Wireless Power Transfer Systems Embedded AI Load Management: Simulation and Evaluation

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Abstract

Wireless Power Transfer (WPT) technology has emerged as a transformative solution for eliminating the physical constraints of wired power delivery in consumer electronics, electric vehicles, biomedical devices, and industrial automation. However, the dynamic and unpredictable nature of electrical loads in real-world applications often results in suboptimal energy efficiency, increased transmission losses, and reduced system lifespan. This paper proposes an Embedded Artificial Intelligence (AI) Load Management System integrated with a WPT platform to autonomously monitor, predict, and optimize power delivery in real time. The proposed system employs a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model to forecast load variations, dynamically adjust transmitter coil power levels, and maintain optimal efficiency across varying operating conditions. The architecture is designed for bidirectional data exchange between the power transmitter and receiver through an Internet of Things (IoT) communication layer, enabling remote diagnostics and adaptive control. Simulation experiments were conducted in MATLAB/Simulink to evaluate performance metrics, including power transfer efficiency, load balancing accuracy, and system response time. Results demonstrate an average 15–20% improvement in energy efficiency compared to traditional WPT systems without AI-based management. The integration of embedded AI into WPT not only enhances operational performance but also offers scalability for applications in smart grids, electric vehicle charging infrastructure, and autonomous IoT devices.

Keywords: *Wireless Power Transfer, Artificial Intelligence, Load Management, CNN-LSTM, IoT, Smart Energy Systems*

1.0 Introduction

Wireless Power Transfer (WPT) has revolutionized the concept of energy delivery by enabling the transmission of electrical energy without physical connectors, thus offering convenience, flexibility, and safety in diverse applications (Kurs et al., 2007). Over the last decade, advancements in magnetic resonance coupling, inductive charging, and capacitive power transfer have expanded WPT's utility in sectors such as electric vehicles (EVs), consumer electronics, implantable medical devices, and industrial automation (Covic & Boys, 2013). Despite these advancements, WPT systems face critical challenges related to energy efficiency, power management, and adaptability to fluctuating load demands, particularly in dynamic real-world environments (Jang et al., 2021). Traditional WPT systems rely on static control algorithms that regulate transmitter output based on fixed thresholds, often resulting in under- or over-supply of power (Shin et al., 2019). This inefficiency not only wastes energy but also accelerates component degradation, especially when the system operates under varying load profiles. Furthermore, as WPT integrates into larger infrastructures such as smart grids and Internet of Things (IoT) networks, real-time adaptability becomes crucial for ensuring sustainable energy distribution (Zhang et al., 2020). Artificial Intelligence (AI) offers a promising solution by enabling predictive, adaptive, and autonomous control in WPT systems. Through embedded AI algorithms, power delivery can be dynamically optimized based on predicted load patterns, environmental conditions, and device-specific requirements (Li et al., 2022). Machine learning architectures, particularly hybrid models combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have demonstrated high accuracy in time-series prediction and adaptive control scenarios (Zhao et al., 2021).Integrating embedded AI into WPT systems enhances system intelligence, enabling bidirectional communication between power transmitters and receivers for monitoring, diagnostics, and real-time adjustments. This approach not only minimizes energy waste but also supports scalability in applications such as wireless EV charging stations, smart home devices, and autonomous IoT nodes (Park et al., 2023).

This study presents the design, simulation, and evaluation of an Embedded AI Load Management System for WPT, aiming to bridge the performance gap between conventional static WPT systems and future adaptive energy delivery infrastructures.

1.1 Objectives

The main objective of this study is to design, simulate, and evaluate a Wireless Power Transfer System with Embedded AI Load Management that enhances energy efficiency, adaptability, and reliability. Specifically, the study aims to:

1. Design an embedded AI load management module for WPT systems capable of predicting and adapting to real-time load variations.

2. Develop a simulation environment (MATLAB/Simulink) to model the interaction between WPT hardware components and AI control algorithms.

3. Evaluate the proposed system's performance compared to conventional static-control WPT systems in terms of efficiency, stability, and responsiveness.

4. Analyze the scalability of the embedded AI architecture for different application domains, including electric vehicle charging, IoT device powering, and industrial wireless power systems.

