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Research Article

Three-State Non-Stationary Hidden Markov Model for an Improved Spectrum Inference in Cognitive Radio Networks

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Abstract

Spectrum manufacturers, operators and regulators are faced with the challenge of meeting the astronomical increase in demand by spectrum users due to the limited available radio spectrum already fixed for licensed or Primary Users (PUs). The emergence of Cognitive Radio Network (CRN) allows unlicensed or Secondary Users (SUs) to opportunistically access spectrum holes left unused by the PUs through spectrum sensing, management, sharing and mobility functionalities with the aid of algorithms and protocols. However, CRN suffers prolonged delay with negative impact on spectral efficiency. In order to improve the spectral efficiency, spectrum inference was introduced. Yet, inaccurate spectrum inference by existing mechanisms could not solve spectrum underutilization effectively due to persistent false alarm, interference and missed detection of PUs. Two-state Non-Stationary Hidden Markov Model (NSHMM) focused only on idle and busy states of PUs while previous work on three-state Stationary Hidden Markov Model (SHMM) did not consider the time-varying property of channel states obtainable in real scenarios where the state transition probability of a PU is time-varying. This work has proposed three-state NSHMM for spectrum inference in CRNs by formulating its parameters and modelling PU's dwell time distributions to realize the time-varying property of the stochastic PU behavior apart from the fuzzy state that takes care of noisy effects and undetermined or incomplete observations in the existing mechanisms where only idle and busy states were mostly recognized. The performance of the proposed mechanism was evaluated using Probability of Detection (PD), Prediction Accuracy (PA) and Spectrum Utilization Efficiency (SUE). The results were compared to the performance metrics obtained from spectrum inference of existing 2-state NSHMM and 3-state SHMM. The simulation results obtained revealed that the proposed three-state NSHMM spectrum inference mechanism gave the best performance with the highest PD, PA and SUE which curtailed PU collision because of its least possible chances of incorrect detection of primary users and least false alarm. The outstanding performance of the proposed NSHMM was due to its non-stationarity as well as the fuzzy state incorporated in the development of the mechanism. Therefore, the proposed three-state NSHMM for an improved spectrum inference in CRNs has grossly abated PU collision, false alarm and spectrum underutilization.

Keywords

Cognitive Radio Network, Spectrum Inference, Probability of Detection, Prediction Accuracy, Spectrum Utilization Efficiency, 3-State NSHMM

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1. Introduction

With the current astronomical increase in the demand for interconnection of devices globally and extreme scarcity of spectrum, it has become important to develop a robust spectrum inference mechanism in Cognitive Radio Networks (CRNs) that can efficiently utilize all the available licensed frequency bands. The primary functionalities of CRNs are spectrum sensing, spectrum management, spectrum sharing and spectrum mobility [1-3]. Spectrum inference was developed to alleviate the processing delays introduced by the four modules in CRNs and to improve the efficiency of spectrum utilization [1, 4-6].

Spectrum inference is also known as "Spectrum Occupancy Prediction (SOP)" or simply "Spectrum Prediction". It is a way of inferring or predicting the PU occupancy state of radio spectrum from already known or measured spectrum occupancy statistics by effectively exploiting the inherent correlations among them in a proactive manner [7]. Such inference is used by the unlicensed or Secondary Users (SUs) to decide where and when to carry out transmissions without affecting PUs. It ensures minimal fluctuation between channels, energy reduction and increase in Quality of Service (QoS). The usefulness of spectrum inference when applied to each functionality of CRN is illustrated diagrammatically in Figure 1 [7, 8].

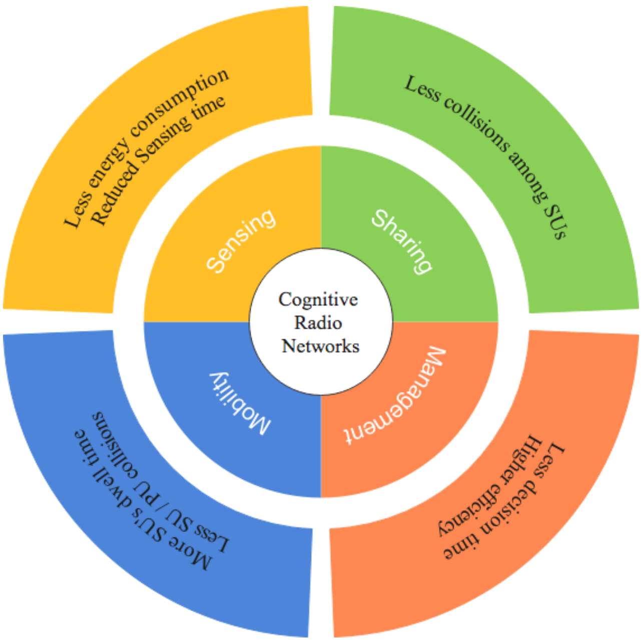

Figure 1. *The Usefulness of Spectrum Inference in CRNs.*

Hidden Markov Model (HMM) is the most widely used spectrum inference mechanism to determine the true status of a licensed user by employing its statistical properties and historical characteristics. It is particularly used when energy efficiency is a major factor to be considered [9-11]. A major weakness of conventional HMM is its inflexibility in the modelling of channel states. Hence, the Non-Stationary Hidden Markov Model (NSHMM) is a variant that addresses the weakness by modelling state transitions of PU's as a function of time for better prediction accuracy, improved spectrum utilization efficiency and robustness [12]. Its application cut across predicting spectrum occupancies, modelling sequential data, part-of-speech tagging and networking [13]. However, the limitations of previous works on two-state NSHMM and three-state conventional or stationary HMM (SHMM) mechanisms characterized by the PU's spectrum being idle or busy and non-consideration of the time-varying nature of PU's, respectively, inspire this research interest [6, 14, 15].

The existence of Markov chain in spectrum occupancy of PUs was validated by [16] from real-time measurements. The work used maximum likelihood (MLH) method for predicting idle or busy state and formulated spectrum sensing problem into a HMM paradigm. However, the PU's behavior pattern could not be well represented by stationary HMM and two states alone. Introduction of a learning-based hidden Markov model (HMM) by [17] was done to predict the channel activities such that channel selection is prioritized. The work showed that the proposed stationary HMM could predict the channel activities with good accuracy after sufficient training but limited to 2-state spectrum inference.

