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AN EVALUATION METHOD OF ENERGY CONSUMPTION AS AN OPERATION PARAMETER IN A CYBER-PHYSICAL SYSTEM

Abstract: The research of energy consumption in an Internet of Things network and its analytical evaluation is the goal of this work. The authors of this work concentrate on developing a model for calculating the actual gain in power consumption in order to estimate the actual energy required. The method suggests measuring the difference in energy usage under three primary battery-powered working modes to maximize a device's lifetime. Due to the fact that each CPS device state has its own energy metrics, it is feasible to choose the best operation course for entire network. The presented technique is certainly viable, as demonstrated by the experimental examination of Zigbee and BLE devices. The comparison of power levels using a temperature sensor in three basic scenarios (power modes) dictates how the CPS device lifetime can be optimized. Multi-regime consumption models, in which the rates of charging and discharging are dependent upon the energy level, are analyzed in this paper. This work aimed to state an optimal energy consumption by finding the right balance between operational power and battery lifetime through mathematical modeling. Therefore, it is easy to determine the energy cost of power stage, for instance, to send data by setting the minimal duration of each working condition in terms of power consumption. Moreover, a reasonable balance of power consumption and battery lifetime which impacts the data collection from sensors is vital to the development of data extraction algorithms. The practical results depict how device should be accessible to be able to lose less power even during switching on/off or how operate more effective if it used for a short period of time. A long-term network could become a reality once battery life is optimized enough to not disturb a user.

Keywords: cyber-physical system; battery management; power consumption; mode; gain.

Introduction

Cyber-physical systems (CPS) represent the integration of physical processes with computing environments and communication networks [1]. These systems can be applied in various fields, such as home automation, smart buildings, etc. Lesch et al. [2] demonstrate a comprehensive CPS literature review and mention that a CPS has common features with an ambient intelligence, or the Internet of Things (IoT). Nowadays, due to the ability to provide greater

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flexibility in operating parameters, IoT has emerged as a large-scale CPS based on the fact that any device has optimal networking possibilities that allow it to collect and exchange data. It means that IoT devices consist of software that connects embedded electronics to interact with the external environment and each other. Currently, the most commonly used communication protocols have penetrated all home automation areas, and without a stable power supply, some already familiar solutions become inaccessible. Regarding the direct developers of IoT devices, the market requires them to create suitable-to-use modules. Moreover, those modules, at the same time, should have low internal power consumption as well as a long service life.

The current level of improvement in CPS permits the usage of low-priced remote interfaces in the field of domestic automation, compared with wired solutions. Modern battery-powered IoT devices are gadgets with various autonomy levels and numerous different communication technologies supported, nevertheless, a few of these protocols are inconsistent with others or have different technical restrictions. At the same time, the focus of any user is to build an energy-efficient domestic network to gather physical data about a local environment permanently without shutdowns.

The market will be dominated by small, affordable batteries with low energy losses as opposed to alternative autonomous options [3]. The cost-effective, energy-efficient, data-driven, and adaptable automation of CPS has been made possible by recent developments in low-cost and low-power Internet of Things technology. However, when hundreds of additional IoT devices are joined to a single network, the amount of energy needed to power these systems and supporting infrastructures will be immense. IoT devices are typically made with low battery capacity, low processing power, restricted memory, and low-power communication protocols in order to keep them compact and inexpensive for mass commercial adoption [4]. Consequently, it is crucial to take into account metrics such as energy consumption, which defines the battery's lifetime, while selecting autonomous IoT devices.

Modern IoT manufacturers build their products without the necessary security safeguards as it has its own ecosystem. Furthermore, IoT devices require non-constant execution times for typical security algorithms, it is difficult to deploy them as sophisticated mechanisms due to their computing, communication, and energy restrictions [5]. Thus, the key limitation when developing and implementing IoT networks and devices is to outline a fair balance between power consumption and battery life. An autonomous IoT device's design specs should be specified to guarantee a longer lifespan – the time amount needed to low the battery's energy. In order to evaluate the lifespan of an IoT device, optimization modeling frameworks have been presented in this study to create a link between send data and battery characteristics.

