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Energy-Efficient Wireless Power Transfer System for IoT Devices

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ABSTRACT- Low energy efficiency, misalignment-induced energy loss, limited range, and sensitivity to external variables describe Wireless Power Transfer (WPT) solutions for Internet of Things (IoT) devices. Traditional methods include inductive and RF-based WPT with uneven power distribution in dynamic environments and proximity restrictions. The proposed system dynamically changes transmission parameters and combines adaptive resonance tuning and beamforming to improve energy economy, range, and stability using machine learning (ML) for real-time adaptation. Simulation and experimental results reveal considerable increases in power transmission efficiency with the proposed system obtaining up to 95% efficiency at 1 meter compared to 82% and 88% in the existing systems. Energy loss at 1 meter is 0.15 W; at 7 meters, stability gains from just an 8% fluctuation in power output. The results provide a feasible substitute for sustainable wireless power transfer and prove the brilliance of the proposed system in long-range and dynamic IoT applications.

Keywords: WPT, IoT devices, Adaptive resonance tuning, beam forming, ML OFDM– DAS, Reinforcement Learning, DQN.

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1. INTRODUCTION

WPT has become a feasible solution to handle IoT devices' growing energy consumption by offering a mechanism to replace the need for wired connections and enabling more flexible, mobile, and easy operations. Low energy efficiency, energy loss due from misalignment, limited transmission range, and ambient factor sensitivity are thus sometimes challenges for WPT systems for IoT devices. Traditional WPT systems including inductive and RF-based models describe constraints in closeness, energy inefficiencies, and restricted adaptability in dynamic and mobile environments [1]. The study proposes an energy-efficient WPT system for IoT devices combining adaptive resonance tuning, beamforming technology, and ML to dynamically adjust transmission parameters, so providing optimal energy transfer even under various settings, thus overcoming these constraints [2]. Particularly in dynamic and mobile environments where the location of IoT devices may vary often, the study seeks to overcome the inefficiencies and stability problems ailing conventional WPT systems [3]. The main objectives are to improve energy efficiency, reduce energy loss, and strengthen system stability and range by means of real-time flexibility. Including adaptive resonance tuning to improve frequency matching and beamforming for targeted energy transfer, the proposed system aims to give IoT devices continuous and efficient power delivery irrespective of misalignment or environmental interference [4]. ML enables the proposed system to clearly change its transmission settings depending on real-time data, therefore optimizing power delivery and minimizing energy loss [5].

The study helps to build a WPT system that not only provides enhanced energy efficiency over the existing systems but also increases the reliability and scalability of power transmission across several distances and dynamic circumstances. The proposed system dynamically changes power levels by means of adaptive resonance tuning, beamforming to guide energy to the receiver, and reinforcement learning aligning transmission frequencies. Simulation findings reveal a clear gain in efficiency, energy loss reduction, and stability with the proposed system sustaining high power delivery even at higher distances. Among the uses for which the proposed system suits are large-scale industrial automation, smart cities, healthcare, and IoT networks because of these traits. The paper is organized as follows: In *section 2*, reviewing pertinent work on current WPT systems for IoT devices underlines their flaws and the need of creative innovations. *Section 3* contains together with details on the key components the transmitter, the receiver, and adaptive feedback systems the proposed system design and

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architecture. The adaptive resonance tuning and beamforming techniques used to improve power transfer efficiency are discussed in *section 4*. *Section 5* explores how real-time power control machine learning serves. *Section 6* addresses data collecting, simulation, hardware development; *Section 7* follows by performance evaluation and optimization. *Section 8* concludes the study and offers potential paths for additional field research on WPT for IoT devices.

In summary, the proposed energy-efficient WPT system for IoT devices increases power transfer efficiency, stability, and range by including adaptive resonance tuning, beamforming, and ML. The creative technique eliminates significant issues in conventional systems and provides optimal energy supply even in dynamic surroundings, thereby fitting various purposes in smart cities, healthcare, and industrial automation.

