IETE Journal of Research

ISSN: 0377-2063 (Print) 0974-780X (Online) Journal homepage: https://www.tandfonline.com/loi/tijr20

SCAN-CogRSG: Secure Channel Allocation by Dynamic Cluster Switching for Cognitive Radio Enabled Smart Grid Communications

M. Monisha & V. Rajendran

IETE JOURNAL OF RESEARCH
https://doi.org/10.1080/03772063.2020.1729259

SCAN-CogRSG: Secure Channel Allocation by Dynamic Cluster Switching for Cognitive Radio Enabled Smart Grid Communications

M. Monisha and V. Rajendran

Department of Electronics and Communication Engineering, Vels Institute of Science Technology and Advanced Studies, Chennai, India

ABSTRACT
Smart grid (SG) communication requires multilevel communication among multiple layers. To handle this paramount spectrum requirement, cognitive radio network (CRN) is one of the promising solutions. However, the integration of CRN for SG communications introduces new challenges in spectrum allocation. Still, achieving high spectrum utilization is restricted by security vulnerability and poor algorithm design. This paper resolves all these issues to achieve the objective of spectrum utilization efficiency. A novel dynamic cluster switching approach is designed for secure channel allocation for cognitive radio-based smart grid (SCAN-CogRSG) communications. Strong authentication is enabled for secondary users (SUs) by Binate physically unclonable function (Bi-PUF) authentication mechanism. The key idea behind Bi-PUF mechanism is to prevent spectrum resources from unauthorized access. The formed neighborhood area network (NAN) clusters are dynamically switched to distribute uniform spectrum availability. For dynamic switching, a novel Topology aware fuzzy-reinforcement learning (TA-FuReil) algorithm is presented. For an effectual channel allocation, feature-based K-means (FK-means) algorithm and tri-objective cuttlefish optimization (TriO-CFO) algorithm are proposed. The formulated objectives are interference minimization, power minimization, and data rate maximization. In the case of priority situations, the one-to-many matching-based TriO-CFO (OMTriO-CFO) algorithm is utilized. The proposed SCAN-CogSG is modeled in NS-3 and validated for performance evaluation. The observed results show betterment in throughput, retransmission probability, latency, and authentication time.

KEYWORDS
CRN; NAN clusters; PUF authentication; Secure channel allocation; Smart grid communications

1. INTRODUCTION

Smart grid (SG) represents the modernized grid system that is specified to monitor, protect, and optimize the operation of conventional electrical grids [1,2]. The major element of SG is bi-directional power and communication flow. The underlying communication network consists of home area networks (HANs), neighborhood area networks (NANs), and wide area network (WAN), which form multiple communication layers[3]. HAN is the local SG network that gathers information from the individual segment, *i.e.* home. Multiple HANs are connected with a NAN gateway, which is responsible to aggregate the data from HANs and transmit it to WAN. The following requirements are needed to be addressed to establish efficient SG communications: bandwidth, latency, data rate, throughput, and reliability [4]. It is clear that SG communications require a huge spectrum for data transmission. On the other hand, the cognitive radio network (CRN) is witnessed as an evolving and promising technology for wireless communications to resolve increasing spectrum insufficiency [5–7]. Spectrum scarcity is the increasing and challenging issue in wireless communications. To tackle this spectrum scarcity problem, CRN uses an unused licensed spectrum, which is often known as spectrum holes. Thus, research interest has been developed in the integration of CRN for SG communications [8]. CRN concept can be adopted in HANs, NANs, and WAN for spectrum efficiency. In the CRN-based SG scenario, the HAN and NAN gateways act as secondary users (SUs), while the TV spectrum is the primary user (PU). It is more beneficial in rural areas where the possibility of TV whitespace is large.

In CRN-based SG communications, spectrum allocation or channel allocation is the major concern to utilize the available spectrum effectually, and it is investigated extensively [9–12]. Channel allocation in CRN requires great attention since ineffectual channel assignment often leads to interference between SUs and PUs. The major objective of channel assignment progress is to mitigate the interference issue and to increase the data rate. In CRN, the channel is allocated in a centralized, distributed, and cluster-based manner [13]. Centralized approaches suffer from the large overhead, while distributed approaches introduce high interference. Thus, the cluster-based approach, which is the hybrid result of centralized and distributed approaches, is followed by many research works. The channel assignment and power allocation are performed based on maximum concurrent multimodality flow (MCMCF) to ensure the high data rate [14]. A centralized spectrum allocation algorithm is designed with a sequential policy [15] to boost up the spectrum usage among SUs. Hidden Markov model (HMM)-based channel allocation scheme uses the bandwidth requirement of SU and channel state as a major constraint [16]. In channel assignment, great effort is needed to improve spectrum efficiency. A comprehensive channel assignment is needed to be designed for optimizing the spectrum allocation in CRN. Although CRN is apt for SG communications, the existing solutions for channel assignment have the following problems:

(1) **Scalability:** Centralized channel assignment increases the overhead and spectrum underutilization and not suitable for large-scale networks. However, SG communications involve a large number of communication entities. Thus, the channel allocation scheme must be suitable for large-scale networks.
(2) **Interference:** In CRN, it is necessary to avoid interference between PUs to improve the overall network performance. Interference among SUs and with PUs is still a prime issue in CRN. In major research works, interference is still a major issue due to ineffectual allocation strategy.
(3) **Security:** Security, which is the significant criterion for channel assignment [17], is not concentrated in the majority of the works. In the presence of malicious SUs, there is a high possibility to assign the available spectrum for malicious SUs, which lead to spectrum underutilization.

With the above problems, the overall problem addressed in this paper is formulated as “spectrum efficiency in CogRSG is degraded by security vulnerabilities and interference constraint”. Through this problem, the following objectives are formulated in this paper:

(1) To improve spectrum utilization efficiency through optimal channel allocation strategy
(2) To elevate security aspects of CRN-based SG communications for preventing malicious SU activities in the network

Paper contributions: As stated earlier, our main intend is to achieve better spectrum efficiency and security in CogRSG. To the best of our knowledge, this is the first work that focuses on security aspects of CRN-based SG communications during channel allocation. To achieve the objectives, we presented our contributions in three-fold as follows:

(1) Binate physically unclonable function (Bi-PUF), which is a strong authentication mechanism, is designed to validate the legitimacy of cHGs, *i.e.* SUs.
(2) An intelligent cluster switching approach is proposed to switch the SUs between clusters for handling varying channel availability status. A novel topology aware fuzzy-reinforcement learning (TA-FuReiL) algorithm is proposed for intelligent cluster switching.
(3) Channel allocation is optimized in both fair allocation and prior allocation scenarios. For fair allocation, feature-based K-means (FK-means) and tri-objective cuttlefish (TriO-CFO) algorithms are working together. In the case of priority allocation, one-to-one matching-based TriO-CFO (OMTriO-CFO) algorithm is proposed. The new objective function is designed for improving spectrum utilization efficiency.

Paper organization: The rest of this paper is organized as follows: Section 2 introduces preliminary knowledge on SG communications and CRN. Section 3 provides a significant review on literature works. In Section 4, the existing problems that are addressed in this paper are defined. Section 5 elaborates on the overall proposed methodologies for solving the research problems. In Section 6, the introduced methodologies are evaluated experimentally. Section 7 concludes all contributions and highlights future research directions.

2. PRELIMINARY KNOWLEDGE

This section presents the background overview of CRN-based SG communications. To explain the CRN-based SG, it is necessary to explain the SG communications. As stated earlier, the communication layer of SG systems comprises HANs, NANs, and WAN [18–20]. The HAN covers client places such as home, industries, etc. Here, the variety of smart devices is deployed to efficiently communicate with the smart meters for optimizing energy consumption. NAN comprises multiple HANs, and it connects the HANs with the WAN. For communication, smart meters are utilized as HAN gateways. WAN is the backbone of SG systems, and it forwards the aggregated information from NAN to the control center. Thus,

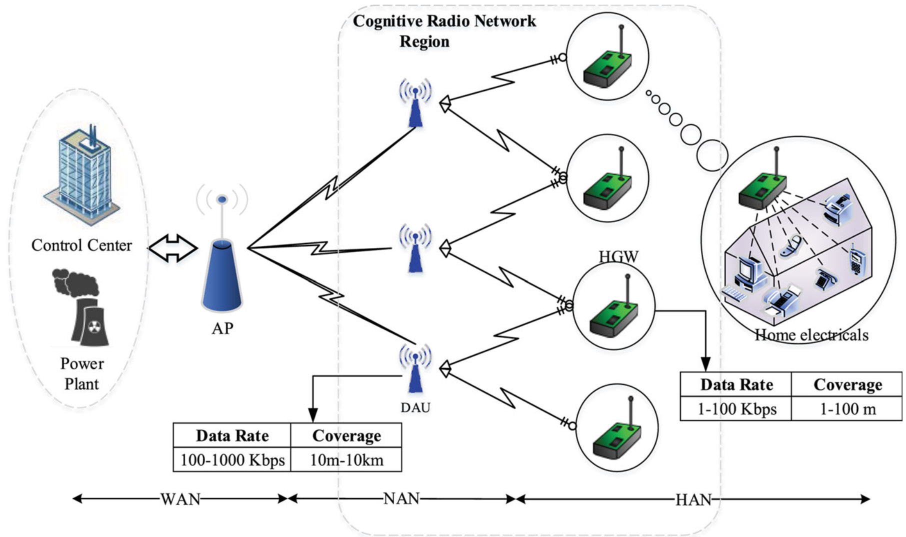

Figure 1: Role of CRN in SG communication systems

communication is established in all three sectors in two directions. Each communication sector requires different data rates since each is dedicated for different applications. The role of CRN in SG communication system is shown in Figure 1. As shown in the figure, the CRN communication can be utilized in SG communications as HANs, NANs, and WAN. At any point, the major requirements are spectrum sensing and allocation. It will be beneficial to use CRN for SG communications in the areas where the primary spectrum is underutilized. So that the spectrum utilization will also be increased along with SG communications. For example, in rural areas, the primary spectrum is almost underutilized [21,22]. In this case, using unused spectrum for smart grids will improve the overall performance.

For SG communication, wireless technologies such as ZigBee, IEEE 802.11ah, IEEE 802.11af, and IEEE 802.22 (TV White Space) have been utilized [23,24]. From those technologies, IEEE 802.22 (CRN standard) hash many advantages like communication range (up to kilometers), data rate, and spectrum utilization. As shown in Figure 1, the CRN will be the better solution for establishing communication in NANs and HANs. CRN has proven its effectiveness in many Internet of things (IoT) applications [25]. However, in SG communications, security plays a pivotal role [26,27]. In general, SG communications are subjected to false data injection attack, malicious user access attack, spoofing attack, and so on. In CRN-based SG communications, unauthorized and malicious user access results in a huge spectrum loss, which degrades the entire network performance. CRN-based SG communications must be optimized with the following development:

- Optimal channel allocation for handling increasing spectrum demand
- Security improvements to prevent the SG system from malicious user access
- Network management to handle the large-scale network

3. RELATED WORKS

In this section, the significant works held on SG communications, channel allocation, and security are analyzed.

3.1 Security in CRN and SG Communications

In the SG system, a fully homomorphic encryption (FHE) algorithm was used for security [28]. The security was provided for smart meter reading by converting them into a ciphertext. Furthermore, the gateway aggregates the ciphertext from all smart meters. The main intent of this work was to secure the reading value from the attackers. FHE has the main drawback that is higher complexity for encryption and homomorphic operations. Joint authentication and encryption were performed by state estimation-based dynamic encryption and authentication (SEDEA) approach [29]. State estimation was performed based on the meter measurements gathered from the smart meters. From the aggregated measurements, the state was estimated by the control center. Based on the state estimated by the control center, the authentication was dynamically changed. Authentication and state estimation in the control center lead to a large number of attackers in the network since the data take time to reach the control center. A three-factor authentication scheme was proposed for enabling authentication between users and smart meters [30]. In three-factor authentication, bitwise XOR operations, elliptic curve cryptography (ECC), and one-way hash functions were performed for security. ECC and hash generation have high computational complexity and XOR operations are less secure. Thus, security level and complexity are the major issues in SG systems.

