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ORIGINAL RESEARCH

Smart performance optimization of energy-aware scheduling model for resource sharing in 5G green communication systems

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Abstract

This paper presents an analysis of the performance of the Energy Aware Scheduling Algorithm (EASA) in a 5G green communication system. 5G green communication systems rely on EASA to manage resource sharing. The aim of the proposed model is to improve the efficiency and energy consumption of resource sharing in 5G green communication systems. The main objective is to address the challenges of achieving optimal resource utilization and minimizing energy consumption in these systems. To achieve this goal, the study proposes a novel energy-aware scheduling model that takes into consideration the specific characteristics of 5G green communication systems. This model incorporates intelligent techniques for optimizing resource allocation and scheduling decisions, while also considering energy consumption constraints. The methodology used involves a combination of mathematical analysis and simulation studies. The mathematical analysis is used to formulate the optimization problem and design the scheduling model, while the simulations are used to evaluate its performance in various scenarios. The proposed EASM reached a 91.58% false discovery rate, a 64.33% false omission rate, a 90.62% prevalence threshold, and a 91.23% critical success index. The results demonstrate the effectiveness of the proposed model in terms of reducing energy consumption while maintaining a high level of resource utilization.

1 | INTRODUCTION

The emergence of 5G green communication systems signifies a revolutionary leap in 21st-century technology, offering faster, more reliable, and secure internet connectivity [1]. These systems minimize energy consumption and infrastructure installation, fostering sustainability and enabling efficient remote monitoring and control [2]. They support the Industrial Internet of Things (IIoT) and cloud computing, reducing energy costs and emissions [3]. Additionally, 5G can enable distributed energy grids, enhancing clean energy production and distribution [4]. 5G green communication systems revolutionize various industries and new technologies, delivering speed, reliability, and sustainability [5]. They provide an alternative to less energy-efficient networks, reducing Carbon dioxide (CO_2) emissions and energy costs while accelerating operations [6]. 5G's higher bandwidth facilitates faster internet access and new tech applications. These systems also improve global data transfer, benefitting businesses and rural areas [7]. The emergence of 5G green communication systems brings vastly increased speed and capacity, drastically improving energy efficiency and supporting numerous applications [8]. It reduces energy wastage while maintaining a stable, reliable connection [9]. These systems serve diverse sectors like automotive, agriculture, and video streaming, improving real-time navigation, environmental monitoring, and cost reductions [10]. Additionally, 5G infrastructure supports "smart" city resources [11]. The energy-aware scheduling algorithm optimizes resource sharing, reducing energy consumption and interference, crucial for enhancing 5G green communication system performance

[12]. The collaborative V2X data correction method involves sharing resources such as computing power, data storage, and network bandwidth among multiple vehicles and infrastructure nodes. It allows for the efficient processing and correction of V2X data, improving the accuracy and reliability of communication between vehicles and infrastructure collaboratively [13].

1.1 | Functions of antenna systems

Antenna systems play a crucial role in energy-efficient 5G green communication systems as they are responsible for transmitting and receiving signals in wireless communication. They are an integral part of the overall energy consumption in a 5G network and can significantly impact the efficiency and sustainability of the system [14, 15]. There are several aspects of antenna systems in energy-efficient 5G green communication systems that need to be considered:

- Multiple Antenna Technology: One of the key technologies used in energy-efficient 5G green communication systems is multiple antenna technology. This involves the use of multiple antennas at both the transmitter and receiver ends, which allows for efficient transmission and reception of signals. This technology enables higher data rates while reducing overall power consumption [16, 17].
- MIMO (Multiple-Input Multiple-Output): MIMO technology is a key feature of energy-efficient 5G green communication systems. It involves using multiple antennas at both the transmitter and receiver ends to increase data throughput and reduce power consumption. MIMO not only improves signal quality but also enables energy savings by spatially multiplexing data streams [18, 19].
- Beam Steering: Beam steering technology is used to direct the signal from the antenna towards a specific user or direction. This ensures that the signal is not wasted in unwanted directions, leading to energy efficiency. By using smart antennas and Beamforming, the communication can be optimized to use less power while maintaining high data rates [20].
- Small Cell Networks: Small cell networks are another important aspect of energy-efficient 5G green communication systems. These networks use small, low-power base stations to cover a smaller area, reducing the overall power consumption. By using small cells, the distance between the user device and the base station is reduced, resulting in less transmitted power and better energy efficiency [21].
- Energy Harvesting: Energy harvesting techniques, such as using solar panels or wind turbines, can be integrated with antenna systems to power the communication devices. This reduces the reliance on traditional energy sources and makes the system more sustainable [22].

The antenna systems play a crucial role in energy-efficient 5G green communication systems, enabling higher data rates, reducing power consumption, and contributing to the overall sustainability of the system. With the advancements in antenna technology, 5G networks can become more energy-efficient and environmentally friendly [23].

Resource sharing and task offloading in IoT fog computing refers to distributing and assigning tasks to different computing nodes (such as edge devices) in a fog computing environment. It enables efficient use of resources and improves the overall performance of IoT applications by reducing network latency and processing delays [24]. Secure and latency-aware digital twin-assisted resource scheduling for 5G edge computing is a system that uses digital twin technology to create virtual replicas of physical resources and uses them to optimize the allocation of resources in 5G edge computing. It ensures data security and low latency by accurately predicting resource demands and adjusting resource allocation in real-time [25]. Cooperative OMA and NOMA systems refer to a combination of multiple access technologies that can be used to deploy 6G networks. In this scenario, users with diverse channel conditions can share the same frequency band through orthogonal or non-orthogonal transmission schemes, increasing network efficiency and capacity [26]. Energy and spectral efficiency optimization using probabilistic-based spectrum slicing is a technique that utilizes probabilistic methods to slice the available spectrum into smaller sub-bands, allowing for more efficient use of energy and spectrum resources. It helps to improve overall system performance and increase capacity for wireless communication networks [27]. Request-based and task-based are the two main scheduling paradigms used in operating systems. They both have different approaches to handling the execution of processes in a system. The main difference between them lies in the way they manage and allocate resources for processes. Table 1 provides the difference between request-based and task-based scheduling.

The request-based scheduling is more suitable for a system with a large number of short processes, while task-based scheduling is better for a system with a smaller number of longer processes [28]. Both have their advantages and disadvantages, and their choice depends on the requirements Power optimization using optimal small-cell arrangements refers to strategically placing small-cell base stations in different deployment scenarios to improve network coverage and capacity while minimizing energy consumption. This involves analysing factors like signal strength, user distribution, and interference patterns to determine the most efficient placement of small cells for optimal power usage [29]. Optimizing vertical handoff using Hybrid Cuckoo Search and Genetic Algorithm is a strategy for improving wireless communication quality by optimizing switching between networks. It combines two optimization techniques, Cuckoo Search and Genetic Algorithm, to find the most efficient handoff decision. This helps enhance wireless networks' overall performance and efficiency [30]. Power optimization with low complexity using a scaled Beamforming approach for a massive MIMO and small cell scenario is a technique that uses advanced signal processing algorithms to reduce power consumption in communication systems with many antennas and small cells. This results in improved energy efficiency with minimal computational complexity, making it suitable for practical implementation [31].

TABLE 1 Comparison of request-based and task-based scheduling.

Sector	Request-based scheduling	Task-based scheduling
Concept	Request-based scheduling is based on the principle of accepting and executing processes based on the order in which they are received by the system.	Task-based scheduling focuses on managing and executing individual tasks within a process, rather than the entire process itself.
Resource allocation	In request-based scheduling, resources are allocated to processes in a first-come-first-served manner. The process that arrives first gets executed first.	In task-based scheduling, resources are allocated to individual tasks within a process as and when they are needed. This allows for better utilization of resources and prevents bottlenecks.
Response time	Request-based scheduling typically has a longer response time as processes are executed in the order they arrive, and new processes have to wait for previous ones to finish.	Task-based scheduling has a shorter response time as individual tasks within a process can be executed concurrently, improving overall efficiency.
Process completion	In request-based scheduling, processes are only completed when all the tasks within them are finished. This can cause delays and inefficiency in completing processes.	In task-based scheduling, individual tasks are completed separately, which allows for faster completion of processes as each task can be executed as soon as its resources are available.
Priority	Request-based scheduling does not consider the priority of a process and sequentially executes it.	Task-based scheduling allows for prioritization of tasks within a process, ensuring that critical tasks are executed first.

The super-efficient GSM Triplexer is a device that supports 5G connectivity for the Internet of Things (IoT) in sustainable smart grid edge computing systems. It enables seamless communication between devices and the metaverse, allowing for efficient energy management in the grid and enhanced user experiences in virtual reality [32]. A high-efficiency diplexer design for sustainable 5G-enabled IoT communication in metaverse transportation systems and smart grids. The diplexer allows simultaneous transmission and reception of different frequency bands, improving overall system efficiency and enabling seamless connectivity in emerging technologies such as the metaverse and smart grids [33]. The main contributions of the research have the following key functionalities.

- Reduced energy consumption: It helps reduce the energy consumption of 5G green communication systems. By scheduling and allocating resources intelligently, energy-aware scheduling algorithms can minimize total energy consumption and maximize the utilization of resources.
- Reducing latency: It improves system performance by reducing latency, bottleneck, and resource contention issues. By improving the efficiency of resource allocations, energy-aware scheduling algorithms can improve the performance of 5G green communication systems.
- Maximum resource utilization: It allows for better utilization of available resources. By choosing the most efficient resources at the right time and allocating resources optimally, energy-aware scheduling algorithms can make sure that available resources are being essentially utilized.
- Reduced operational cost: It reduces operational costs. Energy-aware scheduling algorithms can reduce the operational costs associated with 5G green communication systems by ensuring that the most efficient resources are allocated when required.
- Rapid data transfer: It facilitates faster application data processing. By reducing the scheduling overhead and ensuring the right resources are available at the right time, energy-aware scheduling algorithms can speed up the application data processing in 5G green communication systems.

