International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Edge-CloudBlock-6G: Adopting AI Technology for Intelligent Spectrum Access and Secure Hybrid Beam forming in mmWave Massive MIMO Assisted Cognitive Radio based IoCV Environment

Nazia Tabassum[1], Dr. C.R.K. Reddy[2]

Submitted: 06/05/2024 **Revised**: 19/06/2024 **Accepted**: 26/06/2024

Abstract: Cognitive Radio Network (CRN), as a key technology to improve utilization of radio spectrum and spectrum sensing with Internet of Connected Vehicles (IoCV) which can significantly facilitate vehicle management and route planning to encounter the issues in reliable communication and spectrum access. Though, it faces issues such as high sensing delay, packet loss rate, latency and high throughput. In this proposed work, the existing issues are encountered through edge based Cognitive Radio Network (CRN) in Multi Input Multi Output (MIMO) using 6G (6GCRN-MIMO). Firstly, all Primary Users (PUs), Secondary Users (SUs)and pedestrians are authenticated using cloud based blockchain in order to increase security. The clustering is performed for management of network using modified K-Means (MKM) algorithm and clustering is performed through entry of authenticated users with consideration of several metrics. The intersection safety information is provided over the proposed network for reduction of collision in intersection using Improved Naive Bayes(INB) algorithm. Spectrum sensing and spectrum handoff are performed using Efficient Capsule Network (E-CapsNet) algorithm when PU is inactive while SU is selecting optimal channel through various metrics for reduction of spectrum scarcity. The ERSU is used to collect and store the environment data to perform the secure routing process using Red Fox Optimization (RFO) algorithm. Hybrid beamforming is performed to enhance reliable communication with Asynchronous Advantage Actor Critic Learning (A3CL) method. The proposed approach is simulated by using SUMO and OMNET ++ and validated by comparing it with existing approaches in terms of spectrum efficiency, spectrum sensing and QoS. The results proved that the proposed approach achieved finest performance while compared to existing approaches.

Keywords*: 6G, Spectrum sensing, hybrid beamforming, Internet of Connected Vehicles (IoCV), Cognitive Radio Network (CRN), spectrum handoff, QoS, throughput, efficient-CapsNet algorithm, red fox optimization*

1. Introduction

A developing technology along with the intention of solving spectrum scarcity issues through spectrum hole or sensing and deploying the spectrum which is unoccupied is denoted as a cognitive radio network (CRN) [1],[2]. In addition, it is deployed to develop spectral efficiency in CRN. Mainly, the connection to the internet of connected vehicles (IoCV) such as self-driving cars, autonomous vehicles and etc. are provided through the 5G and 6G which are considered the emerging communication technologies [3]. The methods based on spectrum utilization are permitting the unlicensed users who are otherwise called as secondary users for the execution of spectrum holes or else the cognitive white spaces. The process of spectrum sensing includes various algorithms based on deep learning and machine learning for the enhancement of spectrum sensing capability [4]. The effective spectrum utilization and extremely reliable communication are considered as the foremost objectives of CRN networks.

Meanwhile, the spectrum sensing technology is the foundation of cognitive technology. For unknown spectrum situations, users in the intelligent network need to recognize the spectrum and find free spectra for utilization. Reducing interference to higher priority users such as in the typical CR scenario, secondary users (SUs) opportunistically access the licensed spectrum currently not used by the primary users (PUs). When there is an error in the result of spectrum sensing, that may leads to false alarms or miss detections [5]. False alarms will cause SUs to lose the opportunity to access the spectrum and reduce the network throughput [6]. The false alarms will cause SUs to access the unavailable spectrum and that may interfere against PUs. This may punish the SUs and the SUs may even be prohibited from using the licensed spectrum of the PUs again [7], [8]. Consequently, avoiding miss detection and improving the sensing accuracy are the main objectives of spectrum sensing technology.

In addition, the spectrum sensing and access includes two classes such as dynamic and static [9]. The static spectrum sensing process includes several frequency bands which are accessed through the secondary users and it is denoting that the access spectrum in the channel [10].

[1]*Department of Computer Science and Engineering, Osmania University, Hyderabad, Telangana, India.*
[2]*Head & Professor, Department of Computer Science and Engineering, MGIT, Hyderabad, Telangana, India.*
Email ID: *naziatabassum380@gmail.com[1], crkreddy@gmail.com[2]*

Then, the dynamic spectrum sensing is about the handoff through target channel selection with the sensed spectrum. The process of spectrum handoff is functioning with three conditions such as inactivity of PU detection, not satisfied with the sensed spectrum and failure of SU connection because of mobility [11], [12].

Routing in CR-VANET is more challenging than the conventional routing protocols used for VANETs. VANET routing protocols are of two types namely topology based and position based routing protocols [13]. Additionally, the SUs are utilizing the unoccupied spectrum and the traditional CR routing is not applicable in the CR-VANET because of the mobility nature of vehicle and dynamic spectrum [14]. The high throughput and packet delivery ratio are acquired through the routing process among the vehicles. The massive multiple input multiple output technology (MIMO) have seen significant improvement in recent years [15], [16]. MIMO technology can easily enhance the capacity of transmission by exploiting spatial multiplexing.

On the other hand, CRN is emerged as a promising technique to improve the efficiency of spectrum utilization in the wireless communication system. MIMO technology plays an important role to increase the capacity of the channel and transmission rate of the system [17], [18]. MIMO uses space diversity technique to achieve this requirement of increasing data rate in 5G and 6G communication. The single beamforming process requires the one radio frequency (RF) chain per antenna which results in high cost and power consumption. Thus, hybrid beamforming is used in the proposed system along with massive MIMO for the integration of both high and low dimensional beamforming along with the limited amount of radio frequency (RF) chain [19], [20]. In the proposed system, various deep reinforcement algorithms are proposed for the processes such as spectrum access, hybrid beamforming and routing.

1.1. Aim & Objectives

The foremost intention of this research deals with the regulation of the mobility in network traffic and spectrum that leads to enhance the spectral efficiency of autonomous driving system in CRN-IoCV environment. In addition, this proposed research statements the issues based on high latency, ineffective spectrum utilization, high mobility and security.

The key objective of this proposed research is about regulating the network traffic and mobility along with the spectrum efficiency, energy efficiency and low latency. In addition, various objectives of this research are highlighted in the following.

- To enhance security, we perform encryption and the reports are sensed for the mitigation among PUF and SSDF attacks while processing the spectrum sensing and handoff
- To reduce the energy consumption and latency, edge based roadside unit (E-RSU) is utilized. In addition, it is used to reduce the latency during the clustering and routing process along with the support of past historical information
- To increase security and high throughput during the process of data transmission, we perform the secure routing in network traffic
- To describe flexibility, spectral and hardware efficiency, the secure hybrid beamforming is performed over the creation of dynamic beams through the verification of CSI over blockchain along with the provision of secure beams
- To address the spectrum scarcity and mobility, we perform dynamic spectrum sensing and handoff which leads to enhancing the utilization of spectrum in the CR environment

1.2. Research Motivations

In general, the environment based on IoCV is oppressed extensively through the active exploration through the high energy consumption, security and spectrum sensing. As an additional note, several researches have been investigated with the contribution of wide knowledge to encounter the spectrum scarcity and scalability. But, yet there are various research problems in the process and they are listed in the following.

- High Energy Consumption: The due to a various number of phase shifters (PSs) are deployed to reduce the energy consumption in hybrid beamforming. In addition, the utilization of various PSs is denoted as the difficult process to analyze due to the hardware complexities which leads towards the delay in network and inefficient spectral efficiency. In addition, various RF chains are used in the precoder that increases the hardware complexity and high energy consumption
- Enormous Packet Loss: The path was blocked through the routing attackers who are unsecure and that leads to the congestion among the PUs and SUs in the IoCV environment and low throughput. Thus, the data transmission requires the finest routing path
- Improper Spectrum Sharing: In PU, all the SUs are permitted for the process of spectrum sensing because of the mobile nature of SUs in the sensing environment that affects the spectrum handoff and leads to interference in PUs and improper spectrum sensing

- High Overload: All the SUs are sending the information to FC over the RSU in the existing work. But, RSUs include the less storage which is not capable to store the information and that leads to high overload in RSUs that leads to increase the latency in IoCV environment

1.3. Research Contributions

In this paper, we proposed intelligent spectrum access and secured hybrid beamforming in mmWave massive assisted cognitive radio to spectrum efficiency, energy efficiency, enhanced communication reliability and low latency. The contributions of this research are illustrated as follows,

- As the first process, the security of the entities such as pedestrians, SUs and PUs in the network are ensured over the blockchain. The modified K-means algorithm is used for the clustering process among the authenticated nodes to manage the network with the exploitation of various clustering metrics. In addition, the intersection aware map is created for the reduction of collision in the point of intersection using ERSU and various metrics
- Following that, the spectrum is utilized efficiently through all the SUs in the IoCV environment through the utilization of effective capsule network using the elements such as trust level, congestion, channel availability, SNR and noise for the optimal channel selection. In addition, the sensing reports are encrypted and handed over to the fusion center over SUs
- The optimal routing is utilized for the communication regulation among the vehicles and ERSU is deployed to collect and store the environment data for secure routing process and the secure route is determined using red fox optimization algorithm by the considering number of hops, vehicle speed and link scalability. Through optimal routing process, throughput is increased and packet delivery ratio is enhanced
- Finally, the hybrid beamforming is implemented to enhance the performance using asynchronous advantage actor critic learning method by means of enhancing signal quality and transmission speed

1.4. Paper Organization

This paper is further than it organized into various sections which are described as follows. Section II is about the representation of the existing research works along with its limitations. Section III describes the specific research problems in the existing work along with the appropriate solutions. Section IV demonstrates the proposed spectrum access and secured hybrid beamforming in mmWave massive assisted cognitive radio comprehends the diagrams, workflow of algorithms, pseudocodes, mathematical equations and tabularizations. Section V describes the experimental results of the proposed work through the simulation setup and comparison results of simulation results. Section VI is about the conclusion of proposed research work. Table 1 describes the notions that are used in this work.

Table 1. Notation table

Notation	Description
C_R	Direct trusted value
$K(m)$	Prior probability
p	Kernel dimension
q_n^t	Single capsule
φ	Random value
ϱ	Random amount
$K^{\mathcal{RF}}$	Analog precoder
$K^{\mathfrak{BB}}$	Digital precoder
$G^{\mathcal{RF}}$	Analog combiner
$G^{\mathfrak{BB}}$	Digital combiner
$L[n]$	Matrix of channel
$\mathfrak{y}[n]$	Noise
$d[n]$	Data symbols

2. LITERATURE SURVEY

The author has proposed the secure data processing framework in edge envisioned V2X environment using blockchain along with the utilization of multilayer system model. Mainly, this proposed system includes five layers for the secure data processing such as edge servers, secondary users and primary users. The secondary users were requested for task with the provision of unique ID which is sent to the task administrator in the task scheduling layer. The task administrator is used to assign a task along with the provision of specific task ID as per the parameters such as task type and task time [21]. The container maps are created through the generated container list from the container management layer based on the data provided from the task administrator. The edge node controller is requesting for the task from the container map in the edge layer based on the process to prevent breakage. In this research work, five layer secure data processing was performed to solve delaying problem however it consumes more energy during task offloading that reduces the performance of the work. In this research paper, the author has proposed a method for efficient spectrum utilization over the dynamic channel reservation and spectrum access. The primary user, secondary user and base station are denoted as the three entities in the proposed architecture. The channels are significantly allocated to the users through the utilization of hybrid dynamic channel reservation algorithm and it is deployed for the improvement of dynamic spectrum access. Then, the available spectrum is categorized into two classes such as reserved and non-reserved band. The secondary users are classified into low and high priority levels as per the requirements of QoS to enhance the performance of dynamic spectrum access [22]. The continuous time Markov chain is used to model the ESU scheme and the mathematical expression were derived for various network conditions. In this work, the access spectrum using SU was related to the priority level and that is not enough for the dynamic spectrum access and that results in the spectrum scarcity and ineffective spectrum access.

In this research work, the batch authentication is proposed using blockchain for the internet of vehicles. The foremost intension of this proposed research work is about the performance of authentication using the artificial intelligence in IoV based smart city [23]. The architecture of the proposed system includes initial setup, RSU registration, message sign, authentication and key management. As the first process, the vehicles and RSU are registered in the blockchain for the provision of signature for the registered vehicles and RSU. The authentication is performed for the reduction of computational overhead in the environment. The group key is shared among the clusters in order to the improvement of the security. In addition, the simulation result of the proposed work is obtaining the dynamic performance in computation of cost, storage and security. In this work, the authentication is performed in both the vehicle and RSU without considering the effective metrics for the authentication process for which leads to ineffective authentication. In this proposed work, the detection of high energy using spectrum sensing steps that is particularly through the utilization of collaborative method and it is the key difficulties in cognitive radio which has potential to improve energy efficiency [24]. The author has proposed the combination of low energy adaptive clustering hierarchy (LEACH) with an energy efficient clustering and hierarchical routing algorithm over the utilization of energy efficient scalable routing algorithm (EESRA). In addition, the proposed architecture includes identical channels in the cognitive radio network (CRN) through the utilization of novel machine learning approach which results in the extension of network lifespan.

