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A QOS-AWARE FRAMEWORK FOR SPECTRUM CHARACTERIZATION AND SWITCHING DECISION IN COGNITIVE RADIO NETWORKS

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ABSTRACT

The increasing demand for seamless wireless services coupled with underutilization of limited spectrum due to fixed channel allocation policy have posed numerous challenges to wireless communications. There is need to design appropriate channel allocation strategies for continuous communication by mobile users for higher spectral efficiency. Cognitive radio network (CRN) offers a solution to the spectrum scarcity problem inherent in 4G and other networks through dynamic spectrum access, by allowing unlicensed secondary users (SUs) with cognitive devices to opportunistically access the spectrum holes when the licensed primary users (PUs) are not occupying them. Often times, measurements taken by SUs during the sensing process are uncertain due to multipath fading, shadowing and varying channel conditions. This results in imprecise spectrum detection and selection by SUs during switching decisions causing incessant spectrum handoff and undesirable ping-pong effect. In this paper, a support vector machine (SVM) classifier is used to categorize spectrum into two classes of busy and idle. Then, based on heterogeneous quality of service (QoS) requirements of the SUs, dynamic activities of PUs, and the fluctuating channel state information, a QoS-aware Adaptive Neuro-Fuzzy Inference System (ANFIS) framework is developed for spectrum switching decision using underlay spectrum access model. SVM predicted spectrum holes with 98.8% accuracy. ANFIS model yielded a 91.62% accuracy in the task of allocating spectrum holes to SUs for coexistent with PUs. Results further indicate that the intelligent framework can ensure fairness among SUs, reduce interference, improve throughput, and spectral efficiency. It can be deployed in disaster relief and emergency, public safety, and battlefield environments.

Keywords: QoS-aware, spectrum decision, cognitive radio network, support vector machine, adaptive neuro-fuzzy inference system

INTRODUCTION

Cognitive radio network (CRN) is a fifth generation (5G) radio system that deploys technology which allows the system to obtain knowledge of its operational and geographical environment in order to permit opportunistic and intelligent spectrum access. The network permits unlicensed secondary users (SUs) to coexist with the licensed primary users (PUs) by opportunistically accessing unutilized or underutilized spectrum holes without causing undue interference to PUs and with other SUs (Zakariya *et al*., 2020; Akhtar *et al*., 2018). The 5G concept promises seamless communication with capabilities for higher capacity, higher data rate, low end-to-end latency, reduced cost, consistent quality of experience/quality of service (QoE)/(QoS) provisioning including massive connectivity to Internet of Things (IoT) devices, which existing 4G network cannot offer. Other important features of 5G network include pervasive computing, IPv6 routing for Low-power and Lossy Networks (LLNs), wearable devices with Artificial Intelligence (AI) facilities, and unified global standard.

Two important capabilities that differentiate CRNs from the traditional wireless networks are the ability of the cognitive radio (CR) to adapt spectrum environment and protect the transmission of PUs (Alqahtani *et al*., 2023; Moghaddam, 2018; Cavalcanti and Ghosh, 2008) for efficient spectrum utilization. Figure 1 shows a CRN structure indicating how PUs and SUs can coexist for data transmission. The architecture considers different types of applications that run on the SU device which generate packets with diverse traffic and QoS requirements (Mishra and Mathur, 2014). However, the existing fixed channel allocation scheme indicates that wireless network is challenged with severe spectrum inefficiency. Figure 2 shows how the busy and idle frequency channels are distributed over time. It indicates the prevalence of wastage of inadequate spectrum resources. Again, while some spectrum channels are overcrowded, others are left unutilized or underutilized. While a primary traffic shows a busy channel, indicating that actual data transmission is ongoing by PUs, the larger parts of the spectrum band remain unused or idle and these are known as spectrum holes. Spectrum holes are formed as a result of non-utilization of licensed spectrum resource. With CR technology, the SUs can exploit or access the idle channels but wrong allocation of idle channels can force an SU to vacate current channel once a PU arrives, which leads to an SU switching channel to several different spectrum holes just to continue communication. This incessant spectrum handoff is undesirable for time-critical missions as packet loss may also arise. The CR has intelligence to sense, learn and optimize performance where, the communication system can take predictive actions by referring to diverse optimization algorithms used in different layers of the radio protocol stack for selection of radio access technology (Alqahtani *et al*., 2023; Anandakumar and Umamaheswari, 2017). According to Anjum *et al*. (2016), generated traffic can be classified into four different priority levels with associated sensitivity to latency as shown in Table 1. The QoS traffics are further categorized into real-time (RT) and non-real-time (NRT) traffic. Consequently, it becomes important to develop intelligent dynamic spectrum management schemes to efficiently allocate spectrum resource and ensure the smooth coexistence of users with varied QoS guarantees.

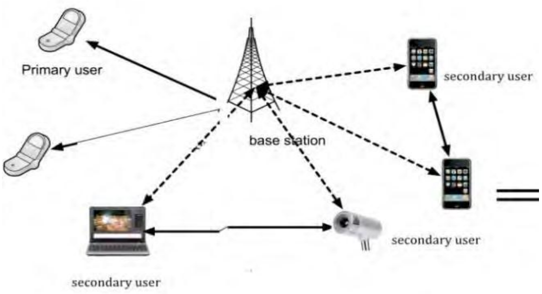

Figure 1: A CRN architecture

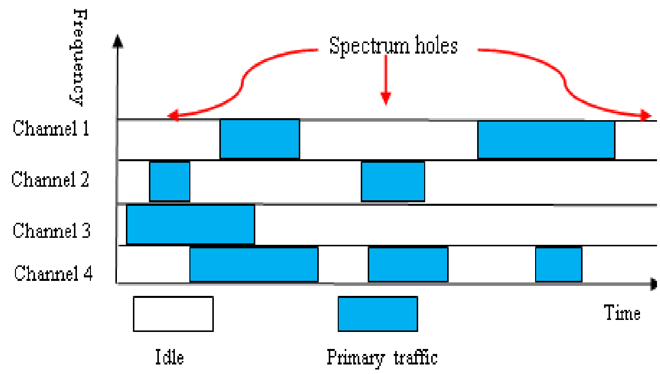

Figure 2: Existing fixed spectrum allocation scheme

Table 1: Traffic type and QoS requirements

Traffic Type	Description	Priority	QoS Type
Voice	Traffic is more sensitive to latency e.g. voice call, audio streaming	Highest priority	RT
Video	Traffic is sensitive to latency e.g. video conferencing, video streaming	Second highest priority	RT
Best effort	Bursty traffic, less sensitive to latency e.g. web browsing	Lower priority	NRT
Backgr ound	Traffic has no strict latency e.g. email, print jobs	Lowest priority	NRT

Although a number of researches have addressed the problem of spectrum holes detection and allocation, many of them do not specify the space big enough to be classified as spectrum hole for specific applications (Tlouyamma and Velempini, 2021; Jasrina *et al*., 2016; Anjum *et al*., 2016), despite using inefficient energy detection approach. Some works do not consider the diverse QoS requirements from the applications of the incoming SU requests (Yawada and Dong 2019). Still, most works consider single or at most two frequency bands such as Television (TV) bands and/or Wireless Fidelity (Wi-Fi), 2G Global System for Mobile Communications (GSM) or 3G Universal Mobile Telecommunications System (UMTS) channels (Giral *et al*., 2021; Hernández *et al*., 2018; Aguilar-Gonzalez *et al*. 2016; Hernández *et al*. 2015a), where the switching decision is not activated by intelligent soft computing techniques (Aguilar-Gonzalez *et al*. 2016; Salgado *et al*. 2016; Vithalani and Vithalani, 2017) on realistic data.

