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A NOVEL OPPORTUNISTIC CHANNEL SELECTION BASED ON TIME SERIES PREDICTION IN COGNITIVE RADIO NETWORKS

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Abstract *— Cognitive radio is a wireless technology that provides solution to meet scarcity of radio spectrum. Here to find out the busy states of any spectrum unit and selection of suitable vacant channel for communication by secondary users are two essential tasks. In this paper a new technique Navien Bayes classifier based on Bayes theorem has been applied to find out the minimum busy probability of any spectrum unit. Various predictions at various steps, their switching probability, collision probability and throughput has been taken in the series. By using previous data of the licensed spectrum, the SU selects the channel with the lowest busy probability within its service time for data transmission. Time series prediction is employed to estimate the near upcoming busy probabilities of the licensed spectrum units,*

Keywords: *Cognitive Radio, Bayes Classifier, Bayes Theorem, switching probability, collision Probability.*

1. INTRODUCTION

With the increase in wireless technologies there is no increase in radio spectrum and it has been limited. From studies it is clear that spectrum is not occupied completely many of the times and much of licensed band remains idle for durations which is a waste of available resource. Studies have proved that there exist unoccupied spaces in the given spectrum and these are considered as spectrum holes. These existence of spectrum holes inspire researchers to bring cognitive radio as new a field to proficiently utilize radio spectrum.

1.1 Cognitive Radio

The role of cognitive radio came into existence where the secondary users (non-license holders) can borrow the idle interference. As there should not be interference with the primary users, cognitive radio user's that is the secondary user should leave the channel as early as possible when primary user is arrived.

The working environment of the SU is time varying; thus, cognitive radio should have the ability to learn from past experience to improve future performance instead of taking instantaneous information into account only. In [19], the authors tried to pursue a better future performance by applying a predictive method, which can forecast the busy– idle states of the primary channels. However, the method is effective only when the traffic patterns (which are specially defined) of primary channels are classified correctly at first; otherwise, its performance would be decreased.

The rest of this paper is organized as follows. Section II reviews the related literature about the spectrum usage models. In Section III, we introduce the basic operations of switching, collision probability and shown that data is being transmitted. In section 4 we have discussed about channel selection algo. Then simulation results and finally conclusion we have.

2.SYSTEM MODEL AND ASSUMPTIONS

In this paper, as shown in Figure 1(a), we consider a wireless scenario that a cognitive cell coexists with PUs. The cognitive cell consists of a cognitive base station (CBS) and many SUs. To improve the sensing efficiency of the SUs, collaborative spectrum sensing is employed. All the SUs in the cognitive cell are divided into several SU clusters by sensing task management module in the CBS. And each cluster is assigned to sense only part of the total available spectrum bands instead of all the spectrum units. Therefore, time needing for spectrum sensing can be significantly reduced. In addition, new methods such as compressive sensing[8], advanced sensing task management schemes [15,11] and novel design of the cognitive radio receiver [9] also can be applied to improve the sensing efficiency and accuracy in spectrum sensing applications.

