Cognitive Radio Based Spectrum Sharing: Evaluating Channel Availability via Traffic Pattern Prediction

Xiukui Li and Seyed A. (Reza) Zekavat

Abstract: **In this paper, a technique is proposed that enables secondary users to evaluate channel availability in cognitive radio networks. Here, secondary users estimate the utilization of channels via predicting the traffic pattern of primary user, and select a proper channel for radio transmission. The proposed technique reduces the channel switching rate of secondary users (the rate of switching from one channel to another) and the interference on primary users, while maintaining a reasonable call blocking rate of secondary users.**

Index Terms: **Cognitive radio, opportunistic channel utilization, spectrum sharing, traffic pattern prediction.**

I. INTRODUCTION

Federal communications commission defines cognitive radio as a radio capable of changing its transmitter parameters based on its interaction with the environment [1]. Cognitive radio addresses the underutilization problem of the spectrum licensed to different organizations, and it supports dynamic spectrum access. When cognitive and non-cognitive users coexist, compared with secondary users (cognitive users), primary users (non-cognitive users) have higher priority in using the licensed channels. Therefore, whenever a primary user is detected [2]–[5], secondary users must vacate the relevant channels or decrease their transmitted power to reduce the interference on primary users.

However, in some situations, due to the activities of primary users, secondary users may need to vacate the current channel and switch to other available channels or terminate communication frequently. This would lead to temporal connection loss of secondary users. In addition, if a secondary user can not vacate a channel in a timely manner, it would interfere with primary users. To reduce the temporal connection loss and interference on primary users, secondary users need to avoid using the channels that are only available for a short time period. Therefore, secondary users should be able to evaluate the probability of channel being available for a given time period.

In general, the traffic stochastic parameters vary slowly. Hence, they can be estimated by using the historical data [6]. Various traffic prediction techniques have been proposed for different wireless systems [7]–[11]. However, the proposed methods or models are only considered for the specific applications in different wireless systems.

In this paper, first, we present methods to evaluate the probability of channel being available for a given time period. Then, we propose a new algorithm which can be implemented in secondary users to predict primary user call arrivals, and compare it with the well-known seasonal autoregressive integrated moving average (SARIMA) model [12]. Finally, the impact of the proposed technique on channel switching rate, call blocking rate of secondary users and spectrum reuse efficiency is investigated.

Here, secondary users monitor the call arrivals of primary users. The observed traffic information of primary users is stored in secondary users. When a secondary user has a transmission request, first, based on the historical traffic information of primary users, it estimates the number of call arrivals and/or the call holding time of primary user within a time interval. Then, according to the estimation results, the secondary user evaluates the probability that a channel would be available (not occupied by primary users) for a given time period. Comparing the evaluated probability with a threshold, the secondary user determines whether to use the channel. The probability threshold maintains a trade-off between the channel switching rate and call blocking rate of secondary users, the interference on primary users and spectrum reuse efficiency.

Through this technique, secondary users can find a suitable channel for radio transmission. Simulations confirm that the proposed technique reduces the channel switching rate of secondary users and, accordingly, the interference on primary users. This work has been partially presented in [13]. Compared to [13], this paper: 1) Details the call arrival process; 2) discusses the resilience of the proposed algorithm when the traffic pattern changes rapidly; 3) suggests a new method to estimate the call holding time of primary users; 4) investigates the approach of threshold determination and verifies it via simulation results; and 5) includes more simulation results on the performance.

The rest of this paper is organized as follows. In Section II, we present methods to evaluate the probability that a channel would be available for a given time period. In Section III, we introduce algorithms which are used to predict the call arrivals of primary users. We describe the call holding time estimation in Section IV. Channel availability determination and threshold selection are analyzed in Section V. Finally, Section VI presents the simulation results and Section VII concludes this paper.

II. PROBABILITY OF CHANNEL AVAILABILITY

In this analysis, we assume multiple channels are licensed to primary users, and secondary users can select any idle channel for communication. However, once a secondary user detects the appearance of primary users, it should vacate the channel immediately to allow primary users to continue using that channel. Therefore, the activities of secondary users do not affect the traffic distribution of primary users. Primary users keep their normal activities regardless of the existence of secondary users. Here,

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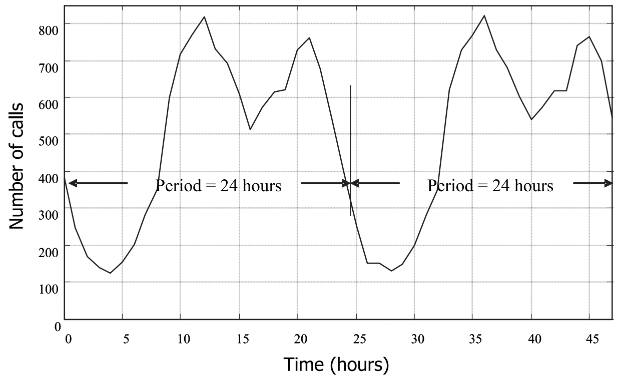

Fig. 1. Call arrival process.

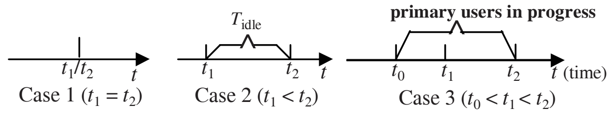

Fig. 2. Three cases for channel availability evaluation.

we assume the number of channels licensed to primary users is constant. In addition, we consider, with a fair scheduling policy, primary users utilize all licensed channel equally.

When secondary users coexist with primary users, if without primary user traffic pattern prediction, secondary users can transmit signals over any channel as long as it is not occupied. However, in some scenarios, with high likelihood, the communication would be interrupted by primary users.

Traffic pattern prediction enables secondary users to estimate the channel utilization in a near future. Generally, traffic pattern of primary users varies with applications, such as voice and data. Here, both primary and secondary users request channels for voice. Two crucial factors in the traffic pattern of voice users are call arrival rate and call holding time. Hence, to estimate the utilization of one channel, secondary users can predict or estimate the call arrival rate and call holding time of primary users that use this channel. Then, according to the prediction and/or estimation results, secondary users are able to evaluate the probability that the channel would be available for a given time period. By comparing the evaluated probability with some threshold, secondary users can decide whether to use this channel.

In general, traffic process can be modeled as a non-stationary stochastic process. For a given application, traffic mostly demonstrates a regular model in an area. For example, traffic can be periodic with a specific period, and it follows similar pattern in each period. Voice communication in traditional wireless networks usually possesses such traffic characteristics [14]. In the following discussion, we assume the traffic for the network is periodic with the period of $T = 24$ hours (one day) and the traffic patterns of primary users in different periods are similar. An example of the call arrival process is shown in Fig. 1.

The call arrivals of primary users can be considered to follow non-homogeneous Poisson process $\{A(t), t \geq 0\}$ [15]. The rate parameter for the process $\{A(t)\}$ is $\lambda(t)$. In general, $\lambda(t)$ may change over time. The expected call arrival rate between the time t_1 and t_2 is:

$$\lambda_{t_1,t_2} = \int_{t_1}^{t_2} \lambda(t)dt. \quad (1)$$

Thus, the number of call arrivals within the time interval $(t, t+\tau]$ follows a Poisson distribution with the parameter $\lambda_{t,t+\tau}$, i.e.,

$$\mathbf{P}\{(A(t+\tau) - A(t)) = k\} = \frac{e^{-\lambda_{t,t+\tau}}(\lambda_{t,t+\tau})^k}{k!}, k = 0, 1, \cdots. \quad (2)$$

We evenly divide one traffic period into 24 time intervals $(t_n, t_{n+1}]$ $(n = 0, 1, \cdots, 23)$; thus, the time duration T_d $(T_d = t_{n+1} - t_n)$ for one time interval is one hour. A common metric employed in the telecommunication industry is the hourly number of calls [7]. Thus, we can assume the rate parameter $\lambda(t)$ maintains constant value λ_n / T_d in each time interval $(t_n, t_{n+1}]$, i.e.,

$$\lambda(t) = \frac{\lambda_n}{T_d}, t \in (t_n, t_{n+1}] \quad (3)$$

where λ_n is the total number of call arrivals in the time interval $(t_n, t_{n+1}]$. Note that, the granularity of the decomposition of the daily traffic variations depends on the traffic characteristics of primary users. Here, we consider the regular wireless voice communication and divide one day into 24 time intervals. However, to make the traffic prediction more accurate, secondary users can dynamically adjust the time duration of each time interval and the number of time intervals divided of a day. This does not affect the analysis conducted in this paper. The adaptive time interval control should depend on the field data of the traffic of primary users.

