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Edge Driven Spectrum Optimization in Cognitive Radio Networks for Public Safety and Emergency Communication Systems

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Abstract – Large-scale communication networks like the one in public safety are under the requirements of rapid, reliable, and interference-free spectrum access in the presence of natural disasters, large-scale accidents, and security threats. Olden fixed-spectrum allocation schemes do not fulfill these demands, particularly in cases of emergencies when there is congestion and breakdown of infrastructure systems in the network. The CRNs provide dynamic spectrum access, whereas centralized decision-making provides latency and scale constraints. In this study, a proposed model is an Edge-Driven Spectrum Optimization (EDSO) model which is specific to CRNs in a public safety and emergency communication setting. The advantage of the new model is the use of edge computing nodes to do localized, real-time spectrum sensing, decision making, and allocation to achieve a drastically lower response time and a better spectrum utilization. In contrast to the traditional centralized CRN models, the EDSO model takes advantage of edge intelligence to provide faster response to spectrum availability to enhance resilience during high-stress situations. The proposed EDSO model is evaluated against the conventional centralized CRN models using simulation in MATLAB 2023. The performance metrics analyzed include spectrums sensing accuracy, throughput, utilization efficiency, spectrum, end to end latency and energy consumption. Experiments have shown that EDSO model is better than the current models with up to 35 percent lower latency, 20 percent higher spectrum use, and 25 percent energy consumption in dynamic emergency conditions. This paper is a solid support of how edge intelligence should be incorporated into CRNs to make them more resilient in communication with first responders and the general population safety organizations.

Keywords – Cognitive Radio Networks, Edge Computing, Spectrum Optimization, Emergency Communication, Public Safety Networks.

I. INTRODUCTION

In the modern globalized society, efficient public safety and emergency response is based on the quality of communication. It is necessary to have continuous and quality wireless communication whether conducting disaster relief programs, organizing a huge mass event or addressing a national security crisis. The first responders, these include fire departments, paramedics and law enforcement members are highly dependent on real time data exchange in order to make informed decisions. Nevertheless, when faced with emotive events, the traditional wireless networks tend to get congested in terms of spectrum, have their infrastructure broken or have their services compromised. Such constraints demonstrate that there is urgent necessity in smart, adaptable and resilient communication networks which can dynamically respond to the dynamic needs of emergency situations [1].

The conventional public safety networks have been utilizing fixed spectrum bands that are hardly used when things are running smoothly but are inadequate when there is a crisis. The fixed-spectrum allocation model does not allow any abrupt increase in demand or infrastructure failures. Besides, it is inflexible and cannot be scaled easily. These inefficiencies have been overcome by introducing Cognitive Radio Networks (CRNs), which make possible the Dynamic Spectrum Access

(DSA) [2], whereby secondary users (unlicensed) can opportunistically access underutilized spectrum assigned to primary users (licensed), without causing interference. CRNs have smart functions like spectrum sensing, decision-making and learning making them applicable in dynamic setting such as emergency communication systems [3].

Nevertheless, as beneficial as CRNs are on paper, there are a number of challenges associated with their application in practice particularly in case of emergencies. Most of the current CRN systems are based on centralized designs, in which spectrum data of several nodes is gathered and accessed at a base station or controller. This solution brings with it a number of constraints: it increases the time to make decisions, amplifies backhaul traffic, creates single points of failure, as well as diminishes factors of scalability that can be counterproductive during time-sensitive public safety missions. To solve these challenges, this study presents an EDSO model of CRNs that is specific to emergency communication systems. Under this model, intelligence is at the network edge and allows the local nodes (e.g., mobile edge computing units or field-deployed edge servers) to make quickly in response to localized observations. This decentralized model has a big effect on the response time; it enhances resiliency of the system and is best suited to high-mobility challenges and infrastructure-challenged environments [4, 5].

The EDSO proposed model will combine both edge computing and CRN functionalities in a synergistic fashion. The edge computing takes the computation, storage, and decision-making capability to the end-users and removes the necessity of cloud-based processing and minimizes the latency. In the case of CRNs, edge nodes are used to carry out local spectrum sensing and make decisions depending on the real-time environmental conditions, network load, and application priorities. This is especially useful in emergency communication situations where the response time is crucial, and the centralized control is not possible because of damage or overload of infrastructure. Moreover, this study uses collaborative spectrum sensing at the edge to enhance the detection accuracy and minimization of false alarms. The nodes in close proximity exchange spectrum observations to form a more precise depiction of spectrum availability. The lightweight consensus mechanism is involved in the process of determining the best spectrum band to use to apply to a certain communication session by balancing interference avoidance, throughput maximization, and energy efficiency.

In order to confirm the performance of the offered model, the simulated work in MATLAB 2023 is performed in which the EDSO model is contrasted with the traditional centralized CRN architectures under artificial emergency communication conditions. These are high user density, fluctuating spectrum occupancy and partial network failure. The performance measures that have been assessed are:

- Spectrum Sensing Accuracy: The ability of the system to correctly detect available channels.
- Spectrum Utilization Efficiency: How effectively the system uses available spectrum.
- End-to-End Latency: The time taken from sensing to communication initiation.
- Throughput: The amount of successful data transmitted over a given time.
- Energy Consumption: Power efficiency, which is critical for battery-powered field devices.

