

A Power-Aware Method for IoT Networks with Mobile Stations and Dynamic Power Management Strategy

Ahmed M. Shamsan Saleh

Department of Information Technology, University of Tabuk, Saudi Arabia
ah_saleh@ut.edu.sa

Received: 1 September 2023 | Revised: 2 October 2023 and 7 October 2023 | Accepted: 8 October 2023

Licensed under a CC-BY 4.0 license | Copyright (c) by the authors | DOI: <https://doi.org/10.48084/etasr.6352>

ABSTRACT

The Internet of Things (IoT) plays a critical role in the digitalization of numerous industries, enabling increased automation, connectivity, and data collection in areas such as manufacturing, healthcare, transportation, and smart cities. This paper introduces a power-aware method for IoT networks using mobile stations and a dynamic power management strategy. The proposed method aims to improve power consumption and total packets received compared to the static-station balanced data traffic method. The proposed method uses a mobile station to dynamically adapt its transmission power based on the network conditions and the strength of the received signal. Furthermore, a dynamic power management strategy is employed to further decrease the power usage of the network by adjusting the power state of each station and IoT node according to its level of activity, data traffic, and communication requirements. Simulation results showed that the proposed method reduced power consumption by up to 64%, increased total packets received by 72%, and, as a result, increased network coverage and lifetime compared to the balanced data traffic method with static stations. This method can be employed in various IoT applications to improve power efficiency and increase network reliability.

Keywords-internet of things; power consumption; mobile stations; dynamic power management

I. INTRODUCTION

The Internet of Things (IoT) is a fast-developing technology that links a wide range of devices and systems to the Internet, allowing them to exchange data and interact with each other [1-3]. IoT devices are widely used in various sectors such as manufacturing, healthcare, transportation, and smart cities [4-5], as they allow the development of new and innovative solutions that can improve the efficiency and effectiveness of numerous systems and processes, resulting in cost savings and improved quality of life for individuals and businesses [6]. However, the deployment and operation of IoT networks present various challenges, one of which is the power consumption of the devices [7-9]. The IoT nodes are regularly powered by batteries, and their power consumption is a crucial factor that affects their lifespan and reliability [10-11]. To extend the lifespan of these nodes, it is important to decrease their power consumption without compromising network performance [12]. This study resolves this problem by dynamically adapting the transmission power of mobile stations according to the network conditions and the strength of the received signal, in addition to using a dynamic power management strategy to further reduce power consumption. The proposed method offers a potentially effective response to the problem of power consumption in IoT networks and can be applied to various areas such as smart cities, healthcare, and transportation.

The main contributions of this study can be summarized as follows:

- It presents a power-aware method with a dynamic power management strategy for IoT networks using mobile stations. This method seeks to improve power consumption and total packets received compared to the balanced data traffic method with static stations.
- The proposed method uses a mobile station to dynamically adapt its transmission power based on the network conditions and the strength of the received signal. This method improves the efficiency of the network and reduces power consumption.
- A dynamic power management strategy is used to further reduce the power consumed by the IoT network. This approach regulates the power consumption of the nodes according to the network traffic and conditions, resulting in a considerable reduction in power consumption.

Several power-aware methods exist for IoT networks. In [13], a dynamic power management scheme was proposed to improve sensor lifespan in IoT-based wireless sensor environments. The method aimed to improve the energy consumed by sensors in IoT networks by automatically regulating the energy levels of individual sensors according to the network surroundings. The method considered factors such

as network traffic and sensor data rates to make informed decisions about the energy levels of each sensor. The proposed scheme was simulated, showing improved energy efficiency and a longer sensor lifespan compared to traditional power management methods. In [14], a distributed approach was presented for balanced data traffic over IoT networks to reduce power consumption. This approach seeks to distribute data traffic equally between IoT nodes, decrease energy consumption, and extend the lifetime of IoT nodes. A distributed algorithm was used to balance data traffic and ensure that each node is equally responsible for data processing and transmission. The results of this approach showed a decrease in power consumption and improved network performance but did not demonstrate dynamic power management and used only static stations within IoT networks. In [15], a fully distributed energy-aware multiple-level clustering and routing algorithm was presented for Wireless Sensor Network (WSN)-based IoT systems. The proposed scheme addressed the problem of power efficiency by adopting a multiple-level clustering technique to divide the WSN into smaller clusters, each with a chosen cluster head responsible for forwarding data. To increase the network lifetime, the cluster heads and routing paths were chosen considering the nodes' energy usage. The proposed method was simulated and compared with conventional single-level clustering techniques, showing encouraging results.

