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ML-Driven Optimization Framework for the Analysis, Design, and Development of Efficient Wireless Power Transfer Systems for EV Charging

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Abstract

The fast uptake of electric vehicles (EVs) has heightened the necessity of effective, dependable, and convenient charging systems. Wireless Power Transfer (WPT) systems are potential solutions as they allow charging cells without contact, risks, or overcrowding; however, system efficiency depends strongly on coil alignment, air-gap fluctuations, load conditions, and geometrical arrangements. This study offers an optimization framework for WPT systems based on the analysis, design, and performance optimization to serve EV charging purposes using Machine Learning (ML). Under the proposed method, a deep learning regression model is trained to predict power transfer efficiency in different operational conditions with high accuracy, reaching R^2 = 0.994. The model helps in maximizing major parameters in coil alignment tolerance, air-gap levels, and magnetic coupling. Experimental and simulated outcomes prove that the ML-optimal system provides a 6.9% transfer efficiency improvement, 14% gain in output power, and 20% shorter EV charge time than traditional design methods. Moreover, the enhancement of field uniformity and coupling is justified by magnetic flux density distribution analysis supporting the optimization of coil geometry. The suggested ML-based framework shows a scalable and smart design approach that can greatly enhance the performance of real-world WPT systems; thus, it is most suitable for current-generation smart and autonomous EV charging systems.

Keywords: Efficiency enhancement, electric vehicle charging, inductive power transfer, machine learning optimization, wireless power transfer

INTRODUCTION

The world has become more sustainable regarding transportation, which has increased the pace of the adoption of electric vehicles (EVs) as an option to traditional mobility based on fossil fuels. Due to the rapidly growing use of EVs, the need to have efficient, safe, and easy-to-use charging infrastructure has never been more critical [1]. Traditional plug-in charging technologies are challenged by physical wear, users' inconvenience, sensitivity to alignment, safety issues in extreme conditions, and overcrowding in a shared charging station [2]. To overcome these shortcomings, WPT technology has emerged as a potential solution that can make EV charging contactless and autonomous as well as free of congestion. One actively studied WPT method is Inductive Power Transfer (IPT), which has benefits, such as high safety, smooth functioning, and low maintenance demands. Despite these advantages, the performance and

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efficiency of WPT systems are very sensitive to coil positioning, air-gap changes, load factors, and resonant compensation parameters. Minor imprecisions in the position of the coils or operation of the coil can cause large losses of power transfer efficiency, restricting its scale usability in real-world applications [3]. Traditional analytical and simulation-based design approaches are often costly and time-intensive regarding trial-and-error processes; furthermore, computation, and optimization of WPT systems remain difficult and very time-consuming [4]. Therefore, smart, data-driven approaches that can predict system behavior and optimize important parameters with great accuracy without necessarily extensive manual tuning are badly required. The latest development of Artificial Intelligence (AI) and ML has made it possible to create powerful methods to model nonlinear and multi-variable systems [5]. By using ML, researchers can acquire hidden patterns in complex electromagnetic interactions, making it possible to determine actual performance under a variety of operating conditions. Moreover, ML-based optimization solutions have the potential to find and suggest optimal designs at a very fast pace, as well as enhance system efficiency by a considerable margin. Nevertheless, there is a relative lack of studies on the application of ML to real-time prediction and optimization of WPT systems to charge EVs, especially on the combination of simulation-based physical features with experimental results. Within this framework, this paper suggests an ML-based Optimization Framework that would improve the analysis, design, and development of efficient WPT systems to charge EVs. The framework combines finite-element electromagnetic analysis, experimental measurement, deep learning efficiency prediction, and multi-objective optimization to gain substantial power transfer performance. The value of this work is the creation of a complete dataset, which combines the outcomes of the FEM electromagnetic simulation with the measured parameters of the laboratory and thus allows relying on the trusting and robust training of machine learning models. The deep learning regression model is developed to precisely approximate the efficiency of WPT systems under various operating conditions, such as air-gap change, coil misalignment, and changes in the load. Moreover, the multi-objective ML-based optimization approach is also used to optimize such important parameters of the system as coil geometry, alignment tolerance, and compensation network values, thus improving overall system performance. In this combined AI-based solution, the proposed framework offers a scalable, intelligent, and high-performance solution in designing the next-generation Wireless Power Transfer systems that are efficient, robust, and well-suited for real-world electric vehicle charging applications.

