

Development of Enhanced Chimp Optimization Algorithm (OFCOA) in Cognitive Radio Networks for Energy Management and Resource Allocation

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ABSTRACT

Transmit time and power optimisation increase secondary network energy efficiency (EE). The optimum resource allocation strategy in cognitive radio networks is the enhanced chimp optimisation algorithm (OFCOA) since the EE maximising problem is a nonlinear fractional programming problem. To control resources and energy, this research offers an energy-efficient CRN opposition function-based chimpanzee optimisation algorithm (OFCOA) solution. Combining the opposition function (OF) with the chimpanzee optimisation technique is recommended. OF in COAs improves decision-making. Spectrum measurements in energy management provide energy-efficient CRN operation. The suggested technique was evaluated using channel occupancy, CRN data, and four major and secondary user scenarios. CPU power, network life, transmission rate, latency, flush, power consumption, and overhead are utilized to evaluate the proposed approach in MATLAB. The proposed method is compared to existing approaches like Particle Swarm Optimisation (PSO), Chimpanzee Optimisation Algorithm (COA), and Whale Optimisation Algorithm.

KEYWORDS

Average Energy, Cognitive Radio Networks, Energy Efficient, Energy Utilization, Resources, Spectrum Sensing

1. INTRODUCTION

Since the launch of mobile networks many years later and the development of small correspondence, research has focused on improving resilient networks, less complexity, and less fatigue while increasing the speed of corporate governance. The main boundary rules of the project, spectral

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characteristic features (SE) (Salma Benazzouza et al., 2021); Energy Efficiency (EE) (Kalpana Devi. M and Umamaheswari. K, 2021); And Energy Harvest (EH) seem to have a huge interest in future telecommunications systems for 5G Smart Radio Systems (5G-CRN) by 2021. While many different regions of the country face serious limit shortages, there are still limit deficits, in addition, that is, in many places, there are definitely problems with the use of limits (Manish Kumar Giri and Saikat Majumder, 2021). Therefore, a large amount of work is required to modernize marginal productivity methods. Like global climate issues, energy efficiency is another potential project area for sophisticated telecommunications companies due to limited access and wasteful use of mobile phone battery power (Rohit. B, Chaurasiya and Rahul Shrestha, 2021). Other things being equal, strategies that increase spectrum efficiency lead to a decrease in energy efficiency (Chih-Lin Chuang et al., 2021).

The Enhanced Chimp Optimisation Algorithm (OFCOA) is a significant development in Cognitive Radio Networks (CRNs) Energy Management and Resource Allocation. It boosts network performance and addresses increased bandwidth demand by improving spectrum utilisation through dynamic resource allocation. OFCOA is also concerned with energy management, aiming to reduce power consumption and transmission costs while also contributing to environmentally friendly communication networks. Its impact extends beyond network advantages to encompass broader environmental and economic advantages. The OFCOA algorithm improves network performance by appropriately distributing resources based on real-time demands and circumstances. This adaptability is crucial in dynamic wireless scenarios. OFCOA allows networks to self-adjust to changing conditions, resulting in smarter and more efficient communication systems. This approach is an important step towards the development of long-term, high-performance cognitive radio systems.

The development of the Enhanced Chimp Optimization Algorithm (OFCOA) in Cognitive Radio Networks (CRNs) shows promise for Energy Management and Resource Allocation. However, further research is needed to validate its performance in real-world CRN scenarios and compare it with existing optimization algorithms. Additionally, the scalability and computational complexity of OFCOA in large-scale CRNs need to be assessed to ensure practical deployment. The Enhanced Chimp Optimization Algorithm (OFCOA) in Cognitive Radio Networks (CRN) needs to be thoroughly examined for its security implications and practical implementation in real-world scenarios. Addressing these gaps is crucial for establishing the algorithm's credibility, efficiency, and applicability in communication systems, contributing to advancements in energy management and resource allocation in wireless networks.

The main test of the 5G architecture is to achieve high spectrum efficiency while using very low cell phone power levels. This problem is solved by offering better interchange between SE and EE by providing Quality of Service (QoS) (Monisha Devi et al., 2021) in 5G-CRN. Limit detection is the main part of the CRN, which takes into account the main part of the CRN, which is the blank validation range. Traditional range detection consists of sophisticated techniques such as filter matching (MF), cyclic detectors, and the most complex eigenvalue indicator i.e. energy detectors. However, energy detection strategies are more complex methods. The low signal has a horrible display at the first noise level (Surya Narayana Sanka et al., 2021). Efficient detection methods such as loop lock detectors are suitable for detecting gaps in range efficiently, although this requires a longer detection time. With a fixed advantage, as the collection time increases, the delivery time decreases. Pilot performance is usually reduced, which does not attract CRN (Rodney Martinez Alonso et al., 2021). MF plots are also very reliable but require prior knowledge of site PU signals. Without previous PU signal data, the representation of the MF system would be dramatically reduced. In addition, the MF strategy requires a separate user for each type of qualification, making it more complex in this way (Nehal M. El Azaly et al., 2021).

Energy efficiency is a top goal in CRN networks since it increases the lifespan of the network design, which improves the spectrum characterization process (Jaya Lakshmi Arikatla et al., 2021). This CRN power is used during spectrum noise and data transmission and reception transactions. This power consumption is increased by unwanted activity on the CRN. Therefore, reducing power

consumption is an important goal in reducing unwanted activity in CRNs. There are many different methods to improve the energy efficiency of CRN (Ayman A. El-Saleh et al., 2021). The need for performance-improving equipment is a disadvantage of conventional spectrum measurement methods. By permitting suitable optimisation methodologies, the efficiency of traditional spectrum measurement techniques can be improved. However, methods for enhancing cyclisation and MP detectors can significantly increase the complexity bar, which lowers RC performance (Chih-Lin Chuang et al., 2021). As per (Pravin M. 2022), In order to improve the overall energy efficiency of the network, this research incorporates the WOFA algorithm and the MATLAB design of coding throughout the whole wireless sensor network. This resolves the wireless sensor network's energy problem and enhances energy in general. The hybrid whale optimisation method was created by Pravin M. in 2022 for an energy-efficient cognitive radio network. Recently, it is believed that artificial intelligence (AI) methods (Dinesh. G et al., 2021, Maddali Arun Kumar and Siddaiah. P 2021) improve the energy efficiency of CRN networks. Researchers have developed a variety of optimisation methods to solve objective functions, such as the whale optimisation algorithm (WOA), grey wolf optimisation algorithm (GWO), spider monkey optimisation (SMO), particle flock optimisation (PSO), and firefly algorithm (FA). Using the RF energy harvesting approach, wireless nodes may transform electromagnetic energy from RF sources (including radio, TV, and cellular base-stations) into electrical energy for use in data transmission and self-powering (Rathish, C. R., and A. Rajaram, 2016). RF energy harvesting is more flexible and sustainable than traditional EH sources (S Rahamat Basha et al. 2022) like the sun, wind, waves, and heat since ambient transmitters may continuously broadcast RF signals with few restrictions on time, space, or locations (Rathish, C. R., and A. Rajaram., 2015, D. N. V. S. L. S. Indira et al. 2022, P. Ganesh, 2022). The contribution of the proposed work is

