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IMPROVING THE QUALITY OF SERVICE OF A COGNITIVE RADIO NETWORK THROUGH SPECTRUM SENSOR OPTIMIZATION

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Abstract

The underutilization of the constrained spectrum by the fixed channel allocation strategy and the increasing demand for seamless wireless services provide several challenges for wireless communications. Mobile users need to create appropriate channel allocation algorithms for continuous communication in order to improve spectral efficiency. The Cognitive Radio Network (CRN) offers a solution to the inherent spectrum scarcity problem in 4G and other networks by allowing unlicensed Secondary Users (SUs) with cognitive devices to utilise available spectrum when licenced Primary Users (PUs) are not using it. This is achieved through dynamic spectrum access. SU measurements made during the sensing process are sometimes unclear because to channel conditions that fluctuate, multipath fading, and shadowing. This causes the SUs to make incorrect choices about switching, resulting in continuous spectrum handoff and the undesirable ping-pong effect. The Support Vector Machine (SVM) classifier proposed in this study splits the spectrum into two categories: busy and idle. Then, using an underlay spectrum access model, a QoS-aware Adaptive Neuro-Fuzzy Inference System (ANFIS) framework is created for spectrum switching decisions. It is based on the fluctuating channel state information, the dynamic activities of PUs, and the heterogeneous Quality of Service (QoS) requirements of the SUs. The present study included three distinct techniques, including the qualitative, experimental, and simulation approaches. The primary finding indicates that adopting a proactive approach during the spectrum decision and channel classification phases enhances the effectiveness of a cognitive network by decreasing the amount of time required to allocate spectrum resources to service units (SUs). This, in turn, lowers the frequency of collisions, resulting in more effective data transfer.

Keywords: Spectrum Sensor; Cognitive Radio Network; Support Vector Machine; Adaptive Neuro-Fuzzy Inference System; Secondary User; Primary User

1. INTRODUCTION

Human civilization depends on networking and communication, two of our most fundamental requirements that are required for forming social relationships and expressing a wide range of emotions and desires. Technological aids to social contact include network management (Tanenbaum and Wtherall, 2011) and digitalization (Gallager, 2008). In light of recent growth in the utilisation of high Quality of Service (QoS) ubiquitous electronic technology, researchers are reconsidering the effects of traditional architectural models and techniques for communications and networking (Haldorai et al., 2022). With the need for spectrum in wireless communication continuing to expand, efficient spectrum utilisation has emerged as a key challenge. The primary system to address this pressing need is Cognitive Radio (CR). According to Mizola (2000), a communication relay (CR) is a platform that is proactive and adaptable, modifying its fundamental elements to guarantee reliable and efficient transmission while optimising the use of available resources. One really successful idea is to combine many wireless networks and use one of them successfully, depending on the communication contexts and different technical standards. There are many different forms of wireless technology that provide Internet connectivity in addition to other activities. Furthermore, this results in the implementation of Software-Defined Radio (SDR) to establish cognitive radio (Haldorai et al., 2022).

According to Haldorai et al. (2018), Cognitive Radio (CR) is an essential platform that aids adaptive resource systems in making more advantageous use of bandwidth (Hossain et al., 2009) and offers a novel perspective in the development of techniques that provide communication networks (Liu and Wang, 2011). In the Cognitive Radio Network (CRN), Secondary Users (SUs), also known as unapproved customers, are expected to be able to sense and analyse their environment, learn from environmental factors, and connect directly to the licenced bands in order to achieve extremely accurate correspondence without interfering with Primary Users (PUs) or licenced users. The Cognitive Radio Network (CRN) is a radio system that uses technology to learn about its operational and geographic surroundings, enabling intelligent and opportunistic spectrum access. Through opportunistic access to underutilised or unoccupied spectrum gaps, the network allows unlicensed Secondary Users (SUs) to coexist alongside licenced Primary Users (PUs) without interfering unduly with PUs or other SUs (Zakariya et al., 2020; Akhtar et al., 2018).

The ability of the Cognitive Radio (CR) to adapt to the spectrum environment and protect the transmission of PUs for effective spectrum utilisation are two significant features that set CRNs apart from traditional wireless networks (Alqahtani et al., 2023; Moghaddam, 2018; Cavalcanti and Ghosh, 2008). When a PU comes, an improperly allocated idle channel may compel an SU to exit its current channel. As a result, an SU may move to many spectrum holes in order to maintain communication. CR technology allows SUs to exploit or access idle channels. For time-sensitive operations, this constant spectrum handoff is problematic since packet loss might occur. According to Alqahtani et al. (2023) and Anandakumar and Umamaheswari (2017), the communication system can take predictive actions by referring to various optimisation algorithms used in different layers of the radio protocol stack for the selection of radio access technology. This means that the CR has the intelligence to sense, learn, and optimise performance.

