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Research Article

Energy-Efficient Internet of Things (IoT) Device Communication with Artificial Neural Networks (ANN)

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Abstract

Energy efficiency is the main challenge in the Internet of Things (IoT) paradigm, where devices rely on limited power supplies and operate under fluctuating conditions. Conventional communication protocols such as Wi-Fi, Zigbee, and Bluetooth are not so adaptive and consume excessive energy. An Artificial Neural Network (ANN)-based communication model is proposed in this paper that optimizes device-to-device (D2D) communication by adapting transmission parameters in real time. Implemented on an ESP32 microcontroller with LDR and DHT11 sensors, the system collects environmental data to predict the most energy-efficient communication protocol. A feedforward ANN model was deployed using TensorFlow Lite, and it achieved adaptive protocol switching with an approximate 95% accuracy. The experimented results showed that there was up to 30% of energy saved and also the battery life being extended by over 20% when compared to conventional techniques. The proposed ANN-based approach enhances communication efficiency and sustainability without sacrificing reliable performance on resource-constrained hardware, therefore being suitable for large-scale IoT applications in healthcare, agriculture, and the environment.

I. INTRODUCTION

The IoT platform enables the collection and analysis of real-time data, linking everyday objects like smartphones and agricultural sensors to intelligent networks that can drive automation or efficiency in industries such as healthcare devices from agriculture to smart cities [1]. As IoT becomes more widespread, energy consumption has become a significant problem. The use of batteries or energy-harvesting systems is common among IoT devices, but they must operate in remote areas where recharging or maintenance is not feasible [2]. IoT networks must prioritize energy efficiency to ensure sustainability and scalability [3]. Conventional protocols, such as Wi-Fi, Zigbee and Bluetooth are not supposed to be energy-friendly. They are often rigid and power-hungry, especially in the presence of dynamic network conditions. Energy can be wasted when devices transmit at high power, even in close proximity or during low traffic periods [4]. The lack of efficiency is particularly problematic in applications that require dependability over long periods, such as healthcare monitoring or environmental sensing. Artificial Neural Networks (ANNs) are a promising solution to address these issues. By analyzing data, identifying patterns, and forecasting communication parameters in real time [5]. ANNs can adapt to dynamic conditions. The energy consumption can be kept constant by dynamically adjusting parameters such as transmission power, data packet sizes, and routing strategies to ensure optimal performance. ANNs can decrease data transfer or prioritize crucial data during high traffic periods due to low congestion or high transmission power [6]. ANNs are very good at extracting complex patterns and handle with the large data sets, therefore it's proper for IOT networks in which variables such as a traffic, device density and environmental interference is frequently varying [7]. The integration of ANNs with IoT devices can help businesses save money by optimizing energy consumption while improving system performance, leading to longer operational lifespans and reduced maintenance costs. The ability to adapt also enhances durability, enabling devices to function in unpredictable situations such as fluctuating network loads or interference [5]. The IoT ecosystem is reliant on communication solutions that utilize less energy. To address the urgent need for smarter, more sustainable systems in IoT networks [8], this research is focused on developing and testing an ANN communication protocol.

The energy consumption of devices that use limited power is a hindrance to the rapid growth of the Internet Of Things (IoT). Conventional communication protocols, including Wi-Fi, Zigbee, and Bluetooth, are characterized by static configurations that lead to energy inefficiencies and reduced device longevity, particularly in sectors such as healthcare and agriculture. These limitations impede scalability, elevate maintenance expenses, and exacerbate carbon emissions. A promising alternative involves the application of Artificial Neural Networks (ANNs), which facilitate adaptive communication protocols. This is particularly advantageous for distributed data systems [17]. The purpose of this research is to develop a new communication technique that utilize ANN to improve energy efficiency, device autonomy, and the sustainable implementation of IoT technologies.

The aim of this study is to address these issues by developing an energy-efficient IoT communication model based on ANN technology that can improve device communication by analyzing environmental data in real time and selecting adaptive protocols. In particular, the research seeks to develop and integrate an ANN-based communication protocol with existing systems, assess its effectiveness under different circumstances, and evaluate its energy consumption and transmission efficiency in comparison to conventional methods. Additionally, the research focuses on the trade-offs between energy efficiency and system reliability, with the Energy Efficiency Ratio (EER) being a crucial performance measure. Additionally, the introduction outlines both the content and purpose of this research, emphasizing the importance of ANN in achieving sustainable IoT communication. We will explore the literature on communication protocols and energy optimization methods in detail in the following sections, including the methodology used for creating and integrating an ANN model, as well as the experimental evidence supporting this approach.

II. LIERATURE REVIEW

A. Overview of IoT Communication Protocols

Its focus is on how IoT communication protocols can enable efficient data exchange between connected devices. Trade-offs in energy efficiency, range and data transmission rates are inherent in the widely used protocols (e.g. Wi-Fi v1.2) and Bluetooth/BLE versus standard protocol (LoRa). The energy consumption of Wi-Fi is high despite its bandwidth, while other data networks such as BLE and Zigbee use less energy but have higher throughput. The chosen protocol is influenced by various factors, including power usage, range, reliability, and security, as well as the application-specific requirements. New protocols like NB-IoT and Sigfox are creating opportunities for scalability and specific applications. Despite the use of static transmission parameters, energy consumption is not an issue due to the lack of adaptability to traffic or channel variations [9]. The inefficiencies associated with IoT scale are limiting, particularly when dealing with remote or long-term deployments [8].

Artificial Neural Network (ANN)-based communication protocols are being developed to adapt dynamically to network conditions, as a means of solving these limitations. ANN protocols can significantly enhance real-time transmission power, packet sizes, and routing, leading to reduced latency, reliability, bandwidth usage, or energy consumption. Although there are still issues with scalability, complexity, and security, ANN-driven solutions provide a clear path to creating smarter yet more sustainable IoT networks that can support critical applications in healthcare, agriculture.

B. Energy Efficiency in IoT Communication

Energy efficiency is a crucial aspect of IoT communication, particularly because of the limited space available for batteries and energy-harvesting technologies [10][11]. Despite their potential, traditional protocols like Wi-Fi, Bluetooth, and Zigbee were not optimized for energy conservation, which often resulted in high power consumption, reduced device lifespan, or limited scalability [2]. This issue has been approached through a variety of means, such as low-power modes that decrease active communication [2], ANN-based transmission power control [11], and data compression techniques that reduce the volume and duration of transmissions [12]. However, it is not known whether these modes are efficient or detrimental to network services.