A channel quality prediction based on Bayesian inference in cognitive radio networks using a novel two-state Non-Stationary Hidden Markov Model (NSHMM) was presented by [1]. The work designed a channel quality metric which accounted for the spectrum sensing accuracy and the expected channel idle duration time. The approach provided more high-quality transmission opportunities and higher successful transmission rates at shorter waiting times for dynamic spectrum access than stationary HMM. However, the work could not resolve false alarm and interference to PU due to the two-state spectrum inference adopted. Two-state spectrum occupancy prediction was presented by [18] using stationary HMM. The work simulated the performance of mean prediction error against the model parameters in terms of channel sensing errors and channel occupancy transitions. The work proved HMM to be a viable spectrum inference technique but did not consider time-varying property of PU and was limited to two states only.

Spectrum inference based on advanced High-order Hidden Bivariate Markov Model for CRN was proposed by [19]. The approach applied two-dimensional parameters (hidden process and underlying process) to describe the channel behavior and fully explored the hidden correlation of previous states for spectrum inference. The method achieved remarkably higher prediction accuracy in a mobile environment based on the results of the extensive simulations carried out. However, there was computational complexity due to high order of

HMM variant employed and only two states of spectrum occupancy were considered which faulted the approach with false alarm and imperfect detection of PUs. In [20], two-state Non-Stationary Hidden Markov Model (NSHMM) and Hidden Bivariate Markov Model (HBMM) was employed for spectrum inference in CRNs through simulations and real-time application. Algorithms for parameter estimation of proposed approach were compared in this work but good performance was obtained with a windowed version of the Baum algorithm and 2-state NSHMM. However, the proposed approach had increased complexities associated with high order 50 employed which adversely degraded the Spectrum Utilization Efficiency (SUE). The work also failed to resolve collisions with the PUs because of the limitation of 2-state NSHMM employed.

The impact of busy and idle states prediction errors on the spectrum and energy efficiency of Cooperative Spectrum Prediction (CSP) in CRNs was studied by [21] using stationary HMM and Multilayer Perceptron (MLP) neural network. The results showed significant improvement in the spectrum efficiency of SU's CSP at the cost of a small degradation in energy efficiency compared to Single Spectrum Prediction (SSP). However, only the busy and idle states were considered neglecting also the time-varying property of the channel states. A novel three-state SHMM for spectrum prediction in CRNs was proposed by [15]. The three hidden states identified by the work as in practical scenarios were "idle", "busy" and "fuzzy" states. The results obtained revealed that the 3-state spectrum prediction technique gave a better performance with improved prediction accuracy, probability of detection and spectrum utilization efficiency over the 2-state HMM. However, the major structural weakness of the HMM mechanism was its fixed geometrical distribution of the channel states which limits its wide range of applications.

The inaccuracies of the two-state spectrum inference mechanisms were aggravated when an idle channel is predicted busy leading to false alarm or when busy channel is predicted idle leading to missed detection and subsequent interference with the PU. More importantly, how long a channel has been occupied by the licensed PU's, or otherwise, would be a major determinant to be considered in order to grossly improve spectrum utilization. Hence, a three-state non-stationary Hidden Markov Model for spectrum inference becomes imperative to effectively and accurately sense, predict and authorize unused/idle frequency band through the consideration of the time-varying property of PU's for an effective spectrum utilization and resource management in CRNs.

In this paper, three-state Non-Stationary Hidden Markov Model (NSHMM) for an improved spectrum inference mechanism in CRNs has been proposed to attain enhanced prediction accuracy, and better utilization of the spectrum with less complexity and reduction of interference to primary users. Forward algorithm, Viterbi algorithm and the Baum-Welch algorithm were employed for the three canonical problems of evaluation, decoding, and learning in HMM variants to be solved. The proposed mechanism was simulated using MATLAB R2020a. The performance of the proposed mechanism was evaluated using Probability of Detection (PD), Prediction Accuracy (PA) and Spectrum Utilization Efficiency (SUE). The results were compared to the performance metrics obtained from spectrum inference of existing 3-state SHMM and 2-state NSHMM while varying Probability of False Alarm (PFA) and Signal-to-Noise Ratio (SNR).

2. The System Mechanism

The three-state NSHMM was proposed in this paper as a mechanism for spectrum inference in CRNs by modelling the PU's dwell time distributions not captured in SHMM mechanism aside incorporating fuzzy state with the busy and idle states of two-state NSHMM spectrum inference mechanism in Cognitive Radio Networks.

2.1. PU's Dwell Time Modelling

The dwell time of a Primary User (PU) is the time duration expended by the PU at a particular state before its transition. The duration of a channel in idle, busy or fuzzy state is proven to be exponentially distributed [22, 23]. If the PU's varying time while at the state s_i is denoted by t, then the probability density function, $f(t)$, is given by Equation (1).

$$f(t) = \lambda e^{-\lambda t} \tag{1}$$

where, λ is the rate parameter of the exponential distribution and the expected value of the varying time, $E[t]$, is given by Equation (2):

$$E[t] = 1/\lambda \tag{2}$$

The allocated time slot length for a PU is denoted by t_s, in order to compute the self-transition probabilities '$a_{ii}(\tau)$' which are the probabilities of channel being in the same state during the whole duration, τ.

Hence,

$$a_{ii}(\tau) = 1 - \int_{t=0}^{\tau t_s} f(t)dt \tag{3}$$

$$a_{ii}(\tau) = e^{-\lambda \tau t_s} \tag{4}$$

Since transition can only take place between two states at a go, the outward state transition probabilities $a_{ij}(\tau)$ is expressed as in Equation (5).

$$a_{ij}(\tau) = 1 - a_{ii}(\tau) = 1 - e^{-\lambda \tau t_s} \tag{5}$$

where, $i \neq j$ at any point in time but both i and j could be 1, 2, 3 at different times representing idle, busy and fuzzy states respectively.

Figure 2 illustrates PU's dwell time of the proposed three-state NSHMM spectrum inference mechanism. Three PU channels are represented in the illustration of a Cognitive Radio Network at varying time slots, t_s.

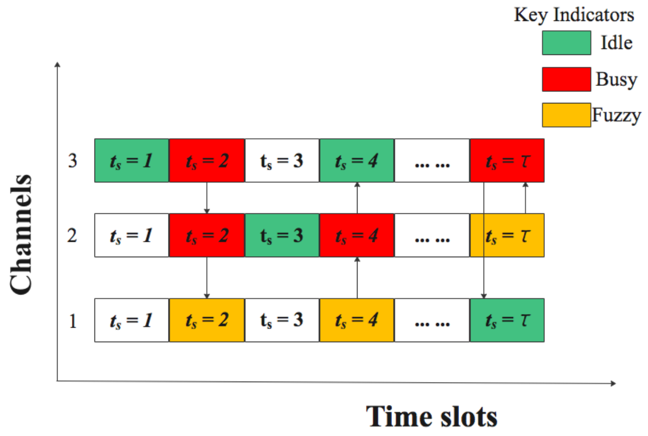

Figure 2. Illustration of PU's Dwell Time of the proposed three-State NSHMM Spectrum Inference.

