Strategically Optimized Cooperative Spectrum Sensing Model for Mobile Cognitive Radios

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Abstract: To address the escalating demand for wireless spectrum, the Cognitive Radio (CR) technology offers a solution for efficiently utilizing the scarce radio frequency (RF) spectrum. Spectrum utilization efficiency of a CR network majorly rely on spectrum sensing. Despite the effectiveness of cooperative spectrum sensing, achieving maximum throughput still poses many challenges. The present research investigates a cooperative spectrum-sensing model involving mobile CRs. We have adopted a non-cooperative game-theoretic model to optimize the sensing strategy to improve the overall throughput. Through evaluating the influence of node mobility on key sensing parameters like false alarm probability and detection probability, valuable insights are acquired regarding the design of efficient spectrum sensing strategies for mobile cognitive radio networks. The key contributions of the research include the impact of node mobility on the sensing strategies of CRs within a cooperative network, for an extensive variety of network conditions. This study illuminates the design of efficient and adaptive spectrum sensing strategies for future mobile cognitive radio networks.

Keywords: **Spectrum Sensing, Evolutionary Game Theory, Throughput Optimization, Node mobility**

1. Introduction

Cognitive Radio (CR) [1] [2] is an innovative and adaptive transceiver equipped with intelligent networking capabilities, allowing it to automatically detect available channels in a wireless spectrum. By continuously monitoring the environment, CR can dynamically adjust its transmission parameters, enhancing radio operating behavior and facilitating concurrent communications [3]. This adaptive behavior leads to a more efficient utilization of the radio frequency spectrum without causing interference to licensed users or primary users (PUs).

The core cognitive capability of CR lies in its ability to sense and gather crucial information from the surrounding environment, such as transmission frequency, bandwidth, power, and modulation details. This spectrum sensing capability empowers secondary users (SUs) or CRs to identify and utilize the best available spectrum, significantly improving overall spectrum efficiency.

However, practical implementation of spectrum sensing faces challenges due to issues like multipath fading, shadowing, and receiver uncertainties, which can compromise detection performance. To address these challenges effectively, cooperative spectrum sensing [4] appears as an appreciated solution. In a cooperative spectrum sensing scenario, CRs within a network collaborate and jointly contribute to spectrum sensing. By pooling their sensing results, the collective decision-making process becomes more robust and reliable, mitigating the impact of environmental challenges.

Participating in cooperative spectrum sensing verifies to be a sensible approach for CRs in a network, as it enhances the accuracy of spectrum detection and enables better decision-making regarding spectrum utilization. This collective effort ultimately optimizes the efficient usage of available spectrum resources and promotes seamless coexistence with licensed users. Cooperative spectrum sensing plays a crucial role in identifying available bandwidth and efficiently allocating channels to SUs based on their demand and requirements. However, a significant issue arises as SUs tend to act selfishly by refraining from participating in spectrum sensing. Instead, they opt to overhear on other SUs' sensing activities and opportunistically transmit, thus secure time and energy without contributing to information acquisition. Consequently, this self-centered strategy results in low throughput for all SUs due to minimal or no participation in spectrum sensing, over the time.

To tackle this challenge, a promising solution is the adoption of an evolutionary game strategy, which has been proposed and evaluated in previous research [5]. The evolutionary game approach enables secondary users to adapt and modify their strategies after learning from other CRs within the network. This adaptability fosters a more cooperative behavior among SUs, leading to enhanced spectrum sensing and information sharing.

However, it is worth noting that the existing research work is limited to static CRs only and does not encompass the involvement of mobile CRs. Incorporating mobility into the analysis would be beneficial as it reflects real-world scenarios and introduces additional dynamics and complexities to the cooperative spectrum sensing problem.

Utilizing an evolutionary game strategy promotes cooperation among SUs and thus improves spectrum sensing efficiency. Therefore, this research should extend the investigation to encompass mobile CRs to provide a comprehensive understanding and practical application of cooperative spectrum sensing in dynamic wireless environments.

Node Mobility

Node mobility indeed plays a critical role in the widespread adoption and appeal of wireless communication. The dynamic movement of wireless nodes has a significant impact on various communication parameters, including capacity, connectivity, routing, convergence, and more.

Capacity [6]: Node mobility affects the available channel capacity, as the changing positions of nodes can lead to variations in signal strengths and interference patterns. Dynamic channel capacity is a critical consideration in wireless networks to ensure efficient data transmission. *Connectivity* [7]: The mobility of nodes directly influences network connectivity. As nodes move, link quality fluctuates, affecting the establishment and maintenance of connections between nodes. Mobility management becomes essential to maintain continuous connectivity. *Routing* [8]: Mobility poses challenges to routing algorithms as nodes frequently change their locations. Dynamic routing protocols need to be employed to adapt to the changing network topology and ensure efficient data delivery. *Convergence* [9]: The convergence of communication in a mobile environment becomes more complex due to nodes' mobility. Convergence refers to the synchronization and coordination of multiple nodes in the network, and mobility adds additional complexity for achieving convergence effectively. Moreover, node mobility can offer considerable benefits in terms of spatio-temporal diversity during sensing. As sensors move, they experience different signal strengths from the PU’s transmissions. This spatio-temporal diversity allows for more comprehensive and accurate information gathering, contributing to improved sensing capabilities and facilitating better utilization of the spectrum.

Despite the inherent mobility feature of CR networks, it is often overlooked by many researchers. The mobility of wireless nodes in the context of CR networks presents both opportunities and challenges that require careful consideration.

Allowing node mobility in CR networks can bring various benefits:

Enhanced Spectrum Utilization: Mobile CR nodes can dynamically explore different parts of the spectrum, improving the chances of finding unused or underutilized channels, leading to more efficient spectrum utilization.

Increased Coverage and Connectivity: Mobility can help extend the coverage area of CR networks and improve connectivity between nodes, especially in scenarios where fixed infrastructure is limited.

Spatio-Temporal Diversity: As mentioned earlier, mobility introduces spatio-temporal diversity, which can enhance spectrum sensing accuracy and lead to better decision-making regarding spectrum usage.

However, incorporating node mobility into CR networks also poses significant challenges:

Spectrum Sensing Mechanism: The spectrum sensing mechanism needs to adapt to the dynamic nature of the network. Frequent spectrum sensing and decision-making become crucial to accommodate node movements and changes in available channels.