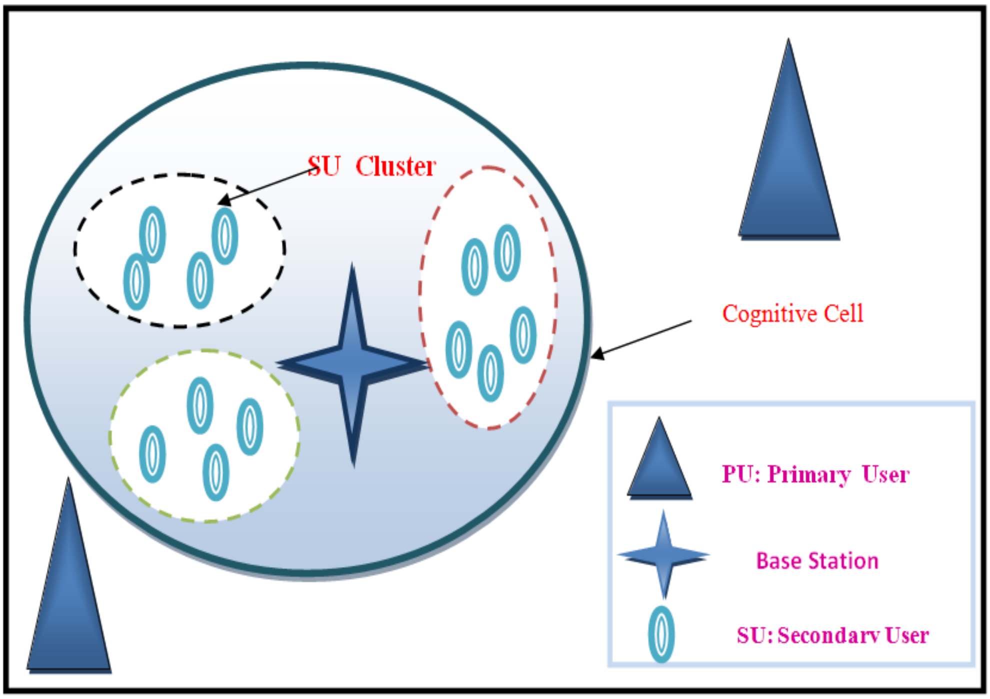


Fig no 1. Wireless scenario of this paper

In the range of cognitive cell, the CBS can effectively exchange data with all the SUs and schedule the SUs for collaborative spectrum sensingThe total available spectrum band for cognitive radio is divided into multiple equal spectrum units, which can be sensed and used by SUs. To obtain busy probabilities of the spectrum units in each time slot (a limited time interval, which is predefined), spectrum sensing must be carried out for M .M >1/ times in one time slot. If Q busy states of the spectrum unit are detected, then the busy probability of the spectrum unit can be described independently by the ratio of Q /M.

Busy Probability (Pb)= Q/M

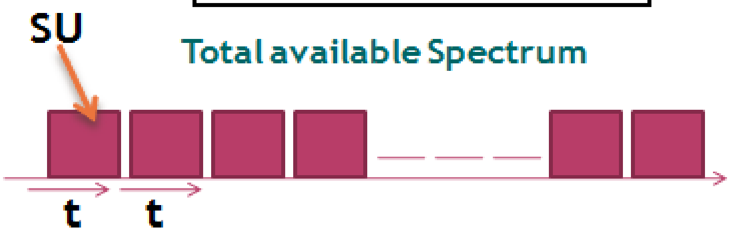


Fig no 2.Division of the available spectrum

3. SWITCHING AND COLLISION PROBABILITY

SUs in the cognitive cell always can obtain information about current available spectrum units from the CBS. Because the performance of proposed solution much relies on historical busy probabilities of the spectrum units, Figure 2 presents the flow chart of how data are transmitted in this presented model. From the figure, we can see that the whole procedure can be divided into three processes, which denote different states of the SU under different conditions:

- P1. The SU chooses the transmission channel according to channel selection strategy and then checks whether the PU appears in the selected channel. If the PU is detected, one collision happens, and the data transmission is blocked.
- P2. Data transmission of the SU continues in selected channel until the PU is detected or all the data is transmitted. If the PU is detected during data transmission, switching happens.
- P3. When the PU appears during data transmission, switch happens, and the SU has to choose a new channel to resume its transmission. Otherwise, transmission goes on until all the user data are transmitted.

