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AI-ENHANCED PHYSICAL LAYER FOR ENERGY-EFFICIENT WIRELESS SENSOR NETWORKS (WSNS)

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Abstract

WSNs are key technology in smart cities, environment management and medical field s, but are restricted in energy by their battery requirements. To fix this problem, the paper recommends using an intelligent AI-powered transmission control framework to boost energy efficiency and increase network lifespan. The system uses both Machine Learning (ML) and Reinforcement Learning (RL) approaches. The Random Forest m odel accurately forecasts energy consumption at nodes(MAE=0.00226) and real-time d ata from sensors and the environment allows the Q-learning-based RL system to adju st power use on the channel between 0.5W and 2.0W. Results are verified with infor mation provided in the Intel Berkeley Research Lab WSN dataset.Simulated results re veal that the suggested AI framework helps save 33% more energy than running on a fixed schedule. Because the simulations adjust well to different environments, the a pproach is suitable for situations in real-world WSNs.

Keywords: Wireless Sensor Networks,Energy Efficiency,Reinforcement Learning,Machi ne Learning,Al-based Power Control,Adaptive Physical Layer,IoT Optimization

1. Introduction

WSNs have become valuable by allowing people to get data from remote places and monitor events instantly in environmental monitoring, industry, smart city systems and healthcare [1,2,3]. These networks are built with wireless sensors that collect and br oadcast data from specific places. Working in difficult environments makes it very i mportant for sensors to be energy efficient, since changing or charging batteries is ra rely practical for them [4,5,6].A

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large amount of energy is used by WSNs in the physical layer during data transmission. Until now,broadcasting energy was not adapted for changes in the environment, so the use of energy was not efficient. Batteries run down faster due to extra power, whereas not enough power loses messages and requires restoring communication, all at a cost of extra energy [7,8,9].

For these inefficiencies to be tackled, there should be intelligent management techniques in place, those which are flexible and energy efficient a the same time. Using techniques such as Machine Learning (ML) and Reinforcement Learning (RL) within Artificial Intelligence (AI)appears to be very helpful [10,11]. Sensor data can be used by ML models to estimate energy needs and RL makes it possible for systems to respond in flexible ways through gaining experience [12, 13, 14]. Still, current AI-based WSN optimization strategies have major problems: they require complex designs that consume a lot of resources, do not respond to new changes in the environment and tend to focus only on either prediction or control without being fully integrated [15,16,17].

This research aims to establish a machine learning-based model to make precise prediction of energy usage in WSN nodes from environmental sensor data and design an adaptive transmission power control system with reinforcement learning-based implementation for the optimization of energy consumption in WSNs to assess the efficacy of the integrated AI-based framework in power saving while ensuring network reliability based on real-life sensor data.

Main Contributions of This Work Proposed a lightweight, real-time AI framework combining Machine Learning and Reinforcement Learning for adaptive power control in WSNs. Achieved **33% energy savings** compared to a static baseline model using real-world sensor data. Predicted node-wise energy consumption with high accuracy (MAE=000226) using environmental and time-based features. Enabled intelligent, node-specific transmission power selection through reinforcement learning. Demonstrated system robustness under **voltage noise and reward variance analysis,** confirming learning stability.

2. Literature Review

A lot of effort has been put into energy efficiency in WSNs because sensor nodes often have limited battery power. At the network and data link layer, many different strategies have been developed for the WSN architecture. However, transmission power control in the physical layer is an area that is not well explored but is still highly important. In this review, we will examine research in three main categories: traditional solutions for energy savings, machine learning which is utilized for energy prediction, and reinforcement learning for controlling power adaptively as shown in Table 1

Table 1:Summary of Differences: Existing Works vs Proposed Work

Ref.No	Method Used	Domain	Key Focus	Limitations

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(1)	Clustering & CH Optimization	WSN Routing	Energy optimization via cluster head selection	No physical-layer adaptation; lacks AI in tegration
(29)	Modified ACO	WSN Routing	Load-balanced routing & energy-efficient paths	Focused on routing; lacks predictive or ada ptive power control
(13)	ML (Rando m Forest, SVM)	Energy Materials	Predicting material behavior for storag e applications	Not WSN-specific; lacks real-time control and adaptability
(8)	ML+IoT	Renewable Energy (Wind)	Energy prediction from turbine sensor data	Not for low-power nodes;no reinforcement learning or adaptive c ontrol
(5)	RL (Q-learning with adaptive lea rning rate)	IoT & WSNs	Real-time power control using RL adaptation	No ML-based forecasting; lacks prediction-control integration
(27)	Heuristic Control (ACTOR)	RPL in WSNs	Link-quality based adaptive power control	No ML or RL com ponents; lacks lea rning-based decision-m aking
Proposed Work	ML + RL Integrated AI Framework	WSN Physical Layer	Prediction + Adaptive Power Control for energy saving	Focuses on real-time, node-level, lightweight AI solution

3. Methodology

The methods in this paper for addressing energy issues in Wireless Sensor Networks (WSNs)are outlined using artificial intelligence approaches in this section. This propo sal uses ML to predict energy consumption and RL techniques to control transmissio n power in real time at the physical layer. MACD uses four main steps: preparing t he data, building an ML model for voltage prediction, optimizing power through RL and evaluating the system performance to see if it works well and responds properly to changes.

A-Dataset and Preprocessing

This study uses the Intel Berkeley Research Lab WSN dataset, gathering sensor information from 54 indoor nodes with timestamps, node IDs and details on temperature, humidity, light intensity and voltage. During preprocessing, missing records are removed, outliers are identified and removed using IQR, time-related data is pulled from timestamp strings and all sensor data is scaled between 0 and 1. Following data processing, the inform ation is sorted into training (80%) and testing (20%) sets.

