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LETTER

Compensation capacitance tunings of wireless power transfer systems using artificial neural network

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Abstract This letter proposes a new method for tuning compensation capacitances of wireless power transfer (WPT) systems using an artificial neural network (ANN). A field solver is used to analyze the compensation capacitances that maximize the output power at a set resonant frequency in a WPT system with ferrite shields. The compensation capacitances can be tuned using the ANN learned from the results acquired by the field solver. The electrical parameters for tuning the compensation capacitances acquired by the proposed method have maximum errors within 3.40% and mean absolute errors within 1.38%.

Keywords: compensation capacitance tuning, wireless power transfer, Qi standard, artificial neural network

Classification: Wireless communication technologies

1. Introduction

In recent years, short-range wireless power transfer (WPT) technologies based on electromagnetic induction and magnetic field resonance have been attracting attention. These short-range technologies utilize the magnetic field due to inductive coupling between the transmitter (Tx) and receiver (Rx) coils, and WPT systems have been applied to various mobile devices, consumer electronics, and electric vehicles (EVs) [1]. The Wireless Power Consortium (WPC) [2] was founded in 2008 and introduced the world's first wireless charging standard, Qi, in 2010. The expansion of wireless charging applications and power transfer abilities has helped advance the Qi standard, which mainly targets short-range WPT applications.

Methods to acquire maximum output power at resonant frequency have been proposed such as compensating the capacitances of Rx [3] and of both Tx and Rx [4]. WPT systems generally have a structure that contains ferrite shields. The ferrite shield is a magnetic material that forms a magnetic field and improves the magnetic field strength in the power transfer region, coupling between the Tx and Rx coils, and power transfer efficiency [5]. However, WPT systems with ferrite shields have the problem that there is no approximate equation to calculate the parasitic resistances and self-inductances of the Tx and Rx coils and the mutual inductance between the Tx and Rx coils, making it difficult to determine the electrical parameters such as resonant frequency and power transfer efficiency.

Machine learning (ML) has been applied to WPT fields. In [6], several ML regression models such as random forest (RF), decision tree, support vector machine, adabooster with decision tree, and XGboost are used to determine the output power, load resistance, and coupling coefficient from harmonic current components and root mean square (RMS) value of input current to identify WPT system characteristics. In [7], RF and deep neural network (DNN) are used to predict the receiver's position from the activation pattern of the transmitter array and the measured power transfer efficiency. However, as far as we have investigated, there is no paper that uses ML to determine the compensation capacitances to acquire the maximum output power at any resonant frequency in WPT systems with ferrite shields.

This letter proposes a compensation capacitance tuning method using an ANN to design WPT systems that achieve maximum output power at any resonant frequency. In general, it is difficult to create a model that represents the relationship between the design and electrical parameters of a WPT system with ferrite shields. In addition, the analysis using a field solver [8] takes an enormous amount of time. The proposed method uses the field solver to acquire the compensation capacitances, power transfer efficiency, and output power when the resonant frequency and the distance between the Tx and Rx coils are varied in advance. Then, by modeling the nonlinear relationship between the design parameters and electrical parameters using ANN, the designer can quickly determine the compensation capacitances, power transfer efficiency, and output power by just inputting the desired resonant frequency and distance between the Tx and Rx coils. If the proposed method is not used, the designer must acquire the compensation capacitances to acquire the maximum output power at the desired resonant frequency by field solver or actual measurement, which requires a huge amount of time. The proposed method has the advantage that the desired compensation capacitances can be acquired instantly by modeling the system in advance using ANN.

2. Theoretical analysis of WPT system

2.1 Concept of wireless charging

Figure 1 shows a conceptual diagram of the WPT system for mobile charging in this letter. The Tx charger is a pad-type wireless charger and the Rx device is a smartphone. The Tx charger is magnetically coupled to the Rx device and

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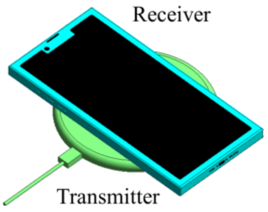


Fig. 1 Concept of WPT system for mobile charging.

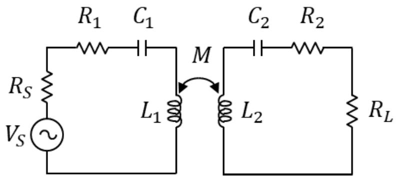


Fig. 2 Equivalent circuit of SS compensated WPT system.

transmits power to the Rx device.

2.2 Theoretical equations

Figure 2 shows the equivalent circuit of the WPT system with the series-series (SS) compensation topology analyzed in this letter. V_S is the RMS value of the AC voltage source, and R_S is the internal resistance of the voltage source. L_1 and L_2 are the self-inductances of the Tx and Rx coils, respectively, and R_1 and R_2 are the parasitic resistances of the Tx and Rx coils, respectively. The parasitic capacitances of the Tx and Rx coils are negligible at low frequency. C_1 and C_2 are the Tx and Rx compensation capacitances in series with L_1 and L_2, respectively. R_L is the equivalent load resistance. M is the mutual inductance between the Tx and Rx coils.

