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An approach of battery adaptation in wireless sensor network with resource aware in extreme environmental area

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ABSTRACT

A wireless sensor network (WSN) is a distributed wireless system that employs sensor nodes to perform various tasks, including sensing, monitoring, data transmission, and delivering information to users via internet communication. Resource availability in WSNs is a critical factor influencing data delivery performance. One of the main challenges is the rapid depletion of resources, particularly batteries, which play a pivotal role in the system's operational sustainability. This study evaluates the impact of battery adaptation through four testing scenarios. The results show that implementing battery adaptation significantly extends system lifespan compared to scenarios without adaptation. In the scenario without both a classification algorithm and adaptation, the system lasts approximately 270 minutes. When battery adaptation is applied without a classification algorithm, the lifespan increases to 330 minutes and 30 seconds. In contrast, the scenario using a classification algorithm without adaptation yields a lifespan of about 185 minutes, while combining the classification algorithm with adaptation extends it to approximately 252 minutes. The findings demonstrate that battery adaptation enhances the longevity and resource efficiency of WSN systems. However, the use of a classification algorithm tends to reduce operational time compared to scenarios that do not employ such algorithms.

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1. INTRODUCTION

The evolution of technology is increasingly oriented toward the connectivity of the physical environment, making modern technological systems highly essential in various domains [1]. However, direct data collection in the field poses significant challenges, including high operational costs and time consuming processes for detecting emerging phenomena, which can lead to inefficiencies and impractical implementations [2]. To address these challenges, the use of wireless sensor network (WSN) technology becomes imperative. WSN enables researchers to obtain comprehensive information remotely, without the need for physical presence in the sensor deployment area [3].

WSN technology facilitates continuous monitoring, tracking, and control, forming a critical foundation for data acquisition that supports informed decision making and action [4]. Moreover, WSN systems can be deployed in inaccessible or hazardous environments, such as monitoring tectonic plate movements deep underground, volcanic activity in mountainous regions, and radiation levels in areas affected by nuclear incidents [5].

In WSN systems, power consumption represents a major challenge due to the limited capacity of onboard batteries [6]. In the context of power electronics and drive systems, this approach can be further enhanced through the application of adaptive charging algorithms, which consider environmental conditions and the power usage patterns of individual nodes [7]. Implementation of resource aware and deep sleep adaptation proposed in this study offers an energy efficient solution for WSN applications, particularly in extreme environmental monitoring scenarios [8].

Resource availability is a key consideration in WSNs, as the performance of data transmission relies heavily on the sufficiency of available battery energy [9]. The dynamic nature of resource availability presents a challenge to system sustainability, with the continuity of WSN operations depending directly on the presence of adequate power. However, these batteries typically have limited energy capacities [10]. Consequently, restricted battery resources can lead to suboptimal performance in data transmission. This research aims to investigate solutions for addressing the limitations posed by battery resources in WSNs. It is expected to contribute to strategies for conserving energy and extending the operational lifespan of WSN systems.

2. LITERATURE REVIEW

WSN technology is highly applicable across various domains such as environmental monitoring, healthcare, and industrial systems, where real time data supervision is essential [11]. However, key challenges in implementing WSNs include ensuring energy efficiency and optimizing data processing [12]. To address these issues, techniques such as data mining and classification algorithms are employed to enhance the efficiency of processing data generated by sensor nodes [13].

Data mining aims to extract meaningful information from large datasets, with classification serving as a key technique to categorize data based on specific attributes [14]. In the context of energy efficiency in WSNs, the deep sleep mode in ESP32 microcontrollers is employed to significantly reduce power consumption [15]. The integration of deep sleep and classification algorithms in WSNs enhances data processing efficiency, enabling applications such as environmental prediction and anomaly detection [16]. This combination of intelligent data processing and power saving strategies plays a vital role in extending operational lifespan and improving the reliability of WSN systems [17].

In conclusion, WSN is a promising technology for real time data monitoring and processing [18]. The application of data mining techniques and classification algorithms enhances the efficiency of handling sensor generated data [19]. At the same time, power efficiency addressed through mechanisms such as deep sleep mode in ESP32 microcontrollers is essential for the long term sustainability of WSN systems [20]. Thus, integrating intelligent data processing with energy optimization enables WSNs to serve as efficient and dependable solutions across multiple application areas [21].