The remaining parts of the research have focused on the following functions. Section 2 provides a detailed discussion of the current research works. Section 3 illustrates the complete specification and structure of the proposed model. Section 4 expressed the system modelling. Section 5 expresses the results and discussion and finally, Section 6 shows the conclusion and future scope of the proposed model.

2 | LITERATURE REVIEW

The comprehensive survey discussed various facets of resource sharing, energy-aware optimization, and green communication systems in the 5G era. These endeavours are driven by the overarching goal of reducing resource consumption, enhancing efficiency, and ultimately contributing to cost savings and environmental sustainability.

Srivastava et al. [34] have discussed the cooperation-based energy-aware reward scheme that aims to improve the overall efficiency and energy consumption of green cognitive radio networks. It incentivizes users to cooperate and share resources in order to reduce energy consumption and promote sustainable practices. This can lead to a more environmentally friendly and cost-efficient network. Riasudheen et al. [35] have discussed the proposed routing scheme that aims to reduce energy consumption and prolong network lifetime in Mobile Ad hoc Networks (MANETs) by leveraging cloud resources in the 5G network. It utilizes an energy-efficient path selection algorithm to route data through the most energy-efficient nodes while offloading computation and storage tasks to the cloud to reduce the energy burden on the mobile nodes. Raeisi-Varzaneh et al. [36] have discussed resource scheduling in edge computing, which refers to the process of optimizing the allocation and utilization of computing resources in a distributed edge environment. This involves dynamically managing and allocating resources such as storage, processing power, and network bandwidth to meet the demands of edge devices and applications, ensuring efficient and timely processing of data at the edge. This also helps minimize latency and improve the overall performance of edge computing systems. KN, S. G., et al. [37] have discussed an energy-aware resource allocation and complexity reduction approach for cognitive radio networks using game theory, which is a cognitive radio network optimization technique that aims to maximize energy efficiency and minimize the complexity of resource allocation by utilizing game theory principles. It involves strategic decision-making for resource allocation among multiple users, considering the trade-off between energy consumption and system performance. Kabir et al. [38] have discussed energy-aware caching and collaboration as a method for improving energy efficiency in communication systems by reducing the amount of data that needs to be transmitted. It involves storing frequently used data locally and sharing it among neighbouring devices, thereby reducing the need for energy-intensive data transmissions. This approach has the potential to reduce the carbon footprint of communication systems and make them more eco-friendly. Tsai et al. [39] have discussed an "Energy-Aware Mode Selection for D2D Resource Allocation in 5G Networks" is a research work that proposes a method to improve power efficiency in 5G networks by optimizing the selection of device-to-device (D2D) communication modes. This approach takes into account energy consumption and network load balance to allocate resources and enhance energy efficiency while maintaining high data rates. Taneja et al. [40] have discussed the energy-aware resource control mechanism that aims to optimize the performance of future green 6G networks by efficiently managing energy consumption. It involves techniques such as dynamic power management and energy-aware scheduling to reduce the network's carbon footprint and increase its overall efficiency. This mechanism will play a vital role in achieving sustainable and environmentally friendly 6G networks.

Mohajer et al. [41] have discussed Energy-aware hierarchical resource management in heterogeneous cellular networks that involve the efficient allocation and utilization of resources considering energy constraints. Backhaul traffic optimization aims to minimize energy consumption and delay in data transmission from base stations to the core network. This approach ensures a more sustainable and efficient operation of cellular networks. Saibharath et al. [42] have discussed the Joint QoS and energy-efficient resource allocation and scheduling in a 5G Network. Slicing is the process of optimizing the allocation and scheduling of resources among different slices in a 5G network to ensure high quality of service (QoS) for users while also minimizing energy consumption. This allows for efficient use of network resources and improved user experience. Sisi et al. [43] have discussed Blockchain technology as a decentralized, secure, and tamper-proof system that has the potential to revolutionize energy-aware mobile crowd-sensing approaches in IoT. It provides a transparent and efficient way to collect and manage data from IoT devices, ensuring data authenticity and integrity while promoting energy efficiency through smart contract-based incentives. Logeshwaran et al. [44] have discussed in the context of 5G wireless personal area networks (WPANs), a smart load-based resource optimization model is proposed to improve the performance of device-to-device (D2D) communication. This model incorporates techniques such as user grouping and resource allocation to efficiently manage the network's resources, reducing interference and enhancing the overall network capacity and quality of service. Salh et al. [45] have discussed a framework that aims to reduce energy consumption in IoT devices by utilizing federated learning and resource allocation techniques. This approach enables efficient edge intelligence in the emerging 5G networks, leading to reduced energy consumption and improved network sustainability.

Zimmo et al. [46] have discussed a Power-aware coexistence of Wi-Fi and LTE in the unlicensed band, which refers to the ability of these two wireless technologies to efficiently share the same frequency band without causing interference with each other. This is achieved through the use of time-domain virtualization, which allocates specific time slots to each technology to avoid collisions and optimize power usage. Lu et al. [47] have discussed that dynamic offloading for energy-aware scheduling in the mobile cloud is a technique that optimizes the allocation of tasks between the mobile device and the remote cloud server based on the energy consumption of the mobile device. This allows for efficient utilization of resources, reduced energy consumption, and improved performance of mobile applications. Liu et al. [48] have discussed the Novel Radio Resource Allocation Scheme, which aims to improve the efficiency and performance of 5G and future sharing networks through multi-dimensional collaboration. This involves dynamically allocating resources such as spectrum, power, and computing among different networks and users while also considering factors such as demand, interference, and network conditions for optimal resource utilization. Wu et al. [49] have discussed hybrid traffic scheduling in 5G and time-sensitive networking (TSN). Integrated networks refer to the combination of different networking technologies to enable efficient and reliable communication in virtual power plants, which are complex energy systems that use renewable energy sources. This approach aims to improve energy management and reduce network delays, ensuring stable and low-latency communication for optimal performance. Kaur et al. [50] have discussed energy-efficiency schemes for base stations in 5G heterogeneous networks focusing on reducing energy consumption and optimizing resource allocation to improve sustainability. This can be achieved through techniques such as dynamic cell clustering, sleep mode operation, and energy harvesting. These schemes aim to minimize the environmental impact and operating costs of 5G networks while maintaining high performance. Mughees et al. [51] have discussed a method that proposes using

TABLE 2 Comprehensive analysis of related works.

Authors	Year	Advantage	Limitation
Srivastava et al. [34]	2023	Promotes collaboration among users and incentivizes energy efficiency, leading to a more sustainable and efficient use of cognitive radio technology.	Lack of consideration for communication limitations and interference in a dynamic and congested wireless environment.
Riasudheen et al. [35]	2020	Minimizes energy consumption in MANETs, resulting in longer battery life and improved network sustainability	Lack of consideration for network stability under changing network conditions and node dynamics.
Raeisi-Varzaneh et al. [36]	2023	Resource scheduling in edge computing improves the efficiency of resource allocation, leading to faster processing and reduced latency.	Limited availability of resources due to the distributed nature of edge computing and potential interference or conflicts between multiple devices.
KN et al. [37]	2020	Improves energy efficiency and reduces complexity, leading to cost savings and improved network performance.	The approach may not apply to all types of cognitive radio networks or scenarios.
Kabir et al. [38]	2021	Reduces energy consumption in communication systems, leading to a more environmentally friendly and cost-effective solution.	The approach may not be feasible for all types of communication systems or network configurations.
Tsai et al. [39]	2023	It enables improved energy efficiency and prolongs battery life for devices in 5G networks.	It only considers the energy consumption of individual devices without taking into account network-wide energy efficiency.
Taneja et al. [40]	2022	It Reduces energy consumption and carbon footprint, promoting sustainability and environmental responsibility in 6G networks.	It may not be suitable for all types of network architectures and may require significant modifications for its implementation
Mohajer et al. [41]	2022	Reduced energy consumption and improved backhaul traffic efficiency in heterogeneous cellular networks.	This approach may not be feasible for smaller or rural cellular networks with limited resources.
Saibharath et al. [42]	2023	The use of Joint QoS and energy-efficient resource allocation and scheduling in 5G network slicing.	It requires sophisticated algorithms and efficient computing power, which may not be feasible for all network providers.
Sisi et al. [43]	2021	The use of Blockchain technology ensures secure and transparent data transfer, contributing to reliable and trustworthy data collection.	Limited scalability due to increasing energy and computational costs associated with Blockchain validation for a large number of IoT.
Logeshwaran et al. [44]	2023	It optimizes resource allocation for better device-to-device communication, enhancing overall performance in 5G-WPAN	The model does not consider interference from other devices in the network.
Salh et al. [45]	2023	It enables efficient use of resources for both energy savings and improving performance in B5G environments.	It does not consider the impact of network congestion and communication delays on resource allocation.
Zimmo et al. [46]	2021	Improved energy efficiency and battery life for devices using both Wi-Fi and LTE in the unlicensed band.	Limited support for devices without time-domain virtualization capability, makes it difficult for all Wi-Fi and LTE devices to coexist.
Lu et al. [47]	2022	Automatically adjusts resource allocation for tasks on mobile devices, optimizing energy consumption and extending battery life.	Lack of consideration for network resource availability may result in suboptimal offloading decisions.
Liu et al. [48]	2023	Efficient utilization of radio resources, leading to improved network performance in 5G and future sharing networks.	A lack of real-world implementation may limit the effectiveness and practicality of the proposed allocation scheme.
Wu et al. [49]	2023	Increased efficiency in communication and coordination between virtual power plants and the power grid, leading to more reliable and sustainable energy management.	Difficulty in implementing and maintaining the complex hybrid scheduling algorithm in a rapidly evolving network environment.
Kaur et al. [50]	2023	Improved network performance and reduced energy costs due to optimized base station operation and energy consumption.	Analysis not based on real-world environmental conditions, leading to potentially inaccurate energy consumption estimates.
Mughees et al. [51]	2023	It can significantly reduce energy consumption in 5G HetNets and improve overall network performance.	Limited generalizability to other types of network architectures and environments.

a combination of multi-agent and deep reinforcement learning techniques to make resource allocation decisions in 5G HetNets. By considering energy efficiency as a key metric and using a parameterized approach, it aims to improve network performance and reduce energy consumption [52]. Tables 2 and 3 show the comprehensive analysis and performance analysis of related works, respectively.

