A soft computing algorithmic technique for circuital analysis of a wireless mobile charger

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ABSTRACT

Wireless energy transfer is emerging as a promising technology for mobile devices because it enhances rapid charging without requiring conventional cables. In this paper, a wireless mobile charger circuit was designed and simulated, the data obtained thereof was used to train an artificial neural network (ANN) using Levenberg-Marquardt (LM) algorithm. The result obtained was validated against that obtained when trained with regular scaled conjugate algorithm. Analysis of the results showed that the proposed technique remains a viable technique for rapidly analyzing several parts of the wireless mobile charger circuit for design and educational purposes, without always executing computationally intensive and time-consuming simulations.

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1. INTRODUCTION

Wireless sensor networks (WSNs) are made of interconnections of individual wirelessly interrogable sensor nodes networked for information sharing. These information are often made up of measurement data obtained locally by each sensor node, which together makes a network that shares distributed resoures within the network and with managers. Since the advent of wireless sensors and their networks, they have found applications in numerous fields, thereby enhancing sensing accuracy across various applications. One of such is in the agriculture and storage sector wherein wireless sensors have been deployed for temperature, humidity and water moisture content sensing and measurement. Another area which is experiencing a growing application of wireless sensors is the smart home industry where these systems have been deployed in order to measure different variables of interest in attempt to ensure thermal comfort and energy management. WSNs have shown great potential in various other applications, from military surveillance to environmental monitoring, condition monitoring and assessment of industrial installations, disaster reliefs, and home automation. One of the biggest challenges facing WSNs, however, is the issue of energy conservation and management [1] as network lifetime is significantly limited by the battery capacity [2], [3]. Over the years, several techniques have been devised in order to combat this energy requirement challenge. A way to address this battery problem is to redesign these sensor nodes such that they have the capacity to harvest energy from latent energy sources around the vicinity of each sensor node. These energy sources might include wave signals from numerous wireless applications around, or vibrations from different moving sources through the adaptation of some form of piezoelectric devices, or the radiation from the sun harnessed with photovoltaic cells. Energy may also be harnessed by these sensor nodes from the wind current passing over these node sensors. However, harvesting energy from the aforementioned sources may yet not be the lasting solution to the persistent energy needs of WSNs owing to the following reasons. Firstly, these sources are not reliable in terms of availability because most of them are either weather dependent (Thereby adding to their unpredictability), or dependent on motion of unpredictable humans and machineries. It is therefore necessary to device a better battery charging solution. The use of wirelessly rechargeable sensor node is therefore a promising technique to address this issue going forward. This is because such network nodes can then be charged from unmanned aerial vehicles in a noncontact manner in order to ensure that the network does not run aground because of dead batteries.

Other proposed solutions include the efforts to minimize power requirements of sensing units using duty cycling, energy provisioning and wakeup radio. However, new developments in sensor energy systems have introduced another dimension to these range of solutions by enabling the design of wireless rechargeable sensor networks (WRSNs), with the use of magnetic coupling technology for charging elements of the network to avoid dead batteries and downtime. Appearing similar to conventional energy scavenging techniques, wireless charging entails a different technology and this improves the reliability and durability of the network [4]. In recent years, wireless charging technology has rapidly evolved from theories to standards and is being adopted in commercial products, especially mobile phones and portable devices. In addition to the aforementioned features, wireless charging improves user-friendliness as the hassle from connecting cables is removed. Also, wireless charging provides better product durability (e.g., waterproof and dustproof) for contact-free devices. Furthermore, it enhances flexibility, especially to devices for which battery replacement or cable connection or charging is costly, hazardous, or impracticable (e.g., body-implanted sensors). Finally, wireless charging can provide on-demand power, avoiding an overcharging problem and minimizing energy costs [1].

Conventionally, in terms of physical connectivity, the charging range of conventional chargers is limited by their cable length. Hence, a mobile wireless charger is often required in order to integrate mobility with charging. This integration, therefore, guarantees that the nodes remain charged above specified threshold to enable them perform sensing, communication, and computation tasks [5].

Soft computing and intelligent computing techniques have become techniques of huge interest in recent decades. One of the qualities attributable to this growing interest is their ability to adapt and learn even complex nonlinear problems with relative ease. Most of these soft computing techniques take their roots from the natural learning capabilities of living animals. Fuzzy inference system [6], for example, does this by adopting a logic that varies over a continuum from total inclusion to complete exclusion, as against the conventional crisp logic of only "0" and "1" [7]–[9]. Optimization problems have also enjoyed their share of the speed and ease of computing offered by soft computing-based optimization techniques like genetic algorithm (GA) and particle swarm optimization [10]. In this vein, artificial neural networks (ANNs) (A connection of computing nodes called neurons) also solve complex matching and classification problems by adopting the neural structures of the human brain [11]–[14].