- We first present a unique EE maximisation model of underlay Cognitive Radio Networks as a nonlinear fractional programming problem with specified constraints, in contrast to prior research that created the paradigm to improve secondary user of underlay Cognitive Radio Networks. We specifically make use of the leftover energy from a previous transmission block, which increases the flexibility of secondary users' energy use and generalises the application scenario.
- Second, simply considering energy and interference limits when optimising EE is insufficient to guarantee the QoS of secondary users. We examine the combined allocation of harvesting time and transmitting power in the EE maximisation issue, and we impose a minimum throughput requirement and residual energy of secondary users into the constraint conditions.
- To address the nonlinear fractional optimum solution of EE maximising, a novel energy-efficient resource allocation strategy based on the Enhanced Chimp Optimisation method (OFCOA) is given. Two advantages of this strategy are rapid convergence and disregard for residual energy starting values.

1.1 Literature Review

In the evolving world of wireless communication, optimising energy management and resource allocation within Cognitive Radio Networks (CRNs) is a significant task. Traditional optimisation algorithms have been helpful, but the need for more flexible and intelligent strategies has resulted in the invention of the Enhanced Chimp Optimisation Algorithm (OFCOA). This algorithm is inspired by chimp foraging behaviour and has novel features designed to solve the complexities of CRNs. Numerous studies have been carried out to investigate CRN optimisation utilising various methodologies such as genetic algorithms, particle swarm optimisation, and simulated annealing. Traditional approaches, on the other hand, usually fail to cope with the constantly changing circumstances inherent in CRNs. OFCOA signifies a paradigm shift by adding bio-inspired ideas into the optimisation process. The system mimics the collaborative and adaptive behaviours observed in chimp foraging, improving its ability to navigate the complexities of CRNs (M. Dinesh et al., 2022).

OFCOA has been used successfully in CRNs, particularly in energy management and resource allocation. By constantly reacting to altering spectrum availability and user needs, OFCOA has demonstrated its usefulness in optimising energy consumption and efficiently allocating resources. In simulations and experiments, researchers evaluated the algorithm's performance using criteria such as throughput, latency, and energy economy. The competitive advantage of OFCOA has been repeatedly highlighted in comparison testing against established optimisation approaches. While the current literature supports the promise of OFCOA, numerous research gaps necessitate further examination. Because the algorithm's performance in large-scale CRNs is not fully known, scalability remains a challenge. Furthermore, the security implications of OFCOA in CRNs demand a more thorough analysis to guarantee that the optimisation process does not inadvertently introduce vulnerabilities or damage network integrity. Furthermore, further study into the actual deployment of OFCOA in real-world CRNs is required, taking into account factors like as hardware limitations, protocol compatibility, and seamless integration into existing communication infrastructures (S Kannan, A Rajaram, 2017).

Addressing these research gaps is crucial for validating and enhancing the use of OFCOA in the complex setting of CRNs. Future research should concentrate on scalability assessments, security considerations, and realistic implementation scenarios, fostering a complete understanding of OFCOA's potential impact on energy management and resource allocation inside CRNs. Finally, the literature on the Development of Enhanced Chimp Optimisation Algorithm (OFEOA) in Cognitive Radio Networks illustrates the algorithm's new technique and promising outcomes in energy management and resource allocation. As CRNs expand, OFCOA stands out as a beacon of adaptive intelligence, offering solutions that have the ability to revolutionise the landscape of wireless communication optimization (RP Prem Anand, A Rajaram, 2022).

2. PROPOSED COGNITIVE RADIO NETWORK SYSTEM MODEL

The concept of cognitive radio, which enables the best possible use of the radio spectrum, relies heavily on dynamic spectrum access. However, CRN networks may be affected due to energy efficiency issues. To solve the energy efficiency problem, the proposed OFCOA is developed in the CRN network by reducing the interference and interference problems. In the proposed OFCOA approach, the functionality's multifunctional nature is taken into account, which improves the network's energy efficiency. The proposed OFCOA algorithm completes the desired task while improving energy effectiveness. The suggested technique is tested by creating a CRN model, which is described in more detail below.

2.1. System Model

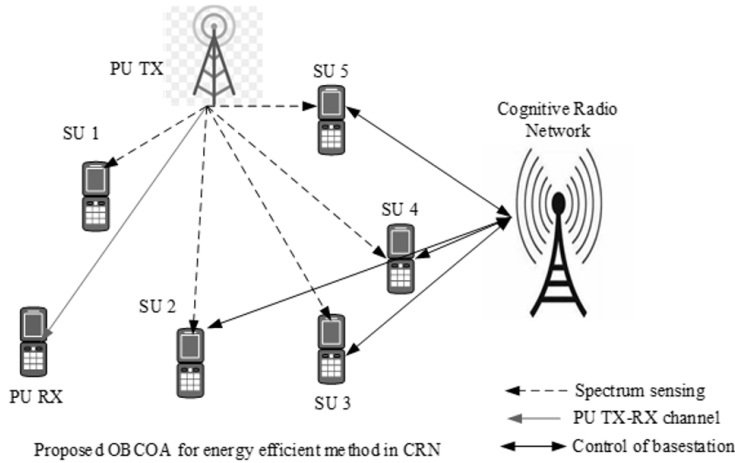
The proposed CRN network consists of secondary users who share an existing similar spectrum with similar geographic locations. The CRN time interval is shown in the figure 1 a and b. CRN time slots are divided into two-time slots such as data transmission and spectrum sharing (Rathish, C. R., and A. Rajaram, 2016)).

