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Intelligent Optimal Resource-Sharing Algorithm for 6G Network

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Abstract*—Wireless communication technology has advanced significantly over the last fifteen years, with the adoption of fourth and fifth generation cellular systems. It has also provided a solid foundation for the sixth generation (6G). 6G will embed AI technologies into the network. It will enable the use of sophisticated deep learning technologies, hence increasing network efficiency and administration. This study introduces the HLEVRA (Horned Lizard Ensemble Voting Resource Allocation), a new allocation approach based on AI principles in 6G cellular systems. The study simulates a 6G user experience with multiple cells and uses the HLEVRA architecture to include important 6G capabilities in the NS3 network simulator. The framework uses a biologically organized optimization method called prey-prediction to adaptively estimate the resource's requirements. Predicted resources are given to users, which helps to accelerate data transmission and reduce system congestion. The framework's performance is assessed using important parameters such as throughput, data transfer rate, energy consumption, communication delay, and packet drop rate. For example, if 100 users connect to a single 6G base station, the proposed HLEVRA method will achieve 14.7 Gbps throughput, 840 Kbps data rate, 0.33 mW energy consumption, 20 ms communication time, and 12.5% packet drop rate. This data demonstrates the framework's capacity to efficiently address critical resource allocation concerns in 6G networks while providing significant certainty.

***Keywords*— 6G Cellular Systems, Horned Lizard Optimization, Data transfer rate, Power consumption, Packet drop.**

I. INTRODUCTION

The primary goal of 2G, 3G, and 4G cellular networks has been to deliver voice and data services [1]. The fifth-generation (5G) system is the first mobile communication technology designed to penetrate industrial environments [2]. This advancement paves the way for carriers and vendors to expand into vertical markets, transforming their revenue-generation strategies. The emerging sixth-generation (6G) technology has introduced ground breaking services such as ubiquitous mixed reality and high-resolution sensing, demanding extreme performance in terms of throughput (Gbit/s for AR/VR applications) and reliability (down to 100 microseconds) [3].

In industrial contexts, wireless networks are anticipated to replace traditional wired network structures such as time-sensitive network (TSN) solutions, Profinet, and EtherCAT (Ethernet for Control Automation Technology), owing to their enhanced data rates, reduced latency, and superior reliability in resource allocation [4]. In some cases, the increasing number of end devices, often referred to as subnetworks, is highlighted in the European 6G white paper [5].

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Recent visions for 6G suggest that independent and uncoordinated subnetworks could support extreme connectivity. This study outlines the design principles and concepts behind these X-subnetworks in 6G [6]. The research explores emerging scenarios, such as in-vehicles, airplanes, robots, and human bodies, emphasizing the "inside everything" notion for X-subnetworks [7]. Connectivity scenarios vary widely, including static and isolated interactive devices or high-speed drones and robots connected to a shared cellular-type network [8].

Wireless connections in these environments often utilize the same frequency bands as cellular phones to link controller actuators and sensors [9]. Even in cases of weak or no connection to larger networks, subnetworks ensure highly reliable and deterministic communication in spatial and temporal domains [10]. However, rapid mobility in these subnetworks can lead to highly dynamic interference, resulting in unacceptably high transmission failure rates [11]. To address this, resource allocation algorithms aim to optimize the use of multidimensional radio resources (e.g., frequency bands and power budgets) under extreme interference and delay constraints, mitigating the impact of high interference power [12]. Resource management for radio systems is a complex problem that typically lacks efficient universal solutions due to its non-convexity and NP-hard nature [13]. Various approaches, such as weighted programming, game theory, geometric programming, minimum mean square optimization, information theory, machine learning, and fractional programming, have been applied to tackle these challenges [14].

Despite these efforts, existing algorithms—whether based on machine learning or traditional methods like Centralized Graph Coloring (CGC)—often rely on information that is difficult to obtain in real-world networks, such as the channels between subnetworks lacking direct communication [15]. This limitation hinders the dynamic optimization of resource allocation [16]. Moreover, current methods struggle to rationalize the interference interactions among agents in mobile subnetwork systems [17]. Factors such as consistent channel selection and the distance between subnetworks can provide insights into potential interference relationships [18]. Deep reinforcement learning (DRL) has recently shown promise in addressing radio resource allocation problems [19]. However, despite significant progress, these approaches still face unresolved challenges [20].

