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Advancing 6G-IoT networks: Willow catkin packet transmission scheduling with AI and bayesian game-theoretic approach-based resource allocation.

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ABSTRACT

The rapid expansion of mobile broadband networks and the proliferation of Internet of Things (IoT) applications have substantially increased data transmission and processing demands. However, the application domains of IoT-enabled models often face resource limitations, requiring rapid responses, low latency, and large bandwidth, surpassing their inherent capabilities. To address these challenges, we propose a fishnet approach-based packet scheduling and resource allocation system, termed Fishnet-6G, to optimize network resource allocation in the proposed 6G networks. Initially, we constructed a Sierpinski Triangle-based network in a 6G-IoT environment, enhancing device connectivity. We utilize the Quantum Density Peak Clustering (QDPC) algorithm to perform clustering for IoT devices, establishing Cluster Head (CH) and Substitute CH (SUB CH) based on actual metrics. Furthermore, traffic prediction is achieved through two processes, grouping, and fair queue status, using the Improved Deep Deterministic Policy Gradient (IMPDDPG) algorithm with a variable sampling rate, resulting in well-organized packet scheduling. Subsequently, we perform optimal packet scheduling by employing the Willow Catkin Optimization (WCO) algorithm, and the scheduled packets are managed within a Fishing Net Topology to reduce energy consumption and system complexity. Finally, we allocate the scheduled packets to the desired resource blocks using the Bayesian Game-Theoretic Approach (BGTA). The proposed approach is implemented using Network Simulator-3.26, and the performance of the Fishnet-6G model is evaluated based on time, transmission rate, energy efficiency, average throughput, latency, and Packet loss rate. Numerical analysis demonstrates that Fishnet-6G outperforms existing approaches across these metrics, showcasing its effectiveness in addressing the challenges of 6G-IoT networks.

Introduction

The rapid expansion of IoT devices has led to notable progress in data generation, contributing significantly to the growth of linked objects inside the IoT systems. It is essential to highlight that this development is experiencing a sustained increase as many objects and

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devices are interconnected in IoT applications [1,2]. As 5G networks continue to improve and expand, concerns arise about their capacity to support the constantly evolving needs of emerging IoT applications fully [3]. The impending era of sixth-generation (6G) mobile communication is marked by the widespread adoption of IoT devices and cellular networks, contributing to a substantial increase in energy consumption and network traffic [4]. The ever-growing demands of intelligent and self-sufficient systems challenge their capabilities and spark the evolution towards the 6G-IoT vision [5]. By 2025, it is projected that there will be over 25 billion IoT devices, putting immense pressure on current multiple access techniques and necessitating the development of B5G wireless systems. In light of this uncertainty, attention has turned towards the potential of 6G wireless technologies to overcome these limitations and propel the transformation of existing networks [6]. Envisioned as a vital component in the development of sustainable smart cities, the 6G-IoT vision incorporates cutting-edge elements such as intelligent edge computing, health analytics, and multidimensional design technology, with a firm emphasis on critical features such as scalability, wireless multi-access, personalized AI, machine learning, cyber security, blockchain, and augmented sensing [3,6–9]. The strategic placement of small cells in a 6G system optimizes coverage and data transmission efficiency, while sensor nodes collect essential information communicated to IoT devices, enabling diverse applications like home automation and healthcare, showcasing the network's sophistication [10,11]. Network architecture and administration must mitigate complexities in the 6G network to provide exemplary performance. The construction of a 6G network presents numerous advantages, encompassing enhanced capacity, extensive coverage, cost-effectiveness, load balancing, and energy efficiency [12].

With the exponential growth in the number of IoT devices, deploying tiny cells densely in a way that supports 6G IoT devices and networks has become necessary to provide optimal coverage. Furthermore, the incorporation of traffic prediction as a vital instrument enhances the network's effectiveness through optimized packet scheduling and seamless traffic flow, ultimately enhancing the overall end-user satisfaction [13]. The deployment of 6G technology may facilitate the seamless distribution of AI applications across wireless networks, employing AI-driven air interfaces, algorithms, protocols, and techniques for transmission, optimization, control, as well as resource and network management [14–16]. The challenges facing 5G network infrastructure due to inadequate resource planning and allocation highlight the urgent need for a 6G-IoT network. This undertaking aims to reduce communication overhead, minimize energy usage, and achieve optimal load balancing through network capacity, scheduling, and resource allocation improvements. This crucial aspect has been greatly neglected in previous research efforts [17]. 6G-IoT necessitates ultra-reliable and low-latency communications (eURLLC), encompassing highly dependable mobile broadband and massive-URLLC services. The outlined use cases (Industrial and Automotive) for 6G eURLLC include machine-type communications (MTC) applications and associated Quality of Service (QoS) requirements. Notably, 6G eURLLC holds the potential to revolutionize manufacturing in Industrial IoT, particularly within the realms of Industry 4.0 and its advanced iteration, Industry 5.0. Its impact on 6G-IoT in Agriculture 5.0, requiring frequent updates, low latency (< 0.001 s), and low jitter, signifies potential advancements in productivity and sustainability [18–20]. In Automotive IoT, the 6G eURLLC could alter the transportation ecosystem by allowing V2X communication, which will enable driverless vehicles [21,22]. Leveraging these emerging technologies in industrial manufacturing enhances product quality, optimizes machine performance, ensures employee well-being, enables predictive maintenance, reduces energy consumption, minimizes environmental impact, and lowers production expenses [23]. The IoT devices and users are subsequently organized into groups to ensure adequate power management for user equipment (UE), and the optimal CH is selected to establish a connection with the advanced base station and request resources. This enhances the efficiency and endurance of the energy network [24]. On the other hand, previous studies have considered the local density and available resources during the clustering process, which has been found to impact performance and result in increased power usage [25,26]. Edge computing systems provide a range of functions, including task organization, priority setting, task scheduling, and resource allocation [27–29]. The scheduling techniques employed by the base station utilize buffer state and Channel Condition Information (CQI) to determine the allocation of resource blocks (RBs) to UEs and the number of resources to be allocated. To mitigate resource scarcity and enhance the efficient allocation of resources, a considerable number of base stations are deployed within the network to facilitate rapid and interference-free distribution [30]. Based on the traffic in existing works, the scheduling process is categorized into immediate and non-real-time. Queuing and traffic priority classification techniques guarantee adequate service quality regarding latency, throughput, and other parameters [31]. Nevertheless, most existing studies fail to consider sufficient and adequate criteria when organizing user requests, leading to substantial energy consumption [32]. Subsequently, the allocation of resources is determined by the ratio between occupied and available resource blocks, influencing resource allocation efficiency and increasing packet loss [33].

Motivation and objectives

The main objective of this study is to enhance traffic scheduling and transmission in the 6G-IoT network. Additionally, this study addresses the concerns related to the excessive use of energy, elevated packet loss ratio, latency, and diminished throughput. So far, related works of literature have not fully touched on the following issues:

- Lack of scalability and energy consumption: In some previous studies, deployments of IoT devices need to be appropriately managed in an IoT environment. However, it leads to decreased connectivity among devices and reduces the flexibility and scalability of the network. The entities are placed randomly, which causes a high packet loss ratio and computational complexities and increases network traffic.
- Excessive packet loss: In most of the existing works, traffic prediction was based on constant sample rate, low sampling rate, and frequency; however, some of the metrics, such as arrival, length of the packet, and finishing time, are not considered which leads to high packet loss and inefficient traffic prediction. The CQI was only considered during scheduling where bandwidth and buffer

status were insufficient, which increases high packet loss. Then, in several existing works, new requests are denied due to a lack of resource availability, which also increases the packet loss ratio.

- Latency: In several existing works, packet scheduling was performed, but packet management was inefficient for packet transmission. At the same time, it leads to high complexity and increases energy consumption. In addition, random sub-flow selection also leads to high complexity in the network due to not considering (i.e., traffic rate, transmission delay) selected a transmission path for transmitting the packets by considering only path bandwidth. However, more than one parameter was needed to choose the optimal path to avoid high jitter and increased latency.
- Inefficient Resource allocation: In several existing works, resource block allocations were performed by considering the quality of service (QoS) and resource block usage. However, only considering QoS and resource block usage was not enough (i.e., spectrum efficiency, resource type, feedback) are not supposed to perform efficient resource allocation, leading to high resource wastage.

This study aims to improve throughput by reducing packet loss, transmission delay, and complexity through traffic prediction, packet scheduling, and transmission on a 6G network. Among the goals of this study are the following:

- To reduce more complexity in packet transmission by performing improved network construction; this reduces the high packet loss ratio and processing complexities.
- To manage the network entities intellectually by performing clustering, which improves energy efficiency and reduces imbalance load among cells and computational complexities.
- To reduce the traffic in packet transmission by performing traffic prediction, which solves the problem of packet retransmission and makes packet scheduling and transmission efficient.

Table 1
Comparing references for packet scheduling and resource allocation using machine learning and deep learning.

Category	References	Concept	Limitations
Packet scheduling and resource allocation using machine learning [35- 39,42–44]	35	Resource allocation was done based on the fully connected layer for bandwidth allocation.	Inefficient resource allocation that leads to poor QoS
	36	IoT traffic is predicted using primary congestion management and the system efficiency of bandwidth allocation.	Less consideration of metrics leads to less traffic prediction.
	37	The channel network and the cellular transmission of the secondary fairness utilizes the cellular and the network fairness utilization.	Prediction of traffic in an IoT environment takes more memory and leads to highly complex.
	38	The problem indicates network traffic and the structures are functionally arranged in the different prediction layers.	IoT devices are poorly managed, leading to a high packet loss ratio.
	39	Proper security of the measure and the maintained preventions outperform the transmission and the consideration of the prediction environment.	The training data size is too small and does not contain enough data samples.
	42	Predicting data transmission quality is crucial for IoT security. There are multiple methods for achieving higher-quality transmissions.	Proper user management needs to be more focused, which causes computational complexities.
	43	The data transmission and the contention network scattering are performed based on the data and devices-based transmission approaches.	The single parameter cannot select the optimal path, leading to packet loss.
	44	Optimizing resource allocation and distributing tasks to multiple mobile devices.	Less consideration of efficient resource allocations and management.
	45	The performance of the proposed resource block was improved by using the cell edger and proportional scheduling.	Disconnected solution, which devours more time due to resource consensus
Packet scheduling and resource allocation using deep learning [45–52]	46	The energy dissipations of the sensor nodes, fault data transmission of tracking events, and the energy level intermediate proficient clustering.	The user demands the resources directly from the base station to demand services. .
	47	The smart packet transmission and the estimated value optimum choosing the distance between the target action values particles and the packet delay rise.	Unwanted large amounts of data for processing increases the complexity and energy.
	48	The packet broadcasting detection and efficiency to provide the link-based path packet overload detection to broadcast efficiency.	The scheduling of power flow within or between the microgrid
	49	The initialization of the multiple energy sources, the consideration of the distribution, and the different initialization generate various solutions.	Inefficient network topology for packet transmission.
	51	The transmission power frequency allocation and the power sources should be appropriately maintained for dynamic consumption.	It is not suitable for real-time scenarios for not static.
	52	Optimizes the input data conversion method to extract the features of spatiotemporal dependencies for prediction accuracy.	This approach has high complexities for training prediction.

- To increase the throughput and decrease the packet loss rate by performing packet scheduling and packet transmission through an optimal path in a 6G network by considering numerous parameters in terms of time and frequency domain.
- To enhance the QoS and power efficiency by allocating optimal resources in a 6G network.

Research contribution

A novel technique has been created in the context of a 6G-IoT environment, which utilizes a fishnet-based packet delivery and scheduling mechanism. The main contribution of the study can be summarized as follows:

- We suggested building a network based on Sierpinski triangles, which decreases the complexity of packet transmission and scheduling and enhances network administration,
- Using IMPDDPG, which addresses the issues of low training efficiency and slow convergence, traffic prediction based on grouping and fair queue status is done to minimize traffic in data transmission.
- We execute scheduling and dynamically alter the scheduling for reasonable packets using the WCO method by considering energy, delay, CQI, deadline, etc., to decrease the packet loss rate and increase throughput. Additionally, the management of packets using a fishnet architecture results in a lightweight process with reduced complexity and energy use.
- We ideally execute QoS-aware allocations of resources utilizing the BGTA algorithm by considering bandwidth, spectrum efficiency, etc., which controls the power consumption to improve the efficiency of power and QoS in 6G networks. To lighten the load on UE and for future usage, user computation and feedback are gathered from users and kept in the cloud infrastructure.
- The proposed approach was tested using Network Simulator-3.26, and its effectiveness was assessed by comparing it to existing algorithms in terms of various performance metrics, including time, transmission rate, energy efficiency, average throughput, latency, and packet loss rate. The approach outperforms existing approaches in terms of all metrics.

Paper organization

The remaining components of this work are organized as follows: Section II discusses the prior work in the transmission of packets and scheduling in the 6G-IoT environment as well as research gaps; Section III emphasizes the overall problem declaration of the existing works and their associated solutions; Section IV discusses the in-depth description of the proposed solution, including equations and a suitable diagram; Section V discusses the simulation arrangement of the proposed work.

Literature survey

Most of the current effort in the 5G and 6G networks conducts resource allocation, packet scheduling, and traffic prediction; nonetheless, it results in high power consumption, a shortage of QoS, and significant packet loss. Even though the current studies focus on these issues, traffic prediction still needs to be adequately addressed. Table 1 presents a summary of the existing work. However, the most pressing problems are still unresolved by current research. The packet scheduling and resource allocation can be categorized using machine learning and deep learning.

Packet scheduling and resource allocation using machine learning

As a result of recent advancements in AI, Machine Learning (ML) has become a helpful tool for building solutions and learning models to improve QoS parameters in IoT and wireless networks [34]. To improve 5G service quality, machine learning, and deep learning can help optimize bandwidth and power transmission dynamically. However, applying deep transfer learning to the neural network for resource allocation could be more reliable. The authors [35] showed that the broadcast neural network outperforms the quality of service and reduced training sample size. This study [36] proposed a statistical learning technique to predict traffic on IoT devices. It used a transportation forecasting model that includes time-series data and neural networks. The model estimated IoT traffic by analyzing accurate network data and system efficiency. The approach used congestion control, admission control, and bandwidth allocation strategies. Experimental results showed that timing sequence forecast models are more effective than other algorithms. This research [37] proposed a scheduling methodology to improve the QoS of video services in LTE networks. It analyzed optimization techniques for packet scheduling, considering channel limitations and QoS requirements. The proposed algorithms were evaluated using the Long-Term Evolution-simulator (LTE-SIM) video flow simulator. The authors [38] tested an experiment on quasi-deterministic traffic policy (QDTP) to predict traffic patterns for IoT gateways. They introduced Quality-Driven Packet Transmission to reduce congestion and improve network performance. The researchers concluded that QDPT significantly enhanced IoT network performance.