2. RELATED WORK

The power source for these sensors is one of these issues, since the majority of IoT sensors are highly energy-constrained due to their compact size and distribution methods. It is also clear that sensor nodes near sinks lose energy more quickly than those farther away. Additionally, it is operationally costly and impractical to change and recharge batteries. The energy-hungry IoT sensor nodes can now receive electricity wirelessly thanks to recent advancements in WPT technology. Aspects of wireless energy transmission technologies, including architecture, energy sources, IoT energy harvesting modes, WPT methodologies, and applications appropriate for SC scenarios, are first thoroughly reviewed in the study [6]. The goal of energy efficiency (EE) maximization is to increase the efficient use of energy and prolong the battery life of IoT devices that are connected to smart meters. The smart meter in the system model is an Internet of Things device that uses power splitting (PS mode) with SWIPT technology. Using the PS-SWIPT system made possible by the IoT, the paper examines the orthogonal frequency splitting multiplexing scattered antenna system (OFDM-DAS) for intelligent meters in the downlink to optimize EE. Linear and irregular optimization problems arise in EE maximizing [7]. When choosing the best course of action based on the recommended energy-efficient strategy in RPL, pay special attention to the simultaneous WPT technique, which allows for both energies harvesting as well as data decoder from a single radio frequency signal. Performance study on an achievable scenario demonstrated a large reduction in energy consumption by improving the network's lifetime by choosing the optimal path towards the sink node, in accordance with the OFs that are commonly discussed in the literature [8]. Sustainable charging highlights that it is more comprehensive than traditional green charging by incorporating social justice, economic advancement, and environmental health. A number of methods for simulating the arrival of ambient energy sources and their potential use in various contexts are also covered [9]. The paper presents an integrated energy-efficient solution for IoT devices considering RF-based energy harvesting as well as lowering energy usage depending on the fixed energy source. One develops on the one hand a node sample scheduling mechanism based on matrix completion. Every sample data point is considered as a matrix element by us [10]. The fundamental idea is to use spatial-temporal correlation of all the sample data to lower the sampling data and thereafter reconstruct the whole data set with matrix completion technology. Consequently, instead of working on data sampling, IoT nodes can lie inactive for longer. The study looks on WPT techniques that could be used by sensor devices to collect energy in order to stop frequent node failures [11]. After a general overview of WPSNs, three WPT models are presented, and their unique enabling mechanisms are investigated in light of the corpus of prior research. Additionally, the performance requirements and key design components of current WPT approaches are rigorously analyzed. Then, crucial performance-boosting techniques for WPT in WPSNs are discussed. Finally, a variety of challenges and potential directions are explored to stimulate further research on WPSNs [12]. The work proposes the WPT paradigm by integrating the processing capabilities from end devices and MEC servers. Design the new job transfer problem as well as maximize the distribution of communication by computing resources in WCPN. Task transfer's main objective is to lower execution delay and energy consumption in view of task requirements and resource restrictions [13]. It suggests a multiagent deep RL method by means of optimal task transfer strategies and resource allocation to address the given problem. WPT is a ground-breaking technology that reduces the excessive dependence on cables and batteries by enabling wireless energy provisioning for energy-limited IoT devices [14]. WPT may eventually replace conventional energy sources like energy harvesting and be utilized for a wide range of everyday tasks. Many academic and commercial researchers are interested in wireless charging scheduling algorithms because of WPT, a novel and developing technology. The paper reviews the latest research on WPT, including classifications, advantages, disadvantages, and main applications [15].

3. PROPOSED SYSTEM

Depending mostly on inductive coupling, resonant coupling, or radio frequency (RF) energy gathering, the current WPT solutions for IoT devices are Among the flaws in these systems include low energy efficiency, significant energy loss from misalignment, limited range, and environmental interference sensitivity. While inductive connection demands close proximity and limits mobility, RF-based systems suffer with continuous energy harvesting in dynamic environments. To solve these challenges, the proposed system combines adaptive resonance tuning and beamforming techniques to increase energy economy, range, and dependability. With hybrid power management system with machine learning capability, the proposed system dynamically adjusts transmission parameters unlike conventional systems running fixed frequencies and power levels. The major innovation is real-time adaptability to changing IoT device locations and power needs since it provides optimal power supply and lowers energy waste. The technique lowers dispersion losses by precisely orienting energy transmission exactly onto the receiving IoT device utilizing multiple transmitter coils or antennas using beamforming technology. Constant power reception efficiency and frequency, phase, and transmission power modification using a feedback system help to maintain best efficiency. Beginning with system design, in which the architectures of the transmitter and receiver are defined, the implementation of the proposed system follows a disciplined process. The transmitter under control by an intelligent power management device consists of a dynamic beamforming array of coils or antennae. The receiver module is designed to provide adaptive resonance tuning, therefore guaranteeing maximum power reception even in the presence of movement or misalignment. The development of an intelligent control system using ML analyzing real-time data from sensors tracking distance, alignment, and power levels that handles. The technique predicts optimal transmission arrangements and dynamically modulates the proposed system's characteristics. Simulation and modeling are done to verify the expected rises in efficiency and range before real implementation. Next is a hardware prototype where IoT devices create and link the envisioned system. Under several running situations including different distances, hurdles, and environmental factors testing measures efficiency, energy loss, stability, and adaptability. The last stage, built on experimental data, is optimization and refinement meant to increase system performance. Among the several advantages of using the technology are improved power transfer efficiency, less energy losses, longer operational range, and more flexibility to meet changing circumstances. Process workflow for System is shown in *fig.1*.