On the other hand, security-aware spectrum allocation is performed in CRN [31]. First, the interference power was computed for PUs based on false alarm probability and miss-detection probability. Then, the dual decomposition method was applied to allocate channel and power in a secure manner. Security constraints are not considered in the channel allocation process. There is a high possibility of unauthorized SU access. In addition, computational complexity is also high in this work. A deep learning approach was incorporated to authenticate cognitive radios [32]. The key idea behind this work was to use the digital fingerprint of IEEE 802.15.4 devices for authentication. The convolutional neural network was adapted for authentication. However, this method is only suitable for IEEE 802.15.4 devices, *i.e.* not suitable for real-time applications. Anomaly-based detection (ABD) was designed to improve spectrum allocation efficiency in CRN [33]. The ABD system was deployed with the functional blocks for monitoring, feature generation, rule generation, a detection module, action module, impact module, and learning module to detect anomalies in the network. Malicious SU detection based on packet features is not efficient since it may lead to traffic congestion in the network. Preventing malicious and unauthorized SUs access in the network is an intelligent way to protect the network resource.

3.2 Channel Allocation in CRN

A two-stage scheme with neuro-fuzzy algorithm was proposed for spectrum allocation in CRN [34]. In the first stage, the fusion center determines the quailed SUs based on the spectrum sensing reports. In the next stage, the spectrum was allocated to qualified SUs based on spectrum efficiency, power, and velocity. The absence of interference constraint degrades the overall network performance. A fuzzy logic-based decision supporter system (FL-DSS) was designed to deal with channel selection and switching [35]. The major aim of this work was to improve overall network throughput by minimizing the channel switching. Interference temperature, SU transmission power, signal-to-interference-to-noise ratio (SINR) and channel transmission range were considered in FL-DSS for decision-making. Available spectrum is allocated to all SUs without considering their legitimacy, *i.e.* high probability to allocate spectrum for unauthorized SUs. Game theory approach was also used for spectrum allocation in CRN [36]. Spectrum allocation without any congestion was the major objective of this work. A potential game theory approach was designed to quickly reach the Nash equilibrium of the game process among SUs. However, formation of multiple games for single SU increases time consumption and complexity.

A channel pre-allocation scheme was designed for the CRN system [37]. Each SU was given with the reputation value, which was further considered for channel allocation. Secondary base station (BS) was responsible for channel allocation. Centralized approach increases time and computational complexity. Furthermore, lack of significant parameters degrades the efficiency of channel allocation. A load balanced particle swarm optimization (PSO) algorithm and modified gravitational search algorithm (GSA) were presented for channel allocation [38]. To alleviate problem of complexity, cluster-based channel allocation was followed in this work. A multifactor differential evolution scheme was presented to assign priority level for incoming traffic. All three algorithms (PSO, GSO, and differential evolution) have convergence issues, which degrades the performance of spectrum allocation. A binary artificial bee colony algorithm was introduced to maximize the utilization of resources via optimal spectrum allocation [39]. The proposed work was intended to resolve the problem of interference between PUs and SUs in CRN. First, the number of usable channels for each SU was determined based on the Euclidean distance between source and destination SUs. Then optimal spectrum allocation was followed by artificial bee colony algorithm. However, artificial bee colony algorithm takes large time to produce optimal solutions, which increase the spectrum allocation time. A dynamic spectrum access technique was proposed for CRN-based industrial IoT networks [40]. The spectrum allocation was performed in a distributed manner by providing cognitive ability. The cognitive ability is introduced by the Q-learning, which is a reinforcement learning strategy. Although Q-learning provides cognitive ability, it takes large time for spectrum allocation. Distributed allocation scheme increases interference in the network.

3.3 Channel Allocation in CRN-Based SG and IoT Systems

There are some research works have held on CRN-based smart grid communications. Asymmetric asynchronous channel hopping (AACH) mechanism was proposed for the cognitive radio-based IoT network [41]. Initially, all SUs were assigned with the set of available channels without any global clock synchronization. Then, channel assignment was performed based on the round robin fashion. However, this work fails to satisfy the bandwidth and data rate requirements of SUs. To improve the spectrum utilization in smart hospitals, CRN-based resource management was introduced [42]. PSO algorithm was presented for resource allocation under power and interference constraint. However, allocation of random channel increases the power requirement. Spectrum allocation in CRN-based smart grid communication was carried out based on the confidence level [43]. Herein, spectrum allocation was concentrated for data aggregator units (DAUs). The objective function was fixed to improve data transmission while minimizing the cost of utility companies. Spectrum allocation without consideration of spectrum availability is not suitable to meet the objective function. Game theoretic approach was proposed for channel allocation [44]. The channel allocation problem was formulated as Stackelberg game and resolved based on the utility function. Channel allocation follows fair allocation and designs adjustable coefficients according to the SINR value. Game theoretic approach increases time complexity and fair allocation strategy limits the efficiency in time-sensitive applications. A distributed CRN-based SG communication architecture was designed [45]. In HANs, NANs, and WAN, the power and channel management was performed jointly. However, without optimal channel allocation strategy, it is difficult to achieve the required data rate.

Summary of Literature: From the critical literature review, we identify the major issues in existing solutions for CRN-based SG communications. The issues are as follows: (i) Existing security solutions concentrate either SG systems or CRN network. There is no clear solution to prevent the malicious and unauthorized user access in the system. Furthermore, the proposed security solutions are less secure but have large computations. (ii) Channel allocation in CRN considers limited parameters, but significant constraints are not considered in literature. Furthermore, the available optimization algorithms like PSO, GSO, and ABC perform based on single objective function, which is not sufficient to improve network performance. (iii) In CRN-based SG communications, channel allocation uses complex algorithms but unable to produce optimum solutions. Thus, security and channel allocation in CRN-based SG communications is still challenging and require an effectual solution.

4. PROBLEM DESCRIPTION

We formulate the dynamic channel allocation problem as an optimization problem. Any SU in the network (SU_i) must be provided with an optimal channel (C_{Opt}) at any given time. The objective formulated for this problem is as follows:

$$O : Max\{\partial, \mathbb{DR}\} \tag{1}$$

The objective is to maximize the spectrum utilization efficiency (∂) and data rate ($\mathbb{DR}$). Let us consider a CRN-based SG (CogRSG) network with n number of SUs, *i.e.* cognitive HAN gateways (*cHGs*) and m number of data aggregator units (DAUs) and always $m < n$. The set of available channels (C_A) must be assigned to *cHGs*, which need to transmit the data. The proper channel assignment needs to overcome the following research problems.

Security: A trust-based channel access policy was proposed for improving spectrum utilization [46]. However, trust value dully depends on past activities, and thus, it is hard to find the legitimate SU with minimum number of activities. This centralized procedure consumes computational and time resource. For instance, if a SU_q is malicious and has no past activities. Then based on prior work, the SU_q has no impact on trust value and can be assigned with channel. When this number of malicious SUs is large, then large resources will be wasted for malicious SUs.

Scalability and Algorithm Inefficiency: Cluster based channel allocation strategies follow cat swarm optimization (CSO) [47] and cuckoo search algorithm (CSA) [48] in CRN-based SG. Cluster formation with fixed topology is not suitable for practical scenario where the channel availability varies over a time period. Channel allocation based on mean square error is inefficient to manage interference, power, and data requirements. CSO and CSA algorithms are not efficient and have convergence problems. Fuzzy logic was designed to find the optimal parameters (the probability of miss detection, signal-to-noise ratio (SNR) bandwidth) required by SUs for transmission [49,50]. Then, optimal channel was assigned based on obtained parameters. The constraint of channel availability is the foremost requirement for CRN, which is not considered. Thus, search channel for determined SU parameters consumes large time. Thus, these works are not suitable for practical scenario with varying channel availability. From the problems, the following research questions are framed:

- How to secure the CRN-SG communications?
- How to improve the spectrum utilization and the scalability of the CRN-SG systems?
- What are the criteria to allocate the available spectrum to SUs?

The aforementioned research problems are considered in this paper. For all the aforementioned research questions, the proposed work proposes better solutions. By overwhelming these problems, we intend to achieve our objectives.

5. PROPOSED SCAN-COGRSG

In this section, proposed secure channel allocation for cognitive radio-based smart grid (SCAN-CogRSG) is explained in detail with proposed methodologies.

5.1 System Overview

The proposed SCAN-CogRSG is particularly designed for CogRSG systems to improve the spectrum utilization efficiency. TV white space spectrum is utilized in this work. The proposed SCAN-CogRSG system consists of the following entities:

cHGs: These are gateways that connect the HAN with NAN clusters. The smart meters in SG system act as *cHGs* in this work. From here, the *cHGs* and *SUs* represent the same that is smart meters. The n number of *cHGs* can be represented as $\{cHG_1, cHG_2, \ldots, cHG_n\}$.

DAUs: DAUs are responsible to gather information from corresponding *cHGs* and transmit it to the cognitive NAN gateway (*cNG*). Another major role of DAUs is to act as cluster head (CH) for NAN clusters. The m number of *DAUs* can be represented by $\{DAU_1, DAU_2, \ldots, DAU_m\}$.

cNG: It is responsible to gather the information from DAUs and transmit it to the WAN. It also acts as a cognitive base station (*CBS*). Form here, *cNG* and *CBS* represent the same entity. The proposed work concentrates on channel allocation, and the spectrum sensing is considered to be reliable. The work is most suitable for rural areas where large TV spectrum is unutilized by PUs. The overall system architecture is depicted in Figure 2. Initially, the system validates *SUs* for authentication. Then clusters are formed based on the distance metric. To improve scalability and spectrum utilization, dynamic cluster switching is performed. Channel allocation is performed under interference constraint. Channel allocation is performed for both fair allocation and priority allocation scenarios.

The SCAN-CogRSG has the following assumptions:

(1) Number of SUs is larger than number of DAUs $n > m$
(2) Number of NAN clusters is equal to m
(3) At given time, idle channels are available for SUs

5.2 *cHG* Validation

The overall cluster-based SCAN-CogRSG system is initiated with SU validation. As stated earlier, in the presence of malicious and unauthorized SU, the spectrum utilization will be fully affected. This work eliminates the unauthorized SU access by validating each cHG initially.

Threat Model: This work considers the threat model that attempts to use the available spectrum. In this work, the malicious (or) unauthorized SUs are smart meters, which are not registered in utility company. The major aim of the malicious SUs is to use the unlicensed spectrum sensed by cHGs for worn benefits. The malicious SU can be denoted as SU_M, and when the number of SU_Ms increases, then there is high possibility to assign the spectrum to the malicious SUs.

Thus, this work validates the SUs initially. The valid SUs are allowed to form NAN clusters, and the invalid SUs are ignored. It is worth to noticing that only clustered SUs will be provided with spectrum. For strong authentication, we propose a Bi-PUF mechanism. The proposed Bi-PUF mechanism utilizes the benefit of PUFs for validating all SUs. PUFs are compatible security solution and have been utilized for IoT devices authentication [51]. PUF-based authentication provides strong authentication against many types of attacks. In the proposed Bi-PUF mechanism, both the SUs and DAUs are authenticated by the CBS. The proposed Bi-PUF mechanism includes the following two phases:

(i) Setup Phase:

SU Registration: First, all SMs that are registered in utility company are registered with CBS also. During registration, PUF is generated and stored in each SM. The PUF includes the challenges ($\mathbb{C}_i \in \mathbb{C}$) and corresponding responses ($\mathbb{R}_i \in \mathbb{R}$). The PUF challenge response pair is represented as follows:

$$PUF : \mathbb{C}_i \rightarrow \mathbb{R}_i \tag{1}$$

For each SU, CBS maintains a tuple with $\{ID, PUF, Loc\}$.

DAU Registration: The DAUs that are responsible to aggregate from all SMs are also authenticated in our work. Thus, all DAUs are registered in CBS with ID. For all registered DAUs, CBS generates secret key (SK) by ECC algorithm.

