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Fuzzy Prediction Based Opportunistic Spectrum Access for Cognitive Radio

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ABSTRACT: In this paper a fuzzy prediction based opportunistic spectrum access for cognitive radio is proposed. The proposed Fuzzy Prediction Based Opportunistic Spectrum Access (FPBOSA) consists of Fuzzy Prediction Based Opportunistic Spectrum Access algorithm and a sensing strategy. The FPBOSA is designed to predict residual idle or busy slots for Listen Before Talk (LBT) scheme. CR predicts residual slots with the help of two new definitions: Channel State Information ($\boldsymbol{CSI}$) and Channel Available Vector ($\boldsymbol{CAV}$). $\boldsymbol{CSI}$ defines residual idle or busy slot of PUs channel. CAVdefines predicted number of slots for PUs channel which remains in idle state for the longest time.

FPBOSA uses Proposed Fuzzy Predictor (PFP) for predicting residual idle or busy slots. PFP uses Fuzzy c-means Clustering algorithms to define Linguistic Variables. After Linguistic variables are defined, TS fuzzy model is used for prediction. On some occasions PFP may produce an invalid output. Invalid output occurs when the output of the predictor is outside the universe of discourse $\boldsymbol{U}$. In such cases, PFP replaces the result with training data which have similar characteristics to inputs that produce invalid output. To find the best much between the inputs which produce invalid output and training data, Euclidean distance is used. The performance of PFP is tested using the Mackay-Glass time series data. The MG time series simulation shows scores of PFP as:$\boldsymbol{timeliness} = \mathbf{3.1892 \times 10^{-4}}$, $\boldsymbol{Precision} = \mathbf{2.1753 \times 10^{-5}}$,$\boldsymbol{Repeatability} = \mathbf{1.2051 \times 10^{-6}}and\boldsymbol{Accuracy} = \mathbf{2925.0472}$.

Proposed sensing strategy consists of a scheduling algorithm. The Proposed sensing strategy maximize throughput by avoiding unnecessary quite periods.Unnecessary quite periods are those slots where the PFP predicts the state without error. Unnecessary quite periods are determined depending on the maximum absolute error of PFP encountered during training phase.

The performance of FPBOSA is compared with that of a basic CR device. The basic CR device relies on sensing to discover an opportunity. The simulation consists of a CR and 4 PU channels. The result shows an increase in throughput and spectrum utilization while the sensing energy is saved.

KEYWORDS: Cognitive Radio, Dynamic Spectrum Access, Fuzzy Predictor, Opportunistic Spectrum Access, sensing strategy, Channel State Information (CSI), channel available vector (CAV).

I. INTRODUCTION

The main idea behind Dynamic Spectrum Access (DSA) is to efficiently manage spectrum usage in response to changing circumstances and objectives in order to maximize Spectrum utilization. IEEE Standards Coordinating Committee 41, formerly known as IEEE 1900, defines DSA as [1]:

Definition 1 (Dynamic Spectrum Access): The near-real-time adjustment of spectrum resource usage in response to changing circumstances and objectives; including interference experienced or created; changes of the radio state (operational mode, battery life, location, etc.); and changes in environmental/external constraints (spectrum, propagation, operational policies, etc…).

According to the above definition, a device observes to learn spectrum resource usage and changes its operating parameters for utilizing spectrum effectively. Current devices lack the capabilities of observing, learning and reconfiguring parameters. Cognitive Radios (CR), first introduced by Joseph Mitola and Gerald Q. Maguire [2], have these and othercognitive capabilities which make DSA a reality.

Generally, DSA access strategies are broadly categorized as Dynamic exclusive-use, Spectrum commons and Hierarchical access model [3]. Hierarchical access model adopts a hierarchical access structure with Primary users (PUs) and Secondary users (SUs). In Hierarchical access model, PUs have higher priority or legacy rights on usage of a

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specified part of spectrum. On the other hand SUs, also known as CR users or unlicensed users, have lower priority and exploit this spectrum in such a way that they do not cause interference to PUs [4]. Two approaches to spectrum sharing between PUs and SUs have been considered: spectrum underlay and spectrum overlay [3].

The underlay approach imposes severe constraints on the transmission power of SUs to operate below noise floor of PUs. For example, SUs can achieve short range transmission with high data rate and extremely low transmission power by spreading transmitted signals over a wide frequency band (UWB) [4].