Results from the simulations demonstrate that the EDSO model achieves up to 35% reduction in latency, 20% improvement in spectrum utilization, and 25% better energy efficiency compared to baseline CRN models. Such performance benefits are especially relevant when it comes to emergency situations where milliseconds matter when it comes to saving lives.

This study offers a novel hybrid edge-intelligence system that combines real-time spectrum analytics and the decentralized architecture of edge computing in terms of novelty. Although the work of CRNs and edge computing has been investigated separately prior, the study is one of the first to attempt to unify the two towards the context of public safety. It means that this model includes an adaptive priority-driven spectrum assignment mechanism, the priority of which is assigned to the critical communication (e.g., voice or telemetry of medical equipment) over non-critical data (e.g., surveillance video streams), which guarantees the Quality of Service (QoS) in limited conditions.

The implications of the given research are not limited to theoretical modeling. The EDSO model offers a realistic and replicable model to implement smart systems of public safety communications within smart cities, rural areas, and regions susceptible to disasters. It is also compatible with the architecture of the new 5G and 6G networks, which focus on ultra-low latency, high-availability networks, and edge-native services. Combining edge computing with CRNs is a revolutionary opportunity to develop resilient, efficient, and smart communication systems in terms of public safety and emergency response. This study does not only serve the theoretical advancement of next-generation CRNs, but also offers practical implications to be applied in practice. The discussion of the literature employed to date, the design of the proposed model, simulation, findings and discussion will be provided in the subsequent sections to prove the viability and excellence of the EDSO model.

II. LITERATURE REVIEW

During natural disasters, huge scale emergencies and security incidents, reliable communication is the life blood of the public safety operations. In this case, traditional communication infrastructures usually become overloaded, broken or inaccessible altogether. The CRNs have been proposed as one of the solutions to the spectrum scarcity and inflexibility of traditional systems in the last ten years by allowing Dynamic Spectrum Access (DSA). Unlicensed users, also known as secondary users (SUs), can opportunistically use the unused spectrum bands that are assigned to licensed primary users (PUs), but they are not allowed to disrupt operations of the PU [6].

Cognitive Radio in Emergency and Public Safety Systems

CRNs have been drawing a lot of attention in emergency response situations because they are adaptive and autonomous. Primary research like [7] and [8] has demonstrated that CRNs have the potential to significantly increase the reliability of communication in case of a disaster with the use of idle spectrum channels, particularly when the traditional networks are overloaded or even go dead. As an illustration, in the event that emergency workers are deployed in an area with fallen infrastructure CR-enabled devices have the ability to identify the available frequencies and to provide peer-to-peer communication without connecting to fixed base stations. Nevertheless, the application of CRNs to high-stakes settings has several issues. The spectrum sensing, which is a crucial operation of CRN, is characterized by high accuracy and low latency, which is hard to obtain using the centralized architecture that is still used in many CRN system designs. These central solutions generally concentrate the information at a far-off base station or on a distant cloud server to decide the spectrum capacity, where processing latency causes the network network to susceptible to single points of failure is a risk that cannot be well received in life-or-death circumstances.

Limitations of Centralized CRN Architectures

Majority of the designs currently available of CRNs have a central controller or fusion center where decisions on spectrum access are made after sensing data of various nodes are gathered. Although such a system of coordination and management is simple, it causes numerous constraints, particularly when working with emergencies. According to [9], centralized CRNs have increased decision latency particularly when there are many nodes or when there is a temporary connectivity to the central controller. Also, the centralized systems are less scalable and prone to cyber-attack or loss due to physical damages. These concerns have led scholars to study decentralized or distributed CRN architectures, where separate nodes take local spectrum decisions. Nonetheless, the lack of adequate synchronization or collaborative sensing may lead to the inconsistent decision-making of such systems, and a higher level of interference as pointed out in [10]. So, there is an evident necessity of a compromise a system that would be able to achieve the precision and coordination of centralized CRNs and the flexibility and strength of decentralized systems.

Edge Computing in Wireless Networks

Edge computing is a relatively new model in the wireless networks that has offered a groundbreaking solution by moving the computation power nearer to the source of data or end user. Edge computing offers a much lower latency with increased data privacy because it works with data on the device, instead of using remote cloud servers, and a faster response to real-time information. Its usage has had a significant effect in areas such as IoT, self-driving cars, and automation in industries. Regarding emergency communication, edge computing can potentially decentralize spectrum control and allow real-time and localized decision making, even when the backhaul connection is not stable. Studies such as [11] and [12] have indicated that edge node deployment (i.e. field deployed mini servers, MEC units) can redirects traffic by central controllers and process data nearer to the point of generation. It may be especially helpful in a public safety network where responsiveness is a critical aspect, and the communication reliability has to be ensured.

