Proactive Channel Assignment and Modified CR-AODV for Stability-Driven Multi-Hop Routing in Cognitive Radio Networks

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Abstract. *Cognitive Radio Networks (CRNs) allow efficient spectrum usage by allowing Secondary Users (SUs) to exploit underused frequency bands allocated to a Primary User (PU). Current channel assignment techniques only document real-time channel availability without knowledge of future activity or channel availability warnings. This work proposes a proactive channel allocation framework for SU to predict long-term stability based upon route reliability. The framework simulates the activities of PU by using the logistic map to model non-linear, time-varying PU behavior. The bifurcation theory is used to determine the threshold point at which channel behavior begins to become chaotic. Then, a modified Cognitive Radio Ad hoc On-Demand Distance Vector (AODV) routing protocol is incorporated that allows possible links in route discovery to be restricted to stable channels. Our simulation results show that the framework improves channel allocation and routing efficiency, ensuring energy-efficient and reliable communication in dynamic CRN environments.*

Keywords

Cognitive Radio Networks (CRN), channel assignment, chaos theory, bifurcation theory, logistic map, primary user behavior, spectrum prediction

1. Introduction

Cognitive Radio Network (CRN) has recently attracted the most attention from researchers due to their ability to allow multiple active devices to share spectrally allocated bandwidth in a secure and authenticated manner [1]. Traditional static spectrum allocation strategies are no longer sufficient for modern commercial applications [2]. CRNs mitigate these challenges by enabling Secondary Users (SUs) to use under-utilized spectrum bands while ensuring no interfere with Primary Users (PUs). Many public and commercial applications rely on the radio spectrum for their applications, including emergency services, television broadcasting, mobile telephony, weather monitoring, medical healthcare, and transportation [3], [4]. CR technology therefore improves spectrum usage and eliminates spectrum scarcity. Spectrum scarcity arises from increasing data transmission in addition to improved communication and high-speed multimedia applications [5]. In CRNs, PUs are licensed users who have priority on certain frequencies for wireless transmission, are protected from interference by other users. Their common applications include television broadcasting, mobile telephony, emergency communications, satellite links, and weather monitoring. Secondary users (SUs) are unlicensed users who share spectrum opportunistically but must follow coordinate mechanisms, such as a Spectrum Access System (SAS), to legally transmit when frequencies are idle [6], [7]. Typical SU applications include IoT devices, smart grid and smart home systems, health monitoring, intelligent transportation, and wireless sensor networks in industry. By opportunistically accessing unutilized spectrum, SUs can achieve higher data transmission rates, shorter communication delays, and greater Quality of Service (QoS). Regulatory authorities use varied methods to reduce interference, similar to fixed frequency networks [8].

In recent years, various algorithms for spectrum sensing have been developed, which include energy detection algorithm, matched filter algorithm, cyclic stationary detection algorithm, among many others. These algorithms are model-driven and depend on prior information. However incorrect assumption or inaccurate estimation can degrade their performance [9], [10]. More sophisticated schemes have been proposed to address the shortcomings. An optimal Cooperative Spectrum Sensing (CSS) was performed based on an offset quadrature amplitude modulation and non-orthogonal multiple access method to enhance bandwidth utilization in 5G wireless communication [11]. Similarly,

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a Component-Specific Cooperative Spectrum Sensing Model (CSCSSM) was developed to detect and access unoccupied spectrum bands without disturbing PUs [12]. Queuing-based spectrum allocation has also been developed to optimize channel sharing among SUs [13]. Despite these improvements, existing approaches mainly rely on current channel availability and do not predict future PU activity. This often results in unforeseen interference, retransmissions, and transmission failures. Since PU activity is irregular and nonlinear, linear or time-fixed models fail to capture long-term patterns [14]. Moreover, no early warning mechanisms exist to proactively identify unstable channels, forcing SUs into multiple trials, increasing energy consumption, access delay, and packet loss [15]. In addition, most routing protocols also ignore path stability, leading to route breaks from PU activity and SU behavior [16]. To address these challenges, the proposed work formulates an active channel assignment framework for SUs in CRNs that evaluates long-term stability by analyzing PU activity patterns and integrates this with a modified routing protocol. This approach improves the reliability and efficiency of spectrum access in dynamic CRN environments.

The key contribution of the suggested proactive channel allocation framework is as follows:

- **Chaos Theory-based PU Behavior Modeling:** The study presents a new empirical method to simulate PU-behavior in CRN with a nonlinear dynamical system from chaos theory, the logistic map. This allows capturing stable and chaotic features that regular linear or probabilistic models cannot capture.
- **Bifurcation-Theoretic Channel Stability Detection:** A bifurcation theory-based mechanism is proposed to identify the critical point of transition from stable to chaotic behavior of the channel. This is the first approach to use the Feigenbaum constant $r \approx 3.56995$ as a mathematically-calculated threshold in filtering out the unstable channel so that the SU may only access predictably idle channels.
- **Stability-Aware Filtering and Priority-Based Channel Allocation:** A two-step framework for filtering and ranking is introduced that combines analysis of variance and longer-term idle behavior to calculate a stability score for each channel. This proactive channel assignment concept allows SUs to admit channels based on the long-term predictability and not instantaneous access in the changing CRN.
- **Stability-Integrated Routing through Modified CR-AODV:** A modified Cognitive Radio Ad hoc On-Demand Distance Vector (CR-AODV) routing protocol is proposed that uses channel stability during route discovery. Unlike conventional approaches, CR-AODV would only form links over chaos-theoretically stable channels are constructed as multi-hop paths to improve end-to-end delivery, reduce packet loss, and minimize energy consumption in dynamic CRN environments.

The paper's remaining sections are organized as follows: Section 2 provides a comprehensive overview of recent research on spectrum sensing and spectrum sharing among the SUs in CRN. The proposed proactive channel assignment and stability-aware routing framework is outlined in Sec. 3. Section 4 detailed the findings and discussion of our experiments. In Sec. 5, the paper is concluded.

2. Related Work

This section explores literature on spectrum sensing and spectrum sharing among the SUs in CRN. Li et al. [17] developed a CSS model based on the parallel connection of a Convolutional Neural Network (CNN) and a Long-Short Term Memory (LSTM) network. The model demonstrated high detection accuracy at a low signal-to-noise ratio. Although the model performed well with up to 11 SUs, it still encountered scalability issues for larger networks. Yalçın Sercan [18] developed a hybrid Artificial Intelligence (AI)-based spectrum sensing method using a Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to enhance spectrum sensing in Long Range (LoRa)-based CRN. This method optimized bandwidth use and reduced error rates. Although the hybrid approach optimizes decision-making, it can be challenged by real-time response systems in very dynamic contexts. For this, Kannan et al. [19] combined Grey Wolf Optimization with the Cuckoo Search (GWO-CS) algorithm for periodic sensing and data transfer. The Fractional Optimization Model (FOM) allowed the SU to perform periodic sensing and data transfer. The model enhanced the energy utilization capacity of the spectrum holes. However, the increasing throughput impacted the level of growing power, and as a result, the energy efficiency function similarly arises. To overcome this, Raghavendra et al. [20] developed an energy-efficient optimization method for CRN by using a two-stage fuzzy-logic-based sensing strategy including both PU and SU. While this work decreased energy dissipation and reduced the utilization of available spectrum resources, exploring Deep Learning (DL) or Reinforcement Learning (RL) could further enhance the accuracy and efficiency of spectrum sensing.