In [16], several ways of decreasing the energy consumed in centralized radio access were investigated for energy-efficient IoT applications. To communicate with IoT devices, radio access must be centrally managed rather than having each device communicate directly with the network. This study evaluated various methods, such as decreasing transmission power, improving IoT utilization, and using sleep modes to decrease power consumption in the centralized radio access network. The results showed that these strategies reduced power consumption and improved energy efficiency. In [17], a data-driven self-learning controller model method was presented for power-aware IoT nodes, based on a double Q-learning strategy. This method used machine learning to improve power consumption in IoT nodes based on historical data. The double Q-learning scheme aimed to reduce the estimation errors in traditional Q-learning algorithms and improve the effectiveness of the self-learning process. The study showed that optimizing power consumption in IoT devices may be achieved successfully using a data-driven self-learning technique. In [18], an effective path selection method was proposed for battery-powered IoT networks based on their network topology. The method was developed to improve the power efficiency of IoT networks by choosing the most efficient paths for data transmission. Path selection was carried out according to network topology, considering criteria such as hop number, link quality, and remaining power of the nodes. A simulation of the proposed method showed an increase in energy efficiency compared to conventional route selection methods. This study showed that in battery-powered IoT networks, taking into account network topology will result in more effective route selection and increased energy efficiency.

In [19], a strategy for securing IoT devices was proposed, using dynamic power management and machine learning. The

proposed method used dynamic power management to optimize the power consumption of IoT devices and reduce their vulnerability to security threats, such as malware attacks and hacking. Dynamic power management was carried out using a machine learning algorithm that estimated the probability of a security risk and accordingly adapted the power consumption of the device. The results showed that dynamic power management and machine learning cooperated to successfully secure IoT devices and increase their power efficiency. In [20], a multipath routing protocol based on a hybrid optimization algorithm was proposed for IoT, considering Quality of Service (QoS) and energy efficiency. This algorithm aimed to balance the requirements of QoS with the reduction of energy usage in IoT networks. This algorithm employed a hybrid optimization method that mixed Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to discover ideal paths that meet QoS requirements and minimize power consumption. The results showed that the proposed QoS-aware energy-efficient multipath routing protocol significantly decreased energy usage and guaranteed QoS requirements in IoT networks.

In [21], an energy-saving Internet of Things (IoT) service management was proposed, employing edge computing and deep learning. Edge computing was used to process data locally, decrease the amount of data sent over the network, and consume less energy. Deep Learning was used to operate IoT services optimally based on historical data and improve energy consumption. Simulations showed that this method had better energy efficiency than conventional IoT service management methods. In [22], an energy-efficient indoor localization technique was proposed for Narrowband Internet of Things (NB-IoT) devices. This method used measurements of Received Signal Strength (RSS) to infer the location of NB-IoT devices in indoor surroundings. By minimizing the number of needed RSS measurements and device transmission power, the proposed solution optimized the energy usage of NB-IoT devices. In comparison to conventional localization techniques, the presented scheme in the study performed better in terms of energy efficiency and localization accuracy. The study showed that the proposed energy-efficient indoor localization technique can successfully minimize NB-IoT device energy usage while ensuring precise localization.

II. PROPOSED METHOD

The proposed approach was designed to reduce power consumption and receive more packets compared to the balanced data traffic method with static stations. The design of the method involved the following phases:

A. Mobile Station Selection (MSS)

In this phase, the mobile station was chosen as the primary component of the proposed power-aware method. The mobile station was selected for its mobility and ability to adapt to its position in the network, which allows it to decrease power usage and improve the total number of packets received. This phase was designed to provide a flexible and adaptable solution that can be easily integrated into existing IoT networks. MSS guarantees that the network is power efficient, scalable, and highly reliable. This phase involves the following steps:

1. Configuring the mobile stations and the IoT network.
2. Specifying the threshold (T) for power consumption (PC) and packets received (PR).
3. Keep track of power consumption PC_i and packets received PR_i of each mobile station i .
4. Choose the mobile station j with the minimum power consumption and maximum packets received: $PC_j \leq T$ AND $PR_j \geq T$, where $j = \text{fun_min}(PC_i), \text{fun_max}(PR_i)$.
5. Allocate the data traffic to the chosen mobile station j .
6. Repeat steps 3-5 for each data traffic.
7. Repeat the procedure to guarantee that the most energy-efficient mobile stations are always chosen for data transmission.
8. Stop.