In the figure 1, data transmission is denoted as D^T and spectrum sharing is denoted as S^S . The mathematical representation of spectrum sensing in the CRN network is as follows.,

$$H^{L0} : Y^{J,L}(I) = W^{J,L}(I) \left[Hypothese0(PU Absent) \right] \quad (1)$$

$$H^{L1} : Y^{J,L}(I) = S^{J,L}(I) + W^{J,L}(I) \left[Hypothese1(PU Absent) \right] \quad (2)$$

Figure 1. An analysis of (a) the CRN network's time slot and (b) a suggested energy-saving technique



where, $J = 1, \dots, N^S$ can be described as secondary users, $I = 1, \dots, K^J$ can be described as time index and $L = 1, \dots, N^{SC}$ can be described as number of subcarriers, $W^{J,L}$ can be described as gaussian distribution based white noise with the zero and variance $\sigma_{J,L}^2$, H^{L1} can be described as hypotheses 1 for the l^{th} subcarrier representing the presence of the PU signal, H^{L0} can be described as hypotheses 0 for the l^{th} subcarrier representing the presence of the PU signal, $S^{J,L}$ can be described primary signaling similar to zero mean and variance with stationary random process $\sigma_{sJ,L}^2$, $K^J = F_J^S T_J^S$ can be denoted as number of samples, T_J^S can be described as sensing time of the j^{th} SU and F_J^S can be described as sampling frequency time. The energy calculation related on neyman pearson framework decision rules of the j^{th} carrier l^{th} subcarrier can be computed based on below equation,

$$E_{J,L}^N = \frac{1}{K^J} \sum_{l=1}^{K^J} \left| Y^{J,L(l)} \right|^2 \langle H^{L0} \rangle H^{L1}, \lambda^{J,L} \quad (3)$$

$$E_{J,L}^N | H^{1R} \sim n \left(\mu^J, \frac{L |R, \sigma_J^2 L |R}{K^J} \right) \quad (4)$$

where, K^J can be described as normal distribution function, $R = 0, 1$ can be described as energy detection and hypotheses related on various hypotheses. The variance is denoted by $\sigma_J^2 L$ and mean is denoted by μ^J . This mean and variance is computed based on below equation,

$$\mu^{J,L} | R = \begin{cases} \sigma_{J,1}^2 & \text{if } R = 0 \\ \sigma_{sJ,1}^2 + \sigma_{J,L}^2 & \text{if } R = 1 \end{cases} \quad (5)$$

$$\sigma_{J,L}^2 | R = \begin{cases} \sigma_{J,1}^4 | R & \text{for } R = 0 \\ E|S^{J,L}|^4 + 2\sigma_{J,L}^2 - (\sigma_{S_{J,I}}^2 - 2\sigma_{J,L}^2)^2 & \text{for } R = 1 \end{cases} \quad (6)$$

With the consideration of the Gaussian PU signal which mathematically formulated as follows,

$$\sigma_{J,L}^2 | R = \begin{cases} \sigma_{J,1}^4 | R & \text{for } R = 0 \\ (\sigma_{S_{J,I}}^2 - 2\sigma_{J,L}^2)^2 & \text{for } R = 1 \end{cases} \quad (7)$$

The probabilities of detection and false alert can be numerically expressed as follows using the formulas described above,

$$Prob^{FJ,L}(\lambda^{J,L}, T_j^S) = q \left(\sqrt{T_j^S F_j^S} \frac{\lambda^{J,L} - \mu^{J,L} | 0}{\sigma^{J,L} | 0} \right) \quad (8)$$

$$Prob^{DJ,L}(\lambda^{J,L}, T_j^S) = q \left(\sqrt{T_j^S F_j^S} \frac{\lambda^{J,L} - \mu^{J,L} | 1}{\sigma^{J,L} | 1} \right) \quad (9)$$

The suggested method aids in the research and improvement of energy efficiency and is based on the CRN system model. The next part illustrates the energy-efficient analysis and aim functions.

2.2. Energy Efficient Analysis

In CRN networks, spectrum definition plays an important role in the energy-efficient operation. In CRN, a large amount of power is used to achieve periodic noise for the spectrum and a high detection probability. Among them, power consumption affects the accuracy of measurement results. Large energy costs are taken into account when transmitting service information in the sound of the shared spectrum. Therefore, the energy-efficient operation is a mandatory operation in CRN networks. Energy efficiency calculations are performed under a variety of conditions. The energy efficiency calculations of the CRN network are described below. In CRN, the energy efficiency function is usually calculated with various spectral noise conditions. In contrast to energy efficiency functions, which are used to explain why a system detects PU when the channel would typically be represented by PU and vice versa, probability functions are used to characterize the free and busy channel states. This situation has an immediate effect on the system's processing power (Kumar, K. Vinoth, and A. Rajaram, 2019, CR Rathish, A Rajaram, 2018). Average power usage and total productivity during gearbox and measurement are strongly correlated. CRN energy consumption is represented as ES per sample. The energy efficiency functions of various spectrum measurement sets are theoretically investigated in the sections that follow:

Condition 1: In this case, SU finds the channel and PU fills the empty space. The probability function in this case is represented by the following phrase,

$$Q^{ON} \times Prob^{DJ,L}(\lambda^{J,L}, T_j^S) \quad (10)$$

In this case, the SU is just utilised for sensing and not for data transmission. This need is demonstrated by the following mathematical equation,

$$E^1 = \sum_{J=1}^{N^s} \sum_{L=1}^{N^{sc}} T_J^S F_J^S E^s Q^{ON} Prob^{DJ,L} \left(\lambda^{J,L}, T_J^S \right) \quad (11)$$

Here, Q^{ON} be defined as the possibility of a busy channel.

Condition 2:In this case, PU fills the empty area but SU is unable to recognised the channel. The following formula is used to determine the CRN's possibility in this circumstance (K. Mahalakshmi et al., 2021),

$$Q^{ON} \times Prob^{MDJ,L} \left(\lambda^{J,L}, T_J^S \right) \quad (12)$$

The SU and PU use this channel continually, which causes the PU gearbox to start. Energy efficiency is quantitatively defined as follows under given circumstances,

$$E^2 = \sum_{J=1}^{N^s} \sum_{L=1}^{N^{sc}} \left(T_J^S F_J^S E^s + Q^{J,L} \left(T^p - T_J^S \right) \right) Q^{ON} Prob^{DJ,L} \left(\lambda^{J,L}, T_J^S \right) \quad (13)$$

Condition 3:The SU acknowledged that the channel was in this case mistakenly occupied but decided against sending any information because of the chance of a false alert. The probability in this scenario may be expressed mathematically as follows,

$$Q^{OFF} \times Prob^{F,J,L} \left(\lambda^{J,L}, T_J^S \right) \quad (14)$$

Energy efficiency is mathematically expressed as follows under these circumstances,

$$E^3 = \sum_{J=1}^{N^s} \sum_{L=1}^{N^{sc}} T_J^S F_J^S E^s Q^{OFF} Prob^{DJ,L} \left(\lambda^{J,L}, T_J^S \right) \quad (15)$$

