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RFID-Based Enhanced Resource Optimization for 5G/6G Network Applications

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ABSTRACT

In the rapidly evolving landscape of 5G/6G networks, efficient resource optimization is critical to addressing the escalating demands for high-speed, low-latency, and energy-efficient communication. This study explores the integration of Radio Frequency Identification (RFID) technology as a novel approach to enhance resource management in 5G networks. The motivation behind this research lies in overcoming persistent challenges such as spectrum congestion, high latency, and inefficient load balancing, which impede the performance of traditional resource allocation methods. To achieve this, RFID tags were embedded in critical network components, including user devices, base stations, and Internet of Things (IoT) nodes, enabling the collection of real-time data on device status, location, and resource utilization. RFID readers strategically placed across the network continuously captured this data, which was processed by a centralized controller using a custom-designed optimization algorithm. This algorithm dynamically managed key network resources, including spectrum allocation, load balancing, and energy consumption, ensuring efficient operation under varying network conditions. Simulations were conducted to evaluate the performance of the RFID-based model against traditional 4G dynamic resource allocation techniques. The results demonstrated substantial improvements in key performance metrics. The proposed system achieved a 25% increase in spectrum utilization, a 30% reduction in average latency, a 15% boost in network throughput, and a 20% decrease in overall energy consumption. These gains highlight the effectiveness of the RFID-based optimization model in meeting the stringent performance requirements of 5G networks, particularly in high-density deployments. This study provides a scalable, cost-effective solution for optimizing resource management in 5G and lays the groundwork for future advancements in 6G networks. By leveraging real-time data and intelligent resource allocation, the proposed model addresses critical challenges in modern communication systems, ensuring enhanced network efficiency, reliability, and sustainability.

1 | Introduction

The global demand for high-speed, low-latency, and reliable connectivity is growing at an unprecedented pace, driven by emerging technologies such as the Internet of Things (IoT), autonomous systems, augmented reality (AR), and virtual reality (VR). The successful implementation of 5G networks is increasingly vital to support these technologies, enabling applications that require ultra-reliable low-latency communication (URLLC) and massive machine-type communications (mMTC). However, the deployment and operation of 5G infrastructure come with significant challenges in resource optimization, particularly in densely populated urban areas and regions with high device connectivity. Traditional resource management techniques used in 4G networks are ill-suited to meet the demands of 5G, especially given the extreme device density, dynamic user behaviors, and varying service requirements that characterize modern 5G ecosystems. The limitations of conventional 4G resource management often lead to problems such as spectrum congestion, inefficient energy usage, and delays in service delivery. These challenges can undermine the quality of service (QoS) for end users and hinder the performance of applications that rely on real-time, high-performance networks. Consequently, optimizing resources within 5G networks is crucial to ensuring scalable, efficient, and resilient connectivity across various use cases, from smart cities to autonomous vehicle networks.

The problem of resource optimization in 5G networks primarily revolves around three key challenges. First, spectrum utilization remains a major concern due to the rapid increase in connected devices, leading to spectrum congestion and inefficient bandwidth allocation. Second, latency optimization is crucial for real-time applications, yet network congestion and suboptimal routing mechanisms introduce delays that affect performance. Third, energy efficiency is a growing concern, as traditional resource allocation strategies result in excessive power consumption, thereby increasing operational costs and environmental impact. Addressing these challenges requires adaptive and intelligent solutions that go beyond conventional static resource allocation methods.

In response to these issues, there is a growing body of research focused on innovative solutions for resource management in 5G environments. Among these solutions, Radio Frequency Identification (RFID) technology has emerged as a promising tool to enhance network performance by providing detailed, real-time data on device location, movement, and network conditions. RFID's capability for real-time location tracking has been widely applied in fields such as inventory management and healthcare, significantly enhancing operational efficiency and accuracy [1, 2]. Furthermore, RFID has been leveraged for efficient resource management in other applications, such as logistics and supply chain operations, where its ability to streamline processes and reduce manual errors has been proven [3]. These studies demonstrate the versatility and adaptability of RFID, underscoring its potential for addressing the complex demands of modern technological ecosystems, including 5G networks. Traditionally used in asset tracking and supply chain management, RFID is now being explored in the context of 5G to support dynamic, real-time resource allocation. By embedding RFID tags in key network elements such as user devices, base stations, and IoT nodes, network operators can gather granular data that informs intelligent resource distribution decisions. To develop a comprehensive understanding of the proposed RFID-based resource optimization framework, it is necessary to introduce key notations that will be utilized throughout the mathematical formulations in later sections. The total available bandwidth in the network is denoted as B, while P_t represents the transmit power of a network node. Network traffic arrival rate is defined as λ spectrum utilization efficiency is expressed as S_u and end-to-end network latency is indicated by L. Additionally, the total energy consumption in the network is represented as E_c. These parameters form the foundation of the mathematical modeling and optimization strategies discussed in subsequent sections of this paper.

Recent studies have highlighted several successful resource management techniques within 5G frameworks. A dynamic resource allocation approach based on Software-Defined Networking (SDN) was leveraged for flexible and intelligent management of 5G networks [1]. This approach significantly improved the accuracy of resource allocation, reducing congestion and enhancing overall network efficiency. Deep learning algorithms were utilized for resource allocation in 5G networks, maximizing spectrum utilization and resulting in better throughput, lower end-to-end delays, improved fairness, and enhanced energy efficiency compared to traditional methods [2]. Furthermore, a study demonstrated how an RFID-integrated dynamic scheduling scheme assigns high-priority subtasks to vehicles, ensuring rapid task execution and reliable transmission links, which is critical for applications such as autonomous driving and remote surgery [3]. Another study developed supervised learning models to predict network traffic in 5G networks, addressing communication efficiency and resource consumption [4]. Additionally, AI-based strategies were explored for optimizing energy consumption in 5G networks while maintaining the desired network performance and user experience [5]. The integration of RFID with advanced machine learning (ML) algorithms holds great promise for optimizing spectrum usage and managing load balancing in 5G networks. Beyond spectrum optimization, RFID technology plays a crucial role in facilitating energy-efficient operations within 5G networks. By providing real-time insights into network traffic and device activity, RFID enables adaptive power management strategies that minimize energy waste. This not only enhances sustainability but also helps reduce operational costs, an essential consideration as 5G networks scale globally.

This study investigates the potential of integrating RFID technology into resource management strategies for 5G networks. By embedding RFID tags into critical network components, such as user devices, base stations, and IoT nodes, the proposed system collects real-time data on device status, network conditions, and user behaviors. The data is then processed through a centralized controller that uses custom optimization algorithms to make data-driven adjustments to bandwidth, power allocation, and load balancing. Compared to traditional resource management techniques, RFID-based optimization enhances spectrum utilization, reduces latency, and minimizes energy consumption, offering a scalable and adaptive solution for the demands of modern 5G environments. Furthermore, this research contributes to the development of more efficient, sustainable, and resilient 5G networks, laying the groundwork for future advancements in 6G connectivity. By exploring the integration of RFID with emerging technologies such as machine learning, IoT, and edge computing, this paper aims to provide a comprehensive framework for next-generation wireless networks. This framework not only addresses the immediate challenges faced by 5G networks but also prepares for the more demanding requirements of 6G, paving the way for truly intelligent, autonomous, and ultra-efficient communication systems.

