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# Priority-Based Adjustment and Dynamic Energy Efficient Resource Allocation Algorithm for D 2 D Communication in 5G WPAN

Zanirah Bint Yakub, Z. M Abdullahi, E. E. Agbon, N.E Ajimah
*Department of Electronics and Telecommunications Engineering*
*Ahmadu Bello University, Zaria Nigeria*

## ABSTRACT

*This study presents the development and validation of an improved energy-efficient resource allocation algorithm for Device-to-Device (D2D) communication in 5G Wireless Personal Area Networks (WPANs). It addresses the challenge of fair and efficient resource allocation between Primary Users (PUs) and Secondary Users (SUs) in dynamic network environments. Existing models, such as the Energy-Efficient Resource Allocation Model (EERAM), tend to prioritize PUs, leaving SUs in waiting queues where allocation is based mainly on waiting time, without considering varying Quality of Service (QoS) requirements. This leads to unfair distribution, inefficient resource utilization, and reduced overall network performance. To address these limitations, the Priority-based Adjustment and Dynamic Energy-efficient Resource Allocation (PADERA) algorithm was developed. PADERA integrates a priority scoring mechanism with dynamic adjustment to allocate resources based on real-time QoS demands and waiting time, ensuring a more balanced and efficient distribution. The algorithm was evaluated against EERAM using key performance metrics, including energy, bandwidth, and power allocation. Results show that PADERA consistently outperforms EERAM. In power allocation, it achieved 96.87% at 100 signals and 91.75% at 700 signals, compared to EERAM's 91.84% and 85.60%, with an average improvement of 6.15%. For energy allocation, PADERA ranged from 95.19% to 93.10%, slightly higher than EERAM's 93.19% to 92.90%. In bandwidth allocation, PADERA decreased from 96.70% to 88.00% as signal load increased, while EERAM declined from 90.67% to 84.91%.*

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## INTRODUCTION

A Personal Area Network (PAN) is a small-scale network that enables communication among nearby devices such as smartphones, tablets, and laptops. When implemented wirelessly as a Wireless Personal Area Network (WPAN), it allows seamless communication without physical connections, offering flexibility and convenience. However, optimizing resources in PANs is essential to ensure efficient performance and prolonged device operation.

One key concern in PANs is energy consumption. This can be minimized through energy-aware routing protocols that direct data transmission in ways that reduce power usage. Devices can also switch to low-power or sleep modes during periods of inactivity, helping to conserve battery life. Interference is another challenge that can affect communication quality; it can be reduced by selecting appropriate frequency bands, adjusting transmission power, and using directional antennas to limit unnecessary signal spread. Efficient bandwidth utilization is equally important and can be achieved through data compression and optimized communication protocols, which help

*Corresponding author: E. E. Agbon*
✉ eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

reduce congestion and improve data transmission efficiency (Logeshwaran et al., 2023a).

Despite these strategies, devices in a PAN often underutilize their internal resources, such as memory and processing power, leading to inefficiencies. To address this, resource managers can be employed. These software tools monitor and allocate resources efficiently across devices, improving overall network performance. However, their effectiveness depends on proper configuration and usage, meaning they are not a complete solution on their own (Logeshwaran et al., 2023b).

In wireless communication networks, including WPANs, resources such as power, spectrum, and communication channels must be allocated based on user requirements. Technologies like wireless power transfer and cooperative communication can further enhance device longevity. Security is also crucial, and protocols such as the Enhanced Optimal Fair Exchange Protocol (EOFEP) improve authentication, integrity, and secure data exchange using digital signatures and public-key encryption.

As PANs integrate with advanced systems like 5G networks, resource optimization becomes more complex due to dynamic traffic patterns and varying channel conditions. Efficient techniques such as resource block (RB) allocation and Device-to-Device (D2D) communication help address these challenges. Additionally, distributed double-sided auction-based mechanisms enable fair and efficient resource sharing between users and network infrastructure. These approaches enhance reliability, improve quality of service, and support stable network operation (Logeshwaran et al., 2024). Overall, effective resource optimization in PANs and related wireless networks improves performance, extends device battery life, reduces energy consumption, and lowers operational costs, while also contributing to environmental sustainability and broader network coverage (Logeshwaran et al., 2023a).

## Related Works

Chen et al. (2019) formulated a spectrum resource allocation model for device-to-device (D2D) communication in heterogeneous cellular networks operating over microwave and millimeter-wave (mmWave) bands. A heuristic algorithm was proposed to maximize system transmission rates, and simulations showed its advantage over existing schemes. However, the solution struggled with fairness due to rapidly changing user demands, resulting in unequal resource distribution between primary and secondary users and degraded service quality in dynamic environments.

Al-Kahtani et al. (2020) explored resource block and power allocation in PD-NOMA-based cellular D2D systems with the aim of improving energy efficiency while managing interference and meeting QoS requirements. The authors introduced a SIC-aware Geometric Water Filling algorithm, which outperformed IWF and OMA approaches. Nonetheless, the method suffered from fairness limitations, as prioritization of certain users or traffic types led to resource imbalance and reduced QoS for others.

