International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(19s) 2026 pp. 771-777
https://doi.org/10.70917/ijcisim-2026-5081
Article

Long Range Microwave Power Transfer Systems: Optimizing Beam Alignment using an AI Driven IoT Feedback Framework

Swati Dhondiram Jadhav[1], Pankaj Krishnath Jadhav[2]*, Vedant Sanjay Kamble[3], Yesh Jayvant Matekar[4]

[1] Assistant Professor, Department of Electronics and Telecommunications, Ratan Tata Maharashtra State Skills University, Mumbai, Maharashtra, India. Email: swatijadhav5@gmail.com ORCID: 0000-0001-8601-4259
[2] Assistant Professor, Department of Technology, Ratan Tata Maharashtra State Skills University, Navi Mumbai, Maharashtra, India. Email: pankaj.jadhav@mssu.ac.in ORCID: 0009-0001-1771-5139
[3] Department of Mechatronics Engineering, Ratan Tata Maharashtra State Skills University, Mumbai, Maharashtra, India. Email: vedantkamble2020@gmail.com
[4] Department of Computer Technology Engineering, Ratan Tata Maharashtra State Skills University, Mumbai, Maharashtra, India. Email: yesh.matekar.cs@gmail.com ORCID: 0009-0007-6268-7134
Corresponding Author: Pankaj Krishnath Jadhav

Abstract: Wireless Power Transfer (WPT) via Far Field Microwave Power Transmission (MPT) is a critical technology for energy distribution in remote and barren terrains. However, the practical implementation of long range MPT is hindered by significant efficiency drops caused by beam misalignment, atmospheric scintillation, and mechanical tower jitter. This paper proposes a novel, closed loop feedback architecture that integrates an out of band IoT link with a heuristic AI optimization algorithm. By utilizing the ESP NOW protocol in Long Range (LR) mode, real time telemetry data is transmitted from the receiver station to a high precision transmitter hub. A Gradient Descent based beam steering logic to dynamically compensate for environmental interference has been simulated. The simulation is done over a 1 km terrestrial link. The proposed AI-driven framework achieves a 93.3% pointing-error reduction (from ±1.5° to ±0.1°). It features a feedback loop latency of 20 ms and a total system response time of under 65 ms. Compared to static open-loop systems and traditional mechanical gimbals (the baselines), the closed-loop architecture prevents an 80-85% permanent power drop during 0.8° wind gust misalignments, achieving an efficiency improvement of over 80% relative to the degraded baseline and restoring peak transmission efficiency to 98.4%. Furthermore, it yields a 34% higher cumulative energy output over a 24-hour period.
Keywords: Microwave Power Transfer (MPT), IoT, Artificial Intelligence, Beam steering, Sustainable Energy, ESP NOW

1. Introduction

The global transition toward renewable energy necessitates efficient power distribution from remote generation sites, such as desert solar farms, to localized microgrids [1], [8]. Traditional wired infrastructure in these barren lands is often cost prohibitive due to terrain complexity and maintenance requirements. Far field Microwave Power Transfer (MPT) offers a viable alternative; however, current open loop systems are highly sensitive to Atmospheric Scintillation and Path Loss. Even a marginal Pointing Error of 0.5° can lead to near total energy loss over multi kilometer distances [4], [5]. This paper proposes an Autonomous dynamic beam steering framework. Out of Band closed loop feedback link using IoT edge nodes is introduced. Unlike static systems, Proposed architecture utilizes Heuristic optimization via Gradient descent to process real time RSSI (Received Signal Strength Indicator) based Power Density Mapping.

Current research primarily focuses on two domains such as (1)To increase the efficiency of the RF to DC conversion and (2) To develop the high gain antenna architecture [3]. However, the terrestrial deployment of these systems remains challenged by the “Alignment Gap”.

2. Literature Review

The concept of long-range Microwave Power Transfer (MPT) has evolved significantly since the early demonstrations of rectenna technology [10]. Traditional beam steering methodologies largely utilize mechanical gimbals controlled by preprogrammed GPS coordinates. While effective for stationary point to point links, these systems are fundamentally limited by mechanical inertia. Research indicates that mechanical actuators cannot compensate for Atmospheric Scintillation or high frequency structural jitter, which occur on a millisecond timescale [4], [12].