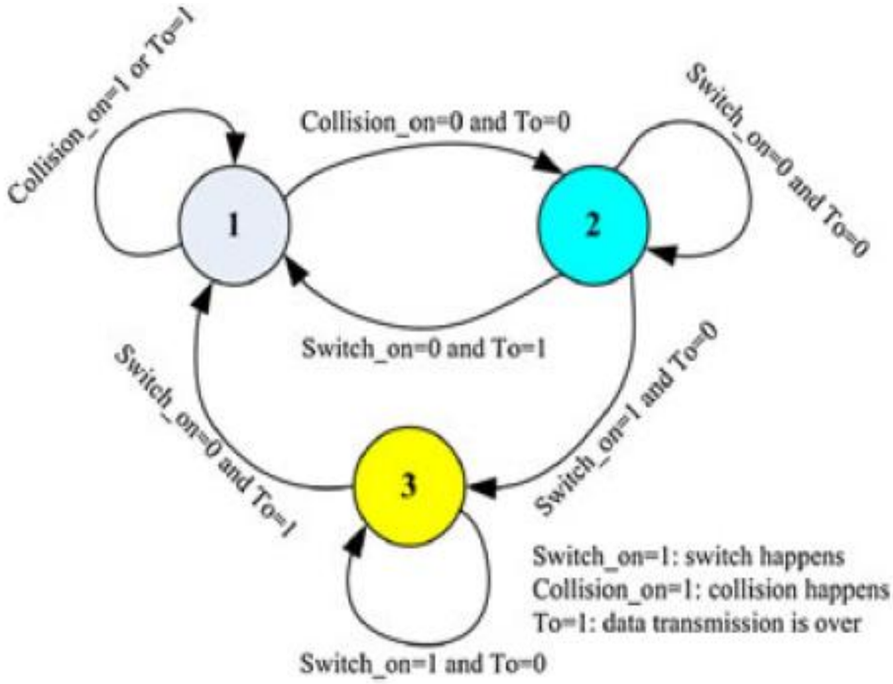


Figure 2. Flow chart of data transmission

4. CHANNEL SELECTION BASED ON NAÏVE BAYS CLASSIFIER

Naive-Bays classifier assumes that the occurrence of a particular feature in a class is dissimilar to the presence of any other feature. Bays Theorem combines prior knowledge of the classes with new facts gathered from training data [9]. Extensive simulations show that the proposed channel selection policy out perform previous solutions in terms of switching alarm, average throughput, average error, and collision probability of SUs.
Navie bayes classifier which basically works on to the principle of bayes theorem,which states that It follows simply from the axioms of conditional probability, but can be used to powerfully reason about a wide range of problems involving belief updates. Given a hypothesis H and evidence E, Bayes' theorem states that-

$$P(H|E) = \frac{p(E|H)}{P(E)} P(H)$$

Naive Bayes classifiers assign observations to the most probable class (in other words, the maximum *a* posteriori decision rule). Explicitly, the algorithm:

1. Estimates the densities of the predictors within each class.
2. Models posterior probabilities according to Bayes rule. That is, for all $k = 1,...,K$,

