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Enhancing Next-Generation Wireless Networks Using Preemptive Energy Conservation Technique

Jagadeesh Selvaraj[1], [2]Noor Alleema Nakeeb, Jaehyuk Cho[3], Sathishkumar Veerappampalayam Easwaramoorthy[4]

[1]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamilnadu.
[2]Department of Computer Science and Engineering,Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamilnadu.
[3]Department of Software Engineering, Jeonbuk National University, Jeonju-si, the Republic of Korea
[4]Department of Computing and Information Systems, Sunway University, 47500 Petaling Jaya, Selangor DarulEhsan, Malaysia

Corresponding author: First A. Author (e-mail: chojh@bnu.ac.kr).

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ABSTRACT Modern wireless networks provide state-of-the-art services to numerous users by utilizing ultrahigh frequency lines and machine-type interaction. Incorporating ultrahigh frequency lines and machine-type interactions to delivermultiple user services is driving the need for creative energy-saving strategies in wireless networks, which are advancing rapidly. The Preemptive Energy Conservation Technique (PECT) is a novel energy preservation method developed for next-generation wireless networks. This method meets each device's unique requirements while accumulating and dispersing energy in an eco-friendly way. The method's core tenet is that it finds energy slot intervals intended for distribution and portable device operating, thus maximizing support for data exchange. The next step is to initiate the conservation operation by utilizing the discovered slot intervals and the projected device demands. Using Naïve Bayes prediction intelligence, PECT finds energy slot intervals specifically for portable device operation and dissemination and then starts conservation actions based on these predictions. This proactive method guarantees sufficient energy allocation for efficient information exchange by improving the speed of data sharing through synchronized wireless networks. Energy usage, delay, communication loss, and the lowest possible conservation ratio are some metrics used to assess the efficacy of the suggested PECT.

INDEX TERMS Artificial Intelligence, Energy Conservation, Preemptive Approach, Information Exchange, Naïve Bayes Prediction, Synchronized Links, Wireless Network.

I. INTRODUCTION

Integrating many devices with varying Quality of Service (QoS) and Quality of Experience (QoE) needs will fall on future wireless networks. Due to the large number of devices, it is necessary to predict how they will behave to create a system that can meet service quality and experience standards [1]. When planning predictive networking systems, it's essential to consider the wide variety of possible future wireless network applications. There are fresh obstacles to energy efficiency due to the proliferation of critical applications and streaming media services supported by network infrastructure. These applications demand quick satisfaction of QoS criteria [2]. Research on energy consumption and savings has garnered significant attention because of the growing concerns about energy efficiency and the operational expenses of networks. Base stations (BSs) are the primary power users in wireless and mobile communication networks, and their power usage can change over time. Improving energy efficiency is one goal of increasing transmission power to meet user QoS needs and maximize user happiness; conversely, lowering transmission power reduces QoS performance. Critical elements in BS energy consumption that necessitate balanced optimization include assessing the compromise between energy usage and the desired quality of service. Academic and business researchers have devised practical ways to lower network operational costs by installing energy-efficient gear, but this has only gone so far [3]. There must be a balance between energy expenses and the decrease in user coverage to reduce network operational costs by deploying more energy-efficient gear. Because it could lead to portable access networks being either over- or under-provisioned concerning user traffic demands, this strategy fails to solve the energy efficiency challenge.

Emerging mission-critical applications like telemedicine, intelligent transportation, virtual/augmented reality (VR/AR), and ultra-reliable and minimal latency communications (URLLC) on 5G networks are challenging current standards to meet all KPIs [4]. Combining device-centric wireless networks with opportunistic networking allows for more efficient use of device and network resources. Examples of such networks include Device-to-Device (D2D), Multi-hop Cellular, and D2D-aided cellular communications. Next Generation Opportunistic Networking (NGO) relies on links' ability to efficiently meet demand and services within a particular timeframe [5].

On the other hand, partial attributes of few-shot examples draw implicit feature observations that can expose the underlying label correlation of rare label categorization, which is counterintuitive. In [6],PACNet, a Part-Aware Correlation Network based on PR and SCM, is presented to investigate the relationship between labels and partial features in detail. In particular, we create an object's partial representation module that lets the model zero in on more unique features by removing object-independent data. The topology optimization problem is expressed as a multi-objective optimization problem by considering the constraints of connection, the objectives of coverage, propagation intensity, and interference intensity all at once. Various cutting-edge serial and parallel multi-objective evolutionary algorithms (MOEAs) in [7] are used to find the solutions.

Optimizing wireless network efficiency and power usage improves calculations and coverage. Wireless network power utilization is tested via the radio access network. Through the mobile communication system, the requested energy is supplied to the node [8]. The transmission was deployed on time and without faults following extensive node checks. Consumption quantifies and conserves energy. Energy forwarding resource management improves with optimization. Multi-layer resource management is deployed during transmission between source and sink nodes. The processing stage includes radio resource energy optimization [9]. The traffic is detected and not sent to the node, improving optimal route detection. Energy is captured by sending it via prediction. Wireless network energy can be saved by employing transmission forecasts. Histogeneous platforms optimize energy conservation and resource exchange [10, 11]. Machine learning and AI improve energy collection. Network energy savings and reliable sharing are handled by energy optimization [12].

Data aids system energy and function operations. Predictions from desired devices are used to evaluate and transmit energy. The usage approach determines processing to optimize this computational stage [13]: processing yields AI and communication energy. Communication is linked to AI-requested device power exchange [14]. An affordable optical transport network (OTN) with high bandwidth, low latency, and significant scalability from the core to the edge and antenna sites is one of several difficulties that have gone unsolved in earlier generations [15]. This algorithm identifies the best way to capture energy and wirelessly send it to required devices. Processing determines radio frequency and implements linear processing in the network. AI can optimize energy utilization by assessing analytic safety and efficacy [16].

A novel approach to improving the efficiency of wireless networks is the Preemptive Energy Conservation Technique (PECT), which combines predictive analytics with proactive energy management. To employ Naïve Bayes predictive intelligence to plan and distribute energy for the operation of portable devices and data dissemination appropriately, PECT can distinguish between energy slot times. This method improves the network's overall efficiency, caters to each device's unique requirements, and guarantees environmentally responsible energy distribution. With these forecasts, PECT can minimize energy use, speed up data exchange, and eliminate communication losses and delays by proactively deploying energy-saving measures. This technology demonstrates the novel sustainability and operational efficiency combinationbythoroughly examining energy use, delay, communication loss, and conservation ratio.

The main objectives and novelty of the article include

- The research describes the Preemptive Energy Conservation Technique, a novel energy conservation method for next-generation wireless networks.
- Then, utilizing the slot intervals and expected device demands, the conservation procedure begins. Naïve Bayes prediction intelligence helps distinguish energy conservation from distribution.
- The suggested PECT's effectiveness is assessed using energy consumption, delay, communication loss, and the lowest feasible conservation ratio.

The rest of the paper is prearranged as follows: section 2 deliberates the related works, section 3 proposes the PECT model, section 4 discusses the results and discussion and section 5 concludes the research paper.

II. RELATED WORKS

To address the substantial energy expenditure in Fiber-Wireless (FiWi) connection networks serving both conventional and Internet of Things (IoT) services, Zhang et al. [17] offered an adaptive frames aggregation approach with load transfer. The approach minimizes energy usage without sacrificing service delay performance by dynamically modifying frame lengths according to wireless network quality and optimizes frame lengths for various service priorities. However, implementing the plan would be difficult, and load transfer procedures might add to the overhead.

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Mobile edge computing (MEC) is an access point in the wireless channel for both energy and task causality constraints. This work aims to increase the energy consumption over a finite horizon, and offline optimization is determined. To examine the knowledge-based computation in MEC channel state information (CSI) and task state information (TSI), it is developed in [18]. The task allocation and offloading are performed to decrease the computation time.

Wireless Power Mobile Edge Cloud (WPMEC) is proposed for computationally intensive data [19]. Wireless Power Transfer (WPT) and Mobile Edge Cloud (MEC) detect low-power battery devices and computation capabilities. The first model determines WPT, whereas the second model covers the offloading and computation in MEC. The network computational energy efficiency is addressed and improved.

An optimal control policy is introduced in [20] to reduce the delay transmission in multi-hop energy harvesting wireless sensor networks (EH-WSNs). This paper uses reinforcement learning (RL) to forward the data from the source to the sink node. The energy harvesting is increased for the neighbouring nodes in WSN. The control action is taken for the sensor node for the information sharing in the wireless medium.

Tam et al. [21] introduced a MOEA/D-LS algorithm to enhance the network lifetime. The relay nodes forward the data to the base station and provide three-dimensional terrains. A hybridization method is evaluated for the evolutionary algorithm concerning decomposition. The performance is improved, and energy consumption is better. The particular local search detects the subproblems.

Energy-Efficient Adaptive Scheduling Scheme (EASS) addresses energy harvesting in cloud-based energy consumption. In [22], the proposed work is used for the Mesh Grid Wireless Sensor Networks to schedule the process at the embedded network. The data packet is delivered to the sink node from the source node, and traffic is detected and avoided for the upcoming scheduling method. The energy efficiency is determined in this work by decreasing the dead nodes ratio.

