

Regression Cooperative Gradient Flying Fox Route Optimization for Energy Efficient Routing in CRN

¹Sundar T and ²Senthilkumar A

¹Department of Computer Science, Periyar University, Salem, Tamil Nadu, India.

²Department of Computer Science, Thiruvalluvar Government Arts College, Rasipuram, Namakkal, Tamil Nadu, India.

¹admin.sundar@gmail.com, ²senthilkumarmca76@gmail.com

Correspondence should be addressed to Sundar T : admin.sundar@gmail.com

Article Info

Journal of Machine and Computing (<https://anapub.co.ke/journals/jmc/jmc.html>)

Doi: <https://doi.org/10.53759/7669/jmc202606015>

Received 29 May 2025; Revised from 12 September 2025; Accepted 13 October 2025

Available online 18 October 2025.

©2026 The Authors. Published by AnaPub Publications.

This is an open access article under the CC BY-NC-ND license. (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Abstract – Cognitive Radio Networks (CRNs) is a formidable evolution in wireless technology owing to its potentiality to resolve spectrum scarcity crisis. In CRNs, cognitive radio user's sense idle spectrum as well as opportunistically entrée sensed spectrum devoid of approved users. The best spectrum is said to be selected opportunistically, shared with other users with no severity to licensed users. Many CRN devices that are fueled by battery possessing constrained energy capacity. Prevailing battery mechanisms yet couldn't contribute CRN devices works for a long time. Therefore, conservation of energy is mandatory as far as routing in CRN is concerned. In this work a machine learning based method called, Regression Cooperative Spectrum Sensing and Gradient Flying Fox Route Optimization (RCSS-GFFRO) for energy and bandwidth aware data routing with spectrum utilization in CRNs is proposed. Protection of primary users (PUs) as well as optimization of secondary user (SU) transmission included in proposed method. In the proposed method a cooperative spectrum sensing using machine learning (ML) model called, Median Regression function is applied. The Median Regression Cooperative Spectrum Sensing in our work with the bandwidth and energy efficiency ensures acceptable probability of interference to primary users due to secondary user's access by measuring the relationship between bandwidth and energy efficiency simultaneously. Next, optimal route identification is performed using Gradient Flying Fox Route Optimization algorithm. By applying gradient optimization function minimizes the interference with primary users and increases secondary user performance via sensing time and transmission time parameters with higher routing performance. Simulation estimated with parameters.

Keywords – Cognitive Radio Networks, Primary User, Secondary User, Median Regression, Flying Fox, Gradient Optimization.

I. INTRODUCTION

By advancements in Information & Communication Technologies (ICT), IoT made for validating prototypes in different filed diversified areas to name a few being, smart homes, smart cities, healthcare and so on. A corresponding novel but extensively accepted and appropriated approach referred to CRN is evinced during discerning enhanced allocation of spectrum. Spectrum shortage used to allow SUs as well as unused spectrum assigned to PUs. Nevertheless, energy efficiency (EE) optimization has demanding issue for safeguarding PUs as of intervention.

To lesser packet collision as well as E2D, Reinforcement Learning basis of routing for Cognitive Radio Network Internet of Things communication called, (RL-IoT Routing) was proposed in [1]. However, energy efficiency involved in routing was not focused. CRN parameters were enhanced in [2] by Enhanced Long Short-Term Memory (ELSTM-RPO). It ensures EF, throughput with minimal delay and improved detection ratio. However, the spectrum utilization efficiency was not focused by ELSTM model.

Study focused on cooperative NOMA-basis of CCRN in [3]. But energy consumption was not reduced by NOMA-based CCRN. Greatest network was chosen in [4] with Fuzzy Ant Colony Optimization basis of Multiple Scheduling Resource Selection Algorithm (FAMSRSA). Designed approach accessed the spectrum available to primary and secondary users. But the energy consumption was not reduced by FAMSRSA.

CRN have pragmatic mechanism for circumventing spectrum inadequacy. However, overcoming several noises issues at radio setting are said to be found widely. With battery constrained sensors there still remains a major issue in addressing energy efficiency.

Multi-dimensional optimization utilized in [5] with ML that were not found to be easily addressed using traditional methods. Yet another method to address spectrum allocation employing ant colony optimization integrated with fuzzy rules and resource selection via multiple scheduling mechanisms was presented in [6]. However, it failed to consider data energy saving mechanism. To address on this issue, a permutation routing problem and multiple channel allocation was proposed in [7] with improved energy saving. Despite improvement in energy savings however lifetime was not improved. To enhance network lifetime, an adaptive clustering method employing clustering hierarchy was designed in [8]. By employing this adaptive clustering method resulted not only in network lifetime but also with minimal error.

For addressing increased demand as far as wireless applications are concerned. Hence, there arise requirements for dynamic spectrum access as an efficient method to improve spectral efficiency.

An energy harvesting algorithm employing Q learning and Reinforcement Learning was designed in [9]. Here the objective not only remained in spectrum sensing but also ensure route optimization therefore minimizing energy consumption with improved network lifetime. Yet another collaborative spectrum sensing method was proposed in [10] via time division scheduling therefore improving average throughput in an extensive manner. However, the throughput and energy efficiency were said to be compromised in case of weak signal environment. To focus on this aspect, three different statistical techniques were applied in [11] that in turn not only improved the signal noise error but also the energy efficiency results. An energy efficiency method employing convolution network and long short term was presented in [12] with improved workload offloading and resource allocation extensively.

As far as novel technology applications are concerned, employing CRN not only address bandwidth scarcity but also fixed spectrum issues. Also CRN routing mechanisms frequently encounters with regard to topology changes and diversity of resources. CRN-basis of cross-layer routing scheme in [13]. An Artificial Intelligence based device to device communication method was proposed in [14] for efficient data transmission in CRN. Yet another reinforcement learning mechanism was presented in [15] with the objective of improving overall routing and network performance.

Contributions of the Paper

Though some research works focused on the energy efficiency aspect, but did not concentrated on the throughput part. Also some literatures though paid attention to end-to-end delay but compromised on the spectrum utilization efficiency in CRN. In order to overcome the existing issues, a Regression Cooperative Spectrum Sensing and Gradient Flying Fox Route Optimization (RCSS-GFFRO) is introduced with the following novel contributions,

- To improve the spectrum utilization efficiency in CRN with minimal end-to-end delay, the RCSS-GFFRO method is designed based on two major processes namely cooperative spectrum sensing model and optimal route identification.
- To ensure spectrum sensing, Median Regression Cooperative Spectrum Sensing model developed in cooperative fashion taking into considerations the energy and bandwidth efficiency separately. Single Median Regression function, a machine learning technique is applied for both minimizing energy efficiency and maximizing the spectrum utilization efficiency in a significant manner.
- To reduce end-to-end delay and improve throughput, RCSS-GFFRO method uses gradient optimization function and applies it to the Flying Fox Route Optimization algorithm.
- Finally, comprehensive experimental assessment is carried out with different types of performance metrics to illustrate the proposed RCSS-GFFRO method over conventional methods.