The purpose of the work is to propose an optimization method and its practical validation for CPS power performance, as well as research the complex structure of energy consumption in various operating modes. The objective is the formulation of optimization effects in terms of energy savings. The paper is organized as follows: Related work section demonstrates other adapted studies and its analysis employed in a field on IoT device energy consumption, Operational parameters section depicts adjusted working characteristics inside the CPS to display the importance of power consumption as a lead factor of successful data exchange. Then, focusing on three different battery activity modes, authors elaborate on analytical model of energy metrics optimization and its practical evaluation leading to all employed conclusions.

Related Work

Bundalo [6] describes CPS in terms of execution time to estimate a peak energy performance that leads to a half-reduction in consumption. The author gives a summary of CPS and highlights its difficulties such as the development of energy-efficient structure. The study also

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discusses methods for enhancing embedded computer systems' energy efficiency while concentrating on variables that influence power usage. Each power mode utilization is a method of power management when reducing the power consumption of each individual module, the total power consumption may be reduced.

Morella et al. [7] state that low-powered data acquisition is the first step for a CPS power performance optimization. In the modern world, an energy capacity is becoming more and more important as maintainability becomes a fundamental concern. Rechargeable batteries are becoming much more common in this market because of their many points of interest. They are being accepted as the control supplier in a wide variety of application scenarios, including CPS. Specifically, lifetime projection is widely regarded as new research since it may help assess the Quality of Service to support maintenance.

Energy storage has a significant impact on human life as well as industrial production, and its popularity is growing as the global eco-community places greater emphasis on sustainability. Since many crucial CPS equipment (electric cars or portable devices) rely on rechargeable batteries, which considered as a special kind of energy storage technology helpful in a variety of application [8]. The usage of electric vehicles rather than fossil fuel-powered ones is encouraged by the present attempts towards carbon neutrality, which in turn promotes the development of high-quality rechargeable batteries with high capacity, energy density, safety, and prolonged cycle life [9]. Furthermore, a key element in guaranteeing the high efficiency, reliability, and security of rechargeable batteries is an efficient management strategy when in use [10].

Additionally, researchers concentrate on battery management systems using CPS frameworks, tracking important performance parameters (state of charge or remaining lifespan) and making use of connection features to enable data gathering, archiving, and analysis [11]. Rechargeable batteries and CPS now have a mutually beneficial connection in which CPS is utilized to encourage and support the usage of rechargeable batteries as energy sources. By dispersing precise energy, this data may be utilized to maximize battery life and save operational expenses [12].

Since it demonstrates how a rechargeable battery is sustainable, the battery lifespan is one of the most significant KPIs for battery management [13]. Cycle life, or the number of cycles until residual capacity falls to less than 80% of the stated amount, is referred to as a rechargeable battery's "lifetime" [14]. The forecast of battery lifespan is an important problem since it serves as a crucial reference for many choices, such as energy consumption control, charging procedure optimization, and temperature management.

Furthermore, lifetime prediction may be useful in many other scenarios, such as accelerated R&D or manufacturing, where it can assist decision-makers in finding products with longer projected lifespans. Battery lifetime prediction may be divided into several types: model-based, data-driven, or hybrid approaches [15]. The physical model of the battery (such as an analogous electric circuit model) is usually created using *model-based techniques*. This model may then be used to estimate the point at which the capacity will fall below the threshold and anticipate the deterioration pattern. Since *hybrid approaches* estimate the residuals of future state estimations using machine learning techniques, they are more accurate than pure model-based approaches. This is due to the fact that they effectively depict the dynamics of the pattern of degradation in the future [16]. In order to establish the battery status update, both model-based and hybrid systems rely on an accurate physical model.