Sultana et al. (2020) applied SCMA to D2D-enabled cellular networks to exploit its overloading capability for massive connectivity. Joint optimization of codebook and power allocation was performed using RACBS-D2D and an iterative GWF-based power allocation scheme. Although simulations demonstrated improved data rates, the approach did not sufficiently address fairness challenges in dynamic D2D environments. Secondary users were more likely to receive fewer resources, negatively affecting throughput and delay.

Du et al. (2021) proposed a joint resource allocation and mode selection framework for D2D communication based on a two-layer approach using DQN for power allocation and strategic decisions for channel assignment and mode selection. Results indicated improved throughput and reduced interference. However, dynamic variations in user demands created difficulties in maintaining fair resource allocation between user groups, resulting in potential performance imbalances in metrics such as latency, reliability, and throughput.

*Corresponding author: E. E. Agbon*
eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

## Wireless Personal Area Networks (WPAN)

A WPAN is a computer network designed for interconnecting devices centered on an individual's workspace, typically within a range of a few meters (Koul, et al., 2024). WPANs enable wireless communication among a variety of devices, such as smartphones, laptops, tablets, and other portable electronics, as well as peripherals like printers and wireless headsets. Also, WPANs represent a critical component of modern wireless communication, providing convenient and efficient connectivity for a wide range of personal devices. By understanding their characteristics, architecture, and applications, and by addressing the associated challenges, WPANs can continue to evolve and play a significant role in our increasingly connected world (Sandeepa et al., 2014).

WPANs are characterized by their short-range communication capabilities, low power consumption, and ease of deployment. The most common standards for WPANs include (Koda et al., 2023):

1. Bluetooth (IEEE 802.15.1): Designed for low-power, short-range communication, typically up to 10 meters. It is widely used for connecting devices like headphones, keyboards to computers and smartphones.
2. Zigbee (IEEE 802.15.4): A specification for low-power, low-data-rate wireless communication, ideal for applications in home automation, industrial control, and sensor networks.
3. Infrared (IrDA): Utilizes infrared light for short-range communication, often found in remote controls and older mobile phones.
4. Ultra-Wideband (UWB): Provides high-bandwidth communication over short distances, suitable for multimedia applications and real-time data transfer.

## Challenges and Future Directions of WPAN

While WPANs offer numerous benefits, they also face several challenges that require ongoing research and development (Ashri, *et al.*, 2023):

1. Security: Ensuring secure communication and data protection in wireless environments is critical. WPANs must implement robust encryption and authentication protocols to prevent unauthorized access and data breaches. Addressing vulnerabilities and threats such as eavesdropping, spoofing, and denial-of-service attacks is essential to maintain network integrity and user trust.
2. Scalability: As the number of devices and connections within a WPAN increases, managing network resources and maintaining performance becomes more complex. Scalability solutions are needed to support growing device ecosystems without degrading network efficiency. Developing dynamic resource allocation methods that can adapt to varying network demands and user requirements is crucial for scalable WPANs.
3. Interoperability: Achieving seamless communication between devices from different manufacturers requires adherence to various standards. Ensuring compatibility and interoperability among diverse devices is necessary for a cohesive user experience. Harmonizing communication protocols and interfaces to facilitate interaction between heterogeneous devices is a key challenge for WPANs.
4. Energy Efficiency: Developing more energy-efficient protocols and hardware is essential to extend battery life and reduce the environmental impact of WPANs. Energy-efficient designs can help mitigate the power consumption challenges associated with continuous device connectivity. Implementing sustainable energy solutions, such as energy harvesting and low-power communication techniques, can further enhance the efficiency and longevity of WPAN devices.

*Corresponding author: E. E. Agbon*
✉ eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

### Resource Optimization in WPANs

1. Effective resource optimization is crucial for the performance and sustainability of WPANs. Key strategies for resource optimization include (Logeshwaran et al., 2023b):
2. Energy-Aware Routing: Implementing energy-efficient routing protocols is essential to prolong the battery life of devices within the WPAN. These protocols aim to minimize power consumption by selecting the most energy-efficient paths for data transmission. Techniques such as dynamic power adjustment and duty cycling (periodically turning off communication interfaces when not in use) help reduce overall energy consumption.
3. Power Management: Power management strategies involve configuring devices to enter low-power states during periods of inactivity or low communication demand. This can include sleep modes, hibernation, and adaptive power scaling. Devices can be programmed to wake up and resume full operation only, when necessary, significantly extending battery life and reducing energy waste.
4. Interference Management: Minimizing interference is critical for maintaining reliable communication within a WPAN. Interference can be reduced by carefully selecting the frequency bands and power levels used for device communication. Directional antennas can also be employed to focus wireless signals in specific directions, reducing the likelihood of interference from other devices and networks.
5. Bandwidth Utilization: Efficient use of available bandwidth is essential for maintaining high performance in a WPAN. Data compression techniques can be used to reduce the amount of data transmitted, thus conserving bandwidth. Additionally, protocols designed for optimal bandwidth utilization ensure that data packets are transmitted efficiently, minimizing delays and maximizing throughput.