3. METHOD

This study is supported by a comprehensive set of hardware and software components that function synergistically to generate accurate data and enable thorough analysis. A detailed overview of the specific hardware and software components employed in this study is presented in Table 1. Table 1 presents the key components used in this study, each playing an essential role in supporting data acquisition and storage processes. The microcontroller utilized is the ESP32 DevkitV1, known for its high performance and integrated wireless communication capabilities. This study also employs the INA219 sensor, which enables real time monitoring of voltage and current in the battery. An external memory card is used as a storage medium, facilitating further analysis of the collected data. The primary power source is a lithium battery, which is critical for maintaining system sustainability, especially in scenarios where efficient power consumption is required [22].

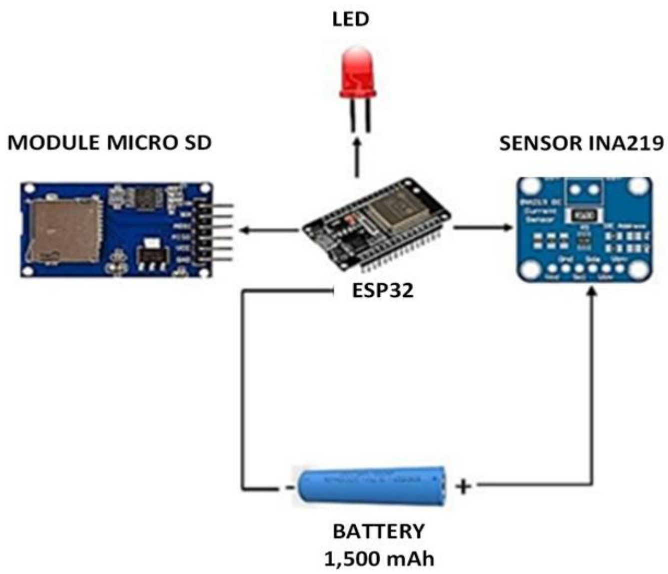
Table 1. Device components for research

Components	Specification
ESP32 DevkitV1	Xtensa dual core LX6 – 160 MHz, 32 bit, 16 MB, Bluetooth, Wifi, GIO Pin (ADC/DAC), 3.3 volt
LED	0.5 W/pcs
Sensor INA219	I2C or SMBus (serial management bus), ±3.2 A
Module micro SD	3.3 V, 6 pins (GND, VCC, MISO, MOSI, SCK, CS)
Memory card	16 GB
2 Lithium battery (Series)	4.2 volt 1,500 mAh (Series) = 8 volt 1,500 mAh

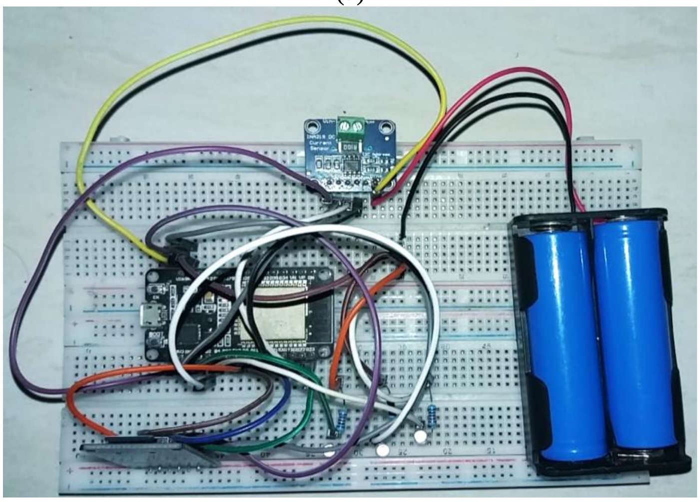
3.1. System architecture

In this research, the system framework is constructed using a set of established WSN components. These include the ESP32 microcontroller, SD card module, INA219 sensor, lithium battery, and LED, all integrated to form a cohesive and functional system. The integration of these components facilitates seamless operation and efficient data exchange, which are essential for the successful execution of the research.