The objective of this work is to develop a QoS-aware framework for efficient spectrum management in CRN by utilizing two intelligent techniques namely, Support Vector Machine (SVM) and Adaptive-Neuro Fuzzy Inference System (ANFIS). The SVM model is used to accurately predict the existence of spectrum holes to facilitate higher detection probability while ANFIS model selects the best available spectrum hole, from the given pool, for allocation to SUs. The significance of SVM is that it allows the data to be precisely classified into one of two classes (idle or busy channels) by defining a margin or hyperplane. Unlike other classifiers, SVM increases the confidence of classification by maximizing the decision surface with less computation, allowing a clear separation of data in the data space. ANFIS implements a hybrid framework that combines the learning capability of artificial neural network and the output of fuzzy logic (FL) decision, for fast, accurate and excellent generalization results. Our channel assignment algorithm, within the framework, ensures that only bandwidth size greater than or equals to 7 MHz are allotted to RT application requests of SUs while the rest are allotted to NRT application requests. The performance of the ANFIS model in the task of efficient channel allocation is evaluated using accuracy metric while precision, recall, and F1-score are used to analyze the performance of the SVM classifier in spectrum holes prediction. This approach can ensure fairness, minimize spectrum handoff, maximize spectral efficiency and network throughput. It can further advance the emergence of new operators, innovative services and wireless technologies for diverse IoT applications. Finally, improved revenue generation to service providers and higher satisfaction to all network users shall be guaranteed. Basically, traffic data was collected from the switching office of a network operator on 3G UMTS and 4G Long-Term Evolution (LTE) networks as primary networks while Wi-Fi data from obtained from the research in Ekpenyong *et al*., (2018). Based on the allotted frequency bands of these networks, the activities of the PUs are considered while SUs with different QoS demands are expected to detect available spectrum holes for possible transmission on the band.
Although, spectrum activities vary with time, frequency and spatial domain, this work explores only time and frequency domains while the spatial domain is kept constant as the experiments are conducted in one geographical location within the same altitude. Lastly, the underlay scheme of spectrum access is adopted where SUs are allowed to share the channel with active PUs provided that an SU interference level does not exceed an acceptable threshold called interference temperature, which is set to 5.1dB. This is unlike the interweave or overlay schemes where SUs must give up the utilized spectrum whenever a licensed PU begins transmission (Khalid and Yu, 2018). Our approach promises adaptation to real-time spectrum conditions, offering regulators, licenses, and the general public flexible, efficient and comprehensive use of the spectrum. It can support network service providers in optimizing the allocation of limited spectrum resources by prioritizing SUs for admission. The spectrum decision shall be network-assisted. The rest of the paper is organized as follows.

Section 2 reviews related literature on CRNs by summarizing various strategies adopted by previous studies for spectrum detection and channel allocation toward efficient spectrum management. Section 3 presents the proposed QoS-aware framework for efficient spectrum switching decision while Section 4 discusses the results obtained from developing the framework with visualized outputs. Section 5 concludes the paper with direction for future works.

RELATED WORKS

CR technology supports the IEEE 802.22 wireless standard to provide transparency in radio resource management by affording cognition for diverse services and applications (Ali *et al*. 2020). This attempts to guarantee fairness to both PUs and SUs. Essentially, spectrum sensing involves the compilation of spectrum measurements and user preferences from the radio environment for proper cognition and flexible spectrum usage. The cognition circle of a cognitive radio is shown in Figure 3, where the CR decides about its action, after observing its environment. An initial switching may lead to an immediate action, while usual operation implies a decision making based on learning from observation, historical data and the consideration of the actual state of the environment. A message may be sent to the SU to dynamically reconfigure its parameters such as transmission power in order to transmit within the allotted frequency channel of available spectrum holes (Tlouyamma and Velempini, 2021).

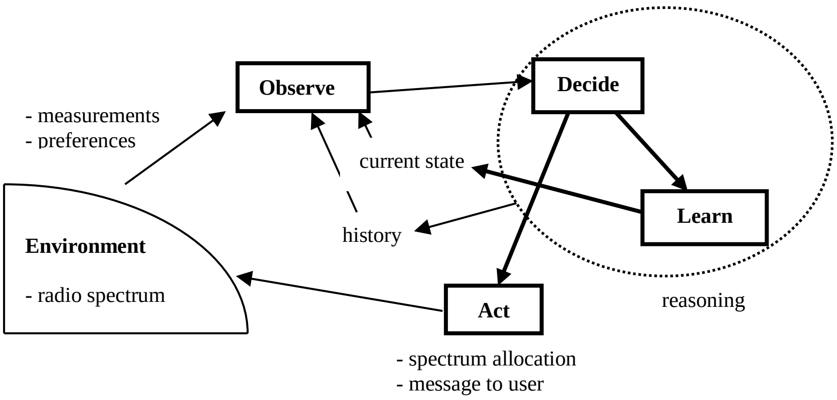

Figure 3: Cognition circle of a cognitive radio

According to Bharatula (2014), the paucity of electromagnetic spectrum is further due to inadequate access techniques rather than non-availability. This has resulted in reconsideration of spectrum usage regulation by the government including the technology of spectrum access itself. Many research have considered overcoming this problem (Asuquo *et al*., 2020; Dhivya, and Murugesh, 2017; Zheng and Hua, 2016; Christian *et al*. 2012; Ghasemi and Sousa, 2008), using reactive measures whereas few works exist on the use of proactive strategies (Ozturk *et al*., 2019; Devanarayana and Alfa, 2015; Dhivya *et al*. 2013). With the current massive connectivity of mobile devices for IoT-based applications (Devaraj *et al*. 2022; Tarek *et al*. 2020), it becomes necessary to deploy appropriate channel allocation schemes to ensure fast end-to-end transmission of data packets, especially with resource-constrained devices. Figure 4 shows a taxonomy of spectrum sensing techniques (Robinson and Asuquo, 2018), which is broadly categorized into cooperative, non-cooperative, and interference-based techniques.

