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ABSTRACT

This paper presents a novel spectrum sensing and resource allocation method for Cognitive Radio Networks (CRNs) using the Hazelnut Tree Search (HTS) algorithm in a frequency-hopping framework. CRNs enable secondary users (SUs) to utilize unused licensed spectrum without causing interference to primary users (PUs). The proposed Spectrum Sensing and Resource Allocation using Hazelnut Tree Search in CRN (SS-RA-HTS-CRN) method detects PU presence, prompting SUs to switch channels to avoid interference, guided by a designated guide node (GN). The HTS algorithm selects optimal sensing nodes and improves spectrum sensing, enhancing resource allocation reliability. Simulations in NS-3.26 show that SS-RA-HTS-CRN achieves delay reductions of 28.93%, 31.9%, and 22.45%, delivery ratio improvements of 28.21%, 17.41%, and 11.565%, and packet drop rate reductions of 35.4%, 44.3%, and 23.12% compared with Energy-Aware Resource Allocation with Backtracking Search Optimization (SS-RA-BSO-CRN), Spectrum Sensing with Hybrid Particle Swarm and Gravitational Search (SS-hybrid PSOGSA-CRN), and Spectrum Sensing using Modified Spider Monkey Optimization (SS-MSMO-CRN). The proposed SS-RA-HTS-CRN method significantly enhances efficiency, reliability, and adaptability in CRNs, making it a promising solution for dynamic spectrum management.

KEYWORDS

Cognitive radio network (CRN); Hazelnut tree search (HTS) algorithm; primary user; secondary user; spectrum sensing (SS)

1. INTRODUCTION

Cognitive Radio Networks (CRNS) is a crucial model for advancing wireless communication and spectrum management [1]. These CRNS are categorized into two types: Primary Users (PU) and Secondary Users (SUs) [2]. PU hold licensed spectrum bands, while SUs detect and utilize available spectrum that is not being used by PU [3]. Unused spectrum can be shared with other users to enhance spectrum efficiency. As the number of PU and SUs increases, the spectrum size remains constant, which underscores the need for CRNS [4–7]. SUs are allowed to use a channel when the primary user is temporarily inactive [8]. Secondary users use unlicensed spectrum that are not occupied by primary users and resume channel use to avoid interference [9].

This manuscript proposes SS-RA using a Hazelnut tree search algorithm for frequency hopping-based CRN. Firstly, in the same channel, the node senses the occurrence of primary users, and then, if detects the primary signal in this channel, it starts moving to other channels in the direction of GN [10,11]. The primary as well as secondary signals use the channel usefully to achieve collision-free communication [12]. Then, the Hazelnut tree search algorithm is used to get the optimum solution with increasing efficiency and reducing interference.

The primary contributions of this research are:

- Data transmission and in-band together with out-of-band spectrum sensing are proposed, resulting in increased efficiency and throughput.
- It only hops when the main signal is in the channel, reducing the amount of interference with the mechanism.
- Channel recovery is fast because it has no sense for $I_{\max}$ time to determine the existence of the primary signal.
- The nodes' ability to transmit data depends on traffic demand, which is increased by increasing throughput and utility values.
- The hazelnut tree search algorithm is used to construct a set of transmissions including sensing nodes that provide the multi-objective function's optimum solution [13,14].
- If primary signals desire to utilize a particular channel, GN has been provided to direct the SUs to hop. Through the cluster head, GN instructs

the group of nodes while keeping track of the channels.

The following manuscript is structured as section 2 describes the literature survey; Section 3 illustrates the proposed methods for SS-RA using the HTS algorithm for the frequency hopping-based CRN, section 4 proves the result and Section 5 gives the conclusion.

2. LITERATURE SURVEY

Some recent related studies are revised in this segment:

Roopa *et al*., [15] have suggested a method for allocating resources and sharing based on the cooperative game theory. Then, the cooperative node selection ensures the maximized payoff. The presented method provides lower delay and lower throughput.

Eappen and Shankar, [16] have presented a Hybrid PSO-GSA for energy efficient spectrum sensing in CRN. The Hybrid PSO-GSA achieves a balanced trade-off in explorations and exploitations. The method provides higher throughput and higher drop.

Dinesh *et al*., [17] have presented an MSMO spectrum sharing in CRNS. Initially, SS and sensing techniques put forward for increasing the requirement of throughput and the quality of service. From metrics like throughput, handoff, success probability, and false alarm probability, the proposed method provides higher throughput and lower network lifetime.

Meena and Rajendran, [18] have presented Spectrum sensing with resource allocation in cognitive radio for effective transmission. It addresses the problem of interference via spectrum sensing and resource allocation for progress of data transmission. The model reached high overhead and low network lifetime.

Balachander and Krishnan, [19] have presented Efficient utilization of cooperative spectrum sensing in CRN utilizing non-orthogonal multiple access (NOMA) for 5G wireless communication. The model achieved a high network lifetime and low delivery ratio.

