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Calculation of Mutual Inductance between Two Planar Coils with Custom Specifications and Positions Using a Machine Learning Approach

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ABSTRACT: Wireless power transmission systems enable the transfer of electricity between grids without the use of physical wires. Different methods are employed for wireless power transfer, each suited to different distances. Inductive coupling, the subject of this study, is typically used for shorter distances. The effectiveness of inductive coupling systems is evaluated using a parameter called mutual inductance. In the present study, an attempt is made to provide a model for calculating mutual inductance in wireless power transfer systems using a machine learning approach. To achieve this goal, finite element simulations are employed, and 64 datasets are generated from mutual inductance calculations in various scenarios. These datasets are used to train machine learning regression algorithms, including linear regression, support vector regression, decision tree regression, and artificial neural networks. The evaluation results, using performance metrics such as R-squared, mean absolute error, and root mean square error, confirm that among these four algorithms, the artificial neural network exhibits higher computational accuracy with an R-squared value of 0.950 for predicting test data.

Key words: Wireless Power Transmission; Mutual Inductance; Planar Coils; Machine Learning; Deep Learning

INTRODUCTION

Wireless power transfer systems provide the capability to transfer power from one grid to another without the need for wired connections (Mirzaei et al., 2023). Various mechanisms, such as inductive coupling, resonant inductive coupling, capacitive coupling, dynamic magnetic coupling, microwaves, and optical waves, are used for wireless power transfer, with each having its applications for different distances. Inductive coupling, which will be the focus of this study, is used for shorter distances (Bhatnagar et al., 2015). In this mechanism, power is transferred between coils through a magnetic field. The transmitter and receiver coils form a transformer, and alternating current in the transmitter coil generates an oscillating magnetic field following Ampere's law. The magnetic field passes through the receiver coil and induces an alternating voltage and current in the receiver coil, following Faraday's law of induction (Asadi et al., 2023). It is said that if two coils are close to each other on the same axis, all the magnetic flux from the transmitter coil will pass to the receiver, and the system's efficiency will be close to unity, which is generally much lower in other wireless power transfer methods (Electronicdesign, 2022). The main advantages of wireless power transfer include simplicity in design, lower cost, suitability for short-distance applications, and operation at lower frequencies. It also reduces the risk of electric shock. These systems have a wide range of applications in medical implants (Ahire et al., 2022b, 2022a; Kim et al., 2018), health monitoring sensors (Chen et al., 2008; Jiao et al., 2019), wireless chargers (Boff et al., 2017; Felt et al., 2016; Jeong et al., 2015), charging electronic devices such as phones and electric vehicles (Rakhymbay et al., 2018; Song et al., 2021; Su et al., 2009), and radio wave-based identification systems (Potyrailo et al., 2009).

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The performance of inductive coupling wireless power transfer systems is assessed with a variable called mutual inductance. A crucial parameter depends on the specifications of the coils, including the number of turns, the radius of the first or last turn, the spacing between turns, and the relative positioning of the coils. On the other hand, machine learning is a field of computer science and artificial intelligence that focuses on developing algorithms and statistical models that enable computers to learn from data and make predictions or decisions without explicit programming. This includes using statistical techniques and algorithms to automatically identify patterns and relationships in data and use these patterns to predict or make decisions about new data. Machine learning has a wide range of applications in various fields. Some of the most common applications of machine learning include:

- Image recognition: Used for identifying objects, people, places, digital images, and more.
- Product recommendation: Widely used by various e-commerce and entertainment companies like Amazon, Netflix, and others for recommending products to users.
- Employee access control automation: Organizations actively implement machine learning algorithms to determine the required level of access for employees in different domains based on their job profiles.
- Fraud detection: Machine learning is used to identify fraudulent activities in various industries like banking, insurance, and e-commerce.
- Spam filtering: Used for filtering emails and spam messages.
- Predictive maintenance: Used to predict the likelihood of machine or equipment failure and perform maintenance before it occurs.
- Data mining: Used to extract useful information from large datasets.
- Natural language processing: Used for analyzing and understanding human language.

