Evaluating the Probability of Channel Availability for Spectrum Sharing using Cognitive Radio

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ABSTRACT

Spectrum sharing between service providers improves the spectral efficiency, probability efficiency of sensing and reduces the call blockage. If the number of service providers is increased to share the spectrum, this may reduce the high traffic patterns of the calls. In this paper, we present an approach for channel availability and call arrival rate. The results are used to evaluate the probability of the channel availability of a frequency band within a time period. In this work, we propose an algorithm for predicting the call arrival rate which used to predict the traffic process.

Keywords - **Cognitive radio, Traffic forecasting, Traffic model, SARIMA, Spectrum sharing, Spectrum utilization**

I. INTRODUCTION

To promote licensed parties to share their non-utilized resources in 2002 FCC issued 98-153 dockets, permitting many users to transmit on single channel, using low power communication based on Ultra Wide Band (UWB) communication. Recently released FCC docket 03-122 revisited rule 15, allowing wireless data users to share channels with radar systems on a LBT basis. Finally FCC realized that Cognitive Radio (CR) techniques are the future substrate that stimulate full growth of “open spectrum" (see FCC docket 03-108 on CR techniques and FCC docket 04-186 on CR in TV spectrum).

Static spectrum assignment, applied to radio frequencies for almost a century, leads to a so called *quasi-scarcity of the spectrum*. It would be thus logical to allow unlicensed users to exploit dynamically (opportunistically) licensed frequencies when they are free (to minimize interference) at a specific place and time. Theoretically, such approach would increase overall frequency reuse and would boost the throughput for applications that opportunistically use the empty frequencies. This way of spectrum access will be called throughout this paper Opportunistic Spectrum Access (OSA).

In this paper, different traffic prediction techniques and the process of evaluating the channel availability for primary users in cognitive radio systems is discussed. When users of different service providers share the licensed spectrum of the primary user, primary user has the highest priority to access that spectrum. In such a case, the secondary user has to vacate the channel and to move on to another available channel. So that, transmit power will be reduced frequently or communication will be dropped. In order to avoid the temporal connection loss or interference with the primary user, the secondary user has to evaluate the channel availability before using the channels of the primary user and predicting the traffic pattern of the primary user. This would increase the channel utilization and reduces the call blockage and interference.

The paper structure follows: In Section II & III, Related work and various traffic models are briefly discussed. Traffic pattern prediction is discussed in section IV. Probabilities of channel availability, Prediction of call arrival rate are discussed in section V and VI. In section VII and VIII, the performance measures of Spectrum sharing and simulation results are presented. Finally, we draw our conclusions in Section IX

II. RELATED WORK

In [2], presented a deterministic fluid model and two stochastic traffic models for wireless models which provide each cell an infinite number of channels such that no call blocking occurs. It discusses about the Markovian traffic model without Poisson arrivals and made connection the deterministic fluid model, nonhomogeneous Poisson process, etc. In addition to this, the paper [3], discuss about different traffic models in Broadband Networks. Similarly, the traffic model built on historical data for the secondary users to predict the primary user’s traffic pattern for the future use [4]. In paper [5], classification method and predictive channel selection method outperforms opportunistic random channel selection both with stochastic and deterministic patterns.

III. TRAFFIC MODELS

Additional spectrum requirement depends on various parameters like number of subscribers, the density of subscribers, terrain, pattern of traffic (voice, data, etc.), deployment of various technological means to improve the efficient utilization of spectrum, the technology itself, etc. When using other multiple-access techniques, such as OFDM, co-channel interference must be avoided. To satisfy this requirement, the dynamic-spectrum management algorithm must include a *traffic model* of the primary user occupying a black space. The traffic model, built on historical data, provides the means for predicting the future traffic patterns in that space. This in turn, makes it possible to predict the duration for which the spectrum hole vacated by the incumbent primary user is likely to be available for use by a cognitive radio operator. In a wireless environment, two classes of traffic data patterns are distinguished, as summarized here [1].

1) *Deterministic patterns*. In this class of traffic data, the primary user (e.g., TV transmitter, radar transmitter) is assigned a fixed time slot for transmission. When it is switched OFF, the frequency band is vacated and can, therefore, be used by a cognitive radio operator.

2) *Stochastic patterns*. In this second class, the traffic data can only be described in statistical terms. Typically, the *arrival times* of data packets are modeled as a *Poisson process*; while the service times are modeled as *exponentially distributed*, depending on whether the data are of packet-switched or circuit-switched kind, respectively.

In any event, the model parameters of stochastic traffic data vary slowly and, therefore, lend themselves to on-line estimation using historical data. Moreover, by building a *tracking strategy* into design of the predictive model, the accuracy of the model can be further improved.

IV. TRAFFIC PATTERN PREDICTION

Different methods and models are proposed inorder to forecast the traffic on different heterogeneous networks. An accurate traffic prediction model should have the ability to capture the prominent traffic characteristics, e.g. short and long dependence, self similarity in large-time scale and multifractal in small-time scale. For these reasons time series models are introduced in network traffic simulation and prediction. Traffic models can be stationary or nonstationary. Stationary traffic models can be classified into two main classes namely [3]:

- Short-range Dependent (SRD)
- Long-range Dependent (LRD)

Short-range dependent models include Markov processes and Regression models. These traffic models have a correlation structure that is significant for relatively small lags. Long range dependent traffic models such as Fractional Autoregressive Integrated Moving Average (F-ARIMA) and Fractional Brownian motion have significant correlations even for large lags [6]. Nonstationary traffic models include artificial neural network, Auto Regressive (AR), Auto Regressive Moving Average (ARMA) with time varying coefficients, Auto Regressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Transform Expand Sample (TES), and Discrete Auto Regressive (DAR) models. These models are used to predict traffic data in Ethernet, Internet, etc.