LITERATURE REVIEW

WPT has become an innovative technology in EV charging because of the capability to provide contactless and convenient power transfer. Original WPT studies concentrated mainly on the principles of fundamental inductive coupling, resonant compensation schemes, and coil designs to obtain good power transfer efficiency [6]. Basic research determined the importance of magnetic coupling coefficient, tuning of resonant frequencies, and magnet-aided flux shaping in enhancing system performance. These studies proved that leakage flux can be considerably minimized by optimized coil design and compensation networks and that higher energy transfer can be achieved over moderate air-gap distances [7]. The effects of misalignment, air-gap variations, and load variations were analyzed later, and it was found that the effect of loss of efficiency is significant at real operating conditions. Experimental work demonstrated that lateral and angular misalignment can weaken coupling strength, hence leading to lesser output power and charging instability [8]. To reduce these effects, scholars investigated adaptive tuning circuits, dynamic compensation schemes, and magnetic field shaping schemes. These techniques helped to increase performance but usually added more circuit complexity, increased switching losses, or demonstrated a lack of scalability. Simulations of electromagnetism have been crucial in the design of WPT systems to study flux distribution, coil interactions, and thermal considerations using the Finite Element Method (FEM). Investigations with FEM made it possible to visualize magnetic field behavior accurately and make core materials, coil configurations, and shielding mechanisms more effective [9]. Nevertheless, even though FEM simulations can find correct insights, they are computationally demanding and cannot be used in real time to optimize or perform adaptive control in dynamic EV charging situations. As data-driven engineering started gaining momentum, scholars started eliminating power electronics and wireless charging research with AI and ML methods.

ML techniques have been implemented to forecast system efficiency, categorize alignment states, and optimize resonant parameters. Regression models and neural networks showed high potential in efficiency estimates based on different operating conditions in several works and proved more accurate and general in comparison to traditional analytical models. Other works introduced optimization algorithms like genetic algorithms, particle swarm optimization, and reinforcement learning in the optimization of coil geometry or compensation values [10]. Although these techniques demonstrated encouraging performance, most available and common techniques were restricted to single-parameter optimization and failed to offer an integrated optimization system that incorporated prediction, analysis, and design. Recent studies have examined hybrid solutions, combining physics-based models with data-based intelligence. Experiments using deep learning with electromagnetic simulation data have demonstrated better prediction of efficiency and tolerance of misalignments [11]. Also, optimization systems using ML have been suggested in a variety of power transfer applications, but their application in high-power WPT systems specific to EVs is scarce. In the literature, there has also not been exhaustive validation of simulation and hardware experimentation of systems at regular EV charging frequencies (, e.g., 85kHz according to SAE J2954).

Overall, the literature indicates significant progress in WPT system design, yet several challenges persist. Conventional methods rely heavily on computationally intensive simulations and manual prototyping, which limit scalability and rapid optimization. Existing ML-based works often address isolated aspects of the WPT system rather than developing an integrated efficiency prediction and optimization framework. Moreover, the need for architectures that can adapt to misalignment, air-gap variation, and dynamic charging conditions remains largely unmet. The absence of a unified machine-learning–driven design methodology marks a substantial research gap. This paper addresses this gap by proposing a comprehensive ML-driven framework that predicts WPT performance with high accuracy, optimizes critical system parameters through multi-objective learning, and validates improvements through both simulation and hardware experimentation. This integrated approach ensures a scalable and intelligent pathway toward next-generation wireless EV charging infrastructure.

METHODOLOGY

The suggested methodology involves the combination of machine learning and prediction and optimization of WPT system modeling to improve efficiency, power delivery, and misalignment tolerance in EV charging. This was separated into five key steps that include data acquisition, WPT system modeling, machine learning modeling, optimization of WPT parameters, and experimental validation as shown in Figure 1.