Table 2 displays data on the energy efficiency and resource utilization of various systems or processes. The left side of the table describes the system or process, while the right

TABLE 3 Performance analysis of related works.

Authors	Model	Network size	Application	Energy efficiency	Resource allocation
Srivastava et al. [34]	Cooperation based energy aware reward scheme	Large	Green Cognitive Radio Networks	High	Low
Riasudheen et al. [35]	Energy-aware routing scheme	Large	Cloud Assisted MANET	Low	High
Raeisi-Varzaneh et al. [36]	Resource scheduling	Large	Edge Computing	Low	High
KN et al. [37]	Energy-aware resource allocation	Medium	Cognitive Radio Networks	Low	Low
Kabir et al. [38]	Energy-aware caching	Small	Green Communication Systems	Low	High
Tsai et al. [39]	Energy-aware mode selection	Small	5G networks	High	Low
Taneja et al. [40]	Energy-aware resource control	Large	Green 6G networks	High	Low
Mohajer et al. [41]	Energy-aware hierarchical resource management	Medium	Heterogeneous cellular networks	High	Low
Saibharath et al. [42]	Resource allocation and scheduling	Small	5G networks	Low	High
Sisi et al. [43]	Energy-aware mobile crowd-sensing	Medium	IoT Networks	Low	Low
Logeshwaran et al. [44]	Load-based resource optimization	Small	5G-WPAN	Low	Low
Salh et al. [45]	Energy-efficient federated learning	Medium	Green IoT Networks	Low	High
Zimmo et al. [46]	Time-domain virtualization	Medium	Wireless Networks	Low	High
Lu et al. [47]	Energy-aware scheduling	Small	Mobile Cloud Networks	High	Low
Liu et al. [48]	Radio resource allocation scheme	Large	5G Wireless Networks	High	Low
Wu et al. [49]	Hybrid traffic scheduling	Large	5G Wireless Networks	Low	High
Kaur et al. [50]	Energy-efficiency scheme	Small	5G heterogeneous Networks	Low	High
Mughees et al. [51]	Energy-efficient joint resource allocation	Large	5G heterogeneous Networks	High	Low

side contains the corresponding energy efficiency and resource utilization ratings.

Energy efficiency: It refers to the amount of input energy required to produce a desired output. A high energy efficiency rating indicates that the system or process requires minimal energy input to produce an output, making it more efficient. On the other hand, a low energy efficiency rating means that a higher amount of energy input is needed to produce the same output, indicating lower efficiency.

Resource utilization: It refers to the amount of resources used by the system to produce the desired output. A high resource utilization rating indicates that the system is utilizing a high amount of resources to produce an output, while a low rating indicates a more efficient use of resources.

It can be seen that systems or processes with high energy efficiency and resource utilization ratings are considered highly efficient and sustainable. This means that they require minimal energy input and use resources efficiently to produce the desired output. On the other hand, systems with low energy efficiency and resource utilization ratings are considered less efficient and not as sustainable. Systems or processes with moderate energy efficiency and resource utilization ratings fall in the middle of the spectrum and may require some improvements to become more efficient and sustainable. Overall, the data in Table 2 can help identify areas for improvement and guide decision-making towards more efficient and sustainable systems and processes. Based on the comprehensive analysis, the following issues were identified. They are,

- Energy efficiency: Energy efficiency is a significant challenge in 5G green communication systems. Developing energy-efficient protocols and techniques is crucial for the success of 5G green communication systems.
- Bandwidth allocation: There is a need to optimize the allocation of bandwidth between different users to ensure efficient usage of the available resources.
- Resource utilization: Developing methods for efficiently utilizing the available resources is essential for providing quality service to users.
- Interference management: Managed interference between 5G green communication systems is a significant challenge, as interference can reduce the quality of service.
- Network security: Security is essential in 5G green communication systems. Ensuring secure communication between devices is essential for adequately functioning the system.

Resource sharing in 5G green communication systems allocates resources such as spectrum, power, and computing among users in a wireless network. By using resource sharing, the network can efficiently use its resources and thus reduce energy consumption. Resource sharing can be achieved in several ways: spectrum reuse, power control, cooperative communication, and load balancing. Spectrum reuse is the most commonly used method to share spectrum resources in 5G, where the same spectrum is used for different users at different times. Power control is used to adjust each user's transmit power, which helps reduce interference. Cooperative communication allows users to cooperate and share their resources. Finally, load balancing distributes the network load among users and reduces energy consumption.

The technical novelty of an energy-aware scheduling model for resource sharing in 5G green communication systems lies in its ability to dynamically allocate resources based on the energy usage of the devices. This approach takes into account the energy consumption patterns of the devices and adjusts the resource allocation accordingly, resulting in reduced energy consumption and improved energy efficiency.

- Energy-oriented approach: The energy-aware scheduling model puts energy efficiency at the forefront, making it a key factor in resource allocation decisions. This is in contrast to traditional models that prioritize throughput or delay in resource allocation.
- Dynamic resource allocation: The model uses real-time energy consumption data to continuously adjust resource allocation, rather than pre-determined static allocations. This dynamic approach allows for better utilization of resources and reduces unnecessary energy consumption.
- Device-specific considerations: The model takes into account the energy consumption patterns of individual devices, rather than treating all devices as equal. This personalized approach ensures optimal resource allocation for each device, resulting in overall energy savings.
- Green communication: This model is specifically designed for 5G green communication systems, where energy efficiency is a critical factor in meeting sustainability goals. By incorporating energy-aware scheduling, this model contributes to the overall goal of reducing the carbon footprint of the communication industry.
- Implement an access control mechanism: The access control mechanism is one of the most effective ways to ensure resource sharing in 5G green communication systems. It involves setting up appropriate policies for granting access to the resources and enforcing them through authentication and authorization protocols.
- Utilize network virtualization: Virtualization of networks has been proven to be a great way of optimizing resource usage in green communication systems. It can reduce latency and increase the overall system's efficiency.
- Optimize resource allocation: Resource allocation in green communication systems should be optimized to ensure that all the resources are utilized efficiently. It can be done by setting up an appropriate scheduling algorithm that can allocate resources to the different nodes in the network.
- Implement network coding techniques: Network coding techniques can be used to reduce the number of resources needed to transmit data. It can help to increase resource sharing in green communication systems.

Resource sharing in 5G green communication systems is the ability of multiple users to access the same resources, such as spectrum, antennas, and communication channels, at the same time. It enables efficient use of resources and is critical for developing a sustainable 5G network. Additionally, resource sharing can reduce costs and increase overall network performance. It can also reduce the energy required to transmit data, as less power is needed to share the same resources.

The energy aware scheduling algorithm is a computational approach that aims to reduce energy consumption without compromising system performance. It is based on established concepts such as dynamic voltage and frequency scaling (DVFS) and task scheduling. The algorithm works by dynamically adjusting the frequency and voltage of the processor based on the current workload and performance requirements. This is achieved by utilizing feedback loops and control theory principles to continuously monitor the system and make real-time decisions for optimal energy efficiency. The novelty of the energy aware scheduling algorithm lies in its integration of various well-known techniques such as DVFS, task scheduling, and control theory. The algorithm leverages the individual strengths of each technique to achieve a more sophisticated and comprehensive energy management strategy. The proposed energy aware scheduling algorithm differs from previous approaches mainly in its incorporation of multiple established concepts to create a more robust and efficient solution for reducing energy consumption. However, it does not introduce any significant new elements or techniques that have not been previously utilized in energy management algorithms.

3 | PROPOSED MODEL

In the 5G communication scenario, the geometry relationship between the 5G transmitter, 5G receivers, the antenna beam, and the channel plays a crucial role in the successful transmission of data. The 5G transmitter and receiver are located at different points in the communication link, with the transmitter being responsible for sending data and the receiver for receiving it. These two devices are connected through a channel, which acts as a medium for the transmission of data. The antenna beam is a directional beam of electromagnetic waves that is used to transmit and/or receive data in a specific direction. In 5G communication, multiple antennas are used to create beams in different directions to improve the performance and capacity of the network. The antenna beam and the channel have a critical geometry relationship as the beam must be directed towards the receiver for successful data transmission. The channel, which acts as a pathway for the beam to travel, must also be clear of any obstacles or interference to ensure a strong and stable signal. To illustrate this relationship, imagine a scenario where a user is using their Smartphone to stream a video. The 5G transmitter is located on a cell tower, sending data to the

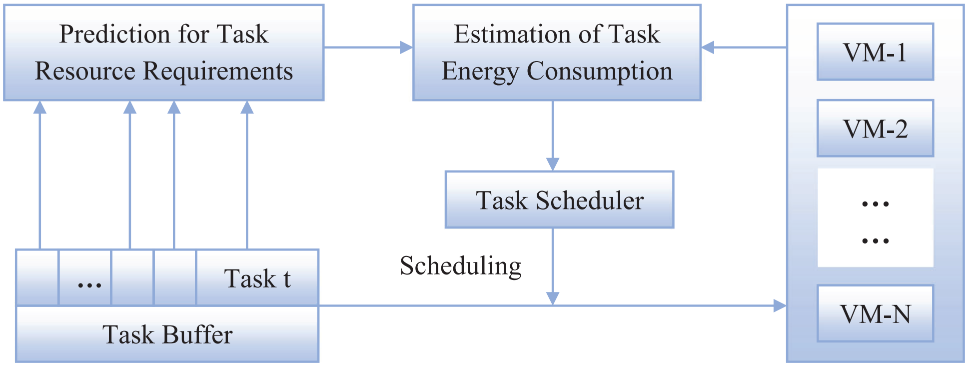

FIGURE 1 Energy-aware scheduling.

user's smartphone through the channel. The antenna beam is directed towards the user's device, allowing for a strong and stable connection. Any obstructions or interference in the channel or the beam's path could result in a weak or interrupted signal, leading to poor video quality or dropped calls. The geometry relationship between these components also plays a crucial role in 5G's ability to support massive connectivity. With the use of multiple beams and precise control over the direction and strength of each beam, 5G networks can efficiently support a large number of devices simultaneously, without causing interference or degradation of the signal. The geometry relationship between the 5G transmitter, receiver, antenna beam, and the channel is essential in ensuring high-speed, reliable, and efficient data transmission in 5G communication scenarios. The energy-aware scheduling algorithm has improved resource sharing in 5G green communication systems by helping optimize communication resource scheduling to reduce energy consumption. This algorithm optimizes the communication resources to minimize the total energy consumption while maximizing the quality of service (QoS) performance. The algorithm considers the energy consumption of different communication links, the data rate of each link, and the number of users connected to the system. It then uses this information to create an energy-efficient scheduling scheme that improves resource sharing in the system. It reduces total energy consumption and allows for better user resource sharing. In addition, the algorithm can be used to dynamically adjust the resource allocation according to the changing traffic conditions in the system. It helps to reduce energy consumption further and improve resource sharing. The functional blocks of energy-aware scheduling as shown in the following Figure 1.