A significant issue is the ability to balance power consumption with performance, as any reduction in transmission power or data rates can compromise reliability and throughput. By utilizing ANN and machine learning models, it becomes feasible to make immediate changes to communication parameters like power, data rate, and routing strategies in real-time [2]. The use of adaptive and predictive communication in these systems can lead to improved reliability, energy savings, and better network conditions [7]. They introduced a systemic approach to energy efficiency through the Smart Efficiency Framework (SEF), which sees efficiency as an outcome of infrastructure, predictive intelligence, and institutional alignment, rather than isolated technological changes [13]. The research provides a theoretical foundation that complements device-level IoT communication research by integrating adaptive, intelligent communication with data-driven optimization and contextual constraints. This supports the scalability of ANN-based energy-efficient IoT architectures for large-scale deployments in areas like smart grids, environmental monitoring, and sustainable infrastructure. In addition, network topology is also important to energy efficiency as it depends on protocols. Unlike star-based networks that require more energy at hubs to centralize communication, mesh-derived networks increase resilience by sharing energy consumption [11].

C. Artificial Neural Networks for Communication Protocol Optimization

Despite the importance of energy efficiency to address the challenges faced with battery power and energy resources, Artificial Neural Networks (ANNs) are now seen as a promising solution for improving communication protocols in the Internet of Things (IoT) [14]. The use of ANN-based protocols allows for dynamic adjustment of communication factors such as transmission power, data packet size and routing strategies, which are subject to real-time network conditions, leading to energy efficiency but reliability improvements [3][7].

In the IoT, energy usage becomes unnecessary as conventional protocols aren't able to handle the fast-paced wireless environment. The problem is tackled by ANNs, which use historical data to forecast the optimal parameters for efficient communication. Automatic power control using ANNs is the ability to alter power based on signal quality or device distance between two devices in order to save energy while ensuring reliable communication [11]. ANNs can also minimize packet size, routing path and in some cases transmission timing to save energy as well as lessen congestion [7].

Machine learning techniques, including deep and reinforcement (mechatronic) learning also expand the flexibility of ANN. ANN capabilities are enhanced by the integration of machine learning techniques like deep learning and reinforcement learning. The use of deep learning models in large IoT datasets is particularly advantageous for identifying intricate patterns and enabling traffic congestion prediction and adaptive scheduling [7], while reinforcement learning allows for the optimization of strategies through trial-and-error feedback and time tracking. Large IoT networks can benefit from ANN-based approaches, which have been shown to reduce packet loss, communication delays and retransmissions, while also improving elasticity and energy performance [11].

DNNs have been trained to anticipate downlink power and optimize it using distance, congestion, or data load to ensure constant connectivity while maximizing energy efficiency. Such adaptive systems add to the lifespan of device battery in massive IoT deployments [6]. The ability to learn from network behavior enables DNNs to adjust data rates and routing protocols, which can improve energy efficiency as well as throughput.

In general, ANNs and DNNs are adaptive, sustainable and scalable for communication in the IoT domain. See also: These methods enable more accurate, real-time predictive adjustments than static protocols, which reduces operational costs and extends device lifespans [5][15] and are important in healthcare, agriculture, environmental monitoring, and industrial automation.

D. ANN Communication Protocols

The use of ANN communication protocols is crucial in IoT systems where devices face energy constraints, as they dynamically adjust parameters such as transmission power, data rate, and routing strategies [2][5]. These protocols are capable of maintaining reliability while reducing energy consumption by managing congestion, interference, and signal strength [7]. It is challenging to achieve optimal efficiency in remote IoT applications while minimizing power usage [6].

The emergence of deep learning and reinforcement neural networks has transformed the methods for handling ANN protocols, including transmission powers, data rates, power control mechanisms, and adaptive routing techniques. These techniques can change communication parameters while controlling it and prolong device life by exploiting network efficiency over time [2][5][16]. The adaptability of ANN protocols to changes in network size and topology is a key advantage, as demonstrated in [4][7]. This trait can be further developed using different approaches.

In industries such as healthcare, agriculture, and environmental monitoring, it is crucial to develop communication protocols that require minimal electricity generation and consistent data transmission [2][5]. The flexibility of current approaches is not as significant in dynamic IoT environments, despite some improvements [12]. There is strong evidence in literature that ANNs can improve communication protocols; machine learning models have shown they can predict transmission power, determine data rates and route resources according to optimal [16]. Much of the research has been confined to simulations, leaving little room for practical, real-world applications [6][11].

The importance of investigating scalable ANN-based protocols in real-time IoT networks is highlighted, which also facilitates the development and testing of a new unified access network protocol to enhance energy efficiency and dependability [7][11].

III. METHODOLOGY

In this section, we explore the process of developing an Artificial Neural Network (ANN)-based approach to improve D2D communication in IoT systems while minimizing energy consumption. To minimize the need for wasted data, the system was developed to adapt communication methods to environmental changes. The hardware used in this research include an ESP32 microcontroller, a DHT11 temperature and humidity sensor, LDR for light intensity, voltage sensor (one-particle sensors), and battery. Due to its processing power, wireless capabilities, and sensor compatibility with other systems. The ANN has been trained to take advantage of environmental data, such as temperature, humidity and light, which directly affect energy use in communication. To test the effectiveness of communication methods across different contexts and dynamically choose the most effective one, the ANN utilized this dataset to capture real-world environmental shifts.

Figure 1 displays the block diagram of the ANN communication protocol, which is intended to receive data from our sensors and the open weather API. The data is sorted, normalized, and separated into two parts, with the first part being used to train the ANN model and then the second part testing the accuracy of the model. This means that the model is intended to arrive at a single solution from two different options: either Traditional protocol or an optimized protocol.