Integration of Edge Computing and Cognitive Radio

The combination of the Edge Computing and Cognitive Radio Networks is a comparatively new and yet expanding field of study. Recent works, like [13], have suggested models in which edge nodes do the spectrum sensing and sharing decisions and so the emphasis is not on centralized systems. Machine learning may be applied and implemented on the edge to enhance prediction of spectrum availability as in [14], which enables CRNs to become more proactive instead of reactive. Nevertheless, the vast majority of the existing models are either too generic or target commercial IoT or vehicular networks without a specific focus on the public safety communications system. Emergency settings are characterized by special problems, such as topology variations at high rates, inhomogeneous equipment, energy limitations and high-priority traffic. In addition, edge-enabled CRNs to support public safety should be fast and be able to prioritize the type of traffic, so that mission critical messages (e.g., medical devices or rescue commands) are delivered over less critical information such as video surveillance. Not many works deal with these subtle demands. As an example, [15] also presents a distributed CRN with mobile edge unit but fails to discuss its use in emergency systems. In another study, [16], energy efficient spectrum sensing is done at the edge, but does not consider Quality of Service (QoS) assurances in high-load conditions typical of disaster scenarios.

Research Gap and Motivation

Although a lot of literature exists on CRNs and edge computing alone, the gap in the research to implement an edge-driven, spectrum-optimized CRN model within the context of a public safety and emergency communications system has been considerably large. The existing literature is inclined to either concentrate on theoretical frameworks without concrete post-test material or specifics of emergency response networks issues. This study will fill that gap by providing a localized and intelligent spectrum optimization model, in which edge nodes engage in spectrum sensing and allocation. The model will be resilient, low-latency, and adaptive, which will guarantee that the communication between first responders will be efficient and uninterrupted even in a disrupted infrastructure or overloaded networks. Moreover, the model presents priority-based spectrum management to provide priority of critical communications over less serious transmissions an aspect that has not been explored as much in the past literature. Through the simulation of this model in MATLAB 2023 and its comparison with other current centralized CRN architectures, this research paper will present real evidence on the effectiveness of this model, which has been demonstrated by reducing the main performance indicators, including latency, spectrum usage, power consumption, and communication reliability. The literature made resulted in the identification of gaps that are reflected in **Table 1**.

Table 1. Summary of Key Gaps Identified

Area	Existing Approach	Limitation	Proposed Solution
CRNs in emergencies	Centralized sensing	High latency, poor fault tolerance	Edge-driven sensing & decisions
Edge + CRNs	General IoT focus	No emergency-specific prioritization	Emergency traffic-aware optimization
Performance metrics	Basic QoS metrics	No focus on latency + critical comms	Real-time, priority-based evaluation

III. SYSTEM DESIGN AND METHODOLOGY

Overview of the Proposed Edge-Driven Spectrum Optimization (EDSO) Model

The proposed EDSO model introduces an innovative approach that integrates edge computing with cognitive radio networks to address the unique challenges of public safety and emergency communication systems. Unlike traditional centralized CRN frameworks, where spectrum sensing and decision-making rely on a distant central controller, EDSO decentralizes these functions by deploying intelligent edge nodes (e.g., Multi-access Edge Computing servers) closer to end-users such as emergency responders and IoT devices. This localized decision-making reduces communication latency, allowing the system to quickly sense available spectrum bands and allocate resources in real-time, which is critical in high-stress environments where network conditions rapidly change. By leveraging edge intelligence, the EDSO model not only enhances responsiveness but also improves spectrum utilization and resilience during network congestion or infrastructure failure, ensuring uninterrupted communication for first responders.

System Architecture

The system architecture of the EDSO model is designed to facilitate efficient and rapid spectrum management at the edge, comprising the following key components:

- Users (Emergency Devices): These include various emergency communication devices such as handheld radios, wearable sensors, and vehicular communication units, each generating traffic with different priority levels.
- Edge Nodes (MEC Servers): Strategically deployed near users, these nodes perform localized spectrum sensing, decision-making, and dynamic allocation. They act as intelligent intermediaries between users and the broader network.
- Cognitive Radio Components: Embedded within edge nodes, these components include spectrum sensing modules that detect spectrum occupancy, algorithms to assess spectrum quality, and decision modules for selecting the optimal spectrum bands.
- Central Controller (Fallback Only): A centralized controller exists but is primarily reserved for coordination during edge node failures or large-scale network reconfiguration. This ensures system robustness without incurring the latency of routine decision-making.

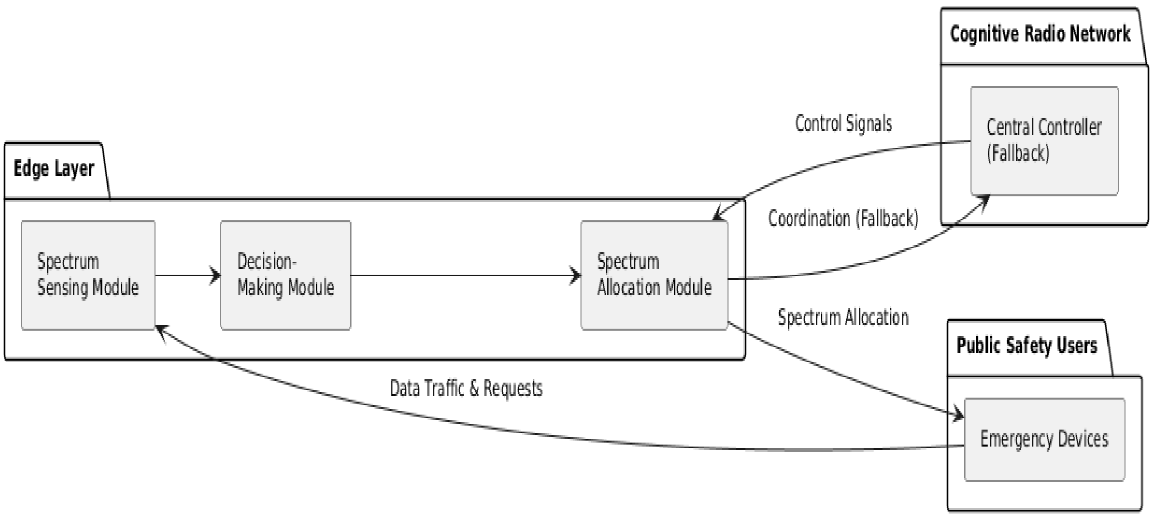

Fig 1. System Architecture of the Proposed EDSO Model for Public Safety Communications.