Organization of the Work

The rest of paper is arranged as follows: Related works are described in section 2. Section 3 illustrates elaborate description of the proposed RCSS-GFFRO. Experimentation setup explained in section 4 for RCSS-GFFRO as well as traditional methods by four distinct performance metrics. At last, Section 5 concludes the paper.

II. RELATED WORKS

Several spectrum resources are allocated and licensed owing to the swift evolution of wireless applications. However, there exists an extensive amount of valuable spectrum being unutilized that proposed spectrum scarcity using spectrum management practices. Spectrum utilization has demanding in wireless transportation.

A multidimensional optimization method to ensure cooperative spectrum sensing was proposed in [16]. Also, machine learning based neural network was presented with the objective of ensuring robustness in spectrum sensing. Yet another non-orthogonal multiple access method employing blockchain mechanism was designed in [17] with improved bandwidth efficiency. A non-orthogonal multiple access employing energy efficiency all pass filter was designed in [18] with improved throughput and energy efficiency.

Study focus on EE aspects in [19] with improved throughput by energy consumption optimization. An energy efficient optimal routing method employing ensemble of particle swarm optimization and artificial bee colony was presented in [20]. By employing this ensemble techniques resulted in the improvement of network lifetime with minimal delay.

A survey of communication model over CRN employing machine learning technique was investigated in [21]. Yet another energy efficiency mechanism employing ant colony distributed mechanism was presented in [22] to ensure energy efficiency. Network stability maintained in [23] with cognitive mechanism. A novel energy efficient mechanism based on

edge computing towards significant routing was presented in [24]. A multi hop routing clustering method was proposed in [25] using machine learning technique to ensure energy efficiency in an extensive manner.

A time aware energy efficient mechanism employing minimum hop neighborhood recovery mechanism was proposed in [26] to focus on the routing delay and energy efficiency aspects. A distributed energy efficient clustering algorithm using fire fly optimization algorithm was designed in [27] to address on the issues of delay incurred during routing in CRN network. To ensure optimization and reliability chicken swarm optimization model was designed in along with deep belief network with the objective of optimizing spectrum sensing. A survey of routing algorithms in CRN was investigated in. An energy efficient optimization mechanism for multiuser CRN employing ensemble of optimization techniques was investigated in.

Motivated by the above stated literature in this work, a novel energy efficient routing methods employing machine learning called, RCSS-GFFRO in CRN developed.

III. PROPOSED RCSS-GFFRO

RCSS-GFFRO is discussed with the objective of identifying energy and bandwidth efficient optimum routing results that lead to minimal end-to-end delay and improved spectrum utilization efficiency. This section first discusses the Median Regression Cooperative Spectrum Sensing. In the second part, optimum routing employing Gradient Flying Fox Route Optimization algorithm is designed.

Median Regression Cooperative Spectrum Sensing

Spectrum sensing has predominant characteristic of CRN. Secondary user has in position with idle channels of approved spectrum band opportunistically without getting by primary users. Channel (band) observed in absence of primary signal. The cooperative spectrum sensing employed in our work utilizes multiple antennas at each secondary user (SU) to enhance energy efficiency.

In our proposed method is modeled as a regression problem, channel availability as well as non-availability. Energy efficiency (EE) and bandwidth efficient nodes estimated for finding position of channel using regression model. In this work a Machine Learning (ML) based regression model called Median Regression is employed for spectrum sensing.

Goal of EE and bandwidth allocation for Cooperative Spectrum Sensing in a CRN using ML-based Median Regression is to make optimal utilization of the spectrum by allocating idle-free frequency bands to unlicensed users while minimizing interference in an energy-efficient manner. With aid of ML-based Median Regression, relationship between one or more variables is measured. Free band in the radio spectrum is detected so that the secondary users (SUs) transmit data without interfering with primary users (PUs). As both the energy efficiency and bandwidth availability results are employed the proposed model is called as Median Regression Cooperative Spectrum Sensing model.

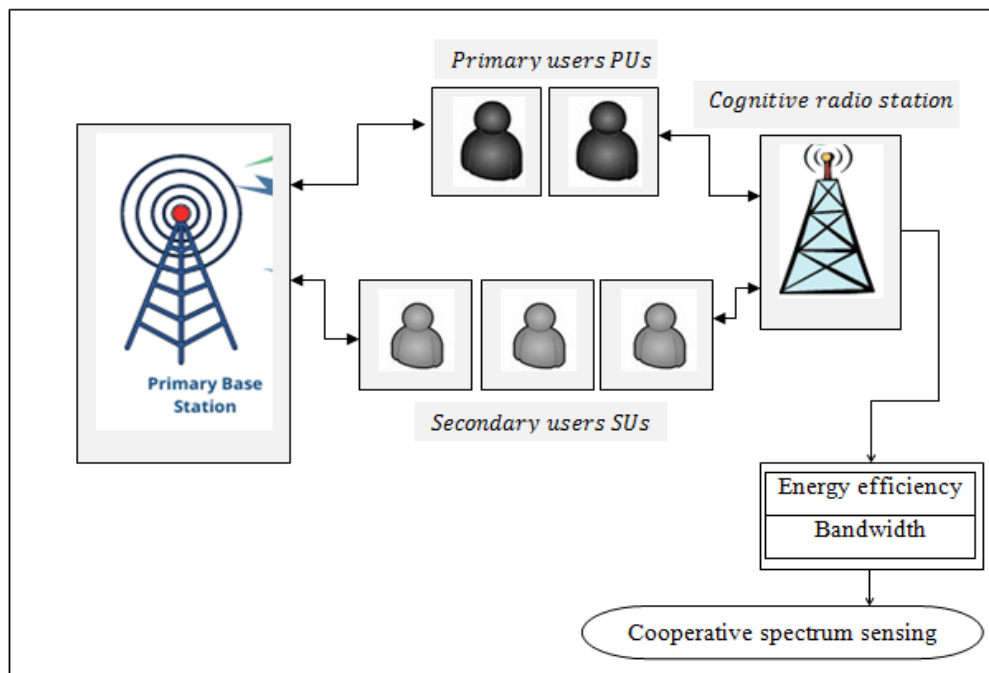


Fig 1. Structure of Median Regression Cooperative Spectrum Sensing.