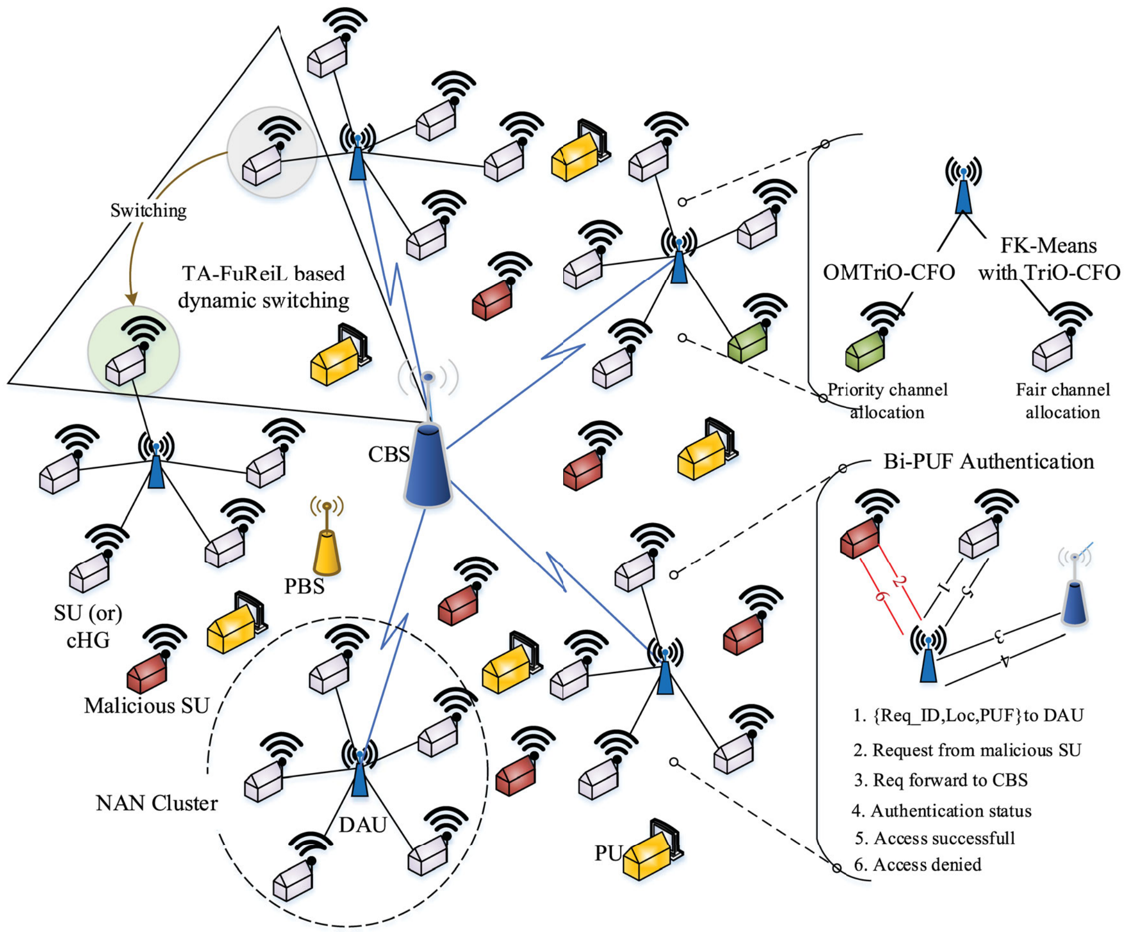

Figure 2: Architecture of SCAN-CogRSG system

(ii) Authentication phase

In this phase, the SUs and DAUs are authenticated based on the registered credentials. SM initiates the authentication process by sending $Auth\_Req$ to DAU. It first generates the $Auth\_req$ as follows:

$$Auth\_Req \rightarrow \{ID \oplus Loc\} \quad (2)$$

The DAU verifies the $Auth\_Req$ by using the registered location of the SU. If the location and ID are legitimate, then it generates the digital signature ($Sign$) and forward the request to the CBS. Thus, the signed authentication request ($Sign(Auth\_Req)$) is generated as follows:

$$Sign(Auth\_Req) \rightarrow Sign_{SK}(Auth\_Req) \quad (3)$$

Then, the CBS validates the signature of DAU and then generates the $\mathbb{C}_i$ to the corresponding SU. On receiving the $\mathbb{C}_i$, SU generates the corresponding $\mathbb{R}_i$ and sends to the CBS as follows:

$$Res \rightarrow \{\mathbb{R}_i \oplus Rand\} \quad (4)$$

The random number is generated by the SU itself. If the challenge response pair is matched, then the SU is authenticated successfully. The major fact is that the challenge–response pair generated by the PUF cannot be spoofed by any unauthorized SUs, which prevent the unauthorized spectrum access.

Pseudocode 1 Description: Initially, the SU sends $Auth\_Req$ to the corresponding DAU. The $Auth\_Req$ consists of ID and location $\{ID, Loc\}$ of the SU. Then the DAU verifies the location of the SU. If the location verification is successful, then it forward the $Auth\_Req$ to the CBS with the digital signature. The CBS verifies the signature of the DAU if the signature is valid and then it sends the corresponding $\mathbb{C}_i$ to the SU via DAU. Finally, the SU generates corresponding $\mathbb{R}_i$ and sends with $Rand$ to CBS. If the $\mathbb{R}_i$ corresponds to the $\mathbb{C}_i$, then it authenticates the SU.

In the proposed CogRSG systems, only valid SUs are allowed to access the available spectrum to improve spectrum efficiency. The SUs that are validated are allowed to form clusters and access the available spectrum.

Pseudocode 1: Bi-PUF mechanism

```
Begin
  For all SUs//Setup Phase
    Generate PUF: ℂ_i → ℝ_i, ℂ_i ∈ ℂ & ℝ_i ∈ ℝ
    Store {ID, PUF, Loc}
  End For
  For all DAUs
    Register {ID}
    Generate {SK}
  End For
  For all SU_i ∈ SUs//Authentication Phase
    Initialize Auth_Req_i → {ID_i ⊕ Loc_i}, i = 1,2,..,n
    Send Auth_Req_i → DAU_j
    Verify {ID_i, Loc_i}
  If ID, Loc = Valid
      Generate Sign(Auth_Req)
      Send Sign(Auth_Req) → CBS
  Else
      Drop the request
    Validate Sign(Auth_Req)
    Send ℂ_i ∈ ℂ → SU_i
    Respond ℝ_i ∈ ℝ → CBS
  If ℝ_i == True
                    SU_i = Valid
  Else
                    SU_i = Invalid
  End for
End
```

5.3 Dynamic Cluster Switching

The proposed work focuses on cluster-based spectrum access in the CogRSG system. All valid SUs are allowed to join with the NAN clusters. Here, m numbers of NAN clusters are formed based on the distance between SU and DAU. The distance is computed in the form of Euclidean distance as follows:

$$Dis = \sqrt{(x_{DAU} - x_{SU})^2 + (y_{DAU} - y_{SU})^2} \tag{5}$$

The distance is computed based on the coordinates of DAU (x_{DAU}, y_{DAU}) and SU (x_{SU}, y_{SU}). The SUs are joined to the NAN cluster, which has $\min(dis)$ factor. Although the SUs are static in this work, the spectrum availability over the clusters caries with the time. Therefore, static clusters introduce the spectrum imbalance in the network. Thus, CogRSG proposes a novel cluster switching approach by using the TA-FuReiL algorithm. CBS monitors the channel availability of each cluster. The major reason for introducing dynamic cluster switching is to avoid spectrum imbalance situations. The spectrum imbalance occurs when the channel availability is low for a cluster having large number of SUs. In this situation, the DAU is unable to assign the channels for all SUs. Thus, CBS performs cluster switching when it detects the spectrum imbalance. Let us consider the j^{th} cluster as imbalanced cluster $\{Cluster_j = SU_1, SU_2, .., SU_p\}$ with DAU_j.The dynamic cluster switching is performed in two steps.

Step 1: Topology Extraction

Before performing dynamic cluster switching, the CBS extracts the current topology of the clusters. For topology extraction, ISOMAP algorithm is proposed. ISOMAP is the nonlinear dimensionality reduction technique that finds the intrinsic geometry of the deployed network accurately [52]. Topology extraction is the process of learning current connectivity status of the imbalanced cluster from the topology information. The topology extraction analyzes the network topology and determines the following features of the imbalanced cluster:

SU Connectivity Degree (κ): SU connectivity degree is defined as the link stability between that SU and DAU.

Distance (dis): This is the measure of Euclidean distance between SU and DAU.

Channel Access Probability ($\wp$): It can be defined as the probability of a SU has channel access within the cluster. This probability is varied based on the number of SUs in the clusters and channel availability.

Trust value ($\mathcal{T}$): It is defined as the level of interference introduced by the particular SU in previous transmissions. This is determined by DAU for each SU.

The ISOMAP algorithm is initiated with the construction of Euclidean distance matrix. The matrix is constructed for all SUs with the DAUs. The Euclidean distance matrix is ($\mathfrak{C}$), which is constructed as follows:

$$\mathfrak{C} = [d(i,j)]_{m\times n} \tag{6}$$

where l represents the number of SUs in the cluster. Then the neighborhood graph is constructed over the SUs by connecting the points i, j. The SU_i and DAU_j is connected if the distance is low or the SU_i is the K-nearest neighbor of the DAU_j. For the k-nearest neighbors, geodesic pairwise distance is computed. A Gram matrix ($\mathbb{G}$) is constructed by applying double centering matrix to the $\mathfrak{C}$. Thus, the $\mathbb{G}$ is given as follows:

$$\mathbb{G} = -\frac{1}{2}[\mathfrak{y}\mathfrak{C}^2\mathfrak{y}] \tag{7}$$

The centering matrix $\mathfrak{y}$ is represented as $\mathfrak{y} = \mathfrak{T} - (11')l^{-1}$. Here, $\mathfrak{T}$ is the identity matrix and 1 is the column vector. Finally, the u-dimensional relative coordinate matrix ($\mathbb{U}$) is computed as follows:

$$\mathbb{U} = V_d^T W_d^{1/2} \tag{8}$$

where V is the matrix of Eigenvectors and W is the diagonal matrix with the corresponding Eigenvalues in the diagonal. From the $\mathbb{U}$, the topology is extracted. Based on the learned topology, the dynamic cluster switching is performed.

Step 2: Dynamic Cluster Switching

When the topology is extracted, the CBS performs cluster switching based on the TA-FuReiL algorithm. The TA-FuReiL algorithm selects optimal SU for switching based on the extracted topology information. From the ISOMAP algorithm, the detailed topology of each DAU is extracted. The TA-FuReiL algorithm is working upon integrated fuzzy and reinforcement algorithm. The fuzzy logic is used to model the human knowledge like decision-making systems [53]. On the other hand, reinforcement learning supports the learning by trial and error to map situations into actions to maximize the numerical reward function [54]. In this work, the fuzzy logic is combined with Q-learning (reinforcement learning) algorithm to make decision on dynamic cluster switching. The fuzzy logic takes decision based on the rule system, while the rule system is updated by Q-learning based on the environment. The topology information extracted by ISOMAP algorithm is fed into FuReiL algorithm, and the optimal SU for switching is selected. The architecture of the TA-FuReiL algorithm is illustrated in Figure 3.

Table 1: Nomenclature

Notation	Description
∂	Spectrum utilization efficiency
$\mathbb{DR}$	Data rate
cHGs	Cognitive home gateways
C_A	Available channel set
SU,SM	Secondary User, Smart Meter
$\mathbb{C}_i \to \mathbb{R}_i$	Challenge-Response pair
$\oplus$	XOR Operation
Rand	Random number
Dis	Distance
κ	SU Connectivity degree
$\wp$	Channel access probability
$\mathcal{T}$	Trust value
$\mathfrak{C}$	Distance matrix
$\mathbb{G}$	Gram matrix
$\mathbb{U}$	Relative coordinate matrix
s, a	State-action
C_C	Centroid channel
FD	Feature distance
M_Score	Matching score

The topology information $(\kappa, dis, \wp, \mathcal{T})$is taken as the input for the TA-FuReiL algorithm. The fuzzy rules applied in the knowledge base are given in Table 1.