Considering $t_n < t < t+\tau \leq t_{n+1}$, i.e., t and $t+\tau$ are within the same time interval $(t_n, t_{n+1}]$, the expected call arrival rate within τ is:

$$\lambda_{t,t+\tau} = \frac{\lambda_n}{T_d}\tau. \quad (4)$$

Similarly, using (1) and (3), we can obtain $\lambda_{t,t+\tau}$ when t and $t+\tau$ are within different time intervals or within different periods. In the following discussion, we consider t and $t+\tau$ are within the same time interval.

When a secondary user finds an idle channel and intends to start transmission over this channel, first, it predicts the number of primary user call arrivals in the current time interval $(t_n, t_{n+1}]$. Using (4), the secondary user obtains the call arrival rate of primary users, $\frac{\lambda_n}{T_d}\tau_{ch}$, within its oncoming call holding time τ_{ch} (the call holding time of its next call). Then, the secondary user evaluates the probability, P_{na}, that no primary user would occupy the channel within the call holding time τ_{ch}. According to (2), P_{na} corresponds to:

$$P_{na} = \frac{e^{-\frac{\lambda_n}{T_d}\tau_{ch}}(\frac{\lambda_n}{T_d}\tau_{ch})^0}{0!} = e^{-\frac{\lambda_n}{T_d}\tau_{ch}}. \quad (5)$$

The oncoming call holding time τ_{ch} for a secondary user is a random variable and it is hard to predict. Therefore, we substitute the average call holding time $\overline{T}$ of the secondary user for τ_{ch} in (5). For a secondary user, $\overline{T}$ can be calculated based on the cumulative total call holding time T_a and the total number of calls N_c within a time duration, i.e., $\overline{T} = T_a/N_c$.

To evaluate the probability that a channel is available for a given time period, secondary users should consider three scenarios discussed in the following.

Cases 1 and 2 (see Fig. 2): Primary users end transmission at time t_1, and a secondary user starts transmission at t_2, $t_1 \le t_2$ ($t_n < t_1 \le t_2 \le t_{n+1}$).

In these two cases, the secondary user only needs to evaluate the probability P_i that no primary user arrives within $\overline{T}$, $i = 1, 2$. According to (5), P_i corresponds to:

$$P_i = e^{-\frac{\lambda_n}{T_d}\overline{T}}, i = 1, 2. \tag{6}$$

Case 3 (see Fig. 2): One primary user starts transmission over a channel at time t_0, and it ends transmission at t_2. A secondary user intends to start transmission at t_1 over this channel (no other channels are available), $t_n < t_0 < t_1 < t_2 \le t_{n+1}$, i.e., at time t_1, the primary user call is still in progress.

In this case, we assume the secondary user is capable of suspending its call for some time duration T_w ($T_w > 0$). Thus, it can wait for the primary user to vacate the channel (otherwise, if $T_w = 0$, the call would drop). To guarantee the secondary user's call does not drop, the call holding time of the primary user, t_h, should satisfy: $t_1 - t_0 < t_h \le T_w + t_1 - t_0$ (if $t_h = t_1 - t_0$, it would be the same as Case 1).

Let C denote the event that the current primary user vacates the channel within T_w and E denote the event that no new primary user arrives within $\overline{T}$. Then, the probability P_3 that the channel would be available to the secondary user corresponds to:

$$\begin{aligned} P_3 &= \mathbf{P}\{C \text{ and } E\} = \mathbf{P}\{C\}\mathbf{P}\{E\} \\ &= \mathbf{P}\{t_h \le T_w + t_1 - t_0 | t_h > t_1 - t_0\}\mathbf{P}\{E\} \\ &= \frac{\int_{t_1-t_0}^{T_w+t_1-t_0} f_{T_h}(t_h)dt_h}{\int_{t_1-t_0}^{\infty} f_{T_h}(t_h)dt_h} e^{-\frac{\lambda_n}{T_d}\overline{T}} \end{aligned} \tag{7}$$

where $f_{T_h}(t_h)$ is the probability density function (PDF) of the call holding time distribution of primary users in the time interval $(t_n, t_{n+1}]$. Note that, the secondary user suspends its call only when all channels are occupied. Otherwise, it should try to find another available channel to use.

In summary, to evaluate the probability that the channel would be available within $\overline{T}$, secondary users should be able to predict the number of primary user call arrivals in the corresponding time interval. In addition, secondary users should obtain the PDF of call holding time distribution of primary users (for Case 3). The next two sections propose solutions to these two problems, respectively.

III. CALL ARRIVAL PREDICTION

A. Call Arrival Prediction Based on Traffic Periodicity

Based on the observations on traditional wireless networks, the traffic process is periodic with the period of $T = 24$ hours [14]. In different periods, generally, the factors that affect the traffic do not change significantly. Therefore, the number of call arrivals has similar increasing or decreasing inclination from one time interval to the next following one in different periods. Namely, in one period, from the time interval $(t_n, t_{n+1}]$ to $(t_{n+1}, t_{n+2}]$, the number of call arrivals increases or decreases from N_1 to N_2, and, in other periods, from $(t_n, t_{n+1}]$ to $(t_{n+1}, t_{n+2}]$, the number of call arrivals also increases or decreases by the number around $|N_2 - N_1|$, where $|a|$ denotes the absolute value of a.

In Section II, we assume the rate parameter $\lambda(t)$ for the process $\{A(t)\}$ maintains constant value, λ_n/T_d, in the time interval $(t_n, t_{n+1}]$ ($T_d = t_{n+1} - t_n, n = 0, 1, \cdots, 23$), and λ_n is the total number of call arrivals in the time interval $(t_n, t_{n+1}]$. Therefore, to estimate the call arrival rate in a given time period, we need to predict the number of call arrivals in the corresponding time interval. Denoting the time interval $(t_n, t_{n+1}]$ in the $(m+1)$th period as $(t_n + mT, t_{n+1} + mT]$, and the corresponding number of call arrivals in this time interval as λ_{n+mT}, the set of observations of the number of call arrivals in different time intervals of different periods can be considered as a discrete-time series $\{\lambda_t\}$ ($t = 0, 1, \cdots$). Thus, we can predict the call arrivals of primary users using the known observations of the number of primary user call arrivals in the past. Here, we discuss one-step prediction of the number of call arrivals in one time interval.

Assuming the current time is within the $(m + 1)$th period, according to (1), λ_{n+mT} in the time interval $(t_n + mT, t_{n+1} + mT]$ ($0 \le n \le 23$) would correspond to:

$$\lambda_{n+mT} = \lambda_{t_n+mT, t_{n+1}+mT} = \int_{t_n+mT}^{t_{n+1}+mT} \lambda(t)dt. \tag{8}$$

Then, the difference of the number of call arrivals, η_{n+mT}, between two consecutive time intervals corresponds to:

$$\eta_{n+mT} = \lambda_{n+1+mT} - \lambda_{n+mT}. \tag{9}$$

From one time interval to the next one, in different periods, the number of call arrivals has similar increasing or decreasing inclination with trivial changes. Therefore,

$$\eta_{n+jT} = \eta_{n+mT} + \delta \tag{10}$$

where $|\delta|$ is a small integer compared with η_{n+mT}. η_{n+jT} and η_{n+mT} are the difference of call arrivals from the time interval $(t_n, t_{n+1}]$ to $(t_{n+1}, t_{n+2}]$ in the $(j+1)$th and $(m+1)$th period, respectively (j and m are nonnegative integers, $j \ne m$).