Interference Management: Mobility can introduce varying interference patterns due to nodes moving in and out of each other's transmission range. Effective interference management techniques are essential to maintain quality-of-service and minimize harmful interference.

Routing and Networking Protocols: Mobility complicates routing protocols and network management, as nodes change their positions frequently. Robust and adaptive routing algorithms are required to ensure reliable data delivery and optimal paths.

Handover and Mobility Management: Handover procedures become critical to maintain connections as nodes move, especially in heterogeneous networks with multiple access points.

Addressing these challenges requires innovative research and the development of novel solutions to optimize the performance of CR networks in mobile scenarios. By considering node mobility as an integral part of CR network design, researchers can unlock the full potential of dynamic spectrum access and leverage the benefits of cognitive radio technology in various applications.

The present work aims to achieve the following objectives:

- Analyze the impact of sensor mobility on spectrum-sensing parameters by conducting an extensive background review and literature survey.
- Determine the overall throughput of SUs based on the mobility parameters of sensors using a proposed system model of cooperative spectrum sensing.
- Analytically identify the optimal sensing strategy to maximize the throughput of SUs through a non-cooperative game theoretical model.
- Validate the performance of the proposed spectrum-sensing model for determining the optimal spectrum sensing strategy for mobile CRs under diverse network conditions.

Section 2 of the paper provides a thorough survey on contextual work. The investigation into the influence of sensor mobility on sensing parameters is detailed in Section 3. Section 4 discusses the proposed methodology, which encompasses the foundation and principles of the game-theoretic model of spectrum sensing, along with the presentation of experimental results. Lastly, Section 4 concludes the research findings and outlines potential avenues for future research.

2. Literature Survey

In Cognitive Radio Networks (CRN), unlicensed SUs take advantage of shared spectrum reusability, subject to strict protection of PU transmissions. To ensure compliance with regulations set by bodies like FCC, efficient spectrum sensing techniques are required for secondary users. Distributed sensing is considered a viable approach to enhance individual user sensing without escalating the collective sensing overhead. Acknowledging the critical sensitivity requirements imposed on individual users within the radio network during deep fade conditions, S.M Mishra et al. (2006) [10] investigated the impact of fading environments on the detection performance of unlicensed users' sensing. Addressing challenges such as licensed users' activity, large-scale bandwidth variation based on spectrum availability, and channel switching processes faced by network users, K.R Chowdhury et al. (2006) [11] examined the influence of applying the TCP rate-controlled algorithm and a window-based transport protocol for Ad-Hoc Networks in CRN. Thoroughly researching the trade-offs in performance related to spectrum sensing, Y.C Liang et al. (2008) [12] made significant contributions in this area. In their study, Ghasemi et al. (2007) [13] emphasized significant performance gains achieved with an infinite number of correlated sensors, albeit constrained by the level of correlation. They derived a lower bound on the probability of missing opportunities for unlicensed access, highlighting the impact of correlated shadowing on collaborative sensing performance degradation.

To minimize both false alarm and misdetection probabilities, Visotsky et al. (2005) [14] proposed increasing the number of independent and identically distributed (i.i.d) shadow fading. The proposed model was originally designed to identify the availability of TV channels, but its applicability extends to broader spectrum sharing scenarios. The study reinforced the concept that collaboration among individual nodes enhances spectrum usage efficiency. However, random sensor selection did not effectively mitigate the impact of shadow fading. Consequently, Selen et al. (2008) [15] introduced and evaluated three distinct algorithms for sensor selection. An important observation was that shadow fading exhibited a strong correlation with closely spaced sensors, thus emphasizing the benefits of selecting spatially sparse sensors. In addition to sensor locations, Alexander et al. (2009) [16] highlighted the significance of sense scheduling as an alternative to cooperative sensing in the spatial domain. However, they observed limited performance gains due to the static nature of sensors. Fixed geographical locations led to a lack of diversity in received signal strengths, thus diminishing the potential benefits.

Furthermore, in the context of a cognitive vehicular network, [17] investigated the combined impact of SU's motion and PU's activities. In a mobile CR network, S Jana et al. (2013) [18] introduced two trust parameters - location reliability and malicious intentions - to enhance the detection of both malicious users and Primary Users (PU). To analyze the accessibility of the spectrum, S Bagchi et al. (2018) [19] presented a Bayesian approach with appropriate prior distributions. DasMahapatra et al. (2019) [20] proposed two prediction-based sensing models and conducted a performance comparison between them. In the context of fading environments, Kumar et al. (2020) [21] investigated the effects of cooperative spectrum sensing and threshold selection on the performance of CR networks. Furthermore, DasMahapatra et al. (2020) [22] focused on minimizing interference with PU by optimizing the sensing period. The game-theoretical approach has gained popularity for resolving resource allocation problems and devising optimal strategies. Z. Xiao et al. (2018) [23] employed a non-cooperative game-theoretical model for spectrum sharing among moving vehicles with Cognitive Radios (CR) in heterogeneous vehicular networks. S Ghosh et al. (2019) [24] utilized an auction-based game-theoretical model to optimize energy and spectrum utilization. In the context of a wireless body area network, D Mohsin et al. (2022) [25] proposed a game theory-based protocol aimed at reducing bit error rate, power consumption, and duty cycle. For relay selection in Cognitive Radio Networks (CRN), J S Banerjee et al. (2022) [26] employed the Stackelberg game-theoretic model.

Based on a comprehensive survey of relevant and recent research, we identified a crucial gap in the field concerning the optimization of sensing strategies for mobile Cognitive Radios (CRs) in a cooperative CR network. While some previous works [5] [27] have addressed strategic optimization for spectrum sensing, they focused solely on stationary sensors. However, in wireless communication devices, considering the mobility of sensors becomes essential.

Considering this, our current research aims to explore the impact of sensor mobility on spectrum sensing parameters and, consequently, how these parameters influence the determination of an optimal sensing strategy. Specifically, we investigate the effects of mobile sensors compared to impractically fixed ones. Through simulations, we seek to uncover the trade-off between cooperation and scheduling resulting from sensor mobility. This study addresses an important aspect of the field and contributes to a more realistic and effective approach to spectrum sensing in mobile CR networks.