The Ant-Q algorithm is proposed to decrease complexity and improve the convergence ratio. Reinforcement Learning (RL) and the discrete power scheme are used to derive this routing. The joint optimization issues are rectified by introducing the Mixed Integer Linear Problem (MILP), in which energy is consumed and throughput is enhanced. In [23], the routing algorithm is used to improve the accuracy level.

Gbadouissa et al. [24] implemented clustered WSNs to manage the numerous resources in the network. The hypergraph theory is introduced to optimize energy and is termed HyperGraph Clustering (HGC). This clustering method improves energy consumption by selecting the cluster head. Energy consumption is enhanced by determining the power-aware WSN to enhance performance.

MFRSEA is presented in [25] for network random essential representation by selecting single or multiple hops. The utilization of crucial representation is examined using the multifactorial evolutionary algorithm. The crossover function optimizes two networks based on the critical representation. The relay nodes are responsible for transmitting the data to the sink nodes.

Slimani et al. [26] investigate how smart radios can improve Wireless Sensor Networks' (WSNs') energy efficiency. It draws attention to how they might modify communication protocols and optimize energy usage to extend the life of sensor devices and lessen their adverse effects on the environment. It also examines the differences between 5G and 6G technology in wireless sensor networks (WSNs), highlighting the emphasis of 6G on achieving low energy consumption as a significant breakthrough in wireless communication.

Deshpande et al. [27] proposed anticipatory networking will be necessary in future wireless networks to forecast device behaviour and maximize efficiency. Anticipatory networking is anticipating data and applying strategies to improve system efficiency. The diversity of application settings, however, presents difficulties. To properly handle these difficulties, this paper provides a thorough overview of predictive networking strategies across several network layers.

Liu et al. [28] introduced an offline transmission scheme to improve the throughput in the cooperative relay system. The classification is done for the online transmission and ensures the QAM level for energy storage. The training data is used for the classification method to determine the relay communication. Compared to online transmission, offline shows better performance.

The energy is harvested by proposing three hybrid placement schemes: Multi-Stage Weighted Election heuristic (MSWE) and Minimum Cost Cross-layer Transmission model (MCCT). In [29], a scalable and energy-efficient scheme (SEES) is developed for the heterogeneous node. The network lifetime throughput for the energy harvesting node in WSN is improved. The energy cost is decreased in this proposed work.

Data distribution is essential in networks of sensors within the Internet of Things systems, but current methods don't adequately handle the variety of IoT applications. To effectively control energy during transmission, Kuthadi et al. [30] suggested the OEM-DD framework for optimized management of energy model data dissemination. It accomplishes effective data distribution and low energy consumption among sensor nodes by using a non-adaptive routing technique, increasing data transmission speeds by 96.33% while using 20.11% less energy in WSN.

Fan et al. [31] investigated how deep learning (DL) and artificial intelligence (AI) support sustainability in fields such as intelligent building management, environmental health, and renewable energy. Although artificial intelligence (AI) has the potential to impact 134 of the 169 goals for sustainable development (SDGs), oversight by regulators is essential for ethics and transparency. AI and DL help with waste management, illness prediction, and energy optimization. However, model openness, data scaling, and ethical considerations must be addressed for sustained adoption. Future research should prioritize tackling these issues to ensure the moral and efficient use of AI and DL.

To provide IoT support for Wireless Sensor Networks (WSNs), including mobile sinks, Preeth et al. [32] presented a unique method called Neuro-fuzzy Emperor Penguin Optimisation (NF-EPO) for creating energy-efficient trajectories. The best cluster head selection uses an adaptable Neuro-fuzzy inference system (ANFIS) that considers node behaviour history, neighbour node sharing, and residual energy. It also uses sink trajectories and rendezvous spots based on emperor penguin optimization (EPO). According to the simulation results, the suggested approach outperforms the existing one in a few areas.

To preserve network resources while offering specific personalized security for each user, a new resource-efficient protection system (NR-EPS) dubbed OSU protection (OSU-P) has been developed for OSU-based OTNs [33].OSU-P assigns protected services to backup connections with limited bandwidth. In the event of a failure, the protection bandwidth is changed to match the service's bandwidth requirements during switching.Successful recovery switching of protected services has little effect on preemptable unprotected services after a network failure is achieved via a deterministic protection algorithm (DPA) and a preemptable service provisioning algorithm based on overlapping risk avoidance. Vehicle networks use a new energy-efficient mobility management protocol (NEMa) [34]. With this protocol, cars' onboard sensors and the network work together to reduce power consumption without sacrificing network throughput or reliability. They analyzed the suggested protocol's efficiency, latency, and network overhead compared to current benchmark solutions for mobility management and their respective energy consumption rates. Deadline Scheduling with Commitment (DSC) method of scheduling shows that our improved version of the widely used Earliest Deadline First (EDF) method may significantly boost the performance of the method [35]. To fulfil the demanding needs of smart grid communications, a new method called Optimal Usage and Dropping Scheduling (OUD) is suggested for the correct allocation and use of Resource Blocks (RBs).Finally, the suggested OUD scheduling method allows for the efficient use of 5G communications in smart grids.

Mai A. Abdel-Malek and Mohamed Azab [36] suggested the UAV-fleet management for extended NextG emergency support infrastructure with QoS and cost awareness. A balanced multi-objective, multi-dimensional convex-optimization problem, the formalized optimization solves the operation management issues of ad hoc UAV deployment. In addition to outlining a framework for managing UAV operations, the article includes numerical analyses and parameters to provide optimum mission-oriented extension coverage before flight. A 5G-sub 6 cellular network optimization issue is modelled to evaluate the efficacy and efficiency of the suggested framework in a scenario including coverage expansion. Longer flight times, overlay network support, and reliable service provisioning were all made possible by the suggested architecture.

Vaibhav V. Deshpande and Rajesh K. Shukla [37] proposed the Fuzzy AHP and Iterative Grey Wolf Jelly Fish Optimization (GWJFO) for Enhancing Energy Efficiency in IoTBased Wireless Sensor Networks. The GWJFO's strategic ability to outline ideal routing patterns, which reduces energy consumption and improves data relay efficiency, makes it special. In addition, the model is enhanced with a Q Learning Method, which is cleverly engineered to find and implement viable alternative routing pathways using a Make Before Break method. This enhancement removes a possible source of error and greatly improves computing efficiency and packet delivery performance. Experiment results from real-time network simulations proved the model was better than the competition, showing improvements in communication speed of 9.5%, energy efficiency of 8.5%, performance of packet delivery under fault conditions of 4.5%, throughput of 10.4%, and network consistency of 5.9% compared to the prior methods.

Ishwari V. Ginimav et al. [38] presented the Deep Learning-based Low-BER Video Streaming Model (DLLBVS) for High-Noise Wireless Networks. The suggested approach begins by estimating frame-level characteristics using an LSTM block and then transmits and receives processed video frames using a modulation platform based on Orthogonal Frequency Division Multiple Access (OFDMA). Data fidelity is improved under varied noise environments by cascading an OFDMA model with a chaotic communication module. To make the chaotic communication module work better in real-time communication settings, Grey Wolf Optimiser (GWO) is used to help set up its hyperparameters. Video frames were pre-processed with the help of dual neural networks to estimate differential frame information sets. Streaming performance for various video kinds is enhanced due to faster streaming speeds made possible by estimating this differential frame information, which helps to increase the number of frames delivered per second. The VARMAx Model, built on iterative Gated Recurrent Units (GRUs), takes this frame data and forecasts when a frame will be removed, which helps with low-error, rapid communications. Throughput and congestion are improved by optimizing data flow using the GRU VARMAx Model. The model was evaluated using AWGN, Rayleigh, and Rician channel types, and its performance was contrasted with that of conventional streaming methods concerning computational complexity, communication jitter, throughput, peak-to-average power ratio (PAPR), communication error rate, and bit error rate (BER). From this comparison, this study can deduce that the proposed model is ideal for many real-time streaming applications due to its reduced communication delay of 3.5%, BER of 8.3%, PAPR of 5.9%, increased throughput of 10.5 %, jitter of 3.9%, and computational complexity of 6.4%.

The Preemptive Energy Conservation Technique (PECT) advances over traditional approaches for optimizing energy use in wireless networks. It does this by integrating proactive management with predictive analytics. PECT uses Naïve Bayes predictive intelligence. This novel approach results in reduced energy waste and increased network efficiency. By catering to the specific requirements of each device, PECT further reduces waste while improving overall performance via ecologically responsible energy distribution. In contrast to reactive methods, PECT begins conservation efforts in advance based on anticipated device demands, ensuring faster data transfer with fewer delays and fewer communication losses. A more comprehensive evaluation of power consumption, latency, and data loss makes PECT a more effective and advanced choice for future wireless networks.