This paper [39] suggested applying machine learning to predict data flow in an IoT environment. The IoT device connectivity has laid the foundation for intelligent applications in emerging regions. Using proper security measures could avoid illegal data interceptions during transmission. To protect data flow in the IoT network, the research recommended using a convolutional neural network (CNN) and support vector machine to improve traffic prediction. The simulations showed that a hybrid model may accurately and effectively forecast data flow in an IoT scenario, improving smart city security. This study [40] presents a lightweight task-scheduling framework for cloud and edge applications from a cloud service provider perspective. They schedule tasks into the resource pool using RSerPool and allow numerous resource allocation policies. Researchers in [41] used secure data communication quality prediction to evaluate secure data transmission. The Elman network was utilized to predict the reliability of fast data transmission. The results showed that this technique has the potential to generate higher-quality predictions than alternative models while requiring a shorter computational time. This study [42] proposed an IoT-based process for optimizing data transfer efficiency in smart city networks. This approach involved using IoT devices for energy harvesting and regulating backscattering signals while implementing a contention-based strategy for network scalability. Compared to TDMA, the contention-based methodology demonstrated superior performance in ensuring precise data transmission. A study on IoT and mobile edge computing resulted in an optimized resource allocation system [43]. Utilizing edge computing on mobile devices reduces resource wastage, improves data transfer speed, and increases processing time. The authors used multiple linear regression and particle swarm optimization to maximize resource utilization.

Packet scheduling and resource allocation using deep learning

In [44] the proposed architectural framework seamlessly integrates reinforcement learning (RL), deep learning (DL), and federated learning to provide a more open system. This approach [45] improved 6G slicing architecture by adding intelligent and automated mechanisms, decreasing vendor dependence. This framework used intelligent processes to manage workloads and make smart decisions, improving user experience. A new scheduling method [46] improved 5G network efficiency. Proportional fair scheduling was used for cell edge users, and a two-stage mechanism assigned resource blocks to primary users (PFs) or secondary users (FUs). The method outperformed others in throughput tests. Energy-efficient clustering for WSN relay selection was suggested [47]. Sensor nodes lose energy and have trouble translating data in dynamic WSNs. Energy-efficient clustering was suggested to address these concerns and reduce event-tracking sensor node energy usage. Mobile nodes choose cluster heads based on energy and position. The technology boosted network efficiency and saved power. This study [48] developed deep distributed Q network (DDQN) packet transmission and scheduling, which optimizes traffic control, data storage, and energy efficiency for large-scale data management. Selecting a channel with the lowest anticipated packet error rate (PER) and lowering retransmission packet delay may enhance smart packet transmission efficiency—a generative acoustic network and DDQN (GAN-DDQN) reduced particle distance. The GAN-DDQN improved transmission packet efficiency while reducing power, latency, and throughput. The 5 G network used adaptive packet transmission and path selection [49]. A queue system maintains data packets that exceed duration slots. A multipath jamming detection approach has been created to provide a link-based path packet overload detection system. It analyzed method features to distinguish them and accurately diagnose packet loss. While mitigating network overload, the suggested solution reduced energy usage and packet loss.

The authors [50] suggested using mobile cloud computing to schedule tasks in an IoT development efficiently. A task scheduling technique that reduces task running time optimization targets has been found. The alignment between task assignments and computer systems was conceptualized as a bipartite graph, and the problem was divided into many subproblems for independent resolution and optimal solution identification. Experimental results showed the approach's efficiency and application. This study implemented Non-Orthogonal Multiple Access NOMA task transmission and resourced allocation strategies for IoT applications [51]. In this case, IoT devices could process the computational workload into subtasks and then send them to servers. The deterministic sub-issues are addressed via Lyapunov optimization. This method helped design a stochastic optimization strategy to reduce IoT device energy consumption while allocating CPU-cycle frequencies and transmission power. Dynamic resource allocation and offloading have improved system performance and reduced energy consumption. This study developed a simple model for traffic prediction in IoT using spatial-temporal correlation [52]. It built lightweight neural networks with excellent processing capability to assess raw data and provide accurate prediction outputs. The convolutional neural network structure is optimized by converting input data into spatio-temporal connection characteristics. The computational complexity of cellular traffic prediction decreased. The accuracy of prediction was assessed using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The suggested model outperformed CNN, ConvLstm, and dense net in the tests. Extensive research has been conducted on deep learning-based resource allocation and intelligent traffic prediction and control to meet the requirements of the data link layer and transport layer in the context of 6G [53]. Implemented machine learning and deep learning techniques for predictive analysis can substantially reduce latency by optimizing the transmission of information between end users.

Resource utilization parameters

This section illustrates the diverse factors affecting resource usage in IoT environments that must be taken into account to enhance the development of IoT resource utilization approaches.

Energy efficiency is essential in wireless energy transfer (WET) for 6G IoT devices, and optimizing energy harvesting techniques and integrating antennas/rectennas into device packages can enhance efficiency and reduce emissions. In [54] the authors presented an innovative model that integrates energy, communication, and computation for the 6G-IoT paradigm. The model efficiently charged IoT devices by utilizing downlink wireless power transfer and utilized collected energy for uplink communication and computation. With optimized transmit-beam via the Improved Ant Colony Optimization (IACO) algorithm, the proposed model achieves impressive results in simulations, with a significantly lower Mean Squared Error (MSE) value of approximately 0.011 compared to other schemes demonstrating improved system efficiency and reduced power consumption. In addition, the proposed model outperformed existing methods, further validated by the affirmation of conv. This paper [55] introduced an IoT-based resource utilization framework, TPRUDF, which used data fusion to handle the complex features of IoT data and optimize resource utilization parameters. TPRUDF employed three phases of data fusion to reduce and fuse IoT data, extract uncorrelated features, and apply multiple resource utilization techniques. The framework is evaluated using a public edge-computing simulator and three real-world smart cities datasets, demonstrating promising results in accuracy, throughput, energy, and delay. Raval et al. [56] proposed a system for energy management in IoT devices. The system used a multi-agent approach based on reinforcement learning, fuzzy logic, and genetic algorithms to optimize energy consumption. The energy consumption of different IoT device components is modeled, and a grey system is used for energy consumption prediction. They suggested potential improvements such as evaluating the system on diverse IoT scenarios, comparing it with other energy management approaches, considering trade-offs between energy efficiency and other performance metrics, and exploring other AI techniques for energy management. This article [57] proposed a cooperative energy-aware resource allocation and scheduling strategy for IoT environments using a multi-criteria decision-making method called Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The proposed TOPREAL approach outperformed existing algorithms in terms of energy savings, with an average improvement of 40.25 %, while maintaining an average improvement of 16.21 % in execution time. It also saves an average of 78.06 processing hours and 63,215 kJ of energy compared to existing scheduling algorithms. The article [58] addressed the energy consumption problem in a massive IoT system model for industrial 6G applications. It introduced a clustering technology to divide the system into different clusters, and the proposed method outperforms other optimization methods in terms of power allocation and information correlation. Another article [59] proposed an integrated energy-efficient strategy for IoT devices based on RF energy harvesting. It focused on optimizing the splitting factors and transmit power allocation to achieve a balance between information rate and energy reception. The performance evaluation showed that the proposed strategy effectively prolongs battery life and supports energy consumption.

In IoT networks, packet loss can have significant implications for reliable data transmission and overall network performance [60]. Some articles focus on improving packet delivery rate and meeting real-time constraints in industrial IoT systems. Article [61] proposed the Bounded Delay Packet Control (BDPC) mechanism, which combines traffic delay and time budget to allocate network resources. It showed significant improvement in the number of packets arriving before the deadline compared to the default Minimal Scheduling Function. A bandwidth control scheme was proposed in [62] to address bottlenecks in IoT environments, outperforming machine learning and deep learning techniques. The proposed scheme notably reduced the negative impact of bottlenecks and improved efficiency. Multiple methods are used to accurately determine bottleneck points based on the anatomy of the IoT environment. The proposed bandwidth control scheme considered the heterogeneity of IoT environments and utilized various communication tools The Simulation results showed that the proposed approach has the lowest packet loss values compared to other learning techniques. This paper [63] discussed the importance of optimal network selection in reducing packet loss in 5G heterogeneous networks for IoT. Small coverage radio access networks can improve network throughput, latency, and packet loss ratio. However, adequate network selection can lead to successful handovers and ping-pong handovers, which negatively impact the quality of services and experience. The proposed method, I-MEREC-TOPSIS, aimed to improve network selection by considering the removal effect of alternatives' attributes. It combined the I-MEREC weight method and the TOPSIS alternative ranking technique. The authors claimed that the proposed scheme has reduced ping-pong handovers and handover failures compared to other methods. In the context of ZigBee networks [64], an efficient end-to-end communication protocol was investigated. The protocol considered clustering, data transfers, cleanliness, and end-to-end latency. The proposed protocol outperformed previous attempts in terms of packet loss, productivity, and end-to-end latency.

Throughput refers to the overall quantity of tasks successfully accomplished by the IoT system. In order to successfully complete all of the user's tasks, it is imperative that the throughput in IoT systems is high. The impact is contingent upon the volume of data and the rate at which it is being generated. Therefore, it is influenced by the extensive and rapidly generated characteristics of data [65]. In [66] wireless-powered cognitive IoT networks proposed a deep-neural network-based relay selection scheme to improve end-to-end throughput. The authors demonstrated the scheme's effectiveness through simulation results, showing improved throughput, reduced energy consumption, and lower network overhead. Simulation results showed that the proposed deep-neural-network-based relay selection scheme achieves comparable throughput to the optimal relay selection scheme while significantly reducing complexity, making it suitable for real-time applications in wireless-powered cognitive IoT networks. The authors [65] investigated the adjustment of nodes' sending rate in IPv6 over Low-power Wireless Personal Area Networks (6LoW-PAN) using a non-cooperative game-based scheme called DeepGame. The technique enabled nodes to learn the optimal action at each game step, leading to the Nash Equilibrium state. Simulation results demonstrated the efficiency of DeepGame in improving IoT network performance, including energy consumption, throughput, and network overhead. The AI-based framework for spectrum selection and access in 5G networks using a greedy model with Fractional Knapsack is shown [67] to handle the large volume of data from IoT devices and improve channel throughput. Simulation results demonstrated the framework's effectiveness regarding spectrum access accuracy and delay.

To optimize system performance, it is crucial to minimize latency. Hence, as the amount of data increases, the processing and waiting times also increase significantly [68]. The work [69] surveyed AI/ML techniques in 6G networks, applying them to optimize networking and resource management, improving latency performance. In [70] a low-latency edge computation offloading scheme was introduced for trust evaluation in finance-level AIoT, employing an online offloading algorithm and presenting a latency model for personal credit evaluation, with results showcasing its effectiveness. The article [71] proposed an asynchronous federated deep reinforcement learning (AFDRL)-based computation offloading framework. The method, articulated in the ARTIST algorithm, optimized task offloading and computation resource allocation. Results demonstrated the framework's success in significantly reducing task offloading and total queuing latency in integrated terrestrial and non-terrestrial power IoT. This article [72] introduced a reward-clipping mechanism using GAN-DQN for intelligent transmission scheduling in 6G-IoT networks. The method addressed the impact of packet size on transmission latency. Results showed the mechanism's effectiveness in improving smart transmission scheduling, ensuring ultra-reliable, low-latency communications in 6G networks. Lastly, the authors [73] proposed a knowledge-assisted deep reinforcement learning (KADRL) based scheme for deploying service function chains (SFCs) in 6G-IoT networks. The method emphasized AI algorithms for efficient resource allocation, reducing end-to-end latency. Results showcased the scheme's success in achieving flexible and efficient resource allocation by deploying SFCs based on Mobile Edge Computing (MEC) and Network Function Virtualization (NFV).

Problem statement

This study predicted 6G traffic using machine learning and a variable sample rate [74]. It predicted real-time network traffic using the Variable Sample Rate-Long Short-Term Memory (VSR-LSTM) algorithm. Frequency, low sampling rate, and consistent sample rate are considered in traffic forecasting. These characteristics formed a traffic loading curve, which created a traffic forecast with regional movement rates. The simulation showed that the VSR-LSTM model predicted traffic patterns more accurately.

- Here, traffic prediction was conducted using a constant sample rate, low sampling rate, and frequency. However, specific metrics such as arrival, packet length, and deadline were not considered, resulting in inefficient traffic forecasts.
- In this work, IoT devices were not appropriately managed, and the entities were placed randomly. At the same time, it led to a high packet loss ratio, inappropriate congestion control, and computational complexities.
- This paper used the LSTM model to predict traffic in an IoT environment. However, it took more memory and training time, leading to high complexity.

The authors [75] proposed a Deep-Q-network-based packet scheduling technique for the IoTs because it demanded more storage and training time. Packet scheduling first used the deep-Q-network (DQN) method, coordinating IoT device communication. The packet priority, buffer rate, control period (CP), and data phase (DP) determined the connection interval (CI) for master-slave communication after connection establishment. CQI specified the CI length and the number of packets each slave must send during the CI, which packet scheduling dynamically determined. According to testing results, the suggested scheduling strategy improved a network's lifespan in a changing environment and ensured high service complexity. Class interval, data period, and control interval are considered for packet scheduling. For optimal packet scheduling, more parameters are needed, causing considerable transmission delay.

- Here, DQN was implemented to perform scheduling using connection intervals. However, DQN needed a large amount of data for processing, increasing the complexity and energy consumption.
- Also, the authors performed a schedule based only on the priority and buffer rate of the packets to achieve throughput. However, the channel quality wasn't considered, leading to a lack of QoS constraints.
- In this work, packets were scheduled, but inefficient packet transmission management was performed, leading to a high packet loss ratio.

The authors of this study [76] gave a wireless network for communication resources based on a deep enhanced learning model. The little base station to which consumers are linked must have what they want as cache states, and the tiny base stations must choose the transmission. At first, the model known as LSTM was used to forecast users' mobile position and consumers' communication conditions based on these two requirements. Additionally, a deeply enhanced learning algorithm is utilized for mobile resource allocation to consider CQI, QoS, resource blocks, and user priority to maximize network throughput in the environment. Also, there was the issue of user traffic allocation in fine-grained resource control. The simulation outcomes showed that the algorithm may increase user experience quality, decrease latency, and reduce energy consumption. Here, resource block allocation and scheduling were performed by considering QoS and resource block usage. However, only considering QoS and resource block usage needed to be increased (i.e., spectrum efficiency, resource type, and feedback are not supposed) to perform efficient resource allocation, which led to high resource wastage and affected QoS. Resource allocation was performed by considering constant power. However, it is unsuitable for real-time scenarios because the power is not static. The user demands the resources directly from the base station, where the UE consumes high power to send their request and order service, leading to high latency. Here, a deep augmented learning algorithm is used for resource allocation. However, augmentation combinations can lead to underfitting. This slowed down training, leading to a considerable strain on resources like available processing time.