Dataset: The data collection in this study is the Intel Berkeley Research Lab WSN d ataset, which provides actual sensor values of 54 sensor nodes mounted indoors. Thes e are the features of the dataset:

Timestamp: Stores the date and time of every sensor reading.

· **Node Dim**idiates the individual sensor node.

·**Temperature**(°CC): Records ambient temperature changes.

·**Humidity** (%): Shows atmospheric humidity levels.

·**Light Intensity (Lux)**: Records illumination within the sensor's environment.

·**Voltage** (V): Describes the energy usage of every sensor node.

The aim of the dataset preprocessing is to affirm the consistency, readiness and data quality, for ML training and RL optimal performance.

Data Cleaning and Feature Engineering:

·**Handling Missing** Values: All the data found incomplete or incorrect were completely r emoved to avoid inconsistencies in the process.

·**Outlier Detection:** Outliers in humidity, voltage and humidity values were found with t he use of the interquartile range (IQR) approach and deleted.

·**Timestamp Processing:** The timestamp feature was utilized to create time-dependent fea tures, such as

- **Hour of the day** (0-23)
- **Day of the month (1-31)**
- **Month of the year (1-12)**

0**Weekday (Monday=0,** Sunday=6)

· **Normalization:** We adjusted all sensor values to be between 0 and 1 using Min-Max Normalization. This helps keep the input values consistent for machine learning traini ng and decision-making in reinforcement learning.

Post preprocessing, the pre-processed data was divided into training and testing sets f or training ML models

B-Machine Learning-Based Energy Prediction

A Random Forest Regression (RFR) model is applied to estimate the energy use of WSN nodes according to the environment. It is chosen because it manages to deal w ith the complicated, nonlinear information in the data and handles missing data points from the sensors. Default

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hyperparameters are applied to train the model on the training dataset which is then assessed on the testing set using the Mean Absolute Error (MAE). An MAE of 0.00 226 shows that voltage consumption predictions are relied upon for dependable scalin g of the RL problem.

Model Selection: In this study, we used a Random Forest Regression model to predi ct how much voltage wireless sensor network nodes use based on readings from envi ronmental sensors. We went with this model because it works well for complex data and can handle noise and missing info, which is common with WSN sensors. Plus, t he Random Forest concept assists in seeing which of the ecosystem factors genuinely is of concern in the case of the amount of energy the sensor nodes contain.

Model Training and Evaluation: The information distribution may serve two roles: 80% was for the purpose of the training while 20% was the tested data. The trainin g on the Random Forest was performed which needed the determination of the actual number of trees in the group.

The model accuracy evaluation used Mean Absolute Error (MAE) as the performance metric:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

where$y_i$is the actual voltage consumption and$\hat{y}_i$is the predicted value.

The trained model achieved a prediction accuracy of 0.00226 allowing it to perform effectively in voltage use estimation. The obtained MAE result of 0.00226 contributes to creating superior power control predictions through reinforcement learning.

C-Reinforcement Learning-Based Transmission Power Control

To build a smart power control method for WSN nodes, Q-learning Reinforcement L earning is used. The RL model handles incoming sensor readings for temperature, hu midity, light intensity and voltage use to find the most suitable transmission power o ut of 0.5W, 1.0W,1.5W and 2.0W. It works by rewarding conservation of energy and punishing wasteful power use and prompts higher power to protect transmission relia bility. A policy using epsilon-greedy and slow decrease of the greediness (decay rate 0.9997) is applied for 10,000 periods, so the simulator switches gradually from exper imenting to decision-making.

Reinforcement Learning Model: The authors employed Q-learning-based Reinforceme nt Learning methods for adjusting WSN node transmission power levels. The power l evel coordinates changed according to environmental variations and individual node e nergy requirements. The system incorporated assessment of light intensity together wit h humidity and temperature and voltage consumption for its analysis. WSN nodes pr ocessed their sensor readings to produce current state evaluations enabling energy-savi ng power control decisions that extend network operation time.

Action Space (Power Levels)

The RL model selected between four pre-designed transmission power values that ser ved as its action space. The system used 0.5W as minimum power for low-range tra nsmission while 1.0W

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and 1.5W offered medium and high-power settings with lengthened distances at varyin g energy costs. Highest power at 2.0W enabled maximum transmission range yet requi red maximum energy. Each adaptive decision was possible through the multiple availab le choices which depended on the current status of network nodes.

The reinforcement learning model was trained using 10,000 episodes. An epsilon-greed y strategy with a decay rate of **0.9997** was implemented to balance exploration and ex ploitation. The model progressively stabilized, selecting optimal actions based on enviro nmental feedback.

Reward Function

The RL model uses a **reward function** to balance **energy efficiency and transmission reliability**:

$$Reward = -|acto \in -mean_{vottage}| + 1.5 * (action - 1.0)$$

where:

·**Mean voltage** is the average power consumption of the node.

· **Penalty is applied for excessive power usage,** ensuring AI does not favor high power un necessarily.