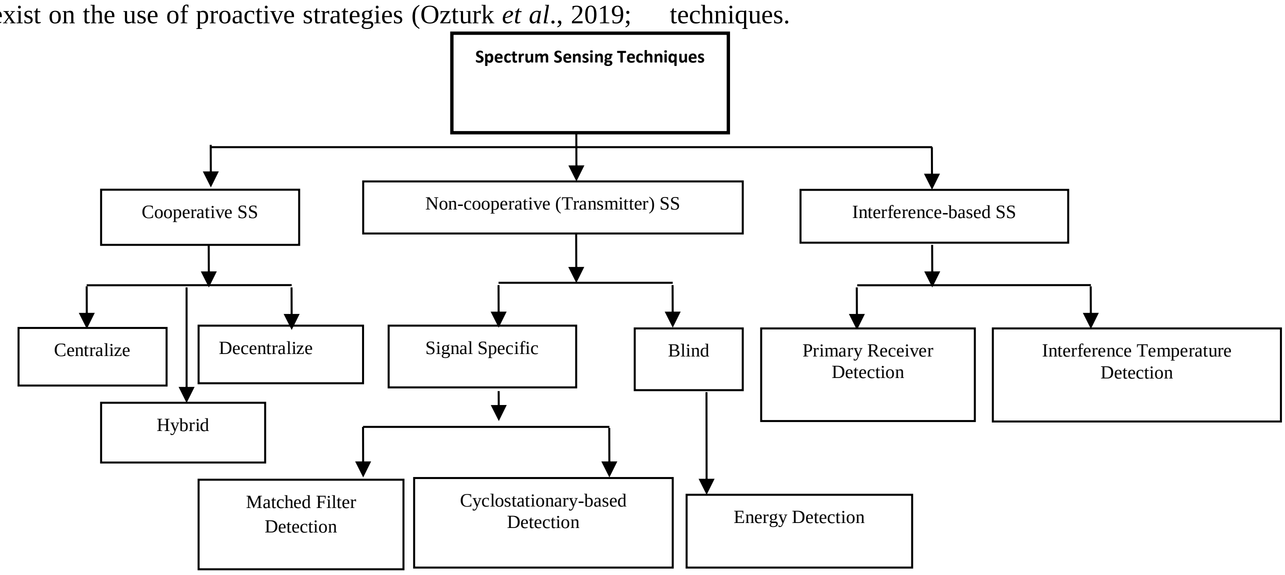

Figure 4: Categories of spectrum sensing techniques

While sensing based on channel history affects energy-efficiency as the same energy needed to operate the device is also used for sensing, which eventually drains its battery and reduces the device's lifetime, blind sensing algorithm does not permit SU device to learn from the environment before taking channel switching decision, whereby any instance sensing from the SU may cause undesirable interference with the transmission of PUs. Interference-based sensing attempts to determine the signal-to-interference ratio (SINR) of the SU and compares it to a threshold called interference temperature. If the SINR of any SU exceeds this threshold for specific bands, then the SU call request will not be admitted into the network. The SU will have to adjust or reconfigure its settings in order to access available spectrum holes

Previous studies have presented different approaches for spectrum sensing and channel allocation including the use of methods like Multi-Attribute Decision Making (MADM), Fuzzy Logic (FL), Machine Learning (ML) and Evolutionary Algorithms (EA). The following sub-sections briefly describe their deployment, strengths, and weaknesses.

However, most of the past works did not explicitly determine the bandwidth size considered as whitespace for opportunistic access by SUs. Some studies only focus on TV bands or combine Wi-Fi and 2G GSM bands, ignoring the utilization of 3G UMTS and 4G LTE spectrums for mission-critical applications especially with the increasing demand for IoT-based services. There is need to also consider the diverse QoS requirements of the SUs for different applications including voice, data, video, streaming, chatting, web browsing, and email downloading services.

MADM Approach

Spectrum allocation in CRN requires the consideration of multi-criteria for efficient spectrum decision. Recently, the use of MADM approach for spectrum switching decision has been common. Giral *et al*. (2021) evaluated the performance of spectral decision algorithms implemented in a multi-user environment that allows multiple access and exchange of information between users, with experimental spectral occupation data. Results indicate that Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method outperforms Vise Kriterijumska Optimizacija kompromisno Resenja (VIKOR) and Simple Additive Weight (SAW). It limitations are that only real power measurements of 2G GSM frequency band were considered as input variables along with simple energy detection sensing method. Noting that continuity of service during handoff with required QoS is an important issue in CRN, Driouache *et al*. (2018) proposed a rank average method for the best access network selection. The authors deployed two MADM methods of TOPSIS and VIKOR, together with Shannon entropy-based weights. Results indicate that rank average outperforms TOPSIS and VIKOR in terms of throughput, end to end delay, packet loss, and significantly reduces the number of unnecessary handoffs related to the ping-pong effects. Although real-time and background applications such as video streaming, Voice over Internet Protocol (VoIP), web browsing, and email services were the simulated SU traffic types, only Worldwide Interoperability for Microwave Access (WiMAX), Wi-Fi, and LTE access networks were considered.

Bernal and Hernández (2017) proposed the design of a dynamic decision-making model in cognitive wireless networks that allows SUs to opportunely harness the spectrum and use channels without affecting the traffic of PUs. The results indicate that the Grey Rational Analysis (GRA) algorithm in combination with SVM algorithm outperforms the one with K-nearest neighbour (K-NN) in terms of choosing an available channel, reducing the PU's interference and diminishing the rate of handoffs. The study was limited to the 2G GSM frequency band with a sweep time of 290ms. Vithalani and Vithalani (2017) proposed the combination of TOPSIS and Analytic Hierarchy Process (AHP) optimization spectrum selection algorithms based on the evaluation of different channels characteristics to obtain an optimized solution in selecting the best available spectrum to satisfy QoS demands of the SUs, without interfering with transmission of the licensed PUs. The study presumed a CRN with a maximum of 8 spectrum holes and used bandwidth (BW), Signal-to-Noise Ratio (SNR), transmission power, and spectrum interference as spectrum parameters for the algorithms. Another work by Kumar *et al*. (2017) investigates the task of optimal network selection for spectrum handoff decision with MADM methods of SAW, TOPSIS, GRA and a cost function to provide wider and optimal choice with QoS. The CR preferences are based on voice, video and data services. Numerical results show that all MADM methods are effective for selecting the optimal network for spectrum handoff with a reduced complexity for the spectrum handoff decision. The study mainly focused on spectrum handoff functionalities while envisaging future CR deployments to facilitate the coexistence of CR networks in overlapping areas.

In Salgado *et al*. (2016), an MADM based on AHP and FL was applied to find a channel with the required characteristics for continuous communication of SUs in CRNs. The authors present a fuzzy algorithm for the spectrum decision function and in particular for the selection of a backup channel in spectral mobility. The evaluation was limited to real experimental data of the spectrum occupancy measured in a Wi-Fi network using metrics such as accumulative average of failed handoffs, accumulative average of performed handoffs and, average of transmission bandwidth. The proposed algorithm provides an effective frequency channel selection where results show a reduction of the rate of channel changes in contrast to the AHP selection method. Similarly, Aguilar-Gonzalez *et al*. (2016) proposed an MADM-based spectrum decision in CRNs aimed at reducing spectrum handoffs and energy consumption during switching to sustain CR user's battery lifetime. Performance evaluation with three MADM techniques – SAW, TOPSIS and VIKOR was limited to real spectrum measurements of TV bands. To achieve high accuracy results, this spectrum decision process was simulated by means of a 1000-round Monte Carlo method using MATLAB.

Hernández *et al*. (2015b) proposed a proactive channels selection scheme based on fuzzy AHP (FAHP) method. The selected criteria for choosing the best backup channel are probability of channel availability, estimated channel time availability, SINR, and bandwidth. These criteria are determined by means of a customized Delphi Method and using the FAHP technique; the corresponding weight and significance is calculated for two applications classified as best effort (BE) and real time (RT). The insertion of the fuzzy logic in the AHP algorithm allows better handling of inaccurate information. The performance evaluation of the proposed method was limited to experimental data realized at the GSM frequency band.

It is important to note that while FL-based approaches can handle uncertainty, imprecision, and vagueness present in radio environment data, other mentioned methods lack the capability to learn from historical data and predict future outcomes for new unseen data.

ML Approach

Hernández *et al*. (2018) proposed the use of the long short-term memory (LSTM) technique based on the deep learning concept in order to reduce the forecasting error present in the future estimation of PUs in the GSM and Wi-Fi frequency bands. The result shows that LSTM has the capacity to significantly improve channel use prediction. However, implementation is feasible in CRNs based on centralized network topologies only.