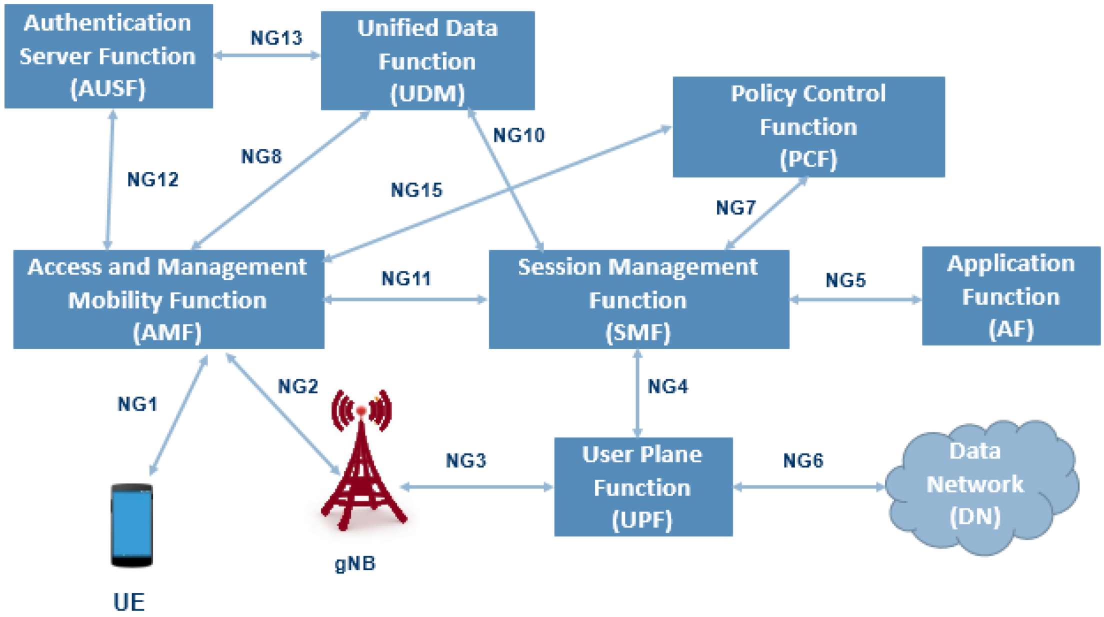

FIGURE 1 | 5G network architecture.

2 | Theory of Work

2.1 | 5G Network Resource Management and Optimization Challenges

5G networks are the next generation of wireless communication technology, offering ultra-fast speeds, low latency, and massive connectivity. Designed to support advanced applications like IoT, autonomous systems, and smart cities, 5G enhances user experiences and enables seamless real-time interactions. Its architecture as shown in Figure 1 integrates cutting-edge technologies like millimeter waves, massive MIMO, and network slicing to optimize performance, reliability, and efficiency. The advent of 5G networks aims to support a new generation of applications requiring high bandwidth, ultra-low latency, and extensive device connectivity. These demands arise from areas such as autonomous vehicles, smart cities, remote healthcare, and the Internet of Things (IoT) [6]. Effective resource management is therefore a fundamental challenge for 5G networks, given the increased device density, varied quality of service (QoS) requirements, and dynamic user demands in high-density urban environments. Unlike 4G networks, where resource allocation strategies often rely on localized and reactive mechanisms, 5G networks necessitate proactive, comprehensive resource management approaches. Traditional methods, such as fixed spectrum allocations and localized load balancing techniques, are increasingly insufficient to meet the demands of 5G's extensive scale and complexity [7]. Studies indicate that flexible, real-time resource allocation strategies are critical for addressing fluctuating user demands and network conditions [8]. With 5G networks designed to support up to one million devices per square kilometer, innovative tools and frameworks are required to optimize resource utilization and avoid congestion and latency issues [9]. Furthermore, localized dynamic scheduling methods, such as proportional fair scheduling commonly used in 4G networks, are inadequate for 5G environments. The research underscores the need for intelligent, data-driven approaches capable of monitoring, predicting, and allocating resources across the network in real-time. This transition is vital for enabling ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC), which are core 5G capabilities [10]. In response, researchers and network operators are increasingly exploring the integration of technologies like Radio Frequency Identification (RFID) to collect real-time network data and optimize resource allocation.

2.2 | RFID Technology and Its Application in Network Resource Management

Radio Frequency Identification (RFID) is a wireless technology that uses electromagnetic fields to identify and track objects, animals, or people through embedded tags. Initially employed in areas like inventory tracking, supply chain management, and asset monitoring, RFID systems as shown in Figure 2 consist of tags, readers, and a backend system that processes real-time data on item location, usage, and movement. This technology enhances operational efficiency by automating processes and providing accurate, real-time information across various industries. In the context of network resource management, RFID's ability to provide real-time insights can improve performance by dynamically monitoring devices and user movements [11]. Embedding RFID tags into network components such as user devices, base stations, and IoT nodes enables 5G networks to gather detailed, real-time data about device locations, usage patterns, and network status. RFID readers distributed across the network collect this data, which is processed by a centralized controller to inform data-driven adjustments in resource allocation. RFID enhances the network's situational awareness, improving load balancing and spectrum allocation [12]. For example, in high-density urban environments where connectivity demands fluctuate rapidly, RFID data offers insights into device mobility and density, facilitating resource allocation to areas with higher demand. RFID's scalability makes it an ideal choice for 5G

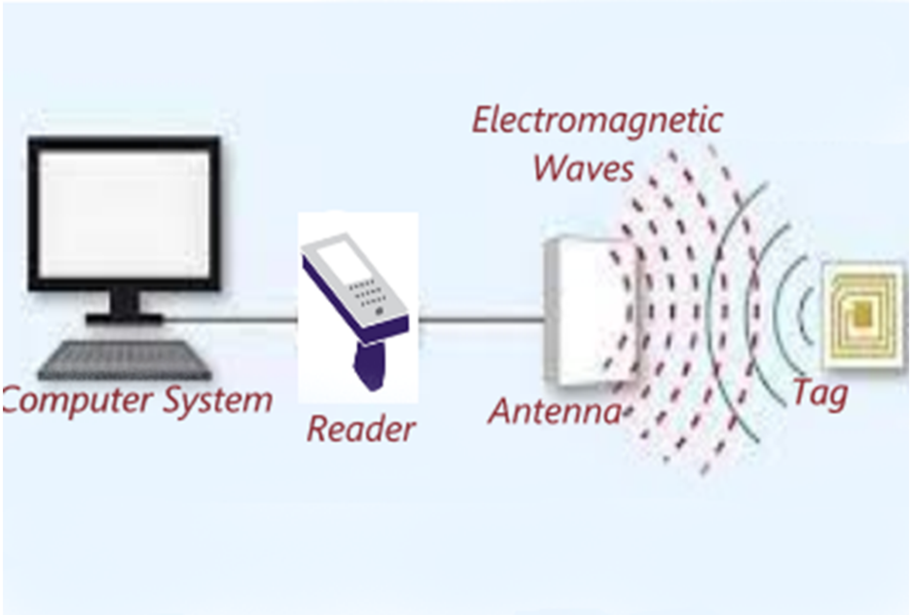

FIGURE 2 | Basic RFID system.

networks as it can handle the vast number of devices and dynamic conditions typical of these networks. The ability to add more RFID tags or readers as the network expands ensures that the technology remains adaptable, supporting larger and more complex network architectures as needed. Moreover, RFID integration is economically feasible for 5G networks due to the relatively low cost of RFID tags and the widespread availability of RFID technology. This affordability enables large-scale deployment in a variety of network elements, reducing operational and maintenance costs over time. RFID's capability to enhance security also plays a vital role in network management. By providing precise tracking of devices and network elements, RFID improves the ability to detect unauthorized access or security breaches, ensuring that only legitimate devices interact with network resources. These security features are critical in safeguarding both the network and the sensitive data it handles. Authors in [13] reviewed trends in the application of RFID technology and highlighted its advantages in enhancing resource planning efficiency. They observed that leveraging real-time RFID data enables 5G networks to optimize resource allocation and maintain performance under high-traffic conditions. This approach allows networks to dynamically adjust during peak usage periods, ensuring critical services remain uninterrupted. Additionally, researchers in [14] noted that RFID technology contributes to energy optimization by allocating resources only where needed, reducing unnecessary power consumption across base stations. By providing enhanced visibility, RFID empowers network operators to anticipate congestion points and reallocate spectrum and processing power to balance loads effectively.