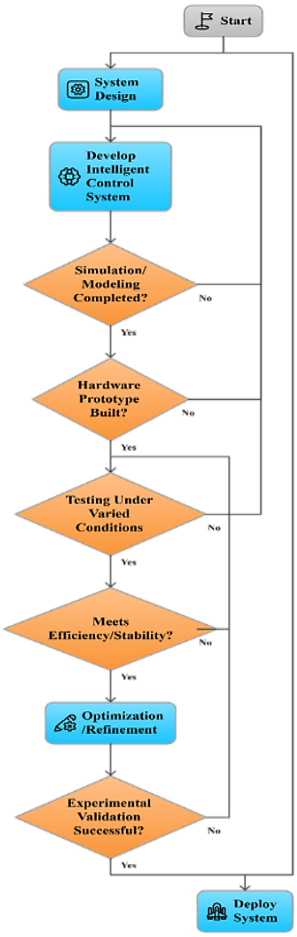

Figure 1. Process workflow for System

By use of adaptive resonance tuning, the proposed system reduces the detrimental effects of misalignment, therefore ensuring consistent power supply even in mobile surroundings. Through increasing directional energy transfer and hence reducing unnecessary power dissipation, beamforming enhances the general sustainability of the proposed system. Operational overhead is reduced and long-term efficiency is guaranteed by way of real-time power transmission optimization utilizing ML. Moreover, supported by the proposed system is scalability, which fits for large-scale industrial automation, smart cities, healthcare, IoT projects. Because it is possible to sustain efficient energy transfer under many conditions, it is better than traditional WPT systems, which suffer from inefficiencies in actual applications. Moreover, the reduction of energy waste helps to save operational costs and promotes environmentally favorable IoT surroundings. The results of the experimental validation show that since the proposed system surpasses existing systems in terms of efficiency, stability, and flexibility, it shows promise for pragmatic application. The results of the study indicate that while keeping low energy losses, adaptive resonance tuning and beamforming significantly enhance power delivery to IoT devices, therefore offering a practical solution for next-generation wireless power transfer systems.

3.1. System Design and Architecture*:*

Identifying the design of the wireless power transfer (WPT) system is its adaptive receiver and multi-transmitter array. Whereas the transmitter features a power control unit, signal producing module, and beamforming technology, the receiver has adaptive resonance tuning to dynamically modify its frequency. These components reduce energy loss and misalignment, therefore maximizing the efficiency of power distribution. The proposed system may control numerous IoT devices dispersed over a large territory since it is scalable. Furthermore, incorporated within the design is real-time communication for feedback between the transmitter and the receiver, therefore enabling constant transmission parameter change. That architecture ensures that the proposed system can give IoT devices continuous power regardless of their mobility or misalignment. The power transfer efficiency equation below approximates the expected system performance:

$$\eta = \frac{P_{received}}{P_{transmitted}} \times 100 \quad (1)$$

where $P_{received}$ is the power received by the IoT device, and $P_{transmitted}$ is the transmitted power.