### Device-to-Device Communication

Device-to-Device (D2D) communication is a technology in wireless networks that enables direct communication between nearby mobile devices without the need to route data through a central base station or network infrastructure (Areqi, et al., 2023). This paradigm shift from traditional cellular communication holds significant potential for enhancing network performance, spectrum efficiency, and user experience, particularly in dense network environments and areas with high user mobility. Furthermore, D2D communication refers to a mode of communication where user devices, such as smartphones, tablets, and laptops, communicate directly with each other using cellular spectrum or unlicensed spectrum, bypassing the base station. This direct communication can occur over various wireless technologies, including Wi-Fi Direct, Bluetooth, and LTE Direct. The primary objective of D2D communication is to leverage the proximity of devices to improve communication efficiency, reduce latency, and offload traffic from the cellular network (Areqi, et al., 2023).

### Challenges in D2D Communication

The following are some of the disadvantages of D2D communication (Salim et al., 2023):

1. D2D communication introduces new interference scenarios, particularly when sharing the same spectrum as cellular users.
2. Direct communication between devices raises security and privacy concerns, as it may be easier for malicious entities to intercept or tamper with the data. Robust encryption and authentication mechanisms are necessary to secure D2D communication.
3. Enabling devices to discover and connect with each other seamlessly and efficiently is critical for the success of

*Corresponding author: E. E. Agbon*
✉ eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

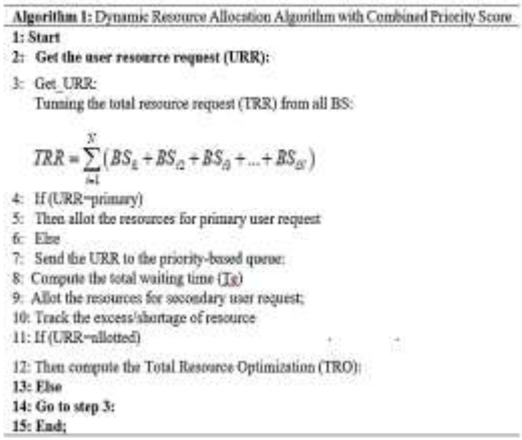
D2D communication. This process must be quick, energy-efficient, and reliable to support diverse applications.

4. Ensuring consistent QoS for D2D communication is challenging due to the dynamic nature of user mobility and varying network conditions. Mechanisms to prioritize traffic and manage QoS are essential for delivering reliable service.

## Energy-Efficient Resource Allocation in D2D Communication

Energy-efficient resource allocation in Device-to-Device (D2D) communication involves distributing resources in a manner that minimizes energy consumption while ensuring satisfactory performance (Logeshwaran *et al.,* 2023b). This is achieved through various techniques such as power control, resource block (RB) selection, scheduling, and interference coordination. The primary objective is to reduce energy consumption while maintaining the desired Quality-of-Service (QoS). By employing energy-efficient resource allocation strategies, D2D communication networks can become more efficient and cost-effective. Algorithm 1 outlines the functionalities of the existing energy efficiency model, highlighting the potential of D2D communication in 5G networks to enhance spectral efficiency (Logeshwaran *et al.,* 2023a).

Table 2.1: Dynamic Resource Allocation Algorithm ((Logeshwaran *et al.,* 2023a)



**Algorithm 1:** Dynamic Resource Allocation Algorithm with Combined Priority Score

```
1: Start
2: Get the user resource request (URR):
3: Get_URR:
   Tunning the total resource request (TRR) from all BS:
       $TRR = \sum_{i=1}^{N} (BS_{i1} + BS_{i2} + BS_{i3} + ... + BS_{iN})$
4: If (URR=primary)
5:     Then allot the resources for primary user request
6: Else
7:     Send the URR to the priority-based queue:
8:     Compute the total waiting time (Tk)
9:     Allot the resources for secondary user request;
10:    Track the excess/shortage of resource
11: If (URR=allotted)
12:    Then compute the Total Resource Optimization (TRO);
13: Else
14:    Go to step 3:
15: End;
```

The existing algorithm addresses key challenges in realizing the full potential of D2D communication, which extends ad hoc networking by enabling direct device-to-device interaction without centralized control. User Resource Requests (URRs) are generated based on input demands, collected by base stations, and aggregated to determine total resource requirements, as expressed in Equation (2.11) (Logeshwaran et al., 2023a).:

$$TRO = \frac{\sum_{r=1}^{R} (R_r)}{T} \qquad (1)$$

Where:

*TRO* indicates the total resource optimization
$R_r$ expresses the total resource request
*T* indicates the total processing time.

