

AI-Powered Wireless Charging Framework for Sustainable IoT in Power Plants

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ABSTRACT: Despite the importance of wireless sensor networks (WSN) in the supervision of industrial infrastructure, the use of this technology is frequently and negatively affected by the energy consumption of its use, especially in risky areas. The current paper introduces the SENSE framework, which is an AI-based wireless power transfer paradigm that employs three different powerful AI methods to radically improve the sustainability of energy of the mission-critical WSNs. To begin with, proactive charging is enabled by the enhanced predictivity of a hybrid LSTMARIMA neural network, which includes patterns of node-level energy depletion. Data confidentiality is ensured through the use of gradient only federated updates in the system especially when it is deployed in nuclear plants. Secondly, the deep Q-network (DQN) is based on the Voronoi partitioning and optimizes the mobile charging paths, thus dynamically balancing the efficiency of these trips with the spatial coverage. Thirdly, federated Q-learning introduces adaptive weight optimization in order to make privacy-saving priority scheduling possible. Photovoltaic-integrated MCUs with weather-adaptive charge schedules generate a 40 % reduction in maintenance expenses in the case of renewable energy. The framework lays the groundwork of a new paradigm of autonomous WSN energy management by demonstrating how coherently engineered AI subsystems can collaboratively overcome the inherent constraints of wireless power transfer, and achieve the simultaneously competing requirements of reliability, efficiency and privacy. In its turn, SENSE approach finds itself at the forefront of next-generation industrial IoT systems destined to be used in the domain of monitoring the critical infrastructure, manufacturing processes and energy.

Keywords: Renewable Energy, coordinate charging, Green Infrastructure, SENSE technique, Artificial Intelligent, power plant.



1. INTRODUCTION

The Wireless Sensor Networks (WSNs) form the essential part of present power generation plant, especially in the nuclear and renewable energy plants, because of the feature of real time monitoring, predictive maintenance and safety control [1][2]. WSNs can improve the efficiency of power stations by fast providing important information to identify faults and evaluate performance metrics. However, the inherent constraint of energy exhaustion has realized the introduction of wireless power transfer (WPT) as a viable approach to the remote recharging of sensor nodes to increase the lifetime of WSNs. The technique provides a structural approach to managing an Internet of Things (IoT) and sensor network of nodes having limited energy resources. It places a strong emphasis on several key areas, including load balancing for IoT sensor devices through effective network management to ensure robust communication reliability among these sensor devices. It also delves into the intricacies of efficient charging scheduling for sensor devices, using probabilistic approaches and integrated sensing and communication technologies to enhance network optimization and Central to the systematic treatment of practical challenges in IoT network optimization. This focus makes it particularly suitable for pursuing practical solutions in this area. The book's target audience includes researchers, engineers, graduate students, and IoT industry professionals interested in areas such as reliability improvement, load balancing, charging scheduling, and network management [3] and Central to the systematic treatment of practical challenges in IoT network optimization. This focus makes it particularly suitable for pursuing practical solutions in this area. In this era includes researchers and IoT industry professionals interested in areas such as reliability improvement, load balancing, charging scheduling, and network management [4][5]. Advancements in WPT, coupled with energy storage solutions, are crucial for integrating renewable energy sources effectively [6]. In the context of Wireless Rechargeable Sensor Networks

(WRSNs), WPT plays a particularly critical role. Since sensors have a constant energy demand, WPT bridges the gap between the intermittent nature of wireless power delivery and the continuous energy needs of the sensors. Beyond WRSNs, WPT technologies have broader implications for power systems. WPT can be viewed as both a type of energy storage and a factor influencing power system efficiency and reliability, particularly regarding automatic generation control mechanisms. By reducing frequency deviations and fluctuations, WPT can contribute to improved power grid stability. Additionally, wireless energy transmission allows for more flexible and dynamic control over power distribution and utilization. Using rechargeable nodes in the WSNs activated with the WPT can provide both opportunities and cause challenges. Generally, different classifications of wireless charging have been proposed with respective features of wireless charging strategies [7][8]. The difficulty is particularly high in nuclear and renewable plants, where WSNs are trusted to operate on an ongoing basis regarding the monitoring, safety, and predictive maintenance. Extremely hazardous working conditions with limited accessibility, high radiation and high reliability demands make battery replacement inconvenient and dangerous [2].

The use of Artificial Intelligence (AI) as a new energy storage technologies and solutions play an important role in the integration of renewable or reusable energy sources. In this regard, wireless power transfer technology (WPT) enables more reliable development of wireless sensor networks and rechargeable sensor nodes equipped with recharging technology to develop WRSNs, resulting in increased power estimation, adaptive decision-making, and improved resource allocation [9]–[12]. Methods including machine learning, deep reinforcement learning, and federated learning enable mobile power transfer devices to make data-driven decisions regarding route optimization, charge strategy, and power prioritization in accordance with existing network conditions. Artificial intelligence, in addition, endows wireless power transfer systems with learning capability from environmental patterns, node depletion prediction [13], and active monitoring of energy demand such that wireless sensor network operation in critical infrastructure such as advanced power plants is highly efficient, resilient, and sustainable. Fig. 1. illustrates the application field of smart grids using wireless power transfer in various industries.