Energy-aware scheduling is scheduling tasks on computer systems to minimize energy consumption. It aims to reduce energy consumption by adjusting the scheduling of tasks in order to reduce the total energy consumption. It is essential for mobile devices, which must conserve energy in order to maximize battery life. Energy-aware scheduling algorithms can take into account a variety of factors, such as the energy requirements of individual tasks, the availability of energy-efficient hardware, the current load on the system, and the current environmental conditions.

3.1 | Methodology

Energy aware scheduling algorithm (EAS) maximizes the efficiency of energy usage in computing systems by dynamically scheduling tasks on processors based on their energy consumption. The main objective of EAS is to reduce energy consumption while maintaining the overall performance of the system. This is achieved by considering energy consumption as an additional factor in the traditional scheduling algorithms. The EAS algorithm follows a two-phase approach, a feedback phase, and a resource assignment phase. The feedback phase continuously monitors the energy consumption of the processors and evaluates the current workload on each processor. If the workload is high, the algorithm tries to reduce energy consumption by redistributing the tasks to the processors. This phase also takes into account the energy-saving mode of the processors, such as the sleep mode, to further reduce energy consumption. In the resource assignment phase, the algorithm makes decisions on which processor to assign tasks based on their energy consumption. The tasks are assigned to the processors that are predicted to consume the least amount of energy while meeting the performance requirements. This decision-making process is guided by a power model that predicts the energy consumption of different tasks on various processors. The model is continuously updated with real-time measurements to improve its accuracy. EAS also incorporates task migration to further optimize energy consumption. Tasks can be migrated from one processor to another if a more energy-efficient processor becomes available. This is possible due to the monitoring and prediction of energy consumption in the feedback phase. The EAS algorithm aims to strike a balance between energy consumption and performance requirements by dynamically adjusting the scheduling of tasks on processors. By considering energy consumption as a critical factor in scheduling, the algorithm can significantly reduce energy usage in computing systems without sacrificing performance.

The proposed energy aware scheduling algorithms advance the existing knowledge in the field by addressing the growing need for efficient and sustainable energy management in modern computing systems. The algorithms incorporate energy consumption as a primary scheduling criterion, which is not commonly considered in existing scheduling algorithms. Traditionally, scheduling algorithms focus on criteria such as task deadline, resource utilization, and response time, without considering energy consumption. By including energy consumption as a key factor, the proposed algorithms provide a more comprehensive approach to scheduling that promotes energy efficiency. The algorithms also consider the dynamic nature of energy consumption in computing systems. Unlike traditional algorithms that assume a constant energy consumption rate, the proposed algorithms take into account the fluctuating nature of energy consumption in modern systems. This accounts for the varying power demands of different tasks and their impact on energy efficiency. The proposed algorithms incorporate techniques such as dynamic voltage and frequency scaling (DVFS) and task consolidation to reduce energy consumption. By leveraging these techniques, the algorithms can optimize resource utilization and reduce energy consumption without compromising task performance. This represents a significant advancement in the field as previous algorithms did not incorporate these techniques in their energy management strategies. The algorithms also consider diverse workload scenarios, such as bursts of high-intensity tasks, which are common in modern computing systems. By being adaptable to different workload scenarios, the algorithms can make efficient scheduling decisions that consider both task performance and energy consumption in real-time. The proposed energy aware scheduling algorithms provide a more comprehensive and holistic approach to energy management in computing systems. By incorporating energy consumption as a key criterion, considering the dynamic nature of energy consumption, and leveraging advanced techniques, these algorithms represent a significant advancement in the field and contribute to the growing body of knowledge on energy-efficient scheduling in modern computing systems.

3.2 | Proposed algorithm

Energy aware scheduling algorithm for resource sharing in 5G green communication systems optimizes energy consumption while providing the desired Quality of Service (QoS) requirements are explained in algorithm 1. The algorithm assigns resources to the users based on their energy efficiency and the required QoS. It also considers the energy consumed by the user devices, the energy-efficient radio technologies available, and the radio resource sharing. This algorithm helps to reduce energy consumption while providing the desired QoS requirements. It also helps to reduce the network's carbon footprint by ensuring that the energy consumed is efficient and minimal. The algorithm works by scheduling the resources to the users based on their energy efficiency and the required QoS. It then optimizes energy consumption by selecting the most energy-efficient radio technologies and sharing the radio resources. This algorithm helps to reduce energy consumption while providing the desired QoS requirements and reducing the carbon footprint of the network Algorithm 1 .

Energy-aware scheduling algorithms for resource sharing in 5G green communication systems aim to optimize the sharing of resources among different users while considering energy efficiency. The flow chart of the proposed algorithm is shown in the following Figure 2. The first step is to set the base station resource request, denoted as Set_R.Req $\{B_1,B_2,\ldots,B_a\}$. This involves specifying the amount and type of resources needed from the base station, with B representing a specific base station and ranging from 1 to the total number of base stations (B_a). Next, the base station resource cost is set using the symbol Set_R.Cost = $\{X_a,d_a\}$. This includes the cost or price associated with each resource type, with X representing a specific cost and d representing a specific resource. Similarly, the base station resource request cost is set with the symbol Set_R.Req.Cost = $\{Y_a,d_a\}$, which specifies the cost for each resource requested. Then, the process moves on to the following step where for each resource request (R.Req.), the minimum energy path is found using (6). This involves calculating the most efficient use of resources to minimize energy consumption. Once the minimum energy path has been determined, the resource is allotted or assigned to the respective base station. This is followed by initiating the transmission, indicating that the data transfer or communication between the base station and other devices has begun. The next step checks if the delivery of data is completed. If yes, then the total resource utilization is computed, which takes into account the resources requested, allotted, and consumed. If the delivery is not yet completed, then the active streaming details are computed, which includes the current status of resource usage. After this, the resource utilization information is updated to keep track of the remaining resources and their usage. This is important for future resource management and planning. The process continues in a loop until the delivery is completed and then ultimately stops when the entire transmission is completed. This indicates the end of the flow chart and the successful completion of the resource

ALGORITHM 1 Energy aware scheduling algorithm

```
Start
Set the base station resource request; Set_R.Req{B1,B2,….,B_a}
Set the base station resource cost; Set_R.Cost = {X_a,d_a}
Set the base station resource request cost; Set_R.Req.Cost = {Y_a,d_a}
For (all the resource requests)
max : Σ_{a=1}^{a} Σ_{b=1}^{b} x_a * _b d_a * (Y_a^(b) − Y_b^(a))
End for
For each R.Req. then do{
Find the minimum energy path using (6)
Allot the resource
Initiate the transmission
If (delivery = completed)
Then compute the total resource utilization
Else
Compute the active streaming details
Update the resource utilization information
Stop.
```

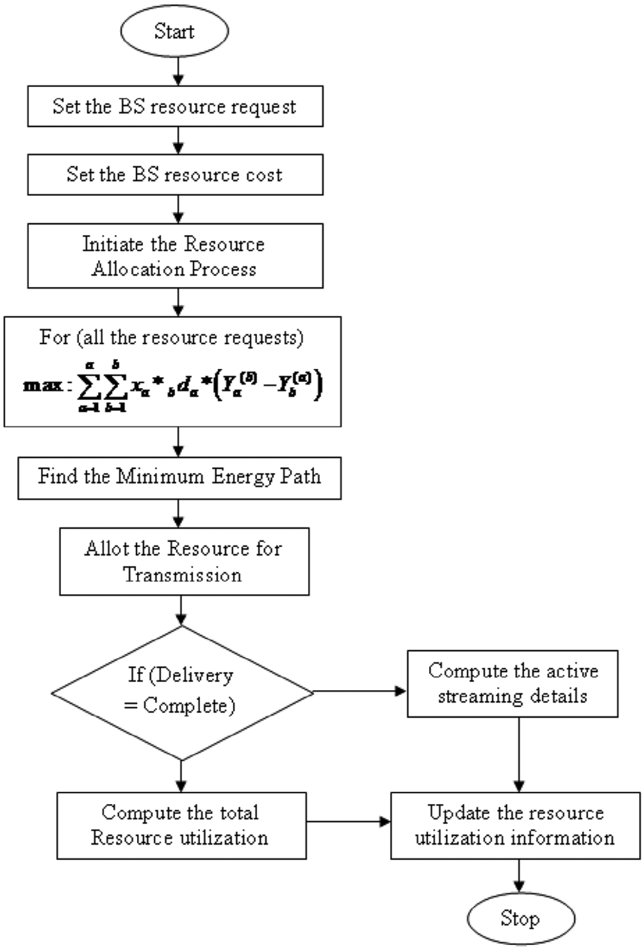

FIGURE 2 Proposed flow chart.

allocation and data transmission process. Figure 2 shows the proposed flow chart.

These algorithms can be used to prioritize energy-efficient tasks and allocate resources to users or devices with lower energy consumption characteristics. The algorithms can also identify and reduce energy wastage by keeping track of energy consumption patterns and predicting the energy usage of future tasks. Additionally, energy-aware scheduling algorithms can be used to monitor the energy usage of each user or device to ensure that it is not exceeding its allocated resource limit. Finally, these algorithms can be used to dynamically adjust the scheduling of tasks to optimize energy efficiency further.