B. Dynamic Power Management Strategy (DPMS)

A DPMS was developed and implemented to control the power consumption of mobile stations and IoT devices. Adjusting the power usage of mobile stations and IoT devices according to data traffic and network conditions, the strategy minimizes the overall power consumption of the network. The DPMS used in the proposed method operates throughout all states of an IoT device's life cycle, including sleep, active, processing, and transmitting. The device consumes a different amount of power during each state, and the DPMS adapts the power usage as necessary. Figure 1 shows the power consumption of the IoT devices in different states.

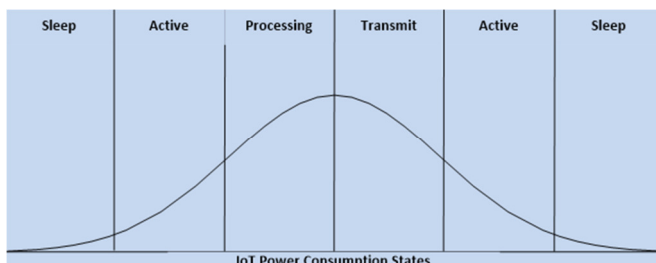


Fig. 1. Power consumption of IoT states.

The proposed DPMS guarantees that devices are using the least amount of power necessary to carry out their functions effectively while preserving energy and increasing the battery life of the devices. The DPMS involves the following steps:

- Step 1: Set the power consumption levels of the IoT device in the sleep, active, processing, and transmitting states.
- Step 2: Keep monitoring the current state of the device.
- Step 3: Using DPMS, adapt the power usage according to the current state.
- Step 4: Repeat steps 2 and 3 until the device changes to a different state.
- Step 5: When the device enters the sleep state, the dynamic power management strategy is terminated.

C. Proposed Power Consumption Model

This model is responsible for calculating the device's power consumption by:

$$TPC = (PCDC) \times (PME (\%) / 100) + (PCSMs) \quad (1)$$

where:

- $PCDC$ is the Power Consumption of Device Components that measures the overall power used by all device's parts, including the processor, sensors, and other components.
- PME stands for Power Management Efficiency, and it indicates the percentage of power that is effectively used by the device after considering the power management approaches implemented in this study.
- $PCSMs$ are Power Consumption of State Modules, which reflect the entire power consumption of all IoT device states, such as sleep, active, processing, and transmission.

Equation (2) was used to calculate an IoT device's $PCDC$:

$$PCDC = (PrP) \times (PrDC(\%) / 100) + (SnP) \times (SnDC(\%) / 100) + (StP) \times (StDC(\%) / 100) \quad (2)$$

where:

- PrP stands for Processor Power and is the amount of power used by the device's processor, and $PrDC$ stands for Processor Duty Cycle and is the percentage of time the processor is active.
- SnP stands for Sensor Power and is the total amount of power consumed by all the sensors in the device, while $SnDC$ stands for Sensor Duty Cycle and is the percentage of time the sensors are active.
- StP stands for Storage Power and is the power consumed by the device's storage component, and $StDC$ stands for Storage Duty Cycle and is the percentage of time the storage component is active.

The following equation was used to determine a device's Power Consumption of State Modules ($PCSMs$), which includes transmitting, sleep, active, and processing states:

$$PCSMs = (SlpP) \times (SlpDC(\%) / 100) + (ActvP) \times (ActvDC(\%) / 100) + (ProP) \times (ProDC(\%) / 100) + (TrP) \times (TrDC(\%) / 100) \quad (3)$$

where:

- $SlpP$ stands for Sleep Power and is the power spent by the module in the sleep state. $SlpDC$ stands for Sleep Duty Cycle and is the percentage of time it is in the sleep state.
- $ActvP$ stands for Active Power and is the power spent by the module when in the active state, and $ActvDC$ stands for Active Duty Cycle and is the percentage of time the module is in the active state.

- *ProP* stands for Processing Power and is the power consumed by the module when Processing data, and *ProDC* stands for Processing Duty Cycle and is the percentage of time the module is in the processing state.
- *TrP* stands for Transmit Power and represents the power utilized by the module when transmitting data, while *TrDC* stands for Transmit Duty Cycle and is the percentage of time the module is in the transmit state.