III. PROPOSED PREEMPTIVE ENERGY CONSERVATION TECHNIQUE

Communication with the multi-user is the next generation that deploys the AI and Wireless network. The network performs different operations in the AI framework, including computation, resource allocation, and sharing. The evaluation determines the energy harvesting and conserved distribution based on the device requirement. Here, the distribution and wireless device operation aid the maximum information exchange in the network.Fig 1a shows the block diagram representation of the proposed method.The PECT is introduced in the paper for next-generation wireless networks. Optimizing resource allocation and operations with ultrahigh frequency lines, machine-type interactions, and AI models improves energy efficiency and meets device needs. The approach identifies energy slot intervals and assesses conservation and dissemination needs using Naïve Bayes prediction. The

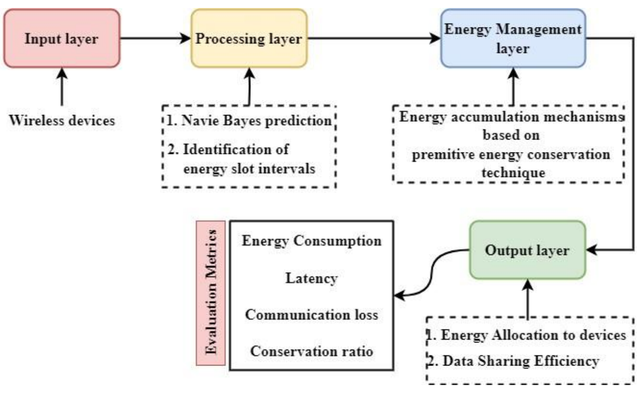

FIGURE 1a Block diagram of PECT

method is assessed by energy consumption, delay, communication loss, and the lowest possible conservation ratio.

The identification of wireless devices determines the energy-conserving process for the next generation. Fig. 1b presents the process flow of the proposed technique.

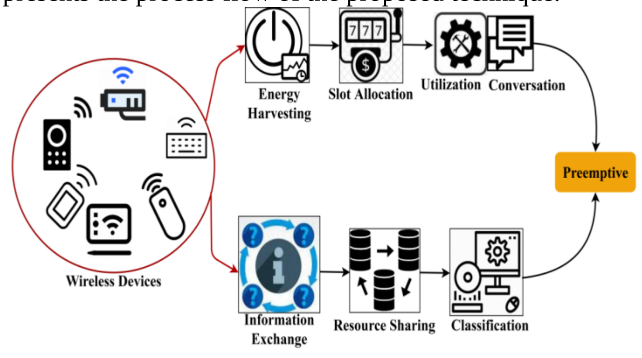

FIGURE 1b Proposed Technique's Process Flow

The proposed technique performs energy harvesting and information exchange processes preemptively. For energy harvesting, slots are allocated, after which the utilization and conservation are estimated. In the conservation process, the shared resources and their classifications are accounted for (Fig. 1). Energy harvesting saves energy and consumes the required energy for the devices. The device need is defined here based on the previous processing state. Information sharing, energy harvesting, and conservation are accomplished using this method. In addition to determining the safe information transmission between the wireless devices, resource allocation is carried out for energy harvesting. In this process, resource allocation is performed for the required devices in AI. The following section is used to determine the resource allocation

A. RESOURCE ALLOCATION

Resource allocation is done based on the state of prior processing and examines energy conservation and harvesting. Here, the conserved distribution is performed based on device requirements and the processing status. The analysis is done by deploying the energy distribution among the corresponding AI devices, examining the wireless device operation, and improving the data exchange. The exchange of information is used to state the energy harvesting and conserved distribution in AI. This approach performs the allocation with the available AI devices, and the processing is monitored. Equation (1) is used to calculate the resource allocation.

$$R = (g_e + q_r) * \left(\frac{E*N}{\sum_I d_0 - w_d}\right) + [(t_0 * q_r) + (e_0 * y_s)] - o_t \tag{1}$$

Resource allocation is done for energy distribution, and energy harvesting is deployed for the number of information exchanges. Here, the energy distribution for the wireless devices is evaluated. The connection is established between the wireless devices in AI and finding out the energy harvesting. The power is distributed to the appropriate devices, and the conserved distribution for energy harvesting is examined. The wireless devices examine the status and request the energy to carryout the particular task. Here, the information exchange is done by determining the resource allocation for shared information. The evaluation is done by sharing the relevant data with the wireless devices on time.

The allocation is performed to determine the status of the devices and examine the wireless connection between the devices. The conserved distribution is performed for the varying information exchange in AI. The resource allocation is done by identifying the distribution of energy to the devices and monitoring the exchange, and it is denoted as R. The information exchange for the various devices is carried out, establishing the energy distribution denoted by I. The information varies for the device requirement, as$\{e_0, e_1, \dots e_n\}$, and examines the distribution of energy to the wireless devices, and it is denoted as w_d. The energy is forwarded to the required devices in AI, and it is defined as g_e, the energy harvesting is maintained in this approach, and it is represented as E.

Here, the wireless device requirement is used to state the connection for the appropriate devices, and it is represented as q_r. The energy is allocated to the desired devices, and the resource allocation is referred to as$d_0$and R is examined. The connection is established to communicate for the wireless devices, denoted as N. The synchronization is done to improve the information exchange on time, and it is mentioned as y_s. The evaluation is denoted as t_0,is performed for the preceding state and offers the pertinent sharing. The time, which is indicated as o_t, is utilized to complete the AI work and look at energy harvesting. To discover how resources are shared with wireless devices, apply Equation 2.

$$h_a = \left.\begin{array}{c} \prod_N^{e_0}(d_0 * w_d) + \left(\frac{d_0 * e_n}{E * I}\right) * q_r \\ q_r = (f_a + e_0) * (d_0 - n_v) \\ f_a = (t_0 - n_v) + \emptyset \\ n_v = (t_0 - x') + f_a(w_d) \end{array}\right\} \quad (2)$$

Resource sharing v is carried out for the necessary wireless devices, the connection is examined, and the outcome is given. Energy collection and distribution are determined by the information that is shared. Mapping with the prior state is used to share with the wireless device. Wireless devices share information, which harvests energy for different types of connections. Mapping with the preceding state accomplishes energy savings and supplies the necessary exchange. By enabling connectivity with wireless devices, data exchange is performed. Lastly, energy distribution for the wireless gadget in AI is completed, and energy conservation is examined. Resource sharing determined by slot evaluation is shown in Fig. 2.

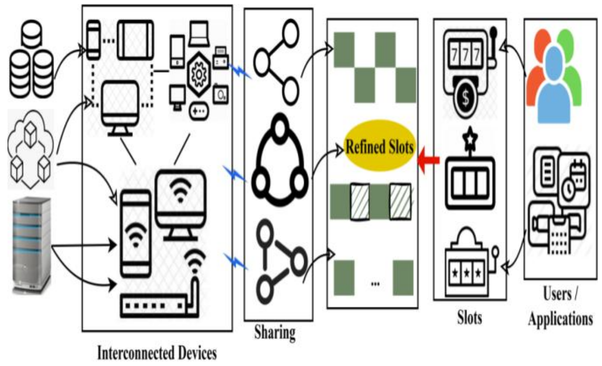

FIGURE 2 Resource Sharing based on Slot Evaluation

The interconnected devices are swift in admitting slots for communication. The available slots are evaluated based on $V$to prevent unnecessary loss. This allocation process maps synchronized devices and slotsto improve efficiency. This improves transmission throughout the allocated time interval, reducing latency (Fig. 2). The evaluation is done by identifying wireless devices and deploying energy harvesting and information exchange. The resource allocation is done according to the device requirement, and the computation is timely. Here, device requirements are utilized to state the energy conservation and thus provide energy distribution. Device requirements are identified by determining the previous state and forwarding the energy to the wireless devices. The forwarding of the information to the devices is done on time and relevancy, and it is represented as $f_a$andn_v. Communication is established for the wireless devices, and information is shared, denoted as $\emptyset$. The mapping is completed with the prior state and pursuing information represented as x'. The energy harvesting and conserved distribution are carried out according to the device requirement and are computed in the equation below.

$$V = \left(\frac{w_d + f_a}{\sum_{w_d}(g_e + d_0)}\right) * \left(E + {y_s}/{N} + e_n\right) + \prod_{h_a}(R * e_0) - o_t \quad (3)$$

$$D = \begin{cases} 1, if\ (h_a * g_e) + \left(\frac{e_0 * n_v / N}{d_0}\right) * I + y_s \\ 0,\ Otherwise \end{cases} \quad (4)$$

In equation (3), the energy harvesting is done by deploying the device requirement state and forwarding the information. Here, energy distribution is used to state the resource allocation and examine the information exchanged with the user. The energy harvesting is defined from the prior state and issues the results to the wireless devices. Here, the identification is determined by the amount of information shared with the wireless devices in AI. The relevant information is exchanged with devices, and the energy-conserving process for the next-generation wireless network is estimated. Finally, the resource allocation is done for varying information sharing and gives energy conservation for the devices.