The primary user needs are prioritized, and resources are allocated to meet them. If secondary user requirements interfere, it is routed to the priority queue. There the total waiting time for the user is calculated. Based on that, resource allocations for secondary users are done. The energy efficient model involves power control using $P_{alloc}$, Resource Block (*RB*) selection, scheduling, interference coordination and URR aggregation. The *RB* selection, scheduling, interference coordination and URR aggregation models are given as follows (Logeshwaran *et al.,* 2023a):

$$RB_{select} = \max\left(\frac{U_i}{I_i}\right) \qquad (2.12)$$

Where:

$RB_{select}$ is the selected resource block
$U_i$ stands for the utility of resource block *i*
$I_i$ represents the interference level of resource block *i*

The scheduling process is given by the following model (Logeshwaran *et al.,* 2023a):

$$S_{sched} = \arg\max_i \left( W_i \times \frac{Q_i}{E_i} \right) \tag{2.13}$$

Where:

$S_{sched}$ is the scheduling decision

$W_i$ stands for weights of device *i*

$E_i$ represents the energy consumption for device *i*

Qi as the queue of user requests *i*

The interference coordination model for WPAN is given as follows (Logeshwaran *et al.,* 2023a):

$$IC_{coord} = \sum_{i=1}^{n} \left( I_{interfere} - I_{threshold} \right) \times H\left( I_{interfere} - I_{threshold} \right) \tag{2.14}$$

Where:

$IC_{coord}$ stands for the interference coordination metric

$I_{interfere}$ is the interference level

$I_{threshold}$ is the interference threshold

*H* represents the Heaviside step function

Finally, the User Resource Request (URRs) aggregation model and the Total Resource Requirement (TRR) are also given as follows (Logeshwaran *et al.,* 2023a):

$$URR_{total} = \sum_{j=1}^{m} URR_j \tag{2.15}$$

Where:

$URR_{total}$ is the total user resource request

$URR_j$ stands for the resource request from user *j*

*m* represents the number of users

$$TRR = \sum_{i=1}^{N} \left( BS_{i1} + BS_{12} + BS_{13} + \ldots BS_{iN} \right) \tag{2.16}$$

where *TRR* indicates the total resource request from all the base stations of the network. BS indicates the base station.

In addition, the model equation for prioritizing User Resource Requests (URRs) in a queue can be formulated considering several factors such as the type of user (primary or secondary), resource availability, and the order of requests. Here, the priority queue model for resource allocation is derived as follows (Logeshwaran *et al.,* 2023a):

Let denote:

$URR_i$ as the *i*-th User Resource Request

$P_i$ as the priority of $URR_i$

$T_i$ as the type of user making $URR_i$ (1 for primary, 2 for secondary)

$R_i$ as the resources requested by $URR_i$

*A* as the total available resources.

*Q* as the queue of user requests

Now, the priority model is given as:

$$P_i = \frac{1}{T_i} \tag{2.17}$$

Here, primary users ($T_i$=1) have a higher priority (i.e., $P_i$ =1), and secondary users ($T_i$ =2) have a lower priority (i.e., $P_i$ =0.5).

The resource allocation decision is represented as (Logeshwaran *et al.,* 2023b):

If $\sum_{j=1}^{i} R_j \leq A$ (for all requests up to the *i*-th request in the queue) (2.18)

Resource allocation in WPANs with D2D communication is crucial for improving network performance, efficiency, and user experience (Logeshwaran et al., 2023a). Efficient allocation of resources such as bandwidth, power, and spectrum enable higher data rates, lower latency, and better energy efficiency.

*Corresponding author: E. E. Agbon*
🖂 eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

This section examines strategies, challenges, and future directions for resource allocation in WPANs, particularly in D2D environments. Resource allocation involves distributing available network resources among devices to optimize performance and ensure fair access. In WPANs, key resources include (Logeshwaran et al., 2024)

1. Bandwidth: The range of frequencies available for communication.
2. Power: The energy required for transmitting and receiving signals.
3. Spectrum: The specific frequency bands allocated for communication.
4. Time slots: The scheduling of communication periods to avoid conflicts and ensure efficient data transfer.

**Performance Metrics**

This study evaluates the efficiency of the proposed model using a set of key performance metrics that capture energy usage, resource allocation efficiency, and overall network performance in 5G D2D communication environments. Each metric provides insight into how effectively system resources are utilized under varying network conditions.

**1. Energy Allocation:** Energy allocation quantifies the total energy consumed during D2D communication, considering device type, operational mode (active or sleep), and the amount of data exchanged. Efficient energy allocation ensures higher processing efficiency and an improved user experience.

The model used for energy allocation is presented in equation (1) (Logeshwaran et al., 2023a).

$$E_u = \sum(P_a * T_a) + \sum(P_s * T_s) \qquad (2.19)$$

Where:

$E_u$ presents the total energy utilized to assign the resource

$P_a$ indicates the active mode power supply

$P_s$ stands for the sleep mode power supply

$T_a$ defines the energy based on data amount

$T_s$ represents the sleep time

**2. Power Allocation:** Power allocation determines the optimal transmission power needed to support effective D2D communication in 5G networks. Proper allocation enhances data transmission reliability while reducing unnecessary energy consumption.