3. Mobility Effects on Spectrum Sensing Parameters

Figure-1 illustrates a basic Cognitive Radio (CR) network featuring mobile Secondary Users (SUs). The assumption is made that these mobile CRs exhibit independent movement, devoid of any correlation among them. Within suburban environments, it is established that the decorrelation distance falls within the 120-200 meters range [28], while maintaining a typical cell radius of 33 km. The mobility of CRs is constrained within the cell, and any movement beyond the cell boundaries results in a loss of connectivity to the network.

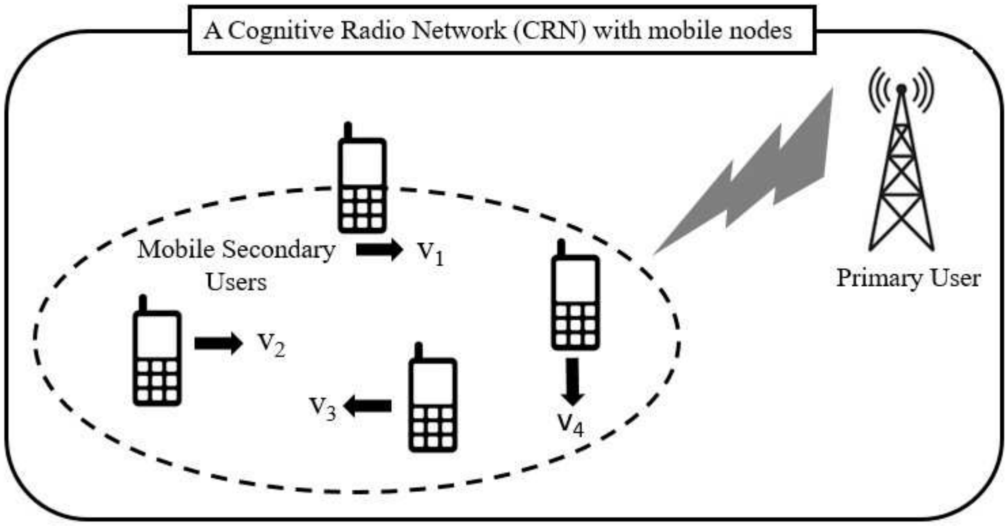

Figure-1: *A CR Network architecture with mobile nodes*

The mobile CRs employ the energy detection method for spectrum availability identification. The energy detector's response is characterized by the received signal power and the noise power, represented by the test statistics denoted as T. The test statistics for the nth mobile CR can be approximated as a Gaussian distribution, as per references [29].

$$T_n \sim \begin{cases} \mathcal{N}\left(N_o, \frac{{N_o}^2}{M_s}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots Hypothesis\ H_0 \\ \mathcal{N}(P_n + N_o, \frac{(P_n+N_o)^2}{M_s}) \dots\dots\dots\dots\dots\dots Hypothesis\ H_1 \end{cases} \tag{1}$$

In this context, P_n denotes the received PU signal strength, N_o represents the noise power, and M_s is the count of sensing samples taken during the sensing period (T_S) within a frame. The expression for P_n can be articulated as follows:

$$P_n = P_R * e^{Y_n} \tag{2}$$

where P_R is the initial received signal strength. The path loss element is presumed to be nearly constant for each CR since the distance from the PU to the CRs within the cell is significantly large compared to the cell radius. e^{Y_n} represents the channel gain between the nth CR and the PU transmitter, considering log-normal shadowing where Y follows a normal distribution $Y \sim \mathcal{N}(0, \sigma^2)$. The impact of multipath fading is disregarded by assuming a wideband PU channel, as discussed in reference [29].

3.1. Test Statistics and Covariance Matrix

To illustrate the temporal correlation of the test statistics for an individual mobile CR, we examine the sensing of the n[th] CR over M consecutive frames at intervals of Δt, employing the energy detection technique. The output of the energy detector is denoted as:

$$X_n = [T_{n1}, T_{n2}, T_{n3}, \dots \dots, T_{nM}]^T \tag{3}$$

Following equation (1), where the test statistics T exhibits Gaussian distribution, X_n becomes an M- variate Gaussian distribution [30]:

$$X_n \sim \begin{cases} \mathcal{N}(\mu_o \times \mathbf{1}, \Sigma_{\boldsymbol{n}}) \dots \dots \dots \dots \dots \dots \dots \dots Hypothesis\ H_0 \\ \mathcal{N}(\mu_1 \times \mathbf{1}, \Sigma_{\boldsymbol{n}}) \dots \dots \dots \dots \dots \dots \dots \dots Hypothesis\ H_1 \end{cases} \tag{4}$$

Here, $\mu_o = (P_{R_0} + N_0) \times \mathbf{1}$ and $\mu_1 = (P_{R_1} + N_0) \times \mathbf{1}$, P_{R_0} and $P_{R_1}$are representing the average received signals power from PU by the test CR within the cell under H_0 and H_1 respectively. Additionally, $\mathbf{1} = [1, 1, \dots \dots \dots, 1]^T$.

The observed X_n exhibits correlation due to varying geo-locations during different sensing events, a consequence of the test CR's velocity. This correlation is attributed to the correlated shadowing (e^{Y_n}). Analyzing the covariance matrix $\Sigma_{\boldsymbol{n}}$ in equation (4) allows for the examination of the temporal correlation of X_n. A common covariance matrix is assumed under both the hypothesis, due to the absence of a closed-form expression for detection probabilities [31]. In scenarios with very low received Signal-to-Noise Ratio (SNR) (approximately -20dB), where, $N_0 \gg P_n$, the variance of test statistics T can be estimated as, [16]

$$\frac{(P_n+N_o)^2}{M_s} \approx \frac{N_0^2}{M_s} + \frac{2N_0P_n}{M_s} \tag{5}$$

The Gudmundson's exponential decaying model is used for estimation of the covariance matrix $\Sigma_{\boldsymbol{n}}$, [30] [32]

$$\textstyle\sum_n \triangleq \frac{{N_o}^2}{M_s}\boldsymbol{I} + \frac{2N_oP_R}{M_s}\begin{bmatrix} 1 & \lambda_n & \cdots & {\lambda_n}^{M-1} \\ \lambda_n & 1 & \cdots & {\lambda_n}^{M-2} \\ \vdots & \vdots & \ddots & \vdots \\ {\lambda_n}^{M-1} & {\lambda_n}^{M-2} & \cdots & 1 \end{bmatrix} \tag{6}$$

Here, $\lambda_n = e^{-\Delta d_n/d_{\text{corr}}} \approx e^{-v_n \Delta \text{t}/d_{\text{corr}}}$ (7)

d_{corr} denotes the decorrelation distance of shadow fading, and Δd_n is the Euclidean distance between the two successive sensing events.

