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AI-ENABLED WIRELESS POWER TRANSFER ARCHITECTURES FOR SUSTAINABLE IoT ECOSYSTEMS

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Abstract

The proliferation of Internet of Things (IoT) devices in smart cities, industrial automation, and healthcare monitoring has created an unprecedented demand for sustainable energy solutions. Traditional battery-powered IoT deployments face significant challenges including limited operational lifespan, environmental hazards from battery disposal, and high maintenance costs associated with manual replacement. This study presents a novel AI-enabled wireless power transfer (WPT) architecture that leverages machine learning algorithms to optimize energy delivery, predict device energy demands, and autonomously manage power distribution across large-scale IoT ecosystems. We propose a three-tier architecture comprising (1) an intelligent RF energy harvesting layer with adaptive rectenna arrays, (2) a reinforcement learning-based power allocation engine, and (3) a cloud-native energy orchestration platform. Through extensive simulation and prototype validation across three distinct IoT scenarios smart agriculture, industrial asset monitoring, and wearable health networks we demonstrate that the proposed system achieves 78.4% energy transfer efficiency (a 34% improvement over conventional directional WPT), reduces network energy waste by 62%, and extends device operational lifespan by 4.7× compared to battery-dependent counterparts. Our findings establish that AI-driven dynamic optimization of WPT parameters including beam-forming angles, transmission power, and duty cycling enables scalable, sustainable IoT deployments that were previously infeasible. This research contributes to the emerging field of intelligent energy harvesting networks and provides a replicable framework for next-generation green IoT infrastructure.

Keywords:

Wireless power transfer, Internet of Things, machine learning, energy harvesting, sustainable computing, reinforcement learning, smart cities, green communication.

1. Introduction

The Internet of Things (IoT) has emerged as a transformative paradigm, with projections indicating over 75 billion connected devices by 2030 (Statista, 2023). These devices permeate critical infrastructure sectors including smart agriculture, healthcare monitoring, industrial automation, and environmental sensing. However, the energy requirements of this massive device ecosystem present a fundamental sustainability challenge. Conventional IoT deployments rely predominantly on electrochemical batteries, which impose severe constraints on operational longevity, introduce environmental toxicity through heavy metal leakage, and necessitate labor-intensive maintenance protocols (Bi et al., 2019; Ku et al., 2016).

Wireless Power Transfer (WPT) technologies encompassing inductive coupling, magnetic resonance, radio frequency (RF) radiation, and laser-based systems offer a compelling alternative by enabling contactless energy delivery to distributed sensor nodes (Tran et al., 2021). Among these, RF-based WPT has garnered particular attention for IoT applications due to its ability to transmit energy over longer distances (up to several meters) and its compatibility with existing communication infrastructure (Kim et al., 2023). Nevertheless, conventional RF-WPT systems suffer from fundamental inefficiencies: path loss increases with the square of distance, misalignment between transmitter and receiver significantly degrades coupling efficiency, and static power allocation fails to account for dynamic device energy demands (Lu et al., 2021).

The integration of Artificial Intelligence (AI) into WPT systems represents a paradigm shift with transformative potential. Machine learning algorithms can model complex, non-linear relationships between environmental variables (device position, obstacle density, interference patterns) and optimal power transfer parameters. Reinforcement learning (RL) agents can learn optimal charging policies through continuous interaction with the environment, adapting to time-varying network conditions without explicit programming (Zhang et al., 2022). Deep neural networks can predict device energy consumption patterns, enabling proactive rather than reactive power allocation. Despite this promise, the systematic integration of AI across the entire WPT-IoT stack from physical layer beam-forming to network-wide energy orchestration remains underexplored.

1.2 Literature Review and Gaps in Knowledge

Recent advances in WPT for IoT have followed three primary trajectories. First, hardware-centric research has focused on improving rectenna efficiency through metamaterial substrates, multi-band harvesting, and impedance matching networks (Tran et al., 2021). Second, protocol-level studies have examined medium access control (MAC) protocols for wireless charging, including polling-based and random-access schemes (Bi et al., 2019). Third, optimization-theoretic approaches have formulated WPT scheduling as convex optimization problems, solvable through standard numerical methods (Lu et al., 2021).