Since energy is taken from the battery and is not refilled, the authors [17] modeled the energy depletion process of an IoT device's battery as a pure Markovian process (*Stochastic Optimization*) without gathering energy data. The authors investigated how energy usage affects an IoT device's lifespan using their model. The proposed model's drawback is that the quantity

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of energy consumed in a unit of time is distributed exponentially. To overcome this constraint, a model considers energy as a continuous variable. It is not compulsory to consider the time takes to use one unit of energy, as it might even be predictable.

Moreover, energy processes are considered to be energy states, which is equivalent to the power required to switch on and send a specific quantity of data. The examination of device energy gain determines the time-dependent energy transition rates between states. The simulation-validated analysis model is employed in this paper to examine how a battery lifetime affects a device performance in a CPS as an IoT network.

CPS operation parameters

The main goal of the authors' [18] prediction is to identify the parameter that has to be adjusted in order to enhance a CPS's ability to collect and process data from its working environment. The CPS operation parameters are displayed in Table 1 and may be explained as follows.

Table 1. CPS parameters analysis.

Parameter	Description	Optimization result
Latency	Time required to transfer information from sensors to actuators and back.	Optimizing latency can improve the system's response to changes in the environment.
Throughput	The amount of data that the system is capable of processing in a certain period of time.	Bandwidth optimization can improve the efficiency of communication between CPS components.
Energy Consumption	The amount of power consumed by the CPS when performing certain operations.	Optimizing energy consumption can increase system autonomy and reduce resources load.
Security	CPS security from external threats and the ability to maintain operation in the face of cyberattacks.	Security optimization includes improving encryption, authentication, and access control mechanisms.
Reliability	The ability of the CPS to perform its functions without interruption or failure.	Reliability optimization includes the development of redundancy and recovery mechanisms, as well as the prevention of failure situations.
Adaptability	The ability of the CPS to change its behavior or parameters in response to changes in the environment.	Optimizing adaptability can improve a system's ability to cope with dynamic conditions.
Scalability	The ability of CPS to expand or contract efficiently based on changes in requirements or the volume of data processed.	Scalability optimization can ensure system stability as load increases.

The CPS network architecture proposed by the authors in [19] uses embedded gateway technology as a mediator to link diverse devices. The gateways' basic functioning concept depends on meeting criteria for security, dependability, adaptability, and scalability. Since the user may add any device, even one that is incompatible with the present network infrastructure, the system with gateway can be grown both horizontally and vertically. The most recent response information or the device's real-time status can be obtained by the user. The CPS devices are able to transmit messages of any size across the gateway, but they are unable to begin identical tasks. As it provides encoded data, Getaway enables the transmission of settings and a suitable answer to the asking device without causing any disruptions.

Assessment techniques for the remaining CPS operating parameters (Latency, Throughput, and Energy Consumption) could involve creating algorithms for optimal sensor data collec-

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tion, enhancing models, utilizing software to adjust to environmental changes, and enhancing the efficiency of data processing and decision-making [20]. Processes that reliably and efficiently accept sensor data are examples of optimized data collecting algorithms. Informed decision-making and network performance are directly impacted by the quality and relevancy of data, making this a crucial component.

CPS energy consumption

An actuator, a CPU, a communication component, a power source or an energy storage (battery) make up an IoT device [21]. Digital data is generated by the sensors after they collect the necessary physical data from the environment. After that, the data may be transferred to cloud (fog) computing data centers for a lighter and more in-depth study. Furthermore, by translating these digital signals into mechanical motions, actuators may be utilized to power a CPS. In order to assess power loss in a device, a battery is a component that analyzes the residual capacity or thermal profile. A battery in certain IoT devices offers independent status updates on power-saving options [22].