Sateesh *et al*., [20] have suggested Spectrum Sensing analysis in CRN utilizing Energy Detector. The intelligent radio dramatically increases range utilization by enabling dynamic range access and granting unlicensed or secondary users access to any unused range provided to prime users. It offers high throughput and low network lifetime.

Xiao *et al*., [21] have suggested Energy efficient resource allocation in delay-aware UAV-dependent CRN with energy harvesting. The delay-related approximate optimization approach (De-AOS) was presented since the EE enlargement was a non-tractable optimum issue. It reached maximal network lifetime and minimal delivery ratio.

Sivakumaran *et al*., [22] have suggested a cooperative spectrum sensing for sensing in Byzantine attacks that was expressed in relay-based CRN. The presented methods provide higher throughput and lower throughput.

The Hazelnut Tree Search Algorithm significantly outperforms existing methods in spectrum sensing and resource allocation. It reduces complexity and enhances efficiency compared to Roopa *et al*.'s game theory approach, and balances exploration and exploitation better than Eappen and Shankar's Hybrid PSO-GSA. It delivers superior throughput and network lifetime compared to Dinesh *et al*.'s MSMO and Meena and Rajendran's 5G approaches. It also achieves higher network efficiency over Balachander and Krishnan's NOMA and improves throughput and delivery ratio compared to Sateesh *et al*.'s energy detection and Xiao *et al*.'s UAV-based CRN. Overall, it offers more effective spectrum management in CRNS.

3. PROPOSED SPECTRUM SENSING AND DATA TRANSMISSION USING HAZELNUT TREE SEARCH ALGORITHM FOR FH-CRN

The Hazelnut Tree Search (HTS) algorithm is used for spectrum sensing with resource allocation in CRN. By applying the HTS to a received signal, it can analyze the spectral content and estimate the power spectral density. This helps determine the existence or nonexistence of primary users in a frequency band, enabling dynamic resource allocation to secondary users without interference. Additionally, the HTS algorithm assists in identifying underutilized frequency bands for efficient resource allocation. Overall, it provides a way to analyze signals and make informed decisions about spectrum utilization and allocation.

3.1 Frequency Hopping Based CRN

Considering the frequency hopping-based CRN with M secondary nodes. Every member node is represented as $N_m (m \in M)$ and capable of spectrum with data transmission. The Cluster Head (CH) is expected to be provided in this cluster and take into account that the primary signal's range is significantly larger than the cognitive radio cluster size. Then sensing the local wideband using every member node outcome is sent to CH. The node transmits the data to use that channel and at the same channel, another node is sensed using the primary signals. The selected hopping channel doesn't have any primary signals; also it doesn't have any interference. Each time the primary signal is included and eliminated from the hopping channel pool, $P_{HC} = \{Cha_1, cha_2, \ldots, cha_C\}$. Here, C denotes the sum number of hopping channels.

3.2 In-Band Along Out-Band Spectrum Sensing

Here, the out-band sensing method contains the Wideband Spectrum Sensing (WSS). Next, the narrow band spectrum is sensed. In the out-band spectrum, transmitting the next data with the next hopping channel, is not presently used. In the sensing model, the node doesn't take part while transmitting any of the data in the sensing narrowband spectrum for the signals of primary. The spectrum sensing and data transmission using the Hazelnut tree search algorithm for FH-CRN shows a Figure 1.

Primary Users (PU): This refers to licensed users who have exclusive rights to a specific spectrum band. These are the devices that are licensed to transmit data across the pre-specified channels. These Primary Users facilitate an interference-free environment.

Secondary Users (SU): It is the unlicensed users who do not have an allocated spectrum. These wireless devices assist in filling in the spectrum gaps present in different frequency bands.

The secondary user who doesn't engage with the primary signal is responsible for the cooperative sensing and reporting that occurs after a special gadget. Using any

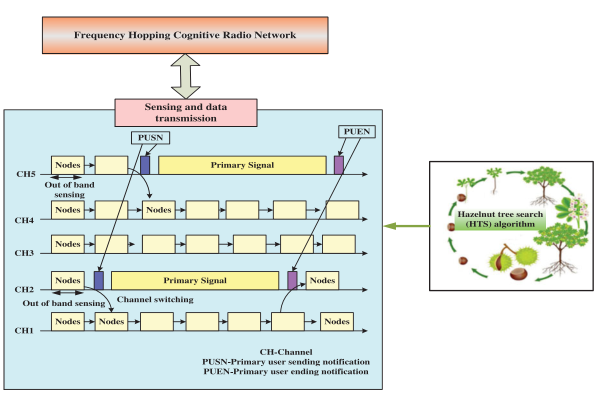

Figure 1: Block diagram for proposed spectrum sensing and data transmission using Hazelnut tree search algorithm for FH-CRN

channel before, primary signals inform the guide node and send the primary user sending notification (PUN) signal. At the end, the user sends the primary user ending notification (PUEN) signal. Moreover, for the PU sending notification, the PU ending notification and the primary users' detection notification, the time is the same such as $t_{PUSN} = t_{PUEN} = t_{PUDN}$. Throughout the time of spectrum sensing, it's the secondary signal's duty to take care of the primary identification of probability (P_D) and its false alarm probability (P_{FA}). To detect sensed signals with each member, 2 hypotheses are followed and are expressed in equations (1)–(2)