The ability of particle swarm optimization (PSO) technique to optimize a neural network modeling of data patterns for TV idle channels prediction was proposed by Ojenge *et al*. (2013). However, data were collected only for two hours every day (5pm to 7pm) within a period of four weeks. This was not sufficient to capture all the various trends associated with TV broadcast. Also, identifying the idle channels does not depict any spatial or temporal information of the expected noise and/or level of interference based on the channels history which is vital in selecting the channels to be used among the idle channels. Spectrum holes prediction using Elman recurrent artificial neural network (ERANN) was proposed by Taj and Akil (2011). The work used the cyclostationary features of modulated signals to determine the presence or absence of primary signals while the input of the ERANN consists of time instances. The inputs and the target output used in the training of the ERANN and prediction were modelled using ideal multivariate time series equations, which are often different from real life RF traffics where PU signals can be embedded in noise and/ or interfering signals.

ANFIS was used for prediction of transmission rate by Hiremath and Patra (2010). This model was designed to predict the data rate (6, 12, 24, 36, 48 and 54 Mbps) that can be achieved in wireless local area network (WLAN) using a 802.11a/g configuration as a function of time. The training data set was obtained by generating a random data rate with an assigned probability of occurrence at a given time instance, thus forming a time series. In this study, real world RF data was not used. More importantly, the research did not take into account the dynamic nature of noise or interference level which can affect the predicted data rates. A FL-based decision system was modelled for spectrum handoff decision in a context characterized by uncertain and heterogeneous information by Bayrakdar and Çalhan (2015) and fuzzy logic transmit power control for cognitive radio. The proposed system was used for the minimization of interference to PU's while ensuring the transmission rate and QoS requirements of SU. The researcher did not, however, include any learning from past experience or historical data.

Other Spectrum Management Approaches

Other methods like matching theory, Markovian models, evolutionary algorithms, and game theory have also been deployed (Zakariya *et al* 2020; Jasrina *et al*. 2016; Butun *et al*. 2010) but with inherent limitations. For example, in matching theory, the preferences of both users and channels are based on the same utility function which primarily captures the rate of transmission. The process of finding the optimal solution with evolutionary algorithms is quite slow and there is always the risk of finding a local minimal and not the globally optimal solution. Markovian models are suitable for modeling and analyzing time series or sequential data. They are not suitable in modeling the dynamic nature of CR users for adaptive spectrum access. Finally, in game theory, finding the pareto-optimal solution is difficult since it is impossible to reallocate spectrum resource so as to make any individual's preference or criterion better off without making at least another individual preference or criterion worse off.

Existing literature shows that methods for spectrum selection and channel allocation in CRNs for SUs continuous communication abound. However, most studies focused on the use of MADM and FL methods on TV, GSM, and Wi-Fi frequency bands, whereas the present research includes currently deployed 3G UMTS and 4G LTE frequency bands in its intelligent spectrum management framework. While most studies attempt to maximize throughput, reduce delay and unnecessary spectrum handoffs, only a few considered SINR of the SU in comparison with the interference temperature on each spectrum. Furthermore, this study considers both RT and NRT applications including messaging, VoIP, email downloading, web browsing, and streaming services. Realistic spectrum data obtained from the switching office of a network operator is used for training and evaluating the intelligent models.

The present study aims to actualize two spectrum management functionalities - spectrum sensing and spectrum switching decision, by developing a QoS-aware framework for accurate spectrum holes prediction, efficient selection and optimal allocation of frequency channels to SUs. It adopts the interference temperature condition to avoid undue interference of SUs with PUs' activities. SVM and ANFIS soft computing techniques are used to implement the procedures in a framework that specifies the unused bandwidth size considered spectrum holes for the different traffic types. The diverse QoS demands from the applications of the incoming SU requests are taken into consideration before SUs are allocated channels from the available frequency bands in the TV, Wi-Fi, 2G, 3G and 4G spectrums.

The choice of SVM algorithm is necessitated in its ability to use appropriate kernel function to define the hyperplane for separating linearly, non-separable data. The kernel function transforms the input data into the desired output label (idle or busy channel) using optimization functions. SVM is prone to less over-fitting as this algorithm is more generalized in practice. Additionally, ANFIS is a simple learning technique that uses fuzzy logic to transform given inputs into a desired output through highly interconnected neural network processing elements and information connections, which are weighted to map the numerical inputs into an output. It provides excellent explanation facilities with semantically meaningful fuzzy rules. Also, the use of optimization routines by ANFIS to adjust parameters can help to reduce error measures and improve channel allocation accuracy.

METHODOLOGY

A QoS-aware proactive approach for spectrum switching decision

Figure 5 shows the proposed QoS-aware framework for effective spectrum holes selection and optimal spectrum switching decision in CRN. The major components of the framework include Radio Environment, Spectrum Database, Spectrum Decision Module which splits into spectrum holes prediction and channel classification by SVM including channel assignment by ANFIS, Spectrum Handoff, Spectrum Sharing, and Performance Evaluation.

The Radio Environment is where spectrum measurements and CR user preferences are obtained to help characterize channels and determine how best to admit incoming request for flexible spectrum usage. At this point, the SINR of the incoming SU is estimated along with the current spectrum occupancy rate. Such SU and PU parameters along with any historical data are stored in the Spectrum Database. Available frequency bands for different networks including TV, Wi-Fi, 2G, 3G, and 4G constitute the Radio Environment.