Spectrum overlay, also known as Opportunistic Spectrum Access (OSA) was introduced by the Defense Advanced Research Project Agency (DARPA) in the next generation (XG) program [5]. Actually, the concept is first proposed by Joseph Mitola, with the name spectrum pooling. IEEE Standards Coordinating Committee 41 formally defines Opportunistic Spectrum Access as [6]:

Definition 2 (OSA):The method by which spectrum users operating on a secondary (and possibly unlicensed) basis within a frequency band with designated primary (and possibly licensed) users exploit unused in-band segments for their own purposes without causing interference to the active interference-intolerant primary users for the duration of the availability of the spectrum in question.

In OSA, CR users transmit on a spectrum band owned by PUs only if the channel is an opportunity for transmission [3]. A spectrum band or channel is considered as opportunity for a pair of secondary user A and B, where A is the transmitter and B is the intended receiver, if they can communicate successfully over this channel while limiting the interference to primary users below a prescribed level determined by the regulatory policy [4]. The simplest opportunity is called spectrum hole and is defined as a band of frequencies assigned to a primary user, but at a particular time and specific geographic location, the band is not being utilized by that user [8].

PUs are interference intolerant. Consequently, CR must be sure that no PUs transmission is present before using a spectrum hole. If PU starts transmission while CR is transmitting, then CR must have the capability to identify the presence of PUs and change to another unused spectrum band. This process of changing operating frequency is called spectrum handoff [9]. CR depends on sensing to discover spectrum hole and for spectrum hand offs.

To avoid interference to PUs, CR senses the channel periodically every T time for $T_s$amount of time followed by transmission for T_d amount of time. This results in slotted time structure consisting of sensing phase followed by a transmission phase. During sensing phase CR stops transmission, for this reason sensing periods are called quite periods [10]. The sum of T_s and T_d is length of a slot T (Fig. 1). OSA access of this type is called Listen Before Talk (LBT).

The availability of spectrum hole depends on activity of PUs. The more time PU has data to transmit, the less time this channel is idle. Therefore, Spectrum sensing is assisted by prediction of PUs traffic activity [8]. Predicting the activity of PUs helps to increase spectrum utilization and throughput of secondary user. Also probability of interfering with PUs is reduced.

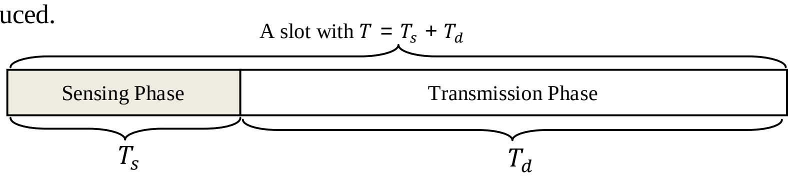

Fig.1: Structure of LBT slot

Generally in a listen before talk (LBT) policy, spectrum sensing problems consists of two main issues: the sensing strategy for scheduling spectrum sensing actions and the signal processing approach for decision making [11]. The former is a strategy issue with the aim of properly scheduling sensing slots and sensing cycle, along with specifying appropriate sensing time. The latter issue refers to signal processing techniques for spectrum detection and estimations, which are executed in each sensing slot. This paper focuses on sensing strategy for scheduling spectrum sensing.

In conventional LBT scheme, SU has to sense all licensed channels one by one to detect idle channels. This is sensing overhead that results in decrease of achievable throughput [12]. For instance, if CR uses N PUs channels and $t_s$time is elapsed for sensing, then Nt_stime is elapsed: One can ask, how can we acquire information on more channels with less sensing time overhead without affecting PUs transmission?

Sensing time overhead is reduced by prediction of PU channel status. But, predicting PUs status has side effects of miss detections, wrong detections and prediction overhead. On the CR perspective, miss detection occurs when the prediction method misses available opportunities. Wrong detection occurs when the prediction method wrongly detects

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unavailable opportunity. Wrong detection results in interference to PUs. Hence, CR should have accurate prediction method to minimize miss detection and wrong detection.

Even though sensing overhead is reduced by prediction, it inquires a cost. Consider a CR assisted by prediction and capable of using N PU channels, at each slot CR predicts status of NPU channels. If the prediction mechanism takes a lot of time, then it is not worth of assisting. Therefore, the prediction mechanism should be fast. In this paper, Fuzzy Time Series predictor is proposed to reduce miss detection, wrong detection and prediction overhead.