$$h_0 : y[m] = w[m] \tag{1}$$

$$h_1 : y[m] = x[m] + w[m] \tag{2}$$

where $m = 1, 2, 3, \ldots M$. M denotes the average node count. At h_0 signal specifies absent, h_1 the signal specifies present. $x[m]$ specifies the primary signal and has the power of ρ_X^2. $w[m]$ specifies the noise of white Gaussian. Here, the mean value is 0 and the variance is ρ_w^2. The probability of identification with a false alarm for the node in every narrowband channel is written in the following Equation (3):

$$\begin{aligned} P_D &= P(t \succ \delta | h_1) \\ &= q\left(\frac{\delta - M(\rho_w^2 + \rho_X^2)}{sqrt(2M(\rho_w^2 + \rho_X^2))}\right) \end{aligned} \tag{3}$$

where δ is a threshold balancing detection accuracy and false alarm rates. Equation (6), C represents an available count of hopping channels. Based on the typical technique, nodes don't perform any of the transmissions in the sensing time resulting in an increase in service disruption time ($t_{serdish}$). Therefore, service distraction is present at the time of primary users' detection notification signal denotes t_{PUDN}, where, t_R represents the reporting period after sensing every channel. Later, more count of hopping channels and service distraction time ($t_{serdish}$) presented the conventional technique. The service distraction time ($t_{serdish}$) is expressed below in Equation (4):

$$t_{serdish} = \begin{cases} \sum_{c=1}^{C} (t_{sen}^{channel} + t_R) & for\ conventional \\ t_R = t_{PUDN}\ for & proposed \end{cases} \tag{4}$$

3.3 Sensing Optimization with Resource Allocation

The major goal of the Cognitive Radio Network is to increase secondary node data throughput while avoiding inaccurate interference with the principal signals. Because of various channel conditions, each node has a distinct traffic requirement. The transmission nodes and sensing nodes are configured by cluster heads following the GN's instructions.

3.3.1 Evaluation Methods and Constraints

Every secondary node is controlled by the needed power for transmission. $P(m, c)$ Represents power using the m^{th} node and the c^{th} hopping channel. For c^{th} channel, $P(m, c)$ reaches the maximum value of $P_{\max}(c)$. $P_{\max}$ Value changed because of its protection requirement of primary users. These constraints can be represented as following equations (5)–(6):

$$P(m, c) \leq P_{\max}(c) \tag{5}$$

$$\sum_{c=1}^{C} P(m, c) \leq \overline{P(m)} \tag{6}$$

here $\overline{P}(m)$ depicts the power budget of node m. Node of traffic demand m represents $D_t(m)$. The maximum number of data rates for the demand of traffic is accurately denoted as $D_t(m) = 1$. Therefore, values of $D_t(m)$ is in the range of zero and one. Then, value zero means a node is not transmitted but senses the spectrum. The sensing detection probability for the c^{th} channel is written below:

$$P_d^k(c) = 1 - (1 - P_d)^{M_{sensex}} \tag{7}$$

here for the c^{th} channel P_d specifies the finding probability of every node, $P_d^k(c)$ represents the finding probability of c^{th}channel, M_{sense} and denotes the count of nodes helps while channel sensing. The channel conditions and the gain of every member channel are defined as the channel capacity. Then it is expressed as:

$$K(m, c) = \log_2\left(1 + \frac{|g_{m,c}|^2 P(m, c)}{\rho^2}\right) \tag{8}$$

where $K(m, c)$ denotes the capacity of m^{th} node in the c^{th} channel, $g_{m,c}$ specifies the channel gain, ρ^2 represents noise power.

3.3.2 Fitness Function

Here, 2 utility functions are demarcated: (i) sensing node, (ii) transmitting node. HTS is used by a group of transmitting and sensing nodes to maximize fitness function within less time. It represents a balanced trade-off between sensing and transmitting usages.

Sensing Utility (S_U^c)

It is defined after the cooperative sensing along with primary detection probability P_d has M_{sense} node of c^{th} channel is expressed in Equation (9)

$$S_U^c = 1 - (1 - P_d)^{M_{sense}} \tag{9}$$

The total sensing utility for every channel is the average number of sensing utilities is given in the following Equation (10)

$$S_U = \frac{1}{C}\sum_{c=1}^{C} S_U^c \tag{10}$$

where C specifies the average number of hopping channel.

Data transmission utility

The member node for the m^{th} data transmission utility is given in Equation (11)

$$D_U^{m,c} = \log_2\left(1 + \frac{|g_{m,c}|^2 P(m, c)}{\rho^2}\right) \cdot \frac{1}{\log_2\left(1 + \frac{|\overline{g_c}|^2 P_{\max}(c)}{\rho^2}\right)} \tag{11}$$

where $\overline{g_c}$ specifies the average gain nodes as members of cluster at c^{th} data transmission channel. Average data transmission of member node m^{th} usage denotes A_d^m. Then, for the member nodes, the average data transmission utility D_U is exhibited in Equation (12),

$$D_U = \frac{1}{M}\sum_{m=1}^{M} D_U^m \tag{12}$$

The weighted sum of sensing utility as (S_U).