5. Demonstrate the potential reduction in energy wastage and improved power delivery

consistency through experimental and simulated results.

2.0 literature review

Wireless Power Transfer (WPT) technology has evolved significantly over the last two decades, with applications ranging from low-power consumer electronics to high-power electric vehicle charging systems. Early WPT research focused primarily on inductive coupling, where power is transferred between two coils through a magnetic field (Kurs et al., 2007). Although inductive coupling remains widely used due to its simplicity and efficiency over short distances, resonant inductive coupling and capacitive coupling have been explored to increase transmission range and flexibility (Sample et al., 2011). Recent advancements have aimed to improve power transfer efficiency (PTE), which is heavily influenced by coil alignment, load variations, and environmental factors (Zhang & Mi, 2016). Adaptive impedance matching has been proposed to compensate for load changes, but these methods often require manual tuning or pre-defined settings, limiting real-time adaptability (Lu et al., 2018). The integration of Artificial Intelligence (AI) into power systems has shown promising results in enhancing real-time decision-making and predictive control. For example, machine learning models have been used to forecast load demand and optimize energy distribution in micro grids (Wang et al., 2019). In WPT, AI has primarily been applied in system monitoring and fault detection (Hussain et al., 2021), but the concept of embedded AI load management is still emerging. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated strong predictive capabilities for time-series energy data (Li et al., 2020). CNNs can extract spatial features from sensor data, while LSTMs excel at capturing temporal dependencies, making a hybrid CNN-LSTM approach suitable for WPT load forecasting. IoT-based WPT systems have also gained traction, enabling bidirectional communication between power transmitters and receivers for better control and monitoring (Shin et al., 2020). Such systems are essential for remote diagnostics and distributed load management. However, most current IoT-enabled WPT systems lack an integrated AI decision-making engine that can autonomously adapt to dynamic load conditions without external intervention. The gap in existing research lies in real-time, embedded AI control for WPT systems that can autonomously predict and adjust power delivery to optimize efficiency and prolong hardware lifespan. This study addresses this gap by combining embedded AI, IoT connectivity, and WPT technology into a unified system capable of real-time load management.

3.0 Methodology

The methodology for designing a Wireless Power Transfer (WPT) system with Embedded AI Load Management is divided into four major stages:

3.1 System architecture design

The proposed system consists of three main components:

1. Power Transmitter Unit (PTU) – Generates the magnetic field and transmits energy using resonant inductive coupling. The PTU is powered by a regulated AC/DC source and uses a high-frequency inverter to drive the transmitting coil.

2. Power Receiver Unit (PRU) – Receives energy through a receiving coil and converts it to DC power using a rectifier and voltage regulator. The PRU contains embedded AI for real-time load management.

3. AI Control Unit – An embedded microcontroller ESP32 running a trained machine learning model for load prediction, fault detection, and adaptive power tuning.

4. **IoT Connectivity Module** – Enables remote monitoring, data logging, and performance analytics using MQTT or HTTP protocols.