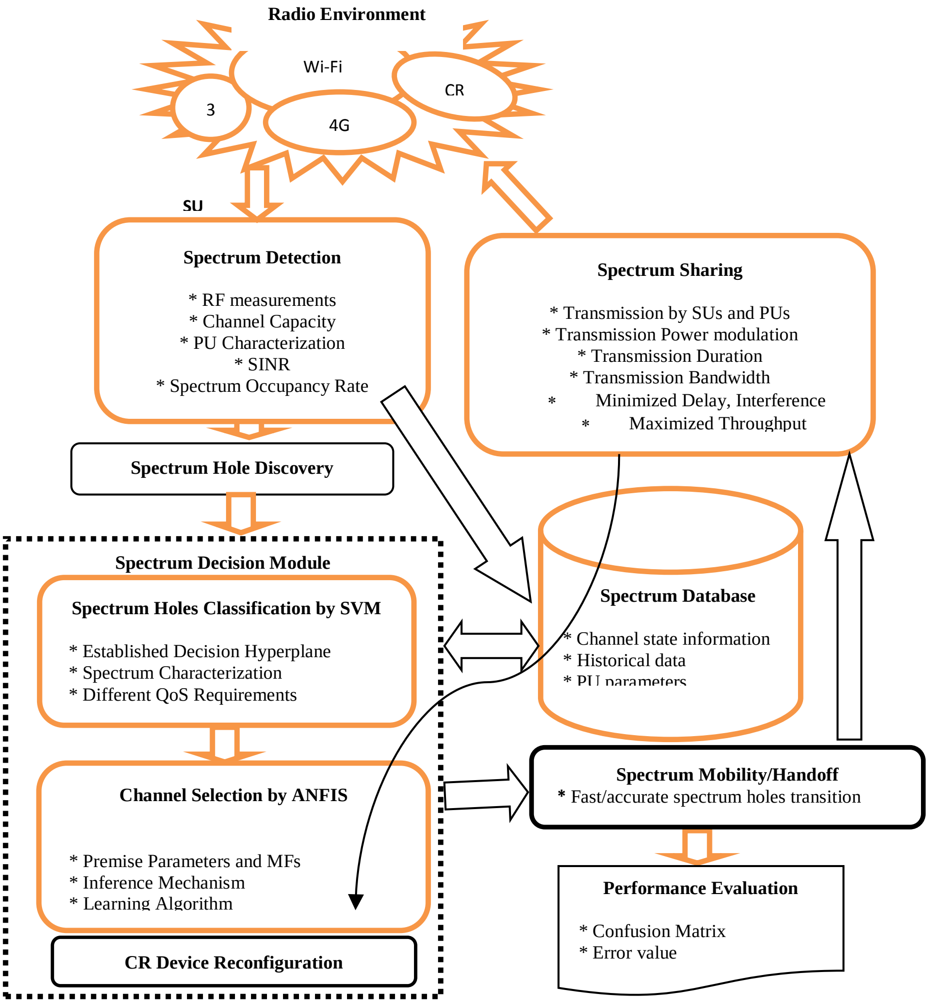

Figure 5: Proposed QoS-aware framework for spectrum switching decision in CRNs

Information from the Radio Environment through spectrum sensing enables detection of unused spectrum bands (spectrum holes) showing different characteristics in terms of bandwidth size. The Spectrum Decision Module then invokes the SVM model to classify available spectrum bands into two labels; idle (free) and busy (used). The Spectrum Decision Module also characterizes free spectrum bands to meet the QoS requirements of SUs. This guarantees that proper spectrum bands from the pool of free spectrums are selected for RT and NRT applications. For training the SVM model to classify spectrum bands into 'used' and 'free' spectrum classes, five parameters were used, of which one served as output parameter. The input parameters are probability of channel availability (PCA), average availability time (AAT), PU signal (PUS), SU signal-to-interference-noise ratio (SU_SINR) while channel state information (CSI) serves as output, classifying spectrum into two labels: 'free' and 'used'. We assume that transmission and sensing cannot take place at the same time by the SU to avoid interference with PU traffic. Thus, an SU is not permitted to transmit during sensing (observation time). Due to this hardware restriction, SUs are to sense the spectrum periodically with sensing period, T_s and observation time, t_s in the proactive mode. The periodic spectrum sensing ensures that interference is avoided based on interference temperature so as to guarantee the efficient use of spectrum resource. This enables determination of spectrum utilization factor and the continuous monitoring of QoS guarantee of an SU's transmission while enabling spectrum sharing due to SU's admission into the network. Figure 6 illustrates this proactive periodic spectrum sensing approach.

Since SUs are allowed to coexist with the PUs within a given frequency band and at a given geographical location, the SU transmitting power must be controlled to avoid any harmful interference to the PUs. Each SU can transmit along with the PU as long as the aggregate interference at the PU's receiver does not exceed a threshold called the interference temperature limit. The interference temperature (T_I) refers to the temperature equivalent of the aggregate radio frequency (RF) power at the PU's receiver antenna per unit bandwidth, resulting from both PU and SU transmitters, and noise. It is expressed mathematically in Equation (1), and regulated for each spectrum band, as follows:

$$T_I(f_c, BW) = \frac{P_I(f_c, BW)}{K \times BW} \quad (1)$$

where, $P_I(f_c, BW)$ is the average interference power in Watts centered at frequency f_c, BW is the bandwidth in Hz, K is Boltzmann constant in Ws/K while $T_I(f_c, BW)$ is the interference temperature in Kelvin. Therefore, the spectrum sensing model is given in Equation (2) as:

$$y(n) = \begin{cases} w(n) & ; \; PU\ absent \\ h \times s(n) + w(n); & PU\ present \end{cases} \quad (2)$$

where, $n = 1, \ldots, N$ and N is sample number; $y(n)$ is the SU's received signal; $s(n)$ is the PU's signal; $w(n)$ is the Additive White Gaussian Noise (AWGN); while h is the channel gain with value less than 1. However, the channel power gain h, is given by:

$$h = 10 \log_{10} {}^{P_r}/_{P_t} \, (dB) \quad (3)$$

where, P_t is the transmit power and P_r is the received power.

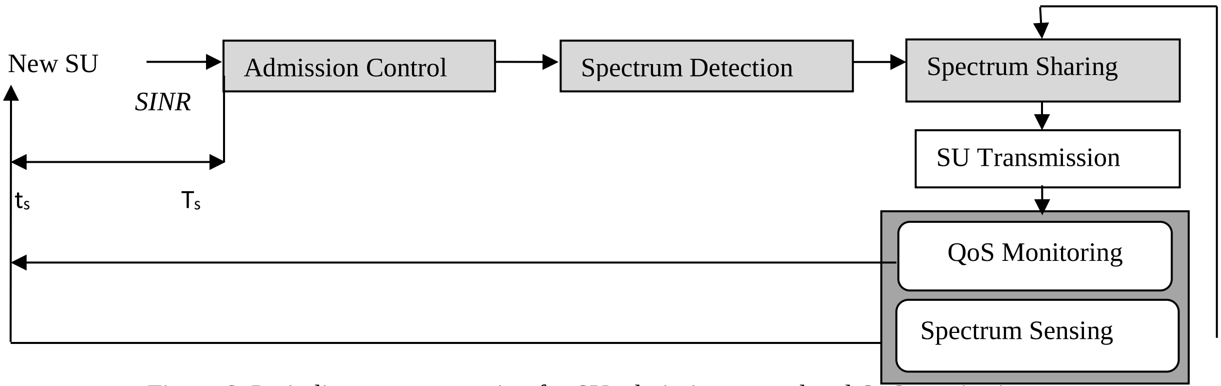

Figure 6: Periodic spectrum sensing for SU admission control and QoS monitoring

Measurements from the primary networks at the Radio Environment are used by SUs to estimate the channel conditions such as the number of available channels (NAC), SINR, number of SUs (NSU), and channel switching delay (SDE). Consequently, to describe the dynamic nature of the CRN, a new parameter, PU activity (PUS), is introduced. It is defined as the probability of the PU appearance during the SU transmission. After spectrum characterization by SVM, the CRN uses ANFIS optimization technique to choose the best free spectrum bands for a given SU application. These parameters served as inputs to the ANFIS model while probability of channel selection (PCS) was the output parameter. These premise parameters and their membership functions (each having as term: Low, Moderate, High) were used by ANFIS inference mechanism and learning algorithm to predict the accuracy of selecting best available free channels for SU applications in CRN.

Moreover, the dynamic and adaptive ANFIS model allocates idle frequency bands based on the time-varying CRN capacity. However, SUs are expected to vacate allocated channels and perform spectrum handoff to other free spectrum holes once a PU appears to utilize the current band or if the SU device re-configuration could not satisfy interference temperature condition. The proposed dynamic channel allocation adopted is done in a way that minimizes incessant spectrum handoff, service quality degradation and undesirable ping-pong effect. Thus, this approach facilitates seamless SU transmission with desired QoS, fast switching decision, higher spectral efficiency, and improved network throughput. The performance of the SVM classifier is evaluated using the generated confusion matrix that presents probability of false alarm and true positive in spectrum holes prediction while the ANFIS model is evaluated using the root mean square error (RMSE) metric.

Spectrum Holes Classification with SVM

The SVM model is trained to generate a linear separator or hyperplane. The training process consists of finding a decision function capable of separating the spectrum bands making use of the optimization function of Equation (4) (Asuquo *et al*., 2023). Then, given a new vector x, the class in which each spectrum channel belongs is determined. This allows the determination of bandwidth size for ranking and assignment to SUs based on QoS requirements.