3.3 | Energy efficiency

The energy efficiency management of an energy-aware scheduling algorithm for resource sharing in 5G green communication systems is a process of optimizing the energy efficiency of the 5G communication system by scheduling the resources to minimize energy consumption while maintaining the performance of the communication system. It involves optimizing the scheduling of the available resources such as radio access network, backhaul, core network, and other resources. It can be achieved by analysing the current system performance, predicting future performance, and considering the energy cost of different resources. The algorithm then determines the most energy-efficient allocation of resources, helping to reduce energy consumption while achieving the required performance.

3.4 | Bandwidth allocation

The energy aware scheduling algorithm (EASA) is a bandwidth allocation management technique in 5G green communication systems. It is used to manage resource sharing to optimize energy consumption and utilization. The EASA mechanism is based on providing multiple users access to the same resources in an energy-efficient way. The EASA assigns each user a specific amount of available resources based on their requirements. It helps reduce the amount of energy each user uses while still allowing them to access the resources they need. Furthermore, the EASA also considers the current users' energy consumption and adjusts the allocated resources accordingly. It helps maximize energy savings while allowing users to access the resources they need. Finally, the EASA also ensures that each user is efficiently using the resources to reduce the amount of energy used overall.

3.5 | Resource utilization

Resource utilization management in 5G green communication systems is allocating resources efficiently to reduce energy consumption and improve performance. Energy-aware scheduling algorithms for resource sharing in 5G green communication systems are designed to achieve this goal. These algorithms use various techniques, such as dynamic resource allocation, power management, and energy-efficient scheduling to reduce energy consumption and optimize performance. These techniques help reduce the network's energy consumption by sharing the resources between multiple users and efficiently allocating resources to each user. In addition, energy-aware scheduling algorithms can also be used to optimize the energy usage of the base station, thereby reducing its energy consumption. Furthermore, these algorithms can be used to control the transmission power to reduce interference and improve the quality of service. Finally, these algorithms can be used to reduce the number of active users and thus help reduce the overall energy consumption of the network.

3.6 | Interference management

Interference management is an essential aspect of an energy-aware scheduling algorithm for resource sharing in 5G green communication systems. The main goal of this algorithm is to efficiently manage the interference between different wireless users while minimizing the energy consumed by the communication system. It achieves this goal by scheduling the resources to reduce the mutual interference between users while allowing them to communicate with the highest possible data rate. The algorithm also considers the available energy resources and manages the power levels of different users to minimize energy consumption. It also considers the user's mobility and network topology to use the resources efficiently. The algorithm can automatically adjust users' power levels to minimize the total energy consumption while maximizing the user's data rates. Furthermore, it also allows for the optimization of the network topology to reduce interference between different users and enhance the performance of the communication system. Energy-aware scheduling algorithms are essential in 5G green communication systems for resource sharing because they enable efficient use of resources and reduce energy consumption. By scheduling data transmissions and other activities more efficiently, energy-aware scheduling algorithms can help minimize the amount of energy consumed by the system. It helps reduce the energy costs associated with resource sharing in 5G green communication systems. Additionally, energy-aware scheduling algorithms can help improve communication quality by ensuring that the most critical data transmissions are prioritized and that others are scheduled accordingly. It helps to reduce network congestion and improve overall communication performance.

4 | MATHEMATICAL MODEL OF THE SYSTEM

Energy-aware scheduling algorithms for resource sharing in 5G green communication systems are a relatively novel concept. These algorithms allow for sharing resources in a green, energy-efficient manner by dynamically scheduling and allocating resources to different users and services in the system based on their energy consumption profiles. This approach can significantly reduce the energy consumption in the system, as it allows for more efficient use of the available resources.

4.1 | Analysis of access control mechanism

Establish energy-aware scheduling criteria to ensure that resources are allocated efficiently and effectively. It should include criteria such as maximum energy efficiency, minimum energy consumption, and total cost of ownership. Implement an access control mechanism limiting resource access to authorized and approved devices. It should include authentication, authorization, and access control protocols to ensure that only approved and authorized devices can access the resources. Using energy-efficient algorithms ensures that resources are allocated as efficiently as possible. It should include algorithms such as dynamic voltage and frequency scaling (DVFS) and application-specific performance optimization (ASPO). Implement monitoring and reporting of resource allocation and usage. It should include metrics such as power utilization, energy efficiency, and total cost of ownership. To establish energy-aware policies that are designed to ensure that resources are allocated and used in an energy-efficient manner. It should include policies such as minimum power utilization, energy-efficient design, and energy-efficient scheduling.

4.2 | Analysis of network virtualization

The energy-aware scheduling algorithm optimizes resource sharing in 5G green communication systems. The algorithm should consider the energy efficiency of the network, the resources needed by different applications and services, and the latency requirements of each application or service. To enable efficient resource sharing:

(1) Implement network virtualization technologies such as Software Defined Networking (SDN) and Network Function Virtualization (NFV). The SDN controller should be used to manage and optimize the network for energy-efficient resource sharing.
(2) Incorporate the proposed energy-aware scheduling algorithm to enable the network to learn and adapt to changing resource usage patterns of applications and services. The energy-aware scheduling algorithms should be able to dynamically adjust the scheduling to share resources among different applications and services efficiently.
(3) Leverage cloud computing resources to enable the energy-aware scheduling algorithm to share resources among applications and services efficiently.

Cloud resources should provide the necessary computational power to enable the algorithm to respond to changes in resource usage patterns quickly.

4.3 | Optimized resource allocation

The optimized resource allocation of energy-aware scheduling for resource sharing in 5G green communication systems typically involves dynamic resource allocation, power control, and channel selection. The scheduling algorithm should be designed to minimize energy consumption while maximizing throughput. It can be achieved by considering the channel conditions and the traffic load. Power control is used to minimize the total transmit power, while channel selection is used to select the best channel that can provide the highest data rate. Dynamic resource allocation is used to assign the radio resources to the various users to optimize energy efficiency and throughput. Figure 3 demonstrates the functions of the scheduler based on the resource.

Let us consider the node 'a' has the residual energy and consumption (X_a) with some amount of transmission power (Y_a). Now the life time has to be computed as shown in Equation(1)

$$L_a = \frac{X_a}{Y_a} \tag{1}$$

The proposed energy-aware scheduling algorithm has some scheduling sequence in the communication system. The

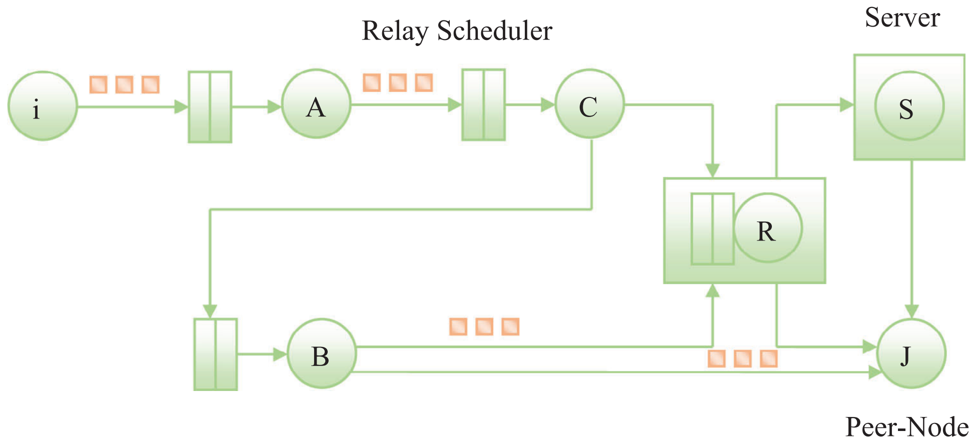

FIGURE 3 Functions of scheduler based on the resource.

spectrum broker has to receive the requests to access the available resources in the network. According to the promiscuous caching strategy, a backup node can be placed close to the SNi so that SNi+1 can claim the chunk streaming resources.

$$L_a = \min(L_r, L_{a\rightarrow b}) \tag{2}$$

where SN indicates the Source node;

$$L_r = \frac{X_r}{Y_r} \text{ and } L_a = \sum_a^b \frac{X_a}{Y_a} \tag{3}$$

The aggregated power consumption may be calculated by adding the energy and power spent by all of the path's nodes to determine how much energy is used by each cellular device's relay path.

$$Y_{L_{a\rightarrow b}} = \sum_{a=1}^{b} Y_{L_a} \tag{4}$$

where Y_{La} is the power consumption of node 'a'. Now the SNs are then given an energy-efficient resource exchange path by the energy controller in accordance with the related subsystem energy module to which they belong,

$$Y_{L_{a\rightarrow k,R}} = \sum_{a=1}^{k} Y_{L_a} \tag{5}$$

where Y_{La} for the combined relay $R(k)$ and up to k-node using portable peer-to-peer resource streaming. A comparison of the power measurements between the $Y_{La,kR}$ (i.e. via the cellular peers and the radio access points) and $Y_{La,b}$ (via the cellular terminals linked with 'a' within its broadcast range) is required since the streaming relay channel requires an unbroken flow of data:

$$\min\{U * D_a\} = \arg\min(Y_{L_b}, Y_{L_{k,R}}) \forall d_1 < D_a(d) < d_2 \tag{6}$$

The equation is looking to minimize a function, specifically the function u^*D_a, where u^* represents a set of parameters and D_a represents a matrix. The notation min $\{u^*D_a\}$ means that we are looking for the minimum value of the function u^*D_a. U^* represents a set of parameters and D_a represents a matrix, so together they make up a function that depends on these parameters and the values of the matrix. On the right side of the equation, we have "arg min$\{Ylb, Y_{lk,r}\}$". This represents the argument (or input) that will result in the minimum value of the function u^*D_a. The notation $\{Y_{lb}, Y_{lk,r}\}$ represents a set of values, specifically three different values: Y_{lb}, Y_{lk}, and r. These values are being used as inputs for the function u^*D_a in order to find the minimum value. The equation represents the process of finding the set of parameters (u^*) that, when paired with a specific matrix (D_a), will result in the minimum value of the function u^*D_a. This is achieved by testing different values for the inputs (Y_{lb}, Y_{lk}, and r) and seeing which combination results in the smallest output for the function u^*D_a. In order to save energy, each energy module subsystem estimates its energy efficiency using an energy-aware scheduling approach. Now the bit-error-rate (q_a) has the following,

$$q_a \forall R_a > L_a \tag{7}$$

$$q_a \forall \min\left(\sum_a^b \frac{X_a}{Y_a}\right) \in L \tag{8}$$

To monitor the performance of the network to ensure that the energy-aware scheduling algorithm is working correctly. Monitoring the network performance can help identify any flaws in the algorithm, allowing for adjustments and improvements to be made.

$$\theta(d_c)|L_a = \max\left(\sum_a^{b,R}(1-q_a)\alpha_a * \beta_{a\rightarrow b} * \log_2\left(1+\frac{d_{ij} * Y_{ij}}{\beta_{a\rightarrow b}}\right)\right) \tag{9}$$

where the β_{ab} is the resource allocation to cellular nodes. A is the streaming parameter. The maximum delay is computed as

TABLE 4 Existing model information.