We considered that CR is moving in a fixed velocity of v_nm/s and it does not change its direction between two consecutive sensing events. Δt is 1s or less.

Now, to extend this hypothesis testing problem with multiple mobile CRs, let's denote $N \times M$ matrix $X = [X_1^T, X_2^T, \dots \dots, X_N^T]$, which is the received signal strength measurement matrix collected from N mobile CRs and each CR senses M times before deciding about the hypothesis.

$$\begin{cases} X \sim \mathcal{N}(\mu_{0,}\Sigma) & : H_0 \\ X \sim \mathcal{N}(\mu_{1,}\Sigma) & : H_1 \end{cases} \tag{8}$$

Then the common covariance matrix Σ is expressed as, [30]

$$\Sigma \triangleq \begin{bmatrix} \Sigma_1 & 0 & \cdots & 0 \\ 0 & \Sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Sigma_N \end{bmatrix}_{NM \times NM} \tag{9}$$

Due to large cell radius, the correlation between the sensing samples collected from different CRs is small enough, therefore $\Sigma_{i,j} \approx 0$.

3.2. Probability of False Alarm ($\mathbf{P_f}$) and Detection ($\mathbf{P_d}$)

To quantify the spectrum sensing performance of mobile CRs a spatio-temporal spectrum sensing is theoretically analysed in [30]. According to [30] the probability of false alarm with a threshold $\eta \in \mathbb{R}$ is given by,

$$P_f \triangleq Q\left(\frac{\eta - \frac{1}{2}\boldsymbol{w}^{\boldsymbol{T}}\Sigma\mathbf{w}}{\sqrt{\boldsymbol{w}^{\boldsymbol{T}}\Sigma\mathbf{w}}}\right) \tag{10}$$

Here, $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$ (11)

And, $\boldsymbol{w} \triangleq \Sigma^{-1}(\mu_1 - \mu_0)$ (12)

From equation (10) probability of detection P_d is given by, [30]

$$P_d = \mathrm{Q}\left(Q^{-1}(P_f) - \frac{(\mu_1 - \mu_0)}{2}\sqrt{\mathbf{1}^{\boldsymbol{T}}\boldsymbol{\Sigma}^{-\mathbf{1}}\mathbf{1}}\right) \tag{13}$$

Where, $\Sigma^{-\mathbf{1}} = diag\{\Sigma_{\mathbf{1}}^{-\mathbf{1}}, \Sigma_{\mathbf{2}}^{-\mathbf{1}}, \dots \dots, \Sigma_{\boldsymbol{N}}^{-\mathbf{1}}\}$ (14)

And, $$\sum_n{}^{-1} \triangleq \frac{M_s}{N_o{}^2}\boldsymbol{I} + \frac{M_s}{2N_oP_R(1-\lambda_n{}^2)}\begin{bmatrix} 1 & -\lambda_n & 0 & \cdots & 0 \\ -\lambda_n & 1+\lambda_n & -\lambda_n & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & -\lambda_n & 1+\lambda_n & -\lambda_n \\ 0 & \cdots & 0 & -\lambda_n & 1 \end{bmatrix} \quad (15)$$

Then, finally, the probability of detection (P_d) can be represented in terms of CR speed as,

$$P_d = Q\left(Q^{-1}(P_f) - \frac{(\mu_1-\mu_0)}{2} \times \sqrt{\frac{NM}{\sigma_n^2} + \frac{M_s}{2N_oP_R}\left(N + \sum_n \frac{\left(1-e^{-v_n\Delta t/d_{corr}}\right)M}{2}\right)}\right) \quad (16)$$

The above equation characterizes the detection probability of a mobile CR with velocity v_n. The CR is a member of a cooperative CR network of N mobile CRs. The Fusion Centre (FC) of the network decides about PU's transmission status after M number of sensing events.

The impact of mobility of CRs, in spectrum sensing and in the non-cooperative spectrum sensing game to maximize throughput, is examined in the next section.

4. Proposed Methodology: A Game Theoretical Framework

In pursuit of achieving objectives 2 and 3 in this study, we have embraced a non-cooperative game theoretical model. Our focus is on attaining an optimal sensing strategy to enhance the overall throughput of individual mobile CRs. Notably, the parameters pertinent to a mobile node within a CR network differ from those associated with a static node. In our earlier work [5], a thorough examination of throughput analysis was conducted for a cooperative CR network. Furthermore, we achieved throughput maximization through strategic manipulation in a non-cooperative spectrum sensing game. It is crucial to acknowledge that all the analyses conducted in our prior work were geared towards static CRs, and the introduction of velocity in the CR introduces changes in numerous parameters.

4.1. Foundation and Principle of Spectrum Sensing Game

The interaction during spectrum sensing and sharing the sensory data amongst the SUs in the network, was analysed by designing a spectrum sensing game [5]. We are continuing with the same sensing model for throughput maximization in the present cooperative mobile sensing node scenario.