2.3 | Machine Learning and RFID-Driven Predictive Resource Optimization in 5G

Machine learning is a branch of artificial intelligence that enables systems to learn from data and improve their performance over time without explicit programming. By using algorithms and statistical models, machine learning identifies patterns and makes predictions or decisions, powering applications such as recommendation systems, speech recognition, and autonomous vehicles. This technology drives innovation across industries by automating complex tasks and uncovering insights from vast datasets. Machine learning (ML) plays a pivotal role in transforming RFID data into actionable insights for resource management in 5G networks. By analyzing both historical and real-time RFID data, ML algorithms can predict network conditions, identify patterns in user behavior, and allocate resources proactively. Techniques such as reinforcement learning, neural networks, and decision trees process large volumes of RFID data to optimize bandwidth, reduce latency, and address QoS requirements [15]. Reinforcement learning, for example, adapts resource allocation strategies based on reward feedback, optimizing load balancing and spectrum efficiency. A study demonstrated how reinforcement learning models utilize RFID-derived mobility and usage data to predict congestion and adjust resource allocations preemptively, ensuring resilient network performance even during peak usage periods [16]. Similarly, supervised learning models, such as support vector machines (SVM) and random forests, can classify network traffic and forecast congestion based on RFID data [17]. These models, trained on historical datasets, can rapidly identify shifts in user patterns or device density and trigger automated resource adjustments. Studies highlighted the effectiveness of this approach, particularly in IoT applications where sudden increases in connected devices could overwhelm network resources [18, 19]. A study emphasized that integrating ML with RFID data fundamentally transforms 5G network management by enabling real-time, data-driven decision-making [20, 21]. This integration facilitates adaptive responses to shifting demands, reducing network downtime and enhancing user experience. Deploying ML algorithms that learn and adapt from RFID data equips network operators with a predictive and responsive optimization strategy—one that will be even more essential in future 6G networks [22, 23]. Additionally, these predictive capabilities offer a scalable solution that can be adjusted as networks grow and evolve. The economic feasibility of this approach is further supported by the low-cost nature of RFID integration, while the continuous learning process ensures a secure allocation of resources, minimizing risks related to congestion, latency, and unauthorized access.

2.4 | Mathematical Formulation for RFID-Driven Resource Optimization

This subsection defines the mathematical formulation used to optimize resource allocation in 5G networks through RFID technology. The key variables utilized throughout the formulation are introduced as follows: N represents the number of devices in the network, while D_i the demand of device i for network resources (such as bandwidth and power). R_i is the resource allocation for device i and C_j is the channel capacity of the base station j. Additionally, P_k represents the power allocated to base station k. The objective is to optimize the resource allocation R_i across all devices while considering the constraints imposed by the network and technological limitations. The optimization problem can be mathematically expressed as Equation (1).

$$\sum_{i=1}^{N} R_i D_i \tag{1a}$$

$$\sum_{i=1}^{N} R_i \leq C_j, \quad R_i \geq 0, P_k \leq P_{max} \tag{1b}$$

Equation (1) ensures that resources are allocated efficiently across the network based on demand, while also ensuring that the total resource usage does not exceed the capacity of any base station or the power supply limits. To solve this optimization problem, machine learning algorithms such as reinforcement learning can be employed, where the algorithm iteratively adjusts R_i based on feedback from the network's real-time conditions. The reinforcement learning process can be framed using Equation (2).

$$Q(s_t, a_t) = Q(s_t, a_t) + \propto \left[R_{t+1} + \gamma \max Q(s_{t+1}, a) - Q(s_t, a_t)\right] \tag{2}$$

where, $Q(s_t, a_t)$ represents the quality of the action a_t at state s_t, $\propto$ is the learning rate, γ is the discount factor, and R_{t+1} is the reward obtained at time step $t+1$.

The optimization process described above is fundamentally linked to several key network parameters. The total available bandwidth in the network, denoted by B, influences the resource allocation for each device. Specifically, the sum of all resource allocations R_i must not exceed the total available bandwidth at any given time, which is represented by the constraint $\sum_{i=1}^{N} R_i \leq C_j$. This ensures that the resource allocation does not surpass the bandwidth capacity of any base station. Additionally, the transmit power of a network node, represented by P_t, is incorporated into the optimization as P_k, which refers to the power allocated to each base station. One of the constraints in the mathematical formulation is $P_k \leq P_{max}$, ensuring that the transmit power for each base station does not exceed the maximum allowable limit.

The network traffic arrival rate, represented by λ, directly impacts the demand D_i for each device, as the demand reflects the resources required by the device to handle incoming traffic. By adjusting the resource allocation R_i, the network can dynamically allocate resources to meet the demand generated by the traffic arrival rate. Spectrum utilization efficiency, denoted by S_u, plays a critical role in optimizing resource allocation. The goal is to allocate resources in a manner that maximizes the spectrum utilization, which contributes to the overall optimization objective $\sum_{i=1}^{N} R_i D_i$, thus maximizing throughput while ensuring that resource allocation is efficient. While the end-to-end network latency, denoted by L, is not explicitly stated in the mathematical formulation, it can be implicitly influenced by the optimization process. By efficiently optimizing resource allocation R_i, the model helps reduce congestion, improve load balancing, and ultimately minimize network latency. The energy consumption in the network, represented by E_c, could be integrated into the optimization problem as an additional cost factor. The energy efficiency of the allocation strategy can be accounted for, ensuring that the total energy consumed by the network does not exceed predefined thresholds. This could be incorporated into the constraints or treated as part of the reward function in reinforcement learning. This formulation provides the foundation for optimizing resource allocation in a 5G network, with RFID-driven mechanisms ensuring efficient use of bandwidth, power, and energy while minimizing latency.

3 | Materials and Methods

An RFID-based resource optimization system for 5G networks was designed using Arduino Mega, ESP32, a virtual terminal as a substitute for the MFRC522, and NetSim. The architecture facilitates seamless data acquisition, processing, and optimization within a simulated environment. The key stages for the RFID-Based Resource Optimization in 5G Networks are system initialization, data acquisition and processing, running the optimization algorithm, checking network conditions, and integration of Proteus and NetSim. The block diagram of RFID-based resource optimization in the 5G Network is shown in Figure 3.

The hardware components shown in Figure 3 were selected for their compatibility and efficiency in IoT-based 5G systems. The Arduino Mega was selected for its robust processing, while the ESP32 enables wireless communication for seamless IoT integration. The LCD and LED provide real-time feedback, and the virtual terminal emulates an RFID reader for flexible testing. The RFID Reader is responsible for detecting or simulating tag data, serving as the initial point for data acquisition and processing, as explained in Section 3.2. The RFID data is then transmitted to the Arduino Mega for processing. This component validates the tag, displays the result on the LCD, and controls the LED indicator. The 16×2 LCD Display and LED Indicator are connected to the Arduino Mega. The LCD displays the detected tag and its access status, while the LED indicates whether access is granted or denied. After processing the data, the Arduino Mega sends it to the ESP32 module. Acting as a wireless gateway, the ESP32 transmits the processed RFID data to the centralized server, where the optimization algorithms described in Section 3.3 dynamically allocate resources. The centralized server returns optimized resource allocation data to the ESP32, which updates the system status and metrics on the LCD. Section 3.4 concludes

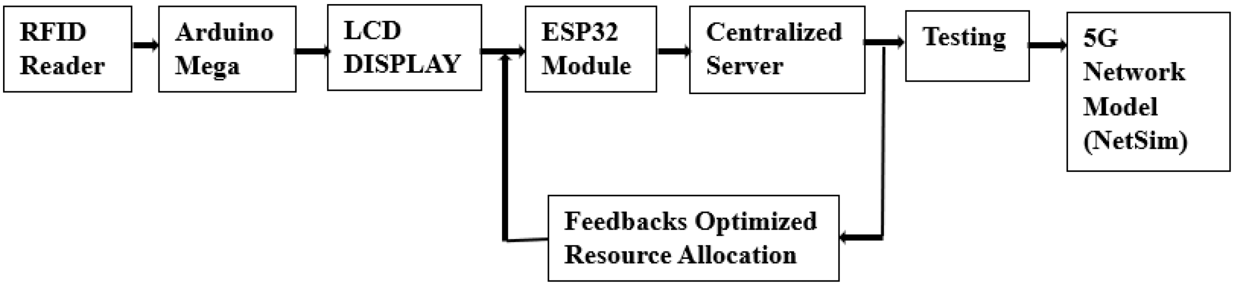

FIGURE 3 | Block diagram of RFID-based resource optimization system for 5G networks.

by validating the efficiency of the feedback mechanism during testing. Section 3.5 emphasizes the bidirectional integration between Proteus and NetSim, enabling communication between the hardware simulation (Proteus) and the 5G network model (NetSim). The ESP32 module plays a pivotal role in this integration by serving as a gateway for transmitting and receiving data between the two platforms. Section 3.1 details the connections among the hardware components, including the RFID Reader, Arduino Mega, LCD Display, LED indicator, and ESP32 Module. Sections 3.1–3.5 are described in detail as follows.

3.1 | System Initialization

The hardware schematic was developed in Proteus, integrating the Arduino Mega (ATmega2560) as the main microcontroller for processing RFID data and managing peripheral components. An ESP32 module enables wireless communication and acts as a gateway for transmitting RFID data to a centralized server. A 16 × 2 LCD display provides real-time feedback by showcasing scanned tag information and system status, while a virtual terminal simulates the RFID reader by sending tag IDs for processing. An LED indicator reflects the system status, such as turning on to indicate access granted. Power is supplied by a 5 V DC source for most components and a 3.3 V DC source for the ESP32.