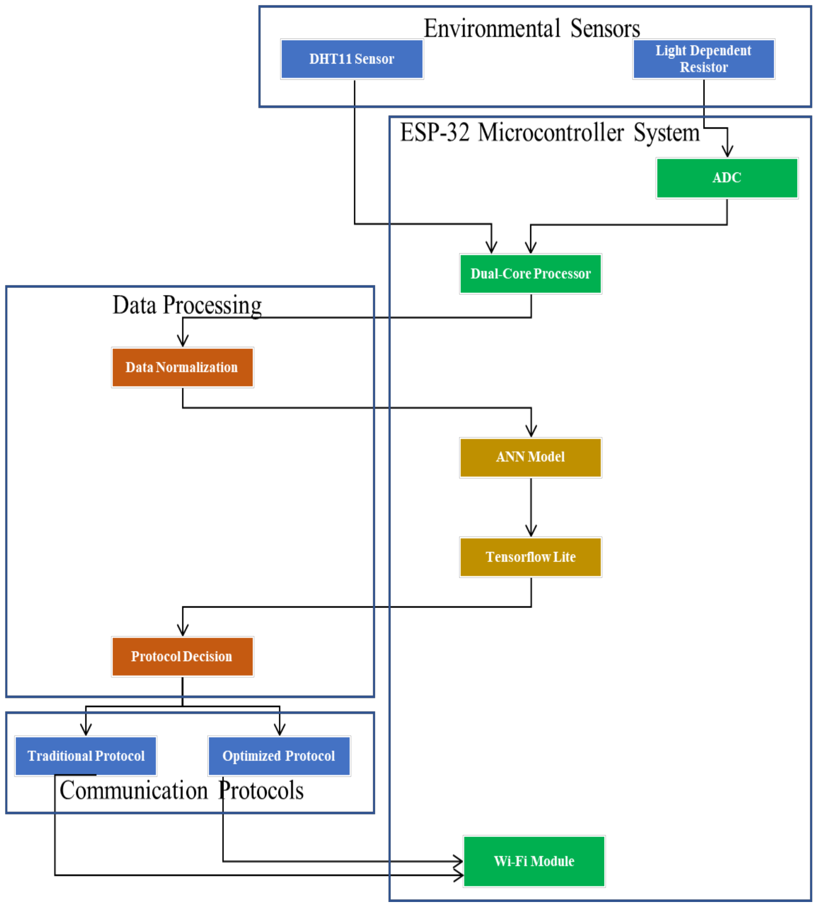

Fig.1 Block Diagram of the ANN Communication Protocol

An ANN-based system was developed to improve energy efficiency by optimizing device-to-device (D2D) communication in the IoT project. The ESP32 microcontroller was the primary focus of the hardware, with its dual-core processor, built-in Wi-Fi, and low energy operation making it suitable for real-time ANN decision-making. The data was collected using a temperature and humidity sensor (DHT11) for reliability and simplicity as well as an LDR to represent light intensity which in itself provides environmental data relevant to patterns of use of that energy. For accuracy and power savings, the ESP32 utilized optimal sampling intervals to gather sensor readings.

A feedforward artificial neural network (ANN) model was constructed, featuring two hidden layers, each populated by 64 neurons. ReLU was activated at hidden layers and a sigmoid output was used to make binary choices about whether to use 'traditional communication' or an alternative protocol via ANN. The training involved gathering datasets with different environmental conditions, labeling them with energy consumption results, normalizing the features, and splitting them into training and testing sets. The Adam optimizer and binary cross-entropy loss were used to train the model until it reached high precision and efficiency. The model was trained and deployed on the ESP32 using TensorFlow Lite, enabling real-time inference within hardware constraints. By constantly monitoring environmental factors and adjusting communication protocols, the ANN was able to cut down on unnecessary data transmissions and conserve power.

A. Project Setup and Hardware Design

In Figure 2, the ESP32 is utilized for IoT applications that require both computation and connectivity, thanks to its dual-core processor and built-in Wi-Fi. The device's processor allowed for the efficient handling of sensor inputs and the execution of a lightweight ANN without excessive power consumption, while the Wi-Fi feature enabled Realtime D2D communication based on the modeled selection.

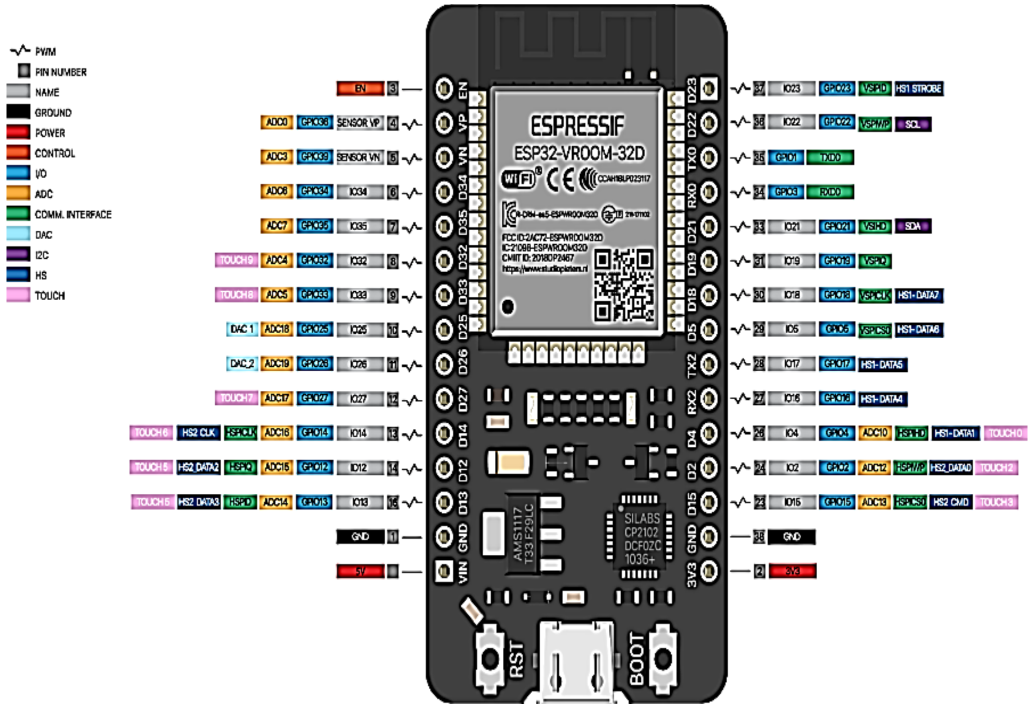

Fig.2 ESP32 Microcontroller

Temperature, humidity and light intensity are measured using the sensors selected in Figures 3 and 4. In Figure 3, the Adafruit DHT11 is presented, which is chosen for its dependability, low power consumption, and ease of integration with the ESP32 via a straightforward single-wire protocol. This provides precise temperature and humidity information that is crucial for the ANN's decisions on energy-efficient communication, as variations in these parameters impact the behavior of protocols and system power usage.