At the first time slot, t_s=1, the proposed mechanism's prediction of Channel 3 indicated it to be idle straight off, hence, no need for further prediction of next possible available channel and the SU would launch for transmission immediately provided that the true channel state is idle. At the second time slot, t_s=2, the first prediction of Channel 3 turned out busy signal, hence the second prediction was initiated. The second attempt also predicted Channel 2 to be busy which prompted another search for possibility of an available channel again. The third prediction was fuzzy and transmission was withheld by the SU in order to avoid interference with the PU. At t_s=3, the mechanism predicted Channel 2 with idle signal of the PU channel which is a green clearance for the SU to utilize the unused spectrum. At t_s=4, the first prediction of Channel 1 was fuzzy which necessitated another prediction attempt. The second prediction confirmed Channel 2 to be busy, hence, there's a good reason to relaunch the NSHMM spectrum mechanism. The third attempt eventually predicted Channel 3 to be idle whereby the SU could proceed with its transmission. This process could go on and on until the whole duration of allotted time slots, τ for the licensed spectrum users is exhausted.

2.2. The Hypothesis and Formulation of Three-State NSHMM Parameters

The proposed three-state NSHMM prediction mechanism based on the SU spectrum inference outcome which is dependent on the true outcome of the PU transmission activities. An additional state named "fuzzy" was introduced in the previous work by [15] to enhance the existing two-state SHMM spectrum prediction model of the PU in busy or idle states.

Let the received signal be denoted by $\mathcal{Y}[t]$ and expressed as follows:

$$H_1 : \mathcal{Y}[t] = w[t] \tag{6}$$

$$H_2 : \mathcal{Y}[t] = x[t] + w[t] \tag{7}$$

$$H_3 : \mathcal{Y}[t] = \ddot{U}[t] \tag{8}$$

where; $\mathcal{Y}[t]$ is the received signal,

$x[t]$ is the primary signal,

$w[t]$ is noise,

$\ddot{U}[t]$ is the undetermined signal

$H_1 : 1 \rightarrow PU\ transmission\ absent\ (idle)$

$H_2 : 2 \rightarrow PU\ transmission\ present\ (busy)$

$H_3 : 3 \rightarrow PU\ transmission\ undetermined\ (fuzzy)$

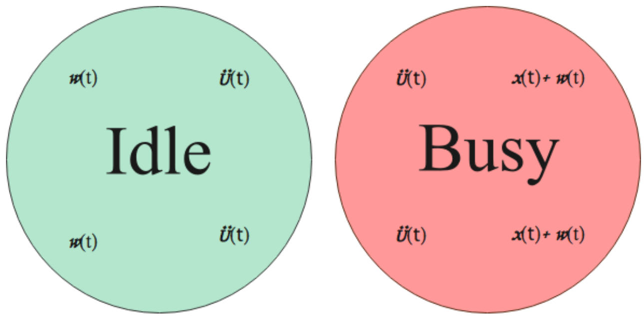

Figure 3. Illustration of Two-State Mechanism.

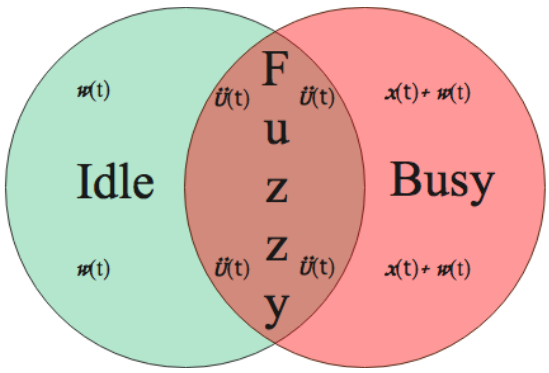

Figure 4. Illustration of Three-State Mechanism.

This can be illustrated diagrammatically as shown in Figures 3 and 4. In Figure 3, the two states are identified as idle and busy which have not truly represented the real Cognitive Radio Network because situations where the PU presence is undetermined was not distinctly identified. The undetermined status would then be classified as either idle or busy which results into PU collision or false alarm. Hence, Figure 4 shows the Venn diagram where the fuzzy state represents the intersection between the idle and busy states in uncertain situations of unknown PU presence. This takes into cognizance the undetermined status separately such that the idle and busy states are clearly identified free of any uncertainty thereby reducing the PU collision as well as false alarm.

The parameters of the proposed three-state NSHMM are initial state probability vector, transmission probability distribution and emission probability distribution which are derived as follows.

NSHMM 'λ_{NS}' is formulated in Equation (9) as follows:

$$\lambda_{NS} = (\pi, A_{NS}, B) \tag{9}$$

where; π is the initial state probability vector and is expressed as:

$$\pi = [\pi_i] = P(q_t = s_i), 1 \le i \le 3 \tag{10}$$

where; $q_t \in S$ represents the state at time instant, t

$$s_i = \{s_1, s_2, s_3\} = S \tag{11}$$

The summation of the initial state probabilities of each state is given as:

$$\sum_{i=1}^{3} \pi_i = 1, \forall \ 0 \le \pi_i \le 1 \tag{12}$$

This approach involves a hidden process (q_t) and an observable process (o_t) both making up a doubly stochastic process which allows observation symbols to be emitted from each state with a finite probability distribution. Non-Stationary Hidden Markov Model (NSHMM) considers how long a channel stays in a certain state before transiting to another which is represented as τ. This is well obtainable in real network where the transition probability of the proposed three-state NSHMM, A_{NS} is a function of τ. Hence, A_{NS} is defined as the probability that the channel changes from state s_i to state s_j with the consideration that it has been on state s_i for τ consecutive time slots. Therefore, the transition probability, A_{NS}, of the parameters of a NSHMM, $\lambda_{NS} = (\pi, A_{NS}, B)$, is formulated as:

$$A_{NS} = a_{ij}(\tau) \tag{13}$$

$$A_{NS} = P\left(q_t = s_j \middle| q_{t-1} = q_{t-2} = \cdots q_{t-\tau} = s_i\right) \tag{14}$$

where, $1 \le i, j \le 3$

The emission probability matrix or observation symbol probability distribution B in each state is the probability that symbol v_k is emitted in state s_j

$$B = b_{jk} = P\left(o_t = v_k \middle| q_t = s_j\right) \ \forall \ 1 \le j \le 3, \forall \ 1 \le k \le 3 \tag{15}$$

where,

$$v_k = \{v_1, v_2, v_3\} = V \tag{16}$$

V represents the space containing observable symbols per state and o_t is the observable value at time instant t.

$$O = o_t \in V \tag{17}$$

The summation of the emission probabilities of each state is given as:

$$\sum_{k=1}^{3} b_{jk} = 1, 0 \le b_{jk} \le 1 \tag{18}$$

3. The Proposed Three-State NSHMM Spectrum Inference Mechanism

The proposed approach makes it possible for a channel to transit to any state in a single transition process as illustrated in Figure 5. The output observation (o_t) at time t is dependent only on the current state and not dependent on the previous states or observations. The time-duration (τ) expended by a channel in a particular state was considered in the computation of the transition probability $a_{ij}(\tau)$, where $1 \le i, j \le 3$.

