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Smart Channel Selection Approach for Cognitive Radio Networks

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Abstract: Cognitive radio is a wireless generation that gives answer to meet scarcity of radio spectrum. Here to find out the busy states of any spectrum unit and choice of appropriate vacant channel for conversation with the aid of secondary customers are two vital tasks. In this paper a brand new technique Navien Bayes classifier based totally on Bayes theorem has been carried out to discover the minimum busy chance of any spectrum unit. Various predictions at diverse steps ,their switching opportunity, collision chance and throughput has been taken in the series. By using historic statistics of the licensed spectrum, the SU chooses the channel with the bottom busy probability inside its provider time for facts transmission. Time series prediction is hired to forecast the near future busy chances of the certified spectrum units.

Keywords: Cognitive Radio, Radio Frequency, WSN

1. Introduction:

Radio frequency (RF) spectrum is a precious but tightly regulated useful resource due to its precise and critical role in wireless communications. With the proliferation of wi-fi services, the demands for the RF spectrum are continuously growing, leading to scarce spectrum sources. On the opposite hand, it's been mentioned that localized temporal and geographic spectrum usage is extremely low [1]. Currently, new spectrum regulations are being advanced through the Federal Communications Commission (FCC) so that it will permit secondary customers to opportunistically get entry to a certified band, whilst the number one person (PU) is absent. Cognitive radio has grow to be a promising strategy to remedy the spectrum scarcity problem inside the subsequent era cellular networks by using exploiting possibilities in time, frequency, and space domains [2],[3]. Cognitive radio is a complicated software program-described radio that robotically detects its surrounding RF stimuli and intelligently adapts its operating parameters to network infrastructure at the same time as assembly person demands. Since cognitive radios are considered as secondary customers for the usage of the licensed spectrum, a critical requirement of cognitive radio networks is they need to efficaciously take advantage of below-utilized spectrum (denoted as spectral opportunities) without causing harmful interference to the PUs. Furthermore, PUs haven't any responsibility to share and change their working parameters for sharing spectrum with cognitive radio networks. Hence, cognitive radios need to be capable of independently come across spectral opportunities without any help from PUs; this capacity is called spectrum sensing, which is considered as one of the most essential components in cognitive radio networks. Many narrowband spectrum sensing algorithms have been studied within the literature [4] and references therein, consisting of matched-filtering, electricity detection [5], and cyclostationary characteristic detection. While present narrowband spectrum sensing algorithms have targeted on exploiting spectral possibilities over slender frequency range, cognitive radio networks will eventually be required to take advantage of spectral possibilities over extensive frequency range from masses of megahertz (MHz) to several gigahertz (GHz) for attaining higher opportunistic throughput. This is pushed by using the well-known Shannon's system that, below sure situations, the most theoretically manageable bit charge is directly proportional to the spectral bandwidth. Hence, specific from narrowband spectrum sensing, wideband spectrum sensing targets to find extra spectral opportunities over extensive frequency variety and attain higher opportunistic combination throughput in cognitive radio networks. However, traditional wideband spectrum sensing techniques primarily based on wellknown analog-to-virtual converter (ADC) may want to result in unaffordably excessive sampling rate or implementation complexity; thus, revolutionary wideband spectrum sensing strategies turn out to be increasingly more critical.

2. Related Work:

Spectrum occupancy fashions are very beneficial in cognitive radio designs. Yunfei Chen, (2016) [9] may be used to boom spectrum sensing accuracy for more reliable operation, to cast off spectrum sensing for higher resource usage efficiency or to choose channels for better opportunistic access, among different programs. In this survey, numerous spectrum occupancy fashions from dimension campaigns taken around the arena are investigated. These models extract one of a kind statistical houses of the spectrum occupancy from the measured statistics. In addition to these models, spectrum occupancy prediction is likewise discussed, wherein the automobile-regressive and/or transferring-average fashions are used to predict the channel status at destiny time instants. After evaluating these one of a kind methods and fashions, several challenges also are summarized based on this survey.