Forecasting usually works in the following way. First, the historical data are analyzed in order to identify a pattern that can be used to describe time series. Then, this pattern is extrapolated, or extended, into the future in order to prepare a forecast. The validity of forecasting rests on the assumption that the pattern that has been identified will continue in the future. A forecasting technique cannot be expected to give good predictions unless this assumption is valid. If the data pattern that has been identified does not persist in the future, this indicates that the forecasting technique being used is likely to produce inaccurate predictions. Then, changes in pattern of data should be monitored so that appropriate changes in the forecasting system can be made before the prediction becoming too inaccurate.

In the following subsections some of the traffic prediction techniques are discussed.

A. *ARIMA Based Traffic Forecasting*

ARIMA and SARIMA models are extensions of ARMA class in order to include more realistic dynamics, in particular, respectively, nonstationary in mean and seasonal behaviors. In practice, many economic time series are nonstationary in mean and they can be modeled only by removing the nonstationary source of variation. The general ARIMA model contains autoregressive (AR) and moving average (MA) parts and explicitly includes differencing in the formulation of the model. The model parameters are: the autoregressive parameter (p), the number of differencing passes (d), and the moving average parameter (q). ARIMA models are classified as ARIMA (p, d, q). The parameter d is restricted to integer values. In FARIMA, this differencing parameter is considered as a fraction.

ARIMA models can be used with some kinds of non-stationary data which is useful for series with stochastic trends and however, they cannot be applied to predict the network traffic which possesses the Long Range Dependent (LRD) characteristics. Traditional AR and ARMA models are used to predict the high speed network traffic data and also captures traffic of the short range dependent (SRD). ARIMA processes work on non-stationary (chaotic) data. ARIMA models are found suitable for prediction and stochastic simulator. Different variations of ARIMA models e.g. simple

ARIMA, ATHENA, SARIMA, subset ARIMA are popular in the short-term traffic forecasting literature [9].

Fractional ARIMA (FARIMA) model has the ability to capture both SRD and LRD characteristics of traffic and to capture the self-similarity of network traffic. It is time-consuming one to discuss a two stage predictor. Detecting the trend with an ARIMA model is implicit i.e., it cannot calculate the exact slope of the trend line.

B. Seasonal ARIMA Based Traffic Forecasting

A simple ARIMA model is made up of three parts, 'AR' i.e. autoregressive part, 'I' i.e. differencing part, 'MA' i.e. moving average part. The model introduces into the ARIMA model a seasonal period parameter (S), a seasonal autoregressive parameter (P), the number of seasonal differencing passes (D), and a seasonal moving average parameter (Q). The equation representing an ARIMA (*p*, *d*, *q*) model for a time-series sequence $Y_t (t = 1,2,...n)$ is

$$\phi(B)(1-B)^d Y_t = \theta(B) Z_t \tag{1a}$$

Where $\phi(B) = (1-\alpha_1 B - \alpha_2 B^2 - ....\alpha_p B^p$ (1b)

And $\theta(B) = (1-\beta_1 B - \beta_2 B^2 - ...\beta_q B^q);$ (1c)

Where Z_t is the white noise sequence and B is the Backshift operator.

A SARIMA (p, d, q) × (P, D, Q)$_s$ model can be represented as [8]:

$$\Phi(B^s)\phi(B)(1-B^s)^D (1-B)^d X_t = \Phi(B^s)\theta(B) Z_t \tag{2}$$

Where $\phi(B)$ and $\theta(B)$ represent the AR and MA parts, $\phi(B^s)$ and $\theta(B^s)$ represent the Seasonal AR and Seasonal MA parts respectively. B is the Backshift operator.

Some SARIMA models though found not the best fit, perform very well compared with the best fit. SARIMA models can capture the daily repetitive nature of traffic flow and the dependence of present traffic conditions on the immediate past. The paper [7] shows that the Bayesian inference of SARIMA models provides a more rational technique towards short-term traffic flow prediction compared to the commonly applied classical inference [10]. In particular, seasonal variations of the ARIMA model perform better than linear regression, historical average, and simple ARIMA [9].

C. Artificial Neural Network Based Traffic Forecasting

One particular class of non-linear models is neural networks (NNs). NNs are unlike other non-linear time series models, in that there is usually no attempt to model the innovations. NN modeling is nonparametric in character and the whole process can be automated in a short space of time. Neural network based traffic prediction approach is complicated to implement. The accuracy and applicability of the neural network approach in traffic prediction is limited [9]. Artificial Neural Network (ANN) can capture the non-linear nature of network traffic and the relationship between the output and input theoretically and however, it might suffer from over-fitting. The Machine learning technique called Support vector machine (SVM) used to forecast the traffic in WLANs. This SVM applied to pattern recognition and other applications such as regression estimation. There are two drawbacks for ANN [11]: one is that ANN is essentially a black box; the other is that its network structure and the weights between neurons are fixed and cannot be adjusted adaptively during the forecasting process.

D. Mean Square Based Network Traffic Forecasting

The mean square error is an absolute error measure; therefore, it is highly influenced by the amplitude of the predicted trace. In order to eliminate this undesirable effect without losing its discriminating capability, a relative error measure is highly recommended. Mean square predictor which requires matrix inversion and autocorrelation computation and which is based on recursive linear regression can eliminate these time-consuming computations in the expense of decreased accuracy. Normalized Least Mean Square (NLMS) based prediction approaches are of particular interest due to its simplicity and relatively good performance. They are suitable for on-line Real-time variable bit rate (VBR) video traffic prediction.

E. Other Traffic Forecasting Methods

A new forecasting technique called the extended structural model (ESM) derived from the basic structural model (BSM). The ESM model is constructed in such a way that extra parameters are estimated to minimize the mean absolute percentage error (MAPE) of the validation sequence [12]. The ESM model shows an improvement in MAPE of the test sequence over both the BSM and seasonal autoregressive integrated moving average. The improved prediction can significantly reduce the cost for wireless service providers, who need to

accurately predict future wireless spectrum requirements.
Exponential smoothing is an intuitive forecasting method that weights the observed time series unequally. The major advantage of exponential smoothing methods is that they are simple, intuitive, and easily understood [11]. Generally, exponential smoothing is regarded as an inexpensive technique that gives good forecast in a wide variety of applications. In addition, data storage and computing requirements are minimal, which makes exponential smoothing suitable for real-time application. The major disadvantage of exponential smoothing methods derives from its basic premise about the model: the level of time series should fluctuate about a constant level or change slowly over time. When the time series takes on an obvious trend, even adaptive exponential smoothing methods will fail to give good forecasting [11].