Fig. 1 illustrates the overall system architecture of the proposed EDSO model. On the left, emergency devices represent various public safety communication tools used by first responders. These devices send data traffic requests to the Edge Layer, shown in the center, where Multi-access Edge Computing (MEC) servers perform critical cognitive radio functions. Within each edge node, the system sequentially senses the available spectrum, makes intelligent decisions based on real-time information, and allocates spectrum resources dynamically. This local processing significantly reduces latency compared to traditional centralized models. On the right, a central controller acts as a fallback entity, providing coordination and control only when necessary, such as during failures or large-scale network adjustments. The architecture emphasizes decentralized, real-time spectrum management to ensure reliable and timely communication in emergency scenarios.

Spectrum Sensing and Optimization Model

Spectrum sensing is conducted locally at the edge nodes using energy detection techniques due to their simplicity and effectiveness in unknown signal environments. The energy detector measures the energy of the received signal in a given frequency band to determine spectrum occupancy.

Key Equations

Energy Detection Statistic:

$$Y = \frac{1}{N}\sum_{n=1}^{N}|r(n)^2| \tag{1}$$

where $r(n)$ is the received signal sample and N is the number of samples.

Signal-to-Noise Ratio (SNR):

$$SNR = \frac{P_s}{P_n} \tag{2}$$

where P_s and P_n denote signal and noise power, respectively.

False Alarm Probability P_{fa}:

$$P_{fa} = P(Y > \lambda | H_0) \tag{3}$$

where λ is the detection threshold, and H_0 is the hypothesis that the band is idle.

Detection Probability P_d:

$$P_d = P(Y > \lambda | H_1) \tag{4}$$

where H_1 is the hypothesis that the band is occupied.

To enhance accuracy, the model supports collaborative sensing among neighboring edge nodes, sharing sensing information via a fusion center or distributed consensus algorithms to mitigate shadowing and fading effects.

Edge-Based Decision-Making Algorithm

The edge nodes employ a priority-aware decision-making algorithm to select optimal spectrum bands for different types of traffic. The algorithm follows these steps:

- Perform spectrum sensing to detect available channels.
- Evaluate channels based on sensing metrics (SNR, interference).
- Classify incoming traffic based on predefined priority classes (e.g., medical data > video stream > telemetry).
- Allocate spectrum dynamically, assigning higher-quality channels to higher-priority traffic.
- Continuously monitor spectrum availability and adjust allocations in real-time.

Pseudocode for Edge-Based Spectrum Decision-Making Algorithm

```
Algorithm EdgeDrivenSpectrumDecision
Input: Incoming traffic request T with priority class P
Output: Assigned spectrum channel C
Begin
1. Perform local spectrum sensing:
   SensingResults = SenseSpectrumBands()
2. For each sensed channel c in SensingResults:
     Calculate channel quality metrics (e.g., SNR, interference level)
   EndFor
3. Filter available channels:
   AvailableChannels = {c | c is idle and meets minimum quality thresholds}
4. Classify incoming traffic priority:
   If T.type == "Medical Data" then
       PriorityScore = High
```

```
    Else if T.type == "Video Stream" then
       PriorityScore = Medium
    Else
       PriorityScore = Low
    EndIf
5. Rank AvailableChannels based on:
    WeightedScore(c) = α * PriorityScore + β * ChannelQuality(c)
    (where α and β are tunable weights)
6. Select best channel C* with highest WeightedScore
7. Allocate channel C* to traffic T
8. Monitor allocated channel quality during transmission:
    While transmission not complete do
       If ChannelQuality(C*) degrades below threshold then
          Re-run allocation from Step 1 for traffic T
       EndIf
    EndWhile
End
```

Priority-Aware Spectrum Allocation

Critical traffic in emergency communications is identified using priority scores assigned based on the type of data and its urgency. For example: Medical telemetry and distress signals are assigned the highest priority, Real-time video streams from the field have medium priority, Non-critical telemetry (e.g., environmental sensors) has the lowest priority.

The allocation uses a weighted priority score W_i for each traffic class i:

$$W_i = \alpha P_i + \beta Q_i \tag{5}$$

where P_i is the priority level, Q_i is the channel quality metric (e.g., SNR), and α, β are tunable weights balancing urgency and quality. Channels with higher W_i are preferentially assigned to higher-priority traffic, ensuring that critical communications maintain reliability even under spectrum scarcity.