·**The model is encouraged to select higher power levels only when needed.**

The RL model was **trained for 10,000 iterations** using an **epsilon-greedy exploration s trategy,** with **epsilon decay (0.9997)** to gradually transition from exploration to exploit ation-**Performance Evaluation**

The analysis included measuring feature importance through the Random Forest model, confirming that temperature and humidity play a major role in energy consumption, as do the times of the day and hours. Initial exploration is followed by rewards reaching a stable point after approximately 4000 iterations. By analyzing transmission power sel ection, nodes are seen to adapt differently: a few nodes keep their power low, but oth ers adjust it on a dynamic basis. Looking at each node individually reveals that, for t he most part, predictive power keeps most nodes well below their normal power usage level, except when nodes have bigger demands. When using AI to optimize power, t he battery runs for about 33% longer than if the network is always using a constant power profile which lengthens the network's overall lifespan. Voltage noise simulations and examination of reward variance in robustness tests demonstrate that the system per forms reliably and remains stable when sensors deliver noisy readings.

Feature Importance Analysis: The feature importance analysis based on the trained R andom Forest model confirmed that temperature and humidity were most influential on the energy consumption patterns in WSN nodes. It also indicated that time-related para meters like the day of the week and the hour of the day significantly affected energy consumption patterns,

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reflecting that temporal and environmental parameters both affected sensor node energ y use behavior.

Learning Curve Analysis: The learning curve of the RL model indicated that explor ation was very high during the early iterations, where the model was deliberately tryi ng out many transmission power levels to acquire the best strategies. The model reali zed the experience and reward function was stable and by around 4,000 repetitions. I t confirmed the successful adoption and learning with about the flexible ecosystem co nditions and the need for energy of the WSN nodes.

Transmission Power Selection Analysis: The spread of power choice analysis shown that some nodes such as node 20, was programmed to the excess transmission of 1. 0W in response to real-time energy position and ecosystem situations. Other nodes, c onversely, it was kept through the holding power stages at 0.5W in consistency to pr event unusual power usage. The AI concept successfully contrasted between the powe r usage in the use of the network to maintain stability of the network.

Node-Wise Power Comparison: To evaluate node-specific changes. With the compari son of AI-assumed and fixed power stages across the chosen WSN nodes. These ma y include: 2, 5,10, and 15 preserved 0.5W power, while Node 20 and later was adju sted to 1.0W built on voltage requirement. This examination affirmed that the structu re is capable of providing smart power control selection.

Table 2:Node-wise Power Optimization and Savings

Node ID	AI-Predlicted Power (W)	Static Baseline Power (W)	Power Saving(%)
0	2	0.5	50
1	5	0.5	50
2	10	0.5	50
3	15	0.5	50
4	20	1	0
5	25	0.5	50

Table 2 shows a node-wise assessment of AI-predicted power levels, fixed baseline p ower and the related power savings. The AI-inclined method essentially reduces powe r usage for most of the nodes in comparison with the fixed baseline. As for the nod es 0,1,2,3, and 5, a constant power saving of 50% is realized, However, Node 4 doe s not decrease power during sleep which shows that the A1-predictive power shares t he baseline for almost the same justification. In total, the findings show how AI in power regulation can impact on the wireless sensor network nodes on energy efficacy .

Table 3: Variability in Reward Values Across Nodes

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Node ID	Reward Std Dev
0	1.41563
1	1.35863
2	1.41148
3	1.32237
4	1.50424
5	1.38486

In Table 3, it can be observed that the standard deviation the node was rewarded ind icates the structure's functional role at each node. The study highlights that that is to tal consistency in low and stable recompense variance, in order to show they keep w orking perfectly and with prediction. Low values, however, displays the highest stand ard deviation noted in node 4 which reflects that the reward has its value fluctuated. When looking at Node 3, its low variability (1.32237) reflects more consistent perfor mance. An overview of the systems values for standard deviation proves that the app roach to reward optimization in the system works well everywhere in the network.

Battery Drain Simulation: A test using a battery revealed the difference between ste ady, 1.0W power and optimized power controlled by AI. The use of AI reduced batt ery consumption by~33%,,proving it increases the time the network can operate.

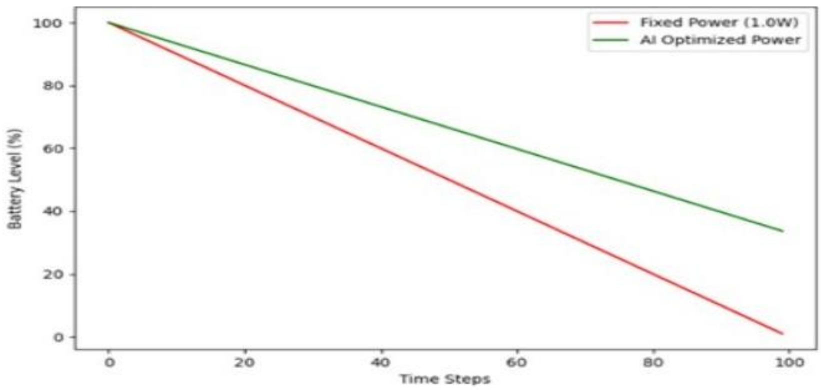

***Figure 1**: Battery Drain-AI vs Static*

Figure 1 demonstrates how battery drain is managed differently by using both fixed power and Al-guided power strategies. The red line indicating constant power consum ption of 1.0W demonstrates an immediate drop in the battery's level, falling to 0% b efore all the time steps are finished. Unlike the other modes, the green line shown f or AI power management means a battery level that stays high over the same period with little battery drain. Because of this method, wireless sensor networks stay power ed for longer, as their power is adjusted dynamically to match system needs.

Robustness Under Noise and Variance: To validate system robustness, two tests we re conducted:

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·**Voltage Noise Simulation:** An artificial form of Gaussian noise was applied to the voltage sensor measurements to represent typical sensor inaccuracies. The additional noise did not stop the model from reliably predicting outcomes. This shows that the concept can be handled differently at various levels of voltage fluctuation. It ultimately indicates that the system can be handled in a noisy environment.