Numerous problems in wireless communication systems have been solved in recent years through the use of ANNs or their variants. These include the estimation of channel state information (CSI) [15] as well as reception diversity combining techniques. The performances of typical ANNs largely depend on the architecture of the network in terms of the neural configuration, activation function deployed for neurons in different layers, as well as the type of initialization and data pre-processing functions deployed. Another crucial factor upon which may affect the overall accuracy of most softcomputing techniques is the weight adaptation technique employed as this controls how the network learns by setting the rules with which the network adjusts its weights.

With advancements in magnetic resonance based wireless energy transfer technology, wireless energy replenishments are now being recently adopted for prolonging lifetime of WSNs. Even though this wireless charging solution is a relatively new technology as at this time, a significant amount of research works have been reported [16]–[21]. This work, therefore, proffers a soft computing technique for easier, rapid and accurate circuital analysis of a wireless mobile charger for research and educational purpose, by training and deploying a tunned Levenberg-Marquardt (LM) trained neural network.

2. METHOD

The performance of ANN for any problem depends on the choice of algorithm amidst other factors. In this article, the Levenberg-Marquardt (LM) algorithm was tuned to train a pre-optimized neural network so as to model outputs of a simulated wireless mobile charger suitable for charging wireless sensor nodes. The Levernberg-Marquardt algorithm is an iterative method that belongs to the class of second-order techniques utilized for optimizing problems involving cost functions similar to mean squares. It leverages quasi-newton optimization methods along with the conventional gradient descent approach. The LM procedure has gained a reputation for its remarkable efficiency when employed in the context of neural networks [22]–[25].

Letting the error $E_k = R_k - Z_k,\ k = 1, \ldots\ldots, N,$ cost function would be defined to quantify the difference between R and (1) in the jth epoch as,

$$E_j = E_j\,(e_k, k = 1, \ldots., N) = \frac{1}{2}\sum_{k=1}^{N} {e_k}^2 \tag{1}$$

where $R = [R_1 \ldots. R_N]^T$ is an N x 1 vector as the target output variable, Z= $[Z_1 \ldots. Z_N]^T$ is an N x1 vector representing the network output, e = $[e_1 \ldots\ e_N]^T$ is a N x1 representing the observed error. Such that a weight matrix can be written as,

$$W = [c_1\, s_1 \ldots\ c_{2n}\ s_{2n}]^T = [W_1 \ldots. W_{4n}]^T \tag{2}$$

where C_1 and S_1 denote the centroid and deviation, respectively, at each iteration. LM algorithm uses Jacobian matrix J_j which is a gradient matrix representing the partial derivatives of e_j with respect to W_j as written in (3). The new weight values for the network is hence written as seen in (4).

$$J_j = \frac{\partial \begin{bmatrix} e_1 \\ e_N \end{bmatrix}}{\partial \begin{bmatrix} W_1 \\ W_{4n} \end{bmatrix}} = \begin{bmatrix} \frac{\partial e_1}{\partial W_1} & \cdots & \frac{\partial e_1}{\partial W_{4n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial e_N}{\partial W_1} & \cdots & \frac{\partial e_N}{\partial W4_n} \end{bmatrix} \tag{3}$$

$$W_{j+1} = W_j - (({J_j}^T J_j) + \mu I)^2 {J_j}^T e(W_j) \tag{4}$$

An ANN was used to model and analyze different circuital sections of a wireless mobile charger. Data extracted from repetitive simulations were used to train and validate the network under MATLAB computing environment. This is particularly aimed at rapidly analyzing the directive gain characteristics and the radiation distribution of the charger across all applicable voltage ranges. The data was utilized to train the neural network whose selected samples are shown in Table 1 using the Levenberg-Marquardt algorithm, employing a random data division, with the performance measure function of mean squared error. As itemized in Table 2, the neural network has three inputs and one output. The network has a total of 20 neurons. The training data were divided into 70%, 15%, and 15% corresponding to the training, validation, and testing data, respectively. In the network, the hidden layer neurons utilize the sigmoid transfer function, while the output layer neuron employs the linear transfer function. Figure 1 shows the design model of the wireless mobile charger which was designed and simulated using Proteus 8 Professional simulation software.