Energy harvesting is defined by determining the mapping with the prior state and sending the data to the wireless devices. Enough energy is sent here to the devices,

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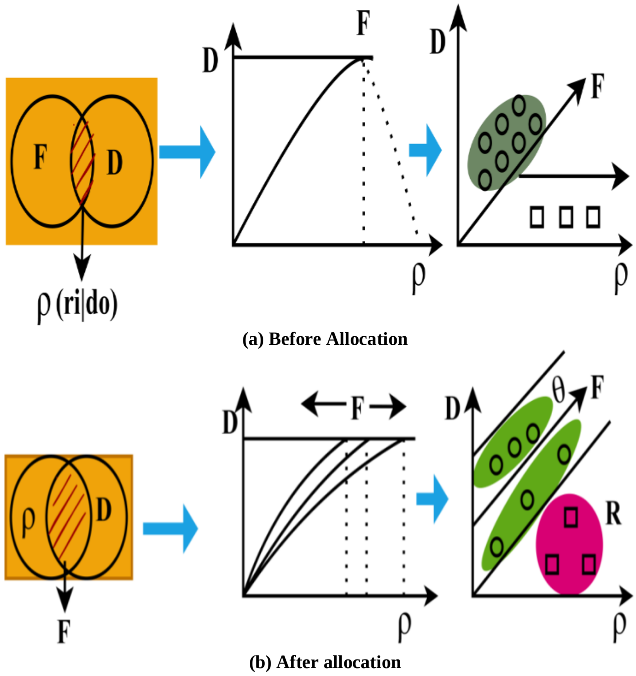
which track the performances. The evaluation V is done by deploying the resource allocation and sharing with the wireless devices. Here, the assessment is carried out to share information on time and energy harvesting. In this processing step, the connection is established with the security devices in AI, and energy conservation is performed. The information exchange is carried out for the energy harvesting method, and it is formulated as$\left(E + y_s/_{N + e_n}\right)$.

The conserved distribution decreases the loss in a wireless network and improves the information exchange. Here, the procedure chooses the suitable wireless device depending on the device's requirement. Energy conservation is carried out in this computing stage by providing wireless devices and mapping onto the previous state. In this case, the user's varied information sharing is considered while allocating resources, and the energy needed for communication is estimated. The conserved energy distribution has forwarded the post to the resource allocation method. The$y_s + e_n$ is done to increase the number of information exchanges with AI devices. In equation (4), the determination is made for the conserved distribution of energy in the wireless network, which provides reliable processing.

The energy is distributed to the user by examining the synchronized process. Information sharing is done by deriving energy harvesting from devices. The device requirement is done for resource sharing and allocation and performs the conserved distribution, and it is represented as r_i. The determination of energy conservation is used to enhance information processing, denoted as D. The synchronization is carried out for energy conservation and is estimated in the if and otherwise conditions. The condition is carried out; otherwise, the condition is executed if the energy-saving distribution is carried out based on the prior state of energy harvesting. The energy slot for energy and mobile device operation is determined using the following equation to maximize the support for information sharing.

$$F = \left.\begin{matrix} (q_r + w_d) * \left(\frac{E+g_e}{N/_{d_0}}\right) + (f_a * I) + y_s \\ N = [(e_n + f_a) * (g_e - o_t)] + l' \\ l' = (h_a * w_d) + (R * r_i) \\ r_i = (N + e_0) * (f_a - q_r) \end{matrix}\right\} \quad (5)$$

The energy slot is identified by determining the resource allocation with the devices and examining energy's conserved distribution. The evaluation is done by deploying the communication and exploring the connection with the end devices in a wireless network. Here, energy harvesting and resource sharing are performed with the devices based on resource allocation. The connection is established with the devices in the wireless network for energy conservation. The energy distribution is done for energy harvesting and distribution to the relevant devices. The energy slot is identified to distribute energy and allow wireless device operation for information exchange. The energy distributionis carried out for the conserved distribution based on device requirements. Fig. 3 presents the possible combinations in identifying energy slots before and after allocation.



(a) Before Allocation

(b) After allocation

FIGURE 3 Combinations in Identifying Energy Slots

In the forehand allocation [Fig. 3(a)], the $\rho\ (r_i|d_o)$ achieves high D through repeated classifications. If $D(g_e, E)$ is high, then an energy slot is available, reducing communication loss. The θ is performed for one-to-one F and R along with ρ values. Contrarily, the after-allocation [Fig 3(b)] requires preemptive classifications based on synchronized slot utilization. Both cases are computed to identify empty and energy-reliable slots for communication. The identification is performed for every iteration step to determine the sufficient energy and execute the energy-conserving process for the next-generation wireless network. The initial step of this proposed work post to the resource allocation, sharing the energy slot is determined for the energy-conserving process. Here, the distribution is forwarded to the devices and provides the conserved energy for the wireless devices concerning harvesting, and it is represented as$(q_r + w_d) * \left(\frac{E+g_e}{N/_{d_0}}\right)$. In this computation step, the energy slot is detected with the prior state of action and estimates the distribution and conservation, and it is denoted as l'. Prediction learning is utilized to distinguish the preservation and distribution of energy in AI for this Naïve Bayes' prediction learning is introduced.

B. PREDICTION LEARNING

It is a predictive learning approach that classifies the conservation and distribution of energy in a wireless network and estimates the reliable information exchange. The probability function defines whether it is conservation or distribution of the energy used to forward the information to the devices to improve the exchange rate. The training data determines the energy conservation for the next generation and forwards the information to the appropriate devices. The energy slots are identified in AI, examining the synchronized connection and enhancing the information exchange. Equation (6) is used to predict energy harvesting and conserved distribution.

$$D(g_e, E) = \left(\frac{^{w_d}/_{g_e}}{q_r}\right) * \sum_{l'} \left[(e_0 + f_a) * \left(N + \frac{I*l'}{E}\right)\right] + \mu(t_0 - x') \quad (6)$$

The prediction is performed with the prior state and gives the result based on energy conservation. Here, energy harvesting and conservation are done by deploying communication and exchanging information. Here, the wireless device is used to forward the energy consumption for the next generation and determine the energy slots. The energy slots define the information exchange with the devices in a wireless network and monitor the performance. The maximum information exchange is performed for energy harvesting in AI to determineenergy conservation. Here, the energy harvesting and conserved distribution are done by deploying the device requirement.

In Naive Bayes' prediction learning, probability is used to define the state of processing in AI. In this approach, the information exchange is done by deploying the previous state. Based on the last state, the energy is forwarded to sufficient devices in a wireless network. Prediction learning is used to define the communication medium preemptively. Concerning this evaluation step, the determination of energy harvesting and energy forwarding is detected. The energy slots are used to examine the energy harvesting for the connection establishment, and it is represented as $\left(N + \frac{I*l'}{E}\right)$. The conserved distribution is done for the energy harvesting for the wireless devices and performs the prediction with the previous history of information, and it is referred to as μ. The probability function is derived for the conservation and distribution of energy.

$$\rho(r_i|d_0) = \frac{\rho(d_0|r_i)*\rho(r_i)}{\rho(d_0)} \quad (7)$$

The probability factor determines energy conservation for the number of information exchanges in AI. Here, the process is termed to examine the distribution of energy for conservation purposes. The evaluation is done by deploying the connection in wireless architecture and provides the conservation of energy. Here, the energy slots are identified to distribute the energy to the appropriate devices in a wireless network and differentiate the preservation. The PECT is introduced for the energy conservation for upcoming generation wireless networks, and this resource allocation is examined. The resource allocation is done by deriving the previous state's conservation process and providing a feasible solution.

Sufficient energy sharing with the devices is examined in the wireless network, and the conservation and distribution of energy are deployed. Here, energy slots are identified for varying information sharing and connect with the end device in a wireless network. The evaluation is carried out for the different information exchanges in a wireless network; the probability is used to define either case, termed as ρ. It can be conservation energy or distribution and deploys the identification phase with the energy distribution. The equation below performs the classification, including energy conservation and distribution.

$$\theta = \begin{cases} (I + g_e) * \left(q_r + \frac{E}{d_0+N}\right) + e_n * f_a(n_v) - t_0 \\ \sum_E^{g_e} f_a * q_r + D[(e_n * h_a) * (r_i - o_t)] - o_t \end{cases} \quad (8)$$

The classification is performed in this proposal to distinguish the conservation and distribution of energy. First, energy harvesting is determined preemptively. The task requires a wireless network; the device needs energy in this processing. The AI requests the energy, and forwarding is carried out for the information. The preemptive is defined as distributing the energy to the device and monitoring the available energy slots to perform the task. This preemptive is one type of scheduling process that deploys the information exchange to the devices and estimates energy conservation. Here, classification is performed using Naive Bayes' method, which deploys probability for conservation and distribution. Fig. 4 presents the classification model for preemptive energy conservation.

