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CHAOTIC EQUILIBRIUM OPTIMIZATION ALGORITHM BASED COOPERATIVE SPECTRUM SENSING AND ENERGY EFFICIENT COGNITIVE RADIO NETWORKS

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Abstract

The need for wireless communication in the present and the future is for green communication. The cognitive radio network must meet the requirements for green communication in order to be the next-generation communication network. So improving energy efficiency is a must for the development of cognitive radio networks. However, sensor performance must be reduced in order to improve energy efficiency. In order to consider the two key indicators of sensing performance and energy efficiency, this research suggests a Chaotic Equilibrium Optimization (CEO) method that may effectively boost energy efficiency while enhancing spectrum sensing performance. The algorithm first learns the initial reliability value of the nodes by training, sorts them based on highest reliability, selects an even number of nodes with highest reliability, divides the chosen nodes into two groups, and then alternates the operation of the two groups of nodes. While they wait for additional instructions from the fusion center, the other nodes that are not now participating in cooperative spectrum sensing are in a state of silence. Experimental demonstrations are effectuated and analyzed the performances of the performances of the proposed work. The proposed work effectively senses the spectrum than the other approaches.

Keywords:

Cognitive Radio, Spectrum Sensing, Chaotic Equilibrium Optimization, Energy Efficiency

1. INTRODUCTION

A cognitive radio (CR) [1] is a transmitter that may be continuously designed and adjusted to use the optimum nearby communication channels in order to reduce customer disruption and capacity. In order to support more connected devices in a specific frequency region at a single location, such a transmitter continuously discovers available frequencies in the range of wireless signals [2] and modifies its broadcast or received characteristics as necessary. The intellectual processor has the potential to set radio-system variables in accordance with the operator's orders. Waveform, procedure, functioning frequency range, and connectivity are some of these factors.

In its networked surroundings, this performs as an independent unit, sharing environmental data with the systems that it encounters and other cognitive radio waves [3]. In spite of decoding the transmitter's outputs, a carrier receiver also monitors the device's performance continuously.Using this data, it can identify the electromagnetic circumstances, channel ailments, link execution, etc., and adjust the broadcasting locations so as to provide the proper level of functionality dependent on a suitable blend of customer specifications, functional boundaries, and legislative constraints. Some suggestions connect software-defined [4] broadcasting, intellectual airwaves, and electronic mesh networks, which constantly change the wavelength band used by statements transferred between successive nodes on a route and the communication protocol used by statements among two specific nodes employing collaborative inclusion.

A newly developed sort of data connection for transmission of information called a cognitive network (CN) [5] employs the latest innovations from numerous academic fields such as predictive modelling, visualization of knowledge, internet connections, and resource administration to address several issues that exist in contemporary networks.A spectrum sensing [6] method known as power monitoring determines if the main consumer is present or not by determining the incoming communication's strength and contrasting it to a preset criterion. The interference power affects how the tolerance expression is calculated. Based on the message intercepted on a specific tone band, spectrum measurement is used in psychological radio to identify whether the primary user is utilising the available spectrum and, consequently, whether another user can utilise the range of frequencies.

An illustration of a range that is the most basic would be an array of colours. The three different types of spectra for atoms are reflection, acceptance, and uninterrupted wavelengths, and every spectrum contains a wide range of data. For instance, there are several other ways for a structure, like a glowing object, to emit radiation. A range of transmission magnitudes at various wavelengths is seen using an electromagnetic detector [7]. It allows for analysis to identify whether signals are within acceptable bounds. It shows erroneous communications, intricate patterns of waves, uncommon, brief occurrences, and distortion.A source's optical density is quantified by an optical scanner as part of its fundamental operation.

If one were analyzing the final result of a low-pass filtrate, an analyzer that measures the spectrum might use the frequency range [8] in order to assess the composition of the filtration's resulting band. It offers greater efficacy and cost-effective spectrum use. It is more affordable, and it increases link trustworthiness. It employs cutting-edge topologies for network connectivity. Large volumes of knowledge are required for systems of thought to acquire knowledge from, as are long phases of creation, slow acceptance, and adverse environmental consequences. A cognition structure is an organism that makes selections depending on its perception of internal situations at the time and then learns from those selections.