Due to the wide variety of applications in cognitive radio networks, the significance in spectral prediction has been multiplied, and numerous applications were studied within the employer of cognitive networks, choice, sharing, mobility, and sensing. These claims had been exploited, even extra, to purpose the reduce of delays inside the processing of information and to enhance the performance of spectrum use. This studies intends to provide a survey and a manual on the state-of-the-art work on spectral prediction, examining state of the artwork inside the inference of the spectrum in cognitive radio networks. For a higher understanding of the prediction roll, the principle spectrum prediction techniques had been summarized, the packages have been labeled, and the relevant research demanding situations had been offered in a dispensed manner. Accordingly, Luis Miguel Tuberquia,(2018) [10] considered a qualitative assessment of different prediction techniques.

In this work, Syed HashimRazaBukhari,(2018) [11] proposed a simulation version for cognitive radio sensor networks (CRSNs) which is an try to combine the beneficial houses of wi-fi sensor networks and cognitive radio networks. The ex-isting simulation fashions for cognitive radios cannot be extended for this motive as they do no longer bear in mind the strict energy constraint in wireless sensor networks. Our proposed version considers the confined power available for wireless sensor nodes that constrain the spectrum sensing process - an unavoidable operation in cognitive radios. This model helps the fundamental requirements of a CR primarily based wi-fi sensor network. As the research trend is shifting closer to CRSNs so it's far need of the time for such a simulator so that every one the future studies and simulations may be primarily based in this module. This module has been designed on NS2 so it's far very bendy to increase for destiny enhancements and channel bonding block could be brought because the extension of this paintings. It will provide the CR users a chunk of big bandwidth to make use of for multimedia applications. Other sorts of PR sports and electricity models can also be incorporated on this module. Another essential destiny enhancement is to test the accuracy of our simulator in real global situations. It will offer a more potent base for the future researchers in this discipline of CRSN.

Hind Ali. M. Saad,(2018) [12] Cognitive radio (CR) is considered as an shrewd wi-fi verbal exchange machine proposed to enhance the usage of the radio electromagnetic spectrum. In CR era the secondary customers take the duty of dynamically sensing and gaining access to any unused channels in the spectrum allotted to the certified users. As spectrum sensing consumes substantial power, predictive techniques for inferring the availability of spectrum holes can reduce electricity intake of the unlicensed users to most effective feel those channels which are in all likelihood to be idle. It also helps to enhance the spectrum utilizations. Several prediction strategies have been used to are expecting spectrum utilization. However, most of present day processes do now not do not forget seasonality in spectrum workload, as an example most of the channels are busy at some point of enterprise hours in mobile telephone bands. Hind Ali. M. Saad,(2018) [12] proposed a channel reputation predictor primarily based on the multiplicative seasonal model called Holt-Winters' method.

To enhance the utilisation performance of licensed spectrum in cognitive radio network, two new channel choice techniques are proposed for the secondary user (SU) in this work. XiaoboTan(2013) [13] proposed answer tries its best to lessen collision and switching chances of the SU all through records transmission. By using ancient statistics of the certified spectrum, the SU chooses the channel with the lowest busy opportunity within its provider time for records transmission. Time series prediction is hired to forecast the near future busy chances of the certified spectrum gadgets, and a novel time collection prediction method named distance factor recursive least square is likewise offered. Simulations show that the performances of the SU, that's measured by collision possibility with primary person, switching chance all through information transmission and throughput within restricted time slots, are all appreciably advanced whilst in comparison with random channel choice technique. Higher prediction accuracy than the traditional recursive least rectangular and lazy mastering techniques is achieved with the aid of proposed time collection prediction algorithm while examined by voice visitors records and Lorenz time series.

3. Methodology:

We will present the proposed method of predicting busy probabilities of candidate spectrum units. The method enables the SU to choose appropriate channel to reduce the probabilities of collision and switching during data transmission.

The Bayes Theorem describes the probability of occurrence of an event related to any condition. For example: if we have to calculate the probability of taking a blue ball from the second bag out of three different bags of balls, where each bag contains three different color balls viz. red, blue, black. Such case where probability of occurrence of an event is calculated depending on other conditions is known as conditional probability.

Conditional Probability P (A/B) = P (B/A)*P (A) /P(B).