In this research work, the author has proposed an interpretation of convolutional neural network and gate recurrent unit (CNN-GRU) network to acquire the local information for the single node spectrum sensing. Here, the CNN is deployed for the spatial feature extraction and the GRU is deployed for the extraction of temporal feature [25]. The combination of network receives the feature extraction process through CNN-GRU network and that acquires the multi feature combination in the final cooperation result. The cooperative spectrum sensing scheme is related to the multi features combination network and that improves the reliability of sensing by the fusion of local information over various sensing nodes. This paper is proposed to enhance the detection performance with the large dynamic signal to noise ratio. The author has proposed the optimal relay and channel selection schemes (ORCS) mainly for the multi constrained QoS multicast routing in CRAHNs. In addition, the distributed minimum spanning tree is used for the process of multicast tree construction. The channels with sufficient common slots, maximum spectrum accessibility and good channel quality are selected for effective channel assignment [26]. The minimum interference, less energy consumption and minimum path delay are used for the selection of relay nodes to meet the delay, energy and interface constraints. The proposed ORCS is deployed for the minimization of end to end delay and energy consumption. In this research work, the multicast routing algorithm is used for the multi constrained QoS performance but it results in the process of network congestion due to the lack of TCP.

In this work, the author has proposed the efficient channel information feedback scheme for the reduction of feedback overhead of multi user multiple input multiple output (MU-MIMO) hybrid beamforming [27]. Mainly, the hybrid beamforming system includes the transmitter which is capable to communicate with the multiple devices at one particular time along with the massive machine type communication (mMTC) in the deployments of 5G. The interference among the receivers is controlled to communicate with multiple devices in the same time and frequency slot, high dimensional channel information. Consequently, the feedback overhead for the channels of the devices is impractically high. The proposed work uses common sparsity of channel and nonlinear quantization for the reduction of overhead. In addition, the proposed system uses minimum mean squared error orthogonal matching pursuit (MMSE-OMP) to recognize the common sparse part of a wide frequency band. In this research work, the MIMO is processing with the beamforming process which is more complex with the consideration of antennas and some other hardware which leads to the high energy consumption. In this paper, the author has proposed a multi sine multiple input multiple output (MIMO) wireless power transfer (WPT) system along with the intention for the enhancement of output DC power. The optimization of multi sine waveform and beamforming leads to the rectenna nonlinearity along with the receiver such as DC and RF. The waveform and transmit beamforming are optimized for the combination of DC, as a function of the channel state information (CSI). The optimal transmit and receive beamformings are provided in closed form and the waveform is optimized in RF. Then, the practical RF combining the circuit by phase shifter and RF power combiner and optimize the waveform, transmit beamforming and analog receive beamforming adaptive to the CSI [28]. The nonlinear rectenna model includes two types of evaluations such as accurate and realistic circuit simulations. The evaluations depicts that output DC power is improved through leveraging the beamforming gain, frequency diversity gain and rectenna nonlinearity. The work includes beamforming which substantially reduce the latency of the initial access along with the comparable failure probability in dense networks.

In this research work, the energy aware Q-learning AODV (EAQ-AODV) routing was proposed by the author. The proposed EAQ-AODV uses Q-learning based reward mechanism for cluster head selection and AODV enabled routing protocol based on different parameters such as residual energy, common channel, number of hops, licensed channel, communication range and trust factor to establish the routing path [29]. The proposed system depicts that the EAQ-AODV routing achieves a performance enhancement in terms of average end to end delay, average energy consumption and network lifetime. In this work, the AODV enabled routing protocols are deployed for the performance enhancement but that leads to the high packet loss ratio and computational complexities due to the improper routing process. The author has proposed the novel RSSI based unsupervised deep learning method to design the hybrid beamforming in massive MIMO systems. Mainly, this paper is proposed with two significant objectives such as a method to design the codebook for the analog precoder and method to design the synchronization signal (SS) in the initial access [30]. The system performance is evaluated over the realistic channel model in various scenarios. Partial CSI feedback is used to enhance the spectral efficiency particularly in the frequency division duplex (FDD) communication. Here, the unsupervised deep learning algorithm is used in the massive MIMO system which leads to the lack of accuracy.

In this research work, the author has proposed the method to ensure the authentication security and the reduction of consensus time to save the computing resources which solves the problems of high computing costs and high communication cost to arise the frequent vehicle authentication handovers [31]. The security analysis is performed to reduce the computational overhead and high handover authentication efficiency. Mainly, IoV is about to connect the traffic participants such as vehicles, pedestrians and roads, through wireless networks and enables information exchange to enhance traffic safety and improve traffic efficiency. While this research work includes the pre authentication and handover authentication, it leads to the high implementation cost and lack of accuracy. In this paper, the signal to leakage plus noise ratio is introduced for the optimization criterion and investigates the HBF design for multi user millimeter wave massive multiple input multiple output (MIMO) systems. The novel two stage HBF scheme is used to optimize the analogue and digital beamformers. In addition, the orthogonal matching pursuit based method and joint design method are used to find the solution in the analogue stage [32]. The digital precoder and combiner are designed to suppress the inter user interference plus noise, aiming at maximizing the sum signal to leakage plus noise ratio of multi user systems in the digital stage. It proves that the performance of HBF scheme remains strong even with the imperfect channel state information. The research work is performed without preceding the initial level security measures and that leads the entry of attackers to affect the system.

In this research work, the author has introduced the physical unclonable function (PUF) in the AKE protocol to ensure that the system is secure even if the user devices or sensors are compromised [33]. In particular, PUF is functioning as a hardware fingerprint generator which eliminates the storage of any secret information in user devices or vehicle sensors. While biometrics is combined with PUF, the user device cannot be used by someone else to be successfully authenticated as the user.

In conclusion, the elaborate security analysis demonstrates that it is free from the influence of known attacks and can achieve expected security properties. The utilization of natively physical unclonable function (PUF) in the AKE protocol leads to the lack of reliability, which is sensible to modeling and physical attacks and its entropy must be ensured for the process. The joint iterative optimization based hybrid beamforming technique for massive MU-MIMO systems is proposed in this research work [34]. The adaptive algorithm is exploiting the stochastic gradients (SG) of the local beamformers and provides low complexity closed form solutions. The efficient adaptive scheme is developed based on the adaptive algorithm and the closed form solutions. The proposed algorithm requires the signal to interference plus noise ratio (SINR) feedback from each user and a limited size transition vector to be exchanged between the transmitter and receivers at each step to update beamformers locally. Here, the adaptive algorithm was deployed but it locates a local optimum, they have difficulty solving discrete optimization problems, difficult to implement efficiently which leads to the numerical noise.

In the proposed overlapping spectrum sharing, the complexity of cognitive environment is considered as a real challenge for a secondary user (SU) to correctly sense the usage of the spectrum in real time. Then, the social awareness aided transmits power control policy for SUs is. First, a social network composed of a group of third party sensing nodes that do not share the spectrum with the PU is established, which helps an SU collect the power information of the PU [35]. Then, dueling Deep Q-Network (DQN) model is designed to achieve efficient dynamic spectrum sharing between the PU and the SU with the power information collected in the social network. Experimental results show that the spectrum sharing success rate is higher and the comprehensive performance is improved with the sensing nodes selected by the social relationship. Moreover, compared with other deep reinforcement learning (DRL) algorithms, the performance of Dueling DQN is more stable on our targeted spectrum sharing problem. In this work, the deep-Q-network was performed for the spectrum process. But, deep-Q-network wanted large amounts of data for the processing which increase the complexity thus it leads to the high energy consumption.

Table 2. Summary of Related Work

Ref.No.	Objectives	Methods and Algorithms	Limitations
[21]	Secure data processing	SHA-256 algorithm	Poor performance
[22]	Efficient spectrum utilization	Enhanced DSA and Hybrid DCR algorithm	Ineffective spectrum access
[23]	Batch authentication	Practical Byzantine fault tolerance consensus algorithm	Ineffective authentication
[24]	High energy detection	LEACH routing algorithm	Poor security
[25]	Detection enhancement	CNN-GRU network	Inefficientspectrum sensing
[26]	Spectrum access and channel quality	QoS multicast routing in CRAHNs	Lack of TCP
[27]	Channel information feedback scheme	Linde–Buzo–Gray algorithm	High energy consumption
[28]	MIMO wireless power transfer	SDR techniques	Reduction of latency
[29]	AODV enabled routing model	EAQ-AODV routing protocol	Improper routing process
[30]	Unsupervised deep learning method	Adam algorithm	Lack of accuracy
[31]	Ensuring authentication security	Practical Byzantine fault tolerant algorithm	High implementation cost
[32]	Analogue and digital beamformers optimization	OMP-SLNR algorithm	Improper security
[33]	Elaborate security analysis	Three factor authentication protocol	Lack of reliability
[34]	Joint iterative optimization	Adaptive hybrid beamforming algorithm	Presence of numerical noise
[35]	Spectrum sharing	Deep reinforcement learning (DRL) algorithms	High energy consumption

3. PROBLEM STATEMENT

The 2 hop routing algorithm for CR-VANT is functioning over the multi objective Harris hawks optimization algorithm for the selection of optimal forwarders. In CR-VANET environment, the SUs are started to sense the spectrum when the channel is allocated in RSU for the successful data transmission and increase the route stability[36]. The main problems of this research are listed as follows,

- The research work includes optimal routing mobility of the vehicle with parameters over the utilization of 2 hop neighbors which is effective because of the dynamic mobility of vehicles in CR-VANET environment which leads to the high routing overhead
- This work includes the parameters based on availability, vehicle state, optimal routing direction, mobility and channel for the provision of optimal way to the destination over the utilization of 2 hop network

with the past information about neighbors and that results in the ineffective path selection

- In this work, the spectrum sensing and segment management were functioning parallel in channel allocation and SUs using RSU and that results in the network collision among SUs in CR-VANET environment

DSA is used to check the availability of channels for SU during the handoff over the deployment of metaheuristic algorithm to reduce complexity and resilient through using SVM-RDA with the provision of total spectrum bandwidth, SU bandwidth, SNR, throughput, handoff delay, unsuccessful handoffs and etc.[37] The main problems of this research are highlighted below

- In this research work, the dynamic spectrum access was deployed to check the availability of the channels but it results in the loss of LTE and that leads to the increase the latency
- Here, SVM algorithm was used for the classification process, however it takes much time for training that leads to high latency, hence it does not suitable for large scale environment
- Here, the spectrum sensing was processed using the machine learning based metaheuristic algorithm without considering the optimal metrics and that leads to high complexity

The efficient free channel selection scheme is used to improve QoS of cooperative CRN derived for integration using MCDM techniques with TOPSIS and EFAHP. The optimality of integrated techniques with parallel channel selection is used to overcome secure transmission and optimal free channel selection for the uninterrupted data transmission[38]. The major problems of this research are listed below,

- The process of channel selection includes the MCDM techniques including the TOPSIS and EFAHP but it results in the reduction of accuracy
- Here, the MCDM techniques was used for the channel selection metrics which takes too much of time for selecting optimal path that leads to high latency. In addition it does not consider the trust factor of the metrics that leads to poor security
- In this work, security of CRN spectrum was not considered which leads to spectrum scarcity during spectrum sensing hence it increase transmission delay
- The hybrid beamforming for mmWave MIMO ISAC were considered to design beam transmission of DFRC and BS. The analog beamformer and digital beamformer are determined to constant envelop constraint of the phase shifter network in mmWave MIMO[39]. The main problems of this work are defined below,
- Here, several entities are used for generating hybrid beamforming however, it needs to be select an optimal manner otherwise it leads to high power consumption that increase high hardware complexity
- In this research work, the trust factor of the SU are does not consider which leads to the high data threaten and poor security

CRN based on CR receiver is used for novel proactive handoff scheme using CSMA/CA. The secondary users have to access spectrum and unlicensed users are coordinated with common CCC[40]. The secondary CR users and its history were stored in CR transmitter and CR receiver to avoid the interface. The major problems of this research are highlighted in the following,

- Here, the PCLs list obtained from DCF mode using the broadcast of SUs and the spectrum sensing using CSMA/CA without considering about trust factor that leads to less security in which the attackers can easily enter into the spectrum
- Hybrid beamforming is performed to solve the computation complexity however, this work not consider the beam characteristics for generating hybrid beams which leads to inefficient beam generation that reduces the performance of hybrid beamforming

3.1. Research Solutions

The problems faced by the existing works are addressed through the proposed solutions which are illustrated as follows. Predominantly, the primary and secondary users in the IoCV environment are authenticated using the blockchain to reduce the major vulnerable threats using ID, PUF and locations. The proposed work implements modified K-means algorithm for clustering process which considers location, direction, distance and local density through this cluster head was elected. Following that, the spectrum sensing is performed through considering the factors such as SNR, noise level and trust factor for every time interval using the efficient capsule network algorithm because it provide an efficient and secure spectrum sensing to perform against the SSDF and PUF attacks. Then, the hybrid beamforming is performed including environmental factors, spectral efficiency, CSI factors such as SINR and RSSI and channel state information (CSI) for efficient beams. In addition, it includes several phase shifters which are arranged in phase array manner for optimal tap selection for reduction of energy consumption. Secure routing is performed by considering the parameters for neighbour are link stability, energy, trust level and velocity. The next neighbour parameters are selected through including the vehicle trajectory, number of hops, vehicle speed and link stability using red fox optimization algorithm.