The time required to deplete completely the battery of an IoT device can be considered as its lifetime. The vast majority of IoT devices run on rechargeable lithium-based batteries. To mimic the battery degrading process, comprehensive data on the energy consumption profile of IoT devices is required. Various operating modes, communication protocols, low-power microcontroller processing, and CPS adjustment are some of the energy-saving approaches used to lower energy usage. Through a calculation of the device's average power consumption in different operation modes, the average power consumption of an IoT device throughout the course of its battery life was determined.

Battery activity periods

Wireless sensors are expected to revolutionize the way a common user monitors environmental parameter. However, the limited battery life of self-powered devices is holding back their widespread adoption. If a wireless sensor's functionality is entirely dependent on its built-in, non-removable battery, and the battery runs out, it becomes just unnecessary junk. A common way to increase a battery lifetime is to use the "pulse" principle of device operation: *short periods of activity are followed by long periods of rest*. IoT-device engineers try to make periods of activity as short as possible and periods of rest as long as possible. Due to the fact that a user wants the battery of an IoT device to last several years without changing. Power consumption and expected battery life require accurate load measurement under different operating states of the device.

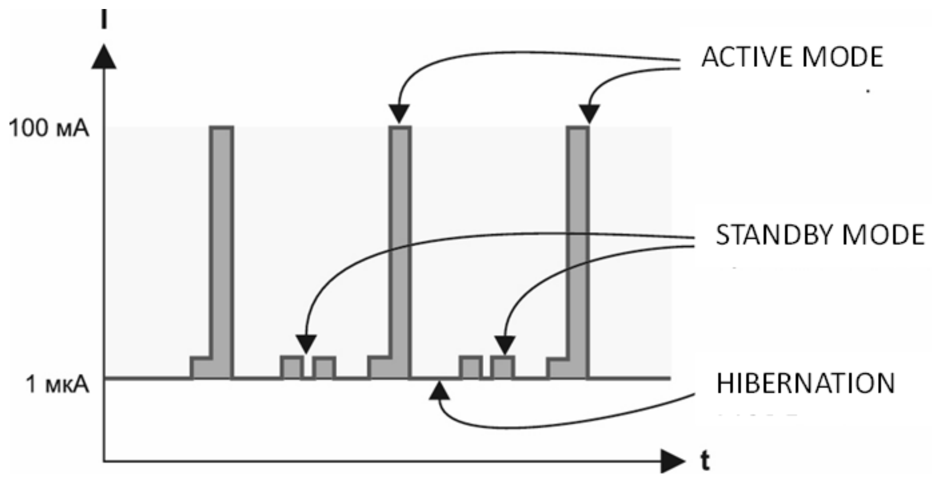

Figure 1. Wireless sensor current consumption levels in three main modes.

The working states of a wireless sensor can be divided into a series of periods of activity, each of which requires a certain level of energy for a certain period of time [23]. In general, there are three customizable operating states (Figure 1):

- **Active Mode** – all modules are on, constant data exchange, peak consumption.
- **Standby mode** (Sleep Mode) – all radio modules are turned off, data is collected and every few seconds the device wakes up to send a message (check status).
- **Hibernation Mode** – everything is disabled, data is not saved, waking up only by timer.

A sleep mode is a state where all unused peripherals are cut off. To maintain connections in a sufficient way, a device needs to wake up at regular intervals. During this, the battery switches between active and hibernation modes. Manufacturers design the device so that it spends most of its time in sleep mode with minimal consumption in current indices. In hibernation mode, only the real-time clock functions are used. By setting the timer, the device wakes up to perform measurements and then transmits data to the server.

Evaluation

Most traditional optimization techniques rely on mathematical models that belong to real-time dynamic procedures and provide an equation-based description of the process. Any optimization problem involves steps like identifying constraints, analyzing the process to be reduced, and modeling the mathematical function of the power consumption. An approach to implementing energy consumption evaluation based on the following algorithms is shown in Table 3.