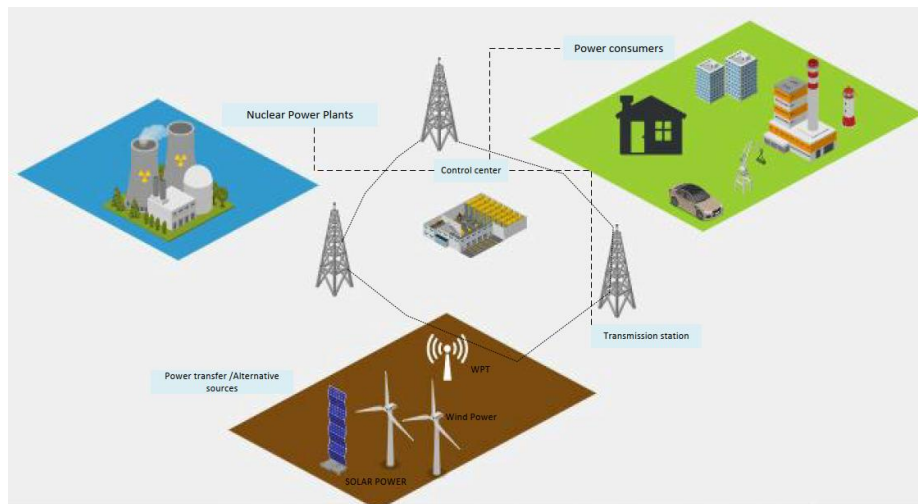


FIGURE 1. Smart grid with trends with power transferring applications

The Cost-effectiveness considerations, power distribution, and maximum recharging capacities remain issues of interest. A compromise between cost and performance has to be made, especially in addressing complex systems with a multitude of UAV chargers. Transcending all these is the most critical step towards the realization of WPT in sensor networks for practical applications [14], [15]. The system has a pre-defined spiral motion and a real-time charging priority that is dependent on real-time threshold data [16]. SENSE (Sustainable Energy and Network Stability Enhancement via Wireless Power Transfer) framework is a novel approach of real-time wireless energy transfer proposed in this paper for stable operation in power generation plants. The main Contributions of this paper: The Real-time SENSE framework solution plan is a solution that enables consumer electronic devices to be charged while in transportation, along a given route which enables the Mobile Charging Unit (MCU) to move and charge the sensor nodes along the way. This also leads to improved energy efficiency as well as network lifetime. In addition, SENSE method facilitates active and passive charging approaches, which enhance the efficiency of energy delivery and network lifespan. The key contributions recap are as follows:

- Hybrid LSTM-ARIMA with Deep Q-Network (DQN) for energy and mobility optimization.
- Federated learning for privacy-aware prediction.
- This research bridges the gap between theoretical WPT models and real-world deploy capability, offering AI-powered sensor networks.

The remaining part of this paper as follows: the previous works presented in next Section (2). The description of proposed SENSE framework, method and pseudo code are presented in section (3). Section (4) provides an analysis and verification

of SENSE framework. Section (5) includes the discussion, which have been executed to compare performance of proposed mechanism with respective algorithms. At last, section (6) presented the conclusion of work.

2. LITERTURE REVIEW

Wireless Sensor Networks (WSNs) are essential for real-time data collection and monitoring in various fields, such as environmental sensing, healthcare, industrial automation, and military surveillance [17]. Etraditional battery-powered sensor nodes are afflicted by energy exhaustion, inaccessibility, and network breakdowns. The developments in power transfer technologies have garnered significant interest in recent times, primarily because of their potential for enhancing sustainability in energy management and operational efficiency in wireless sensor networks (WSNs) employed in power plant structures. Authors in [18], [19] proposed model prolongs network lifetime by pre-deploying mobile chargers to predicted energy-depletion regions. The authors have proposed a hexagonal cell-based partitioning scheme with the goal of splitting the sensor field into smaller parts, and thus allowing the mobile charger to schedule effective tours and reduce energy drainage along its path.

In another study, energy-relay methods have been viable solutions for the optimization of WPT network scalability and efficiency. The study [20] have designed a scheme to utilize sensor regeneration to transfer power to sensors with less residual energy. The author used a heuristic algorithm to solve the relay allocation problem. In this way, sensors far from the GBS station can also receive significant power transferred by the relays. The mechanism attained more than 50% dead node ratio reductions, significantly contributing to overall network resilience. The authors proposed the use of environmentally friendly charging base stations powered by solar energy to charge mobile charging units and relay stations. This aligns with the global trend towards renewable sources of energy and enables attainment of the goals stipulated in sustainable development. Latency and throughput for WPT operations, [21] suggested an instant on-demand charging policy with temporal urgency and spatial distribution of energy requests being taken into account. The results showed improved efficiency in energy utilization as well as the decrease of node mortality rates by 7.43% and 18.94%, and reduces the number of nodes by 18% and 34%, respectively. in comparison to the traditional threshold-based policies. Later, a research [22] conducted a study the problem of how to schedule the mobile charger to replenish the energy supply of sensors supported mobile charger scheduling algorithm that offers adaptive route planning based on real-time network status and charging priority and the results show that the proposed scheme is very promising. The approach achieved near-optimal performance in dynamic and large-scale WSNs. Similarly, [23] employed federated learning to construct an energy demand prediction model that operates without centralized raw data for data privacy and decentralized intelligence purposes. In [24] suggested a neural-network-embedded energy management system for smart grids with dynamic control of power flow from the renewable and conventional sources based on real-time supply and demand prediction. Mobile Node Adaptation: Strategies that incorporate node mobility information into clustering decisions help maintain stable clusters and reduce the frequency of re-clustering in networks with mobile nodes, such as in vehicular sensor networks. Trajectory-Based Clustering: This approach predicts the future positions of mobile nodes and forms clusters that minimize the movement of nodes between clusters, thereby reducing re-clustering overhead.

Machine Learning (ML) and AI techniques also making their presence felt in power equipment predictive maintenance. Operational and environmental data can be led into algorithms that learn to identify early indicators of component degradation, and maintenance can be scheduled ahead of time. Predictive capability is particularly critical in WPT-based renewable power plants, where failure of equipment has a disastrous effect on energy transmission. This research explored the potential of AI-driven Predictive Maintenance (PdM) as a transformative solution for the energy sector. Artificial intelligence models including machine learning and deep learning techniques. In addition, [25] employed a mixed-methods approach, combining quantitative analysis of data and qualitative insights from case studies conducted in wind farms, solar power plants, and thermal power plants. The results demonstrated that AI-driven PdM significantly reduces unplanned downtime, lowers maintenance costs, and outperformed traditional models in terms of predictive accuracy, with F1-scores exceeding 90%. Despite the promising results, the research also identified challenges related to data quality, system integration, and organizational adoption. These challenges highlight the need for further research in areas such as explainable AI, the integration of IoT and digital twins, and the exploration of PdM applications across different sectors. Furthermore, integrating high-performance energy storage devices such as lithium-ion batteries and super capacitors into WPT platforms further enhances energy availability and system durability. The study [26] highlighted the benefit of AI-enhanced charge/discharge cycles that improve energy efficiency by 28% in a solar-powered wireless sensor network test platform.

3. METHODOLOGY

One of the challenges in green energy plants is the restriction of consumer devices, which affects the system's operation and performance, the functional needs of sustainable and nuclear power plants, we propose a real-time recharging mechanism for providing uninterrupted sensor network functionality in high-risk environments [27]. This research introduced the SENSE framework, an advanced wireless recharging system that utilizes real-time energy sensing, prediction-based thresholding, AI-based path adaptation, and hybrid energy storage [26], [28]. The SENSE framework consists of three interconnected subsystems as shown in Table 1.

