

Artificial Intelligence-Based Automatic Positioning Simulation System for Wireless Charging Coils in Electric Vehicles

Yufei Niu

*School of Mechanical and Electrical Engineering, China University of Mining & Technology-
Beijing, Beijing, China*

2310150203@student.cumtb.edu.cn

Abstract. Conventional wired charging for EVs has some major drawbacks, particularly in the areas of convenience and safety. To solve these problems, the wireless charging technology has been extensively publicized. The accurate positioning of the transmitting and receiving coils is essential for achieving high charging efficiency. In this paper, an automatic coil-positioning simulation framework based on Back Propagation (BP) neural network is proposed. Based on simulation data and artificial intelligence, we make use of data-driven BP model with current, voltage and inductance as input and coil coordinates as output to describe the nonlinear relationship between inductance and coil positioning. Then the accurate localization is achieved by dynamic coupling parameters. Simulation results show that the framework enhances the accuracy and robustness of wireless coil positioning under various operating conditions. The obtained results offer a key technology for accurate automatic alignment and efficient energy transfer in wireless electric vehicle charging. The BP network structure contains several hidden layers with dropout regularization to avoid overfitting and generalize to various coil geometries. The training used supervised dataset extracted from electromagnetic simulations with different misalignment, separation and load conditions varying operating regimes. Subsequently, cross validation verifies the high prediction accuracy and less sensitivity of measurement noise and parameter fluctuation. At the same time, the framework exhibits a certain tolerance to external disturbances (such as parasitic capacitance and coupling variations). These results validate that automatic coil positioning technology can provide a feasible solution for maintaining high-efficiency energy transfer in dynamic onboard automotive environments.

Keywords: Wireless Charging, Automatic Positioning, Backpropagation Neural Network

1. Introduction

With added benefits of being emissions and energy environmentally friendly, EVs have continuously captured an increasing share of the market and have become the most environmentally friendly mode of transportation. Current charging methods are mostly wired, which limits the flexibility of the interface, interoperability among brands, and relatively low safety performance. In contrast,

wireless charging has received increasing attention due to its potential efficiency benefits and lack of concerns related to physical contact hazards. The key principle of wireless power transfer lies in the use of electromagnetic induction or resonance to achieve contactless power transfer. In such a contactless system, the spatial alignment accuracy between the transmitting and receiving coil has a direct impact on the transfer efficiency. Misalignment between the two coils happens due to center offset or angular tilt which will lead to a nonlinear decrease of mutual inductance M , decrease the effective magnetic coupling region and increase the flux leakage. Therefore, accurate coil positioning is very important to realize high-efficiency and stable power transfer. Up to now, a large amount of research work has been conducted by researchers in academia. At the beginning, people used electromagnetic-field theory to establish the fundamental couplings between the coil and the electromagnetic-field. Then, the charging efficiency was enhanced by optimizing the coil's geometry and winding configuration as well as choosing proper core material. Recently, people focus on the real-time alignment and tilt compensation, adopt automated positioning algorithms, and use data-driven control strategies to enhance the robustness under practical variations. So far, the research is still ongoing. The combination of theory and hardware prototype will be focused on to realize scalable and reliable wireless charging for large-scale EV and wider range of markets all over the world.

As demonstrated in reference [1], decoupling between the transmitter coil array composed of four unipolar coils was achieved by incorporating an additional set of decoupling coils. The vehicle's precise position within a two-dimensional plane was determined by measuring the current differential between diagonal coils, thereby resolving the initial alignment issue during static charging. Similarly based on the concept of auxiliary coils. Reference [2] proposes a detection coil assembly comprising four helical coils for common DD/DD coupling mechanisms. This design effectively reduces mutual interference by optimising the decoupling between the helical coils and the receiving coil. With the advent of sensor technology, reference [3] examined the impact of coil angle on leakage inductance and proposed a novel tracking positioning system. The system has an infrared sensor on the transmitting coil which tracks the position of the receiving coil, and it allows the transmitting coil to move along and line up with the receiver's axis, compensating for angular offset with increased transmission efficiency. Reference [4] also used a similar cheap sensing method in their solar powered dynamic wireless charging system, multi-channel relays and infrared receiver sensors were placed inside the power transmission track and on the vehicle, and a NodeMCU microcontroller apparently evaluated logic and controlled accordingly. This shows an apparent increase in transmission power according to the position of the vehicle. Also there is great potential for sensor technology to compensate for dynamic charging systems, more so for the possibility of low-cost dynamic charging systems. Most importantly, results shown here support this notion of more accessible charging systems. Considering a broader analytical approach, reference [5] proposes a solution for dynamic wireless charging systems (DWCS) which is to support our notion of mitigating the limitations of conventional fixed charging infrastructure. This method could potentially allow electric vehicles to charge while in motion with optimization primarily based on the real vehicle position and speed.

