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Optimising electric vehicle wireless charging systems using neural networks to enable free-position parking

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Optimising electric vehicle wireless charging systems using neural networks to enable free-position parking

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Abstract : This study explores wireless power transfer (WPT) systems for public electric vehicle charging, focusing on optimising the transmitter design to enhance interoperability across various receiver coil geometries and alignment conditions. Due to the complex non-linear relationships inherent to WPT systems, traditional optimisation methods are computationally expensive. Therefore, this study proposes an approach using artificial neural networks (ANNs) trained on finite element method (FEM) data to develop a surrogate model of the WPT system. This model is integrated into a blackbox optimisation solver, enabling faster identification of improved transmitter designs. The proposed method achieves computational speeds 6,000 times faster than traditional FEM simulations, with post-validation on the final solutions verifying prediction errors below 0.6%. The results demonstrate a significant acceleration in the optimisation process, establishing this method as an effective framework for developing practical WPT systems for public charging applications.

Optimising Electric Vehicle Wireless Charging Systems Using Neural Networks to Enable Free-Position Parking

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1. Introduction

The public charging network for **Electric Vehicles (EVs)** will soon include **Wireless Charging**. The most popular **Wireless Power Transfer (WPT)** technique uses a magnetic field to transfer energy between inductive coils [1].

Advantages of **hands-free** Wireless Charging [2; 3]:

- **User Convenience**
- **Autonomous EV Compatible**
- **Smart Grid Compatible**

Challenges [4]:

- **Coil Misalignment** while parking.
- **Geometric Incompatibility** from different receiver coil variations.

These cause drops in the system's **Power Transfer Efficiency (PTE, η)**.

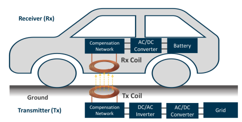


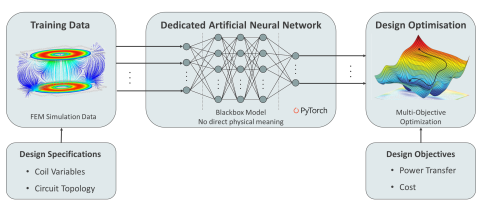
Figure 1: Wireless EV Charging System

2. Optimisation Method

Design Optimisation typically implements **Analytical Models** and **Finite Element Method (FEM) Simulations**, which are time-consuming and resource-intensive [5; 6].

This study leverages **Artificial Neural Networks (ANNs)** trained on FEM data as a **Surrogate Model**. This model is used by a **Blackbox Optimiser** to expedite the optimisation process [7].

Machine Learning Data-Driven Workflow



3. System Design

The WPT system is represented by two models:

1. **3D Model** - Magnetic Characteristics (MC), Ansys Maxwell

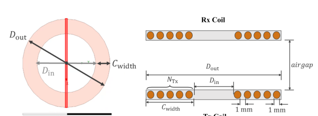


Figure 2: Ansys Maxwell 3D Model Geometry

2. **Circuit Model** - Electric Characteristic (EC), PLECS

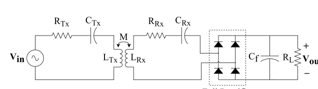


Figure 3: PLECS Circuit Diagram

4. Data Collection

A uniform random distribution of data was sampled across the continuous design space, using a Latin hypercube space-filling method [8] in pyDOE [9].

The final dataset:

- 4,125 samples points.
- 62 hours of simulation time.

5. Surrogate Model Development

The Surrogate Model uses two consecutive ANNs:

1. The **Magnetic Characteristics** (MC) Model
2. The **Electric Characteristics** (EC) Model

With each ANN Model defined as:

Table 1: ANN Model Parameters

Feature	Value
Batch Size	10
Epochs	300
Layers	3
Nodes per Layer	100

With ReLU activation functions, ADAM optimiser for back-propagation, and RMSE loss function.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Both models achieve a **final training loss** $<$ **3%** and R^2 **score** $>$ **0.85**.

Figure 4: ANN Training and Test Loss (MC)

Figure 5: ANN Training and Test Loss (EC)

6. Stochastic Scenario-based Optimisation

To determine the average system performance, each transmitter coil design is tested against 75 random receiver coil samples.

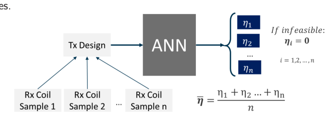


Figure 6: Stochastic Scenario-Based Optimisation

7. Blackbox Optimisation

Two optimisation algorithms were used for comparison:

1. **MADS** - Mesh Adaptive Direct Search
   Stochastic – Uniform Random Sampling (Python SciPy) [10]
2. **QMC** - Quasi-Monte Carlo
   Deterministic – Variable Mesh Grid Search (C++ NOMAD 3.9) [11]

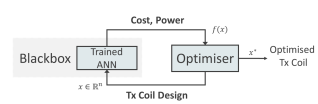


Figure 7: Blackbox Optimisation Process

Two coil misalignment ranges were also compared:

Table 2: Receiver Coil Misalignment Ranges

Misalignment Range	x-axis	y-axis	z-axis
SAE J2954 [12]	$\pm 100mm$	$\pm 75mm$	$100mm - 250mm$
Real-world [13]	$\pm 400mm$	$\pm 800mm$	

8. Optimisation Results

The Pareto front plots show the impact of misalignment range on transmitter performance. In both cases, coils with fewer turns and mid-size outer diameters have the highest average performances.

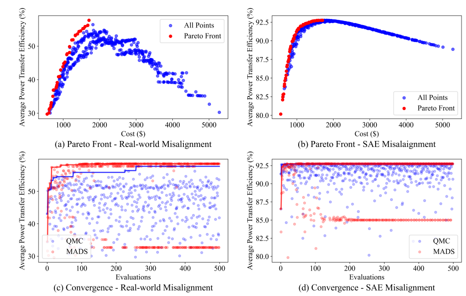


Figure 8: Blackbox Optimisation Results

As shown above, the MADS algorithm converges with fewer evaluations, outperforming the QMC algorithm.

9. Post-Validation

The best transmitter designs from the optimisation stage were re-simulated to confirm the error of the ANN.

Table 3: Post-validation Results

Misalignment Range	Optimal Tx Coil Design		Average PTE		
	Diameter (mm)	Turns	ANN (%)	FEM (%)	error (%)
SAE J2954	718.1942	35.5129	58.5129	59.0228	0.5099
Real-world	700.3000	35.9696	92.7521	93.3353	0.5832

10. Contribution and Future Work

The proposed design optimisation framework is:

- **6,000 times faster** than traditional FEM simulations
- High accuracy with **prediction errors** $<$ **0.6%**.

The performance of the optimised transmitter coil design under:

- **SAE-defined misalignment:** Average PTE = 92.751%.
- **Real-world misalignment:** Average PTE = 58.51%, below the 85% threshold.

To address the low performance under real-world conditions, future research will focus on the development of a multi-coil transmitter system.
This research demonstrates the effectiveness of ANN-based optimisation for WPT system design, paving the way for more efficient, convenient, and adaptable public charging solutions.

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