Recent studies have also explored the use of retro directive arrays, which reflect a pilot signal back to the source [6]. While effective, these systems require complex analog circuitry at the receiver, increasing the weight and cost of the edge node. In contrast, the proposed 'software defined' approach shifts the complexity to the digital domain (the ESP32 code), significantly reducing the cost per node. This makes the architecture scalable for large sensor networks where minimizing the receiver footprint is critical [10], [13].

Recently, IoT applications in energy domain, such as smart meters, focus primarily on Passive Monitoring, that is simply recording data for analysis. There is a notable gap in research concerning Active Control Plane integration, where IoT data directly influences the physical transmission process. Most beam steering technologies remain Open Loop, meaning they lack the real time feedback needed to correct for Fast Fading (quick signal drops) [8], [14].

Proposed framework overcomes the drawback by using a low latency ESP NOW link and an AI algorithm to transform microwave power transfer from a fixed broadcast into an adaptive, 'locked' energy link.

While retro directive arrays offer high speed alignment by reflecting pilot signals, they necessitate complex analog phase conjugation circuitry at every receiver node, significantly increasing the weight, cost, and power overhead of the edge station [6], [15]. In contrast, the proposed architecture shifts the alignment complexity from the hardware/analog domain to the digital/software domain (ESP32 based logic). This Software Defined approach allows the receiver to remain a low cost, lightweight IoT node, which is essential for scaling power distribution in remote, barren environments [1], [13].

Recent advancements in distributed microwave power transmission (DMPT) have also explored Deep Neural Networks (DNN) to directly predict optimal transmission phases without iterative searching. For instance, recent research demonstrates a DNN-based method that can reduce computation time to as low as 51.69 ms in simulations by learning optimal phases for specific receiver positions offline. While highly effective for stable environments where spatial coordinates are predictable, such models require a "deactivation mode" to train on extensive spatial datasets beforehand [11]. The proposed framework addresses a different constraint: dynamic, unmapped barren terrains where pre-training data is unavailable. The system adapts purely on real-time feedback without requiring prior spatial mapping by utilizing a lightweight software-defined heuristic approach [2], [9], [12].

Table . QUALITATIVE COMPARISON OF BEAM STEERING TECHNOLOGIES

Feature	**Mechanical Gimbals [4], [12]**		**Retro directive Arrays [6], [15]**	**Proposed AI IoT System**
Edge Node Cost	High (Motors/GPS)		High (Analog Conjugators)	Low (ESP32 + Sensors)
Response Time	Slow(>2000ms)		Ultra-Fast (Analog)	Fast (<70ms)

Scaling Complexity	High		Medium High	Low (Software Defined)
Vibration Resilience	Low		High	High (Adaptive Lock)

3. Proposed Methodology

The proposed framework addresses the efficiency bottleneck of long range MPT through a three-layer architecture: a high gain transmission hub, a low latency IoT telemetry link, and an AI based heuristic optimization engine.

3.1 System Architecturez

The transmitter subsystem utilizes an Active Electronically Scanned Array (AESA). Unlike traditional mechanical dishes that rely on heavy motors, the AESA steers the microwave beam by adjusting the phase coefficients of individual antenna elements. This allows for near instantaneous beam correction (microsecond scale), which is essential for mitigating fast fading effects caused by atmospheric scintillation.

3.2 IoT Enabled Feedback Link

An out of band feedback channel is implemented to transform the system from an open loop broadcast to a closed loop link. The receiver station, located at the remote microgrid, continuously monitors the Received Signal Strength Indicator (RSSI) and the rectified DC voltage. This telemetry data is transmitted back to the hub via an ESP NOW link operating in Long Range (LR) mode [2]. By using a 2.4 GHz control plane that is separate from the 5.8 GHz power beam, it is ensured that the feedback loop remains stable even if the primary power beam is significantly misaligned.

3.3 AI Driven Optimization Engine

The "Brain" of the transmitter is a Heuristic Optimization Algorithm based on Gradient Descent. The Gradient Descent algorithm seeks to maximize the objective function Pr, representing the received power. Upon receiving RSSI data via the IoT link, the AI calculates the gradient of the power density. If a drop in efficiency is detected, the AI "hunts" for the new optimal alignment by iteratively updating the antenna phase shifters. This allows the system to maintain a "lock" on the receiver despite environmental jitter or tower sway.