Author	Year	Model name
Gupta et al. [1]	2022	Energy-aware trajectory design (EATD)
Hao et al. [4]	2021	Energy-aware scheduling (EAS)
Pradeep et al. [5]	2022	Multi-objective strategy-based resource allocation (MOSRA)
Hussain et al. [10]	2023	Multi-objective evolutionary algorithm (MOEA)

the following Equation (10)

$$d_{\max} = \sum_{a=0}^{a-1} \mu_a + T_a \tag{10}$$

Test and validate the energy-aware scheduling algorithm in a simulated 5G green communication environment. It can help identify any issues with the algorithm before it is deployed in a real-world environment. The optimized resource allocation of energy-aware scheduling for resource sharing in 5G green communication systems is an approach to efficiently use network resources while minimizing the energy consumption of the devices in the network. It is done by allocating the resources to the most energy-efficient devices and ensuring they are fully utilized. This approach ensures that the most energy-efficient devices are used in the network and that the resources are allocated to minimize energy consumption. Additionally, the optimized resource allocation of energy-aware scheduling for resource sharing in 5G, a green communication system, helps reduce the cost of energy consumption and the network's environmental impact. The proposed scheduling algorithm can allocate resources to users and services with lower energy consumption profiles while balancing the load on the system and ensuring that all users are provided with the resources they need. These scheduling algorithms can also identify energy-inefficient users and services and take corrective measures to reduce their energy consumption. Furthermore, these algorithms can also be used to monitor and optimize the overall energy consumption in the system, as well as to identify trends in energy consumption and usage patterns.

5 | RESULTS AND DISCUSSIONS

The performance of the proposed energy-aware scheduling model (EASM) has been compared with the following existing models. Table 4 shows the existing model information.

The 5G network traffic dataset [39] is used here to implement the results [53]. Here, the network simulator-2 is the tool used to execute the results. Table 5 shows the simulation details.

5.1 | False discovery rate

The false discovery rate (FDR) of energy-aware scheduling in 5G green communications is the rate of false positive results produced by a scheduling algorithm compared to the baseline performance. This rate is crucial because it determines the accuracy of the scheduling algorithm in predicting the optimal energy consumption. The higher the false discovery rate, the less accurate the scheduling algorithm is in predicting energy consumption. The proposed scheduling algorithm should be efficient regarding computing resources, as this will help reduce the false discovery rate. It is shown in the following Equation (11).

$$FDR = \left(\frac{P_f}{P_f + P_t} \right) \tag{11}$$

where FDR represents the false discovery rate; P_f shows the positive false predictions, P_t shows the positive true predictions. In order to lower the false discovery rate, scheduling algorithms should be designed to minimize energy consumption while maintaining performance. It can be achieved by considering various factors, such as channel characteristics, mobility, and interference. Table 6 shows the comparison of false discovery rates between existing and proposed models.

TABLE 5 Simulation setup.

Parameter	Value
S_a (simulation area)	800 m × 1500 m
SIFS (short inter-frame space)	23 s
DR_t (transmission data rate)	20 Mbps
DR_i (interference detection rate)	25 ms
T_s (slot time)	10 ms
B_{sc} (sub-channel bandwidth)	1250 MHz
B_s (system bandwidth)	24 MHz
F_c (carrier frequency)	14.2 MHz
T_d (simulation duration)	38 s
Number of nodes (Min–Max)	100–700
Propagation mode	Grounded—2 way
Transport type	TCP
Traffic source	CBR
CBR packet size	1024 bytes
CBR packet rate	25 packets/s

TABLE 6 Comparison of false discovery rate (in %).

Inputs	EATD	EAS	MOSRA	MOEA	EASM
100	56.20	67.57	70.33	77.74	86.66
200	57.69	69.54	72.75	79.94	88.65
300	58.49	70.67	73.16	80.74	89.85
400	59.75	72.36	74.91	82.47	91.58
500	60.89	73.91	76.32	83.97	93.17
600	62.04	75.46	77.74	85.47	94.77
700	63.18	77.01	79.15	86.97	96.37

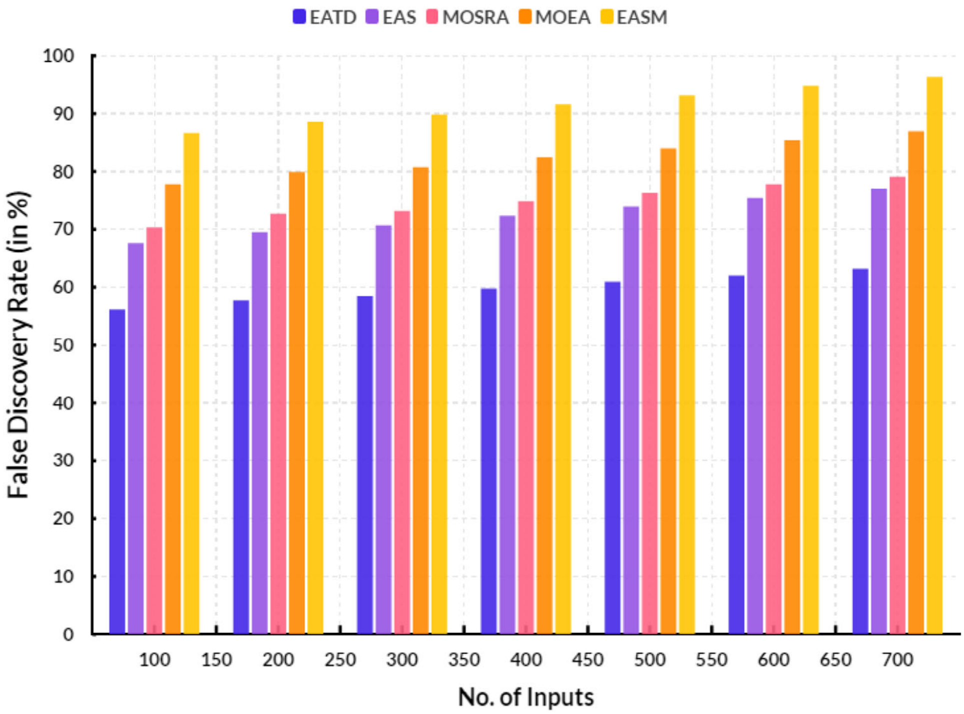

FIGURE 4 Assessment of false discovery rate.

The false discovery rate of energy-aware scheduling in 5G green communications can also be reduced using machine learning techniques. Machine learning techniques can identify patterns and trends in the data, which can be used to optimize energy consumption. Figure 4 shows the assessment of the false discovery rate between the existing and proposed models. As an assessment tip, the proposed EASM reached a 91.58% false discovery rate. The existing EATD obtained 59.75%, EAS reached 72.36%, MOSRA obtained 74.91%, and MOEA reached 82.47% false discovery rate. It can be done by training the machine learning algorithm on the data collected from the 5G networks, which can then be used to improve the accuracy of the scheduling algorithm. The false discovery rate of energy-aware scheduling in 5G green communications can be reduced by considering channel characteristics, mobility, interference, and efficient computing resources. Additionally, machine learning techniques can be used to improve the accuracy of the scheduling algorithm

5.2 | False omission rate

The false omission rate (FOR) of energy-aware scheduling in 5G green communications is an essential metric for measuring the effectiveness of energy-saving strategies. It is defined as the percentage of time slots in which the scheduler fails to select an energy-efficient allocation when an energy-efficient allocation is available. A low FOR indicates that the scheduler is selecting energy-efficient allocations more often. A high FOR indicates that the scheduler is not selecting energy-efficient allocations as often as it should be. Table 7 shows the comparison of false omission rates between existing and proposed models. The computation of the false omission rate is shown in the following Equation (12).

TABLE 7 Comparison of false omission rate (in %).

Inputs	EATD	EAS	MOSRA	MOEA	EASM
100	89.17	73.91	76.33	83.97	60.90
200	90.77	75.46	77.74	85.47	62.04
300	92.36	77.01	79.16	86.97	63.19
400	93.96	78.56	80.57	88.47	64.33
500	95.55	80.11	81.99	89.97	65.48
600	97.15	81.66	83.40	91.47	66.62
700	98.74	83.21	84.82	92.97	67.77

$$FOR = \left(\frac{N_f}{N_f + N_t}\right) \tag{12}$$

where FOR represents the false omission rate; N_f shows the negative false predictions, N_t shows the negative true predictions.