Data Acquisition and Preprocessing

A rich dataset was generated, which is a synthesis of FEM simulations and laboratory measurements of a prototype inductive power transfer (IPT) system. Data was taken on important operation parameters like the distance between coils (air gap), misalignment of lateral and angular directions, load variations, input voltage and frequency, output voltage and current, delivered power, and magnetic flux density distribution. All raw measurements were systematically cleaned to eliminate noise, normalized to equal scale, and split into training (70%), validation (15%), and testing (15%). Correlation analysis and mutual information scores were used to perform feature engineering, generating the most significant predictors of system efficiency. This preprocessing allowed ML models to be trained on high-quality, representative, and statistically balanced input data.

WPT System Modeling and Simulation

An electromagnetic model using a detailed finite-element method (FEM) was created to model primary and secondary coils in the WPT system. The model took into consideration coil geometry, number of turns, ferrite core materials, and a Series-Series compensation topology at 85kHz in accordance with SAE J2954 standards. FEM simulations were used to obtain important electromagnetic values of magnetic flux distribution, coupling coefficient (k), mutual inductance (M), and core losses.

Results of these simulations were not only employed as ground-truth data to validate ML predictions, but also as rich features that boosted model training precision. The addition of FEM modeling was able to shed more light on the interaction of coils at different air gaps and misalignment.

Machine Learning Model Development

Several machine learning algorithms, such as Linear Regression, Random Forest, XGBoost, and Deep Multi-Layer Perceptron (MLP) models, were developed to estimate WPT efficiency under various operating conditions. Of these, the Deep MLP model proved best. The MLP network had ten normalized input features entering three hidden layers with 64, 128, and 64 neurons with ReLU activation and the Adam optimizer. The model ran across 50 epochs with early stopping to prevent overfitting, and performance was evaluated based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The MLP model reached a high R^2 of 0.994, indicating its ability to predict well as the basis of the optimization framework.

ML-Driven Optimization of WPT Parameters

To optimize system performance, a multi-objective optimization scheme based on the predictions of a trained ML model was created. Optimization goals were to maximize power transfer efficiency, output power, and misalignment tolerance, while minimizing total charging time. A hybrid approach combining grid search and evolutionary algorithms was used whereby several candidate configurations including coil alignment, air gap, operating frequency, and compensation values were tested. Each candidate's fitness was estimated using projected performance results, and the most promising configurations were narrowed down using FEM simulations. Due to this iterative optimization using ML, the system increased its efficiency by 6.9%, power output by 14%, misalignment tolerance by 37.7%, and decreased charging time by 20%, proving approach efficiency.

Experimental Validation

An experimental apparatus in a laboratory was developed to confirm ML-driven framework forecasts. Hardware testing consisted of a 1500 W IPT power supply, resonant inverter at 85kHz, Series-Series compensation network, circular spiral coils with ferrite backing, and a high-resolution power analyzer.