With the expanding use of machine learning, techniques and statistical algorithms have been applied to calculate mutual inductance for a specific variable, which can be used for mutual inductance as well.

In summary, mutual inductance is a crucial concept in inductive coupling systems. The value of mutual inductance between two coils depends on their physical specifications and relative positions. Mutual inductance plays a vital role in achieving efficient power transfer in inductive wireless systems. By optimizing the design and placement of coils, engineers can maximize mutual inductance and achieve efficient power transfer over short distances. Therefore, providing a model for calculating mutual inductance is of great importance.

In recent years, numerous studies have been conducted in the field of mutual inductance calculation for coils in wireless power transfer systems based on inductive coupling. However, each of the models presented for calculating a specific type of coil is used, and they do not cover all the coil geometries. For example, Shi and colleagues (Shi et al., 2019) performed mutual inductance calculations by providing a theoretical model only for two flat circular coils. They assumed both coil axes to be parallel in all calculations and neglected angular misalignments in their calculations. The calculations performed are not flexible for other geometries. The model presented has been evaluated with experimental calculations, and in most case studies, the calculation error was less than 3%. In another study by Luo and Wei (Luo & Wei, 2016), an analytical model for mutual inductance calculation for two flat circular coils and two flat quadrilateral coils was provided. In this study, only one dimension of coil alignment (an angle) was investigated. Additionally, the effects of parameters on the coil geometries were not mentioned. The relative error of the calculations was assessed compared to finite element simulation results, with a maximum value of 3.55%. Sokhui and colleagues (Sokhui et al., 2019) introduced a novel method for measuring mutual inductance using the Fast Fourier Transform, which matches the experimental results. They also assumed both coil axes to be parallel in all calculations and disregarded angular misalignments. Tavakkoli and colleagues (Tavakkoli et al., 2019) conducted a numerical model for calculating mutual inductance for two flat coils with various sides. In this study, spatial and positional misalignments were not considered. The results of the calculations were evaluated with finite element simulations and experimental measurements, which confirmed each other. Additionally, circular coils were equated with coils with a high number of sides. The results showed that the error of this equation was less than 1% for sides with a count of 30 and more. Furthermore, Liu and colleagues (Liu et al., 2019) also studied flat circular coils and provided a model for calculating their mutual inductance in any relative position. The results obtained in this study do not cover calculations for other geometries. The percentage of measurement variations compared to experimental and modeling methods was limited to 6.14%. In another study by Hussain and Woo (Hussain & Woo, 2022), mutual inductance calculation was only performed for two flat circular coils. In this study, spatial misalignments were disregarded. Additionally, the effects of parameters on coil geometries were not mentioned. In this study, the presented model was evaluated with finite element simulation methods, defining various case studies, with the highest error reaching 59.3%.

Gong and colleagues (Gong et al., 2022) proposed a method for identifying mutual inductance based on a combination of particle swarm optimization and genetic algorithm for coupled magnetic resonance wireless power transfer systems in practical applications. By configuring algorithm parameters and operational process planning, mutual inductance identification and load identification at each phase change angle were achieved. The accuracy of the parameter identification method and the constant output voltage control were confirmed by simulation and experimentation. The maximum relative error for mutual inductance identification was determined to be 3.17%.

On the other hand, machine learning regression algorithms and deep learning algorithms are widely used in various fields to predict continuous numerical values. Here are some common application areas where regression algorithms are applied:

1. Stock Market Prediction: Regression algorithms can be used to analyze historical stock data and predict future stock prices, aiding investors and traders in making informed decisions (Kumar et al., 2020).

2. Housing Price Prediction: Regression algorithms can analyze historical housing data, including factors such as location, size, and amenities, to predict house prices. This information is valuable for real estate agents, buyers, and sellers (Akinosho et al., 2020).