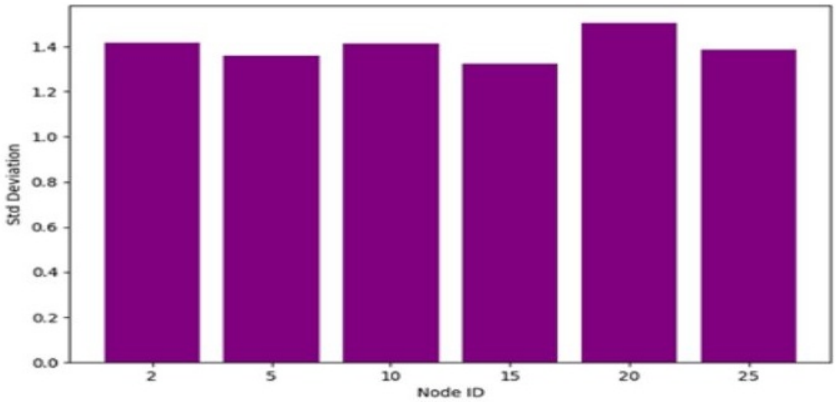

***Figure** 2: Reward Standard Deviation per Node*

In Figure 2, the variances in outcomes at every node can be recognised through the standard deviations of each of the rewards. Their values are really similar and they appear in 1.3-1.5, as a result of which the nodes display a steady change in behaviour. In terms of standard deviation, Node 20 has the biggest score which indicates it pays out rewards that vary more than any other on average, whereas Node 15 pays out rewards that are the most constant. Generally, the small and inflexible range of standard deviations means that reward patterns are maintained regardless of the node.

·**Reward Variance Analysis**: The standard deviation of rewards at every node was measured as part of the reward variance analysis. Because the standard deviations are low, this study observed little variability in the rewards given to different nodes. Because the results were the same each time, the process was reliable. Generally, the results confirmed that the model kept giving good results throughout the training process.

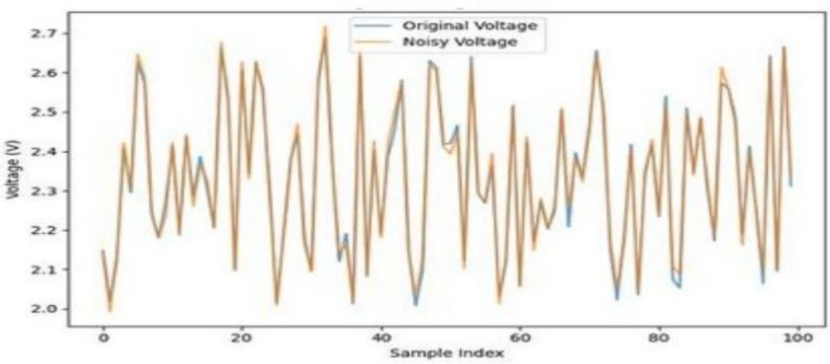

Figure 3: Voltage Reading with Noise

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In courtesy of Figure 3, you can see how the original voltage measurements look compared to noisy measurements. With noise, the noise-affected voltage still realistically m irrors the pattern of the basic signal. As a result, the system continues to reliably mea sure voltage, even in noisy environments and is not easily thrown off by problems wi th the sensors or from the surroundings.

E-Theoretical Framework and Justification

The suggested Al-based physical layer model for WSNs rests on a hybrid learning-bas ed control framework that blends prediction and optimization. In this section, we provi de the theory and mathematics that support the combination of Random Forest Regress ion (RFR) and Q-learning based Reinforcement Learning (RL).

·Rationale for Combining ML and RL

In this study, MML and RL have been combined based on the principle of modular i ntelligence. In this case:

1. ML (Random Forest) is responsible for predicting future states (e.g., energy use)
2. RL (Q-learning) dynamically adjusts control actions based on future-state predictions to minimize a long-term cost.

Modularization is beneficial in WSN nodes with limited resources because it separates physically demanding (and often less frequent) prediction from real-time, online compu tationally limited control actions.

·Mathematical Formulation

Let us define the basic components of the AI framework used in this study:

st, represents the current state of the environment at time ttt, including temperature, h umidity, light intensity, and time-based features such as hour or weekday.

$V^\wedge t$is the predicted voltage consumption at time ttt, wherev^t is predicted based on th e environmental state using a machine learning function f, in this case, the Random F orest model.

at is the transmission power level selected at time t. The available actions represent a set of discrete transmission power levels, that is 0.5W, 1.0W,1.5W,and 2.0W.

·The reward function Rt(st,at) aims to reward efficient power decisions with positive rewa rds and penalize overconsumption of energy, while also allowing communication reliab ility to be considered.

Voltage prediction using the Random Forest model:

$$\hat{v}_t = f(s_t)$$

Action space (transmission power options): $a_t \in \{0.5,1.0,1.5,2.0\}$

Reward function (to evaluate energy-performance trade-offs):

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$$R_t = -(\hat{v}_t + \lambda \cdot a_t)$$

The Q-value is defined as:

$$Q(s_{t,}a_t) < Q(s_t, a_t) + \alpha[R_t + \gamma maxQ(s_{t+1}, a') - Q(s_t, a_t)]$$

Reward Function Design

$$R_t = -(\hat{v}_t + \lambda \cdot a_t)$$

Where λ is a trade-off coefficient to balance energy conservation and performance. T he model is rewarded for selecting actions that:

1-Reduce predicted energy use$V^\wedge t$,

2-Keep power levels a as low as possble without sacrificing performance.