Given the interesting results shown here, reference [6] gives issues with measuring mutual inductance, this happens in systems with positioning surfaces on the receiver side. These surfaces often have less strict design limitations. It is focused on geometry configurations which seems to be suggesting mutual inductance variations in the oscillatory motion of transmitter and receiver coil, this gives evidence to support our method of mutual inductance determination using magnetic field vector potential method. Therefore, this shows the considerable strength of the theoretical

background and design tools for wireless charging systems that can charge devices with varying orientations in practical deployment. Admittedly, the system still requires additional interpretive analysis. Another significant aspect that has been addressed in this study is the output current pulsations, which is inherent in dynamic charging. From this particular interpretative perspective, reference [7] tends to propose that a multi-coil receiver could be configured generally from the structural perspective of the receiving end. This approach greatly smooths the current fluctuations caused by the movement of the vehicle and the alternating coil switching. This way the battery life of electric vehicles will enhance with the practicality and reliability of dynamic charging systems predominantly. What tends to emerge as theoretically important is the robust design for sustained operational efficiency in dynamic environment. Reference [8] suggests a system which exhibits high sensitivity and accurate detection performance for the metal object that seems to suggest that the safety of wireless charging process could be improved. The exact mode of operation of this integration still remains to be interpreted.

Within the broad analytical framework presented in this study, the current scenario regarding the hardware as well seems to be intense; the associated costs seem to be high and feasibility seems to be noticeably limited. Due to the complexity of these theoretical relationships, this study investigates magnetic-field transmission mechanisms of multi-parameter varying environments with considerable nonlinearities and other complicated features--which is highly important in this study--by modeling concrete charging situations in the simulation platform of COMSOL Multiphysics simulation software to obtain mutual inductance M corresponding to different coil positions. Based on the enriched information, the model preliminarily proves its possibility to identify unknown receiver coil positions with high accuracy and good robustness and may even bring fundamental improvements to the whole performance and robustness of the wireless charging system in the future. As shown in the above analytical results, the dual advantages of it are worth noting. Based on above discussion, the method is also expected to be robust under realistic tolerances and various conditions.

2. Physical modelling of coil positioning systems

In this paper, we discuss an LCC-LCC compensation topology. The aim of this study is to reveal the essence of coil position. The topology is robust. It is robust even under severe LCL-LCL conditions. The circuit can satisfy both constant voltage and constant current requirements. It may even satisfy much higher efficiency. It is worthwhile to further study it. In addition, we further analyze the relationship between coil displacement and measurable electrical parameters. These relationships are not simple. But they offer new insights into the hidden system parameters.

What appears to warrant further interpretive consideration here is how the circuit model and what appears to be the mutual inductance equivalent circuit are ostensibly illustrated in Figure 1.

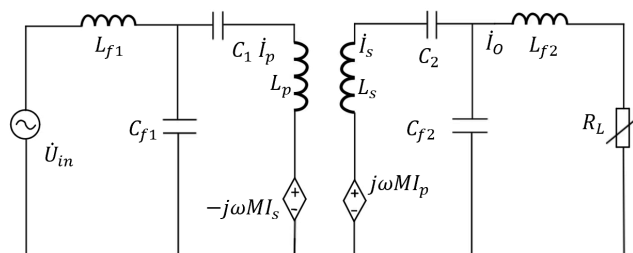


Figure 1. LCL-LCL wireless coil power transmission compensation topology

Calculation of reflection impedance for the primary and secondary coil segments give the results below.

$$Z_{RF} = \frac{\omega^2 M^2}{Z_R} \quad (1)$$

Where ω is fixed at the operating frequency, and Z_R represents the self-impedance of the secondary coil.