Slot structure of LBT i.e. length (in time) of $T_s$and $T_d$affects the performance of both PUs and SUs. The longer transmission phase durationT_d, the longer time available for transmission. On the other hand, longer duration of $T_d$results in longer interference time to PU [15]. Interference time refers to the time period starting from PUs switching from off to on and lasting until the incumbent SU detects PUs switching and vacates the spectrum. Shorter length of time slot helps to decrease interference time to PU. On the contrary, shorter duration of time slot leads to smaller time for transmission of CR. The dilemma here is how CR can have shorter slot, but at the same time increase transmission time. Scheduling algorithm is proposed in such a way that CR keeps shorter slot structure while increasing throughput of Cognitive Radio.

II. Related work

[13] proposes binary time series approach for spectrum hole prediction. For a slotted LBT scheme, at a particular time, the slot is either busy or idle. CR can keep track of H past data for prediction. Auto Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA) can be used to estimate future occupancy of a slot. [14] Propose AR, MA and ARMA to predict spectrum occupancy of Chinese TV bands (603.25 - 843.25 MHz). In [36] an A spectrum hole prediction model for CR systems over a fading channel is presented. Upon this model, a Kalman filter predictor is proposed. In [12], [16]-[21] HMM is used for predicting probabilities of being busy or idle state. [22] proposesMulti Layered Perceptron (MLP) based predictor which does not require a prior knowledge of PUs'traffic characteristics.

To reduce the probability of miss detection and wrong detection, prediction method should be accurate. Prediction accuracy of AR, MA and ARMA models compared to HMM and ANN is limited, due to non-stationary traffic characteristics of PUs. HMM in terms of prediction have several drawbacks. HMM assumes that the probability of being in a state at time t only depends on the previous state at $t-1$[23]. But in reality the probability of being in a given state depends on multiple past states. HMM also assumes that probabilistic model of spectrum usage is fixed [22], while Probability model is strongly varying over time [7]. Beside these assumptions, HMM require a large amount of data for training [22], [24].

Since most of the traffic characteristics of licensed users encountered in reality are non-deterministic in nature. For such cases intelligent prediction algorithms are preferred. ANN is one of such good methods to model nonlinear systems. But, the performance of ANN suffers from a series problem of being trapped in local minima [24].

Concerning LBT slot structure, [16], [17] decide the minimum length of LBT slot depending on the response delay of CR hardware platform. [12] minimizes sensing overhead by taking correlation of channels operating on the same service into account. In [22] busy slots are not sensed in order to minimize sensing energy.

III. Proposed FUZZY PREDICTION BASED OSA (PFPBOSA)

A. *Proposed OSA Algorithm*

Consider a CR user that access spectrum opportunistically from N PU channels using LBT scheme. PU channel traffic is modeled as an alternating renewal process in which a cycle consisting of idle duration followed by busy duration, repeats (renews) in time. Renewal of a cycle is said to occur when the channel becomes idle (i.e. the primary user stops transmitting on the channel) [25]. This means, PU channel is free for a certain period of time followed by busy period.

CR is proposed to predict residual idle or busy slots, instead of predicting the status of PU channel (either busy or idle) in each slot or its status after k number of slots. The duration of busy and idle time is predicted by the Proposed Fuzzy Predictor (PFP).

The main goal of FPBOSA is to gain complete information of PU channels. Complete information about PU channels is obtained by predicting residual busy or idle slots. To achieve complete information on PU channels, CR makes use of the following two definitions:

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Definition 3 (Channel State InformationCSI_i) is a vector of length 2 where,$CSI_i(1)$(The first element): indicate the state of the i^{th}PU channel i.e. busy or idle state. $CSI_i(1) = 1$ indicate busy PU channel while$CSI_i(1) = 0$ indicate idle PU channel.$CSI_i(2)$(The second element of the vector): indicate the expected time (predicted by proposed fuzzy predictor) that PU channel i remains in the state indicated by$CSI_i(1)$.

Definition 4 (Channel Available Vector (CAV)): is a vector of length 2 used for providing information about the best PU channel. From available N PU channels the one with high number of predicted idle slot is the best channel.CAV (1): indicate the selected best PU channel for usage. (CR gives index to all PU channel). CAV (2) : indicate the predicted time that the selected best channel (CAV (1)) is available. CAV=[0,0], If there is no available free channel from the N PU channels.