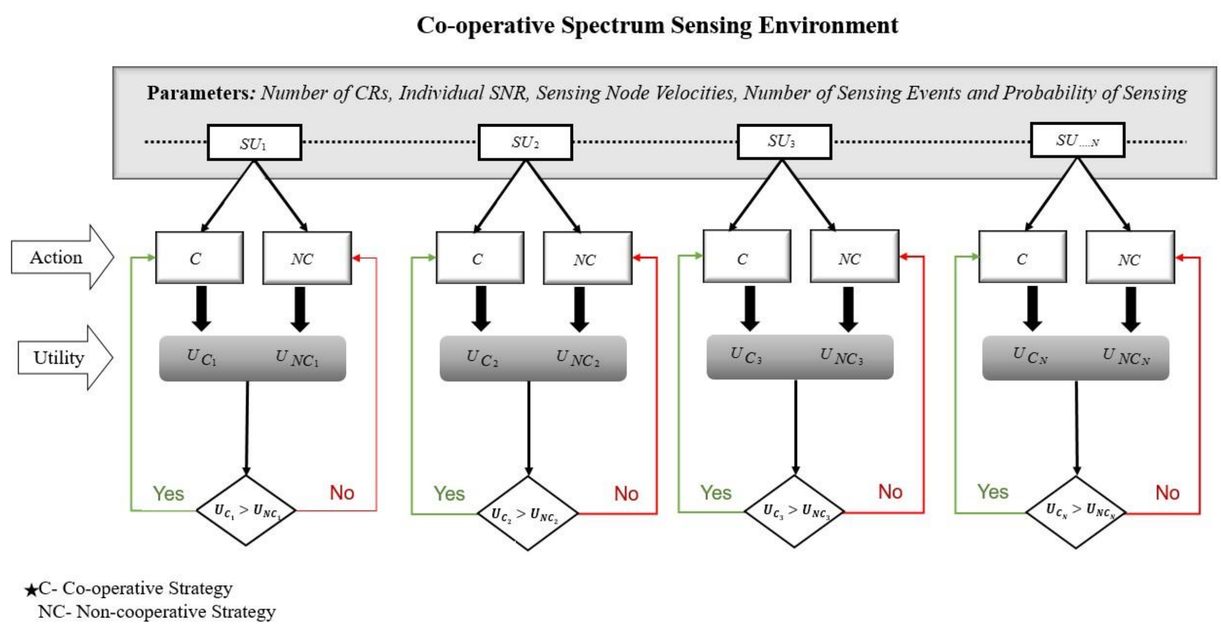

Figure-2: *Sensing strategy of CRs with throughput as utility.*

Figure-2 illustrates the behavior and utility considerations of a CR within a cooperative sensing CR network. Each CR assesses its utility, defined as individual throughput, based on actions like cooperative sensing and non-cooperative sensing. The throughput is influenced by various parameters including the number of sensing CRs, individual Signal-to-Noise Ratio (SNR), node velocity, and the number of sensing events. CRs opt for actions that result in superior utility, participating in sensing only when their individual throughput is higher with a particular action. Analyzing the system model allows for the determination of CRs' average individual throughput.

System Model

The sensing model consists of one PU and k homogeneous and/or heterogeneous SUs, opportunistically accessing the licensed spectrum of the PU. These CRs operate in half-duplex mode, meaning they cannot sense and transmit simultaneously. The SUs communicate the sensing results through a narrowband signaling channel, as illustrated in Figure-3.

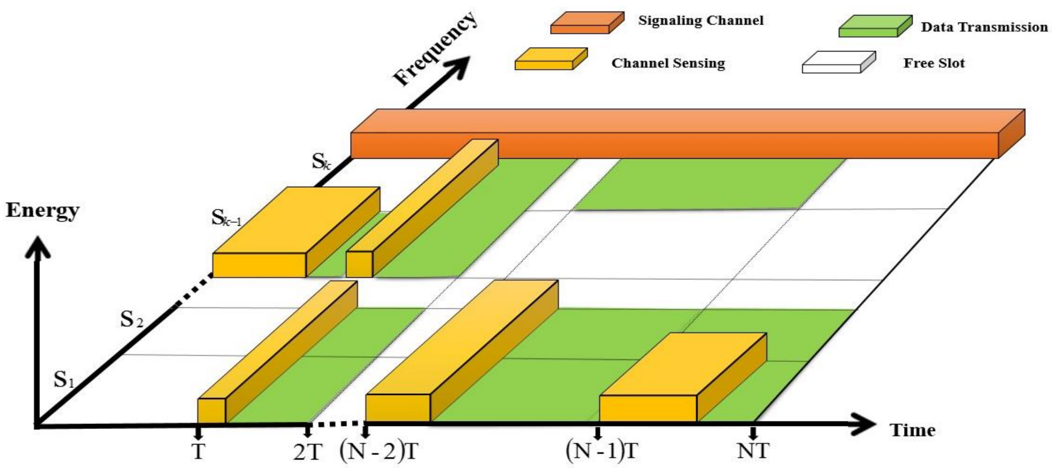

Figure-3: *The CR System Model*

Throughput Architecture of SUs

Game theoretic analysis [33] of such sensing model to maximize the average throughout in terms of utility function is represented as below.

The SUs $S_K \in \check{S} = \{S_1, S_2, S_3, \dots, S_k\}$ of the network, can have only two pure strategies, i.e. either to cooperate in sensing (C) or not (NC). Considering the SUs choosing pure strategy S forms a set, $S_s = \{S_1, S_2, \dots, S_J\}$, then the payoff function of the contributor to sensing $S_j \in S_s$, can be represented as, [27] [34]

$$U_{C,S_j} = P_{H_0}(1 - \frac{T_S(N)}{|S_S|T})(1 - P_F^{S_S})r_{S_j}, if\ |S_C| \in [1, k] \quad (17)$$

Here, $|S_C|$ represents the number of contributors and r_{S_j} is the data rate of the secondary user S_j under hypothesis H_0. We also considered that sensing cost is divided equally among all sensing SUs. Therefore, the payoff function of all other SUs ($S_i \notin S_s$), who have chosen pure strategy R, is given by,

$$U_{NC,S_i} = P_{H_0}(1 - P_F^{S_S})r_{S_i}, if\ |S_C| \in [1, k-1] \quad (18)$$

Here S_i is the SU that is not contributing to sensing. It expects higher throughput, relying on other contributor's decisions. If no SU contributes then$|S_C| = 0$ and $P_F = 1$, then the payoff function becomes,

$$U_{NC,S_i} = 0, if\ |S_S| = 0 \tag{19}$$

Since SUs try to maximize their payoff values, contributors to sensing may have stable throughput but non-contributing SUs may save more time for transmission but with the risk of zero throughputs.