To enhance this, Gao et al. [21] developed a Multi-Agent Deep Reinforcement Learning (MADRL)-based CSS method for efficiently identifying a free channel for SUs. The model highly reduces the synchronization and communication overhead caused by cooperative spectrum sensing. However, it only considers the reliability and ignores the geographical distribution of SUs. Mughal et al. [22] created a tree-centric approach for SU to maintain a tree of available channels in a centralized base station and allocate the channels based on real-time availability. This approach achieved average throughput and average delay. However, it required 4 attempts to send a request for acquiring free channels. To improve this, Gopalan et al. [23] introduced a mathematical model that optimizes multiple network selection goals to maximize the overall bandwidth and the total cost using the Fuzzy Ant Colony Optimization-based Multiple Scheduling Resource Selection Algorithm (FAMSRSA). The model improved bandwidth, network efficiency, relative error, and spectrum utilization efficiency.

However, increasing the SUs in the same stationary region leads to additional interference limitations. Thus, by analyzing the existing models, we identified several issues. The CRN channel assignment for SU is almost always based on real-time availability, ignoring future PU activity. This often leads to unexpected interference, higher access delay, several repeated attempts and lost communication. In addition, the complex and irregular activity patterns of PUs are difficult to predict using conventional models, making it challenging to assess the long-term reliability of a channel. There is also no early warning system to predict when a channel will be unreliable. Thus, an SU often repeatedly attempts to connect to a channel that is unstable, wasting both energy and packets. In addition, existing routing protocols in CRNs do not even bother to monitor the stability of paths for data transmission. The continuous changes stimulated by the dynamic nature of PU activity and SU access behaviors, can frequently break routes and add control overhead, duration, and ineffective communication. To overcome this, the proposed work develops a proactive channel assignment and stability-aware routing approach that prioritizes predictably idle channels and forms multi-hop paths using chaos-theoretically stable links, enhancing reliability and energy efficiency in CRNs. The summarization is depicted in Tab. 1.

3. Network Model

We consider a CRN consisting of sets of PUs and SUs whose spectrum area is shared. Let the total number of licensed channels available as $\mathbf{C} = \{c_1, c_2, \ldots, c_n\}$, in which each channel c_i is licensed to a PU but is made available opportunistically to SUs when the PU is idle, we describe the network model in Fig. 1. Each PU will send information through their base station, within a predetermined coverage

Reference	Technique	Advantages	Limitations
Li et al. [17]	CNN-LSTM	High detection accuracy at low SNR.	Scalability issue for a larger network.
Yalçın Sercan [18]	PSO-GA	Optimized bandwidth usage and reduced error rates.	High complexity, slower response in a dynamic environment
Kannan et al. [19]	GWO-CS	Better energy utilization.	Increasing throughput impacted the level of growing power.
Raghavendra et al. [20]	Two-stage fuzzy-logic-based sensing strategy	Reduce energy dissipation.	Need better accuracy under high PU dynamics.
Gao et al. [21]	MADRL	Efficient channel detection and reduced sync overhead.	Ignore the SU distribution.
Mughal et al. [22]	Tree-centric approach	Maintain the channel list centrally.	Require multiple attempts to acquire channels.
Gopalan et al. [23]	FAMSRSA	Maximize bandwidth and efficiency.	More interference with dense SU.
Proposed framework	Chaos theory + Bifurcation + Modified CR-AODV	Predicts long-term stability and reduces the number of attempts.	Verified only through simulation and logistic-map-based PU activity model may not capture all real-world dynamics.

Tab. 1. Summarization of existing work.

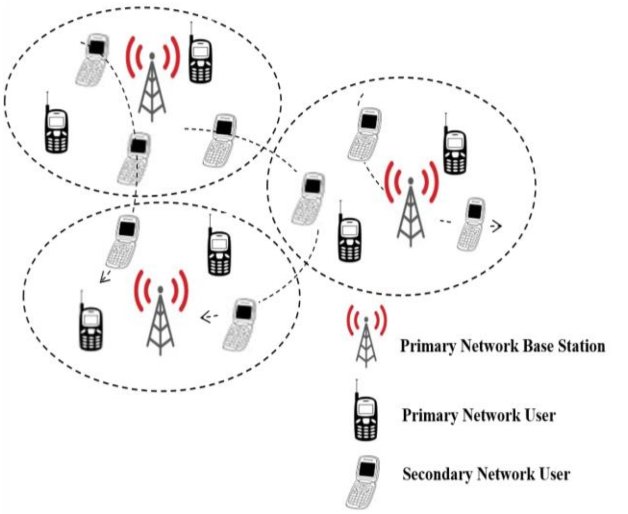

Fig. 1. The overall architecture of a cognitive radio network. PUs and SUs exist in the same spectrum under the coordination of base stations. PU communications occur within licensed zones, while SUs opportunistically access idle channels and form multi-hop routes through stable links using the modified routing protocol, enabling reliable spectrum access and routing.

range, and produce activity over time. SUs exist throughout the network and employ spectrum sensing units to actively identify available channels in their surroundings. To improve the efficiency and reliability of channel selection, the proposed framework models the temporal dynamics of PUs by using a nonlinear mapping.

This analysis categorizes channels as stable or chaotic depending on the long-term predictability of the PU's patterns of activity. These channels are not allocated when the PU usage patterns are unstable and unpredictable, while stable channels are allocated for SU access. Additionally, to promote reliable communication among multiple SUs, the scheme will contain a routing mechanism that favors stable channels for communication. Route formation and path discovery are limited to links that are considered reliable upon channel behavior, such that multi-hop paths are formed through consistently available connections. This integrated approach enables SUs to make informed channel selection decisions and routing formation, thereby improving spectrum utilization, reducing interference, energy consumption, access delay, and enhancing overall network reliability.