Various researches such as (Giweli et al., 2016; Rajaguru et al., 2020; Fraz et al., 2023; Nasser et al., 2023) has been embarked on to improve network QoS and efficiency, but despite the success attained, there is still room for improving the performance throughput. Thus, the goal of this study is to use two clever approaches, Adaptive-Neuro Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM), to provide a QoS-aware framework for effective spectrum management in CRN. While the ANFIS model chooses the best available spectrum hole, from the provided pool, for allocation to SUs, the SVM model is utilised to accurately anticipate the existence of spectrum holes to permit greater detection probability.

2. METHODOLOGY

The methodologies used for this study are the qualitative, experimental and simulation approach respectively. The qualitative approach presented the overall methodology of the study which guided the various studies reviewed and identification of limitation. The experimental approach was used to find out the coordination protection problem on the different zones of the transmission lines. Combining experimental and simulation approaches offers a comprehensive strategy for developing spectrum sensor systems. Starting with experimental prototype development, physical hardware and software components are integrated and tested to assess real-world performance. Field trials in operational environments provide valuable data on spectrum sensing capabilities and system robustness. Meanwhile, simulation tools aid in model development, parameter optimization, and scenario analysis, enabling rapid prototyping and exploration of various operating conditions. Presenting simulation results allows for cross-validation and refinement, ensuring accurate representation and optimization of the system's behaviour. This synergistic approach facilitates the development of spectrum sensor systems with enhanced performance, reliability, and efficiency.

2.1 Data Collection

In this paper, 16.89 MB csv file dataset which was acquired from Kaggle (Prata, 2022) was used for the system. A total of 80% of the dataset is used for training and 20% is used for testing. The dataset used for the study is comprised of 23 attributes such as frequency band, occupancy, interference, sensing measurements, sensing durations, sensing techniques, location data, coverage maps, traffic load, noise level, signal characteristics, time stamps, temporal trends, activity patterns, preferences etc.

The dataset is first normalised and then goes through a pre-processing step where it is discretized. Continuous data normalisation is achieved by standardisation. Data standardisation is carried out using the Scikit-learn StandardScaler().fit_transform() tool for efficiency. Indexing helps with the normalisation of categorical data. The Scikit-learn LabelEncoder().fit_transform() method is utilised to translate the categories to $[0, n - 1]$. The continuous features are discretized using the quartile of the features, and the bin number is then assigned based on the indices. Discreteization or binning reduces processing costs while improving the datasets classification performance. After that, one hot encoding is carried out using the features.

3. SPECTRUM SENSING FOR QOS-AWARE MANAGEMENT

Specifically, the current work seeks to provide a QoS-aware framework for precise spectrum hole prediction, effective selection, and optimal frequency channel allocation to SUs in order to realise two spectrum management functionalities: spectrum sensing and spectrum switching decision. In order to prevent SUs from unduly interfering with PUs' operations, it employs the interference temperature condition. The methods are implemented in a framework that determines the unused bandwidth size deemed spectrum gaps for the various traffic kinds using soft computing techniques, namely SVM and ANFIS. Before SUs are allotted channels from the available frequency bands in the TV, Wi-Fi, 2G, 3G, and 4G spectrums, the various QoS needs from the applications of the incoming SU requests are taken into account.

The SVM algorithm's capacity to define the hyperplane for linearly separating non-separable data using the suitable kernel function is what makes it necessary to choose it. Using optimisation functions, the kernel function converts the input data into the required output label (busy or idle channel). Because SVM is a more practical method, it is less likely to overfit. Furthermore, ANFIS is a straightforward learning method that maps numerical inputs into an output by weighting neural network processing units and information connections that are strongly coupled. Fuzzy logic is used to translate inputs into a desired output. It offers superior explaining capabilities with fuzzy rules that have semantic significance.Moreover, ANFIS's optimisation procedures for parameter adjustments can assist lower error measures and increase the accuracy of channel allocation.

3.2 Proposed QoS Spectrum Switching Decision System

The suggested QoS-aware system for choosing the best spectrum switches and gaps in CRN is depicted in Figure 1. The Radio Environment, Spectrum Database, Spectrum Decision Module which divides into SVM-classified channels and predictions of spectrum holes as well as ANFIS-assigned channels, Spectrum Handoff, Spectrum Sharing, and Performance Evaluation are the main parts of the system. Spectrum measurements and CR user preferences are collected in the Radio Environment to aid in channel characterization and the optimal way to accept incoming requests for flexible spectrum usage. At this stage, the existing spectrum occupancy rate and the incoming SU's SINR are estimated. The Spectrum Database contains these SU and PU characteristics as well as any previous data. The Radio Environment consists of the frequency bands that are available for use by various networks, such as TV, Wireless Fidelity (Wi-Fi), 2G, 3G, and 4G. Through spectrum sensing, information from the radio environment may be utilised to identify vacant spectrum bands, or "spectrum holes," that exhibit a variety of bandwidth-size properties. Next, the available spectrum bands are categorised into two categories by the Spectrum Decision Module: idle (free) and busy (utilised). This is done by using the SVM model. In order to satisfy SUs' QoS needs, the Spectrum Decision Module also characterises open spectrum bands. This ensures that appropriate spectrum bands are chosen for Real-Time (RT) and Non-Real-Time (NRT) applications from the pool of available spectrums. Five parameters were utilised for training the SVM model, one of which was an output parameter, to categorise spectrum bands into "used" and "free" spectrum classes.Probability of Channel Availability (PCA), Average Availability Time (AAT), PU Signal (PUS), and SU Signal-To-Interference-Noise Ratio (SU_SINR) are the input parameters. The output, Channel State Information (CSI), divides the spectrum into two categories: "free" and "used."