Rearranging (9), λ_{n+1+mT} corresponds to:

$$\lambda_{n+1+mT} = \lambda_{n+mT} + \eta_{n+mT}. \tag{11}$$

Given λ_{n+mT} and η_{n+mT}, we can use (11) to predict λ_{n+1+mT}. However, η_{n+mT} is not obtained until we have the observation data of λ_{n+1+mT}. This is contradictory.

Based on (10), there is only small difference between η_n's in different periods. Hence, we can calculate the average value of η_n using the data in the recently past N_p periods and substitute the average value $\overline{\eta}_n$ for η_{n+mT} in (11) to predict λ_{n+1+mT}. Therefore, one step prediction of λ_{n+1} in the $(m + 1)$th period, $\hat{\lambda}_{n+1+mT}$, corresponds to:

$$\hat{\lambda}_{n+1+mT} = \lambda_{n+mT} + \overline{\eta}_{n+N_pT} \tag{12}$$

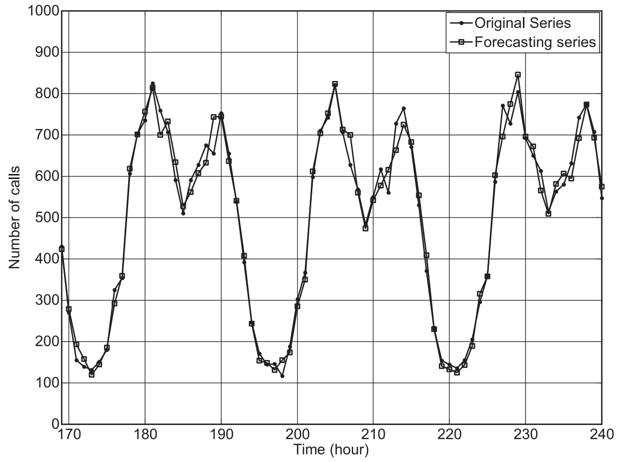

Fig. 3. Call arrival prediction (traffic has no changing trend).

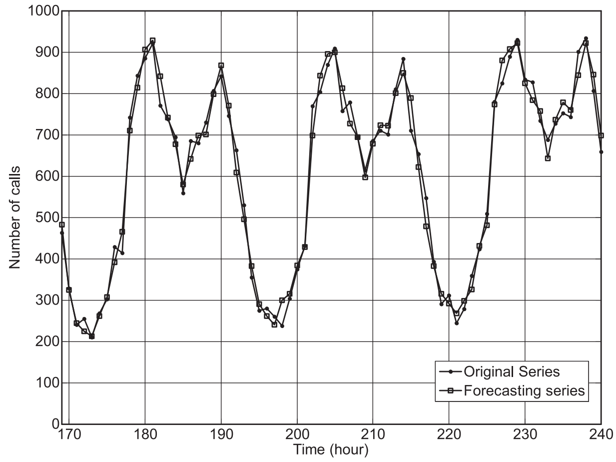

Fig. 4. Call arrival prediction (traffic has increasing trend).

where λ_{n+mT} is the observation of the number of call arrivals in the time interval $(t_n, t_{n+1}]$ of the $(m+1)$th period and $\overline{\eta}_{n+N_pT}$ is the average value of the difference of call arrivals from $(t_n, t_{n+1}]$ to $(t_{n+1}, t_{n+2}]$ in the past N_p periods, which corresponds to $(m > 0)$:

$$\begin{aligned}\overline{\eta}_{n+N_pT} &= \frac{1}{N_p}\sum_{i=m-N_p}^{m-1} \eta_{n+iT} \\ &= \frac{1}{N_p}\sum_{i=m-N_p}^{m-1} \left(\lambda_{n+1+iT} - \lambda_{n+iT}\right).\end{aligned} \tag{13}$$

If $m = 0$, secondary users do not have the historical data of primary user call arrivals. Therefore, we define:

$$\begin{cases} \overline{\eta}_{n+N_pT} = \lambda_n, & \text{if } m = 0 \text{ and } n = 0, \\ \overline{\eta}_{n+N_pT} = \lambda_n - \lambda_{n-1}, & \text{if } m = 0 \text{ and } n > 0. \end{cases} \tag{14}$$

According to (14), the call arrival prediction in the first some periods is not accurate due to the unavailability of enough data. Practically, secondary users can consider the first some periods as training phase. During the training phase, secondary users are able to gradually obtain more observation data of the number of call arrivals in each time interval. Then, the accuracy of $\overline{\eta}_n$ can be improved.

Nonetheless, even if secondary users employ the training phase, sometimes, due to the abrupt traffic variation, the observation value λ_{n+mT} might not be on the right track. Hence, to reduce the prediction error caused by the abrupt variation in the previous observation λ_{n+mT}, (12) can be modified as:

$$\hat{\lambda}_{n+1+mT} = \lambda_{n+mT} + \overline{\eta}_{n+N_pT} + e_{n+mT} \tag{15}$$

where e_{n+mT} is used to reduce the error caused by λ_{n+mT}, and corresponds to:

$$e_{n+mT} = \frac{\hat{\lambda}_{n+mT} - \lambda_{n+mT}}{2}. \tag{16}$$

Substituting (16) into (15), $\hat{\lambda}_{n+1+mT}$ corresponds to:

$$\hat{\lambda}_{n+1+mT} = \left[\frac{\lambda_{n+mT} + \hat{\lambda}_{n+mT}}{2}\right] + \overline{\eta}_{n+N_pT} \tag{17}$$

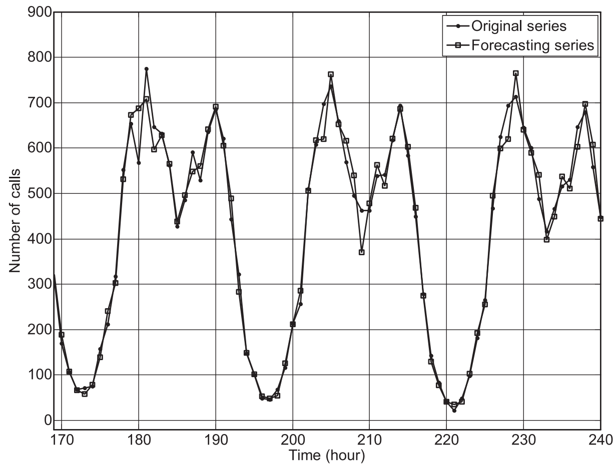

Fig. 5. Call arrival prediction (traffic has decreasing trend).

where λ_{n+mT} is the observation of the number of call arrivals in the time interval $(t_n, t_{n+1}]$ of the $(m+1)$th period, whereas $\hat{\lambda}_{n+mT}$ is the predicted number of call arrivals in $(t_n, t_{n+1}]$ of the $(m+1)$th period based on the previous observation λ_{n-1+mT}. Here, we assume λ_{n-1+mT} does not have abrupt variation and the prediction result $\hat{\lambda}_{n+mT}$ is accurate. To predict λ_{n+1+mT}, we take the value averaged over the observation λ_{n+mT} and the predicted result $\hat{\lambda}_{n+mT}$ as the number of call arrivals in $(t_n, t_{n+1}]$. Thus, abrupt variation in the observation λ_{n+mT} would not affect the prediction result $\hat{\lambda}_{n+1+mT}$ significantly.

This prediction algorithm can be applied to any similar periodic time series. We simulate the field data of primary user call arrivals and use this algorithm to implement one-step prediction. Considering the first 4 periods as the training phase, Fig. 3 shows the comparison of forecasting call arrival series with original one which does not have changing trend across periods. Figs. 4 and 5 show the comparison results when the traffic has increasing and decreasing trend across periods, respectively. The root mean square error for these three comparisons are 29.4, 32.2, and 32.0, respectively. The prediction error in Fig. 4 or Fig. 5 is greater than that in Fig. 3 due to the traffic trend changing.