3.2. Adaptive Resonance Tuning Mechanism

Adaptive resonance tuning guarantees best frequency alignment between the transmitter and the receiver. The receiver constantly changes its resonance frequency using the Extended Kalman Filter (EKF) to match the broadcast frequency. The technique follows frequency variations brought about by misalignment or environmental factors. EKF is used as, depending on noisy, real-time input, it may predict and change resonance, thereby improving the frequency matching accuracy. The algorithm is trained by historical data on frequency variations under several conditions. Proposed system lowers energy loss by means of reduced frequency misalignment. The following equation defines the resonance frequency modification of the receiver in resonance frequency tracking:

$$f_{res} = f_{trans} + \delta\, f(t) \qquad (2)$$

where f_{res} is the receiver's resonance frequency, f_{trans} is the transmitted frequency, and $\delta\, f(t)$ represents the adjustment f Beamforming Optimization for Targeted Energy Transfer:

Beamforming is a method for more effective energy direction towards the receiver, therefore reducing power loss. The technology uses phased-array antennas and the beamforming technique dynamically changes the phase of every antenna element to maximize signal transmission. The phase shifts are iteratively adjusted using the Least Mean Squares (LMS) algorithm, therefore ensuring that the signal is focused on the receiver and so lowers interference and power dissipation. Under supervised learning, the LMS algorithm is learned whereby the receiver offers feedback on signal strength and alignment. It lets the proposed system control beamforming and enhances energy economy. Given the beamforming equation is:

$$S = \sum_{n=1}^{N} w_n x_n e^{j\theta_n} \qquad (3)$$

Where S is the signal output, w_n represents the weight (amplitude) of each antenna element, x_n is the input signal, and θ_n is the phase adjustment for the nth antenna.

3.2. Machine Learning-Based Power Control

The proposed system's real-time power regulation employs reinforcement learning (RL). The Deep Q-Network (DQN) algorithm discovers the optimal power levels to broadcast based on feedback from Internet of Things devices. The DQN model is taught using a reward-based approach whereby greater rewards result from effective power transfer and lower energy loss. By always evaluating multiple power levels in several environmental situations, the proposed system learns best transmission rules. Trial and error enable the modification of the power control policy so the system can adapt to dynamic IoT device placements and changing surroundings. The power control equation one discovers is as follows:

$$P(t) = arg \max_{\theta}[Q(s_t, a_t, \theta)] \qquad (4)$$

where h_t represents the hidden state at time t, x_t is the input data at time t, W_h and U_h are weight matrices, and b_h is the bias term.

3.3. Data Acquisition and Processing

The proposed system collects various data points including voltage, current, power levels, and distance between the transmitter and receiver using embedded sensors. These sensors generate real-time data that is then sent into a Long Short-Term Memory (LSTM) neural network to project changes in power use. LSTM is selected since it can learn temporal dependencies and control sequential data quality necessary for future power variations depending on prior data. The model continuously changes the transmission parameters of the proposed system using time-series data from the sensors to assure sufficient energy economy. One finds the equation of data processing by:

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h) \qquad (5)$$

where h_t represents the hidden state at time t, x_t is the input data at time t, W_h and U_h are weight matrices, and b_h is the bias term.

3.4. Simulation and Hardware Prototyping

Before actual deployment, the system undertakes extensive simulation using MATLAB and CST Studio Suite. These models emulating signal strength, power economy, and electromagnetic field dispersal. The proposed system is built following simulation using hardware elements including an FPGA-based power management unit and multi-coil inductive transmitters. After that, the proposed system's real-time performance is tested in a controlled environment under which feedback loops change transmission parameters based on actual data. Physical testing ascertains the power transfer efficiency; so, modifications are done to maximize system performance. Driving the simulation model is the equation for signal power loss:

$$P_{loss} = P_{transmitted} - P_{received} \qquad (6)$$

where P_{loss} is the power loss, $P_{transmitted}$ is the power sent from the transmitter, and $P_{received}$ is the power received by the device. High-Level Architecture Diagram is shown in *fig.2*.