It is clear that the present literature is unable to address the issue of user equality among CU or to enhance sensing capabilities or energy efficiency on the basis of user equality. To solve the aforementioned concerns, this study proposes a new dynamic grouping-based energy-saving algorithm. Major Contributions are:

- The algorithm divides the selected nodes into two groups and selects a small subset of nodes with the highest dependability to participate in cooperative spectrum sensing in a sensing cycle.

- In order to continually identify the target frequency band, the two sets of nodes each operate in turn, considering consideration the effectiveness of spectrum sensing and energy efficiency.
- In line with research results, the clustering algorithm used in this paper has higher energy efficiency than the conventional technique.

The rest of the work is organized as follows: in section 2 the literature survey of the relevant works is addressed. The system model is stated in section 3. Proposed CEO based interleaving clustering is explained in section 4. The experimental demonstration is explained in section 5. Finally, the work is concluded in section 6.

2. LITERATURE SURVEY

Kaschel et al. [9] have presented a dynamic Cognitive Radio Sensor Networks (CRSN) structure for collaborative spectrum measurement activities that take station movements into account while predicting the consumption of electricity. To accurately estimate the system utilisation of energy, it is imperative to use the proper detector configuration in wavelength monitoring. The statistical results support the obtained lowering of energy usage levels while meeting the requirements of the suggested solution but being less than ideal. However, it is inadequate to expand outcomes to bigger network configurations.

Hu et al. [10] have described a sensing-based cognitive satellite-terrestrial network (SCSTN) that combines a decentralized collaborative spectrum monitoring network with the cognition satellite-terrestrial connection. The above description is connected to the total quantity of dispersed collaborative connections, the sensor time, the energy recognition minimum of the perceiving node, and the standard level of fusion. The foundation of this strategy is reliable monitoring of the status of the core terrestrial connection. Thus, the substantial bandwidth efficiency of the satellite transmission system is not taken into consideration.

Wan et al. [11] have implemented an energy-efficient cooperative spectrum sensing scheme for the cognitive Internet of Things (CIoT), determined by spatial relationships. It can be divided into multiple clusters to reduce transmission costs and guarantee adequate detection reliability. The top of the cluster is close as the participating units’ complete shared spectrum monitoring jobs individually by twisting and sending a regional test value. The focal point of the cluster then aggregates the sensor information and uses the probability ratio test to get the group’s determination by using the geographic relationship of the elements. The system improves energy savings while simultaneously delivering superior detection effectiveness. Still, the likelihood of lacking identification can remain at a comparatively low level.

Yin et al. [12] have evaluated a decision-driven time-adaptive spectrum sensing scheme to enhance wavelength effectiveness and conservation of energy through better utilisation of assets. The subsystem communicates information in the frame’s distribution period once the physical unit (PU) is found to be missing during the detection phase; alternatively, the subsystem uses each frame of time to conduct an additional detection of spectrum movement, where the full framework period consists of the standard period of time for the transfer of data in the present frame and the time allotted for bandwidth monitoring in the frame that follows. It can efficiently increase secondary performance, energy effectiveness, and bandwidth utilisation in certain settings. Furthermore, a professional signal generator with rapid connectivity rejects the time spent on physical processors for sensor decisions.

Lin et al. [13] have implemented soft decision cooperative spectrum sensing with the entropy weight method for cognitive radio sensor networks. It is necessary to emphasise, nonetheless, that in minimal signal-to-noise situations, data gathered from sites that have inadequate route characteristics would have an impact on the fusion outcomes and decrease general detection efficiency. This would significantly enhance the efficacy of the highly reliable regional test findings and the efficiency of joint spectrum perception. Additionally, even if the overall number of nodes rises, the speed of the system won't change dramatically.