The traffic model using a fuzzy logic approach does not require huge data sets and does not make any statistical assumptions [13]. It is widely used in time forecasting. It is relatively simple and quick to compute. Hence it is fast and secure.

The ARIMA/GARCH traffic prediction model can be used to build effective congestion control schemes, e.g. dynamic bandwidth allocation and admission control.

V. PROBABILITY OF CHANNEL AVAILABILITY

A. *Channel Availability Evaluation*

The Channel availability talks about the channel assigned for CDMA and GSM networks. Spectrum usage deals with the availability of the free channel which is not used by the primary users. The Primary users are said to be a licensed owner of a frequency band and the one who uses the spectrum opportunistically for communication of the licensed user are called Secondary users. Secondary users sense the presence of primary user with the help of Cognitive radio. It tunes the spectrum band or channel which is not currently in use for communication. If the primary user returns to the channel in which the secondary user is active, then the secondary user has to vacate the channel. This type is called as a forced termination. Then the secondary user has to shift to another available channel and continues its process. Sometimes this type of shifting may leads to interruption in communication. Inorder to overcome this difficulty, the secondary user has to predict the channel availability of the primary user and then they have to go utilizing the channel in an efficient manner.

Since the availability of the channel for the secondary user depends upon the traffic of the primary user, number of the secondary user has been service also varies with the primary user traffic [22]. The amount of service that can be squeezed in from the free bands in a spectrum accessed by unrestricted primary users is called the capacity of secondary users.

In order to assess the communication environment, all communication channels may be monitored at least once and preferable several times per second. Through repetitive monitoring of the communication spectrum, an accurate history of channel usage can be developed. Once an accurate usage history is established, predictive methods can be used to select a channel likely to be available. In one aspect of the present disclosure, the channel selection process is based on evaluation of available frequencies based on three criteria:

- The most recent spectrum activity scan--If a channel shows activity in the current scan, it is presumed to be busy for the next operational period and is excluded from selection for use.
- Database of excluded frequencies--If a channel falls within a range of excluded frequencies; it is excluded from selection for use.
- Availability prediction based on historic use--The channel prediction algorithm attempts to reduce the chances of interference by steering the channel selection to those frequencies which are least likely to show activity by other stations in the next operational period.

The proposed work follows the coordination in a distributed manner. The goal of coordination in spectrum sharing is to distribute concurrent, conflicting links across channels to avoid interference and improve throughput. The control messages carry information of traffic load, available channels, and usage on each channel. The key challenge in this module is how to address heterogeneity in channel availability and traffic load during channel selection.

B. *Evaluating the probability of Channel Availability*

Traffic pattern prediction enables the secondary users to estimate the channel availability and channel utilization. There are two factors considered in the traffic pattern prediction in the voice communications. They are call arrival rate and call holding time. In order to estimate the call arrival rate and call holding time of the primary user that uses the channel. According to the prediction or estimation results, the secondary users are able to evaluate the channel availability for a given period of time. The secondary user can decide to use the channel with the help of the threshold value with the estimated or evaluated probability.
In a traditional way of evaluating the call arrival process of a wired or wireless networks was done with the help of Poisson process. In a Cognitive

radio system, the number of subscribers licensed to a service provider is low or the call request/ call attempt is found to be low. In such cases, the secondary user can easily share the available spectrum among them.

We consider the number of call arrivals of primary user within a period of time t is limited. Hence, considering the total number of call arrivals of primary user is N_A within t, then the call arrival would follow the Binomial distribution i.e., $X \approx Y(N_A, P)$ where P is the probability of the service request of an user.

The mean E_λ of binomial distribution is N_A.P. Hence, P will be given as

$$P = \frac{E_\lambda}{N_A} \qquad (1)$$

$$= \frac{\lambda t}{N_A} = \lambda \Delta t \qquad (2)$$

where λt is the number of user arriving i.e., call arrival rate and Δt is the mean value of the call arrival. From equ (2), $\Delta t = \frac{t}{N_A}$. E_λ is the mean number of call arrivals for a given time period t and λ refers the mean number of call arrivals per unit time. This gives the call arrival rate of the primary user.

We have to calculate the probability of the number of primary user arrival in certain time duration. For this, we can decide that the arrival of users within a time t and not focusing on the waiting times, but concentrating on the number of the users. We can assume that the probability of users in a given time t as [16-18]

$$P_{pu} = \binom{N_A}{0} P^0 (1-P)^{N_A - 0}$$

$$= (1-P)^{N_A}$$

$$= (1 - \lambda \frac{t}{N_A})^{N_A} \qquad (3)$$

Where N_A is large. (3) is an approximated one got from the Poisson distribution.

Apply non-homogeneous Poisson process to consider the call arrivals of the primary user. Let A(t) (for $t \geq 0$) be the number of call arrivals arriving in the time interval[0,t] with A(t) = 0. The rate parameter of the call arrival process is A(t) is a(t) where a(t) may change over time. The expected call arrival rate between time t_1 and t_2 is given as

$$A_t = \int_{t_1}^{t_2} a(t)dt \qquad \because [P(A \leq t_2)] \qquad (4)$$

The number of call arrivals A_t to occur during any time interval of length t, then it will be given using Poisson process as [14]

$$P[A(t)=n] = P_n(t) = \frac{e^{-\lambda t}(\lambda t)^n}{n!} \qquad (n=0,1,2\ldots) \qquad (5)$$

Since A_t is Poisson with parameter λt; an average of
λt arrivals occur during a time interval of length t, so λ be the average number of call arrivals per unit time or the call arrival rate.