This study contributes the following:

- The 6G cellular user environment is initially modeled with multi-cellular users.
- A novel Hybrid Lizard Evolutionary Resource Allocation (HLEVRA) approach is implemented using the NS3 programming framework with enhanced features.
- Desired resources are identified through the activation of the Lizard optimization prey-finding mechanism.
- Predicted resources are allocated to each 6G cellular user, facilitating data transmission.
- The effectiveness of the proposed model is evaluated based on metrics such as throughput, data transfer rate, energy consumption, communication delay, and packet drop rates.

The subsequent sections of this investigation are structured as follows: Section 2 reviews recent related works. Section 3 provides a detailed explanation of the proposed methodology. Section 4 discusses the outcomes of the resource-sharing framework and its comparison with existing models. Finally, Section 5 concludes the study.

II. RELATED WORK

Xia et al. [21] proposed an Attention-based Graph Neural Structure (A-GNS) for resource management in 6G networks. Instead of focusing on channel gain, the model prioritized power received and signal strength. Utilizing a multi-head attention layer, the model effectively extracted relevant features while discarding irrelevant subnetworks. This approach outperformed traditional models in resource management and demonstrated improved convergence speed. However, it faced limitations in handling massive data scalability.

Energy efficiency is a critical concern in IoT networks. To address this, James et al. [22] introduced a dynamic resource model leveraging an optimization-based approach to enhance energy efficiency. Their model combined a modified Kuhn–Munkres algorithm with Lagrangian decomposition to optimize dynamic resource allocation. The proposed joint resource algorithm significantly improved energy efficiency in large-scale 6G-IoT environments.

Quingtian et al. [23] implemented a reinforcement learning-based model to optimize resource allocation in 6G networks, aiming to minimize latency. The model employed a double deep Q-network to allocate resources and effectively manage diverse network requests. Performance validation demonstrated ultra-low latency and a high number of accepted requests. However, the model's complexity posed a significant challenge.

Kai et al. [24] developed a dynamic nested neural structure to allocate resources dynamically in 6G networks. The model incorporated the Markovian decision process for learning from massive IoT data. Results showed reduced delay times and an improved average hit rate compared to other algorithms. Despite these achievements, the parallel execution of multiple tasks introduced resource conflicts.

Ramoni et al. [25] proposed a multi-agent Q-learning model for resource allocation, where resources were selected based on Q-heuristics. This approach focused on the combined selection of channels and transmit power. The system's two-level quantization and learning parameters enhanced the convergence rate, demonstrating robustness in interval sensing, threshold quantization, and switching delays. However, the model exhibited poor performance in low percentiles.

Allocating resources to meet the unique requirements of every cellular user remains a complex challenge due to the difficulty of accurately predicting desired resources. To overcome these limitations, the current study incorporates an optimization approach with an ensemble model as a prediction mechanism. Performance validation against existing models will underscore the effectiveness of the proposed model.

III. Proposed Methodology

A novel Horned Lizard Ensemble Voting Resource Allocation (HLEVRA) strategy was planned to be introduced in this research to share the needed resources to connect 6G cellular users. Initially, the required cellular users were created in the cellular environment with limited energy resources. Consequently, a novel HLEVRA is designed with the features needed to perform different tasks such as monitoring, resource prediction, and allocation.

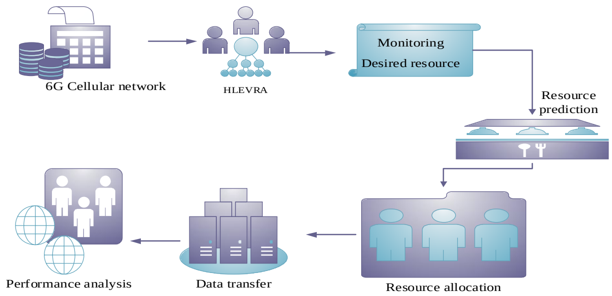

Fig.1 Proposed methodology

Here, the horned Lizard optimizer's best solution predicted the desired resources of every cellular user. After allocating the resources, the data was shared, and the performance was measured in terms of throughput, data transfer rate, energy consumption, communication delay, and packet drop. The overall methodology is represented in Fig 1.