Ding et al. [14] have developed an energy-efficient channel switch in networks of cognitive radios for additional users. It enables subordinates to take advantage of the information lag acceptance to halt communications and remain on the present pathways for bandwidth availability chances. The information is delay-tolerant; it could be more environmentally friendly for them to stand by on the present path once it is felt to be congested. Based on their findings, it is more accurate and efficient. However, channel flipping is not always preferable because it consumes a lot of energy.

Awasthi et al. [15] highlighted a suboptimal iterative search algorithm to increase efficiency by making the most of the sensing and transmission times. According to the analysis of the training, under the restriction of the likelihood of persistent use impedance, the reduction in energy consumption can be optimised at one specific location for both detection and broadcast timeframes. The suggested algorithm beats both the comprehensive search technique and substandard strategies in terms of simplicity and performance. Nevertheless, it has a substantial statistical challenge.

Bala Vishnu et al. [16] suggested a team-based hybrid sensing method for cognitive radio wireless sensor networks that employs a collaboration-oriented methodology and mixes reactive and proactive detection. The secondary channel allocation feature was developed to lengthen the time that may be used without negatively affecting physical activity interruption. Selecting only one sensing node restricts the variable bandwidth distribution when the physical unit is occupied. It results in less energy usage, greater data transfer, and effective channel management with no loss of frequency precision. Thus, a few unsolvable issues include channel connection, implementation, and processing.

3. SYSTEM MODEL

In the system model depicted in Fig.1, a cognitive radio router (CRR), multiple CU, and numerous PU are dispersed over the cognitive radio network region. The first user has priority, and the secondary user must wait until the first user’s free frequency band is available before using it. Below is a description of how these users interact with one another. While PU without any traffic to broadcast continues to be silent, PU with data to be transmitted intends to send their data packets to CRR first to discover potential secondary relays.

The second step is a CRR broadcasts inquiries it gets from the PU to all the CUs in its service region. According to the data they have access to and their personal data and power budget, CU that require a primary channel compute energy efficiency and report back to the CRR whether they intend to cooperate or not. Ultimately, the CRR alerts the relevant PU to setup a wireless link with the CU if feasible after receiving the CU's decision.As a result the proportion of nodes participating in cooperative spectrum sensing possesses an unpredictable correlation with sensing effectiveness and remains unchanged linearly with an upsurge in nodes, the practical operation of a cognitive radio network does not require all nodes to be participating in cooperative spectrum sensing at the same time. As a result, the algorithm described in this article groups the nodes, and each group operates independently. The remaining groups are either transmitting data or resting while one group is at work [18].

It ought to be emphasized that in the structure of this paper, the PU can continue to be readily coupled with a particular CU to locate the secondary medium even though some CU might decline to take part because of the huge number of CU in the CRN. The CU that is effectively paired onto the PU continues to send out the data relay transmission of the PU to help the CU better grasp the numerous a priori elements of the PU and allow other CU to wait for opportunities to occupy the PU frequency band. The two groups that were chosen each contribute something to this paper [19]. The other group transmits data while the first group does the spectrum sensing operation. Even though the not chosen node has subpar sensing capabilities, it remains in a quiet condition and fails to play role in cooperative spectrum sensing.

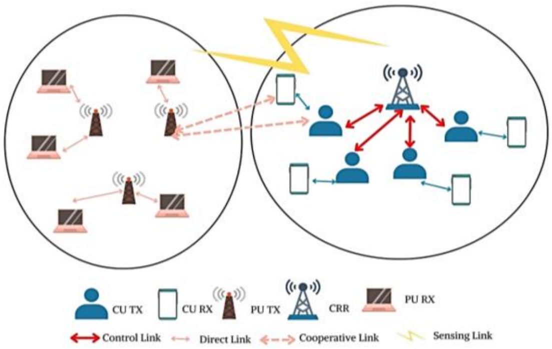

Fig.1. System model of proposed spectrum sensing Cognitive radio network

4. FORMATION OF DYNAMIC INTERLEAVING CLUSTERING BASED ON NODE ENERGY CONSUMPTION AND SENSING PERFORMANCE

All nodes learn to acquire the initial dependability value before the nodes are clustered. To represent each node's effectiveness more accurately in providing a theoretical basis for choosing nodes, the beginning reliability values of each node will be determined, the learning intensities of each node will be the same, and they will all participate in the training under the same conditions. Each node has a comparable learning intensity, independent of its sensing capacity and transmission effectiveness. Since each node learns under identical circumstances, it is easier to assess its performance and get ready for choosing effective nodes.