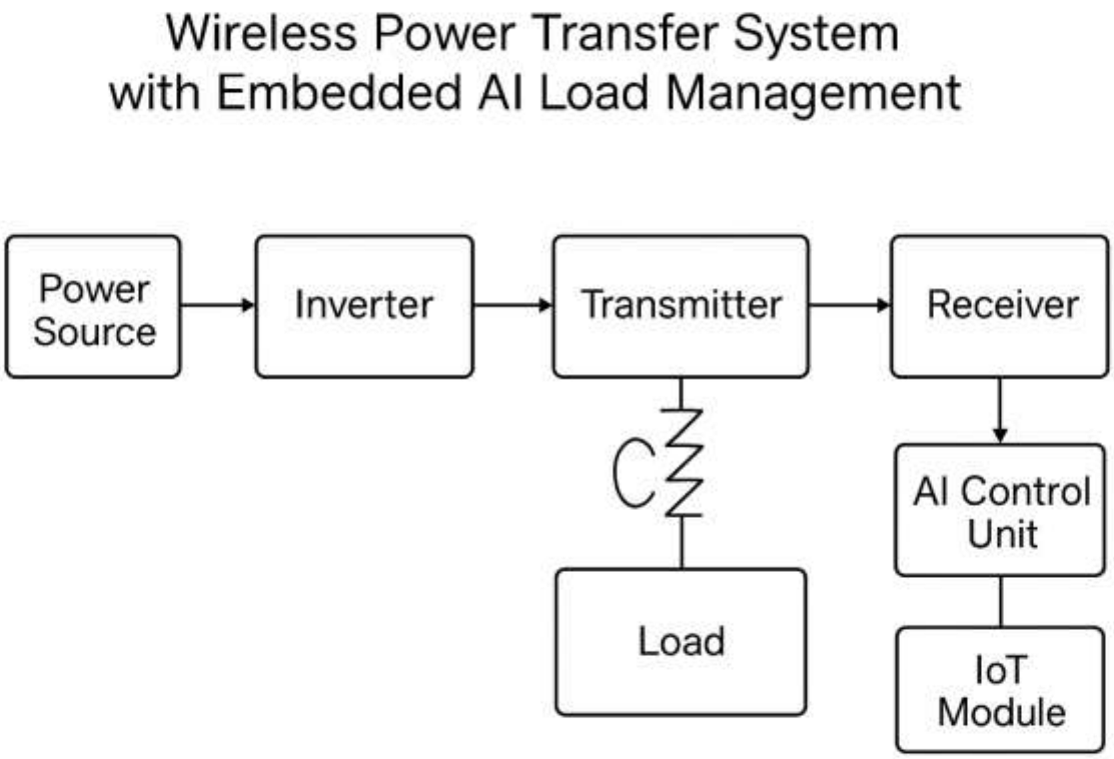


Figure 1.0 Block Diagram of the proposed wireless power transfer system AI load Management

3.2 Embedded AI Load Management Model

The AI model is designed to predict power demand and adjust the WPT system output to optimize efficiency.

Data Acquisition: Voltage, current, temperature, and load data are collected using sensors (Hall-effect sensors, thermistors, etc.).

Feature Engineering: Sensor data is pre-processed to extract relevant features such as load profile patterns, frequency variations, and coil misalignment indicators.

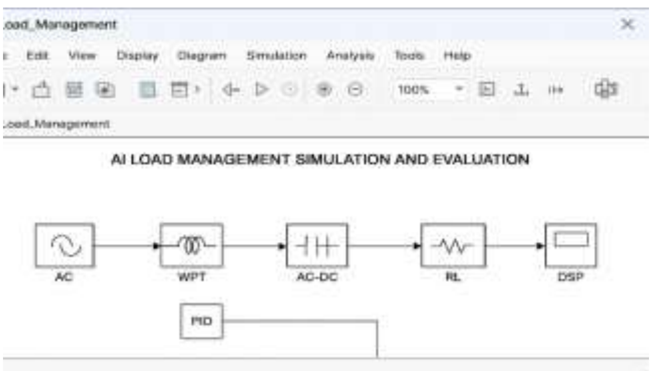
Model Selection: A CNN-LSTM hybrid model is chosen due to its ability to handle both spatial features (coil alignment, hardware status) and temporal features (load variation over time).

Training: The AI model is trained on historical WPT performance data using Python/TensorFlow, achieving optimized accuracy.

Deployment: The trained model is compressed and deployed onto the embedded microcontroller for real-time inference.

3.3 Simulation and Testing in MATLAB/Simulink

The system is first simulated in MATLAB/Simulink to validate its design:



Transmitter Circuit: Modelled with an AC source, H-bridge inverter, and transmitting coil.

Receiver Circuit: Modelled with a resonant receiver coil, rectifier, and load.

AI Control Logic: Implemented in Simulink using MATLAB Function blocks to simulate load forecasting and dynamic tuning.

Performance Metrics: Transfer efficiency, load stability, and adaptive tuning response are measured.