Initially, the 6G cellular environment is implemented in the NS3 stimulator. Afterward, the suggested technique, HLEVRA, with the required features, is activated to optimize the 6G data transmission. Initially, optimization observes the needed resources of the 6G network. Consequently, the resource tasks are optimally allocated to the definite functions, and the data transmission is processed. Subsequently, the proposed approach's effectiveness was determined by energy consumption during data transmission, communication delay, drop in data packets, rate of data transfer, and throughput. Afterward, the outcomes are correlated with recent techniques for the validation process..

IV. Results and Discussion

The simulation of the resource-sharing framework for 6G Cellular systems was carried out in the UBUNTU 22.04.4 LTS operating system and implemented in the NS3 simulation programming environment. NS3 software is mainly used for research on network components and communication systems. It is based on C++ programming and offers bonds with Python. The experimentation process is of in a realistic manner together with no difficulties of interference. The simulation circumstances are combined into a list, and the simulation is processed based on the optimistic time in an ascending manner. The 6G cellular environment was initially simulated; the proposed approach, HLEVRA, was initiated to monitor the resources. The proposed approach allocates the resources to necessary tasks, and the data processing of the model is undertaken to generate the model's effectiveness. The model's effectiveness is analyzed in terms of throughput, rate of data transfer, usage of energy, delay in communication, and drops in data packet transmission.

A. Case Study

To ascertain the effectiveness of the suggested methodology, a valid functional analysis is carried out with a linear distribution of results. The study includes throughput, transfer rate of data, energy usage, drop in data packets, and delay in data communication. The optimization allocates the resources, and the data is processed. The acquired findings are matched and related with the latest model to interpret the advancement percentage in the model's effectiveness. This suggested technique attained superior outcomes in all correlated experiments.

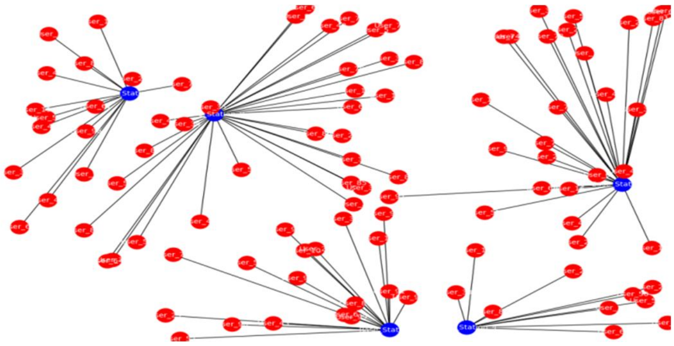

Fig 2 6G cellular network diagram

The station is shown as a blue circle, and the numbers of users are represented as a red circle. The line connecting the link among the users and station is black. The 6G cellular environment developed in the NS3 stimulator is shown in Fig 2.

B. Throughput

Throughput is the amount of data packets received by the channel or the 6G network technology. It was generated in bits gained per unit period. It is a required parameter for connecting and linking data processing systems. Throughput is considered the upper limit of the data processing system. This is because the more throughput there is, the more data will be processed in a particular duration. The throughput variation among the number of users in the suggested technique is shown in Fig 3

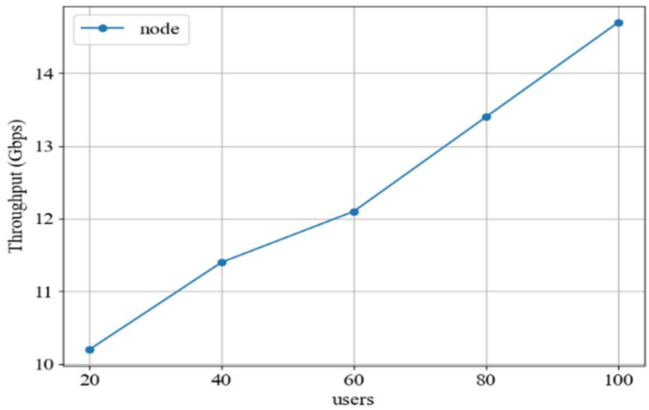

Fig 3 Throughput vs. number of users in the proposed approach

The throughput of the suggested approach increases with the increase in the number of users. The unit of throughput is noted in Gbps. The initial reading of the throughput is indicated at 20 users, which is 10.2 Gbps. When the user number connected to the station is 40, the throughput is raised to 11.4 Gbps.