From **Fig 1**, spectrum-sharing scenario assumes wherein PUs comprises of 'PT', 'PR' primary transmitter as well as receiver. SUs comprises of a 'ST', 'SR' secondary transmitter as well as receiver that are said to synchronize in the same frequency band. PU transmitter as well as receiver is 'PT', 'PR' synchronize by put ' $K: k = 1, 2, 3, \dots, K$ '. Secondary network

carry out in SUs opportunistic transmission at communal spectrum include ‘S: $s = 1, 2, \dots, S$ ’ Physical Resource Structures (PRSs). Channel State Information (CSI) is hypothesized by channel gains ‘ $CG_{s,1}, CG_{s,2}, \dots, CG_{s,K}$ ’.

First, Bandwidth or Spectral efficiency in CRNs in our work is measured based on the amount of information transmitted between transmitter and receiver. PRSs used for each ‘SU k ’ broadcast data which transmission link has ‘ $k \rightarrow s$ ’.

$$Dis_{sk} = \sqrt{(p_k - p_s)^2 + (q_k - q_s)^2} \quad (1)$$

From the above mathematical formulate (1), Euclidean distance has ‘ Dis_{sk} with ‘ $k - th$ SU’ as well as base station ‘BS’ positioned in ‘ p_k, q_k ’ and ‘ p_s, q_s ’. In order to design resource allocation pattern, probabilities of SUs accomplishing their communications improved. BS allocates fraction of ‘PRS s ’ fragment by optimal transmission power ‘ TP_{js} ’ directly managed via PUs’ behavior at SU. Then, bandwidth of ‘ $k - th$ SU’ accessible to be ‘PRS s ’ is mathematically represented as given below.

$$BE_{sk} = \log 2(1 + \alpha_{sk}) \quad (2)$$

$$\alpha_{sk} = \frac{TP_{sk}CG_{sk}}{\beta^2 + \gamma_k} \quad (3)$$

$$\gamma_k = TP_s |CG_{sk}|^2 \quad (4)$$

From the above mathematical formulates (2), (3) and (4) ‘ BE_{sk} ’ denotes the Shannon Bandwidth efficiency ‘ BE_{sk} ’ with ‘ α_{sk} ’ representing the noise ratio obtained via transmission power ‘ TP_{sk} ’, channel gain ‘ CG_{sk} ’, noise spectral density ‘ β^2 ’ and interference occurred due to concurrent transmission ‘ γ_k ’ respectively. Energy availability niche: Initially SU enters the energy availability niche in which the ST acquires energy for a time span ‘ $Dur - t$ ’ and the available energy is mathematically represented as given below.

$$E_{avail} = CG_{PT \rightarrow ST} TP_{PT} (Dur - t) \quad (5)$$

From the above mathematical formulate (5), energy availability efficiency of ST ‘ E_{avail} ’ is obtained, channel gain of energy as of primary to secondary transmitter is ‘ $CG_{PT \rightarrow ST}$ ’, constant transmission power of primary transmitter ‘ TP_{PT} ’ for a time span ‘ $Dur - t$ ’. Second, ‘ST’ convey information bits to ‘SR’ with the assumption that the energy consumed by ‘ST’ does not exceed available energy ‘ E_{avail} ’ and initial energy ‘ E_{init} ’ as given below.

$$TP_{ST} PC_{ST} \leq E_{avail} + E_{init} \quad (6)$$

From the above mathematical formulate (6) ‘ TP_{ST} ’ and ‘ PC_{ST} ’ denotes the transmission power and power consumption of secondary transmitter ‘ST’. Then the feasible throughput ‘ $Throughput$ ’ of secondary transmitter ‘ST’ is mathematically represented as given below.

$$Throughput(t, TP_{ST}) = t \log_2 \left(1 + \frac{TP_{ST} CG_{ST \rightarrow SR}}{TP_{PT} CG_{PT \rightarrow SR} + \delta^2} \right) \quad (7)$$

Subject to $Throughput(t, TP_{ST}) \geq Throughput_{min}$

From the above mathematical formulate (7), ‘ $CG_{ST \rightarrow SR}$ ’ and ‘ $CG_{PT \rightarrow SR}$ ’ refers to channel gain as of ‘ST’ to ‘SR’ as well as ‘PT’ to ‘SR’. Then the energy efficiency function is formulated as given below.

$$fun: \max_{t, TP_{ST}} EE(t, TP_{ST}) = \frac{Throughput(t, TP_{ST})}{TP_{ST} PC_{ST}} \quad (8)$$

From the above mathematical formulate (8) the energy efficient maximization results ‘ $\max_{t, TP_{ST}} EE(t, TP_{ST})$ ’ are obtained for the proposed method. Finally, employing Single Median Regression function, a machine learning technique is employed in measuring the relationship between one or more variables (i.e. bandwidth or spectral efficiency and energy efficiency results). By employing Single Median Regression function identifying higher energy efficiency and bandwidth efficient nodes is obtained. Assuming that the independent variables ‘ $EE_1^i(PU_1), EE_2^i(PU_2), \dots, EE_a^i(PU_m)$ ’ and the models parameters ‘ $BE_{sk}(SU_1), BE_{sk}(SU_2), \dots, BE_{sk}(SU_n)$ ’, then the spectrum efficient prediction results is mathematically expressed as given below.

$$Res_i = \max \sum BE_{sk} * EE_a^i \quad (9)$$

From the above mathematical formulate (9), spectrum efficient prediction results ‘ Res_i ’ are arrived at based on the higher energy efficiency and bandwidth nodes with which different route paths are said to be further discovered in the

optimal routing model in the next subsection. The pseudo code representation of Median Regression Cooperative Spectrum Sensing is given below.

Algorithm 1: Median Regression Cooperative Spectrum Sensing

Initialize Primary Users ' $PU = PU_1, PU_2, \dots, PU_m$ '; Secondary Users ' $SU = SU_1, SU_2, \dots, SU_n$ ', ' $\gamma_k = 5dB - 35 dB$ ', ' $\beta = 2 * 10^{-11}$ watts/Hz'

Repeat [bandwidth efficiency]

Calculate distance for ' $k - th$ SU ' and ' BS ' at ' p_k, q_k ' and ' p_s, q_s ' according to (1)

Calculate bandwidth efficiency ' $k - th$ SU ' accessible ' PRS s' according to (2), (3), (4)

Until all Primary Users ' PU ' and Secondary Users ' SU ' ' BE_{sk} ' is measured

Repeat [energy efficiency]

Calculate energy availability niche according to (5)

Evaluate available energy ' E_{avail} ' and initial energy ' E_{init} ' according to (6)

Evaluate feasible throughput ' $Throughput$ ' of ' ST ' according to (7)

Formulate energy efficiency function according to (8)

Calculate spectrum efficient prediction results according to (9)

Until spectrum sensing completed for a specific session

End

As stated in the above algorithm the entire pseudo code representation is split into two parts, one for measuring bandwidth or spectral efficiency and the other for measuring energy efficiency separately and then combining both employing median regression. First, for each ' $SU k$ ' transmits data through Physical Resource Structures (PRSs) ' PRS s' Shannon Bandwidth efficiency is measured. Second, energy efficiency function is derived based on the energy availability niche function. Finally, spectrum efficient prediction results are arrived at using Median Regression function. This in turn aids in minimizing energy consumption with improved spectrum utilization efficiency.