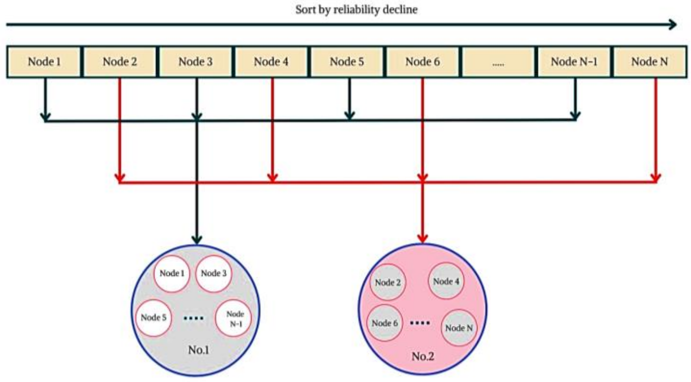

Fig.2. Time sharing concept of proposed work while clustering the nodes

A node's dependability value is determined by the fusion centre and kept there. The chance of no error and learning capacity are referred to as the node dependability in this context, and formula is used to determine its value using the following eqn.

$$\psi_j = \frac{e^{R_j}}{\sum_{j=1}^{M} e^{R_j}} \tag{1}$$

The j^{th} node's corresponding learning intensity is R_j and M is the total number of nodes. It is not necessary to transmit the node's reliability emphasis because it has been determined by the fusion center and retained there. For participation in cooperative sensing, the fusion center selects the highest reliability N (N, M, N is an even number) sites and interconnects the selected N nodes through two groups. While considering the time-sharing structure of clustering, let us assume the sensing interval is T with the sensing operation as $t_1 = 0.5T$ and the time required for the passage of data is $t_2 = T - t_1 = 0.5T$. Hence the consumption of energy at the j^{th} node while at the sensing interval is determined as,

$$e_j = 0.5TF_a e_0 + m_j\left(G_0 + l_j h_j^2\right) \tag{2}$$

The sensing nodes' adoption frequency is determined as F_a and the sampling frequency is similar for all the nodes. At one sampling the energy consumption by a single node is referred as e_0. For the passage of data along the unit distance the power requited is implied as G_0 and the channel gain is l_j. The data transmission distance is implied as h_j^2.

4.1 CHAOTIC EQUILIBRIUM OPTIMIZER (CEO) ALGORITHM BASED INTERLEAVE CLUSTERING

The simple well-mixed fluid mass equilibrium on an initial quantity, which uses a mass balance equation to explain the level of an inert constituent in the control volume because of its many different origin and collapse processes, served as the basis for the Equilibrium Optimizer (EO) strategy [17]. The EO concept is motivated on the management of volume fluid equilibrium of masses. Physics established the system of balancing mass for preserving mass entering. Additionally, Kent map of chaotic map to enhance the generation rate of EO model and the new algorithm is developed in the name of CEO algorithm.

$$A\frac{dV}{dt} = qV_{sim} - qV + F \tag{3}$$

The particle's focus *A*, controlling volume *V*, and flow of volumetric rate is *q*. The volume under control within V_{equi} is particle concentration at the condition of equilibrium without generation and $A\frac{dV}{dt} = 0$ attain an equilibrium (*equi*) stable state.

$$\frac{dV}{\delta V_{equi} - \delta V + \frac{H}{\nabla}} = dt \tag{4}$$

$$V = V_{equi} + \left(V_0 - V_{equi}\right)G + \frac{H}{\delta \nabla V}\left(1-G\right) \tag{5}$$

$$G = \exp\left[-\delta\left(1-t_0\right)\right] \tag{6}$$

The t_0 initial start time and M_0 the concentration interval.