When the resonant angular frequency $\omega_0 = \frac{1}{\sqrt{L_1 C_1}} = \frac{1}{\sqrt{L_2 C_2}}$, C_1 and C_2 can be expressed as

$$C_1 = \frac{1}{\omega_0^2 L_1}, \tag{1}$$

$$C_2 = \frac{1}{\omega_0^2 L_2}. \tag{2}$$

The output power (P_{out}), and power transfer efficiency (η) can be expressed as [9]

$$P_{out} = \frac{\omega_0^2 M^2 V_S^2 R_L}{\left\{(R_1 + R_S)(R_2 + R_L) + \omega_0^2 M^2\right\}^2}, \tag{3}$$

$$\eta = \frac{\omega_0^2 M^2 R_L}{(R_2 + R_L)\left\{R_1 (R_2 + R_L) + \omega_0^2 M^2\right\}}. \tag{4}$$

However, in an actual WPT system with ferrite shields, the electrical parameters cannot be calculated because there is no approximate equation to calculate the parasitic resistances and self-inductances of the Tx and Rx coils and the mutual inductance between the Tx and Rx coils.

3. Compensation capacitance tunings using ANN

3.1 Significance of proposed method

In this letter, the compensation capacitances that maximize output power in a WPT system with ferrite shields are analyzed at the set resonant frequency using the field solver. If the compensation capacitances are close to the actual measurement, the learning model can be incorporated directly into Tx and Rx to instantly calculate the compensation capacitances that match the desired resonant frequency, and the compensation capacitances can be tuned. On a measured basis, by varying the compensation capacitances from minimum to maximum, measuring the resonant frequency at which the output power is maximum, creating a learning model, and entering the resonant frequency at which the system operates, the Tx and Rx compensation capacitances can be instantly and automatically tuned. The proposed method can also be used in the design phase to determine the range of compensation capacitances to be incorporated into Tx and Rx depending on the resonant frequency at which Tx and Rx operate.

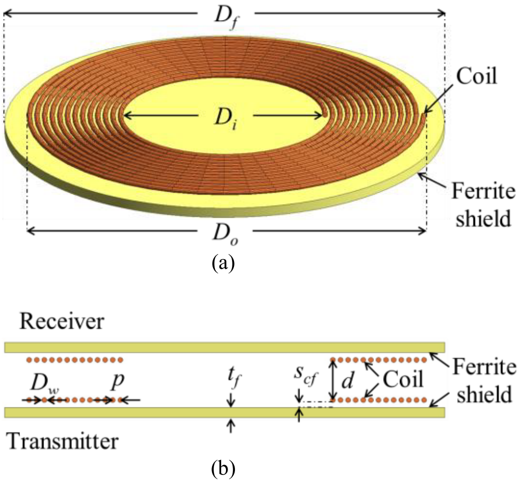


Fig. 3 Transmitter and receiver structure: (a) coil and ferrite shield model and (b) cross section view of WPT system.

Table I Design specifications of WPT system

Parameter	Symbol	Value
Resonant frequency (kHz)	f_0	100-200
AC voltage source RMS (V)	V_S	5
Internal resistance of voltage source (Ω)	R_S	0.5
Equivalent load resistance (Ω)	R_L	50
Distance between Tx and Rx coils (mm)	d	4-12
Coil outer diameter (mm)	D_o	40
Coil inner diameter (mm)	D_i	20
Number of coil turns	N	13
Coil wire pitch (mm)	p	0.76
Coil wire diameter (mm)	D_w	0.5
Coil material	-	Cu
Ferrite shield diameter (mm)	D_f	44
Ferrite shield thickness (mm)	t_f	1
Spacing between coil and ferrite shield (mm)	s_{cf}	0.5
Ferrite relative permeability	μ_r	131
Ferrite loss tangent	tan$D$	0.008

3.2 Designs of transmitter and receiver

Figure 3 shows the Tx and Rx structures used in this work, where (a) is a model of the coil and ferrite shield and (b) is a cross section view of the WPT system. This system is an inductive WPT system with Tx and Rx. The structures of Tx and Rx are symmetric. Tx and Rx consist of a coil, compensation capacitor, and ferrite shield. Table I lists the design specifications of the WPT system.