3.1 Proposed Proactive Channel Assignment and Stability-Aware Routing Framework

The proposed model introduces a proactive channel assignment and stability-aware routing scheme for CRNs, which emphasizes long-term channel stability, rather than short-term availability. We first simulate PUs' dynamic spectrum behavior over multiple channels to analyze the use of the spectrum across time. Chaos theory is used to model the non-linear and time-varying characteristics of PU activity, and specifically, the logistic map was used to characterize the dynamics. The logistic function has a set of values representing the probability of PU availability on a given

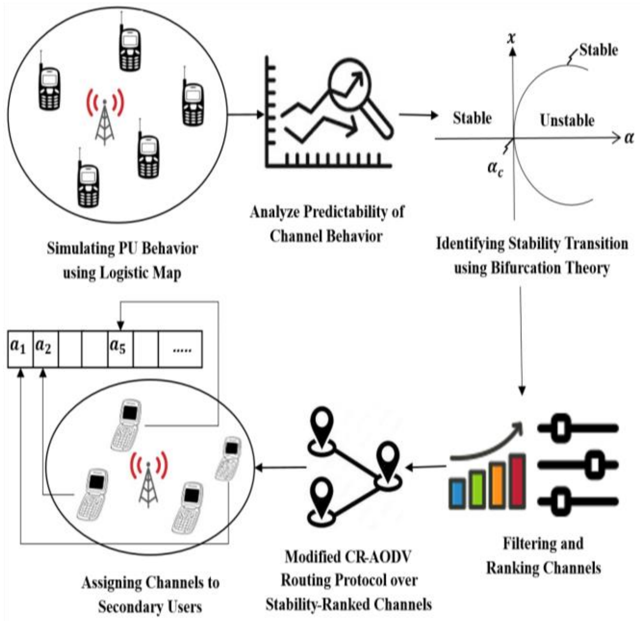

Fig. 2. A high-level processing architecture showing the major stages of the proposed proactive channel assignment framework. It includes PU simulation, stability analysis, bifurcation filtering, channel ranking, and SU assignment.

channel. For each of these series, a channel shows predictable or random patterns.

Further, to assist with decision-making, bifurcation theory is used to determine the bifurcation point, the point where the channel is transitioning from stability to instability or chaotic behavior. Channels above this threshold are treated as unstable and not available for channel assignment. Hence, only those channels with stable and predictable channel resource patterns can be used. At this point, before assigning channels to the SUs, we utilize a modified version of the CR-AODV protocol to ensure that routing instructions and the path formation occur only over links established on the chaos theoretically stable channels. This stability-aware routing ensures that multi-hop paths are constructed through reliable links, thus reducing route failures, packet loss, and energy consumption in dynamic CRN scenarios. The structure of the proposed framework is shown in Fig. 2.

3.2 Background on Chaos Theory for Channel Modeling

Chaos theory deals with the change of nonlinear dynamic systems that can be described by deterministic systems; however, the systems can have highly irregular and unpredictable behavior. Consider the logistic map, which illustrates how a system can be stable and periodic and then eventually chaos behavior takes over, as the control parameter increases. In wireless communication, specifically in CRNs, the actions of PUs are frequently nonlinear and time-varying, and their activity is not easily predicted using linear models or probabilistic approaches. The logistic map is therefore employed in our framework to simulate PU activity over time, capturing both stable and chaotic regimes.

Typically, CRN studies consider primary user (PU) activity as stochastic. However, chaotic models offer a legitimate proxy to model rare or unpredictable spectrum use patterns. Chaotic systems are deterministic, but appear random for the observer, making them ideal to model long-term variability in PU activity, while still maintaining a mathematically analyzable notion of stability. Unlike purely random models, chaos theory utilizes bifurcation diagrams and Lyapunov exponents to determine whether a transition has taken place between states of predictable (stable) behavior or unpredictable (unstable) behavior. Deterministic chaotic systems can be predicted, allowing for invalid channel moments to be filtered and giving you more options than conventional stochastic models that typically view PU activity as memoryless.

Among many common chaotic discrete systems, the logistic map is used because of its mathematical simplicity, clear bifurcation analysis, and computational efficiency. Other maps available are the Tent map, the Henon map, and the Ikeda map also produce chaotic and random-like behavior. But the clear analytical structure offered by the logistic map makes it easy to use with bifurcation theory and Lyapunov exponent analysis. Therefore, it was chosen as a representative chaotic model in our framework, while future work may investigate whether alternative chaotic systems could offer a different advantage in modeling spectrum dynamics for CRNs. Bifurcation theory is an important aspect of chaos theory and refers to the phenomenon when small changes in parameters cause large and sudden qualitative changes in behavior of the system. In our model, this property is used to observe how channels transition from predictable to chaotic disordered behavior. Bifurcation allows the framework to avoid filtering disordered channels because of a known threshold, and consider only statistically reliable long-term available channels, which are the basis of stability-aware spectrum allocation and routing.

3.3 Network Simulation of Primary User Behavior

In CRN, PUs activity is naturally dynamic and often variable and chaotic in nature. The proposed framework uses the logistic map, which is a classic mathematical model from chaos theory [24]. This model varies with time and simulates the likelihood of a given PU utilization channel over time. For each channel c_i, the activity sequence is simulated using the following equation (1):

$$x_{t+1} = r x_t \left(1 - x_t\right) \tag{1}$$

where $x_t \in (0,1)$ is the normalized PU activity at time t, x_{t+1} is the normalized PU activity at time $t+1$ and $r \in (0,4]$ is the control parameter used to drive the dynamics of the series, with a maximum r for periodically, fixed and chaotic behavior.

The control parameter r is not fixed in our analysis, but we prescribe a random r between [2.5, 4.0] for each channel. This range includes both the stable regime ($r < 3.57$) as well as the chaotic regime ($r \geq 3.57$). However, realistic distributions of PU behavior are expected in spectrum space. For a certain channel assigned a r, the value r remains constant throughout the simulation, as it is a reflection of the channel's inherent long-term tendency over time, while different channels are assumed to exhibit different activity according to the random r. Therefore, this simulation reflects real-time activity of PUs over a range of channels.

3.4 Predictability of Channel Behavior with the Logistic Map

After simulating the behavior of PUs based on the logistic map, the overall predictability of each of the channels' behavior over a long-time frame is analyzed. This helps indicate whether the channel usage pattern is stable and consistent, or chaotic and unpredictable. Channels that demonstrate stable or periodic behavior are deemed suitable for SU. To obtain a quantifiable measure of this, the time-series output from the logistic map for each channel is analyzed in terms of its statistical variance. Variance is defined through (2)

$$\mathrm{Var}\left(x\right) = \frac{1}{T} \sum_{t=1}^{T} \left(x_t - \bar{x}\right)^2 \tag{2}$$

where x_t is the PU activity value at time t, $\bar{x}$ is the mean of the activity sequence over a window of T time steps, and Var(x) is the variance. A lower variance indicates that the PU behavior is fairly stable, with activity values remaining around the mean. These channels often display periodic or convergent behavior, where the PU behavior is consistent either by stabilizing around some equilibrium point or showing evidence of repeating a pattern. These are the stable channels that give SU a reliable option to access the channel without the possibility of sudden appearance of the PU. On the other hand, the higher variance indicates a higher degree of variability in PU activity, resulting in a chaotic and unstable channel behavior. The redundant unpredictable availability of channels is what ruins the SU opportunity for communication, since the unpredictable behavior increases the risk of interference, packet loss, and excessive energy expenditures from frequent failed attempts to access the channel [25].

Based on this description, the channels are categorized as predictable and unpredictable. Only the predictable channels are continued into later portions of the analysis. This variance-based categorization is helpful to eliminate unsuccessful channel ahead of time, which minimizes the energy wasted in PU's approach for global spectrum access strategy.