4. PROPOSED WORK

The proposed 6G based CRN-IoCV system model consist of various vehicles that are denoted as the secondary users (SUs) and the E-RSU are considered as the primary users (PUs). Here, the edge computing is deployed for the provision of supplementary resources to RSU for the performance such as routing and collection of intersection information. In addition, the SUs are capable to access the licensed spectrum which sends the sensing report to fusion center (FC) for the enhancement of environment security. The malicious SUs are also included in the network and it is employed to exploit the whole network through its malicious features and that leads to less spectral efficiency and security threats. The malicious SUs can affect the network parameters such as packet delivery ratio, delay and throughput. In addition, the transmission speed is increased through the utilization of 6G communication and that leads to increase the high throughput during the process of data transmission among IoCV. Additionally, all the transactions are stored in the network using blockchain. This proposed work is mainly concentrating on the security and spectrum efficiency in the data transmission using the secure routing and spectrum sensing in IoCV environment. The hybrid beamforming using massive MIMO in CRN is proposed to obtain the spectral efficiency. Moreover, the consecutive phases in this proposed work has been highlighted in the following.

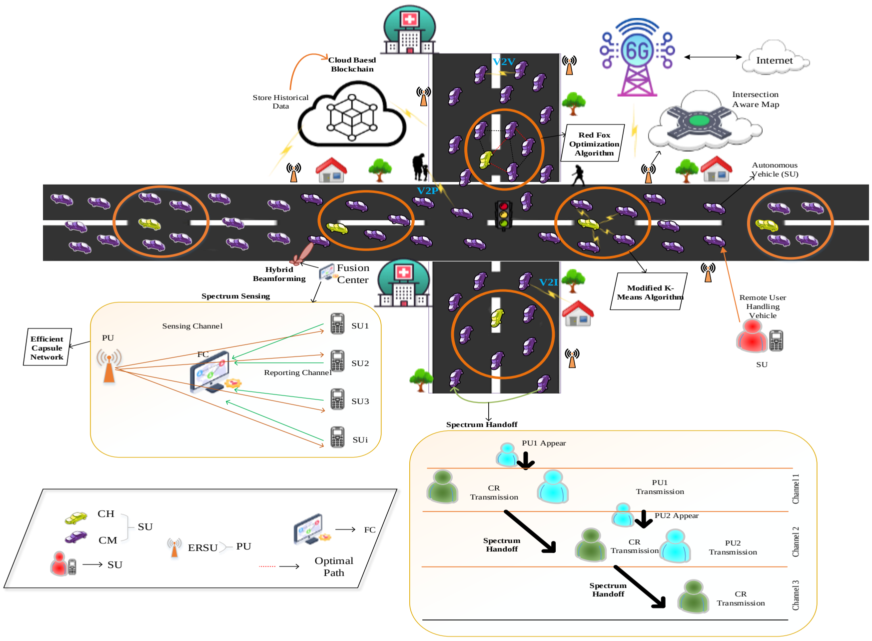

Fig 1. 6GCRN-MIMO System Model

4.1. Network Alignment

The several pedestrians, SU and PU presented in this IoCV environment are authenticated through blockchain. And for the authentication process, we have to consider the ID, PUF and locations. In addition, the cloud based blockchain is used to increase the security level of V2X environment. In this environment, PUs is denoted as E-RSU and vehicles are denoted as the SUs. This E-RSU is proposed for the reduction of latency and energy consumption. Following that, the clustering process is performed for the management of the network using the modified K-Means algorithm and the clustering is performed through the entry of the authenticated users along with the consideration of location, direction, distance and local density. The modified K-Means algorithm is used for the efficient clustering process through scaling the large datasets.

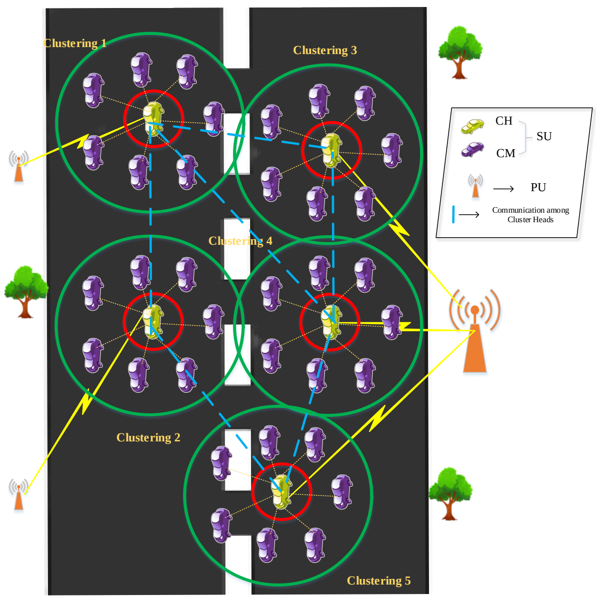

Fig 2. Clustering of SUs

The modified K-means clustering algorithm is deployed to acquire the better clustering process. Fig 2 illustrates the clustering of SUs. The proposed modified K-means algorithm includes three significant processes. The first process is about the deployment random enhancement of vehicles and the output of the clustering through the addition of noise judgments to acquire the number of clusters. Following that, the K-means clustering algorithm is used for the optimization of cluster centers. Then, the clustering result is acquired through the provided data and capturing an excellent clustering head. The modified K-means algorithm process is about the determination of cluster head. The detailed description about the steps that are involved in the modified K-means algorithm as follows,

Step 1. Set clustering number K

The clustering number of K-means algorithm is functioning among two and $\sqrt{\eta}$ in which η is denoted as the number of vehicles. In addition, this process required various clusters for the distribution of cluster heads and the vehicles are considered as the intensive points, thus the clustering number is $\left[\frac{\sqrt{\eta}}{2}, \sqrt{\eta}\right]$.

Step 2. Clustering number C optimization by binary inversion

The conversion of clustering number $C$from decimal to binary and a digit of binary number is flipped randomly for the generation of new binary number. Then, the binary number is converted to decimal for the obtaining new C.

Step 3. Clustering center optimization

The same number of clustering C values is not fixed in the center point of location to acquire the center point's initial distribution and the optimal clustering center is acquired using squares for error (SSE).

$$\text{SSE} = \sum_{a=1}^{C} \sum_{b=1}^{\eta} (y_{ab} - \ddot{Y}_a)^2 \quad (1)$$

Where, C is denoted as number of clusters, η is considered as the number of vehicles in clustering and $(y_{ab} - \ddot{Y}_a)^2$ is the error sum of squares in all the vehicles.

Step 4. Output optimized clustering center

The optimal clustering center is to find and set the modified K-means clustering algorithm to solve the issues and acquire the information about vehicles to capture the center cluster.

Algorithm 1. Modified K-Means Clustering Algorithm

Input: Number of vehicles, clustering termination condition, number of clustering iterations and noise radius rate the cluster head has to be elected in the constructed clustering process as per the trust which includes two types such as direct trust and indirect trust computations.

Output: An effective clustering result

1: Initialization to record the number of vehicles

2: Entry of authenticated users

3: Acquiring current data points intervals

4: SSE evaluation for optimal solution using equation (1)

5: Selection of clustering heads (2) - (4)

6: Distance calculation among vehicles and center points

7: SSE calculation and determination of clustering condition

8: End

Firstly, the direct trust computation in clustering is denoted by means of,

$$C_{R_{mn}} = \text{tanl}(\textstyle\sum_{O=1}^{n} {}^{\delta}{}_{o} * {}^{\beta}{}_{o} * {}^{\eta}{}_{o}) \quad (2)$$

WhereC_R is denoted as the direct trusted value among m and n, ${}^{\eta}{}_{o}$ is the number of experience o upon the trustee nodes, n is the total number of various experiences, ${}^{\beta}{}_{o}$ is the weight of experience to its importance and ${}^{\delta}{}_{o}$ is +1 if experience is positive and -1 if it is negative.

$$C_I(m, n) = H\big(\text{Beta}(\theta|t1 + t2 + 1, r1 + r2 + 1)\big) = \frac{t1+1}{n1+1} * \frac{t2+1}{n2+1} \quad (3)$$

Where $n1$ and $n2$ are the number of total interactions among nodes m and o and between nodes o and n respectively; $t1$ and $r1$ are the number of successful and failed interactions between nodes m and o respectively and $t1$and $r2$, number of successful and failed interactions between nodes $o$and n respectively. Recommendation trust is the successful probability of the $(n1 + n2 + 2)^{\text{th}}$ interaction.

In addition, the maximum RSSI for data transmission among the cluster members are created. The following equation is about the RSSI data transmission.

$$\text{RSSI} = C' \frac{1}{\eta} \sum_{n=1}^{\eta=1} f_{t,r} \quad (4)$$

Where C' is denoted as the path gain from analog to digital conversion and FFT into account, $f_{t,r}$ is considered as the received symbol on n^{th} subcarrier within the signal tafter FFT.

The intersection safety information is provided over the proposed network for the reduction of collision in intersection. The E-RSU is used to collect the intersectional information which is stored in the past historical data such as, location, RSSI, trajectory, destination and vehicle speed. The intersection information is predicted through the consideration of past historical data over the utilization of improved Naive Bayes.

Bayesian decision theory is denoted as the most significant process in decision making along with the framework of probability in which the highest probability is selected as the decision. The foremost idea is about assuming the ideal conditions along with appropriate possibilities of classification task. While comparing the sample probabilities in various categories with the optimal category for the selection process in the optimal category.

Mainly, the improved Naive Bayes are deployed for the reduction of collision in the network and manages the network along with the efficient manner.

Consequently, the Bayesian optimal classifier alters through minimizing classification error rate for selecting the classification and that maximizes the posterior probability $K(m|y)$ for each sampley. As per the Bayes' theorem, $K(m|y)$ can be written as,

$$K(m|y) = \frac{K(m)K(y,m)}{K(y)} \tag{5}$$

Where $K(m)$ is denoted as the prior probability, which represents the probability of event m occurring before event y occurs and $\frac{K(y,c)}{K(y)}$ is considered as an adjustment factor and the possibility function. It is mainly deployed to make the estimated probability closer to the true probability.

As per the law of large numbers, when the training set encompasses the sufficient independent and identically distributed samples, $K(m)$ be estimated over the frequency of various types of sample.

The probability functions $\frac{K(y|c)}{K(y)}$ is deployed in joint probability with all the attributes of y which is not that much easy for the direct estimation This is based on the Bayesian formula $K(m|y) = \frac{K(m)K(y,m)}{K(y)}$ to estimate the main difficulty of the posterior probability $K(m|y)$. The naive Bayes classifier undertakes that all the probability distributions are conditionally independent and affects the classification to solve all the issues in this process. As per the assumption, let n be the number of attributes, y_a is the value of y in the a^{th} attribute and formula $K(m|y) = \frac{K(m)K(y,m)}{K(y)}$ can be rewritten as follows,

$$K(m|y) = \frac{K(m)K(y,m)}{K(y)} = \frac{K(m)}{K(y)} \prod_{a=1}^{n} K(y_a|m) \tag{6}$$

In addition, the $K(m)$ is denoted as the same for all the categories and the expression of the naive Bayes classifiers are acquired through the following equation.

$$v_{nb}(y) = \text{argmax } K(m) \prod_{b=1}^{l} K(y_a|m) \tag{7}$$

The foremost training process of naive Bayes classifiers are deployed to estimate the probability of class prior $K(m)$ as per the training set L and the estimation of conditional probability includes all the attributes $K(y_a|m)$.