IoT traffic forecasting has been investigated in this study [77] utilizing machine learning techniques. Gated recurrent units (GRU-NN) first forecast traffic via transfer learning. The three steps of the proposed GRU-NN predictor's operation include data pre-processing, model training, and transfer phase. Continuous data are transformed into discrete records during the data pre-processing stage. Furthermore, the GRU-NN predictor's training phase was its most crucial stage. A GRU-NN model is suggested in this phase for learning the model, and the transfer phase also plays an essential role in handling the issue of inadequate offline data for IoT traffic by transferring a substantial quantity to the training module and utilizing MAE, RMSE, which MRE, and MSE, the suggested GRU-NN model's outcomes are assessed. Finally, the results demonstrated that GRU-NN offers the most precise forecast. Here, the authors selected a path for transmitting the packets by considering only path bandwidth. However, a single parameter could not determine the optimal path that led to high jitter and packet loss. In this study, proper user management is not focused, which can cause computational complexities, bad imbalance, high packet loss ratio, and increased energy consumption in the user. Here, a gated recurrent unit was used for traffic prediction. GRU models still need help, such as slow convergence rate and low learning efficiency, which result in too long training time and even under-fitting. In this study [78], the authors suggested utilizing deep learning to correctly classify and anticipate the time-varying network characteristics of IoT devices. The proposed research first expanded a set of attributes encompassing flow, packets of data, and device-level features to characterize IoT devices in the setting of carrier aggregating approaches employing spectrum carriers in an intelligent environment. A two-step pre-processing method that scales the dataset employed a Min Max scaler method and allocated relevant weights to the essential characteristics was proposed. Feature selection techniques were used to choose the features based on how well they contributed to categorizing IoT devices using the LSTM algorithmic structure. These findings demonstrate that the suggested approach achieves 99.9 % correctness in traffic forecast. Further, machine learning algorithms were utilized for traffic prediction. These algorithms always produce overfitting or underfitting because the training data size is too small and needs to contain more data samples; hence, it leads to high errors as it is not suited for traffic prediction. In this work, entities are randomly considered whereas they are not grouped separately, which increases delay, high energy consumption, and decreases the life span of the network. Here, the min-max scaler was used for assigning the nominal features. However, it has one reasonably significant downside: it needs to handle features better, which leads to computational complexities and traffic.

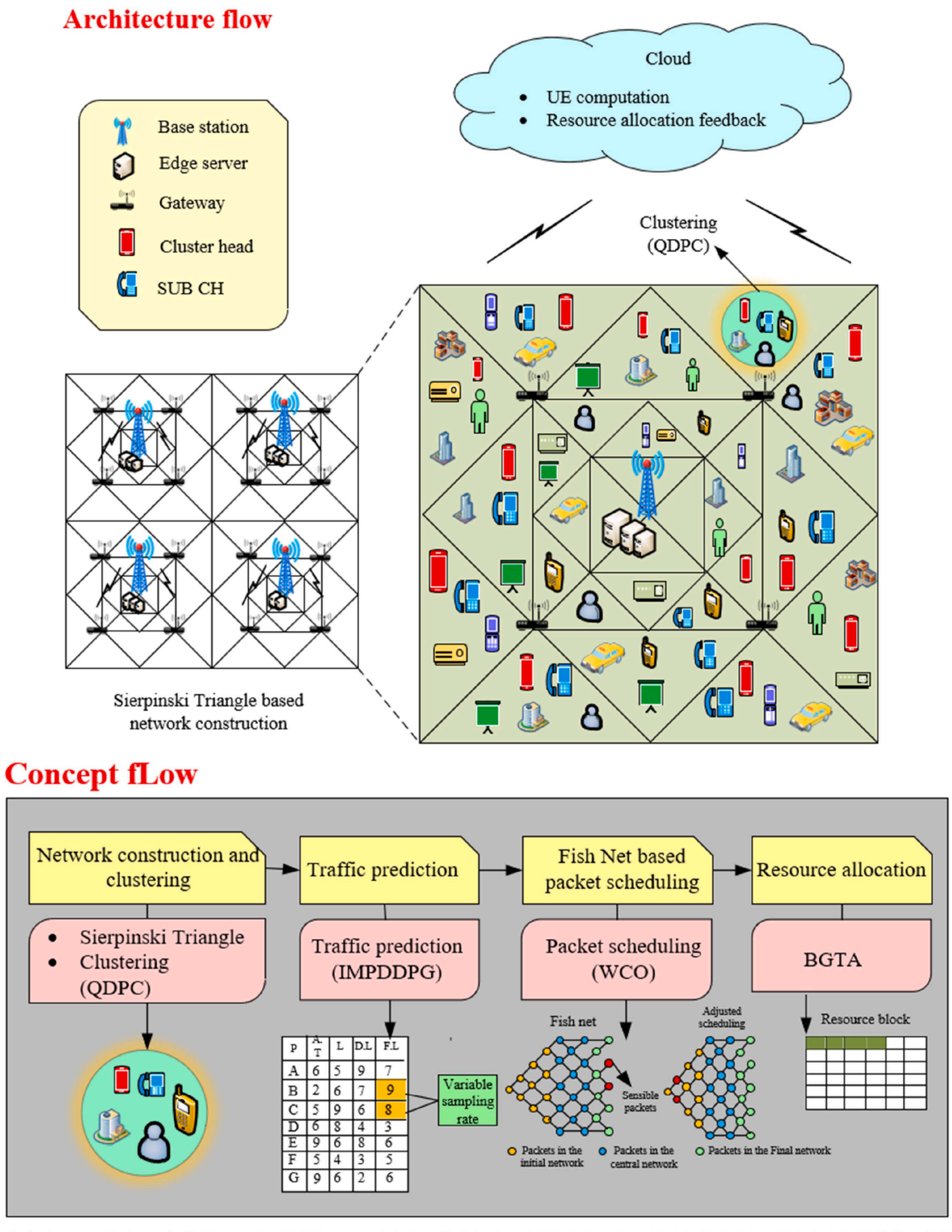

Fig. 1. Overall Architecture of the Proposed Work.

Research solution

To overcome the problem faced by the existing works, IoT devices are deployed randomly, and the network is constructed based on the Sierpinski triangle architecture. Clustering is performed for IoT devices using QDPC by edge server. The IoT devices' proposed work cluster head and sub-cluster head are chosen based on the effective metrics. The traffic is predicted based on two processes, namely grouping and fair queue status. The variable sampling rate of the process is predicted using the IMPDDPG algorithm. The packet scheduling is performed by adopting the WCO algorithm to solve complex problems into the single stage of performance and the distribution of robustness and scalability. Finally, the resource is allocated using the BGTA approach by considering the effective metrics for resource allocations. The optimal resource allocation of the management process is distributed and stored in cloud infrastructure.

Proposed work

System model

This research mainly focuses on traffic prediction, scheduling, and resource allocation for 6G networks. In addition, we focus on network construction and ensure UE power management by clustering. Cloud computing was utilized for storing UE computation and feedback. IoT devices are responsible for data information, and base stations are responsible for IoT devices communicating. Further, clustering is performed in the edge server, offering high-speed data processing and reducing energy consumption. Fig. 1 represents the overall architecture of the proposed work. This work consists of several entities, such as IoT devices, base stations, gateways, and cloud and edge servers, which are mentioned below:

- **IoT devices:** IoT devices are responsible for sharing the information and data flow between things, devices, and users. They play a crucial role in transmitting and receiving packets of information. They serve as the source of data and information in the network.
- **Base Stations:** The base station links the server source and the user in the environment. It enables real-time communication and secure clustering to be performed. It allows sending data information over the long range by using low power.
- **Gateways:** Gateways serve as intermediaries between the data source and devices in the network. They enable real-time data communication between components like IoT devices, base stations, and cloud servers.
- **Cloud:** Cloud servers are responsible for storing and processing data in the cloud infrastructure. They gather user computation and feedback from the network and store it for future usage. Cloud servers are crucial in managing network resources and optimizing network performance. It is used for secure storage, flexibility, and quality control.

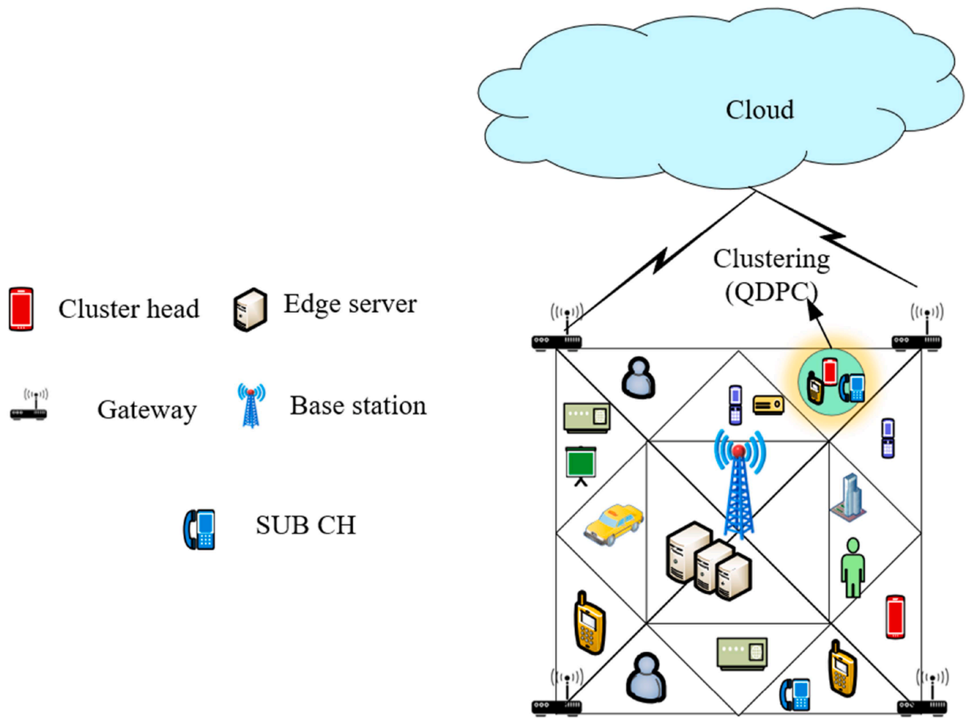

Fig. 2. The relation between each component in the proposed architecture.

- **Edge server:** It provides an entry point into a network and enhances privacy protection and data security. Clustering and packet scheduling are performed by an edge server, which offers high-speed data processing and reduces energy consumption. Edge servers are deployed at the network edge and perform high-speed data processing. They are responsible for clustering IoT devices using the QDPC algorithm. Edge servers help reduce energy consumption and improve network efficiency.

These components work together to enable efficient traffic prediction, scheduling, and resource allocation in the 6G network. IoT devices generate data, which is transmitted through base stations and gateways. Edge servers perform clustering of IoT devices, while cloud servers store and process data. The proposed research aims to optimize the performance of these components and improve overall network efficiency. The network construction is based on the Sierpinski triangle architecture. This fractal triangle structure is created by connecting the center points of the sides of the initial triangle to form four smaller triangles. This process is repeated for each smaller triangle, resulting in a network with multiple clusters. Each triangle represents a single cluster, and every seven triangles are connected to a gateway. The proposed architecture also incorporates various algorithms and techniques for traffic prediction, packet scheduling, and resource allocation. These include the QDPC algorithm for clustering IoT devices, the IMPDDPG algorithm for traffic prediction, the WCO algorithm for packet scheduling, and the BGTA used for resource allocation. The architecture of the proposed work combines these elements to create a system that enhances network administration, reduces packet transmission and scheduling complexity, and improves overall performance, as illustrated in Fig 2. The Sierpinski triangle-based network construction provides benefits of improved information transfer, increased connectivity among devices, and flexibility and scalability of the network. It also helps to avoid high energy consumption and communication overheads. The proposed architecture aims to optimize performance metrics, including time, transmission rate, energy efficiency, average throughput, latency, and packet loss rate. The Fishnet-6G model

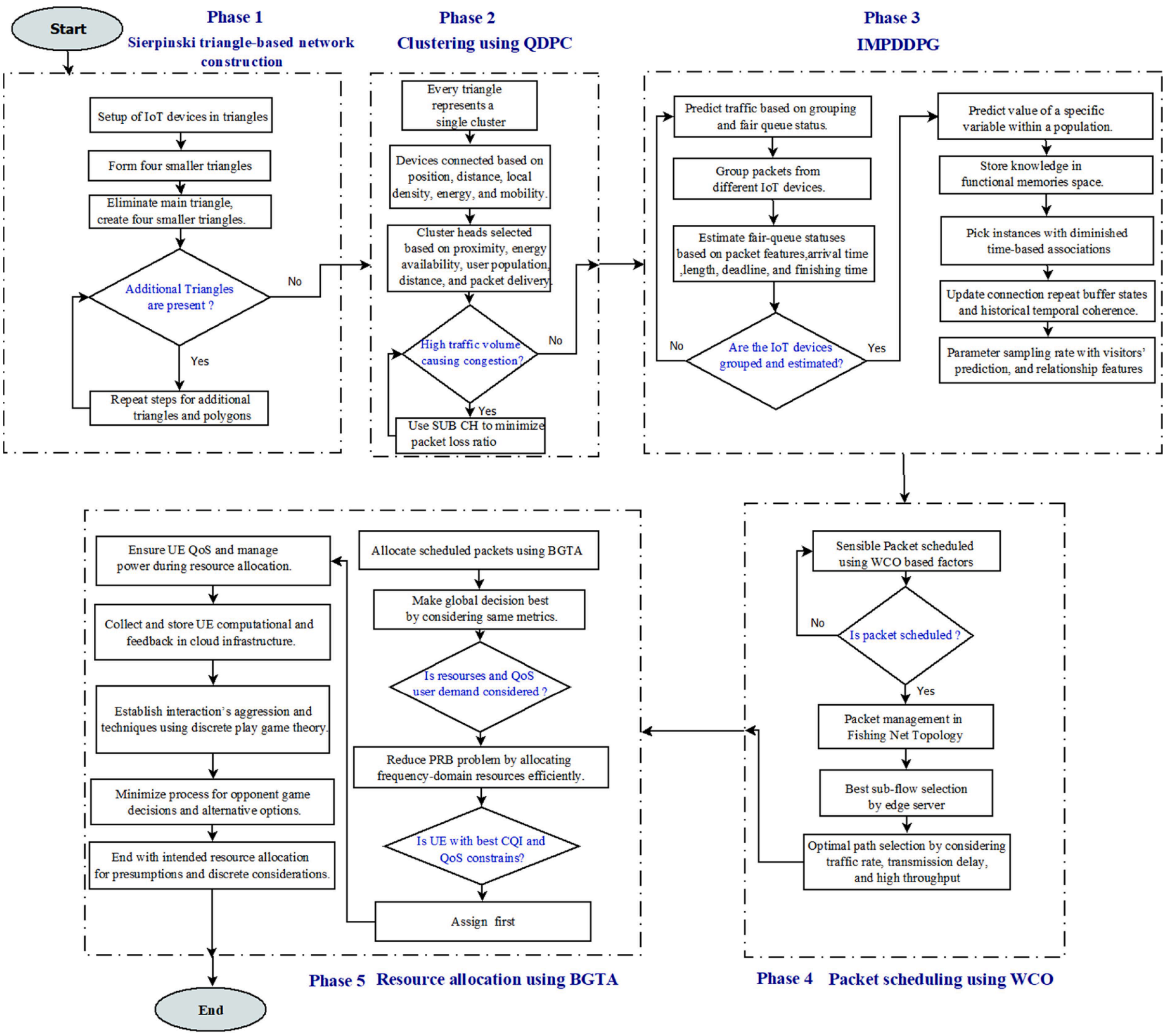

Fig. 3. The flowchart of the proposed architecture.

outperforms existing approaches regarding these performance metrics by utilizing AI and Bayesian game-theoretic methods. Overall, the proposed architecture based on the Sierpinski triangle-based network construction and incorporating various algorithms and techniques aims to enhance the efficiency and performance of 6G-IoT networks. Fig. 3 illustrates the flowchart of the proposed architecture for this study.