3. Energy Load Forecasting: Regression algorithms can analyze historical energy consumption data to predict future energy loads. This is useful for energy companies to optimize production, distribution, and pricing strategies (Zhang et al., 2021).

4. Medical Diagnostics: Regression algorithms can analyze medical data, such as demographic information, symptoms, and laboratory test results, to predict diseases or diagnose certain conditions, helping healthcare professionals in treatment planning and decision-making (Alballa & Al-Turaiki, 2021).

5. Sales Forecasting: Regression algorithms can analyze historical sales data, marketing efforts, economic indicators, and other factors to predict future sales volumes. This assists businesses in production planning, marketing strategies, and resource allocation (Xu & Chan, 2019).

6. Weather Forecasting: Regression algorithms can analyze historical weather data, such as temperature, humidity, and wind speed, to predict future weather conditions. This information is crucial for meteorologists, weather scientists, and industries like agriculture and transportation (Yagli et al., 2019).

7. Traffic Flow Prediction: Regression algorithms can analyze historical traffic data, including factors like time of day, day of the week, and weather conditions, to predict traffic congestion and flow patterns. This aids traffic management, route planning, and infrastructure development (Shafiq et al., 2020).

These are just a few examples of how regression algorithms are applied in various domains. The adaptability of regression algorithms allows them to be used in a wide spectrum of predictive modeling domains where the prediction of numerical values is required.

While many studies have been conducted in the field of mutual or inductive coupling, there is still a need for presenting a model for performing calculations and optimizing the mutual inductance of coils with different sides, varying distances, numbers of turns, and arbitrary positions. In this context, the current research evaluates the impact of geometry, distance, and angle on the mutual inductance of coils and determines the performance of wireless power transfer systems using machine learning and deep learning algorithms such as neural networks in a software environment.

METHODOLOGY

Mutual inductance is the basis for the operation of transformers, motors, generators, and, in general, all types of electrical devices that interact with magnetic fields. Mutual inductance between two coils can be calculated using the well-known Neumann formula, as shown in Equation (1). In this equation, μ_0 represents the permeability of the coil's core, $d\overrightarrow{l_1}$ and $d\overrightarrow{l_2}$ are elements of the transmitting and receiving coils, and R is the distance between these elements.

$$\boldsymbol{M = \frac{\mu_0}{4\pi} \iint \frac{d\overrightarrow{l_1} . d\overrightarrow{l_2}}{R}} \tag{1}$$

As evident from the equation, the level of mutual inductance applied to a coil depends to a large extent on the relative positions of these two coils. If the physical distance between two coils is small, almost all of the magnetic flux generated by the first coil will pass through the second coil. In this case, a significant electromotive force will be generated, resulting in strong mutual inductance between the two coils. Conversely, if the physical distance between two coils is large, the magnetic flux produced by the first coil will pass through the second coil to a lesser extent than before. As a result, the generated electromotive force is weaker, leading to a smaller mutual inductance between the two coils. Therefore, the extent of mutual inductance depends to a considerable degree on the relative position and separation distance of the two coils.

Moreover, the geometric configuration of the coils also has an impact on the level of mutual inductance and cannot be disregarded. Typically, the level of mutual inductance between two coils is denoted by a coefficient, which ranges from 0 to 1. This coefficient, known as the coupling coefficient, is determined directly by the mutual inductance and is obtained from Equation (2). In this equation, k is the coupling coefficient, M is the mutual inductance, and L_1 and L_2 are the self-inductance coefficients of each of the coils. If the power transfer between the two coils is complete, the coupling coefficient is 1, and if there is no power transfer, the coupling coefficient is 0.

$$\boldsymbol{k = \frac{M}{\sqrt{L_1 L_2}}} \tag{2}$$

With the information provided, it can be acknowledged that the mutual inductance between two coils determines the performance of wireless power transfer between two grids. By calculating the mutual inductance between two coils, it becomes possible to measure the received power in the receiving grid.