Condition 4:In this instance, SU is accurately recognising it because the channel is empty. The following sentence serves as a representation of the probability function in this situation,

$$Q^{OFF} \times \left(1 - Prob^{F,J,L} \left(\lambda^{J,L}, T_J^S \right) \right) \quad (16)$$

The energy-efficient and spectrum sensing behaviour is mathematically described as follows,

$$E^4 = \sum_{J=1}^{N^s} \sum_{L=1}^{N^{sc}} \left(T_J^S F_J^S E^s + Q^{J,L} \left(T^p - T_J^S \right) \right) Q^{OFF} \times \left(1 - Prob^{F,J,L} \left(\lambda^{J,L}, T_J^S \right) \right) \quad (17)$$

Based on the aforementioned information, the computation that follows is performed to determine the average energy use,

$$E^{avg} = \frac{E^1 + E^2 + E^3 + E^4}{T^p} \quad (18)$$

The following is the formulation of the suggested full objective function,

$$OBF = Min(E^{avg}) \quad (19)$$

The OBF may be used to define the objective function in this situation. Data transmission efficiency and decreased spectral noise are the recommended target functions for CRN networks. Based on the opposition function, the target function is determined using the COA approach. The section that follows provides a detailed explanation of the proposed technique's whole procedure.

2.2.1. Oppositional Function-Based Chimp Optimization Algorithm

The proposed procedure is primarily aimed at power reduction in CRN networks. CRN network power consumption is reduced, which ensures energy efficiency and spectrum-conscious system operation. In the proposed methodology using COA, the mathematical formula is as follows:

2.2.2.1. Motivation

The chimpanzee society is typically the fission-fusion society. The affiliation of a society may be utilised for many different purposes across time when seen as a single society. In addition, in society, each member has certain special responsibilities and abilities, which can change over time. From the considerations in this algorithm, the goal of the independent concept develops. Because of this, every group of chimpanzees searches for a location with distinctive traits that was created only for them. Most typically, chimpanzees fall into one of four categories: attackers, pursuers, barriers, and mahouts. Based on this type, the behavior of chimpanzees in the hunting process is modified for effective hunting. In the chimpanzee algorithm, mahouts collect prey without participating in the hunting process. There are obstacles in the plant that create a barrier for the victim to escape. The pursuers quickly caught the prey. Eventually, the attacker determined the victim's escape route to the bottom canopy. Attackers need to be more effective in detecting ongoing victim changes. Moreover, after a successful hunt, the attackers collected a larger piece of meat (K. Mahalakshmi et al., 2021, J. Divakaran et al., 2022).

Chimpanzee calculations link age, IQ, and real capability to the sort of assault. Sims can also modify their general approach or methodology while working on a particular assignment. Chimpanzee Chase exchanged his ability to slaughter animals for society perks like attractive help and educational opportunities. Create a new chance for yourself and your future gain. The pursuit may be indirectly impacted by chimpanzees. Both humans and chimpanzees employ social incentives. Chimpanzees thus have a competitive edge over other social predators. The sexual incentive can be used as a last option to make the Sims crazy. Large chips therefore remove the error of purchasing your own meat. Depending on how Sim behaves in social situations, the two core phases of investigation and abuse can be separated. There are methods for finding, stopping, and removing victims so that their locations may be investigated. In essence, abuse is viewed as an attack on the victim.

2.3. Oppositional Based Chimp Optimization Algorithm

The COA model used oppositional learning (OBL) to increase attention. Utilising this process of learning enables convergence and results in the best possible global solution. Conflicting populations

show up in the search space at the same time in this scenario. According to the OBL theory, opposing numbers are more likely to reflect a complete response than random numbers (S. Shitharth et al., 2021, Kumar, A., & Sivakumar, P. 2022, Raj, M. G., & Pani, S. K. 2022). Points and opposing numbers can also be specified. The opposite variable from a midpoint in the equation below can be used to identify the kind of glass in an interplanetary solution:

$$x^0 = A + B - X \quad (20)$$

where the points A and B in the search area are. The following mathematical statement is used to get the opposite outcomes from the initial population of COA:

$$P = (x^1, x^2, \dots, x^d) \quad (21)$$

The outcomes are displayed as follows, where the beginning population of the COA is the exact opposite:

$$OP(x_1^0, x_2^0, \dots, x_d^0) \quad (22)$$

$$x_i^{op} = A^i + B^i - x^i \quad (23)$$

where, $x^i \in [A^i, B^i]; i = 1, 2, \dots, d$.

The COA employs this opposing function to reduce the energy consumption of the CRN. The proposed method improves the representation of CRNs in terms of spectrum measurement and data transmission. The energy requirements of the CRN network are successfully matched with the transmission behavior and spectrum specification by using the suggested technique. In the next section, the effectiveness of the created approaches is reviewed.

3. RESULT AND DISCUSSION

This proposed model's simulation was carried out in MATLAB. The implementation specifications for the suggested technique are shown in Table 1. The recommended strategy seeks to achieve the target operational energy efficiency. Energy efficiency goals are achieved with OFCOA. OFCOA is used to determine the optimal spectrum discovery process that ensures proper operation and reduces CRN power consumption. This section assesses the success of the suggested strategy in terms of variables including overhead, throughput, gearbox ratio, power consumption, longevity, and flush. Four potential scenarios were looked at for the evaluation of these attributes. The suggested method's performance is assessed using these four criteria, and the results are contrasted with those of COA, WOA and PSO. The efficiency of the suggested tactic was confirmed by the comparison study. 100 users were produced by the architecture, and they examined four circumstances. The table lists the steps necessary to put the proposed plan into table 1.

3.1. Performance Analysis

The efficiency of the provided technique is verified using performance metrics. The recommended optimisation produces objective functions that are energy-efficient.

Table 1. Implementation parameters

S. No	Description	Value
1	Initial idle power	0.035
2	Initial receive power	0.395
3	Initial transmit power	0.660
4	Initialization of users	100
5	Initial energy	10
6	Simulation time	100
7	Maximum packets	2500
8	Dimension of Y	1000
9	Dimension of X	1000
10	Antenna	Omni Antenna
11	MAC	802_11
12	Propagation	Two ray rounds
13	Channel	Radio channel

The proposed methodology is supported by four conditions, which are presented in Section 3. The capabilities of the proposed methodology with four conditions are shown in Figure 2. The proposed methodology has reached a maximum processing value of 40000. The delivery rate of the proposed methodology with four conditions is shown in Figure 3. The methodology proposed has reached the maximum value of the transmission factor is 99. The proposed methodological delay with four conditions is shown in Figure 4. In the proposed methodology, the maximum delay value of 50 has been reached. The network lifespan of the proposed methodology with four conditions is shown in Figure 5. The proposed methodology has reached a maximum network lifespan value of 15000.