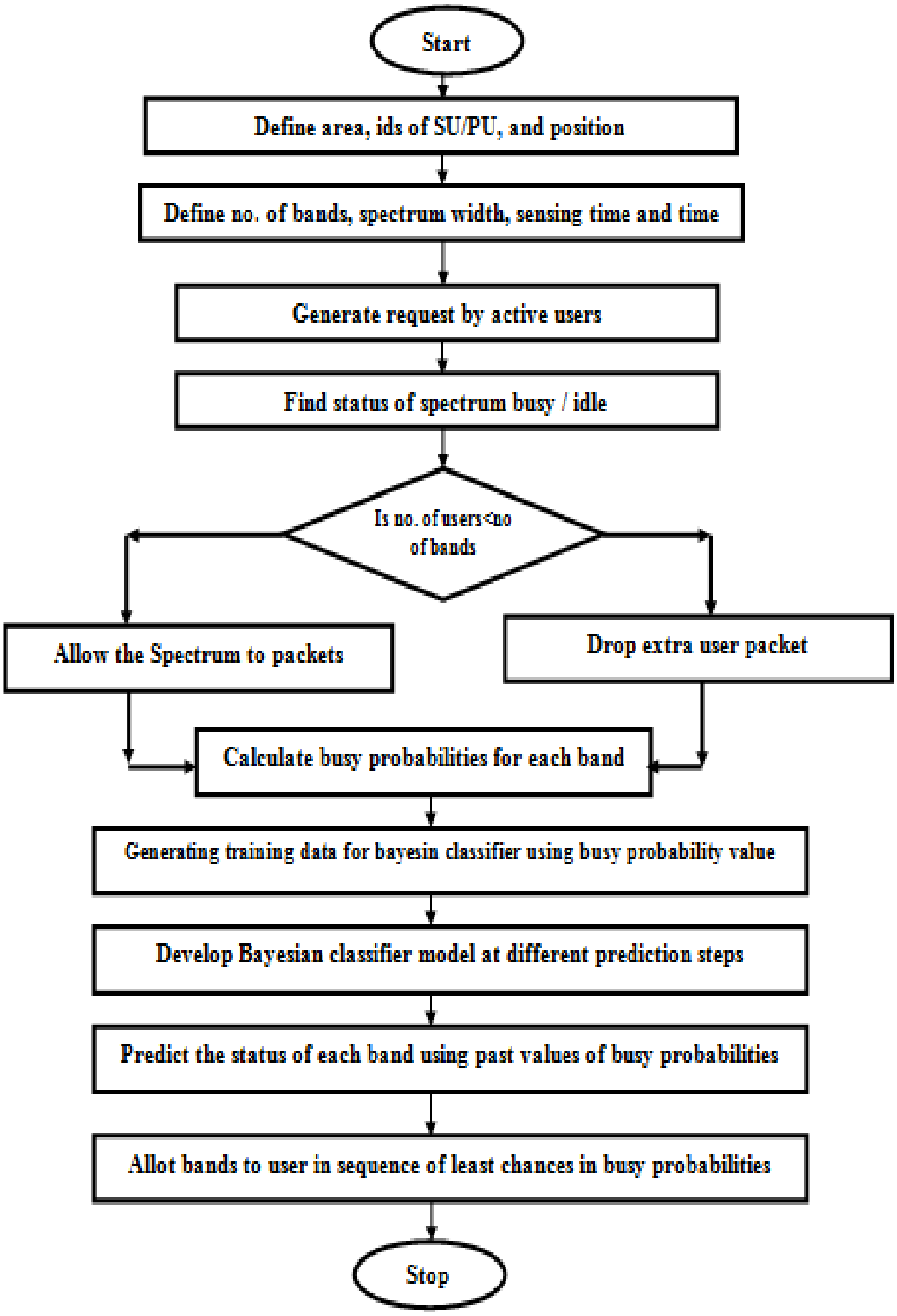
$$\hat{P}(Y=k|X1,..,XP) = \frac{\pi(Y=k)\prod_{j=1}^{p}(Xj|Y=k)}{\sum_{k=1}^{k}\pi(Y=k)\prod_{j=1}^{p}P(Xj|Y=k)}$$

where:

- Y is the random variable corresponding to the class index of an observation.
- $X_1,...,X_P$ are the random predictors of an observation.
- $\pi(Y=k)$ is the prior probability that a class index is k.

Simulation parameters Used –

Area	**(100 * 100) meters**
Base center near the station	**[40, 20]**
No. of Primary users	**2**
No. of Secondary users	**15**
No. of	**9**



5.PERFORMANCE EVALUTION

In this section the results and analytical observations are described in detail..In the figure 4.1 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 communicationg to each other in a given cognitive cell environment. Figure4.1 (b) demonstrates the number of active users in a round that are ready to send packet. It can be seen that it has 15 users all total and some of them have zero and most of them have 1one status. In such a way the number and ids of active users varies. Figure 4.1 (c) displays the status of spectrum band. In this figure it can be seen that y axis is the busy probability of each band and x axis is the band id varying from 1 to 9 (total 9 bands).