3.3 Compensation capacitance tuning algorithm

Figure 4 shows the ANN model used for the compensation capacitance tunings in this work. The numbers of neurons in the input and output layers are 2 and 3, respectively. In this work, the NN hyperparameters to be set are the numbers of neurons and layers in the hidden layer, the activation function, the loss function, the optimization algorithm, the evaluation function, the maximum number of trials, the batch size, and the value, mode, and number of consecutive trials to prevent over-learning to be monitored. The optimal hyperparameters depend on the training data and need to be tuned each time the ANN is trained. Since the number of training data is small, the maximum number of trials is set to 1,000 and the batch size is set to 1 so that the ANN is trained without splitting the training data. The activation function is set to ReLU because the design and electrical parameters have a nonlinear relationship. The number of consecutive trials to be monitored is set to 10 so that it is smaller than the maximum number of trials. The other hyperparameters are set to general parameters. The loss function is the mean squared error (MSE), the optimization algorithm is Adam, the evaluation function is the mean absolute error (MAE), the value to be monitored is the MSE of the output parameters of the validation data, and the mode to be monitored is the auto. Under these conditions, the numbers of neurons and layers in the hidden layer are tuned so that the mean and standard deviation of the maximum errors of the results acquired by the field solver and the proposed method become smaller. As a result, the numbers of neurons and layers in the hidden layer became 64 and 1, respectively. Too large or too small values of the hyperparameter values increase the errors.

Figure 5 shows the flowchart of the proposed compensation capacitance tuning algorithm using the ANN. In this work, Scikit-learn is used as the standardization library and Keras is used as the ANN library. The following steps are taken.

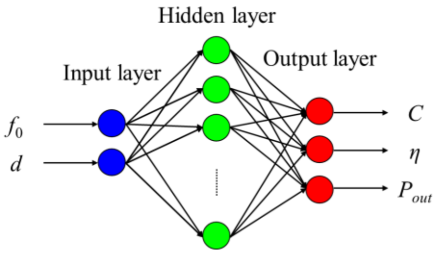


Fig. 4 ANN model used for compensation capacitance tunings.

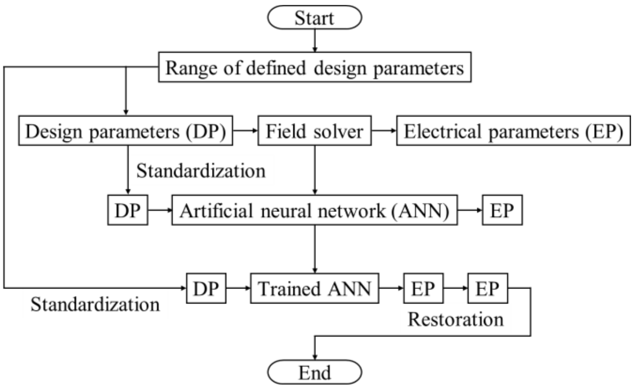


Fig. 5 Flowchart of compensation capacitance tuning algorithm using ANN.

In step 1, the range of the design parameters is defined. In step 2, the field solver analyzes the electrical parameters from the design parameters selected from the defined range.

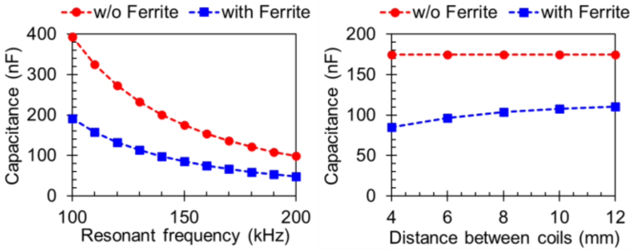
In step 3, ANN learns the nonlinear relationship between the design and electrical parameters. The design and electrical parameters acquired from step 2 are used as input and output parameters for training and validation data to train the ANN. The training and validation data are standardized. Furthermore, the training data are fitted to the ANN so that the value to be monitored becomes smaller. To prevent over-learning, this process is terminated when the value to be monitored stops decreasing for 10 consecutive times.

In step 4, the trained ANN calculates the electrical parameters from the design parameters. The design parameters selected from the defined range that were not selected in step 2 are used as input parameters for the test data to test the trained ANN. The design parameters of the test data are standardized. The design parameters of the test data are incorporated into the trained ANN and the calculated electrical parameters are restored from the standardization.

4. Experimental results

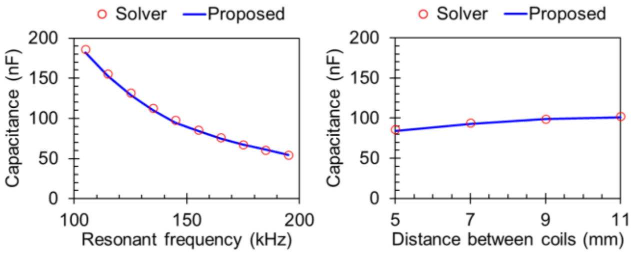
The algorithm for the compensation capacitance tunings using an ANN was run in Python using Scikit-learn and Keras libraries.