To further explain space considered spectrum hole in this work. Let assume that the frequency band within 1920-1944 MHz for uplink communication in 3G spectrum is split as shown in Figure 7. It is important to note that '1' indicates that the channels are being used and declared 'busy' while '0' indicates that the channels are free and declared 'idle'. However, only idle channels that add up to a difference of 7 MHz and more are utilized as spectrum holes for assignment to RT applications of SUs. Other whitespaces less than 7 MHz are assigned to NRT applications to avoid undue interference with PUs, reduce incessant handoff and undesirable ping-pong effect. This accommodates the spectrum measurements guidelines for TV frequency bands according to the technical details from the IEEE 802.22 standard (Wang *et al*. 2010), pointing to the fact that there is a functional signal bandwidth of 5.5MHz for a 6MHz TV channel while 2G are deployed in blocks as small as 6.8MHz to as large as 74.6Mhz.

1920	1922	1924	1928	1930	1932	1935	1936	1938	1940	1942	1944
1	1	0	0	0	1	0	0	0	0	0	1

space considered spectrum hole for RT
1942 – 1935 MHz = 7 MHz

Figure 7: QoS-aware spectrum holes detection

Ideally, given a dataset with n dimensional features and a target variable $\{(X_1, y_1), (X_2, y_2), \ldots, (X_m, y_m); i = 1, \ldots, m\}$, where, $X \epsilon R^n$, $y \epsilon R$. The objective of the SVR model is to find a function $f(x)$ with at most ε-deviation from the observed target, y. Since the relationship between X and y is non-linear, a non-linear SVR model formulated as a maximization problem is given as follows:

$$\max \left\{ \frac{1}{2} \sum_{i=1, j=1}^{m} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \langle \Phi(X_i), \Phi(X_j) \rangle - \varepsilon \sum_{i}^{m} (\alpha_i + \alpha_i^*) + \sum_{i}^{m} y_i (\alpha_i - \alpha_i^*) \right\}$$

Such that:

$$\sum_{i=1}^{m} (\alpha_i + \alpha_i^*) = 0; 0 \leq \alpha_i, \alpha_i^* \leq C \qquad (4)$$

where, α_i and α_i^* are the model weights, ε is epsilon, and C is the complexity and number of support vectors. The dot product is computed in Equation (5) as:

$$\left(\phi(x). \phi(X_i)\right) = K(x, X_i) \qquad (5)$$

where, $\phi(X_i)$ and $\phi(x)$ are the mapped vectors. The $\phi(X_i)$and $\phi(X_j)$ mapping functions are computed using radial basis function kernel, $K(x, X_i)$ using Equation (6) as follows:

$$K(x, y) = \exp(-\frac{1}{2\sigma^2} ||x - y||^2) \qquad (6)$$

The output of the SVR algorithm, which is the predicted spectrum availability, is obtained as expressed in Equation (7).

$$y_i = \sum \alpha_i K(x, X_i) + b \qquad (7)$$

where, y_i is the predicted spectrum hole, α_i is the model's weight; b is the bias; and $K(x, X_i)$is the kernel function. The step-wise analysis of the SVR structure used in this work is presented in Figure 9.

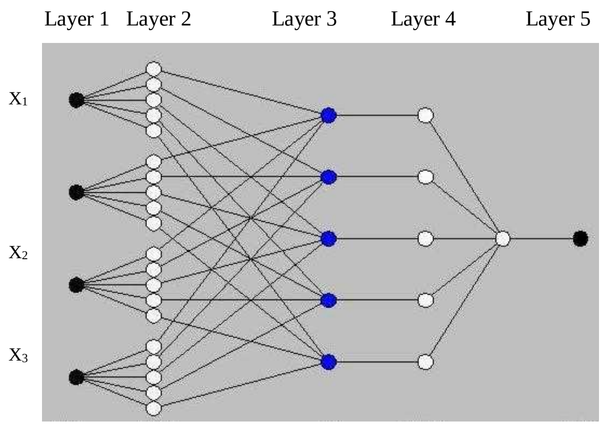

Figure 9: ANFIS structure for channel allocation optimization

After splitting each spectrum band into two classes of free (idle) and used (busy) channels, the decision hyperplane is obtained with the SVM model during network training. Cognizance is taken of certain spectrum characteristics such as PCA, AAT, PUS, and SU_SINR. The spectrum of frequencies with bandwidth size greater than or equals to 7 MHz are assumed to have the greatest availability probability, estimated availability time and a low PUS are labelled as channels suitable for supporting the transmissions of RT applications (VoIP, streaming), while the rest of the points are labelled as channels for the transmission of NRT applications (email, messaging, downloading). It is expected that SUs admitted by the base station during spectrum allocation process are delivered the best quality channels first for RT applications, and the moderate quality channels to NRT applications. However, if the range of frequencies in a category is exhausted, an SU may use the spectrum of the other category, subject to, in the worst case, degradation in the QoS.

Channel allocation optimization with ANFIS

The ranking of the channels with ANFIS model was implemented in MATLAB using Takagi-Sugeno inference type. Figure 9 describes the structure of the ANFIS scheme. The channel characteristics are found in the input layer; the membership functions are defined in the next layer (high and low for each input); the third and fourth layers calculate the rules and establish the Takagi-Sugeno type inference; the fifth layer performs the summation of the outputs in order to obtain the scores for each channel and determine the ranking. The parameters X_1, X_2, X_3, X_4 in the ANFIS structure denotes NSU, NAC, PUA, and SDE respectively while PCS

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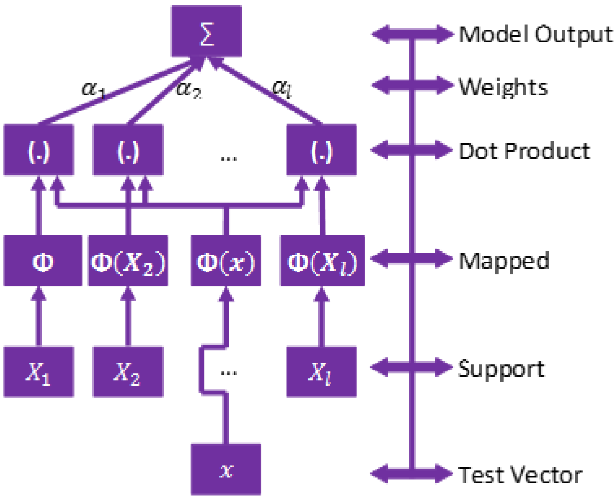

Figure 8: Structure of SVR Model

Membership functions (MFs) were created for each parameter, with defined Universe of Discourse (UoD), where three linguistic terms of Low, Moderate, and High resulted in 81 fuzzy rules for the inference mechanism. The decision was made to work with only three linguistic terms in order to limit the amount of computing resources required by the system, and thus reduce the algorithm's compilation time. The parameter set of the adaptive ANFIS network allows fuzzy systems to learn from the data they are modelling. In the proposed ANFIS-based channel selection model, the number of training epochs, the number of MFs and the number of fuzzy rules have to be accurately tuned. Mapping of those parameters were done to avoid the system over fitting or under fitting the data. To improve the rate of convergence, this adjusting was obtained by using the hybrid learning algorithm where the least square method (LSM) and gradient descent method (GDM) are combined. The lesser difference between ANFIS channel selection probability output and the desired objective means a better (more accurate) ANFIS system.