As per fuzzy logic, a SU is selected for switching as follows (Table 2):

$$\text{IF } \kappa \ \& \ \& \ dis = HIGH \ and \ \wp \&\& \ \mathcal{T} = \text{LOW}, \\ \text{THEN SU} = \text{SWITCH} \tag{9}$$

However, these IF − THEN rules limit the performance of fuzzy logic in decision-making. Thus, we prosed fuzzy with Q-learning algorithm. The output crisp value is computed as follows:

$$Output = \frac{\sum_{z=1}^{NR} \alpha_z \times \gamma}{\sum_{z=1}^{NR} \alpha_z} \tag{10}$$

Here, NR represents the number of rules, α represents the degree of truth for rule z, and γ represents the output

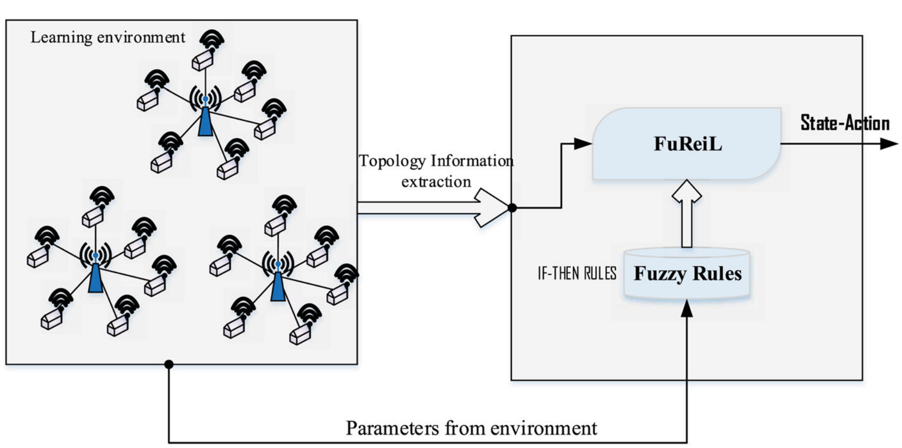

Figure 3: Process of TA-FuReiL algorithm

Table 2: Fuzzy rules for TA-FuReiL algorithm

κ	*dis*	$\wp$	$\mathcal{T}$	Output
Low	Low	Low	Low	PS
Low	Low	Low	High	NS
Low	Low	High	Low	PS
Low	Low	High	High	NS
Low	High	Low	Low	PS
Low	High	Low	High	NS
Low	High	High	Low	PS
Low	High	High	High	NS
High	Low	Low	Low	S
High	Low	Low	High	PS
High	Low	High	Low	PS
High	Low	High	High	PS
High	High	Low	Low	S
High	High	Low	High	S
High	High	High	Low	S
High	High	High	High	PS

constant value. The TA-FuReiL algorithm is performed as follows.

The TA-FuReiL algorithm captures the history information of target application into Q-table. Each instant in the Q-value table is assigned to a certain rule that describes state-action pairs.

Next, the ϵ-greedy exploration policy is applied to learn from the environment. In general, the action with the best reward will be selected to explore the state-action pair.

The fuzzy weighted average of the consequences of the rule is determined as follows:

$$Action = \sum_{z=1}^{NR} \alpha_z \times \gamma \tag{11}$$

Then the Q-value of an action (a) current state (s) is computed by

$$Q(a,s) = \sum_{z=1}^{NR} (\alpha_z(s) \times q[z, a_z]) \tag{12}$$

The current state of the system is computed in terms of SNR value and the current channel state since the considered fuzzy inputs are affected by the channel state and SNR value. Thus, we have updated the current state of the system to find optimal SU for switching. The reward value r is computed based on (i) the number of SUs need to be switched and (ii) channel access probability improvement. Then the new state s' is calculated as follows:

$$s' = \sum_{z=1}^{NR} \alpha_z(s').\max_w(q[z, a_w]) \tag{13}$$

Here, the $\max(q[z, a_w])$ denotes the maximum of the q-values applicable in the state s'. The reinforcement error signal is computed as follows:

$$\varDelta Q(s,a) = r + \beta \times s' - Q(S < A) \tag{14}$$

The error signal is computed by considering the discount rate (β) that determines the importance of future rewards. In each step, the q-value is updated as follows:

$$q[z, a_z] = q[z, a_z] + \omega.\varDelta Q.\alpha_z(s) \tag{15}$$

The value of the learning rate (ω) is computed between $[0, 1]$. Thus, the current action regarding dynamic switching is performed based on the reward function as follows:

$$r = \{\min \aleph \,\&\&\, \max \wp\} \tag{16}$$

For each fuzzy rule, more than one action is considered, and the actions are varied based on the reward function.

Pseudocode 2: TA-FuReiL algorithm

```
Begin
  Initialize the network
  Compute ℭ, 𝔾, 𝕌      //Topology Learning
  Learn ϰ, dis, ℘, 𝒯
  Initialize Q-values    //Dynamic Switching
  For all SU_i ∈ Cluster_j
    Apply IF − THEN
    Observe the current s
  For s{SNR, CSI}
      Repeat
      Choose a_z
      Compute a from a_z
      Receive reward r
      Compute ΔQ(s, a)
      Update Q-values
                         s ← s'
  End For
  Until convergence achieved
  End For
  Find optimal SUs
  Switch SUs → Cluster_k, k ≠ j
End
```

Pseudocode 2 Description: First, the topology is learned by ISOMAP algorithm. The ISOMAP algorithm generates the current topology information such as κ, *dis*, $\wp$, $\mathcal{T}$ from the system. Then the topology information is fed as input for the FuReiL algorithm. In the FuReiL algorithm, the decision on dynamic switching is made based on the current topology information. The fuzzy rules are updated, and the action for each rule is taken by the Q-learning algorithm. Finally, the optimal SUs are selected for switching and switched to another NAN cluster.

Thus, dynamic switching by the TA-FuReiL algorithm minimizes the number of switching and improves the channel access probability. When the optimal SUs are determined by the TA-FuReiL algorithm, the CBS switches those SUs to the nearer DAU to improve the channel utilization. The dynamic cluster switching prevents the system from spectrum scarcity and balances the channel availability over the NAN clusters.

5.4 Channel Allocation

After dynamic cluster switching, the DAU allocates the available channels to SUs. The major objective of this work is to maximize the data rate and spectrum utilization through optimal channel allocation. In the CogRSG system, the priority level of data can be varied for different applications. Thus, we propose a novel channel allocation scheme for both fair allocation and priority allocation scenario. For spectrum allocation, FK-means algorithm is performed in phase I and the TriO-CFO algorithm is performed in phase III. In phase II, the spiral construction process takes place. Both scenarios can be detailed as follows:

(i) Fair Allocation (Scenario-I)

In fair allocation scenario, all SUs have same priority level, *i.e.* all SUs have nonemergency data. In this scenario, DAU assigns channels in three phases. Let consider a cluster $\{Cluster_j = SU_1, SU_2, .., SU_p\}$ with DAU_j. The available channels for that $Cluster_j$ can be $C_A = \{C_1, C_2, .., C_H\}$. The fair allocation is performed as follows:

Phase I: In this phase, all available channels in C_A are clustered by FK-means algorithm. The reason behind channel clustering is to minimize the optimal channel allocation time. In the prior work, the optimal channel for SU is searched with all channels in available channel sets. This type of search takes more time to determine the optimal channel for each SU. Thus, we group the channels based on the channel features. The channel features considered in this work are bandwidth (BW), SNR, and channel state information (CSI). In FK-means algorithm, all channels in C_A are initialized, and the features are determined. First, k centroid (C_C) channels are selected randomly. Then feature distance (FD) is computed between each channel and centroid channel. The feature distance is formulated as follows:

$$FD_1(C_i, C_{C1}) = |BW_i - BW_{C1}| \tag{17}$$

$$FD_2(C_i, C_{C1}) = |SNR_i - SNR_{C1}| \tag{18}$$

$$FD_3(C_i, C_{C1}) = |CSI_i - CSI_{C1}| \tag{19}$$

$$FD = \sum FD_1, FD_2, FD_3 \tag{20}$$

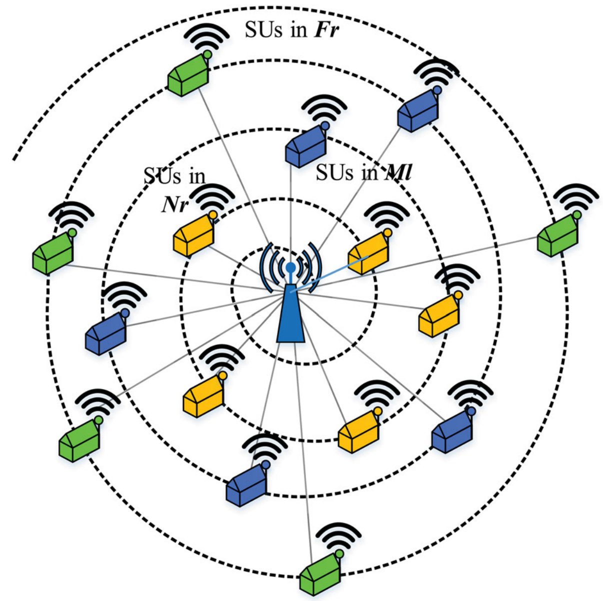

Figure 4: Spiral pattern construction

Each channel is assigned to a centroid channel, which has minimum FD. In this manner, all channels are clustered by FK-means algorithm. In this work, $k = 3$; thus, the channels are clustered as high quality (HQ), medium quality (MQ), and low quality (LQ) group. The reason behind this cluster formation is to serve HQ channels for needful SUs.

Phase II: In this phase, DAU categorizes the SUs into three categories. For that, the NAN cluster is divided into three layers by forming spiral pattern over the cluster. This separation of three layers provides the distance information between DAU and SUs. The spiral pattern is constructed based on radius (τ) and angle (θ) [55]. The following equations are used for spiral construction:

$$x(\theta) = e^{\tau\theta}\cos(\theta) \tag{21}$$

$$y(\theta) = e^{\tau\theta}\sin(\theta) \tag{22}$$

Here, the radius value is the Euclidean distance between DAU and the SU, which is located far away from the DAU.

As shown in Figure 4, the spiral pattern is constructed, and the SUs are categorized in to near (Nr), middle (Ml), and far (Fr). The fact behind this separation is that the SUs located nearer to the DAU require minimum power for data transmission. But the SUs located far away from the DAU require large power and BW. Thus, categorizing SUs into three categories improves the channel allocation process.

Phase III: In this phase, the optimal channel is allocated for SUs based on triple objectives. For that, we proposed a TriO-CFO algorithm. First, the SUs in the *Fr* category are considered, and the channels in *HQ* cluster are assigned. The proposed TriO-CFO algorithm is performed on three major objectives as follows:

$$TriO = \begin{cases} \min(I) \\ \min(TP) \\ \max(\mathbb{DR}) \end{cases} \tag{23}$$

The objectives are formulated as minimizing interference (I) and transmission power (TP) while maximizing the data rate (DR). Based on these objectives, the proposed TriO-CFO algorithm is performed as follows:

Initialization: First, the population is initialized as points in d-dimensional search space as follows:

$$R[i].points[j] = random * (UL - LL) + LL \tag{24}$$

The above equation describes the initialization of ith population (R) in jth dimension with the upper and lower limits (UL, LL) correspondingly. Each individual point in the population represents a single cell that is associated with two values such as fitness ($F(i)$) and vector of d-dimension continuous values.

Fitness evaluation: Then each point is evaluated based on $F(i)$ to find the best solution. The fitness function is formulated from objective function as follows:

$$F(i) = \max(TriO) \tag{25}$$

The best point is determined from the fitness evaluation and that point is kept as *Best* solution. Then the population is divided into four groups as g_1, g_2, g_3, g_4. From the *Best* solution, the average of *Best* points are computed as stored in Avg_{Best}. Each group performs individually and shares the best solution. g_1, g_4 work as local search, and g_2, g_3 work as global search.