The new optimal model parameter of NSHMM, λ_{NS}*=(π*, A_{NS}*, B*), was computed for the proposed model in CRNs. The states of the channel S_i of NSHMM have values of "1" for idle state, "2" for busy state, and "3" for fuzzy state. The past observation sequence in T consecutive slots remains as $O = o_1, o_2, o_3 \dots, o_T$

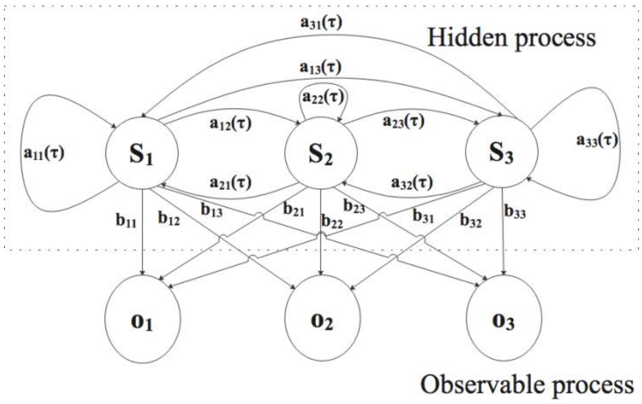

Figure 5. Three-State Non-Stationary Hidden Markov Mechanism.

3.1. The Prediction Process of the Proposed Mechanism

The proposed spectrum inference mechanism predicts the channel state at (T+1)st slot in the following procedural steps:

Step 1: Initialization: Set the initial parameters of the proposed model $\lambda_{NS_0} = (\pi_0, A_{NS_0}, B_0)$

Step 2: Observation: The observed data sequence $O = o_1, o_2, \dots, o_T$ was collected by the CRN

Step 3: Estimation: The optimal parameter of the proposed model, λ_{NS}^{*}, was estimated here.

Step 4: Training: Given the observed sequence, the parameters of the model was trained using the Baum-Welch algorithm for maximizing the likelihood associated with the model and compute $P(O|\lambda_{NS}^{*})$

Step 5: Decoding: Computed joint probabilities $P(O, q_t = s_i|\lambda_{NS}^{*})$ for $1 \leq i \leq 3$

Step 6: Prediction: The NSHMM future state '$o_{(T+1)_{NS}}$' at time (T+1) was predicted by Equation (19) where; $P(O,1|\lambda_{NS}^{*})$, $P(O,2|\lambda_{NS}^{*})$ and $P(O,3|\lambda_{NS}^{*})$ are the joint probabilities that an observation sequence o_T in a three-state NSHMM will be followed by idle, busy and fuzzy channel state at a future time (T+1), respectively.

Step 7: Transmission. SU's transmit if $o_{(T+1)_{NS}} = 1$, otherwise repeat step 4.

The overview of the proposed Three-State NSHMM Spectrum Mechanism is presented in Figure 6.

$$o_{(T+1)_{NS}} = \begin{cases} 1, if \;\; P(O,1|\lambda_{NS}^{*}) > P(O,2|\lambda_{NS}^{*}) \;\; and \;\; P(O,1|\lambda_{NS}^{*}) > P(O,3|\lambda_{NS}^{*}) \\ 2, if \;\; P(O,2|\lambda_{NS}^{*}) > P(O,1|\lambda_{NS}^{*}) \;\; and \;\; P(O,2|\lambda_{NS}^{*}) > P(O,3|\lambda_{NS}^{*}) \\ 3, if \;\; P(O,3|\lambda_{NS}^{*}) > P(O,1|\lambda_{NS}^{*}) \;\; and \;\; P(O,3|\lambda_{NS}^{*}) > P(O,2|\lambda_{NS}^{*}) \end{cases} \tag{19}$$

3.2. Simulation of the Three-state Spectrum Inference Mechanism NSHMM

The channel or source nodes in the primary network of the proposed mechanism is in the proposed three states namely - idle, busy or fuzzy. When in idle state, the channel is available for source nodes among the SUs of the CRN to transmit information. When a source node is in a busy state, it indicates that there is an already established connection in the primary network. Hence, the channel is unavailable for the SUs. Meanwhile, in a situation of unknown availability of the channel being introduced as fuzzy state, SUs are undetermined as regards transmitting any information thereby preventing unforeseen interference with the PUs. The simulation of the proposed mechanisms was done using MATLAB R2020a. The performance a newly proposed communication system in the presence of real noise is reflected by deliberately generating and sending some amounts of noise through it. Hence, Additive White Gaussian Noise (AWGN) was added during the simulation being the basic and generally accepted noise model which imitates various random processes present in nature [24, 25]. The Rayleigh fading channel was used to statistically model the faded signal envelope because no direct line of sight (NLOS) component was involved which makes the measurements over the NLOS paths accurate. An important parameter in communication system design is the maximum bandwidth which is set at 20 MHz in the simulation to suitably allow the frequency spacing of the channels [26]. MQAM was preferred among other modulation schemes because of its high data throughput and eminent usage in a variety of radio communications or data transmission applications as it combines the properties of Amplitude Shift keying (ASK) and Phase Shift Keying (PSK) [27, 28].