Finite Element Simulations

In the current study, simulations were initially conducted to calculate the mutual inductance between two coils using Ansys Maxwell software. These simulations have been validated against results from other studies in the literature. Once the results' accuracy was confirmed, repeated simulations were carried out for coils with different specifications to generate data in this regard. The collected data were used to train machine learning models, including linear regression, support vector regression, decision tree regression, and artificial neural networks. Various algorithms were compared with each other, and the accuracy of their predictions was evaluated.

It is necessary to introduce the influential variables on the coils before proceeding. Influential variables can be categorized into two groups: those related to the coil's structure and those related to the coils' positions. Structural variables include ten parameters (five for each coil pair): the number of sides, the number of turns, the outermost side's length, the distance between turns, and the wire thickness. Figure 1 schematically represents these structural variables.

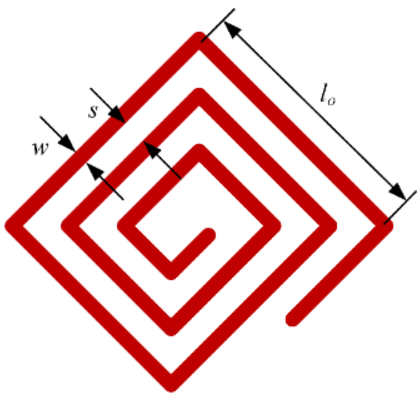

Figure 1. Structural variables of the coils.

Position-related variables consist of six parameters (three spatial and three angular variables). Spatial variables are the Cartesian coordinates of the receiver coil's center concerning the transmitter coil's center, connected by an axis. Angular variables include Euler angles, representing the rotation of the receiver coil concerning the transmitter coil. Figure 2 illustrates the positional variables of the coils.

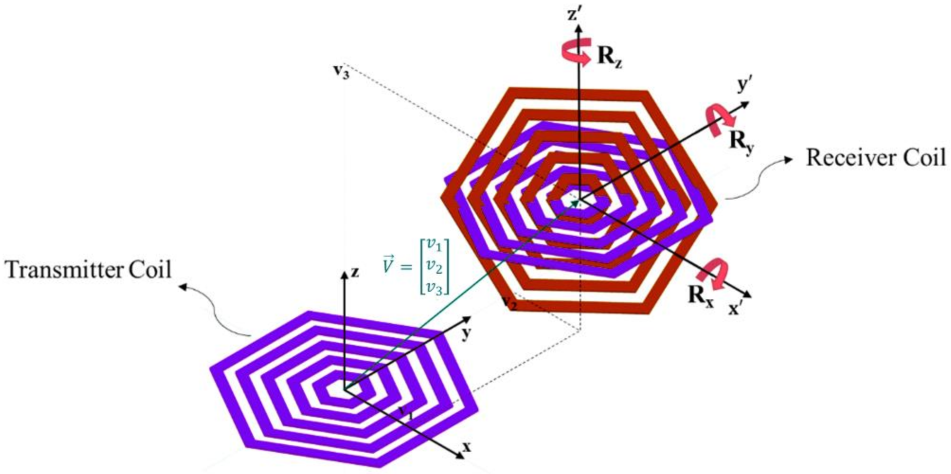

Figure 2. Positional variables of the coils.

Before data generation, it is essential to ensure the results obtained from simulations. To this end, several coil pairs were randomly selected for calculating mutual inductance. The simulation results were compared with results from the method presented by Tavakkoli et al. (Tavakkoli et al., 2019) to validate the simulations. Three randomly selected coil pairs, according to Table 1, formed seven case studies, as shown in Table 2. These seven case studies were compared using both simulation and the method presented by Tavakoli et al. (Tavakkoli et al., 2019) to ensure the accuracy of the applied simulations.

Table 1. Specifications of randomly selected coils for validation.

Coil	Outer radius (mm)	Number of turns	Number of sides	Thickness of wire (mm)	Distance between turns (mm)
C1	40	15	20	1	0.5
C2	30	10	12	1.5	0.5
C3	20	7	8	1.5	0.5

Table 2. Randomly selected conditions for validation case studies.