Through tuning calculations for the coil on the two sides, the imaginary part of the input impedance is eliminated, and a purely resistive impedance for stable and efficient power transmission is obtained.

$$\begin{cases} \omega L_{f1} = \frac{1}{\omega C_{f1}} & \omega(L_p - L_{f1}) = \frac{1}{\omega C_1} \\ \omega L_{f2} = \frac{1}{\omega C_{f2}} & \omega(L_s - L_{f2}) = \frac{1}{\omega C_2} \end{cases} \quad (2)$$

When the system is resonance, the input current of the primary coil and the load-side output current can be illustrated by equations below:

$$\begin{cases} I_{in} = \frac{U_{in} M^2 R_1}{(\omega L_{f1} L_{f2})^2} \\ I_{out} = \frac{U_{in} M}{j\omega L_{f1} L_{f2}} \end{cases} \quad (3)$$

With this analytical method, Equation. (3) reveals the hidden relationship below: with the certain operating condition, I_{out} is proportional to M . More importantly, as the relationship is complicated, M is actually primarily decided by the relative spatial position of the transmitter and receiver coil. Neumann's formula illustrates this geometric relationship of magnetic coupling. This provides a theoretical basis for a critical conversion: changing spatial positioning problems into electrical measurement problems. Specifically, any coil displacement will change the value of M , and then change the value of I_{out} in the linear operation area. So, if we monitor parameters like I_{out} or input impedance, we can reliably infer the value of M with different load conditions.

Finally, the following conclusion can be reached: Mutual inductance M plays an important role as the bridge connecting geometric space and electrical quantity in the data-driven localization of the coil. M is calculated based on Neumann's formula as follows:

$$M = \frac{\mu_0}{4\pi} \oint_{C_1} \oint_{C_2} \frac{dl_1 \cdot dl_2}{|r_1 - r_2|} \quad (4)$$

The relationship between the positioning of coil and mutual inductance in the wireless charging system is nonlinear and complicated. Methods based on electromagnetic field calculation can hardly obtain analytical solutions because the integral will be complicated when they are expressed analytically. Especially, the expression of vector and inverse distance will be complicated. Usually, the method establishes the model based on the ideal assumption. However, the assumption may not be valid in the real scene. The wire thickness in practical application, the existence of ferromagnetic objects, and the side effect of high frequency may cause the deviation from the model and then decrease the accuracy of the model. Faced with this situation, artificial intelligence plays an

important role. Backpropagation neural network has the advantage of strong prediction, which shows potential in accurately predicting the optimal positioning of the wireless charging coil of electric vehicle. This is a breakthrough in solving the above problems.

3. Analysis of the BP localization algorithm in coil positioning systems

With the rapid development of information technology, the collection, processing and modeling of data have become more efficient, which is helpful for the data collection of wireless charging localization. BP neural network has the ability of nonlinear mapping, self-learning and generalization. The BP neural network is called so because its neurons are arranged in layers as shown in the input layer, hidden layer and output layer. The data goes through these layers and is gradually adjusted step by step to obtain the output. Subsequently, the network would compare its output and target. After comparison, the network adjusts its parameters by using a learning method based on gradients, which is called backpropagation. That is to say, when the relationship between input and output is undefined, the BP network can still be used to model and predict system output. Therefore, the BP network is very suitable for precise localization and performance estimation. A diagram illustrating the structure of a BP neural network is provided in Figure 2.