The historical busy probability of the ith spectrum unit at time slot t can be expressed as $\{p_i(t), i = 1,2,\cdots\}$. Let $P_j(t) = [p_i(t-1),\cdots,p_i(t-m)]^T, Y_i(t_h) = p_i(t+h)$, where m is the embedding dimension, h is the prediction step and $y_i(t_h)$ is the busy probability of the ith spectrum unit after h time slots. If there is a mapping F between Φ and Γ, which can be written as $F: \Phi \to \Gamma$, with

$$\Phi = \{P_i(m+1), P_i(m+2), \cdots, P_j(m+N)\} = \begin{pmatrix} p_i(m) & p_i(m+1) & p_i(m+N-1) \\ p_i(m-1) & p_i(m) & p_i(m+N-2) \\ \vdots & \vdots & \vdots \\ p_i(l) & p_i(2) & p_i(N) \end{pmatrix}$$

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and $\Gamma = \{Y_i(m_1), Y_i(m_2), \cdots, Y_i(m_N)\}$; thus, the problem of time series prediction can be formulated as mapping reconstruction on the basis of (Φ, Γ). And the (Φ, Γ) are known as the training examples. After the map- ping reconstruction is completed, for a historical busy probabilities vector $P_j(q)$, we always can compute the pre- diction value of $y_i(qh)$ by applying the equation given as follow:

$$\hat{Y}(qh) = F(P_i(q)) \quad (1)$$

When $h = 1$, the prediction is defined as one-step pre- diction, whereas when $h > 1$, the prediction is defined as multistep prediction.

Actually, many prediction methods have been proposed for time series prediction, such as recursive least square (RLS) [5] and lazy learning (LL) [6]. Autoregressive model, moving average model and autoregressive moving average model are the main models of time series anal-ysis. According to the conclusion in [7], autoregressive model (simultaneously its order also can be determined) is employed. Thus, the prediction of the busy probability can be described by the equation as follows:

$$\hat{Y}(m_k) = \theta P_i(m + k) + e(k) \quad (2)$$

where $1 \le k \le N$, $e(k)$ is prediction error between $\hat{Y}(m_k)$ and $Y_i(m_k)$, which can be written as $e(k) = Y_i(m_k) - \hat{Y}(m_k)$. And θ is defined as prediction coeffi-cient vector with $\Theta = [\vartheta_1, \theta_2, \cdots; \vartheta_m]$. We notice that the key to find the mapping F is the estimation of Θ. In con-ventional RLS method, the cost function used to estimate Θ can be denoted as

$$J(\Theta) = \sum_{k=1}^{N} e^2(k) \quad (3)$$

Compared with conventional RLS method, the main improvement of the DF-RLS proposed in this paper is the similarity measurement of time series, which defined asdistance factor between the $P_i(q)$ and the training exam-ples $P_i(m + k)$. The cost function of DF-RLS can be modified as

$$J(\Theta) = \sum_{k=1}^{N} \beta_i(k) e^2(k) \quad (4)$$

And $\beta_i(k)$ is the distance factor, which is defined as

$$\beta_i(k) = \frac{1}{|P_i(q) - P_i(m+k)|^2} \quad (5)$$

where $|.|^2$ is a two-norm operator. From the equation, we can find the Euclidean distance between the two time series is employed as similarity measurement. It indicates that the more similar of the two busy probability series $P_i(q)$ and $P_i(m - k)$, the more it contributes to the cost function. Thus, the prediction coefficients can be computed by applying the following equation:

$$\Theta(k + 1) = \Theta(k) + \beta_i(k + 1)(k + 1)e(k + 1) \quad (6)$$

with

$$e(k + 1) = Y(m_{k+1}) - \Theta(k)P_i(m + k + 1), \quad (7)$$

$$(k + 1) = g(k + 1)P_i(m + k + 1), \quad (8)$$

$$g(k + 1) = g(k) - \frac{\beta_i(k+1)g(k)P_i(m+k)P_i(m+k)^T g(k)}{\beta_i(k+1) + P_i(m+k)^T g(k)P_i(m+k)} \quad (9)$$

After a series of iterations, the prediction coefficients are obtained. Thus, the predicted busy probability $\hat{Y}(q_h)$ can be computed by

$$\hat{Y}(q_h) = \Theta P_i(q) \quad (10)$$

Because the derivations of the proposed method follow the same way as conventional RLS method, only the main iterative process of DF-RLS is presented in this paper, as shown in algorithm 1.