No.	Coil 1	Coil 2	Displacement coordinates (mm)	Rotation angles (deg)
1	C1	C2	(0,0,50)	(0,0,0)
2	C1	C2	(0,0,50)	(60,10,10)
3	C1	C3	(0,0,50)	(45,10,10)
4	C2	C3	(0,0,50)	(30,20,20)
5	C1	C2	(-20,20,50)	(0,0,0)
6	C1	C2	(-10,10,50)	(60,10,10)
7	C1	C3	(10,20,50)	(45,10,10)

Machine Learning

To generate data, 64 simulations were conducted using Ansys Maxwell software. The collected data from simulations were used for training machine learning algorithms, including linear regression, support vector regression, decision tree regression, and artificial neural networks. The primary process for training data-driven models is illustrated in Figure 3. In this process, data is first collected, then processed and randomly separated into training and testing datasets. Testing data is not used throughout the model-building process. The training data, along with the relevant parameters for each selected algorithm, is used to train the model. After model training, feature data (input) is fed into the model, and target data (output) is calculated. On the other hand, target data values are separated in advance, and model accuracy is determined by calculating the error. If the presented model does not have sufficient accuracy, adjusting the parameters of each algorithm can enhance model accuracy. Ultimately, with acceptable accuracy in calculations, the presented model is suitable for calculating each target value. In this study, three-quarters of the 64 data sets were used for training machine learning algorithms, and the remaining quarter was kept for evaluating the accuracy of the calculations. The evaluation used scoring metrics such as R-squared, mean absolute error, and root mean square error.

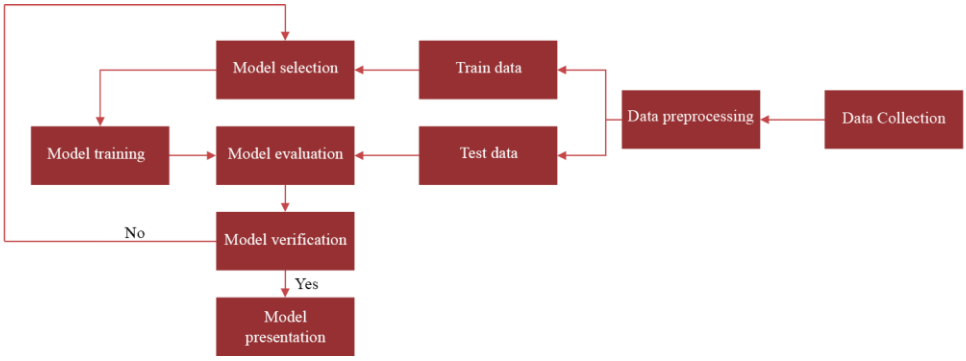

Figure 3. Data-driven model training and evaluation process.

RESULTS AND FINDINGS

Simulation

The results obtained from the simulations have been compared to the results obtained from the method presented by Tavakkoli and colleagues (Tavakkoli et al., 2019) in Table 3. The relative error of the simulations is less than 1%, indicating the accuracy of the conducted simulations.

Table 3. Comparison of results obtained from simulations and the method presented by Tavakkoli and colleagues (Tavakkoli et al., 2019).

No.	Mutual inductance calculated by simulation (nH)	Mutual inductance calculated by Tavakkoli et al. method (nH)	Relative error (%)
1	479.005	476.528	0.520
2	318.605	318.624	0.006
3	114.324	115.406	0.938
4	52.546	52.060	0.933
5	317.020	316.792	0.072
6	163.479	164.886	0.853
7	53.613	53.980	0.680

Machine Learning

Linear Regression

In the linear regression algorithm, the calculation accuracy is according to Table 4.

Table 4. Evaluation of the Linear Regression model for calculating mutual inductance between two coils

	RMSE	MAE	R-squared
Training	13.673	6.286	0.993
Testing	23.491	18.815	0.937
Total	16.722	9.468	0.989

Figure 4 also illustrates the predicted values compared to the actual values in the linear regression algorithm. It is evident that the closer the points are to the $y = x$ line, the higher the calculation accuracy.