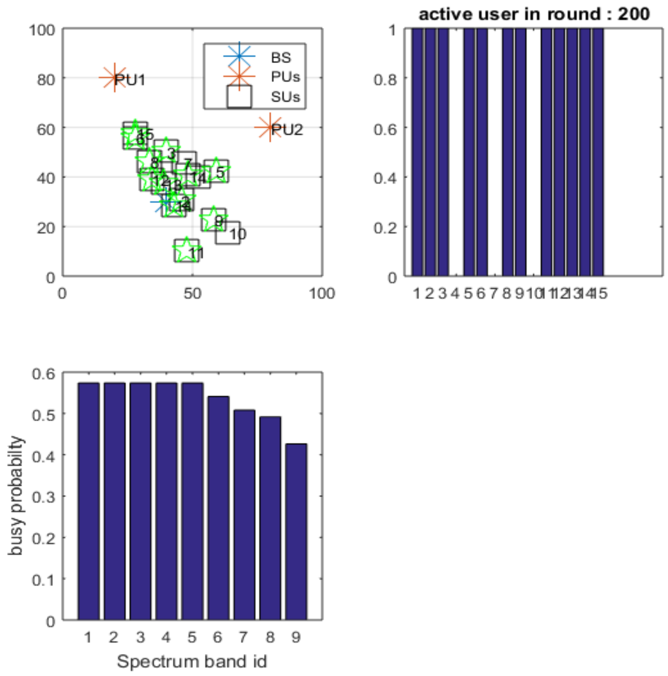


Figure 4.1: (a) WSN network with different users.(Top left) (b) Active user at round r=200 (top right) (c) busy probability(bottom left)

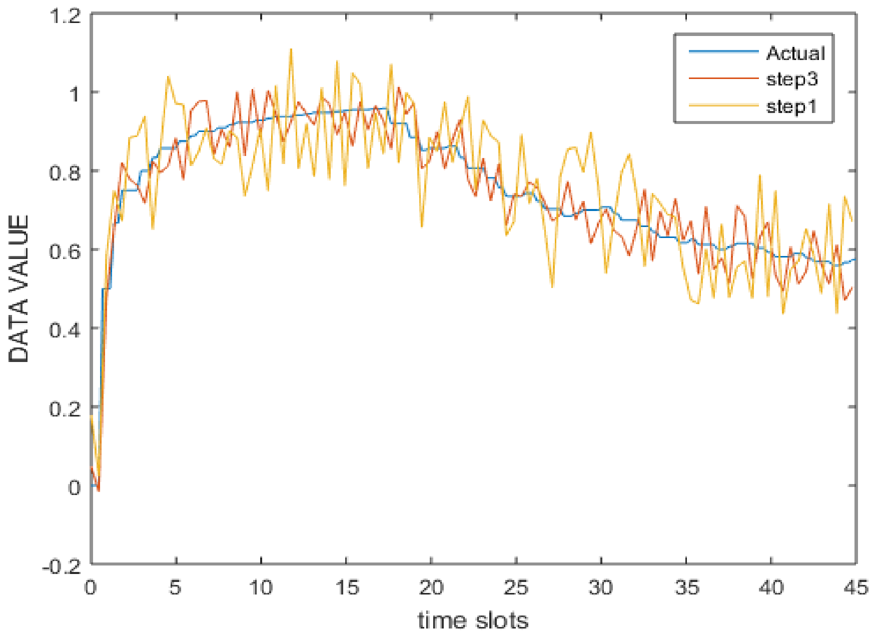


Figure 4.2: Representations of the actual and estimated busy probability.

Figure 4.2 represents the data value that are predicted and the actual data value.at different time slots.x axis is the time slots from 0 to 45 seconds and the data value is varying from 0 to 1 in actual data and the predicted value using one step and 3 step prediction. All the values are fitted using the same approximate curve the predicted value and the actual value as well. That's why we can say that it satisfies all the predicted values.