Figure 6 shows the compensation capacitance of the training data for the WPT system without and with ferrite shields, where (a) is the resonant frequency characteristics when the distance between the Tx and Rx coils $d = 4$ mm and (b) is the distance characteristics between the Tx and Rx coils when the resonant frequency $f_0 = 150$ kHz. The number of training data used to train the ANN is 55. The design parameters of the training data are in the range of Table I. The design parameter set combinations for the training data are 11 for the resonant frequency (f_0) and 5 for the distance between the Tx and Rx coils (d). The Tx and Rx compensation capacitances of the WPT system without ferrite shields were acquired by substituting the calculated Tx and Rx self-inductances [10] into equations (1) and (2). The Tx and Rx compensation capacitances of the WPT system with ferrite shields were acquired from analysis using the field solver.



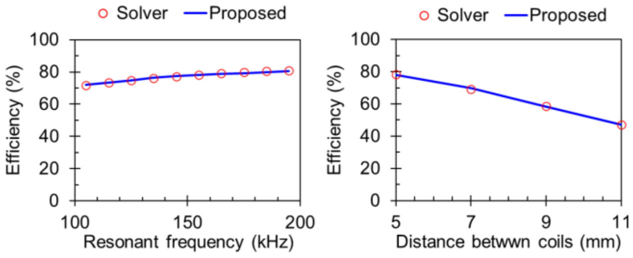
(a) (b)

Fig. 6 Comparison of compensation capacitances without and with ferrite shields: (a) resonant frequency characteristics and (b) distance characteristics between Tx and Rx coils.



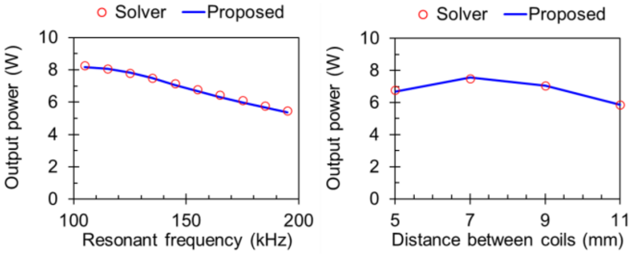
(a) (b)

Fig. 7 Comparison of compensation capacitances acquired from solver and proposed method: (a) resonant frequency characteristics and (b) distance characteristics between Tx and Rx coils.



(a) (b)

Fig. 8 Comparison of power transfer efficiencies acquired from solver and proposed method: (a) resonant frequency characteristics and (b) distance characteristics between Tx and Rx coils.



(a) (b)

Fig. 9 Comparison of output powers acquired from solver and proposed method: (a) resonant frequency characteristics and (b) distance characteristics between Tx and Rx coils.

The WPT system with ferrite shields has a stronger magnetic field strength than the WPT system without ferrite shields, so the Tx and Rx self-inductances become larger and the Tx and Rx compensation capacitances become smaller. As d increases, the WPT system with ferrite shields has the Tx and Rx coils move away from the Rx and Tx ferrite shields respectively, the magnetic field strength becomes weaker, the Tx and Rx self-inductances become smaller, and the Tx and Rx compensation capacitances become larger.

Figures 7, 8, and 9 show the compensation capacitance (C), power transfer efficiency (η), and output power (P_{out}) of the test data acquired from the field solver and proposed method, where (a) is the resonant frequency characteristics when the distance between the Tx and Rx coils $d = 5$ mm and (b) is the distance characteristics between the Tx and Rx coils when the resonant frequency $f_0 = 155$ kHz. The design parameters of the test data are within the design parameters of the training data. The number of test data is 40. The design parameter set combinations for the test data are 10 for f_0 and 4 for d. The maximum errors of C, η, and P_{out} are 3.40%, 0.88%, and 2.13%, respectively. The MAEs of C, η, and P_{out} are 1.38%, 0.39%, and 0.68%, respectively.

Table II Processing times

Process	Time (s)
Training time	11.81
Test time per design	0.005

Table II lists the processing times of the proposed method. The experiments were performed on an Intel Core i7-12700 CPU with 2.1 GHz and 16 GB RAM. The field solver takes an average of 204 seconds to analyze a single design. The proposed method is able to determine the electrical parameters for tuning the compensation capacitances per design about 37,000 times faster than the field solver.

5. Conclusion

This letter proposed a method for compensation capacitance tunings of WPT systems using an ANN. A field solver is used to analyze the compensation capacitances that maximize the output power at a set resonant frequency in a WPT system with ferrite shields. The ANN learned from the results acquired by the field solver is used to tune the compensation capacitances. In this experiment, the proposed method using two design parameters was able to determine the electrical parameters for tuning the compensation capacitances faster than the field solver with sufficient accuracy. The NN hyperparameters need to be tuned each time the ANN is trained. This is because the accuracy of the ANN may decrease as the numbers of training data and the input and output parameters change.

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