TABLE I. THROUGHPUT VS. USER NUMBERS IN THE SUGGESTED APPROACH

Number of users	Throughput (Gbps)
20	10.2
40	11.4
60	12.1
80	13.4
100	14.7

At 60 users connected to the station, the throughput rises to 12.1 Gbps. At 80 users connected to the station, the throughput attained was 13.4 Gbps. At 100 users connected to the station, the throughput achieved was 14.7 Gbps. The statics of the proposed approach from 20 to 100 users in the throughput parameter is shown in Fig 3.

C. Data Transfer Rate

Data Transfer Rate is the quantity of information transmitted from one transmitting point to the ending receiving point. Data Transfer Rate differs from the Throughput parameter in that data transfer rate deals with the total amount of data transmitted and received within a particular duration. The throughput is the adequate amount of data transferred within a definite period of time. The multi-output, multi-input approach is integrated into 6G technology to maintain data transfer rate stability. The data transfer rate experienced by a single user when more alternate users are connected in the proposed system is expressed in Fig 4.

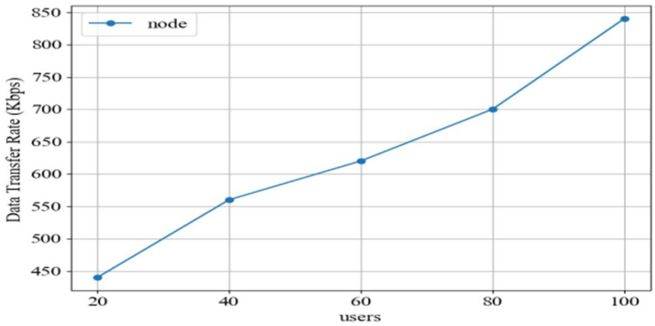

Fig 4 Data transfer rate vs. user number in the suggested approach

When 20 users are connected to the station, a single user experiences 440 Kbps of data. After that, the number of users is raised to 40, and then the data transfer rate in the suggested technique is 560 Kbps. At 60 users, the proposed technique has a data transfer rate of 620 Kbps per user.

TABLE II. THROUGHPUT VS. USER NUMBER IN THE SUGGESTED APPROACH

Number of users	Data transfer rate (Kbps)
20	440
40	560
60	620
80	700
100	840

At 80 users, the data transfer rate in the suggested approach was 700 Kbps. At 100 users, the data transfer rate is 840 Kbps. The statistics of the rate of data transfer of the suggested approach are represented in Table 3.

D. Energy Consumption

An increase in the capacity of processing or transmitting data shows its impact as a higher energy consumption. In the 6th generation, wireless communication, computing, and transmission capabilities are higher. Hence, energy consumption is an essential parameter in prediction. In the proposed approach, the power usage is optimized by neglecting the computation time of similar tasks by previously allocated tasks.

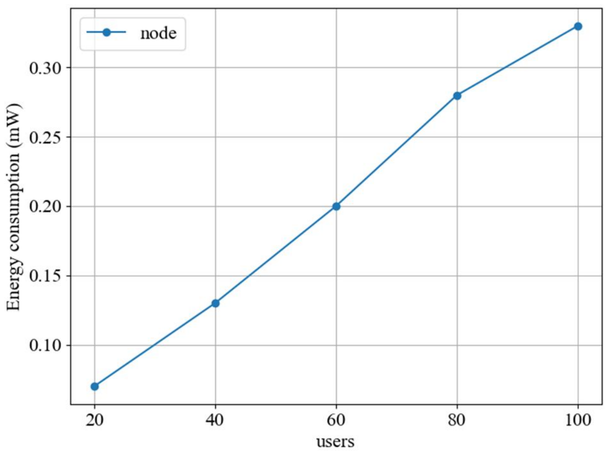

Fig 5 Energy consumption vs. user numbers in the suggested approach

The energy consumption of the proposed approach against the number of users is plotted in Fig 7. The initial energy consumption was noted for 20 users, which was 0.07 mW. When 40 users were connected to the station, their energy consumption was noted to be 0.13 mW.