The connections include linking the virtual terminal to the Arduino in place of the RFID module, with the Arduino TX (Pin 3) connected to the virtual terminal RX and the Arduino RX (Pin 2) to the virtual terminal TX. For communication between the ESP32 and Arduino, the ESP32 TX connects to Arduino (Pin 19), and the ESP32 RX connects to Arduino (Pin 18). The LCD display is connected through RS (Pin 60) and Enable (Pin 59), with data pins D4 to D7 wired to Pins 58, 57, 56, and 55, respectively. The LED indicator connects via its positive terminal to Pin 13 through a 220 Ω resistor, while the negative terminal is grounded. Finally, the Arduino and LCD are powered by the 5 V source, and the ESP32 is powered by the 3.3 V source, as shown in Figure 4.

3.2 | Data Acquisition and Processing

The Arduino Mega handles RFID tag data acquisition, processing, and communication with the ESP32 for network transmission. The system processes tag data from the virtual terminal, updates the LCD display, and determines access status based on predefined conditions. The Arduino sketch is designed to read RFID-like data, display it on an LCD, and validate access. The following pseudocode outlines the algorithm for data acquisition and processing in Proteus.

RFID Data Acquisition and Processing Pseudocode:

```
1. Initialize system:
   ○ Setup LCD display
   ○ Setup Serial communication (Virtual
     Terminal) at 9600 baud
   ○ Setup Serial1 communication (for ESP32)
     at 115200 baud

2. Display "RFID System" on the LCD screen

3. Loop:
   ○ Check if data is available from the
     Virtual Terminal (Serial):
     • If data is available:
       a. Read RFID tag ID
       b. Display "Tag Detected" on the LCD
       c. Display the tag ID on the LCD (sec-
          ond line)
       d. Transmit tag ID to ESP32 over
          Serial1
   ○ Validate the tag ID:
     • If tag ID == "12345ABC":
       - Print "Access Granted" to Serial
       - Turn on LED (set pin 13 HIGH)
     • Else:
       - Print "Access Denied" to Serial
       - Turn off LED (set pin 13 LOW)
```

This implementation processes tag IDs sent via the virtual terminal, transmits the data to the ESP32 over Serial1, and updates the LCD and LED based on access validation. The LCD displays detected tag information, while the LED reflects the access status, providing a clear and interactive system response. The data acquisition process involves receiving RFID tag inputs through a virtual terminal, which emulates a physical RFID reader. Tag detection is initiated when the virtual terminal sends simulated RFID tag IDs to the Arduino Mega. The Arduino processes the incoming tag ID, checks its validity, and determines the corresponding access status. The LCD displays the detected tag ID and access status, while the LED provides a visual indication, turning on for valid tags and off for invalid ones. The parsed data is then sent to the ESP32 module, which acts as a gateway, forwarding the

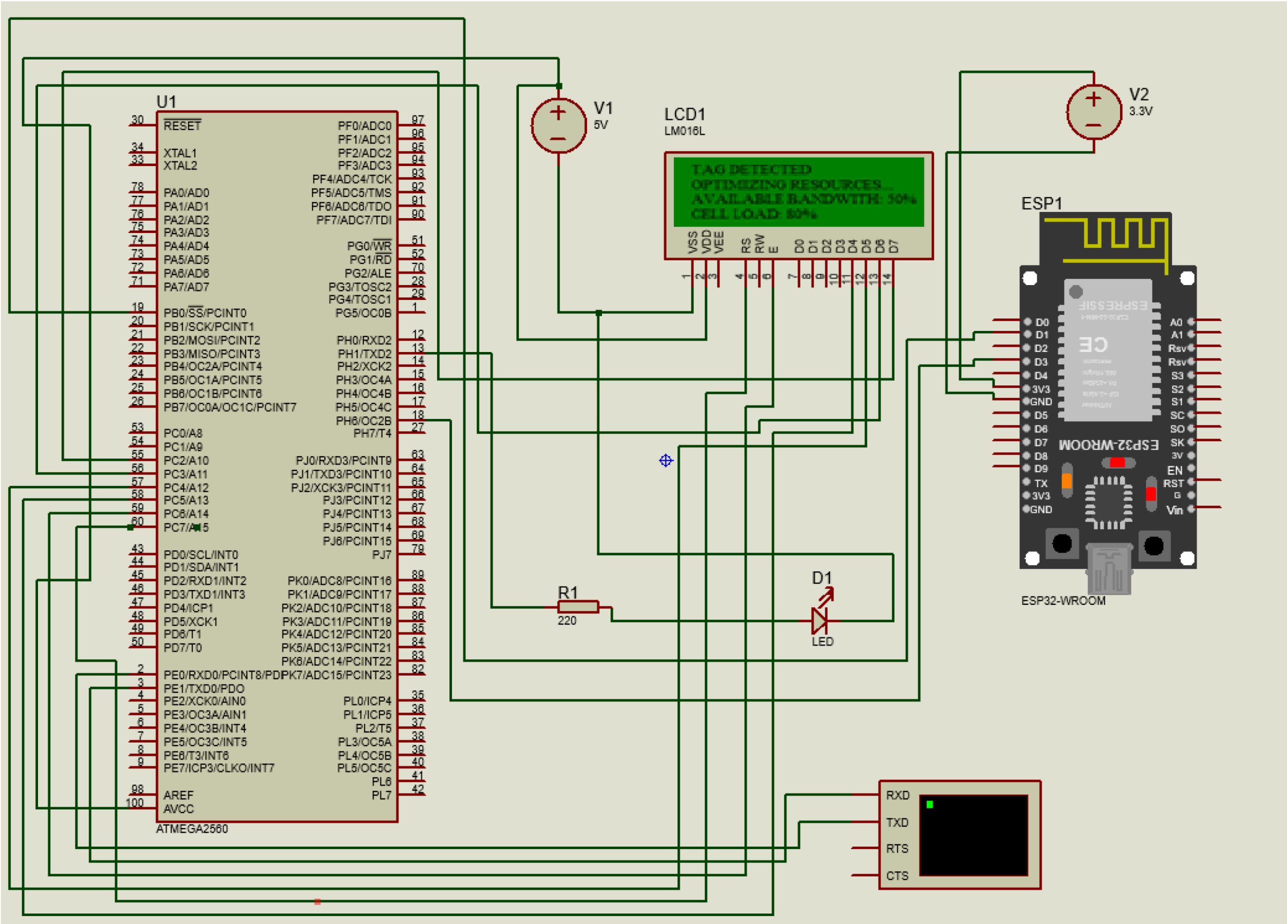

FIGURE 4 | RFID-based resource optimization system.

tag information to the centralized server over Wi-Fi. The centralized server processes the received data to manage resource allocation dynamically, enabling efficient optimization in the simulated 5G network. This workflow ensures the effective acquisition, validation, and transmission of tag data, which is essential for the dynamic optimization of network resources.

3.3 | Optimization Algorithm

The RFID-based resource optimization system employs a dynamic algorithm to efficiently allocate bandwidth and distribute load in a 5G network. This approach ensures real-time adjustments to enhance network performance and reduce latency. The system collects real-time tag information via RFID readers while monitoring the status of network nodes, including bandwidth usage and traffic load. Bandwidth allocation is determined by tag priority, where VIP tags are given higher precedence, and traffic load is evenly distributed across available resources to minimize latency. Additionally, the system uses historical data to predict future demand, enabling proactive adjustments to resource allocation. Building upon this framework, the optimization process dynamically allocates network resources in real-time based on RFID data. The system processes inputs such as tag IDs, network load, and bandwidth usage to ensure efficient resource utilization across the network. The RFID tag data is analyzed to determine resource allocation priorities, with VIP tags allocated maximum bandwidth while other tags receive resources proportional to their usage. The system continuously monitors network conditions, identifying high-load nodes and redistributing resources to maintain balance. Predictive models, leveraging historical data, forecast future network demands, enabling proactive adjustments to resource allocation. The optimization algorithm is as follows:

Pseudocode for the Optimization Algorithm:

1. Initialize priority list and network nodes:
   - priority_list = {"12345ABC", "VIP001", "VIP002"}
   - network_nodes = {"Node1": {"bandwidth": 100, "load": 50}, "Node2": {"bandwidth": 150, "load": 70}, "Node3": {"bandwidth": 120, "load": 30}}
2. Function to allocate resources:
   - Check if the tag is in priority_list:
     - If Yes, allocate maximum bandwidth.
     - If No, allocate bandwidth proportional to usage (e.g., usage * 0.8).
3. Function to monitor and balance network load:

   ○ Identify nodes exceeding load threshold (e.g., 80%).
   ○ Transfer excess load to nodes below a defined load threshold (e.g., 60%).