If there are N training examples, only one time of iter-ation is needed for conventional RLS method in each pre- diction, but for the proposed DF-RLS method, N times of iteration are required. Despite the computation complexity of the proposed method is increased, whereas the following simulation results demonstrate that the accuracy of predic-tion results of the proposed is improved when compared with the conventional RLS method.

To improve the utilisation efficiency of licensed spectrum in cognitive radio network, two new channel selection strategies are proposed for the secondary user (SU) in this paper. The proposed solution tries its best to reduce collision and switching probabilities of the SU during data transmission. By using historical information of the licensed spectrum, the SU chooses the channel with the lowest busy probability within its service time for data transmission. Time series prediction is employed to forecast the near future busy probabilities of the licensed spectrum units, and a novel time series prediction method named distance factor recursive least square is also presented. Simulations prove that the performances of the SU, which is measured by collision probability with primary user, switching probability during data transmission and throughput within limited time slots, are all significantly improved when compared with random channel selection method. Higher prediction accuracy than the conventional recursive least square and lazy learning methods is achieved by proposed time series prediction algorithm when tested by voice traffic data and Lorenz time series.

Algorithm 1 Main iterative process of Bayesian algorithm

1: Initialisation: $\Theta(0) = [0, 0, \cdots 0]_{1\times m}$,
2: for $k = 1; k \le N; k + +$; do
3: Compute $\beta_i(k)$ by using Equation (5);
4: $\hat{Y}(m_k) = \Theta(k - 1)P_i(m + k)$ by Bayesian Prediction model
5: Compute $e(k)$ by using Equation (7);
6: Update $\Theta(k)$ by using Equations (6), (8) and (9);
7: end for
8: $\hat{Y}(q) = \Theta P_i(q)$

3.1. Channel Selection Algorithm

According to the system model and assumptions, Figure 4 shows that the total available spectrum is divided into s spectrum units and an exclusive ID is assigned to each of them. The total spectrum units can be denoted as aspectrum set S, with $S = \{u_1, u_2, \cdots; u_s\}$. If more than one spectrum units are idle at the same time, how the SU chooses transmission channel to improve its trans- mission performance is a crucial problem. Two strategies are proposed for channel selection based on the estimated probabilities.

Strategy A: If the service time slots are $\rho Tpsu$, according to the sensing information from the spectrum sensing mod-ule, $d(1 \le d \le s)$ spectrum units are idle at t, which can be denoted as an idle spectrum units set U, with $U subseteq$ S. Then, the busy probabilities prediction module forecasts the busy probabilities of $u_\alpha(u_\alpha \in U, 1 \le \alpha \le d)$ in the followingtime slots, which can be denoted as

$$\hat{p} = [\hat{p}(t+1), \hat{p}(t+2), \cdots; \hat{p}(t+\rho)] \quad (11)$$

Thus, the selected channel is

$$C_{sl} = \arg\min\{\frac{1}{\rho}\sum_{i=1}^{\rho}\hat{p}(t+i)\} \quad (12)$$

The channel selection strategy A is summarised in algorithm 2.

Strategy2: The SU would occupy only one spectrum unit with strategy A. Although the selected spectrum unit has the minimum mean busy probability among the can dedicate spectrum units, its busy probability cannot always maintain at low level during data transmission, such as