The Non-Stationary Hidden Markov Model (NSHMM) considers the time duration that a channel was used at a state prior to transition. Hence, the transition probability of the proposed mechanism is a function of time $a_{ij}(\tau)$ which is the main distinction of this model from that of three-state spectrum inference mechanism of SHMM. The hidden channel occupancy states considered for the proposed mechanism remain *idle, busy* and *fuzzy*. Simulation of the model presented in Figure 6 was done by first setting the initial probability as $\lambda_{NS_0} = (\pi_0, A_{NS_0}^{*}, B^{*})$. The same observable sequence was collected as those of the previous work done on three-state stationary HMM. However, a different optimal model parameter, λ_{NS}^{*}, was estimated then training was required to maximize $P(O|\lambda_{NS}^{*})$. Computation of the joint probabilities at the decoding stage of the simulation derived $P(O, s_i|\lambda_{NS}^{*})$. Hence, the prediction decision which determines the future channel state followed the rule as stated in Equation (19). The proposed spectrum inference mechanisms were simulated using MATLAB R2020a and the simulation model parameters are given in Table 1. Future research could investigate the practical hardware constraints, such as sensor accuracy or energy efficiency, that might affect the implementation of the proposed mechanism in real CRNs.

Table 1. *Simulation parameters for the proposed mechanism.*

Parameters	Type
Modulation scheme	MQAM
Constellation size	128
Fading Channel	Rayleigh
Noise	AWGN
Bandwidth	20 MHz
Signal to Noise Ratio	(0:2:20)
Detector	Energy Detector
Detector Threshold	3 dB
Detection Mode	Root Mean Square
Probability of False Alarm	(0:0.01:0.1)

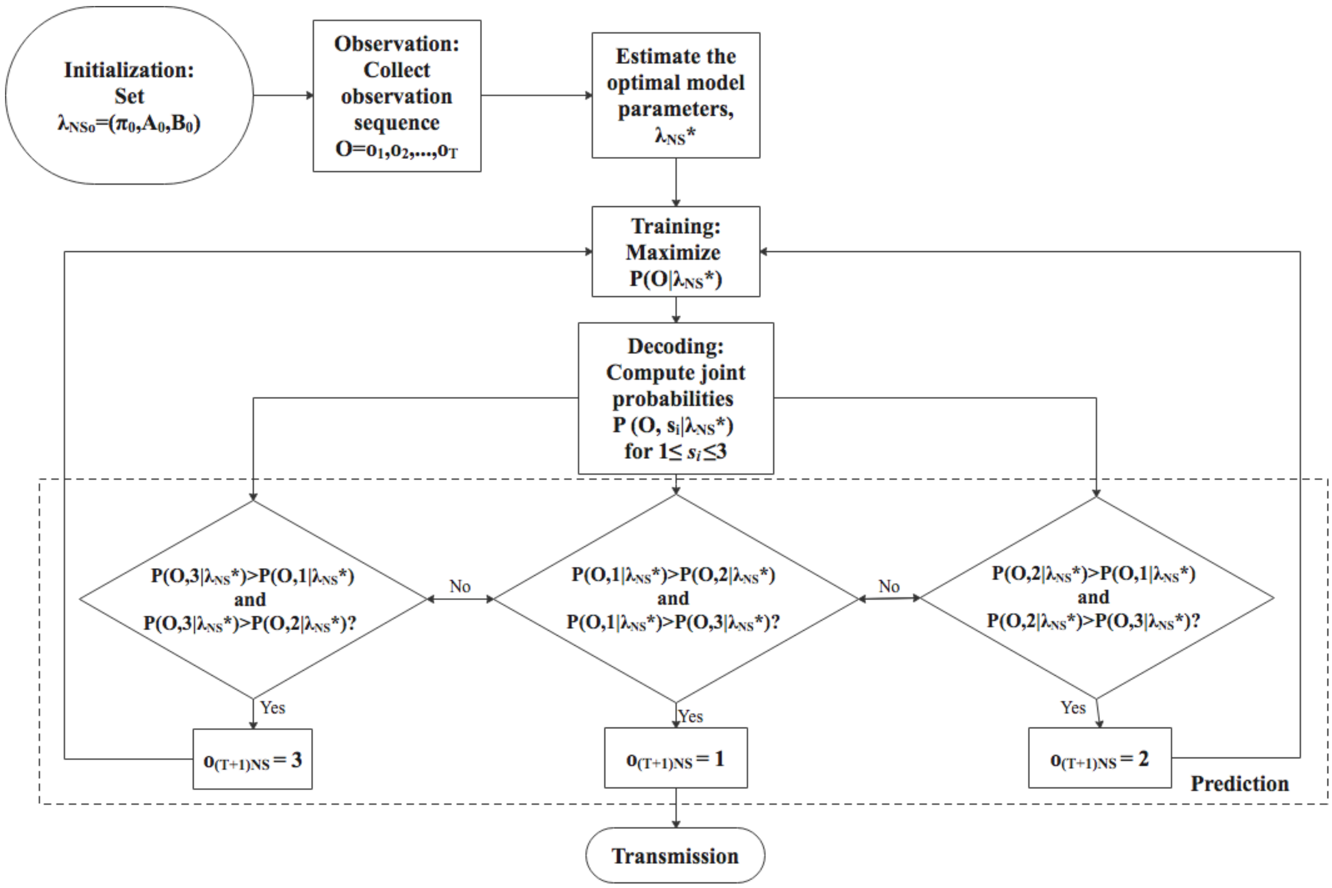

Figure 6. *Overview of the Proposed Three-State NSHMM Spectrum Inference Mechanism for CRN.*

3.3. Performance Metrics of the Proposed Mechanism

The performance metrics used in evaluating the performance of the proposed spectrum inference mechanism are presented in this section. These include probability of detection, probability of missing, prediction accuracy, and spectrum utilization efficiency which are indicators of the robustness and adaptability of the mechanisms for an efficient spectrum utilization. The performance metrics were compared with those of two-state SHMM and three-state NSHMM simulated with ten thousand (10,000) prediction outcomes obtained from each model while varying SNR, Probability of False Alarm (PFA). *M-ary* QAM was the modulation of choice in the interest of this research because of its ability to carry higher data rates than ordinary amplitude or phase modulated schemes and it is mostly used for digital transmission in radio communication applications.

Probability of False Alarm, PFA, is the rate of detection failures that occur in relation to the presence of PU. In cognitive radio, PFA is an important performance metric that expresses the chances of wrongly detecting the presence of PU when the spectrum is not actually occupied. The higher the PFA, the more the amount of wrong detection of PU which leads to wastage of spectrum. Hence, low PFA limits spectrum underutilization and at the same time increases PU protection [29, 30]. As documented by [31] for practical applications, the IEEE 802.22 recommends PFA of not more than 0.1 which this work has complied with.

3.3.1. Probability of Detection

Probability of detection, PD, is the probability that the proposed mechanism accurately detects the presence of PU in the channel. It indicates the rate of correct PU signal detections in the channel. PD is the metric used to define the correctness of PU detection.