To ensure the effective use of spectrum resources, periodic spectrum sensing makes sure that interference is avoided depending on interference temperature. As a result of SUs being admitted into the network, spectrum sharing is made possible, allowing for the calculation of the spectrum utilisation factor and ongoing monitoring of the QoS guarantee of an SU's broadcast. This proactive periodic spectrum sensing method is shown in Figure 2.

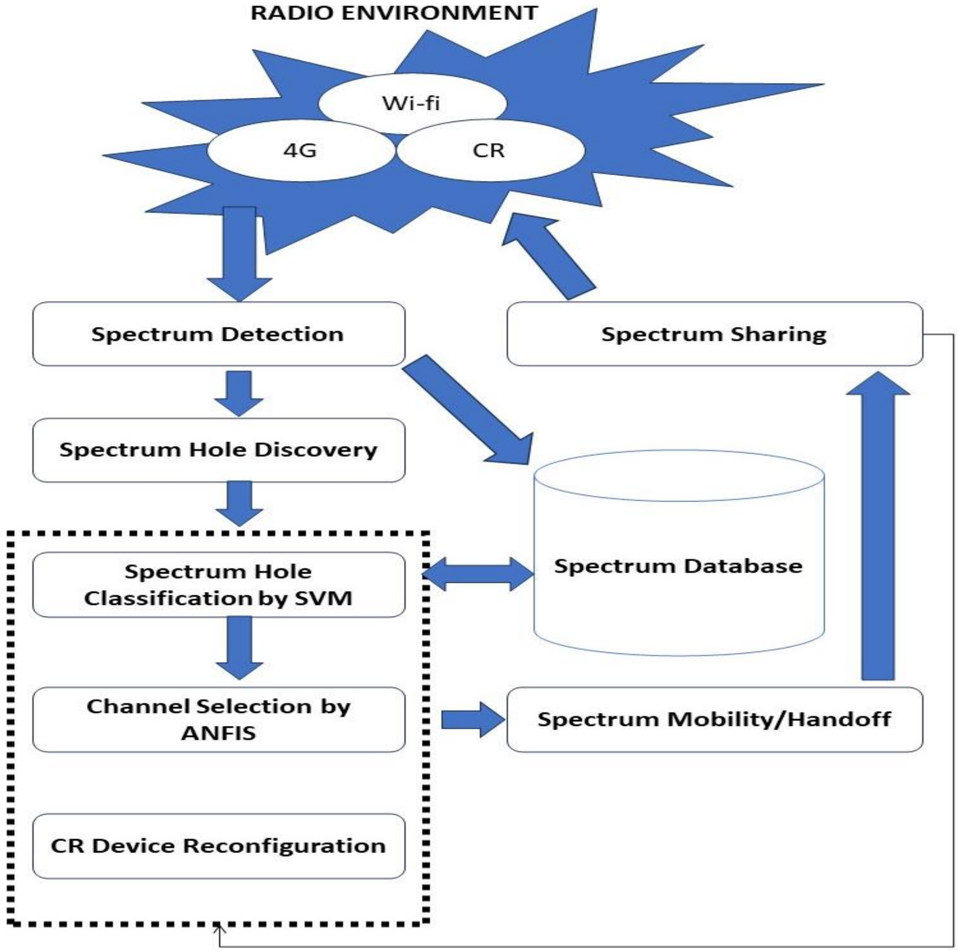

Figure 1: Proposed QoS-aware framework for spectrum switching decision in CRNs

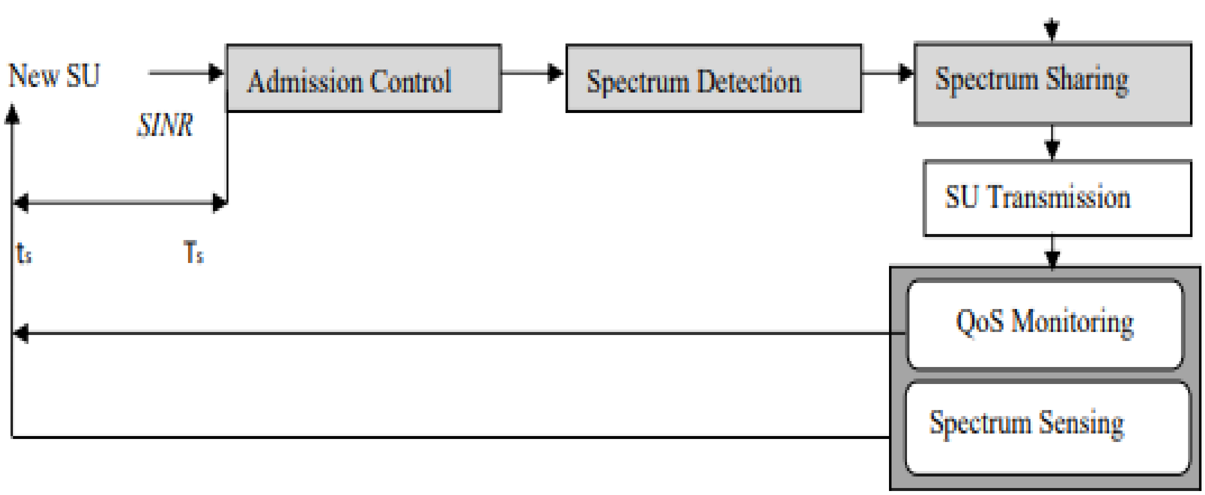

Figure 2: Periodic spectrum sensing for SU admission control and QoS monitoring

Since SUs and PUs are permitted to coexist within a specific frequency range and geographic area, the transmitting power of the SUs needs to be managed to prevent any detrimental interference to the PUs. As long as the total interference at the PU's receiver stays below a certain level, known as the interference temperature limit, each SU can broadcast alongside the PU.

a. Spectrum Holes Classification with SVM

The SVM model is trained to produce a hyperplane or linear separator. Using the optimisation function of Equation (1), the training method entails determining a decision function that can separate the spectrum bands (Asuquo et al., 2023a). Next, the class to which each spectrum channel belongs is found given a new vector x. This makes it possible to calculate the bandwidth size needed for SU assignment and ranking according to QoS criteria.