Here, we discuss the effect of traffic trend changing on the prediction. In a new period, if the traffic trend changes, λ_n in the time interval $(t_n, t_{n+1}]$ would change. For example, if the traffic has an increasing trend, then, according to (8), λ_n in the new period would increase. According to (9), η_n would change if the next observation λ_{n+1} increases faster than the previous observation λ_n. Based on (13), the change of call arrivals is reflected in the updated $\overline{\eta}_n$, which is used to predict call arrivals λ_{n+1} in the next period. However, if the traffic trend changes exceptionally across periods, the updated $\overline{\eta}_n$ could not track the change of call arrivals accurately and would lead to prediction error in the next period. Generally, traffic trend changes slowly. Therefore, this algorithm would have good performance.

In addition, we need to consider the effect of abrupt traffic changes on the prediction. (17) can reduce the prediction error when the observation of call arrivals in the previous time interval has abrupt variation. However, when some factors that affect the traffic, such as weather or special events, change abruptly, a large number of call arrival observations might be affected substantially. Two scenarios are possible: 1) Call arrivals in the current and all the following periods are impacted. In this case, call arrivals would change with similar trend in those impacted periods. According to (13) and (17), the algorithm can still follow the track of traffic change. However, in the first several periods after the factors change, the call arrival prediction would involve error because $\overline{\eta}_n$ is updated slowly; 2) only limited n_k call arrivals $(\lambda_i, \cdots, \lambda_{i+n_k-1})$ are impacted. According to (17), the prediction for $\lambda_i, \cdots, \lambda_{i+n_k}$ would generate error, and this would lead to minor error in the prediction for λ_{i+n_k+1}. Generally, those abrupt changes only occur occasionally, and the generated error would not propagate. Moreover, the impact of abrupt traffic changes on $\overline{\eta}_{i-1}, \cdots, \overline{\eta}_{i+n_k-1}$ would diminish when the number of periods increases and more data are available. Therefore, prediction errors in such cases are acceptable. The simulation results of call arrival prediction for these two scenarios are shown in Figs. 6 and 7. They indicate the resiliency of the proposed algorithm with abrupt traffic changes.

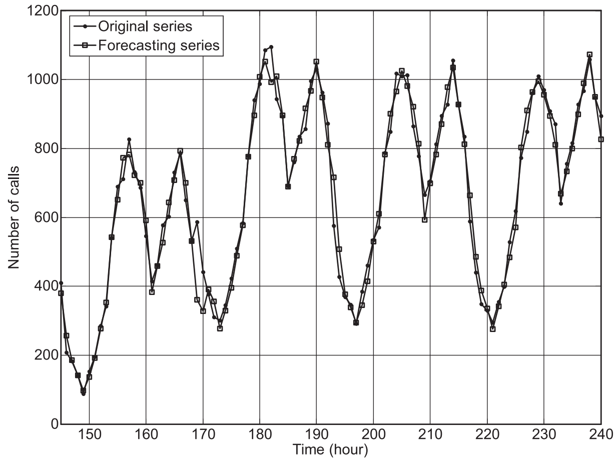

Fig. 6. Call arrival prediction with abrupt traffic change (Scenario 1).

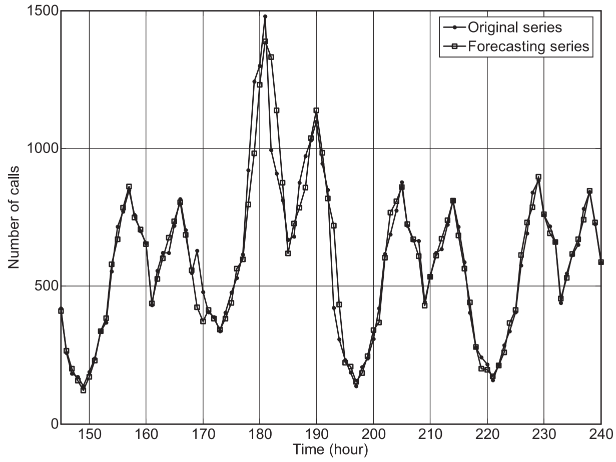

Fig. 7. Call arrival prediction with abrupt traffic change (Scenario 2).

In conclusion, the proposed algorithm is applicable when the traffic is periodic, and the number of call arrivals in each time interval does not change abruptly very often. However, the traffic may change with slow increasing or decreasing trend.

B. Call Arrival Prediction Based on SARIMA Model

SARIMA is a classical model for a discrete time series [12], and it can be applied to predict the traffic of wireless network [14]. The set of observations of the number of call arrivals in different time intervals of different periods can be considered as a discrete-time series. Therefore, we can use SARIMA model to fit the non-stationary call arrival process $\{\lambda_t\}$ $(t = 0, 1, \cdots)$, and predict the number of call arrivals λ_{l+1} given the known observations of call arrivals $\lambda_i, i \in \{1, \cdots, l\}$.

$\{\lambda_t\}$ is a SARIMA $(p, d, q) \times (P, D, Q)_s$ process with period s if the differenced series $Y_t = (1-B)^d(1-B^s)^D\lambda_t$ is a causal ARMA process defined by:

$$\begin{aligned}&(1-\phi_1 B - \cdots - \phi_p B^p)\left(1-\Phi_1 B^s - \cdots - \Phi_P (B^s)^P\right) Y_t \\ =&(1+\theta_1 B + \cdots + \theta_q B^q)\left(1+\Theta_1 B^s + \cdots + \Theta_Q (B^s)^Q\right) Z_t\end{aligned} \tag{18}$$

where p and P are the non-seasonal and seasonal autoregressive orders, respectively; q and Q are the non-seasonal and seasonal moving average orders, respectively, and d and D are the numbers of the regular and seasonal differences required, respectively. In addition, $\phi_1, \cdots, \phi_p$, $\Phi_1, \cdots, \Phi_P$, $\theta_1, \cdots, \theta_q$, and $\Theta_1, \cdots, \Theta_Q$ are coefficient parameters. B is the backward operation, i.e., $B\lambda_t = \lambda_{t-1}$, and $Z_t \sim \mathcal{N}(0, \sigma^2)$ [12].

With the simulated field data of $\{\lambda_t\}$, we calculate the autocorrelation of $\{Y_t\}$ with different d and D and find that $d = 1$ and $D = 1$ make the process $\{Y_t\}$ stationary. With period $s = 24$, the differenced observation Y_t corresponds to:

$$Y_t = (1-B)(1-B^{24})\lambda_t = \lambda_t - \lambda_{t-1} - \lambda_{t-24} + \lambda_{t-25}. \tag{19}$$

Rearranging (19),

$$\lambda_t = Y_t + \lambda_{t-1} + \lambda_{t-24} - \lambda_{t-25}. \tag{20}$$

Considering h-step prediction, and setting $t = l + h$:

$$\lambda_{l+h} = Y_{l+h} + \lambda_{l+h-1} + \lambda_{l+h-24} - \lambda_{l+h-25}. \tag{21}$$

Using P_l to denote the best linear predictor, according to (21),

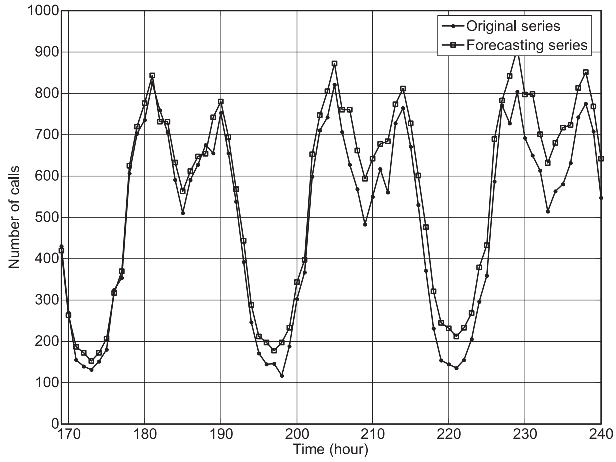

Fig. 8. Call arrival prediction based on SARIMA model (traffic has no changing trend).