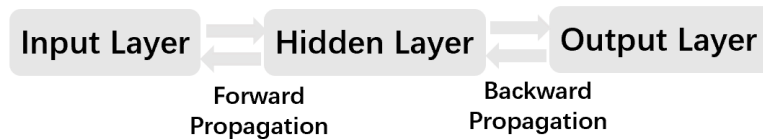


Figure 2. BP neural network structural model

Selecting appropriate feature neurons because these feature neurons impact the ability of the model to learn data patterns correctly.

features that have low noise make learning more efficient, while high-noise or redundant features can slow down learning and increase the likelihood of convergence problems. This highlights the critical relationship between input data attributes and training efficiency. For a backpropagation neural network with m input neurons, s hidden neurons, and n output neurons. Providing useful guidance for feature selection and design of neural network.

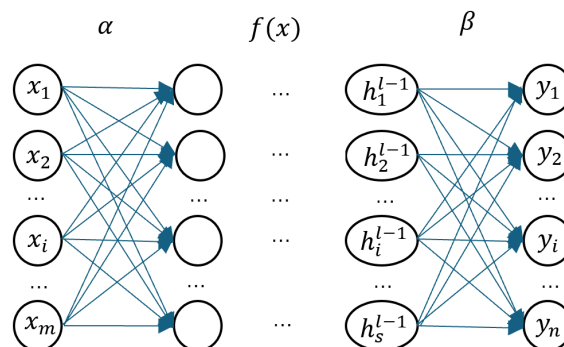


Figure 3. BP neural network mathematical model the relationship between each hidden layer is defined by the following set of equations

$$\begin{cases} y_1 = h_{11}x_1 + h_{12}x_2 + \dots + h_{1m}x_m \\ y_2 = h_{21}x_1 + h_{22}x_2 + \dots + h_{2m}x_m \\ \dots \\ y_n = h_{n1}x_1 + h_{n2}x_2 + \dots + h_{nm}x_m \end{cases} \quad (5)$$

The coefficient h in the above system of equations is the weighting factor. Next, introduce the sigmoid activation function. ($f(x) = \frac{1}{1+e^{-x}}$), As its threshold lies between 0 and 1, and the output image forms a continuous smooth curve, this facilitates the stability of the backpropagation algorithm. The sigmoid activation function applied to the weighted sum of the input layer serves to modulate the weight coefficients.

$$h_s = \frac{1}{1+e^{h_{s-1}}} \quad (6)$$

Following multiple rounds of bidirectional feedback, the output layer is represented as:

$$y_n = \beta_{1n}h_{s1} + \beta_{2n}h_{s2} + \dots + \beta_{mn}h_{sm} \quad (7)$$

These results suggest that there are nonlinear relationships in the hidden layer, which in general speak of a nonlinear black box. This makes the analytical solution a challenging endeavor. In the case of EV wireless charging square coil layouts are most predominantly preferred. What also seems important in this regard is that these are layouts that also seem to allow for what seems to be an orderly arrangement, such that coils can be installed fairly easily on to the underside of the vehicle chassis. What seems to follow from this analysis, given the multidimensional nature of the evidence, is that this consideration at least seems to aid in what may be an orderly arrangement, by seemingly addressing the analytical challenges predominantly associated with these systems. What the positioning objective seems to generally indicate, therefore, appears to be to determine what appears to represent the relative spatial relationship between the parked vehicle and the charging coil, while carefully considering what appears to be the lateral, longitudinal, and angular offsets. What appears to be the case is that within a Cartesian coordinate system, the transmitter coil midpoint ostensibly appears to represent the origin, from this particular interpretive perspective. What the receiver coil midpoint position tends to indicate, therefore, appears to be represented by what seems to be coordinates tending to correspond to what appears to be the three output-layer neurons in this BP.

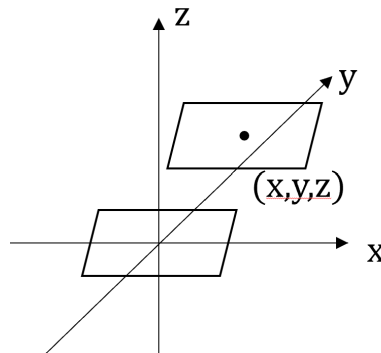


Figure 4. Coil position diagram

For input neurons, since the spatial position of the coil is related to the magnetic field strength, and the magnetic field strength can be represented by the mutual inductance M between the input and output coils, this parameter can be determined via the following relationship:

$$\psi_{sec} = MI_{pri} + L_{sec}I_{sec} \quad (8)$$

For the secondary winding with $I_{sec} = 0A$, the expression for mutual inductance M can be derived as follows:

$$M = \frac{\psi_{sec}}{I_{pri}} \quad (9)$$

Set the relative positions of the coil in three directions as output neurons, and set mutual inductance (M) as input neurons. Thus, we obtain the BP neural network model employed in the wireless charging coil positioning model for electric vehicles, as shown in Figure 5:

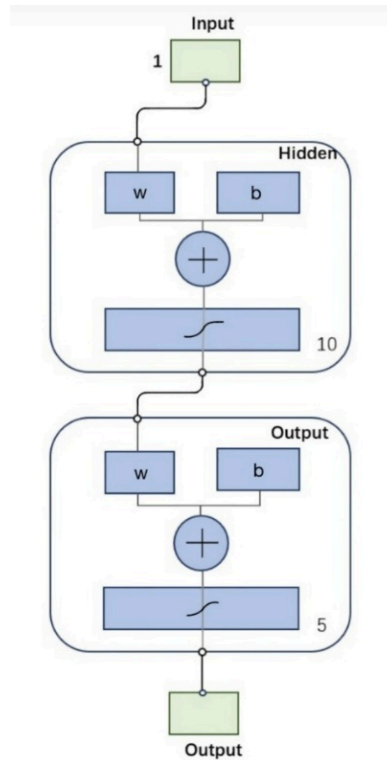


Figure 5. Wireless charging coil positioning for electric vehicles using BP neural networks

4. Simulation analysis of coil positioning system

Data for training and evaluating the BP network were generated via electromagnetic finite-element simulations conducted in COMSOL Multiphysics. Coil parameters were selected per SAE-J2954 for light-duty EV wireless charging and summarized in Table 1. The simulations spanned misalignment, horizontal and vertical gaps, and geometric variations to capture coupling dynamics under typical operating conditions. These data underpin training and validation, enabling the BP model to generalize across practical wireless charging variations.

Table 1. Wireless charging simulation coil parameter configuration

Parameters	Data
Primary coil dimensions	50cm
Secondary coil dimensions	30cm
Primary coil turns	8
Secondary coil turns	8
Primary coil thickness	8mm
Secondary coil thickness	8mm
Frequency	80kHz

What appears to be predominantly driven by considerations of space efficiency, the currently utilized charging coils tend to adopt a square disc configuration. Within this broader analytical framework, and in what seems to be accordance with established electric vehicle parameter standards, this paper appears to employ offset values ostensibly ranging from 0 to 40 cm along the x-axis (in 0.5 cm increments), 0 to 40 cm along the xy diagonal (likewise in 0.5 cm increments), and 13 to 16 cm along the z-axis (also in 0.5 cm increments). What this tends to indicate is a cumulative figure of approximately 166 data sets. What the investigation appears to indicate, the simulated coil itself seems to be represented in Figure 6:

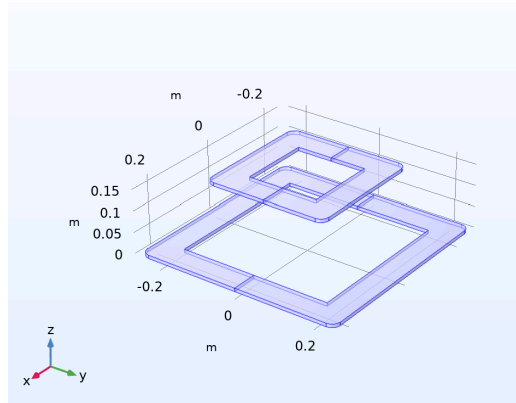


Figure 6. Coil model simulation

A key methodological step was the division of the 166-sample dataset into random subsets to ensure robust evaluation and prevent overfitting. The data was split as follows: 70% for training, 15% for validation—used to fine-tune hyperparameters—and the remaining 15% for testing the final model's generalization performance.