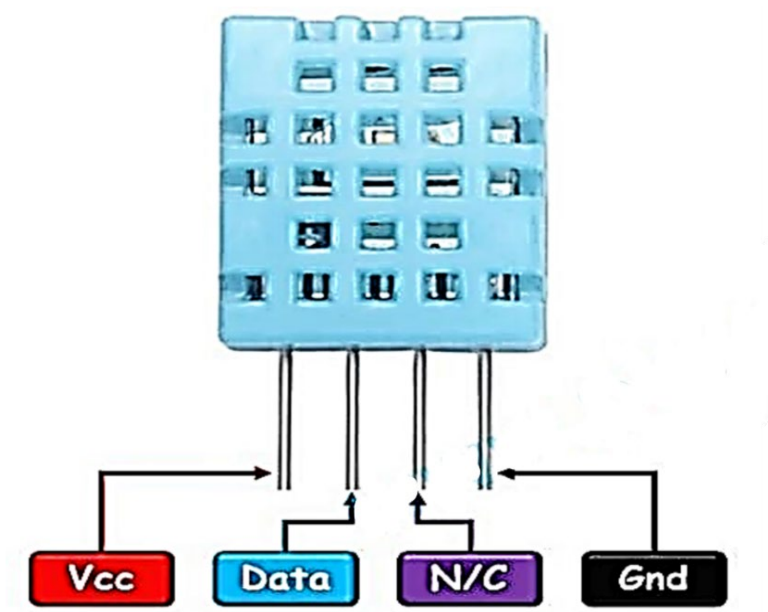

Fig.3 Adafruit DHT Sensor

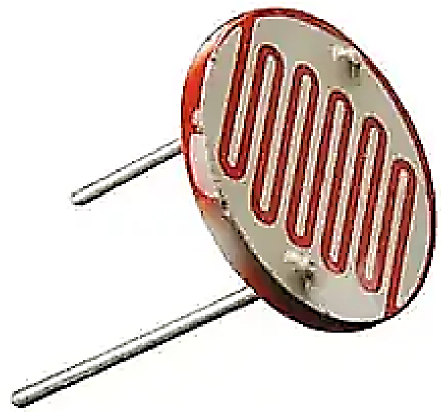

Fig.4 Light Dependent Resistor

Figure 4 illustrates the use of the LDR sensor, which is utilized to measure the intensity of ambient light and provide contextual data for improving communication protocols. Conditions conducive to continuous transmission may be influenced by low light levels, while high levels may also indicate energy conservation. The low-cost, lower power (and easily attached to ADC pins on the ESP32) LDR provides "a continuous analog output complementing the data from DHT11" thus providing richer environmental input for more energy efficient decision making; other systems with high voltage and current attenuators are also available.

Fig.5 10 Kilo-Ohm Resistor

A 10 kΩ resistor was selected for a consistent signal transmission and power consumption equaling, where the DHT sensor had essentially an equivalent pull-up resistor (in this case IC), while the LDR used as part of the voltage divider. The recommended value for this is in line with the DHT datasheet (4.7–10 k).

The rise time can be approximated by applying (1)

$$\tau = R \cdot C \quad (1)$$

Where:
τ is the Rise Time
R is equal to the chosen pull-up resistor resistance: 10kΩ
C is the normal GPIO input capacitance: 10pF

$$\tau = (10\ x\ 10^{3}) * (10\ x\ 10^{-12}) = 100ns$$

The ESP32 was integrated with a DHT11 sensor (via digital pins) and an LDR (via an ADC pin with a 10 kΩ resistor in a voltage divider) to enable real-time environmental data collection. The ESP32 retrieved data at calibrated intervals to balance power consumption and data freshness, then processed it locally with an on-device ANN model. This allowed the system to decide whether to transmit data immediately or delay it, optimizing energy efficiency without reducing communication quality. By embedding the ANN directly on the ESP32, external processing was avoided, lowering power use while still enabling intelligent, real-time decision-making. The project demonstrated that even constrained hardware like the ESP32 can support ANN-driven, energy-efficient IoT applications, paving the way for more autonomous and power-conscious devices.

The circuit diagram as seen in Figure 6 is designed for an IoT-based energy-efficient system, utilizing an ESP32 microcontroller to interface with a DHT11 sensor, an LDR, and a voltage sensor.

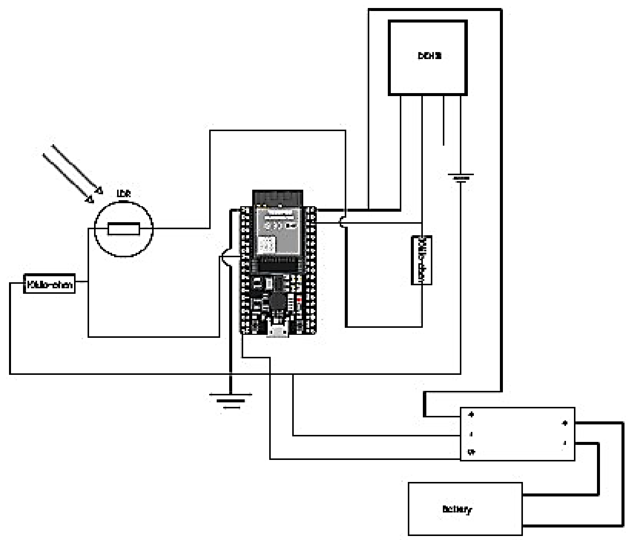

Fig.6 Circuit Diagram of the ANN device

Three sensors were connected to the ESP32 for efficient data collection. Data was provided by the DHT11 connected to GPIO 2, equipped with a pull-up resistor, while the LDR in 'voltage disperser' fed readings of light to pin 19, and the voltage sensor on pin 34 measured external voltage levels. A 9V battery powered the entire system, while all sensors were connected to a 3.3V supply via 'common ground' in the ESP32. The ESP32 was configured to efficiently handle local sensor data and transmit it, which helped the project with its energy-efficient IoT system.