TABLE IV. ENERGY CONSUMPTION VS. USER NUMBER IN THE SUGGESTED APPROACH

Number of users	Energy consumption (mW)
20	0.07
40	0.13
60	0.2
80	0.28
100	0.33

When 60 users were connected to the station, the suggested approach's energy consumption was 0.2 mW. Then, the user number is raised to 80 users, and the recommended approach has an energy consumption of 0.28 mW. For 100 users, the suggested technique consumed energy of 0.33 mW. The statistics of the usage of energy by the proposed technique are represented in Table 4.

E. Communication Delay

Communication delay begins when the data packet is processed in the specified layer on the stack protocol. It terminates when the represented data packet reaches the origin layer as a target. The delay in data transmission and processing will affect the service quality and the experience quality of the end user. The delay in both the stating and the terminating point is considered.

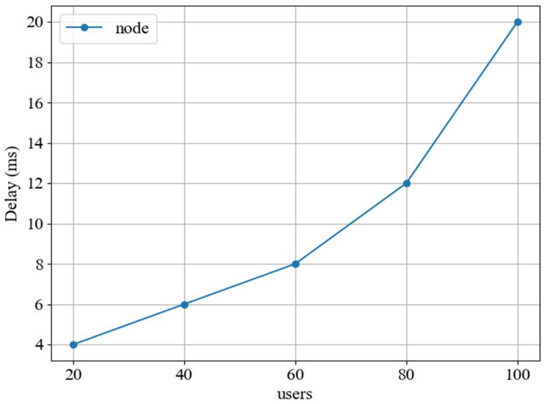

Fig 6 Delay vs. number of users in the proposed technique

The communication delay in the suggested approach against user number is represented in Fig 6. At 20 users, the suggested approach delays communication by 4ms. When the number of users is raised to 40, the suggested technique will cause a delay in communication of 6ms.

TABLE V DELAY VS. NUMBER OF USERS IN THE SUGGESTED APPROACH

Number of users	Delay (ms)
20	4
40	6
60	8
80	12
100	20

After that, the number of users was raised to 60, and the communication delay noted was 8ms. When 80 users were connected to the station, the communication delay in the proposed system was 12 ms. For 100 users, the maximum communication delay of 20 ms was seen in the proposed approach.

F. Packet Drop

Packet Drop refers to the numerical amount of packet data that could not reach its receiving point once processed from the transmitting end. Packet drop is provoked by insufficient signal strength and congestion of nodes overloaded in the network system. The packet drop in the suggested approach per number of users is illustrated in Fig 7.

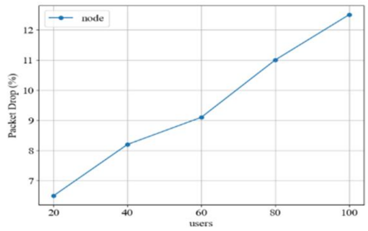

Fig 7 Packet drop vs. users for a simulation time of 50 seconds

The proposed approach possesses a packet drop of 6.5% when 20 users are connected, 8.2% packet drop when 40 users are connected, 9.1% packet drop when 60 users are connected, 11% packet drop when 80 users are connected, and 12.5% packet drop occurred when 100 users are connected. The statistics of the packet drop of the proposed approach are represented in Table 6.