4.1.1 Set the Candidate Solution and Exponential Term:

Whenever the average supporting is being used, four of the most effective particles are utilized for exploring the search space, and the formula below is used to explain the equilibrium pool vectors.

$$\vec{V}_{equi,\,pool} = \vec{V}_{equi_1}, \vec{V}_{equi_2}, \vec{V}_{equi_3}, \vec{V}_{equi_4}, \vec{V}_{equi_{avergae}} \tag{7}$$

Each particle is revised and adopted by the random selection at every cycle. The time has been modified as well for all candidate solutions. The exploration and utilization of the EO method are balanced utilizing the critical function of the term exponential (*G*). [0, 1] is the range for δ as random vectors. the quantity of iterations necessary to minimize iteration variable *t*.

$$\vec{G} = e^{-\vec{\delta}\left(t-t_0\right)} \tag{8}$$

$$t = \left(1 - \frac{iter}{Maximum\ iter}\right) \tag{9}$$

$$\overleftarrow{t_0} = \frac{1}{\delta}\ln\left(-a\ \ sign\left(\vec{S}-0.5\right)\left[1-e^{-\vec{\delta}t}\right]\right)+t \tag{10}$$

where, the constant is *a* to control the exploitation and exploration stage.

4.1.2 Rate of Generation:

The exploitation stage is improved to demonstrate the accurate solutions enabled via generation rate (g_r). The decay constant is *k* with the initial value is $\overrightarrow{gr}_0$.

$$\overrightarrow{gr} = \overrightarrow{gr}_0 e^{-\vec{k}\left(t-t_0\right)} \tag{11}$$

At this stage, the movement of chaotic creates one-dimensional chaotic maps that can be used in rudimentary systems. Kent map is chosen from a set of eight chaotic maps to improve the rate of generation efficiency of EO because chaotic maps have higher rates of converge and local optimum avoidance. The following is an illustration of the Kent of chaotic map with respect to EO generation rate:

$$\overrightarrow{gr_{m+1}} = \begin{cases} \dfrac{0.5S_1 gr_m}{\alpha}, & 0 \le gr_m \le \alpha \\[2ex] \dfrac{\left(1-gr_m\right)}{\left(1-\alpha\right)}, & \alpha < gr_m \le 1 \end{cases} \tag{12}$$

where, α and gr_m are the controlling parameters. The term of generation probability throughout the updating procedure is *Q*. The role of generating likelihood in the CEO rule update is used to improve exploitation and exploration.

$$\vec{V} = \vec{V}_{equi} + \left(\vec{V} - \vec{V}_{equi}\right)\vec{G} + \frac{\vec{G}}{\delta A}\left(1-\vec{G}\right) \tag{13}$$

A is the unit that is under consideration. Global search is used to find the ideal position. Special guidelines: The detection chance results in this paper are not significantly affected by a substantial increase or reduction in the number of nodes since the likelihood of detection is established by the efficiency of the nodes, rather by the number of nodes. The increase in detection likelihood is not facilitated by cooperative sensing nodes whose node efficiency is below the threshold. The algorithm described in this paper only chooses good nodes that perform well is better than the threshold for joining cooperative spectrum sensing, rather than selecting all nodes to engage in cooperative spectrum sensing.

Therefore, modifications to the number of nodes won't have a big effect on the outcomes of the detection likelihood. When the number of nodes varies, the technique described in this paper still performs quite well. Nevertheless, the fusion center's calculation workload will rise when the number of nodes improves unexpectedly and noticeably. This is because the fusion centre must periodically assess the efficiency of all nodes; thus, The workload on the fusion center will decrease if the number of nodes is reduced, whereas it will increase if the number of nodes is abruptly increased.

5. EXPERIMENTAL RESULT AND DISCUSSION

A number of experiments have been set up to confirm the effectiveness of the method used in this article. The series of tests aims to confirm how well the combining algorithm performs properly. A parameter illustration for the recommended approach is shown in Table.1. During the experimental simulation, 36 nodes are placed at random in a circle with a circumference of 1000 m, and then the period optimization algorithm decides how long the next sensing interval will last. The system with x64-based Windows 10 Professional Edition machine with an Intel(R) Core(TM) i5-8500 CPU running at 3.00 GHz, 64-bit operating system, 8.00 GB of RAM is used.