From the histogram of errors in Figure 7, the great majority of residuals are contained within a narrow band around zero, with no apparent systematic bias. The small bars and near-normal shapes for training, validation, and test sets may be taking aim at low error dispersion and stable predictions. This pattern is particularly pronounced for this analytic frame.

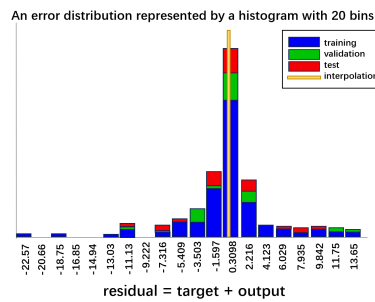


Figure 7. Neural network fitting training results

In this analytic frame, the evaluation uses mean squared error (MSE) and the coefficient of determination (R) for fit quality in cautions of what follows.

In this scenario, MSE is influenced by the magnitude of error because the more error is squared (mathematically). Therefore, the practitioner prefers a lower MSE. Further, an R that approaches 1 means that predictive power of indeed.

Figures 8 and 9 demonstrate that the model fits the data well, suggesting that this BP neural network can effectively predict the nonlinear system.

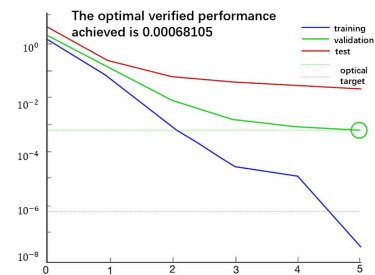


Figure 8. Mean Squared Error between actual and predicted values

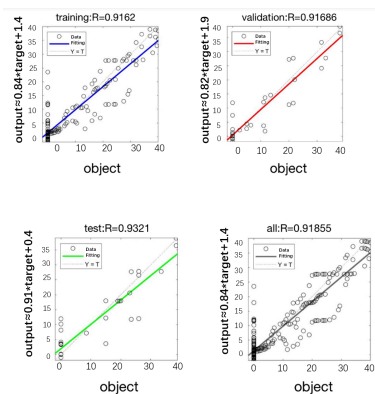


Figure 9. R-squared between actual and predicted values

5. Research outlook

Although this study seems to support what may be regarded as advances in theory and practice, what this seems to indicate most regarding these findings is that in general most aspects seem to point to the need for further optimization, ostensibly due to experimental constraints and model complexity.

What this seems to indicate regarding future developments seems to be the inclusion of multi-sensor fusion with both visual cameras and millimeter-wave radar which seems to be generally indicative of a direction toward improved measurements of coil position and status, ostensibly due to experimental constraints, thereby enriching the input information repository.

In temporal scenarios, what this seems to indicate for future developments seems to be the inclusion of CNN and LSTM combinations to capture temporal information for lightweight architectures. Furthermore, what this seems to indicate regarding future developments seems to be that transfer learning seems to improve computational efficiency and accuracy, while an expanded dataset coverage seems to conceivably improve model generalization.

What this seems to indicate overall regarding these developments seems to be that these approaches seem to be aimed at providing substantially robust performance across various operating conditions.

6. Conclusion

However, one thing for sure, the result of this study is that the relationship between the coil displacement and mutual inductance parameters is not linear at all, which is largely on the basis of electromagnetic coupling relations adopted by wireless charging systems. In this study, in this regard, they also built BP neural network model with multidimensional positional data as input and mutual inductance parameters as output inference.

In methodological aspect, simulations of coil data also demonstrated the fine tuning of several hyperparameters of the network, i.e., the depth of the network, activation functions, and learning rates to improve the accuracy of the results. As a data driven method, this method successfully avoids the process of analytical derivation and minimizes the error of previous modeling methods, which provides more accurate and reliable solution to infer the parameters of wireless power transmission system.

As shown in the final experimental results, our method greatly improves over mutual-inductance linear fitting or geometric positioning methods. Given usually horizontal offsets ($<10\text{cm}$) and vertical offsets ($<5\text{cm}$), the average positioning error is 3.5cm .