Local search-g_1: This search uses a group of chromatophore cells. This search deals with the reflected color due to the interaction between chromatophore and iridophore cells. The new solutions are determined from the stretch and shrink process in chromotophores and the reflected light from iridophores. This can be formulated as follows:

$$Reflection_j = RD * g_1[i]Points[j] \tag{26}$$

$$Visibility_j = VD * (BestPoints[j] - g_1[j]) \tag{27}$$

where RD and VD denote the reflection degree and visibility degree of jth point in the ith cell ($Point[j]$). The new population from g_1 is formulated as follows:

$$new[j] = Reflection_j + Visibility_j \tag{28}$$

Global search-g_2: This search is assisted by the iridophore cells, which reflect the incoming light from the outside. In this search, the reflection is reformulated as follows:

$$Reflection_j = R * BestPoint[j] \tag{29}$$

In this search, the reflection value is updated, and based on this updated reflection value, the VD is also updated.

Local search-g_3: This search is assisted by leucophore cells, which are working as a mirror. They reflect the incoming light same from the environment, for example, it reflects white as white. Thus, the reflection and visibility can be modified as follows:

$$Reflection_j = R * BestPoints[j] \tag{30}$$

$$Visibility_j = VD * (BestPoints[j] - Avg_{Best}) \tag{31}$$

Global search-g_4: This search is assisted by leucophore cells as in g_3. In this manner, new solution is updated in each search, and best solution is determined in each search. This process is repeated until the stopping criteria met. Then optimal solution, *i.e.* channel, is assigned for each SU.

In this work, this process is performed for all SUs until each SU is provided with the required channel. For each SU, the solution space is updated by eliminating the assigned channel. The HQ channels are assigned to SUs in Fr group and then to Ml group.

(ii) Priority Allocation (Scenario-II)

This case is considered, if the SUs have priority data for transmission. In this scenario, some SUs have time-sensitive data for transmission. For priority allocation, we proposed the OMTriO-CFO algorithm. To minimize the channel allocation time, we ignore FK-means and spiral construction process. Instead we perform one to many matching between priority SU (SU_P) and available channels. When SU_P is identified, then the multiple matching channels are determined from the C_A set. For that, matching score (M_Score) is determined for all channels as follows:

$$M\_Score = BE_i + SNR_i \tag{32}$$

The channels that have higher M_Score are selected for next stage. Then TriO-CFO algorithm is applied on the qualified channels for optimal channel allocation. Determining multiple matches improve spectrum utilization and minimize time consumption/

Pseudocode 3: Channel allocation scheme

```
Begin
  For each Cluster_j ∈ CogRSG
  Initialize SUs → {SU_1, SU_2, .., SU_p}, C_A → {C_1, C_2, .., C_H}
  For all C_i ∈ C_A        //Fair Allocation
    Define k
    Initialize kC_C
    Learn BW, SNR, CSI
    Compute FD_1, FD_2, FD_3
    Find FD(C_i, C_Cj),  i = 1,2,..,H; j = 1,2,..k
  If FD(C_i, C_Cj) == Low
    | Assign C_i → C_Cj
  Else
      Search with another group
    Find HQ, MQ, LQ
  End For
  Find τ, θ
  Construct Spiral Pattern
  Find Nr, Ml, Fr SUs
  For each SU ∈ Fr search in HQ
  For each SU ∈ Ml search in MQ
  For each SU ∈ Nr search in LQ
    Initialize population with C
  For each C_i
      Formulate TriO
      Evaluate F(i)
      Find BestPoint
      Divide population→ g_1, g_2, g_3, g_4
      Do Local Search − g_1
        Generate new[j]
      Do Global Search − g_2
        Update Reflection
      Do Local Search − g_3
        Update Reflection, Visibility
      Do Global Search
        Assign optimal channel
    End For
  End For
  Initialize SUs        //Priority Allocation
  For all C_i ∈ C_A
    Compute M_Score
    Find Matching Channels
    Execute TriOCFO
  End For
End
```

Pseudocode 3 Description: The channel allocation process is initiated with clusters and channel initialization. First, fair allocation is detailed, which performs FK-means algorithm, spiral construction, and TriO-CFO algorithms consequently. Finally, optimal channel is assigned for each SU. Channel clustering and SU categorization minimizes the time complexity for channel allocation. Then priority allocation is detailed in which one to many matching is performed based on matching score and then optimal channel allocation is performed by the TriO-CFO algorithm. In this manner, the proposed work handles both priority and fair allocation channel allocation issues.

Table 3: Simulation parameters

Parameter	Values
Simulation area	1000 × 1000 m
Standard	IEEE 802.11af
Number of SUs	120
Number of malicious SUs	Up to 10% (Varying)
Number of DAUs	8
Number of CBS, PBS	1
Number of NAN clusters	8
Frequency range	54–88 MHz
Bandwidth	6 MHz
Number of channels	25
Transmission scheme	OFDM
Number of subcarriers	192
SNR range	5 dB
Packet size	1024 kb
Packet interval	0.1 s
Number of packets	Minimum 100
Data rate	10 Mbps
Transmission duration	Maximum 100 ms
VD, *RD*	1, −1
Simulation time	100 s

Thus, the proposed SCAN-CogRSG system improves the data rate and spectrum utilization by eliminating invalid SUs, dynamic cluster switching, and optimal channel allocation.

6. EXPERIMENTAL EVALUATION

In this section, the proposed SCAN-CogRSG system is evaluated through extensive simulations. This section comprises two subsections as simulation setup and performance evaluation.

6.1 Simulation Setup

The proposed SCAN-CogRSG system is modeled in network simulator-3.26 simulation tool. NS-3 is the discrete event network simulator that supports various wireless networks and protocols. We construct the network with SUs, PUs, DAUs, PBS, and CBS.

In Table 3, the essential simulation parameters considered in simulation are enlisted. IEEE 802.11af is specifically aimed to use CRN networks. The physical layer is working on orthogonal frequency division multiplexing (OFDM).The simulation testbed created in NS-3 is shown in Figure 5. In Figure 6, the simulation results for network initialization, cluster formation, communication, and Netanim are illustrated. With the simulation setup, the experiments are performed, and the results are observed.

Case study: The prime application area of proposed SCAN-CogRSG is smart grid communication. Advance metering infrastructure (AMI) is one of the applications of SG communications. AMI is the main functionality

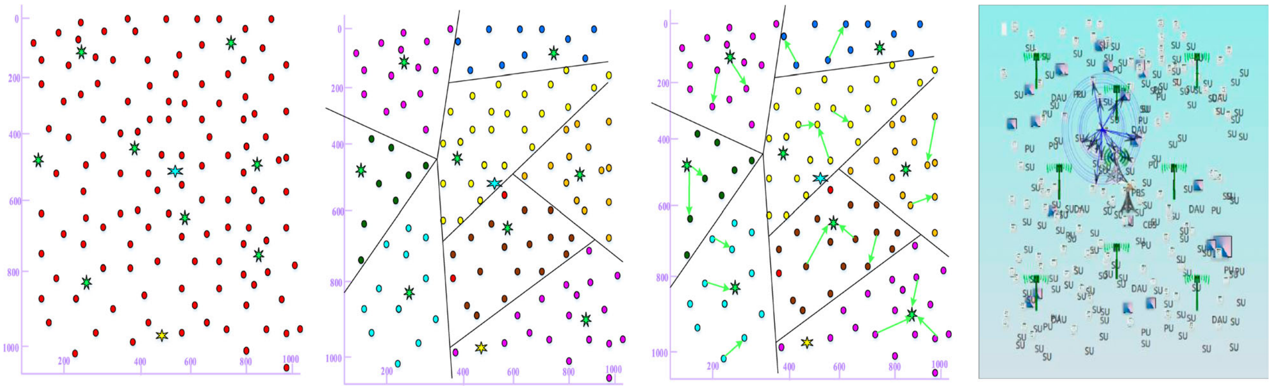

Figure 5: Simulation environment of SCAN-CogRSG with $n = 120$, $m = 8$: (a) network initialization, (b) cluster formation, (c) communication, (d) NetAnim result

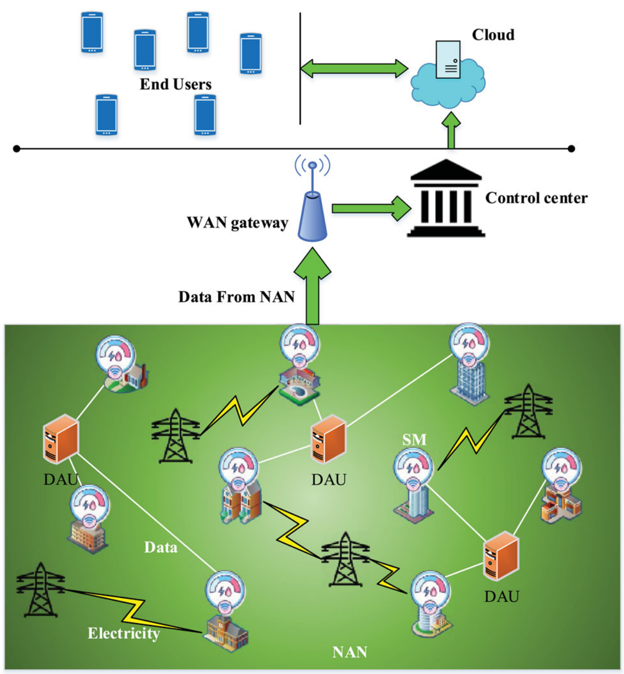

Figure 6: SCAN-CogRSG for AMI applications

block of major SG applications. It includes pricing, distribution, and automation functions. In AMI applications, SMs are the core blocks and the DAUs are responsible for data aggregation.

In Figure 6, the application scenario of proposed SCAN-CogRSG system is illustrated. As shown in the figure, the main functionality of AMI is to determine the electrical distribution and pricing using SMs. The SMs are responsible to collect the electrical usage from all home devices (mobile phones, lamps, TVs, etc.) and to calculate the pricing for the electrical usage. The pricing applications are delay tolerant and have few minutes to hours delay tolerance. In this application, we follow fair allocation policy and assign the optimal channel for each SU. In case of automation applications, we follow priority allocation strategy. In growing IoT era, utilization of unutilized spectrum for SG communications will improve the overall cost and efficiency. Thus, our proposed work is most suitable for smart city applications.

6.2 Comparative Study

The proposed SCAN-CogRSG is analyzed in terms of performance metrics. The considered evaluation metrics are throughput, retransmission probability, latency, and authentication time.

6.2.1 Performance Metrics

Throughput is defined as the amount of data can be processed (or) transmitted in a given amount of time. In SCAN-CogRSG, SUs perform sensing and transmission in each time period. Although our major focus is channel allocation, the time is utilized for spectrum sensing too. Thus, the throughput of proposed system is formulated as follows:

$$Th = \frac{T_F - T}{T_F}(1 - P_f)P_c \tag{33}$$

Here, the P_C defines the probability that the PU is idle during time frame $(T_{PRF} + T_F)$. This idle period can be utilized by the SUs in the system. It is worth mentioning that, the SU transmission occurs when the PU is idle at given period of time. Similarly, the latency achieved by the proposed system depends on the several parameters. The latency of the system is computed from the following

Table 4: Comparison on prior research works

Work	Network design	Channel Allocation	Pros	Cons
CSO	Cluster based CRN-SG	CSO algorithm	Better network management	1 Not applicable for practical scenario 2 Slow convergence
CSA	Cluster based CRN-SG	CSA algorithm	Suitable for large-scale network	1 Channel allocation is not efficient 2 Slow convergence rate
Fuzzy	CRN-SG	Fuzzy based approach	Optimal parameters are determined	1 Large time consumption 2 Not suitable for practical scenario
Adaptive fuzzy	CRN-SG	Adaptive fuzzy logic	Parameters can be determined	1 Time consumption is high

equation:

$$Latency = \tau_P + \tau_S \tag{34}$$

where $\tau_P = s/c$ (the propagation delay), and $\tau_s = ON/Th$(the seritalization delay). Here, c denotes the speed of light and ON is the OFDM packet size.

Retransmission probability shows the ability of channel allocation scheme. The retransmission probability defines the amount of data retransmitted due to data loss and interference. When the interference with PU is low, then the retransmission probability will be small. In addition, optimal channel allocation also helps to improve the retransmission probability. If the optimal channel is assigned to SU, then the retransmission probability will be minimized.