Table.1. Parameter illustration

Parameters	**Ranges**
Number of solution particles	50
Number of iteration	100
Number of nodes randomly distributed	36

Diameter	1000 m
The percentage of PU's working frequency	50%
Node frequency	1 MHz
Starting duration of spectrum sensing	1 *ms*

5.1 EXPERIMENTAL INVESTIGATION ANALYSIS:

The efficacy of the algorithm suggested in the present paper is compared to that of the equivalent develop conjunction method and the corresponding node choosing technique, and both of the primary metrics of recognizing performance—spectrum identification probabilities and false detection probability are utilized to demonstrate the superiority of the node selection algorithm.Fig.3 illustrates the current condition of detecting probabilities and demonstrates that if the SNR is less than 210 dB, it outperforms CRSN [9], SCSTN [10], EECSS [11] and SIS [15] method. The proposed technique splits the chosen CU into two distinct categories, and each group alternately conducts spectrum sensing activities not interfering with the PU's security. As a result, its likelihood of being detected is higher than that of other algorithms such as CRSN [9], SCSTN [10], EECSS [11] and SIS [15].

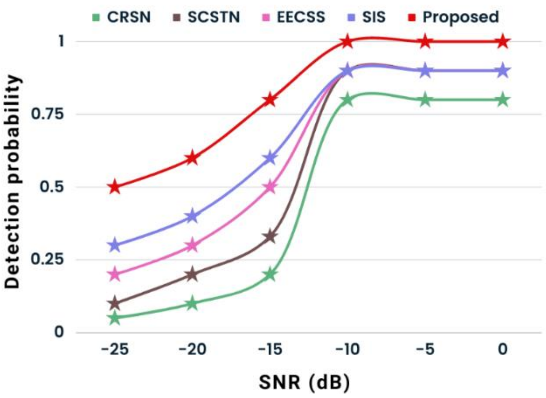

Fig.3. State-of-Art result of detection probability

The Fig.4 illustrates the state-of-the-art originate for energy efficiency. To demonstrate the better performance of the proposed algorithm commonly in case of efficiency in energy, it has been contrasted to the CRSN [9], SCSTN [10], EECSS [11], and SIS [15] algorithm. The assessment of the five methods is performed off according to the identical limitations. To demonstrate the superior accomplishment of proposed work, the SNR was altered to confirm the effectiveness of the technique used through the present paper.Fig.2 shows that the suggested method has greater energy efficiency than the CRSN [9], SCSTN [10], EECSS [11], and SIS [15]. It happens since the suggested approach for spectrum sensing operations, while the existing technique of nodes serves for data transfer operations, substantially raising the quantity of energy employed over data transmission and reducing the energy employing for spectrum that was sensing activities.

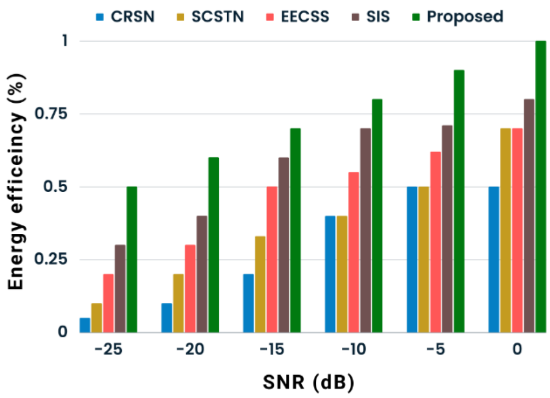

Fig.4. State-of-art result of energy efficiency

The Fig.5 provides the assessment of transmission power. The relationship between energy consumption and transmission power demonstrates that whenever the amount of increases, energy consumption (EC) follows suit. Yet, when the amount of power transmission is increased again after reaching an excessive level, consumption of energy gradually decreases. Because beneficial throughput increases in conjunction with transmitted power, and consequently EC is believed that it possesses a value that is directly proportional to speed and inverted with respect to power supply and demand, including the power of transmission. Following peaking, the rise in throughput is outweighed by the increase in power consumption, which causes the EC function to progressively deteriorate. Up to a particular, an increase in bandwidth outpaces an increase in power directly, which causes the EC functionality to expand. The suggested method may attain the maximum value for EC quicker than current methods like CRSN [9], SCSTN [10], EECSS [11], and SIS [15] because it has a better convergent frequency and can get a closer approximation to the optimal number or the actual ideal value.