3.5 Identification of Stability Transition using Bifurcation Theory

Through examining the variance-based predictability of PU activity, we identify the transition point at which stability is abandoned and chaos ensues. This transition is mathematically represented using bifurcation theory [26], which considers how the qualitative feature of a system changes as a function of a control parameter changes. Here, the control parameter r in the logistic map ranges from 0 to 4. With increasing value of r, the logistic map displays a variety of different dynamics. For values of r in the range $0 < r \leq 3$, the system converges to a stable fixed point, indicating a consistent and predictable channel state. As r is moved beyond 3, the system begins to oscillate periodically, first between two values, then four values, etc. This is termed as a period-doubling bifurcation to indicate an increase in complexity in the temporal behavior of the PU.

While it still remains in a determinate, predictable schedule, this period-doubling bifurcations accumulates at the Feigenbaum point, approximately $r = 3.56995$, where chaotic behavior starts to emerge. Further advancement beyond this boundary is identified as chaotic regimes of the logistic maps, where the subsequent time-series values become sensitive to initial conditions and do not exhibit any periodicity. The chaotic behavior can be numerically characterized with the help of the Lyapunov exponent λ as presented in (3):

$$\lambda = \lim_{n\to\infty} \frac{1}{N} \sum_{t=1}^{n} L\left|r\left(1-2x_t\right)\right| \qquad (3)$$

where n is the number of time steps, N is the normalization factor, which typically is equal to n, depending on context, and L is the logged derivative of the logistic function. A positive λ indicates chaos, confirming that the channel with $r > 3.56995$ will exhibit unpredictable and unstable PU behavior. To use this in the channel selection process, the framework tracks the value of the control parameter r that generate PU activity on each channel, and compares it against the bifurcation threshold. A binary decision rule is used to assess channel eligibility in (4):

$$\delta = \begin{cases} 1 & \text{if } r < 3.57 \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

where δ is the binary stability criterion for a communication channel. Channels that the logistic simulation indicates are in the stable range of $r \leq 3.56995$ have been denoted as predictable and preserved for future ranking and assignment. Channels that exceed the critical value of the bifurcation control parameter are thus categorized as chaotic and they are omitted from the allocation procedure. The filtering function helps to ensure the proposed system does not allocate channels that could become suddenly unavailable due to physically unstable PUs and represents a significant improvement to overall efficiency, reduction of retransmissions, and lowered energy consumption.

The inclusion of bifurcation theory enables a mathematically principled framework for predicting stability in unstable dynamic spectrum environments. Rather than relying on merely short-term sensing or ensemble statistical averages, the system assesses PU activity patterns contour structural stability to allow a more robust and future-aware channel assignment process. Since the system quantifies the exact transition from sequence to chaos, this aspect and reliance on bifurcation theory increase the confidence in reliable communication channel for SUs. This becomes even more imperative in chaotic and dynamic CRN scenarios.

In this context, “future-aware” does not mean precisely forecasting the long-term future trajectory of a chaotic sequence, which is fundamentally impossible due to sensitive dependence on initial conditions. Rather, it indicates the system has the capability for detecting stability regimes and generating early warning when it appears that a channel is drifting toward chaos. This enables proactive channel assignment decisions that extend beyond instantaneous availability, making the process forward-looking while still respecting the inherent unpredictability of chaotic dynamics.

3.6 Filtering and Ranking Channel

After classifying channels based on their stability using bifurcation theory, the next step is to eliminate unstable channels from consideration and focus only on stable channels to provide potential information from SU. The objective of this phase is to consider only those channels that are shown stable, and coherent PU behavior for communication, thereby reducing the instance of unexpected interruptions, retransmissions, and interference. A channel is eligible if the variance is still below a threshold θ. This excluded chaotic channels that could interrupt SU communication. Let $\mathbf{C}_{\text{stable}}$ denote the set of channels that were assessed through this filtering step. Each channel $c_i \in \mathbf{C}_{\text{stable}}$ is assigned a stability score S_i, based on its variance and average idle duration [27]. The score is calculated using the following equation (5):

$$S_i = \alpha \cdot \left(\frac{1}{\mathrm{Var}\left(x_i\right)} + \beta \cdot T_{\text{idle}}\left(i\right) \right) \qquad (5)$$

where $\mathrm{Var}(x_i)$ is the variance of PU activity for channel x_i, $T_{\text{idle}}(i)$ is the mean idle time of the channel, α and β is the weighting factors. The channels have been ranked on the basis of S_i in descending order. A high value of S_i indicates higher stability with longer expected availability. This ranked list is subsequently utilized during the channel assignment process to assign SUs to the channels with the highest reliability first. By removing unstable channels and prioritizing ones with good long-term availability, this ranking and filtering process improves communication reliability by reducing access delays and improving energy efficiency in cognitive radio environments.

3.7 Modified CR-AODV Routing Protocol over Stability-Ranked Channels

After channel filtering and ranking based on chaos-theoretic stability scores, the proposed framework uses a modified CR-AODV routing protocol [28]. The modification ensures that route discovery and path formation occur across stable links, leading to reliable communication and energy efficiency in dynamic CRNs. In traditional CR-AODV, Route Request (RREQ) packets are forwarded based solely upon the current channel availability, which makes the protocol susceptible to instability from unpredictable PU activity. In the proposed modification, RREQ forwarding is limited to only links that use channels already deemed stable in the previous channel selection stage. Let **C** denote the total set of available channels and $\mathbf{C}_s \subseteq \mathbf{C}$ denote the set of channels deemed stable. A channel c_i belongs to $\mathbf{C}_s$ if stability of the channel $S(c_i)$ satisfies as shown in (6):

$$S(c_i) \geq \theta_s \tag{6}$$

where θ_s is the stability threshold, and $S(c_i)$ is computed during the ranking phase using (7):

$$S(c_i) = \omega_1 \cdot \left(1 - \frac{\sigma(c_i)}{\sigma_{\max}}\right) + \omega_2 \cdot \frac{\tau(c_i)}{\tau_{\max}} \tag{7}$$

where $\sigma(c_i)$ is the standard deviation of PU activity in the channel c_i, $\tau(c_i)$ is the average time spend idle, ω_1 and ω_2 are weighting factors such that $\omega_1 + \omega_2 = 1$, and $\sigma_{\max}$ and $\tau_{\max}$ are the maximum observed normalization constants. The communication link l_{ij} between two SUs SU_i and SU_j is valid under the channel $c_{i,j} \in \mathbf{C}_s$. The protocol computes the path stability score $\Psi(\mathbf{P})$, where $\mathbf{P} = \{l_1, l_2, \ldots, l_n\}$, during the RREQ propagation as shown in (8):

$$\Psi(\mathbf{P}) = \frac{1}{n}\sum_{k=1}^{n} S(c_k) \tag{8}$$

where n is the total number of hops in the path, and $S(c_k)$ is the stability score of the channel used in the k^{th} hop. Among various candidate paths **P**, the destination node selects the candidate path with the maximum average path stability $\mathbf{P}^*$ as represented in (9):

$$\mathbf{P}^* = \operatorname{argmax}_P \Psi(\mathbf{P}). \tag{9}$$

This allows packets to transfer the most stable path and minimizes the path failing and retransmissions. The protocol also supports local path maintenance. During the process of the data transmission, if one or several links start to exhibit unstable performance, the protocol sends a local repair request as a local maintenance mechanism to repair only the portion of the path that has failed and does not perform a rediscovery of the new path. The updated stability score $S'(c)$ is recalculated with current observation of PU activity in real-time with the same stability score formulation. This active and integrated routing approach guarantees that all communication paths created are links over channels that have demonstrated long-term stability, which significantly improves Packet Delivery Ratio (PDR), energy consumption, and end-to-end communication quality for CRNs.