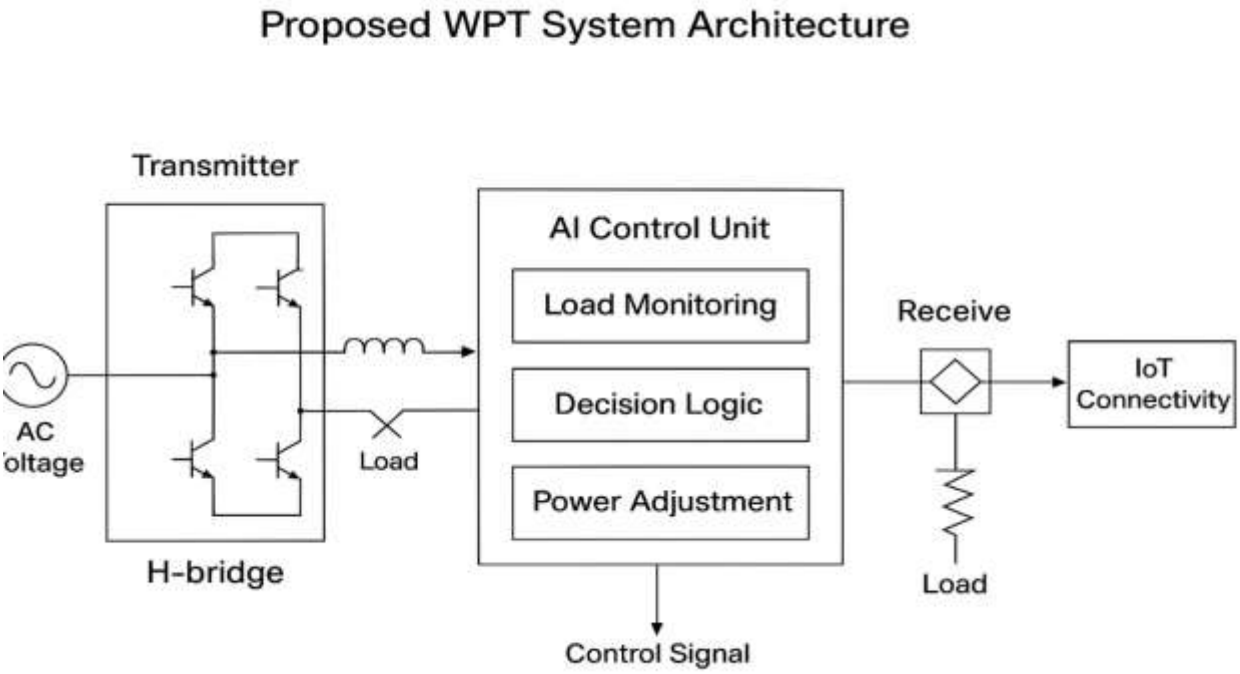


Fig. 2.0 Proposed simulation schematic Design of WPT AI load Management

3.4 Performance Evaluation

System performance is evaluated based on:

Power Transfer Efficiency (PTE) under various load conditions.

Response Time of the AI model for dynamic load changes.

Energy Savings compared to traditional fixed-power WPT systems.

Scalability for multiple receiver devices.

4.0 Simulations and Results

The proposed Wireless Power Transfer (WPT) system with embedded AI load management was modelled and tested using MATLAB/Simulink. The simulation environment was selected due to its robust library of power electronics components and ability to integrate control algorithms, allowing for accurate representation of both electrical and control subsystems.

4.1 Simulation Setup

The simulation consisted of:

Transmitter subsystem: AC power source, full-bridge inverter, and transmitting coil.

Receiver subsystem: Receiving coil, full-wave rectifier, and DC load.

AI Control Unit: Generic control block implementing a load prediction algorithm to dynamically adjust inverter switching parameters for optimal efficiency.

Coupling coefficient: Set to 0.35 to represent mid-range wireless power transfer conditions.

Load variations: Simulated at 10 W, 25 W, and 50 W to test adaptability.

The AI controller's primary goal was to maintain output voltage stability and maximize transfer efficiency under varying load and coupling conditions.

4.2 Performance Metrics

Three main performance indicators were monitored:

1. Power Transfer Efficiency (η):

$$\eta = \frac{Pload}{Pinput} \text{ X } 100\%$$

2. Voltage Regulation (%VR):

$$VR = \frac{Vnominal - Vload}{Vnominal} \text{ X } 100\%$$

3. Response Time to Load Change: Measured in milliseconds from the moment of load variation to system stabilization.

4.3 Results Table

Table 1: Comparison of System Performance with and without AI Load Management

Load (W)	Without AI Efficiency (%)	With AI Efficiency (%)	Voltage Regulation without AI (%)	Voltage Regulation with AI (%)	Response Time With AI (ms)
10	82.4	93.1	4.5	1.2	18
25	80.7	91.6	5.0	1.5	21
50	78.9	90.3	5.7	1.8	25