If the number of call arrivals A_t to occur within the time interval $(t + \Delta t)$ which follows a Poisson distribution with parameter $\lambda_t, t + \Delta t$, i.e.,

$$P[A(t+\Delta t) - A(t) = n] = P[A(\Delta t) = n]$$

$$= \frac{e^{-\lambda_{t,t+\Delta t}} (\lambda_{t,t+\Delta t})^n}{n!} \qquad (n=0,1,2..) \qquad (6)$$

Thus, (6) gives the chance of call arrival rate in the time interval $[t, t+\Delta t]$ is Poisson distributed with mean equal to the length of the interval. Also, the probability of no arrival during the interval $[t, t+\Delta t]$ is given as

$$1 - \lambda \Delta t + o(\Delta t)$$

and the probability of more than one arrival occurring between $[t, t+\Delta t]$ is

$$o(\Delta t)$$

Here, Network user's behavior may be measured as the time of calls, the average length of the call or the number of calls made in a certain period of time. For Telecommunication companies, they often use call inter- arrival time and call holding time to calculate the call blocking rat, Interference and to determine the spectrum utilization efficiency. In the analysis of network traffic, the call inter-arrival time are exponentially distributed, while the call holding time fits a lognormal distribution.

Generally, a traffic period will be divided into 24 time intervals. The number of user calls is considered as the important calling behavior pattern in the voice network [15]. A general metric followed in the telecommunication industry is the hourly number of calls. Hence, the 24 time intervals will be considered as

$$(t_n, t_{n+1}) \qquad (n = 0,1,2,\ldots 23)$$

Then the time duration will be t_d i.e.,

$$t_d = t_{n+1} - t_n \tag{7}$$

for one time interval i.e. one hour. Thus, the call rate parameter $\lambda(t)$ will take the constant value $\frac{\lambda_n}{t_d}$ in each interval of time (t_n, t_{n+1}) i.e.,

$$\lambda(t) = \frac{\lambda_n}{t_d} \qquad [t \in t_n, t_{n+1}] \tag{8}$$

where λ_n is the total number of call arrivals in the time interval (t_n, t_{n+1}).

Consider the number of call arrivals within the time interval $t_n \langle t \langle t + \Delta t \le t_{n+1}$ i.e., t and Δt are within the same time interval (t_n, t_{n+1}). Hence, the expected call rate Δt is given as

$$\lambda_{t,t+\Delta t} = \frac{\lambda_n}{t_d}\Delta t \tag{9}$$

If we consider, (4) and (8), we get call arrivals with different time intervals and period of time. This provides the number of call arrivals of the primary user within the time interval (t_n, t_{n+1}). From this we can predict or evaluate the channel for the secondary user. From (7), we get the call arrival rates of the primary user. If the secondary user finds the channel to access, it plans to start its transmission over this channel. Before that, it predicts the call arrival of the primary user in the current time interval. If no primary user occupies the channel during the time interval, it has to evaluate the probability of no primary user for call holding time. From (6), we can generate the probability as

$$P = \frac{e^{\frac{-\lambda_n}{t_d}\Delta t}\left(\frac{\lambda_n}{t_d}\Delta t\right)^0}{0!} = e^{\frac{-\lambda_n}{t_d}\Delta t} \tag{10}$$

It is difficult to predict the ongoing call holding time of a secondary user. This can be taken in a random manner. Hence in (10), the call holding time is replaced with the average call holding time of the secondary user and calculate $\bar{t}$ based on the total number of calls within a time duration and cumulative total call holding time.

In the following discussion, we can consider the total number of arrivals of primary user N_A for the secondary user. For this, we have to consider three approaches inorder to predict the average call holding time $\bar{t}$ of a secondary user. This $\bar{t}$ is calculated using the historical calls and it does not depend upon the last call.

Approach 1: Primary user ends its transmission at one time t_1 and secondary user starts its transmission at the same time t_2 i.e.,

$$t_1 = t_2$$

Here, the secondary user has to estimate the probability of the arrival of the primary user within the time $\bar{t}$. Thus, the probability P_0 of no primary user's arrival within the time $\bar{t}$ is given by

$$P_0(t) = e^{-\lambda t} \tag{4}$$

Approach 2: The arrival of users between time $t_1=0$ and $t_2=1$, not by focusing on the waiting time but concentrating on the number of arrivals of the user. This approach does not tell immediately when the users arrive, but it only provides the information that in a given time interval the number of customers should have a Poisson distribution, with a parameter which is proportional to the length of the interval i.e., it must be non-decreasing. The number of arrivals that have occurred in the interval (t_1, t_2) and it is given by

$$t_1 < t_2$$

Here, the primary user ends its transmission at t_1 and secondary user starts its transmission at t_2. The probability that there is no occurrence before time t is, according to the current approach, equal to $e^{-\lambda t}$. Hence, the probability $P_0^{'}$ of the no arrival of the primary user will be given by

$$P_0' = t_1 + t_2$$

$$P_0'(t) = -\lambda P_0(t)$$

$$P_0'(t) = -\lambda e^{-\lambda t} \qquad (5)$$

Where (t_1+t_2) = P (no occurrence before $t_1 + t_2$)

= P (no occurrence before t_1) P (no occurrence between t_1 and t_2);

Approach 3: In this approach, the primary user starts its transmission at t_0 and ends at t_2. The secondary user intends to start its transmission at t_1. This will be given as

$$t_0 < t_1 < t_2$$

We have to assume that the secondary user holds the call for some time otherwise it would drop the call T_h. In this case, the event that representing the current primary user vacate the channel within T_h is X and no primary user arrives within the time $\bar{t}$ is Y. when the probability P_1 will be available within the time duration T_h + $\bar{t}$ and given as

$$P_1 = \text{Probability}\{X \text{ and } Y\}$$

$$= \text{Probability}\{X\}.\text{Probability}\{Y\}$$

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

Thus,

$$P_1 = \int_0^{T_h + t_1 + t_2} f(t)dt \cdot \lambda^{-\lambda t} \qquad (6)$$

Where f(t) represents the probability density function (pdf) call holding time of the primary user.

It is hard to obtain practically the probability density function (pdf) for the secondary users. Hence, the secondary user has to estimate the call holding time of the current primary user and probability of no primary user arrival within time $\bar{t}$. Then only the secondary user has to proceed, otherwise it has move to the other available spectrum or to drop the call.