Existing WPT-IoT architectures predominantly employ fixed transmission parameters (power, frequency, beam direction) determined during deployment. These static configurations cannot adapt to dynamic changes in device density, mobility patterns, or environmental obstacles. While Zhang et al. (2022) proposed adaptive power control, their approach relied on simplified heuristic rules rather than learning-based optimization, limiting scalability.

Current research typically addresses individual WPT components in isolation either rectenna design, beamforming algorithms, or network protocols without considering cross-layer interactions. The energy efficiency gains achievable through joint optimization across physical, network, and application layers remain unquantified.

Most AI-WPT implementations rely on cloud-based processing, introducing latency that precludes real-time adaptation for mobile IoT devices. Edge-native intelligence that balances computational constraints with optimization responsiveness has not been systematically investigated. Prior studies predominantly evaluate WPT systems using technical metrics (efficiency, received power) without considering lifecycle environmental impact, carbon footprint, or circular economy principles. The sustainability implications of large-scale AI-WPT deployments remain poorly characterized.

Existing validation is typically confined to single application scenarios (e.g., only smart homes or only healthcare), limiting understanding of how environmental heterogeneity affects system performance. This study addresses these gaps through a unified, cross-layer AI-WPT architecture validated across multiple IoT domains with comprehensive sustainability assessment.

1.3 Research Objectives, Questions, and Hypotheses

To design, implement, and evaluate an AI-enabled wireless power transfer architecture that autonomously optimizes energy delivery across heterogeneous IoT ecosystems while minimizing environmental impact and operational costs.

Research Questions:

1. RQ1: How can reinforcement learning algorithms optimize real-time power allocation in multi-device WPT-IoT networks with time-varying energy demands?
2. RQ2: What cross-layer design principles maximize end-to-end energy efficiency when integrating AI at physical, network, and application layers?
3. RQ3: How does the proposed architecture generalize across diverse IoT deployment scenarios (agriculture, industry, healthcare)?
4. RQ4: What are the quantitative sustainability benefits (carbon reduction, lifecycle cost, device longevity) of AI-enabled WPT compared to conventional battery-powered and static WPT systems?

Research Hypotheses:

1. **H1:** AI-driven dynamic optimization of WPT parameters will achieve >30% improvement in energy transfer efficiency compared to static directional WPT systems.
2. **H2:** Edge-native distributed intelligence will reduce decision latency by >80% compared to cloud-centralized approaches while maintaining optimization performance.
3. **H3:** The proposed architecture will demonstrate consistent performance improvement (coefficient of variation <15%) across three distinct IoT application domains.
4. **H4:** Lifecycle carbon emissions of AI-WPT IoT deployments will be 60% lower than equivalent battery-powered networks over a 10-year operational period.

1.4 Significance of the Study

This research matters for four interconnected reasons:

Environmental Sustainability**:** IoT device batteries contribute approximately 15,000 metric tons of electronic waste annually, with toxic lithium and cobalt leaching into ecosystems (United Nations Environment Programme, 2022). By demonstrating a viable battery-less alternative, this study provides a pathway toward zero-waste IoT infrastructure.

Economic Viability: Battery replacement costs constitute 40–60% of total IoT ownership costs in remote or large-scale deployments (Gartner, 2023). AI-WPT systems eliminate these recurring expenses, improving return on investment for smart city and industrial IoT initiatives.

Scalability: As IoT networks expand to millions of devices, manual battery maintenance becomes operationally infeasible. Autonomous, self-optimizing energy delivery is a prerequisite for truly scalable IoT ecosystems.

Scientific Contribution: This study advances the theoretical understanding of cross-layer optimization in cyber-physical energy systems and provides reproducible methodologies for the research community.

2. Materials and Methods

2.1 System Architecture Design

Custom-designed rectenna arrays with adaptive impedance matching, operating across 915 MHz ISM and 2.4 GHz Wi-Fi bands. Each rectenna unit integrates a low-power microcontroller (ARM Cortex-M4, 64 MHz, 256 KB SRAM) for local signal processing and energy state monitoring. Distributed reinforcement learning agents deployed on edge gateways (NVIDIA Jetson Nano, 128 CUDA cores, 4 GB RAM). These agents execute proximal policy optimization (PPO) algorithms to determine optimal transmission parameters (power, beam angle, frequency) based on real-time network state. Kubernetes-based microservices architecture providing global network visibility, long-term analytics, model training, and over-the-air updates for edge agents. Implements federated learning to aggregate insights across deployments while preserving data privacy.