Total fitness function

The total fitness functions of data transmission utility (D_U) and is written in Equation (13)

$$T_U = \beta_1 S_U + \beta_2 D_U \tag{13}$$

where β_1 and β_2 are the weight factors and $\beta_1 + \beta_2 = 1$. If more is the sensing node, also is the sensing utility. The main aim is to increase the function of utility without disturbing primary users and maintain the equilibrium in both the sensing node and the transmitting node. This is written in the following Equation (14):

$$M = M_{sense} + M_{trans} \tag{14}$$

Then, for getting optimum sensing and data transmission, the Hazelnut tree search algorithm is used.

3.3.3 Stepwise Procedure of Hazelnut Tree Search (HTS) Algorithm Used for Obtaining Optimum Spectrum Sensing and Data Transmission

In this segment, the HTS algorithm is used for choosing the best optimum values. The Hazel is the type called a larger shrub and deciduous tree. The lifecycle of hazel trees is seed, sprouts, seedlings, saplings, matures and death, and continues process. The detailed discussion regarding the Hazelnut tree search (HTS) algorithm for obtaining optimum spectrum sensing and data transmission is specified below,

Step 1: Initialization.

Initialize the randomly distributed population of D trees for the generalized unconstraint$E$-dimensional problems $f(y) = f(y_1, y_2, \ldots.., y_E)$.

Step 2: Random Generation.

Afterwards, the initialization generates randomise the position of each element of the population or randomly generates the sensing and data transmission utility in the CRN. Each tree and each element are represented by the following equations (15)–(16)

$$\text{Each tree } G_j = [g_{j1}, g_{j2}, \ldots, g_{jE}] \tag{15}$$

$$\text{Each element } g_{ji} = V(0,1) \times (UB_i - LB_i) + LB_i \tag{16}$$

where $V(0,1)$ specifies uniform distribution of random numbers between [0, 1] range. UB_i and LB_i specifies the bounds of upper and lower G_j in i^{th} dimensions.

Step 3: Fitness Function.

To initialize values, a random solution is created. The fitness function is evaluated then the objective function is used to maximize the utility functions and decrease the noise power. Then, the fitness function Equation (17) is given as follows:

$$\begin{aligned} &\textit{Fitness function} = \textit{Maximize} \\ &\left(\begin{aligned} &\textit{sen sin g utility } (S^c_U) \textit{ and data transmission utility } (D^m_U) \\ &\textit{and Minimize } (\textit{noise power } (\rho^2)) \end{aligned} \right) \end{aligned} \tag{17}$$

Step 4: Growing trees

The growing of a tree G_j is written in the following Equation (18)

$$G_j^{T+1} = G_j^T + \left(\beta R + (1 - \beta) \frac{1}{1 + \alpha} R \right) \tag{18}$$

where G_j^T specifies the tree position G_j at the present generations of T, R specifies the growth of tree rate G_j at the absence of neighbouring trees, α specifies index competition, β and specifies the switch probability to control the growth of tree in space/dense area.

Step 5: Fruit scattering phase.

In fruit scattering, the trees based on their present fitness of descending order, and then $\{G_1, G_2, \ldots., G_N\}$ trees are selected in the process of fruit scattering. Here, N specifies the number of trees that are selected at T iteration for taking part in the phase of fruit dispersal and is written in the given Equation (19)

$$N^T = [l^T \times Z] \tag{19}$$

where l^T specifies scattering fruit rate at T iterations is controlled using the number of trees to be participated at the fruit scattering process, Z specifies population size. This phase of fruit scattering increases the algorithm exploration to keep the algorithm converging much faster before searching the whole solution space.

Step 6: Termination.

Here, the Hazelnut tree search algorithm is used for optimizing the value of spectrum sensing along data transmission for FH-CRN. It iterates the growth of fruit scatter along root spread phases until it meets the termination conditions algorithm. At last, the tree gets the optimum solutions.

4. RESULT AND DISCUSSION

The proposed Spectrum Sensing with resource allocation uses the Hazelnut tree search algorithm in frequency hopping based on the Cognitive radio Network SS-RA-HTS-CRN is discussed in this section. These results validate the effectiveness of using the Hazelnut tree search algorithm for spectrum sensing with resource allocation in a frequency hopping based CRN, offering improved efficiency and performance. The simulation is performed on a PC with Intel Core i5, 2.50 GHz Central Processing Unit, 8GB RAM, and Windows7. The efficiency of the SS-RA-HTS-CRN technique is examined through performance metrics. The acquired outcomes are evaluated in the existing SS-RA-BSO-CRN [15], SS-hybrid PSOGSA-CRN [16] and (SS-MSMO-CRN) [17] models.