D. The Pseudo-Code of the State Modules

To provide a clearer understanding of the state modules, the pseudo-codes for each state are given, outlining the essential activities and transitions that occur within each state.

```

1. Pseudo Code During the Sleep State
start_time = current_time()
while (true):
    # Measure current power consumption
    current_power = measure_power()
    # Record power consumption data
    power_data.append(current_power)

    # Enter sleep state
    enter_sleep_state()
    # Check if time limit has been reached
    if (current_time() - start_time >= time_limit):
        break
# Calculate average power consumption
average_power = sum(power_data) / len(power_data)
# Print out results
print("Average power consumption during sleep
state: ", average_power)
    
```

```

2. Pseudo Code During the Active State
start_time = current_time()
while (true):
    # Measure current power consumption
    current_power = measure_power()
    # Record power consumption data
    power_data.append(current_power)
    # Perform active tasks
    perform_active_tasks()
    # Check if time limit has been reached
    if (current_time() - start_time >= time_limit):
        break
# Calculate average power consumption
average_power = sum(power_data) / len(power_data)
# Print out results
print("Average power consumption during active
state: ", average_power)
    
```

```

3. Pseudo Code During the Processing State
start_time = current_time()
while (true):
    # Measure current power consumption
    current_power = measure_power()
    # Record power consumption data
    power_data.append(current_power)
    # Perform processing tasks
    perform_processing_tasks()
    # Check if time limit has been reached
    if (current_time() - start_time >= time_limit):
        break
# Calculate average power consumption
average_power = sum(power_data) / len(power_data)
# Print out results
print("Average power consumption during
processing state: ", average_power)
    
```

```

4. Pseudo Code During the Transmit State
start_time = current_time()
while (true):
    # Measure current power consumption
    current_power = measure_power()
    # Record power consumption data
    power_data.append(current_power)
    # Transmit data
    transmit_data(data)
    # Check if time limit has been reached
    if (current_time() - start_time >= time_limit):
        break
# Calculate average power consumption
average_power = sum(power_data) / len(power_data)
# Print out results
print("Average power consumption during transmit
state : ", average_power)
    
```

III. PERFORMANCE EVALUATION

The performance of the proposed method was evaluated in numerous simulation tests in various scenarios and settings.

A. Simulation Environment

Contiki OS and the Cooja simulator were used to simulate and test the proposed method. The IoT devices were spread across a 200x200 m area, with simulation times being 10, 20, 50, and 100 minutes. There were 16 IoT nodes and 4 mobile stations in the field. Figure 2 shows the simulation environment model and Table I lists the simulation parameters.

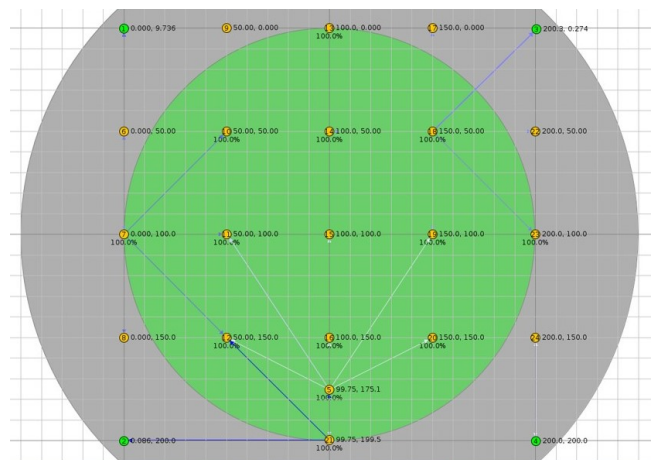


Fig. 2. Simulation environment model.

TABLE I. SIMULATION PARAMETERS

Name	Value
Version	Instant Contiki 2.7
Time	10,20,50, 100 min
Tx/INT Ranges	100/150 m
Mote Type	Sky mote
Transmit Power	21 mA
Processing Power	10 mA
Active Power	2400 μA
Sleep Power	1000 μA
Interval Time	1 s
Channel Frequency	2.4 GHz
Radio Medium	UDGM
No. of Nodes	16
No. of Stations	4

B. Results and Discussion

This section provides a detailed analysis of the results, highlighting the significant patterns or trends that occurred compared to the balanced data traffic approach [14]. Figure 3 shows that the proposed method outperformed the balanced data traffic approach with static stations in terms of total power consumption, which was reduced by approximately 64%. This is because the dynamic power management strategy and the proposed power-aware approach with mobile stations optimized power consumption by adjusting the power mode of each station and IoT node based on its level of activity and communication requirements. This led to significant energy savings compared to the balanced data traffic approach with static stations. The proposed method dynamically adjusted the power mode considering various factors, such as network conditions and received signal strength, to achieve energy efficiency in IoT networks.