Figure 2. Analysis of throughput

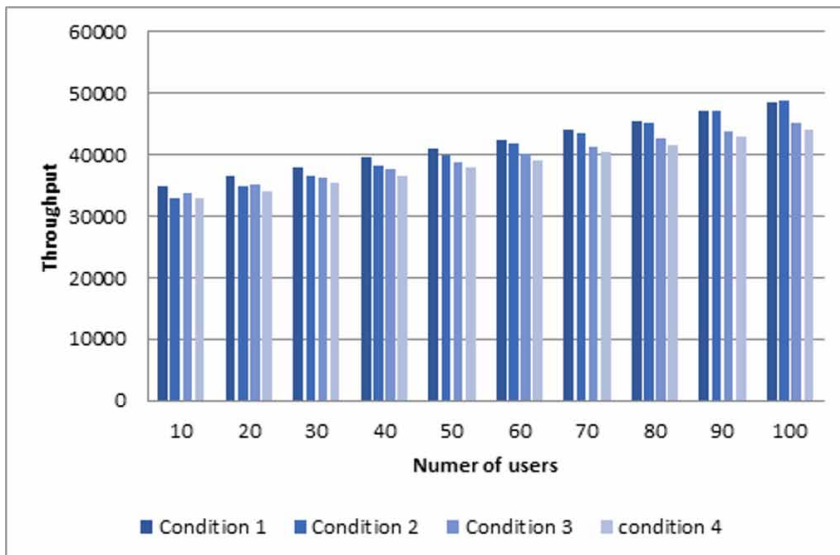


Figure 3. Analysis of delivery ratio

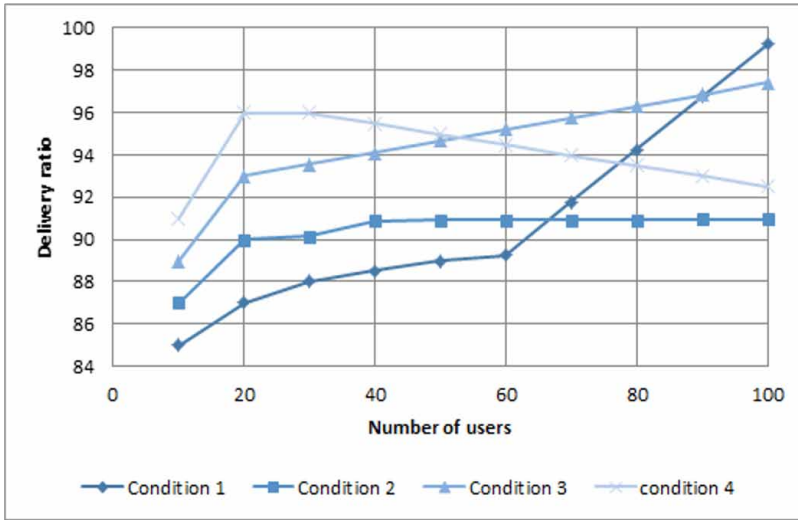
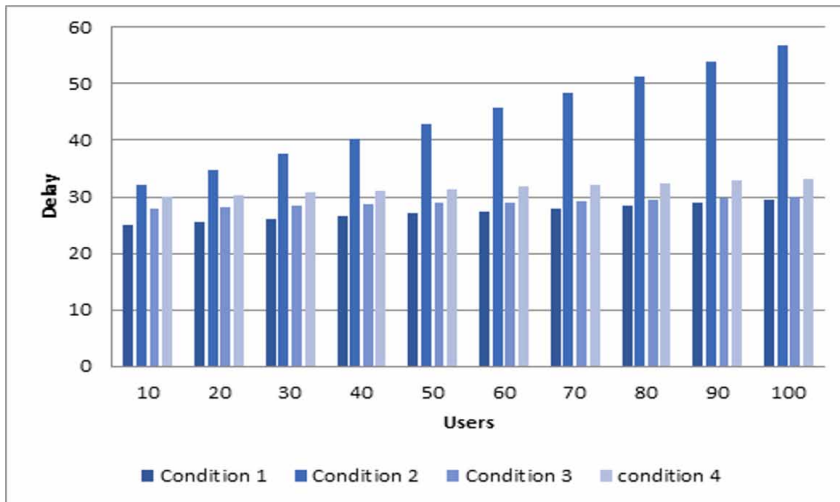


Figure 4. Analysis of delay



The power consumption of the proposed methodology with four conditions is shown in Figure 6. to achieve a maximum power consumption value of 35%. The overhead of the proposed methodology with four conditions is shown in Figure 7. The proposed methodology achieves a maximum overhead of 14,200. The reduction of the proposed methodology with four conditions is shown in Figure 8. The proposed methodology yields a maximum reduction of 7,500.

3.2. Comparison Analysis

The suggested method is contrasted against more well-known techniques like WOA, COA, and PSO in order to verify it. Performance indicators such dropout, latency, processing speed, network life, transmission ratio, and power consumption are used to compare the proposed method to other approaches.