NS-3.26 simulation tool [18] is chosen here due to its robust capabilities in simulating dynamic network environments, which are essential for analyzing Cognitive Radio Networks (CRNS). It supports a wide range of communication protocols, making it suitable for modelling the interactions between Primary Users (PU), Secondary Users (SU), and other network components like MIMO-FC. The simulator's dual-language support C++ for core simulation and Python for scripting provides flexibility and efficiency in implementation. NS-3.26's

Table 1: Simulation parameter

Parameter	Value
Maximum allowable transmission power $P_{\max}$	105 mW
Minimal secondary node transmission power $P_{\min}$	45 mW
Noise power ρ^2	15 mW
Population size	25
Data utilization ratio	0.9
Number of secondary hopping channels C	10–35
Utility weights β_1, β_2	0.9
Single node primary detection probability P_d	0.14
Single channel sensing time $t_{sen}^{channel}$	4–12 ms
Single channel sensing reporting time t_R	10 ms

ability to simulate realistic wireless communication scenarios, including spectrum sensing and resource allocation, allows for accurate performance evaluation of the proposed method. Its strong community support, extensive libraries, and continuous updates further enhance its suitability for this research, ensuring reliable and reproducible outcomes. Table 1 depicts the simulation parameter.

4.1 Performance Metrics

The following metrics are considered to confirm the efficacy of the SS-RA-HTS-CRN technique.

4.1.1 Delay

It represents the time taken to transfer the packet from the sender to the receiver using Equation (20):

$$delay = S_t - R_t \tag{20}$$

where S_t denotes message sending time, R_t denotes the time of message receiving.

4.1.2 Delivery Ratio

The ratio of data packets transferred to the base station including certain node counts is specified in Equation (21):

$$PDR = \frac{\sum No.of\ packets\ received}{\sum No.of\ packets\ send} \times 100\% \tag{21}$$

4.1.3 Overhead

Each transmission contains additional data known as overhead. But particularly it is required to direct the data to its proper destination.

4.1.4 Network Lifetime

It is determined with the help of Equation (22):

$$Network\ Lifetime = \frac{I_{energy}}{C_{energy}} \times T_{cycle} \tag{22}$$

where I_{energy} represents the initial energy, C_{energy} represents the consumed energy and T_{cycle} is the time cycle.

4.1.5 Throughput

It determines the rate of data transmitted to the base station by various nodes using Equation (23):

$$Throughput = \frac{No.of\ packets\ sent * packet_{\ size}}{Time} \tag{23}$$

4.2 Simulation Phase 1: Performance Comparison of Various Methods

Figures 2–7 depict the simulation of the proposed SS-RA-HTS-CRN is analyzed with existing SS-RA-BSO-CRN, SS-hybrid PSOGSA-CRN and SS-MSMO-CRN respectively. In this segment, the above-mentioned performance metrics are examined.

Figure 2 depicts delay analysis. The SS-hybrid PSOGSA-CRN-based method attains very little presentation of maximal delay after 100 rounds. The SS-RA-HTS-CRN performed all 100 rounds and attained slightly better output with less delay. At node 20, the proposed SS-RA-HTS-CRN attains 64.01%, 70.31% and 34.25% lower delay. At node 40, the proposed SS-RA-HTS-CRN attains 29.45%, 26.46% and 12.35% lower delay. At node 60, the