4. Predict future demands:
   ○ Use historical data to predict load for each node.
   ○ Adjust bandwidth proactively if predicted load exceeds thresholds.

5. Execute allocation, load balancing, and demand adjustment in a continuous loop.

The optimization algorithm ensures dynamic allocation of network resources, adjusting to real-time network demands while maintaining efficient resource utilization. Key functions, such as load balancing and future demand prediction, contribute to maintaining optimal network performance. This implementation was validated through simulations in NetSim, where performance metrics such as latency, throughput, and energy efficiency were analyzed under varying network conditions. The validation demonstrated the effectiveness of the system in addressing the dynamic demands of 5G networks, ensuring a balance between resource efficiency and quality of service. A flowchart illustrating the optimization steps in Figure 5 provides a clear overview of the process, encompassing data analysis, real-time adjustments, and feedback loops for continuous improvement. This process highlights the adaptability and scalability of the optimization framework in meeting the requirements of next-generation networks.

The algorithm described in Section 3.3 processes RFID tag data, prioritizes tags, allocates resources dynamically, monitors network load, and predicts future demand. These operations align with the principles outlined in the mathematical formulation of Section 2.4, where devices' demands (D_i) are prioritized

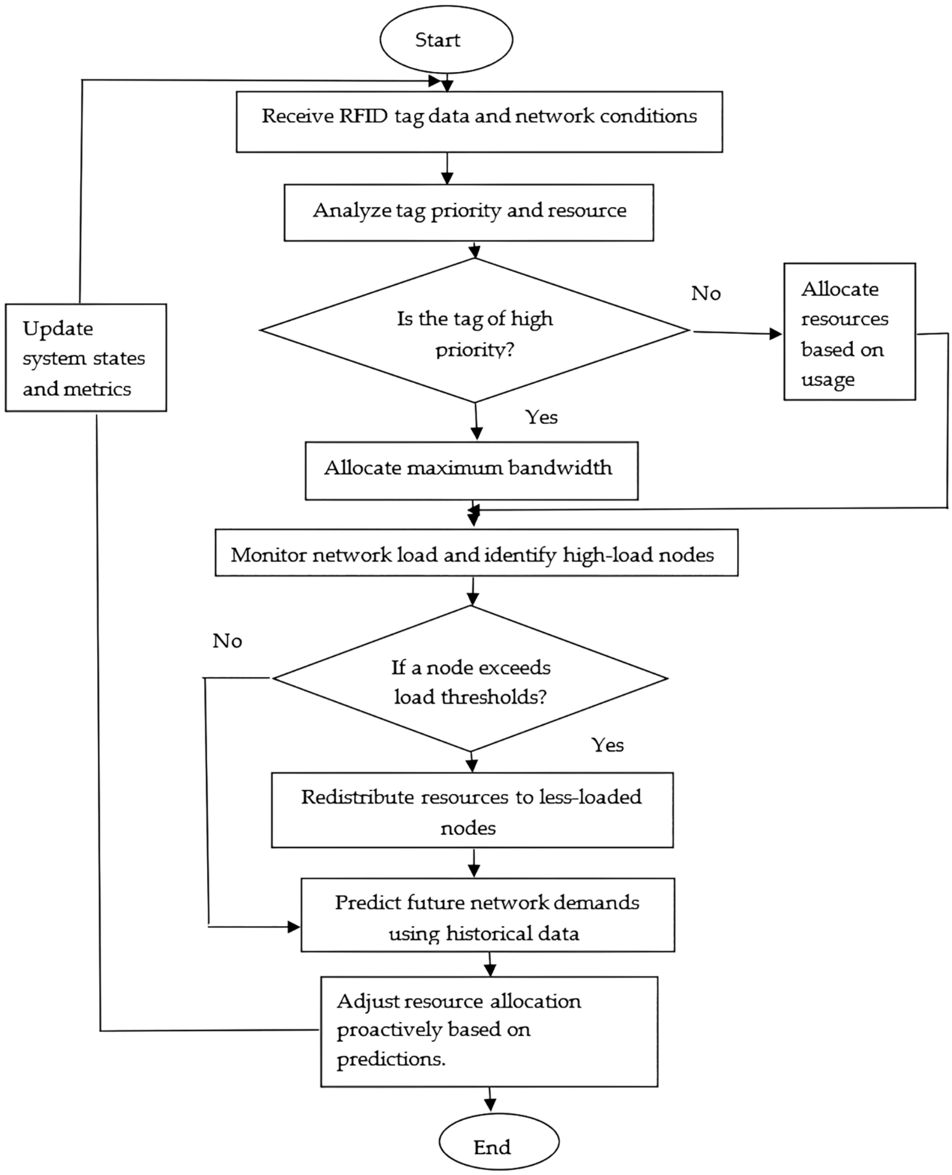

FIGURE 5 | RFID-based optimization flowchart for 5G networks.

based on their tags, and resource allocation (R_i) is adjusted according to the current network conditions. Section 2.4 discusses how resource allocation (R_i) must be optimized, with bandwidth and power as primary factors to manage within constraints. Section 3.3 builds upon this framework by outlining a practical algorithm that allocates bandwidth based on RFID tag priority, where VIP tags receive higher priority, similar to how devices with higher resource demands are handled in the mathematical formulation. Furthermore, the load balancing across network nodes and the predictive adjustment of bandwidth in Section 3.3 reflect the constraints and objectives described in the formulation, particularly in ensuring that resources are allocated while respecting the total bandwidth capacity and power constraints. In Section 2.4, the reinforcement learning algorithm adjusts resource allocation in real-time based on network feedback. This concept is implemented in Section 3.3, where the system adjusts network load by redistributing resources based on real-time data, such as monitoring load and bandwidth usage at different network nodes. The goal in both sections is to minimize latency and improve resource efficiency, which is a central theme in both the formulation and the algorithm.

3.4 | Testing the System

Testing of the RFID-based resource optimization system was conducted to evaluate its performance and validate its functionality under simulated conditions. The testing process began with system initialization, where the Arduino Mega, ESP32, LCD, and virtual terminal were set up in the Proteus environment. The virtual terminal was used to simulate RFID tag data input. Testing involved inputting sample data, such as 12345ABC\n, into the system via the Virtual Terminal and observing responses on the LCD, LED, and Virtual Terminal. During testing, the LCD displayed tag detected, while the Virtual Terminal logged access status and communicated with the ESP32. The LED provided a visual indication of access status by turning on or off accordingly.

The processed data was transmitted to the ESP32 via serial communication and forwarded wirelessly to a centralized server using MQTT. The integration with the 5G network simulation in NetSim enabled the centralized server to use this data for real-time resource optimization. Metrics such as bandwidth allocation, latency reduction, and load balancing were monitored. The system was tested under varying network loads, with key metrics analyzed, including the accuracy of tag detection, system responsiveness, and the effectiveness of dynamic resource allocation. Expected outcomes included real-time detection and validation of RFID tags, accurate data transmission from Proteus to NetSim, and efficient resource optimization, reflected in reduced latency, improved throughput, and balanced network loads. This thorough testing process ensured the system performed as intended in a simulated 5G network environment.

3.5 | Integration of Proteus and NetSim

In NetSim, the 5G architecture is modeled, including essential components like gNB (base stations), AMF (Access and Mobility Function), SMF (Session Management Function), and UPF (User Plane Function) as shown in Figure 6. The simulated 5G network connects user equipment (UE) such as the ESP32 to the internet and remote servers. NetSim provides a platform to analyze network behavior, optimize bandwidth allocation, and manage dynamic traffic loads through the core network. The communication between Proteus and NetSim is established using a middleware application. The ESP32 in Proteus is programmed to send data packets via Wi-Fi using a standard protocol such as UDP or MQTT. The data packet contains resource metrics, including bandwidth requests, current load conditions, and system parameters.

Below is the algorithm that runs on the ESP32 in Proteus and sends system metrics via MQTT. It defines how the ESP32 module in Proteus transmits system resource metrics to the middleware.