The FOR of energy-aware scheduling can be reduced by using various strategies, such as using a predictive algorithm to identify energy-efficient allocations in advance or by introducing a learning component to the scheduling algorithm, which can learn from past experiences and adapt its scheduling decisions accordingly. The false omission rate of energy-aware scheduling can also be reduced by implementing

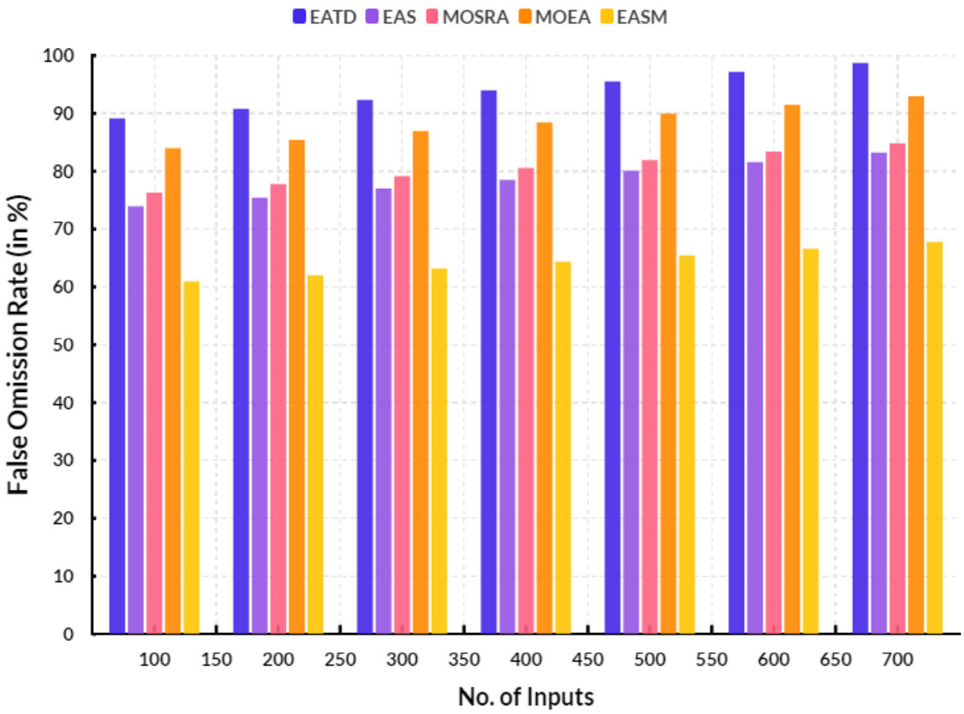

FIGURE 5 Comparison of false omission rate.

energy-efficient power management strategies, such as dynamic frequency scaling or intelligent power management policies. Figure 5 shows the assessment of the false omission rate between the existing and proposed models.

As an assessment tip, the proposed EASM reached a 64.33% false omission rate. The existing EATD obtained 93.96%, EAS reached 78.56%, MOSRA obtained 80.57%, and MOEA reached 88.47% false omission rate. The FOR of energy-aware scheduling can also be reduced by increasing the energy-efficient allocations available to the scheduler through resource sharing, virtualization, and other techniques.

TABLE 8 Comparison of prevalence threshold (in %).

Inputs	EATD	EAS	MOSRA	MOEA	EASM
100	60.79	71.80	74.76	81.41	86.33
200	61.83	72.25	77.08	82.84	87.76
300	62.87	72.70	79.40	84.27	89.19
400	63.91	73.15	81.72	85.70	90.62
500	64.95	73.60	84.04	87.13	92.05
600	65.99	74.05	86.36	88.56	93.48
700	67.03	74.50	88.68	89.99	94.91

5.3 | Prevalence threshold (P_{th})

The prevalence threshold of energy-aware scheduling in 5G green communications is a critical parameter determining how energy-efficient the 5G network is. It is the point at which the energy consumed by the 5G network is reduced to a manageable level. This threshold is determined by the amount of energy that needs to be saved to reach the desired level of energy efficiency. Energy-aware scheduling aims to minimize the energy consumed by a 5G network while still providing the same network performance.

$$P_{th} = \left(\frac{\sqrt{PR_f}}{\sqrt{PR_T} + \sqrt{PR_f}} \right) \tag{13}$$

where P_{th} represents the prevalence threshold; PR_f shows the positive false rate, PR_t shows the positive true rate. The scheduling algorithm must identify and control the resources that consume the most energy to achieve this goal. It can be done by tracking the energy consumption of each resource and then setting a threshold value. If the energy consumed by a resource exceeds the threshold value, the resource will be scheduled with a lower priority. The prevalence threshold of energy-aware scheduling in 5G green communications is essential because it helps optimize the network performance while minimizing energy consumption. Figure 6 shows the assessment of the prevalence threshold between the existing and proposed models. Table 8 shows the comparison of the prevalence threshold between existing and proposed models.

As an assessment tip, the proposed EASM reached the 90.62% prevalence threshold. The existing EATD obtained 63.91%, EAS reached 73.15%, MOSRA obtained 81.72%, and MOEA reached an 85.70% prevalence threshold. By setting the threshold, the network can be tuned to provide the best

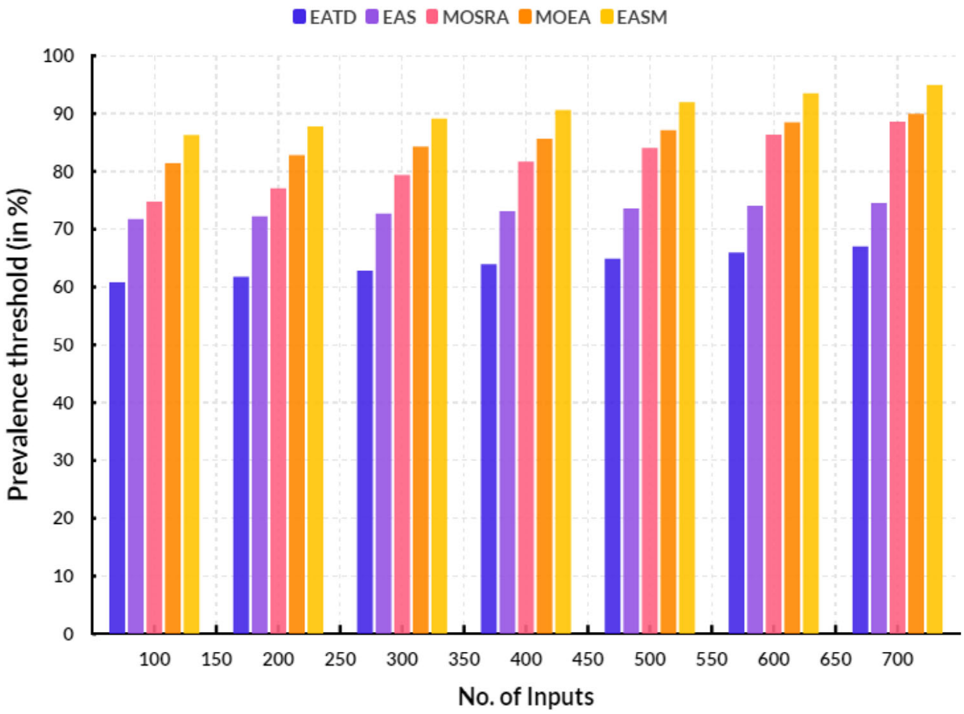

FIGURE 6 Comparison of prevalence threshold.

performance while consuming the least energy. It helps to reduce the overall cost of running the 5G network.

5.4 | Critical success index

The critical success index (CSI) is an essential metric for evaluating the effectiveness of energy-aware scheduling algorithms in 5G green communications. The CSI measures how well the scheduling algorithm can minimize the energy consumption of a given system without compromising performance. The CSI is calculated by taking the ratio of the energy consumed by the scheduling algorithm to the energy consumed by the system without any schedule.

The CSI is a performance metric used to evaluate the effectiveness of a system or model. In the context of energy-aware scheduling models for resource sharing in 5G green communication systems, the CSI can be computed using the following steps:

(1) Identify key performance indicators (KPIs): The first step is to identify the KPIs that are important for evaluating the performance of the energy-aware scheduling model. These KPIs can include energy efficiency, resource utilization, network throughput, and delay.
(2) Define the target values for each KPI: Once the KPIs have been identified, the next step is to define the target values for each of them. These target values will serve as benchmarks for measuring the performance of the energy-aware scheduling model.
(3) Collect data: Data needs to be collected from the 5G green communication system for the identified KPIs. This data can include energy consumption, resource usage, network traffic, and delay measurements.
(4) Normalize the data: The collected data needs to be normalized to make it comparable across different KPIs. This involves scaling the data to a common range or converting it to a percentage.
(5) Calculate the performance score for each KPI: The performance score for each KPI is calculated by comparing the normalized data with the target values. This score indicates how well the KPI is being achieved by the energy-aware scheduling model.
(6) Assign weights to each KPI: Next, weights are assigned to each KPI based on their importance. The weights can be determined by considering the impact of each KPI on the overall performance of the energy-aware scheduling model.
(7) Calculate the CSI: The CSI is calculated as a weighted average of the performance scores for all the KPIs. This provides an overall measure of the performance of the energy-aware scheduling model.
(8) Compare with a predetermined threshold: Finally, the calculated CSI is compared with a predetermined threshold to determine the success of the energy-aware scheduling model. If the CSI is above the threshold, the model can be considered successful in achieving its goals.