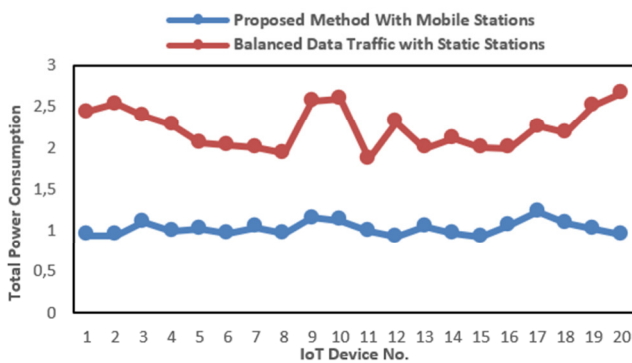


Fig. 3. Total power consumption vs. number of IoT devices.

Figure 4 shows that the proposed method increased the received packets by 72% compared to the balanced data traffic method. In IoT networks with static stations, the number of hops or intermediate nodes between the source and destination significantly affects packet delivery and latency. A multi-hop path with static stations introduces more delay and increases the chance of packet loss due to interference or congestion in the intermediate nodes. In contrast, a one-hop path used by mobile stations offers a direct and effective communication path, particularly as the mobile stations travel in the direction of the destination. As a result, when compared to the multi-hop path used in static stations with the balanced data traffic approach, the proposed method used a one-hop path with mobile stations and a dynamic power management strategy, resulting in better packet delivery and fewer packet losses. The dynamic power management strategy optimizes power usage and ensures that mobile stations and IoT nodes run at a suitable power level to maintain the desired quality of service.

Figure 5 shows the difference in transmit power consumption between the proposed and the balanced traffic method, which was reduced by up to 65%. Transmit power consumption in an IoT network has a significant impact on the overall power consumption and battery life of the devices. Compared to the balanced data traffic approach with static stations, which uses a fixed and higher power level to

guarantee packet delivery in a multi-hop path, the suggested power-aware method with mobile stations and a dynamic power management strategy achieved lower transmit power consumption. Furthermore, in the proposed method, mobile stations adjust their transmit power according to their distance from the destination and the strength of the received signal, reducing power consumption.

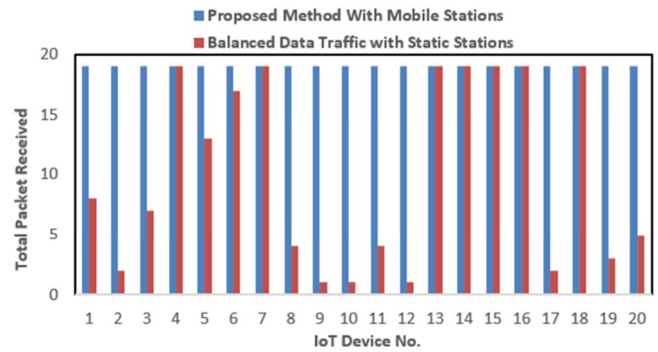


Fig. 4. Total packets received vs. number of IoT devices.

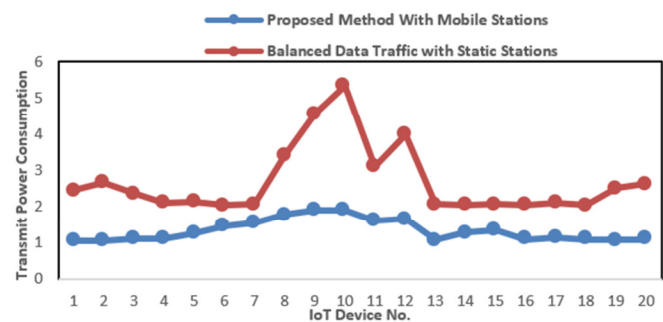


Fig. 5. Transmit power consumption vs. number of IoT devices.

Processing power consumption is another significant aspect that influences energy efficiency. Figure 6 shows that the dynamic power management strategy with mobile stations reduced processing power consumption by adapting the processing rate and mode of each IoT node based on network conditions and traffic demands. The IoT nodes adjust their processing rate and mode based on the number of packets received, the quality of service requirements, and the remaining battery life. This leads to lower processing power use compared to the balanced data traffic approach with static stations that use a fixed processing rate and mode regardless of network conditions and traffic demands. The dynamic power management strategy helped balance the processing load among nodes and reduce processing power consumption by approximately 59% during idle or low activity periods.

Figure 7 shows that the proposed power-aware strategy outperformed the balanced traffic approach by up to 40% in terms of power consumption during the sleep mode. The proposed method optimized the usage of sleep power by putting the nodes to sleep when not active or required. IoT nodes can enter sleep mode when there is no incoming or outgoing traffic or when network conditions allow for longer sleep periods, leading to decreased sleep power use compared

to the balanced data traffic scheme. Furthermore, the dynamic power management strategy helps coordinate sleep intervals between the nodes and ensures that the network is still responsive to incoming traffic while maintaining energy efficiency.