Sierpinski triangle-based network construction and clustering

In 6G-IoT, many devices are deployed randomly, leading to high network traffic. To avoid this, we construct a Sierpinski Triangle-based network construction in a 6G-IoT environment, in which the network is built based on an equilateral triangle and subdivided into four smaller congruent equilateral triangles. Repeat the step with each of the smaller triangles. Each triangle consists of N number of IoT devices. Every seven triangles of IoT devices are connected to a gateway. However, the gateway provides a faster way to make transmission and reduces the complexity. This network structure helps to improve information transfer at a high rate per area, increases connectivity among devices, and increases the flexibility and scalability of the network. Further, this type of network construction also avoids high energy consumption and communication overheads. Each triangle consists of N number of IoT devices.

Sierpinski's renowned fractal triangle was created through the overall framework for structural development, recognition of factors, fundamental arrival, shipping of compact triangles, and functionality of the equilateral triangle. The advantages include equal creation and setup of the grouping within the framework and proposed work. The **First Step** Connect the center points of the first triangle's sides to form four smaller triangles. By combining the square zone functionality and the rectangular arrangements, the IoT devices are first set up in triangles with equal sides for the diagonal creation and the structural building for the two diagonal vectors. The **Second Step is** to eliminate the main triangle. Connect the center points of both sides of each triangle to create four smaller triangles at the bottom of each triangle in the positioned rectangular area. Repeat steps 1 and 2 for the additional rectangles in the third **step.** The **next step** is to repeat the process for the polygons closest to the base station's location. Every triangle stands for a single cluster. The functional elements' dimensions and determinants of the resulting set have been reduced during development. The triangle illustrates proportions akin to Sierpinski triangles, and diverse principles guide the construction of the four-triangle development. The obtained clusters are reported in the form of an unequal cluster.

Clustering is the optimal method for minimizing the quantity of control overhead messages produced in an IoT network [79]. So, the edge server uses the QDPC to cluster IoT gadgets following network creation. Clustering increases the effectiveness of energy use, communication across networks, topology control, and latency reduction. The study suggested groups connect devices according to their physical position, distance, local density, energy, and mobility and then select cluster heads based on the users' proximity to the cluster the center, their energy availability, the cluster's user population, their distance, and the percentage of packets delivered. Most customers will be connected to the CH with low power, which is known to cause traffic congestion. To solve this problem, SUB CH minimizes packet loss ratio when CH has high traffic volume, low energy straight, buffer state, and poor connection quality. The network user is also connected to an edge server, rapidly processing data and lowering the UE's power consumption. Fig. 4 represents

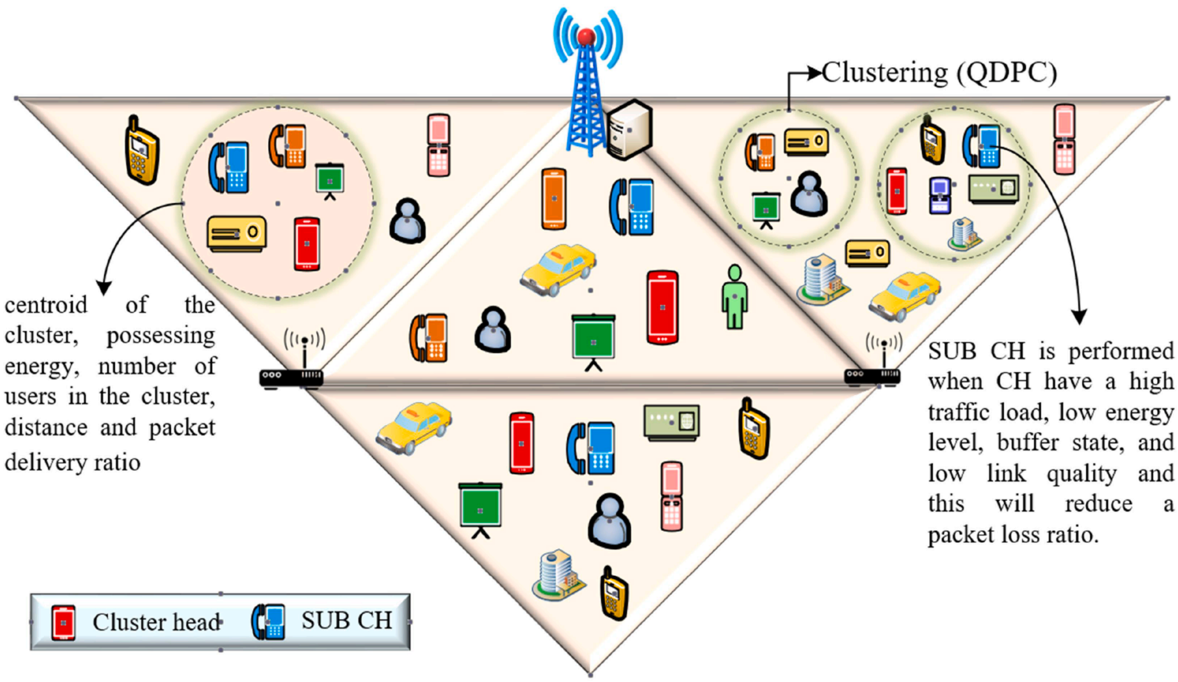

Fig. 4. Clustering using QDPC.

the clustering architecture using QDPC. The IoT devices are grouped in a density to reach their highest clustering process using effective metrics, and the outcome is better through more deep look arrangements with recognizing outliers reliant on the outlier analysis. Structures and performances of the established and suppositions layers for the organization of the knowledge beyond the reach of this clustering method. The issues with computing minimum density are detecting data potential, finding anomalies, peak grouping of virtuality, setup of abilities and framework for belongings detection, and intention of both functional and structural and fundamental unit of the abilities of the accomplished unit.

In this system, cloud computing, clustering, and the QDPC algorithm synergistically enhance the 6G proposed network performance. Cloud computing is a centralized hub for storing UE computation and feedback, relieving UE of computational burdens while optimizing network resources through cloud servers. Concurrently, clustering, executed by the edge server using QDPC, groups IoT devices based on physical position, distance, local density, energy, and mobility metrics. This clustering process, guided by QDPC, significantly improves energy efficiency, communication, and topology control, and reduces latency by identifying cluster heads and sub-cluster heads. QDPC, a specialized algorithm for IoT device clustering, quantizes density peaks based on similarity measures, organizes devices into groups, and enhances communication efficiency while minimizing energy consumption. The accompanying model-based diagram and description offer a comprehensive visual and explanatory insight into the collaborative functioning of cloud computing, clustering, and QDPC, elucidating their roles in optimizing the system's energy usage and communication efficiency within the 6G network.

The structural characteristics and the Gaussian real estate are more profound than detecting anomalies elements that determine the density features of every detection determine the characteristics of density clustering; its products adopt the clustering for identifying unusual events and apply the density reach their highest clustering and calculate the clustering placement. The recognition performance and the density accumulating properties are only briefly mentioned.

$$\Re(y_i) = \sum_{y_j} z\left(dst\left(y_i, y_j\right)\right) \tag{1}$$

Where z is a clustering based on the density of the center of the estimation, a traffic-based gathering of the unknown factors, and the organization of IoT device nodes to the categorization along with the data speculation.

$$\mathrm{K}(\mathrm{y_i}) = \arg \underset{\mathrm{y_j}:\Re\left(\mathrm{y_j}\right)>\Re(\mathrm{y_i})}{min} \mathrm{dst}\left(\mathrm{y_i}, \mathrm{y_j}\right) \tag{2}$$

The nearest-higher departure (*yi*) is the aloofness among *yi* and its nearest-higher.

$$\tau(y_i) = dist(y_i, K(y_i)) \tag{3}$$

Naturally, if the location in question has the most significant separation between the density and the overall network structure's factors that determine similar separation for all of the components and those with greater a division origin component, the beginning elements' own the cluster densities are categorized to provide the neighbor distances. This concept of network-building dispersion for the closest divisions of the consideration's constituents turns those consideration constituents into Euclidean distance concerns.

$$\Re(y_i) > \Re_r \ and \ \tau(y_i) > \Re_r \tag{4}$$

These components are categorized, and each will produce its cluster. The closest higher definition of cluster outliers is described in greater depth. The differentiation of the element nodes and the characteristics information of the component specified origin and element networks of the differentially classified operations by the higher separation node topologies of the threshold areas is done by categorizing the element cluster.

$$\Re(y_i) < \Re_r \ and \ \tau(y_i) < \Re_r \tag{5}$$

The whole quantum decision process of density peak aggregation to identify the closest neighbor with a higher value follows the same methodology as the classical minimum searching routine to identify the most relative higher values.

$$E_i(j) = \begin{cases} dst\ \left(y_i, y_j\right),\ if\ \Re_j > \Re_i \\ \quad +\varnothing,\ if\ \Re_j \le \Re_i \end{cases} \tag{6}$$

Form the meaning of nearest higher discovery minimizer of decisive the nearest higher of *yi*,

$$y(y_i) = arg\underset{j}{min} E_i(j) \tag{7}$$

The determining factor of the structural and functional components of the acquired minimizer of the assessing transformation and the resulting unitary classical series may be utilized for assessing the network components and concentration to achieve functional reorganization. The transformation is accomplished for any components in the functional spherical unitary query.

$$W_i|j\rangle|0^{\phi p+1} = |j\rangle|E_i(j)\rangle \tag{8}$$

For any $j \in \{0,\ldots,m-1\}$, W is the number of qubits needed for storing the length up to the necessary level of precision, so we add a further element to signal $+$. As a result, higher links are clustered by the density peak's quantization with a similarity measure. This graph constitutes a component that satisfies the encouraged roots, functioning identification of outliers, grouping of the essential elements, and clustering varied by the difference unit of the gradient that established the functional characteristics of the requirement buildings of the differences in the varied arranged separating root.

IMPDDPG-based traffic prediction

After clustering the IoT devices, traffic is predicted based on two processes, namely grouping and fair queue status:

1. The grouping process is done based on the packets from the different IoT devices.
2. The fair-queue statuses are estimated based on their features, such as packets, arrival time, length, deadline, and finishing time.

The IMPDDPG reinforcement learning algorithm accurately predicts real-time network traffic by grouping and analyzing fair queue status, utilizing a variable sampling rate as shown in Fig. 5 However, the variable sampling rate is the process of predicting the value of a specific variable within a population. Here, IMPDDPG has a significant advantage in continuous control problems and solves the issues of low training efficiency and slow convergence. This way, traffic is predicted and makes efficient packet scheduling and transmission.

In the replayed nature of the determinants, the maximum space for memories method uses the functional memories space to store knowledge. It randomly picks a set of instances in which the experience of time-based associations of the highly experienced characteristics is significantly diminished by the updated network. The connection updates' repeat buffer states and historical temporal coherence feature encounters. The introduction of technologies for parameter sampling rate with visitors' prediction, relationship features, and the investigation of the factors that influence arrives at by effective mechanisms and the determination of an adequate agent of structural analysis and the attained equally important agent investigation of the equal principles.

$$\psi^{'}(L_u) = \zeta\left(L_u|\alpha_u^{\zeta}\right) + M(\lambda, v, \varphi) \tag{9}$$

Among them, $M(\lambda, v, \varphi)$is the primary distribution between packet schedule and risk assessment varied among the nodes. The architectural features of the disturbance variables should have their origins from the investigation method and the properties in the action component that characterize the various enabled in the agent structure.

$$w^*(G_r, \Re_r) = e[s(G_r, \Re_r) + \Phi argmax_{\Re_r}(w^*(G_{r+1}, \Re_{r+1}))] \tag{10}$$

Where w^*characterizes the optimal value function, e is the deep network, only one step reward, and Φ is known as protocol validation, predictions estimation for the present location. Repeated measures of the best estimate of the current structure of G and $\Re$ are possible. Neural networks can predict the critic network's indefinitely approximated upgrading errors.

$$\Xi_\sigma\left(u|\delta^3\right) = \left[\left(\Re(G_r, \Re_r) + \Phi w^{'}\left(G_{r+1}, \Re_{r+1}|\delta^{3^{'}}\right) - w\left(G_r, \Re_r|\delta^3\right)\right)\right] \tag{11}$$

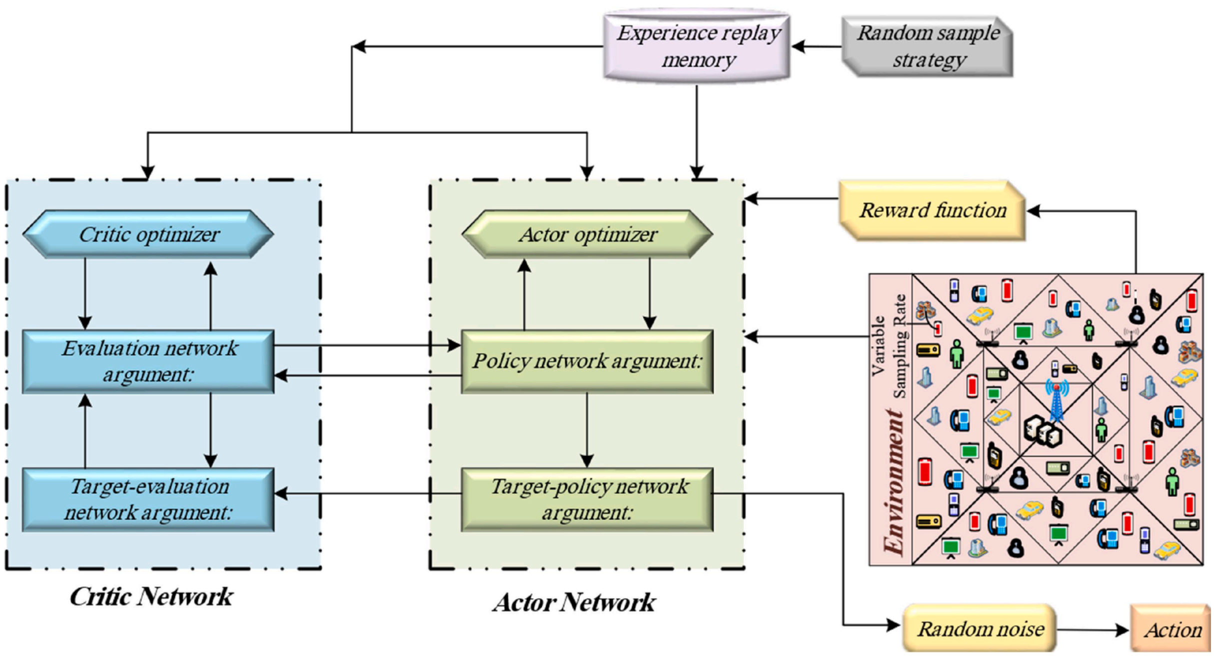

Fig. 5. Traffic prediction using IMPDDPG.