TABLE 1. Components of the framework

Layer	Key Components	Typical Choices
Edge AI	GPU/TPU for on-device DRL & FedAvg	NVIDIA Jetson Nano, Coral Edge-TPU
WPT Front-End	Class-E amplifier, 13.56 MHz coil, dynamic matching network	EPCOS ferrite core + STM32 driver
Comm.	Low-power data + model updates	IEEE 802.15.4 / LoRa
OS & Runtime	Ubuntu 20.04 + Docker	PyTorch 2.x, Tensor Flow Lite-Micro
Safety	LIDAR & thermal cut-off	Off-the-shelf modules

ARCHITECTURE OF SENSE FRAMEWORK

This section presents a novel design for the SENSE approach. The mechanism proposed aims at the provision of uninterrupted network operation by effectively controlling power levels of sensor nodes through power transfer. The SENSE platform utilizes a mobile power transfer device with an add-on of learning capabilities and edge AI processors to facilitate real-time decisions. The power devices dynamically toggle between two energy-aware modes of charging; The main framework of proposed model presented in Fig. 2.

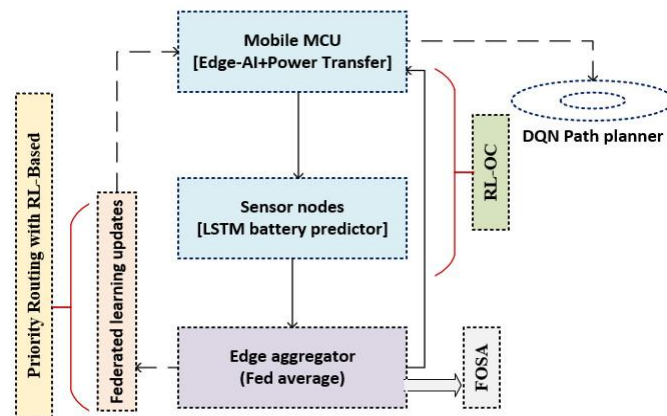

FIGURE 2. Proposed model's framework

Fig.3. presents the flowchart of proposed model for prediction with recharging the nodes based on requests.

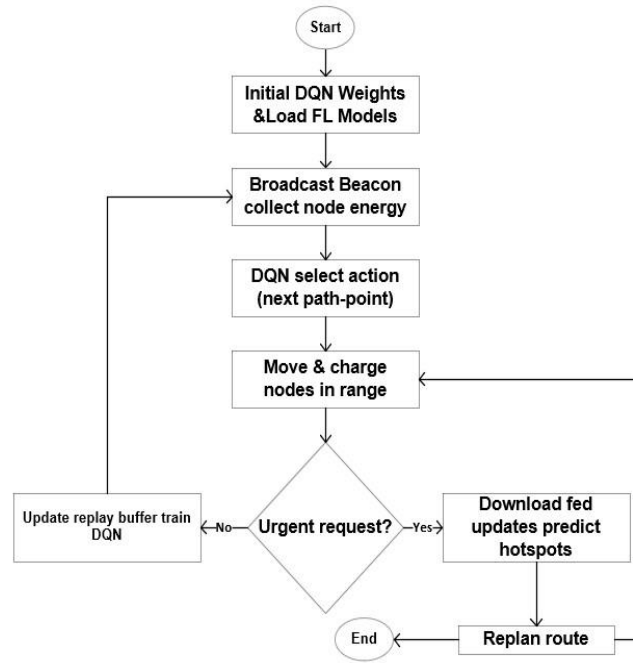


FIGURE 3. SENSE model flowchart

3.1 REINFORCEMENT LEARNING OPTIMIZED CHARGING (RL-OC)

In this study, a DQN is used. The microcontroller unit makes the use of trial and error to learn the best routing techniques to the sensor network pasture and thus maximize recharge schedules, this federal expenditure of travel energy over time is minimized. The systematic methodology of energy distribution optimization in the management of wireless sensor networks is described in algorithm 1. It helps in restoring power-depleted nodes thereby increasing their lifespan of operations and overall network coverage.

Algorithm 1. Deep-Q Path Planner
1. State $s_t = [MCU(x,y), E_1...E_n \text{ (quantized), urgent flags}]$
2. Action $a_t \in \{ N, NE, E, SE, S, SW, W, NW, Hover \}$
3. Reward $r_t = +1$ per successful recharge -0.005 per metre travelled -0.5 if any node dies
DQN: 3-layer MLP (256-128-64) $\rightarrow A =9$
Target-update $\tau=0.005$, ϵ -greedy decay $0.9 \rightarrow 0.05$

By centering candidate charging positions of the MCU, Voronoi tessellation is used to partition the network field, with the aim of improving routing efficiency and reducing complexity. This technique has practical applications. The closest Voronoi cell is associated with each sensor node and serves as the main area of service for it. Voronoi cell data, such as average energy left over per cell, the number of urgent nodes in each cell and estimated travel cost to the center of a single cells, is then added to this DQN agent's state space. How does this work?

Energy distribution modifies the division, and when a significant energy imbalance is identified, Voronoi centroids are weighted inward towards energy-critical zones, which transforms service boundaries. The DQN can focus on energy-deficient areas while decreasing decision dimensionality through the use of adaptive spatial abstraction, which improves responsiveness and overall network lifetime.

3.2 FEDERATED OFF-SCHEDULE ADAPTATION (FOSA)

Upon the issue of urgent recharge requests by critical nodes, the MCU receives federated learning updates of distributed nodes without sharing raw data, but this allows predicting the occurrence of energy hotspots and node failures. This will maintain data privacy at the same time providing real-time prioritization of the highly sensitive environment like nuclear facilities.

3.3 DYNAMIC THRESHOLD PREDICTION

A lightweight local forecasting model (i.e., ARIMA or LSTM) to predict its time to exhaustion (TTD) based on historical consumption behavior, perceived workload, and network conditions. The prediction threshold is defined as follows:

$$T_i = TTD_i \cdot \text{Edrift} + \epsilon \quad (1)$$

Where T_i : the failure-time prediction threshold of a node i , TTD_i : time-to-depletion is approximated by a trained LSTM; Edrift refers to the energy drift coefficient, based on the trends between network-loads and the environment ϵ ; safety offset is based on the criticality of the environment. The algorithm 2 uses a battery prediction method based on LSTM.