Thus, the work aims to reduce the training error where the output error is used to adapt the premise parameters by means of a standard back-propagation algorithm thereby minimizing the RMSE cost function defined as:

$$\mathrm{RMSE} = \frac{1}{2}\sum\left\|t^i - a^i\right\|^2 \quad (8)$$

where, $t^i$and a^i are the target output and the actual output, respectively. In Equation (8), the squared error is minimized by division by 2 and is called the least squares estimator. Therefore, the hybrid learning algorithm is applied directly and structured by defining linear and nonlinear parameters illustrated at each iteration (epoch), where the GDM updates the nonlinear parameters, while the LSM follows to identify the linear parameters.

RESULTS AND DISCUSSION

Experimental Setup

The widely used IEEE 802.11 Wi-Fi network in a campus environment for wireless multimedia services is studied along with TV bands in Uyo City, 2G, 3G and 4G networks. TV band of 170MHz to 225MHz, Wi-Fi frequency band of 2.4 GHz to 2.5 GHz, 2G spectrum ranges of 800MHz - 1800MHz, 3G spectrum ranges of 1900MHz to 2025MHz and 4G spectrum ranges of 1920MHz - 2600MHz were studied. Each range is divided into a multiple of channels. CRNs offer enormous advantages in spectrum band utilization such that when a licensed PU is unavailable by virtue of time and location, an unlicensed SU can utilize or share the spectrum to eliminate wastage in terms of bandwidth utilization and revenue generation.

The experiment is conducted in Matrix Laboratory (MATLAB) software R2021a version on Intel(R) Core(TM) i5-4300U CPU @ 1.90GHz 2.50 G with 8.00GB RAM. The study assumes a CRN with a maximum of 80 CR transmissions that coexist with 30 PUs in a field of 100 x 100 m^2. PUs operate at the TV, Wi-Fi, 2G, 3G and 4G frequency bands for uplink transmissions where SUs are expected to opportunistically access the spectrum holes based on the interference temperature principle. The interference temperature is a threshold for which SUs must handoff to another channel if its SINR exceeds this value. The threshold is set to 5.1dB while the minimum switching delay is set to 20ms.

Channels considered big enough to be used as spectrum holes for assignment to incoming RT applications of SUs must be equal to or greater than 7 MHz. The rest are assigned to NRT applications. This is to ensure efficient spectrum allocation by preventing incessant handoff and undesirable ping-pong effects where SUs might be advised by the system to vacate current spectrum holes once a PU arrives to avoid unnecessary interference. Also, it will ensure link-quality is maintained between communicating SU pairs. Each channel has a two-state status of BUSY and IDLE respectively. A time-critical application is considered in this work whereby any given data packet whose transmission delay is greater than the threshold is considered invalid and must be re-transmitted. While SVM performs classification to determine available spectrum holes, ANFIS optimizes the task of best channel assignment to SUs for effective spectrum decision and management in CRN.

SVM Performance Evaluation

A dataset of 700 data points, split in the ratio of 7:3 was used to train and test the SVM model. Key parameters used include probability of channel availability (PCA), average availability time (AAT), primary user signal (PUS) and SU signal-to-interference ratio (SU SINR). The output is spectrum hole prediction, where '0' indicates absence of PU (availability of whitespace) and '1' indicates presence of PU (non-availability of whitespace). The sample dataset is shown in Table 2 while Figure 10 shows the scatter plot where blue dots represent '0' and red dots represent '1'. Results indicates that 49.1% of the spectrum are unoccupied by PUs while 50.29% are occupied.

Furthermore, the confusion matrix in Figure 11 indicates the predictive performance of the model where the highest training accuracy of 98.8% was obtained from Linear SVM model, after 10-fold cross validation at 2.413sec. This spectrum hole detection result is satisfactory as detection probability of 0.9 and false alarm probability of 0.1 are recommended. Quadratic, cubic, fine Gaussian, medium Gaussian, and coarse Gaussian SVM models yielded accuracy of 97.8%, 98.2%, 96.5%, 98.2%, and 98.2% respectively. However, with testing data, the confusion matrix in Figure 12 shows the Linear SVM classifier prediction performance with Recall of 1.0, Precision of 0.5215, F1-score of 0.6855 and specificity of 0.9901. Since Recall refers to sensitivity, which is a measure of correct classification in the positive category and specificity is used to measure the fraction of negative patterns that are correctly classified, SVM produces satisfactory results in the task of predicting spectrum holes for timely and accurate channel assignment to SU requests. The confusion matrix in Figure 12 further indicates that no spectrum hole was wrongly predicted as available and only one spectrum hole was wrongly classified as unavailable. Figure 13 shows a graphical illustration of the SVM result, which informs the choice of Linear SVM for further experiment while Figure 14 reveals SINR values of SUs. Only those SUs with SINR values less than interference temperature were admitted.

Table 2: Sample Dataset for SVM Model

PCA	AAT	PU Signal	SU SINR	Output
0.732568007	0.398429225	0.477556782	5.37257041	1
0.467872767	0.976423146	0.482225991	6.43469645	1
0.517135412	0.558478157	0.198488311	5.59150028	1
0.917457271	0.336719311	0.360167618	4.059909627	0
0.961885404	0.758974112	0.484323599	2.699873409	0
0.731044041	0.638627795	0.275496135	4.826861025	0
0.675205513	0.314197354	0.613269125	5.676402172	1
0.769564548	0.519711713	0.220157895	1.701510081	0
0.673446419	0.809569192	0.161455987	3.158535137	0
0.433863743	0.739078305	0.741155148	4.70502875	1
0.622212212	0.635649802	0.898272493	7.201489251	1