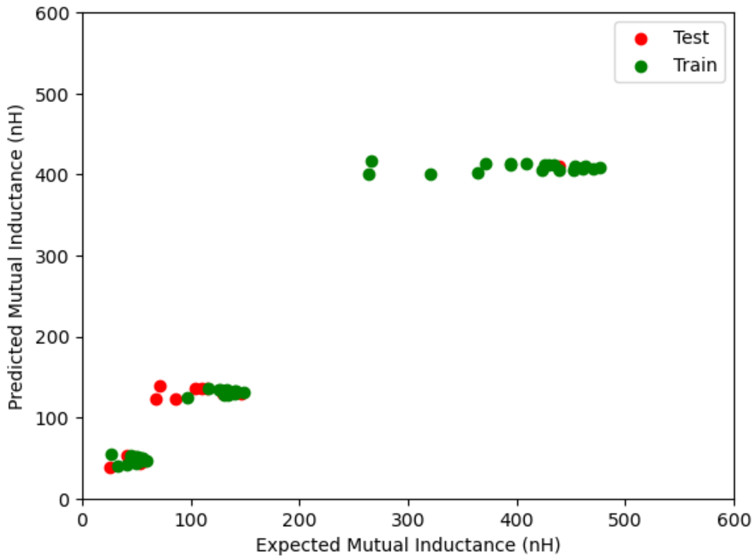

Figure 4. Predicted values compared to actual values in the Linear Regression algorithm

Support Vector Regression

In the support vector regression algorithm, the calculation accuracy is according to Table 5. It should be noted that a linear kernel is used in this algorithm.

Table 5. Evaluation of the Support Vector Regression model for calculating mutual inductance between two coils

	RMSE	MAE	R-squared
Training	797.430	176.290	0.931
Testing	46.360	567.270	0.853
Total	964.410	767.280	0.932

Figure 5 shows the predicted values compared to the actual values in the Support Vector Regression algorithm.

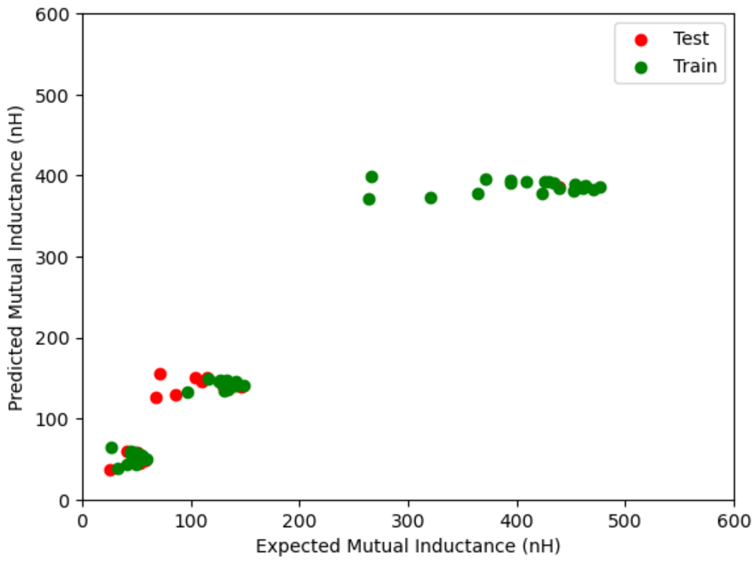

Figure 5. Predicted values compared to actual values in the Support Vector Regression algorithm.

Decision Tree Regression

In the decision tree regression algorithm, the calculation accuracy is according to Table 6.

Table 6. Evaluation of the Decision Tree Regression model for calculating mutual inductance between two coils

	RMSE	MAE	R-squared
Training	0.000	0.000	1.000
Testing	829.21	398.16	0.946
Total	1.011	164.4	0.995

Figure 6 also illustrates the predicted values compared to the actual values in the Decision Tree Regression algorithm.