The model for power allocation is given in equation (2) (Logeshwaran et al., 2023a).

$$P_{alloc} = \frac{E_u}{T} \qquad (2.10)$$

Where:

$P_{alloc}$ represents the power allocation to allocate the resource

$E_u$ stands for the total energy utilized to allocate the resource

$T$ means the total waiting time

**3. Bandwidth Allocation:** Bandwidth allocation ensures that adequate bandwidth is assigned based on data transmission requirements. In 5G systems particularly in D2D communication high bandwidth is essential for maintaining fast and reliable throughput.

Equation (3) defines the bandwidth allocation model (Logeshwaran et al., 2023a).

$$B_{alloc} = \left(\frac{D_e * \left(\frac{100}{R_d}\right) * 8192}{T_{RW} * 3600}\right) \qquad (2.11)$$

Where:

$B_{alloc}$ represents the bandwidth allocated to device *i*

$D_e$ indicates the entire amount of data transferred

$R_d$ is the data duplication ratio

$T_{RW}$*n* stands for the length of the replication widow time

The simulation parameters are detailed in Table.1

Table 1: Simulation Parameters

| Parameter | Value | Description |
|---|---|---|
| Simulation Surface | [1850, 2000] (m) | Surface dimensions in meters |
| SIFS | 45 µs | Short Inter-Frame Space |
| TR$_{TX}$ | 6.5 Mbps | Transmission Data Rate |

*Corresponding author: E. E. Agbon*
eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

| Parameter | Value | Description |
|---|---|---|
| $DR_I$ | 20 ms | Interference Detection Rate |
| Ts | 12 ms | Slot duration |
| BWsc | 678 GHz | Sub-channel Bandwidth |
| BWs | 12 MHz | System Bandwidth |
| CF | 11.8 MHz | Carrier Frequency |
| T | 28 seconds | Simulation duration |
| A | 1500 bytes | Average packet size |
| C | 10 connections | Number of connections |
| $TR_{TP}$ | 20 ms | Round-trip propagation time |
| Data Size | 1 Mb | Amount of data in bits |
| Pa | 0.5 W | Active mode power supply |
| Ps | 0.1 W | Sleep mode power supply |
| Ta | 70% of T (19.6 s) | Active time of resource allocation |
| Ts | 30% of T (8.4 s) | Sleep time |
| N_BS | 5 base stations | Number of base stations |

## METHODOLOGY

The main objective of the developed priority score model is to maximize network efficiency while meeting QoS requirements for both primary and secondary users. To ensure proper resource allocation to secondary users, a priority score ($P_{se}$) will be a function of both users waiting time and QoS requirement. In this aspect from theory, the priority score for the secondary user *i* is the sum of two ratios:

1. The ratio of the user's waiting time to the maximum waiting time given as:

$$UE_{waiting} = \frac{W_{se}}{max(W_{se})} \qquad (3.1)$$

2. The ratio of the user's QoS requirement to the maximum QoS requirement given as:

$$UE_{QoS} = \frac{QoS_{se}}{max(QoS_{se})} \qquad (3.2)$$

**Theorem:** The theorem that supports the formulation of priority score model is The Weighted Sum Model (WSM). It is a common approach for multi-criteria decision making, where each criterion is assigned a weight, and the overall score is the sum of the weighted criteria.

**Implication**: The$P_{se}$model follows the WSM principle, where waiting time and QoS requirements are the criteria, and $\alpha$ and $\beta$ are the weights. This ensures a balanced approach to decision-making, considering multiple factors.

Thus, $P_{se}$ is formulated as shown in equation (14):

$$P_{se} = \alpha \cdot \left(\frac{W_{se}}{max(W_{se})}\right) + \beta \left(\frac{QoS_{se}}{max(QoS_{se})}\right) \qquad (3.3)$$

Where:

$W_{se}$ is the waiting time of the secondary user in the priority queue

$max(W_{se})$is the maximum waiting time among all secondary users and it normalizes $W_{se}$

$QoS_{se}$ stands for the Quality-of-Service requirements specific to the secondary user

$max(QoS_{se})$ denotes the maximum QoS requirement among all secondary users and it normalizes $QoS_{se}$

$\alpha$ and $\beta$ are weighting factors such that their summation is equal to 1

### Assign Initial Weights

Furthermore, to illustrate how the weights $\alpha$ and $\beta$ can be allocated based on certain criteria or considerations, this study will formulate an equation that defines their values.

Corresponding author: E. E. Agbon
✉ eagbonehime1@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.