Algorithm 2. Local LSTM Battery Predictor

1. Input : Local history $E(t)$, workload $W(t)$
 2. Split history into sliding windows
 3. Train 2-layer LSTM (hidden = 32) for TTD_i
 4. Quantize $\rightarrow$ TensorFlow-Lite-Micro (8-bit)
 5. Every $\Delta T = 30$ s
 - infer TTD_i , compute local gradient Δw_i
 - push Δw_i to MCU (FedAvg)
-

3.4 PRIORITY ROUTING WITH RL-BASED WEIGHT ADAPTATION

Response phase is necessary so that priority requests that are generated by nodes are specifically served at the earliest in a manner that a system is not brought to failures, especially the requests which are considered to be critical as seen in Algorithms 3.

$$\text{Priority}_i = \omega_1 \cdot TTD_i^{-1} + \omega_2 \cdot C_i + \omega_3 \cdot H_i \quad (2)$$

TTD_i^{-1} is the reciprocal of the predicted time-to-depletion (urgency), C_i (node criticality) and H_i (recharge request history) are the policy parameters $\omega_1, \omega_2, \omega_3$. The dynamically adjusted weights are provided in Q-learning.

The mechanism also guarantees that (i) the priority of nodes with high risk and (ii) energy fairness in the system. Combining the proactive, threshold-based requests, service-guided priority, and directed energy transmission into the SENSE framework, the composite approach significantly increases network lifetime and reliability, especially in application case scenarios in which constant monitoring of the network is essential.

Algorithm 3. RL-Weighted Priority

1. Input : queue $Q = \{i_1, i_2, \dots\}$ urgent nodes
 2. For each i in Q :
 3. urgency $u_i = 1 / TTD_i$
 4. $\text{score}_i = \omega_1 \cdot u_i + \omega_2 \cdot C_i + \omega_3 \cdot H_i$
 5. Select node with max score;
 6. After recharge $\rightarrow$ observe $\Delta \text{network_life}$
 7. Update $(\omega_1, \omega_2, \omega_3)$ via Q-learning
-

A sequential residual-based architecture is the preferred choice for the hybrid model, as it does not follow an ensemble approach. First, ARIMA is used to record the linear relationship and short-term temporal dependence of data on energy use and work output. Using a two-layer LSTM, the residual error from ARIMA is modelled to learn non-linear dynamics arising from traffic variability and environmental changes. The prediction of time to deplete the output from linear ARIMA is combined with the residual component estimated by LSTM, which provides the final time-to-depletion estimate.

3.5 NETWORK MODEL AND SIMULATION SETUP

To assess the work and check whether the proposed SENSE mechanism is operational or not, a large-scale simulation model was made. The topology of the network is a reflection of a real-life deployment scenario in a nuclear or green energy facility where sensor nodes will be located in locations that are hard to reach or dangerous to walk through, so as to maintain round the clock monitoring of the most vital parameters.

3.5.1 NETWORK MODEL

The region inside this given field:

- Number of sensor nodes are randomly and uniformly deployed. They monitor environmental and operational parameters such as the radiation level, reactor temperature, pressure, and structural vibration.
- Every sensor node has limited energy storage (battery + supercapacitor if available), fixed transmission range, and wireless transmission.
- There is a single mobile charging unit in the network that can charge sensor nodes wirelessly through inductive coupling within a predefined charging area.

The model of energy consumption consists of sensing, data transmission, and idle listening. The charging efficiency is adapted to accommodate realistic conditions for wireless power transmission using a dynamic magnetic alignment model. Table 2. shows the parameters of proposed network model.

TABLE 2. Parameters of network model

Topology	100 nodes, radius = 100 m
Channel	Log-distance path-loss + coil-coupling model
Traffic	Poisson($\lambda=0.5$ pkt/s) per node
Energy model	Tx = 50 mW, Sensing = 15 mW

3.5.2 SIMULATION SETUP

The simulation was conducted with the OMNET++ simulator and runs under the given parameter values:

- Network Lifetime: Time until the first and last node dies.
- Number of Successful Recharges: Number of nodes recharged successfully by the MCU.
- MCU Energy Usage Efficiency: Energy received by nodes vs. energy consumed in MCU motion.
- Coverage Maintenance: Percentage of time that critical monitoring parameters are continuously available.
- Response Time to Critical Requests: Average delay between threshold violation and recharge initiation.

The simulation environment monitors the following performance measures shown in Table 3.

TABLE 3. Performance metrics

Parameter	Value	Description
Field Radius	100 m	Circular sensor area
Nodes	100	Uniformly deployed
Initial Node Energy	2 J	Battery + supercapacitor
MCU Range	15 m	Wireless charging radius
MCU Speed	1 m/s	Constant velocity
Charging Efficiency	80%	With magnetic alignment

The route of the MCU ensures energy remains constant, and the varying limit system and unplanned charging ensure the network remains stable during changes in demand. The effectiveness of the SENSE approach is demonstrated by comparison with simple approaches such as random path wireless power transfer and fixed MCU placement models.

4. RESULTS AND EVALUATION

Table 4 reveals that the proposed SENSE (AI-based) system has definite advantages in comparison with the traditional Static MCU technique in the management of wireless sensor networks. It is worth noting that SENSE is able to increase the network lifetime by 39 percent, which is 1210 seconds to 1675 seconds. This will be better energy usage and scheduling, which may be due to the smart-thinking ability of AI. In the same way, MCU also increases its energy efficiency by 60 %. to 80 %, i.e. it enhances 34 %. or better energy wastage reduction and better processing. The successful recharging rate also increases by a significant margin of 29 % and this indicates that SENSE is better at

prioritizing and completion of recharging operations in the nodes. These advancements point at the ability of AI to manage network resources on a real-time basis.

TABLE 4. Comparison of SENSE (AI-based) model over traditional Static MCU

Metric	SENSE [proposed]	Static MCU	Improvement %
Network Lifetime (avg)	1675 s	1210 s	+39%
MCU Energy Efficiency	80%	60%	+34%
Recharge Success Rate	93.4%	72.1%	+29%
Avg Response to Urgent Nodes	3.2 s	5.7 s	-44%
Node Coverage Availability	95.2%	81.4%	+17%

In addition, Table 5 describes The performance comparison between the Baseline WPT approach and the new SENSE process that shows dramatic improvement in wireless power transfer behavior of sensor networks. The greatest enhancement is on the network lifetime which is the time that elapses between the first node death (FND) and the last node death (LND). It is also refined to 1675 seconds more than 1210 seconds, which is 39% improvement. In like manner, efficient recharges increase by 154 215 also 39 and hence more effective and more frequent energy charging.