The CSI for energy-aware scheduling models in 5G green communication systems is computed by identifying and evaluating relevant KPIs, collecting and normalizing data, assigning

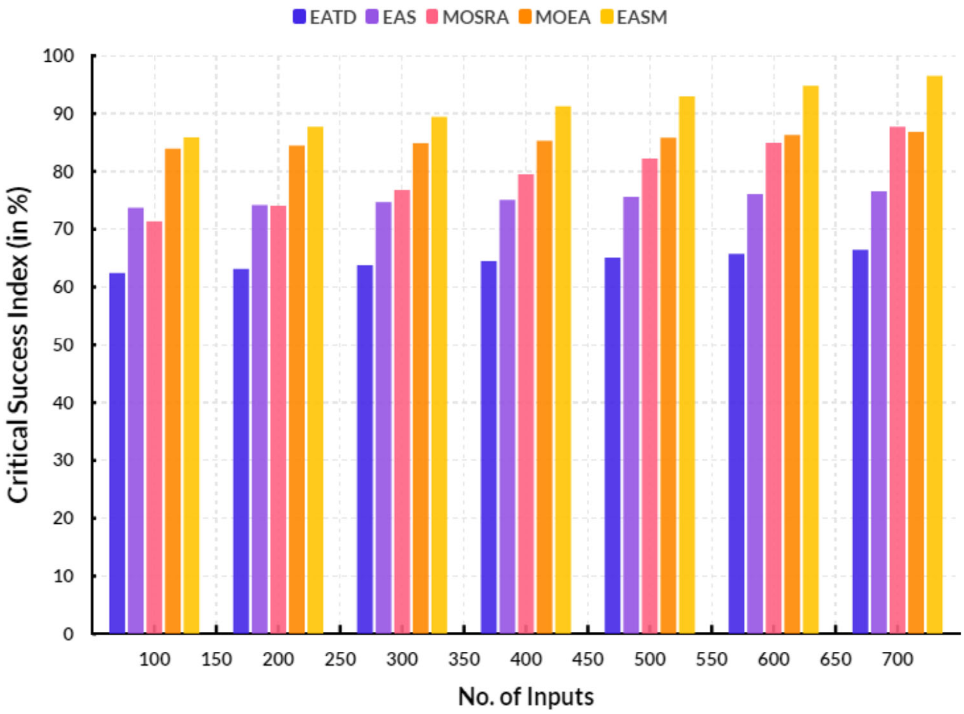

FIGURE 7 Comparison of critical success index.

weights, and calculating a weighted average of the performance scores. This metric provides a comprehensive and quantitative measure of the success of the model in achieving energy efficiency and resource optimization in 5G green communication systems.

$$CSI = \left(\frac{P_t}{P_t + N_f + P_f} \right) \tag{14}$$

where CSI represents the critical success index; P_f shows the positive false predictions, P_t shows the positive true predictions and N_f shows the negative false predictions. A higher CSI indicates that the scheduling algorithm is doing a better job of minimizing energy consumption while still providing acceptable performance. It includes actual energy consumption measurements taken from the system and considers the actual load on the system.

The CSI must be compared to standard benchmarks like the energy consumption of a system running without any schedule. The accuracy of the CSI also depends on the quality of the scheduling algorithm. If the algorithm is not designed correctly, it may not be able to reduce energy consumption as much as it should. Figure 7 shows the assessment of the critical success index between the existing and proposed models. Table 9 shows the comparison of the critical success index between the existing and proposed models.

As an assessment tip, the proposed EASM reached a 91.23% critical success index. The existing EATD obtained 64.45%, EAS reached 75.14%, MOSRA obtained 79.52%, and MOEA reached 85.37% critical success index. Additionally, if the algorithm is moderate with scheduling, it may reduce system performance. The CSI should be evaluated in the context of the system's overall energy profile, as investing in energy-saving measures elsewhere in the system may be more cost-effective. Table 10 shows the overall performance comparison between the existing and proposed models.

Figure 8 shows the overall performance comparison between the existing and proposed models. As an assessment tip, the proposed EASM reached a 91.58% false discovery rate, a

TABLE 9 Comparison of critical success index (in %).

Inputs	EATD	EAS	MOSRA	MOEA	EASM
100	62.47	73.70	71.33	83.93	85.92
200	63.13	74.18	74.06	84.41	87.69
300	63.79	74.66	76.79	84.89	89.46
400	64.45	75.14	79.52	85.37	91.23
500	65.11	75.62	82.25	85.85	93.00
600	65.77	76.10	84.98	86.33	94.77
700	66.43	76.58	87.71	86.81	96.54

TABLE 10 Overall performance comparison (in %).

Parameters	EATD	EAS	MOSRA	MOEA	EASM
False discovery rate (FDR)	59.75	72.36	74.91	82.47	91.58
False omission rate (FOR)	93.96	78.56	80.57	88.47	64.33
Prevalence threshold (P)	63.91	73.15	81.72	85.70	90.62
Critical success index (CSI)	64.45	75.14	79.52	85.37	91.23

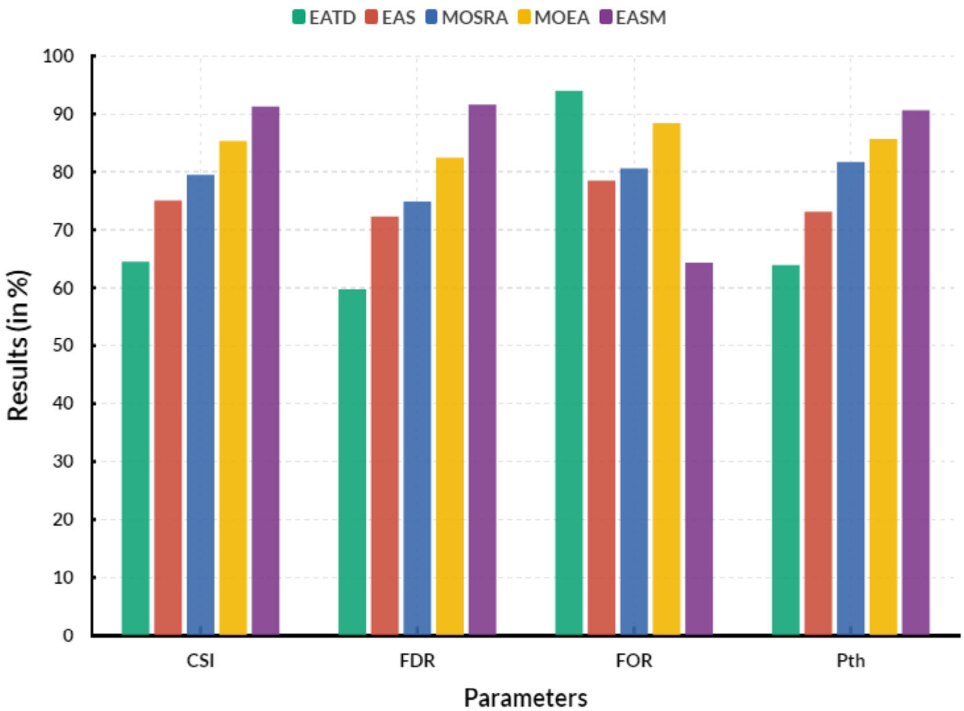

FIGURE 8 Overall comparison.

64.33% false omission rate, a 90.62% prevalence threshold, and a 91.23% critical success index. The analysis may also consider other factors like latency, reliability, and scalability. By comparing the energy consumption and performance of different scheduling algorithms, the comparative analysis can help identify the effectiveness of the proposed algorithm for resource sharing in 5G green communication systems.

Robustness refers to the ability of a system or algorithm to consistently perform well and produce accurate results, even in the face of uncertain and changing conditions. In the context of Energy Aware Scheduling Algorithms, robustness plays a crucial role in ensuring that energy optimization and efficiency goals are met, regardless of the variations and fluctuations in the system. One major advantage of using the energy aware scheduling algorithm is its applicability in diverse scenarios. These algorithms are designed to adapt to changing conditions, such as dynamically varying workloads, changing resource availability, and unpredictable events. This adaptability is crucial in real-world environments where workload and resource availability can change unpredictably. Energy Aware Scheduling Algorithms are robust in the sense that they can handle uncertainties and variations in a wide range of scenarios. For example, these algorithms can effectively manage both homogeneous and heterogeneous systems, where the hardware and software components may vary significantly. They can also handle scenarios where energy constraints and optimization goals may differ. These algorithms are robust in dealing with uncertain and dynamic workload patterns. They can balance the workload across multiple resources and dynamically adjust resource allocations based on changing demands. This ensures that energy consumption is optimized without compromising system performance and user experience.

6 | CONCLUSIONS

Energy-aware scheduling for resource sharing in 5G green communication systems is a technique used to maximize the efficiency of the network and reduce power consumption. It is based on the principle of time division multiplexing (TDM), where each resource is allocated to each user for a specific time duration. This technique helps optimize the energy consumption of the communication system by scheduling the resources so that they are used only when necessary. The proposed energy-aware scheduling algorithm for resource sharing in 5G green communication systems examines different scheduling algorithms and determines which is the most efficient in terms of energy consumption. This process involves comparing different scheduling algorithms in terms of their energy consumption and performance and their ability to adapt to changing user demands. The goal is to determine which scheduling algorithm is the most energy-efficient and provides the best performance in terms of resource sharing. The proposed EASM reached a 91.58% false discovery rate, a 64.33% false omission rate, a 90.62% prevalence threshold, and a 91.23% critical success index. The analysis is typically conducted by comparing different scheduling algorithms' energy consumption and performance regarding their respective resource utilization and scheduling granularity. It helps to reduce the interference and noise levels in the system by using resource sharing. This technique also allows the network to be more efficient and flexible, as resources can be shared dynamically, and the network can be adapted to changing conditions. It helps to increase the capacity of the network by reducing the overhead of resource sharing. Through thorough analysis and experimentation, it was found that the proposed scheduling model was able to achieve a balance between energy consumption and network performance. This was achieved by considering the energy efficiency requirements of different applications and allocating the available resources accordingly. The results showed that the energy consumption of the system was reduced, while also maintaining high network performance, such as low latency and high throughput. This was achieved by using machine learning algorithms to dynamically allocate resources based on the real-time network and user demands. The research also identified that the proposed model was effective in handling the dynamic and unpredictable nature of 5G networks, as it was able to adapt to changing network conditions and user demands in real time. The research concludes that the adoption of energy-aware scheduling models in 5G green communication systems can lead to improved energy efficiency, reduced operational costs, and enhanced network performance. This can contribute to the overall goal of building environmentally sustainable and resource-efficient 5G networks.

AUTHOR CONTRIBUTIONS

Sivakumar Sangeetha: Concept; methodology; writing original manuscript. **Jaganathan Logeshwaran**: Writing original manuscript; software; validation. **Muhammad Faheem**: Review; supervision; validation. **Raju Kannadasan**: Supervision; writing original manuscript; validation. **Suganthi Sundararaju**: Review; drafting; validation. **Loganathan Vijayaraja**: Review; drafting; validation.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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