Typically, these weights are chosen based on the specific objectives of the resource allocation algorithm and the characteristics of the network environment. The generalized equation as used in this study is given as:

$$\alpha + \beta = 1 \tag{3.4}$$

This equation ensures that the total weight assigned to waiting time $W_{se}$ and QoS requirements $QoS_{se}$ sums up to 1, indicating a complete allocation of importance between these two factors. The values of $\alpha$ and $\beta$ was determined based on the following considerations:

1. If waiting time $W_{se}$ is considered more critical in the resource allocation process, a higher weight can be assigned to $\alpha$, for example, α will be equal to 0.7 and *β* will be equal to 0.3.
2. Alternatively, if meeting QoS requirements $QoS_{se}$ is more crucial, *β* can be given a higher value, such as α will be equal to 0.3 and *β* will be equal to 0.7.
3. For a balanced approach where both waiting time and QoS requirements are equally important, *α* and *β* could be set to 0.5 each
4. This study further considered the case where α and *β* might be adjusted dynamically based on real-time network conditions or user demands.

**Development of a Dynamic Adjustment Model**

The developed work defines a mechanism where the weights *α* and *β* are adjusted based on the performance feedback from the network. A feedback control system approach was employed where the weights are updated iteratively based on observed performance metrics. The step are as follows:

1. ***Initialization***: Start with initial values for *α* and *β*, denoted as $\alpha_0$ and $\beta_0$.
2. ***Feedback Measurement***: Measure performance metrics such as throughput, network data speed, resource allocations, or user satisfaction (QoS metrics).
3. ***Error Calculation***: Calculate the error or deviation from desired performance based on these metrics.
4. ***Adjustment Rule****:* Update *α* and *β* based on the error and a tuning parameter *k* that controls the rate of adjustment. Thus, the dynamic adjustment model is given as:

$$\alpha_{t+1} = \alpha_t - k \cdot \frac{\partial E}{\partial \alpha} \tag{3.5}$$

$$\beta_{t+1} = \beta_t - k \cdot \frac{\partial E}{\partial \beta} \tag{3.6}$$

Where:

$\frac{\partial E}{\partial \alpha}$ and $\frac{\partial E}{\partial \beta}$ represent the partial derivatives of the error function with respect to *α* and *β,* respectively

$E$is the error function that measures the deviation from desired performance metrics.

*k* is a learning rate or tuning para meter (with value 0.1) that controls the speed of adjustment.

$\alpha_t$and $\beta_t$ are the current values of *α* and *β* at iteration *t*

$\alpha_{t+1}$and $\beta_{t+1}$ are the updated values at iteration t+1.

Typically, *k* (learning rate) is set to a small value (e.g., 0.001, 0.01, etc.) to ensure stability and smooth convergence. Higher values of *k* can lead to faster convergence but may risk instability or oscillations. Lower values ensure more cautious adjustments but might require more iterations for convergence. Hence, an average value of 0.1 will be used for k in this study.

Furthermore, the error function $E$ is also given as:

$$E = f(metric) \tag{3.7}$$

Where $f$ is a function that combines various performance metrics into a single error measure.

The partial derivative of *E* with respect to *α* and *β* are given as:

$$\frac{\partial E}{\partial \alpha} = \frac{\partial f}{\partial \alpha}(metrics) \tag{3.8}$$

$$\frac{\partial E}{\partial \beta} = \frac{\partial f}{\partial \beta}(metrics) \tag{3.9}$$

5. ***Iteration****:* Repeat steps 2-4 iteratively based on updated performance measurements

*Corresponding author: E. E. Agbon*
✉ eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

By adjusting α and β such that α + β = 1, the resource allocation algorithm can flexibly balance the importance of waiting time and QoS requirements based on network objectives. The developed dynamic resource allocation algorithm incorporates the priority score $P^*{}_{se}$, which depends on these weights and their dynamic adjustment. Thus, the overall priority score, considering all possible values of α and β, denoted as $P^*{}_{se}$, is expressed by the following conditional model:

$$P^*{}_{se} = \begin{cases} 0.7 \cdot W_{se} + 0.3 \cdot QoS_{se} & \text{if waiting time is prioritized} \\ 0.3 \cdot W_{se} + 0.7 \cdot QoS_{se} & \text{if QoS requirements are prioritized} \\ 0.5 \cdot W_{se} + 0.5 \cdot QoS_{se} & \text{if a balanced approach is taken} \\ \left(\alpha_t - k \cdot \frac{\partial E}{\partial \alpha_t}\right) \cdot W_{se} + \left(\beta_t - k \cdot \frac{\partial E}{\partial \beta_t}\right) \cdot QoS_{se} & \text{if dynamic adjustment is taken} \end{cases} \quad (3.10)$$

Where:
$k$ is a learning rate or tuning parameter (with value 0.1) that controls the speed of adjustment.
$\alpha_t$and $\beta_t$ are the current values of $\alpha$ and $\beta$ at iteration $t$
$\frac{\partial E}{\partial \alpha}$ and $\frac{\partial E}{\partial \beta}$ represent the partial derivatives of the error function with respect to $\alpha$ and $\beta$, respectively.
$W_{se}$ is the waiting time of the secondary user in the priority queue
$QoS_{se}$ stands for the Quality-of-Service requirements specific to the secondary user

### *Activating Resource Allocation*

The final step in the methodology involves activating resource allocation using outputs from Sections 3.3.1 and 3.3.3, which develop the Priority Score Model and the Dynamic Adjustment Model. The Priority Score Model ensures fair allocation to secondary users (SUs) by considering their waiting time and QoS needs, while the Dynamic Adjustment Model updates allocation priorities based on real-time network conditions. Using the computed priority scores and dynamically adjusted weights (α and β), resources are allocated proportionally through Equation (21). This ensures that users with the highest demand receive priority, allowing the system to adapt to changing conditions while maintaining a balance between fairness and efficiency.