TABLE VI. PACKET DROP VS. NUMBER OF USERS FOR SIMULATION TIME OF 50

Number of users	Packet drop (%)
20	6.5
40	8.2
60	9.1
80	11
100	12.5

V. COMPARISON

The effectiveness of the suggested technique was achieved by comparing the outcomes of the suggested model and the latest investigation works. For comparison, parameters such as Throughput, Rate of Data Transfer, Consumption of energy, delay in communication, and drop in data packets during data transmission are considered. The suggested model was compared along with the latest investigation works. The throughput of the suggested technique was compared with the Linear Upper Confidence Bound (LINUCB), Energy Aware Linear Upper Confidence Bound (EA-LINUCB), Upper Confidence Bound (UCB), Energy Aware Upper Confidence Bound (EA-UCB), Conventional, and Random 6G algorithms [26]. The Data transfer rate, communication delay, and packet drop of the proposed technology are correlated with the Multi-access edge computing server-based Internet of Things (MEC-IOT), Deep Q-Networks Packet Scheduling algorithm (DQN-PS), Deep Deterministic Policy Gradient with Prioritized Experience Reply DDPG-PER and Fishnet 6G [27]. The energy consumption in the suggested technique is correlated with Conventional, TCCO, Efficient Caching and Offloading Resource Allocation (ECORA), and Metaheuristic with Blockchain-based Resource Allocation Technique (MWBA-RAT) [28]. For the fulfillment of comparison, the simulation process of the suggested approach is carried out in an NS3 simulator with a definite number of nodes in 6G cellular systems. Following that, the comparison will be carried out.

A. Throughput

An increase in the throughput value denotes that more effectively received data is needed. It enhances the comfort of the user and improves the functioning efficiency. Despite that, if the throughput increases, it causes latency; if latency is minimized, it reduces throughput. The comparison of the proposed model and the recent approaches is represented in Fig 8.

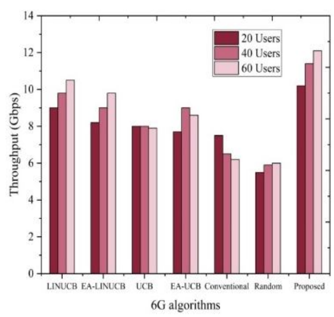

Fig 8 Correlation of throughput in the proposed approach with recent 6G algorithms

The LINUCB approach has throughput of 9 Gbps, 9.8 Gbps, and 10.5 Gbps at 20, 40, and 60 users. The EA-LINUCB technique possesses throughput of 8.2 Gbps, 9 Gbps, and 9.8 Gbps at 20, 40, and 60 users. The UCB approach has a throughput of 8 Gbps, 8 Gbps, and 7.9 Gbps at 20, 40, and 60 users when connected with the station.

TABLE VII. CORRELATION OF THROUGHPUT IN THE PROPOSED APPROACH WITH RECENT 6G ALGORITHMS

6G algorithms	20 users	40 users	60 users
LINUCB	9	9.8	10.5
EA- LINUCB	8.2	9	9.8
UCB	8	8	7.9
EA-UCB	7.7	9	8.6
Conventional	7.5	6.5	6.2
Random	5.5	5.9	6
Proposed	10.2	11.4	12.1

The EA-UCB approach has a throughput of 7.7 Gbps, 9 Gbps, and 8.6 Gbps at 20, 40, and 60 users. The conventional 6G algorithms possess throughput of 7.5 Gbps, 6.5 Gbps, and 6.2 Gbps for 20, 40, and 60 users. The random 6G algorithm has a throughput of 5.5 Gbps, 5.9 Gbps, and 6 Gbps at 20, 40, and 60 users. The proposed model possesses throughput of 10.2 Gbps, 11.4 Gbps, and 12.1 Gbps at 20, 40, and 60 users connected with the network station. The statistics of the comparison of the throughput model are shown in Table 7.

B. Data Transfer Rate

The Data Transfer Rate authenticates the information transmission or receiving speed between the network elements. The data transfer rate of the proposed approach is correlated with the recent 6G algorithms and is shown in Fig 10.

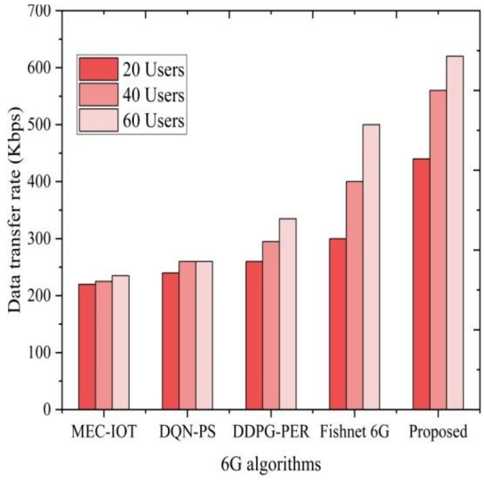

Fig 9 Correlation of data transfer rate in the proposed approach with recent 6G algorithms

The MEC-IOT model has a data transfer rate of 220 Kbps at 20 users, 225 Kbps at 40 users, and 235 Kbps at 60 users connected stations. The DQN-PS model has a data transfer rate of 240 Kbps at 20 users, 260 Kbps at 40 users, and 260 Kbps is still maintained at 60 users connected to the network station.