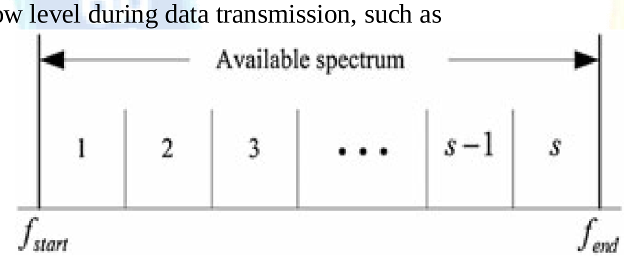

Fig. 1. Division of the available spectrum

Algorithm2: Channel selection algorithm: strategy
Updates the information of idle spectrum units;
if $U \neq \varphi$ then
Load the historical busy probabilities of d spectrum units;
$for \alpha = 1; \alpha \le d; \alpha++; do$
Generates the αth training examples $(\Phi, \Gamma)_\alpha$;
for $j = 1; j \le \rho; j++$; do
DF-RLS: $\Theta_\alpha \leftarrow F : (\Phi \leftarrow \Gamma)_\alpha$;
$\hat{p}(1,j) \leftarrow \hat{p}(t-j) \leftarrow \Theta_\alpha P_\alpha(t+j)$;
end for
end for
Select channel according to Equation (12);
end if

Its busy probability periodically increases and decreases rapidly within a limited time slots. Therefore, the transmission of SU may be interrupted if the data transmission cannot be completed during the interval. Meanwhile, other idle spectrum units, which would provide the SU wider transmission bandwidth, are not utilised. In this case, throughput of the SU will be decreased because of the increase of switching times and the bandwidth limitation of the transmission channel. If the SU can occupy more spectrum units and transmit all the data with fewer time slots, the transmission performance of the SU would be improved.

When service time slots of the SU are $\rho Tpsu$, U is the idle spectrum units set at t. The SU checks whether there are adjacent spectrum units in U at first. If there is no adjacent spectrum unit, strategy A is applied for channel selection; otherwise, the available spectrum units are divided into several spectrum groups. Spectrum group is defined as a series of adjacent spectrum units. For example, when $U = \{u_1, u_2, u_4, u_6, u_7, u_8\}$, the idle spectrum units would be divided into three spectrum groups; they are $G_1 = \{u_1, u_2\}$, $G_2 = \{u_4\}$ and $G_3 = \{u_6, u_7, u_8\}$. We assume that there are η spectrum groups, and one spectrum group $G_v(1 \le v \le \eta)$ consists of σv spectrum units. The candidate channels are consisted of $\chi(1 \le \chi \le \sigma v)$ adjacent spectrum units in G_v; thus, the actual time slots of the SU needing to transmit all the user data are reduced to ρ_{ac}, which is defined as

$$\rho_{ac} = \lceil \rho/\chi \rceil \quad (13)$$

where dl is an operator, which rounds · to the nearest integer greater than or equal to ·. So, the busy probability of the $\tau th(1 \le \tau \le n)$ candidate channel (consists of χ_τ adjacent spectrum units) in G_v during the following ρ_{ac} time slots can be computed by

$$\hat{P}v\tau = \frac{1}{\chi_\tau} : \sum_{j=1}^{\chi_\tau}[\frac{1}{\rho_{ac}}\sum_{i=1}^{\rho_{ac}}\hat{p}(t+i)]\} \quad (14)$$

where$\hat{p}(t+i)$ is the prediction busy probability of the j th spectrum unit in the candidate channel at the following ith time slot. After the busy probabilities of all candidate channels in G_v are calculated, the minimum busy prob- ability $\hat{p} = \min\{\hat{p}1 \le \tau \le n\}$ and the correspond-ing candidate channels C_v are stored. Then, the selected channel is

$$C_{sl} = C_v(v = \arg\min \ldots\{\hat{p}\}) \quad (15)$$

When the service time slot of the SU is small and a channel consisted of χ spectrum units is selected for data transmission, according to Equation (13), despite the ρ/χ is small, at least one time slot would be assigned to the SU for data transmission. Hence, during this time slot, lots of idle spectrum units would be occupied by one SU to transmit small

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amount of user data, whereas the other SUs can not access these spectrum units anymore. In this case, the spectrum efficiency of the cognitive radio network would be significantly decreased. To avoid this problem, a spectrum efficiency threshold σ_{se} is defined to guarantee that the SU would occupy suitable number of spectrum units for data transmission. The threshold indicates that the number of spectrum units in one spectrum group is constrained; that is,

$$\chi = \{\chi = 1,2 \cdots \sigma v; \text{ and} \frac{\rho}{\chi} \geq \sigma_{se}\} \quad (16)$$

Thus, the channel selection strategy B is summarised in algorithm 3.