Ideally, given a goal variable and a dataset with n dimensional characteristics $\{(X_1, y_1), (X_2, y_2), \ldots, (X_n, y_n); i = 1, \ldots, n\}$, where, $X \epsilon R^n$, $y \epsilon R$. Finding a function $f(x)$ with an at most ε-deviation from the observed goal, y, is the aim of the SVR model. Given the non-linear nature of the connection between y and X, the following is a non-linear SVR model expressed as a maximisation problem:

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

Such that:

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

where, $\alpha_i$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 (2) as:

$$(\emptyset(x).\emptyset(X_i)=K(x,X_i)) \qquad (2)$$

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 (3) as follows:

$$K(x,y)=\exp(-\frac{1}{2a^2}\|x-y\|^2) \qquad (3)$$

The output of the SVR algorithm, which is the predicted spectrum availability, which is obtained as expressed in Equation (4).

$$y_i=\sum\alpha_i\,K(x,X_i)+b \qquad (4)$$

where $y_i$is the kernel function, $K(x,X_i)$ is the anticipated spectrum hole, and α_i is the weight of the model. Figure 3 shows the step-by-step study of the SVR structure employed in this work.

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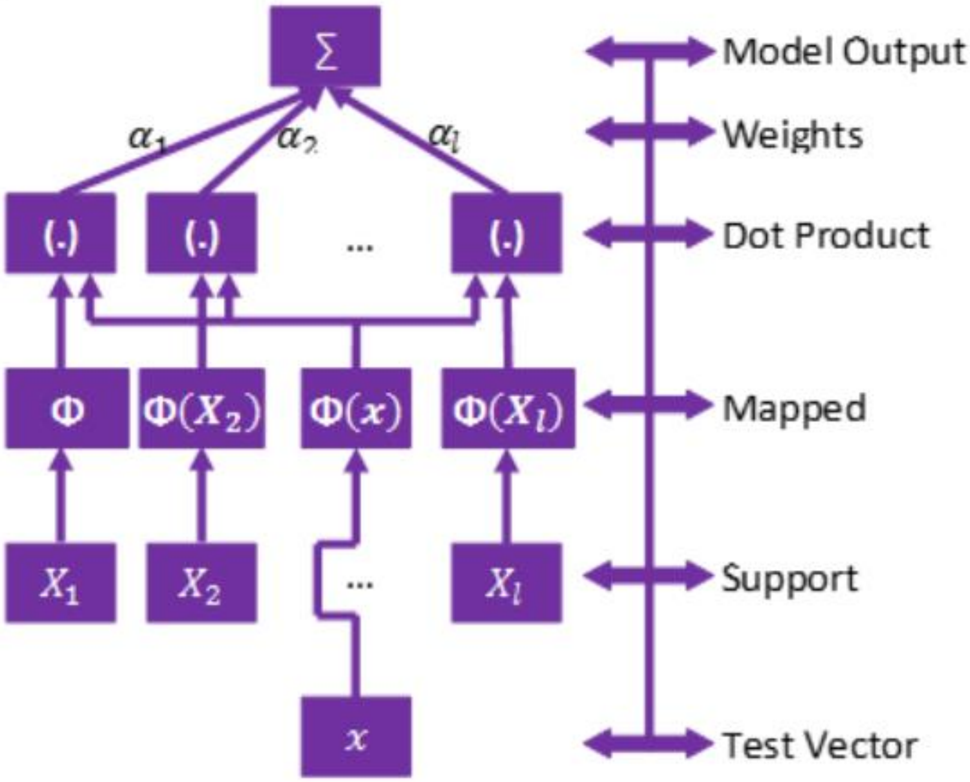