Figure 1(a) illustrates the system framework developed in this study, which is based on WSN components. Figure 1(b) shows this simulation setup and system architecture provides a comprehensive overview of the operational mechanism of the proposed WSN. In this setup, the ESP32 microcontroller functions as the central processing unit, responsible for transmitting a data stream composed of random values. The INA219 sensor measures battery voltage in real time, enabling continuous power monitoring throughout system operation. An LED serves as a visual indicator to signal active data transmission. All measurement data and generated data streams are stored on an SD card module, ensuring data availability for subsequent analysis. The entire system uses a battery that supplies energy to all components in the WSN. This design enables the system to operate autonomously and efficiently in both data management and power consumption monitoring.



(a)



(b)

Figure 1. System architecture: (a) illustrated simulation and (b) simulation setup

3.2. Adaptation mechanism

This structured process ensures that the system responds effectively to changing conditions, particularly in terms of power management. The flow of the adaptation process is illustrated in Figure 2. Figure 2 illustrates the adaptation mechanism implemented in this study, which comprises several sequential stages. The process begins with random data streaming, where the data received by the sensor node is transmitted in real time to the sink node. This is followed by a resource monitoring phase, where the battery status is continuously evaluated to detect critical power conditions. If the battery level is within the normal range (>50%), all generated data is stored. However, when the battery level falls below the critical threshold (<50%), the system initiates a battery adaptation process [23].

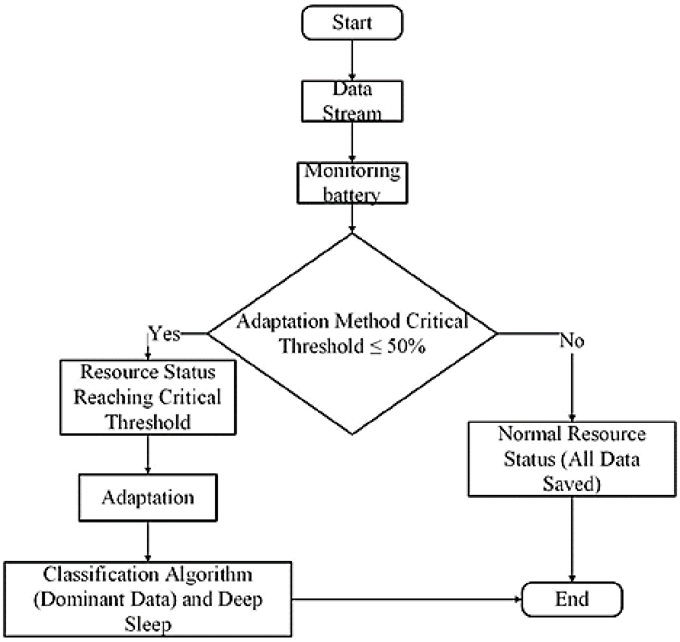


Figure 2. Adaptation mechanism

In this research, the adaptation process incorporates two key mechanisms: classification algorithms and deep sleep procedures. The deep sleep protocol is triggered when battery voltage reaches specific thresholds. When the voltage is between 6.0 V – 5.5 V, the system enters a deep sleep mode for 5 seconds as an initial energy saving response. If the voltage drops further to between 5.5 V – 5.0 V, the deep sleep duration is extended to 10 seconds. As the battery level decreases to the 5.0 V – 4.5 V range, the system increases the deep sleep interval to 15 seconds. Finally, when the battery level reaches 4.5 V – 4.0 V, the system prolongs the deep sleep duration to 20 seconds, demonstrating a highly adaptive response to critical energy conditions. The following section illustrates the process of dominant data extraction using the classification algorithm. Figure 3(a) presents the flowchart of the classification algorithm used to determine the dominant data to be transmitted as the system's output. The classification process involves identifying the mode from an array of randomly generated integers, which represents the most frequently occurring value in the dataset [24].

The algorithm begins with the initialization of the variable $n = 10$, indicating that the array $data[]$ will contain ten elements. Executed from the index $i = 0$ to $i = n - 1$, where each element of the array is populated with random data between 0 and 9 using the $random(0, 9)$ function. Once all elements are populated, the program invokes the $mode(data, n)$ function to identify the $mode$ of the array. If no mode is detected (i.e., no value occurs more than once), all elements in the array are refreshed with new random values, and the process is repeated.