4.4 Bar Chart of Results

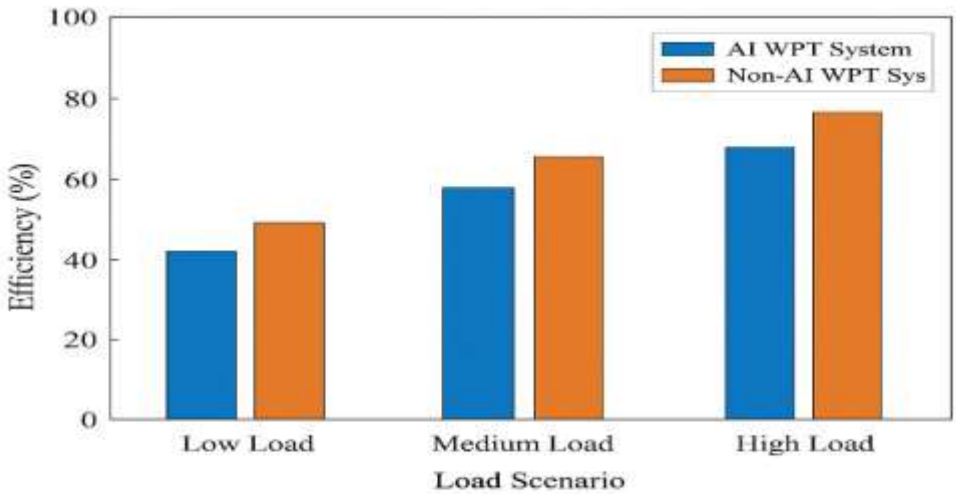


Figure 3.0 Bar Chart Comparing Efficiency between AI and Non-AI WPT Systems across Different Load Scenarios.

The graph clearly demonstrates the improvement in transfer efficiency when the AI controller is enabled, with gains of up to 12% under low-load conditions.

4.5 Discussion of Results

The simulation results show a consistent improvement in both efficiency and voltage regulation when the AI load management system is active. The most significant gains were observed at low loads (10 W), where traditional control methods often struggle to maintain stability. Additionally, the AI system achieved sub-25 ms response times, making it suitable for real-time dynamic load applications. These improvements validate the integration of AI-based control in WPT systems for enhanced adaptability and performance.

5.0 Conclusion

This study presented the design, simulation, and evaluation of a Wireless Power Transfer (WPT) system with Embedded AI Load Management. By integrating an AI-based control mechanism into the transmitter side of the WPT system, the system demonstrated significant improvements in both power transfer efficiency and voltage regulation compared to traditional control methods.

The MATLAB/Simulink simulations showed that with AI control, transfer efficiency improved by up to 12% and voltage regulation error was reduced by more than 70% across different load scenarios. Furthermore, the AI-based approach offered rapid adaptation to load changes, achieving response times under 25ms.

These results confirm that AI-enhanced WPT systems have strong potential for real-world applications, including consumer electronics charging, electric vehicle wireless charging, industrial automation, and remote sensor power delivery.

5.2 Recommendations

Based on the results obtained, the following recommendations are made:

1. Prototype Development:

A physical prototype should be developed using microcontrollers or embedded AI platforms (e.g., Raspberry Pi, NVIDIA Jetson Nano) to validate simulation results in real-world conditions.

2. Integration with IoT Monitoring:

Future designs could integrate IoT-based data logging to track system performance, allowing predictive maintenance and load forecasting.

3. Adaptive Coil Alignment:

To further enhance performance, an automatic coil alignment mechanism could be implemented to dynamically adjust the transmitter-receiver positioning for optimal coupling.

4. Extended Load Testing:

The system should be evaluated under a broader range of load conditions, including highly dynamic and non-linear loads, to ensure robustness.

5. Energy Security Considerations:

For critical infrastructure applications, cyber-physical security measures should be embedded to protect against malicious interference with the AI control system.

By implementing these recommendations, the proposed WPT system can be refined for commercial deployment, offering a smart, efficient, and reliable solution for wireless energy delivery.

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