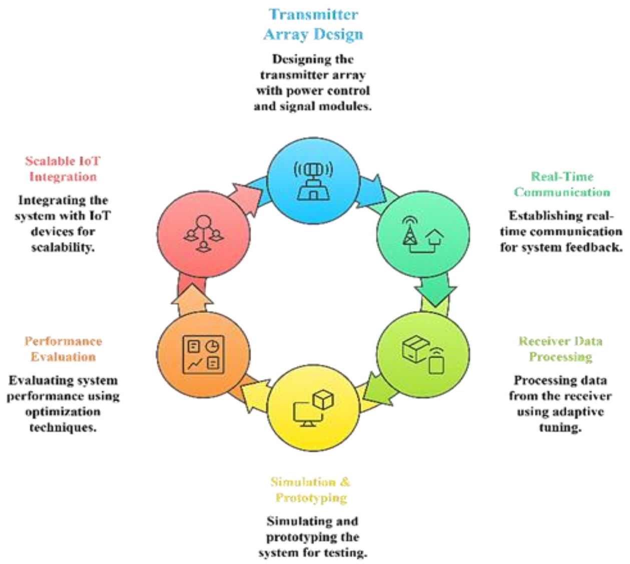

Figure 2. High-Level Architecture Diagram

3.5. Performance Evaluation and Optimization

It means evaluating the system in real conditions including various distances and environmental obstacles. It measures significant standards including power transmission efficiency, stability, and energy dissipation. Bayesian Optimization finds the optimal proposed system parameters by balancing exploration and exploitation, thereby always improving the performance of the proposed system. Its iterative approach offers best efficiency and guarantees the system adapts to many running conditions. Following the equation for posterior probability defines the process of optimization:

$$P(\theta|D) \propto P(D|\theta).P(\theta) \tag{7}$$

where $P(\theta|D)$ is the posterior probability of the parameters θ given the data D, $P(D|\theta)$ is the likelihood of the data given the parameters, and $P(\theta)$ is the prior distribution of the parameters.

Start
Initialize_transmitter()
Initialize_receiver()
Initialize_sensors()
Initialize_ML_Model()
while True:
  distance = Get_distance()
  received_power = Get_received_power()
  signal_quality = Get_signal_quality()
  adjusted_frequency = Adjust_resonance_frequency(Get_current_resonance_frequency(),Calculate_target_resonance_frequency())Update_receiver_frequency(adjusted_frequency)
  optimal_phase_shift = Optimize_beamforming(signal_quality)
  Apply_beamforming(optimal_phase_shift)
  power_transmission = ML_Model.predict(Get_current_state(distance, received_power, signal_quality))
  Transmit_power(power_transmission)
  if Check_for_misalignment(distance):
    Re-align_system()
    Update_beamforming()
  if Evaluate_power_transfer_efficiency(received_power, transmitted_power) < threshold:
    Optimize_system_parameters()
  Log_data(distance, received_power, signal_quality)
  Update_ML_Model()
End

The pseudo code explains for Internet of Things devices how a WPT system with energy economy works. It starts with activating the transmitter, receiver, sensors, and machine learning model. Every iteration of the proposed system collects distance, received power, and signal quality data. Beamforming is set to focus energy on the receiver and modulates the frequency of the receiver for best alignment. A RL model estimates optimal power levels, hence regulating power flow. The proposed system tracks alignment, evaluates power transfer efficiency, and, if necessary, modifies parameters. Records of data help to facilitate continuous learning and development.

In summary, by means of adaptive resonance tuning, beamforming, and machine learning for real-time corrections, the proposed Wireless Power Transfer (WPT) system improves efficiency, range, and stability. Validated by simulations and hardware testing with exceptional performance above current approaches, it lowers energy loss, maximizes power management, and guarantees consistent IoT device charging.actor over time.

4. RESULTS AND DISCUSSION

The results and analysis reveal, in terms of power transfer efficiency, energy loss, and system stability, the greater performance of the proposed system than of the existing systems. Regularly surpassing the existing systems in all respects over various distances, the proposed system shows higher power efficiency, lower energy loss, and better consistency in power delivery. These advantages become increasingly evident at greater distances, therefore highlighting the promise of the proposed system for more consistent and efficient operation over extensive areas.

Table 1. Power Transfer Efficiency (%)

Distance(m)	Proposed System	Y. Wang et al. [10]	S. M. A. Huda et al. [11]
1	95	82	88
3	92	75	85
5	89	68	80
7	86	60	75

Table 1 demonstrates across a range of 1, 3, 5, and 7 meters the power transmission efficiency (%) of the proposed system and the existing system [10] and [11]. Though it still remains better at all distances, the proposed system constantly exhibits higher efficiency than the existing systems since values start from 95% at 1 meter and decrease as the distance increases. For one meter, for example, the proposed system obtains 95% whereas the current systems get 82% and 88%, respectively. While existing systems decline sharply to 60% and 75%, respectively, the proposed system maintains 86% at 7 meters. In terms of power transmission efficiency, it shows especially over longer distances that the proposed system surpasses the existing systems.