For example, $CSI_i = [0{,}10]$ means, the first PU channel CR can access is idle$CSI_i(1) = 0$ for the current and next 10 slots ($CSI_i(2) = 10$). $CAV = [3{,}9]$ means that PU channel 3 is the best channel ($CAV(1) = 3$) for access with predicted free 9 slots from the current one ($CAV(2) = 9$).

The pseudo code of Proposed Fuzzy Prediction Based OSA algorithm is shown below. An explanation follows on the subsequent paragraphs.

Step 1: Start algorithm by selecting available channel

1. **for** Channel=1 to N

Step 2: for all channels undergoingstate changepredict CSI using the Proposed Fuzzy Predictor

2. **If**$CSI_{Channel}(2) == 0$
3. **If**$CSI_{Channel}(1) == 0$
4. $CSI_{Channel}(1) = 1$
5. $CSI_{Channel}(2) = PFP(x_{on}(n-3), x_{on}(n-2), x_{on}(n-1), x_{on}(n))$
6. $n = n + 1;$
7. **else if**$CSI_{Channel}(1) == 1$
8. $CSI_{Channel}(1) == 0$
9. $CSI_{Channel}(2) = PFP(x_{off}(k-3), x_{off}(k-2), x_{off}(k-1), x_{off}(k))$
10. $k = k + 1;$
11. **end if**

Step 3: for all channels without state change update CSI by subtracting expired slot

12. **else**
13. $CSI_{Channel}(2) = CSI_{Channel}(2) - expired\ slot$
14. **endif**
15. **endfor**

Step 4: Select candidate idle channel for conditional use

16. **for** Channel=1 to N
17. **if**$CSI_{Channel}(1) == 0$
18. **select** Channel as candidate for use
19. **end if**
20. **end for**

Step 4: Select the best channel by sorting according to the predicted residual idle slot and update CAV

21. **Sort** selected channel according to decreasing $CSI_{Channel}(2)$
22. **Select** channel with maximum $CSI_{Channel}(2)$
23. $CAV(1) = selected\ channel$;
24. $CAV(2) = CSI_{selected\ channel}(2)$

Step 5: After selecting the best channel go to the proposed sensing strategy

25. **Go** to Proposed Sensing Strategy

Where, $x_{on}$and $x_{off}$are the on and off histories of the PU channel. FPBOSA assumes that CR keeps the history of PUs channel usage.The history can be recorded by observing PUs channel usage. The algorithm consists of a method to predict or update CSI and a part to select best channel.

- Predicting or Updating (Line 1- Line 15)

Predicting residual slots helps to avoidprediction at each slot. Instead FPBOSA either updates or predicts CSI at every slot. How the proposed algorithm differentiates between prediction and update is crucial.The activity change of

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PUs channel (i.e. change of state) is used to differentiate between slots that need prediction and those that do not. Whenever there is change of state, CR predicts the number of slot of the new state. Change of PU activity happens when$CSI_{Channel}(2) = 0$. If $CSI_{Channel}(2) = 0$ then on the next slot this channel will change a state (Line 2). Therefore, for all PU channels in which$CSI_{Channel}(2) = 0$there is need for prediction. Consequently, the algorithm calls Proposed Fuzzy Predictor (Line 5 and Line 9). The next state will be busyif the previous state is idle (Line 4) and vice versa (Line 8).

For other slot lengths$CSI_{Channel}(2) > 0$, the algorithm should update$CSI_{Channel}(2)$by subtracting the expired number of slots (Line 13). The expired slot depends on when FPBOSA is invoked. If the algorithm, for instance, runs at every end of a slot then the expired slot equals one. Alternatively, a counter can be set to count the expired slots. The main advantage of updating is it helps to reduce prediction overhead (helps to avoid calling PFP at each slot).

- Best channel selection

On the CR perspective the best channel is the one which remains in idle state for longer period. So, after channel state of each channel$CSI_i(2)(i = 1,2, \ldots, N)$ are predicted or updated, CR searchesfor all idle predicted PU channels. Available idle channels are arranged according to the number of idle slots (Line 21). Then, channel available vector is updated to the best channel (Line 23 and Line 24). The best channel is one which remains idle for most slots. The next step is to go to the proposed sensing strategy.