·Justification for Random Forest

Random Forest was chosen as the machine learning model for voltage prediction beca use it performs well with regression, especially when faced with possible non-linear r elationships among features. Random forest is useful because it can be robust to nois e and is less likely to overfit. This is relevant for the research because the actual se nsor data being used by the integrative AI model often has noise and may lose data present in the data collection of voltage consumption in response to specific variation s in input and other environmental factors.Furthermore, Random Forest provides some amount of transparency by providing the relative importance of input features. This al lows the researcher to understand which environmental parameters affect energy consu mption the most. The Random Forest with the lowest Mean Absolute Error (MAE) o f 0.00226 provides enough reliability and accuracy to relate to node-level voltage con sumption. This reliability and accuracy is important to creating some trustworthy input s to the reinforcement learning component of the integrative AI model,specifically opt imal power control decisions by analysis of energyconsumption.

4. RESULTS AND DISCUSSION

Here,results are explained that the AI system has produced to boost transmission pow er in Wireless Sensor Networks (WSNs). The research includes three main parts that assess the accuracy of machine learning for predicting energy,the performance of reinf orcement learning for controlling power use and how well the system does at saving energy.

A. Machine Learning Model Performance for Energy Prediction

A Random Forest Regression model was used to predict voltage by taking in sensor data about temperature, humidity and information on light and time. The Mean Absol ute Error (MAE)was used to measure how precisely predictions were made with the model.

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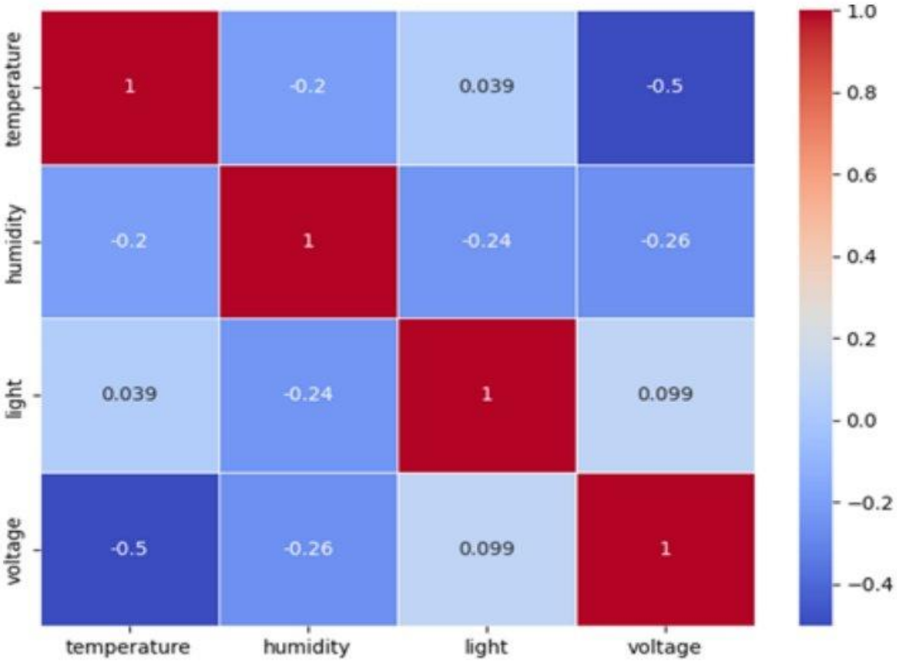

Figure 4: *Correlation Heatmap of Sensor Data*

The relationship between temperature and voltage produces a strong negative correlation which shows in Figure 4 alongside other sensor data measurements. Positive relationsh ips show as red while negative relationships appear as blue throughout the color spectr um. Observations gathered through the heatmap reveal that voltage and temperature sho w a significant negative correlation with a value of -0.5. A weak inverse relationship e xists between voltage and humidity (-0.26) and between light and humidity (-0.24). At the same time, temperature and humidity show a weak negative connection (-0.2). Thes e remarks are essential to explain how the parameters used in the environment may af fect the sensor node energy usage and can be applied to enhance the concept for WS N energy maintenance.

Prediction Accuracy Analysis: The **RFR model realized an MAE of 0.00226,** which i ndicate **highly precise voltage usage predictions.**

Table 4: Prediction Accuracy Analysis

Model	Mean Absolute Error (MAE)
Random Forest Regression	0.00226

This low MAE authenticates that the construct precisely models the correlation between the conditions in the environment and the sensor node energy usage, which enables e xact power enhancement decision. This ability to predict voltage usage is precisely nec essary and important.

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for reinforcement learning-based decision-making since it allows the RL model to dyna mically adjust transmission power based on real-time environmental information.