The assumption of enough independent and distributed samples which are identical are assuming the L_m to represent the set of samples of type m in the training data set L along with the prior probability as,

$$K(m) = \frac{|L_m|}{|L|} \tag{8}$$

When, the discrete attribute is assuming the L_{m,y_a} in which that represents the set of samples in L_m and its value is y_a on the a - th attribute for the conditional probability $K(y_a|m)$ and that is denoted as,

$$K(y_a|m) = \frac{|L_{m,y_a}|}{|L|} \tag{9}$$

While the continuous attribute is deployed as probability density function and it supposed as $k(y_a|m) \sim \cancel{n}(\Omega_{m,a}, \beta_{m,a}^2)$ which leads to,

$$k(y_a|m) = \frac{1}{\sqrt{2\pi\beta_{m,a}}} \exp(-\frac{(y_a - \Omega_{m,a})^2}{2\beta_{m,a}^2}) \tag{10}$$

Algorithm 2. Improved Naive Bayes Algorithm

1: Rumors datasets are initialized W

2: For $a = 1$ to n do

2.1: A sample y_a from W randomly

2.2: The maximum value $argmax\ K(m) \prod_{b=1}^{l} K(y_a|m)$ and assign it to m_a for the calculation

2.3: $K_{bs} \leftarrow K(b|X = M_s)y_{ba} + (1 - K(b|X = M_k)(1 - y_{ba})$

3: End

4.2. Deep Learning Based Secure Spectrum Sharing

The process of spectrum sensing is performed for the enhancement of spectrum utilization in the network. An issue based on spectrum scarcity is addressed through the performance of spectrum sensing ad transmitting the sensing report to the fusion center (FC) using SU. Fig 3 represents the proposed spectrum sensing techniques using efficient-CapsNet algorithm. In the proposed system, the SUs are encrypted to transmit the FC and sense the report to enhance the security and mainly to act against the eavesdropping attack in network. The transmission delay is occurred in the spectrum mobility management because of the nature of vehicles. Thus, the spectrum handoff is performed when the PU is inactive and then, SU is selecting the optimal channel through the consideration of following elements such as trust level, congestion, channel availability, SNR and noise.

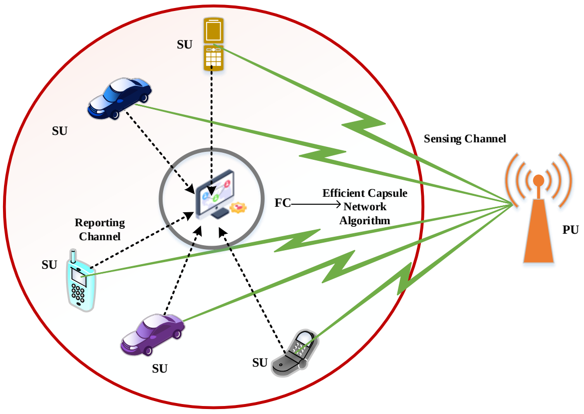

Fig 3. Spectrum Sensing

Table 3. Summary of Metrics

Metrics	**Explanation**	**Equation**
Trust level	It is considered as the default level of devices access in the network	$\ddot{\Upsilon} = \frac{\bar{\dot{o}} + \mathrm{ɣ} + \varrho}{\varpi}$
Congestion	It is denoted as the occurrence of network which is overrun with more data packet traffic than it can cope with	-
Channel availability	It is the probability of licensed channel which is available for the communications among unlicensed users	$C = \frac{\sqrt{\rho}}{\tau}\left(\frac{\mathrm{ƀp}}{\mathrm{ƀ} + 2\mathrm{p}}\right)^{\frac{2}{3}}$
SNR	It is the measure of strength of the desired signal relative to background noise	$SNR = 10.log_{10}\left(\frac{\emptyset_{signal}}{\emptyset_{noise}}\right)$
Noise	It is the additional unwanted signals that impair or hinders the normal traffic of desired data signals within a broadband network	-

While SU is detecting the optimal channel then it performs the secure handoff for the collision among SU and PU and it reduces the transmission delay. The SSDF and PUF attacks are mitigated through the performance of secure spectrum sensing and handoff. The utilization of efficient-CapsNet algorithm leads to the process of spectrum sensing with spectrum handoff.

$$\text{Spectrum Sensing} = \begin{cases} \text{Inactive PUs spectrum handoff} \\ \text{Active PUs no spectrum handoff} \end{cases} \tag{11}$$

In efficient-CapsNet, the network is widely divided into three various parts in which the first two are considered as the foremost instruments of the primary capsule layer to interact with the input space. Then, the last part of network functions over the self-attention algorithm for rout low level capsules.

$$\mathrm{H}^{1+1}(\mathrm{Y}^1) = \mathrm{ReLU}\left(\mathrm{Conv}_{\mathrm{p}\times\mathrm{p}}(\mathrm{Y}^1)\right) \tag{12}$$

In this ReLU activation functions, p is denoted as kernel dimension. The inputs are extracted in the primary caps layer to set the convolutional layers. The effective operation in this process is deployed to simplify and reduce the number of parameters that are essential for the capsule creation process. In addition, the dubbed squash operation is functional to create variant of original activation function in efficient capsule network.

$$\mathrm{squash}(\mathrm{q}_\mathrm{n}^\mathrm{t}) = \left(1 - \frac{1}{\mathrm{d}||\mathrm{q}_\mathrm{n}^\mathrm{t}}\right)\frac{\mathrm{q}_\mathrm{n}^\mathrm{t}}{||\mathrm{q}_\mathrm{n}^\mathrm{t}||} \tag{13}$$

Where $\mathrm{q}_\mathrm{n}^\mathrm{t}$ is denoted as single capsule along with the entry of n^t based on $\mathrm{q}_{(\mathrm{n},:)}^\mathrm{t}(\mathrm{q}_{\mathrm{n}0}^\mathrm{t} \coloneqq \{\mathrm{q}_{\mathrm{n},\mathrm{i}}^\mathrm{t}|\mathrm{n}^\mathrm{t} = \mathrm{n}_0^\mathrm{t}\})$ along with the $\mathrm{q}_\mathrm{n}^\mathrm{t} \in \delta^{\mathrm{it}}$. Mainly, it is used in two significant phases with the provision of support the gradient in training process. When it comes to self-attention routing, it is functional in rout active capsules.

$$\alpha_{(\mathrm{n}^\mathrm{t},\mathrm{n}^{\mathrm{t}+1},:)}^\mathrm{t} = \varepsilon_\mathrm{n}^{\mathrm{Rt}} \times \mathrm{S}_{(\mathrm{n}^\mathrm{t},\mathrm{n}^{\mathrm{t}+1},:,:)}^\mathrm{t} \tag{14}$$

Here, the total input of capsule in the layers $\mathrm{q}_\mathrm{n}^{\mathrm{t}+1}$ are weighted for the prediction vectors from the capsules $\varepsilon_\mathrm{n}^\mathrm{t}$. Mainly, the $\mathrm{S}_{(\mathrm{n}^\mathrm{t},\mathrm{n}^{\mathrm{t}+1},\mathrm{a}^\mathrm{t},\mathrm{a}^{\mathrm{t}+1})}^\mathrm{t}$ is denoted as the whole tensor with all the weight matrices, $\mathrm{n}^\mathrm{t}$is the weight matrix to predict the properties of all the $\mathrm{n}^{\mathrm{t}+1}$, $(\mathrm{q}_\mathrm{n}^{\mathrm{t}+1})$ is computed with the following equation,

$$\mathrm{q}_\mathrm{n}^{\mathrm{t}+1} = \varepsilon_{(,:\mathrm{n}^{\mathrm{t}+1},:)}^{\mathrm{Rt}} \times \left(\mathrm{G}_{(,:\mathrm{n}^{\mathrm{t}+1})}^\mathrm{t} + \mathrm{H}_{(,:\mathrm{n}^{\mathrm{t}+1})}^\mathrm{t}\right) \tag{15}$$

Here, $\mathrm{H}_{(,:\mathrm{n}^{\mathrm{t}+1})}^\mathrm{t}$ is the matrix of log priors in which all the weights are learnt at the parallel time and $\mathrm{G}_{(,:\mathrm{n}^{\mathrm{t}+1})}^\mathrm{t}$ is the matrix of all the coupling coefficients that are created through self-attention algorithms. Following that, the coupling coefficients are computed with the starting process of the self-attention tensor as $\vartheta_{\mathrm{n}^\mathrm{t},\mathrm{n}^\mathrm{t},\mathrm{n}^{\mathrm{t}+1}}^\mathrm{t}$ along with the following equation.

$$\vartheta_{:,:,\mathrm{n}^{\mathrm{t}+1}}^\mathrm{t} = \frac{\varepsilon_{(,:\mathrm{n}^{\mathrm{t}+1},:)}^\mathrm{t} \times \varepsilon_{(,:\mathrm{n}^{\mathrm{t}+1},:)}^{\mathrm{Rt}}}{\sqrt{\mathrm{h}^\mathrm{t}}} \tag{16}$$

Where $\vartheta_{:,:,\mathrm{n}^{\mathrm{t}+1}}^\mathrm{t}$ is the symmetric matrix for all the capsules in $\mathrm{n}^{\mathrm{t}+1}$. Then, the $\sqrt{\mathrm{h}^\mathrm{t}}$ is about the stabilization and regulation of training among the coupling coefficients and log priors.

$$\mathrm{G}_{(,:\mathrm{n}^{\mathrm{t}+1})}^\mathrm{t} = \frac{\exp\left(\sum_{\mathrm{n}^{\mathrm{t}+1}} \vartheta_{:,:,\mathrm{n}^{\mathrm{t}+1}}^\mathrm{t}\right)}{\sum_{\mathrm{n}^{\mathrm{t}+1}} \exp\left(\sum_{\mathrm{n}^{\mathrm{t}+1}} \vartheta_{:,:,\mathrm{n}^{\mathrm{t}+1}}^\mathrm{t}\right)} \tag{17}$$

Most significantly, the coefficients in coupling among the capsule layer t and the all the capsules $\mathrm{t} + 1$. In the margin loss and reconstruction regularize, the scalar is representing the output layer through the vectors. The probability is represented through the length of installation vector along with the capsule entity exists and it is computed through the below mentioned equation.

$$U_{n^U} = \mu_{n^U} \max(0, a^+ - ||\tau_n^U||)^2 + \partial(1 - \mu_{n^U}) \max(0, ||\tau_n^U|| - a^-)^2 \quad (18)$$

Here, μ_{n^U} is a class in n^U which is representing the a^+, a^- is the hyper parameters.

Algorithm 3. Efficient Capsule Network Algorithm

Input: Status of encrypted PUs

Output: Initiation of spectrum handoff

1: Begin

2: Encryption of SUs to transmit FC

3: Report sensing for security enhancement

4: Selection of optimal channel using equation (22)

5: Spectrum handoff is performed using the following equation

$$Spectrum\ Sensing = \begin{cases} Inactive\ PUs\ sepectrum\ handoff \\ Active\ PUs\ no\ spectrum\ handoff \end{cases}$$

6: End

4.3. Optimal Routing

The communication among the vehicles is maintained through the optimal routing which is denoted as the most significant process in V2X. The E-RSU is used collect and store the environment data to perform the secure routing process. The relative velocity, trust, energy and link stability are considered for the performance of next forwarder selection. In addition, the red fox optimization algorithm is used to determine the secure route through the consideration of link stability, vehicle speed, number of hops and vehicle trajectory over the selection of next forwarder.

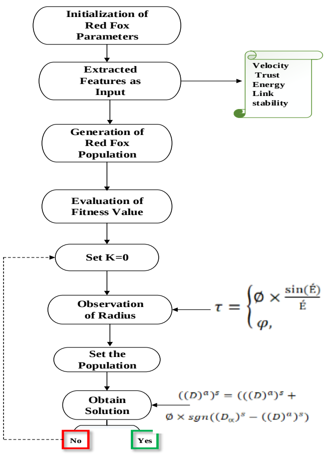

Fig 4. Flow of Red Fox Optimization Algorithm

The red fox optimization (RFO) is one of the novel metaheuristic optimization algorithms because it is stimulated through the lifestyle of hunting among the red foxes. In the process of hunting, the fox is closer to the prey even though it is hidden behind the bushes and finally the fox attacked the prey. In addition to that, it includes some other exploration and exploitation. Both the exploration and exploitation are defined as per the process of fox nearing to prey by selecting the faraway location due to the attack possibility. The initialization of RFO is modeled through the random individual generation.

$$D = [d_0, d_1, \dots, d_{n-1}] \quad (19)$$

$$(D)^a = [(d_0)^a, (d_1)^a, \dots, (d_{0-1})^a] \quad (20)$$

Where a is denoted as the number of population, $(D_b^a)^s$ is about the description of d_a is in iteration s and the b is described as the problem dimension in the searching space.

The condition function is assumed as CF in K^n in which the n denotes the parameters in the range of $(i, j)^n$. In which the $i, j \epsilon K$.

While, the global optimal is suggested for to obtain the optimum solution $CF((D)^a)$ and the individuals are assumed as for the particular process to support the exploration process as a group.