Figure 3: Structure of SVR Model (Asuquo et al., 2023b)

During network training, the SVM model is utilised to get the decision hyperplane after dividing each spectrum band into two classes: used (busy) and idle (free). Some spectrum features, including PCA, AAT, PUS, and SU_SINR, are considered cognizant. While the remaining points are designated as channels for the transmission of NRT applications (email, messaging, downloading), the spectrum of frequencies with bandwidth size greater than or equal to 7 MHz is assumed to have the greatest availability probability, estimated availability time, and a low PUS. These channels are suitable for supporting the transmissions of RT applications (VoIP, streaming).It is anticipated that throughout the spectrum allocation process, SUs accepted by the base station would initially receive the highest-quality channels for real-time applications (RT) and the lower-quality channels for non-real-time applications (NRT). In the event that a category's frequency range is depleted, an SU may utilise the spectrum of the other category, but this might potentially result in a decrease in quality of service.

b. ANFIS for Channel Allocation Optimization

Using the Takagi-Sugeno inference type, the ANFIS model ranking of the channels was developed in MATLAB. The ANFIS scheme's structure is shown in Figure 4. The input layer contains the channel characteristics; the next layer defines the membership functions (high and low for each input); the third and fourth layers compute the rules and create the Takagi-Sugeno type inference; the fifth layer summarises the outputs to get the scores for each channel and establish the ranking. In the ANFIS structure, the parameters X1, X2, X3, and X4 stand for

Number of SUs (NSU),Number of Available Channels (NAC), PU Activity (PUA), and channel Switching Delay (SDE), respectively, whereas Probability of Channel Selection (PCS).

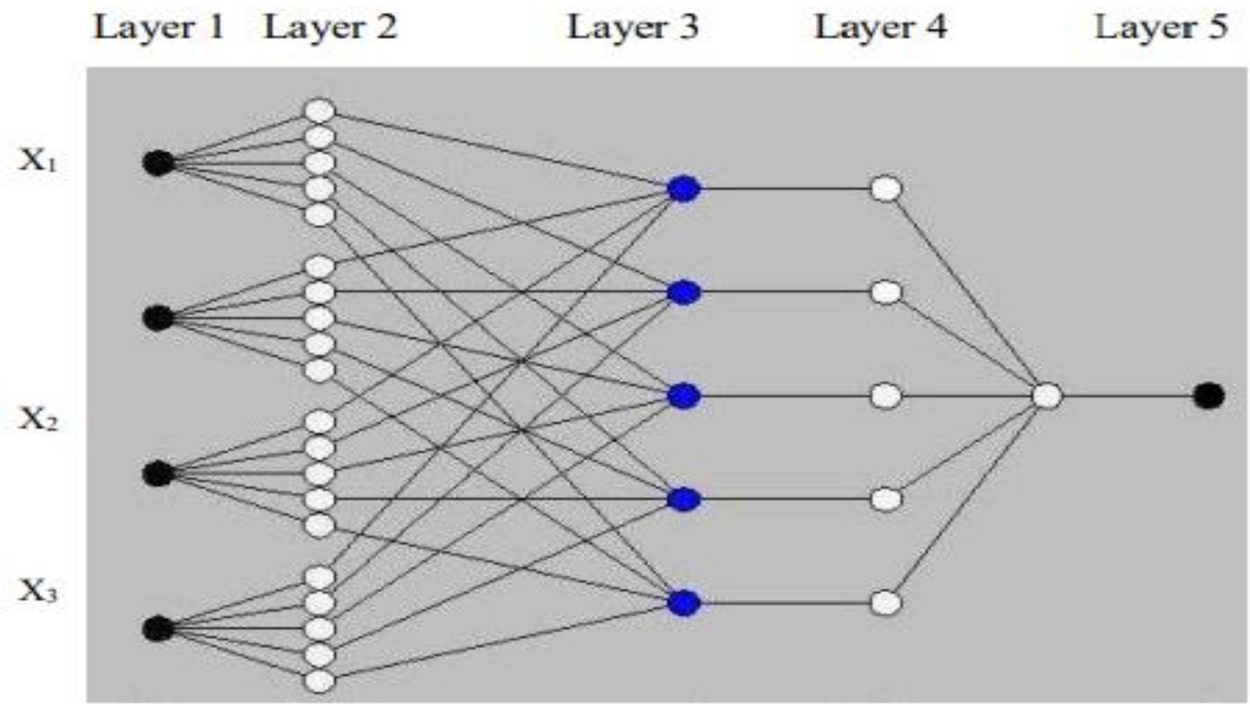

Figure 4: ANFIS structure for channel allocation optimization (Asuquo et al., 2023b)