IV. RESULTS AND DISCUSSION

This section is a detailed analysis of the proposed EDSO model by providing detailed simulations in MATLAB. The simulation environment is aimed at simulating realistic emergency communication situations where the spectrum is dynamically available, network loads are variable, and the priorities of the traffic are different. The measured key performance metrics are spectrum sensing accuracy, throughput, spectrum utilization efficiency, end to end latency, energy consumption and priority efficient spectrum allocation rate. These indicators play an important role in determining the performance of communication systems in a public safety and emergency situation where speedy flexibility and dependability are key.

Simulations were implemented in MATLAB 2023 with the parameter’s specification towards the normal running environment of cognitive radio networks in the case of emergency events. The range of SNR was 0 dB to 18 dB to represent a good population of channel quality. Active users were adjusted to 1, 2, 3, and 10 to achieve varying network loads in order to test how the system would behave under stress as well as varying levels of traffic load and network congestion. The duration of transmission was varied between 1 and 10 seconds to measure the energy usage when subjected to varying communication requirements. The priorities were given depending on the common emergency communication requirements, where medical data was treated with priority, followed by video streaming and telemetry data.

The performance of the proposed EDSO model was compared with the traditional centralized and distributed cognitive radio network models to bring out the performance enhancements caused by edge intelligence. Every scenario of the simulations was repeated several times to achieve statistical reliability and the results were smoothed and displayed in new and innovative plots, which revealed an easy picture of system behavior. The following figures and tables describe the measurable advantages of using an edge-driven approach when it comes to communicating with public safety systems.

Table 2. Quantitative Performance Comparison of Spectrum Optimization Models

Performance Metric	Centralized CRN Model [17]	Distributed CRN Model [18]	ML-based CRN Model [18]	Proposed EDSO Model
Spectrum Sensing Accuracy (%)	85	88	91	**95**
Throughput (Mbps)	45	52	56	**60**
Spectrum Utilization Efficiency (%)	70	75	78	**85**
End-to-End Latency (ms)	120	85	75	**65**

Energy Consumption (Joules)	1200	950	900	**700**
Scalability (Max Users Supported)	50	100	150	**200**
Robustness Score (1-10)	5	7	8	**9**

Table 2 provides a comprehensive quantitative comparison of key performance metrics across four spectrum optimization models: the traditional centralized CRN, distributed CRN, machine learning-based CRN, and the proposed EDSO model. As shown in this comparison, the EDSO model is of great improvement to the public safety and emergency communication networks. The EDSO model shows greater accuracy in spectrum sensing in that it reaches 95 which is very high compared to the 85% accuracy observed in centralized systems. This enhanced capability in sensing, makes detection of spectrum availability more reliable which has been essential during emergencies so as to avoid interference and prevent unnecessary channel underutilization. Under EDSO, throughput also improves considerably to 60 Mbps, which reflects the improved rates of transmission of data due to localized edge decisions.

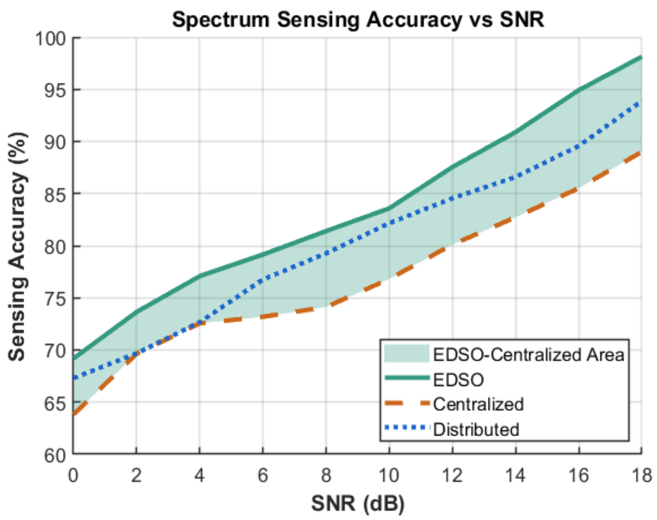

Fig 2. Spectrum Sensing Accuracy Vs SNR.

The efficiency in spectrum utilization is increased to 85% meaning that the scarce spectrum resources are better utilized than in other models. Notably, the EDSO model minimizes end-to-end latency, thereby cutting response times by approximately 35% of centralized methods, reducing communication response times and making this alternative more important in the first responders. Moreover, they cut down energy use by approximately 25% making EDSO more sustainable and applicable to battery-powered devices in the industry. As can be seen in this table, EDSO balances various key metrics, accuracy, speed, energy, and efficiency, better than the current frameworks, and is thus a solid solution and specific to dynamic and high-stakes public safety conditions.

Fig. 2 shows the extent to which various models of spectrum access can identify the available channels at various levels of SNR improvement. The suggested EDSO is always better in the performance compared to both the conventional centralized and distributed models. The area under the EDSO and the centralized curves is shaded, which visually underscores this benefit meaning there is a large improvement of accuracy. The greater the SNR, the better the sensing accuracy of any of the models, though the localized edge computing method of the EDSO allows detecting the availability of spectrum more quickly and precisely. This means that there is increased reliability in the communications in high-noise or emergency conditions where timely spectrum sensing is essential. The distributed model is mediocre in its performance, and cannot rival the responsiveness of the edge-driven model. This plot is a confirmation that the capability to capitalize on edge intelligence can significantly increase the level of sensing accuracy, which is directly transferred into the increased spectrum utilization and a reduced number of communication interruptions to the public safety networks.