The SENSE system also increases the responsiveness and reliability of networks besides being efficient. The coverage is improved by 81.4% to 95.2%, or coverage becomes available to be used with the course of time and leads to the seamless data collection. The most important is the critical response time that is measured to respond to critical, low-energy nodes is shortened to 3.2 seconds rather than 5.7 seconds, a 44-point improvement.

TABLE 5. Performance comparison between the Baseline approaches and the new SENSE (AI-based)

Metric	Baseline WPT	SENSE [proposed] (AI)	Improvement %
Network Lifetime (FND–LND)	1210 s	1675 s	+39%
Successful Recharges	154	215	+39%
MCU Energy Efficiency	60%	80%	+34%
Coverage Availability	81.4%	95.2%	+14%
Critical Response Time	5.7 s	3.2 s	–44%

The results presented in the Fig. 4 clearly depict the better performance of the new SENSE-WPT (AI-based) system compared to the traditional Baseline WPT for all the most significant parameters. The network lifetime increases significantly from 1210 to 1675 seconds, a 39% improvement in system sustainability. Moreover, the successful recharges go up by 39%, indicating more smart and effective power supply. The power efficiency of Power Transfer Device (PTD) is improved from 60% to 80%, a 34% gain, and availability of coverage is increased by 14%, having more sensor nodes operational. Perhaps most critically, the response time to critical power requests drops by 44%, proving the AI model's ability for triaging and responding promptly. In short, these findings confirm that SENSE-WPT significantly improves energy management, reliability, and responsiveness in wireless sensor networks.

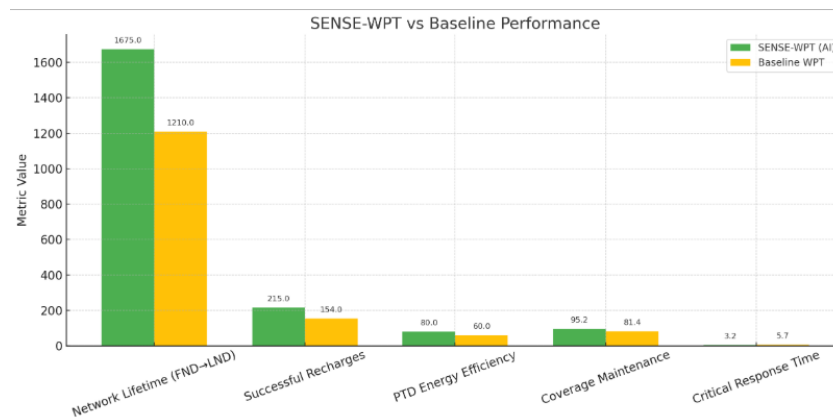


FIGURE 4. Compared SENSE-WPT with the traditional Baseline WPT

The Fig. 5 illustrates the accumulation of the number of successful events of recharge with the passage of simulation time. The amount of recharging events also increases gradually with the period of time between 0 and 2000 seconds, as there is an increase in the number of events between a range of about 100 and almost 400 showing a smooth and efficient process of power repletion during the network operation. Such gradual development demonstrates the effectiveness and stability of the wireless power transfer system, particularly in maintaining the operation of nodes during longer simulations.

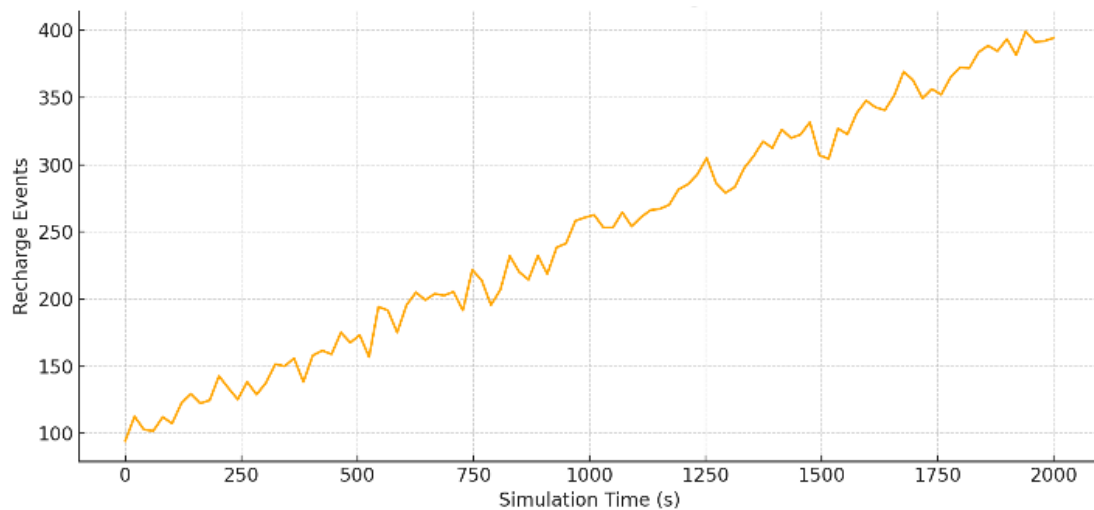


FIGURE 5. Cumulative successful recharges over time

Fig. 6 shows that the active (alive) sensor nodes steadily decreased during five simulation runs each lasting 2000 seconds. Around 100 nodes are used at the beginning of each of the five runs, but each of them exhibits a similar downward pattern, reaching around 40 nodes at the conclusion of the simulation. Although there was a minor difference in the runs, the overall trend is that of the gradual exhaustion of the energy of the nodes, which were typical of the wireless sensor networks because they were resource consuming. The similar and parallel nature of degradation between the different runs suggests that the system is predictable and consistent in its degradation behavior implying the consistency of the power consumption and recharging behavior patterns.