Figure 5. Analysis of network life time

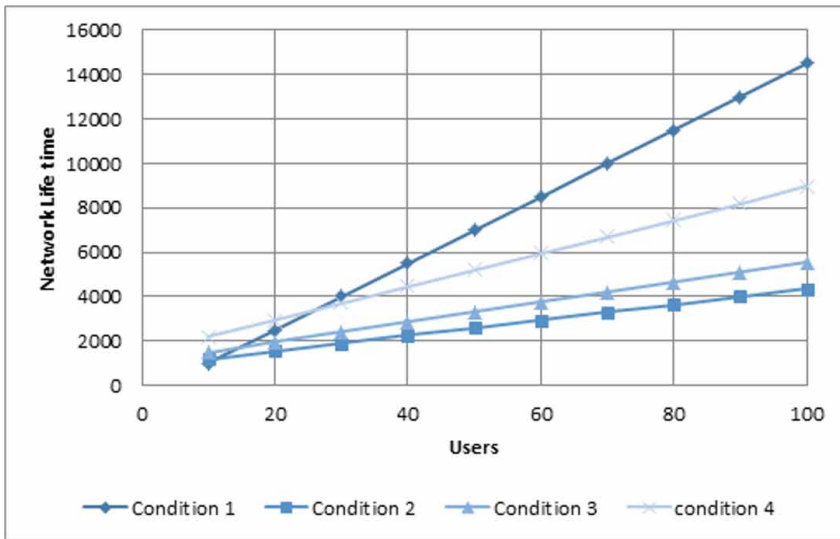
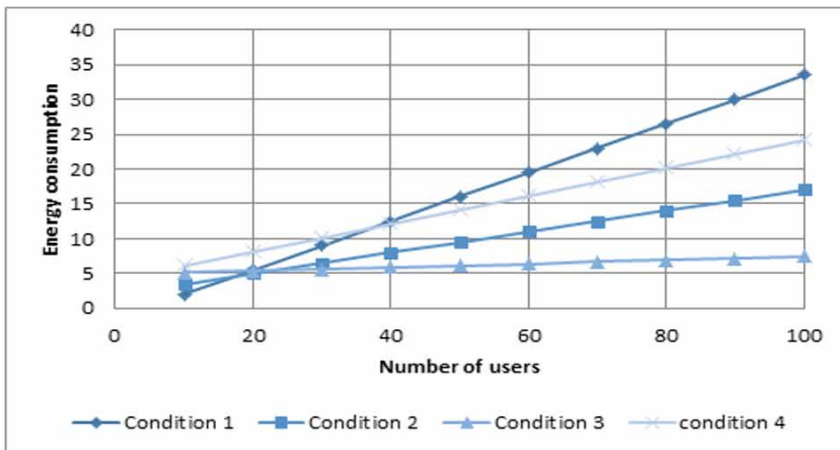


Figure 6. Analysis of energy consumption



The throughput comparison is shown in Figure 9. In Figure 9, the proposed method achieves a throughput value of 40000. Similarly, COA, WOA, and PSO throughputs of 38000, 28000, and 32000, respectively, have been achieved. The comparative research shows that the recommended method offers the best value for processing power. A comparative analysis of the delay is shown in the figure 10. The 10 proposed methods achieve 30 times the delay value. Similarly, delay values of 42, 30, and 82 were achieved for COA, WOA, and PSO, respectively. The comparison study reveals that the proposed approach has a low latency value. Figure 11 displays a gearbox ratio comparison. The suggested method offers a transmission ratio of 99 in Figure 11. Similar results were obtained for COA, WOA, and PSO at transmission ratios of 82, 78, and 75, respectively. In the comparison investigation, the recommended approach had the greatest delivery rate. Figure 12 displays a comparison of network lifespans. Network lifespan estimates resulting from the suggested method are shown in Figure 12 of 14200. Values of 13800, 13500, and 13000, respectively, for COA, WOA,

Figure 7. Analysis of overhead

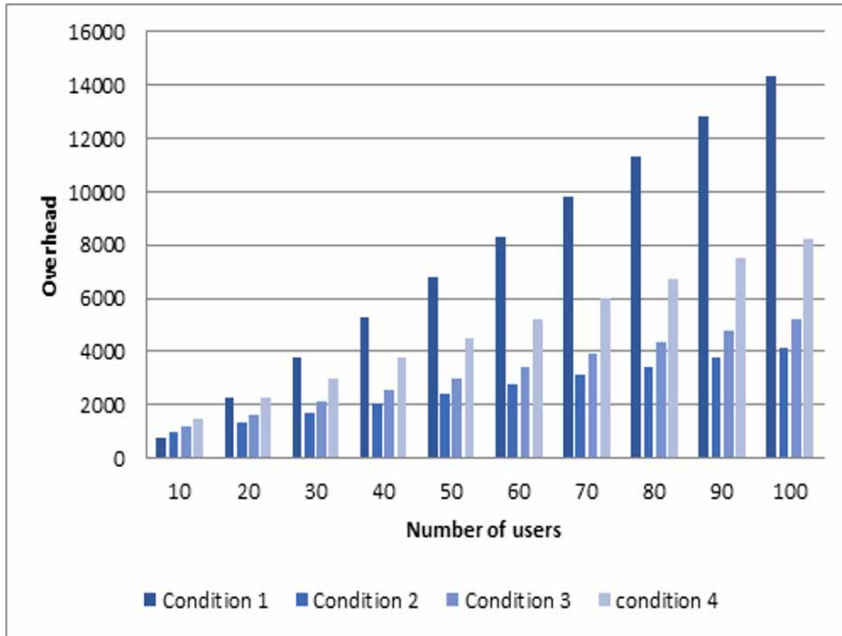
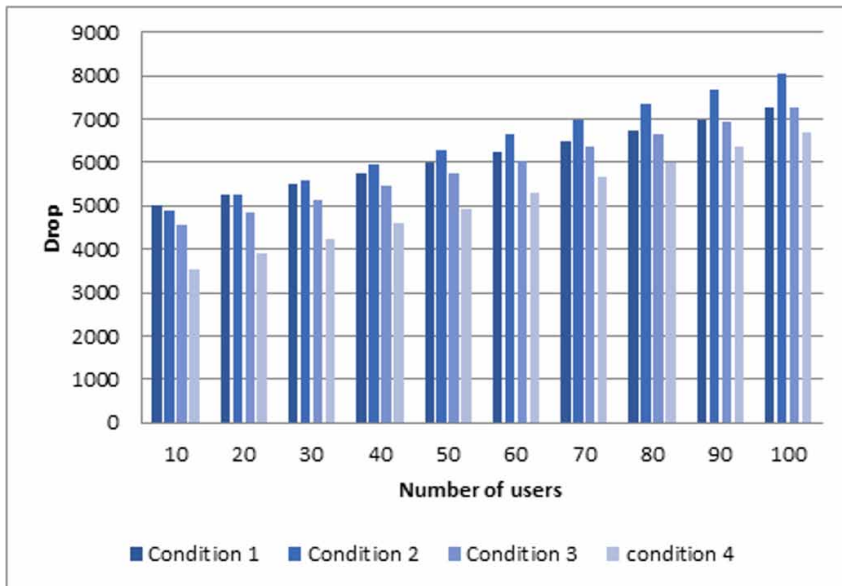


Figure 8. Analysis of drop



and PSO network longevity, were attained. The comparison analysis shows that the proposed method offers the network's maximum benefit. The power consumption comparison is shown in Figure 13. In Figure 13, the proposed method yields a 32-bit power consumption value. Similarly, COA, WOA, and PSO achieve power consumption values of 40, 45, and 50 respectively. From the comparative analysis, the proposed technique gives low energy consumption values. A comparative analysis of the