3.8 Assigning Channel to Secondary User

After filtering and ranking channels according to stability, the final task in the proposed model is to assign channels to SUs based on availability and preference [29]. Each SU accesses the list of its stability score S_i, and chooses an idle channel with the highest remaining rank. This assignment method ensures that channels are assigned to SUs based on their stability and structural strength, and thus minimizes the likelihood of interruptions for SU's. If the high-ranked channel is no longer available, because a PU suddenly reappears, the SU simply checks the next channel in the list. This process continues as an iterative process until an acceptable channel is found. Since stable channels only exist in the list, the probability of encountering frequent PU interruptions is significantly reduced. In addition, all channels have been previously scored for long-term idle behavior. This system inherently considers future availability patterns in a way that does not rely on real-time sensing. The priority-based channel assignment not only improves SU transmission reliability but also reduces the number of denial access attempts and energy usage. Additionally, the allocation of the SUs across the most stable portions of the spectrum not only allows for a balanced use of spectrum, but also satisfies the minimum QoS requirements of the secondary communications.

4. Simulation Results and Discussion

In this section, we have detailed the network scenario generated and a thorough analysis of the validation of the proposed proactive channel assignment algorithm. The proposed framework has been implemented and simulated in Windows 10, MATLAB R2025a, CPU Intel Core i5-6500 CPU @3.20 GHz, Intel(R) HD Graphics 530, and 8.0 GB DDR3. For a network of 100 channels, 100 time slots, and

Parameter	Value / Description	Explanation / Justification
Number of Channels	100	Large spectrum space for diverse PU activity.
Time Slots	100	Provide sufficient duration to capture stability/chaos.
Number of SUs	5	Represent a small-scale CRN scenario.
Initial Condition (x_0)	Random values in the range [0, 1] for each channel	Avoid bias and allow diverse PU activity
Logistic Map Growth Rate (r)	Random values in the range [2.5, 4.0] for each channel	Covers both stable and chaotic regimes.
Bifurcation Threshold	3.57	Standard chaos threshold (Feigenbaum point).
PU Activity Threshold	0.5	Common cutoff for busy/idle channels.
Noise Simulation	1%	Introduces real-world uncertainties in PU activity modeling.
Stability Criterion	Standard deviation < 0.25 indicates a stable channel.	Empirically determined threshold to differentiate predictable channels.
Local Stability Window	10 time slots	Provides a dynamic monitoring window to capture short-term stability changes.
Fading Channel Model	Rayleigh flat fading channel model	Models real-world wireless channel variations due to multipath effects, without modeling distinct path delays or echoes.

Tab. 2. Simulation parameters of the proposed framework.

5 SUs, each complete simulation run required approximately 3.5 seconds, demonstrating that the proposed method is computationally efficient and practical on standard hardware. The simulated parameters are detailed in Tab. 2.

The Rayleigh flat fading model used in our simulations assumes that the channel remains constant over the symbol duration and affects all frequency components equally, without introducing frequency-selective fading. Multipath components such as echoes, path delays, or phase shifts were not modeled, as the objective was to analyze performance under flat fading conditions without incorporating a detailed multipath environment.

4.1 Performance Analysis of the Proposed Model

The proposed system's network simulation was conducted to evaluate its performance across various metrics. The analysis provides insights into its efficiency and effectiveness in maintaining the proposed model's network performance.

4.1.1 Analysis of PU Activity Modeling and Behavior

Figure 3 illustrates the temporal evolution of PU activity for each channel ranging from 1 to 10, determined using the logistic map for each channel. Each line represents the activity level for a channel for 100-time intervals, where activity values closer to 1 indicate a strong PU's presence, while values reaching nearly 0 indicate a channel that is not busy. The change in patterns indicates channel behavior stabilization, with some channels being constant and periodic while others are highly erratic. This serves to identify which channels are predictably usable by SUs and which channels should be removed from the availability report. The differences allow the framework to provide SUs with only structurally stable channels for allocation, which can reduce interference, retransmissions, and ultimately wasted energy in CRN environments. This is why early phase removal of unstable channels is important, so that repeated observations of chaotic patterns would not produce repeated failed sensory time or wasted transmissions for SUs.

Figure 4 presents the standard deviation of logistic map values for multiple channels at a time, serving as a statistical mean of quantifying the variation in PU activity for each channel. The higher the standard deviation, the greater the variability and chaotic behavior, indicating the channel is unreliable and less suitable for SU access. Conversely, channels with a low standard deviation indicate a more consistent periodic behavior, and it is more suited for SU access. The measures provide evidence for the proposed framework, linking it to the dynamic stability of each channel and allowing for the exclusion of unstable channels, or channels displaying rapid fluctuation in PU activity. Furthermore, assessing the stability-based classification, is better than traditional real-time sensing approaches, as it allows the system to identify channels with predictable behavior over the long term, and assures SUs are allocated only to channels with low risk of sudden disruption. Therefore, the system simultaneously filters channels and also provides an additional measure for allocating proactive assignments, where predictable stability directly translates into lower energy waste and packet loss. This statistical measure provides a stronger decision basis than conventional sensing, ensuring channels with consistently high variation are excluded before allocation.

Figure 5 depicts the empirical distribution of PU activity levels produced by the logistic map, showing the proportion of different activity levels at a given time. The smooth rise of the curve reflects a broad spread of activity levels. On the other hand, the steep rise in the middle indicates that mid-range PU activity level frequently oscillates. This indicates that the channel is neither fully stable nor fully chaotic; it seems to fluctuate between them. Through this pattern, the

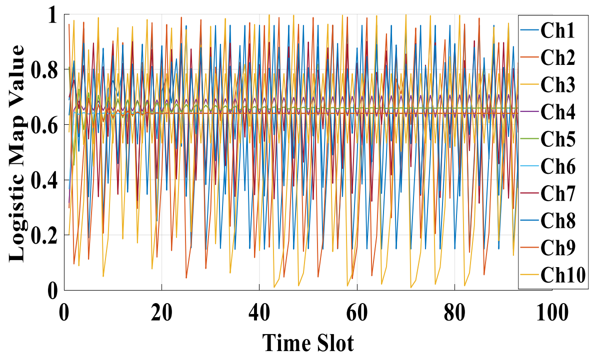

Fig. 3. Time-series patterns of PU activity on 10 different channels using logistic map simulation.