Table 1. Selected samples of training data

TIME	TR1(S1)	U1(VI)	U1(VO)
0	1.36E-19	-1.86E-21	-1.92E-30
0.000103	0.524178	4.37E-06	-8.10E-13
0.000306	1.832330	0.550973	-8.68E-07
0.000402	2.708590	1.335350	-0.005200
0.001072	9.296990	7.867380	-0.496470
0.006185	30.315400	30.356400	-0.497320
0.014000	-1.127830	28.650100	-0.497660
0.020220	15.243200	28.260400	-0.497700
0.033500	-1.058700	26.837500	-0.497780
0.061880	22.745700	27.417700	-0.497750
0.103491	27.890500	26.865500	-0.497786

Table 2. ANN network parameters

ANN Parameters	Values
Type of transfer function (hidden layer)	Sigmoid
Type of transfer function (output layer)	Linear
Training algorithm	Levenberg-Marquardt, Scaled Conjugate Gradient
Total number of neurons	20
Total number of weight elements	161
Maximum epochs	1,000

Selected sample of the training data extracted from the wireless mobile charger is presented in Table 1. As highlighted in Figure 2, the network inputs are ‘TIME’, ‘TR1’ and ‘U1’ corresponding to the time (in sec), time response (in sec), and voltage (in volts). While the output of the network is the output voltage ((VO) in volts). During training, at each iteration, input data from each datapoint in the training dataset is supplied at the network input, which then traverses from neuron to neuron within the network, interacting with the layer weights and respective activation function enroute the network output.

The observed output is evaluated with the expected corresponding target as specified in the training data. The discrepancies between the two, commonly refered to as the error, is obtained, and as contained in the training algorithm, the network weights are adapted accordingly with the aim of minimizing the error in the next iteration. The performance of the neural network is then continuously evaluated with the validation dataset in order to avoid overtraining or undertraining whilst attaining network convergence. Once satisfactory performance is reached with respect to the network specifications, the training is halted and resulting values of the weights and biases at this point is saved for the network. The network is then deployed and fed with the testing dataset and the performance thereof is evaluated.

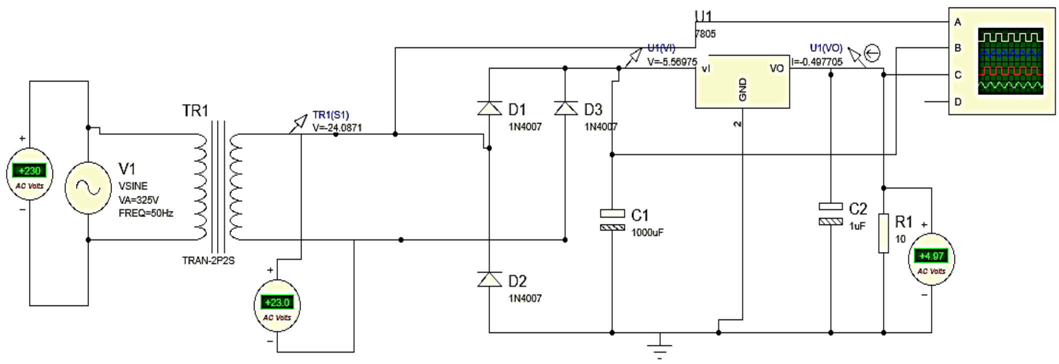


Figure 1. Circuit diagram of the wireless charger

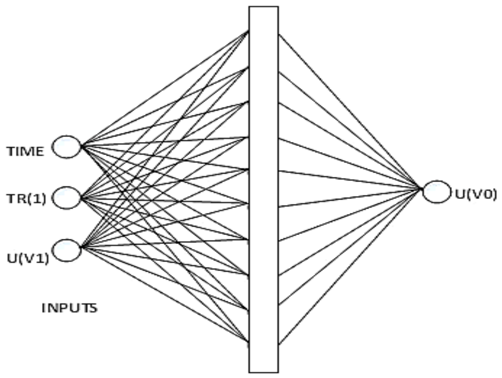


Figure 2. Architecture of the network

3. RESULTS AND DISCUSSION

The ANN was trained based on the Levenberg-Marquardt (LM) algorithm and the output was analyzed using regression and mean squared error (which is the average squared difference between output and target). As a way of cross-validating the performance of the network under the specified condition, the network was trained using the scaled conjugate gradient Quasi-Newton algorithm and the performances obtained in both cases were compared. The results observed for the two algorithms are presented in Table 3.

Table 3. Performance of the algorithm of the training

Algorithm	Training Regression R	Validation Regression R	Test Regression R
Levenberg-Marquardt	0.99984	0.99983	0.99992
Scaled Conjugate Gradient	0.98615	0.99815	0.97568

The total training data for the network (21,279) was segmented into 3 samples; training (14,895), validation (3,192) and testing (3,192). To assess the network's generalization, the training values were utilized, and the training process was halted when further improvement in generalization ceased. The LM model exhibited a remarkable training regression of 0.99984, and during testing, it achieved a regression of 0.99992, completing the process after 27 iterations. On the other hand, the scaled conjugate gradient method attained a training regression of 0.98615 and a testing regression of 0.97568, finalizing after 39 iterations. The oscilloscope and analogue analysis graph presented in Figures 3 and 4 highlight specific sections of the input and output variables of the neural network.