PD over a Rayleigh Fading channel has been formulated and expressed mathematically by [1] as given in Equation (20).

$$PD = e^{-\frac{\chi}{2}}\sum_{t_s=0}^{m-2}\frac{1}{t_s!}\left(\frac{\chi}{2}\right)^{t_s} + \left(\frac{1+\bar{\xi}}{\bar{\xi}}\right)^{m-1}\left[e^{-\frac{\chi}{2(1+\bar{\xi})}} - e^{-\frac{\chi}{2}}\sum_{t_s=0}^{m-2}\frac{1}{t_s!}\left(\frac{\chi\bar{\xi}}{2(1+\bar{\xi})}\right)^{t_s}\right] \tag{20}$$

where, t_s is the allotted time slots, the threshold of the Energy Detector is denoted by χ and the time bandwidth product is denoted by m, while $\bar{\xi}$ represents the average SNR of the SU on the primary channel.

3.3.2. Prediction Accuracy

Prediction accuracy, PA, is the rate of correct predictions achieved by the proposed spectrum inference mechanism. The Receiver Operation Characteristics (ROC) and the confusion matrix table are veritable tools used to reveal the accuracy of prediction of the spectrum inference mechanism [32-34]. *PA* was derived by the ratio of the true outcomes to the total outcomes of the proposed mechanism as expressed in Equation (21).

$$PA = \frac{True\ outcomes}{Total\ outcomes} \tag{21}$$

3.3.3. Spectrum Utilization Efficiency

In cognitive radio, the available spectrum for data transmission is non-contiguous which implies that the transmitter is required to transmit over several non-adjacent bands. It is generalized that multiple non-contiguous bands in CRNs are equivalent to a continuous band in traditional wireless communication systems having the same total bandwidth [35, 36]. Hence, the ratio of channel capacities of non-contiguous spectrum to those of contiguous spectrum with same total bandwidth has been identified as the Spectrum Utilization Efficiency. This work has derived the idle Spectrum Utilization Efficiency (SUE) as the fraction or percentage of the number of idle slots predicted by the proposed mechanism to the total number of actual idle slots available in the system over a particular period of time. This is expressed in Equation (22).

$$SUE = \frac{Number\ of\ idle\ slots\ predicted}{Total\ number\ of\ actual\ idle\ slots} \tag{22}$$

4. Performance Evaluation of the Proposed Three-State NSHMM Mechanism

The proposed Three-State NSHMM for Spectrum Inference Mechanism in CRN was evaluated using PD, PA and SUE and the results were compared with those of two-state NSHMM and three-state SHMM. The PFA values of 0.05 and 0.1 and SNR values of 10 dB and 20 dB were chosen for the comparison purposes because of their notable significances at mid-way and extreme end of the Performance Metrics with no bias to tradeoff that maintains a balance between PU protection and minimizing spectrum wastages.

4.1. Results of Probability of Detection

Figures 7 and 8 show the Probability of Detection (PD) versus Probability of False Alarm (PFA) for the proposed three-state NSHMM and the existing two-state NSHMM and three-state SHMM at SNRs of 10dB and 20dB respectively. The SNR values of 10 dB and 20 dB were chosen for the comparison purpose due to their notable significances on the PD. In Figure 7, PD values of 0.7521, 0.5571 and 0.4493 were obtained at PFA of 0.05 for the proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively, while the corresponding PD values at PFA of 0.1 were 0.9024, 0.6684 and 0.5391, respectively.

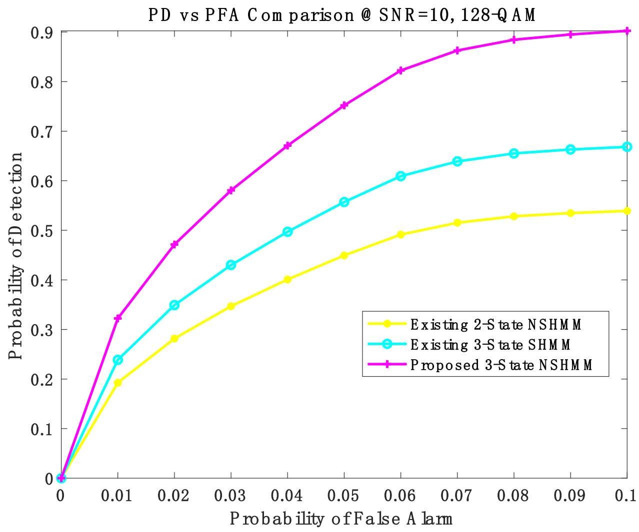

Figure 7. *PD versus PFA for the Proposed 3-State NSHMM and Existing Mechanisms at SNR of 10 dB.*

In like manner, Figure 8 represents PD versus PFA for the proposed 3-State NHMM, the existing 3-State SHMM and 2-State NSHMM at SNR of 20 dB. 0.9783, 0.7247 and 0.5844 were the PD values gotten at PFA of 0.05 for proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively, while the corresponding values at PFA of 0.1 were 0.9990, 0.8696 and 0.7013.

Consequently, the results obtained reveal that irrespective of the SNR considered, the proposed three-state NSHMM for spectrum inference mechanism in CRN gave higher Probability of Detection than the existing three-state SHMM and two-state NSHMM because of the consideration of the time-varying stochastic PU property aside identification of fuzzy state. It can be confirmed that PD increases as PFA increases for the three mechanisms at the expense of poor spectrum management. More importantly, the proposed mechanism complies with IEEE 802 standard where 10% or less of PFA is recommended and minimum PD of 90% is required for an efficient system. The proposed mechanism already attained PD of 97.83% at PFA of only 5% and PD of 99.9% at PFA of 10% which is very commendable as an highly efficient spectrum inference mechanism.