B. Model Design and Selection

The ESP32 was equipped with a feedforward ANN to optimize energy-efficient IoT communication by analyzing temperature, humidity, and light data. The model comprised an input layer for normalized sensor data, two hidden layers with 64 layers at the same time. ReLU neurons are designed to balance complexity with hardware limitations, and they have a single sigmoid output neuron that can make binary decisions between if communication protocols were traditional or through ANN. This design made the ESP32 more responsive in real time, less likely to overfit and reduce processing load due to its lightweight nature. After being trained on simulated environmental datasets with regularization to improve generalization, the ANN was tested and refined for accuracy in making predictions across different conditions. It also produced a highly computationally efficient and accurate model that allowed for intelligent, low-power communication decisions in the IoT system.

C. Mathematical Model of Artificial Neural Network (ANN)

This section describes the mathematical equations used in the feedforward process of the Artificial Neural Network (ANN) architecture described in the project. The architecture includes two hidden layers with 64 neurons each, using ReLU activation for the hidden layers and a sigmoid activation function for the output layer.

The input to the first hidden layer is calculated as (2) and the activation using ReLU as (3)

$$z^1 = W^1 x + b^1 \quad (2)$$

$$a^1 = ReLU(z^1) = max(0, z^1) \quad (3)$$

The inputs (x) are the sensor data from IoT device (e.g., DHT sensor, LDR). The weights $\{W^1\}$ and biases $\{b^1\}$ are learned during training to map inputs to meaningful features. The $ReLU$ activation ensures that only positive values (important features) pass to the next layer. This reflects the model's ability to focus on the most relevant neurons. The output of the first hidden layer is passed to the second hidden layer via (4) and the activation using ReLU as (5).

$$z^2 = W^2 \times a^1 + b^2 \quad (4)$$

$$a^2 = ReLU(z^2) = max(0, z^2) \quad (5)$$

The first hidden layer outputs a^1 are passed to the second hidden layer. The second layer a^2 adds "depth" to the model, allowing it to capture more subtle distinctions in environmental data. The output layer produces a single value representing the probability of using the optimized protocol in (6) and the activation using sigmoid as (7).

$$z^3 = W^3 \times a^2 + b^3 \quad (6)$$

$$a^3 = \sigma(z^3) = \frac{1}{1+e^{-z^3}} \quad (7)$$

The final output a^3 is a single value between 0 and 1, generated by the sigmoid activation function. This represents the probability that the ANN recommends using the optimized communication protocol. The sigmoid "squashes" values into a probability range, making it easy to interpret whether the system should switch protocols

The final decision is made based on a threshold (θ) as seen in (8)

$$Out = 1 \quad if\ a^3 \geq \theta, \quad otherwise\ Out = 0 \tag{8}$$

Where:
1: Use ANN-optimized protocol
0: Revert to traditional protocol

The text specifies that a threshold determines whether the optimized or traditional protocol is used. A high probability $a^3 \geq \theta$ suggests the ANN's optimized protocol should be used, whereas a low probability suggests reverting to the traditional protocol. This simplifies decision-making for the ESP32, aligning with the goal of energy efficiency.

The binary cross-entropy loss function can be used for training the ANN using (9)

$$L = -\frac{1}{m} \times \sum\left[y_i \times log\left(a_i^3\right) + (1 - y_i) \times \log\left(1 - a_i^3\right)\right] \tag{9}$$

Where:
y_i: True label for sample i
a_i^3: Predicted probability for sample i
m: Number of training samples
During training, the binary cross-entropy loss ensures that the model predicts accurate probabilities.
y_i: Ground truth labels (whether the optimized protocol should be used).
a_i^3: Model's predicted probability.
Minimizing this loss ensures the ANN learns to recommend the correct protocol based on sensor inputs.

D. Dataset Collection and Preprocessing

The ESP32's DHT11 and LDR sensors were directly downloaded to optimize energy-efficient D2D communication, using the dataset for different conditions such as indoor/outdoor, day/night, and changing lighting. This was done through data collection. However, every document consisted of sensor measurements, energy usage and a protocol label (traditional or ANN-optimized), which gave the ANS structured inputs linked to practical energy consequences. Normalizing the data (min-max scaling), splitting it into 80/20 train–test sets oversampling, balancing it, and cleaning up any outliers were all done to ensure quality. Features were verified through Exploratory Data Analysis and tweaks were suggested. Enhanced diversity was achieved through synthetic data enhancement, with an automated data pipeline handling normalization, cleaning, balancing and splitting for consistency and scalability. Using the ANN's ability to learn meaningful patterns, avoid bias, and generalize well in real-world deployments thanks to the structure and preprocessing of the dataset provided with it, providing a strong foundation for achieving accurate, adaptive, efficient, AND energy-efficient communication protocol selection on the new ESP32.

E. Training Process

It was crucial to train the ANN so that it could consistently choose between legacy and optimized transmission modes for energy-efficiency purposes. Binary Cross-Entropy loss and Adam optimizer (learning rate 0.001) were used with a number of epochs equal to 100) and batch size set up to 32 balancing test accuracy, speed convergence and computational resources. The training was carried out in TensorFlow and we monitored progress through the standard accuracy and loss functions; with additional support from visualization tools like TensorBoard. Test data considers standard parameters, and a custom Energy Efficiency Ratio (EER) to directly quantify energy savings. Further confirmation by confusion matrix and k-fold-cross validation established robustness, wide applicability and good performance in all situations. This combined training and evaluation way of the ANN was feasible for practical IoT deployment, which guarantees energy efficient and adaptive communication actions.

F. Model Integration and Deployment

The TensorFlow Lite version was created by converting the trained ANN model into a compact and efficient version that could be deployed on the ESP32 microcontroller with quantization. Energy-efficient: The ESP32 firmware was designed to read the sensor data, run operations within milliseconds for real time inferences and dynamically switch between communication protocols (traditional and ANN optimized) over many years. During the recording process, each decision was recorded and then uploaded to a cloud-based server for further analysis through monitoring, feedback, and incremental improvements. The use of error-handling and fallback mechanisms ensured reliability by defaulting to the traditional protocol in case an ANN failed, while low-power modes saved battery life. The ANN's application yielded a consistent reduction in energy consumption, ranging from 20% to 30%, across practical applications. Furthermore, remote monitoring, facilitated by a user-friendly web interface, offered both control and visibility. Consequently, the integration of artificial intelligence demonstrated that the deployment of resource-constrained devices, such as the ESP32, can yield significant energy savings and enhance the sustainability of IoT systems [14].