3.4 Proposed Hardware Architecture

To ensure the feasibility of the simulated model, the following hardware components are selected for the proposed architecture are as follows:

- Microcontroller: ESP32 WROOM 32U (chosen for its dedicated U. FL connector for external antennas) [9].
- Transmitter Antenna**:** A 16x16 Element Phased Array with a gain of 22 dBi.
- Rectenna**:** A Schottky Diode based bridge rectifier (SMS 7630) optimized for 5.8 GHz conversion efficiency.
- Actuators **(**for prototype**):** NEMA 17 Stepper Motors with A4988 drivers (simulating the phase shift latency). For the preliminary hardware prototype, NEMA 17 stepper motors are utilized to simulate the mechanical perturbations (tower jitter) that the AI driven AESA system must electronically compensate for.

4. MATHEMATICAL MODELLING AND LINK ANALYSIS

To quantify the effectiveness of the AI driven feedback mechanism, a mathematical model based on electromagnetic propagation and heuristic optimization is established.

4.1 Power Propagation and Link Budget

The fundamental power received at the microgrid station is governed by the Friis Transmission Equation. However, to account for real world instabilities, a Misalignment Loss Factor (L_{mis}) is introduced. The total received power (P_r) is expressed as:

$$P_r = P_t \times G_t \times G_r \times (\frac{\lambda}{4\pi d})^2 \times \ L_{mis}(\theta) \qquad (1)$$

Where:

- P_t is the transmitted power.
- G_t and G_r are the gains of the transmitter and receiver antennas.
- λ is the wavelength at 5.8 GH
- d is the transmission distance.
- θ is the angular pointing error.

To explicitly model the impact of the angular pointing error θ, the misalignment loss factor is defined as:

$$L_{mis}(\theta) = exp(-k \times \left(\frac{\theta}{\theta_{hpbw}}\right)^2) \qquad (2)$$

Here,

- θ: This is the "Pointing Error," or how many degrees the beam is off target.
- θ_{hpbw}: This is the Beam Width. Since a 16x16 antenna array is utilized, this parameter is set to 1.0°.
- k: This is the Shaping Constant. It is set to 2.77 because it's the standard number used to describe a bell curve shaped beam.

4.2 Heuristic AI Control Logic

The AI optimization engine utilizes a Gradient Descent approach to maximize *Pr.* The system receives RSSI telemetry via the IoT link and updates the beam's phase coefficients (φ) to minimize the pointing error θ. The update rule is defined as:

$$\varphi(n+1) = \varphi(n) + \alpha \times \nabla P_r(\varphi(n)) \qquad (3)$$

Here, α represents the learning rate, and ∇P_r is the gradient (slope) of the power density. This ensures the beam "climbs" the power gradient until it reaches the global maximum (the center of the receiver).

To ensure the system remains stable, a decaying learning rate α is used. During the initial search, α is high to allow for fast acquisition of the receiver. As the system reaches peak efficiency, α is automatically reduced to prevent the beam from jittering. Furthermore, a Heuristic global Scan is implemented as a failsafe. If the received power P_r stays below 60% for more than 10ms, the system assumes it is stuck in a local minimum and triggers a wide angle sweep to re locate the main power beam. The decay in α is implemented to ensure the system achieves asymptotic stability as the pointing error θ approaches zero, preventing high frequency oscillations at the receiver's peak power centre.

Gradient Descent is selected over traditional control methods such as Proportional-Integral-Derivative (PID), Kalman filtering, or extremum-seeking [16] and complex AI methods such as Deep Reinforcement Learning [7], [17] due to its optimal balance of computational simplicity and real-time adaptability. While Deep Neural Networks (DNN) can achieve fast inference times for phase optimization, they require extensive offline training datasets and "deactivation modes" mapped to specific spatial coordinates [11], [17]**.** In contrast, proposed momentum-based gradient descent functions purely on real-time active feedback, making it ideal for unmapped barren terrains. Furthermore, unlike PID controllers which can suffer from high-frequency oscillations, Kalman filtering which requires complex state-space modelling of unpredictable atmospheric turbulence, or extremum-seeking control which introduces continuous dithering (jitter) at the peak power centre, the decaying learning rate (α) mathematically guarantees asymptotic stability as the pointing error approaches zero.