ESP32 Data Transmission:

1. Initialize Wi-Fi connection using predefined credentials.

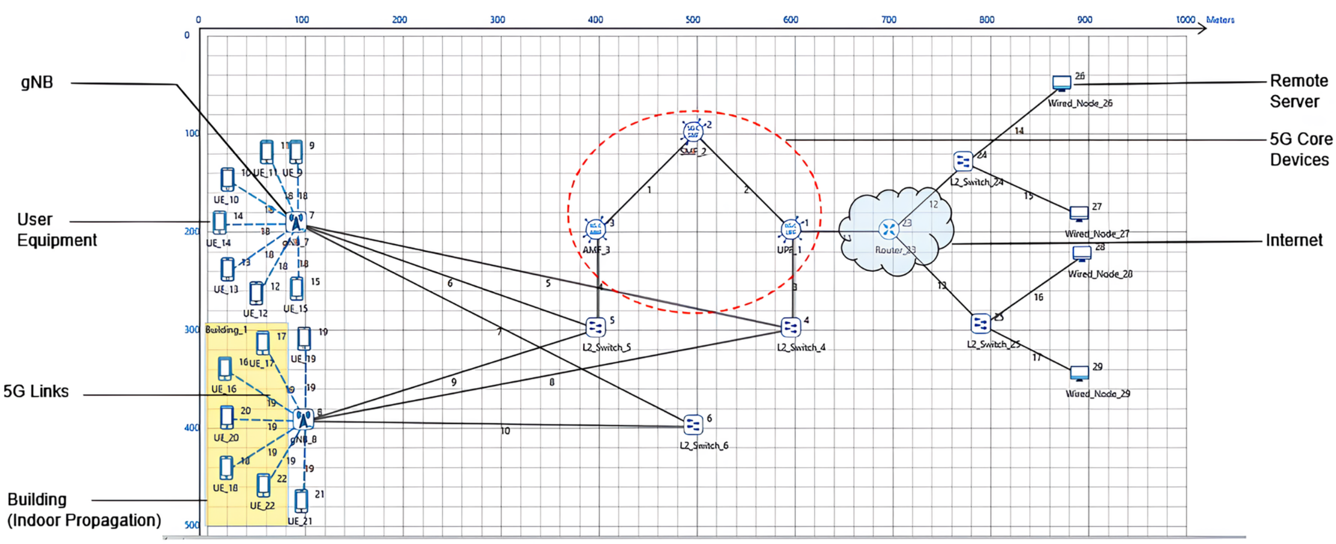

FIGURE 6 | 5G network in NetSim.

2. Connect to the MQTT broker at the specified IP and port.
3. Repeat Every 5 Seconds:
   a. Collect System Metrics (bandwidth, load).
   b. Convert Data into JSON format for structured transmission.
   c. Publish Data to the MQTT broker under a specific topic.
   d. Print transmission logs for debugging.
4. Continue Data Transmission unless interrupted.

This packet is received by a middleware application that bridges Proteus and NetSim by forwarding the data to NetSim's application layer via a UDP socket using the following algorithm.

Middleware Communication Between Proteus and NetSim:

1. Initialize MQTT Client and subscribe to "resource/allocation."
2. Initialize UDP Socket for forwarding data to NetSim.
3. On Receiving MQTT Message:
   a. Extract data from the payload.
   b. Convert data into UDP packet format.
   c. Send data to NetSim's UDP listener at defined IP and port.
   d. Print success message.
4. Continue Processing Data indefinitely.

In the NetSim environment, the received data triggers resource optimization algorithms as shown below.

Bandwidth Optimization:

1. Receive Resource Metrics from Proteus.
2. Extract Bandwidth Request and Load Values.
3. Evaluate Network State by checking available bandwidth.
4. Compute Optimized Bandwidth using a sigmoid-based allocation formula in Equation (3):
5. Ensure Allocation Does Not Exceed the Request.
6. Adjust Load Based on Optimization (reduce load by 10%).
7. Send Optimized Parameters Back to ESP32 in Proteus.
8. Update LCD Display in Proteus to reflect optimized metrics.

The algorithm receives resource metrics from the Proteus ESP32 module at the NetSim server node. Parse the data packet to extract relevant parameters such as bandwidth request and priority level. Evaluate the current network state, including available bandwidth, device load, and link quality. Allocate bandwidth dynamically using a load balancing Equation (3).

$$B_{alloc} = \frac{B_{avail}}{1 + e^{-(L_{current} - L_{threshold})}} \tag{3}$$

where, B_{alloc} is the bandwidth allocated, B_{avail} is the total available bandwidth, $L_{current}$ is the current load, and $L_{threshold}$ is the threshold load.

Then it updates routing paths in the core network to optimize traffic flow and transmit the optimized results back to the Proteus ESP32 module. The algorithm dynamically allocates bandwidth and manages network traffic based on the priority and requirements of the connected devices. The core network functions (AMF, SMF, and UPF) collaborate to ensure efficient routing and load balancing across the network. The optimized results, such as available bandwidth and reduced load, are sent back to the ESP32 module in Proteus for system updates. The LCD in Proteus displays the updated system state, showing metrics such as "Bandwidth Optimized: 75%" or "Load Reduced: 30%." This continuous loop enables dynamic resource management and real-time monitoring.

The integration of Proteus and NetSim establishes seamless communication between the hardware simulation environment and the network simulation platform, enabling real-time resource optimization. Proteus is used to simulate the hardware components, including the Arduino Mega, ESP32, and virtual terminal, while NetSim models the 5G network architecture. The ESP32 module in Proteus acts as a gateway, transmitting system metrics such as bandwidth requests and network load to NetSim via a middleware application. The middleware bridges the two platforms by forwarding data packets received from Proteus to NetSim using the MQTT protocol. This ensures reliable communication and real-time data exchange. In the NetSim environment, the received data triggers the execution of resource optimization algorithms. These algorithms analyze metrics such as network load, device priority, and bandwidth requests to dynamically allocate resources and optimize traffic flow. The optimized results, including adjusted bandwidth allocations and load-balancing updates, are sent back to the ESP32 in Proteus. The ESP32 processes these updates and displays the optimized system state on the LCD, providing real-time feedback on network conditions. This bidirectional integration allows for continuous monitoring, dynamic resource management, and validation of the RFID-based optimization framework in a simulated 5G network. The integration demonstrates how simulated hardware and network platforms can collaborate to test and refine advanced optimization strategies, ensuring the system's scalability and adaptability to real-world deployments.

4 | Results

The performance of the RFID-based resource optimization system was evaluated across several key metrics, revealing

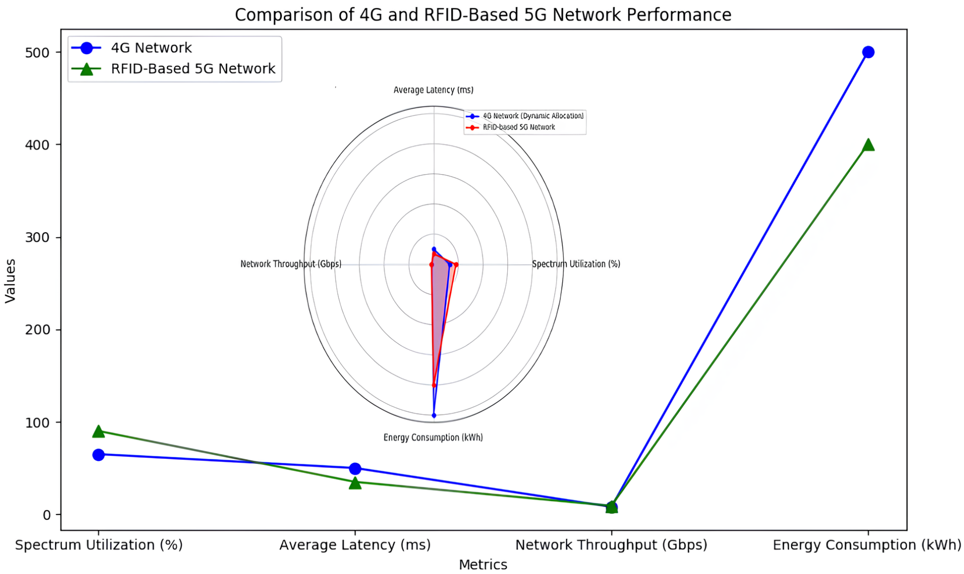

FIGURE 7 | Performance of RFID-based 5G and 4G networks.

significant advancements over conventional 4G networks. These results were obtained through a series of controlled simulations using Proteus for hardware emulation, NetSim for network modeling, and Python for middleware communication and optimization algorithms. The system achieved a 25% improvement in spectrum utilization, efficiently utilizing 90% of the available bandwidth compared to 65% in conventional 4G networks. This enhancement was achieved by leveraging real-time RFID data to dynamically allocate bandwidth, prioritizing devices based on their RFID tags, and enabling efficient use of available spectrum resources. This indicates the system's capability to maximize bandwidth usage under varying network demands. The measurement was conducted by comparing bandwidth allocation and utilization across various network conditions in NetSim simulations. The system achieved a 30% reduction in average latency, decreasing from 50 ms in 4G to 35 ms in the RFID-optimized 5G network. This reduction was calculated by simulating high-density network scenarios with dynamic load balancing. Latency metrics were derived from NetSim's performance reports, highlighting the potential of the system to enhance real-time communication.