$$\Re_r = \sigma^{'}\left(G_r|\delta^{3^{'}}\right) \tag{12}$$

Where the first two terms in a packet's identifying values signify each subsequent term's actual value, and the result of the current criticize networks squared the building process error is acquired, the gradient descent bringing up method is used to improve the capability of policy evaluation, the actor network's prediction, and the productive policy of the in different ways changed, adjusted neural networks for determining the category of the appropriate procedure.

$$\beta(D_3) = \Gamma[-w(G_r, \sigma(G_r))] \tag{13}$$

Where $\Gamma(\cdot)$the expectancy operator is defined. The policy network then updates independently in the direction of performance objective promotion. As a result, the update error related to the network stated as accurate gradient may be written as,

$$\eta_\tau\left(r|D^3\right) = \psi_{r,t}n\left(D^3\right) = \Phi w^{'}\left(G_{r+1}, \Re_{r+1}|\delta^{3^{'}}\right)\Phi\left(r|D^3\right) \tag{14}$$

A strategy of soft updating is employed for target network $w^{'}$ and D^3 can expressed as

$$D^n \leftarrow \varnothing D^n + (1-r)D^n \tag{15}$$

$$D^3 \leftarrow \varnothing D^3 + (1-r)D^3 \tag{16}$$

Here, the experience technique is used to avoid back-and-forth correlations during training, which improves the consistency and effectiveness of learning. You can define the likelihood of the rated experience as follows,

$$PO_j = A_j^r \Bigg/ \left(\sum_T A_T^r\right) \tag{17}$$

$$A_j = 1/rnk(j) \tag{18}$$

where $\sum_T(\cdot)$ is the total index of experience pool and r denotes the hyperparameter to compute degree of priority which ranges from 0 to 1. Lower r leads to uniform conventional sampling DDPG, $rnk(\cdot)$ is the rank of prominence degree of set experience that can be estimated by,

$$rnk(j) = \sqrt{\eta_\tau(i)} \tag{19}$$

By utilizing replay knowledge, these experiences have led to significant changes in the way that priority-generated work is constructed and how the variable obtained in the completed nature of feature assemblies for the vector quantity for risk evaluation is determined. To access the packet validations, the achievement associated with the packet authentication and the inquiry validation in the number of packets must first be engaged. The Pseudocode for traffic prediction illustrated bellow:

Pseudocode for traffic prediction
Input: Clustered node
Output: Traffic prediction
Begin
Prepare critic net PO_j and actor D^n with masses L_u
Adjust target net η_τ and Ξ_σ with masses $w^*(G_r, \Re_r)$
for episode =1: K **do**
Prepare relay network R for action explorations
Obtain initial comment public r_i
for $T = 1$: K **do**
Choice act $\Re_r = \sigma^{'}(G_r|\delta^3)$ for rule and guess
Perform action A_j and detect prize $\alpha_u^\zeta$and new state-run α_{u+1}^ζ
Stock transition $(A_j, L_u, \Re_{r+1})$ in T
Model a chance minibatch of M change $(A_j, L_u, \Re_{r+1})$ after T
Usual $PO_j = A_j^r/\left(\sum_T A_T^r\right)$
Inform critic by curtailing loss $\zeta(L_u|\alpha_u^\zeta) + M(\lambda, \nu, \varphi)$
Apprise actor rule using tried policy incline (15)
Update target system (16) and (17)
End for
End for
End

Fishnet-based packet scheduling

After traffic prediction, packet scheduling is performed to reduce the jitter and transmission latency and improve the goodput and throughput. Here, packets are scheduled and transmitted to the receiver, reducing transmission delay and congestion. For packet scheduling, we proposed WCO algorithm by considering bandwidth, CQI, energy, delay, transmission rate, queue length, buffer rate, completion time, and data size. The reason for adopting the WCO algorithm is to solve complex tasks, and the characteristic leads to easy adaptability, robustness, and scalability. Here, dynamically adjusts the scheduling for sensible packets (i.e., video call, medical emergency call, online games) using WCO algorithm by considering QoS, bandwidth, cool deadline, hot deadline, criticality, and laxity of the task. After scheduling, packets are managed in Fishing Net Topology, which reduces energy consumption and complexity and makes the process lightweight. After completion of packet scheduling and management best sub-flow is selected by the edge server for packet transmission, which reduces the transmission delay. Finally, the optimal path is chosen considering traffic rate, transmission delay, and high throughput. This process reduces energy consumption and increases network lifetime. Fig. 6 represents the packet scheduling using the WCO algorithm.

The randomized vector organization of the atmosphere's velocity and trajectory causes the willow catkin to fall down the trees in a predetermined pattern. A vector can be used to depict the wind numerically. Consequently, transforming a vector into the mathematical equation it represents, as well as the typical specific setups for gearbox direction vector and calculating components speed and control. You can get T and N by doing the following:

$$\begin{cases} N = -\omega r \times cos(\omega a) \\ T = -\omega r \times sin(\omega a) \end{cases} \tag{20}$$

The multifaceted plane's two-dimensional symbol, the order pairs and elements, the shipment proportion of the ordering pairs and components, the slant of the north, and the method that an arrangement's structural qualities are maintained are all represented by the letters r. After that, we break down the primarily modified particle matter orientations and the evolving configurations for harmonizing the symbol's existing location.

$$Y_{i+1} = Y_i + b \times (L \times U) + (2 - b)(W_x - Y_i) \tag{21}$$

where Y_i displays the positions of the several variables that were acquired in the current iteration, the global optimal architectural agreements, the current triggering of the proposed unit, and the randomly placed updating particle. In the iteratively updated present position and the erratic moving placement of the produced stick, the capacity to fall into the optimal location of the executed individual configurations through preventing the specified orientations is applied to the routes and persons' distances.

$$XC = 1 - \frac{|W_x - Y_i|}{\| Y_i - W_x\|} \tag{22}$$

$$E = \frac{XC}{\sum_{i=1}^{X} XC_i} \tag{23}$$

$$\begin{cases} \omega r = \vartheta \times \left(\sum_{i=1}^{X} E_i |W_x - Y_i| \right) + (1 - \vartheta) \times t_2 \times H \\ \omega a = ars\left(\frac{Y_i \cdot W_x}{\| Y_i\| \times \|W_x\|} \right) + t_3 \times \frac{\pi}{8} \end{cases} \tag{24}$$

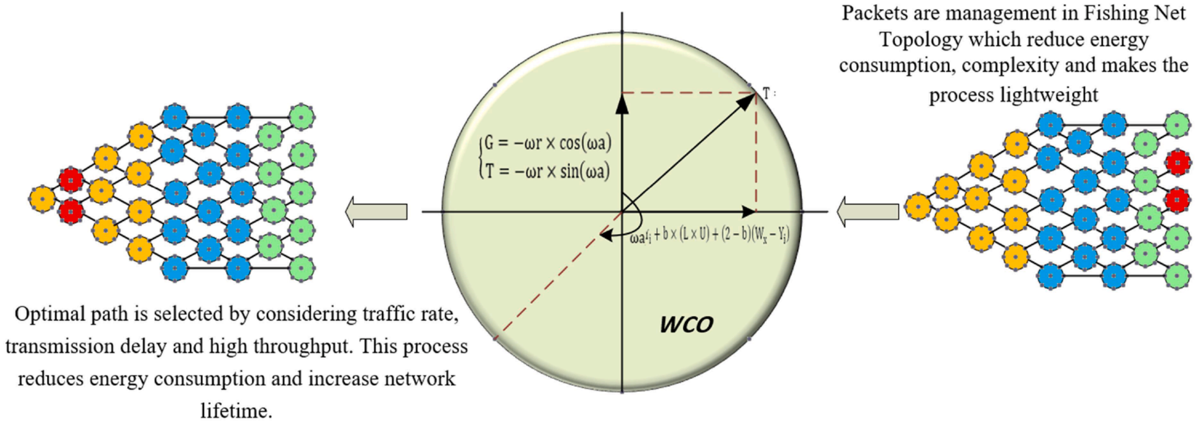

Fig. 6. The packet scheduling using the WCO algorithm.

Where $Ei \leq T$, Eqs. (22) and (23) are used to determine the thereby affecting their, and the computation of the XC indicates how far off the overall distance and the rate of packet delivery ratios are. H is a number generated randomly using packet confirmations, speed factors, important distributions of resources, packet confirmation information, and situations in which scalability is required to interfere with storage and normalized packet delivery ratios. Normalizing the equations in the interval occurs during random number generation [0,1].

The time frame maintained of the allotted resources preparations for the transmission of packets completion and the electrical activation latency of the chosen edge transmitting rate of tiny step delays in transmission and the proportion of packets delivered is then taken into consideration, followed by the traffic forecast. the variant's typical distributes' edge transmissions. The pseudocode for packet scheduling is illustrated bellow:

Pseudocode for packet scheduling
Input: Traffic predicted area **Output:** scheduled packets **Begin**
Prepare site place G, max repetitions R, aptness value
while (u < *maxiteration or minimum THD*) **do**
for $i = 1$: M **do**
if $Ei > E$ **then**
Produce ωa and ωr using (20)
Else
Generate W_x and Y_i using (21)
End if
Inform the pop using (22) and (23)
Analyze suitability value of packet scheduling Update speed and packet delivery ratio
End for End while
End

Game theory-based resource allocation

Scheduled packets are allocated to the demanded resource blocks using BGTA by considering metrics such as CQI, spectrum efficiency, resource type, energy efficiency, traffic, QoS, delay, bandwidth, and feedback. Whereas BGTA makes the global decision best, resource estimation methodology is simple, direct, and computationally efficient. Here, the BGTA considers both resource and QoS (user demand), which makes the resource allocation faultless, and BGTA is performed dynamically and optimally by reducing the Physical Resource Block (PRB) problem (i.e., inefficient allocate the frequency-domain resources). The UE with the best CQI and QoS constraints are assigned first. The allocation of optimal resource blocks to the UEs ensures the UEs' QoS and manages the power during resource allocation. The UE computational and feedback are collected from the users and stored in cloud infrastructure to reduce the UE burden and for future use.

In deciding the intended resource allocation, we consider the interaction's aggression and techniques to establish how the stated function will be used and expressed in discrete play game theory. In problem-solving, the course of the functioning layer by layer and the organization of various players should be achieved for multiple cost-function competitors. The function minimizes the process for opponent game decisions and alternative options for symbolizing different strategies for dividing resources and decision-making$B_j = \{b_{i,1}, b_{i,2}, \ldots, b_{i,n}, \ldots b_{i,n}\}, N \in [2, \partial]$ and utility function given by $f_i(b_{i,n}, b_{i,n'})$. B_j consists of two resource allocation definitions for presumptions and discrete considerations for the best-acquired notification and the tasks unit among all the supporting data depending on the conflict's characterization.

$$\begin{cases} B_1(R_1, H) = sign\left(r_1\left(b_{1,w}, b_{2,n}\right) - q_2 r_1\left(b_{1,n}, b_{2,Y}\right) - r_1\left(b_{1,n}, b_{2,n}\right)(q_1 + q_3)\right) \\ B_2(R_1, H) = sign\left(r_1\left(b_{1,w}, b_{2,n}\right) - q_3 r_1\left(b_{1,n}, b_{2,Y}\right) - r_1\left(b_{1,n}, b_{2,w}\right)(q_1 + q_2)\right) \end{cases} \tag{25}$$

Alternative functions and the path that uses the utility source minimization are the mechanisms of game-theoretical techniques. The best solutions consistently outperform the range of solutions, and Player 1 is confident in their abilities to combat the strategy. With sufficient probabilities, a function readily yields a substantial method.

$$b_1(R_1, H) > 0, b_2(R_1, H) > 0 \tag{26}$$

$$b_1(R_1, H) < 0, b_2(R_1, H) < 0 \tag{27}$$

The observed phenomenon can be attributed to the registration of players, wherein a balanced numerical chance is provided. This registration process involves the complex coordination of path selection, incorporating trade-offs between fundamental and functional components of the distribution. Additionally, the balanced function parameters and the state of equilibrium play a crucial role in the dissemination process.

$$\begin{cases} b_1(R_1, H) < 0, b_2(R_1, H) < 0 \\ b_1(R_1, H) > 0, b_2(R_1, H) > 0 \end{cases} \tag{28}$$

The aforementioned discussion on the kernel function's utility configurations and the discovery of the expected exponential utility indicates the existence of specific variations within the constrained range. The subsequent issues are categorized into several divisions, with each segment being prompted by a unique analysis of a certain established policy, which exhibits exponential growth. The trade-off involves considering the trade-offs between the functional sensitivity of certain variations in cost, a normalized bounded utility function, and the intersections of fused differential zed effectiveness of the original sources of the take procedure. This trade-off aims to find a compromise between maintaining a safe distance based on danger assessment during travel and mitigating variations in distance.

$$b_{lj} = \exp\left(\frac{-\partial_{rs} + \partial_{min}}{\partial_{max} - \partial_{rs} + \varnothing}\right) \tag{29}$$

$$\partial_{max} = min\left(\partial_{max,r}, \partial_{max,q}, a_{max,z}\right) \tag{30}$$

The variable b_{lj} represents the optimal allocation of assets determined by the determinant's approach. This allocation is subject to considerations such as issues, obligations for reporting inconsistencies, and arrangements. The geographic distribution of the estimated anonymized predicted obstacle, the variations in the calculated equilibrium account distribution of resources, and the implications of the eliminated structural and functional components as defined in the packet's characteristics and tangible confirmation are all significant factors to consider. In order to ascertain the rate of challenges, it is necessary to consider the provided speed and arrangement elements.