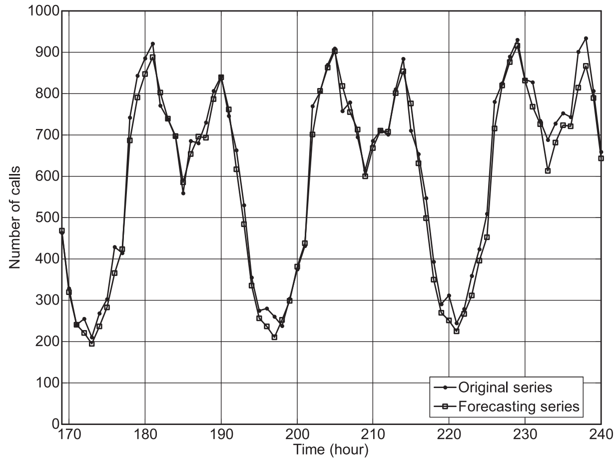

Fig. 9. Call arrival prediction based on SARIMA model (traffic has increasing trend).

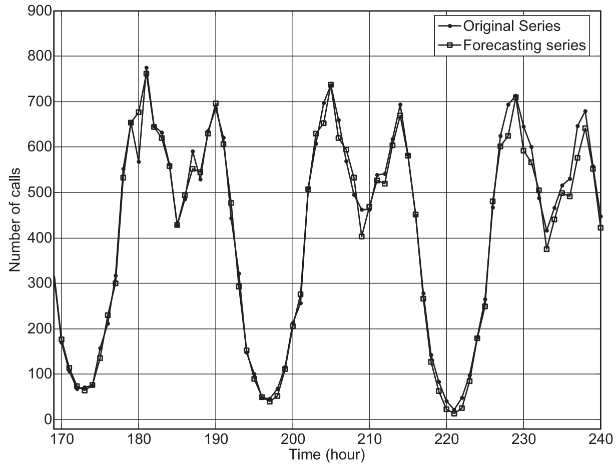

Fig. 10. Call arrival prediction based on SARIMA model (traffic has decreasing trend).

we have:

$$P_l\lambda_{l+h} = P_lY_{l+h} + P_l\lambda_{l+h-1} + P_l\lambda_{l+h-24} - P_l\lambda_{l+h-25}. \tag{22}$$

After calculating P_lY_{l+h} of Y_{l+h}, we can compute the prediction $P_l\lambda_{l+h}$ of λ_{l+h} recursively by noting that $P_l\lambda_{l+1-j} = \lambda_{l+1-j}$ for $j \geq 1$. For one-step prediction ($h = 1$), according to (22), $P_l\lambda_{l+1}$ corresponds to:

$$P_l\lambda_{l+1} = P_lY_{l+1} + \lambda_l + \lambda_{l-23} - \lambda_{l-24}. \tag{23}$$

The linear prediction for ARMA process $\{Y_t\}$ (P_lY_{l+h}) can be implemented by the innovations algorithm [12]. We use the software ITSM2000 [12] to predict λ_{l+1} when traffic has no changing trend or traffic has increasing/decreasing trend. The results are shown in Figs. 8–10 with root mean square error 70.0, 35.5, and 27.3, respectively.

Compared with the prediction algorithm proposed in Subsection III-A, SARIMA model is more flexible and can be applied to different traffic processes. However, its implementation complexity is relatively higher. The algorithm proposed in Subsection III-A is easy to be implemented and does not lose prediction performance.

IV. ESTIMATION OF CALL HOLDING TIME

In general, in different time intervals of one day, different types of calls dominate. For example, probably business calls dominate from 9:00am to 10:00am in weekdays, whereas private calls dominate from 5:00pm to 6:00pm. The average call holding time of different types of calls is different. Therefore, in different time intervals (the traffic process is periodic with period $T = 24$ hours, and each period is divided into 24 time intervals evenly), the average call holding time of primary users is different. Accordingly, we assume the call holding time of primary users in different time intervals follows exponential (or gamma [16]) distribution with different parameters [17]. For example, call holding time in the time interval (9:00am, 10:00am] follows exponential distribution with parameter μ_1, whereas call holding time in the time interval (5:00pm to 6:00pm] follows exponential distribution with parameter μ_2. In one channel, if secondary users can detect the arrival and completion of primary user calls, then they are able to estimate the average call holding time ($\bar{\mu}$) of primary users in each time interval. The estimated $\bar{\mu}$ can be used as the parameter of the exponential distribution for call holding time T_h in the corresponding time interval, i.e., $T_h \sim \text{Exponential}(\bar{\mu})$. The probability density function for the call holding time distribution can be denoted as $f_{T_h}(t_h; \bar{\mu})$.

Thus, for Case 3 discussed in Section II, substituting $f_{T_h}(t_h; \bar{\mu})$ for $f_{T_h}(t_h)$ in (7), the probability P_3 corresponds to:

$$P_3 = \frac{\int_{t_1-t_0}^{T_w+t_1-t_0} f_{T_h}(t_h; \bar{\mu})dt_h}{\int_{t_1-t_0}^{\infty} f_{T_h}(t_h; \bar{\mu})dt_h} e^{-\frac{\lambda_n}{T_d}\overline{T}}. \tag{24}$$

To show the accuracy between P_3 obtained from (24) and that obtained from (7), we conducted simulations and generate the results of P_3 according to (7) and (24), respectively. We assume: 1) The number of primary user call arrivals in different time intervals varies from 150 to 700, and the mean value of call holding time in different time intervals varies from 30 to 300 seconds; 2) the call arrival rate of secondary users is 180 calls/hour,

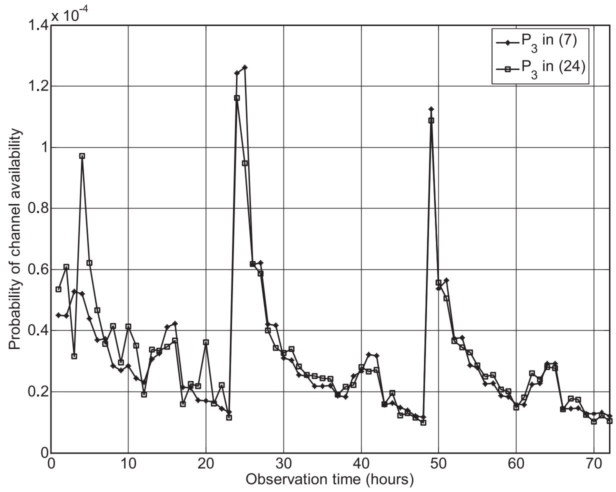

Fig. 11. Sample results of probability P_3 obtained through (7) and (24).

and the mean value of call holding time is 60 seconds; 3) the time duration T_w for which secondary users can suspend their calls is 2 seconds. The simulation results are shown in Fig. 11. When the observation time increases, the difference between the probability P_3 obtained from (7) and that obtained from (24) decreases, because secondary users can obtain more data on the traffic of primary users and the estimation for the parameter of call holding time distribution is more accurate.

V. DECISION OF CHANNEL AVAILABILITY AND THRESHOLD DETERMINATION

A. Decision of Channel Availability

Based on our discussion on call arrival prediction and parameter estimation for call holding time distribution in Sections III and IV, we can summarize how to evaluate the channel availability.

We divide one period (24 hours) into 24 time intervals. The time duration for each time interval is: $T_d = 1$ hours $=$ 3600 seconds. If the current time is within the time interval $(t_{n+1}, t_{n+2}]$, secondary users can predict the number of primary user call arrivals λ_{n+1}, and estimate the average call holding time $(\bar{\mu})$ of primary users in this time interval.

For Cases 1 and 2 discussed in Section II, the probability P_i that a channel would be available to the secondary user corresponds to:

$$P_i = e^{-\frac{\hat{\lambda}_{n+1}}{3600}\overline{T}}, i = 1, 2 \tag{25}$$

where $\hat{\lambda}_{n+1}$ is the predicted result of λ_{n+1}, and $\overline{T}$ is the average call holding time of the secondary user.