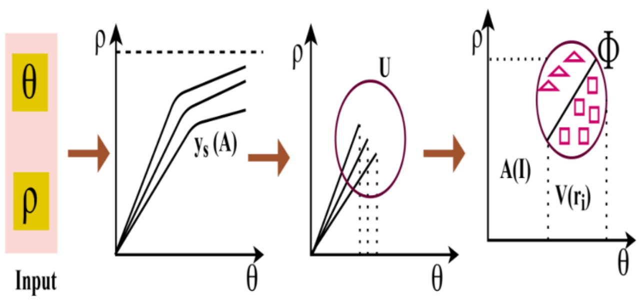


FIGURE 4 Classification Model Illustration

The θ and ρ are the inputs classifying $\emptyset$ under $A(I)$and $V(r_i)$. In this classification, the U requiring θ is identified, provided ρ is high. This identification reduces the dropouts' ability to assign resources for the communication required. Therefore, identifying U required instances is mandatory for leveraging the performance (Fig. 4). The identification is made energy slots, and distribution is carried out for the varying information exchange. The evaluation is done by determining the prediction for energy harvesting and conservation. The proposed method, PECT,maximizes the information exchange; Naïve Bayes' is used for preemptive communication. For this approach, classification is estimated in the above equation for sufficient energy transmitting, and it is referred to as θ. The conserved distribution is determined for the information exchange with the required devices. Concerning the energy slots, the distribution is performed from that classification is executed. The conservation of energy is evaluated by

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combining equations (5) and (6), and it is formulated in the following equation (9).

$$V(r_i) = \left. \begin{array}{c} (F + g_e) * n_v + \left[y_s * \left(\frac{w_d * E / R}{l'} \right) \right] * (\mu + y_s) - \rho \\ y_s = n_v * g_e(f_a) * p_m \\ p_m = h_a + (F * I) - o_t \\ I = (l' * \mu) - t_0 \end{array} \right\} \quad (9)$$

The evaluation is carried out for energy conservation. In this approach, harvesting is done for the varying information exchange between the devices in AI. The synchronized connection is ensured in this approach to improve the information exchange rate in this proposal. The PECT method is developed for harvesting and conservation and distributes the energy to the requested devices in a wireless network. Examining this conservation, the classification is used to process the information preemptively. The preemptive is used to decrease the failure in a wireless network, and it is termed asp_m. The resource is shared with the devices, deploys the connection, and maintains synchronization.

The synchronized transmission is determined for the preemptive processing and estimates the energy harvesting and conservation. Here, the prediction is made for the information exchange, and the energy slots are examined. The prediction is evaluated by introducing the Naïve Bayes method, including the PECT method for energy conservation. Identifying energy slots examines the probability factor and provides the energy. Finally, the distribution is done by determining the information exchange on time with relevant information to the devices. Thus, the evaluation is derived from the above equation, and communication is established by equating the below equation.

$$\emptyset = (l' * n_v) + \left(\frac{h_a}{\sum e_0 (f_a + q_r)} \right) * f_a(e_0) + F(\mu) - t_0 \quad (10)$$

Communication is established for sharing relevant information with the devices. Here, resource sharing is done by determining the energy distribution for the number of information exchanges. The sharing is done through the allocation of resources and performs the information forwarding to the devices. Here, the connection is established between the two devices in a wireless network, the energy slots are determined, and energy harvesting is provided. The communication is established by detecting the appropriate information sent as advice requests. The prediction is made by distributing the energy to the devices and deploying the energy slots. This derivation addresses the communication loss, and the information shared is decreased.

The identification is done for the energy slot allocation and performs the forwarding of information on time. The relevancy is maintained for the number of information exchanges based on conserved distribution. Here, the resource allocation is done by determining the identification of the task and providing the prediction. The prediction is performed by mapping the information with the previous state and providing the result. By pursuing this process, communication is done for the information exchange with the devices and determines the sharing formulated as$\left(\frac{h_a}{\sum e_0 (f_a + q_r)} \right)$. The equation below determines the preemptive process, which includes the connection and improves the information exchange rate.

$$p_m(D) = (e_0 + N) * h_a - (q_r + V) * \sum l' + n_v(f_a) \quad (11)$$

The preemptive manner is followed in this work to improve the performance of energy harvesting and conservation. Here, the information exchange rate is enhanced by using Naïve Bayes' prediction method. The identification of energy slots is used to evaluate the sharing of resources to the allocated devices. The probability factor determines whether the processing is done for the energy distribution method. The conserved distribution is done by selecting the classification method. The distribution and conservation are classified in this proposal to evaluate the preemptive manner.

If the task needs the energy to perform the particular task, then the energy is forwarded. Post to the energy forwarding, the device from the waiting state arrives ready to accomplish the task. This state change from waiting to a ready state decreases the failure and loss, and it is defined as the preemptive process. The above equation determines the preemptive process for the shared resources in a wireless network. The naïve Bayes method determines the energy slots by performing classification. Finally, the following equation analyses the synchronized connection with the wireless network devices.

$$y_s(A) = n_v(e_0) + \left[(h_a * w_d) + \left(\frac{d_0 * l'}{e_n} \right) \right] * \prod_{f_a} r_i + R(E) \quad (12)$$

The analysis A is done around the synchronized connection between the devices, and the energy is distributed to the requested devices in AI. The relevant information is forwarded to the devices and deployedto the conserved distribution. Concerning device requirements, energy harvesting and conserved distribution are executed. Resource allocation is examined for the information sent to the devices. The device requirement is stated from the previous state and provides reliable processing. Here, energy slots determine the synchronized processing with the AI devices. The following equation performs the information exchange post to the synchronization.

$$A(I) = e_0(q_r) * (t_0 + D) * \left(\frac{\sum_{l'} (g_e + h_a)}{r_i + E} \right) + n_v(R * y_s) \quad (13)$$

The information exchange is done if a synchronized connection is established between the devices. If the connection is established securely, communication is performed among the devices. Based on the requirement, the energy distribution defines the conserved energy distribution to the devices. The information exchange process is presented in Fig. 5.

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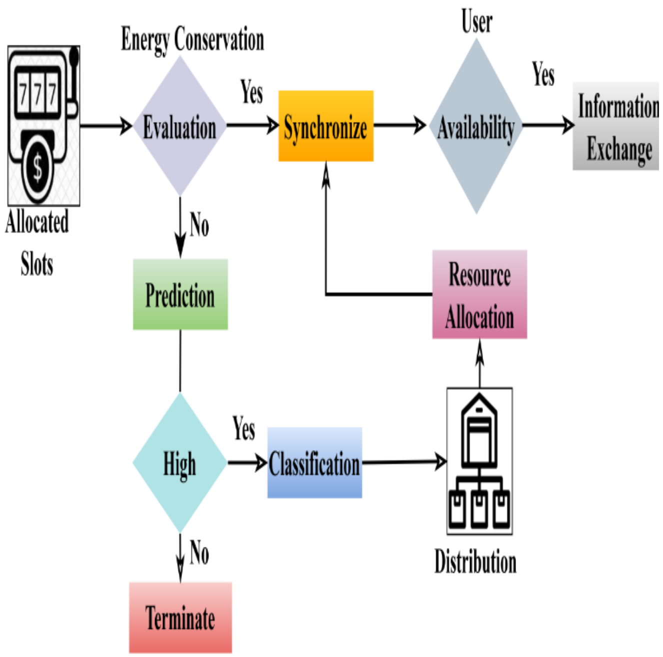


FIGURE 5 **Information Exchange Process**

In the information exchange, two decision-making processes are validated for user and energy conservation. First, the preemptive process is followed for energy distribution and deploys the probability factor. Here, the classification is used to examine the relevant extraction of information from the previous state. Then, the mapping is performed with the state earlier, and the result is provided on time. Second, energy harvesting and information exchange are used to determine the energy slots for the classification model. Finally, the equation below states the energy utilization and enhancement.

$$U = (d_0 * w_d) + \left(D + \frac{\emptyset}{e_0 * y_s}\right) - c_k(t_0) * A + [F(l') - s_0] \quad (14)$$

In the above Equation, energy utilization is improved by increasing the information exchange derived in the above equation. The analysis is done for the information exchange that estimates the synchronized information sharing with the user. The evaluation is done by deploying the prediction with the previous state and enhances the utilization U. If the utilization factor is improved, then the latency and loss are detected and decreased, denoted as c_k and s_0. The evaluation is done for the information exchange post and the device communication. The scope of the proposed work is addressed by introducing PECT and Naïve Bayes' prediction learning that includes probability factors. The probability is used to state energy harvesting and conservation and enhance utilization and information exchange. This methodology decreases latency and loss and improves energy harvesting and conservation distribution.