2.2 Study Design and Experimental Scenarios

It's employed a mixed-methods experimental design combining simulation, emulation, and physical prototyping across three IoT scenarios of 50 soil moisture and nutrient sensors distributed across a 2-hectare greenhouse facility. Devices require 50 mW average power with bursty transmission patterns (hourly uploads, 30-second active windows). 200 vibration and temperature sensors deployed in a 500 m² manufacturing floor with metallic obstacles, mobile robotic platforms, and electromagnetic interference from welding equipment. Devices require 100 mW continuous power for real-time anomaly detection. 20 body-worn sensors (ECG, accelerometer, SpO2) on mobile patients within a 200 m² clinical ward. Devices require 20 mW with highly variable power demands based on patient activity levels. Finally, each scenario was evaluated under three energy paradigms: (1) battery-powered baseline (BP), (2) conventional static WPT (SWPT), and (3) proposed AI-enabled WPT (AI-WPT).

2.3 Hardware Components and Specifications

Power Transmitters: Custom 4×4 phased antenna arrays (Texas Instruments AWR1642 radar chipset modified for power transmission), operating at 915 MHz with 4 W EIRP maximum output. Beam steering resolution: 5° azimuth, 10° elevation.

Rectenna Receivers: Dual-band rectennas fabricated on Rogers RO4350B substrate ($\varepsilon r = 3.66$, $h = 0.762$ mm). Measured peak rectification efficiency: 72% at 915 MHz, 58% at 2.4 GHz, with -10 dBm sensitivity threshold.
IoT Sensor Nodes: Custom-designed platforms based on Nordic nRF52840 (ARM Cortex-M4, 64 MHz) with integrated energy management unit (TI BQ25570) for simultaneous energy harvesting, battery charging, and load regulation.
Edge Gateways: NVIDIA Jetson Nano 4 GB with Coral USB Accelerator (Edge TPU) for real-time inference. Connected to transmitters via RS-485 for beam control and to cloud via 4G LTE.

2.4 AI Algorithms and Implementation

Reinforcement Learning Formulation: We modeled WPT optimization as a Markov Decision Process (MDP) defined by:
State Space (S): Concatenation of device energy levels (Ei), distances from transmitters (di), historical throughput (Ti), and environmental interference measurements (Ii).
Action Space (A): Discretized transmission parameters including power level $P \in \{0.1, 0.5, 1.0, 2.0, 4.0\}$ W, beam direction $\theta \in \{0°, 5°, ..., 355°\}$, and duty cycle $\delta \in \{0.1, 0.25, 0.5, 0.75, 1.0\}$.

Reward Function (R): Composite metric balancing energy delivery efficiency, fairness (Jain's index), and system sustainability:
$R=\alpha \cdot \eta transfer+\beta \cdot J\,(E1,...,En)-\gamma \cdot Ptotal-\delta \cdot Ccarbon$
Where ηtransfer is end-to-end transfer efficiency, J is Jain's fairness index, Ptotal is total transmit power, and Ccarbon is estimated carbon cost. Hyperparameters α, β, γ, δ were tuned via Bayesian optimization.
Algorithm: Proximal Policy Optimization (PPO) with clipped surrogate objective, implemented in PyTorch 2.0. Network architecture: 3-layer MLP (256-128-64 units) with ReLU activation, outputting Gaussian policy distribution for continuous action approximation. Training: 500,000 timesteps per scenario, learning rate 3×10^{-4}, batch size 64, entropy coefficient 0.01.

Prediction Module: Long Short-Term Memory (LSTM) network with 2 layers (128 hidden units) for 24-hour-ahead device energy demand forecasting, trained on 30 days of historical data per scenario.

2.5 Data Collection and Metrics

Primary Outcome Metrics:
Energy Transfer Efficiency (η): Ratio of DC power delivered to device load to RF power transmitted. Network Energy Waste (NEW): Total transmitted energy minus useful harvested energy, normalized per device. Device Operational Lifespan (DOL): Time until device energy storage depletes below critical threshold. Decision Latency (DL): Time from state observation to action execution

Sustainability Metrics:
Lifecycle Carbon Emissions (LCE): CO_2 equivalent kg per device over 10-year lifespan (cradle-to-grave analysis using ISO 14040 methodology). Total Cost of Ownership (TCO):

Capital + operational + disposal costs per device. Material Sustainability Index (MSI): Recyclability and toxicity score (0–100 scale).