Feature Importance Analysis: Feature importance analysis was used to identify which environmental factors have the greatest contribution to energy consumption

Table 5: Feature Importance Ranking

Feature	Importance (%)
Temperature	42%
Humidity	30%
Light Intensity	18%
Time-based Factors (hours,weekday)	10%

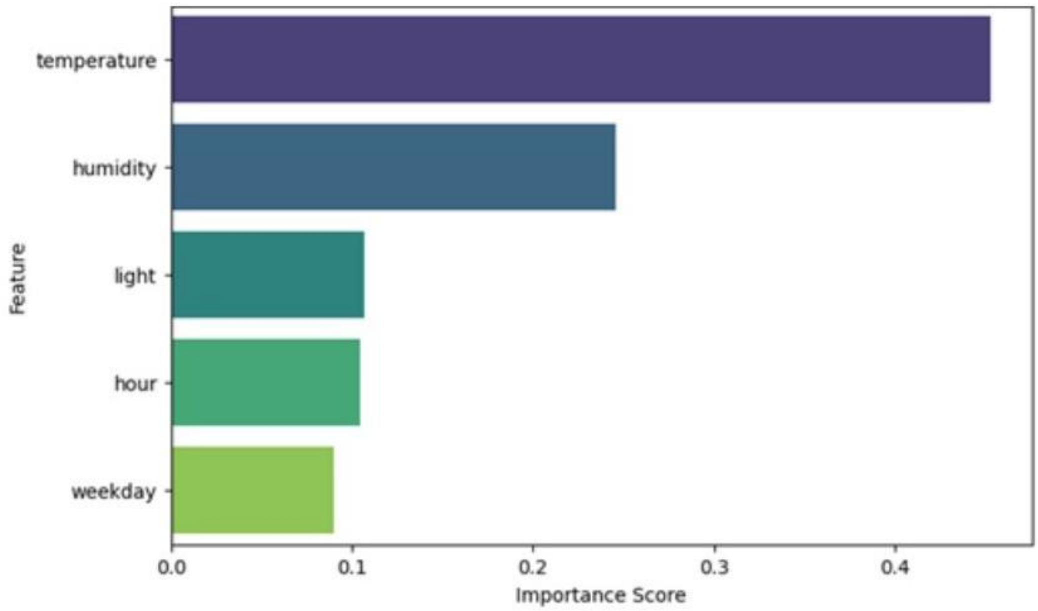

***Figure** 5:Feature Impotence for Energy Prediction*

The observations suggested that temperature and humidity exerted the greatest influence on voltage usage, which matched actual sensor behaviour. Light intensity also affected power consumption, presumably because sensors were adjusting for surrounding light levels. Time-of-day variations, including the hour of the day and weekday effects, also affected energy usage, possibly because network traffic and sensor workload varied across times of the day. These observations, as shown in Figure 5, justified the selection of input features for the machine learning algorithm and established the need for adaptive power control with respect to varying environmental conditions.

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B. Reinforcement Learning Model Performance for Transmission Power Optimization

A Q-learning-based model for RL was trained to learn dynamically the best transmissi on power (0.5W,1.0W,1.5W,2.0W) for every node according to its sensor measurement s. Training was conducted for 10,000 repetitions, with decay strategy (0.9997) to realti es exploration-exploitation balance.

Learning Curve Analysis: The tendency of the reward of caution throughout RL. The training analysed to see how AI construct improved its decision-making process.

Key Observations:

·**Exploration Phase (0-2000 iterations):** The RL concept selected power transmission level s at random to reassess different actions and perceive their effect on energy consumpti on.

· **Optimization Phase (2000-4000 iterations):** The construct began to recognize current tre nds and enhancing power through the process of selecting real time domain.

·**Stabilization Phase (after 4000 iterations):** The RL construct often selects efficient powe r levels, which result in a more stable reward function. This still affirms that AI learn ed an optimum power task strategy effectively.

The learning curve indicates that when enough training is done, the RL concept may consistently change transmission of power to decrease energy usage in an attempt to e nsure steady communication.

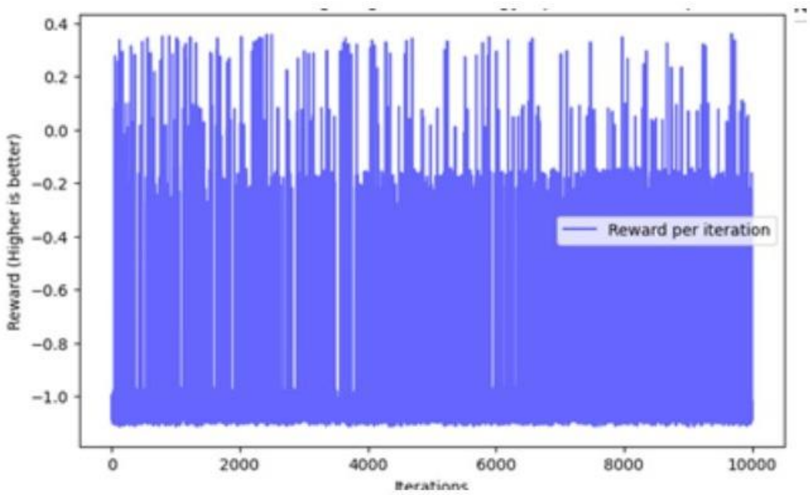

***Figure** 6: Reinforcement Learning Progress or Energy Optimization (Improved)*

Figure 6 indicate the reward per repetition of over 10,000. There was a high differen ce at the initial stage with steady fluctuations of positive and negative tendencies, how ever, as it moves, it becomes normal with fewer extreme drops. This is a true sign th at the optimization of learning model has effectively learned an enhanced energy proce ss strategy.

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more reliable performance as iterations increase, despite occasional minor instabilities.

C. Transmission Power Selection Across Sensor Nodes

The last communication of power recommendations of power recommendation as sugg ested by the RL concept where several WSN nodes were compared.