For every parameter, Membership Functions (MFs) were developed using a specified Universe of Discourse (UoD). The inference method produced 81 fuzzy rules based on the three linguistic words Low, Moderate, and High. Working with only three linguistic concepts was decided upon in order to minimise the amount of processing power that the system needed, hence cutting down on the compilation time of the method. Fuzzy systems have the ability to learn from the data they are modelling thanks to the adaptive ANFIS network's parameter set. Accurate tuning is required for the number of training epochs, MFs, and fuzzy rules in the proposed ANFIS-based channel selection model.To prevent the system from either overfitting or underfitting the data, those parameters were mapped. This adjustment was made using a hybrid learning technique that combines the Gradient Descent Method (GDM) and Least Square Method (LSM) to increase the pace of convergence. An improved (more accurate) ANFIS system is shown by a smaller discrepancy between the ANFIS channel selection probability output and the intended aim. Therefore, the goal of the study is to minimise the RMSE cost function, which is defined as the training error when the output error is used to adjust the premise parameters using a normal back-propagation technique:

$$RMSE = \frac{1}{2}\sum\left\|t^i - a^i\right\|^2 \quad (5)$$

where, $t^i$and a^i are the target output and the actual output, respectively. The least squares estimator in Equation (2) is obtained by dividing the squared error by two. As a result, the hybrid learning method is used in a direct and organised manner, with the definition of both linear and nonlinear parameters shown at each epoch (iteration), where the LSM finds the linear parameters and the GDM updates the nonlinear parameters.

Algorithm of the Rule-BasedFuzzy Inference System(FIS) model

The ANFIS algorithm, also called the Adaptive Neuro-Fuzzy Inference System or just ANFIS, is based on the Fuzzy Inference System (FIS). It is also referred to as a hybrid system that combines the capabilities of conventional fuzzy logic systems with artificial neural networks by increasing the performance of each method and lowering the technique's drawbacks to create an adaptive system (Zahed et al., 2013).The Fuzzy Inference Algorithm is created through the application of fuzzy if-then rules, which are also known as linguistic variables. If X and Then Y represent the Fuzz sets that are characterised by the Membership variables. These rules are primarily utilised to detect erroneous and unknown variations that arise after a decision has been made at the output. The FIS model algorithm is given as follows:

The FIS algorithm (Meghana and Reddy, 2020):

4. *Start*
5. *Input the Spectrum Sensing (SS) Data*
6. *Calculate the membership degree of SS*
7. *Input the SNR*
8. *Inference of the SS and SNR*
9. *Calculate the power of the SU*
10. *Output the Fuzzy inference Logic Controller-1 (FLC-1)*
11. *Input the Power of SU(P_{SU}), Velocity of SU (V_{SU}) and Channel Hold-Time (HT) to FLC-2*
12. *Calculate membership degree of P_{SU}, V_{SU} and HT*
13. *Inference of the P_{SU}, V_{SU} and HT*
14. *Calculate the Handoff (HO) Probability (HOprob)*
15. *Stop*

Based on the fuzzy logic controller's rule-base algorithm, the likelihood of Spectrum Handoffs (HOs) in relation to the P_{SU} and V_{SU}. The technique demonstrates that even at large P_{SU} levels, the likelihood of Spectrum HOs stays extremely low. When the V_{SU} value is at its highest, it indicates that there is only a high possibility of Spectrum HOs when the P_{SU} value is low and the V_{SU} value is high (Vinay and Cullen, 2013). When the velocity of SU (V_{SU}) increases, the probability of Spectrum HOs also increases. However, the increase in HOprob is dependent on the status of the Channel hold-time; as a result, HT controls HOprob, reducing the likelihood of ping-pong effect at high velocities.

4. SYSTEM IMPLEMENTATION

Matrix Laboratory (MATLAB) software R2018a version running on an Intel(R) Core (TM) i5-4300U CPU running at 1.90GHz 2.50 G with 8.00GB RAM is used to conduct the experiment. In a field of 100 × 100 $m2$, the research assumes a CRN with a maximum of 80 CR broadcasts coexisting with 30 PUs. For uplink transmissions, PUs operate in the TV, Wi-Fi, 2G, 3G, and 4G frequency bands. Based on the interference temperature theory, SUs are anticipated to opportunistically exploit the spectrum gaps. If SUs' SINR is higher than the interference temperature threshold, they have to switch to a different channel. To reduce waste in terms of bandwidth usage and income generation, the threshold is set at 5.1dB and the minimum switching delay at 20ms. Channels that are deemed large enough to be assigned to incoming RT applications of SUs as spectrum holes have to be at least 7MHz in size. The remaining ones are tasked with NRT applications. This is done to guarantee that spectrum is allocated efficiently by avoiding ping-pong effects and continuous handoffs. In certain cases, the system may even urge SUs to leave their existing spectrum gaps once a PU arrives in order to minimise unwanted interference. Additionally, it will guarantee that communicating SU pairings retain connection quality. There are two states for each channel: IDLE and BUSY, respectively. This paper considers a time-critical application wherein every given data packet whose transmission delay exceeds the threshold is deemed illegitimate and needs to be retransmitted.While ANFIS optimises the process of optimum channel assignment to SUs for efficient spectrum choice and management in CRN, SVM conducts classification to identify available spectrum gaps.