$$b_{kl} = \begin{cases} 1, & collision \\ 0, & otherwise \end{cases} \tag{31}$$

Additionally, we discuss the verification of the initial state velocity, fluctuations within the defined parameters of stability, and factors to mitigate variations in distance for resource allocation.

$$b_{VC} = exp\left(\frac{-1}{|Y_{int} - Y_{trm}| + \vartheta}\right) exp\left(\frac{-1}{|X_{int} - X_{trm}| + \vartheta}\right) \tag{32}$$

Where the conventional trade-off involved considering the lateral elements, distance-bounded subdivisions, and risk evaluation of functions in order to achieve optimal resource allocation and distribution. The risk field was classified based on its functions and streamlined with suggested topic features, while the possibility field was streamlined by incorporating key proposed update elements. This process ensures that the surrounding reactions are aligned in order to minimize the disparities in separation. It can be shown that $b_{VC} \in |0,1|$, $b_{lj} \in |0,1|, b_{sz} \in |0,1|$, and $b_{VC} \in |0,1|$. Therefore, it is feasible to readily derive the biased aggregate of individuals' cost of the efficiency function distribution within the framework of four-sector expenditure calculation (33).

$$y = b_{VC} b_{vc} + b_{lj} b_{lj} + b_{sz} b_{sz} + b_{kl} b_{kl} \tag{33}$$

where (Y_{int}, X_{int}) is the direct of the connection and (Y_{trm}, X_{trm}) is the incurable synchronize the nominated strategy. ϑ is to circumvent nothing dominator. Additionally, the control effort is estimated and the relative velocity and the variations.

$$b_{VC} = exp\left(\frac{|Y_{trm} - X_{int}|}{b_{max}}\right) \tag{34}$$

The distribution of resources and the subsequent modifications in the structural and functional configurations of the kernel function are crucial for the identification and classification of features. The achievements and the prevailing factors. The process of determining the relative velocity and analyzing the probability distributions of the participants. In light of the alterations in spatial proximity with respect to each other. The Pseudocode for resource allocation is:

Pseudocode for resource allocation
Input: scheduled packets
 Output: allocation of resources
 Begin
 Fix a initial outline function B_j
 Prepare a utility function f_i
 Well-ordered Probability measures b_{kl}
 if $b_{max} \leq 1$ **then**
 Assess the set feature slash (27)
 First-rate packet for allocation planetary b_{VC} (28)
 For $m = 1\ldots, m_{max}$ **do**
 Expand the utility suggest resources
 Choice packet utility function notch $b_{sz} b_{sz}$
 Bargain limit dimension structures target X_{int}
 End for
 elseif
 Get $b_1(R_1, H)$ coldness variations
 Regulate target role ϑ
 End if
 End

Experimental results

This section introduces the suggested packet scheduling approach in the context of 6G-IoT environment, utilizing Fishnet-6G technology. The experimental research consists of three distinct phases, namely simulation setup, comparative analysis, and research summary. The results section demonstrates that the proposed study attains a higher level of performance in comparison to prior research.

Simulation setup

The performance of this research is enhanced by the implementation of the simulation results of the proposed work using the NS-3.26 network simulator. The proposed framework was subjected to a comparative analysis with various performance metrics, revealing that our work exhibited superior performance in comparison. The system configuration is presented in Table 2, while the network parameter settings are displayed in Table 3.

Study implementation

In NS3, we construct a Sierpinski Triangle-based network with 100 IoT devices, 1- 6G base station, 4 gateways, and 1 cloud and 1 edge server. Initially, the edge server clusters the IoT device using the Quantum Density Peak Clustering algorithm (QDPC). Next, perform the traffic prediction process using IMProved Deep Deterministic policy gradient (IMPDDPG). Next, perform the packet scheduling using the Willow Catkin Optimization (WCO) algorithm. After scheduling, packets are managed in Fishing Net Topology. Next, resource allocation is performed using the Bayesian Game-Theoretic Approach (BGTA). Finally, in comparative analysis we plot the results graph for number of Traffic vs. time, number of users Vs transmission rate, Number of users Vs energy efficiency, Number of users Vs average throughput, Number of users Vs latency and Simulation time Vs packet loss rate.

In the realm of 6G-IoT, we implement a Sierpinski Triangle-based network construction in NS3 to tackle challenges stemming from random device deployment, leading to increased network traffic. This method involves constructing the network based on equilateral triangles, with each triangle subdivided into smaller congruent triangles as illustrate in Fig 7(a). Each segment accommodates N IoT devices, and seven triangles are linked to a gateway to streamline transmission complexity. This NS3-based network structure aims to boost information transfer rates, device connectivity, flexibility, and scalability, while mitigating energy consumption and communication overheads. Sierpinski's fractal triangle is integrated into NS3, involving steps such as connecting center points and eliminating the main triangle for additional clusters. Clustering, utilizing Quality-Driven Packet Transmission (QDPC), is underscored for minimizing control overhead messages in the IoT network as shown in Fig. 7(b). The clustering architecture, visually represented in NS3, highlights effective metrics for grouping IoT devices and identifying outliers. The integration of cloud computing, clustering, and the QDPC algorithm is emphasized for synergistically enhancing the performance of the proposed 6 G network in the NS3 simulation. Cloud computing acts as a centralized hub, relieving User Equipment (UE) of computational burdens. Clustering, driven by QDPC, improves energy efficiency and communication within the NS3 simulation. The collaborative functioning of cloud computing, clustering, and QDPC is visually presented within the NS3 environment, elucidating their roles in optimizing energy usage and communication efficiency in the simulated 6G network.

In NS3, post-clustering IoT devices, traffic prediction involves grouping and fair queue status evaluation. Grouping categorizes IoT device packets, and fair queue assesses statuses based on features. Utilizing the IMPDDPG reinforcement learning algorithm within NS3, real-time traffic prediction employs a variable sampling rate (Fig. 7(c)), ensuring efficiency and faster convergence. This approach facilitates efficient packet scheduling and transmission within the NS3 simulation environment. In replayed determinants, NS3′s memory method uses functional memories, reducing the impact of time-based associations. Technologies for parameter sampling rate and visitor prediction are introduced in NS3, contributing to improved structural analysis.

Following traffic prediction in the NS3 simulation environment, packet scheduling is executed to minimize transmission latency, and enhance throughput. In this context, packets undergo scheduling and transmission to the receiver, mitigating transmission delay and congestion. For packet scheduling, we introduce the WCO algorithm within NS3, considering factors such as bandwidth, CQI, energy, delay, transmission rate, queue length, buffer rate, completion time, and data size. That is, Fig. 7(d) illustrate while performing the optimization, the effect of these parameters. The adoption of the WCO algorithm is driven by its efficacy in addressing complex tasks, showcasing adaptability, robustness, and scalability. This algorithm dynamically adjusts scheduling for critical packets (e.g., video calls, medical emergencies, online games) based on QoS, bandwidth, cool deadline, hot deadline, task criticality, and laxity. Subsequently, packet management occurs within the Fishing Net Topology, reducing energy consumption, complexity, and overall process weight. Following packet scheduling and management, the edge server selects the best sub-flow for packet transmission,

Table 2
System constraints.

Hardware configuration	Hard disk	62 GB
	RAM	3GB
	Mainframe	Pentium dual core and above
Software conformation	Network simulator	NS-3.26
	Operating system	Ubuntu 14.04 LTS

Table 3
Simulation parameter.

Network parameters	Value
Number of IoT devices	100
6G base stations	1
Number of gateways	4
Cloud	1
Edge	1
Recreation area	1500 × 1700 m
Recreation area	1500 × 1700 m
Simulation time	340s
Initial energy	130J
Node mobility	8 m/s
Components	Wi-Fi, Ipv4, Internet
Broadcast range	150m
No. of packets	~1400
Mobility type	Random waypoint
Channel bandwidth	120 MHz
Packet data rate	140 Mbps
Traffic type	TCP/IP, UDP
No. of retransmission	8
Size of packets	84,148, 276,612, 1012 bytes

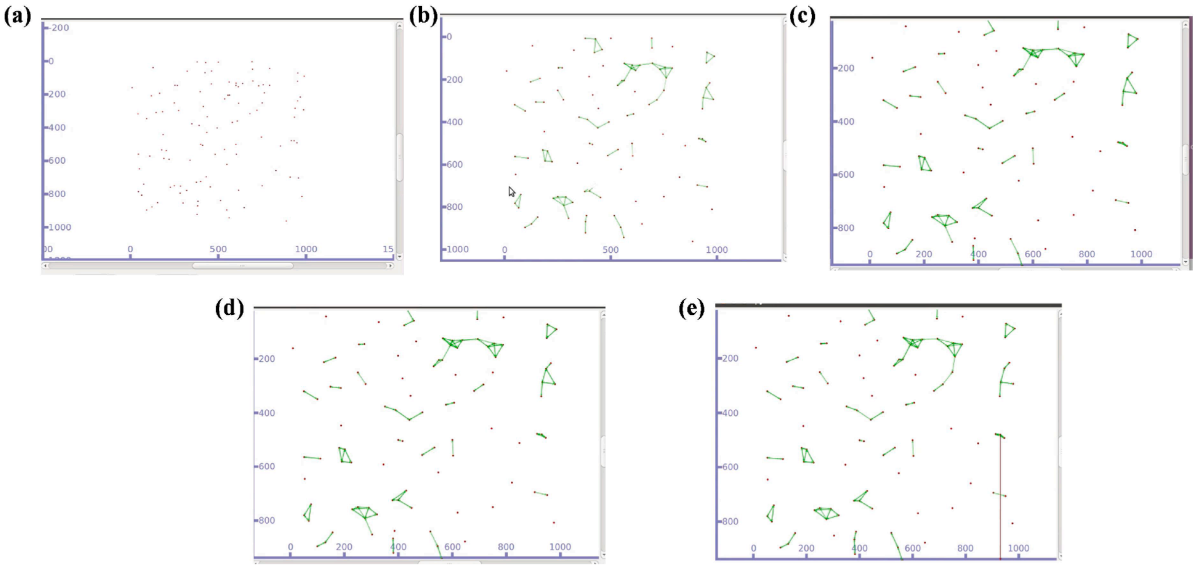

Fig. 7. Representation of NS3 screen while performing each phase (a) a Sierpinski Triangle based network. (b) QPDC. (c) IMPDDPG (d) packet scheduling by WCO. (e) resource allocation by BGTA.

minimizing transmission delay. Ultimately, an optimal path is chosen, considering traffic rate, transmission delay, and high throughput, contributing to reduced energy consumption and extended network lifetime in the NS3 simulation.

In NS3, scheduled packets are assigned to requested resource blocks using the BGTA algorithm, taking into account metrics such as CQI, spectrum efficiency, resource type, energy efficiency, traffic, QoS, delay, bandwidth, and feedback. BGTA, making optimal global decisions, utilizes a straightforward, direct, and computationally efficient resource estimation methodology. The algorithm dynamically and optimally performs resource allocation, effectively addressing the PRB problem by efficiently distributing frequency-domain resources as shown in Fig. 7(e). Priority is granted to UEs with the best CQI and QoS constraints, ensuring optimal allocation, QoS maintenance, and power management. UE computational and feedback data are stored in the cloud infrastructure to reduce UE burden and for future use. When determining resource allocation intentions, interactions and techniques are assessed through discrete game theory, emphasizing layered functioning and organizing players for multiple cost-function competitors in problem-solving. Following the execution of the proposed approach in each phase, the final representation, depicted in Fig. 8, is obtained. Subsequently, the results are compared with existing approaches, showcasing different time intervals for capturing figures. This comparison yields graphs for metrics such as the number of traffic vs. time, number of users vs. transmission rate, number of users vs. energy efficiency, number of users vs. average throughput, number of users vs. latency, and simulation time vs. packet loss rate, as elaborated in the upcoming section.

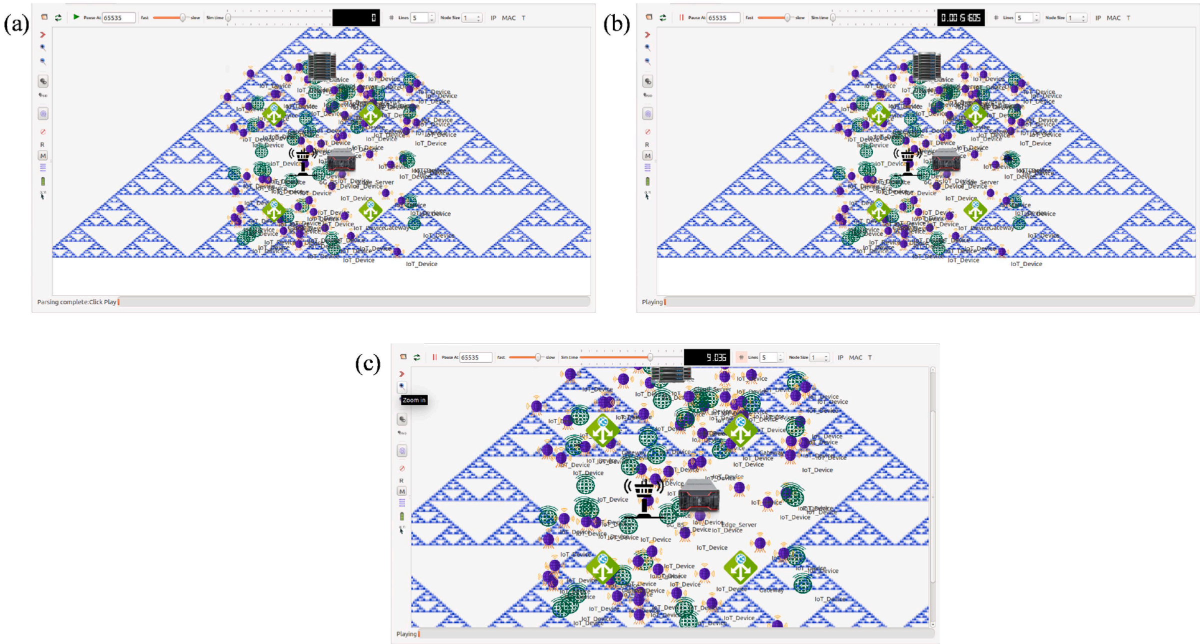

Fig. 8. The performing of the proposed architecture after using NS3 at different times (a), (b), and (c).