While the area is not denoted as the sufficient prey then the individual will move on to another location to acquire the chance to attack the prey. Then, the location is shared with other while other found an apt location for prey so the individuals are adapted for the cost value and the squared Euclidean distance is functional in this regard.

$$H(((D)^a)^s, (D_\propto)^s) = \sqrt{((D)^a)^s - (D_\propto)^s} \quad (21)$$

In addition, all the individuals are mitigated through the optimum solution which mentioned in the following.

$$((D)^a)^s = (((D)^a)^s + \emptyset \times sgn((D_\propto)^s - ((D)^a)^s) \quad (22)$$

Where, $\emptyset$ is addressed as random value. Following that, the new individuals in new location have to suggest the proper solution or else the prevision solution will be remaining the same. The optimization algorithm is modeled through the assumption of random value $\emptyset$ at the range of [0, 1.5].

$$\begin{cases} \text{move closer} & \text{if} \emptyset > \frac{3}{4}, \\ \text{stay and hide} & \text{if } \emptyset \leq \frac{3}{4} \end{cases} \quad (23)$$

The enhanced cochleoid formula is deployed to find the members who are moving around. Following that, the variable τ is defined as the radius and that is based on the two variables such as ∅ about the range of [0, 0.4] is denoted as random value and É as the fox observation angle with the range of [0, 3π] with the model of mathematical terms such as,

$$\tau = \begin{cases} \emptyset \times \frac{\sin(\acute{E})}{\acute{E}}, & \text{if} \acute{E} \neq 0 \\ \varphi, & \text{if } \acute{E} = 0 \end{cases} \quad (24)$$

Where φ is denoted as the random value among 0 and 1 and the following model is about the nearing process of fox population.

$$\begin{cases} d_0^f = \emptyset \times \tau \times \cos(\acute{E}_1) + d_0^{act} \\ d_1^f = \emptyset \times \tau \times \sin(\acute{E}_1) + \\ \emptyset \times \tau \times \cos(\acute{E}_2) + d_1^{act} \\ d_1^f = \emptyset \times \tau \times \sin(\acute{E}_1) + \\ \emptyset \times \tau \times \sin(\acute{E}_2) + \\ \emptyset \times \tau \times \cos(\acute{E}_3) + d_2^{act} \\ \vdots \\ d_{n-1}^f = \emptyset \times \tau \times \sum_{c=1}^{n-2} \sin(\acute{E}_1) + \\ \emptyset \times \tau \times \cos(\acute{E}_{n-1}) \\ + d_{n-2}^{act} + d_{n-2}^{act} \\ d_{n-1}^f = \emptyset \times \tau \times \sin(\acute{E}_1) + \\ \emptyset \times \tau \times \sin(\acute{E}_2) + \cdots + \\ \emptyset \times \tau \times \sin(\acute{E}_{n-1}) + \\ \emptyset \times \tau \times \sin(\acute{E}_{n-1}) + d_{n-\emptyset}^{act} \end{cases} \quad (25)$$

In addition, the worst members are eliminated and various new members have been included to the individuals to fix the size of population. As the similar process, two optimum members are acquired such as $(D(1))^s$and $(D(2))^s$are the denoted as the alpha couple in iteration. Following that the territory center is obtained as follows.

$$K_n^s = \frac{1}{2}(D(1))^s - (D(2))^s \quad (26)$$

Then, the territory diameter is defined through the Euclidean distance.

$$K_n^s = \sqrt{(D(1))^s - (D(2))^s} \quad (27)$$

Consequently, the variable ϱ is defined as the random amount among 0 and 1.

$$\begin{cases} \text{New nomadic candidate}, & \text{if } \varrho > 0.45, \\ \text{Reproduction of alpha couple}, & \text{if } \varrho \leq 0.45 \end{cases} \quad .....(28)$$

The searching space is deployed to acquire the random locations and the new members are set up through the alpha couple such as,

$$D^r = \frac{\varrho}{2}(D(1))^s - (D(2))^s \quad (29)$$

Mainly, the parameters that have been used in RFO are highlighted such as, ∅ = 0.2 and $\acute{E}_0 = 1$.

4.4. Effective Hybrid Beamforming

The transmission speed is improved through the enhancement of signal quality over the performance of beamforming. The digital and analog beamforming is deployed to acquire the high hardware complexity and inefficiency of spectrum because of the high amount of RF chains. The asynchronous advantage actor critic learning method is utilized for the process of hybrid beamforming to enhance the performance through the usage of multiple agents which allows for efficient exploration and faster convergence towards optimal policies. The integration of analog precoder with combiner and digital precoder with combiner is used to increase the network optimization and reduce the multi user interface noise through the presence of actor in asynchronous advantage actor critic learning method. Optimal N-taps is predicted to increase the performance of signal power and time and this is done through the presence of critic in asynchronous advantage actor critic learning method. The azimuth angle, elevation angle, array factor, direction of angle, beam score and CSI are used to create the hybrid beams. Form this, the azimuth angle and elevation angle are predicted through acquiring the feedbacks collected from the users. Additionally, the feedbacks from the users are collected and updated through the presence of the third agent. The environmental factors such as humidity, temperature and weather, spectral efficiency, SINR and RSSI are used to predict the CSI. The secure hybrid beamforming is produced through retrieving this information using cloud based blockchain.

The total transmitted power($Ꞵ_{TP}$) is obtained through connecting the $K^{\mathcal{RF}}$ and $K^{\mathfrak{BB}}$ along with the formulation as follows,

$$\sum_{n=1}^{n} ||K^{\mathcal{RF}} K^{\mathfrak{BB}}[n]||^2 \leq Ꞵ_{TP} \quad (30)$$

Where, analog precoder($K^{\mathcal{RF}}$) is done time domain and digital precoder ($K^{\mathfrak{BB}}$), n is the subcarriers. The combination of analog precoding and digital precoding consequences are done inthe fusion centerthrough the analog and digital combiner. As the first process, the analog combiner ($G^{\mathcal{RF}}$)associates the received signal in analog domain, cyclic prefix over the hybrid precoder which is removed and provided to the digital combiner ($G^{\mathfrak{BB}}$), along with the frequency domain. The complete analogdigital precoding and analogdigital combining received signal matrix as follows,

$$S(n) = G_{\varrho}^{\mathcal{R}}[n]L[n]K^{\acute{E}}[n]d[n] + G_{\varrho}^{\mathcal{R}}[n]\eta[n] \quad (31)$$

$$K^{\mathcal{RF}} K^{\mathfrak{BB}}[n] = K_{\acute{E}}[n] \quad (32)$$

$$G^{\mathcal{RF}} G^{\mathfrak{BB}}[n] = G_L[n] \quad (33)$$

Where, $L[n]$ represents the matrix of the channel among fusion center and PUs, $\eta[n]$ is the noise such as the additive white Gaussian noise, $d[n]$ represents the data symbols at each subcarrier.

The reinforcement learning includes an agent for the interaction with environment through number of discrete time steps as $\check{T}$ and the agent used to observe the state which is defined as process which selects an action over the establishment of effective actions.

In addition, a policy ƥ is deployed to guide an agent for the functions of mapping from the states towards the action. Until the agent reaches the terminal state in limited time, this process will be continued with the reset of environment and start of new episode.

At the outset based on the reinforcement learning process the tuple is defined as $(\check{T}, {}^{\delta}{}_{\check{T}}, {}^{\beta}{}_{\check{T}}, {}^{\delta}{}_{\check{T}+1}, ȸ_{\check{T}}, ƥ, \bar{ō})$. The ${}^{\delta}{}_{\check{T}}$ denotes the state, ${}^{\beta}{}_{\check{T}}$denotes the action of every agent which isshared, $\bar{ō}_{\check{T}}$ denotes observation of agents. The $ȸ_{\check{T}}$ is denoted as reward function.Following that, the agent is observing the next state and that is defined as ${}^{\delta}{}_{\check{T}+1}$ which receives the feedback in the form of the rewar

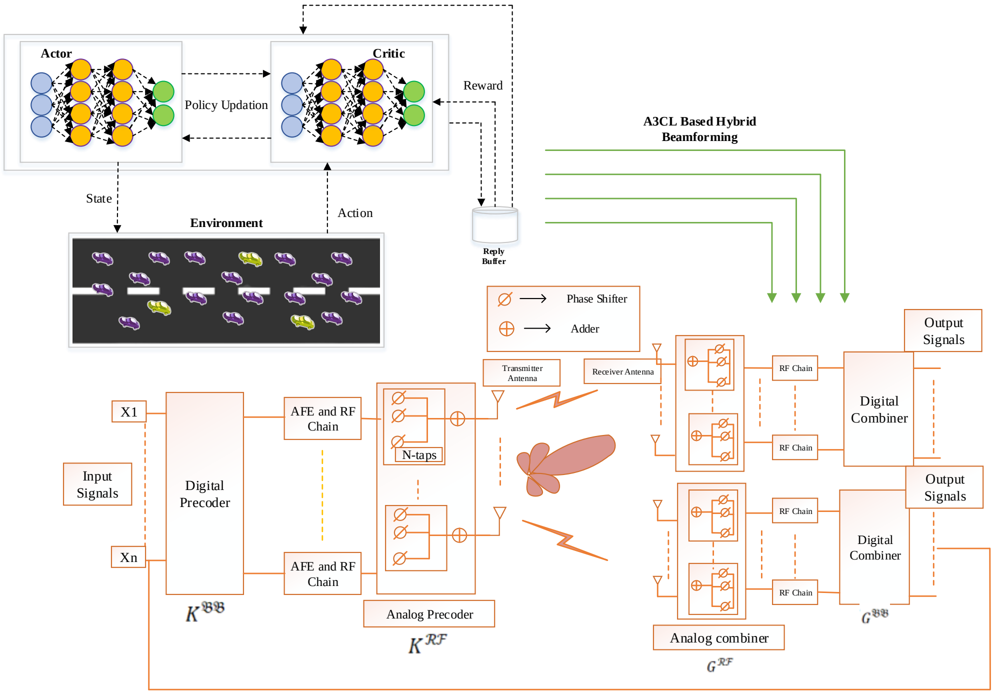

Fig 5. A3CL based Hybrid Beamforming

Remote-to-Local (R2L):

The asynchronous advantage actor critic learning method deployed to achieve the result based on state of art based on various gaming tasks with the utilization of single DNN of policy and value functions. The agents are used to calculate the gradients and sending the updates to the server with $\check{T}_{max} = 5$ actions. To ensure that the agents are sharing common policy through the central server propagation of new weights and the following equation is about the policy functions.

$$P_{ƥ}(\partial) = \log ƥ({}^{\beta}{}_{\check{T}} | {}^{\delta}{}_{\check{T}}; \partial) \left(ɣ_{\check{T}} - S({}^{\delta}{}_{\check{T}}; \partial_{\check{T}}) \right) + \alpha E(ƥ(({}^{\delta}{}_{\check{T}}; \partial)) \tag{34}$$

Where, $\partial_{\check{T}}$ is defined as the values of parameters ∂ at the time $\check{T}$. Mainly, $ɣ_{\partial} = \sum_{a=0}^{h-1} \varphi^{a}\, e_{\check{T}+a} + \varphi^{h}\, S({}^{\delta}{}_{\check{T}+h}; \partial_{\check{T}})$ is for the process of estimation which is discounted as reward in the time interval of $\check{T}$ to $\check{T}+h$ which is called as upper bounded through $\check{T}_{max}$ in which the $E(ƥ({}^{\delta}{}_{\check{T}}; \partial))$ is denoted as the entropy term utilized in the favor of exploration in training process. The φ is the factor which is controlling the strength of entropy regularization term and cost of estimated value function is highlighted as follows,

$$P_{\check{V}}(\partial) = (ɣ_{\check{T}} - S({}^{\delta}{}_{\check{T}}; \partial))^{2} \tag{35}$$

The process of collecting gradients $\nexists\partial$ from the cost of functions through the utilization of standard non centered RMSProp algorithm as optimization is denoted as training.

$$\begin{aligned} \mu &= \sigma\mu + (1-\sigma)\nexists\partial^{2} \\ \partial &\leftarrow \partial - \vartheta\nexists\partial/\sqrt{\mu+\varepsilon} \end{aligned} \tag{36}$$

The gradients μ might be divided or detached among the agent threats through the shared implementation as robust.

5. Experimental Results

In this section, we represent experimental results of proposed work and existing work. This experimental research includes three subsectionssuch as simulation setup, comparison analysis and research summary. The result section is about the illustration of proposed work which achievesthe finest performance while comparing with the previous works.

5.1. Simulation Setup

The proposed work is about the exploitation of edge technology and blockchain technology for the routing, hybrid beamforming and secured spectrum access in mmWave massive MIMO. The simulation result of this proposed work is implemented by Objective Modular Network is Tested in C++ (OMNET++) and simulation of urban mobility (SUMO) which improves the performance of this proposed research. The proposed framework is compare with several performance metrics and proven that our work achieves the finest performance. Table 4 illustrates the configuration of simulation setup of the proposed work and Table 5 defines the configuration of network parameters.