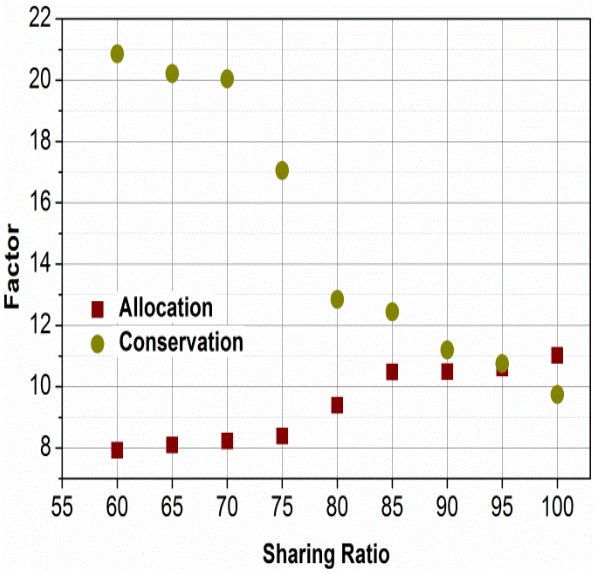
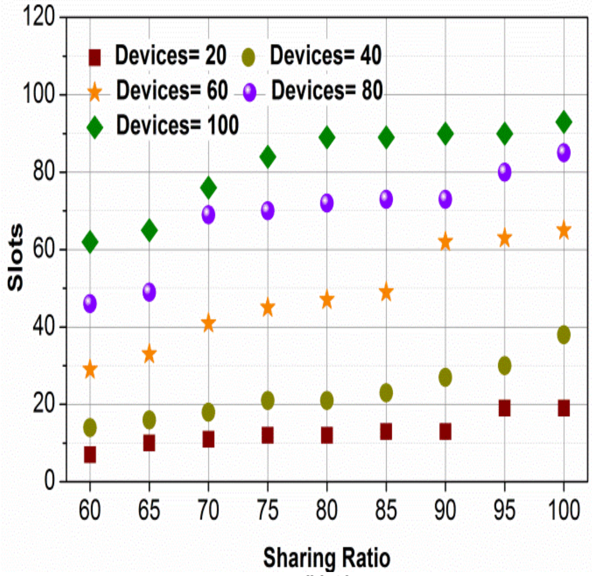


FIGURE 6(a) **Allocation and Conservation**



(b) Slots

FIGURE 6(b) **Comparative Analysis under Sharing Ratio**

Figs 6(a) and 6(b) present the allocation, conservation, and slots for different sharing ratios. The sharing rations increases h_a and R such that the slots are increased. In this process, accounting for the device density, the slots are increased to prevent early U point identification. Through the θ process, identifies multiple U such that R is high. For the shared R, the high F is distributed based on $D(g_e, E)$ at the initial stages. In the pursuing slots, the distribution is modelled based on $\rho(r_i, d_o)$. The classification approximates the prediction and probability of increasing the efficiency.

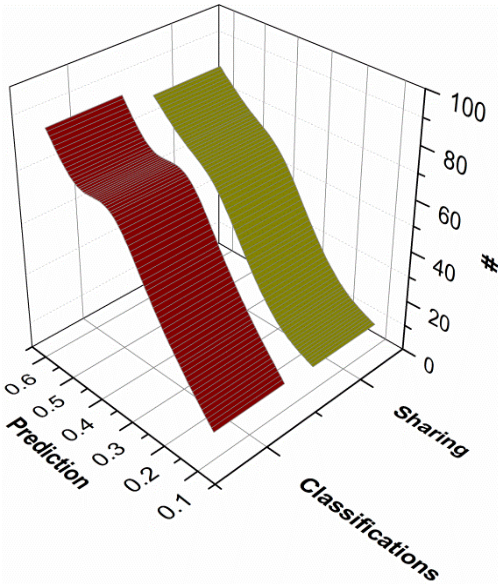
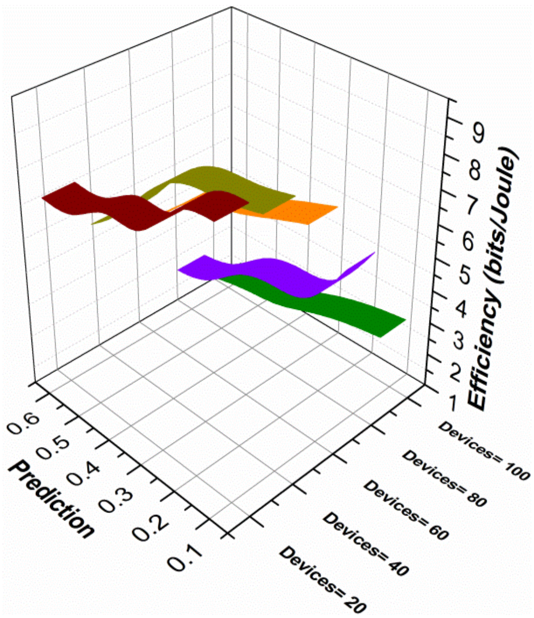


FIGURE 7 (a) **Sharing and Classifications**



(b) Efficiency

FIGURE 7 (b) **Comparative Analysis under Prediction**

The sharing, classification, and efficiency analysis for different prediction factors is analyzed in Figs. 7(a) and 7(b), respectively. The prediction factor increases the chance of $A(I)$; hence θ increases. As θ increases, h_a and R are predominant for leveraging different intervals. Therefore F increases with communication loss. The change in U through classification is identified in different information-sharing rates, for which θ is improved. As the θ is improved, the efficiency in different intervals is retained for leveraging D and V. This process is uncompromisable for achieving high efficiency in different F. The energy utilization is shared for all R regardless of the users in various intervals, increasing the efficiency.

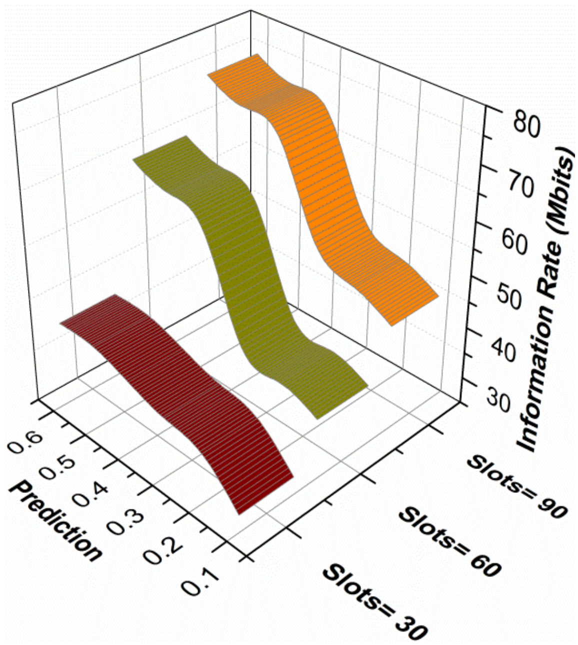


FIGURE 8 **Information Rate under Prediction**

Fig. 8 presents the analysis for information rate under different prediction factors. This abruptly increases the slots for which allocation is performed. The allocation pursues different slots for h_a and V. Therefore, F and $P_m(D)$ are ensured in providing different $y_s(A)$ achieving fair efficiency. The changes are observed and recurrently classified in different intervals, maximizing efficiency.

The Preemptive Energy Conservation Technique (PECT) might reap several advantages for future wireless networks. PECT uses Naïve Bayes predictive intelligence to optimize energy allocation, reduce waste, and promote eco-friendly behaviors. Identifying energy slot intervals optimizes energy allocation for portable devices and data transmission, improving network performance. PECT lowers dead time, communication delays, and data exchange. To illustrate the technique's ability to balance network efficiency and energy conservation, energy use, latency, communication loss, and conservation ratio are carefully tested. PECT's high-performance wireless network is environmentally friendly and efficient, setting a new benchmark for energy management.

IV. RESULTS AND DISCUSSION

In this section, the performance of the proposed technique is analyzed using network simulator experiments. The experiment consists of 100 wireless devices exploiting varying slots up to 100 for communication. In the communication process, the data rate is varied between 20 and 160 Mbits. A shared resource is the source for transmitting and accessing information between the devices. The experimental analysis results are validated using energy utilization, conservation ratio, communication loss, latency, and efficiency metrics. From the related works section, the methods SEES [29], HGC [24], and POS [19] are accounted for comparative analysis.

A. ENERGY UTILIZATION

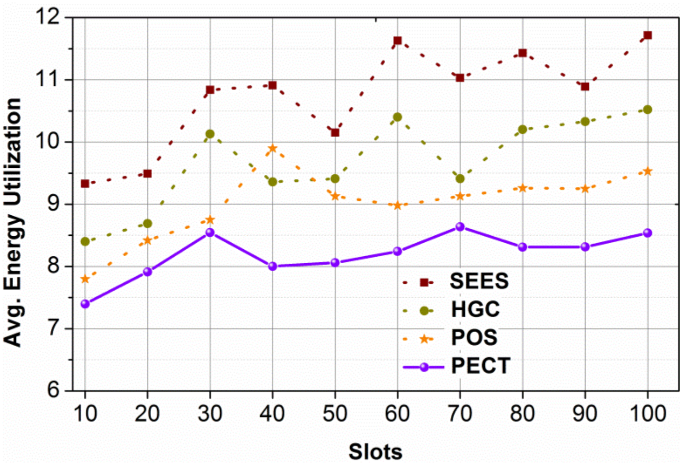
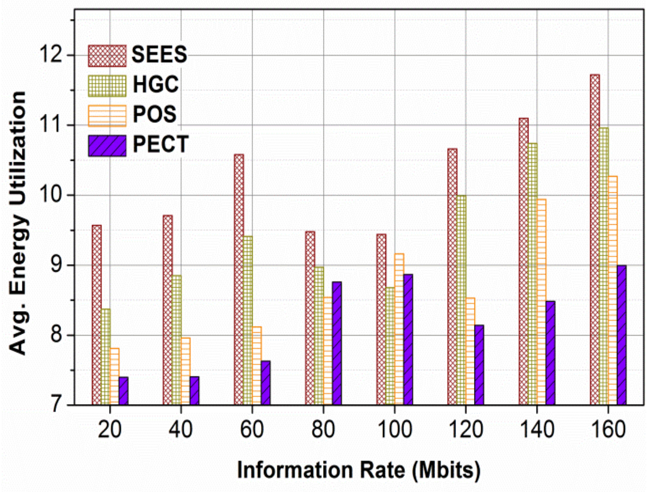


FIGURE 9 (a) Slots



(b) Information Rate
FIGURE 9 (b) Avg. Energy Utilization

Fig 9(a) and 9(b) compare the average energy utilization for different slots and information rates. The proposed technique achieves less utilization by two specific operations. First, predict the energy requirements of the devices through F in different resource access intervals. This process is required to vary the criteria and shortages for performing communication. Secondly, the $p_m(D)$ is responsible for sharing and utilization based on user availability. It is performed to ensure lossless information exchange between the devices. In all the communication slots, $y_s(A)$ between the users is analyzed to achieve fair distribution. This prevents multiple devices from handling the same information, so energy utilization is confined. Besides, the shared conservation validation is performed for increasing the V by which energy utilization is confined. The preemptive processes are excluded if the energy is completely drained, so the device operation is not observed. This feature is also periodically updated in the proposed technique for energy minimization.