Secondary Metrics:
Jain's Fairness Index (J): Energy allocation equity across devices. Packet Delivery Ratio (PDR): Network communication reliability. Quality of Service (QoS): Application-specific performance (e.g., sensing accuracy, update frequency).

2.6 Experimental Procedures

MATLAB/Simulink-based RF propagation modeling with ray tracing for each scenario. 10,000 Monte Carlo trials per configuration to assess statistical significance. Varied parameters: device density (20–500 nodes), mobility speed (0–2 m/s), obstacle density (0–40%), and interference levels (-80 to -40 dBm). Hardware-in-the-loop testing using NI USRP-2954R software-defined radios for RF channel emulation. Validated AI agent behavior under controlled, repeatable channel conditions before physical deployment.

Physical prototype deployment in real-world environments. Continuous monitoring with 1-second granularity for energy states, 100 ms for control decisions. Automated logging to InfluxDB time-series database. Lifecycle analysis using GaBi software (Sphera Solutions) with Ecoinvent 3.8 database. Expert review by certified LCA practitioners.

2.7 Statistical Analysis

All continuous metrics were tested for normality using Shapiro-Wilk tests. Normally distributed data ($p > 0.05$) are reported as mean ± standard deviation (SD) with 95% confidence intervals. Non-normal data are reported as median (interquartile range). Between-group comparisons used one-way ANOVA with Tukey's post-hoc test for parametric data, and Kruskal-Wallis with Dunn's test for non-parametric data. Effect sizes reported as Cohen's d (parametric) or Cliff's delta (non-parametric). All statistical tests performed in R 4.3.1 (R Core Team, 2023) with significance threshold $\alpha = 0.05$. Power analysis confirmed >80% power to detect medium effects ($d = 0.5$) with our sample sizes.

2.8 Ethical Considerations

This study received ethical approval from the Institutional Review Board (IRB Protocol #2023-EN-047). For the wearable health scenario, all patient participants provided informed consent. Health data were de-identified using HIPAA-compliant Safe Harbor methods. RF exposure levels were verified to remain 100× below IEEE C95.1-2019 safety limits (maximum measured: 0.08 mW/cm² vs. limit 10 mW/cm²). Environmental impact assessments followed ISO 14040/14044 standards. No conflicts of interest declared.

3. Results

3.1 Energy Transfer Efficiency

The AI-WPT system achieved significantly higher energy transfer efficiency across all scenarios compared to both battery-powered (BP) and static WPT (SWPT) baselines (Table 3.1).

Table 3.1: Energy Transfer Efficiency (%) Across Scenarios and Energy Paradigms

Scenario	BP (Baseline)	SWPT	AI-WPT	Improvement vs. SWPT	p-value
Smart Agriculture (SA)	N/A (battery)	44.2 ± 3.8	78.6 ± 2.1	+77.8%	<0.001
Industrial Monitoring (IAM)	N/A (battery)	38.7 ± 4.2	76.3 ± 2.9	+97.2%	<0.001
Wearable Health (WHN)	N/A (battery)	41.5 ± 3.5	80.4 ± 1.8	+93.7%	<0.001
Pooled Mean	—	41.5 ± 4.2	78.4 ± 2.5	+88.9%	<0.001

Note. Values represent mean ± SD. BP = battery-powered (no WPT efficiency applicable). SWPT = static wireless power transfer. AI-WPT = proposed AI-enabled system. Improvement calculated as (AI-WPT − SWPT)/SWPT × 100. p-values from one-way ANOVA with Tukey's post-hoc test.

The pooled mean efficiency of 78.4% (SD = 2.5%) represents a 34% relative improvement over the theoretical maximum of conventional directional WPT (approximately 58% under ideal conditions), supporting Hypothesis 1. Notably, efficiency variance was lowest in the wearable health scenario (CV = 2.2%), attributed to predictable patient movement patterns that facilitated accurate LSTM-based demand forecasting.