It is difficult to predict the mean number of call arrivals per unit time and to estimate the call holding time of the primary user. This will be explained in the following section of predication of call arrival rate.

VI. CALL ARRIVAL RATE PREDICTION

To estimate the call arrival rate of the primary user within a given time, secondary users has to predict the number of call arrivals within a given time. The call arrival rate λ is 18calls/second and it is illustrated in the Fig. 1. The licensed frequency bands can be used to carry voice or data in a cognitive system. The traffic pattern of primary users may vary with application. Taking the time interval into account, within a given period and the corresponding number of calls in that interval and set of number of call arrivals at various time intervals are also observed using discrete time series method.

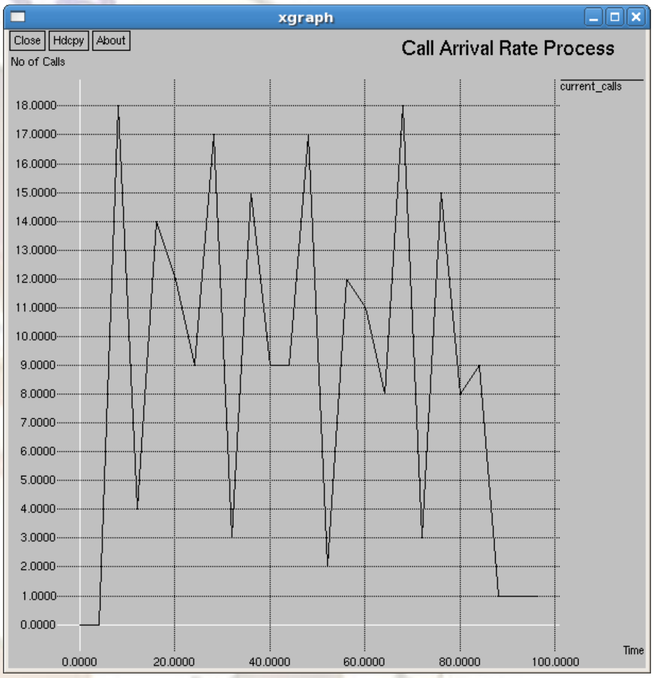

Fig. 1. Call Arrival Rate Process

By using this, secondary users can able to predict the number of call arrivals during a given time period. So that, it is possible to predict the call arrivals of primary user in the future and secondary users can able to predict the number of call arrivals of the primary user also. This can be predicted using the SARIMA model as a one-step prediction of number of call arrivals at a given time period.

From Section 4.2, consider the (2), A SARIMA (p, d, q) × (P, D, Q)$_s$ model can be represented as

$$\Phi(B^s)\phi(B)(1-B^s)^D(1-B)^d X_t = \Theta(B^s)\theta(B)Z_t$$

Where Φ, Θ, P, D, Q represents the seasonal counterparts of ϕ, θ, p, d, q and S is the seasonal autoregressive orders. From this λ_t is given as

$$Y_t = (1-B)^d (1-B^s)^D \lambda_t \qquad (7)$$

From the simulated data field of λ_t, with a period of s=24, Y_t corresponds to

$$Y_t = (1-B)(1-B^{24})\lambda_t \qquad (8)$$

Where d=1 and D=1. Equ (8) becomes

$$Y_t = \lambda_t - \lambda_{t-1} - \lambda_{t-24} - \lambda_{t-25} \qquad (9)$$

Thus, λ_t becomes

$$\lambda_t = Y_t + \lambda_{t-1} + \lambda_{t-24} - \lambda_{t-25} \qquad (10)$$

In practice, by applying the *h step* prediction, the linear predictor of Y_{n+h}, which is the best in the sense of minimizing the h-step (10) is given as [19 - 21]

$$\lambda_{n+h} = Y_{n+h} + \lambda_{n+h-1} + \lambda_{n+h-24} - \lambda_{n+h-25} \qquad (11)$$

The best linear Prediction P_t is the calculation of the estimate of the future values Y_{n+h} (h>0) based on the current information [21]. P_t is given as follows from (11)

$$P_t\lambda_{n+h} = P_tY_{n+h} + P_t\lambda_{n+h-1} + P_t\lambda_{n+h-24} - P_t\lambda_{n+h-25} \qquad (12)$$

After calculating the best linear predictor of ARMA process Y_t, we can compute the prediction $P_t\lambda_{n+h}$ of Y_t. For one step prediction, taking h=1, then (12) becomes

$$P_t\lambda_{n+1} = P_tY_{n+1} + \lambda_n + \lambda_{n-23} - \lambda_{n-24} \qquad (13)$$

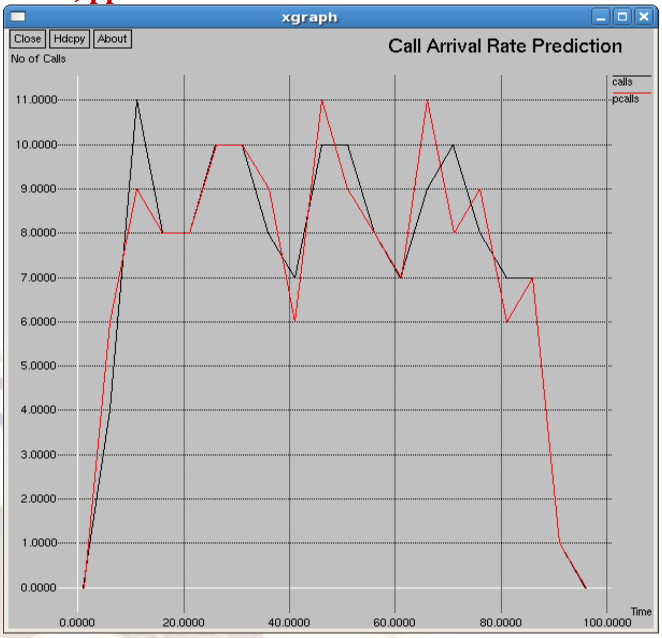

Fig. 2. Call Arrival Rate Prediction

Fig. 2 gives the call arrival rate prediction of the original calls and the forecasting (primary) calls. The call arrival rate predication is based on the mean square error. It is an absolute error measure with respect to the predicted traced variance. This figure visually demonstrates that the proposed predictor is capable of tracking the input trace in spite of variations.