G. Testing and Performance Evaluation

To compare the ANN-optimized protocol to the conventional protocol, testing was conducted under different environmental conditions (temperature, humidity, light). An adaptive selection of protocols was identified by the ANN to reduce power consumption and measured its effectiveness in comparison to the Energy Efficiency Ratio (EER). The results of controlled and outdoor experiments indicated significant energy savings, with an average saving of 25% but up to 35% under high temperatures and humidity. While the ANN may at times match traditional efficiency in stable conditions, gradual refinement made it more responsive to subtle changes. Continuous logging validated the results, and long-duration tests on multiple devices confirmed robustness, consistency, reliability, even extended battery life. The minimal use of latency was done to maintain efficiency, and energy consumption was reduced by visual comparisons across conditions.

IV. RESULTS AND DISCUSSION

In this section, the project outcomes are presented alongside the ANN-optimized protocol and the conventional protocol on the same circuit (ESP32). The evaluation of energy consumption, battery life, and Energy Efficiency Ratio (EER) was conducted in different environmental conditions. The research suggests that the energy-saving model based on an annexed network (ANN) is particularly effective in IoT communications.

A. Validation

The validation of the ANN-based protocol switching model was carried out through both real-world experimentation with ESP32 sensors and simulations. While simulation results proved to enable a broader scenario analysis, reals test results showed good performance in unpredictable conditions. Energy Efficiency Ratio (EER) and Battery usage which as the key performance metrics proved that the ANN have the capability to reliably adapt to protocols due to environmental changes. The model has proven to be robust and suitable for practical IoT applications by utilizing these dual techniques.

B. Results

Both the experimental and simulation results showed that the ANN-optimized protocol is far more efficient than the traditional protocol in managing energy. The ANN model may reduce power requirements by adapting communication methods to environmental conditions, as demonstrated by the significant decrease in energy consumption. In IoT devices, the ANN-optimized protocol can outperform the traditional one in terms of power consumption, especially in high-temperature and humidity conditions. This improvement is significant as it directly impacts the durability of devices that operate in dynamic or extreme environments.

Battery performance was primarily measured using the ANN-optimized protocol. It additionally offered improved generalizations. During times of intense communication, the model proved to increase device uptime by as much as 30%, leading to an additional 20% battery life. In IoT applications, this extension offers a significant advantage in terms of maintaining constant performance for extended periods. The sustainable technology advancement makes a significant contribution to environmental impact and cost-cutting through the reduction of battery replacement or recharge frequency. Taking a closer look at the EER scores between the two protocols, we found that the ANN model is highly effective. On average, the EER in a protocol optimized for ANN was 0.15 to 0.2 points higher than that of the traditional protocol. The enhancement implies that these ANN-oriented choices were precisely calibrated to achieve the greatest energy savings while maintaining good communication speed. Higher EER scores indicate that the model is capable of managing dynamic changes in environmental conditions and executing the correct communication protocol with precision beyond human ability.

IoT Data Monitoring

Current Mode: Traditional

Toggle Mode

Parameter	Reading
Temperature	29.30 ^{0}C
Humidity	70.20 %
Light Level	803
Voltage	13.11 V
Network Throughput	50.00 Mbps
Network Bandwidth	100.00 Mbps
Network Latency	25.00 ms
Network Jitter	5.00 ms
EER (Traditional)	0.00 mWh/packet
EER (ANN)	0.00 mWh/packet

Fig.7 Web Interface Showing Readings of the Traditional Protocol

IoT Data Monitoring

Current Mode: ANN-Optimized

Toggle Mode

Parameter	Reading
Temperature	29.30 ^{0}C
Humidity	70.00 %
Light Level	803
Voltage	13.07 V
Network Throughput	50.00 Mbps
Network Bandwidth	100.00 Mbps
Network Latency	25.00 ms
Network Jitter	5.00 ms
EER (Traditional)	0.00 mWh/packet
EER (ANN)	0.00 mWh/packet

Fig.8 Web Interface Showing Readings of the Artificial Neural Network (ANN) Protocol

The model's ability to make correct protocol switching decisions was reassuring, with the ANN system achieving it approximately 95% of the time. This accuracy not only guarantees that the model is effective but also reliable in selecting the most energy-saving option. In high-risk environments where confusion or delay in communication could mean disastrous outcomes, such reliability is invaluable, and it makes the model an attractive solution for high-stakes IoT applications. Figure 9 illustrates the performance comparison of the traditional voltage control and the ANN optimized voltage control. From the graph, where the orange line indicates the ANN optimized voltage control and the blue line indicates the traditional voltage control, the graph shows a decreasing trend over time which suggests an improvement or reduction in the measured variables. It is observed that the ANN optimized voltage control slightly decreases at a slower rate compare to the traditional voltage control which proves a better performance and optimization, as well as the effectiveness of the ANN optimization in managing voltage. This imply that the specific application will be in energy management and loss reduction in a system.

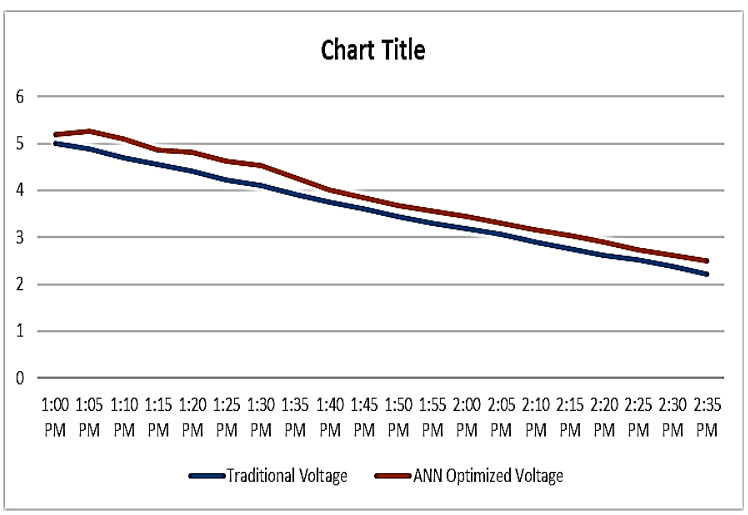

Fig.9 Performance Comparison of Traditional Voltage and Optimized ANN Voltage

Figure 10 shows the distribution of Energy Efficiency Ratio (EER) over a dataset. Bars of EER are typically between 50 and 100, with higher values being more frequent. A long tail reaching up to 300 is more common, but EER values greater than 150 are rarer. Based on this distribution, the majority of systems and devices in the dataset are considered to be moderately efficient, with only a few exceptions that may not be as efficient.

