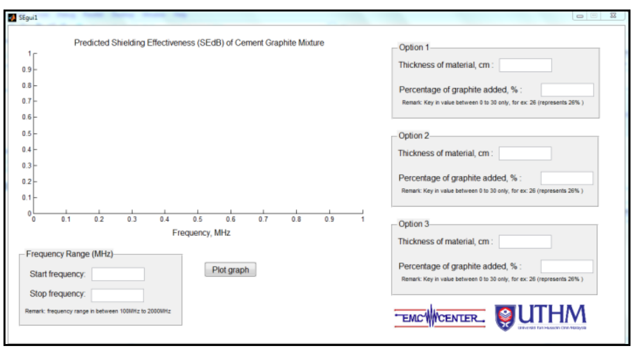


Figure 3 Layout of the GUI for SE prediction

The layout of the GUI is shown in Figure 3. Firstly, users have to define the operating frequencies (in MHz) range at which point they can then simply key in the intended thickness and percentage of graphite in different options in order to compare their resultant SE. Based on the prediction, users can simply adjust the thickness and percentage of graphite in order to achieve cost-effective configuration.

For example, it is reported in [13] that a narrowband high power electromagnetic pulse has high peak electric fields usually greater than 100 V/m. It is assumed that there is an environment with electric field strength of 100 V/m, and the designers have to estimate the percentage and thickness of material (mixture of cement and graphite) so that the electric field can be reduced to certain levels. 1 V/m is chosen as the acceptable level of an electronic device since it is mentioned in IEC 61000-6-2:2009 that electronic devices that are used in industrial environments can be tested with an electric field strength of 1 V/m between 80 MHz and 1000 MHz. Hence, the shielding required for each acceptable level can be calculated as shown:

Case 1: E_i = 100 V/m, E_t = 1 V/m, the required shielding is:

$$SE_{dB} = 20\log\left(\left|\frac{E_i}{E_t}\right|\right)$$

$$SE_{dB} = 20\log\left(\left|\frac{100}{1}\right|\right) = 40dB$$

There are a few options to be chosen by designers in order to achieve 40 dB of shielding, as illustrated in Figure 4. In option 1, designers can choose thinner samples with a higher graphite percentage. Besides this, they can also reduce the percentage of graphite whilst increasing the thickness of the sample, as shown by option 2. Option 3 may also be a choice. Hence, the decision can be made based on the requirements in the design.

7.0 CONCLUSION

This work presents a method to determine the shielding effectiveness of cement-graphite mixture. The ANN proposed in this research can accurately predict the dielectric constant and loss tangent by only introduce 0.08 and 0.02 of difference respectively. The proposed graphical user interface which is embedded with ANN is user friendly. It can show the comparison of shielding effectiveness from different options. So based on the comparison, the building designer can make the decision based on either the specific requirements or to achieve cost-effective design.

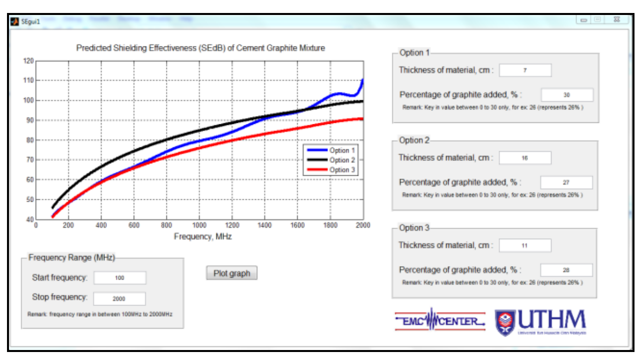


Figure 4 Alternatives to achieve SE more than 40 dB

Acknowledgements

The authors would like to thank the Office of Research Innovation Commercialization and Consultancy Management (ORICC) fund, Vot No E15501, Universiti Tun Hussein Onn Malaysia for supporting the expenses to this conference.

References

[1] Yee S. K. and Mohd Jenu M. Z. 2013. Shielding Effectiveness of Concrete with Graphite Fine Powder in Between 50 MHz to 400 MHz. *Asia-Pacific International Symposium and Exhibition on Electromagnetic Compatibility (APEMC)*, Melbourne, Australia. 20-23 May 2013.

[2] Guan H., Liu S., Duan Y., and Cheng J. 2006. Cement Based Electromagnetic Shielding and Absorbing Building Materials. *Cement and Concrete Composites*. 28(5): 468–474.

[3] Ogunsola A., Reggiani U., and Sandrolini L. 2009. Shielding Properties Of Conductive Concrete Against Transient Electromagnetic Disturbances. *IEEE International Conference on Microwaves, Communications, Antennas and Electronics Systems, COMCAS 2009*, (1).

[4] Krause A., Nguyen L., Tuan C., Bonsell J., Chen B., Blasey J. D., Zemotel J. P., McNerney H., and Metzger F. J. 2012 Conductive Concrete As An Electromagnetic Shield *IEEE International Symposium on Electromagnetic Compatibility*, 85–87.

[5] Ellgardt A. and Mansson D. 2013. Modeling Shielding Effectiveness For Composite Walls Of Concrete And Carbon Filaments. *Progress in Electromagnetics Research M*. 28: 15–25.

[6] Ogunsola A., Reggiani U., and Sandrolini L. 2005. Shielding Effectiveness Of Concrete Buildings *IEEE 6th International Symposium on Electromagnetic Compatibility and Electromagnetic Ecology, 2005.* 65–68.

[7] Schulz R., Plantz V. and Brush D. 1988. Shielding Theory And Practice *IEEE Transactions on Electromagnetic Compatibility*. 30(3): 187–201.

[8] Luo M. and Huang K. 2011. Prediction Of The Electromagnetic Field In Metallic Enclosures Using Artificial Neural Networks *Progress In Electromagnetics Research*.

[9] Ceperic V. and Baric A. 2009. Modelling Of Electromagnetic Immunity Of Integrated Circuits By Artificial Neural Networks. *20th International Zurich Symposium on Electromagnetic Compatibility*.

[10] Liao S., Zhang L., Xu J. and Zhang Q. 2010. Neural Network Modeling For Electromagnetic Structures. *Asia-Pacific International Symposium and Exhibition on Electromagnetic Compatibility (APEMC)*.

[11] Bernacki M. and Przemyslaw Wlodarczyk. 2005. Principles Of Training Multi-Layer Neural Network Using Backpropagation. [Online]. From: http://home.agh.edu.pl/~vlsi/AI/backp_t_en/backprop.html. [Acessed on December 2014].

[12] Yee S. K. and Mohd Jenu M. Z. 2014. Piecewise Empirical Model for Shielding Effectiveness Prediction of Graphite-Cement Powder Mixture. in *International Integrated Engineering Summit*.

[13] 2013. EEE Draft Recommended Practice for Protecting Public Accessible Computer Systems from Intentional EMI. 1–26.