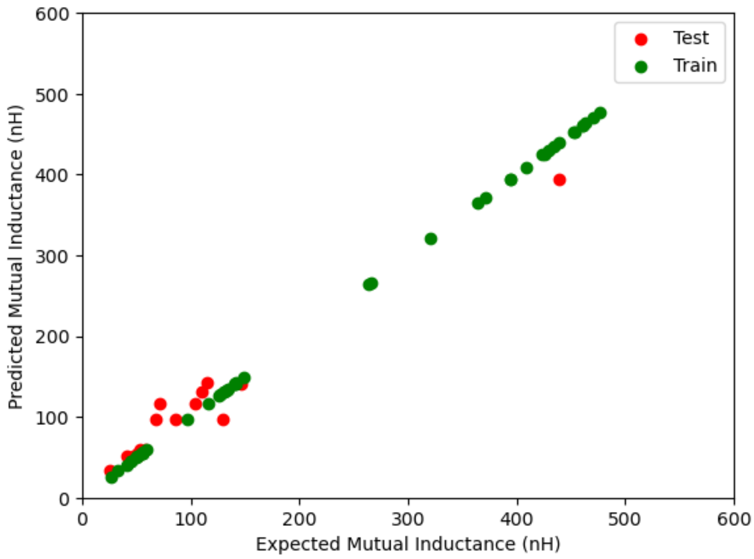

Figure 6. Predicted values compared to actual values in the Decision Tree Regression algorithm.

Artificial Neural Network

In the artificial neural network algorithm, the calculation accuracy is according to Table 7. The designed network has 4 hidden layers with 64, 32, 16, and 8 nodes. The activation function of the network is ReLU, and the Adam optimization method is used to determine weight values.

Table 7. Evaluation of the Artificial Neural Network model for calculating mutual inductance between two coils

	RMSE	MAE	R-squared
Training	0.993	0.960	1.000
Testing	100.210	951.170	0.950
Total	965.100	21.600	0.995

Figure 7 shows the predicted values compared to the actual values in the Artificial Neural Network algorithm. Figure 8 also demonstrates the structure of the designed artificial neural network.

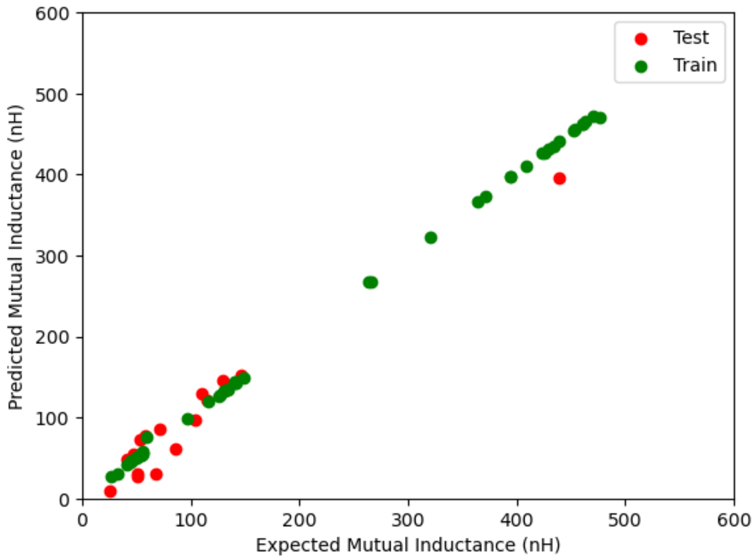

Figure 7. Predicted values compared to actual values in the Artificial Neural Network algorithm.