Comparative analysis

This section presents a comparison analysis of the Fishnet-6G framework and existing efforts, namely MEC-IoT, DDPG-PER [80], and DQN-PS [75]. The MEC-IoT is ideal way of offloading the tasks to MEC server directly linked to IoT systems, and the MEC servers operate independently. The paper [75] proposed a practical DQN-based packet scheduling algorithm for coordinating the transmissions of multiple IoT devices and improving energy efficiency in a dynamic network environment. The authors of the paper focused on energy efficiency and throughput as performance metrics. However, they acknowledged that only a little work has considered QoS in IoT-related studies. On the other hand, the paper [80] addressed the joint decision offloading and resource allocation problem for MEC federation in the Industrial IoT (IIoT) using deep reinforcement learning (DRL). The authors of this paper considered MEC federation, energy model formulation, delay model formulation, and the use of DRL to solve the problem. Their hypothesis is that their proposed approach can optimize task offloading and resource allocation in IIoT systems. We justify our selection of these existing approaches by pointing out that the majority of current efforts in the next generation network space focus on resource allocation, packet scheduling, and traffic prediction. However, these approaches are suffered from high power consumption, a lack of QoS, and significant packet loss. We argue that our proposed Fishnet-6G framework addresses these issues by incorporating AI and Bayesian game-theoretic approaches into packet scheduling and resource allocation. The differences between the existing approaches and the Fishnet-6G framework lie in their underlying algorithms and methodologies. MEC-IoT focuses on offloading tasks to MEC servers, DQN-PS utilizes deep Q-networks for packet scheduling, and DDPG-PER employs deep deterministic policy gradient with prioritized experience replay for resource allocation. In contrast, the Fishnet-6G framework combines various algorithms, such as QDPC, IMPDDPG, WCO, and BGTA, to address different aspects of packet scheduling and resource allocation. The weaknesses of the existing approaches, include computational complexities, high packet loss ratio, and increased energy consumption. The Fishnet-6G framework overcomes these weaknesses by utilizing a Sierpinski Triangle-based network construction, clustering with QDPC, traffic prediction with IMPDDPG, packet scheduling with WCO, and resource allocation with BGTA. we confirm the hypothesis by evaluating the performance of the Fishnet-6G framework against the existing approaches in terms of various metrics, including time, transmission rate, energy efficiency, average throughput, latency, and packet loss rate. The suggested work demonstrated numerically that the Fishnet-6G framework outperforms the existing approaches in all these metrics

The proposed approach, fishnet-6G for the formation of 6G-IoT environment was evaluated using the statistical confidence intervals to analyze the resource allocation and packet scheduling for the time, transmission rate, energy efficiency, average throughput, latency, and packet loss rate. Each simulation is run 25 times and the results are obtained with a 95 % confidence interval. Table. 5 show the mean and standard deviation of each metrics to analyze the performance of each algorithm.

Impact of time

The aforementioned statistic is employed for the purpose of estimating the duration required for the implementation of the Fishnet-6G framework. The duration of the longest time period represents the time required by the system to schedule packets. An effective system should possess a minimal execution time, as time is commonly characterized as the duration required to accomplish packet scheduling.

The illustration in Fig. 9 demonstrates the contradiction between time and accuracy. Based on the comparing findings, the proposed study demonstrates a shorter completion time in comparison to three previous works, namely MEC-IoT, DQN-PS, and DDPG-PER. The existing literature on data storage primarily focuses on presenting the distributions of construction information for branches and the scheduling approach placement for essential generations. However, these works tend to overlook the significance of metrics and the temporal arrangements of distribution in packet scheduling. Furthermore, they exhibit a reduced level of regard for the determinations pertaining to the distributions of the processing units. The organization of safe differentials in the order of consideration of network operations has the potential to improve the storage of information and the functionality of class-based data storage. The factors that need to be considered are the protected methodology for organizing and establishing a connection between the data's distinctive features and the secure manner in which the information is generated. The acquisition of confirmation about storage methods involves varying levels of packet considerations for user information. These considerations encompass different levels of security and partially created network settings for data storage and setups.

The Fishnet-6G technique demonstrates improved performance by reducing the time required for the eight lanes of traffic by a factor of 1.5 Gbits/s. This improvement is achieved with the implementation of DDPG-PER 2, DQN-PS 2.5, and MEC-IoT 3 as the departing projects. The proposed task exhibits an average completion time of 3.5 Gbits/s over 20 distinct traffic kinds, hence showcasing superior performance compared to previous endeavors such as DDPG-PER 's 4.5 Gbits/s, DQN-PS's 5 Gbits/s, and MEC-IoT 's 5.5 Gbits/s. The graph visually presents the numerical findings that demonstrate the superior performance of our proposed strategy compared to earlier endeavors.

Impact of transmission rate

The packet transmission rate is the volume of data sent through the channel of transmission via an information interface in a specific length of time.

$$TRNS = c\frac{tp}{\varpi} \tag{35}$$

where, the variable tp represents the designated time period, whereas ϖ denotes the duration between the initial and subsequent transmissions of packets. Fig. 10 illustrates the comparison between time and accuracy. Based on the comparing findings, the proposed study demonstrates a shorter completion time compared to two previous studies, namely MEC-IoT, DQN-PS, and DDPG-PER. The suggested study employed a fishnet topology to manage scheduling, resulting in decreased complexity and process weight, as well as reduced energy consumption. The optimal sub flow is selected by the implementation of packet scheduling and management by the edge server, resulting in a reduction of transmission delay. The previous research focused on scheduling and organizing determinants for scheduling and functional packet transmission. This was achieved by avoiding the determination and categorization of packet arrangements for structural packet transmission, and implementing packet management for arranging the packets. The concept of time travel in packet transmission and the implementation of structural scheduling have recently been established as procedures for arranging packet transmission and organizing packet ordered pairs.

The Fishnet-6G method's performance in terms of transmission rate experiences a decrease of 300 kbps when the number of users is 20. This decrease is observed in conjunction with the departure of three projects, namely DDPG-PER with a reduction of 275 kbps,

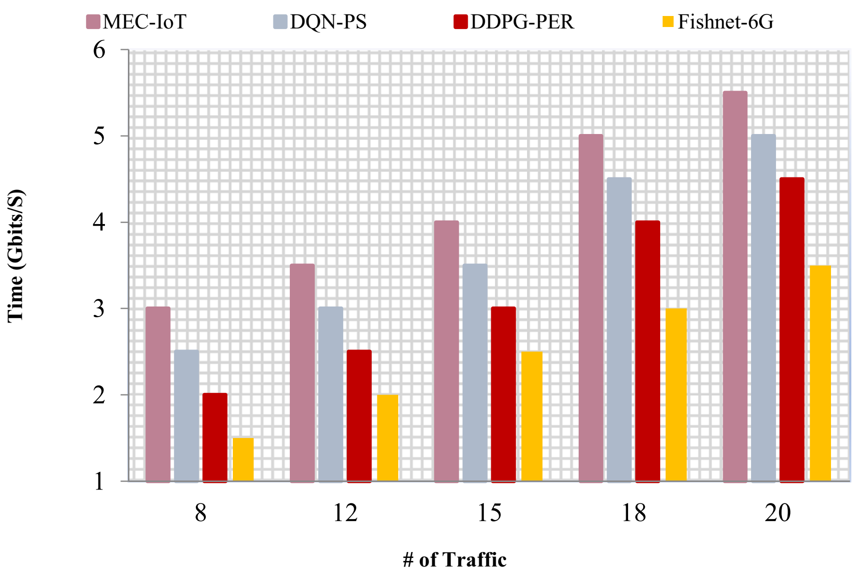

Fig. 9. Time Vs Number of Traffic.

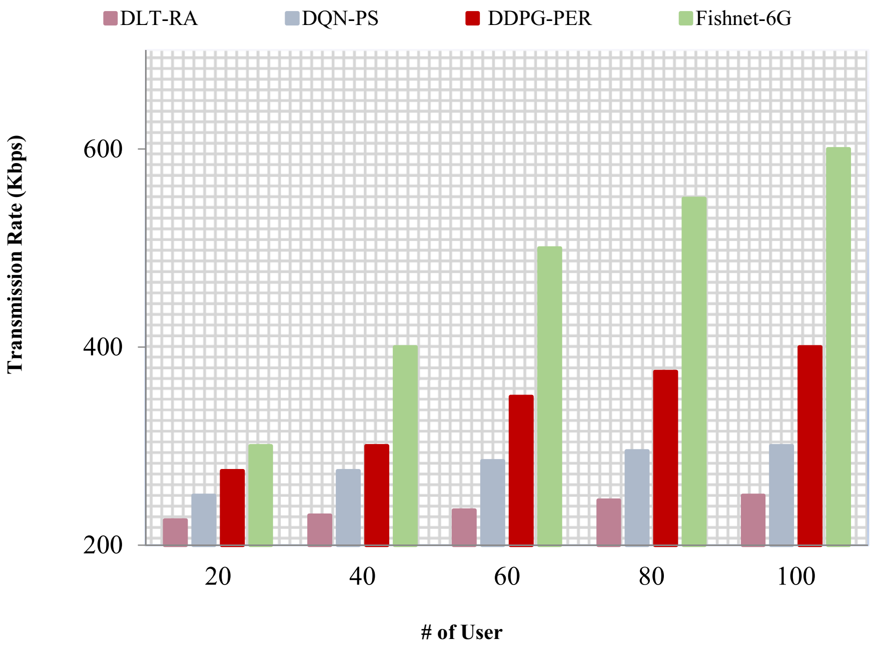

Fig. 10. Transmission Rate Vs Number of User.

DQN-PS with a reduction of 250 kbps, and MEC-IoT with a reduction of 225 kbps. The proposed work exhibits an average transmission rate of 600 kbps for a sample size of 100 distinct users, hence showcasing superior performance compared to previous endeavors such as DDPG-PER 's 400, DQN-PS's 300, and MEC-IoT 's 250. The numerical findings depicted in the graph demonstrate the superior performance of our proposed methodology in comparison to earlier endeavors.

Impact of energy efficiency

Energy efficiency is the use of the least amount of energy possible to complete a job or produce a desired outcome. The energy

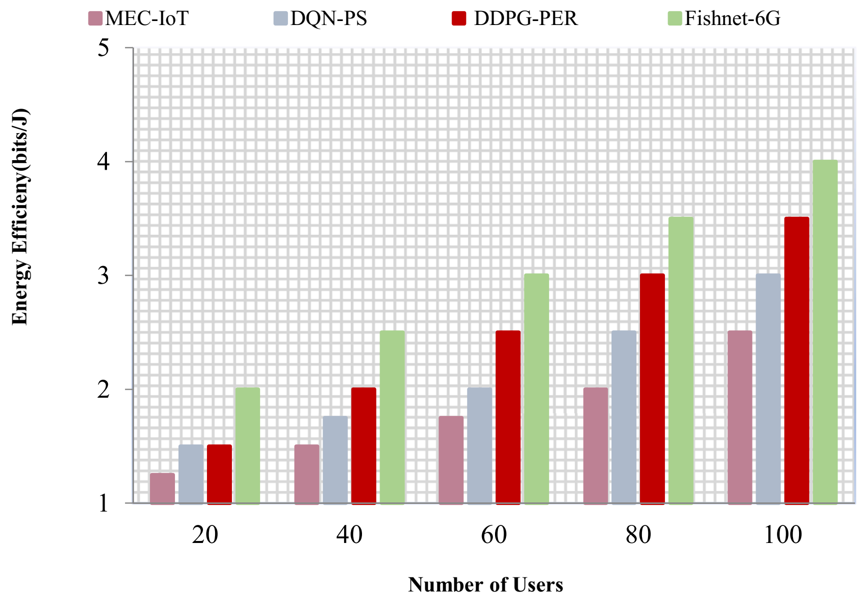

Fig.11 . Energy Efficiency Vs Number of User

Fig. 11. Energy Efficiency Vs Number of User.

efficiency e is calculated as follows,

$$\vartheta^{e} = \vartheta^{t} - \vartheta^{o} \tag{36}$$

The variable ϑ^{t}represents the energy expended during the process of transmitting packets, which is subtracted from the overall energy reserve. Fig. 11 presents a comparison between the number of users and the energy saving solutions that have been recommended and are currently in place. Additionally, compared to past efforts, the suggested task is more energy-efficient. The use of BGTA, which takes into account QoS (user demand) and resources in both directions and makes resource allocation perfect, is principally responsible for this improvement in energy efficiency. The dynamic and optimal execution of BGTA involves resolving the issue of PRB, which refers to the inefficient allocation of frequency-domain resources. Ideally, the UE exhibiting the highest CQI and QoS constraints should be prioritized for assignment. The existing study focused on resource allocation and distribution, taking into account key metrics and determining the optimal configurations for minimal energy distributions. It also addressed energy mission management and resource allocation in packet transmission, as well as the utilization of energy in formations. Additionally, the study examined the ordered pairs of functional range and determined the transmission range features in relation to the proposed work.

The Fishnet-6G technique demonstrates a 2 bits\J decrease in energy efficiency when the number of users reaches 20. This reduction is observed in comparison to existing works such as DDPG-PER 1.5, DQN-PS 1.5, and MEC-IoT 1.25. The proposed study demonstrates an average of 4 bits\J for a sample size of 100 users, indicating superior performance compared to existing approaches such as DDPG-PER 3.5, DQN-PS 3, and MEC-IoT 2.5. The numerical data depicted in the graph suggest that our suggested approach exhibits superior performance compared to existing work.

Impact of average throughput

Throughput (B^{t}) is defined as the ratio of the user's request or the quantity of packets to the amount of time required for data transfer, which may be written as,

$$B^{t} = (\text{packet size}) / (\text{time taken}) \tag{37}$$

Fig. 12 presents a comparison between the throughput and packet size of the proposed and current studies. The Figure presents a graphical depiction that illustrates the comparison between the throughput of the proposed methodology and that of the existing models, with respect to the varying number of users. The aforementioned observation highlights the superior latency performance of the proposed work in comparison to the existing MEC-IoT, DQN-PS, and DDPG-PER initiatives. The main objective of achieving low latency is to ensure the quality of service by implementing efficient allocation strategies for appropriate resource blocks to the UEs. Additionally, it involves power management throughout the process of resource allocation. The computational and feedback data from the UE is gathered and stored in a cloud infrastructure in order to alleviate the burden on the UE and facilitate its future utilization. The previous studies focused on evaluating the efficiency of data transmission by taking into account both latency and the inherent characteristics of structural and functional packet elimination. Additionally, these studies aimed to determine the optimal process for achieving functional goals while considering the determined work nature of the structural packet loss rate. They also explored the ordering of pairs of packet transmission, packet allocation, and the factors influencing energy consumption. Furthermore, resource allocation and the formation of energy features and structures were considered in these investigations.