Gradient Flying Fox Route Optimization

As far as cognitive radio network (CRN) is concerned, routing refers to the procedure of ascertaining the path data packets take to travel between source and destination node. Routing is predominant for reliable and efficient communication in CRNs that functions in dynamic environments where channel conditions, topology and spectrum availability transpose suddenly. Hence, in this section to minimize end-to-end delay and improve throughput while ascertaining the path data packets take to travel between source and destination node, a Gradient Flying Fox Route Optimization algorithm is presented. **Fig 2** shows the flow structure of Gradient Flying Fox Route Optimization model.

Gradient Flying Fox Route Optimization algorithm employed in **Fig 2** in our work adapt to changing conditions and identify optimal routing solutions by simulating survival strategy of flying foxes. For spirited convergence speed by imparting local as well as global exploration, Gradient Flying Fox Route Optimization algorithm utilized in proposed method with improving overall throughput. It comprises movement of CRN nodes due to topology change and optimal identification of route data packets to travel between source and destination node.

Migratory Behaviors of CRN Nodes Due To Topology Change

Flying fox character (i.e., CRN nodes consisting of PT/PR and ST/SR) ' CRN_i ' has far as of optimal result in population. However, flying fox has probability to fly (move) to location of perfect solution, then, migration result is mathematically formulated as given below.

$$Y_{ij}^{t+1} = Y_{ij}^t + Const * rand (CP_{ij}^t - Y_{ij}^t) \quad (10)$$

From the above mathematical formulate (10), ' Y_{ij}^t ' denotes the ' $j - th$ ' node of the flying fox (i.e. either primary or secondary transmitter or receiver) individual ' i ' in the ' $t - th$ ' iteration and ' CP_{ij}^t ' represents the ' $j - th$ ' node current path corresponding to individual ' i ', constant ' $Const$ ' and random ' $rand$ ' respectively. When CRN nodes nearer toward best route, then other adjacent CRN nodes are also searched with the intent of avoid congestion and in case performs migration as mathematically given below.

$$NY_{ij}^{t+1} = Y_{ij}^t + Rand_{1j} * (CP_{ij} - Y_{ij}^t) + Rand_{2j} * (Y_{CRN_{1j}}^t - Y_{CRN_{2j}}^t), CRN \in PU, SU \quad (11)$$

$$Y_{ij}^{t+1} = \begin{cases} NY_{ij}^{t+1}, & \text{if } Rand_{3j} \geq PT \\ Y_{ij}^t, & \text{Otherwise} \end{cases} \quad (12)$$

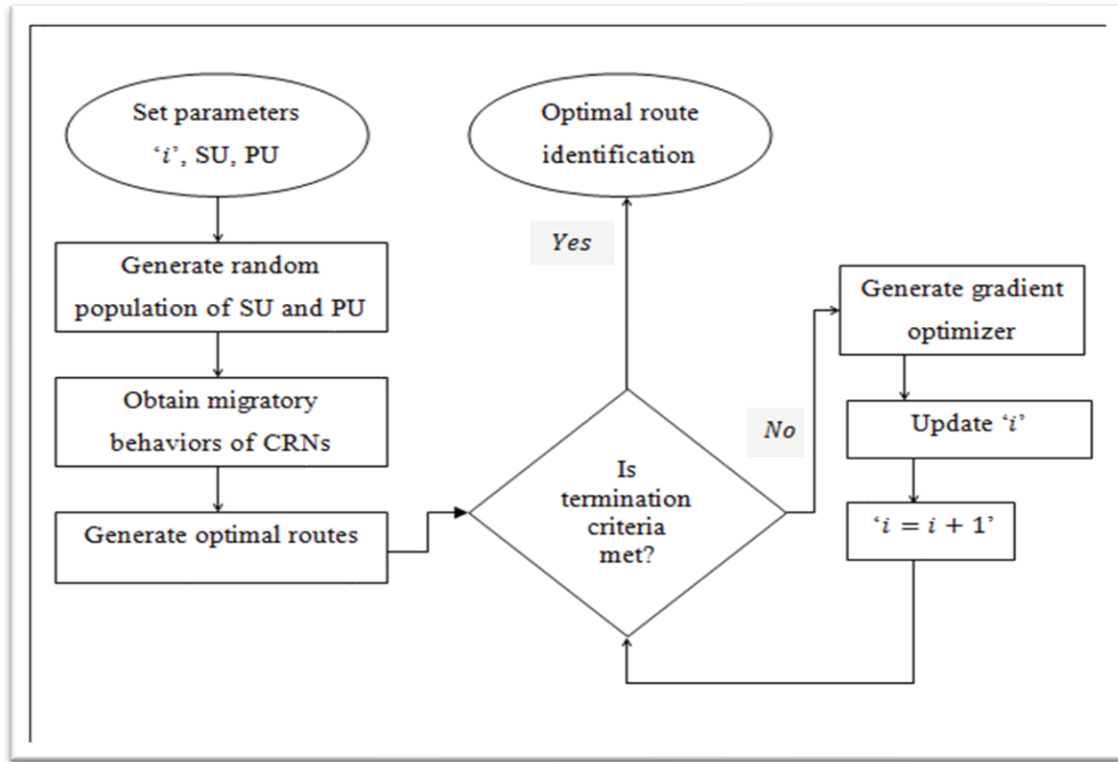


Fig 2. Flow Structure of Gradient Flying Fox Route Optimization.

From the above mathematical formulates (11) and (12), ' $Rand_{1j}$ ', ' $Rand_{2j}$ ' and ' $Rand_{3j}$ ' is distributed between '0' and '1', conditional checking made with probability threshold ' PT ' for corresponding two arbitrarily selected CRN nodes ' $Y_{CRN_{1j}}^t$ ', ' $Y_{CRN_{2j}}^t$ '. The above process is generated in such a manner that the original CRN node ' i ' is not same as the newly evolved CNR node, hence ensuring the probability of exploring other locations or paths.