The above equations of throughput are extended in general form applicable for large range of network conditions in [5]

The expression of the utility function of the cooperating SU k_1 is [5] [35],

$$\overline{U_{k_1}}(C, x_k) = D_1 \left\{ A(1 - \frac{\tau}{k}) \prod_{i=2}^{k} x_i \right\} + D_1 B_1 \sum_{m=1}^{k-1} \left(1 - \frac{\tau}{k-m}\right) \sum_{\sigma_i \delta_i} \prod_{p=m}^{k-2} B_{(\sigma_i = k-p)} x_{(\sigma_i = k-p)} \prod_{\delta_i} (1 - x_{(\delta_i = k-q)}) \tag{20}$$

Here, $\mathbb{x} = \{x_2, x_3, x_4, \ldots, x_k\}$ is the set of cooperation probabilities of SUs, and σ_i is the i^{th} set of all possible $C_{(k-1)-m}^{k-1}$ combinations of $\mathbb{x}$ and $\delta_i = p/\sigma_i$, that means δ_i belongs to $\mathbb{x}$ but not belongs to σ_i, $(\sigma_i, \delta_i \subseteq \mathbb{x})$.

Similarly, the equation of throughput of the non-cooperation k_1SUs is [5],

$$\overline{U_{k_1}}(NC, x_k) = D_1 \left\{ \prod_{i=2}^{N} B_i x_i + \sum_{m=0}^{k-2} \sum_{\sigma_i \delta_i} \prod_{p=m}^{k-2} B_{(\sigma_i = k-p)} x_{(\sigma_i = k-p)} \prod_{\delta_i} (1 - x_{(\delta_i = k-q)}) \right\} \tag{21}$$

In the previous section, we have investigated the impact of mobility of CR on spectrum sensing parameters. Equation (10) and (16) are representing the false alarm (P_f) and detection probabilities (P_d). These parameters may be utilized to evaluate the effect of node mobility in a cooperative spectrum sensing game.

4.2. Experimentation and Results

To establish a simulation environment closely resembling reality, we considered a cooperative Cognitive Radio (CR) network with parameters closely aligned with IEEE802.22 standards.

For the experiments, we adopted the following values for the network parameters.

Table 1: *Sensing Parameters and Their Experimental Values*

Parameter Name	***Symbol***	***Values***
Sensing sampling frequency	f_s	6Mhz
Noise power	N_0	$-95.2dBm \approx 3.01 \times 10^{-13}watt$
Signal power	(P)	$-116\,dBm \approx 2.5 \times 10^{-15}watt$
Frame duration	T_b	20ms
Decorrelation distance	d_{corr}	150m

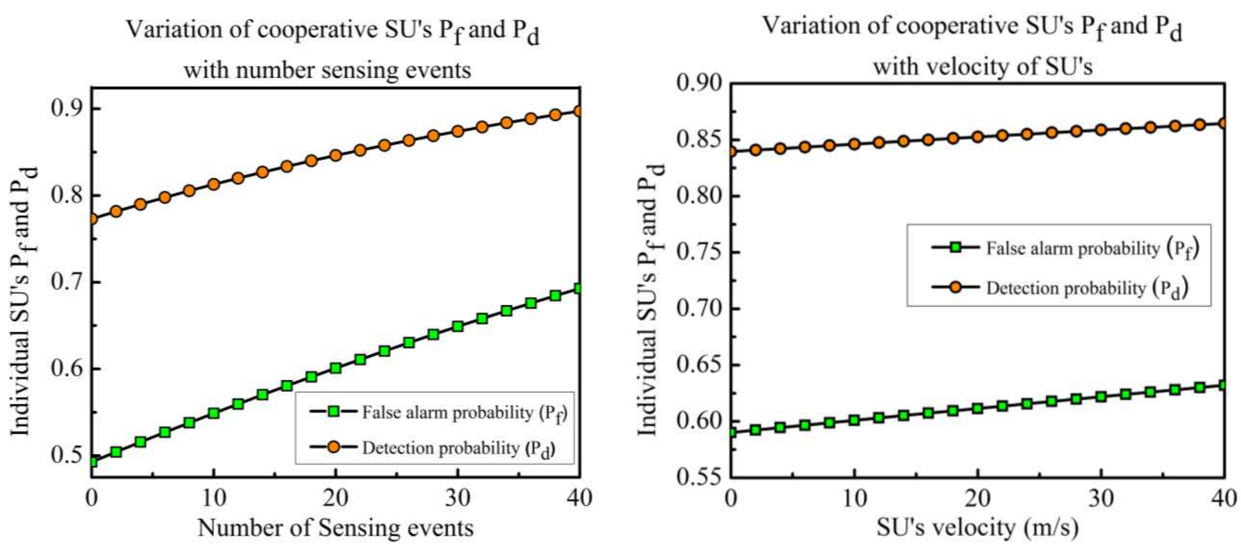

Figure-4 a): *Effect of number of sensing events on P_f and P_d*

b)*: *Effect of SU's speed on P_f and P_d

The variable N represents the number of mobile CRs, and it is examined under various conditions. Similarly, the variable M, denoting the number of sensing events conducted before making a decision, is also explored across different network conditions. The frame duration is assumed to be 20 ms, and the sensing interval (Δt) aligns with the frame duration, assuming one sensing event in each frame. The velocity of each CR is treated as a variable to assess its impact on sensing outcomes. Furthermore, it is assumed that CRs maintain a constant velocity between two successive sensing events and move in a straight trajectory. The simulation encompasses both homogeneous and heterogeneous CRs for a comprehensive analysis.

For five mobile CRs, all with uniform velocity 10 m/s, operating in -20dB receive SNR environment, the variation of false alarm (P_f) and detection probability (P_d) with the number of sensing events (M) is shown in figure-4 a). In the given situation, both P_f and P_d are increasing with the number of sensing events. These CRs are obeying the rules of collaborative sensing. During hypothesis H_1 due to the combined effect P_d increases and during H_0, due to low receive SNR, P_f decreases.

Figure-4 b) demonstrations the impact of sensing node velocity in m/s on P_f and P_d in the similar environment as mentioned in the previous state. Additionally, we assumed 20 sensing events for each five sensing CRs, which are moving with the same and constant velocity. From figure-4 b), it is clear that the detection probability is improved for mobile sensors in comparison to static one.