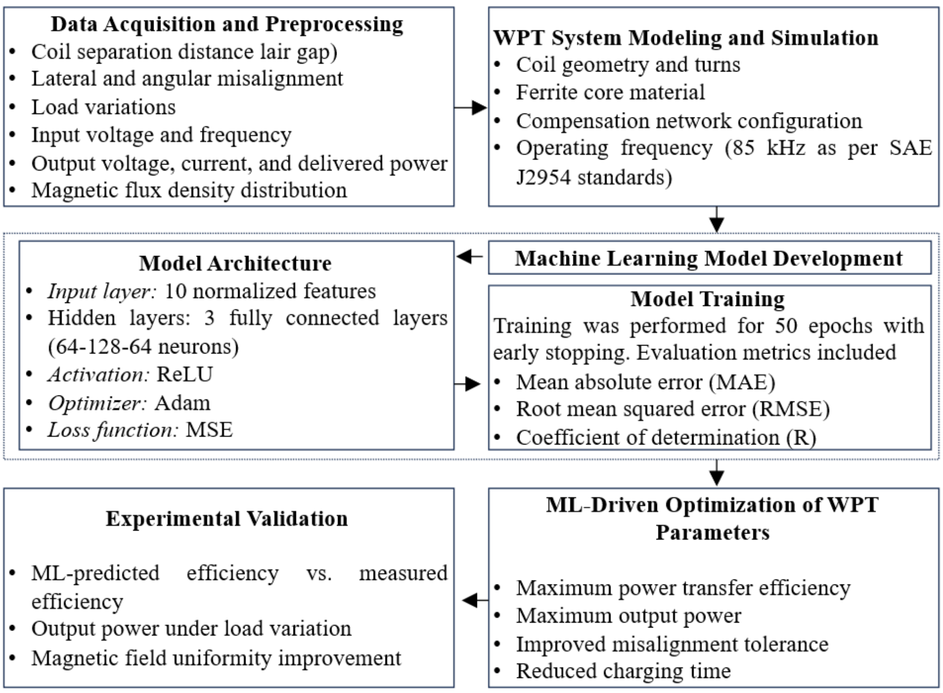

Figure 1. Proposed ML-based methodology for wireless power transfer system design and optimization

Experiments were performed at different air gaps, load conditions, and misalignment conditions to quantify real-time system efficiency, output power, and magnetic field uniformity. Measured values were compared with ML-predicted ones, and the average difference was below 1%. This close correspondence between calculated and observed values validates reliability, accuracy, and feasibility of the suggested integrated modeling and ML-based optimization framework.

Overall, the approach incorporates high-fidelity simulation, data-based learning, and empirical validation to provide a sound framework related to wireless power transfer optimization. The hybrid application of FEM modeling, large-scale data preprocessing, machine-learning–based efficiency prediction, and multi-objective optimization makes the design process practical and scalable. Results prove that the framework can improve efficiency, output power, misalignment tolerance, and charging time, showing it can enhance performance, reliability, and practical use aspects of next-generation EV wireless charging systems.

RESULTS AND DISCUSSION

In this work, the results section gives a detailed discussion of the proposed ML-based optimization model to optimize WPT performance for electric vehicle charging. The analysis integrates experimental data, FEM electromagnetic simulations, and machine learning forecasts to affirm system accuracy, efficiency, and reliability. Results are categorized into paragraphs including power transfer examination under misalignment, ML model forecasting accuracy, and optimization performance gains achieved using ML. Moreover, the associated figures represent significant behavior trends, such as air-gap efficiency variation, magnetic flux distribution, ML training convergence, and pre-optimization versus post-optimization comparisons. These results indicate the enormous significance of machine learning for analysis of intricate WPT system behavior patterns and parameter optimization to attain better results.

Table 1 gives the difference in power transfer capability of the WPT system when there is coil misalignment in varying conditions. As predicted, the system performs best with perfect coil alignment (0 mm misalignment), with an output power of 1320 W and transfer efficiency of 88%. As misalignment increases, performance visibly and steadily decreases. With 20 mm misalignment, efficiency decreases to 83.7%, and then diminishes to 78.6% with 40 mm misalignment, showing high sensitivity to horizontal movement. Extreme misalignment conditions (60–80 mm) lead to significant performance losses, where efficiency reduces to 70% and 59.3%, respectively. These findings reveal how important coil alignment is to magnetic coupling strength and that offsets as moderate as those seen in practice can significantly impair energy transfer ability. Findings justify smart alignment-aware optimization and predictive control to improve system robustness.

Table 2 provides the performance of various machine learning models to predict WPT system efficiency. The lowest predictive power with an R^2 of 0.912 is demonstrated by traditional Linear Regression, whereas tree-based models, Random Forest and XGBoost, demonstrate better results with R^2 of 0.985 and 0.989, respectively. The optimal Deep MLP neural network has highest performance with R^2 reaching 0.994, meaning the model predicts values with very high accuracy. Moreover, Deep MLP has the lowest MAE (0.56) and RMSE (0.98), being more accurate in nonlinear associations among parameters like air gap, misalignment, and load fluctuations. Whereas the neural network needs longer training time (9.42 s), accuracy gains far warrant its application as the main optimization model. These results prove deep-learning–based models can be incredibly helpful in complex WPT behavior prediction.