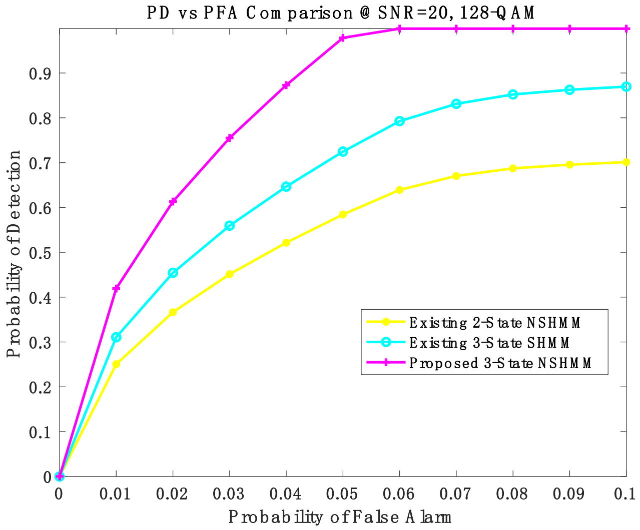

Figure 8. *PD versus PFA for the Proposed 3-State NSHMM and Existing Mechanisms at SNR of 20 dB.*

4.2. Results of Prediction Accuracy

Figures 9 and 10 show the values of prediction accuracy obtained from the proposed mechanism of three-state NSHMM plotted against varying SNR of 0 dB to 20 dB along with those of existing three-state SHMM and two-state NSHMM at different PFA. The PFA values of 0.05 and 0.1 were chosen for the comparison purpose due to their notable significances on the PA. Figure 9 is the PA versus SNR for the proposed 3-State NSHMM in comparison with the existing 2-State NSHMM and 3-State SHMM at PFA of 0.05. PA values of 0.8012, 0.6449 and 0.5584 were obtained at SNR of 10 dB for the proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively, while the corresponding PA values at SNR of 20 dB were 0.9827, 0.7793 and 0.6668, respectively.

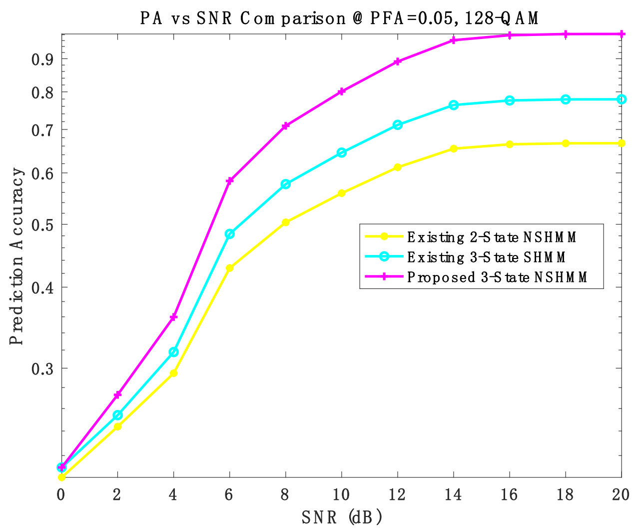

Figure 9. *PA versus SNR for the Proposed 3-State NSHMM and Existing Mechanisms at PFA of 0.05.*

Also, Figure 10 depicts PA versus SNR for the proposed 3-State NSHMM in comparison with the existing 2-State NSHMM and 3-State SHMM at PFA of 0.1. The PA values obtained at SNR of 10 dB were 0.9181, 0.7215 and 0.6128 for the proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively, while 0.9991, 0.8904 and 0.7491 were the corresponding PA values obtained at SNR of 20 dB for the proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively. The results obtained revealed PA increases as SNR increases for the mechanisms due to ratio of maximum to minimum eigenvalue that increases as signal strength increases. More importantly, the results revealed that the proposed three-state NSHMM for spectrum inference mechanism in CRN gave better prediction accuracy than the existing three-state SHMM and two-state NSHMM due to the non-stationarity property of the PU channel considered along with the fuzzy state which prevents interference to PU and reduces false alarm.

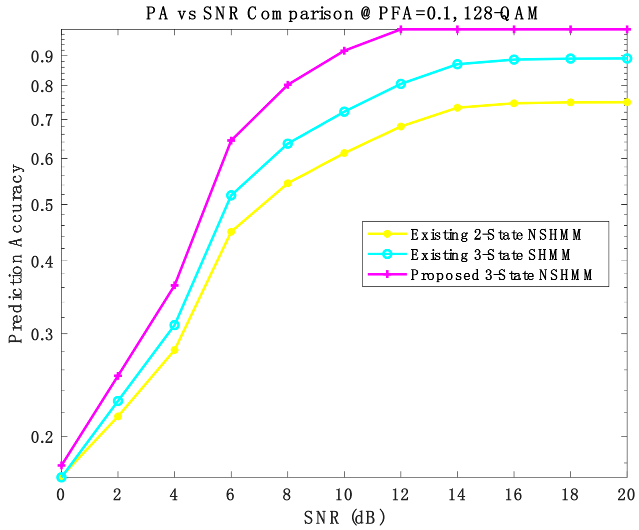

Figure 10. *PA versus SNR for the Proposed 3-State NSHMM and Existing Mechanisms at PFA of 0.1.*

4.3. Results of Spectrum Utilization Efficiency

Figures 11 and 12 display the Spectrum Utilization Efficiency (SUE) versus SNR of the proposed mechanism of three-state NSHMM plotted against varying SNR of 0 dB to 20 dB along with those of existing three-state SHMM and two-state NSHMM at PFA 0.05 and 0.1. Figure 11 shows SUE versus SNR at PFA of 0.05 for the proposed 3-State NSHMM in comparison with the existing 2-State NSHMM and 3-State SHMM.

The SUE values obtained at SNR of 10 dB were 0.7270, 0.5180 and 0.5180 for the proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively, while the corresponding values at SNR of 20 dB were 0.8908, 0.5923 and 0.5410, respectively.

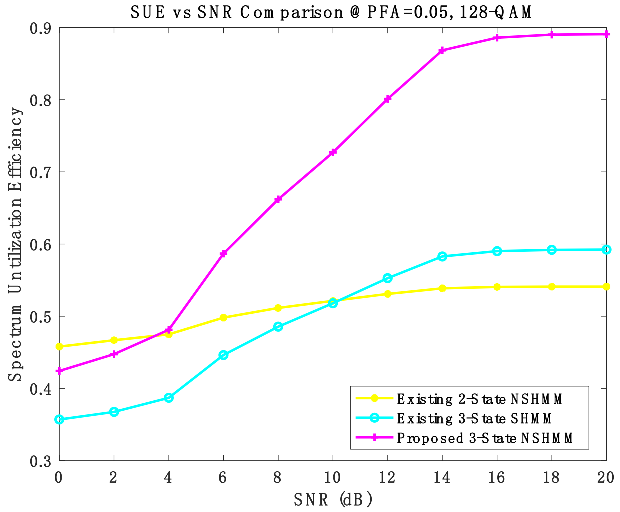

Figure 11. *SUE versus SNR for the Proposed 3-State NSHMM and Existing Mechanisms at PFA of 0.05.*

Similarly, Figure 12 depicts SUE versus SNR for the proposed 3-State NSHMM in comparison with the existing 2-State NSHMM and 3-State SHMM at PFA of 0.1. The SUE values obtained at SNR of 10 dB were 0.8202, 0.5412 and 0.4692 for the proposed 3-State NSHMM, existing 3-State SHMM and 2-State NSHMM, respectively, while the corresponding SUE values obtained at SNR of 20 dB were 0.9084, 0.6608 and 0.5145.