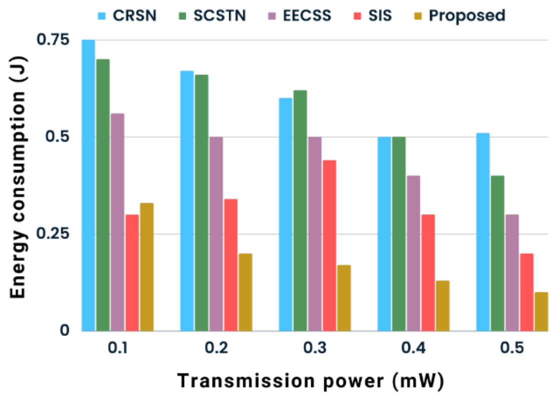

Fig.5. Comparison energy consumption based on transmission power

The Fig.6 depicts a state-of-the-art examination of bandwidth sensing. A greater sensing bandwidth necessitates a smaller transmission capacity, which results in a low opportunity transit rating and, eventually, a reduced energy efficiency rating as detecting capacity grows. The maximum value attained via CRSN [9], SCSTN [10], EECSS [11], and SIS [15] has been reduced than that that was initially predicted due to an absence of crossings in these networks and the resulting low subsystem utilization level.

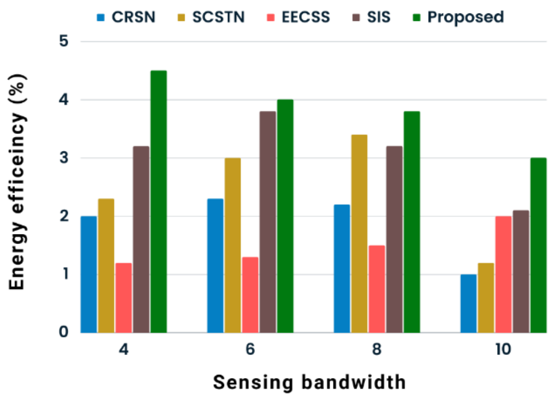

Fig.6. Comparison energy consumption based on sensing bandwidth

6. CONCLUSION

Energy efficiency is a crucial sign of how cognitive radio networks are progressing. The paper suggests a CEO based clustering algorithm to increase the energy effectiveness of cognitive radio networks. The method rejects nodes with unreliable behavior and only chooses an even percentage of reliable users to engage in cooperative sensing. It additionally significantly increases energy efficiency but also effectively enhances spectrum sensing capability. Due to the lack of crossings in these networks and the associated low subsystem utilization level, the highest value reached with minimum energy consumption via CRSN, SCSTN, EECSS, and SIS has been lower than that which was previously projected.

REFERENCES

[1] J. Yuan, and E.G. Larsson, "Intelligent Reflecting Surface-Assisted Cognitive Radio System", *IEEE Transactions on Communications*, Vol. 69, No. 1, pp. 675-687, 2020.

[2] R. Alghamdi, A. Shams and N. Saeed, "Intelligent Surfaces for 6G Wireless Networks: A Survey of Optimization and Performance Analysis Techniques", *IEEE Access*, Vol. 8, pp. 202795-202818, 2020.

[3] M.M. Vijay and D. Shalini Punithavathani, "A Memory-Efficient Adaptive Optimal Binary Search Tree Architecture for IPV6 Lookup Address", *Mobile Computing and Sustainable Informatics*, Vol. 2022, pp. 749-764, 2022.