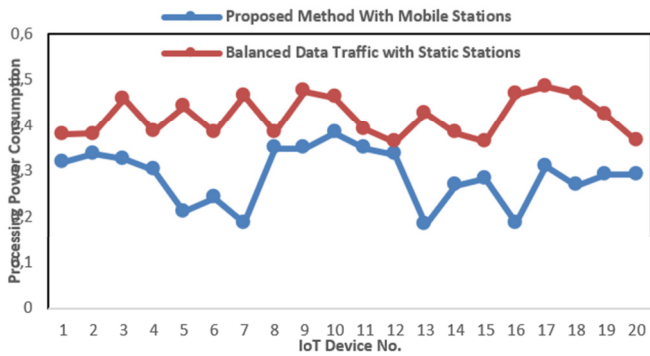


Fig. 6. Processing power consumption vs. number of IoT devices.

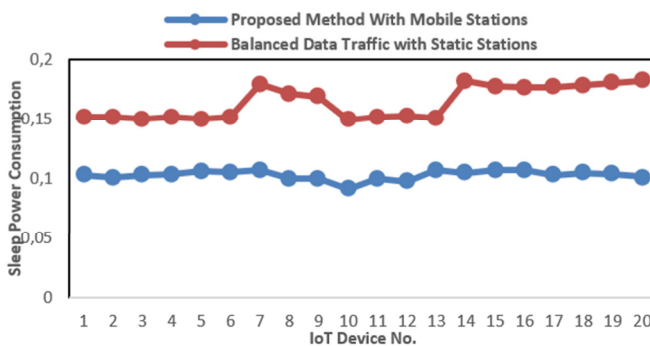


Fig. 7. Sleep power consumption vs. number of IoT devices.

Active power consumption is another important component in IoT networks, which determines how much energy the devices use while active or listening. Figure 8 shows that the proposed strategy reduced active power usage by adapting each node's power level following traffic demands. The proposed method changed the device's power level based on the distance from the destination, and the traffic load. This reduced active power usage by up to 62%, resulting in increased energy efficiency and longer battery life when compared to the balanced data traffic method with static stations.

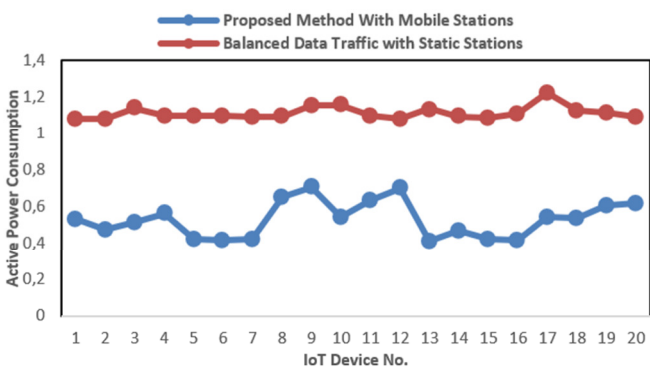


Fig. 8. Active power consumption vs. number of IoT devices.

Figures 9 and 10 show the total number of packets received and the total power consumed at various simulation times. The proposed approach outperformed the balanced approach in terms of total packets received by 72% and total power consumption by approximately 64%. The dynamic power management strategy increased power consumption according to network conditions and traffic demands. By adjusting the energy level and mode of each station and coordinating the sleep intervals among the nodes, the proposed method can balance energy usage among network devices and reduce unnecessary energy consumed during idle or low activity periods. In contrast, the balanced data traffic approach with static stations uses a fixed energy level and mode regardless of network conditions and traffic demands. In the proposed strategy, the nodes in the IoT networks adapted their energy level and mode based on the distance from the destination, signal strength, and traffic load, which improved packet delivery and reduced packet loss rate.

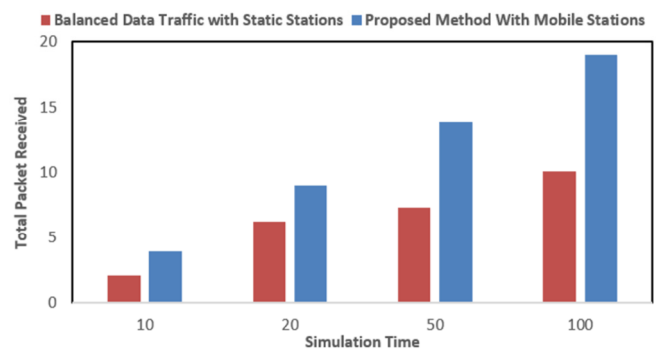


Fig. 9. Total packets received vs. simulation time.