Optimal Route Identification

With the intent of identifying path data packets, two CRN nodes ' CRN_1 ' and ' CRN_2 ' are selected arbitrarily to cross over for generating offspring ' OS ' to fine tune the CRN nodes already allocated with the path. The resulting mathematical expression is formulated as given below.

$$OS_1 = RN * CRN_1 + (1 - RN) * CRN_2 \quad (13)$$

$$OS_2 = RN * CRN_2 + (1 - RN) * CRN_1 \quad (14)$$

From the above mathematical formulates (13) and (14) offspring ' OS_1 ' or ' OS_2 ' (i.e., new solutions or new paths data packets for travelling among source as well as destination node selected in an optimal manner). In our work, offspring or new paths data packets arrived at based on the sensing time and transmission time. In the proposed model two periods, i.e., sensing time ' ST ' (i.e. based on sensing period) and transmission time ' TT ' (i.e. based on transmission period) are considered and also synchronized slotted framework with normalized length ' $ST + TT = 1$ ' is applied. Then, the gradient optimization function employing sensing and transmission time is mathematically stated as given below.

$$\frac{\partial}{\partial T} \log L(T), \text{ where } T = ST + TT \text{ [compute gradient of log likelihood]} \quad (15)$$

$$T' = T + \frac{\partial}{\partial T} \log L(T) \text{ [update]} \quad (16)$$

From the above equations (15) and (16) employing gradient optimization function the sensing and transmission time are computed and followed by which updates are made accordingly. ' n ' pairs of SUs perform separately spectrum sensing for identifying primary signal by approved spectrum, through sensing time. In both time iteration, certified spectrum switches arbitrarily among free-state ' fs ' as well as occupied-state ' os '. Possibility of approved spectrum has ' oc ' denoted as ' $Prob_{os}$ ' and ' fs ' has denoted as ' $Prob_{fs}$ ' respectively. When received transmit data packets indicate ' Res_i ', to secondary receiver through transmission era therefore ensuring optimal routing. The pseudo code representation of Gradient Flying Fox Route Optimization is given below.

Algorithm 2: Gradient Flying Fox Route Optimization

Initialize ‘Const = 0.5’, ‘rand = [0,1]’, ‘Rand_{1j}, Rand_{2j}, Rand_{3j}, RN between 0 and 1’, ‘= 0.5’, Data packets ‘DP’

Repeat

Migratory behaviors of CNR nodes due to topology change

Calculate migration result according to (10)

Measure probability of avoiding congestion by analyzing other adjacent CRN nodes according to (11) and (12)

Optimal route identification

Perform optimal route identification by generating offspring ‘OS’ according to (13) and (14) respectively

Compute gradient optimization function involving sensing and transmission time according to (13)

Sensing period

$$ST \rightarrow Prob_{os} + Prob_{fs} = 1$$

Transmission period

If (Res_i = free)

ST transmits DP to SR

End if

Until optimal route identification results

As given in the above Gradient Flying Fox Route Optimization algorithm, the overall process is split into two parts. First, using Flying Fox Route Optimization migratory behaviors of CNR nodes due to topology change is observed. Gradient optimization function used to optimal route identification involving sensing and transmission time. This in turn assists in improving routing performance in CRNs with minimal end-to-end delay and improving overall throughput.

IV. RESULTS

Experimental results created in NS-3 simulator. Assume population size has 10, as well as entire run has 50. RCSS-GFFRO, traditional RL-IoT Routing [1] and ELSTM-RPO [2] discussed with several metrics. Network metrics described in **Table 1** to estimate experiments.

End-to-End Delay (E2E)

It defines to total time consume for data packet toward journey between source and destination, confining all hops and probable delays experienced with the CRN, inclusive of queuing delays, sensing delays, transmission delays and propagation delays caused by the arbitrary nature of spectrum access in a cognitive radio environment.

$$E2E = PU_MAR[QD + SD + TD + PD] \quad (17)$$

Table 1. Simulation Parameters

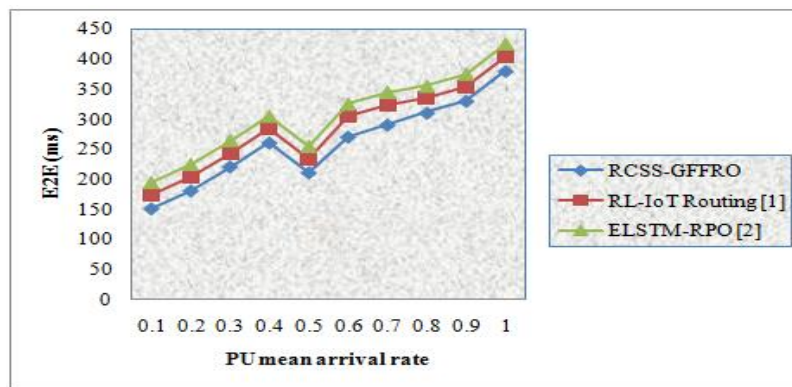
S. No	Network parameters	Initialization values
1	Number of iterations	5, 10,...50
2	PU mean arrival rate	0.1, 0.2,...1.0
3	Number of users	5, 10, ...50
4	Node type	Cognitive
5	Sensor field	100m*100m
6	Data rate	1Mbps
7	Bandwidth	3Mhz
8	Initial energy	0.5J
9	Receiver frequency	2.4GHz
10	Transmitter frequency	1.8GHz
11	SU packet length	10Kb

Where, queuing, sensing, transmission, propagation delays are ‘QD’, ‘SD’, ‘TD’ and ‘PD’, ‘PU_MAR’ represents PU mean arrival rate. E2E outcome are given in **Table 2** by applying equation (17).

Table 2. Tabulation for E2E using RCSS-GFFRO, RL-IoT Routing [1] and ELSTM-RPO [2]

PU mean arrival rate	E2E (ms)		
	RCSS-GFFRO	RL-IoT Routing [1]	ELSTM-RPO [2]
0.1	150	175	195
0.2	180	205	225
0.3	220	245	265
0.4	260	285	305
0.5	210	235	255
0.6	270	305	325
0.7	290	325	345
0.8	310	335	355
0.9	330	355	375
1	380	405	425

E2E using proposed RCSS-GFFRO for the CRN and two existing methods, RL-IoT Routing [1] and ELSTM-RPO [2] illustrated in **Fig 3**. PU mean arrival rate indicated in Here horizontal axis, whereas vertical axis denotes E2E. Two inferences are made from the above pictorial representation. First, the end-to-end delay analyses results were neither found to be inversely or directly proportional to the PU mean arrival rate, in other words, increasing the PU mean arrival rate did neither increased nor decreased the end-to-end delay. The reason for the minimization of end-to-end delay using the proposed RCSS-GFFRO method was due to the application of Gradient Flying Fox Route Optimization algorithm. By applying this algorithm the migratory behaviors of CNR nodes due to topology change were initially observed. Followed by which identification of optimal routes towards data packet transmission was made between source and destination node using gradient optimization function. This in turn minimized end-to-end delay across the entire CRN network was reduced using proposed RCSS-GFFRO with 10% as well as 16% over [1], [2].