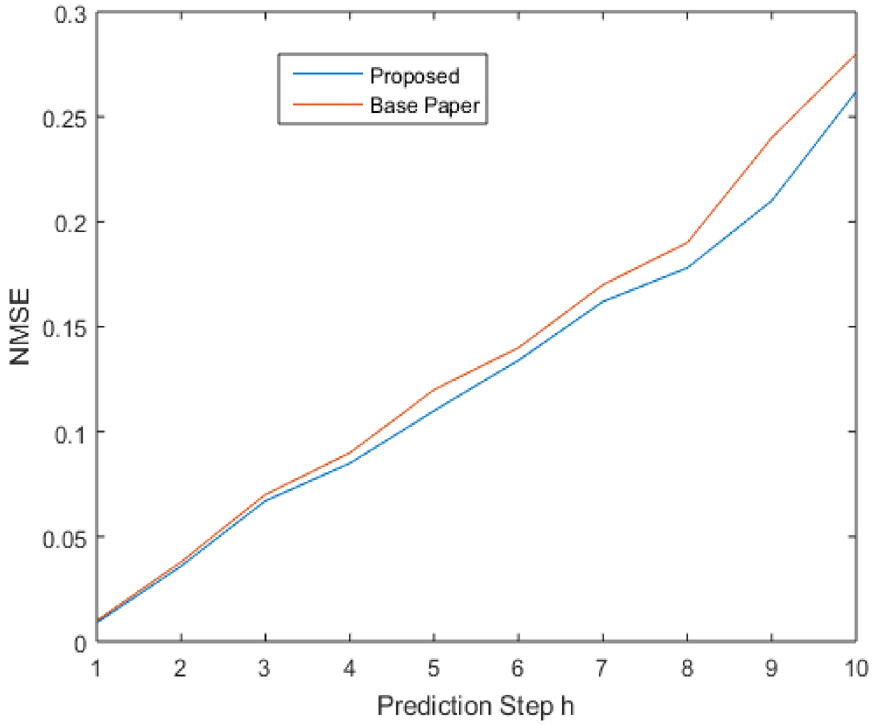


Figure 4.3 Error (NMSE) in proposed model and base paper.

Figure 4.3 displays 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

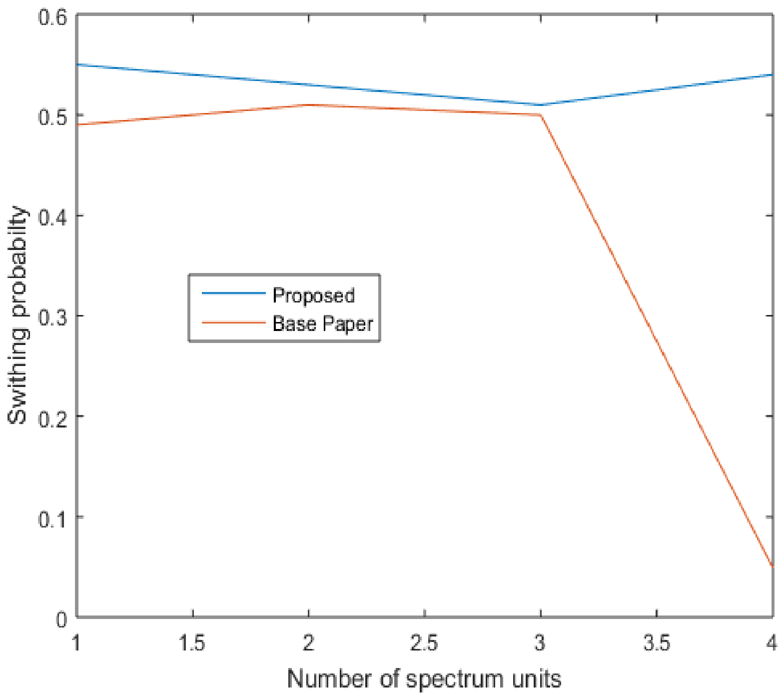


Figure 4.4 Switching Probability vs no.of spectrum units

Figure 4.4 displays the switching probability of the bands from ideal state to busy state and vice versa. In proposed work switching probability is higher It observed that this switching probability s consistent and in between 0.5 to 0.6.