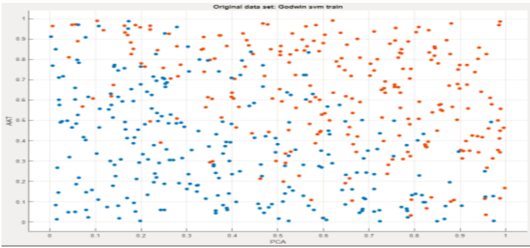

Figure 10: Scatter plot of data points indicating free and used spectrums

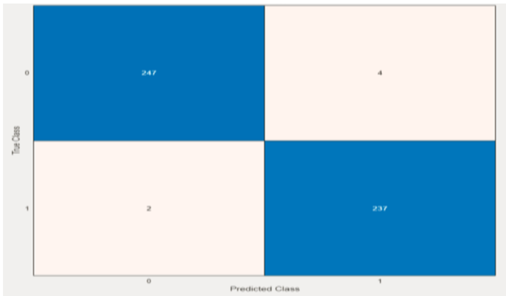

Figure 11: SVM training confusion matrix

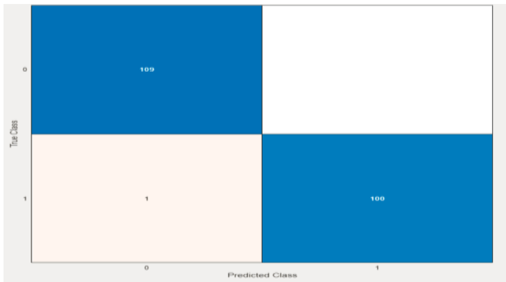

Figure 12: SVM testing confusion matrix

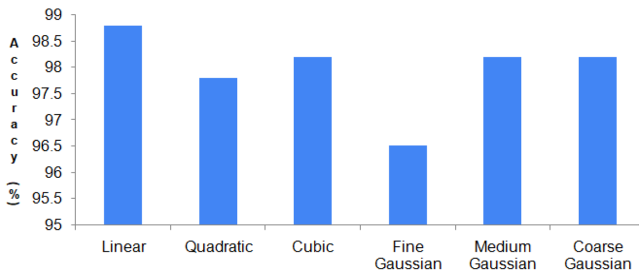

Figure 13: Comparison of SVM models' accuracy performance

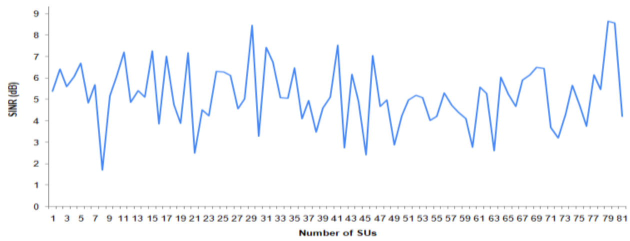

Figure 14: SINR values of SUs

ANFIS performance evaluation

For determining the probability of best channel selection, the parameters used by the ANFIS model are described in table

3, NSU, NAS, PUA, and SDE served as input parameters. After data pre-processing to handle missing values and ensure data quality, a total of 560 data pairs was used for the experiment and split into two for model training and testing in the ratio of 7:3. Table 4 shows the sample ANFIS dataset. Figure 16 indicates that a training error of 0.0862661 was obtained which results to an accuracy of 91.37% at epoch 50. However, at epoch 10, ANFIS was able to generalize the result. Further experiment reveals that a testing error of 0.0837601 was obtained which results to an accuracy of 91.62%. Finally, Figure 17 shows that as the number of channels increases, the probability of channel selection also increases thereby improving throughput and minimizing switching delay. Thus, ANFIS is robust and shows a good generalization capability in the tasks of allocating channels from the pool of available free spectrums to SU requests. This accurate prediction can ensure timely channel assignment, minimize delay and enhance overall throughput of the cognitive radio network.

Table 3: Simulation parameters for ANFIS Model

Parameter	Description
FIS type	Sugeno
Inputs/Output	4/1
Inputs MF type	Gaussian
Output MF type	Linear
Number of input MFs	12 for all inputs
Number of fuzzy rules	81
Number of linear parameters	405
Number of non-linear parameters	24
Total number of parameters	429
Number of nodes	193
Number of training data pairs	392
Number of testing data pairs	168
Number of epochs	50
Optimization method	Hybrid
Error tolerance	0

Table 4: Sample Data for ANFIS Experiment

NSU	NAS	PUA	SDE	PCS
31	1	0.33067113	0.032293475	1
34	0	0.256336771	0.314836976	1
21	1	0.034459587	0.0065274	0
11	0	0.290486492	0.357890171	1
32	2	0.465206556	0.26391198	1
50	2	0.224778274	0.155482575	0
52	1	0.038806847	0.070548058	1
15	2	0.448138173	0.453706191	0
62	3	0.079910958	0.005004113	1

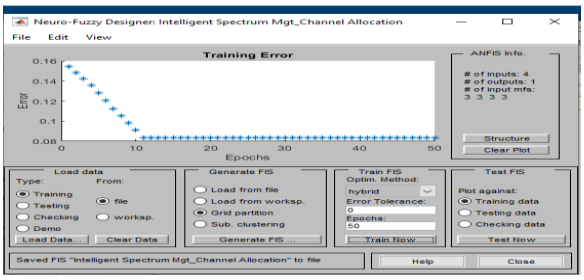

Figure 15: ANFIS training window

Implication of the Results

Channel assignment is considered a serious availability issue in information security, where requested services must be delivered to legitimate users. This study is limited to data collected from the switching office of a network operator for 2G, 3G and 4G frequency bands.

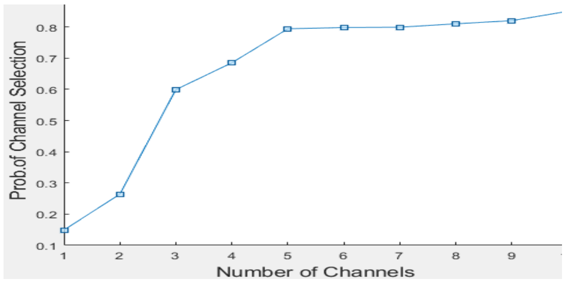

Figure 16: Channel selection probability

However, data for TV bands in Uyo city and Wi-Fi spectrum occupancy from a previous study (Ekpenyong *et al.*, 2018) in a university campus were used. The analysis of the spectrum occupancy rate over the five frequency bands (TV, Wi-Fi, 2G, 3G, and 4G), specifically at the uplink, verifies the high availability of spectral opportunity for selection to SUs. This work deployed hybrid intelligent techniques for improved spectrum holes detection and efficient channel allocation in CRNs. A recall of 1.0, specificity of 0.9901 and F1-score of 0.6855 indicates that the Linear SVM model can achieve precise spectrum holes detection with minimal false alarm which enhances SUs to make prompt switching decisions, avoiding frequent spectrum handoff with associated ping-pong effect. The accuracy of 91.62% shows that ANFIS model was able to effectively handle the uncertainty, imprecision and vagueness inherent in the measurements from varying channel conditions. This indicates a good generalization capability and robustness of the model in the task of allocating channels to SUs. The proposed framework allows multiple access to diverse frequency bands and, when deployed in a multi-user environment like healthcare, public safety, disaster relief and emergency, can support continuous end-to-end transmission of time-critical data packets for analysis and decision making.

CONCLUSION

The increasing number of IoT devices and the associated diverse applications accumulate additional pressure on network resources including bandwidth availability. Often times, IoT devices do send small number of packets to update a remote server or a cloud system including remote health monitoring applications and smart city systems. However, the fixed channel allocation policy obstructs access to unutilized spectrum thereby affecting seamless connectivity and continuous data transmission. Spectrum scarcity problem requires the consideration of adaptive and dynamic CR technology to achieve interference-free and on-demand IoT solutions for a number of applications. This work shows that the use of SVM and ANFIS models can significantly enhance effective spectrum holes detection and optimal channel allocation in CRN thereby supporting SUs to opportunistically exploit spectrum holes for RT and NRT service demands. Idle channels from the available frequency bands in the TV, Wi-Fi, 2G, 3G and 4G spectrums were considered for different applications with QoS requirements.

With the interference temperature principle and bandwidth size limit for spectrum holes access, SUs can leverage on the CR technology and easily realize maximal spectrum utilization.
Experimental results indicate that Linear SVM classifier outperforms others in the task of classifying spectrum into free and busy channels with prediction accuracy of 98.8%. Also, the classifier was able to achieve a recall of 1.0 and specificity of 0.9901, both of which indicate satisfactory performance in predicting available spectrum holes for assignment to SUs. Finally, ANFIS result indicates an accuracy of 91.6% at epoch 10. This shows that ANFIS has a good generalization capability and can be deployed for implementation in CRNs for fast spectrum switching decision. Secondary IoT devices can effectively utilize spectrum resources by successfully transmitting and receiving delay-sensitive data packets with minimal disruption. Future works would consider the development of a system that integrates this framework into a CRN infrastructure for deployment by network operators. Also, the channel assignment to requesting SUs shall be network-assisted.

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