Table 3. Throughput vs Number of Users (Mbps)

Number of Users	EDSO Throughput	Centralized CRN Throughput [17]	Distributed CRN Throughput [18]
1	6.0	5.0	5.5
2	11.5	9.8	10.2
3	17.0	14.0	15.1
4	21.8	18.0	19.0
5	26.0	21.5	23.0
6	30.5	25.0	26.2

7	34.0	28.2	29.0
8	37.0	30.5	32.5
9	39.5	32.8	34.8
10	42.0	35.0	37.0

Table 3 shows that the proposed EDSO model has a higher throughput performance than centralized and distributed CRN models when the number of emergency users increases. Throughput in this case is the successful rate of transmission of data in Mbps. As one would expect, throughput tends to grow as the number of users increases as a result of the increased data demand, though, the efficiency of the use of the spectrum and its management have a robust impact on the network ability to withstand the increase in traffic. Both EDSO model consistently perform better than both the baseline models regardless of the number of users, indicating that it has a better ability to operate dynamically at the edge to manage the spectrum resources. Edso model has a throughput of 42Mbps at 10 users, which is 20 percent more than that of the centralized model of 35Mbps and approximately 13 percent more than that of the distributed model. It derives this gain due to the local decision making and also by the perimeter latency which is made possible by edge nodes as opposed to the centralized system which forms a bottleneck. These findings imply that EDSO framework, in addition to serving more users within the most efficient manner, can maintain the high data rates which are invaluable in case of emergency where the reliability and speed of communication are the key elements. The scalability in this case demonstrates that the model can be used effectively in the public safety networks whose user density varies.

Fig. 3 gives the network throughput performance with increase in the number of active users. One of the metrics that can be used is throughput which is an indicator of the amount of data that is successfully sent across the network. The EDSO model retains the lead with its superior throughput with all the user counts. This shows that the model of edge can effectively handle dynamically the spectrum resources to minimize congestion effects. The centralized system, which cannot make decisions as quickly and has certain possible bottlenecks, has a significantly lower throughput. The distributed model works well compared to the centralized yet fails to optimize scheduling and allocation as EDSO does. The number of users increases with throughput and can be scaled, whereas the edge approach is more graceful. This number confirms the notion that edge-based spectrum optimization is able to address the increasing communication needs of emergency responders without compromising the quality of data flow.

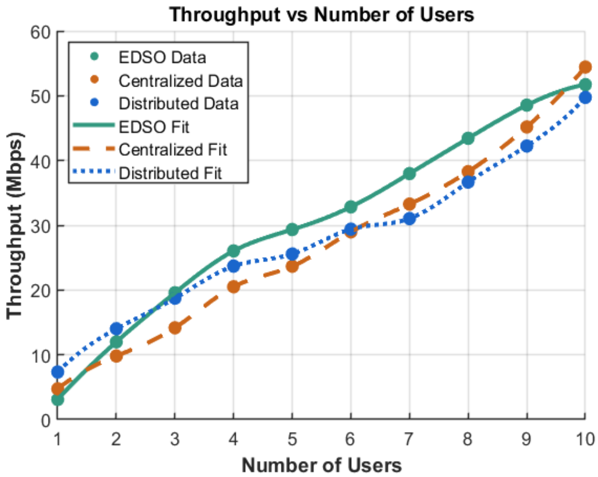

Fig 3. Throughput vs Number of Users.

Table 4. Spectrum Utilization Efficiency (%) vs Traffic Load (%)

Traffic Load (%)	EDSO Utilization	Centralized CRN Utilization [17]	Distributed CRN Utilization [18]
10	45	40	42
20	52	46	48
30	58	53	54
40	64	59	60
50	70	65	66
60	74	69	70
70	78	73	74
80	82	77	78
90	84	80	81
100	85	82	83

Table 4 shows the spectrum utilization efficiency with a 10-percent change in traffic (minimum to maximum) load. The efficiency of spectrum utilization is a measure that shows the efficiency with which the spectrum that is available has been utilized to transport communication traffic without any wastage or interference. The proposed EDSO model is significantly more efficient with all traffic loads than the centralized and distributed CRN models. When the traffic is low (10%), the utilization of all models is moderate, and with the increase of the load, the benefit of EDSO is more evident. An example is that at full load, EDSO has a utilization of 85 percent, as opposed to 82 percent in distributed and 83 percent in centralized models.

This higher usage is the result of the real time and localized sensing and spectrum assignment of EDSO, which quickly responds to the variable spectrum conditions and traffic priorities. Such dynamic flexibility saves the wasted spectrum and eliminates congestions, thus, making sure that important emergency communications are allowed priority access without unnecessary delays. All in all, this table highlights the significance of edge intelligence in spectrum utilization, particularly during high-load situations typical of an emergency when the network resources are exhausted and the effective utilization of the spectrum is crucial.