TABLE VIII. CORRELATION OF DATA TRANSFER RATE IN THE PROPOSED APPROACH WITH RECENT 6G ALGORITHMS

6G algorithms	20 users	40 users	60 users
MEC-IOT	220	225	235
DQN-PS	240	260	260
DDPG-PER	260	295	335
Fishnet 6G	300	400	500
Proposed	440	560	620

The DDPG-PER model has a data transfer rate of 260 Kbps at 20 users, 295 Kbps at 40 users, and 335 Kbps at 60 users. The Fishnet 6G model has a data transfer rate of 300 Kbps for 20 users; 40 users connected to the network system possess a data transfer ratio of 400 Kbps, and for 60 users, the data transfer rate is 500 Kbps. The proposed approach has a data transfer ratio of 440 Kbps at 20 users, 560 Kbps at 40 users, and 620 Kbps at

60 users connected with the station. The statistics of the correlation of the proposed approach with the recent 6G algorithms are represented in Table 8.

C. Energy Consumption

The power usage must be efficient to meet the computational processing on both the transmitting and receiving ends. Power usage must be limited to the optimum level to counter the increasing size of the computation process. The energy consumption by the proposed approach is compared with the recent 6G models, as shown in Fig 11.

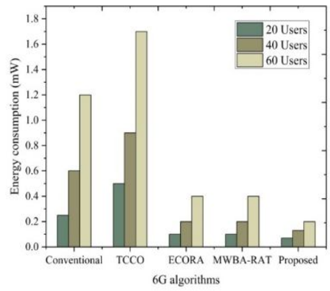

Fig 11 Correlation of energy consumption in the proposed approach with recent 6G algorithms

The conventional 6G algorithm has an energy consumption of 0.25 mW when 20 users are connected to the station; at 40 users, the energy consumed is 0.6 mW, and at 60 users, the energy consumed is 1.2 mW. The TCCO model consumes energy of 0.5 mW at 20 users, 0.9 mW at 40 users, and 1.7 mW at 60 users connected to the station.

TABLE IX. CORRELATION OF ENERGY CONSUMPTION IN THE PROPOSED APPROACH WITH RECENT 6G ALGORITHMS

6G algorithms	20 users	40 users	60 users
Conventional	0.25	0.6	1.2
TCCO	0.5	0.9	1.7
ECORA	0.1	0.2	0.4
MWBA-RAT	0.1	0.2	0.4
Proposed	0.07	0.13	0.2

The ECORA technique has an energy consumption of 0.1 mW at 20 user connections, 0.2 mW at 40 user connections, and 0.4 mW at 60 user connections. The MWBA-RAT approach has an energy consumption of 0.1 mW at 20 user connection, 0.2 mW at 40 user connection, and 0.4 mW at the 60 user connection. The approaches, ECORA and MWBA-RAT, have the same energy consumption per user. The comparison statics of the suggested technique and the recent 6G techniques are shown in Table 9.

D. Communication Delay

Communication delays must be kept as low as possible to maintain quality service in a network system: the more communication delays, the more discomfort for the end user. The communication delay of the suggested approach and recent 6G algorithms is illustrated in Fig 12.

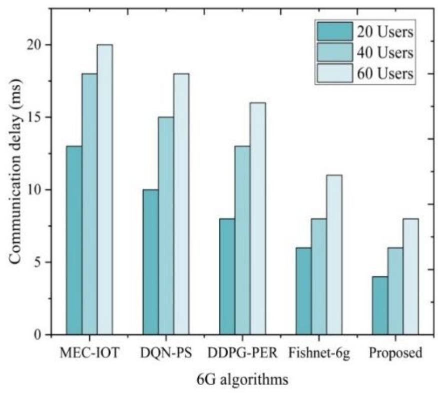

Fig 12 Correlation of communication delay in the proposed approach with recent 6G algorithms

The MEC-IOT algorithm has a communication delay of 13 ms when 20 users are connected to the station, 18 ms at 40 user connection, and 20 ms at 60 user connection. The DQN-PS approach possesses a communication delay of 10 ms at 20 user connection, 15 ms at 40 user connection, and 18 ms at 60 user connection.