In this section, proposed SCAN-CogRSG is compared with existing works such as CSO [47], CSA [48], fuzzy [49], adaptive fuzzy [50]-based channel allocation schemes, and deep learning-based [32] authentication scheme. Table 3 shows the comparative analysis on the prior channel allocation schemes. Comparisons are made for two scenarios as follows.

Experiment I: In this scenario, fair allocation is performed. All SUs have non-time sensitive data and all SUs are considered with same priority level.

Experiment II: In this scenario, priority allocation is performed. In this scenario, some SUs have time-sensitive data. These SUs are dynamically changed and the performance is evaluated (Table 4).

In both experiments, we have performed simulations with varying number of SUs and idle channels. Initially, 120 SUs are fixed and the number of idle channels is varied as 5, 10, 15, 20, and 25. The results are observed for the performance metrics. Then, the number of channels is fixed as 25 and the number of SUs is varied as 20, 40, 60, 80, 100, and 120. Then, the results are observed. The observed results are plotted in graphs for better analysis.

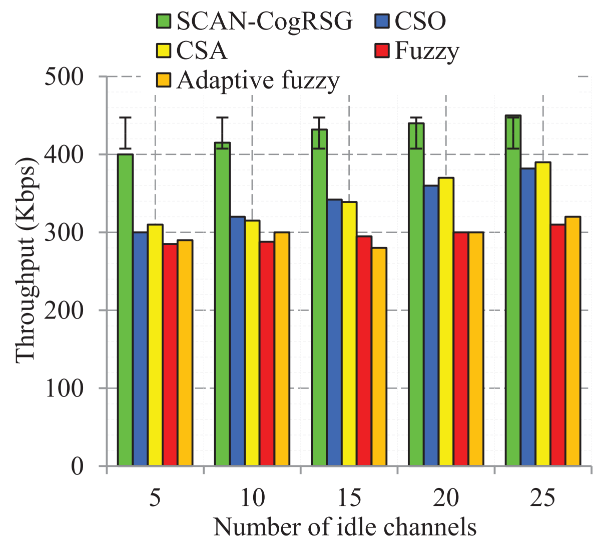

Figure 7: Throughput vs. number of idle channels

6.2.2 Throughput Efficiency

As stated earlier, throughput depends on the spectrum availability and utilization. We analyze throughput efficiency for both fair and priority allocation.

In Experiment I:

In this scenario, we compare throughput efficiency with varying number of idle channels and number of SUs. Both comparative plots are depicted in Figures 7 and 8.

When the number of idle channels is increased, then the throughput is also increased since the increasing number of idle channels provides the high possibility for data transmission. Although the proposed work increases the throughput effectually, the previous fuzzy and adaptive fuzzy systems has uncertain throughput for varying number of idle channels. This is due to the inefficient channel assignment. In most of the previous research works, channel availability is not considered during channel assignment. This is the major reason for throughput degradation. However, in the proposed SCAN-CogRSG system, dynamic switching is enabled by the TA-FuReiL algorithm based on the channel availability. Thus, the

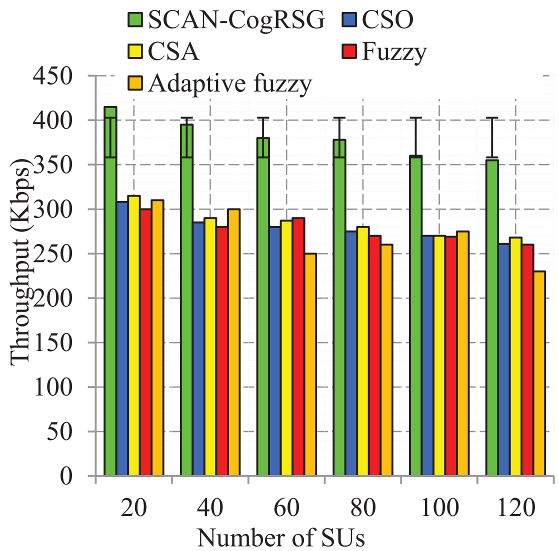

Figure 8: Throughput vs. number of SUs

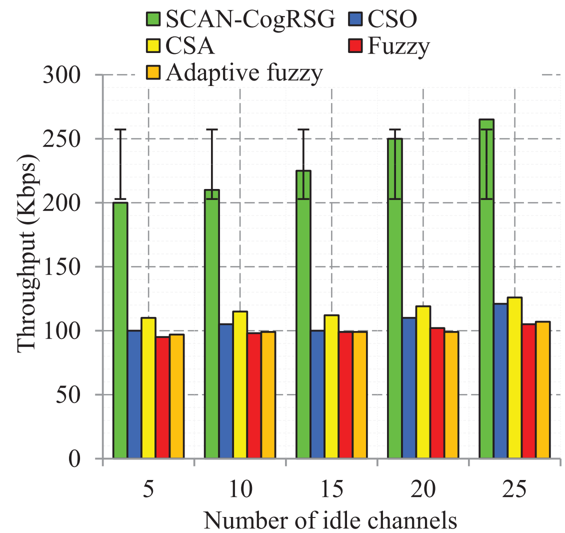

Figure 9: Throughput for priority allocation

proposed work achieves throughput up to 450 kbps, which is 100 kbps higher than prior fuzzy and adaptive fuzzy algorithms.

In the presence of large number of SUs, it is necessary to assign available channels to all SUs. Thus, the throughput is decreased with the increase in number of SUs. Even in the presence of 120 SUs, proposed SCAN-CogRSG achieves throughput up to 350 kbps, which is relatively higher than prior research works. Averagely, 380 kbps of throughput is achieved in the proposed SCAN-CogRSG system. The major reason behind improved throughput efficiency is that the proposed SCAN-CogRSG follows channel assignment with the objectives of interference, transmission power, and data rate in the TriO-CFO algorithm. Thus, the proposed work assigns most suitable channel for each SU in the network. But in the previous research works, channel allocation is performed without considering significant metrics, specifically channel availability is not considered. Thus, throughput is degraded in the prior research works.

In Experiment II:

In this scenario, we compare throughput efficiency with varying number of idle channels. In priority allocation, it is necessary to consider the priority level of data to achieve better performance.

In Figure 9, the graphical comparison for throughput efficiency is illustrated. The analysis shows that none of the existing works have attained better throughput for the priority data. In the previous works, the priority scenario is concentrated in CSO and CSA algorithms. However, both works fail to achieve better throughput due to inefficient algorithm design and parameters consideration. In the proposed SCAN-CogRSG, priority channel allocation is performed by the OMTriO-CFO algorithm, which achieves better throughput than prior research works.

6.2.3 Retransmission Efficiency

For an effectual system, the retransmission probability, *i.e.*, number of retransmissions, will be low as possible. The retransmission probability shows the efficiency of the proposed channel allocation schemes.

In Experiment I:

In this scenario, retransmission probability is analyzed and compared with respect to varying number of idle channels. It is obvious that, more number of idle channels minimizes the retransmission probability.

In Figure 10, retransmission probability is compared for fair allocation. In fair allocation, all the data have same priority level. In the proposed SCAN-CogRSG system, 5%–15% of the data are retransmitted due to sudden interference and channel unavailability. Similarly, the CSO algorithm retransmits 10%–25% of data that are 10% higher than the proposed work. The inefficiency of existing channel allocation algorithm leads to higher retransmission probability. But fuzzy-based system retransmits 32% of data that are not fair for the SG communications. Thus, the prior research works are not suitable for SG communications.

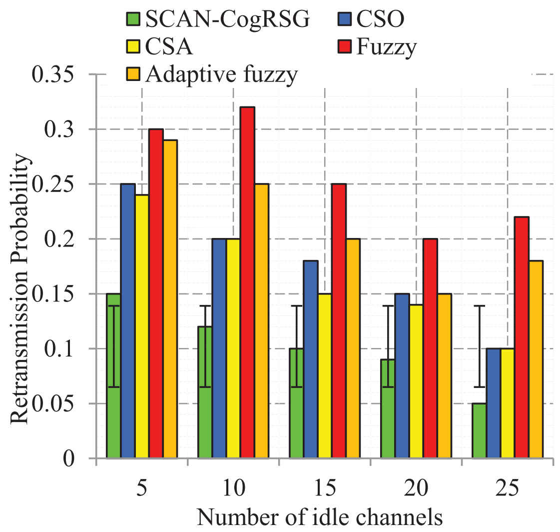

Figure 10: Retransmission probability in fair allocation

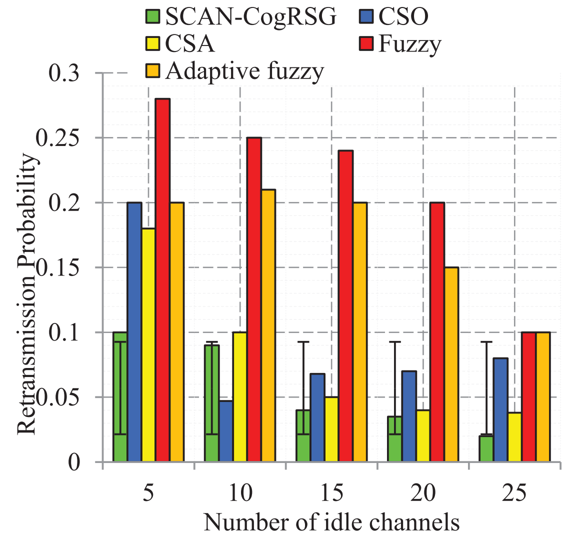

Figure 11: Retransmission probability in priority allocation

In Experiment II:

In this scenario, some SUs have higher priority than others. Thus, the retransmission probability must be lower for this scenario. If any priority data are retransmitted, then the transmission latency will be increased, which further results in performance degradation. Thus, it is important to minimize the retransmission probability for the priority data.

In Figure 11, the retransmission probability achieved for priority allocation is analyzed. Here, the analysis shows that the proposed work achieves better retransmission probability than other works. The retransmission probability in SCAN-CogRSG is 10% even in the presence of 5 idle channels. When the number of idle channels is increased, then the retransmission probability is decreased to 2%, which is much lower than existing works. In prior works, up to 30% data are retransmitted. For time-sensitive applications, 30% of retransmission probability is not fair. When more number of sensitive data are retransmitted, then the entire system will be inefficient. Thus, retransmission probability analysis shows that the proposed SCAN-CogRSG system is suitable for both sensitive and nonsensitive applications since it follows dedicated channel allocation schemes.

6.2.4 Latency Efficiency

When retransmission probability is increased, it is obvious that the latency will also be increased. In addition, improper channel allocation and interference are the major reasons for large latency.

In Experiment I:

In this scenario, the applications are delay tolerable, which can accept slight latency in data transmission. However, the general latency requirement for SG applications is 20 ms to few seconds.

In Figure 12, the latency of the proposed and existing works is compared for fair allocation scenario. Latency will be high when the allocated channels are not efficient for particular SU, and channel allocation time is large. Our proposed SCAN-CogRSG provides 5 ms to 10 ms of latency, which is acceptable for most of the sensitive applications. However, in CRN-based SG communications, the PU activity is unpredictable and the idle period of a channel is varying. Thus, it is necessary to minimize the latency for all data. In the previous research works, the channel allocation schemes consume large time and the channel allocation ignores major parameters. Thus, the prior works provides large latency when compared with the proposed work.

In Experiment II:

In this scenario, the data must be transmitted without high latency. Due to the time-sensitive nature of the data, the latency must be minimized. It is good to maintain the latency within few milliseconds to achieve better performance.