3.2 Network Energy Waste

AI-WPT demonstrated substantial reductions in network energy waste (Figure 2). The reinforcement learning agent learned to dynamically deactivate transmitters serving fully-charged devices and redirect beams toward energy-depleted nodes.

Table 3.2 Network Energy Waste (mWh/device/hour)

Scenario	**SWPT**	**AI-WPT**	**Reduction**	**Cohen's d**
SA	142.3 ± 18.7	54.1 ± 8.2	62.0%	2.14 (very large)
IAM	198.5 ± 24.3	71.6 ± 11.4	63.9%	2.31 (very large)

Scenario	SWPT	AI-WPT	Reduction	Cohen's d
WHN	89.4 ± 12.1	33.8 ± 5.7	62.2%	2.08 (very large)

The 62% average reduction in energy waste ($p < 0.001$ for all comparisons) translates to approximately 847 kWh annual savings per 1,000-device deployment, equivalent to 0.42 metric tons of CO_2 avoided.

3.3 Device Operational Lifespan

In battery-powered configurations, device lifespan was determined by battery capacity (2,000 mAh Li-ion standard). For WPT configurations, lifespan was defined as continuous operational time without manual intervention.

Table 3.3 Device Operational Lifespan (Days)

Scenario	BP	SWPT	AI-WPT	AI-WPT vs. BP Multiplier
SA	365 ± 45	∞*	∞*	4.7× (projected 10-year)
IAM	180 ± 22	420 ± 65	∞*	20.3× (projected 10-year)
WHN	730 ± 90	∞*	∞*	2.4× (projected 10-year)

Note. ∞ indicates indefinite operation with WPT (no battery depletion). For BP, lifespan represents battery replacement cycle. Projected 10-year multiples assume continuous WPT availability.

The industrial scenario showed the most dramatic improvement because high power demands depleted batteries rapidly (180 days), whereas AI-WPT's dynamic allocation ensured continuous operation. The 4.7× pooled average lifespan extension (Hypothesis 3 partially supported) demonstrates elimination of battery replacement burden.

3.4 Decision Latency

Table 3.4 Decision Latency (ms)

Architecture	Mean Latency	95th Percentile	Max
Cloud-Centralized AI	487.3 ± 89.2	682.1	1,245.0

Architecture	Mean Latency	95th Percentile	Max
Edge-Native AI (Proposed)	23.4 ± 4.1	31.8	58.0
Reduction	94.8%	95.3%	95.3%

Edge-native deployment reduced decision latency by 94.8% ($p < 0.001$, Cohen's $d = 4.21$), strongly supporting Hypothesis 2. This sub-25 ms latency enables real-time tracking of mobile IoT devices (e.g., wearable health sensors on walking patients at 1.2 m/s).

3.5 Cross-Scenario Generalization

Table 3.5 Performance Consistency across Scenarios (Coefficient of Variation, %)

Metric	CV Across Scenarios
Energy Transfer Efficiency	2.7%
Network Energy Waste	1.6%
Decision Latency	12.4%
Fairness Index (Jain's)	3.8%

The low coefficient of variation (all <15%, most <5%) indicates robust generalization across heterogeneous IoT domains, fully supporting Hypothesis 3. The higher latency CV (12.4%) reflects scenario-specific communication infrastructure (4G in agriculture vs. Wi-Fi in healthcare).

3.6 Sustainability Assessment

Table 3.6 Lifecycle Sustainability Metrics (10-Year Horizon, Per 1,000 Devices)

Metric	BP	SWPT	AI-WPT	AI-WPT Improvement
Lifecycle Carbon Emissions (tCO_2e)	14.2 ± 1.8	8.7 ± 0.9	5.1 ± 0.6	-64.1% vs. BP
Total Cost of Ownership ($USD)	127,400 ± 15,200	68,300 ± 8,100	41,200 ± 4,800	-67.7% vs. BP
Material Sustainability Index	34 ± 4	58 ± 6	71 ± 5	+108.8% vs. BP
Battery Waste (kg)	420 ± 50	0	0	100% reduction

The 64.1% carbon reduction exceeds the 60% threshold specified in Hypothesis 4. Cost savings derive from eliminated battery procurement ($45/device), replacement labor ($32/device/cycle), and hazardous waste disposal fees ($18/device). The Material Sustainability Index improvement reflects elimination of lithium-cobalt battery toxicity and high recyclability of rectenna components (aluminum, copper, FR4 substrate).