For Case 3, according to (24), the probability P_3 corresponds to:

$$P_3 = \frac{\int_{t_1-t_0}^{T_w+t_1-t_0} f_{T_h}(t_h; \bar{\mu})dt_h}{\int_{t_1-t_0}^{\infty} f_{T_h}(t_h; \bar{\mu})dt_h} e^{-\frac{\hat{\lambda}_{n+1}}{3600}\overline{T}}. \tag{26}$$

Introducing prediction technique to cognitive radio systems would impact the communication performance of both primary and secondary users. To maintain a trade-off between performance measurements including channel switching rate and call blocking rate of secondary users, interference on primary users and spectrum reuse efficiency, secondary users can set a threshold P_{th} ($P_{th} \in [0, 1]$) to determine whether to use a channel. If the probability P_i ($i = 1, 2, 3$) is not less than this threshold, i.e.,

$$P_i \geq P_{th} \tag{27}$$

then, a secondary user can proceed to use the channel. Otherwise, it would abandon using the channel.

In summary, when a secondary user is in idle status (no transmission request), it detects primary user call arrivals in a channel and stores the relevant traffic information. Once it has transmission request, first, based on the recorded traffic information, the secondary user predicts the number of primary user call arrivals in the current time interval. Then, it checks the channel occupation status. If one channel is not occupied, the secondary user evaluates the probability that this channel would be available within its average call holding time $\overline{T}$, and, then, compares the evaluated probability with the threshold to decide whether to use the channel. If all channels are occupied (Case 3), the secondary user would drop the call if $T_w = 0$; if $T_w > 0$, the secondary user would estimate the parameter of the call holding time distribution of primary users and evaluates the channel availability by incorporating the prediction and estimation results. The whole process is summarized in the flow chart of Fig. 12.

Here, we assume secondary users have the capability of collecting large amount of data on primary user calls. One application of this scenario can be a sensor network deployed in a given area to monitor the weather condition. Each sensor node is equipped with cognitive radio and functions as a secondary user. These static sensor nodes are not licensed any channel for communication. After deployment, these sensor nodes monitor the weather condition and analyze the measured data. Meanwhile, they collect the traffic data of licensed users of primary networks operating in the corresponding area. When sensor nodes need to report the data on the weather condition to a center, they can use the approach proposed in this paper to find available channels and communicate with other sensor nodes or the center over these channels. These sensor nodes are static and are equipped with necessary hardware, software, power supply (e.g., solar power) and other resources to support collecting the traffic data of primary users and analyzing weather condition. They use the detected available channels to wirelessly communicate with other sensor nodes or the data center.

B. Threshold Determination

The probability threshold P_{th} in (27) is determined by the requirements on performance measurements, whereas performance measurements are affected by the probabilities of false alarm and missed detection. Here, false alarm refers to the condition that a secondary user judges that primary users would appear whereas, actually, no primary user appears; missed detection refers to the condition that a secondary user judges that no primary user would appear whereas, actually, primary users appear.

According to (27), if $P_i \geq P_{th}$, the secondary user would start transmission over the corresponding channel. This means that

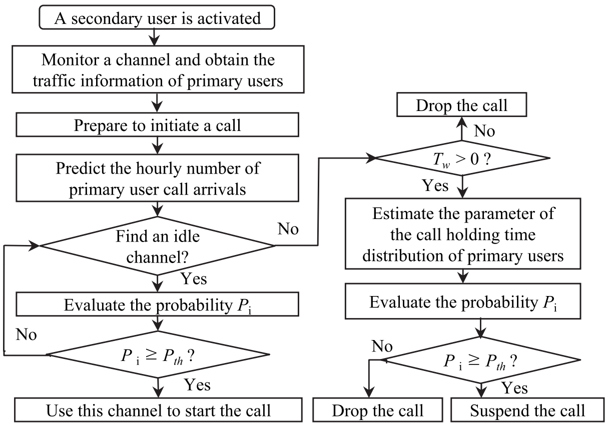

Fig. 12. Flowchart for the channel availability evaluation.

the secondary user assumes the probability that primary users would appear in this channel is 0. However, actually, primary users would appear with probability $1 - P_i$. Hence, in this case $(P_i \geq P_{th})$, the probability of missed detection is $1 - P_i - 0 = 1 - P_i$, i.e.,

$$P_{miss} = \mathbf{P}\{\text{decides no primary user would appear} \mid \text{primary users appear}\} = 1 - P_i. \tag{28}$$

According to (27), if $P_i < P_{th}$, a secondary user would not use the channel. In other words, the secondary user assumes that primary users would appear in the channel with probability 1. However, actually, the probability that primary users would appear is only $1 - P_i$. Therefore, in this case $(P_i < P_{th})$, the probability of false alarm is $1 - (1 - P_i) = P_i$, i.e.,

$$P_{false} = \mathbf{P}\{\text{decides primary users would appear} \mid \text{no primary user appears}\} = P_i. \tag{29}$$

In summary,

$$\begin{cases} P_{miss} = 1 - P_i, & \text{if } P_i \geq P_{th}, \\ P_{false} = P_i, & \text{if } P_i < P_{th}. \end{cases} \tag{30}$$

When the probability of false alarm increases, 1) the call blocking rate of secondary users increases due to the increased announcements on channel unavailability; 2) the channel switching rate of secondary users and the interference on primary users decrease, and, 3) spectrum reuse efficiency decreases. On the other hand, when the probability of missed detection increases, the call blocking rate of secondary users decreases, but, the interference on primary users increases definitely.

In channel availability decisions, the occurrence rate of false alarm or missed detection is related to the probability threshold P_{th}. If P_{th} increases, the occurrence rate of false alarm increases whereas the occurrence rate of missed detection decreases; if P_{th} decreases, on the contrary, the occurrence rate of false alarm decreases whereas the occurrence rate of missed detection increases. If we only aim to reduce the interference of secondary users on the primary users, we need to minimize the occurrence rate of missed detection, and accordingly, we need to increase the probability threshold P_{th}. However, this would lead to a higher occurrence rate of false alarm, and, as a result, it increases the call blocking rate of secondary users and decreases the spectrum reuse efficiency (due to the increased announcements that channels are not available, although they might be available). Therefore, to balance the performance in terms of the call blocking rate of secondary users, spectrum reuse efficiency and interference on primary users, we consider equating the occurrence rate of false alarm with that of missed detection to find the probability threshold.

Therefore, within a time interval, if, for one channel, a secondary user makes N decisions on channel availability, out of the N decision results, the occurrence times of missed detection should be equal to the occurrence times of false alarm.

Let N_m denote the number of cases that $P_i \geq P_{th}$ in the N decisions $(0 \leq N_m \leq N)$, and $P_{i,k}$ denote the evaluated probability of channel availability for the kth $P_i \geq P_{th}$ case, $k \in \{1, 2, \cdots, N_m\}$. According to (30), if N is large enough, the occurrence times of missed detection, N_{miss}, can be approximated by:

$$N_{miss} \approx \sum_{k=1}^{N_m} (1 - P_{i,k}) = N_m - \sum_{k=1}^{N_m} P_{i,k}. \tag{31}$$

Similarly, the occurrence times of false alarm in the N decisions is:

$$N_{false} \approx \sum_{j=1}^{N-N_m} P_{i,j} \tag{32}$$

where $P_{i,j}$ is the evaluated probability of channel availability for the jth $P_i < P_{th}$ case, $j \in \{1, 2, \cdots, N - N_m\}$.