**Fig 3.** E2E.

Throughput Analysis

Throughput analysis (Th) in CRN refers to the procedure of assessing and measuring the data transmission rate (throughput) within a CRN. It is analyzing how effectively SUs be able to employ spectrum related to PUs while reducing interference, taking into considerations like, spectrum sensing performance and routing allocation strategies. 'Th' estimated as given below.

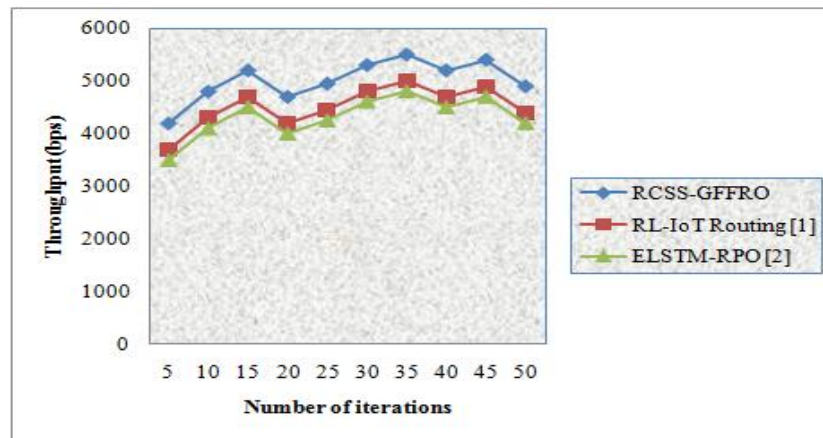
$$Th = \frac{n}{CRN_{avg}} \quad (18)$$

From (18) 'n' is number of sent bits per n data bit and average population size in CRN 'CRN_{avg}' including both 'PU' and 'SU' respectively. The results of throughput analysis by applying equation (18) are given in **Table 3**.

Table 3 and Fig 4 given above shows the graphical representation of throughput with respect to 50 numbers of iterations performed using the three methods, RCSS-GFFRO, RL-IoT Routing [1] and ELSTM-RPO [2] respectively. From the above graphical representation for the first 15 iterations, the throughput was found to be high using all the three methods whereas a dip in throughput was observed for the next 5 iterations, next increased for the 15 iterations and so on. However, simulations performed for the first 5 iteration, the throughput using RCSS-GFFRO method was observed to be 4200 bps, whereas using [1] and [2] it was found to be 3700bps and 3500bps respectively.

Table 4. Tabulation for Throughput Analysis using RCSS-GFFRO, RL-IoT Routing [1] and ELSTM-RPO [2]

Number of iterations	Throughput (bps)		
	RCSS-GFFRO	RL-IoT Routing [1]	ELSTM-RPO [2]
5	4200	3700	3500
10	4800	4300	4100
15	5200	4700	4500
20	4700	4200	4000
25	4950	4450	4250
30	5300	4800	4600
35	5500	5000	4800
40	5200	4700	4500
45	5400	4900	4700
50	4900	4400	4200

**Fig 4.** Throughput Analysis.

Contrary to conventional [1], [2], RCSS-GFFRO of throughput has better. By Gradient Flying Fox Route Optimization model, initially, the migratory behaviors of CRN nodes owing to the change observed in topology were observed. Followed by which optimal identification of route was measured using gradient of likelihood function. Throughput using RCSS-GFFRO improved by 11% and 16% than [1], [2].

Energy Efficiency (EE)

Energy efficiency analysis in CRN refers to the procedure of measuring how efficiently a CRN uses energy while maintaining optimal spectrum utilization and making cooperative decision between secondary users (SUs) to minimize unnecessary energy expenditure. The energy efficiency analysis is mathematically represented as given below.

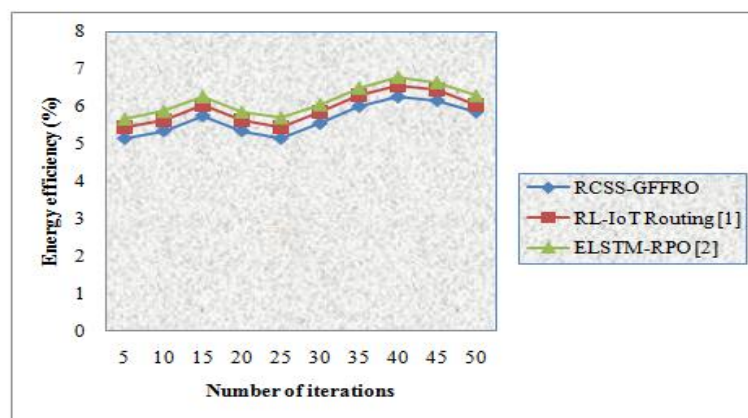
$$EE = E_{SS} + (V_0 + V_1)E_{DT} \quad (19)$$

From the above equation (19) ' E_{SS} ' and ' E_{DT} ', is energy required for spectrum sensing as well as information broadcast. Licensed spectrum not utilized by the primary user ' V_0 ' and licensed spectrum utilized by the primary user ' V_1 ' respectively. The results of energy efficiency analysis by applying equation (19) are given in **Table 4**.

The performance of energy efficiency (vertical axis) for fifty different numbers of iterations (horizontal axis) has been analyzed and is shown in **Fig 5** using the three methods, RCSS-GFFRO, RL-IoT Routing [1] and ELSTM-RPO [2]. As shown in the above figure the RCSS-GFFRO method energy efficiency is comparatively better to other methods [1] and [2]. This is evident from the simulation with 5 numbers of iterations where the energy efficiency using RCSS-GFFRO method was observed to be 5.15 whereas the energy efficiency for [1] and [2] was found to be 5.45 and 5.66 respectively. With this inference the energy efficiency of RCSS-GFFRO was observed to be better than [1] and [2]. The reason was due to the application of Median Regression Cooperative Spectrum Sensing algorithm. By applying this algorithm two important factors, bandwidth or spectral efficiency energy efficiency while performing cooperative spectrum sensing were measured separately. Followed by which the two factors were combined using median regression function. RCSS-GFFRO of EE enhanced with 11% and 16% than [1], [2].

Table 4. Tabulation for Energy Efficiency Analysis using RCSS-GFFRO, RL-IoT Routing [1] and ELSTM- RPO [2]

Number of iterations	Energy efficiency (%)		
	RCSS-GFFRO	RL-IoT Routing [1]	ELSTM-RPO [2]
5	5.15	5.45	5.66
10	5.35	5.65	5.87
15	5.75	6.05	6.26
20	5.35	5.65	5.85
25	5.15	5.45	5.69
30	5.55	5.85	6.05
35	6	6.30	6.50
40	6.25	6.55	6.79
45	6.15	6.45	6.65
50	5.85	6.05	6.29

**Fig 5.** Energy Efficiency Analysis.

Spectrum Utilization Efficiency Analysis

As far as CRN is concerned spectrum utilization efficiency refers to the potentiality of secondary users (SUs) to efficiently utilize unoccupied portions of the spectrum belonging to primary users (PUs), hence improving the overall data transmission while reducing interference to the primary user, hence arriving at optimal utilization of available and accessible radio spectrum. The results of spectrum utilization efficiency analysis are given in **Table 5**.