Given the above results and system challenges, the level of precision obtained is quite remarkable. Moreover, the method obtains the above-mentioned level of accuracy with a significant decrease of the computational cost, which is the clear advantage of this method. Within the above-mentioned level of precision, it works robustly in a large variety of cases.

Importantly, the results also show that the method has strong real-world deployment potential. Our results have shown that the method can be applied in a variety of existing wireless charging infrastructure and control system in a scalable way.

The results of our study have shown some evidences to support the adoption of new technical approaches to the intelligent positioning in the wireless charging systems for electric vehicles. Thus, it has shown the effectiveness of neural networks to solve nonlinear positioning problem. Within this broad framework, these approaches appear to have a promising theoretical justification. In future, the deep integration of the multimodal sensing, edge computing, and adaptive learning technologies is expected to further enhance the positioning accuracy and reliability of the wireless charging coils. All these aspects warrant further attention. Based on the above context, one may argue that at least a stronger technological basis is warranted to the commercialization and large-scale deployment of the wireless charging for electric vehicles within the proposed parameters.

References

- [1] J. Xiao, Y. Mo, S. Chen, W. Gong, X. Wu and Q. Chen, "A static wireless charging position detection system for electric vehicles based on four-coil decoupling, " 2023 IEEE 6th International Conference on Information Systems and Computer Aided Education (ICISCAE), Dalian, China, 2023, pp. 206-209, doi: 10.1109/ICISCAE59047.2023.10392728.
- [2] H. He, G. Wei, X. Zhi and Y. Zhang, "Research on Wireless Charging Localization System for Electric Vehicles Based on Auxiliary Coil, " 2024 11th International Forum on Electrical Engineering and Automation (IFEEA), Shenzhen, China, 2024, pp. 1373-1376, doi: 10.1109/IFEEA64237.2024.10878714.
- [3] V. Ramakrishnan, D. S. A, P. Balakrishnan, N. R, B. C and V. R, "Enhancement of Power Transfer Efficiency in Wireless Charging of Electric Vehicles by Positioning System with Sensor-based Technology, " 2023 IEEE International Transportation Electrification Conference (ITEC-India), Chennai, India, 2023, pp. 1-6, doi: 10.1109/ITEC-India59098.2023.10471373.
- [4] D. K. Kohar, A. K. Pati and A. Biswas, "Experimental Design of Solar Powered Dynamic Wireless Charging of Electric Vehicle, " 2023 International Conference on Smart Systems for applications in Electrical Sciences (ICSSSES), Tumakuru, India, 2023, pp. 1-5, doi: 10.1109/ICSSSES58299.2023.10199542.
- [5] D. V. Prasad, V. S. Lande, A. P. Bornare, P. B. Waghmare and M. Sujith, "Dynamic Wireless Charging System for Electric Vehicles, " 2024 8th International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, 2024, pp. 608-612, doi: 10.1109/ICISC62624.2024.00106.
- [6] I. Y. Semykina, A. -K. S. Velilyaev and N. N. Smoktal, "On the Coils' Mutual Inductance Determination of a Wireless Power Transfer System With a Quasi-Free Positioning of the Receiver, " 2025 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), Sochi, Russian Federation, 2025, pp. 344-349, doi: 10.1109/ICIEAM65163.2025.11028257.
- [7] T. D. Hiep, N. H. Minh, N. T. Diep, T. T. Minh and N. K. Trung, "Output Current Pulsation Reduction with Multi-coil Receiver in the Dynamic Wireless Charging Systems for Electric Vehicles, " 2023 12th International Conference on Control, Automation and Information Sciences (ICCAIS), Hanoi, Vietnam, 2023, pp. 133-138, doi: 10.1109/ICCAIS59597.2023.10382395.
- [8] H. Wang, Y. Wu, Z. Shen, W. Pan and Y. Zhang, "A Metal Object Detection System for Electric Vehicle Wireless Charging System Based on Strip Multi-polar Detection Coils, " 2023 6th International Conference on Energy, Electrical and Power Engineering (CEEPE), Guangzhou, China, 2023, pp. 1470-1475, doi: 10.1109/CEEPE58418.2023.10167105.