Table 2. Energy Loss (W)

Distance(m)	Proposed System	Y. Wang et al. [10]	S. M. A. Huda et al. [11]
1	0.15	0.38	0.28
3	0.20	0.50	0.35
5	0.25	0.60	0.45
7	0.30	0.75	0.55

Table 2 presents, at various distances, the energy loss (in watts) for the proposed system and the existing systems [10], and [11]. The energy loss in every system rises with distance. Compared to both the current systems, the proposed system displays lower energy loss over all distances despite a continuous variation in energy efficiency. For instance, the proposed system loses 0.15

W at one meter, while the he-existing systems lose 0.38 W and 0.28 W correspondingly. Greater distances enable the tendency to continue, therefore demonstrating the more efficient reduction of energy loss by the proposed system technology.

Table 3. System Efficiency (Variation in Power Delivery in Watts)

Distance (m)	Proposed System	S. Singireddy et al. [10]
10	45.21	39.77
15	40.89	27.58
20	32.45	22.23
25	25.11	19.51

Table 3 contrasts the different systems' efficiency at varying distances, measured in watts provided. The proposed system performs better than the existing system [10] on every measurement distance. The efficiency difference grows as one gets farther away from the transmitter; at 15 meters, the proposed system produces 40.89 watts, while the baseline approach's efficiency drops to 27.58 watts, followed by 32.45 watts and 25.11 watts at 20 and 25 meters, respectively, compared to just 22.23 watts and 19.51 watts for the proposed system. It demonstrates that the proposed system has much higher power efficiency at longer ranges.

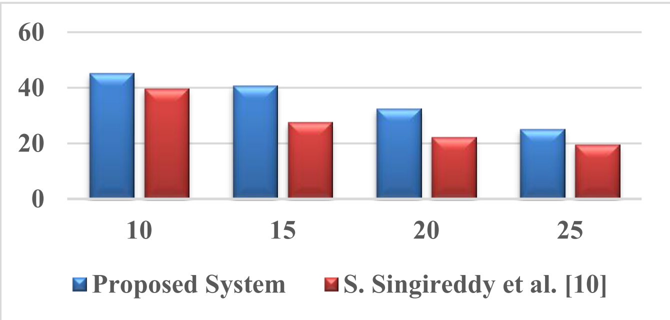

Figure 3. Visual representation for System Stability (Variation in Power Delivery)

In terms of efficiency, stability, and range, the proposed WPT technology demonstrates very notable improvements over existing technologies. Beamforming, ML ensures optimal power delivery even in dynamic surroundings with probable misalignment by using adaptive resonance tuning. These techniques eliminate the typical issues experienced by conventional WPT systems including energy loss and restricted range and provide a scalable, flexible solution for IoT devices scattered over great distances. Improved adaptation to external conditions made feasible by dynamic change of transmission parameters assures continuous power transfer over longer distances and in mobile settings. Moreover, it provides more sustainable and reasonably priced substitutes for IoT installations, including industrial automation and smart cities, so substantially reducing energy losses than present technologies. Such technology could change the way IoT devices are distributed given constant and efficient power sources for a wide range of use cases. Its low energy loss and high-power efficiency not only support long-term sustainability but also seem to let IoT systems grow. Future system developments will most likely increase its scalability and ML techniques, therefore improving its performance in many different settings.

5. CONCLUSION

In conclusion, the proposed energy-efficient WPT system shows great advancement in addressing the limits of current systems like low energy efficiency, misalignment-induced energy loss, and limited range. By combining adaptive resonance tuning, beamforming, and machine learning, the proposed system dynamically modulates transmission parameters, so enhancing power delivery even in mobile and dynamic IoT environments. Experiments demonstrate its benefits in terms of stability, energy loss lowering, and power economy. Though it depends on real-time data processing for optimization, which under severe load conditions could create delays, the system does have certain limitations. Moreover, the scalability of the technology for large-scale projects could complicate the guarantee of continuous operation. Moreover, the energy transfer efficiency of the gadget could worsen in quite adverse environments. The key goals of future research will include improving ML algorithms for enhanced real-time flexibility, raising system scalability for industrial-scale applications, and optimizing performance under various environmental conditions. Furthermore, looked at will be including energy collecting techniques to match the power transfer system and ensure long-term sustainability in IoT networks.

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