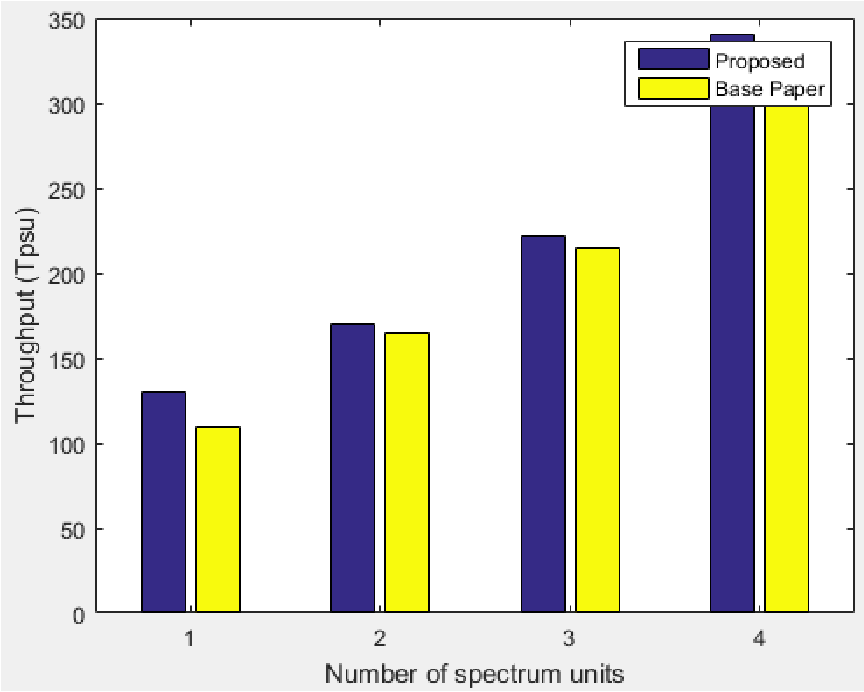


Figure 4.5 Throughput vs no. of spectrum units

Further the graphs of figure 4.5 shows the overall network throughput at different values of spectrum units. 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.

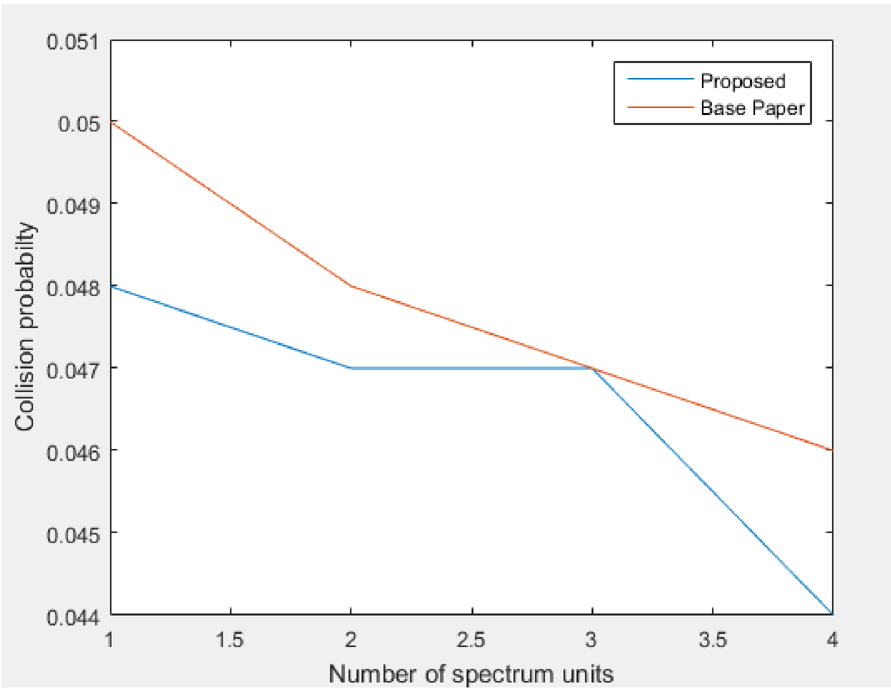


Figure 4.6 Collision Probability vs no.of spectrum units

Figure 4.4 displays the collision probability of the bands from ideal state to busy state and vice versa. In proposed work collision probability is lower, which will significantly improve the system's performance. All the analytical results have been verified using the MATLAB simulation tool.

6.CONCLUSION

In this network, the crucial issues are the channel allotment among SUs and the packet collision between SUs and PUs.We adopt the Bayesian classifier based cooperative spectrum sensing method to reduce the probability of sensing errors and alleviate the interference to PUs. In order to solve the problem of channel competition among SUs each SU can implement data transmission in an idle channel .Additionally, we present a channel selection policy for multi-SU based on competitive set.