In strategy A, only one spectrum unit would be occupied for data transmission. Therefore, if strategy A is employed as channel selection method in the cognitive cell, data transmission rate of the SU would be limited as its bandwidth can be utilised for data transmission is fixed. By contrast, strategy B is much more flexible. If there are many idle spectrum units, the number of spectrum units occupied for data transmission can be adjusted according to the user's requirements. Thus, the SU employed with strategy B can vary its transmission rate at a larger range than the one with strategy A. This ability is important especially when transmission rate adaptation is required by the user.

To collect busy probability information, the SU needs to sense the spectrum units several times in one time slot. Thus, determining a proper sensing frequency would be an important factor to consider. If the sensing frequency is too low, it would bring large observation errors to observed busy probability. In this case, because of the inaccurate prediction, the proposed solution may miss the transmission opportunity with lower busy probability. The following simulations demonstrate that the busy probabilities are accurate enough if they can represent the basic busy/idle situation of spectrum unit. Blindly increasing the sensing frequency can not bring much benefit because of high sensing overhead, such as the consumption of energy and time.

Algorithm3: Channelselectionalgorithm:strategyB
1: Updates the information of idle spectrum units U;
2: Load the historical busy probabilities of d spectrum units;
3: if $U \neq \varphi$ and there are adjacent spectrum units in U then
4: Find η spectrum groups: $\{G_1, G_2 \cdots G_\eta\}$;
5: for $v = 1; v \leq \eta; v++do$
6: χ is selected according to Equation (16);
7: n candidate channels are searched;
8: for $\tau = 1; \tau \leq n; \tau++do$
9: for $j = 1; j \leq \chi_\tau; j++do$
10: Generates the jth training examples $(\Phi, \Gamma)_j$;
11: $:_{ji} \leftarrow F : (\Phi \leftarrow \Gamma)_{ji}, i$ from 1 to ρ_{ac};
12: $\hat{\Gamma} v\tau \leftarrow \frac{1}{\chi_\tau}\hat{p} \leftarrow \frac{1}{\rho_{uc}}\sum_{i=1}^{\rho_{ac}} \theta_{ji}\Gamma_{ji}(t+i)$;
13: end for
14: end for
15: $\hat{p} = \min\{\hat{p}1 \leq \tau \leq n\}$;
16: end for
17: Select channel according to Equation (15);
18: else
19: Strategy A is applied;
20: end if

The channel selection latency of the proposed solution can be further reduced with the aid of channel sensing sequence management. Meanwhile, searching all the candidate channels to find the one with the lowest busy probability would consume a lot of time. To reduce the time consumption, once the future busy probability of one channel is below a predefined threshold, the searching operation stops. These are the two possible ways to reduce the channel selection latency.

4. Result and Discussion:

In this chapter the results and analytical observations are described in details regarding the response generated by our approach for explaining the response that are generated by development of algorithm for improved prediction strategy of ideal and busy channels in a WSN network using Bayesian prediction process.

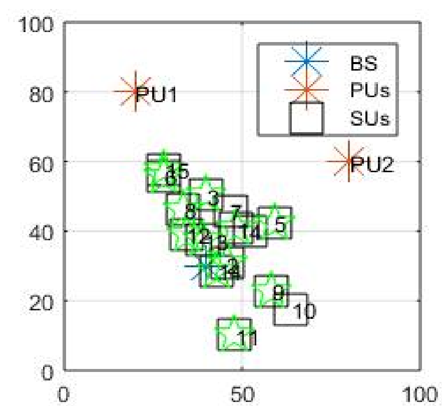

Fig 2: WSN network with different users.

In the fig 2 it has been shown that in a network area of 100 x 100 meter there are several users some are behaving as primary user and some are secondary user. They are communicating to each other.in a given cognitive cell environment.