Upon successfully identifying a $mode$, the result is stored in the $modes[]$ array, and the first value (i.e., the most dominant one) is assigned to the $modeValue$ variable. The algorithm terminates once the dominant value has been identified and stored. This flowchart provides a straightforward method for classifying dominant values within a dataset and can be applied in various data analysis and decision making scenarios.

Figure 3(b) illustrates the relationship between the classification algorithm and the deep sleep mechanism. The classification algorithm is employed to identify and transmit only the dominant data, thereby reducing the processing load when the system detects a critical battery condition [25]. Concurrently, the deep sleep mode conserves power by minimizing system uptime, with the sleep duration dynamically adjusted based on the battery voltage level [23]. The integration of these two mechanisms results in a more energy efficient system, enabling WSN devices to operate longer under limited power conditions.

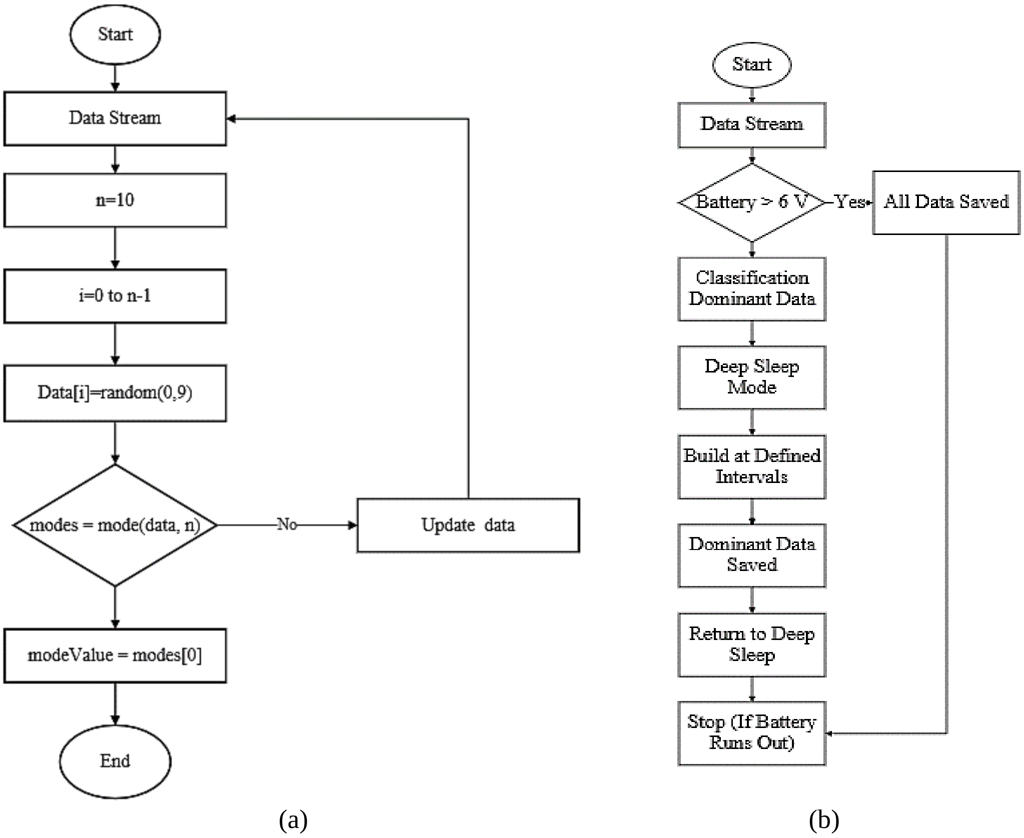


Figure 3. Classification algorithm of (a) flowchart classification algorithm and (b) relationship between deep sleep and the classification mechanism

4. RESULT AND DISCUSSION

A series of carefully designed testing scenarios was conducted to thoroughly evaluate the system workflow and assess the effectiveness of the adaptation mechanisms applied to the WSN system. The scenarios were structured to capture the system's dynamic responses to adaptation, offering deeper insights into its behavior when faced with challenges commonly encountered in real world operational contexts.