Table 5. Tabulation for Spectrum Utilization Efficiency using RCSS-GFFRO, RL-IoT Routing [1] and ELSTM- RPO [2]

Number of users	Spectrum utilization efficiency (%)		
	RCSS-GFFRO	RL-IoT Routing [1]	ELSTM-RPO [2]
5	93.55	88.15	78.55
10	90.45	85.45	75.35
15	88	83.15	73.15
20	86.35	81.55	71.25
25	84	78.35	68.55
30	80	75.25	65.45
35	75	69.35	59.35
40	82.35	77.55	67.55
45	85	80.25	70.55
50	88	83.15	73.25

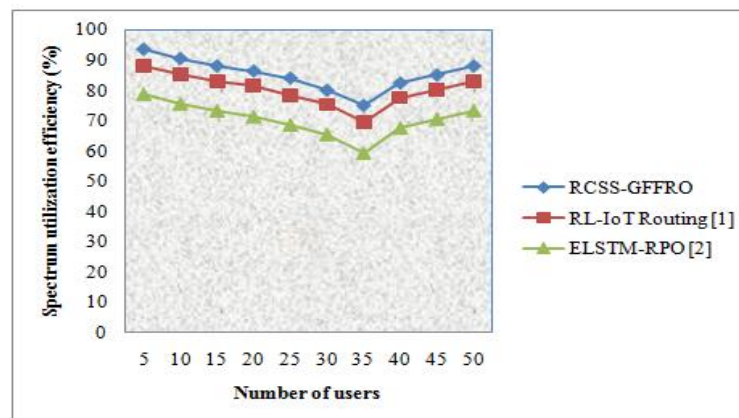


Fig 6. Spectrum Utilization Efficiency.

Finally **Fig 6** given above shows the spectrum utilization efficiency results using the proposed RCSS-GFFRO and two existing methods RL-IoT Routing [1] and ELSTM-RPO [2]. For first set of 35 users a down trend was observed for the spectrum utilization efficiency results however an increasing trend was observed for the result of 15 users. This corroborates the objective that even though users enhances in CRN network there was not compromise in the spectrum utilization efficiency results. The reason behind improvement in spectrum utilization efficiency results employs Median Regression Cooperative Spectrum Sensing. Shannon Bandwidth efficiency was applied and followed by which energy efficient maximization results were obtained separately. Finally, a machine learning technique employing Single Median Regression function was applied to combine the two metrics. This in turn improved the overall spectrum utilization efficiency results of the proposed RCSS-GFFRO with 6% and 21% than [1], [2].

V. CONCLUSION

Selecting spectrum efficient routing in CRN maximize overall network throughput while reducing interference with licensed primary users (PUs), efficiently using the available spectrum significantly. Recently, many spectrum efficient routing algorithms have been developed to ensure throughput efficient data transmission in CRN. In this work a suitable Regression Cooperative Spectrum Sensing and Gradient Flying Fox Route Optimization (RCSS-GFFRO) for minimum end-to-end delay and improved spectrum utilization efficiency is developed. First, a machine learning technique based Median Regression Cooperative Spectrum Sensing is applied with bandwidth and energy efficiency measures with minimal probability of interference to primary users by evaluating relationship between bandwidth and energy efficiency simultaneously. Second, identification of optimal route is made employing Gradient Flying Fox Route Optimization algorithm that in turn reduces the interference with primary users and increases secondary user performance via sensing time and transmission time. A comprehensive experimental evaluation is performed using diversified performance metrics with respect to the distinct numbers of users and PU mean arrival rate. Contrary to state-of-art-works, overall performance results illustrate that presented RCSS-GFFRO method achieves higher spectrum utilization efficiency.

CRedit Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Sundar T and Senthilkumar A; **Methodology:** Sundar T; **Software:** Senthilkumar A; **Data Curation:** Sundar T; **Writing- Original Draft Preparation:** Sundar T and Senthilkumar A; **Visualization:** Sundar T; **Investigation:** Senthilkumar A; **Supervision:** Sundar T; **Validation:** Senthilkumar A; **Writing- Reviewing and Editing:** Sundar T and Senthilkumar A; All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest

Data Availability Statement

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

Funding

No funding agency is associated with this research.

Consent to publish

All the authors gave permission to Consent to publish.

References

- [1]. T. Safdar Malik et al., "RL-IoT: Reinforcement Learning-Based Routing Approach for Cognitive Radio-Enabled IoT Communications," *IEEE Internet of Things Journal*, vol. 10, no. 2, pp. 1836–1847, Jan. 2023, doi: 10.1109/jiot.2022.3210703.