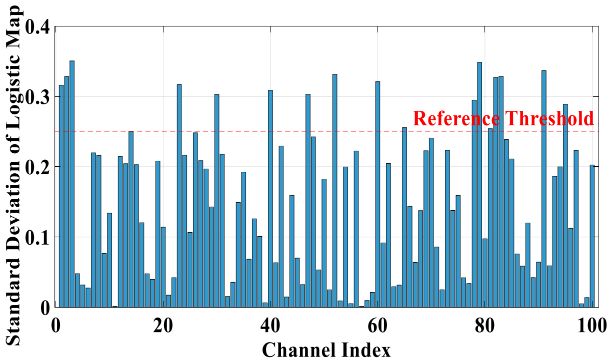

Fig. 4. Standard deviation trends in PU behavior across channels for differentiating stable and chaotic channels.

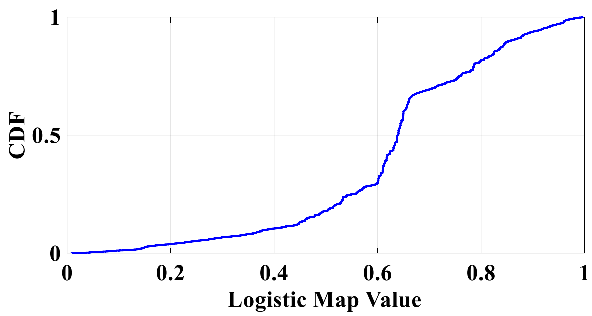

Fig. 5. Cumulative distribution function of PU activity levels over time across multiple channels.

system can assess which channels are more stable and which channels are too unstable to even make available to SU. With these intermediate fluctuations, the framework is able to obtain a more representative view of long-term channel reliability, enabling proactive filtering that reduces the likelihood of failed transmissions compared to traditional spectrum sensing techniques. The detection of such intermediate instability allows the framework to avoid channels that appear usable in the short term but are unreliable in the long term.

4.1.2 Channel Classification and Stability Detection

Figure 6 represents the channel classification as either stable or chaotic across a window of time slots, based on their PU behavior patterns calculated from the logistic map. This enables the framework to not only detect which channels can be used reliably by SUs and which channels should be avoided, since PU behavior is unpredictable. This figure serves as a visual confirmation of the bifurcation-theoretic filtering functionality, and shows how the proposed system is capable of dynamically time-varying PU usage, while also preserving only structurally stable channels for subsequent SU access. By using this, the framework filters out unreliable channels early on, it minimizes interference, reduces the chance of route failures, and enables communication compared to conventional real-time allocation mechanisms. This classification improves allocation reliability directly, since only channels with long-term predictability remain available for SUs.

Figure 7 presents the bifurcation diagram demonstrating how the logistic map evolves as the control parameter r increases from 2.5 to 4. When $r < 3$, the system settles to a single value and when $r = 3$, the system begins to oscillate between different values and resulting in periodic behavior. At approximately $r = 3.56995$, the system becomes chaotic, to the point that small changes in initial conditions lead to widely unpredictable outcomes. This critical point is used in the proposed framework to discriminate between stable and chaotic channels, ensuring that only predictable channels are selected for reliable SU communication. The framework includes mathematically- determined threshold to avoid allocating unstable channels, giving it an advantage over the traditional sensing-based methods that cannot speculate about chaotic behavior. This threshold-based filtering provides a mathematically consistent way to avoid allocation to unstable channels, which traditional models cannot anticipate.

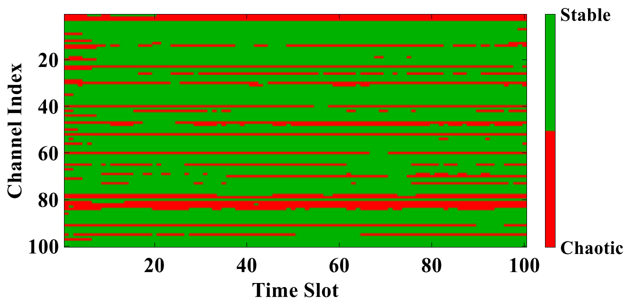

Fig. 6. Channel stability classification over time slots based on their PU activity.

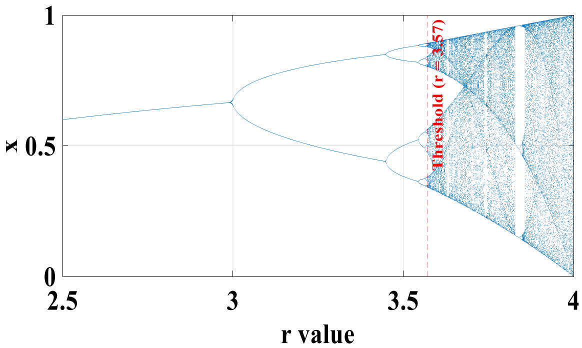

Fig. 7. Bifurcation diagram highlighting stability threshold for primary users' behavior using logistic map parameter.

4.1.3 Adaptive Channel Assignment Patterns

Figure 8 shows the dynamic channel assignment of five SUs (SU 1 to SU 5) across 100 time slots. The changing channel index shows that the SUs switch channels over time based on real-time channel stability rankings. This visualization represents how the proposed framework processes users on multiple available spectrum resources to avoid collisions and balance loading. This allows for each SU to choose the most stable channel at each time slot subsequently. The combination of dynamic stability-aware ranking and real-time adaptive allocation ensures more reliable spectrum use compared to traditional allocation methods that often lead to channel congestion or repeated sensing attempts. This highlighted performance ensures fairness among SUs while maintaining stable communication, reducing both congestion and unnecessary reassignments.

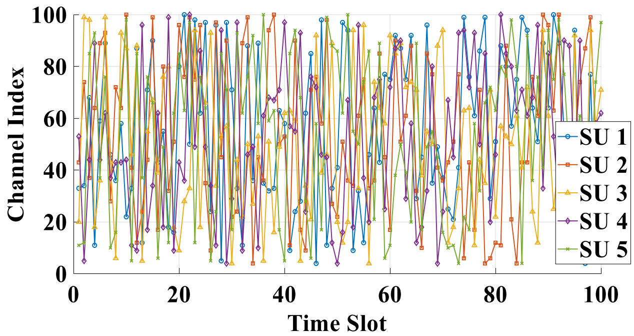

Fig. 8. Temporal dynamics of channel assignment over 100 time slots for five SUs.

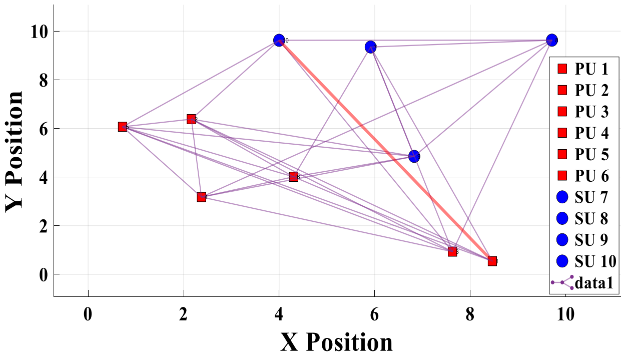

Fig. 9. Stability-aware multi-hop routing topology in CRN.