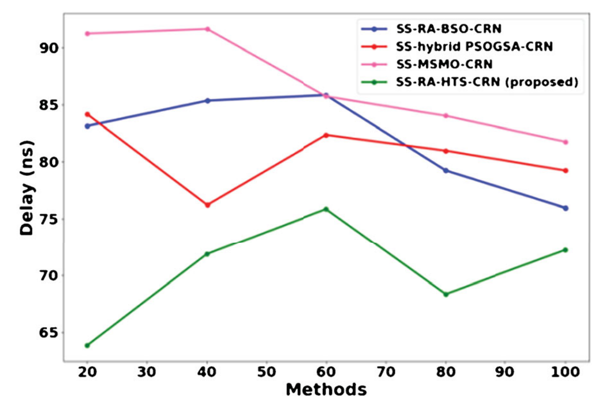

Figure 2: Delay analysis

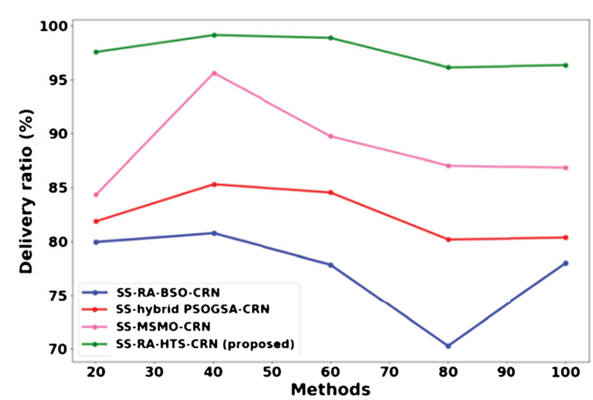

Figure 3: Delivery ratio analysis

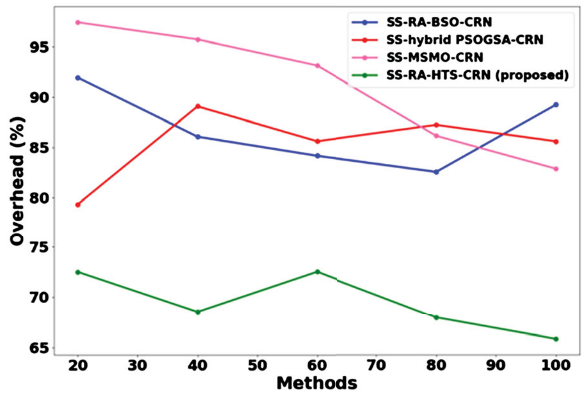

Figure 4: Overhead analysis

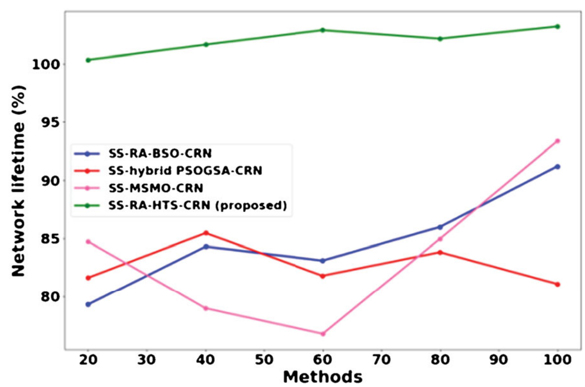

Figure 5: Network lifetime analysis

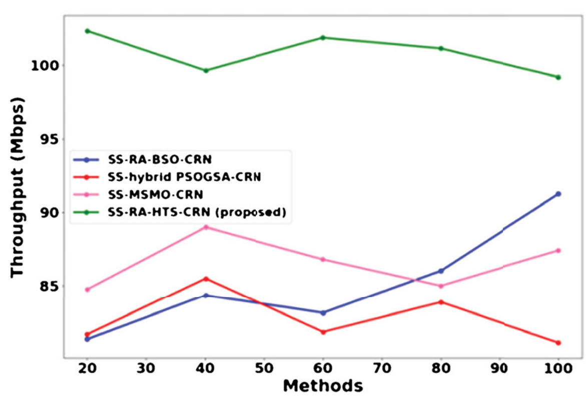

Figure 6: Throughput analysis

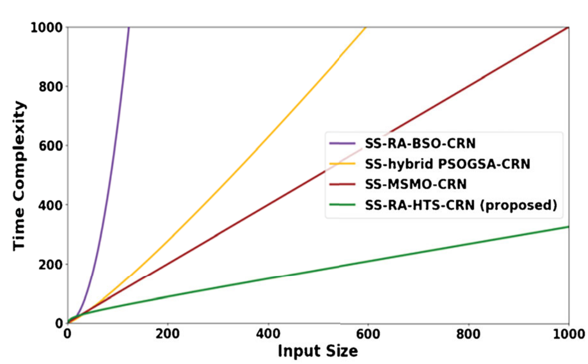

Figure 7: Time complexity analysis

proposed SS-RA-HTS-CRN attains 33.86%, 28.45% and 22.56% lower delay. At node 80, the SS-RA-HTS-CRN attains 37.57%, 37.56% and 35.46% lower delay. At node 100, the SS-RA-HTS-CRN attains 46.78%, 36.57% and 24.35% lower delay.

The delivery ratio is tabulated in Figure 3. Here, the proposed routing approach successfully delivered the delivery ratio of 99.56% for 100 nodes. The proposed SS-RA-HTS-CRN completed all 100 rounds and achieved a higher delivery ratio. At node 20, the SS-RA-HTS-CRN reaches 44.01%, 12.31% and 23% higher delivery ratio. At node 40, the SS-RA-HTS-CRN reaches 35.46%, 25.57% and 26.57% higher delivery ratio. At node 60, the SS-RA-HTS-CRN reaches 13.56%, 11.76% and 15.68% higher delivery ratio. At node 80, the proposed SS-RA-HTS-CRN attains 36.57%, 24.56% and 16.67% higher delivery ratio. At node 100, the proposed SS-RA-HTS-CRN attains 27.57%, 22.68% and 26.57% higher delivery ratio.

The overhead of different approaches is shown in Figure 4. Here, the proposed routing approach delivers lower overhead for 100 nodes. The proposed SS-RA-HTS-CRN did all 100 rounds and reached slightly better output with the least overhead. At node 20, the SS-RA-HTS-CRN achieves 27.57%, 37.57% and 27.48% lower overhead. At node 40, the SS-RA-HTS-CRN method provides 33.86%, 49.67% and 28.54% lower overhead. At node 60, the SS-RA-HTS-CRN method provides 22.75%, 19.45% and 16.47% lower overhead. At node 80, the SS-RA-HTS-CRN method provides 48.56%, 28.46% and 28.56% lower overhead. At node 100, the SS-RA-HTS-CRN method provides 33.67%, 29.56% and 27.47% lower overhead.