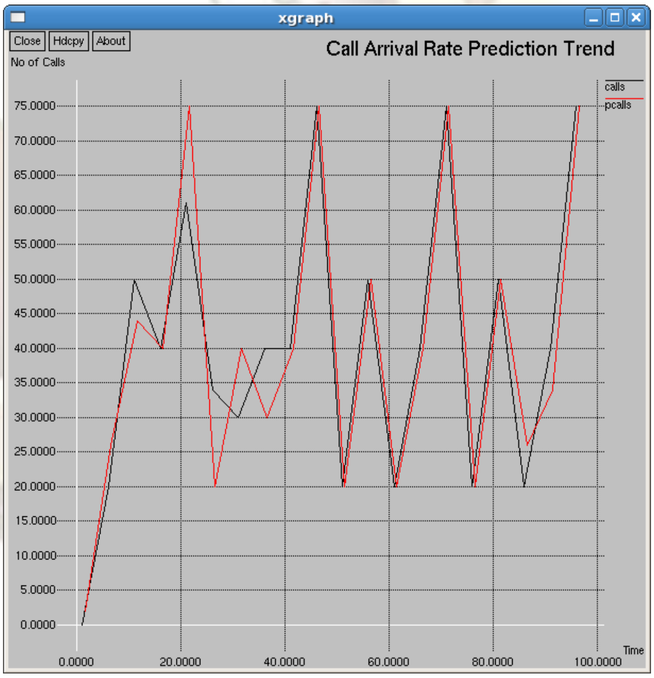

Fig. 3. Call Arrival Rate Prediction with Trend

Fig. 3 shows the call arrival rate prediction with changing trend value. Here, the prediction error is much greater than that of the Figure 2. This is the change made during the call arrival rate with increased or decreased trend in a given time period. The traffic trend changes significantly if there is a change in the time or space. The traffic trend changes are done in a long term process and this is carried out by means of considering the trend changes in the two or more consecutive periods which helps to track the call arrival rate.

VII. Performance Metrics

In this section, we look into the performance metrics which are used to evaluate the traffic prediction of spectrum sharing between service providers. The metrics includes block counting, service unavailability, sensing efficiency and free spectrum calculation.

A. *Call Block Count*

The blocking probability for CR nodes R_{BL} is defined as the ratio of total blocked calls (or spectrum requests) over total calls processed by all service providers.

$$R_{BL} = \lim \frac{n_{BL}^{(total)}(t)}{n_{processed}^{(total)}(t)}$$

B. *Service Unavailability (Spectral Efficiency)*

Higher Spectrum efficiency is anticipated compared to service provider systems because the blocking count of user system is lower. Thus more calls can contribute to the maximize channel utilization.

$$\eta_s^{n^{(sp)}} = \lim \frac{1}{t}\int_0^t \frac{n_{busy}^{n^{(sp)}}(t)}{N_{ch\text{-}total}^{n^{(sp)}}(t)}dt$$

C. *Probability Efficiency (System Efficiency)*

Probability efficiency metric for service provider is determined by the processed traffic intensity and the total traffic loaded to service provider within the observation time.

$$\eta_{sys}^{(i)} = \frac{E_p^{(i)}}{E_{in}^{(i)}}$$

D. *Revenue (Cost) Efficiency*

Within the observation time, cost is determined by the number of processed calls and the length of call holding time. We define the metric $c_e^{(i)}$ to reflect the cost efficiency. $c_e^{(i)}$ is the ratio of the cost earned within the observation time t over total input traffic intensity for service provider sp, is defined as

$$c_e^{(i)} = c^{(i)}/E^{(i)} = \alpha^{(i)}.E_p.t^{(i)}/E^{(i)} = \alpha^{(i)}.t^{(i)}.\eta_s^{(sp)}$$

where $\alpha^{(i)}$ is the unit price ($/second/channel) for service provider sp and $c^{(i)}$ is the average income within the observation time.

E. *Free Spectrum Calculation*

Free Spectrum will be calculated using the allocated and limited allocated spectrum values. Number of n users in service providers calls in the system at time *t* will be negligible when compared with overall performance [23-24].

VIII. Simulation Results of Traffic Prediction

In this section, Using NS2 simulation the performance of the overall system efficiency has been evaluated. The call arrivals are modeled using the Poisson distribution, while the call holding times are exponentially distributed.

Fig. 4 predicts that in the simulation, two base stations are defined (Node 0 and 1). Blue color node indicates the currently accessing the service provider of the spectrum by the BS. Orange color nodes indicate that the nodes are already accessed the service in previous time periods.

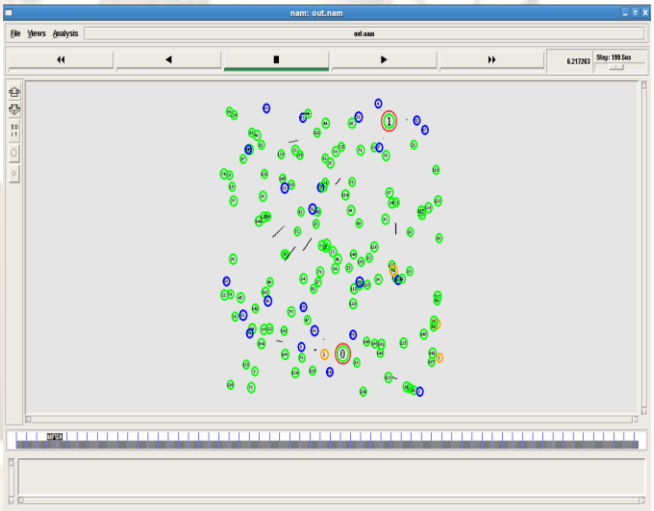

Fig. 4. Current accessing of the spectrum

Fig. 5 represents the service access between BS and mobile devices are carried out dynamically. Due to mobility, nodes are moving in the network by choosing random position in topography and the service are accessed dynamically.