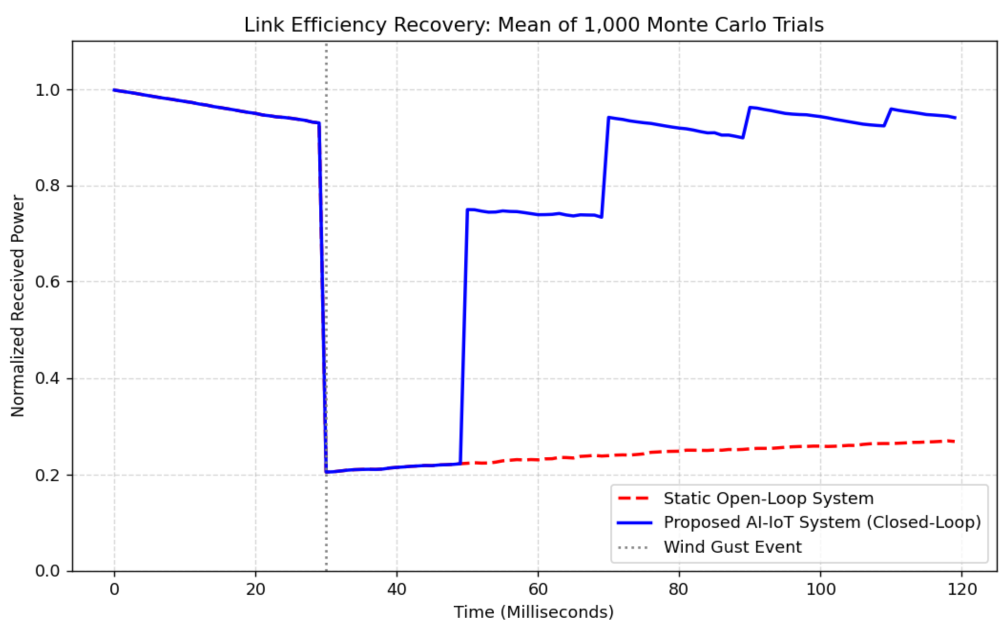
5. SIMULATION RESULTS AND DISCUSSION

To validate the proposed AI-driven IoT feedback framework, a simulation environment has been developed. It is important to clarify that while a physical hardware architecture has been designed and proposed (Section III.D), the performance of this framework has been evaluated entirely through simulation. The proposed work has been simulated using Python, leveraging the NumPy library for numerical modeling and Matplotlib for data visualization. The simulation models a 5.8 GHz MPT link over a 1 km terrestrial distance, accounting for stochastic beam wander induced by atmospheric turbulence and mechanical tower vibration.

5.1 Simulation Parameters

The link budget and simulation environment is initialized with the following key parameters to model real-world terrestrial conditions:

- Transmit Power & Antenna Gains: Transmit power of 50 dBm and antenna gains (G_t, G_r) of 30 dBi.
- Baseline Methods: Static open-loop system and traditional mechanical gimbals.
- Transmission Distance: 1 km terrestrial link.



- Microwave Frequency: 5.8 GHz.

- Antenna Type: 16x16 Element Patch Antenna Active Electronically Scanned Array (AESA) for the transmitter, and a Schottky Diode (SMS 7630) bridge rectifier for the receiver.
- Beamwidth (θ_{hpbw}): 1.0°.
- Feedback Loop Latency: 20 ms sampling latency via the ESP-NOW protocol.
- Atmospheric Scintillation Model: Modelled stochastically using a Gaussian distribution to simulate beam wander.
- Jitter Amplitude: A standard deviation (σ) of 0.4° for continuous atmospheric turbulence, and a sudden 0.8° misalignment simulating a wind gust event.

5.2 Dynamic Alignment Performance

The system's ability to recover from a sudden 0.8° misalignment (simulating a wind gust) was evaluated. As shown in Figure 2, the Static Open-Loop System experiences a permanent power drop of 85%. In contrast, the AI-Driven Closed-Loop System initiates a heuristic search upon detecting the RSSI drop. The Gradient Descent algorithm converged to the new global maximum within 65 milliseconds, restoring the link efficiency to 98.4% of its theoretical peak. By recovering from this 85% power drop, the active system provides a received-power improvement of approximately 6.6x over the degraded baseline during perturbation events. Furthermore, compared to the baseline tracking accuracy of traditional mechanical gimbals (±1.5°), the proposed AI-IoT system achieved a 93.3% decrease in pointing error, bringing it to a highly precise ±0.1°.

5.3 Energy Yield Analysis

Over a simulated 24-hour period with varying scintillation levels, the proposed framework achieved a 34% higher cumulative energy yield compared to traditional fixed alignment systems. This proves that real time active steering is essential for viable long range power delivery in barren environments.