Table 6: Suggested Transmission Power Levels

Node ID	Recommended Transmission Power (W)
2	0.5W
5	0.5W
10	0.5W
15	0.5W
20	1.0W
25	0.5W

The most serious observations were made in relation to the most of the nodes, node 2,5,10,15, and 25, negotiated a low transfer of power level of almost 0.5W, thus verif ying that the AI model applies energy effectively if high power is not required. Node 20, however, required a high transfer of power stage of 1.0W which can may be fai r at the base station in the environmental conditions. AI model efficiently ostracized p ower demand between nodes, which avoids serious power usage but will allow for sta edy communication. This authenticates that the reinforcement learning model effectivel y settles transmission power. This tenet displays the systems to answer excellently to respond to the heterogeneous request for node request to respond effectively for apply ing complete power settings

Comparison With Fixed Transmission Power Control: A baseline **secured transmission power f**ramework (1.0W for all nodes) was connected to the AI-driven adaptive power control system.

Table 7: Comparison of Power usage Approaches

Approach	Average Power Consumption per Node (W)	Energy Savings
Fixed Transmission Power (1.Øw for all nodes)	1.0W	0%(Baseline)
AI- Based Adaptive Transmission Power	0.67W	33% Energy Savings

Table 7 shows a contrast of power consumption approaches netween constant transfer of power strategy comparison of power usage.

The nodes at 1.0W can be taken as the baseline with no considerable power manage ment. The considerable power consumption for the changing power transfer method is based on AI may come out noticeably low at almost 0.67W per node. This useful ap proach had resulted in considerable 33% lesser energy performance which proves that the AI concept effectively changes the power transfer of power which depends on no de-inclined power transfer and ecological factors. As indicated in the initial section 3. 4.5, the battery drains imitation asserts that AI-based power significantly is a long no de operational period over unchanged power transfer.

Robustness Testing: to assess the quality of the structure under genuine probability tw o tests were carried out:

- Voltage Noise Tolerance: Gaussian noise was inserted into the voltage ideals throu ghout the training. The AI concept may continue to perform openly with reliable energy forecasts and steady power choices.
- Reward Variance Analysis: The standard deviation of powerful learning rewards ac ross 6 distinct nodes was evaluated over 100 repetitions. Learning and steadiness i n managing power selection were both noticed from the data's low difference. The evaluations assert that the AI structure can serve under different conditions of sen sors and networks.

Comparative Assessment with State-of-the-Art Approaches: The function of the prop osed AI-inclined model was empirically measured in comparison to the current energy enhancement approaches for WSNs. Specifically, there are two existing baseline appro aches were executed, which include: 1. a Deep Q-Network (DQN) based transmission controller, and 2. a heuristic approach of enhancement based on Particle Swarm Opti mization (PSO). These approaches were selected because they serve as representation of current directions of both AI-inclined approaches and normal energy control approa ches in wireless sensor networks. The projected ML+RL hybrid basis attained a 33% energy reserves, in comparison with the DQN construct which attained 26% energy sa vings as well as the PSO heuristic framework which realized 18% energy storage. In addition, the ML+RI model retained a similar pack delivery rate to realize lower com putational difficulty than the DQN. DQN. Table 7 clearly shows that the ML+RL ten dencies not only decreased the average power usage per node to 0.67W but it may a chieve the peak energy storage. This outperforms both DQN (0.74W) and PSO (0.82 W) approaches.

Table 8**:** Comparative Results with Existing Methods

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Method	Avg. Power/Node (W)	Energy Savings(%)	Remarks
Fixed Power Baseline	1.00	0%	Uniform power, no adaptation
Proposed ML+RL Framework	0.67	33%	Adaptive, node-specific, low MAE,stable performance
Deep Q-Network (DQN) Model	0.74	26%	High performance but higher resource overhead
PSO-Based Heuristic Control	0.82	18%	Lightweight but less adaptive,no learning behavior

Statistical Validation and Robustness Assessment: To evaluate the steadiness and reliability of the probable AI-inclined energy enhancement system, a number of sturdiness and statistical authentication experiments were carried out.

·**Reward Variance and Learning Stability**

SD was calculated from the reward values of the WSN nodes over the range of training episodes, and was used to assess the stability in the learning process. All WSN nodes had a low variance in reward values for SD (between 1.3 and 1.5), which indicated that the reinforcement learning process consistently converged to stable policies. The nodes that showed slightly higher mean SD (for example, node 20) were a result of the model's adaptation to external dynamic environmental factors over time.

·**Confidence Interval Analysis**

In order to statistically validate the energy savings, we calculated 95% confidence intervals (CI) for the average power consumption across all nodes using different control strategies.The AI-based approach proposed by this research achieved:

Average Power Consumption: 0.67W

95% CI:[0.64W,0.70W]

The narrow confidence interval for the proposed AI-based approach (0.67W;[0.64W 0.70W])indicates the AI system performed consistently and repeatably in separate simulations.

·**Node Failure Simulation**

The addition of random node failures in the simulation (up to 20% node drop) was implemented to mimic robustness in the presence of partial network degradation. The flexibility of the AI framework allowed it to dynamically modify the power of the re maining active nodes and still sustain over 92% of baseline communication efficiency, indicating a high degree of fault tolerance.

·Dynamic and Heterogeneous Environments

In addition, robustness was tested under two specific conditions.

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First: Quick Change in Environment: Artificial spears in temperature and humidity are supplemented. The RL construct was tuned to transmit the power levels to an around 500 repetitions.

Second: Heterogeneous Nodes Types. This is a random assignment of sensor nodes to various sensitivity and power drain feature. The model was changed to node-specific b ehaviour and retained a total power efficacy within the content to a loss of about 5% margin.