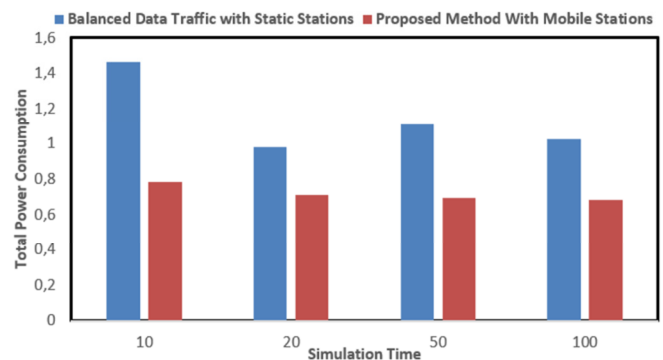


Fig. 10. Total power consumption vs. simulation time.

In general, the proposed dynamic power management method for mobile IoT networks provides a comprehensive and effective solution to optimize energy usage and improve network performance. The above results showed that the proposed method outperformed the balanced data traffic approach in terms of total packets received and total power consumption, demonstrating its potential to reduce energy costs, prolong battery life, and improve network efficiency in IoT applications.

IV. CONCLUSION

This study presented a dynamic power management strategy to improve power efficiency and prolong battery life for IoT device networks. The proposed method uses a combination of techniques, such as adjusting transmit power, processing power, sleep power, and active power, to optimize power consumption based on network conditions and traffic demands. The results showed that the proposed method performed better than the balanced data traffic method in terms of total power consumption, packet reception, and power utilization for transmitting, processing, sleep, and active states separately. The use of the dynamic power management strategy in mobile stations helps distribute energy usage among network devices and reduces unnecessary energy depletion during low activity periods, resulting in improved energy efficiency, longer battery life, and reduced maintenance costs for the IoT network. However, the presented method requires further investigation of the impact of different channel models on the performance of the IoT network to ensure that it can work well in various environments, as it was not tested in real-world environments. However, in the future, the integration of the proposed scheme with other network management strategies, such as security and QoS management, will be investigated to achieve comprehensive and efficient network management.