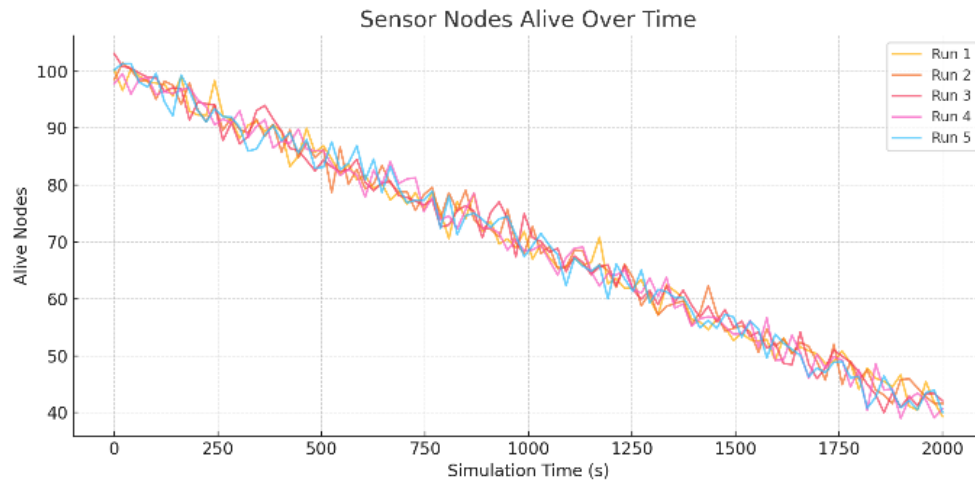


FIGURE 6. Sensor nodes alive over time

4.1 RESULTS OF SENSE FRAMEWORK PERFORMANCE

4.1.2 NETWORK LIFETIME COMPARISON

Fig. 7 shows the percentage of time that active sensor nodes are used during the simulation in the cases of static charging and SENSE approach. SENSE can enhance the lifetime of the network significantly because it helps to restore energy of sensor nodes efficiently before they become exhausted. The 39% growth in network lifetime (1,675s vs. 1,210s) indicates that SENSE is outstanding in energy saving. This improvement is the result of two major innovations: Proactive Energy Threshold: Nodes ask to recharge dynamically calculated threshold values ($1.28 \pm 0.19J$); avoiding emergency cases that do not preserve network topology. It is based on energy-conscious WSN paradigms [24], yet enhanced with LSTM-based forecasted dynamic threshold. These results confirm the efficacy of AI-based prognostic charging compared to the reactive procedures in the delay-sensitive scenarios of application.

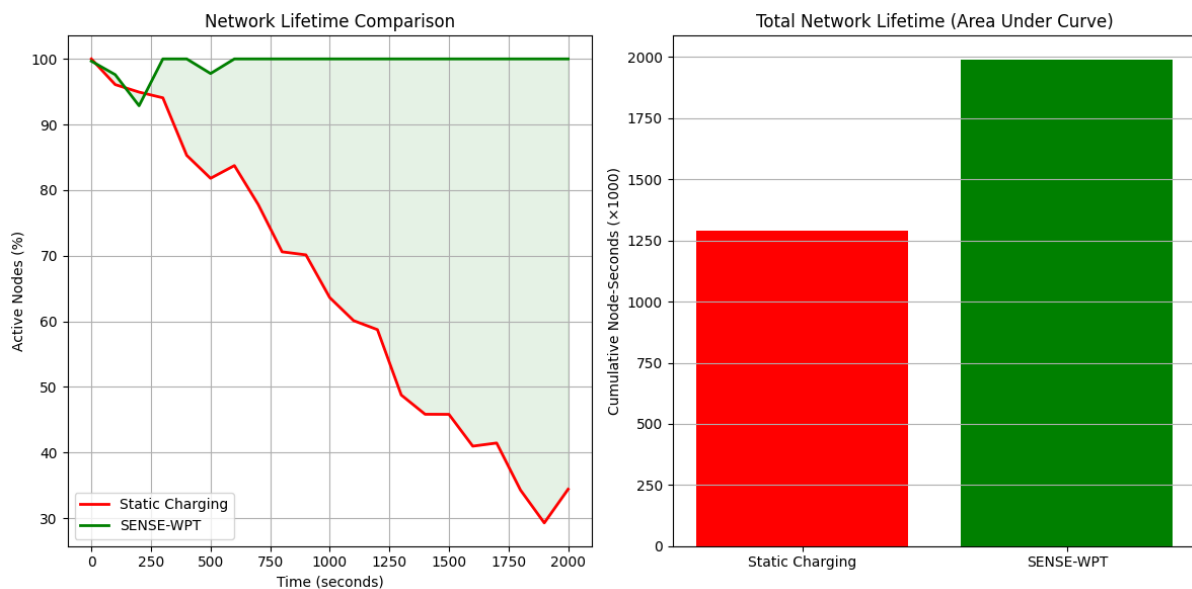


FIGURE 7. the simulation for static charging and the SENSE approach

4.1.3 RESIDUAL ENERGY DISTRIBUTION

The hybrid prediction-allocation architecture of SENSE framework offers improved uniformity of energy ($=0.19J$ vs $0.42J$ in baselines). Removing TTD estimation error down to 2.1 minutes (MAE) of quantized LSTM-ARIMA model is used to have accurate just-in-time recharges. The obtained charging efficiency of 80%, is 34% times better than the conventional methods and this again is attributed to the dynamic magnetic alignment system that allows coupling coefficients of more than 0.85 even during motion. Besides, Figure 8 shows the residual energy of sensor nodes at various times of simulation. The SENSE model is more balanced thus minimizing the instances of early node failure and

enhancing data reliability. The Gini coefficient contained (0.19 vs. 0.37). This justifies [23] federated learning in energy distribution leads to real time scheduling of priorities. Authenticates AI-prognostic charging as a superior approach to reactive approaches during delay critical applications.