B. CONSERVATION RATIO

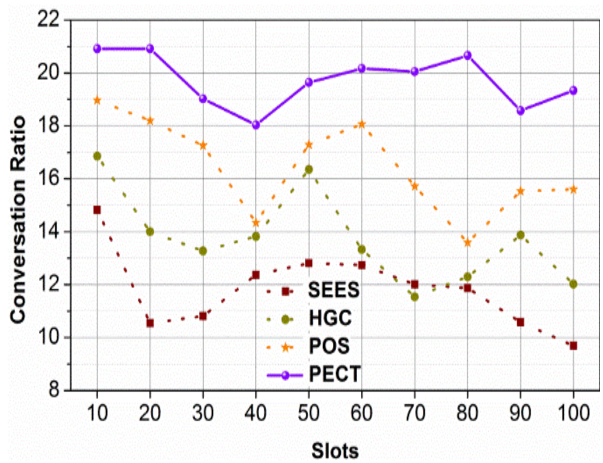
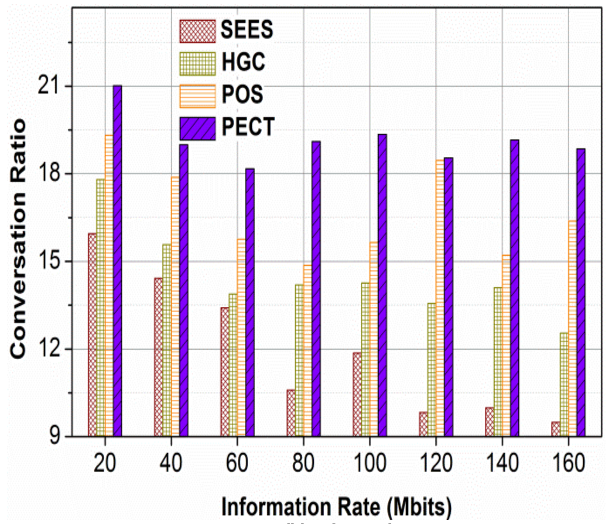


FIGURE 10 (a) Slots



(b) Information Rate
FIGURE 10 (b) Conservation Ratio

The PECT achieves high energy conservation compared to the other methods [Refer to Figs 10 (a) and 10 (b)]. In this technique, $v\ (r_i)$ is performed based on $\emptyset$. The output of θ is U identification, after which the device remains unfunctional. The $A(I)$ is achieved by F and V through the classification. In the allocated slots, $\rho(r_i|d_o)$ is computed to verify if D occur. The change in $\rho(r_i|d_o)$ requires different devices to handle the same information. The reducing U is predicted through θ process for different slots and information rates. This prevents early device drain (energy) and malfunctioning. The V performed in different F is distributed for retaining the preemptiveness $\emptyset$. Therefore, the R is performed based on v after deserving U through the θ. The output ensures valid slots and energy deficiency for which conservation is required. Hence, further allocations are based on preferred decisions before the classification process. This provides a high energy conservation ratio of PECT for different slots and information rates.

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C. COMMUNICATION LOSS

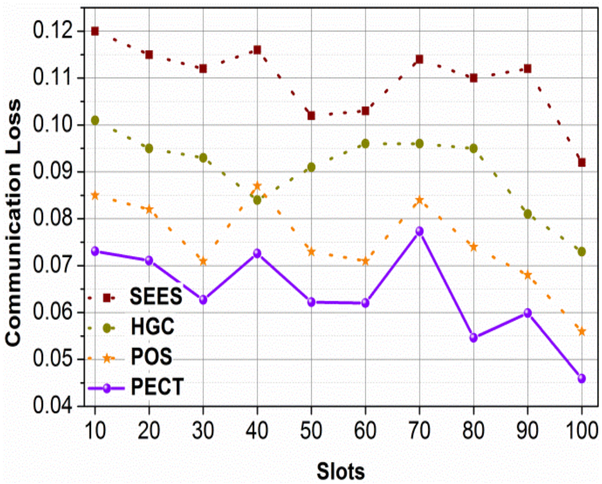
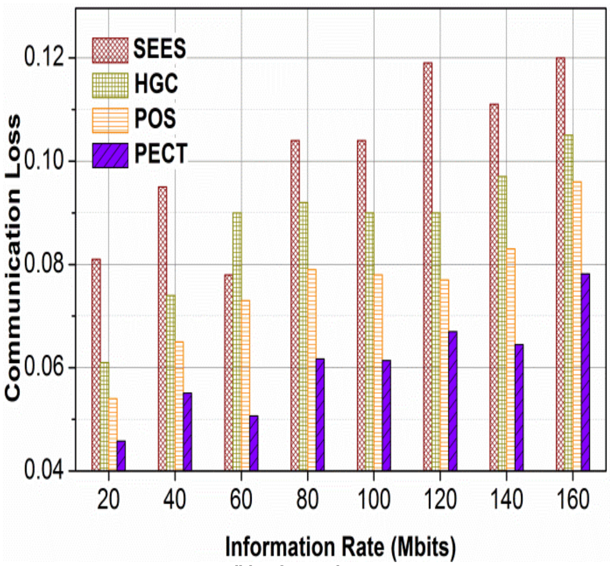


FIGURE 11 (a) Slots



(b) Information Rate
FIGURE 11 (b) Communication Loss

PECT achieves less communication loss compared to the other methods for different slots and information rates [Refer to Figs. 11 (a) and 11(b)]. The proposed technique verifies $p_m(D)$ before initiating $\emptyset$, and hence D is modified. In this process, $P(\mu) - t_o$ is computed during U point observation. This improves the $\emptyset$ in different intervals, retaining the $D(g_e, E)$. The D is performed if a device goes inactive after U identification. The consecutive way is to identify$y_s(A)$ indifferent F such that the changes are optimal. Therefore, the θ is increased for improving v such that not many devices are inactive $\emptyset$. Hence, the communication is preserved, retaining the liveliness of the slot. Contrarily, V increases the $A(I)$ and F required throughout the process. In this, the change in $\rho(r_i|d_o)$ and $D(g_e, E)$ are identified, and hence, further classifications are timed throughout the $\emptyset$ process. This retains the slots for complete transmission, reducing communication loss.

D. LATENCY

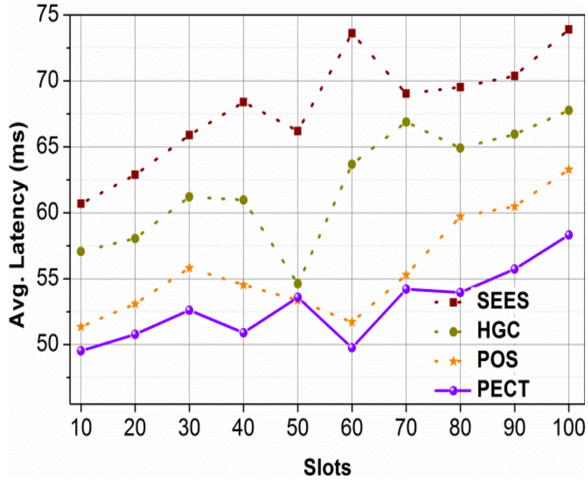
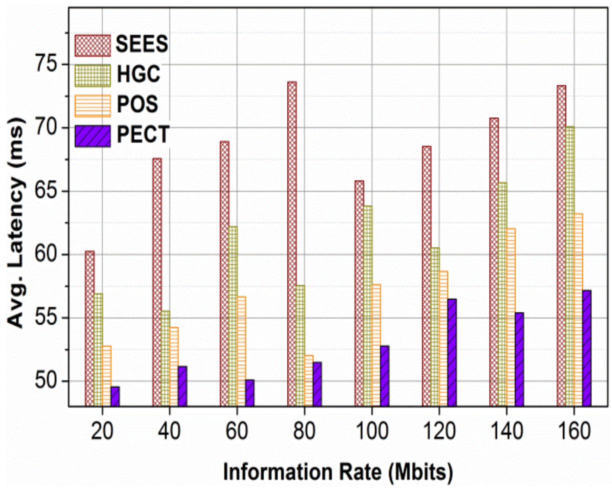


FIGURE 12 (a) Slots



(b) Information Rate
FIGURE 12 (b) Avg. Latency

Frequent link failures and devices malfunctioning due to energy drain and deficiency are confined to the proposed technique. The proposed technique's energy distribution is different for slots and information rates. For the changing slots, F is allocated based on $D(g_e, E)$ at the initial stages. In the pursuing states, this factor is updated using θ other than blindh_a. This improves the energy retainment in the slots, preventing a communication delay. In the information rate-based allocation,$y_s(A)$ between the devices is verified for improving the efficiency in $\emptyset$. The pursing in information exchange is validated for U point through θ. This identifies weak/energy-drained devices, improving concurrency. Therefore, the change in communication path/ $y_s(A)$ is updated using $V(r_i)$ for preventing loss. This prevents periodic neighbour replacement, reducing latency regardless of the information rate. A comparative analysis is presented in Fig.12 (a) and 12 (b) for slots and information rate, respectively.