The ratio of the priority score for each secondary user ( $P_{se}$ ) to the sum of the priority scores of all secondary users ( $\sum_{i=1}^{N} P_{si}$ ) represents the proportional allocation of resources to each secondary user. This ratio $P_{se} \big/ \sum_{i=1}^{N} P_{si}$ ensures that resources are distributed fairly among secondary users Based on their priority scores, a higher value indicates greater need or urgency for resource allocation, considering factors such as waiting time and QoS requirements. The sum of all priority scores is used to normalize the allocation, ensuring that available resources are distributed proportionally among users. Thus, the resource allocation for each secondary user relative to the total available resources is given by:

$$R_{alloc}\left(se\right) = \left( \frac{P^*{}_{se}}{\sum_{i=1}^{N} P_{si}} \right) \times R_{total,se} \quad (3.11)$$

Where:

$R_{alloc}\left(se\right)$ is the resource allocation for each secondary users

$P^*{}_{se}$ represents the conditional priority score for each secondary user

$\sum_{i=1}^{N} P_{si}$ stands for the sum of the priority scores of all secondary users ensures that the resources

Corresponding author: E. E. Agbon
✉ eagbonehime1@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.

are allocated (either channel allocation, BW allocation etc.) proportionally based on their priority.

$R_{total,se}$ is the total available resources for secondary users after meeting the need of primary users.

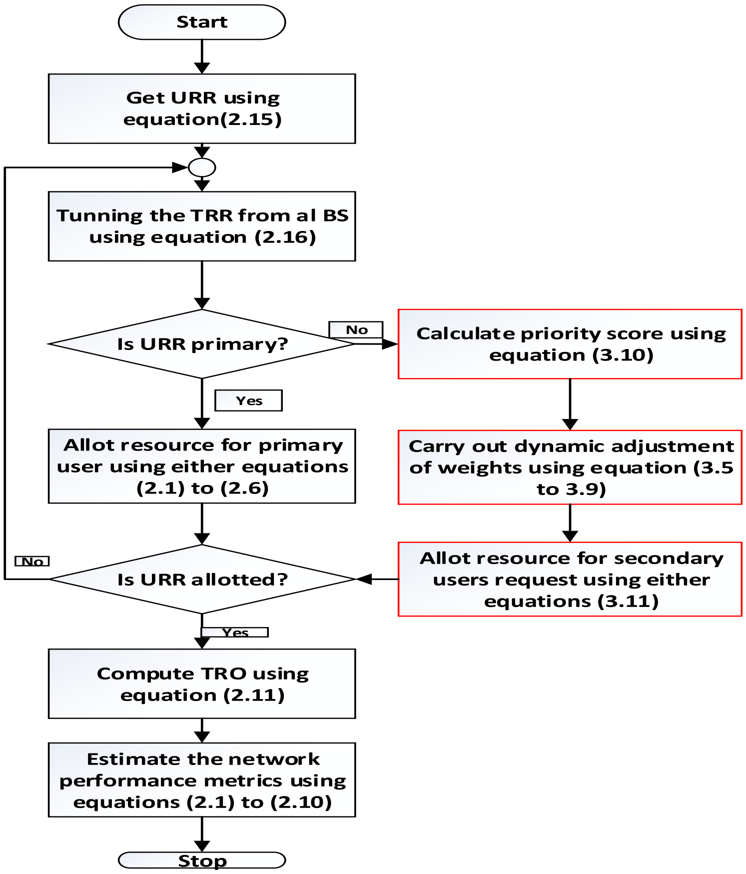


Figure 1: Flowchart for the Developed PADERA) Algorithm

## RESULTS AND DISCUSSION

This section presents a comparative analysis of the Priority-based Adjustment and Dynamic Energy-efficient Resource Allocation (PADERA) algorithm and the Enhanced Energy-efficient Resource Allocation Mechanism (EERAM) in dynamic D2D communication environments. EERAM uses static prioritization of primary users, which often results in inefficient resource use and reduced fairness for secondary users. In contrast, PADERA adopts a dynamic, demand-aware strategy that balances resource allocation between users, improving overall efficiency and QoS. Results across key metrics including energy, power, and bandwidth show that PADERA consistently outperforms EERAM. It achieves better resource utilization, maintains performance under increasing network load, and provides more equitable service, demonstrating the effectiveness of dynamic resource allocation in modern wireless networks.