- [2]. S. Saranya and P. Jayarajan, “Enhanced deep learning-based optimization model for the optimal energy efficiency-oriented Cognitive Radio Networks,” *Ain Shams Engineering Journal*, vol. 15, no. 12, p. 103051, Dec. 2024, doi: 10.1016/j.asej.2024.103051.
- [3]. D. Balakumar and S. Nandakumar, “Blockchain-enabled cooperative spectrum sensing in 5G and B5G cognitive radio via massive multiple-input multiple-output nonorthogonal multiple access,” *Results in Engineering*, vol. 24, p. 102840, Dec. 2024, doi: 10.1016/j.rineng.2024.102840.
- [4]. S. Harihara Gopalan, M. Muzammil Parvez, A. Manikandan, and S. Ramalingam, “Cognitive radio spectrum allocation using Nash equilibrium with multiple scheduling resource selection algorithm,” *Ain Shams Engineering Journal*, vol. 15, no. 5, p. 102688, May 2024, doi: 10.1016/j.asej.2024.102688.
- [5]. Q. Wu, B. K. Ng, and C.-T. Lam, “Energy-Efficient Cooperative Spectrum Sensing Using Machine Learning Algorithm,” *Sensors*, vol. 22, no. 21, p. 8230, Oct. 2022, doi: 10.3390/s22218230.
- [6]. A. B. Bomgni, M. L. F. Sindjoun, D. K. Tchibonsou, M. Velepini, and J. F. Myoupo, “NESEPRIN: A new scheme for energy-efficient permutation routing in IoT networks,” *Computer Networks*, vol. 214, p. 109162, Sep. 2022, doi: 10.1016/j.comnet.2022.109162.
- [7]. M. Kalra, A. Vohra, and N. Marriwala, “LEACH based hybrid energy efficient routing algorithm for dynamic cognitive radio networks,” *Measurement: Sensors*, vol. 24, p. 100419, Dec. 2022, doi: 10.1016/j.measen.2022.100419.
- [8]. X. He, H. Jiang, Y. Song, C. He, and H. Xiao, “Routing Selection With Reinforcement Learning for Energy Harvesting Multi-Hop CRN,” *IEEE Access*, vol. 7, pp. 54435–54448, 2019, doi: 10.1109/access.2019.2912996.
- [9]. S. Elghamrawy, A. H. Ismail, and A. E. Hassanien, “Energy consumption optimization in green cognitive radio networks based on collaborative spectrum sensing,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2024, no. 1, Sep. 2024, doi: 10.1186/s13638-024-02402-3.
- [10]. H. S. Fouda and M. M. Fouda, “Three Novel Statistical Tests-Inspired Spectrum Sensing Techniques for Cognitive Radio,” *IEEE Open Journal of the Communications Society*, vol. 5, pp. 7041–7056, 2024, doi: 10.1109/ojcoms.2024.3487825.
- [11]. U. K. Lilhore et al., “Optimizing energy efficiency in MEC networks: a deep learning approach with CyberTwin-driven resource allocation,” *Journal of Cloud Computing*, vol. 13, no. 1, Aug. 2024, doi: 10.1186/s13677-024-00688-8.
- [12]. G. Dhiman and R. Sharma, “SHANN: an IoT and machine-learning-assisted edge cross-layered routing protocol using spotted hyena optimizer,” *Complex & Intelligent Systems*, vol. 8, no. 5, pp. 3779–3787, Nov. 2021, doi: 10.1007/s40747-021-00578-5.
- [13]. S. Mishra, “Artificial Intelligence Assisted Enhanced Energy Efficient Model for Device-to-Device Communication in 5G Networks,” *Human-Centric Intelligent Systems*, vol. 3, no. 4, pp. 425–440, Sep. 2023, doi: 10.1007/s44230-023-00040-4.
- [14]. D. Godfrey, B. Suh, B. H. Lim, K.-C. Lee, and K.-I. Kim, “An Energy-Efficient Routing Protocol with Reinforcement Learning in Software-Defined Wireless Sensor Networks,” *Sensors*, vol. 23, no. 20, p. 8435, Oct. 2023, doi: 10.3390/s23208435.
- [15]. T. Balachander, K. Ramana, R. M. Mohana, G. Srivastava, and T. R. Gadekallu, “Cooperative Spectrum Sensing Deployment for Cognitive Radio Networks for Internet of Things 5G Wireless Communication,” *Tsinghua Science and Technology*, vol. 29, no. 3, pp. 698–720, Jun. 2024, doi: 10.26599/tst.2023.9010065.
- [16]. Hiwrekar Yadneshwar Baburao and Dr Manav Thakur, “Review of Routing Approaches for Cognitive Radio Networks in Flood Management Systems,” *Web of Science*, Vol. 25, Jan 2022.
- [17]. P. K. Udayaprasad et al., “Energy Efficient Optimized Routing Technique With Distributed SDN-AI to Large Scale I-IoT Networks,” *IEEE Access*, vol. 12, pp. 2742–2759, 2024, doi: 10.1109/access.2023.3346679.
- [18]. M. Jalil Piran et al., “Multimedia communication over cognitive radio networks from QoS/QoE perspective: A comprehensive survey,” *Journal of Network and Computer Applications*, vol. 172, p. 102759, Dec. 2020, doi: 10.1016/j.jnca.2020.102759.
- [19]. K. A. Sharada, T. R. Mahesh, S. Chandrasekaran, R. Shashikumar, V. V. Kumar, and J. R. Annand, “Improved energy efficiency using adaptive ant colony distributed intelligent based clustering in wireless sensor networks,” *Scientific Reports*, vol. 14, no. 1, Feb. 2024, doi: 10.1038/s41598-024-55099-1.
- [20]. H. H. El-Sayed, E. M. Abd-Elgaber, E. A. Zanaty, F. S. Alsubaei, A. A. Almazroi, and S. S. Bakheet, “An efficient neural network LEACH protocol to extended lifetime of wireless sensor networks,” *Scientific Reports*, vol. 14, no. 1, Nov. 2024, doi: 10.1038/s41598-024-75904-1.
- [21]. G. Liu, Z. Liu, V. S. Sheng, L. Zhang, and Y. Yang, “A Novel Energy-Efficient, Static Scenario-Oriented Routing Method of Wireless Sensor Network Based on Edge Computing,” *Wireless Communications and Mobile Computing*, vol. 2022, no. 1, Jan. 2022, doi: 10.1155/2022/3450361.
- [22]. J. Wang and C. Liu, “An imperfect spectrum sensing-based multi-hop clustering routing protocol for cognitive radio sensor networks,” *Scientific Reports*, vol. 13, no. 1, Mar. 2023, doi: 10.1038/s41598-023-31865-5.
- [23]. H. R. E. H. Boucekara, A. F. Salami, Y. A. Sha’aban, M. Nahas, M. S. Shahriar, and M. A. Alanezi, “TUBER: Time-aware UAV-based energy-efficient reconfigurable routing scheme for smart wireless livestock sensor network,” *PLOS ONE*, vol. 19, no. 1, p. e0292301, Jan. 2024, doi: 10.1371/journal.pone.0292301.
- [24]. K. Gökhan Nalbant, S. A. Alsubhany, A. Hassan Alshehri, M. Hatira, and B. J. Choi, “An intelligent algorithm for energy efficiency optimization in software-defined wireless sensor networks for 5G communications,” *PLOS ONE*, vol. 19, no. 6, p. e0301078, Jun. 2024, doi: 10.1371/journal.pone.0301078.
- [25]. S. M. and L. E., “Chicken swarm optimization modelling for cognitive radio networks using deep belief network-enabled spectrum sensing technique,” *PLOS ONE*, vol. 19, no. 8, p. e0305987, Aug. 2024, doi: 10.1371/journal.pone.0305987.
- [26]. Harpreet Kaur, Nitin Gupta, “Routing in Cognitive Radio Networks - A Survey”, *International Journal of Engineering Research and Applications*, Vol. 5, Dec 2015
- [27]. A. Saikia and A. J. Gogoi, “Energy Efficiency Optimization of Multiuser Cognitive Radio Network,” *International Journal of Electronics and Communication Engineering*, vol. 11, no. 8, pp. 11–21, Aug. 2024, doi: 10.14445/23488549/ijece-v11i8p102.

Publisher’s note: The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations. The content is solely the responsibility of the authors and does not necessarily reflect the views of the publisher.