5. RESULTS

In order to assess how well the cognitive network performs when the arrival rate is exponential and can grow up to 100 requests per time slot, the proactive strategy with SVM, the reactive strategy without classification, and the proactive strategy with ANFIS classification were compared. In this scenario, the cognitive network is unable to meet the transmission needs of secondary users. Depending on how much bandwidth an application needs, it can request 1-3 channels for Best Effort (BE) or 5-7 channels for Real Time (RT). During the simulation, the following metrics were assessed: Throughput (Th), successful transmissions (Te), RT success probability (Equation 4), and BE success probability (Equation 5), as well as the likelihood of overall success in the transmissions that were completed (Equation 6)(Sarmiento et al., 2017).

$$P_e = \frac{NoTx_e}{NoTx_T} \qquad (6)$$

Where $NoTx_e$is the number of successful transmissions, and $NoTx_T$, the total number of transmissions

$$P_{e(RT)} = \frac{NoTx_{e(RT)}}{NoTx_{T(RT)}} \qquad (7)$$

Where $NoTx_{e(RT)}$is the number of successful RT transmissions, and $NoTx_{T(RT)}$ is the total number of RT transmissions

$$P_{e(BE)} = \frac{NoTx_{e(BE)}}{NoTx_{T(BE)}} \qquad (8)$$

Where $NoTx_{e(BE)}$ is the number of successful BE transmissions, and $NoTx_{T(BE)}$) is the total number of BE transmissions.

Figure 5-7 displays the results obtained for PU traffic located in the GSM band (Uplink). The reactive scenario without ranking (R-no rank) is represented by the green-coloured line, the proactive scenario with ANFIS (P-ANFIS) by the red-coloured line, and the proactive scenario with SVM (P-SVM) by the green-coloured line. The link between the total number of transmission attempts and the number of successful transmissions (for RT and BE) is depicted in Figure 5.

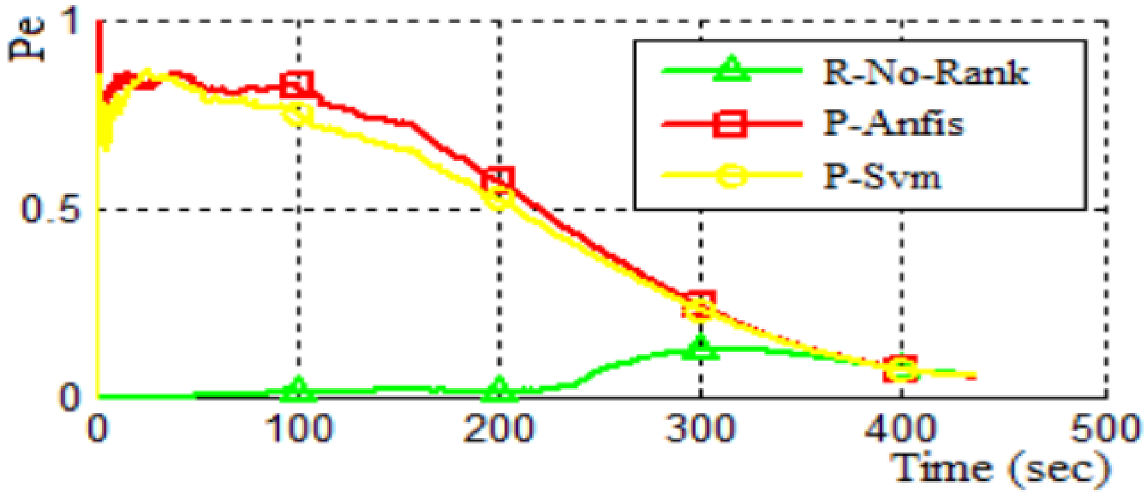

Figure 5: Probability of success in RT and BE transmissions

Due to the elevated presence of PUs and/or low QoS criteria at the beginning of the simulation, the system repeatedly assigns low quality channels. Because there isn't many SUs at the start, the system leaves the rest of the spectrum including the best unassigned, which causes SUs to repeatedly fail in their transmission attempts. This trend is maintained for the first 225 seconds of the simulation, as shown in Figure 5. When it comes to successful transmissions (Figure 6), it's important to note that the three models' actions either increase or, in the worst-case scenario, remain constant because the records provided by the algorithms are cumulative. As a result, it's observed that the proactive methodologies outperform the reactive ones for a significant portion of the simulation, but after the 200th second, the value starts to increase at a faster rate until the number of completed transmissions surpasses that of ANFIS and SVM. The system throughput for the three situations is compared in Figure 7, and it is clear that, on average, they are comparable.