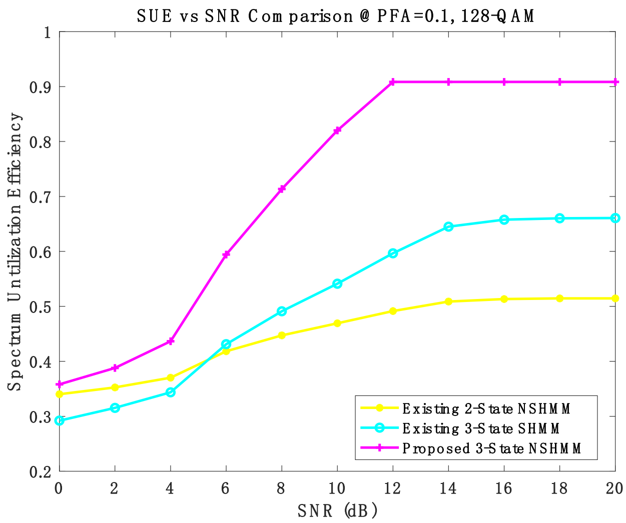

Figure 12. *SUE versus SNR for the Proposed 3-State NSHMM and Existing Mechanisms at PFA of 0.1.*

The results showed that at low SNR of 4 dB and below, the SUE values of the existing 2-State NSHMM were higher than those of the proposed NSHMM and even the existing 3-State SHMM due to low signal strength. This means transmission was not encouraged for the CR user with low signal strength because information should be sent as quickly as possible over the channel before the licensed user regain its ownership. The SUE of the existing 2-State NSHMM was almost independent of SNR because there was no provision for the fuzzy state as a result of some noisy observations in the mechanism. On the contrary, the SUE of the proposed 3-State NSHMM mechanism increased as the signal strength increased and was much higher than the corresponding values of the existing 2-State NSHMM and 3-State SHMM from any SNR above 4 dB at considerably suitable PFA of 0.05 for an efficient spectrum management. Therefore, at high SNR, the combination of the non-stationarity property and the fuzzy state are advantageous for high SUE in the proposed mechanism because the magnitude of the signal has suppressed that of the noise and transmission rate is encouragingly faster.

Hence, the non-stationarity factor and the fuzzy state incorporated in the proposed mechanism improved its SUE values as the PFA and SNR were increased which was not achievable by the existing 3-State SHMM and 2-State NSHMM where the SUE values were low and almost static or independent of the signal strength in terms of the SNR.

5. Conclusions

This work has proposed three-state Non-Stationary Hidden Markov Model (NSHMM) for spectrum inference mechanism in Cognitive Radio Networks (CRNs). The three-state NSHMM were formulated from the existing two-state Non-Stationary Hidden Markov Model (NSHMM) and three-state Stationary Hidden Markov Model (SHMM). Using the formulated three-state NSHMM, the optimal model parameters were computed for the proposed spectrum inference mechanism in CRNs. The "*fuzzy*" state introduced in the Non-Stationary Hidden Markov Model provided a clear distinction between the proposed mechanism and the existing spectrum prediction models where channel's undetermined state due to noisy or incomplete observations was not recognized. The two assumptions of HMMs which are Markov and Independence assumptions governed the proposed mechanisms wherein it was possible for a channel to transit to any state in a single transition process. The proposed mechanisms predicted the next channel state as applicable from the past observation sequence in consecutive time slots by following the prescribed procedural steps.

The proposed three-state spectrum inference mechanism and the existing counterparts were simulated using MATLAB R2020a. The NSHMM considered how long a channel has been in a state before its transition to another. Hence, the state transition probabilities of the proposed mechanism considered the non-stationarity property of primary channels which had effect on the outcomes of the performances. The performances of the mechanism were evaluated and compared using Probability of Detection (PD), Prediction Accuracy (PA) and Spectrum Utilization Efficiency (SUE) while varying Probability of False Alarm (PFA), Signal-to-Noise Ratio (SNR).

The results obtained revealed that the proposed three-state NSHMM for spectrum inference mechanism gave the best performance with the highest Probability of Detection (PD), Prediction Accuracy (PA), Spectrum Utilization Efficiency (SUE) which curtailed PU collision because of the least possible chances of incorrect detection of primary users and least false alarm. At PFA of 0.05 and SNR of 10 dB chosen as tradeoff in order to maintain a balance between PU protection and minimizing spectrum wastages, the proposed mechanism improved the Probability of Detection by 35.00% over three-state SHMM and 67.39% over two-state NSHMM; the Prediction Accuracy increased by 24.24% and 43.48% over three-state SHMM and two-state NSHMM, respectively while the Spectrum Utilization Efficiency of the proposed mechanism achieved 40.35% increment over both the existing three-state SHMM and two-state SHMM. The outstanding performance of the proposed NSHMM was due to its non-stationarity nature as well as fuzzy state incorporated in the development of the mechanism. Therefore, the proposed three-state NSHMM for spectrum inference mechanisms in CRNs has grossly abated PU collision, false alarm and spectrum underutilization.

Abbreviations

ASK	Amplitude Shift Keying
PU	Primary User
CRN	Cognitive Radio Network
SU	Secondary User
MHz	Megahertz
NLOS	No Direct Line of Sight
NSHMM	Non-Stationary Hidden Markov Model
SHMM	Stationary Hidden Markov Model
PD	Probability of Detection
PA	Prediction Accuracy
PSK	Phase Shift Keying
SUE	Spectrum Utilization Efficiency
PFA	Probability of False Alarm
SOP	Spectrum Occupancy Prediction
QoS	Quality of Service
HMM	Hidden Markov Model
MLH	Maximum Likehood
BSS	Blind Source Separation
HBMM	Hidden Bivariate Markov Model
CSP	Cooperative Spectrum Prediction
MLP	Multilayer Perceptron
SSP	Single Spectrum Prediction
PBS	Primary Base Station
MQAM	M-ary Quadrature Amplitude Modulation
AWGN	Additive White Gaussian Noise
SNR	Signal-to-Noise Ratio

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The data supporting the outcome of this research work has been reported in this manuscript. However, the raw data is available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflicts of interest.

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Research Field

Emmanuel Oluwatosin Rabiu: Cognitive Radio Network and its Application, Satellite Communications, Antenna Systems, Resource Allocation in Wireless Networks, Control Systems, Robotics and Automotive Engineering.