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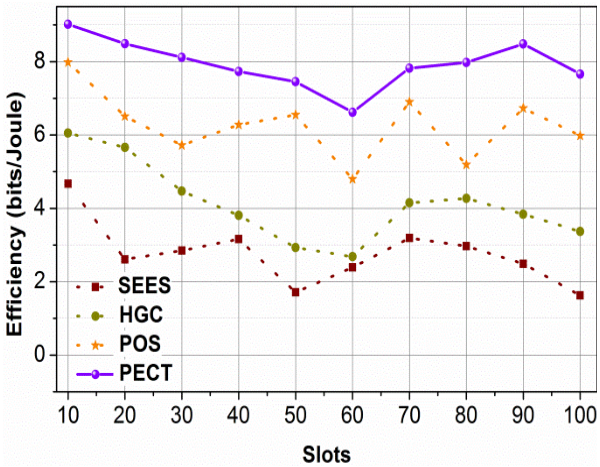
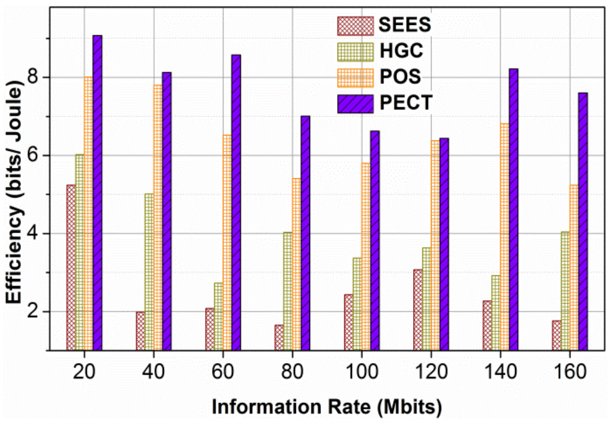
E. EFFICIENCY



(a) Slots



(b) Information Rate
FIGURE 13 Efficiency

The energy exploited per information bit of the proposed technique is higher than the considered methods. Based on classifications, the $p_m(D)$ and $A(I)$ is retained with less communication loss and latency. This increases the flow of information between the devices, requiring less energy. Further, the U at different classification points are identified for h_a and $A(I)$ reallocation. Therefore, the $A(I)$ is less impacted due to periodic F updates and replacements. For the deficient F, V is encouraged such that R are enhanced for increasing $A(I)$. The θ based $V(r_i)$ Estimation pursues different intervals for maximizing transmissions. The D in both the classified and unclassified intervals is based on $\rho(r_i|d_o)$ and hence $p_m(D)$ is retained. The U identified intervals are allocated with new F to the wireless devices, increasing the $\emptyset$. Therefore, the information exchanged between the devices is high under different F. For handling considerable information, the $y_s(A)$ through θ is high such that h_a is high for different intervals. These two factors achieve the high efficiency of the proposed method for slots [Fig. 13(a)] and information exchange [Fig 13 (b)]. In Tables 1 and 2, the comparative analysis summary for slots and information rate is presented.

TABLE 1
COMPARATIVE ANALYSIS SUMMARY (SLOTS)

Metrics	SEES	HGC	POS	PECT
Avg. Energy Utilization	11.715	10.52	9.53	8.538
Conversation Ratio	9.69	12.02	15.6	19.338
Communication Loss	0.092	0.073	0.056	0.0459
Avg. Latency (ms)	73.9	67.76	63.29	58.32
Efficiency (bits/ Joule)	1.63	3.37	5.98	7.658

The proposed technique reduces energy utilization, communication loss, latency communication loss, and latency by 9.69%, 8.33%, and 14.63%. On the other hand, it improves conservation ratio and efficiency by 13.8% and 17.4%.

TABLE 2
COMPARATIVE ANALYSIS SUMMARY (INFORMATION RATE)

Metrics	SEES	HGC	POS	PECT
Avg. Energy Utilization	11.72	10.96	10.27	8.997
Conversation Ratio	9.49	12.54	16.38	18.85
Communication Loss	0.12	0.105	0.096	0.0782
Avg. Latency (ms)	73.32	70.08	63.21	57.167
Efficiency (bits/ Joule)	1.76	4.04	5.24	7.604

The proposed PECT achieves 9.05% less energy utilization for the different information rates, 8.64% less communication loss, and 16.9% less latency. In addition, it improves the 12.09% high conservation ratio and17.2%.Efficient energy conservation and network performance are optimized by PECT, as shown by its thorough review of important metrics including energy use, latency, communication loss, and conservation ratio. This strategy revolutionizes energy management in next-generation networks by achieving a balance between both parameters, leading to a wireless network that is both more sustainable and performs better. Compared to more conventional reactive approaches, PECT is light years ahead due to this cutting-edge technology, which guarantees energy conservation while improving network functioning and efficiency.

V. CONCLUSION

This article introduces a preemptive energy conservation technique to leverage next-generation wireless networks' energy efficiency. The proposed method identifies service-requiring users and allocates sufficient communication energy slots. In this allocation, predictive learning is employed. Based on the learning prediction, the slots are assigned and are open for resource allocation and sharing. The energy requirement and pre-emotiveness classification are analyzed at the end of the communication. This analysis uses Naïve Baye's learning to achieve synchronized communication between the users and wireless devices. The probability-based classification and information exchange between the devices improves energy conservation. Besides, the energy harvesting and deficiency are precisely identified for further energy slot allocations. The wireless architectures are exploited to handle multiple energy-sufficient communication links and prevent communication loss. The proposed technique reduces energy utilization, communication loss, latency, and latency by 9.69%, 8.33%, and 14.63%. On the other hand, it improves conservation ratio and efficiency by 13.8% and 17.4%.

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Jagadeesh Selvaraj has completed his Bachelor's, Master's,and Ph.D. in Computer Science and Engineering from Anna University. Chennai. He is currentlyan Associate Professor of Computer Science and Engineering at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamilnadu.His research area is WSN. He has more than 10 years of Teaching Experience and 3+ years of Industry Experience. He has published more SCI and Scopus-indexedJournal Articles. His current research areas Bigdata, Machine Learning and Deep Learning.

Noor Alleema Nakeeb, Professor, Department of Computer Science and Engineering working at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamilnadu.Obtained her Bachelor Degree in Computer Science from Madras University, Chennai in 2004, Master degree in the Department of Computer Science and engineering from Anna University ,Chennai in 2006 and Ph.D. Degree in the Department of Computer Science from Sathyabama Institute of Science and Technology in 2021. Having more than 15 years of Teaching Experience and specialized in the various Domains like IOT, Mobile Ad Hoc networks (MANETs). She has published a number of Conference papers and Journal articles on a range of research areas such as Mobile Ad-hoc Networks,IOT, ML and Networking.

Jaehyuk Cho received the Ph.D. degree in computer science from Chung-Ang University, South Korea, in 2011, with a focus on mobile and embedded computing systems. He was a Professor with the Department of Electronic Engineering, Soongsil University. He was a National Research and Development Program Project Manager with the Korea Institute of Science and Technology Evaluation and Planning (KISTEP), Seoul. He was a Senior Researcher with LG CNS, Seoul. He is currently a full-time Professor with the Department of Software Engineering, Jeonbuk National University, Jeonju, South Korea. His research interests include applied AI, data process, big data of sensors, the IoT, smart city, and SW platform systems.

Sathishkumar Veerappampalayam Easwaramoorthy is a Lecturer in the Department of Computing and Information Systems at Sunway University, Malaysia. He has held significant roles, including Postdoctoral researcher positions at the Department of Software Engineering, Jeonbuk National University, Republic of Korea and the Department of Industrial Engineering, Hanyang University, Republic of Korea. In 2021, he served as an Assistant Professor in the Department of Computer Science and Engineering at Kongu Engineering College, Erode, India. He earned his Bachelor's degree in Information Technology from Madras Institute of Technology, Anna University in 2013 and a Master's degree in Biometrics and Cyber Security from PSG College of Technology in 2015. Through the Korean Government Scholarship Program, he completed a one-year Korean Language program at Inha University and earned a doctoral degree from the Department of Computer and Communication Engineering at Sunchon National University in 2021.