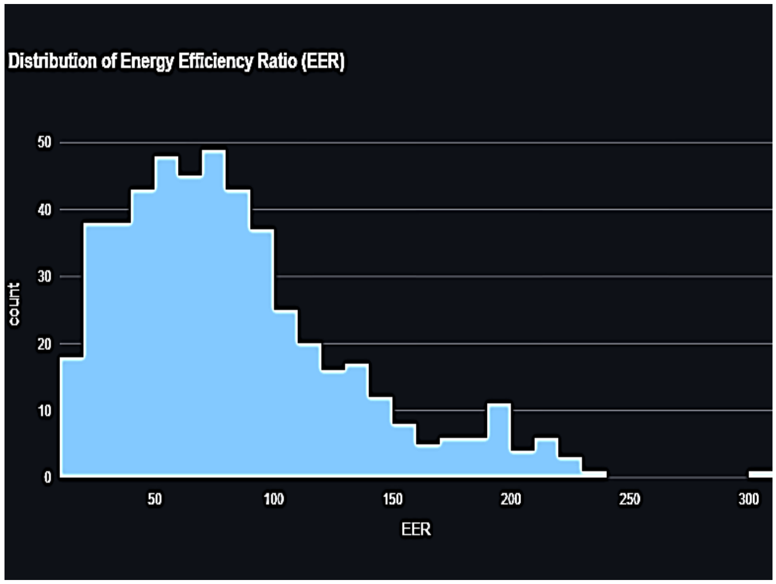

Fig.10 Distribution of Energy Efficiency Ratio (EER)

Figure 11 further illustrates the relationship between Signal strength and Energy Consumption. This relationship is depicted by a scatter plot. There is no apparent relationship between Signal Strength and Energy Consumption, as the points are distributed evenly without any clear trend. The energy usage is typically limited to a range of 2 to 8 units, regardless of the Signal Strength value. The presence of Signal Strength in this dataset does not necessarily indicate that Energy Consumption is a crucial variable.

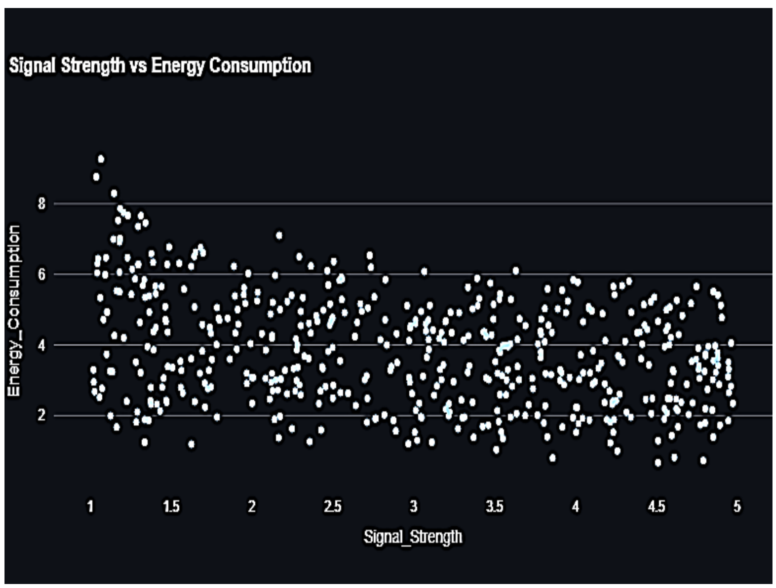

Fig.11 Signal Strength vs. Energy Consumption

C. Discussion

The results and outcomes of the ANN-optimized model developed has proven the potential of AI in improving the efficiency of IoT devices. The developed ANN model proves to be timely and transformative as this has the potential in addressing the challenges of IoT devices which significantly face energy consumption challenges. This therefore makes it important for a more efficient energy management in remote systems. This study demonstrates how AI-driven protocol selection can adjust to environmental conditions, which in turn allows for optimal communication with minimal power usage. in other to be able to adjust communication, the developed model also considers environmental factors such as temperature, humidity, and light levels which causes a decrease in power consumption. This proves to be a significant improvement over conventional communications method. The potential of energy conservation from AI driven choices demonstrates to have a huge impact and improvement in the EER and battery life. Added to the high costs of frequent battery replacements and operational down-time, the impact of the model is even more severe. ANN-optimized protocols could save energy for battery-based IoT systems that operate in remote or off-grid areas, potentially leading to longer device life and lower maintenance costs. Consequently, this approach offers advantages in terms of both operational efficiency and environmental impact mitigation, thereby contributing to the sustainability of IoT deployments. Furthermore, the model is also fast in responding to changing environmental data. With the ability to switch protocols in less than 100 milliseconds, the system can respond rapidly to environmental changes, resulting in minimal energy consumption during data transmissions. In real-time applications like environmental monitoring or industrial IoT, this degree of responsiveness is crucial; rapid changes in conditions necessitate swift reactions to prevent inefficiencies or data loss.

V. CONCLUSION

In this study, the developed ANN-based protocol selection model has proven to be a promising technique in the optimization of the energy consumption in IoT device communication. The model's ability to use real-time environmental data for communication decisions resulted in energy savings and reliable performance. This project has shown that implementing ANN-driven solutions on devices with limited resources, such as the ESP32, can result in significant energy savings for IoT applications. The results underscore the efficacy of the Artificial Neural Network (ANN) methodology, especially within contexts characterized by fluctuating environmental parameters. Employing a combination of experimental and simulation techniques, we ascertained the model's capacity to react to environmental shifts with both accuracy and rapidity, simultaneously adjusting its communication strategies. This model's inherent adaptability renders it applicable across a broad spectrum of Internet of Things (IoT) applications, encompassing areas such as environmental monitoring and the enhancement of energy efficiency in industrial automation.