Table 4. System configuration

Hardware Configuration	Random Access Memory (RAM)	8GB
	Hard Disk	1TB
	CPU Processor	Intel(R) Core(TM) i5-4590S CPU @ 3.00GHz 3.00 GHz
Software Configuration	Operating System	Windows 10
	Simulation Tool	OMNET++, SUMO

Table 5. Network Parameters

Parameters	Values
Simulation time	400seconds
Parameters for Channel	
Channel’s bandwidth	20MHz
Total no of channels	25
Spectrum range	15 to 550 MHz
Parameters for Packets	
No of packets	~5500
No of packets generated	1048
Packet’s size	512
Interval of packets	3s
Parameters for 6G	
Spectral efficiency	250 bps/Hz
Data rate	Maximum 3Tbps
End-to-end delay	1.5 ms
Parameters for Network	
Area of simulation	1350 × 1250
Fusion center numbers	4
Speed of the vehicle	15-35 m/s
No. of primary users	8
No. of secondary users	66
No. of vehicles	100
No. of ERSUs	4
Acceleration of vehicles	$3.5^{metre}/_{sec^2}$

5.2. Comparative Analysis

The comparison in proposed research work 6GCRN-MIMO with various existing works such as CR-VANET, EFAHP-TOPSIS, HBF-mmWave MIMO and CRN-TCS are performed in this section to evaluate the performance. In addition, various performance metrics are considered to analyze the performance such as sensing delay, total transmit power, spectral efficiency, probability of bit error rate, probability of detection, route acquisition delay, communication overhead, packet loss rate, throughput and latency which is categorized three partitions such as spectrum sensing analysis, spectrum efficiency analysis and QoS analysis. In addition, the above mentioned metrics have been defined as follows,

i) Sensing Delay: The SUs occurred in the environment requires some time for the spectrum sensing and this sensing delay is deployed to estimate the time utilized by SUs for spectrum sensing process. It is calculated through the ratio based on sensed channels and transmitted packets as mentioned in the following equation.

$$\acute{\omega} = \frac{\mathrm{SC}}{\mathrm{TP}} \tag{33}$$

Where, $\acute{\omega}$ is considered as the sensing delay, SC is the representation of number of sensed channels and TP denotes the number of transmitted packets.

ii) Total Transmit Power: It is denoted as the amount power requires for data transmission from SUs to PUs using number of hops.

iii) Probability of Detection: It is about the estimation of FC’s performance through the mitigation of detection of network attacks.

iv) Route Acquisition Delay: It is the metric used to calculate the total time which is required for the data transmission process.

v) Communication Overhead: It is deployed to measure the routing overhead through the ratio of total number of packets that are generated for the route selection process.

$$\nexists = \frac{RS}{TP} \tag{34}$$

Where, $\nexists$ is denoted as the communication overhead, RS is the number of route selection and TP is defined as the total number of transmitted packets.

vi) Packet Loss Rate: It is deployed to measure the lost data packets in network through the ratio of number of packets lost ϱ to the data group sent $^{\beta}$ which is expressed as follows.

$$ƥ = \frac{\varrho}{\beta} \tag{35}$$

vii) Throughput: It is the amount of data delivered for all the SUs in the existing network and it is measured through the ratio of data size Ÿ to the amount of time t required for data transmission.

$$ɳ = \frac{t}{Ÿ} \tag{36}$$

viii) Latency: It is denoted as the time delay among the source nodes and destination nodes in the system that is being observed.

a) Spectrum Sensing Analysis

The analysis of spectrum sensing is performed through various metrics such as sensing delay and total transmit power and it results in the effective and secured spectrum sensing process.

1) Sensing Delay Comparison

An effective spectrum sensing is deployed to enhance the routing performance through low sensing delay. Fig 6 denotes the comparison of sensing delay in data traffic among the proposed method 6GCRN-MIMO with various existing methods such as HBF-mmWave MIMO, CRN-TCS and EFAHP-TOPSIS. While the data traffic increasing, the sensing delay will also increase at the mean time. EFAHP-TOPSIS method performs spectrum sensing without considering CRN spectrum metrics which leads to spectrum scarcity and increases the transmission delay. In CRN-TCS method, the PUs are observed in licensed channel, the CR user starts sensing of other licensed channels to continue its transmission which leads to delay. In the proposed 6GCRN-MIMO method, efficient capsule network algorithm is used for spectrum sensing with the consideration of several metrics such as trust level, congestion, channel availability, SNR and noise for the reduction of sensing delay. Through the analytical results, it has been proved that the proposed 6GCRN-MIMO method acquires low sensing delay with the maximum of 24ms when the data traffic level is 10 meanwhile the existing methods have been various up to 15ms from the proposed method.

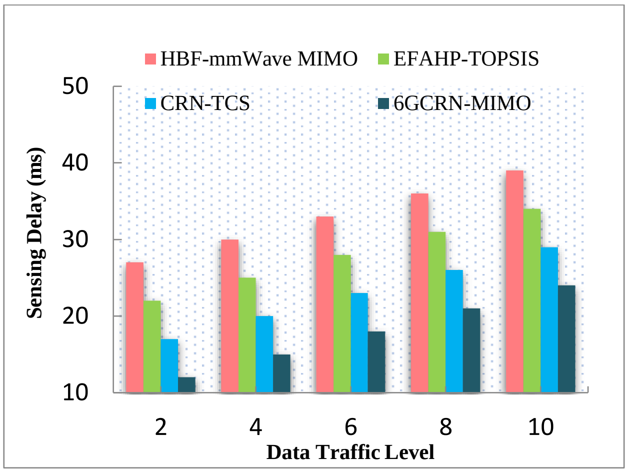

Fig 6. Sensing Delay vs. Data Traffic Level

2) Total Transmit Power Comparison

The reduction of total transmit power leads to effective data transmission process with high security and low latency. Fig 7 depicts the comparison of total transmit power with the number of SUs to show the difference among the proposed method 6GCRN-MIMO with various existing methods such as HBF-mmWave MIMO, CRN-TCS and EFAHP-TOPSIS.

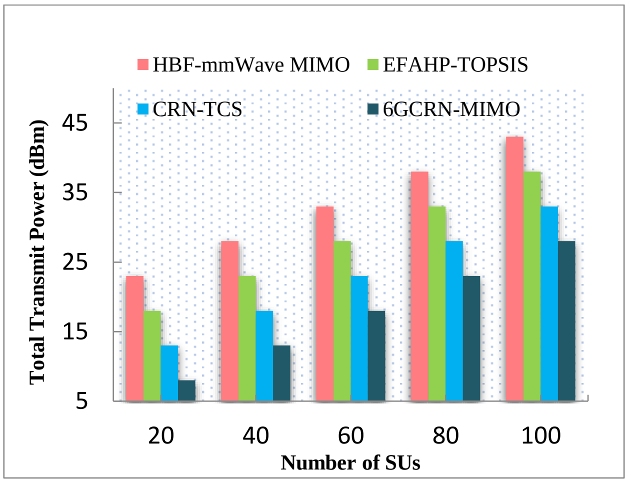

Fig 7. Total Transmit Power vs. No of SUs

The number of SUs will be increased while the total transmit power increases. The HBF-mmWave MIMO method is positioned to reduce the deployment of energy phase shifters through the implementation of the analog precoder, on the other hand, it increases the transmission delay which leads to enhance the transmit power. EFAHP-TOPSIS method is performing the channel selection for data transmission among the PUs and SUs which increase the traffic and leads to high transmit power. The proposed 6GCRN-MIMO method is performing with the secure data transmission along with the transmission rate in high through the execution of efficient clustering process using modified K-Means algorithm and improved Naive Bayes for the reduction of collision in the network which manages the network for secured spectrum sensing to reduce the transmit power. While comparing the total transmit power among the proposed and existing methods, the proposed 6GCRN-MIMO method shows low total transmit power maximum as 28dBm while the functioning with 100 SUs but the existing methods have difference about 25dBm from the proposed method.

b) Spectrum Efficiency Analysis

The spectrum efficiency is analyzed over the performance of various metrics such as spectral efficiency, probability of bit error rate and probability of detection to enhance the spectrum efficiency in the proposed 6GCRN-MIMO method through the implementation of data transmission among the limited channel bandwidth with the adequate spectrum scarcity and spectrum wastage.

1) Spectral Efficiency Comparison

The spectrum efficiency is increased through the appropriate spectrum utilization with the reduction of spectrum scarcity. Fig 8 is about the demonstration of spectral efficiency comparison with number of SUs among the proposed 6GCRN-MIMO method with the existing methods such as HBF-mmWave MIMO, CRN-TCS and EFAHP-TOPSIS.

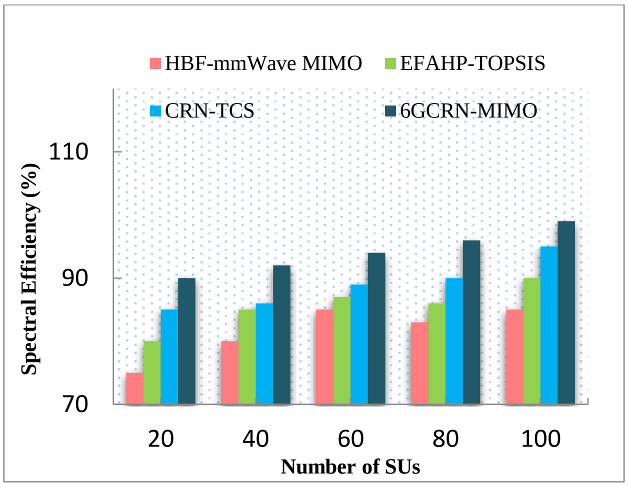

Fig 8. Spectral Efficiency vs. No of SUs

In HBF-MIMO method, hybrid beamforming is performed with various phase shifters for the minimization of the energy utilization to increase the latency which leads to decrease the spectral efficiency. On the other hand, that results in the increase of both spectral efficiency and number of SUs as simultaneously. In the EFAHP-TOPSIS method, MCDM techniques are deployed to perform optimal channel selection process but that leads to increases the network traffic meanwhile the energy consumption also be increased.The proposed 6GCRN-MIMO method is performing spectrum sensing through the efficient capsule network along with the limited and selective phase shifters for the reduction of energy consumption which leads to enhance the spectral efficiency. The proposed 6GCRN-MIMO method has been demonstrated as it acquires high spectral efficiency with the maximum of 98% while the functioning with 100 SUs in the meantime the existing methods have the huge difference as 13% from the 6GCRN-MIMO proposed method.

2) Probability of Bit Error RateComparison

Secure and efficient packet transmission without errors is executed through the low probability of bit error rate. Fig 9 illustrates the probability of bit error rate comparison with the signal noise ratio (SNR) among the proposed 6GCRN-MIMO method with the existing methods such as HBF-mmWave MIMO, CRN-TCS and EFAHP-TOPSIS. EFAHP-TOPSIS method is performing the channel selection for data transmission among the PUs and SUs which increase the network traffic and leads to increase the error rate in transmission. HBF-mmWave MIMO method is performing the data transmission among the PUs and SUs with the improper channel selection and that results with high error rate while transmitting data packets. The proposed 6GCRN-MIMO method is performing with the secure packet transmission without error using the modified K-Means algorithm for the effective data transmission which reduces the bit error rate. While comparing the bit error rate among the proposed and existing methods, the proposed 6GCRN-MIMO method acquires the low bit error rate with maximum of 55% while the SNR is 25 but the existing methods have difference about 30% from the proposed method.

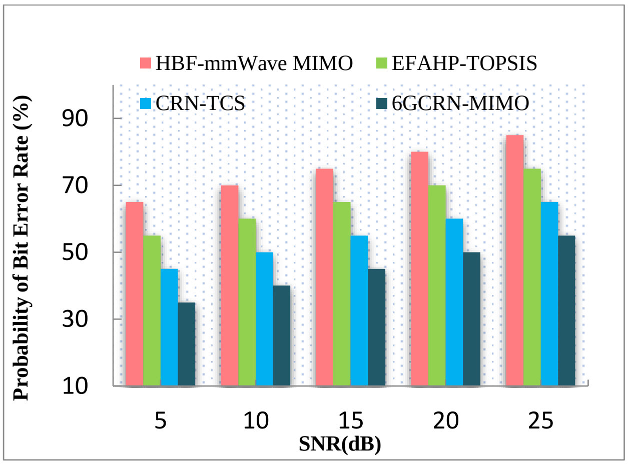

Figure 9. Bit Error Rate vs. SNR

3) Probability of Detection Comparison

The data is transferred efficiently through the high detection probability which results in high spectrum security. Fig 10 demonstrates the comparison among probability of detection with the signal to interference plus noise ratio (SINR) to show the difference between the proposed 6GCRN-MIMO method with various existing methods such as HBF-mmWave MIMO, CRN-TCS and EFAHP-TOPSIS. Most significantly, the increase in the SNR will increase the probability of detection. In the CRN-

TCS method, the communication among channels is performed through the transmission of RTS which results in increasing the security threats due to low detection probability. In the proposed 6GCRN-MIMO method, the secure spectrum sensing is implemented to detect and mitigate several attacks such as PUF and SSDF attacks through encrypting the sensing report and secure routing with the utilization of efficient capsule network algorithm as per the trust levels which leads to increase the probability of detection in the proposed 6GCRN-MIMOmethod while comparing with the other existing works. From the numerical results shown in the graph indicates that out proposed work performs better than existing works because the proposed 6GCRN-MIMOmethod acquires the high detection probability maximum as 0.95 when the existing methods are pushed back with the difference of 0.25 as detection probability.