In Figure 13, the latency provided by proposed and existing works is analyzed. The analysis illustrates that proposed SCAN-CogRSG system provides latency for priority allocation lower than fair allocation. In our work,

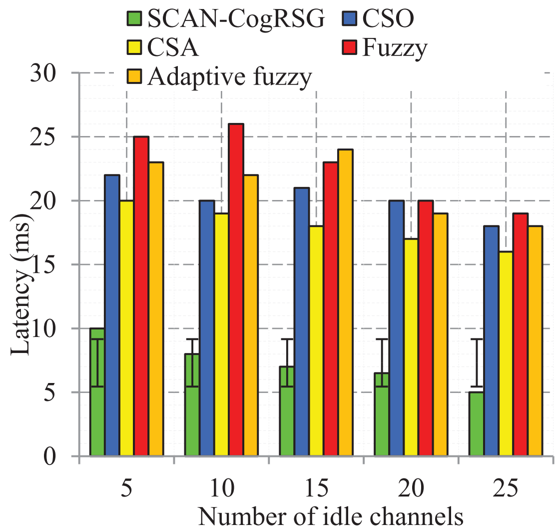

Figure 12: Latency in fair allocation

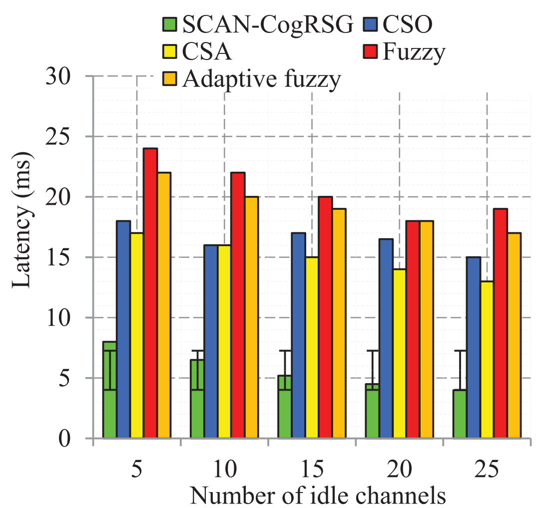

Figure 13: Latency in priority allocation

latency for priority allocation is 3 ms to 7 ms, which is relatively lower than previous research works. In the proposed work, priority allocation is followed by the OMTriO-CFO algorithm, which minimizes the channel allocation time. Thus, the latency in proposed work is much lower than prior works. In fuzzy based methods, priority allocation also follows the fair allocation procedure, which is not suitable for handling time-sensitive data. Fuzzy method provides 24 ms of latency in the presence of 5 idle channels. In this much of latency, the performance of the system will be degraded.

6.2.5 Authentication Efficiency

Security is one of the aspects of our work. To improve security, we perform Bi-PUF authentication. As PUFs are strong, authentication is efficient. However, this section analyzes the time consumption for authentication.

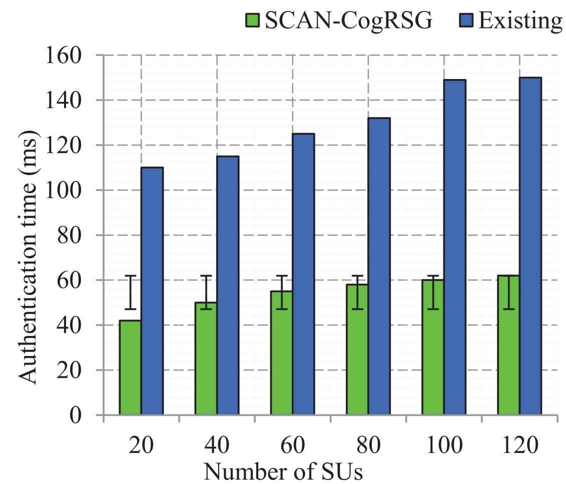

Figure 14: Authentication time analysis

Figure 14 shows the time consumption for authentication. The proposed work is compared with the existing deep learning method. The analysis shows that proposed work consumes lesser time than the deep learning method. But in the security aspect, the proposed work is stronger than the deep learning approach. Thus, this analysis confirms that proposed work is efficient in both time consumption as well as security aspects.

Security Analysis:

In the experiments, 10% of SUs are considered as malicious and this value is varying. The overall analysis shows that the proposed SCAN-CogRSG achieves better performance. The major reason behind this result is that the proposed work eliminates the malicious SUs at the initial stage through PUF-based authentication process. Whenever the malicious SU attempts to use the available spectrum, the SU must be authenticated. However, the malicious SU is identified in the Bi-PUF authentication process. Thus, the discussed threat model is mitigated by Bi-PUF authentication. This can be seen from the other performance metrics. When the malicious SUs have used the spectrum, then the throughput will be low and the retransmission probability will be high. But the analysis shows that the proposed work achieves better throughput and retransmission probability, which means the proposed work eliminates the malicious SUs in initial stage. Furthermore, the authentication time is also lower than prior research work. Therefore, the proposed SCAN-CogRSG achieves better overall performance without increase in authentication time.

6.2.6 Summary of Obtained Results

In aforementioned analysis, it can be seen that proposed work is far better than prior research works. This section

Table 5: Overall analysis on obtained mean values

Parameter			CSO	CSA	Fuzzy	Adaptive fuzzy	SCAN-CogRSG
			Observed Mean Value				
Throughput (Kbps)	Fair allocation	No of idle channels	340.8	344.8	295.6	298	427.4
		No of SUs	279.8	285	278.1	270.8	380.5
	Priority allocation		107.2	116.4	99.8	100.2	230
Retransmission Probability (ms)	Fair allocation		0.176	0.166	0.258	0.214	0.1
	Priority allocation		0.09	0.08	0.214	0.172	0.05
Latency (ms)	Fair allocation		20.2	18	22.6	21.2	7.3
	Priority allocation		16.5	15	20.6	19.2	5.6

Table 6: Analysis on proposed work

Proposed algorithm		Contribution
Bi-PUF mechanism	1	Validates each SU in the system
	2	Eliminate Unauthorized SUs
	3	Improves throughput for authorized SUs by eliminating invalid SUs
	4	Improves spectrum utilization by preventing available spectrum from invalid SUs
TA-FuReiL	1	Balances the NAN clusters
	2	Minimizes latency by minimizing channel allocation time
	3	Improves spectrum utilization by balancing clusters
TriO-CFO	1	Allocates channels in an effectual manner
OMTriO-CFO	2	Minimizes latency and retransmission probability
	3	Increases throughput and data rate by assigning optimal channel
	4	Minimizes the interference level with PUs

summarizes the overall obtained results for analysis. The mean values obtained for each performance metric is depicted in Table 5.

The major reason behind the results is ineffectiveness of channel allocation schemes. In previous research works, channel availability is not considered and the considered metrics are limited, which is not suitable for SG applications. However, the proposed SCAN-CogRSG system introduces novel algorithms to resolve the existing issues.

In Table 6, the proposed contributions and their effects on obtained results are presented. Thus, every proposed methodology improves the performance in terms of performance metrics. It is obvious that improvement in throughput and retransmission probability increases the data rate and spectrum utilization. When the available spectrum is fully utilized, then the throughput will be improved.

6.3 Complexity Analysis

This section analyzes the complexity attained by the prior and proposed works. The computational complexity is computed based on time and resources consumed by an algorithm to be executed. In complexity analysis, the number of loops, calls, and iterations are considered for each algorithm. In the proposed SCAN-CogRSG system, three algorithms as Bi-PUF, TA-FuReiL, and TriO-CFO are executed for SU validation, dynamic switching, and channel allocation, respectively.

Table 7: Complexity analysis

Algorithm	Best case	Worst case
Bi-PUF	$\sim O(1)$	$\sim O(n)$
TA-FuReiL	$\sim O(1)$	$\sim O(2n)$
TriO-CFO	$\sim O(n)$	$\sim O(n^2)$

In Table 7, the complexity analysis is presented for each proposed algorithm in best and worst cases. The complexity of the proposed channel allocation algorithm is lower than prior works due to involvement of SU validation and channel grouping. Thus, the proposed work allocates the optimal channel for each SU without an increase in complexity.

7. CONCLUSION

In this paper, channel allocation problem is concentrated in CRN-based SG and resolved by SU validation, dynamic cluster switching, and optimal channel allocation processes. First, invalid SUs are eliminated from the system by using Bi-PUF mechanism, which uses PUF for authentication. With the valid SUs, NAN clusters are formed and the clusters are balanced by enabling dynamic switching. The dynamic switching is performed based on topology learning progress. For that, TA-FuReiL algorithm is proposed. When the clusters are balanced, then the channel allocation process is initiated. The available channels are grouped by FK-means algorithm and channel allocation is performed by the TriO-CFO algorithm under triple objectives. To handle priority allocation, OMTriO-CFO algorithm is also presented. The proposed methodology for channel allocation is evaluated through extensive simulations in ns-3.26. The obtained results show that proposed SCAN-CogRSG achieves better data rate and spectrum utilization through achieving throughput, latency, and retransmission probability. To the best of our knowledge, this is the best work to concentrate on secure channel allocation in CRN-based SG communications. This will open up many research directions in secure channel allocation in CRN-based SG systems. In future, we have planned to extend this work with lightweight cryptography schemes for data security and multi-objective based channel allocation. In addition, we have also planned to concentrate on cooperative spectrum sensing (CSS) strategies to further improve the system performance.

REFERENCES

1. N. Shaukat, S. M. Ali, C. A. Mehmood, B. Khan, M. Jawad, U. Farid, Z. Ullah, S. M. Anwar, and M. Majid, "A survey on consumers empowerment, communication technologies, and renewable generation penetration within smart grid," *Renew. Sustainable Energy Rev.*, Vol. 81, pp. 1453–75, 2018.

2. D. Jiang, Y. Wang, Z. Lv, S. Qi, and S. Singh, "Big data analysis-based network behavior insight of cellular networks for Industry 4.0 Applications," *IEEE Trans. Ind. Inf.*, 2019.

3. M. H. Rehmani, M. Reisslein, A. Rachedi, M. Erol-Kantarci, and M. Radenkovic, "Integrating renewable energy resources into the smart grid: Recent developments in information and communication technologies," *IEEE Trans. Ind. Inf.*, Vol. 14, pp. 2814–25, 2018.

4. M. Faheem, S. B. Shah, R. A. Butt, B. Raza, M. Anwar, M. W. Ashraf, M. A. Ngadi, and V. C. Gungor, "Smart grid communication and information technologies in the perspective of Industry 4.0: Opportunities and challenges," *Comput. Sci. Rev.*, Vol. 30, pp. 1–30, 2018.

5. W. Zhang, C. Wang, X. Ge, and Y. Chen, "Enhanced 5G cognitive radio networks based on spectrum sharing and spectrum aggregation," *IEEE Trans. Commun.*, Vol. 66, pp. 6304–16, 2018.

6. M. Liu, T. Song, J. Hu, J. Yang, and G. Gui, "Deep learning-inspired message passing algorithm for efficient resource allocation in cognitive radio networks," *IEEE Trans. Veh. Technol.*, Vol. 68, pp. 641–53, 2019.

7. K. Elangovan, and S. Subashini, "Particle bee optimized convolution neural network for managing security using cross-layer design in cognitive radio network," *J. Ambient Intell. Humanized Comput.*, 1–9, 2018.

8. L. K. Chhaya, P. Sharma, A. Kumar, and G. Bhagwatikar. "Integration of cognitive radio with heterogeneous smart grid communication architecture," 2018.

9. W. Zhang, Y. Sun, L. Deng, C. K. Yeo, and L. Yang, "Dynamic spectrum allocation for heterogeneous cognitive radio networks with multiple channels," *IEEE Syst. J.*, Vol. 13, pp. 53–64, 2019.

10. M. A. Rahman, Y. Lee, and I. Koo, "Joint relay selection and power allocation through a genetic algorithm for secure cooperative cognitive radio networks," *Sensors*, 2018.

11. D. Jiang, W. Wang, L. Shi, and H. Song, "A compressive sensing-based approach to end-to-end network traffic reconstruction," *IEEE Trans. Network Sci. Eng.*, Vol. 5, no. 3, pp. 1–12, 2019.

12. L. Huo, and D. Jiang, "Stackelberg game-based energy-efficient resource allocation for 5G cellular networks," *Telecommun. Syst.*, Vol. 72, no. 3, pp. 377–88, 2019.

13. W. Singh, and N. Marchang, "A review on spectrum allocation in cognitive radio network," *Int. J. Commun. Networks Distrib. Syst.*, Vol. 23, pp. 172–93, 2018. 10.1504/IJCNDS.2019.10014474.

14. A. Salah, H. M. Abdel-Atty, and R. Y. Rizk, "Joint channel assignment and power allocation based on maximum concurrent multicommodity flow in cognitive radio networks," *Wireless Commun. Mobile Comput.*, Vol. 2018, pp. 3545946:1–14, 2018.