REFERENCES

- [1] A. Al-Marghilani, "Comprehensive Analysis of IoT Malware Evasion Techniques," *Engineering, Technology & Applied Science Research*, vol. 11, no. 4, pp. 7495–7500, Aug. 2021, <https://doi.org/10.48084/etasr.4296>.
- [2] J. Marietta and B. Chandra Mohan, "A Review on Routing in Internet of Things," *Wireless Personal Communications*, vol. 111, no. 1, pp. 209–233, Mar. 2020, <https://doi.org/10.1007/s11277-019-06853-6>.
- [3] I. A. Alameri, "MANETS and Internet of Things: The Development of a Data Routing Algorithm," *Engineering, Technology & Applied Science Research*, vol. 8, no. 1, pp. 2604–2608, Feb. 2018, <https://doi.org/10.48084/etasr.1810>.
- [4] R. Hassan, F. Qamar, M. K. Hasan, A. H. M. Aman, and A. S. Ahmed, "Internet of Things and Its Applications: A Comprehensive Survey," *Symmetry*, vol. 12, no. 10, Oct. 2020, Art. no. 1674, <https://doi.org/10.3390/sym12101674>.
- [5] M. Hamdani, M. Youcefi, A. Rabeih, B. Nail, and A. Douara, "Design and Implementation of a Medical TeleMonitoring System based on IoT," *Engineering, Technology & Applied Science Research*, vol. 12, no. 4, pp. 8949–8953, Aug. 2022, <https://doi.org/10.48084/etasr.5040>.
- [6] O. Peter, A. Pradhan, and C. Mbohwa, "Industrial internet of things (IIoT): opportunities, challenges, and requirements in manufacturing businesses in emerging economies," *Procedia Computer Science*, vol. 217, pp. 856–865, Jan. 2023, <https://doi.org/10.1016/j.procs.2022.12.282>.
- [7] N. Charef, A. Ben Mnaouer, M. Alokaily, O. Bouachir, and M. Guizani, "Artificial intelligence implication on energy sustainability in Internet of Things: A survey," *Information Processing & Management*, vol. 60, no. 2, Mar. 2023, Art. no. 103212, <https://doi.org/10.1016/j.ipm.2022.103212>.
- [8] A. M. Shamsan Saleh, B. M. Ali, M. F. A. Rasid, and A. Ismail, "A survey on energy awareness mechanisms in routing protocols for wireless sensor networks using optimization methods," *Transactions on Emerging Telecommunications Technologies*, vol. 25, no. 12, pp. 1184–1207, 2014, <https://doi.org/10.1002/ett.2679>.
- [9] B. Rana, Y. Singh, and P. K. Singh, "A systematic survey on internet of things: Energy efficiency and interoperability perspective," *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 8, 2021, Art. no. e4166, <https://doi.org/10.1002/ett.4166>.
- [10] R. Govindarajan, S. Meikandasivam, and D. Vijayakumar, "Performance Analysis of Smart Energy Monitoring Systems in Real-time," *Engineering, Technology & Applied Science Research*, vol. 10, no. 3, pp. 5808–5813, Jun. 2020, <https://doi.org/10.48084/etasr.3566>.
- [11] F. Mazunga and A. Nechibvute, "Ultra-low power techniques in energy harvesting wireless sensor networks: Recent advances and issues," *Scientific African*, vol. 11, Mar. 2021, Art. no. e00720, <https://doi.org/10.1016/j.sciaf.2021.e00720>.
- [12] Y. Miao, K. Hwang, D. Wu, Y. Hao, and M. Chen, "Drone Swarm Path Planning for Mobile Edge Computing in Industrial Internet of Things," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 5, pp. 6836–6848, Feb. 2023, <https://doi.org/10.1109/TII.2022.3196392>.
- [13] C. Arivalai and M. Thenmozhi, "Dynamic Power Management for Improving Sensor Lifetime in Internet of Things Based Wireless Sensor Environments," *Journal of Computational and Theoretical Nanoscience*, vol. 18, no. 3, pp. 913–921, Mar. 2021, <https://doi.org/10.1166/jctn.2021.9712>.
- [14] A. M. S. Saleh, "Balanced Data Traffic Over Internet of Things Network to Reduce Power Consumption using Distributed Scheme," in *2022 2nd International Conference on Computing and Information Technology (ICCIIT)*, Tabuk, Saudi Arabia, Jan. 2022, pp. 310–313, <https://doi.org/10.1109/ICCIIT52419.2022.9711633>.
- [15] İ. A. Turgut and G. Altan, "A fully distributed energy-aware multi-level clustering and routing for WSN-based IoT," *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 12, 2021, Art. no. e4355, <https://doi.org/10.1002/ett.4355>.
- [16] B. Mahapatra, A. Kumar Turuk, and S. Kumar Patra, "Exploring power consumption reduction in centralized radio access for energy-efficient centralized-Internet of Things implementation," *Transactions on Emerging Telecommunications Technologies*, vol. 31, no. 10, 2020, Art. no. e4045, <https://doi.org/10.1002/ett.4045>.
- [17] T. Paterova, M. Prauzek, and J. Konecny, "Data-Driven Self-Learning Controller Design Approach for Power-Aware IoT Devices based on Double Q-Learning Strategy," in *2021 IEEE Symposium Series on Computational Intelligence (SSCI)*, Orlando, FL, USA, Sep. 2021, pp. 01–07, <https://doi.org/10.1109/SSCI50451.2021.9659989>.
- [18] T. Taami, S. Azizi, and R. Yarinezhad, "An efficient route selection mechanism based on network topology in battery-powered internet of things networks," *Peer-to-Peer Networking and Applications*, vol. 16, no. 1, pp. 450–465, Jan. 2023, <https://doi.org/10.1007/s12083-022-01426-0>.
- [19] N. Chawla, A. Singh, H. Kumar, M. Kar, and S. Mukhopadhyay, "Securing IoT Devices Using Dynamic Power Management: Machine Learning Approach," *IEEE Internet of Things Journal*, vol. 8, no. 22, pp. 16379–16394, Aug. 2021, <https://doi.org/10.1109/JIOT.2020.3021594>.
- [20] M. Srinivasulu, G. Shivamurthy, and B. Venkataramana, "Quality of service aware energy efficient multipath routing protocol for internet of things using hybrid optimization algorithm," *Multimedia Tools and Applications*, vol. 82, no. 17, pp. 26829–26858, Jul. 2023, <https://doi.org/10.1007/s11042-022-14285-x>.
- [21] D. Li, M. Lan, and Y. Hu, "Energy-saving service management technology of internet of things using edge computing and deep learning," *Complex & Intelligent Systems*, vol. 8, no. 5, pp. 3867–3879, Oct. 2022, <https://doi.org/10.1007/s40747-022-00666-0>.
- [22] I. Keshta *et al.*, "Energy efficient indoor localisation for narrowband internet of things," *CAAI Transactions on Intelligent Technology*, <https://doi.org/10.1049/cit2.12204>.