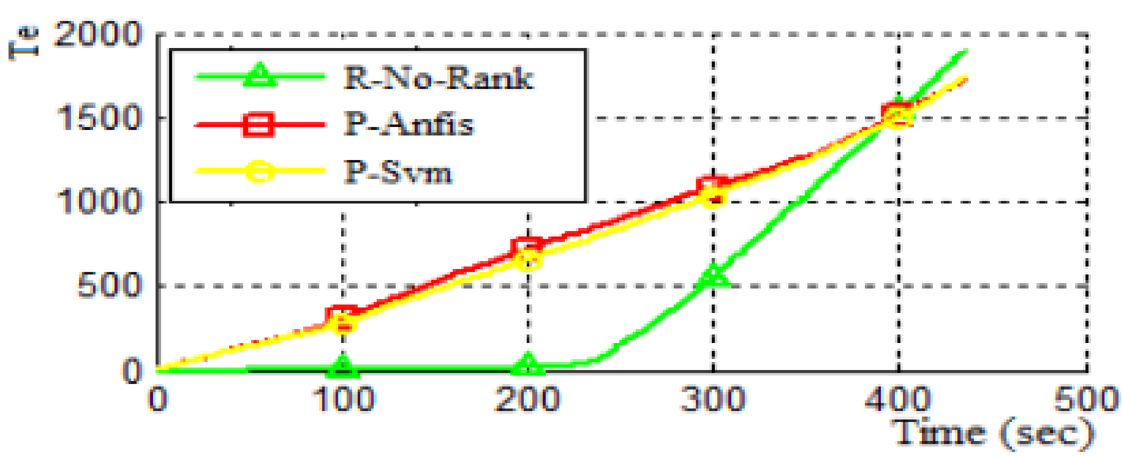

Figure 6: Successful transmissions

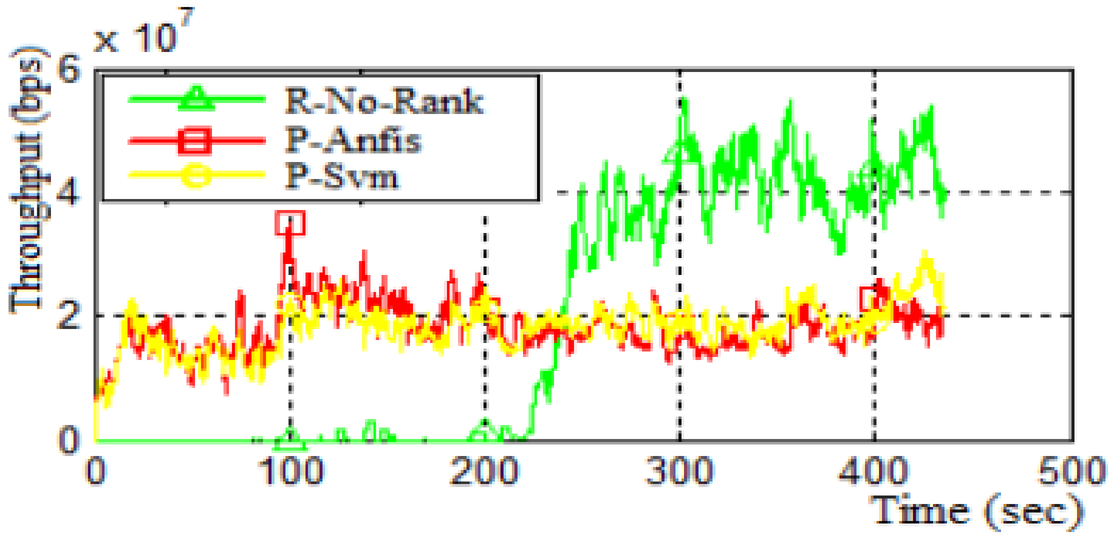

Figure 7: Throughput Result

According to a thorough analysis, the system without ranking exhibits a throughput close to null in the early stages of the simulation because it keeps assigning channels that don't meet SU requirements, leaving the best spectra free; this behaviour persists until those channels can be assigned (due to increased spectrum availability combined with a high number of SUs), which causes the throughput to abruptly increase. With ANFIS and SVM, on the other hand, the bands with higher congestion, less QoS, and more PUs are assigned to a later stage of the simulation.

6. CONCLUSION

This study demonstrates how the application of SVM and ANFIS models can greatly improve the optimum channel allocation and effective spectrum hole detection in CRN, enabling SUs to take advantage of spectrum holes for RT and NRT service demands. For various applications with QoS requirements, idle channels from the accessible frequency bands in the TV, Wi-Fi, 2G, 3G, and 4G spectrums were taken into consideration. Through the use of the interference temperature theory and the bandwidth size constraint for accessing spectrum holes, SUs may effectively utilise CR technology to achieve maximum spectrum utilisation.

This paper suggests a proactive approach that anticipates the arrival of secondary users, allowing channels to be assigned in the future to be reserved early and in advance. This proactive approach would replace the reactive strategy, which is commonly used for [handling] channel requests, processing, and assignment in cognitive networks (in the spectrum decision stage). The proactive approach would use a spectrum classification system based on ANFIS and SVM learning methodologies to prioritise. The conclusion drawn from the data analysis is that, in terms of processing time at the base station (BS), a proactive approach outperforms a reactive one, hence optimising the spectrum selection step. Similar trends were found in the majority of the responses received when using SVM or ANFIS after evaluating the proposed spectrum decision system under network saturation conditions. This system integrates the sub-stages of PU characterization, obtaining of the arrival probability of SUs requesting QoS criteria, and early establishment and assignment of SU-channel/channels pairs.

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