The active users in each round are ready to send packet. It can be shown that it has 15 users all total and some of them have zero and most of them have 1one statusrepresenting busy/idle state. In such a way the number and ids of active users varies. Similarly the status of spectrum band is also allotted or unalloted. The number of bands are less than the number of users. If active users are less than the number of bands then some bands will remain ideal and if active users are equivalent to number bands then all the bands will be busy and if active users are more than the bands then packet drop will occur.

In the proposed work multi step prediction is applied to estimate the status of all the bands prior to channel allotment autonomously by the network head. The busy probability in upcoming round is predicted by using the Bayesian Prediction model. The data used to predict is initially generated for 60 to 100 rounds.Then using last busy probability values 3 to 10 steps back the upcoming instance busy probability of all bands is predicted by Bayesian model.

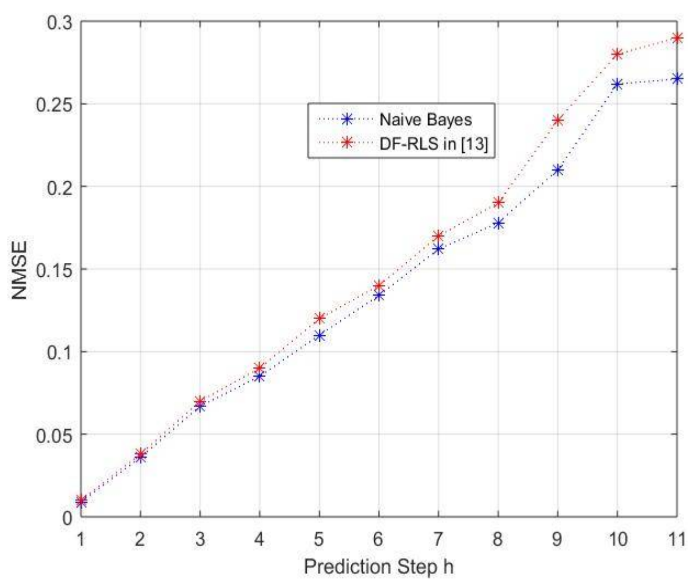

Fig. 3(a): Error (NMSE) in proposed model and base paper at 300 iterations.

Fig 3(a) represents the error in the data value that are predicted and the actual data value at different time slots. The x axis is the prediction steps and the NMSE value is varying from 0 to 0.3. The normalized mean square error in prediction of busy probability at different prediction steps as the prediction steps are increased the errors are increased. The maximum error observed here is 0.3.

Figure 3(b) is also representing the plots for NMSE when algorithm runs for different iterations varying for 200,300,400 and 500 iterations. It is observed that as the prediction steps are less than 4 the NMSE is low but at higher predictions steps from 4 to 11 the NMSE increases.

The throughput of the Bayesian and DF-RLS are calculated from the generated results and all the results are saved for different number of spectrum units and it has been also run for multiple values of iterations.

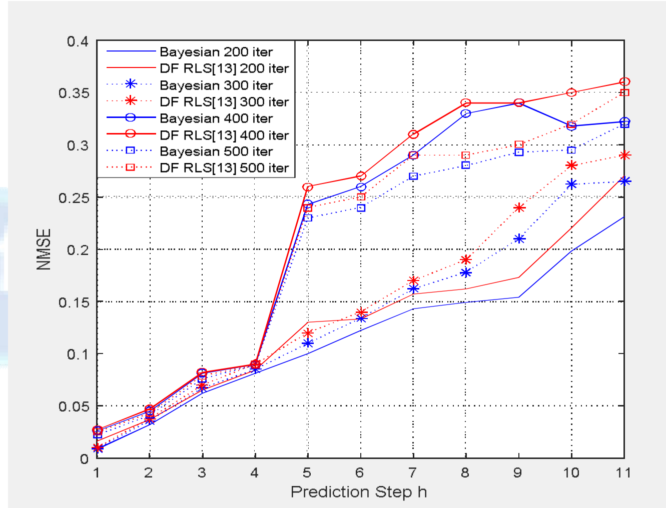

Fig 3(b): Error (NMSE) in proposed model and base paper at 200,300,400 and 500 iterations.