Table 2. Proposed method of an energy consumption evaluation

#	Evaluation stage	Description	Application
1	Experimental	Empirical data collection on real energy consumption	Analysis of energy efficiency through the log database (accumulated data) and comparisons with situations that are as similar as possible to the current case to create a set of energy consumption scenarios.
2	Analytical model	Mathematical models for energy gain calculation	IoT networks with a large number of parameters, where an efficient energy consumption is required as structured data is absent.

Stage 1. Experimental

The process begins with the formation of energy consumption requirements. The first step towards measuring device parameters is collecting data on energy consumption. A battery contains a certain amount of energy, W·h, and has a capacity, estimated in mA·h described in a IoT device battery datasheet. If the power consumed by the device is known, then the battery life can be calculated using the formula:

$$\text{Battery Life (hours)} = \frac{\text{Energy (W·h)}}{\text{Power Consumption (W)}} \tag{1}$$

In accordance with this, the battery operating time can be expressed by the following formula:

$$\text{Operating time (h)} = \frac{\text{Capacity (mA·h)}}{\text{Current consumption (mA)}} \tag{2}$$

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On the other hand, battery energy is equal to the product of the voltage (V) and the battery capacity (A·h). The actual voltage is the empirically obtained on the battery discharge curve (Figure 2), which correctly relates to its State of Charge (SoC).

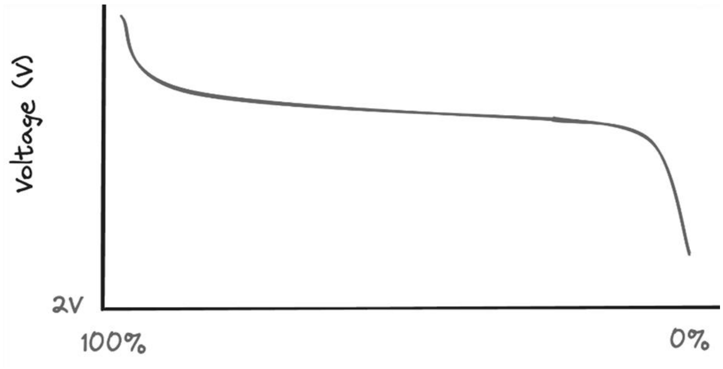

Figure 2. Loss in State of Charge as a discharging curve.

Manufacturers usually calculate State of Charge through battery voltage, as it is easy and doesn't require much effort [24]. The only problem is that the monitored voltage values are difficult to read, their rise/fall are non-linear (Figure 2), and they change under different operating conditions. However, in real-world conditions, actual battery life is usually less than estimated. This is usually explained by poor battery quality. As IoT manufacturers provide detailed battery specifications, however, it can be stated that there is a variation in actual capacity within 1 out of 10 same-type batteries, so the device stops working sooner than expected [25].

Another approach is to calculate operating time on the device empirically. Considering two time periods, for instance, a 60-min interval, calculate the amount of battery charge that was depleted during that period (device drained 3% of battery in the 1st hour, 5% during the 2nd hour, 2% in next 60 minutes). Then a user can make an average of these values and obtain the result that device consumes approximately 3% charge per hour. Using this 3%-delta and the duration over time, it becomes easy to calculate the expected battery life as follows:

$$\text{Actual Operating time (hour)} = \frac{100}{\text{Delta (per hour)}} \tag{3}$$

Most IoT manufacturers are aware of the battery characteristics of the devices they produce. If a device had one firmware installed but was never updated, then it would likely consume the same amount of energy on average day after day over its lifetime. At the same time, IoT software can be constantly updated. The device software is what makes IoT companies unique and valuable, so keeping their equipment up-to-date is vital. However, such updates often entail a certain regression of devices and can significantly reduce battery life.