4.1. Testing without a classification algorithm and without adaptation

Figure 4(a) presents a graph illustrating a significant decline in battery capacity once the voltage drops to 7 V, observed in the test scenario without classification algorithms and adaptation mechanisms. This rapid decrease is primarily caused by continuous real time data transmission, which results in excessive battery consumption. Under these standard operating conditions, the battery sustained operation for 16,223 seconds, during which the system generated a total of 39,951 data entries. The average battery usage was recorded at 0.0924613203 milliampere seconds (mAs). These results prove the effectiveness of the adaptation strategy in saving energy and extending the system's operational time.

4.2. Testing without a classification algorithm and with adaptation

Figure 4(b) shows the improvement in system performance during testing without the use of a classification algorithm, but with the implementation of battery adaptation. The adaptation strategy is carried out by activating deep sleep mode when the battery voltage reaches a critical threshold, so that power consumption is reduced and battery life is extended. After adaptation is activated at a voltage of 6 V, the system is able to operate for 19,830 seconds by generating 18,764 data, and the average battery consumption is 0.0756429652 milliampere seconds (mAs). These results prove the effectiveness of the adaptation strategy in saving energy and extending the system's operational time.

4.3. Testing with a classification algorithm without adaptation

Figure 4(c) shows the test results with the classification algorithm without adaptation. In this scenario, the battery only lasted for 11,103 seconds with a total of 34,176 data generated, and an average consumption of 0.135098622 milliampere seconds (mAs). The graph shows a sharp decrease in battery capacity when the voltage reaches 7 V, indicating high energy consumption due to the continuous classification process. In the absence of an adaptation mechanism, the use of a classification algorithm significantly increases power consumption. The WSN system becomes more energy-intensive due to the ongoing execution of classification processes, resulting in accelerated battery depletion. This highlights the limitations of operating without an optimized energy management approach.

4.4. Testing with a classification algorithm and with adaptation

Figure 4(d) illustrates the testing scenario involving the implementation of a classification algorithm combined with deep sleep mode as an adaptation strategy when the battery reaches a critical threshold. Initially, the system transmits random data, followed by the identification of dominant data during the adaptation phase. As a result, two types of data are generated random data during normal operation and dominant data during the activation of deep sleep mode.

This test highlights the importance of dynamic adaptation in battery powered systems. When the voltage drops to 6 V, the adaptation mechanism is activated to save energy. The system operated for 15,136 seconds, generating 23,004 data entries with an average power consumption of 0.0991014799 milliampere seconds (mAs). The graph shows a steep decline in battery capacity before adaptation is applied. After the activation of deep sleep mode and classification, the system demonstrates a significant improvement in endurance. These results confirm the effectiveness of the adaptation strategy in extending battery life and enhancing system performance under energy-constrained conditions.

Figure 5 presents a comparative graph of all testing scenarios, based on battery voltage measurements recorded at one second intervals. The graph highlights a noticeable and rapid decline in battery capacity around the 7 V mark, particularly in scenarios without adaptation. In contrast, when adaptation mechanisms are applied, the graph displays a more gradual and stable reduction in battery capacity, especially once the battery reaches 6 V. The visual comparison underscores a key finding scenarios that implement battery adaptation consistently demonstrate longer operational lifespans than those without adaptation.