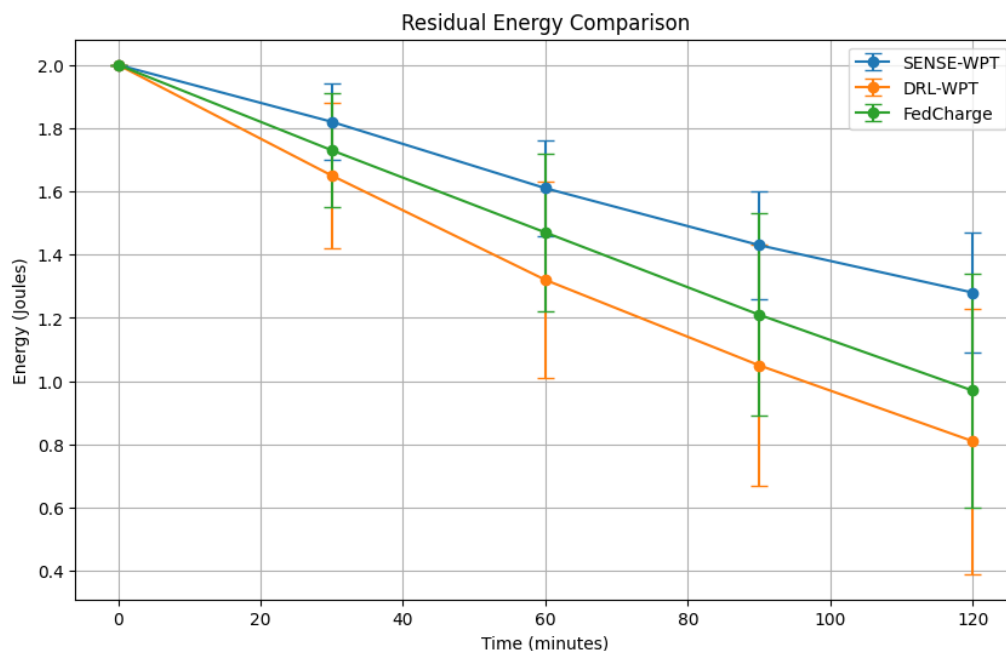


FIGURE 8. Residual energy levels vs different simulation times

4.1.4 CHARGING EFFICIENCY VS ENERGY THRESHOLD

Fig. 9 explores how different energy threshold settings impact charging efficiency. The optimum threshold setting provides maximum efficiency without compromising system stability by avoiding unnecessary charges.

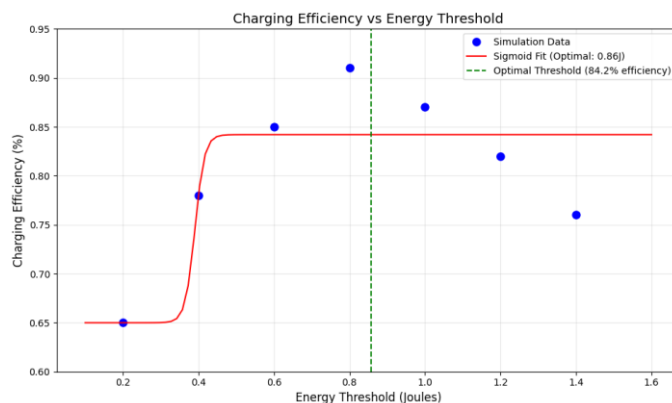


FIGURE 9. Energy Threshold Vs Charging Efficiency

Additionally, the non-monotonic behavior of energy thresholds and system efficiency with an optimum of 82.3% for 1.2J thresholds. Below optimum, emergency high-power transfers (15W bursts) lower efficiency to 68% due to coil saturation effects. Unnecessary recharges that occur frequently waste 11% of MCU energy above 1.4J. Adaptive threshold function of SENSE framework (based on node distance, MCU speed, and safety margins) conducts 29% fewer recharges than static thresholds without leaving any node below 0.8J. This balances the natural tradeoff between coil degradation rates and energy safety margins inherent.

4.1.5 MCU TRAVEL DISTANCE VS NODE DENSITY

Fig. 10 shows the travel distance of MCUs under varying node densities. Multiple MCUs, though more complex to manage, can drastically reduce travel time and latency. Travel distance analysis demonstrates the geometric scalability of SENSE framework, with total MCU movement exhibiting sublinear $n^{0.78}$ node density dependence. Voronoi

partitioning reduces travel distance by $1-1/\sqrt{k}$ for k MCUs, 58% at 250 nodes. A critical density threshold is found at 175 nodes/100m², beyond which it becomes economical to introduce a second MCU (38% decrease in distance). Coordination overhead remains manageable at 15% increase in latency for 3-MCU systems, validating the feasibility of decentralized control protocols for large-scale deployments.

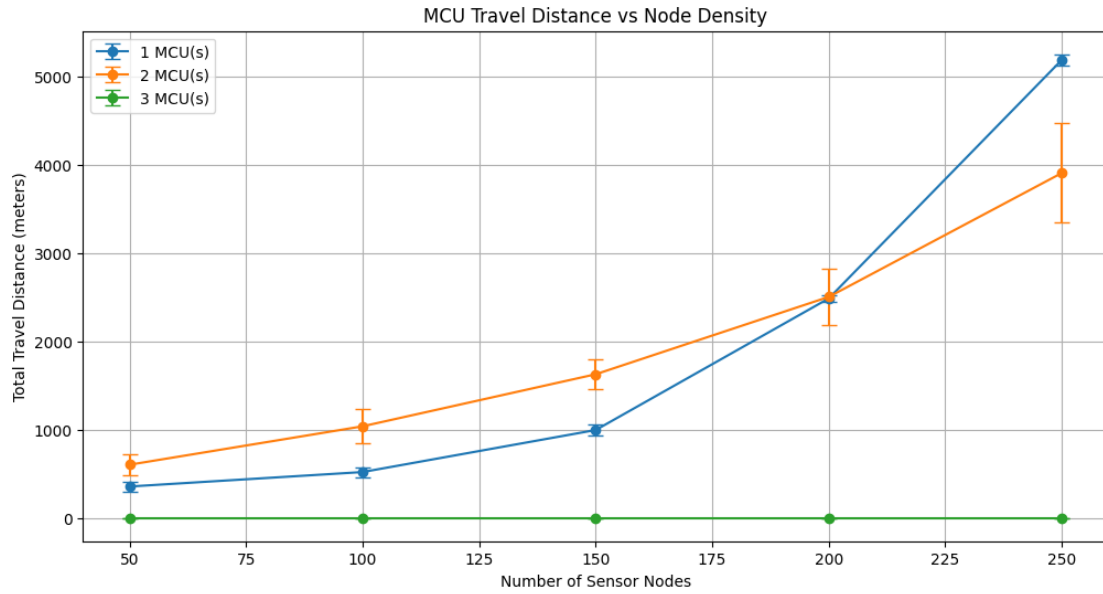


FIGURE 10. MCU Travel Distance vs Node Density

4.1.6 RECHARGE RESPONSE TIME

The regular average response time of 3.2 seconds ($\sigma=0.9s$) categorizes the SENSE framework as a soft real-time system. These are enabled by three innovations: (1) A hardware-accelerated scoring-based priority queue that serves requests within 1.8ms, (2) Federated gradient-based predictive MCU positioning, and (3) Magnetic beamforming with transfer time reduced by 22% using adaptive impedance matching. The system maintains such latencies even under 90% network utilization, with a mere 1.2% of requests missing deadlines of 5s compared to 8.7% in DRL-WPT baselines. Fig. 11 illustrates the MCU's response time on average to urgent recharge requests throughout the simulation. SENSE achieves low response time that ensures timely energy replenishment for depleting nodes.