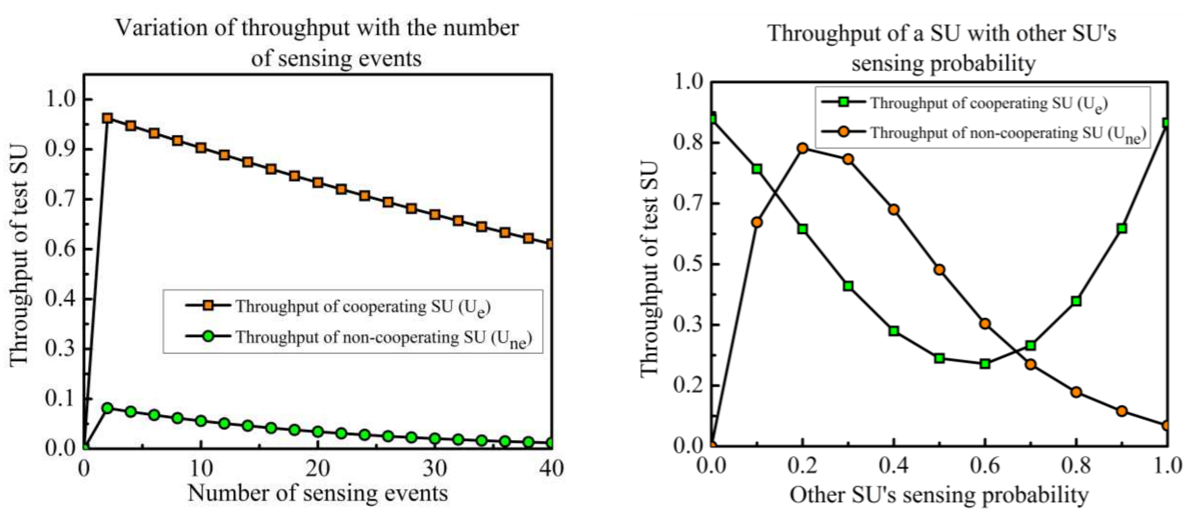

Figure-5 a): *Throughput of mobile test CR with number of sensing events.*
b): *Throughput of a mobile and homogeneous test SU for cooperating and non-cooperating strategies with sensing probability of other SUs.*

In a cooperative CR network, each SU has a choice either to participate in sensing or not. The SUs choose their strategy according to the payoff function that is associated with the strategy. The strategical analysis is reported in detail in [5] by implementing the evolutionary game theory. The same game-theoretical model is adopted here to examine the impact of motion of the sensing nodes on throughput and then to choose the optimum sensing strategy to maximize throughput.

Here it is assumed that the number of CRs (stationary and/or moving) have formed a collaborative sensing network. The sensing scheme they have followed is as shown in figure-3. As per the sensing policy adopted here, the sensing duration per frame per SU is reduced by a factor of the number of cooperating SUs. The reduced sensing time per frame yields more time for data transmission. Therefore, given the utmost sensing accuracy, the more the number of sensing CR, the more the throughput. On the other hand, not cooperating in sensing i.e. no time spend for sensing. This may produce better throughput as long as other CRs senses the spectrum precisely. Sensing accuracy depends on many factors including the number of sensing events. Figure- 5 a) depicts the variation of throughput of a mobile CR with a uniform speed of 10 m/s with the number of sensing events for both cooperating and non-cooperating strategies. The network is assumed to be consists of five homogeneous SUs and the received SNR for all CR is -20dB. Then, the throughput analysis is carried out for different network conditions. Figure-5 b) represents throughput analysis of a five homogeneous mobile SUs' network scenario. The speed of all SUs is assumed to be 10 m/s, receive SNR is -20dB and 20 sensing events. The throughput of both the strategies of a test CR is represented with the probability of cooperation probability of other CRs. The through is represented in a normalized scale. It may be observed from the figure that at a very low and very high cooperation probability of other CRs, cooperation strategy of test CR provides better throughput then not participating strategy. But with the moderate probability of cooperation of other CRs, the non-cooperating strategy of test CR provides better payoff with respect to cooperative strategy. Accordingly, SUs can choose to play an optimal strategy to maximize its' throughput.

Figure- 6 a) represents the throughput analysis of ten mobile SUs' spectrum sensing game. The rest of the network conditions are the same as the previous network. Another situation, with a different velocity of homogeneous CRs, is assumed for simulation.

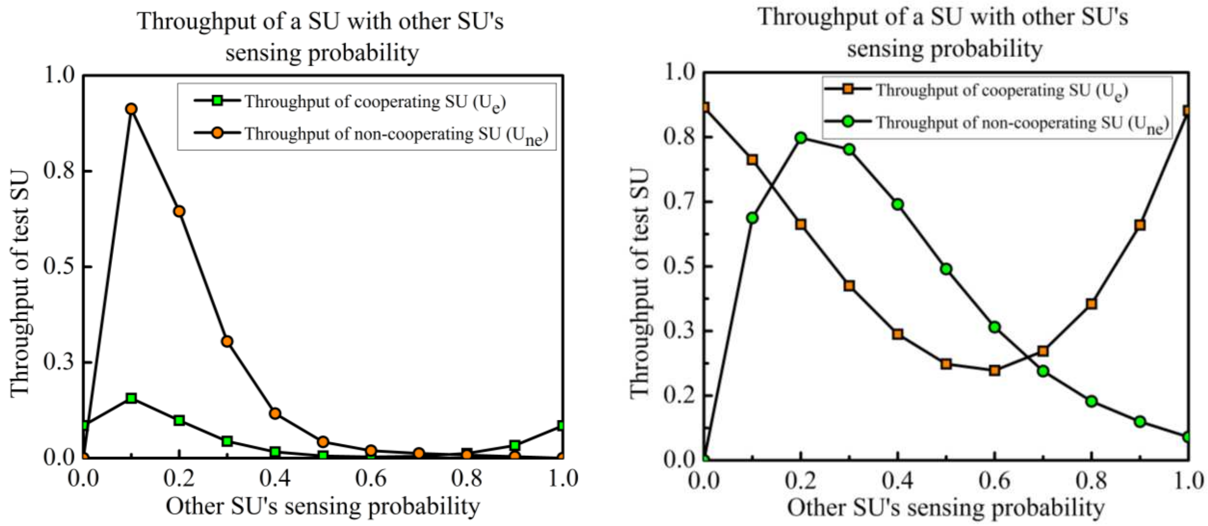

Figure-6 a): *Throughput of a mobile and homogeneous test SU, in a ten SU game scenario.*

b): *Throughput of a mobile and homogeneous test SU, in a five SU game scenario.*

Figure-6 b) shows the throughput analysis for five homogeneous SUs with a uniform velocity of 5m/s. Twenty sensing events are supposed, at receive SNR -20dB.