[4] M. Singh, N. Kumar and A. Garg, "Deep-Learning-Based Blockchain Framework for Secure Software-Defined Industrial Networks", *IEEE Transactions on Industrial Informatics*, Vol. 17, No. 1, pp. 606-616, 2020.

[5] C. Saju and T. Jarin, "Modeling and Control of a Hybrid Electric Vehicle to Optimize System Performance for Fuel Efficiency", *Sustainable Energy Technologies and Assessments*, Vol. 52, pp. 1-12, 2022.

[6] B. Soni and M. Lopez Benítez, "Long Short-Term Memory based Spectrum Sensing Scheme for Cognitive Radio using Primary Activity Statistics", *IEEE Access*, Vol. 8, pp. 97437-97451, 2022.

[7] W. Miao and H.V. Poor, "DC Arc-Fault Detection based on Empirical Mode Decomposition of Arc Signatures and Support Vector Machine", *IEEE Sensors Journal*, Vol. 21, No. 5, pp. 7024-7033, 2020.

[8] H. Golpira, B. Francois and H. Bevrani, "Optimal Energy Storage System-Based Virtual Inertia Placement: A Frequency Stability Point of View", *IEEE Transactions on Power Systems*, Vol. 35, No. 6, pp. 4824-4835, 2020.

[9] H. Kaschel and M.J.F.G. Garcia, "Energy-Efficient Cooperative Spectrum Sensing Based on Stochastic Programming in Dynamic Cognitive Radio Sensor Networks", *IEEE Access*, Vol. 9, pp. 720-732, 2020.

[10] J. Hu and L. Gou, "Energy-Efficient Cooperative Spectrum Sensing in Cognitive Satellite Terrestrial Networks", *IEEE Access*, Vol. 8, pp. 161396-161405, 2020.

[11] R. Wan, L. Hu and H. Wang, "Energy-Efficient Cooperative Spectrum Sensing Scheme based on Spatial Correlation for Cognitive Internet of Things", *IEEE Access*, Vol. 8, pp. 139501-139511, 2020.

[12] W. Yin and H. Chen, "Decision-Driven Time-Adaptive Spectrum Sensing in Cognitive Radio Networks", *IEEE Transactions on Wireless Communications*, Vol. 19, No. 4, pp. 2756-2769, 2020.

[13] H. Lin and Y. Liu, "Soft Decision Cooperative Spectrum Sensing with Entropy Weight Method for cognitive radio sensor networks. *IEEE Access, 8,* pp.109000-109008, 2020.

[14] H. Ding, Y. Ma and Y. Fang, "Energy-Efficient Channel Switching in Cognitive Radio Networks: A Reinforcement Learning Approach", *IEEE Transactions on Vehicular Technology*, Vol. 69, No. 10, pp. 12359-12362, 2020.

[15] M. Awasthi, M.J. Nigam and V. Kumar, "Optimal Sensing and Transmission of Energy Efficient Cognitive Radio Networks", *Wireless Personal Communications*, Vol. 111, No. 2, pp. 1283-1294, 2020.

[16] J. Bala Vishnu and M.A. Bhagyaveni, "Energy Efficient Cognitive Radio Sensor Networks with Team-based Hybrid Sensing", *Wireless Personal Communications*, Vol. 111, No. 2, pp. 929-945, 2020.

[17] A. Faramarzi, and Seyedali Mirjalili, "Equilibrium Optimizer: A Novel Optimization Algorithm", *Knowledge-Based Systems*, Vol. 191, pp. 1-14, 2020.

[18] M.M. Vijay and D. Shalini Punithavathani, "Implementation of Memory-Efficient Linear Pipelined IPv6 Lookup and its Significance in Smart Cities", *Computers and Electrical Engineering*, Vol. 67, pp. 1-14, 2018.

[19] Tangsen Huang, Xiang Dong Yin and Xiao Wu Li, "Energy-Efficient and Intelligent Cooperative Spectrum Sensing Algorithm in Cognitive Radio Networks", *International Journal of Distributed Sensor Networks*, Vol. 18, No. 9, pp. 1-12, 2022.