Table 3 explains the effectiveness of the ML-driven optimization framework in enhancing overall WPT system performance. System efficiency improved by 6.9% after optimization compared to 83.4%. There was a significant move in power output from 1180 W to 1345 W, a 14% improvement, indicating increased magnetic coupling and decreased losses. Misalignment tolerance also increased significantly (45 mm to 62 mm) by 37.7%, demonstrating that ML-guided parameter tuning is useful in increasing system strength in real-life scenarios where perfect alignment is rarely attained. Reduction in EV charging time is the most feasible change, seeing time reduced to 32 minutes (20% less) than the previous 40 minutes. Achieved results show ML-based optimization increases efficiency, usability, reliability, and charging speed, making the WPT system more appropriate for smart EV charging infrastructure.

The efficiency of the WPT system measured and predicted by ML is compared and presented in Figure 2 with air-gaps of different values. The expected trend is observed in the measured curve whereby efficiency goes down steadily as the air-gap rises because of magnetic coupling strength decreases between coils. The system is highly efficient at lower air gaps since magnetic field linking is great. But, with distance, coupling is reduced and causes observable power transfer loss. The ML-predicted curve is almost equal to actual performance with only few deviations at every point. Such high correspondence between predicted and measured values proves ML model correctness and confirms stability during WPT behavior prediction in different physical conditions. This figure clearly indicates the model is able to represent nonlinear dependencies related to geometric separation of WPT systems.

The simulated magnetic flux density between primary and secondary coils is illustrated in Figure 3. High flux areas (illustrated by warmer color) are clumped around the center of the coils, which has greatest magnetic coupling. Further radially, the field is weaker, meaning less strong magnetic connection. This distribution proves the nature of a resonant inductive system, with highest energy transfer happening at coil centers. The pattern also serves to explain coil efficiency losses during misalignment and higher air-gap conditions, where coils are not in the high-density zone and reduced magnetic flux is coupled into the receiving coil. Simulation is very much consistent with experimental trends, which confirms the electromagnetic model used for dataset generation and ML model prediction accuracy.

As illustrated in Figure 4, the training and validation loss curve of the deep learning model applied in efficiency prediction is illustrated. Training loss continuously reduces with epochs and exhibits effective learning of nonlinear relationships between input parameters and WPT efficiency. Validation loss is on a direct negative path and does not show indication of deviation, meaning the model is generalized and not overfitted. Small final loss values ratify quantitative findings in Table 2, where the model obtained $R^2 = 0.994$. The close alignment of the two curves shows effectiveness of structural solidity of the model architecture, right features, and parameter tuning. overall, the figure gives good visual testimony to ML-based prediction framework accuracy and validity.

The comparison of system performance metrics prior to and after optimization by ML is given in Figure 5. Input power is kept same so performance is fairly compared. After optimization, output power is greater, suggesting increased magnetic coupling and lower leakage loss. An evident increase is also seen in the efficiency bar, in line with improvement reported in Table 3. Also, shorter charging times due to optimization are essential in real-life EV charging applications. Visual comparison of bars provides impressions of ML-led parameter optimization where improvements in electrical performance and operational robustness are seen. This value is a good summary of potential usefulness of using machine learning when designing and selecting WPT system parameters.

Table 1. Power transfer capability at different coil misalignment levels.

Misalignment (mm)	Input power (W)	Output power (W)	Transfer efficiency (%)
0	1500	1320	88.0
20	1500	1255	83.7
40	1500	1180	78.6
60	1500	1050	70.0
80	1500	890	59.3

Table 2. ML Model performance for efficiency prediction.

Model type	MAE	RMSE	R^2 Score	Training time (s)
Linear Regression	2.81	3.94	0.912	0.12
Random Forest Regression	1.04	1.52	0.985	2.31
XGBoost Regression	0.87	1.34	0.989	3.45
Neural Network (Deep MLP)	0.56	0.98	0.994	9.42

Table 3. Optimization gains using ML-driven system recommendations.