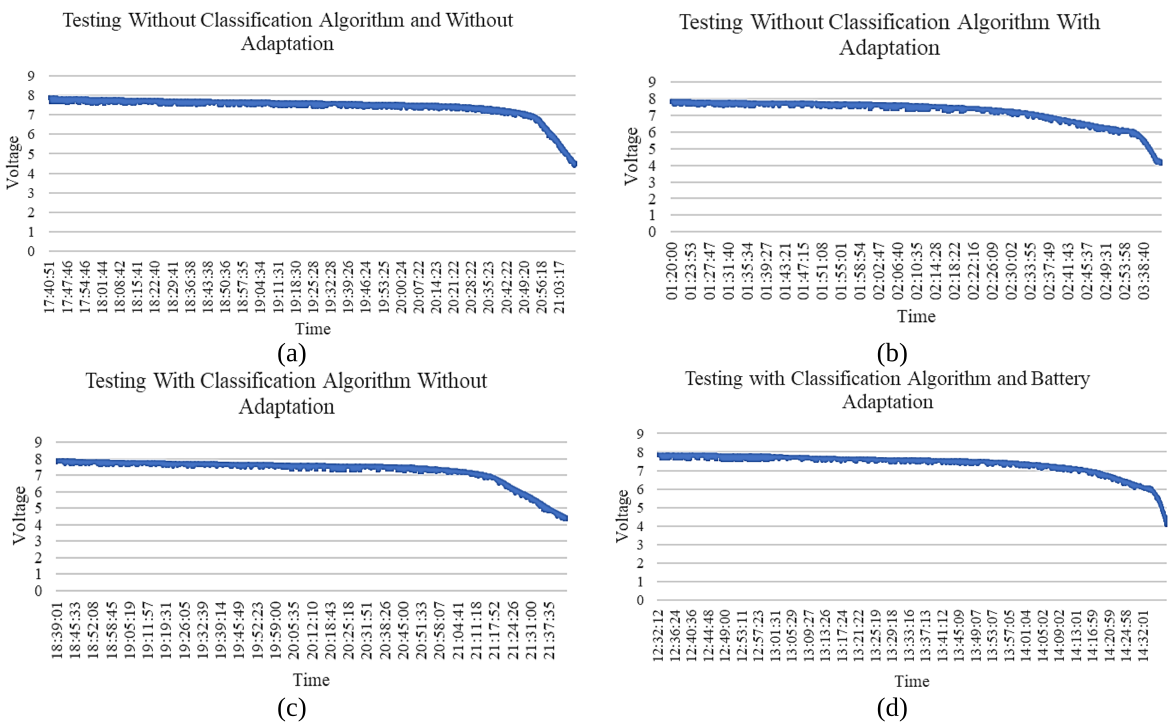


Figure 4. Testing scenario of (a) graph testing without a classification algorithm and without adaptation, (b) graph testing without a classification algorithm with adaptation, (c) graph testing with a classification algorithm without adaptation, and (d) graph testing with a classification algorithm and with adaptation

A key focus of this study is the impact of classification algorithms on battery consumption. While classification enhances data processing by identifying and grouping relevant information, it also increases computational demands. Each incoming data point must be analyzed and categorized, requiring more processing power than simply transmitting unfiltered data. This increased workload leads to higher energy consumption.

This is clearly reflected in the results in the scenario without adaptation, where the use of a classification algorithm resulted in the battery lasting only 11,103 seconds, compared to 16,223 seconds in the non-classification scenario. Although classification improves processing efficiency, it significantly accelerates battery depletion. These findings underscore the necessity of effective adaptation strategies to counterbalance the increased power usage introduced by classification, thereby maintaining system longevity and reliability.

Table 2 presents a comparative analysis of system performance across three scenarios without classification, with classification only, and with classification combined with battery adaptation. In the absence of classification, the system transmits raw data without processing, resulting in lower energy consumption and a battery life of 16,223 seconds. Introducing the classification algorithm improves data handling by organizing and processing information before transmission. However, this increases computational load and energy consumption, reducing battery life to 11,103 seconds, highlighting a trade-off between data efficiency and power usage. When classification is integrated with a battery adaptation strategy, such as deep sleep mode, the system conserves energy during critical battery conditions by reducing activity. In this scenario, the battery lasts 15,136 seconds. These results demonstrate that adaptation strategies can effectively balance data processing demands with energy efficiency, enhancing system sustainability under constrained power conditions.

While the integration of classification algorithms and deep sleep adaptation mechanisms has proven effective in testing scenarios, several limitations must be considered for real-world implementation. Environmental variability presents a major challenge. Factors such as extreme temperatures, high humidity, and electromagnetic interference can adversely affect battery capacity and overall system stability. For instance, both low and high temperatures can accelerate battery degradation, limiting the effectiveness of deep sleep mechanisms in conserving energy.