To deploy more versatility, we extend our work for heterogeneous SUs. We considered for different network scenarios. Here we assumed both static and mobile sensing nodes with arbitrarily chosen speed. The number of participating CRs in the network and the number of sensing events are also varied. The throughput of the test CR with cooperating strategy is represented and compared (Figure-7 a)), for the below-mentioned network conditions.

Condition_1: A CR network of five SUs. Test CR is moving with speed 10 m/s and other CRs with 20 m/s. The number of sensing events is 20 and the receive SNR is -20dB.

Condition_2: A CR network of five SUs. Test CR is moving with speed 5 m/s and other CRs with 20 m/s. The number of sensing events is 20 and the receive SNR is -20dB.

Condition_3: A CR network of five SUs. Test CR is moving with speed 20 m/s and other CRs with 5 m/s. The number of sensing events is 20 and the receive SNR is -20dB.

Condition_4: A CR network of ten SUs. Test CR is moving with speed 5 m/s and other CRs with [10, 15, 20, 15, 10, 20, 5, 0, 0] m/s respectively. The number of sensing events is 20 and the receive SNR is -20dB.

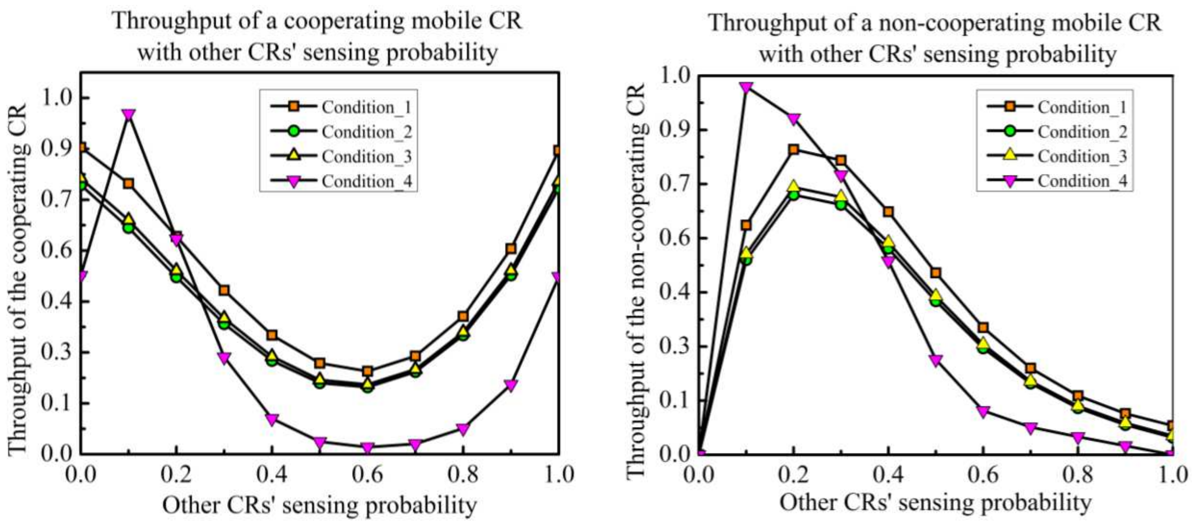

Figure-7 a): *Throughput of a cooperating CR with sensing probability of other CRs in different network conditions.*

b): *Throughput of a non-cooperating CR with sensing probability of other CRs in different network conditions.*

Figure-7 b) shows the throughput of the test CR with the non-cooperating strategy with sensing probability of other heterogeneous CRs, for the mentioned network conditions.

5. Conclusion and Future Scope

To design a reliable as well as realistic CR engine, which is intelligent and efficient enough to achieve the maximum possible utility function in terms of throughput, we must not ignore the mobility factor of the wireless node. The throughput of a CR is closely related to the efficiency of spectrum sensing. In this work, we briefly addressed the issues of spectrum sensing efficiency maximization by sensing strategy optimization for static CR in a cooperative network. The work is extended considering mobile CR nodes. The mobility of wireless nodes affects many communication parameters such as connectivity, capacity, convergence, etc.

Initially, we examined the effects of node mobility of a cooperative CR network on spectrum sensing. Relations of spectrum sensing parameters like false alarm probability P_f and detection probability P_d with the velocity of the sensing nodes are represented. The number of sensing samples, number of sensing events, receive SNR, number of CRs in the network, etc. are taken into account when representing P_f and P_d.

Therefore, the robustness of the system is tested through simulation through MATLAB software. The spectrum sensing game is re-modelled with mobile CRs. The optimum strategy to maximize throughput at different network conditions is tested and verified through the game-theoretic approach. The throughput is represented and compared for pure cooperating and non-cooperating strategies with varying sensing probability of other CRs of the network, at diversified network conditions.

The present research work may be extended to verify the mobility impact on spectrum sensing through prototype experimentation. The adverse effect of mobility of sensing nodes may be mitigated through the Fusion Centre rule of cooperative sensing. Game theory may be deployed to upgrade cooperative sensing policy to maximize spectrum sensing outcomes.

6. Declarations

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Conflict of Interest

The authors declare that they have no conflict of interest.

Availability of Data & Material

Derived data supporting the findings of this study are available from the corresponding author on request.

Code availability

It is available from the corresponding author on request.

Author's contribution

(a.) Suddhendu DasMahapatra has conceptualized and written the main manuscript, including the formulation, data collection, and analysis.

(b.) Madhusudan Maiti has reviewed the main manuscript and carried out the literature survey.

(c.) Dibyendu Chowdhury has reviewed the main manuscript and carried out data collection.

(d.) Pritam Bhattacharjee has reviewed the manuscript for technical content, English checking, and did the overall supervision.

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