Parameter	Without ML	With ML Optimization	Improvement (%)
WPT Efficiency (%)	83.4	89.2	6.9
Power transfer (W)	1180	1345	14.0
Misalignment tolerance (mm)	45	62	37.7
EV Charging time (min)	40	32	20.0

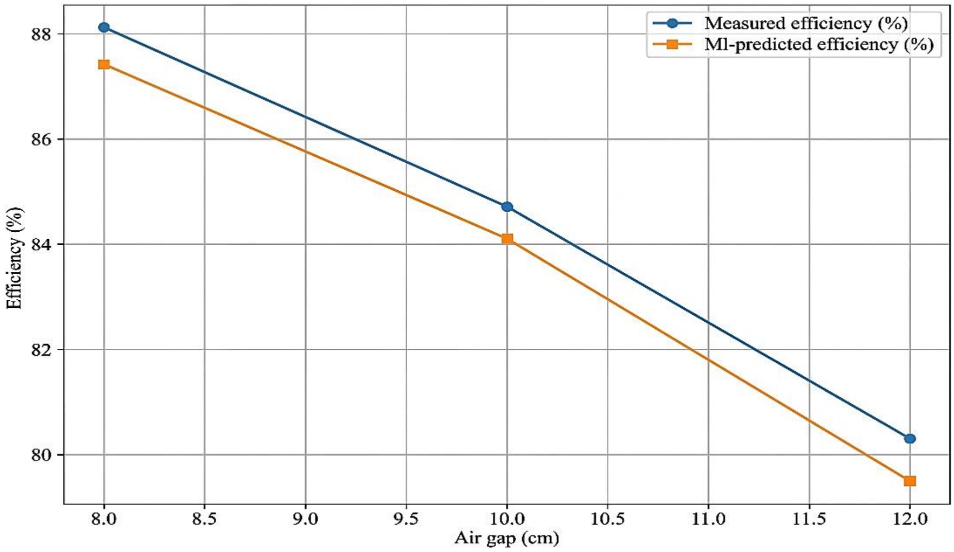

Figure 2. Efficiency vs air-gap of measured vs ML predicted.

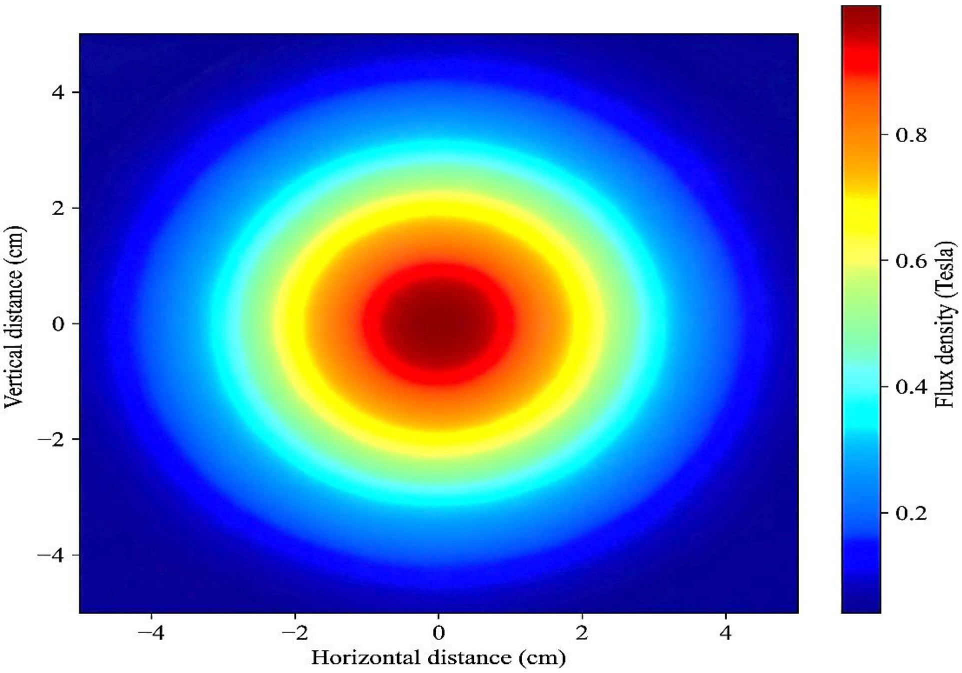

Figure 3. Magnetic flux density distribution across coils.