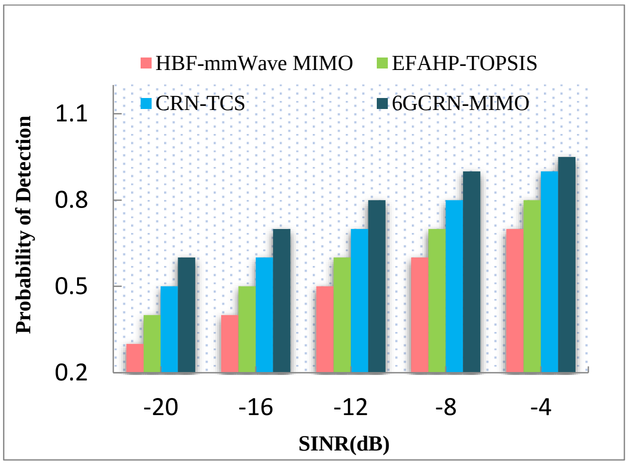

Fig 10. Probability of Detection vs. SINR

c) QoS Analysis

QoS analysis is determined as the analysis of data transmission and ensures high performance in terms of metrics such as route acquisition delay, communication overhead, packet loss rate, throughput and latency.

1) Route Acquisition Delay Comparison

The route acquisition delay is reduced through the effective routing path with the adequate spectrum. Fig11 represents the comparison of route acquisition delay with number of routing hops among the proposed 6GCRN-MIMO method with the existing methods such as CR-VANET, CRN-TCS and EFAHP-TOPSIS. When number of routing hops increases corresponding route acquisition delay also increases. In the CRN-TCS method, the communication among channels is performed through the transmission of RTS which results in increasing the security threats due to low detection probability. In the CR-VANET method, 2 hop routing is implemented with ineffective path selection that increases the route acquisition delay which leads to network traffic. In the proposed 6GCRN-MIMO method, an effective spectrum sensing and routing are performed through the consideration of various parameters with high security to reduce the route acquisition delay when compared with other existing works. Through the experimental results, it has been proved that the proposed 6GCRN-MIMO method acquires low route acquisition delay with the maximum of 80ms with the number of routing hops as 10 meanwhile the existing methods are differentiated by 15ms from the proposed method.

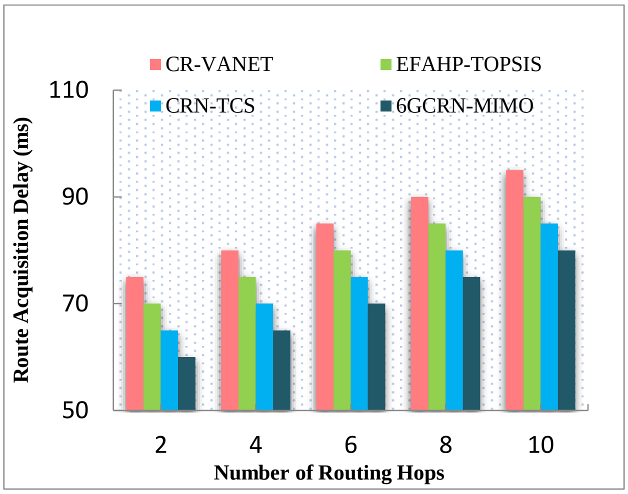

Fig 11. Route Acquisition Delay vs. No of Routing Hops

2) Communication Overhead Comparison

An effective channel selection and routing reduces the communication overhead in that way minimizing the packet loss. Fig 12 illustrates the comparison of communication overhead with the number of entities among the proposed 6GCRN-MIMOmethod with the existing methods such as CR-VANET, CRN-TCS and EFAHP-TOPSIS. The communication overhead is increases while there is increase in number of entities. In the CR-VANET method, the insufficient hopping such as 2 hop routing is performed in a dynamic environment that increases the communication overhead.

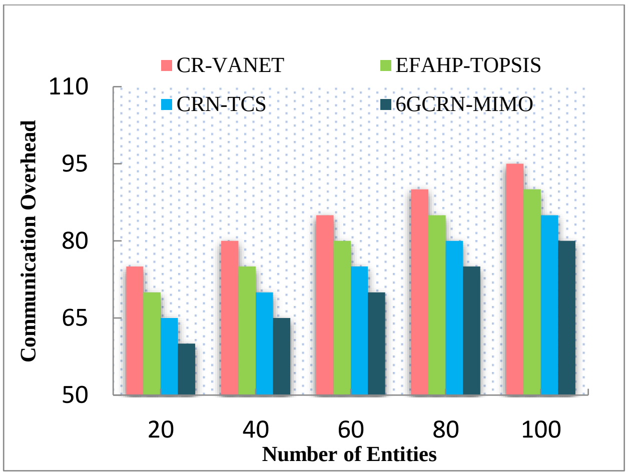

Fig 12. Communication Overhead vs No of Entities

In CRN-TCS method, the PUs are observed in licensed channel, the CR user starts sensing of other licensed channels to continue its transmission which leads to increase the communication overhead. In the proposed 6GCRN-MIMOmethod, the secure spectrum sensing and routing are implemented through considering various metrics such as trust level, congestion, channel availability, SNR and noise to reduce the communication overhead and that leads to mitigates SSDF and PUF attacks. This indicates that the proposed 6GCRN-MIMOmethod acquires the low communication overhead maximum as 80 when the existing methods are pushed back with the difference of 15 which shows the proposed work performs better than existing works.

3) Packet Loss RateComparison

A decrease in packet loss increases the packet delivery ratio. Fig 13 illustrates the comparison of packet loss rate with the number of SUs for the proposed 6GCRN-MIMOmethod with the existing methods such as CR-VANET, CRN-TCS and EFAHP-TOPSIS. In EFAHP-TOPSIS method, the data is transmitted over the utilization of MCDM but that result in the high packet loss. In the CR-VANET method, routing is performed as per the 2 hop neighbors but it lacks to consider the mobility environment which increases the routing overhead that leads to high packet loss. In the proposed 6GCRN-MIMOmethod, several parameters such as congestion, channel availability, SNR and trust level are considered for secure routing using the red fox optimization algorithm to reduce the packet loss. The proposed 6GCRN-IoCV method achieves a low packet loss rate as 75% while the other existing works have the difference from 15% of packet loss rate.

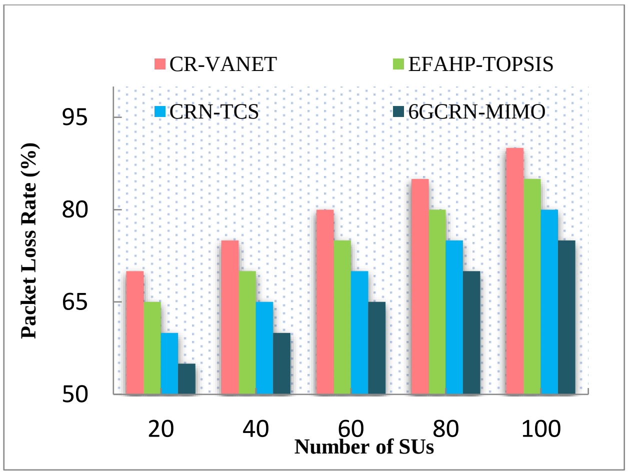

Figure 13. Packet Loss Rate vs. No. of SUs

4) Throughput Comparison

The QoS is improved through the execution of network with high throughput. Fig 14 depicts the comparison of throughput with the number of SUs for the proposed 6GCRN-MIMOmethod among the existing methods such as CR-VANET, CRN-TCS and EFAHP-TOPSIS. There is a gradual increase in throughput while the number of SUs is increased. In the CR-VANET method, the data transmission among the PUs and SUs is performed with a lack of optimal channel selection which increases the latency and decreases the throughput. In the CRN-TCS method, the communication is performed with CRs and PUs which leads to increases the security threats that reduce the throughput. In the proposed 6GCRN-MIMOmethod, the spectrum sensing is effectively performed by encountering network traffic and enhancing the throughput during data transmission, the secure routing is proposed through the utilization of red fox optimization algorithm to perform against the blackhole attack and Sybil attack. The comparison of throughput among the proposed and existing works results that the proposed 6GCRN-MIMOmethod acquires high throughput as 400Kbps with the functions of 100 SUs but the existing works are differentiated with 70Kbps of throughput.

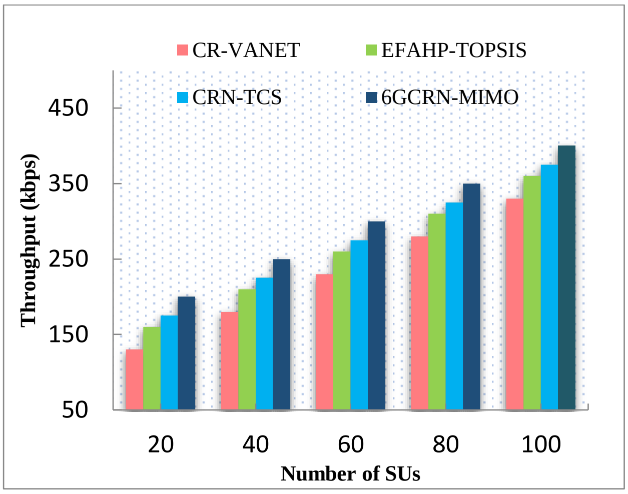

Figure 14. Throughput vs. No. Of SUs

5) Latency Comparison

Through maintaining fast data transmission process, the latency will be reduced for the effective network execution. Fig 15 shows the latency comparison with the number of SUs for the proposed 6GCRN-MIMOmethod among the existing methods such as CR-VANET, CRN-TCS and EFAHP-TOPSIS. In CRN-TCS method, all the channels for the simulation are taken to be high bandwidth and they are using the cloud based elements which leads to slow down the process results in high latency.

In the CR-VANET method, the data transmission among the PUs and SUs is performed with a 5G environment which increases the latency. In the proposed 6GCRN-MIMOmethod, the edge based components and adopting artificial intelligence technologies are used for the ultra-speed data transmission among PUs and SUs. The PU traffic is decreased resulting in higher channel availability, thereby reducing the latency. While comparing the latency among the proposed and existing methods, the proposed 6GCRN-MIMO method obtains the low latency with maximum of 80 while the SNR is 25 but the existing methods have difference about 15 from the proposed method. So, the 6GCRN-MIMO method has proved that it acquires low latency.