Our proposed policy can achieve higher throughput compared with the conventional random policy with lower collision probability because of very low prediction error. Furthermore, the collision will never be detected by themselves and may last for a quite long time when several SUs collide with each other in the conventional random policy. Hence, the channel competition among SUs will largely limit the performance of conventional random policy. In future we can include that while SUs detect the collision in the initial phase and stop transmission in the next phase to avoid longer ineffective transmission in our future scopes policy. Such simulations may show that the proposed cooperative sensing method and channel selection policy outperform previous solutions in terms of probability of false alarm, average throughput, average waiting time, and energy harvesting efficiency of SUs.

7. References

[1] Ala Al-Fuqaha, "Opportunistic Channel Selection Strategy for Better QoS in Cooperative Networks with Cognitive Radio Capabilities," IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, VOL. 26, NO. 1, JANUARY 2008

[2] Tevfik Y¨ucek and H¨useyin Arslan, "A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications," IEEE COMMUNICATIONS SURVEYS & TUTORIALS, VOL. 11, NO. 1, FIRST QUARTER 2009

[3] Vamsi Krishna Tumuluru, "A Neural Network Based Spectrum Prediction Scheme for Cognitive Radio," Center for Multimedia and Network Technology (CeMNeT) School of Computer Engineering, Nanyang Technological University, Singapore.

[4] S. Senthuran, "Opportunistic Channel Sharing based on Primary User Transition Probabilities in Dual Mode Cognitive Radio Networks," IEEE Communications Society subject matter experts for publication in the IEEE ICC 2011 proceedings.

[5] Moshe Timothy Masonta, "Spectrum Decision in Cognitive Radio Networks: A Survey," Member, IEEE,2012

[6] Vamsi Krishna Tumuluru, "Channel status prediction for cognitive radio Networks," *Wirel. Commun. Mob. Comput.* 2012; 12:862–874 Published online 4 August 2010 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/wcm.1017

[7] XIAOSHUANG XING, "SPECTRUM PREDICTION IN COGNITIVE RADIO NETWORKS," 1536-1284/13/$25.00 © 2013 IEEE IEEE Wireless Communications • April 2013

[8] P. Pavithra Roy, "Hidden Markov Model based Channel state prediction in Cognitive Radio Networks," International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181 IJERTV4IS020426 www.ijert.org (This work is licensed under a Creative Commons Attribution 4.0 International License.) Vol. 4 Issue 02, February-2015

[9] Chen, Yunfei, "A Survey of Measurement-based Spectrum Occupancy Modelling for Cognitive Radios," October 20, 2014 DRAFT

[10] Luis Miguel Tuberquia, "Spectral Prediction: Approaches in Cognitive Radio Networks," International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 10 (2018) pp. 8051-8063 © Research India Publications. http://www.ripublication.com

[11] Syed Hashim Raza Bukhari, "NS-2 Based Simulation Framework for Cognitive Radio Sensor Networks," Bukhari, SHR, Siraj, S orcid.org/0000-0002-7962-9930 and Rehmani, MH (2018) NS-2 based simulation framework for cognitive radio sensor networks. Wireless Networks, 24 (5). pp. 1543-1559. ISSN 1022-0038 https://doi.org/10.1007/s11276-016-1418-5

[12] Hind Ali. M. Saad, "An Improved Energy Detection Scheme Based on Channel Prediction in Cognitive Radio Networks," Hind Ali. M. Saad et al. / UofKEJ Vol. 8 Issue 2, pp. 10-15 (August 2018) [13] Xiaobo Tan1, "Opportunistic channel selection based on time series prediction in cognitive radio networks," Trans. Emerging Tel. Tech. (2013) © 2013 John Wiley & Sons, Ltd. DOI: 10.1002/ett

14. Xu Y, Wu Q, Wang J. Game theoretic channel selec- tion for opportunistic spectrum acess with unknown prior information, In IEEE International Conference on Communications (ICC 2011) , Kyoto, 2011;

[15]. Wang J, Xu Y, Anpalagan A, et al. Optimal dixtributed interference avoidance : potential and learning. Trans-actions on Emerging Telecommunications Technologies 2012; 23: 217236.

[16]. Liu Y, Jiang M, Tan X, Lu F. Maximal independent set based channel allocation algorithm in cognitive radios, In IEEE Youth Conference on Information, Computing and Telecommunication, Beijing, 2009; 7881.