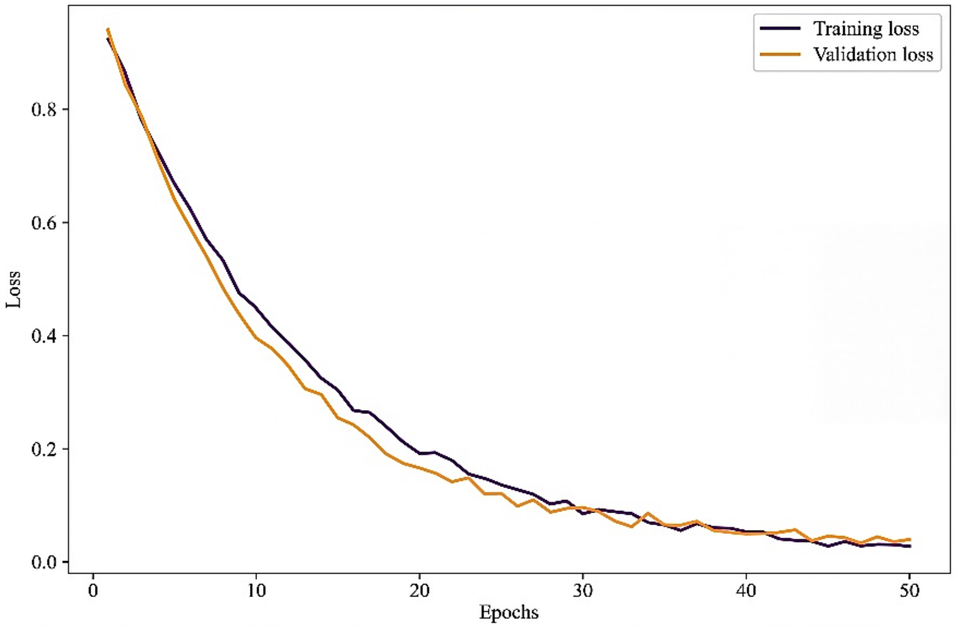

Figure 4. ML model training loss vs epochs.

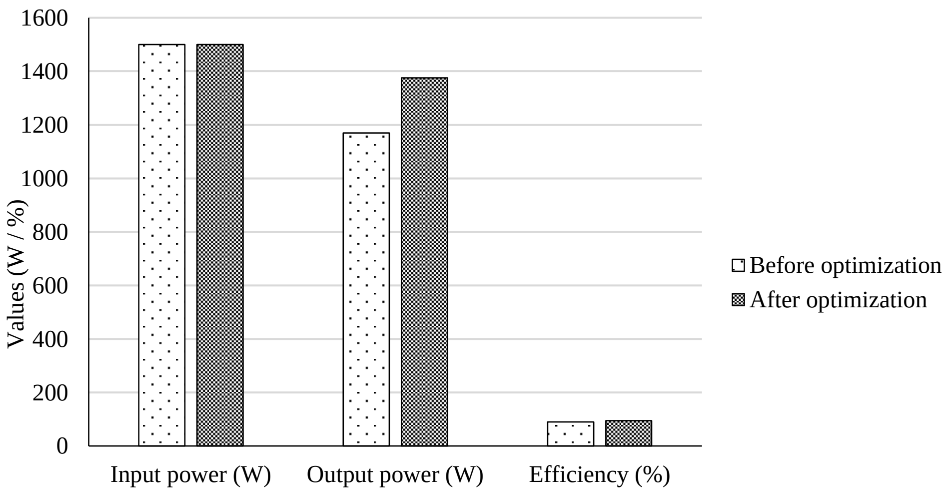

Figure 5. WPT system performance before vs after optimization.