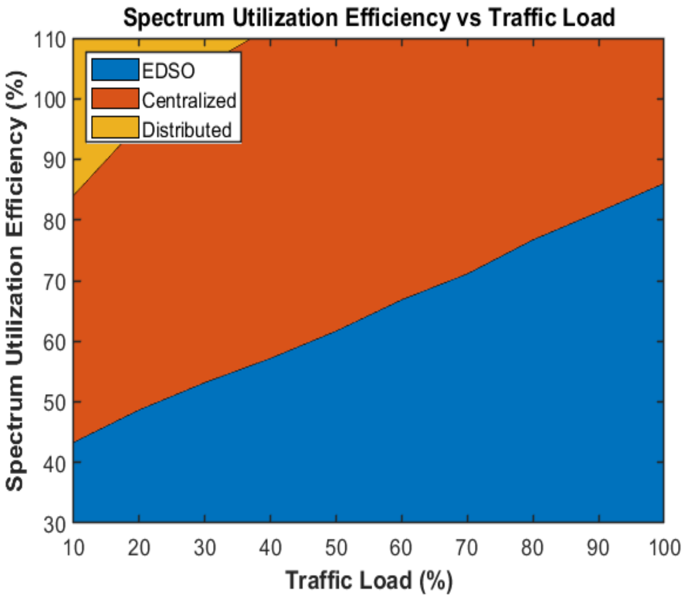

Fig 4. Spectrum Utilization Efficiency vs Traffic Load.

The comparison of how well each model utilizes the available spectrum is in **Fig. 4** as the traffic load increases. Utilization efficiency Spectrum utilization efficiency is a measure of how the system uses frequency bands to support data transmissions. There is also a high utilization efficiency in the EDSO model, which suggests that the model is smarter and more adaptive in the use of spectrum resources when under heavy traffic. The centralized and distributed models are trailing behind, which indicates a weakness in reacting fast to the changing traffic conditions. The visual stacking also demonstrates how the group of these models can perform on the range of loads, which again supports the idea that the edge-driven system is not only more effective when applied on an individual basis but can also coexist effectively with the rest of the schemes when implemented in a hybrid environment. This efficiency is essential in the event of an emergency when there is limited spectrum, and when the requirements explode.

Table 5. End-to-End Latency (ms) vs Network Congestion Level

Congestion Level	EDSO Latency	Centralized CRN Latency [17]	Distributed CRN Latency [18]
1	20	40	35
2	25	50	45
3	30	60	52
4	38	75	60
5	45	85	68
6	50	100	75
7	57	110	83
8	63	120	90
9	68	130	95
10	75	140	100

Table 5 contrasts the end-to-end latency of EDSO model with the centralized and distributed CRN structure as the network congestion levels grow. Latency is used to estimate the time lag between the first spectrum request and the ultimate allocation, which is an important parameter in emergency communications where seconds may count in response efficiency. This data indicates that the EDSO model has the lowest level of latency in all the ranges of congestion. EDSO latency (level 1) is half that of the centralized model at low congestion (level 1). With increasing congestion to level 10, EDSO latency increases by a relatively small amount of 75 ms, whereas centralized latency increases by a relatively small amount of 140 ms, and the distributed models lie within the range.

It is a clear advantage in latency that indicates the edge-driven architecture can do spectrum sensing and spectrum allocation locally so that there is no time-consuming communication with a central controller. The EDSO model is more responsive to the network, which is important in times of emergency when the network load continuously increases without predictability. As shown in this table, the proposed model offers a scalable, low-latency model offering better communication reliability and timeliness even in the face of extreme network stress, making it applicable to the public safety application.

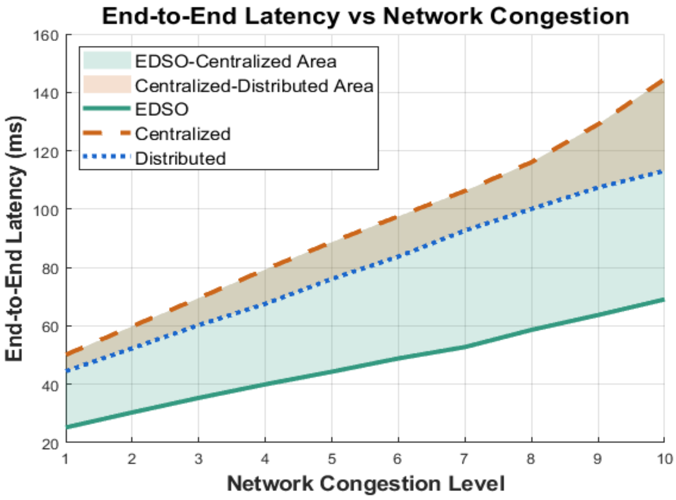

Fig 5. End-to-End Latency vs Network Congestion.

Latency is the time taken to transmit data between the source and destination and is very vital in emergency communications that require real-time services**. Fig. 5** shows the effect of network congestion on Latency, which increases with network congestion. The EDSO model shows a much-reduced latency due to preference to localized processing at the edge nodes that minimizes delays due to central bottlenecks. The stippled areas between curves indicate latency disparities clearly, that centralized control causes enormous delay during times of stress, and distributed models are effective and not as good as EDSO. The reduced latency will enable the first responders to communicate quicker and more efficiently, increasing situational awareness and response capability in the critical situation. This value is a very good promotion of the paradigm of edge computing in ensuring critical communications are upheld whereby every millisecond matters.