Therefore, to maintain equal occurrence times of missed detection and false alarm, according to (31) and (32), we have:

$$N_m - \sum_{k=1}^{N_m} P_{i,k} = \sum_{j=1}^{N-N_m} P_{i,j}. \tag{33}$$

Rearranging (33), N_m corresponds to:

$$N_m = \sum_{k=1}^{N_m} P_{i,k} + \sum_{j=1}^{N-N_m} P_{i,j}. \tag{34}$$

Dividing both sides of (34) by N, we have:

$$\frac{N_m}{N} = \frac{1}{N} \left(\sum_{k=1}^{N_m} P_{i,k} + \sum_{j=1}^{N-N_m} P_{i,j} \right). \tag{35}$$

The left hand side of (35) is the approximate probability of $P_i \geq P_{th}$ when N is large enough, i.e., $\mathbf{P}\{P_i \geq P_{th}\} \approx N_m/N$, whereas the right hand side of (35) is the average value of the evaluated probability results, which is denoted as P_{avg} and corresponds to:

$$P_{avg} = \frac{1}{N} \left(\sum_{k=1}^{N_m} P_{i,k} + \sum_{j=1}^{N-N_m} P_{i,j} \right) = \frac{\sum P_i}{N} \tag{36}$$

where $\sum P_i$ is the summation of the evaluated probabilities of channel availability over all N decisions.

Hence, we have:

$$\mathbf{P}\{P_i \geq P_{th}\} = P_{avg}. \tag{37}$$

In general, to find P_{th} in terms of P_{avg}, we need to know the PDF of P_i. Within one time interval, the predicted number of call arrivals would be around the mean number of call arrivals in this time interval. According to (25) and (26), the evaluated probability of channel availability would also be around the average value P_{avg}. These evaluated probability results are mostly within the range of $(1-\alpha)P_{avg}$ to $(1+\alpha)P_{avg}$ ($0 \leq \alpha \leq 1$, α is used to vary the range). Considering P_i is uniformly distributed between $(1-\alpha)P_{avg}$ and $(1+\alpha)P_{avg}$, according to (37), we have:

$$\int_{P_{th}}^{(1+\alpha)P_{avg}} \frac{1}{2\alpha P_{avg}} dp_i = P_{avg}. \tag{38}$$

Applying some mathematical manipulations, P_{th} corresponds to:

$$P_{th} = P_{avg}(1 + \alpha - 2\alpha P_{avg}). \tag{39}$$

Substituting (36) into (39), we have:

$$P_{th} = \left(\frac{\sum P_i}{N}\right)\left(1 + \alpha - 2\alpha\left(\frac{\sum P_i}{N}\right)\right), 0 \leq \alpha \leq 1 \tag{40}$$

where $\sum P_i$ is introduced in (36). According to (39), when $P_{avg} < 0.5$, the probability threshold P_{th} monotonically increases with α; when $P_{avg} \geq 0.5$, P_{th} monotonically decreases with α. Therefore, when $P_{avg} < 0.5$ and α increases, P_{th} increases. Channels would be considered available if the evaluated probability P_i of channel availability is greater than P_{th}. Hence, when P_{th} increases, it is more likely that channels are declared unavailable. Accordingly, the occurrence times of false alarm increases and the occurrence times of missed detection decreases. As a result, the call blocking rate of secondary users increases and the spectrum reuse efficiency decreases. On the contrary, when $P_{avg} \geq 0.5$ and α increases, P_{th} decreases. Thus, the occurrence times of false alarm decreases and the occurrence times of missed detection increases. Accordingly, the call blocking rate of secondary users decreases and the spectrum reuse efficiency increases.

Within a time interval, for one channel, the secondary user can set the threshold P_{th} according to (40) using the past evaluated probability results. Note that, within a time interval, the selection of P_{th} is impacted by the number of primary user call arrivals. Therefore, in different time intervals, P_{th} should be set dynamically.

VI. SIMULATION

In this section, we introduce performance measures, and analyze the associated simulation results to investigate the impact of the proposed prediction technique on communication performance.

A. Performance Measures

1) Spectrum Loss is defined as:

$$S_L = \frac{\sum_i W^{(i)} T_e^{(i)}}{T_{ob}} \tag{41}$$

where T_{ob} is the observation time, and $T_e^{(i)}$ is the total idle time of channel i within T_{ob} (the bandwidth of channel i is $W^{(i)}$).

2) Call blocking rate of secondary users is defined as:

$$R_b = \frac{N_b}{N_T} \tag{42}$$

where N_b is the number of blocked secondary user calls within the observation time T_{ob}, and N_T is the total number of call attempts made by secondary users within T_{ob}.

B. Simulation for Communication Performance Investigation

We conduct simulations to generate the results of performance measures and study the impact of the proposed prediction technique on communication performance. Here, we assume: 1) The observation time is 4 periods (96 hours); 2) two frequency bands licensed to two different service providers can be used by secondary users, and, $W^{(1)} = W^{(2)} = W$, where $W^{(i)}$ is the bandwidth of frequency band i; 3) the traffic patterns of primary users for frequency band 1 and 2 are similar, and the traffic period T is the same ($T = 24$ hours); 4) each traffic period is divided into 24 time intervals evenly, and the duration for each time interval is 1 hour; 5) call arrivals of primary users follow non-homogeneous Poisson process (the number of call arrivals in different time intervals varies from 200 to 950), and the mean value of call holding time is 3 minutes; 6) call arrivals of secondary users follow homogeneous Poisson process (the call arrival rate is 180 calls/hour), and the mean value of call holding time is 2.5 minutes; and 7) the time duration T_w for which secondary users can suspend their calls is 0.

Before initiating a call, a secondary user first checks the availability of frequency band 1. If this frequency band is not available, then, it checks the availability of frequency band 2. If neither is available, the call would be blocked. If any frequency band is available, the secondary user would start transmission over the frequency band. Here, for a secondary user, a frequency band would be considered available if 1) the frequency band is currently not occupied and 2) the probability that the frequency band would not be occupied by primary users within $\overline{T}$ is not less than a threshold ($\overline{T}$ is the average call holding time of the secondary user).

First, for each of the two frequency bands, the probability threshold in each time interval is set according to (40). We vary the parameter α in (40) to generate the performance measure results, which are shown in Table 1. It is observed that, in both situations (with and without prediction), the call blocking rate of secondary users is high. When the prediction technique is employed, with $\alpha = 0.1$, the channel switching times of secondary users is 89.47% less than that of without prediction. However, the call blocking rate of secondary users is 2.29% higher, and total spectrum loss is 31.38% higher. This is due to the fact that, with prediction, secondary users do not use the frequency band

Table 1. SIMULATION RESULT COMPARISON (SU: Secondary User).

Measures	No prediction	With prediction ($\alpha = 0.1$)	With prediction ($\alpha = 1$)
Switching times of SUs	57	6 (89.47% less)	0 (100% less)
Blocking rate of SUs	97.10%	99.32% (2.29% higher)	99.89% (2.87% higher)
Total spectrum loss	$0.0545 \cdot W$	$0.0716 \cdot W$ (31.38% higher)	$0.0771 \cdot W$ (41.47% higher)

which will be occupied by primary users with higher probability. Comparing with the results for $\alpha = 0.1$, when $\alpha = 1$, the channel switching times of secondary users decreases; however, both call blocking rate and spectrum loss increase. Obviously, with prediction, the channel switching times of secondary users reduces significantly with slight loss of the call blocking rate performance.

In addition, simulations are conducted to verify the threshold determination according to (40). Here, within one specific time interval, we assume: (a) The number of primary user call arrivals is 310 for frequency band 1, and it is 320 for frequency band 2; (b) the mean value of call holding time of primary users is 3 minutes. First, to generate the false alarm and missed detection results under different probability thresholds, we set $P_{th} = 10^{-6}, 2 \times 10^{-6}, \cdots, 2 \times 10^{-5}$ for both frequency bands. The results of occurrence times of false alarm and missed detection are shown in Fig. 13. Then, we run the simulation with the threshold P_{th} specified by (40). The final generated thresholds for both frequency bands are sketched in Fig. 13. It is observed that, for each frequency band, the threshold selected based on (40) is close to the cross point of false alarm and missed detection curves, which is also the balance point of false alarm and missed detection.