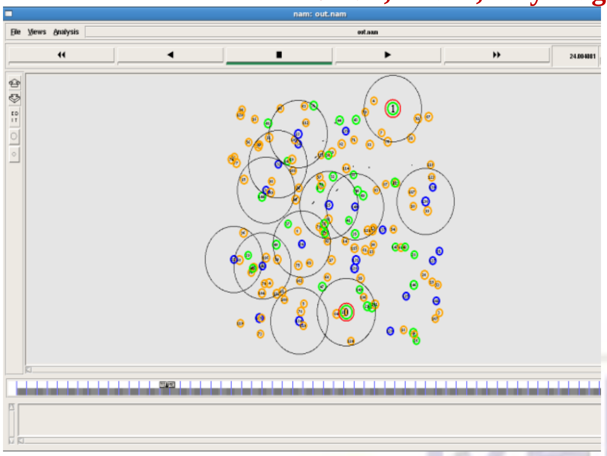

Fig. 5. Service performed in a dynamic manner

Fig. 6 represents the active users during the traffic pattern prediction. The active users are increased due to the decreased call blocking. Since the call arrival rate is predicted and assigned the channels based on the prediction of the call arrival rate and call holding time, traffic of the call arrivals are reduced. So that, we can increase the active users after predicting the traffic of the primary user.

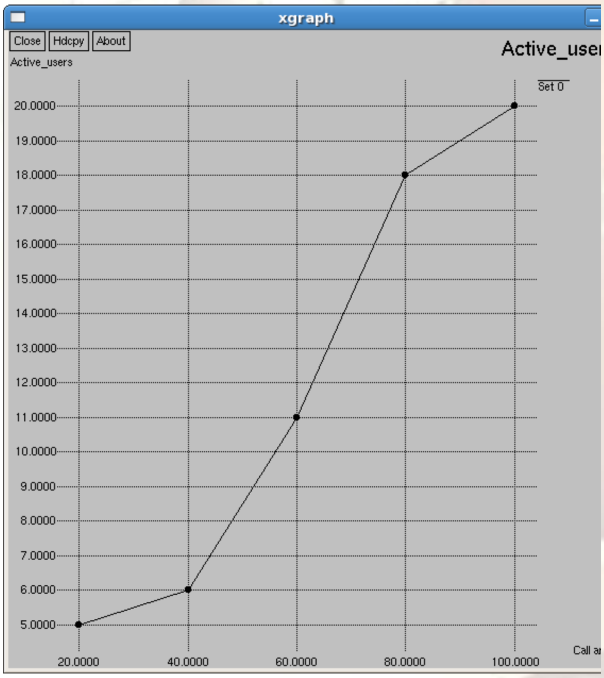

Fig. 6. Call Arrival Rate VS Active users

Fig. 7 gives the call blocking rate during the traffic prediction. It seems that the function of the offered traffic is greater than the given number of channels, and the arriving calls will be blocked. During the high traffic loads, the proposed work significantly reduces the connection call blocking and increases the number of simultaneous transmission due to the proper channel assignment strategy.

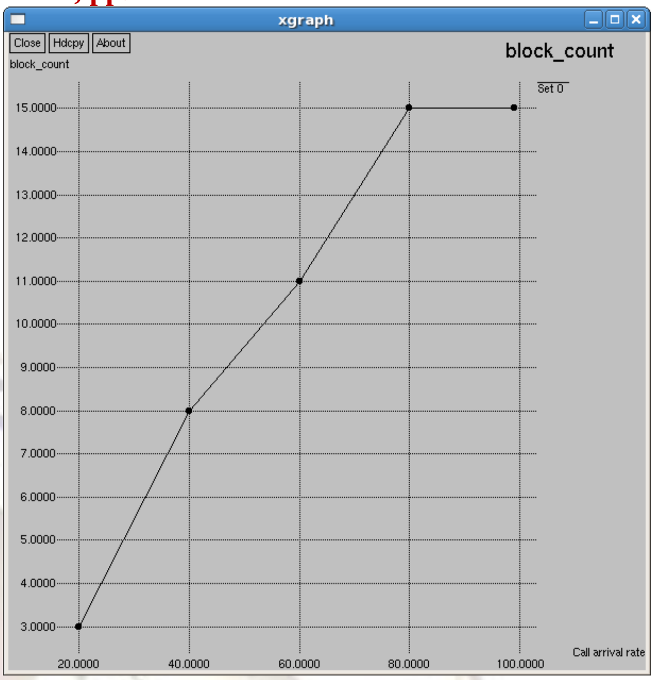

Fig. 7. Call Arrival Rate VS Call blocking

As the call blocking decreases, then the occupied spectrum will be less and there is the possibility of getting more spectrum. Fig. 8 shows that the occupied band after calculating the free spectrum utilization, as the call blocking decreases. It depicts that for maximum service provider limited portion of a spectrum is occupied and it also shows that the free spectrum available for further spectrum utilization.

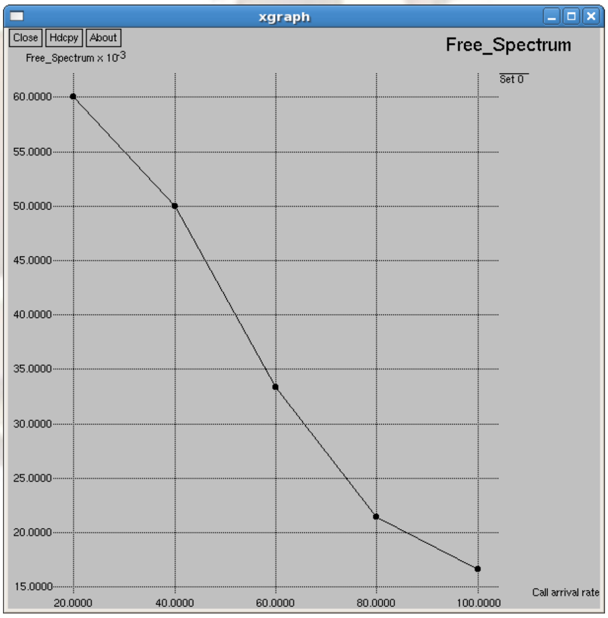

Fig. 8. Call Arrival Rate VS Free Spectrum

As primary users (PU) have priorities to use the spectrum when secondary users (SU) co-exist with them, the interference generated by the SU transmission needs to be below a tolerable threshold of the PU system. Thus, to manage the interference to the PU system and the mutual interference among SUs, power control schemes should be carefully designed. As the number of call arrivals increases with the maximum utilization of the channels, Interference has been reduced during the heavy traffic load as illustrated in the Fig. 9.