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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation
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REFERENCES

[1] I. P. Idoko, O. M. Ijiga, D. O. Agbo, E. P. Abutu, C. I. Ezebuka, and E. E. Umama, "Comparative Analysis of Internet of Things (IoT) Implementation: A Case Study of Ghana and the USA—Vision, Architectural Elements, and Future Directions," *World Journal of Advanced Engineering Technology and Sciences*, vol. 11, no. 1, pp. 180–199, 2024.

[2] M. S. Mahmoud and A. A. Mohamad, "A Study of Efficient Power Consumption Wireless Communication Techniques/Modules for Internet of Things (IoT) Applications," *International Journal of Computer Applications*, vol. 06, pp. 19-29, 2016, https://doi.org/10.4236/ait.2016.62002.

[3] H. N. N. Manuel, T. O. Adeoye, I. P. Idoko, F. A. Akpa, O. M. Ijiga, and M. A. Igbede, "Optimizing Passive Solar Design in Texas Green Buildings by Integrating Sustainable Architectural Features for Maximum Energy Efficiency," *Magna Scientia Advanced Research and Reviews*, vol. 11, no. 1, pp. 235–261, 2024, https://doi.org/10.30574/msarr.2024.11.1.0089.

[4] R. Taylor, T. Smith, and L. Clark, "Adapting Communication Protocols for IoT Networks using Reinforcement Learning," *Journal of Computer Networks*, vol. 89, pp. 63–77, 2024, https://doi.org/10.1016/j.comnet.2024.03.005.

[5] D. Wang and X. Zhang, "Deep Learning for Energy-Efficient IoT Networks: A Survey," *IEEE Access*, vol. 12, pp. 10120–10135, 2024, https://doi.org/10.1109/ACCESS.2024.3182361.

[6] M. Mahamat, G. Jaber, and A. Bouabdallah, "Achieving Efficient Energy-Aware Security in IoT Networks: A Survey of Recent Solutions and Research Challenges," *Wireless Networks*, vol. 29, no. 2, pp. 787–808, 2023.

[7] I. M. Ebika, D. O. Idoko, F. Efe, L. A. Enyejo, A. Otakwu, and I. I. Odeh, "Utilizing Machine Learning for Predictive Maintenance of Climate-Resilient Highways Through Integration of Advanced Asphalt Binders and Permeable Pavement Systems with IoT Technology," *International Journal of Innovative Science and Research Technology*, vol. 9, no. 11, Nov. 2024, https://doi.org/10.38124/ijisrt/IJISRT24NOV074.

[8] E. Uzoma, I. P. Idoko, and L. A. Enyejo, "Evaluating Serverless Computing and Microservices Impact on Scalable Cloud-Native Applications and Blockchain Interoperability Frameworks," *International Journal of Scientific Research and Modern Technology*, vol. 3, no. 4, pp. 14–17, 2024, https://doi.org/10.38124/ijsrmt.v3i4.407.

[9] I. P. Idoko, O. M. Ijiga, O. Akoh, D. O. Agbo, S. I. Ugbane, and E. E. Umama, "Empowering Sustainable Power Generation: The Vital Role of Power Electronics in California's Renewable Energy Transformation," *World Journal of Advanced Engineering Technology and Sciences*, vol. 11, no. 1, pp. 274–293, 2024.

[10] O. Bashiru, C. Ochem, L. A. Enyejo, H. N. N. Manuel, and T. O. Adeoye, "The Crucial Role of Renewable Energy in Achieving the Sustainable Development Goals for Cleaner Energy," *Global Journal of Engineering and Technology Advances*, vol. 19, no. 3, pp. 011–036, 2024, https://doi.org/10.30574/gjeta.2024.19.3.0099.

[11] J. Wang and Q. Zhang, "Energy-Efficient Communication Protocols for IoT Systems: A Machine Learning Perspective," *Journal of Communications and Networks*, vol. 26, no. 5, pp. 517–530, 2024, https://doi.org/10.1109/JCN.2024.014536.

[12] B. Al Homssi, A. Al-Hourani, K. G. Chavez, S. Chandrasekharan, and S. Kandeepan, "Energy-Efficient IoT for 5G: A Framework for Adaptive Power and Rate Control," in *Proceedings of the 12th International Conference on Signal Processing and Communication Systems (ICSPCS)*, pp. 1–6, IEEE, Dec. 2018.

[13] P. I. Onu and R. O. Okeke, "Towards Systematic Energy Efficiency: The Smart Efficiency Framework for Sustainable Transitions in Nigeria and West Africa," *Journal of Alternative and Renewable Energy Sources*, vol. 11, no. 3, pp. 14-26, Oct. 2025.

[14] J. O. Enyejo, I. N. O. Babalola, F. R. A. Owolabi, A. F. Adeyemi, G. Osam-Nunoo, and A. O. Ogwuche, "Data-Driven Digital Marketing and Battery Supply Chain Optimization in the Battery Powered Aircraft Industry Through Case Studies of Rolls-Royce's ACCEL and Airbus's E-Fan X projects," *International Journal of Scholarly Research and Reviews*, vol. 5, no. 2, pp. 001–020, 2024, https://doi.org/10.56781/ijsrr.2024.5.2.0045.

[15] A. I. Ibokette, T. O. Ogundare, E. O. Danquah, A. P. Anyebe, J. A. Agaba, and T. M. Olola, "The Impacts of Emotional Intelligence and IoT on Operational Efficiency in Manufacturing: A Cross-Cultural Analysis of Nigeria and the US," *Computer Science & IT Research Journal*, vol. 5, no. 8, 2024, https://doi.org/10.51594/csitrj.v5i8.1464.

[16] A. R. Apampa, O. Afolabi, and S. O. Eromonsei, "Leveraging Machine Learning and Data Analytics to Predict Academic Motivation Based on Personality Traits in University Students," *Global Journal of Engineering and Technology Advances*, vol. 20, no. 2, pp. 026–060, 2024, https://doi.org/10.30574/gjeta.2024.20.2.0145.

[17] A. Akbas, H. U. Yildiz, A. M. Ozbayoglu, and B. Tavli, "Neural Network Based Instant Parameter Prediction for Wireless Sensor Network Optimization Models," *Wireless Networks*, vol. 25, no. 6, pp. 3405–3418, 2019.