## ENERGY ALLOCATION

Figure 2 shows energy allocation versus the number of signals, based on Equation (2.1). As the number of signals increases, energy allocation decreases for both PADERA and EERAM due to higher demand on limited energy

Corresponding author: E. E. Agbon
eagbonehime1@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.

resources. PADERA drops slightly from 95.19% to 93.10%, while EERAM decreases from 93.19% to 92.90%. However, PADERA performs better by dynamically adjusting allocation, ensuring improved efficiency and fairness compared to EERAM.

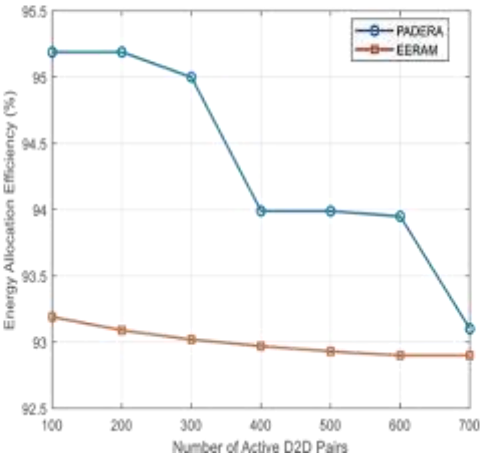


Figure 2: Energy Allocation Comparison between EERAM and PADERA

## POWER ALLOCATION

Figure 3 shows the power allocation against the varying number of signals in the network, based on Equation (2.2). The results indicate that power allocation decreases as the number of signals increases due to higher competition for limited power resources. However, PADERA maintains a higher and more stable power allocation, decreasing slightly from 96.87% at 100 signals to 91.75% at 700 signals. In contrast, EERAM shows a more significant decline, dropping from 91.84% to 85.60% over the same range. This sharper reduction in EERAM is due to its static resource prioritization, which often delays allocation for secondary users. In comparison, PADERA's dynamic allocation strategy distributes power more efficiently, reduces losses, and better accommodates increasing network demand.

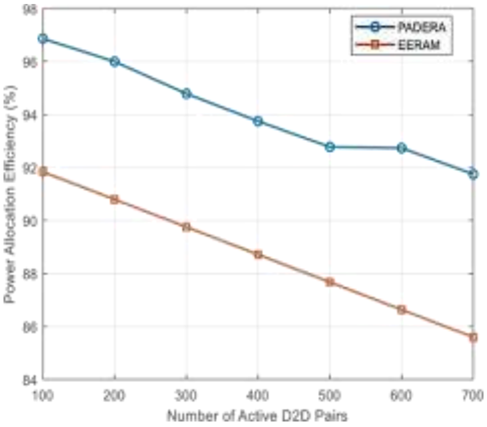


Figure 3: EERAM and PADERA Power Allocation Comparison

## BANDWIDTH ALLOCATION PERFORMANCE METRICS

Figure 4 shows bandwidth allocation versus the number of network signals, based on Equation (2.3). Bandwidth allocation decreases for both PADERA and EERAM as the number of signals increases due to higher network congestion and limited available bandwidth. PADERA declines from 96.70% at 100 signals to 88.00% at 700 signals, while EERAM drops from 90.67% to 84.91%. EERAM's static allocation approach worsens this reduction by relying mainly on waiting time rather than actual bandwidth needs. In contrast, PADERA dynamically adjusts bandwidth allocation, enabling more efficient resource use and better performance under increasing network load.

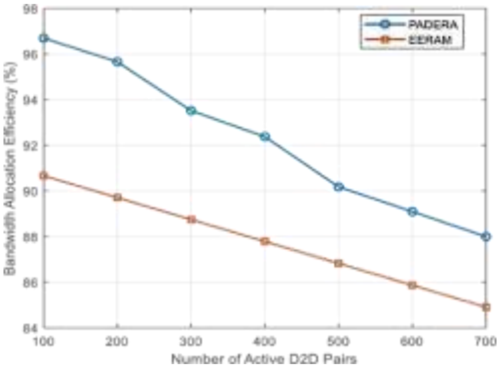


Figure 4: EERAM and PADERA Bandwidth Allocation Comparison

*Corresponding author: E. E. Agbon*
✉ *eagbonehime1@gmail.com*
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

## CONCLUSION

This study developed the PADERA protocol as an enhanced alternative to EERAM for resource allocation in dynamic wireless networks. Simulation results showed that PADERA consistently outperformed EERAM by reducing delay, improving throughput, increasing energy allocation efficiency, and enhancing overall resource utilization. Unlike EERAM, which statically prioritizes primary users, PADERA dynamically adjusts resource distribution based on real-time QoS requirements, ensuring greater fairness between primary and secondary users. The results confirm that PADERA achieves higher efficiency in energy, power, bandwidth, spectrum, and channel allocation, while delivering lower end-to-end delay and higher network throughput.

## RECOMMENDATIONS

Future work should examine PADERA's scalability in large, dense networks and evaluate its performance in other wireless environments, including ad hoc and cellular networks.

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*Corresponding author: E. E. Agbon*
✉ *eagbonehime1@gmail.com*
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*

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*Corresponding author: E. E. Agbon*
✉ eagbonehime1@gmail.com
*Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria Nigeria.*