Table 4 shows samples of input data, the expected output and the simulated results obtained from both the LM algorithm and scaled conjugate (SCG) algorithm for the neural network. The performances of both algorithms were evaluated by comparing the closeness of the outputs of the neural network with the expected values under each algorithm. These comparisons are shown in Figures 5(a) and 5(b). Results obtained in this work showcases the adaptability of ANNs and their associated algorithms for various engineering problems. The neural network successfully captured and modeled various subsections of a wireless mobile charger in this scenario.

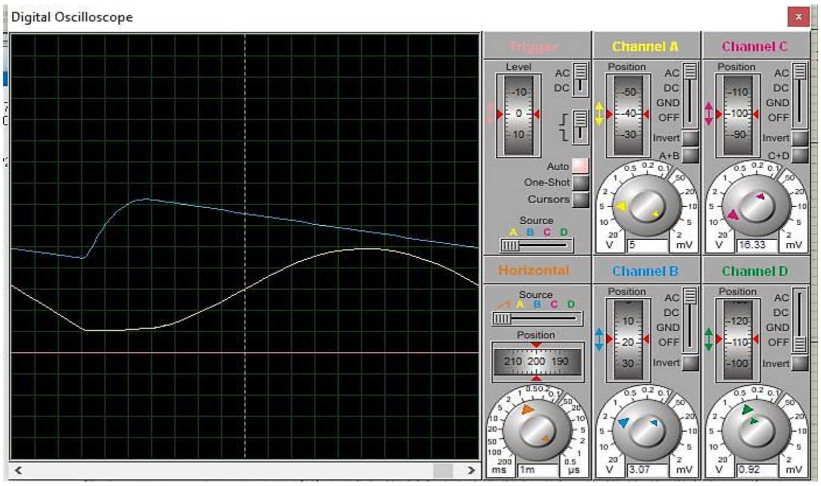


Figure 3. A section of the output on the oscilloscope

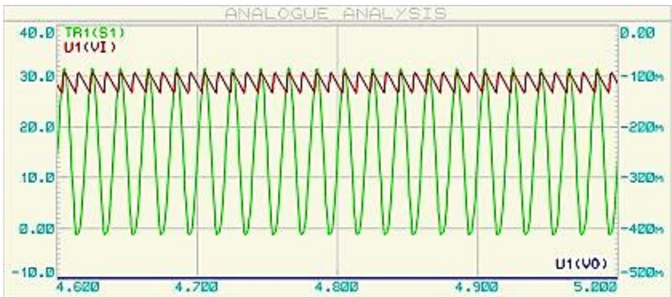
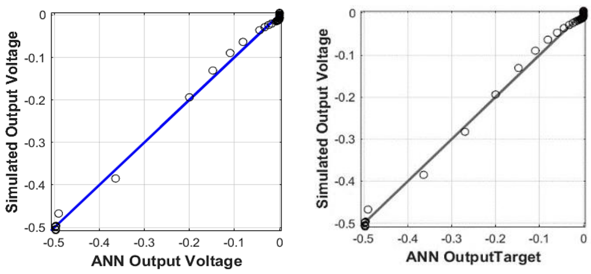


Figure 4. Analogue analysis graph



(a) (b)

Figure 5. The neural network testing performance for; (a) LM algorithm and (b) SCG algorithm

Table 4. Comparison of selected samples of predicted and measured output

Network Input	Measured Output (V)	Network Outputs	
Time (s)	Voltage (V)	LM_ANN	LM_SCG
0.02738	-0.49772	-0.51495	-0.6263
0.03405	-0.4978	-0.51495	-0.6265
0.04071	-0.49765	-0.51495	-0.6265
0.004738	-0.49732	-0.51495	-0.6266
0.005405	-0.4972	-0.51495	-0.6266
0.005645	-0.49724	-0.51495	-0.6266
0.005755	-0.49726	-0.51495	-0.6266
0.005831	-0.49727	-0.51495	-0.6266
0.005903	-0.49728	-0.51495	-0.6266
0.005948	-0.49729	-0.51495	-0.6266

4. CONCLUSION

This paper develops a soft computing technique for rapid circuital analysis of a wireless mobile charger by training an ANN with extracted data of interest from simulated circuit of the wireless mobile charger. This enables users to quickly and accurately analyze the expected responses of different sections of the circuit with the trained network, without necessarily performing computationally intensive simulations over again. The evaluation of the network's performance indicates that the approach remains a valid method for modeling and analyzing the circuit of a wireless mobile charger. for research and development, as well as for educational purposes.

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