Moreover, in another scenario, for both frequency bands, we set the same probability threshold (varying from 10^{-17} to 10^{-1}) in all time intervals. Simulation results of performance measures including call blocking rate, switching times of secondary users and spectrum loss are shown in Fig. 14. Similarly, the call blocking rate of secondary users is high in both situations (with or without prediction). With prediction, the call blocking rate is only slightly higher. When the probability threshold P_{th} increases, both call blocking rate of secondary users and spectrum loss increase; however, channel switching times of secondary users decreases. When P_{th} increases from 10^{-10} to 10^{-3}, the channel switching times of secondary users reduces to zero (accordingly, the interference on primary users reduces), whereas the call blocking rate of secondary users and spectrum loss only increase by 1.52% and 26.51%, respectively.

In summary, mostly, secondary users can not find available frequency bands (the call blocking rate of secondary users is high), unless the frequency band utilization rate by primary users is very low, or frequency bands are licensed to primary users who have deterministic traffic patterns (such as TV transmitters). In addition, when the prediction technique is employed, the interference on primary users reduces significantly with only slight loss of the secondary user's call blocking rate performance.

VII. CONCLUSIONS AND DISCUSSION

In this paper, we proposed algorithms that enable secondary users to predict the call arrivals of primary users, and we presented methods to evaluate the probability that a channel would be available for a given time period. Comparing the evaluated probability with a threshold, secondary users can determine whether to use a channel. In addition, we discussed the probability threshold determination. The probability threshold maintains a trade-off between the channel switching rate and call blocking rate of secondary users, interference on primary users and spectrum reuse efficiency. Simulations were conducted to verify that employing traffic pattern prediction technique reduces the channel switching rate of secondary users and the interference on primary users.

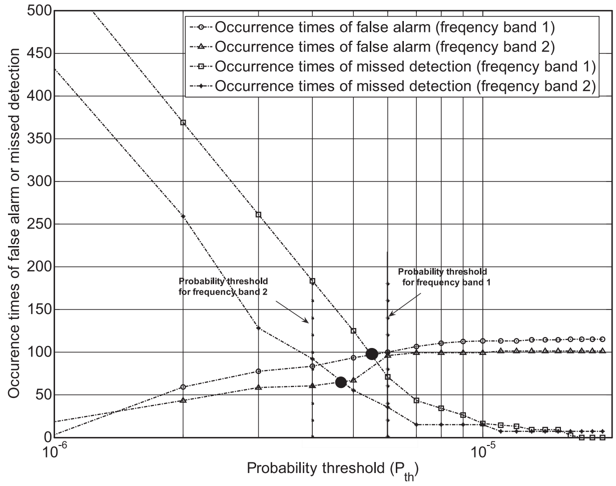

Fig. 13. Trade-off of false alarm and missed detection.

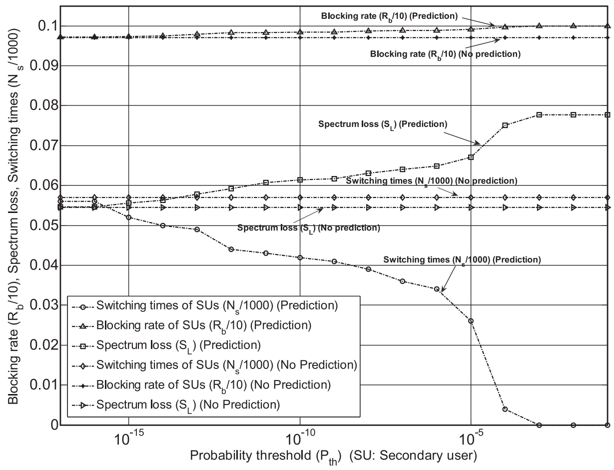

Fig. 14. Performance vs. different probability thresholds.

It should be noted that, in heterogeneous networks, due to the difference in the services, primary users might have different traffic patterns. Therefore, the proposed technique in this paper can not directly be applied to support multiple traffic types in heterogeneous networks. However, based on the collected historical traffic data of primary users and taking advantage of the intelligence of cognitive radios (observing, learning and acting function, etc.), secondary users can analyze the traffic characteristics of primary users, and generate the corresponding traffic pattern (this is not discussed in this paper, and we consider it as a future study). Then, secondary users can use the proposed approach to evaluate the probability of channel being available for a given time period and find a suitable channel for communication. However, the algorithms used to predict the traffic pattern of primary users may need to be developed or modified based on those proposed in this paper.

REFERENCES

[1] R. W. Brodersen, A. Wolisz, D. Cabric, S. M. Mishra, and D. Willkomm, 2004 White Paper: "CORVUS-A cognitive radio approach for usage of virtual unlicensed spectrum," [Online]. Available: http://bwrc.eecs.berkeley.edu/Research/MCMA/.

[2] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Proc. Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers*, vol. 1, Nov. 2004, pp. 772–776.

[3] N. Han, S. Shon, J. H. Chung, and J. M. Kim, "Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems," in *Proc. ICACT 2006*, vol. 3, Feb. 2006, p. 6.

[4] B. Wild and K. Ramchandran, "Detecting primary receivers for cognitive radio applications," in *Proc. IEEE DySPAN 2005*, Nov. 2005, pp. 124–130.

[5] G. Ganesan and Y. Li, "Cooperative spectrum sensing in cognitive radio networks," in *Proc. IEEE DySPAN 2005*, Nov. 2005, pp. 137–143.

[6] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, pp. 201–220, Feb. 2005.

[7] H. Chen and L. Trajkovic, "Trunked radio systems: Traffic prediction based on user clusters," in *Proc. International Conference on Wireless Communication Systems*, 2004, Sept. 2004, pp. 76–80.

[8] P. Moungnoul, N. Laipat, N., T. T. Hung, and T. Paungma, "GSM traffic forecast by combining forecasting technique," in *Proc. International Conference on Information, Communications, and Signal Processing*, 2005, Dec. 2005, pp. 429–433.

[9] M. Papadopouli, H. Shen, E. Raftopoulos, M. Ploumidis, and F. Hernandez-Campos, "Short-term traffic forecasting in a campus-wide wireless network," in *Proc. IEEE PIMRC 2005*, vol. 3, Sept. 2005, pp. 1446–1452.

[10] F. Kohandani, D. W. McAvoy, and A. K. Khandani, "Wireless airtime traffic estimation using a state space model," in *Proc. CNSR 2006*, May 2006, p. 8.

[11] Y. Akinaga, S. Kaneda, N. Shinagawa, and A. Miura, "A proposal for a mobile communication traffic forecasting method using time-series analysis for multi-variate data," in *Proc. IEEE GLOBECOM 2005*, vol. 2, Nov. 2005, p. 6.

[12] P. J. Brockwell and R. A. Davis, *Introduction to Time Series and Forecasting*, 2nd ed., New York: Springer-Verlag , 2002.

[13] X. Li and S. A. Zekavat, "Traffic pattern prediction and performance investigation for cognitive radio systems," in *Proc. IEEE WCNC 2008*, March, 2008, pp. 894–899.

[14] Y. Shu, M. Yu, J. Liu, and O. W. W. Yang, "Wireless traffic modeling and prediction using seasonal ARIMA models," in *Proc. IEEE ICC 2003*, vol. 3, May 2003, pp. 1675–1679.

[15] D. Snyder and M. Miller, *Random Point Processes in Time and Space*, 2nd ed., New York : Springer-Verlag, 1991.

[16] Y. Lin and I. Chlamtac, "Large effective call holding times for a PCS network," in *Proc. IEEE PIMRC 1996*, vol. 1, Oct. 1996, pp. 143–147.

[17] C. Jedrzycki and V. C. M. Leung, "Probability distribution of channel holding time in cellular telephony systems," in *Proc. IEEE VTC 1996*, vol. 1, 28 April-1 May 1996, pp. 247–251.

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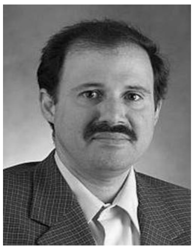

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