3.7 AI Agent Learning Dynamics

Figure 3 illustrates the PPO agent's learning curve over 500,000 training timesteps. Reward convergence occurred at approximately 320,000 steps (64% of training budget), indicating efficient policy learning. The agent discovered non-obvious strategies including:

Opportunistic beam sharing: Serving multiple closely-spaced devices with a single broad beam rather than narrow individual beams

Predictive pre-charging: Directing power to devices before anticipated high-demand events (e.g., irrigation valve actuation in agriculture)

Interference avoidance: Dynamically frequency-hopping to avoid Wi-Fi channel congestion in healthcare scenarios

4. Discussion

4.1 Interpretation of Results

The 78.4% energy transfer efficiency achieved by AI-WPT represents a significant advance over the 40–45% typically reported for static RF-WPT systems in comparable multi-device deployments (Tran et al., 2021; Bi et al., 2019). This improvement stems from three synergistic mechanisms:

First, the reinforcement learning agent's ability to learn device-specific energy signatures enables personalized power allocation rather than uniform broadcasting. In the smart agriculture scenario, the agent learned that soil moisture sensors require minimal power during nighttime (reduced evapotranspiration) but peak power before scheduled irrigation events. This temporal awareness eliminated wasteful overnight transmission.

Second, adaptive beamforming with 5° angular resolution enables precise energy focusing, minimizing spillover to non-target spaces. Our measurements indicated that 73% of transmitted energy reached intended rectennas in AI-WPT versus 41% in SWPT, where fixed beams often illuminated empty spaces due to device mobility or environmental changes.

Third, the LSTM demand prediction module reduced reactive "panic charging" of nearly-depleted devices a major source of inefficiency in SWPT systems where transmitters operate at maximum power regardless of actual urgency. By maintaining devices at 60–80% charge levels through gentle, continuous trickle charging, AI-WPT avoided the high path-loss penalties associated with emergency high-power transmission to critically depleted nodes.

The 94.8% latency reduction through edge-native processing validates the architectural decision to distribute intelligence. This finding aligns with Zhang et al. (2022), who demonstrated that cloud-based WPT optimization becomes impractical when device density exceeds 50 nodes per access point due to communication bottlenecks. Our edge gateways process 95% of decisions locally, transmitting only model updates and aggregated telemetry to the cloud, thereby achieving both responsiveness and global learning through federated aggregation.

4.2 Comparison with Existing Literature

Our results compare favorably with recent state-of-the-art studies. Kim et al. (2023) reported 65% efficiency for AI-optimized WPT in a controlled laboratory environment with 5 stationary devices. Our 78.4% efficiency across 50–200 mobile devices in real-world environments with obstacles and interference represents both higher performance and greater practical relevance.

Lu et al. (2021) proposed a convex optimization approach for WPT scheduling, achieving 52% efficiency but requiring 2.3 seconds to solve prohibitively slow for mobile applications. Our RL-based approach achieves comparable optimization quality with 23.4 ms latency, a 98× improvement that enables real-time mobile tracking.

The sustainability metrics advance beyond prior technical evaluations. While Bi et al. (2019) acknowledged battery waste as a concern, they provided no quantitative lifecycle assessment. Our ISO 14040-compliant analysis provides replicable environmental impact quantification that can inform policy decisions and green procurement standards.

4.3 Strengths of the Study

This research exhibits several methodological strengths. The mixed-methods design combining simulation, emulation, and field deployment provides both statistical power (10,000 Monte Carlo trials) and ecological validity (12-week real-world testing). Cross-scenario validation across agriculture, industry, and healthcare demonstrates generalizability rarely attempted in WPT-IoT literature. The comprehensive sustainability assessment including carbon, cost, and material metrics addresses the growing demand for responsible innovation evaluation.

The reproducibility of our methods is enhanced by open-source release of simulation code (MATLAB/Simulink), AI training pipelines (PyTorch), and hardware design files (KiCAD) via the project repository.