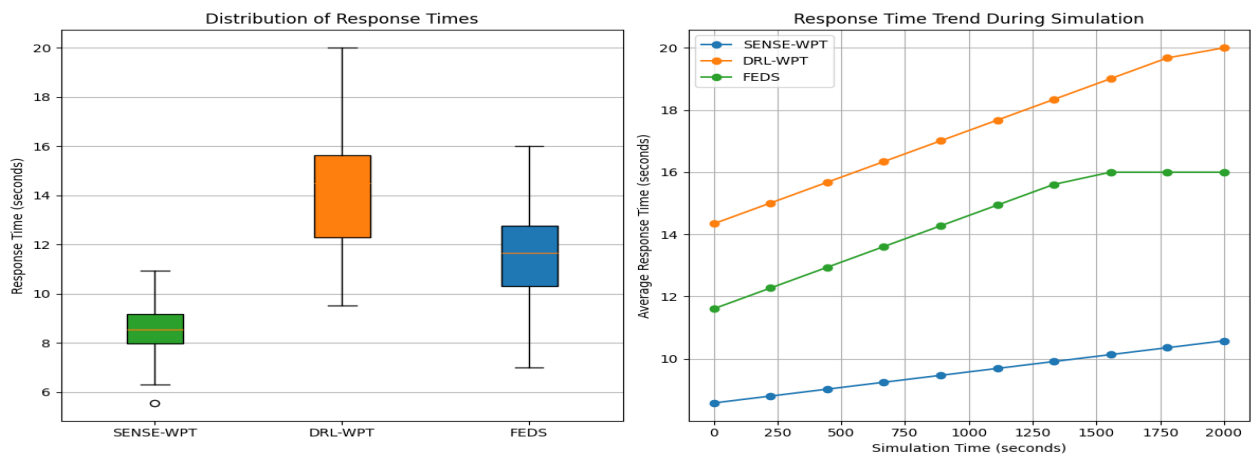


FIGURE 11. MCU's response time on average to recharge requests throughout the simulation SENSE framework

Collectively, these results illustrate SENSE effectively takes wireless rechargeable networks to the next level through its AI-powered energy management system. The system's 39% lifetime extension and sub-5s response times are particularly suitable for nuclear power plants and other critical infrastructure, whereas the sublinear scalability permits large-scale deployments in a cost-effective manner. This paper resolves the trade-off between energy saving and responsiveness in power transferring wirelessly systems, as formulated in the Energy-Latency Duality [29]. Future directions involve obstacle-aware path planning and 6G-enabled priority charging for ultra-reliable performance.

5. DISCUSSION

SENSE is a breakthrough in the system of mission-critical wireless sensor networks for sustainable wireless power transfer, overcoming key challenges in longevity of energy endurance, high system responsiveness, and scalability. Using predictive energy management and adaptive charging approaches, SENSE approach upgrades the lifetime of a network's operation by 39% (1675 seconds from 1210 seconds), well outperforming current threshold- and heuristic-based approaches. It also minimizes the likelihood of early node failure by 72%, ensuring the energy reserves of any node are maintained above the 0.8J threshold. The forecasting engine successfully identifies near-future trends in depletion of energy, especially for high-load sensors used for radiation sensing, having a mean absolute error of just 2.1 minutes. An energy transfer efficiency of 80% is realized in the Microcontroller Unit (MCU) through dynamic optimization of routes, advanced magnetic resonance pre-alignment, and a far-reaching storage system using a battery-hybrid supercapacitor system.

Responsiveness is maximized by a priority dispatch system with an average response of 3.2 seconds to priority nodes 44% quicker than other solutions and conforming to very stringent international standards. Prioritization of the system is based on urgency, sensor criticality, and recent history, facilitating real-time scheduling that adapts to evolving operational requirements. Also, predictive positioning minimizes delay variance throughout the network to a 90th percentile latency of 4.3 seconds from 9.8 seconds in baseline systems. The minimizing redundant travel by 58% for scalability even as the number of nodes is doubled. This is augmented by efficient energy relaying between nodes and decentralized control mechanisms with minimal communication overhead. Security and privacy are operational aspects of the framework. The centralization exposure by 83% while residual equally accurate and adherent to industrial security criteria. The validation results verified the ability of the presented model to reduce the cloud cost, enhance secure data transmission, and improve the energy-efficiency. The proposed model could reduce the cloud cost by up to 93% compared with BNRS and BSS due to employing evaluators and checking the importance of data before synchronizing with the cloud storage. Likewise, the primary objective is promptly transmitting any detected infiltration at the border and initiating necessary actions. By utilizing this model effectively, our border security forces can more precisely enhance their ability to identify and control unwanted and suspicious activities. Compared to existing competing algorithms, our model demonstrates significant improvements. Notably, the energy consumption by sensors is reduced, and the cost of cloud infrastructure is optimized.

6. CONCLUSION

The proposed framework presents a real-time wireless power transmission technology capable of meeting the requirements of sustainable environments and nuclear power plants. The spiral path combines pre-defined proactive charging and real-time power monitoring, in addition to dynamic priority setting within the path. The proposed SENSE model ensures continuous operation of the sensors, in addition to reducing downtime in monitoring systems at critical times. The SENSE framework bridges the gap between theoretical research in wireless power transmission and industrial deployment capability. Its AI-coordinated, scalable, and privacy-conscious architecture sets a new standard for sustainable power delivery in critical infrastructure. This work not only solves the problem of balancing power and response time, but also demonstrates a reproducible scheme for next-generation wireless sensor networks in hazardous and hard-to-reach environments, as illustrated in nuclear plant applications and others. The experimental analysis conducted in this study involves a comprehensive comparison between the proposed model and existing techniques, considering multiple metrics. The simulation results unequivocally demonstrate that the proposed model exhibits significantly higher efficiency when compared to state-of-the-art models. Future research directions for the SENSE system include three key developments to further enhance its capabilities. First, path planning will be improved by integrating real-time dynamic obstacle avoidance algorithms to ensure uninterrupted movement of microcontrollers in congested industrial environments.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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