The network lifetime analysis is illustrated in Figure 5. At node 20, the SS-RA-HTS-CRN method provides 33.75%, 28.46% and 37.46% higher network lifetime. At node 40, the SS-RA-HTS-CRN method provides 29.46%, 47.35%, and 27.45% high network lifespan. At node 60, the SS-RA-HTS-CRN method provides 37.57%, 28.56%, and 33.45% greater network lifespan. At node 80, the SS-RA-HTS-CRN method provides 46.28%, 37.46%, and 39.56% greater network lifespan. At node 100, the proposed SS-RA-HTS-CRN method provides 38.46%, 19.35% and 27.45% greater network lifetime. For SS-RA-HTS-CRN, the integration of energy consumption rate factors in the constrained fitness function is responsible for increasing the network lifetime.

Figure 6 compares the throughput of various strategies. The SS-RA-HTS-CRN method utilizes 100 nodes and then transmits data at 0.97Mbps maximum speed as well as 0.88Mbps minimum speed. The SS-RA-HTS-CRN performed all 100 rounds and attained higher throughput. The SS-RA-HTS-CRN approach has decreased overhead, less latency and a more even allocation of energy amongst nodes owing to maximize throughput. At node 20, the SS-RA-HTS-CRN method provides 42.74%, 41.27% and 30.02% higher throughput. At node 40, the SS-RA-HTS-CRN method provides 32.74%, 39.56% and 21.74% higher throughput. At node 60, the SS-RA-HTS-CRN method provides 28.45%, 27.45% and 11.74% higher throughput. At node 80, the SS-RA-HTS-CRN method provides 36.47%, 29.46% and 17.35% higher throughput. At node 100, the SS-RA-HTS-CRN method provides 37.58%, 29.56% and 25.48% higher throughput.

Time complexity

The time complexity of Hazelnut tree search (HTS) depends on the computational cost for evaluating the objective function. In the event that the objective function is computationally costly, the function's evaluation would account for a larger portion of the time complexity than the HTS. If the objective function contains time complexity$O(f(N))$, here $f(N)$ implies a computational cost for evaluating the process for N variables, HTS needs P iterations including populace size N, which the entire time complexity denotes $O(P^{*}N^{*}f(N))$.

Figure 7 shows time complexity analysis. Here, the proposed SS-RA-HTS-CRN CPU processing time along with memory utilization are raised linearly with regard to the value of input data. To lesser training data, SS-RA-BSO-CRN, SS-hybrid PSOGSA-CRN, and SS-MSMO-CRN are quicker, but, the proposed SS-RA-HTS-CRN outperforms other models for high training data.

5. CONCLUSION

This manuscript successfully implements frequency hopping-based CRN for spectrum sensing with resource allocation utilizing the HTS. For more effective real-time communication systems, concentrate on CRN's performance improvement. The performance of the proposed SS-RA-HTS-CRN algorithm provides 66.408%, 73.619% and 11.65% lower overhead, 6.48%, 26% and 15.14% higher network lifetime, 13.86%, 24.84% and 13.85% higher throughput compared with existing algorithm such as SS-RA-BSO-CRN, SS-hybrid PSOGSA-CRN and SS-MSMO-CRN respectively. In future work, there are several areas to explore for "Spectrum Sensing with Resource Allocation utilizing deep learning for Frequency Hopping based CRN." These include deep learning for better performance, enhancing robustness and adaptability to dynamic CRN environments, mitigating interference between primary and secondary users, addressing security and privacy challenges, and conducting practical implementations to validate the proposed approach. By focusing on these aspects, further advancements can be made in improving the efficiency, effectiveness, and practical applicability of the CRN system.

SUPPLEMENTARY MATERIAL

Supplemental data for this article can be accessed online at http://dx.doi.org/10.1080/03772063.2024.2412148.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

REFERENCES

1. T. Balachander, and M. M. Krishnan, "Carrier frequency offset (CFO) synchronization and peak average power ratio (PAPR) minimization for energy efficient cognitive radio network (CRN) for 5G wireless communications," *Wirel. Pers. Commun.*, Vol. 127, no. 3, pp. 1847–1867, 2022.

2. H. Touati, A. Chriki, H. Snoussi, and F. Kamoun, "Cognitive radio and dynamic TDMA for efficient UAVs swarm communications," *Comput. Netw.*, Vol. 196, no. 1, pp. 108264, 2021.

3. N. Sureka, and K. unaseelan, "Investigations on detection and prevention of primary user emulation attack in cognitive radio networks using extreme machine learning algorithm.," *J. Amb. Intell. Humaniz. Comput.*, Vol. 1, no. 1, pp. 1–10, 2021.

4. Veeramuthu Venkatesh, "Precision centric framework for activity recognition using Dempster Shaffer theory and information fusion algorithm in smart environment," *Soft Compu. Int. Sys. Tech. App.*, 2117–2124, 2019.