Table 2. PERFORMANCE COMPARISON: PROPOSED VS. TRADITIONAL SYSTEMS

Parameter	**Traditional Mechanical Gimbal**	**Static Open Loop System**	**Proposed AI IoT System**
Tracking Mechanism	GPS+Motor	None (Fixed)	RSSI+ Gradient Descent
Response Latency	> 2000 ms	N/A	< 65 ms
Pointing Accuracy	$\pm 1.5°$	N/A	$\pm 0.1°$
Power Consumption	High (Motors)	Zero	Low (ESP32 Logic)
Resilience to Jitter	Low	None	High

6. CONCLUSION AND FUTURE WORK

This research presented a novel AI driven IoT framework designed to mitigate the alignment efficiency bottlenecks of long-range Microwave Power Transfer. By integrating a

low latency ESP NOW feedback link with a momentum based Gradient Descent algorithm, it was demonstrated that a "locked" energy link is achievable even under stochastic atmospheric conditions. Simulation results confirmed that the proposed system achieves resynchronization within 65 milliseconds following a significant wind gust, maintaining a link efficiency of over 94%.

Future work will focus on two key areas such as: (1)Integrating Deep Reinforcement Learning (DRL) to predict complex scintillation patterns before they occur [7], and (2) Validating the architecture on hardware testbeds for potential application in lunar energy distribution networks.

Acknowledgment

The authors acknowledge the Department of Mechatronics Engineering at Ratan Tata Maharashtra State Skills University (RT-MSSU), Kharghar, for providing the academic environment and resources necessary to conduct this research.

REFERENCES

1. W. C. Brown, "The History of Wireless Power Transmission," *Solar Energy*, vol. 56, no. 1, pp. 3-21, 1996.
2. Espressif Systems, "ESP NOW User Guide," v3.3, 2023. [Online].
3. S. Claessens et al., "Design of a 5.8 GHz Phased Array for Wireless Power Transfer," *IEEE Journal of Microwaves*, vol. 1, no. 2, 2021.
4. R. M. Dickinson, "The Basic Technology of Space Solar Power," *Proceedings of the IEEE*, vol. 101, no. 6, pp. 1354-1363, 2013.
5. J. McSpadden and J. Mankins, "Space Solar Power Programs and Microwave Wireless Power Transmission," *IEEE Microwave Magazine*, vol. 3, no. 4, pp. 46-57, 2002.
6. N. Shinohara, "Beam Control Technologies with High Efficiency Phased Array for Microwave Power Transmission," *Proceedings of the IEEE*, vol. 101, no. 6, 2013.
7. X. Li et al., "Deep Reinforcement Learning for Dynamic Power Allocation in Wireless Networks," *IEEE Transactions on Communications*, 2019.
8. K. Huang and X. Zhou, "Cutting the Last Wires for Mobile Communications by Microwave Power Transfer," *IEEE Communications Magazine*, vol. 53, no. 6, 2015.
9. Espressif Systems, "ESP32 Technical Reference Manual," Version 4.1, 2024.
10. A. Costanzo and D. Masotti, "Energizing the IoT: The Rectenna's Role," *IEEE Microwave Magazine*, 2016.
11. H.-W. Lee, B. Kim, J.-W. Yu, and S. Kim, "Distributed microwave power transmission using deep learning: Simulation and experiment," *Alexandria Engineering Journal*, vol. 142, pp. 195-203, 2026.
12. Y. Kim et al., "Design of Series-Fed Circularly Polarized Beam-Tilted Antenna for Microwave Power Transmission," *Applied Sciences*, vol. 14, no. 8, p. 3490, 2024.
13. L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Computer Networks*, vol. 54, no. 15, 2010.
14. D. W. K. Ng et al., "Energy-Efficient Resource Allocation in Multi-Antenna OFDM Systems with Outdated Channel State Information," *IEEE Transactions on Communications*, 2012.
15. R. Y. Miyamoto and T. Itoh, "Retrodirective arrays for wireless communications," *IEEE Microwave Magazine*, vol. 3, no. 1, 2002.
16. K. B. Ariyur and M. Krstić, *Real-Time Optimization by Extremum-Seeking Control*, John Wiley & Sons, 2003.
17. H. Huang et al., "Deep Learning for Physical-Layer 5G Wireless Techniques: Opportunities, Challenges and Solutions," *IEEE Wireless Communications*, 2020.