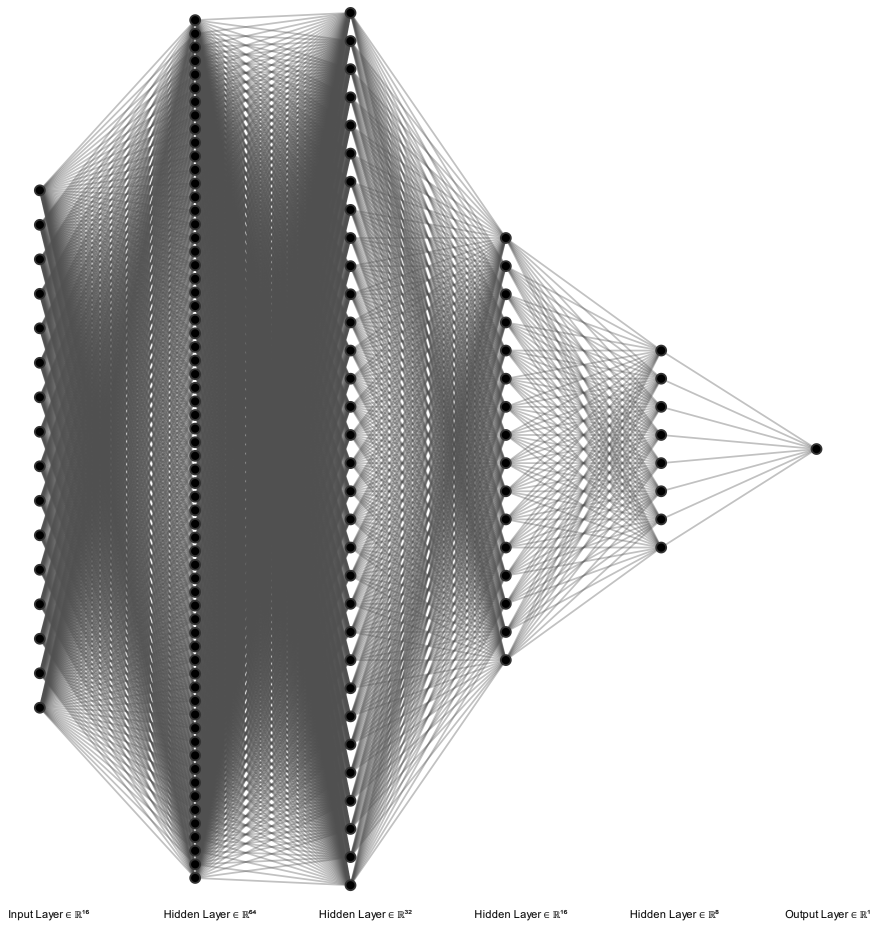

Figure 8. Structure of the designed Artificial Neural Network.

In conclusion, the best performance among the four machine learning regression algorithms, including Linear Regression, Support Vector Regression, Decision Tree Regression, and Artificial Neural Network, is attributed to the Artificial Neural Network algorithm. Each of these algorithms had calculation accuracies of 0.937, 0.853, 0.946, and 0.950, respectively, for predicting testing data.

CONCLUSION

Mutual inductance in wireless power transfer systems represents the influence of one current-carrying wire on another wire and is determined by the current and the mutual magnetic field of that system. To calculate mutual inductance in wireless power transfer systems, Maxwell's equations can be used. The complexity of this equation has led researchers to simplify it using various methods to provide simpler equations and models. Each of these equations applies to a limited range of flat coil configurations, although extensive studies have been conducted in this field.

Therefore, in the present study, an artificial intelligence and machine learning approach has been used to develop a model for calculating mutual inductance. In this study, finite element simulations were used to generate a series of data for calculating mutual inductance under various conditions. These datasets have been validated with less than a 1% relative error compared to previous literature studies. One-fourth of the datasets were kept for testing, and three-fourths were used for training four regression algorithms: Linear Regression, Support Vector Regression, Decision Tree Regression, and Artificial Neural Network. The results obtained have been evaluated using metrics like RMSE, MAE, and R-squared. Each of these algorithms had calculation accuracies of 0.937, 0.853, 0.946, and 0.950, respectively, for predicting testing data. The Artificial Neural Network exhibited the best performance among these four methods.

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