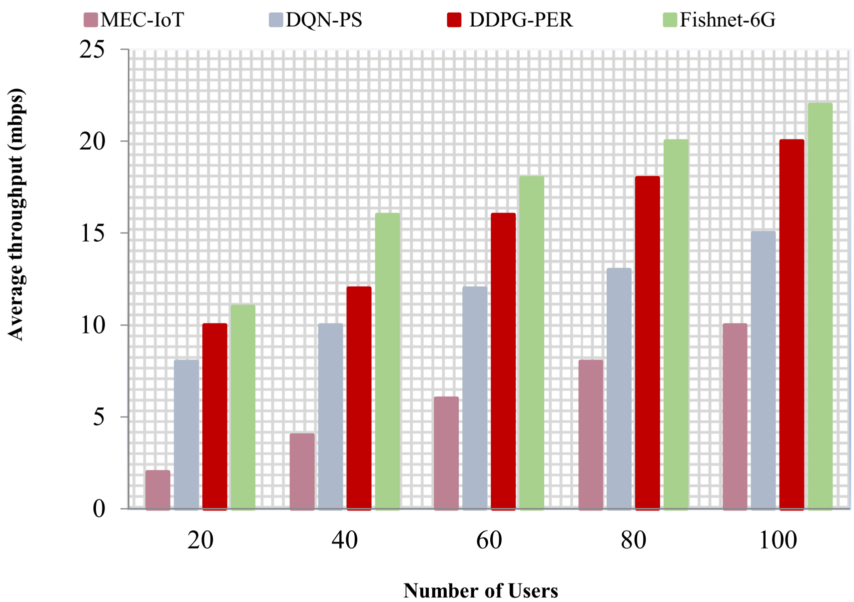

Fig. 12. Average Throughput Vs Number of User.

The Fishnet-6G approach demonstrates an 11mbps increase in average throughput impact when implemented with 20 users. This improvement is observed in the DDPG-PER 10, DQN-PS 8, and MEC-IoT 2 rendering projects. The proposed study involves the participation of an average of 100 users to accomplish a traffic rate of 22 mbps. This showcases a superior performance compared to previous projects such as DDPG-PER, which achieved a rate of 20 mbps, DQN-PS with 15 mbps, and MEC-IoT with 10 mbps. The graph visually presents the numerical findings, which indicate that the technique proposed by us outperforms past endeavors.

Impact of latency

Latency (lt_{ς}) is used to assess how long it takes to complete data encryption, authentication, access control, and vulnerability analysis. Lt is defined as the difference between the entire amount of time and the amount of time required to complete a particular job from the tasks listed above. It can be written as

$$lt_{\varsigma} = time_{lt} - \psi_{time} \tag{38}$$

The variable $time_{lt}$ represents the duration required for executing the packet scheduling process. Fig. 13 presents a graphical depiction that illustrates the comparison between the latency of the proposed methodology and the latency of existing methods, with respect to the number of users. It is evident from the analysis that the proposed work exhibits lower latency compared to the existing MEC-IoT, DQN-PS, and DDPG-PER initiatives. The key rationale for achieving low latency in this context involves the first process of aggregating the packets originating from multiple IoT devices. Furthermore, the determination of fair queue statuses relies on several queue characteristics, including packet count, arrival time, queue length, deadline, and completion time. Moreover, the IMPDDPG algorithm is employed for the purpose of predicting real-time network traffic by taking into account the grouping and fair queue state. Variable sampling rate refers to the methodology employed to estimate the value of a certain variable based on assumptions made inside a packet. The present study focused on the analysis of IoT devices, specifically examining the performance estimation and feature determination for managing scheduling processes and classification. This investigation aimed to reduce construction time and enhance associations by validating elements at a specific level of consideration. Additionally, the study involved identifying packet loss and determining the assumptions and characteristics of proposed units, as well as constructing energy management units and their functionalities.

The Fishnet-6G technique is designed to decrease latency for a group of 20 users by 6 ms. In comparison, existing works such as DDPG-PER achieve a latency of 8 ms, DQN-PS achieves 10 ms, and MEC-IoT achieves 12 ms. The proposed work demonstrates an average execution time of 15 ms for a sample size of 100 users. This performance surpasses that of existing systems such as DDPG-PER (20 ms), DQN-PS (22 ms), and MEC-IoT (24 ms). The numerical data depicted in the graph indicates that our suggested approach exhibits superior performance compared to existing work.

Impact of packet loss rate

Average packet loss ratio measures the quantity of lost packets relative to the total number of packets during delivery (ξ^{A}) that can be formulated as,

$$\xi^{A} = \frac{PL^{F}_{lost}}{G_F} \times 100\% \tag{39}$$

The average packet loss from the whole packet can be quantified as PL^{F}_{lost} . Fig. 12 illustrates a graphical figure that offers a

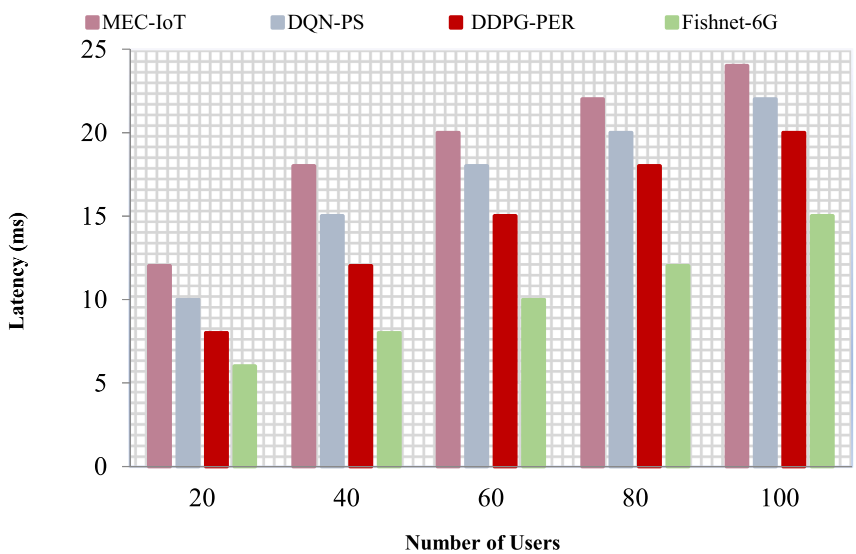

Fig. 13. Latency Vs Number of User.

comparison between the proposed work and existing models in terms of packet loss, specifically in relation to the number of users. Based on the observation of Fig. 14, it is evident that the suggested study has achieved a lower level of packet loss compared to previous works such as DDPG-PER, DQN-PS, and MEC-IoT. The primary objective of implementing packet scheduling is to minimize packet loss rate, hence reducing jitter and transmission latency while enhancing goodput and throughput. In this context, the scheduling and transmission of packets to the receiver effectively mitigates transmission delay and congestion. Packet scheduling aims to minimize energy usage, reduce complexity, and enhance the lightweight nature of the operation. Upon the conclusion of packet scheduling and management, the edge server selects the most optimal subflow for packet transmission, resulting in a reduction of transmission delay. The previous research focused on packet scheduling and determining the minimum flow for the proposed construction work.

The Fishnet-6G approach demonstrates improved efficiency by reducing packet loss by 12 % during a simulation period of 50 s. Notably, the DDPG-PER work accounts for 15 % of packet loss, followed by DQN-PS at 20 % and MEC-IoT at 25 %. The proposed work exhibits an average simulation duration of 300 s for 30 % of various packet loss scenarios, hence showcasing superior performance compared to previous endeavors such as DDPG-PER 's 40 %, DQN-PS's 50 %, and MEC-IoT 's 55 %. The numerical findings depicted in the graph demonstrate that the technique we propose surpasses previous endeavors.

Research summary

In this part, we provide a summary of the experimental findings that demonstrate the higher performance of the suggested Fishnet-6G framework. Table 4. summarizes the motivation and expected benefits of this study. The proposed work's performance is listed in terms of time, transmission speed, energy efficiency, average throughput, latency, and packet loss rate, which are all stated in the figures. The performance criteria used in the numerical analysis of planned and existing works are shown in Table 5. The following are some of the research's key findings:

- For improving network management, we proposed Sierpinski triangle-based network construction which reduces the complexity in the packet scheduling and transmission.
- For reducing high complexity, clustering is performed by edge server using QDPCA which reduces processing time and computational complexities and increases the life span of the network.
- For reduce traffic in data transmission, traffic prediction is performed based on grouping and fair queue status using IMPDDPG which solves the problem of low training efficiency and slow convergence.
- To reduce the packet loss rate and increasing the throughput, we perform scheduling and dynamically adjust the scheduling for sensible packets using WCO algorithm by considering energy, delay, CQI, deadline etc. Further, packets are managed in fish net topology which reduces energy consumption, complexity and makes process lightweight.
- To improve the power efficiency and QoS in 6G networks, we optimally perform QoS aware resource allocation using BGTA algorithm by considering bandwidth, spectral efficiency, etc., which manages the power consumption. The UE computational and feedback are collected form the users and stored in cloud infrastructure to reduce the UE burden and for future use.

Conclusion

This study proposes a fishnet technique to overcome the significant issues related to packet scheduling and resource allocation in the context of the 6G-IoT environment. The primary objective of this study is to implement the Sierpinski triangle-based network construction in a 6G-IoT environment to mitigate the issues of excessive energy consumption and communication overhead. The edge server utilizes QDPC to provide clustering for IoT devices. The suggested study aims to group IoT devices based on relevant metrics. This clustering process involves the identification of cluster heads and sub-cluster heads, which are executed by an edge server. Subsequently, the process of traffic prediction is conducted through two distinct stages, namely grouping and fair queue status assessment, employing the IMPDDPG algorithm with variable sampling rate. Packet scheduling is executed by considering the relevant metrics and employing the WCO algorithm. Following the establishment of a schedule, the management of packets is conducted inside the fishing net architecture, resulting in a reduction in energy consumption, complexity, and overall process weight. The allocation of scheduled packets to the requested resource blocks is accomplished using BGTA, while taking into consideration the operational indicators. The proposed approach was tested using Network Simulator-3.26, and its effectiveness was assessed by comparing its performance to existing methods taking into account various permanence metrics, including time, transmission rate, energy efficiency, average throughput, latency, and packet loss rate. The efficacy of our methodology is examined by quantitative analysis, which substantiates that our technique surpasses existing methodologies across all metrics. The future work will consider cases high availability in cases of Base Station failures and massive IoT V2X environment to support the next generation of wireless networks.

CRediT authorship contribution statement

Ali. M. A. Ibrahim: Conceptualization, Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Zhigang Chen:** Funding acquisition, Supervision, Writing – review & editing, Resources. **Hala A. Eljailany:** Investigation, Writing – review & editing. **Genghua Yu:** Writing – review & editing. **Aridegbe A. Ipaye:** Software, Writing – review & editing. **Khalid A. Abouda:** Writing – review & editing. **Wail M. Idress:** Writing – review & editing.

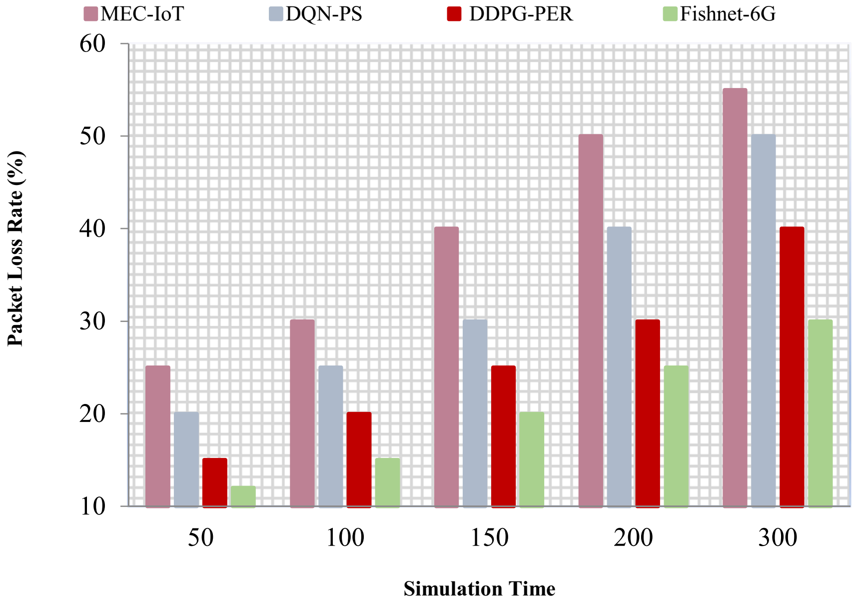

Fig. 14. Packet Loss Rate Vs Number of User.

Table 4
Summary of the motivation and expected benefits.

Phase	Motivation	Expected Benefits
Sierpinski Triangle-based Network Construction	Structured network formation to optimize information transfer, connectivity, and overall network efficiency. Mitigation of high network traffic resulting from the random deployment of IoT devices in 6 G networks. The complexity of packet transmission and scheduling can be reduced	Improved information transfer rates and heightened connectivity among devices. Enhanced scalability and flexibility of the network. Reduction in energy consumption and communication overheads. Increased connectivity among devices
Quantum Density Peak Clustering (QDPC)	Efficient clustering of IoT devices post-network creation for enhanced energy usage, communication, topology control, and latency reduction.	Improved energy efficiency by strategically clustering devices. Enhanced communication across the network and efficient control of network topology. Reduced latency for faster data processing and transmission.
Cluster Head (CH) and Substitute CH (SUB CH)	Effective organization of IoT devices based on physical parameters. Strategic selection of cluster heads and substitute cluster heads to manage traffic congestion and packet loss.	Efficient device connection and optimized distribution of tasks within the network. Minimized packet loss during high traffic volume or low energy availability.
Grouping and Fair Queue Status with IMPDDPG Algorithm	Accurate real-time traffic prediction through grouping and fair queue status estimation. Addressing issues of low training efficiency and slow convergence.	Accurate real-time traffic predictions for efficient packet scheduling and transmission. Improved adaptability and responsiveness in continuous control problems.
Willow Catkin Optimization (WCO) Algorithm and Fishing Net Topology	-Dynamic adjustment of packet scheduling for different types of packets using WCO algorithm. Reduction of energy consumption and network complexity through Fishing Net Topology.	Adaptive and robust packet scheduling based on diverse packet types. Lightweight packet management process with reduced energy consumption.
Bayesian Game-Theoretic Approach (BGTA) for Resource Allocation	Global decision-making for resource allocation considering various metrics. Addressing the Physical Resource Block (PRB) problem for optimal resource allocation.	Faultless resource allocation based on a wide range of metrics. Efficient allocation of frequency-domain resources, ensuring improved QoS.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 5
The mean and standard deviation of each metrics to analyze the performance of each algorithm.

	MEC-IoT		DQN-PS		DDPG-PER		Fishnet-6G	
	mean	St Div	mean	St Div	mean	St Div	mean	St Div
Time	4.2	0.25	3.7	0.2	3.2	0.18	2.5	0.14
Transmission rate	237	50	281	60	340	70	470	80
Energy efficiency	1.8	0.18	2.1	0.2	2.5	0.16	3	0.3
Average throughput	6	0.6	11.6	0.2	15.2	0.18	17.4	0.15
Latency	19.2	1	17	0.75	14.6	0.5	10.2	0.4
Packet loss rate	40	2	33	1.5	26	1	20.4	0.6

Data availability

Data will be made available on request.

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