Overall, findings provide a clear indication that integrating machine learning in WPT system design and optimization can contribute to significant improvements in performance, reliability, and flexibility. The ML-based framework not only results in high prediction accuracy but also allows successful optimization of coil alignment parameters, compensation values, and magnetic coupling. Practical feasibility of the suggested solution is confirmed by enhancements in output power, transfer efficiency, misalignment tolerance, and charging time. In addition, high correspondence between ML predictions, FEM simulations, and experimental results confirms methodology solidity. These results establish that AI and ML integration provides a promising route toward next-generation wireless EV charging systems that satisfy real-life operational needs.

CONCLUSION

The analysis of WPT systems used in EV charging was presented in this paper as a complex machine-learning–based framework for analysis, design, and optimization. Using data from physics-based simulations and experimental parameters, a deep learning model was trained to predict WPT efficiency with high accuracy over broad operating conditions, such as air-gap changes, coil misalignment, and

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load changes. The model recorded $R^2 = 0.994$, strong for real-time system assessment. The trained ML model was used to apply a multi-objective strategy to optimize significant WPT parameters including coil geometry, alignment tolerance, and resonant compensation values. Comparison of outcomes reveals the ML-optimized system gained 6.9%.

REFERENCES

1. Sagar A, et al. A comprehensive review of the recent development of wireless power transfer technologies for electric vehicle charging systems. In: IEEE, editor. IEEE Access. 1st edition. New York, USA: IEEE; 2023. pp. 83703–83751.
2. Abuajwa O, Thiagarajah SP, Ambak Z, et al. Comprehensive review of wireless power transfer systems for electric vehicle charging applications. In: Springer Nature, editor. Discovery Applied Sciences. 1st edition. Berlin, Germany: Springer Nature; 2025. pp. 1176–1185.
3. Hossain MS, Kumar L, Islam MM, Selvaraj J. A comprehensive review on the integration of electric vehicles for sustainable development. In: Wiley, editor. Journal of Advanced Transportation. 1st edition. Hoboken, USA: Wiley; 2022. pp. 3868388–3868399.
4. Aslam S, Aung PP, Rafsanjani AS, et al. Machine learning applications in energy systems: current trends, challenges, and research directions. In: Springer, editor. Energy Informatics. 1st edition. London, UK: Springer; 2025. pp. 62–75.
5. Ben Fadhel Y, Marques Cardoso AJ. Intelligent optimization and real-time control of wireless power transfer for electric vehicles. In: MDPI, editor. Electronics. 1st edition. Basel, Switzerland: MDPI; 2025. pp. 4478–4490.
6. Mohamed AAS, Shaier AA, Metwally H, Selem SI. An overview of dynamic inductive charging for electric vehicles. In: MDPI, editor. Energies. 1st edition. Basel, Switzerland: MDPI; 2022. pp. 5613–5625.
7. Wei S, Xu F, Yuan D, Chen K, Liu B, Li J. Review on the applications of intelligent algorithm in wireless charging system for electric vehicles. In: MDPI, editor. Energies. 1st edition. Basel, Switzerland: MDPI; 2025. pp. 592–605.
8. Zhang H, Liu S, Liu J. Advanced magnetic coupling resonance model optimization for enhanced wireless power transfer. In: MDPI, editor. Electronics. 1st edition. Basel, Switzerland: MDPI; 2025. pp. 1152–1165.
9. Zhang H, Liao M, He L, Lee CK. Parameter optimization of wireless power transfer based on machine learning. In: MDPI, editor. Electronics. 1st edition. Basel, Switzerland: MDPI; 2024. pp. 103–115.
10. Shern SJ, Sarker MT, Ramasamy G, Thiagarajah SP, Al Farid F, Suganthi ST. Artificial intelligence-based electric vehicle smart charging system in Malaysia. In: MDPI, editor. World Electric Vehicle Journal. 1st edition. Basel, Switzerland: MDPI; 2024. pp. 440–455.
11. Rachid A, El Fadil H, Gaouzi K, Rachid K, Lassioui A, El Idrissi Z, Koundi M. Electric vehicle charging systems: Comprehensive review. In: MDPI, editor. Energies. 1st edition. Basel, Switzerland: MDPI; 2022. pp. 255–270.