5. S Madhawa, U Balakrishnan, "Employing invariants for anomaly detection in software defined networking based industrial internet of things," *J. Int. Fuzzy Sys.*, Vol. 35, no. 2, pp. 1267–1279, 2018.

6. P Balakrishnan, and T S Somasundaram, "SLA enabled CARE resource broker," *Fut. Gen. Com. Sys.*, Vol. 27, no. 3, pp. 265–279, 2011.

7. S Madhawa, P Balakrishnan, and U Arumugam, "Roll forward validation based decision tree classification for detecting data integrity attacks in industrial internet of things"," *J. Int. Fuzzy Sys.*, Vol. 36, no. 3, pp. 2355–2366, 2019.

8. N. Chaudhary, and R. Mahajan, “Identification of spectrum holes using energy detector based spectrum sensing,” *Int. J. Inf. Technol.* , Vol. 13, no. 3, pp. 1243–54, 2021.

9. S. J. Yoo, A. P. Shrestha, M. Seo, C. H. Han, M. Park, and K. E. Lee, “Joint spectrum sensing and resource allocation optimization utilizing genetic algorithm for frequency hopping–based CRNS,” *Int. J. Commun. Syst.*, Vol. 31, no. 13, pp. e3733, 2018.

10. S. Soundararajan, B. R. Tapas Bapu, S. Sargunavathi, and I. Poonguzhali, “Self-attention based generative adversarial network with Aquila optimization algorithm espoused energy aware cluster head selection in WSN,” *Int. J. Commun. Syst.*, Vol. 37, no. 5, pp. e5690, 2024.

11. P. Rajesh, and F. H. Shajin, “Optimal allocation of EV charging spots and capacitors in distribution network improving voltage and power loss by Quantum-Behaved and Gaussian Mutational Dragonfly Algorithm (QGDA),” *Electr. Power Syst. Res.*, Vol. 194, pp. 107049, 2021.

12. B. Meenakshi, and D. Karunkuzhali, “Enhancing cyber security in WSN using optimized self-attention-based provisional variational auto-encoder generative adversarial network,” *Comput. Stand. Interfaces*, Vol. 88, pp. 103802, 2024.

13. H. Emami, “Hazelnut tree search algorithm: a nature-inspired method for solving numerical and engineering problems,” *Eng. Comput.*, Vol. 1, no. 1, pp. 1–25, 2021.

14. I. DahaBelghiti, I. Berrada, and M. E. Kamili, “Scalable framework for green large cognitive radio networks,” *Cogn. Comput. Syst.*, Vol. 1, no. 3, pp. 79–84, 2019.

15. K. N. Shyleshchandra Gudihatti, M. S. Roopa, R. Tanuja, S. H. Manjula, and K. R. Venugopal, “Energy aware resource allocation and complexity reduction approach for cognitive radio networks using game theory.,” *Phys. Commun.*, Vol. 42, no. 1, pp. 101152, 2020.

16. G. Eappen, and T. Shankar, “Hybrid PSO-GSA for energy efficient spectrum sensing in cognitive radio network.,” *Phys. Commun.*, Vol. 40, no. 1, pp. 101091, 2020.

17. G. Dinesh, P. Venkatakrishnan, and K. M. A. Jeyanthi, “Modified spider monkey optimization – An enhanced optimization of spectrum sharing in cognitive radio networks,” *Int. J. Commun Syst.*, Vol. 34, no. 3, pp. e4658, 2021.

18. M. Meena, and V. Rajendran, “Spectrum sensing and resource allocation for proficient transmission in cognitive radio with 5G,” *IETE J. Res.*, Vol. 68, no. 3, pp. 1772–88, 2022.

19. T. Balachander, and M. M. Krishnan, “Efficient utilization of cooperative spectrum sensing (CSS) in cognitive radio network (CRN) using non-orthogonal multiple access (NOMA),” *Wirel. Pers. Commun.*, Vol. 127, no. 3, pp. 2189–210, 2022.

20. C. Sateesh, K. Janardhana Gupta, G. Jayanth, C. Sireesha, K. Dinesh, and K. Ramesh Chandra, “Performance analysis of spectrum sensing in CRN using an energy detector,” in *Innovative data communication technologies and application: proceedings of ICIDCA 2021*, Singapore: Springer Nature Singapore, 2022, pp. 447–59. Vol. 1, no.1, pp.1-1.

21. H. Xiao, H. Jiang, F. R. Shi, Y. Luo, and L. P. Deng, “Energy efficient resource allocation in delay-aware UAV-based cognitive radio networks with energy harvesting,” *Sustain. Energy Technol. Assess.*, Vol. 45, no. 1, pp. 101204, 2021.

22. A. Sivakumaran, B. T. Maharaj, and A. S. Alfa, “Secure spectrum sensing in relay-based CRN,” *Wirel. Netw.*, Vol. 1, no. 1, pp. 1–16, Aug.2021.

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