Figure 9. Comparison analysis of throughput

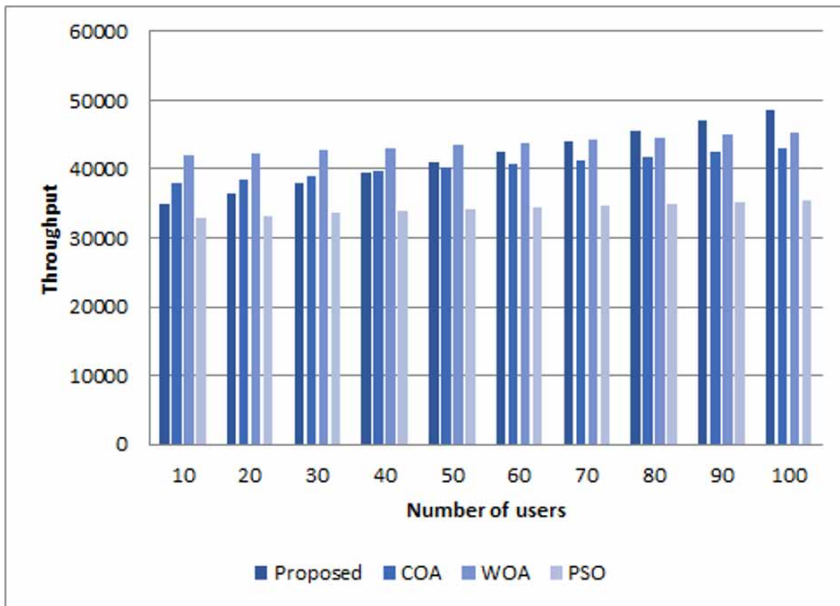
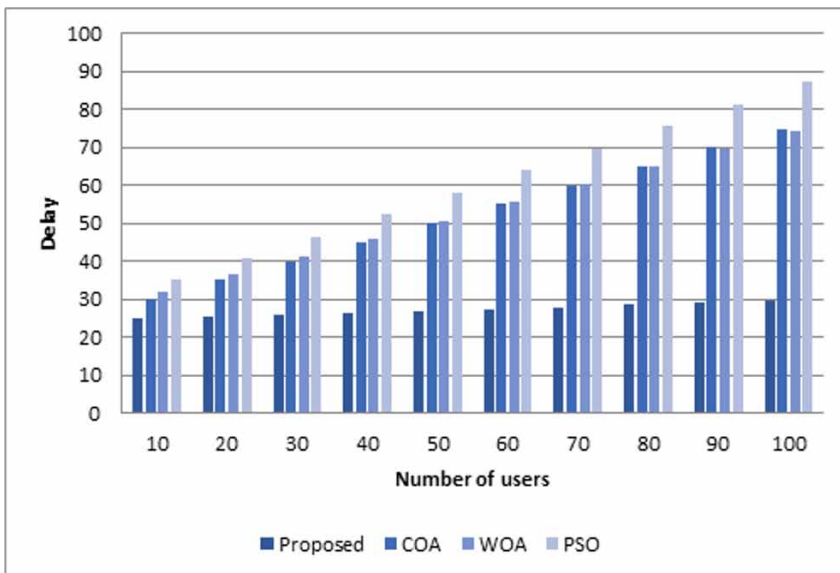


Figure 10. Comparison analysis of delay



fall is shown in Figure 14. In Figure 14, a value of 7000 drops is achieved by the proposed method. Similarly, COA, WOA, and PSO were achieved at decline values of 7500, 7800, and 8500 respectively. From the comparative analysis, the proposed methodology gives low decline values. A comparative analysis of overhead costs is shown in Figure 15. In Figure 15, the proposed method achieves a value of 14,000 overhead costs. Similarly, COA, WOA, and PSO were achieved at declining values of

Figure 11. Comparison analysis of delivery ratio

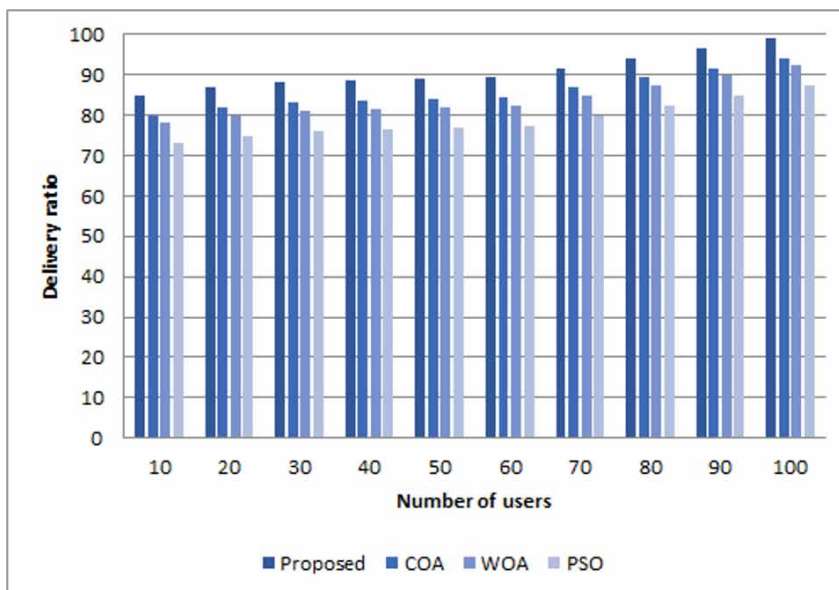
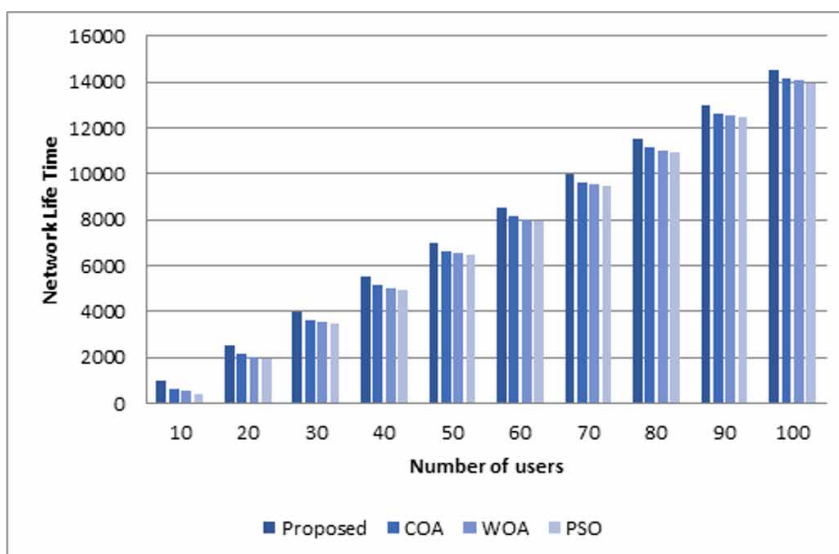


Figure 12. Comparison analysis of network life time



14500, 15000, and 15500 respectively. From the comparative analysis, the proposed methodology provides low overhead.