The result are demonstrated in figure 4 as the bar plot. In this figure the y axis represents the throughput value as packet successfully transmitted per unit time. The x axis represents the number of spectrum units if the number of spectrum is low then it cause large dropout due to lower chances of availability of spectrum band as the spectrums increases throughput has also increased.

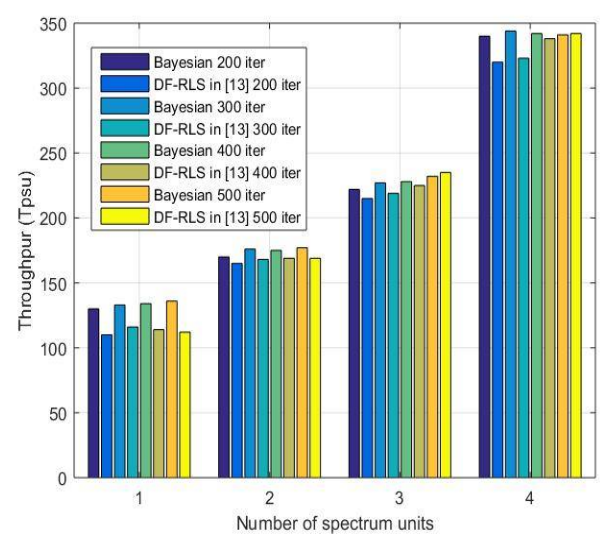

Fig 4: Throughput values at different number of spectrum units for proposed model and base paper at 200,300,400 and 500 iterations.

The overall network throughput at different values of spectrum units is compared one by one. The spectrum units are varied from 1 to 4 and thereafter the data throughput is generated and the plot for this value represents that as the spectrum units are increased the throughput increases and the through put maximum goes to the 340 approx. and for all spectrum units value the proposed Bayesian approach throughput is found to be higher than the DF-RLS work.

Figure 5 represents the value of packet delivery ratio that are derived for different network area size of the field where the nodes are assumed to be placed. The x axis is the network area and it can be observed that as the area network is increased from the value 2500 m^2 to 90000m^2 the packet decreases due to large transmission distance in between the nodes. Hence delivery failure instances are increased.

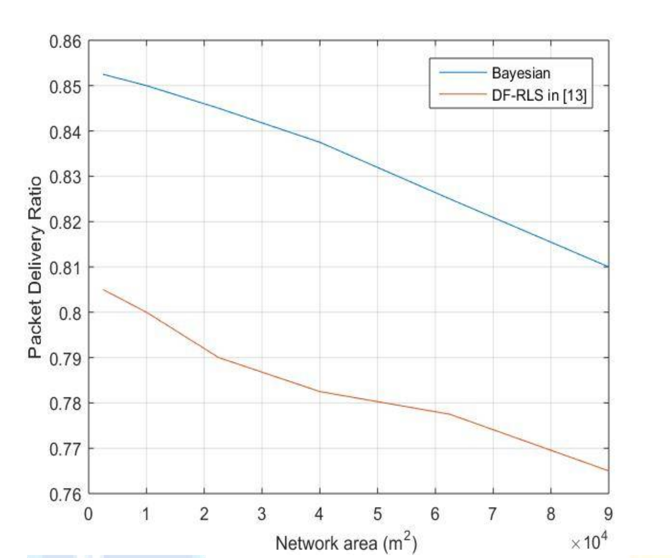

Fig 5: Packet Delivery Ratio with respect to network area.

5. Conclusion:

In this thesis, we adopt cooperative sensing technique to avoid the packet collision among SUs and PUs and attention on a manner to gather the spectrum sensing statistics of SUs for cooperative sensing. In order to lessen the channel opposition among SUs, we first don't forget the transmission version for a SU which could opportunistically get entry to every channels operating either the busy or the proper state version and the busy channels by means of manner of using the channel priority set of rules era. Then we propose a predictive set based channel choice coverage the usage of Bayesian Classification set of guidelines for multi-SU in which all SUs competing for records transmission or energy harvesting inside the identical channel will shape a dedicated set. Extensive simulations display that the proposed cooperative sensing approach and the channel choice policy out carry out previous answers in phrases of switching alarm, common throughput, common errors, and collision chanceof SUs.

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