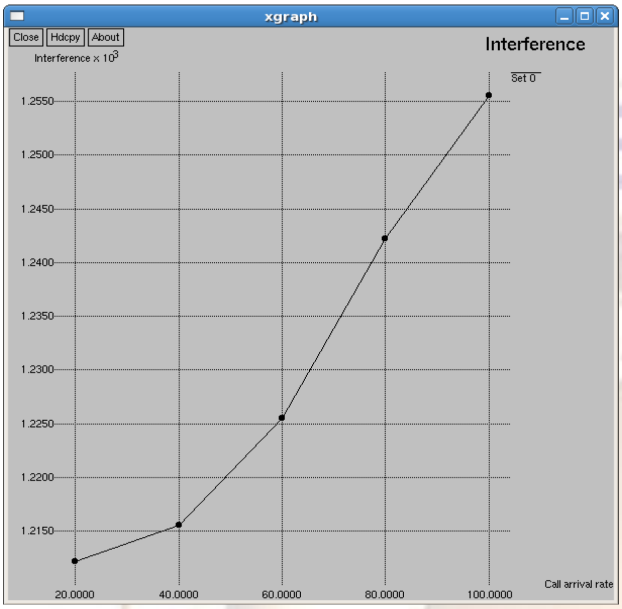

Fig. 9. Call Arrival Rate VS Interference

Fig. 10 shows the system efficiency against the call arrival rate. When the traffic is high, the dropped calls increases with decreasing total processed calls. During the call arrival prediction due to the high traffic loads, the system efficiency increases. This can be reduced, when the number of call arrival rate decreases.

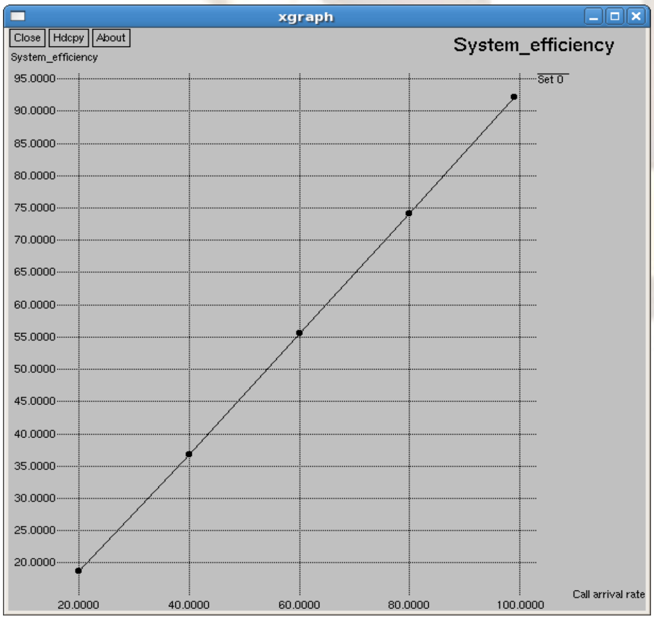

Fig. 10. Call Arrival Rate VS System Efficiency

Fig. 11 shows the channel utilization during the traffic pattern prediction against the call arrival rate. The figure shows that as the mean call arrival increases, the channel utilization also increases. As the call blocking rate is lower; thus, more calls can contribute to the spectrum utilization. Using this, higher spectral efficiency has been evaluated.

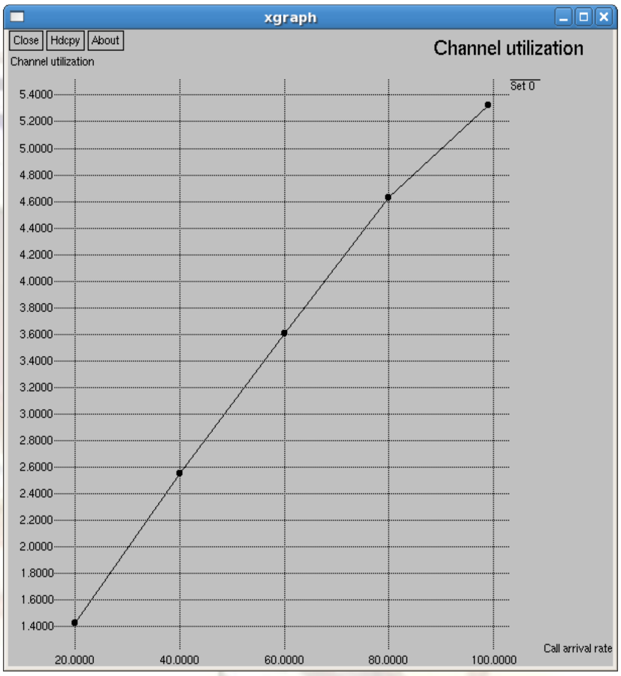

Fig. 11. Call Arrival Rate VS Channel Utilization

IX. CONCLUSION

The proposed algorithm predicts the call arrival rate of primary users and it gives an approach to predict the call holding time of the primary users. Predicting the probability of call arrival rate provides the secondary user regarding the channel availability to determine whether to use the channel or not. This proposed algorithm leads to the optimal transmission and observation time to maximize sensing efficiency satisfying the strict interference constraint of primary networks. This prediction enhances the channel utilization of primary users and enhances the communication of primary users. The simulated results show that there is a decrease in the call blocking and reduced interference. This helps to improve the channel utilization and avoids the scarce resource of the spectrum.

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