15. M. Devi, N. Sarma, and S. K. Deka, "Spectrum allocation in cognitive radio networks – A centralized approach," *Adv. Comput. Commun. Paradigms*, 2018.

16. S. Senthilkumar, and C. G. Priya, "Hidden Markov model based channel selection framework for cognitive radio network," *Comput. Electr. Eng.*, Vol. 65, pp. 516–26, 2016.

17. S. Kar, S. Sethi, and R. K. Sahoo, "A multi-factor trust management scheme for secure spectrum sensing in cognitive radio networks," *Wireless Pers. Commun.*, Vol. 97, pp. 2523–40, 2017.

18. M. M. Rana, "Architecture of the internet of energy network: An application to smart grid communications," *IEEE Access*, Vol. 5, pp. 4704–10, 2017.

19. X. Deng, T. He, L. He, J. Gui, and Q. Peng, "Performance analysis for IEEE 802.11s wireless mesh network in smart grid," *Wireless Pers. Commun.*, Vol. 96, pp. 1537–55, 2017.

20. D. Jiang, L. Huo, Z. Lv, H. Song, and W. Qin, "A joint multi-criteria utility-based network selection approach for vehicle-to-infrastructure networking," *IEEE Trans. Intell. Transp. Syst.*, Vol. 19, pp. 3305–19, 2018.

21. N. Mansoor, A. Islam, M. Zareei, and C. Vargas-Rosales, "RARE: A spectrum aware cross-layer MAC protocol for cognitive radio ad-hoc networks," *IEEE Access*, Vol. 6, pp. 22210–27, 2018.

22. M. Zareei, I. A. Muzahidul, S. Baharun, C. V. Rosales, L. Azpilicueta, and N. Mansoor, "Medium access control protocols for cognitive radio ad hoc networks: A survey," *Sensors*, 2017.

23. S. Alam, M. F. Sohail, S. A. Ghauri, I. M. Qureshi, and N. Aqdas. "Cognitive radio based smart grid communication network," 2017.

24. E. U. Ogbodo, D. G. Dorrell, and A. M. Abu-Mahfouz, "Cognitive radio based sensor network in smart grid: Architectures, applications and communication technologies," *IEEE Access*, Vol. 5, pp. 19084–98, 2017.

25. H. A. Salameh, S. Almajali, M. Ayyash, and H. Elgala, "Spectrum assignment in cognitive radio networks for internet-of-things delay-sensitive applications under jamming attacks," *IEEE Internet Things J.*, Vol. 5, pp. 1904–13, 2018.

26. O. R. Boudia, S. M. Senouci, and M. Feham, "Elliptic curve-based secure multidimensional aggregation for smart grid communications," *IEEE Sens. J.*, Vol. 17, pp. 7750–7, 2017.

27. K. Mahmood, S. A. Chaudhry, S. H. Naqvi, S. Kumari, X. Li, and A. K. Sangaiah, "An elliptic curve cryptography based lightweight authentication scheme for smart grid communication," *Future Generation Comp. Syst*, Vol. 81, pp. 557–65, 2018.

28. S. Tonyali, K. Akkaya, N. Saputro, A. S. Uluagac, and M. Nojoumian, "Privacy-preserving protocols for secure and reliable data aggregation in IoT-enabled Smart Metering systems," *Future Generation Comp. Syst*, Vol. 78, pp. 547–57, 2018.

29. T. Liu, J. Tian, Y. Gui, Y. Liu, and P. Liu, "SEDEA: State estimation-based dynamic encryption and authentication in smart grid," *IEEE Access*, Vol. 5, pp. 15682–93, 2017.

30. M. Wazid, A. K. Das, N. Kumar, and J. J. Rodrigues, "Secure three-factor user authentication scheme for renewable-energy-based smart grid environment," *IEEE Trans. Ind. Inf.*, Vol. 13, pp. 3144–53, 2017.

31. L. Xu, L. X. Cai, Y. Gao, J. Xia, Y. Yang, and T. Chai, "Security-aware proportional fairness resource allocation for cognitive heterogeneous networks," *IEEE Trans. Veh. Technol.*, Vol. 67, pp. 11694–704, 2018.

32. K. Merchant, S. Revay, G. Stantchev, and B. Nousain, "Deep learning for RF device fingerprinting in cognitive communication networks," *IEEE J. Sel. Top. Sign. Process.*, Vol. 12, pp. 160–7, 2018.

33. Y. Jararweh, H. A. Salameh, A. Alturani, L. A. Tawalbeh, and H. Song, "Anomaly-based framework for detecting dynamic spectrum access attacks in cognitive radio networks," *Telecommun. Syst.*, Vol. 67, pp. 217–29, 2018.

34. G. P. Raman, and V. Perumal, "Neuro-fuzzy based two-stage spectrum allocation scheme to ensure spectrum efficiency in CRN-CSS assisted by spectrum agent," *IET Circuits, Devices Syst.*, Vol. 13, pp. 637–46, 2019.

35. A. Ali, L. Abbas, M. Shafiq, A. K. Bashir, M. K. Afzal, H. B. Liaqat, M. H. Siddiqi, and K. S. Kwak, "Hybrid fuzzy logic scheme for efficient channel utilization in Cognitive Radio Networks," *IEEE Access*, Vol. 7, pp. 24463–76, 2019.

36. Z. Teng, L. Xie, H. Chen, L. Teng, and H. Li, "Application research of game theory in cognitive radio spectrum allocation," *Wireless Networks*, 2019.

37. Y. Zeng, L. Xu, X. Yang, and X. Yi, "An efficient privacy-preserving protocol for database-driven cognitive radio networks," *Ad Hoc Networks*, Vol. 90, 2019.

38. G. Bharathi, and K. M. Jeyanthi, "An optimization algorithm-based resource allocation for cooperative cognitive radio networks," *The J. Supercomputing*, 1–21, 2018.

39. X. Zhang, X. Zhang, L. Han, and R. Xing, "Utilization-oriented spectrum allocation in an underlay cognitive radio network," *IEEE Access*, Vol. 6, pp. 12905–12, 2018.

40. F. Li, K. Lam, Z. Sheng, X. Zhang, K. Zhao, and L. Wang, "Q-learning-based dynamic spectrum access in cognitive industrial internet of things," *Mobile Networks Appl.*, Vol. 23, pp. 1636–44, 2018.

41. S. Mohapatra, P. K. Sahoo, and J. Sheu, "Spectrum allocation with guaranteed rendezvous in asynchronous cognitive radio networks for internet of things," *IEEE Internet Things J.*, Vol. 6, pp. 6104–16, 2019.

42. M. Iqbal, M. Naeem, A. Ahmed, M. Awais, A. Anpalagan, and A. Ahmad, "Swarm intelligence based resource management for cooperative cognitive radio network in smart hospitals," *Wireless Pers. Commun.*, Vol. 98, pp. 571–92, 2017.

43. K. Ma, P. Liu, J. Yang, X. Wei, and C. Dou, "Spectrum allocation and power optimization for demand-side cooperative and cognitive communications in smart grid," *IEEE Trans. Ind. Inf.*, Vol. 15, pp. 1830–9, 2019.

44. A. Mohammadi, M. J. Dehghani, and E. Ghazizadeh. "Game theoretic spectrum allocation in Femtocell networks for smart electric distribution grids," 2018.

45. T. Jiang, "Distributed framework for cognitive radio based smart grid and according communication/power management strategies," *China Com*, 2016.

46. S. Kar, S. Sethi, and R. K. Sahoo. "A trust-based technique for secure spectrum access in cognitive radio networks," 2018.

47. S. Alam, A. N. Malik, I. M. Qureshi, S. A. Ghauri, and M. Sarfraz, "Clustering-based channel allocation scheme for neighborhood area network in a cognitive Radio based smart grid communication," *IEEE Access*, Vol. 6, pp. 25773–84, 2018.

48. S. Alam, A. N. Malik, I. M. Qureshi, S. A. Ghauri, and M. Sarfraz, "Joint power and channel allocation scheme for IEEE 802.11af based smart grid communication network," *Future Gener. Comp. Syst*, Vol. 95, pp. 694–712, 2019.

49. M. W. Khan, and M. Zeeshan, "QoS-based dynamic channel selection algorithm for cognitive radio based smart grid

communication network," *Ad Hoc Networks*, Vol. 87, pp. 61–75, 2019a.

50. M. W. Khan, and M. Zeeshan, "Fuzzy inference based adaptive channel allocation for IEEE 802.22 compliant smart grid network," *Telecommun. Syst.*, 1–15, 2019b.

51. A. Babaei, and G. Schiele, "Physical unclonable functions in the internet of things: State of the art and open challenges," *Sensors*, 2019.

52. L. Liberti, and C. D'Ambrosio. *The Isomap algorithm in distance geometry*. Palaiseau: SEA, 2017.

53. R. Neelaveni, and B. Sridevi, "A novel Neyman–Pearson criterion-based adaptive neuro-fuzzy inference system (NPC-ANFIS) model for security threats detection in cognitive radio networks," *Soft Comput.*, 1–9, 2019.

54. S. Jang, C. Han, K. Lee, and S. Yoo, "Reinforcement learning-based dynamic band and channel selection in cognitive radio ad-hoc networks," *EURASIP J. Wireless Commun. Networking*, Vol. 2019, pp. 1–25, 2019.

55. M. U. Asad, Y. Nianmin, and M. Aslam. Spiral mobility based on optimized clustering for optimal data extraction in WSNs, 2018.

Authors

M. Monisha was born in Madurai, India, in 1990. She received the BTech degree in Electronics and Communication Engineering from Kalasalingam University, Srivilliputtur, India, in 2011, and the ME degree in Wireless Technology, Thiagarajar College of Engineering, Madurai, India, in 2013. From June 2013, she has been with the Department of Electronics and Communication Engineering, Vels Institute of Science Technology and Advanced Studies (VISTAS), Chennai, India, as an Assistant Professor. Her current research interests include Wireless sensor network, Cognitive Radio & Software Defined Radio Communication, and Digital Communication System. M. Monisha is a member of International Fellow of Engineering Research and Publication (IFERP), and a Research advisor in IMRTC-USA. She is also the member of several prestigious associations like International Association of Engineers (IAENG) and Asia Society of Researchers.

Corresponding author. Email: nishakrithik20@gmail.com

V. Rajendran was born in Madurai, India, in 1955. He received the BSc degree in Physics from the Thiagarajar College, Madurai, India, in 1977, and the MTech degree in Physical engineering from the Indian Institute of Science, Bangalore, India, in 1979. In 1993, he received Ph.D in Electrical and Electronics engineering from Chiba University, Japan. In 2015, he joined the Department of Electronics Engineering, SSN College of Engineering, and Chennai, India, as a professor. Since 2005, he has been with National Institute of Ocean Technology, Chennai, India, as a project director and head (Marine Instrumentation & Ocean Acoustics and Ocean Observation Systems). He is currently the professor and director in the department of Electronics and Communication Engineering, Vels Institute of Science Technology and Advanced Studies (VISTAS), Chennai, India. His current research interests include Underwater wireless sensor network, Cognitive Radio & Software Defined Radio Communication, HF radar, Tsunami warning system and Underwater noise measurement systems. Dr V. Rajendran is a Life fellow of Ultrasonic Society of India, India (USI), January 2001, Associate Member of Acoustical Society of America, USA, January 2010, Member of IEEE, USA, January 2010, Life fellow of Institution of Electronics and Telecommunication Engineering (IETE), India, January 2012. He was elected twice as Vice Chairman – Asia Execution Board of Data Buoy Co-operation Panel (DBCP) of Intergovernmental Oceanographic Commission (IOC)/World Meteorological Organization (WMO) of UNSCO, in October 2008 and September 2009. He was Awarded MONBUSHO Fellowship, Japanese Govt. Fellowship (1988–1989) through Ministry of Human Resource and Development, Govt. of India. He also received Jaya Distinguished Scientist Award '07 from Jaya Engineering College during their 9th Graduation Day on 26th April 2008 and a Special achievement award on Teacher days (2016 and 2018), VISTAS for Publication articles and research.

Email: director.ece@velsuniv.ac.in