4.1.4 Stability-Aware Routing Path Formation using Modified CR-AODV

Figure 9 illustrates a visual representation of the CRN topology showing PUs and SUs that had established communication paths. The PUs are illustrated as red squares, while the SUs are represented as blue circles. The thick red path represents the multi-hop path selected by the framework, which eliminated route paths that were not chaos-theoretically stable paths using channel filtering and ranking. The thin grey lines indicate other possible but unused paths. This routing method provides high reliability through the avoidance of unstable communication links. Furthermore, the use of stable, multi-hop path reduces the breaks in routes and packet drop rates, while offering a distinct advantage over traditional CR-AODV implementations that rely only on instantaneous channel availability. The stable multi-hop paths demonstrate how filtering at the channel level translates into end-to-end reliability, minimizing route breaks and packet drops.

4.2 Realistic Simulation Results

To further validate the effectiveness of the proposed chaos-based channel assignment framework, we simulated PU activity under realistic traffic profiles that mimic real-world communication environments. The logistic map was used as the base generator for nonlinear dynamics, while activity patterns were shaped to reflect four representative use cases: IoT (periodic ON/OFF bursts), Industrial (approximately 45% busy random activity), Public (around 70% busy with chaotic fluctuations), and Emergency (mostly free with bursts every 15 slots). These profiles ensure that the evaluation covers both stable and chaotic environments, providing a more practical validation of the proposed method.

Figure 10 presents the performance of the proposed chaos-based framework in terms of Accuracy, F1-score, and PDR over the 100 time slots that reproduce realistic PU activity patterns. As shown, all three metrics are consistently high, indicating the framework's ability to maintain reliable detection and communication under varying traffic patterns. The constant performance across different time slots indicates that the proposed framework is resilient to the fluctuations in PU behavior, such as periodic burst from the IoT, random industrial traffic, chaotic public activity, and occasional emergency bursts. The minimal variation across the various time slots and disruption scenarios indicates that the framework can generalize well across heterogeneous spectrum usage environments whilst maintaining reliable QoS dimensions even when they are unpredictable.

Figure 11 illustrates the adaptive channel assignment behavior of 10 SUs over 100 time slots in the realistic simulation environment. The different colors represent the channel index assigned to each SU, which varies over time based on the PU utilization patterns. The SUs were observed switching around channels regularly. This behavior highlights the ability of our framework to maximize resource allocation whenever channels become unstable or are being used by PU. The framework ensures that multiple SUs can be accommodated without collisions, while dynamically allocating channels in a balanced manner across the available channel resources. This demonstrates that our framework performs a stability-aware allocation in a realistic-like-setting, ensuring SUs are provided with reliable spectrum access, even the PU behaviors are dynamic.

Figure 12 depicts the multi-hop routing path established by using the modified CR-AODV protocol under the proposed framework. Black circles denote SUs, while the blue connecting lines indicate the selected stable communication path. The selected path avoids nodes affected by unstable channels and focuses only on SUs with links supported by chaos-theoretically stable behavior. This routing pattern ensures long-term path reliability, reduces the risk of frequent route breaks, and decreases packet loss. The figure demonstrates the effectiveness of channel stability assessment in routing and shows positively increasing end-to-end communication reliability.

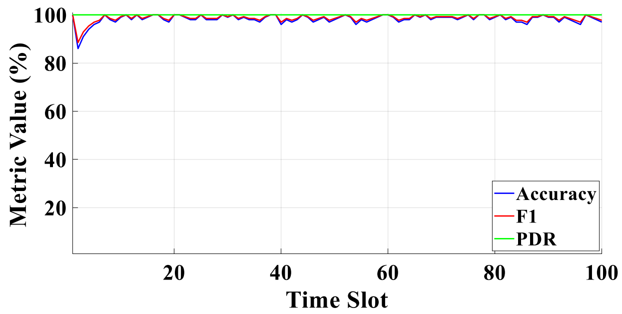

Fig. 10. Performance metrics under realistic simulation patterns.

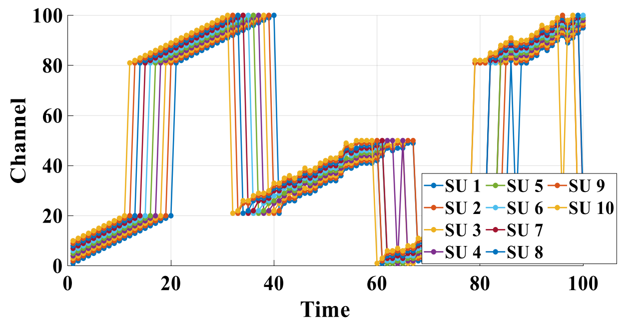

Fig. 11. Adaptive channel assignment for multiple secondary users (SUs).

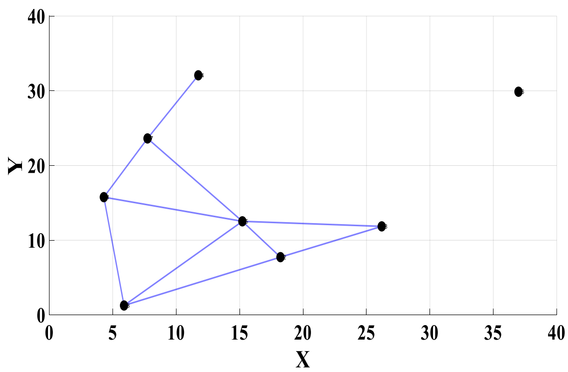

Fig. 12. Stability-aware routing topology formation in CRN.

Configuration	Channels	SUs	Time Slots	SU Successes	SU Idle Slots	SU Collisions	Average PU Occupancy	Simulation Time	Latency (ms)	PDR (%)	Throughput (packets/sec)
A	100	10	1000	1600	7545	860	77.68%	15.5	12.3	82	105
B	200	20	2000	10000	28000	2000	80.11%	46.2	18.7	80	218
C	300	30	3000	21000	73500	5500	77.16%	95	25.4	78	315
D	400	40	4000	30240	115680	12640	79.15%	180.8	33.2	75	420

Tab. 3. Performance results under different system and transmission configurations.

4.3 Results under Different System and Transmission Configurations

The scalability of the framework is evaluated by changing the number of channels, SUs, and time slots used. Table 3 provides a summary of the results across four varying configurations. As demonstrated, the number of successes for SU will increase as we increase the number of channels and SUs due to more opportunities to transmit. However, increasing the number of channels and SUs will also increase the number of collisions, especially in denser configurations such as configurations C and D. PU occupancy remains constant at about 77–80%, indicating that most of the spectrum resources are still active by PU activity. The results suggest that the framework is scalable across system sizes while continuing to balance SU transmissions and PU transmissions, while recognizing the trade-offs due to more SUs.