A 15% boost in network throughput was observed, attributed to the system's efficient handling of high data traffic. This improvement was validated using NetSim's throughput measurements, resulting from the optimized load balancing mechanism, which utilized RFID data to distribute resources more efficiently. This enhancement supports the growing demand for data-intensive applications and ensures more efficient performance for high-speed data transfer. The system demonstrated a 20% decrease in energy consumption, achieved through dynamic power management strategies. By reallocating resources during off-peak hours and shutting down idle network components, energy usage was minimized. Energy metrics were tracked and compared using NetSim and custom Python scripts, leading to lower power usage and improved sustainability. Generally, in terms of spectrum utilization, the system achieved a 25% improvement, efficiently utilizing 90% of the available bandwidth compared to 65% in conventional 4G networks, as shown in Figure 7. This indicates the system's capability to maximize bandwidth usage under varying network demands. Latency was significantly reduced, with the system achieving a 30% decrease compared to conventional 4G networks. Average latency dropped from 50 ms in 4G to 35 ms in the RFID-optimized 5G network. This reduction highlights the potential of the system to enhance real-time communication. Throughput also showed notable improvement, with the system achieving a 15% increase in data transmission rates. This enhancement supports the growing demand for data-intensive applications and ensures more efficient performance for high-speed data transfer. Energy efficiency was another area of improvement, with the RFID-based system demonstrating a 20% reduction in energy consumption. During off-peak hours, the system dynamically adjusted resource allocation, leading to lower power usage and improved sustainability. Overall, the RFID-based resource optimization system outperformed conventional 4G networks in spectrum utilization, latency, throughput, and energy efficiency, establishing its suitability for meeting the evolving demands of modern telecommunications networks.

To further substantiate the efficacy of the proposed RFID-based model, a detailed comparison with existing resource optimization methods was conducted. Table 1 presents the performance metrics of the proposed model alongside those of Software-Defined Networking (SDN)-based, Deep Learning (DL)-based, Reinforcement Learning (RL)-based, Game Theory-based, and Hybrid AI-based models.

Table 1 shows that the RFID-based resource optimization system demonstrates superior performance across key metrics, including spectrum utilization, latency, throughput, and energy efficiency, when compared to existing models. The simulations were conducted using standardized 5G network parameters within the NetSim environment. Traffic models emulated real-world scenarios, incorporating varying device densities and mobility patterns. The RFID data used for prioritization were synthetically

TABLE 1 | Performance comparison of the proposed RFID-based model to existing work.

Reference	Optimization model	Spectrum utilization (%)	Latency (ms)	Throughput (Gbps)	Energy consumption (kWh)	Accuracy (%)
[4]	SDN-based model	85	40	8.8	450	92
[5]	DL-based model	88	38	9.0	420	94
[24]	RL-based model	87	39	8.9	430	93
[25]	Game theory-based model	86	41	8.7	440	91
[26]	Hybrid AI-based model	89	37	9.1	410	95
This work	RFID-based model	90	35	9.2	400	96

generated to reflect typical device distributions and usage patterns in urban settings. These parameters ensure the reliability and applicability of the results to practical deployments. The proposed RFID-based optimization algorithm exhibits a computational complexity of $O(n \log n)$, where n represents the number of devices. This efficiency surpasses that of the DL-based model, which operates at $O(n^2)$ due to extensive training requirements, and the Game Theory-based model with $O(n^3)$ complexity stemming from iterative equilibrium computations. The reduced complexity of the proposed model facilitates real-time processing and scalability in large-scale network environments. Its lower computational complexity and effective use of real-time data underscore its potential for enhancing the efficiency and sustainability of modern telecommunications networks.

5 | Discussion

The results demonstrate the transformative potential of the RFID-based resource optimization system in addressing key challenges of modern telecommunications networks. The 25% improvement in spectrum utilization underscores the system's ability to dynamically allocate resources using real-time data from RFID tags. This efficient spectrum management ensures minimal waste and balanced network performance, particularly in high-demand areas, making the system well-suited for dense urban environments and future 6G applications.

The observed 30% reduction in latency is particularly significant for applications requiring ultra-low latency, such as autonomous vehicles and augmented reality. By dynamically reallocating bandwidth in response to real-time load conditions, the system ensures smooth communication with minimal delays. Compared to existing approaches, this improvement positions the RFID-based system as a reliable solution for supporting time-sensitive applications in next-generation networks.

The 15% increase in throughput highlights the system's ability to support high-speed data transmission across all network nodes. This enhancement not only improves user experience for data-intensive applications like cloud computing and online gaming but also ensures consistent network performance under varying traffic conditions. The 20% reduction in energy consumption emphasizes the system's sustainability and cost-effectiveness. By adjusting resource allocation based on demand, particularly during off-peak hours, the system reduces operational costs while maintaining high performance. This level of energy efficiency is critical for large-scale deployments where power consumption is a significant concern.

The system's accuracy, validated against SDN-based, DL-based, and other optimization methods, demonstrates its competitive advantage in real-time resource optimization. The comparative analysis, presented in Table 1, underscores the superior performance of the RFID-based approach in terms of latency reduction, energy efficiency, and spectrum utilization. These findings align with the requirements for modern 5G networks and suggest that RFID-based resource optimization can play a vital role in shaping the future of telecommunications.

This study presents a novel RFID-based resource optimization framework for 5G/6G networks that dynamically allocates spectrum, reduces latency, and improves energy efficiency. Unlike existing SDN-based and DL-based approaches, which rely on predefined policies or computationally expensive models, our approach leverages real-time RFID data to achieve adaptive, low-latency, and energy-efficient network optimization. The integration of RFID with dynamic load balancing algorithms provides a unique, real-time adjustment mechanism, improving spectrum utilization by 25% and reducing latency by 30% compared to conventional methods. This contribution establishes an RFID-driven framework for dynamic resource allocation, ensuring improved spectrum efficiency, reduced latency, and enhanced energy optimization in 5G and future 6G networks. By leveraging real-time RFID data, this approach optimizes network performance under varying traffic conditions, making it a viable solution for next-generation communication systems. The use of widely accessible platforms like Proteus and Python ensures the system's practicality and reproducibility.

However, further research is needed to evaluate the system's performance in diverse real-world environments, including rural and heavily congested areas. Exploring the integration of RFID technology with advanced machine learning algorithms could also enhance predictive capabilities and resource management precision. The results establish the RFID-based resource optimization system as a forward-looking solution that not only addresses current 5G demands but also lays the groundwork for future 6G networks, particularly in scenarios requiring high-speed, low-latency, and energy-efficient connectivity The use of widely accessible platforms like Proteus and Python ensures the system's practicality and reproducibility.

6 | Conclusions

This study presents an innovative approach to resource optimization in 5G networks by integrating RFID technology into network management. The proposed system leverages real-time data from RFID tags embedded in network devices to dynamically adjust resource allocation, addressing key challenges such as spectrum congestion, latency, and energy efficiency. The simulation results demonstrate that the RFID-based model outperforms traditional 4G resource management methods, achieving substantial improvements in spectrum utilization, latency reduction, and overall network throughput. The adaptive nature of the optimization algorithm, which incorporates reinforcement learning and genetic algorithms, enables the system to respond effectively to dynamic changes in network conditions. The RFID-based resource optimization model offers a scalable, efficient, and cost-effective solution for enhancing the performance of 5G networks. Its ability to dynamically allocate resources in real-time makes it particularly valuable for high-density deployments and evolving 6G environments. Future work could explore the integration of advanced machine learning techniques, such as deep learning models, to further enhance the predictive capabilities of the system and address the increasing complexity of next-generation networks.