4. CONCLUSION

In this article, the energy-efficient OFCOA method is developed in CRN for energy management as well as resource allocation. The proposed method is a combination of OF and COA. In COAs,

Figure 13. Comparison analysis of energy consumption

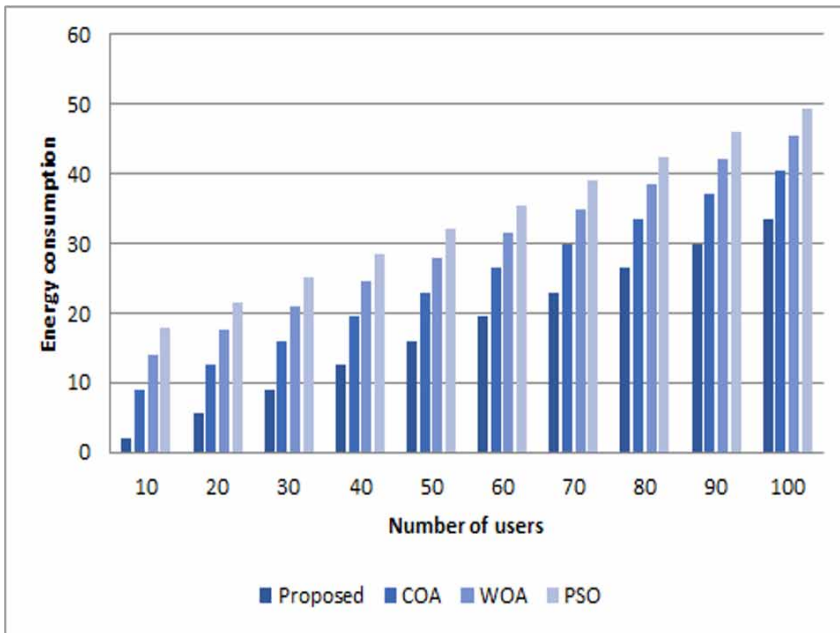
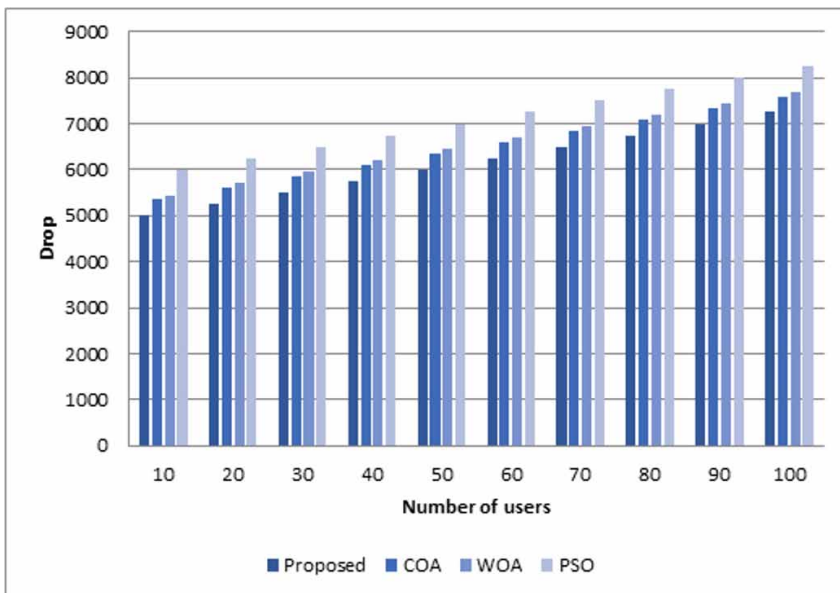
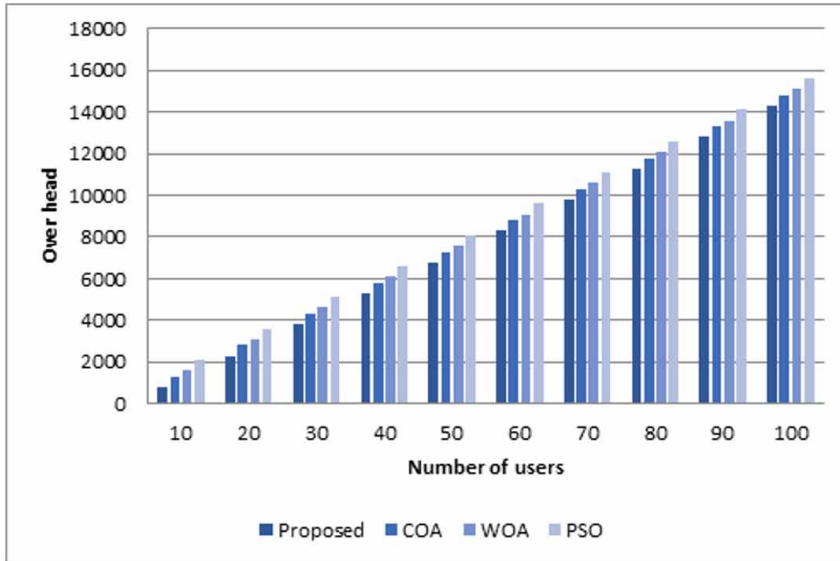


Figure 14. Comparison analysis of drop



optimal decision-making is enhanced by the use of OF. The proposed method provides energy-efficient operation in RRS by managing power consumption by taking into account spectral measurements. The four PU and SU scenarios with channel occupancy and detection in the CRN network are used to test the suggested approach. Performance indicators such as CPU power, network life, transmission rate,

Figure 15. Comparison analysis of overhead



latency, flush, power consumption, and overhead are used to assess the effectiveness of the suggested approach when it is implemented in MATLAB. Four alternative CRN network configurations are used to test the suggested methodology. CRN is implementing the suggested technique to boost energy effectiveness through spectrum control. Performance measures were employed to assess the suggested approach. The methodological research’s findings indicate that low power consumption, low latency, low dropout rate, quick transmission speed, little overhead, and extended network life were attained. In the meanwhile, we discovered that the energy efficiency would be significantly impacted by the design of the PU network scenario and the beginning energy of the secondary user power supply. Future resource allocation will allow the CRN network to expand in an effective and energy-balanced manner.

CONFLICT OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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