TABLE X CORRELATION OF COMMUNICATION DELAY IN THE PROPOSED APPROACH WITH RECENT 6G ALGORITHMS

6G algorithms	20 users	40 users	60 users
MEC-IOT	13	18	20
DQN-PS	10	15	18
DDPG-PER	8	13	16
Fishnet-6G	6	8	11
Proposed	4	6	8

The DDPG-PER model has a communication delay of 8 ms at 20 user connections, 13 ms at 40 user connections, and 16 ms at 60 user connections. The Fishnet 6G has a communication delay of 6ms at 20 user connection, 8 ms at 40 user connection, and 11 ms at 60 user connection. The proposed approach possesses a 4 ms communication delay at 20 user connection, a 6 ms delay at 40 user connection, and an 8 ms delay at 60 user connection. The comparisons of the proposed approach with the recent 6G algorithms are illustrated in Table 10.

E. Packet Drop

An increase in the packet drop percentage indicates that the number of data packets delivered to the end user is not at the necessary level. Hence, it develops additional cloud computation time for retransmitting the data. Thus, it causes delays in data transmission with additional power usage. Therefore, the packet drop parameter must be appropriately optimized. The packet drop of the suggested approach with the recent 6G algorithms is illustrated in Fig 13.

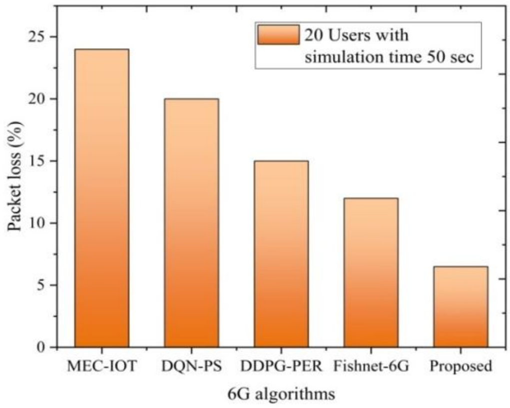

Fig 13 Correlation of packet drop in the proposed approach with recent 6G algorithms

The proposed approach has a packet drop of 8% when 20 users are connected for 50 sec. The MEC-IOT has a packet loss of 24%, the DQN-PS has a packet loss of 20%, the DDPG-PER has a packet loss of 15%, and the Fishnet 6G has a packet loss of 12%. The above packet drop is determined for 20 users connected to the station for a simulation time of 50 sec. The correlation of the packet drop in the proposed approach is compared with the recent 6G algorithm and is shown in Table 11.

TABLE XI. CORRELATION OF PACKET DROP IN THE PROPOSED APPROACH WITH RECENT 6G ALGORITHMS

6G algorithms	Packet loss for a simulation time of 50 sec
MEC-IoT	24
DQN-PS	20
DDPG-PER	15
Fishnet-6G	12
Proposed	6.5

VI. CONCLUSION

An innovative HLEVRA is implemented in the resource-sharing framework of 6G cellular systems. With multi-cellular users, the 6G cellular user environment is initiated. Afterward, an NS3 programming environment with sufficient features of HLEVRA was executed, and the prey-finding process was optimized to find the desired resources. The resources are optimally allocated to the 6G cellular users, and the data transmission is initiated. During data transmission, the functional assessment of the suggested approach is analyzed, and the outcomes are correlated with the latest models. The suggested approach's throughput and data transfer rate is 12.1 Gbps and 620 Kbps at 60 user stations, which is 15.2% and 24% higher than other compared models. The energy consumed by the proposed approach for data transmission is 0.2 mW at 60 users connected to the 6G station, which is 50% less than other compared models. The delay in communication and packet drop of the proposed model is 4 ms and 6.5% specifically, 33% and 5.5% lower than other models. The outcomes indicate that the proposed approach is an innovative technique in the 6G Cellular Systems. The energy efficiency optimization was not carried out in this investigation. Henceforward, executing energy efficient optimum packet loss technique through the utilization of the currently suggested approach provides improved 6G cellular systems.

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