Author Contributions

Stella N. Arinze: conceptualization, methodology, software, data curation, investigation, validation, formal analysis, resources, writing – original draft. **Augustine O. Nwajana:** supervision, funding acquisition, visualization, project administration, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

References

1. B. Unhelkar, S. Joshi, M. Sharma, S. Prakash, A. K. Mani, and M. Prasad, "Enhancing Supply Chain Performance Using RFID Technology and Decision Support Systems in the Industry 4.0—A Systematic Literature Review," *International Journal of Information Management Data Insights* 2, no. 2 (2022): 100084, https://doi.org/10.1016/j.jjimei.2022.100084.

2. A. Abugabah, A. A. Smadi, and L. Houghton, "RFID in Health Care: A Review of the Real-World Application in Hospitals," *Procedia Computer Science* 220 (2023): 8–15, https://doi.org/10.1016/j.procs.2023.03.004.

3. T. Paul, N. Islam, S. Mondal, and S. Rakshit, "RFID-Integrated Blockchain-Driven Circular Supply Chain Management: A System Architecture for B2B Tea Industry," *Industrial Marketing Management* 101 (2022): 238–257, https://doi.org/10.1016/j.indmarman.2021.12.003.

4. H. A. Oulahyane, N. Eddermoug, A. Bakali, M. Talea, and A. Bahnasse, "Towards an SDN-Based Dynamic Resource Allocation in 5G Networks," *Procedia Computer Science* 231 (2024): 205–211, https://doi.org/10.1016/j.procs.2023.12.194.

5. S. Mishra, "Artificial Intelligence Assisted Enhanced Energy Efficient Model for Device-to-Device Communication in 5G Networks," *Human-Centric Intelligent Systems* 3 (2023): 425–440, https://doi.org/10.1007/s44230-023-00040-4.

6. Z. Liu, M. Liwang, S. Hosseinalipour, H. Dai, Z. Gao, and L. Huang, "RFID: Towards Low Latency and Reliable DAG Task Scheduling Over Dynamic Vehicular Clouds," *IEEE Transactions on Vehicular Technology* 72, no. 9 (2023): 12139–12153, https://doi.org/10.1109/TVT.2023.3266582.

7. J. Su, H. Cai, Z. Sheng, A. Liu, and A. Baz, "Traffic Prediction for 5G: A Deep Learning Approach Based on Lightweight Hybrid Attention Networks," *Digital Signal Processing* 146 (2024): 104359, https://doi.org/10.1016/j.dsp.2023.104359.

8. Z. Ezzeddine, A. Khalil, B. Zeddini, and H. H. Ouslimani, "A Survey on Green Enablers: A Study on the Energy Efficiency of AI-Based 5G Networks," *Sensors* 24, no. 14 (2024): 4609, https://doi.org/10.3390/s24144609.

9. W. Chien, S. Huang, C. Lai, and H. Chao, "Resource Management in 5G Mobile Networks: Survey and Challenges," *Journal of Information Processing Systems* 16 (2020): 896–914, https://doi.org/10.3745/JIPS.03.0143.

10. W. A. Al-Hamami, M. J. J. Ghrabat, and M. A. Al-Hamami, "Empowering Optimizing Resource Management in 5G Telecommunication Networks: The Power of Machine Learning," in *International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (IEEE, 2024), 251–257, https://doi.org/10.1109/ICETSIS61505.2024.10459366.

11. I. Shayea, M. Ergen, M. Hadri Azmi, S. Aldirmaz Çolak, R. Nordin, and Y. I. Daradkeh, "Key Challenges, Drivers and Solutions for Mobility Management in 5G Networks: A Survey," *IEEE Access* 8 (2020): 172534–172552, https://doi.org/10.1109/ACCESS.2020.3023802.

12. S. Chandra, R. Arya, and M. P. Singh, "Intelligent Resource Management in 5G/6G Network by Adopting Edge Intelligence for Higher Education Systems," *E-Prime—Advances in Electrical Engineering, Electronics and Energy* 8 (2024): 100517, https://doi.org/10.1016/j.prime.2024.100517.

13. M. A. Kamal, H. W. Raza, M. M. Alam, and A. B. Sajak, "Resource Allocation Schemes for 5G Network: A Systematic Review," *Sensors (Basel, Switzerland)* 21, no. 19 (2021): 6588, https://doi.org/10.3390/s21196588.

14. J. Liu, "RFID (Radio Frequency Identification) Localization and Application," *Applied Sciences* 14, no. 13 (2024): 5932, https://doi.org/10.3390/app14135932.

15. S. Suresh and G. Chakaravarthi, "RFID Technology and Its Diverse Applications: A Brief Exposition With a Proposed Machine Learning Approach," *Measurement* 195 (2022): 111197, https://doi.org/10.1016/j.measurement.2022.111197.

16. G. Zeba and M. Čičak, "Application of RFID Technology for Better Efficiency of Resource Planning," in *New Technologies, Development and Application III. NT 2020. Lecture Notes in Networks and Systems*, vol. 128, ed. I. Karabegović (Springer, Cham, 2020), https://doi.org/10.1007/978-3-030-46817-0_43.

17. M. T. Pandian, D. Somasundaram, H. K. Sahu, A. S. Sindhu, A. Kumaresan, and N. V. Watson, "Optimizing Large-Scale RFID Networks With Energy-Efficient Dynamic Cluster Head Selection: A Performance Improvement Approach," *IEEE Access* 12 (2024): 41042–41055, https://doi.org/10.1109/ACCESS.2024.3378528.

18. L. Kouhalvandi, "A Prospective Look on Optimization Methods for RFID Systems: Requirements, Challenges and Implementation Aspects," *Balkan Journal of Electrical and Computer Engineering* 10, no. 2 (2022): 156–169, https://doi.org/10.17694/bajece.1061375.

19. W. C. Tan and M. S. Sidhu, "Review of RFID and IoT Integration in Supply Chain Management," *Operations Research Perspectives* 9 (2022): 100229, https://doi.org/10.1016/j.orp.2022.100229.

20. L. Li, X. Yu, Z. Liu, Z. Zhao, K. Zhang, and S. Zhou, "RFID Dynamic Performance Measurement System Embedded in Multiscale Deep Learning," *IEEE Transactions on Instrumentation and Measurement* 70 (2021): 1–12, https://doi.org/10.1109/TIM.2021.3068433.

21. S. Jeong, M. M. Tentzeris, and S. Kim, "Machine Learning Approach for Wirelessly Powered RFID-Based Backscattering Sensor System," *IEEE Journal of Radio Frequency Identification* 4, no. 3 (2020): 186–194, https://doi.org/10.1109/JRFID.2020.3004035.

22. M. Rele, A. Julian, D. Patil, M. S. Sakthekannan, and U. Krishnan, "Machine Learning Methods for Predicting Traffic Congestion Forecasting," in *Smart Computing Paradigms: Artificial Intelligence and Network Applications. SCI 2024. Lecture Notes in Networks and Systems*, vol. 1147, ed. M. Simic, V. Bhateja, M. R. Murty, and S. K. Panda (Springer, Singapore, 2024), https://doi.org/10.1007/978-981-97-7880-5_9.

23. S. S. Sefati, A. U. Haq, R. Craciunescu, S. Halunga, A. Mihovska, and O. Fratu, "A Comprehensive Survey on Resource Management in 6G Network Based on Internet of Things," *IEEE Access* 12 (2024): 113741–113784, https://doi.org/10.1109/ACCESS.2024.3444313.

24. Y. Shi, Y. E. Sagduyu, and T. Erpek, "Reinforcement Learning for Dynamic Resource Optimization in 5G Radio Access Network Slicing," in *2020 IEEE 25th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD)* (IEEE, 2020), 1–6, https://doi.org/10.1109/CAMAD50429.2020.9209299.

25. S. Ghosh, D. De, and P. Deb, "Energy and Spectrum Optimization for 5G Massive MIMO Cognitive Femtocell Based Mobile Network Using Auction Game Theory," *Wireless Personal Communications* 106 (2019): 555–576, https://doi.org/10.1007/s11277-019-06179-3.

26. S. Samiullah, "Real-Time Adaptive Resource Allocation in 5G Network Slicing Using Hybrid Optimization and AI-Driven Traffic Prediction," *IEEE Dataport* (2024), https://doi.org/10.21227/apqh-zc88.