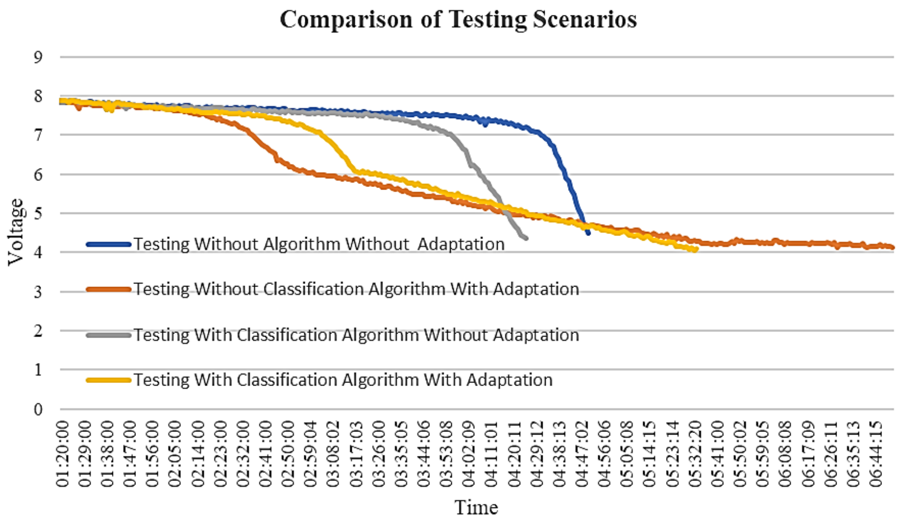


Figure 5. Comparison of all testing scenarios

Table 2. Results comparison before and after adaptation

Aspect	Without classification	With classification	With classification and with adaptation
Battery life	16,223 seconds	11,103 seconds	15,136 seconds
Data processing	Data is sent directly without selection	Data is classified before transmission	Data is classified and deep sleep is applied
Energy comsumption	Low (only data transmission)	High (classification process)	Lower (deep sleep saves energy)
Transmission efficiency	Inefficient (raw data is transmitted)	More efficient (only relevant data is sent)	Highly efficient (combination of classification & adaptation)
Power usage	Stable but not optimal	Higher due to additional processing	Reduced with deep sleep mechanism
System endurance	Limited, drains quickly	More optimal in data processing	Most optimal, balancing data and energy efficiency

Moreover, large scale deployments face hardware related constraints. Components such as the ESP32 module and INA219 sensor have inherent limitations in terms of operational durability and power efficiency, particularly in dense sensor networks. In systems with a large number of nodes, inter device communication can significantly increase energy demands, thereby reducing the effectiveness of sleep based power management strategies. Additionally, inconsistencies in hardware specifications, such as differences in manufacturing quality or component tolerances, may impact overall system performance and reliability.

5. CONCLUSION

This study demonstrates that the integration of classification algorithms and deep sleep strategies can effectively optimize power usage in wireless sensor based systems. The classification algorithm is instrumental in identifying dominant data, enabling more efficient data processing, while the deep sleep mechanism conserves energy by reducing system activity when the battery reaches critical levels. Experimental results reveal that in the absence of adaptation, the battery depletes more rapidly. In contrast, the implementation of deep sleep significantly extends battery life. By dynamically adjusting the duration of deep sleep based on battery voltage levels, the system achieves greater energy efficiency without compromising data processing quality.

Despite the demonstrated effectiveness of these methods, several challenges remain for large scale and real world deployment. Environmental variability and hardware limitations can impact the stability and performance of energy saving strategies. Factors such as temperature fluctuations, electromagnetic interference, and inconsistent hardware quality may reduce the overall effectiveness of both classification and adaptation mechanisms. To further enhance the efficiency and effectiveness of battery adaptation strategies in wireless sensor systems, future research can explore the following areas:

- Development of more power efficient classification algorithms. Future work should focus on designing classification algorithms that require less computational power while maintaining accuracy. This may include reducing algorithmic complexity, optimizing parallel processing workflows, and leveraging lightweight, energy efficient artificial intelligence models.
- Implementation of adaptive deep sleep strategies. Deep sleep mechanisms can be further improved by employing machine learning based predictive methods. These approaches can dynamically adjust sleep durations based on historical power consumption patterns, allowing the system to respond more intelligently and responsively to real-time battery conditions.
- Optimization of energy efficiency across system components. Additional research should target energy optimization not only at the algorithmic level but also across core system components such as the CPU, memory, and bandwidth within ESP32 based IoT systems. Fine tuning the performance of these elements can contribute to a more balanced and efficient power usage profile.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Satria Gunawan Zain	✓	✓	✓	✓			✓			✓	✓		✓	✓
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study were generated independently by the authors during the course of the research. All data were obtained through original work conducted by the research team and do not involve the use of third party data. The data that support the findings of this study are available from the corresponding author, [JMP], upon reasonable request.

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