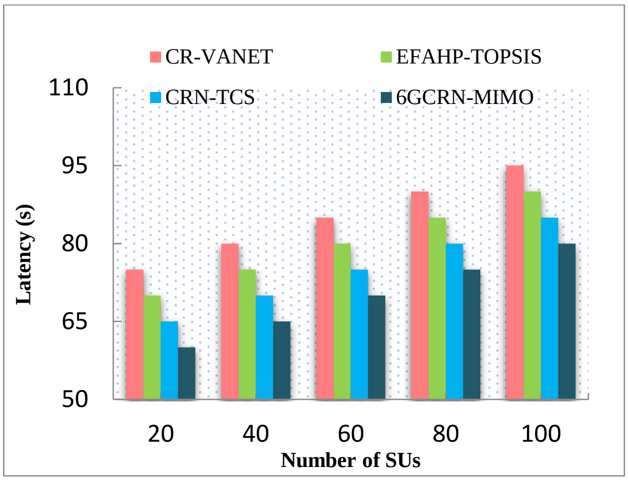

Fig 15. Latency vs. No. Of SUs

Research Summary

This section provides the brief discussion about the performance of the proposed 6GCRN-MIMOmethod. The numerical analysis about the performance of the proposed method along with the existing methods presented in table 6 the previous section with the Fig 6 - 15 depicts the comparison of performance metrics and proves the efficiency of the proposed approach in terms of spectrum sensing, spectrum efficiency, and QoS. The spectrum sensing and spectrum efficiency are included in the proposed method to increase the performance of total transmit power, sensing delay, probability of detection, bit error rate and spectral efficiency. The clustering process is performed in the proposed method to increase the throughput and decrease delay during data transmission among PUs and SUs. Hybrid beamforming is performed in the proposed method to integrate the high dimensional analog for computational efficiency with the metrics such as RSSI, SINR and more. The secured routing is implemented for the reduction of route acquisition delay, packet loss rate and communication overhead and to increase the throughput and decrease the latency. The total process of the proposed method proves with the effective results in QoS while compared to existing methods. The research study is organized in the well thought-out way and in addition each and every objective of the proposed research is explained in the following with the clear explanation about the highlights,

- For regulating the network efficiently, we have proposed the intersection of secure information and clustering to avoid the latency and network collision during the process of vehicle communication
- For the reduction of network traffic and enhance the throughput during data transmission, the secure routing is proposed through the utilization of red fox optimization algorithm to perform against the blackhole attack and Sybil attack
- For improving the spectral efficiency and hardware efficiency through performing the hybrid beamforming to provide the secure hybrid beams to enhance transmitting speed and signal quality

For addressing the issues in mobility and spectrum scarcity, we have performed the secure spectrum sensing and handoff for the enhancement of spectrum utilization, reduction of transmission delay and mitigation of PUF attack and SSDF attacks in the environment

Table 6. Average numerical analysis of proposed vs. Existing works

Performance Metrics			**HBF-mmWave MIMO**	**EFAHP-TOPSIS**	**CRN-TCS**	**6GCRN-MIMO**
Spectrum Sensing Analysis	Sensing Delay (ms)	Data Traffic Level	33	28	23	18
	Total Transmit Power (dBm)	Number of SUs	33	28	23	18
Spectrum Efficiency Analysis	Spectral Efficiency (%)	Number of SUs	81.6	85.6	89	84.2
	Probability of Bit Error Rate (%)	SNR	75	65	55	45
	Probability of Detection	SINR	0.5	0.6	0.7	0.79
			CR-VANET	**EFAHP-TOPSIS**	**CRN-TCS**	**6GCRN-MIMO**
QoS Analysis	Route Acquisition Delay (ms)	Number of Routing Hops	85	80	75	70

	Communication Overhead	Number of Entities	85	80	75	70
	Packet Loss Rate (%)	Number of SUs	80	75	70	65
	Throughput (kbps)	Number of SUs	230	200	275	300
	Latency (s)	Number of SUs	85	80	75	70

6. Conclusion and Future work

In edge assistance IoCV environment based on 6G, lack of reliable communication and spectrum access are the major issues. In this research, the 6GCRN-MIMO framework is proposed to execute the regulation of effective spectrum mobility and network traffic. Firstly, the SU and PU presented in this IoCV environment are authenticated through blockchain with the consideration of ID, PUF and locations. The modified K-Means algorithm is used to perform the clustering through the entry of the authenticated users along with the consideration of location, direction, distance and local density. The cluster head has elected in the constructed clustering process based the trust and maximum RSSI for the data transmission between the cluster members. The spectrum sensing is performed for the enhancement of spectrum utilization in the network using efficient- CapsNet algorithm. SU is selecting the optimal channel through considering the elements such as trust level, congestion, channel availability, SNR and noise. The performance of secure spectrum sensing and handoff are used to mitigate the SSDF and PUF attacks. The red fox optimization algorithm is performed to determine secure route through over considering the link stability, vehicle speed, number of hops and vehicle trajectory over the selection of next forwarder which enhance the communication among vehicles through the spectrum mobility management. Hybrid beamforming using asynchronous advantage actor critic learning method is performed as the final process to improve the spectral efficiency. The proposed 6GCRN-MIMO method achieved better performance in terms spectrum sensing, spectrum efficiency and QoS analysis.

References

[1] Khan, A.U., Abbas, G., Abbas, Z.H., Tanveer, M., Ullah, S., & Naushad, A. (2020). HBLP: A Hybrid Underlay-Interweave Mode CRN for the Future 5G-Based Internet of Things. IEEE Access, 8, 63403-63420.

[2] Zhang, T., Zhang, D., Qiu, J., Zhang, X., Zhao, P., & Gong, C. (2019). A Kind of Novel Method of Power Allocation With Limited Cross-Tier Interference for CRN. IEEE Access, 7, 82571-82583.

[3] Zonoozi, A., Kim, J., Li, X., & Cong, G. (2018). Periodic-CRN: A Convolutional Recurrent Model for Crowd Density Prediction with Recurring Periodic Patterns. International Joint Conference on Artificial Intelligence.

[4] Nandan, N., Majhi, S., & Wu, H. (2021). Beamforming and Power Optimization for Physical Layer Security of MIMO-NOMA Based CRN Over Imperfect CSI. IEEE Transactions on Vehicular Technology, 70, 5990-6001.

[5] Pari, D., & Natarajan, J. (2022). Secure Spectrum Access, Routing, and Hybrid Beamforming in an Edge-Enabled mmWave Massive MIMO CRN-Based Internet of Connected Vehicle (IoCV) Environments. Sensors (Basel, Switzerland), 22.

[6] Xu, X., Zhang, X., Liu, X., Jiang, J., Qi, L., & Bhuiyan, M.Z. (2020). Adaptive Computation Offloading With Edge for 5G-Envisioned Internet of Connected Vehicles. IEEE Transactions on Intelligent Transportation Systems, 22, 5213-5222.

[7] Deepanramkumar, P., & Jaisankar, N. (2022). BlockCRN-IoCV: Secure Spectrum Access and Beamforming for Defense Against Attacks in mmWave Massive MIMO CRN in 6G Internet of Connected Vehicles. IEEE Access, 10, 74220-74243.

[8] Qureshi, K.N., Ahmed, M., Jeon, G., & Piccialli, F. (2021). An Enhanced Multi-Hop Intersection-Based Geographical Routing Protocol for the Internet of Connected Vehicles Network. IEEE Transactions on Intelligent Transportation Systems, 22, 3850-3858.

[9] (2020). IEEE Standard for Spectrum Sensing Interfaces and Data Structures for Dynamic Spectrum Access and Other Advanced Radio Communication Systems. Dynamic Spectrum Access Decisions.

[10] Cai, P., & Zhang, Y. (2020). Intelligent cognitive spectrum collaboration: Convergence of spectrum sensing, spectrum access, and coding technology. Intelligent and Converged Networks.

[11] Soni, B., Patel, D.K., & López-Benítez, M. (2020). Long Short-Term Memory Based Spectrum Sensing

Scheme for Cognitive Radio Using Primary Activity Statistics. IEEE Access, 8, 97437-97451.

[12] Koçkaya, K., & Develi, I. (2020). Spectrum sensing in cognitive radio networks: threshold optimization and analysis. EURASIP Journal on Wireless Communications and Networking, 2020, 1-19.

[13] Priya M, K., Raja Kumar, R.V., Indumathi, P., & Satheeswaran, C. (2018). Spectrum and Traffic Aware Routing Protocol with cooperative information collection method for CR-VANET. 2018 International Conference on Recent Trends in Electrical, Control and Communication (RTECC), 35-40.

[14] Liu, J., Ren, P., Xue, S., & Chen, H. (2012). Expected path duration maximized routing algorithm in CR-VANETs. 2012 1st IEEE International Conference on Communications in China (ICCC), 659-663.

[15] Akter, S., & Mansoor, N. (2020). A Spectrum Aware Mobility Pattern Based Routing Protocol for CR-VANETs. 2020 IEEE Wireless Communications and Networking Conference (WCNC), 1-6.

[16] Ghafoor, H., & Koo, I. (2016). Spectrum and connectivity aware anchor-based routing in cognitive vehicular ad hoc networks. 2016 Eighth International Conference on Ubiquitous and Future Networks (ICUFN), 679-684.

[17] Nissel, R. (2022). Correctly Modeling TX and RX Chain in (Distributed) Massive MIMO—New Fundamental Insights on Coherency. IEEE Communications Letters, 26, 2465-2469.

[18] Choi, H., & Baji'c, I.V. (2022). Scalable Video Coding for Humans and Machines. 2022 IEEE 24th International Workshop on Multimedia Signal Processing (MMSP), 1-6.

[19] Schwarz, S. (2020). Recursive CSI Quantization of Time-Correlated MIMO Channels by Deep Learning Classification. IEEE Signal Processing Letters, 27, 1799-1803.

[20] Liu, J., Mishra, K.V., & Saquib, M. (2022). Precoder Design for Joint In-Band Full-Duplex MIMO Communications and Widely-Distributed MIMO Radar. ICC 2022 - IEEE International Conference on Communications, 4679-4684.

[21] Aujla, G.S., Singh, A., Singh, M., Sharma, S., Kumar, N., & Choo, K.R. (2020). BloCkEd: Blockchain-Based Secure Data Processing Framework in Edge Envisioned V2X Environment. IEEE Transactions on Vehicular Technology, 69, 5850-5863.

[22] Khan, A.U., Abbas, G., Abbas, Z.H., Baker, T., & Waqas, M.M. (2020). Spectrum efficiency in CRNs using hybrid dynamic channel reservation and enhanced dynamic spectrum access. Ad Hoc Networks, 107, 102246.

[23] Bagga, P., Sutrala, A.K., Das, A.K., & Vijayakumar, P. (2020). Blockchain-based batch authentication protocol for Internet of Vehicles. J. Syst. Archit., 113, 101877.

[24] Kalra, M., Vohra, A., & Marriwala, N. (2022). LEACH based hybrid energy efficient routing algorithm for dynamic cognitive radio networks. Measurement: Sensors.

[25] Xu, M., Yin, Z., Zhao, Y., & Wu, Z. (2022). Cooperative Spectrum Sensing Based on Multi-Features Combination Network in Cognitive Radio Network. Entropy, 24.

[26] Indumathi, G., & Vaithianathan, V. (2021). Optimal relay and channel selection schemes for multiconstrained QoS multicast routing in cognitive radio ad hoc networks. International Journal of Communication Systems, 34.

[27] Lee, W., & Song, H. (2021). Efficient Channel Feedback Scheme for Multi-User MIMO Hybrid Beamforming Systems. Sensors (Basel, Switzerland), 21.

[28] Shen, S., & Clerckx, B. (2020). Joint Waveform and Beamforming Optimization for MIMO Wireless Power Transfer. IEEE Transactions on Communications, 69, 5441-5455.

[29] Joon, R., & Tomar, P. (2022). Energy Aware Q-learning AODV (EAQ-AODV) routing for cognitive radio sensor networks. J. King Saud Univ. Comput. Inf. Sci., 34, 6989-7000.

[30] Hojatian, H., Nadal, J., Frigon, J., & Leduc-Primeau, F. (2020). Unsupervised Deep Learning for Massive MIMO Hybrid Beamforming. IEEE Transactions on Wireless Communications, 20, 7086-7099.

[31] Li, Q., Su, W., Zhang, P., Cheng, X., Li, M., & Liu, Y. (2022). Blockchain-Based Method for Pre-Authentication and Handover Authentication of IoV Vehicles. Electronics.

[32] Zhang, R., Wang, Y., & Feng, Y. (2022). A leakage-based hybrid beamforming design for multi-user mmWave massive MIMO systems. IET Communications.

[33] Jiang, Q., Zhang, X., Zhang, N., Tian, Y., Ma, X., & Ma, J. (2021). Three-factor authentication protocol using physical unclonable function for IoV. Comput. Commun., 173, 45-55.

[34] Ruan, H., Xiao, P., Xiao, L., & Kelly, J.R. (2021). Joint Iterative Optimization-Based Low-Complexity Adaptive Hybrid Beamforming for Massive MU-

MIMO Systems. IEEE Transactions on Communications, 69, 1707-1722.

[35] Wang, Y., Li, X., Wan, P., Chang, L., & Deng, X. (2021). Dueling deep Q-networks for social awareness-aided spectrum sharing. Complex & Intelligent Systems, 8, 1975 - 1986.

[36] Hossain, M.A., Noor, R.M., Yau, K.A., Azzuhri, S.R., Z'Abar, M.R., Ahmedy, I.B., & Jabbarpour, M.R. (2021). Multi-Objective Harris Hawks Optimization Algorithm Based 2-Hop Routing Algorithm for CR-VANET. IEEE Access, 9, 58230-58242.

[37] Srivastava, V., Singh, P., Malik, P.K., Singh, R., Tanwar, S., Alqahtani, F., Tolba, A.M., Marina, V., & Răboacă, M.S. (2023). Innovative Spectrum Handoff Process Using a Machine Learning-Based Metaheuristic Algorithm. Sensors (Basel, Switzerland), 23.

[38] Jayakumar, L., & Janakiraman, S. (2019). A novel need based free channel selection scheme for cooperative CRN using EFAHP-TOPSIS. J. King Saud Univ. Comput. Inf. Sci., 34, 1326-1342.

[39] Qi, C., Ci, W., Zhang, J., & You, X. (2022). Hybrid Beamforming for Millimeter Wave MIMO Integrated Sensing and Communications. IEEE Communications Letters, 26, 1136-1140.

[40] Rajpoot, V., & Tripathi, V.S. (2019). A novel proactive handoff scheme with CR receiver based target channel selection for cognitive