Stage 2. Analytical model

To optimize the energy consumption in a CPS, it is necessary to compose function to maximize the battery life of the entire network, without reducing its functionality. Thus, energy consumption (EC) of the *i-th* device spent on one transmission can be calculated using the formula:

$$EC_i = (TA_i \times PA_i \times D_i) + (TS_i \times PS_i) + (TH_i \times PH_i) \tag{4}$$

where PA – power consumption of the *i-th* device in active mode required for 1 kb data, TA - data transmission time, D - transferred data size in kb. Also, TS – stands for a time range when a device is in a sleep mode, PS – power consumption in a sleep mode. Moreover, TH is a duration of hibernation operating state and PH is device consumed power during the hibernation status.

Consequently, P is a number of data packets transmitted within curtain *t*-interval and average *T*-interval between packets transmission:

$$P = \frac{t}{T} \tag{5}$$

The total consumption of the device during time t will be following:

$$E_{total} = EC \times P \tag{6}$$

Therefore, it is easy to determine the energy cost of each node for sending a certain quantity of data by knowing the duration of each working condition. Creating techniques and protocols that effectively and precisely influence data collection from sensors is vital to the development of data extraction algorithms. The review of IoT operational parameters pertains to enhancing its effectiveness, precision, or flexibility in response to dynamic conditions, such as changes in data attributes. This is a crucial area of study as well-informed decision-making and system performance are directly impacted by the accuracy and relevancy of the data.

Case study

The performance and energy usage of an energy-efficient CPS network are significantly impacted by the connection technology selected. Low-power consumption IoT devices are made for long-range connectivity, whereas short-to-medium communication ranges are ideal for battery-powered IoT devices. Power consumption is influenced by operational range, data rate, and power employed between two nodes. Currently, practically every IoT module that is available for self-development supports Zigbee or BLE protocols. Power consumption is a major constraint for IoT devices since they are likely to have to depend on batteries. Some IoT devices can be powered from the mains, for example a smart power socket or central temperature controller. It is interesting to note that commercial examples of such devices often already incorporate Wi-Fi modules.

According to Table 3, BLE and Zigbee have low power consumption, which makes them appropriate for energy-efficient applications and battery-powered devices. Short-range communication between devices, including smartphones and other consumer electronics, is facilitated by BLE. Security systems, thermostats, and smart lighting are just a few of the gadgets that employ ZigBee technology, which is intended for home automation. It is obvious that Wi-Fi protocol uses more energy than other presented standards. This is due to maintaining constant wireless connections and enabling fast data transfers use more energy.

Table 3. Comparative analysis of IoT protocols.

IoT protocol	Description	Range	Data Transfer Rate	Energy Consumption
Wi-Fi	well-suited for connecting devices with high bandwidth requirements.	~ 10-200 m	100 Mbps - 1 Gbps	Moderate ~ 250 mA
Zigbee	supports extended range and scalability with low latency.	~ 10-100 m	20 - 250 Kbps	Low ~ 50 mA
Bluetooth Low Energy	suitable for short-range connections in close proximity.	~ 10 m	1 Kbps - 1 Mbps	Low ~ 13 - 40 mA

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However, mobile IoT devices, such as remote controls or smart buttons, are powered from batteries and use alternative wireless technology such as Bluetooth Low Energy (BLE). Hortelano et al. [26] described how to use BLE mesh technology to reduce an IoT's power usage. The study covers burst transmissions and an IoT network with low power sensor nodes. Conversely, Zigbee provides an option as a wireless protocol created especially for sensor applications requiring less power. BLE connects faster and wakes up far faster than Zigbee, which wakes up much slower and uses more power, according to research in [27].

At specific active periods, a 9-bit data packet was broadcast via the experiment setup described in this study. A further part of the installation equipment came with the Expressif ESP8266 chipset and BLE beacon. For experimentation, two considered cases are when State of Charge capabilities of the two devices (ESP8266 as a Zigbee protocol and BLE beacon as BLE) are used to power a temperature sensor (DS18S20) and calculate its consumption. The total power consumed in two cases is calculated using Equation (4).