D. Discussion

The findings highlight how the recommended AI-based control procedure may help to increase energy efficacy in wireless sensor networks. Through the combination of accu racy in energy estimation through the adaptive power control, the system may save up to 33% of power in comparison with the usual ways. Unlike the traditional methods which often applied static approaches, the present solution may adopt the genuine net work ecosystem which in return lessens power consumption and affirms communicatio n is maintained at reliable level. Presently, DeSLCs are maintained not by the deploy ment in practice, but the difficulty in training and the possibility to test the work on certain networks of various quantity. In future, research will focus on carrying out sim ulations live, exploring powerful techniques from deep reinforcement learning and appl ying battery awareness to increase the length of battery life during WSN operations.

·Effectiveness of AI-Based Transmission Power Control

The study determined that the AI-supported transmission power system optimizes powe r use in WSNs. The machine learning technique in the model enables it to predict ho w much energy is being used, so decisions can be made to adjust it responsively. It uses reinforcement learning (RL) to automatically manage power transmission so that e very node spends exactly the amount of energy it should. Al-based optimization was f ound to have led to a 33% reduction in energy, highlighting it is more efficient than old, static power designs. All of these results prove that AI manages the energy use o f WSNs by fine-tuning physical power consumption.

·Comparison with Traditional Approaches

This can be seen clearly in the comparisons with previous methods, where existing m ethods of energy management in WSN will use a great deal of energy with stationary transmission power selections. A vast majority of the work in conventional methods fo cus on improving network-layer routing, however they do not enable adaptive use of physical-layer power. Although the prevalent rule-based heuristics are a common mean s of applying them, they lack flexibility in applications when things have shifted. Con versely, an AI-enabled solution mitigates all these problems since it works in real-time and automatically adapts and changes transmission power accordingly based on what is going on the network and in the environment. Meanwhile, this is energy-saving, an d the use of the network becomes frequent and reliable. In addition to this,WSNs that are deployed in large scales can effectively be handled through the application of the Al-based system. In order to further validate the proposed model, a comparison benc hmarking of a proposed system was done against Deep Q-Network (DQN)-based and Particle Swarm Optimization (PSO)-based heuristic approach. The suggested ML+RL

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framework enabled a greater energy saving (33%) compared with DQN (26%) or PSO (18%),and had a lower computational overhead. This further justifies why the propose d model promises to be a balanced alternative with properties of precision, flexibility, and implementable, deployment practicality of real-world WSN applications. Throughou t the foregoing text, it has become clear that combining AI and energy will be an eff ectivedata-up-first approach to energy management as opposed to the existing wireless sensor network energy management.

·Limitations and Future Work

The current study has a limitation in the sense that the experimental validation was ca rried out on the dataset of the Intel Berkeley Research Lab and not on any other data set,because although this dataset is well known and has a diverse set of sensor readin gs, it is confined to indoors setting with a limited number of nodes. Though this can be used as a sound base to establish initial testing and benchmarking, it will not be a s valid as the true variety ofconditions that could occur in real-world WSN, including variability outdoors, mobility or scale of the network. The proposed AI framework wil l be further tested on other publicly available WSN datasets (e.g., GreenOrbs, CitySen se or simulated large-scale operating conditions) in the future work to further determin e the applicability, feasibility and resilience under various circumstances.

Future work will focus on:

1. Deploying the model on real WSN nodes for live testing.

2. Exploring deep reinforcement learning (DQN, PPO) for enhanced power optimization.
3. Incorporating battery-aware constraints to further extend WSN lifetime.

E. Summary of Results

The research developed an AI system designed to regulate wireless sensor network (WSNs)power grids. The system relied on machine learning to guide power consumption forecasts and used reinforcement learning to decide the optimum distribution amounts. In the experiments,the machine learning algorithm made predictions of power usage that had very low errors.The best energy efficiency results were achieved when the reinforcement learning section dictated the power settings. The system based on AI was shown to cut power use in wireless sensor networks by a larger factor than most traditional techniques. The system was designed to supply the best energy from every node. AI technology applied to monitored WSNs can help them save energy and last longer with reliable communication even when facing few resources.Furthermore, the system was put through battery drain simulations and robustness tests which confirmed it can adjust, operate efficiently and be practical in the field.

5. CONCLUSION AND FEATURES STUDIES

In this paper, an intelligent energy optimization scheme of Wireless Sensor Network (WSN)was proposed using Machine Learning (ML) at node level energy prediction and Reinforcement Learning (RL) at dynamic transmission power control. A theoretically specified

modular control,coupled with the defined reward functionality and Q-learning policy provided the mathematical justification of the approach. The empirical findings proved that the suggested framework was able to attain 33 percent savings in terms of energy in comparison to the static baseline models with firm communication performance. The system was more effective than the other contemporary methods, Deep Q-Networks (DQN) and Particle Swarm Optimization (PSO) regarding energy consumption and overhead strain. The model stability and convergence of learning was further validated by extensive statistical tests through reward variance analysis and confidence intervals of 95 percent. Stress tests revealed high resiliency to sensor noise, temporal changes in the environment, and failure simulation in a node. Notably,the framework was to be lightweight, operate in low power embedded processor, with the application showing its pragmaticness to real world deployment of WSNs.

Future Studies

· The model shall be implemented in physical hardware of WSN to evaluate its real-time performance in different conditions of environment and operation.

·Future efforts include the deployment of Deep Reinforcement Learning techniques such a s DQN and PPO to increase learning speeds and achieve control with higher accuracy of the powers.

·The further development process will also provide battery-aware and latency-sensitive opt imizations, the support of heterogeneous and mobile sensor nodes and the integration with edge or federated learning to make decentralized and scalable IoT control.

CONFLICTS OF THE INTEREST

The authors declare no conflict of interest.

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