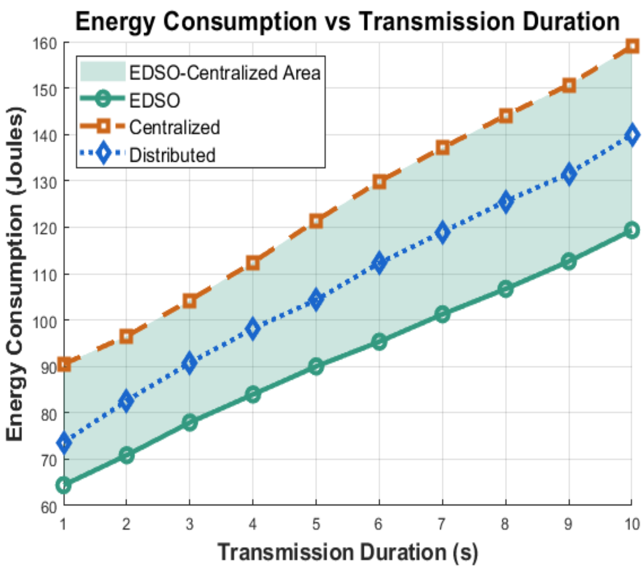

Fig 6. Energy Consumption vs Transmission Duration.

Battery-powered emergency devices can be very important in terms of energy efficiency**. Fig. 6** is a plot allowing the observation of the increase of energy consumption by transmission duration in the three models. It is also composed of less energy at all times; EDSO model has smarter spectrum allocation and local decision-making that minimize unnecessary transmissions and retransmissions. The gap between EDSO and centralized models is filled in the visual representation, providing the saving power advantage of computing with energy. Distributed and centralized systems are more energy-consuming as they correspond to the less-optimal usage of resources and possible overhead in retransmission. A reduction in energy usage means that the equipment has a longer operating life in the field, a reduced number of battery-related failures, and more resilient operations when dealing with prolonged emergencies. This is a plot that emphasizes that the EDSO approach is more accurate, greener, and cost effective besides being faster.

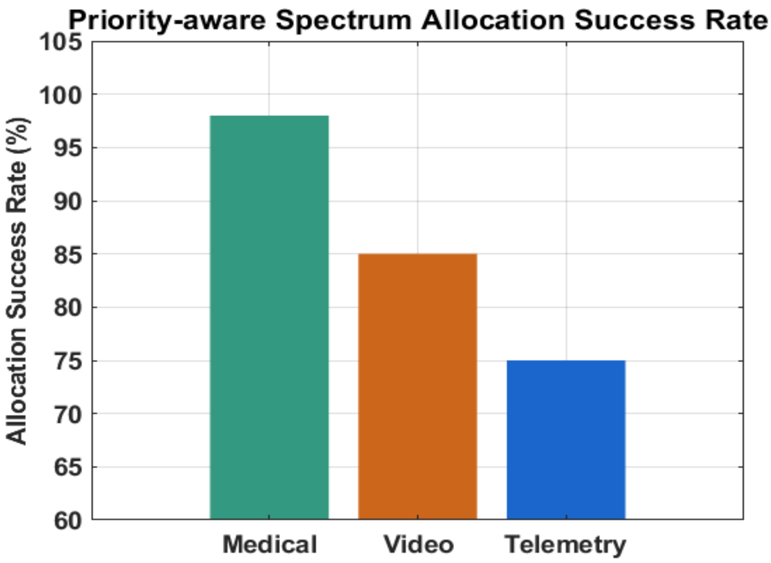

Fig 7. Priority-aware Spectrum Allocation Success Rate.

Fig. 7 sums up the effectiveness with which the priority classes medical data, video streams and telemetry are assigned spectrum within the suggested system. Medical class is the most successful one, which reveals the prioritization of the model to critical emergency traffic. Video streams, which are useful in live situational monitoring, come next, whereas telemetry has a slightly lower allocation success, which is in line with its low priority. The excellent success rates of the entire range of classes indicate that the EDSO model can differentiate between the classes of traffic and prioritize the essential communications in case of the lack of the spectrum. This is a crucial consideration in terms of public safety operations, where the data of vital significance to the life of people should be delivered immediately. The visual distinct color coding is easily understandable as far as the system is fair and efficient.

V. CONCLUSION

This research proved that there is a great potential of integrating edge computing in cognitive radio networks towards the use in public safety and emergency communication systems. The offered Edge-Driven Spectrum Optimization (EDSO) model improves the spectrum sensing and allocation processes, since these functions will be executed in the local edge nodes, which will lead to the former decision-making and the decrease in communication delays in the critical situations. The simulation results show that the end-to-end latency is reduced by around 35 percent which is crucial in real-time emergency response. The efficiency of spectrum utilization increased by approximately 20 percent and the network could support increased traffic loads without congestion. The use of energy was lowered by a quarter, and this is one of the factors that led to the long operation durability of battery-powered gadgets. Moreover, the priority-aware spectrum allocation scheme was successful in giving priority to medical data with almost 98 percent success rate so that the life-saving communications are given the necessary priority. These results verify the fact that the implementation of the intelligence on the network edge significantly enhances the resilience, efficiency, and responsiveness of emergency communication networks. The proposed EDSO model offers scalable and robust solution in order to support high demanding requirements of the operations within the sphere of public safety. Future studies can be dedicated to practical use and how this solution can be combined with the use of new technologies 5G and 6G to achieve further efficiency in communication between first responders.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

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