Table 4. Experimental results by Analytical model

Duration	**ESP82 (Zigbee) E total (9bit packet size)**			**BLE beacon E total**		
	Active	Standby	Hibernation	Scenario 1	Scenario 2	Scenario 3
1 min	~ 20 mW	~ 31 mW	~ 14 μW	~ 15 mW	~ 15 mW	~ 2.6 μW

In the first scenario, a network is built with one of the battery-based pieces of equipment integrated with a temperature sensor and can be considered to be in *Active mode* (Table 4). Temperature sensor is connected to GPIO pin on the ESP8266. Assuming that, the Zigbee device would read the temperature data and transmitting it. In the second case, a temperature sensor is plugged out of the network making the chip battery operate in *Standby Mode*. Regarding the third state of the network, the chip is disconnected from the network assuming it is in *Hibernation status*. Energy gain obtained during operation modes described as:

$$Gain = \frac{\text{Energy in Active mode}}{\text{Energy gained}} \times 100\ \% \tag{7}$$

Table 5. Actual gained energy comparison

	Basic Power Consumption	**Energy Gained**	**Energy Gain**
Zigbee	~ 20 mW	~ 6 mW	~ 30 %
BLE	~ 15 mW	0 mW	0 %

Zigbee depicts a slight power change with a 30% increase (Table 5). The longer the sensor node can stay in a low-power state and save energy, the shorter the duration in this mode will be. However, long sleep periods reduce the device's battery life cycle. If real-time monitoring is not necessary, then it makes sense to allow the device to sleep for a shorter period of time, and then transmit any data collected during that time as a single packet. IoT technologies that are intended for ultra-low power applications, such as Bluetooth Low Energy, can save energy costs and enhance network performance. BLE has lower overall power consumption than Zigbee. Since BLE uses almost the same amount of energy to run processes, it can spend more time sleeping, thereby not using much power. Overall, BLE consumes less power than Zigbee, allowing the device to remain in low-power sleep mode for longer periods of time, thereby contributing to solutions to problems associated with real-time data monitoring. Using BLE, new devices discovering can help extend the lifetime of a sensor node by providing real-time data monitoring only when needed.

Based on the results of this experiment, when the temperature sensor is combined with chipsets such as ESP8266 or BLE, BLE is energy efficient for use in IoT devices, but battery powered Zigbee based IoT devices are practical. The results demonstrated the fact that Zigbee is effective when used for a short period of time. In case if a module is not utilized in the operating mode for a predetermined amount of time, the suggested method progressively switches it into low operating modes.

Here are some key effects on the device's operation after its power consumption is analyzed:

- Data collection frequency, avoiding overcoming excessive loads.
- Appropriate sensor selection to fulfill CPS power parameters.
- Data compression, filtering, and processing with low-powered algorithms.

Conclusion

The authors' goal in this study is to develop a model that can be used to effectively calculate the growth in consumption in order to estimate energy consumption (power) in CPS. The article suggests figuring out the difference (increase) in energy usage under the three primary battery-powered working modes to maximize a device's lifetime. The ideal course of action for utilizing the item may be ascertained by examining the varying power consumption figures of each mode. The suggested approach's feasibility is well demonstrated by the experimental evaluation.

Due to their low power consumption, BLE and Zigbee protocols are appropriate for battery-powered devices and energy-efficient applications. Short-range communication between devices, including smartphones and other consumer electronics, is facilitated by BLE. The majority of well-known home automation stations and gadgets, including security systems, smart lighting, and thermostats, are based on ZigBee connectivity. Enabling fast data transfer and maintaining constant wireless connections consumes more energy, hence reducing the total lifespan of the device.

Proposed evaluation method solely describes the time-dependent energy rates. The pace at which the battery content varies is determined by the disparity between power consumption in three various battery modes. In order to assess different energy-management strategies and examine the battery life of an IoT device it is necessary to analyze multi-regime consumption models in which the rates of charging and discharging are contingent upon the energy level.

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