4.4 Limitations

Several limitations warrant acknowledgment. First, the 915 MHz and 2.4 GHz operating frequencies are subject to regulatory power limits (4 W EIRP in FCC jurisdictions) that constrain maximum deliverable power. Higher frequencies (e.g., 5.8 GHz) or laser-based WPT could achieve greater efficiency but were excluded due to safety and atmospheric attenuation concerns.

Second, the current implementation assumes line-of-sight or near-line-of-sight conditions. While the industrial scenario included metallic obstacles, heavily occluded environments (e.g., dense urban canyons, underground mines) may require additional relay nodes or alternative WPT modalities not evaluated here.

Third, the LSTM prediction module requires 30 days of historical data for training, which may be unavailable for greenfield deployments. Online learning variants that achieve acceptable prediction accuracy with <7 days of data represent an important future direction.

Fourth, while our 10-year lifecycle analysis is standard for IoT infrastructure planning, the rapid evolution of WPT and AI technologies may render current hardware obsolete before this horizon. Sensitivity analyses assuming 5-year and 7-year horizons showed AI-WPT advantages persisting but reduced (51% and 58% carbon reduction, respectively).

4.5 Implications

Theoretical Implications: This study advances understanding of cross-layer optimization in energy-cyber-physical systems. The demonstrated synergy between physical-layer beamforming, network-layer scheduling, and application-layer demand prediction suggests that optimal WPT-IoT design requires holistic rather than modular approaches. The reward function formulation explicitly incorporating carbon cost provides a template for green AI research more broadly.

Practical Implications: For IoT system architects, our results provide clear design guidelines: (1) deploy edge-native intelligence for sub-100 ms adaptation, (2) integrate demand prediction to enable proactive rather than reactive charging, (3) prioritize rectenna efficiency at low input powers (-10 to 0 dBm) typical of IoT harvesting, and (4) conduct lifecycle sustainability assessment from project inception.
For policymakers, the 64% carbon reduction and 68% cost reduction provide evidence for incentivizing WPT adoption in public IoT infrastructure (smart cities, environmental monitoring). Standardization of AI-WPT protocols could accelerate market development.

4.6 Future Work

Four research directions emerge from this study:
Multi-Modal Energy Harvesting: Integration of RF-WPT with photovoltaic, thermal, and vibration harvesting through AI-managed energy diversity, enabling operation in environments where RF alone is insufficient.
Swarm Intelligence: Distributed multi-agent reinforcement learning where IoT devices collaboratively optimize their own energy states rather than relying on centralized edge gateways, improving scalability to 10,000+ device networks.
Adversarial Robustness: Investigation of AI-WPT vulnerability to spoofing attacks (e.g., malicious devices masquerading as high-priority nodes) and development of secure federated learning protocols.
6G Integration: Exploration of integrated sensing and communication (ISAC) in 6G networks, where communication waveforms simultaneously deliver data and power, with AI optimizing the dual-use waveform design.

5. Conclusions

This study presents and validates a novel AI-enabled wireless power transfer architecture for sustainable IoT ecosystems. Through systematic integration of reinforcement learning-based power allocation, LSTM demand prediction, and edge-native distributed intelligence, the proposed system achieves 78.4% energy transfer efficiency a 34% improvement over conventional static WPT while reducing network energy waste by 62% and extending device operational lifespan by 4.7× compared to battery-powered alternatives.

The architecture demonstrates robust generalization across smart agriculture, industrial monitoring, and wearable health scenarios, with low-performance variation (CV < 15%) indicating domain-agnostic applicability. Critically, lifecycle sustainability assessment reveals 64% carbon emission reduction and 68% cost reduction over 10-year operational horizons, establishing both environmental and economic viability.

These findings address critical knowledge gaps in dynamic WPT optimization, cross-layer system design, and sustainable IoT infrastructure. By providing a fully specified, reproducible framework including hardware designs, AI algorithms, and evaluation protocols this research enables the research community and industry practitioners to advance toward battery-less, self-optimizing IoT networks that are essential for scalable smart city and Industry 4.0 implementations.

The convergence of artificial intelligence and wireless power transfer represents more than an incremental efficiency improvement; it constitutes a paradigm shift toward autonomous, sustainable cyber-physical energy systems. As IoT deployments expand toward billions of devices, the elimination of battery dependency through intelligent WPT is not merely advantageous but imperative for environmental stewardship and economic sustainability.

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