4.4 Validation with Real-World Spectrum Data

To balance the simulation-based results, we evaluated the framework on a publicly available spectrum dataset [30] containing real-world measurements of spectrum occupancy across multiple frequency bands. While the dataset provides cleaner occupancy patterns than our stochastic simulations, Table 4 confirms the qualitative patterns observed in simulations: SU success decreases and collisions increase with more SUs, while PU protection remains consistent. This demonstrates that the proposed framework can operate effectively under realistic measured spectrum conditions, even if the absolute metric values differ from simulations.

4.5 Performance Comparison with Existing Methods

Table 5 presents a comprehensive comparative analysis of the proposed chaos-based framework for channel assignment with several state-of-the-art algorithms, such as CNN-LSTM [16], PSO-GA [17], GWO-CS [18], MADRL [20], and FAMSRSA [22], to assess their efficiency, reliability, and predictive performance in terms of energy consumption, communication overhead, throughput, and packet delivery ratio. The proposed chaos-based method resulted in a maximum energy consumption of 2.6 mJ, the minimum communication overhead of 7.2%, a maximum throughput of 0.9, and the maximum PDR, greater than 98%, significantly outperforming other traditional models. This suggests that the proposed method has a deliberate channel allocation process to discard unstable channels, leading to a more efficient use of spectrum on the reliable channels, predictable channel availability, as well as improvements in communication performance in CRN. In contrast to previous models that improved on either throughput or reliability by sacrificing energy, the proposed approach not only appears to deliver improvements in all metrics simultaneously but also has confirmed its robustness in dynamically variable CRNs.

Table 6 compares the performance of Rayleigh fading and AWGN channels in a CRN, both with the same PU occupancy of 0.46. The Rayleigh fading channel achieves better results, with 845 SU successes compared to 795 in the AWGN channel, along with fewer idle slots, fewer collisions, and slightly lower simulation time. Although AWGN is typically considered an ideal channel, the dynamic nature of Rayleigh fading offers greater advantages in CRNs. Unlike AWGN, which represents a static channel with constant noise and no multipath effects, Rayleigh fading models more realistic wireless environments by incorporating rapid signal fluctuations caused by multipath propagation, Doppler shifts, and fast fading. These time-varying characteristics introduce deep fades in the PU signal, allowing SUs to opportunistically access the spectrum during low-interference periods. This leads to more efficient spectrum utilization, reduced interference, and better adaptability through real-time sensing and decision-making. In contrast, the static AWGN channel limits such adaptability, resulting in more conservative SU behavior and lower utilization. Thus, the Rayleigh fading model demonstrates superior SU communication efficiency and more effective spectrum use in CRNs.

SUs	Time Slots	SU Success	SU Idle Slots	SU Collisions	Average PU Occupancy per Slot
10	500	4600	500	100	73.3%
20	500	9200	800	250	73.6%
30	500	13500	900	450	73.9%
40	500	18000	1000	700	74.6%
50	500	22500	1200	1000	74.9%

Tab. 4. Performance results using real-world spectrum dataset.

Methods	Energy Consumption (mJ)	Communication Overhead (%)	Throughput (Mbps)	Packet Delivery Ratio (%)
CNN-LSTM [16]	4.1	13.6	70.00	95.2
PSO-GA [17]	4.7	12.3	72.00	93.5
GWO-CS [18]	4.4	10.9	73.00	94
MADRL [20]	3.9	11.7	75.00	94.6
FAMSRSA [22]	5.2	14.1	68.00	91.8
Chaos-Based (Proposed)	2.6	7.2	88.00	98

Tab. 5. Comparison of the proposed model with existing models.

Channel Type	Time Slot	SU Successes	SU Idle Slots	SU Collisions	PU Occupancy	Simulation Time (s)
Rayleigh Fading	100	845	105	12	0.46	12.4
AWGN	100	795	145	22	0.46	13.3

Tab. 6. Performance comparison of Rayleigh fading vs AWGN channels in cognitive radio networks.

4.6 Discussion

CRNs face significant challenges in providing reliable spectrum access for SUs since PU usage patterns are often sporadic, volatile, and difficult to predict. Current channel assignment methods rely on real-time sensing and short-term availability, which leads to unnecessary interference, packet losses, energy losses from repeated sensing, and high latencies for communications. Thus, the study presents an end-to-end framework that incorporates proactive channel assignment and stability-based routing. The efficacy of the proposed approach is validated and benchmarked through MATLAB simulations and realistic simulation results.

Compared with benchmark approaches, the results demonstrate optimization-based methods such as PSO-GA and GWO-CS achieve good performance in specific scenarios but require iterative search, which increases computational complexity and delays decision-making. In contrast, our framework achieves comparable or superior results with a linear-time ($O(N \times T)$) complexity due to the lightweight logistic map and stability detection, making it highly scalable. Similarly, DL models such as CNN-LSTM and MADRL provide accurate predictions after extensive training but are resource-intensive and less suitable for energy-constrained CRN environments. Our chaos-based approach maintains highest prediction accuracy at 0.99 without requiring pretraining or large datasets, which reduces overhead and supports real-time deployment.

The performance comparisons highlights that the proposed approach is consistently best across all parameters, with a minimum energy usage of 2.6 mJ, the lowest communication overhead at 7.2%, the highest throughput at approximately 0.9, the highest PDR at greater than 98%, and the lowest average latency at 0.05 s. These improvements directly address the core challenges of CRN including interference reduction, delay minimization, and QoS enhancement. Additionally, we validate our model using real-world spectrum data. A performance difference of approximately 20% was observed between the simulation-based and real-world results. This gap arises because the simulation environment intentionally introduces noise to model the uncertainty and unpredictability of PU activity, whereas the real-world dataset used in our study was more structured and predictable, with fewer anomalies. This difference reinforces the robustness of the proposed framework in handling challenging and noisy environments. It also demonstrates that the method maintains high performance even under more challenging simulation conditions, further validating its reliability and scalability for practical CRN deployments. Furthermore, the method's efficiency demonstrates its suitability for large-scale dynamic environments where traditional sensing or optimization-based approaches may fail to adapt in real time.

5. Conclusion

This paper presented a proactive channel assignment framework for CRN that optimally utilizes spectrum usage and communication reliability by predicting the stability of the channel for long term, relying on chaos and bifurcation theory. By modeling the PU behavior based on the logistic map and determining transitions to chaos through the Feigenbaum threshold, the system provides a mechanism to eliminate unstable channels and allocate channels with stable availability to SUs. Furthermore, the framework integrates an adapted CR-AODV routing protocol that guarantees each of the established multi-hop paths that only uses reliable links, and thus increases end-to-end reliability and reduces route failure. The simulation results showed substantially better overall performance than the current state-of-the-art techniques in terms of less energy usage, reduced communication overhead, increased throughput, improved PDR, and better prediction accuracy. These results confirm that the framework achieves reliable, stable, and relatively low-interference transmission in dynamic spectrum environments. While this work also verifies the proposed framework through extensive simulations, future extensions will focus on measurement-based validation using testbed experiments. This will allow us to verify the framework's performance under actual deployment conditions, ensuring even greater reliability and applicability in real-world CRN environments.

Source code:
https://github.com/lw9318457/project32319.git [31]

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[31] Source code link: https://github.com/lw9318457/project32319.git

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