B. *Proposed Fuzzy Predictor (PFP)*

Conventional time series is defined as a sequential set of data measured over time [26]. Fuzzy time series (FTS), first proposed by Q.Song and B.S.Chissom, extends conventional time series to that of fuzzy Sets. FTS is defined as [27]:

Definition (FTS) : Let $Y(t)(t = \cdots,0,1,2, \ldots)$, a subset of R, be the universe of which fuzzy sets$\mu_i(t)(i = 1,2, \ldots)$are defined and let $F(t)$ be a collection of $\mu_i(t)(i = 1,2, \ldots)$. Then, $F(t)$ is called a fuzzy time series on $(t)(t = \cdots,0,1,2, \ldots)$.

It can be noted from above definition that the main difference between conventional time series and FTS is that the observations in conventional time series are real valued numbers, while in FTS observations are linguistic variables. The purpose of FTS is to predict the future values by understanding past values. Basic FTS prediction algorithm contains four steps, initially suggested by Q.Song and B.S.Chissom [28-30]. Like basic FTS predictor, the Proposed FTS Prediction method contains four steps and an output validator.

Step 1: Universe of discourse definition and interval partition

The first step is to define universe of discourse U. U is defined as:

$$U = [(D_{min} - \sigma), (D_{max} + \sigma)] \qquad \text{eq. (1)}$$

where, D_{min}, $D_{max}$and σ are the minimum, maximum and standard deviation of training data respectively. Then training data is partitioned into k interval in order to define linguistic variables (LVs). So far, Fuzzy c-means clustering algorithm (FCM) is the best method to partition training data. Because FCM takes uncertainty into account by giving degree of membership of each data to each cluster i.e. data can belong to more than one cluster. Hence, FCM algorithm is used for partitioning U.

Step 2: Defining fuzzy sets and fuzzifying time series

The outputs of FCM in step 1 are cluster centers. Depending on the number of cluster centers k Linguistic Variables (LVs) are defined. LVs are characterized by Membership Functions (MFs). The two most widely used MFs are Modified Triangular MF and Trapezoidal MFs. A method to find the optimum MF between Modified Triangular MF and Trapezoidal MF is applied. However, it is not discussed in this paper.

Step 3 and 4: Prediction Model

The prediction is done by using Takagi–Sugeno (TS) fuzzy rules. TS first order rules are of the form:

$$if\ x_1 is\ \mu_1\ and \ldots\ x_n is\ \mu_l then\ y = p_0 + p_1 * x_1 + \cdots + p_n * x_n \qquad \text{eq. (2)}$$

where, x_i, $i = 1,2, \ldots, n$are input variables, $\mu_1$is the degree of membership of x to fuzzy set A_1andp_j, $j = 0,1, \ldots, n$ are consequent parameters. The consequent parameters are obtained using the least square learning algorithm

Step 5: Output validation

On some occasions PFP may produce an invalid output. Invalid output occurs when the output of the predictor is outside the universe of discourse U. In such cases, the output should be corrected to a reasonable value. When the output is invalid, PFP replaces the result with training data which have similar characteristics to inputs that produce invalid output. To find the best much between the inputs which produce invalid output and training data, Euclidean

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distance is used. For example, let the predictor produce invalid output for the input x_1, x_2, x_3 *and* x_4. For N number of training data, output validator searches the minimum of Euclidean distances given by:

$$(x_1 - x_i^t)^2 + (x_2 - x_{i+1}^t)^2 + (x_3 - x_{i+2}^t)^2 + (x_4 - x_{i+3}^t)^2, i = 1,2, \dots, (N-3) \quad \text{eq. (3)}$$

where, x_i^t is the i^{th} training data. The invalid output is replaced by the output of the predictor with input $x_i^t, x_{i+1}^t, x_{i+2}^t, x_{i+3}^t$, where i is index of training data that has minimum distance.

Summary of PFP for M order is shown in Fig. 2. The knowledge base contains TS fuzzy rules and a database. The database contains universe of discourse U defined in Step 1, MF definition in Step 2 and time series historical data. The Fuzzifier, Fuzzy inference engine and Deffuzzifier perform prediction mechanism in step 3 and step 4. TS fuzzy model is used as inference engine. Deffuzzification is performed by using centroid of area. Finally, output validator checks the validity of the output. In cases of invalid output, Euclidean distance is used to replace the invalid output with more reasonable value.

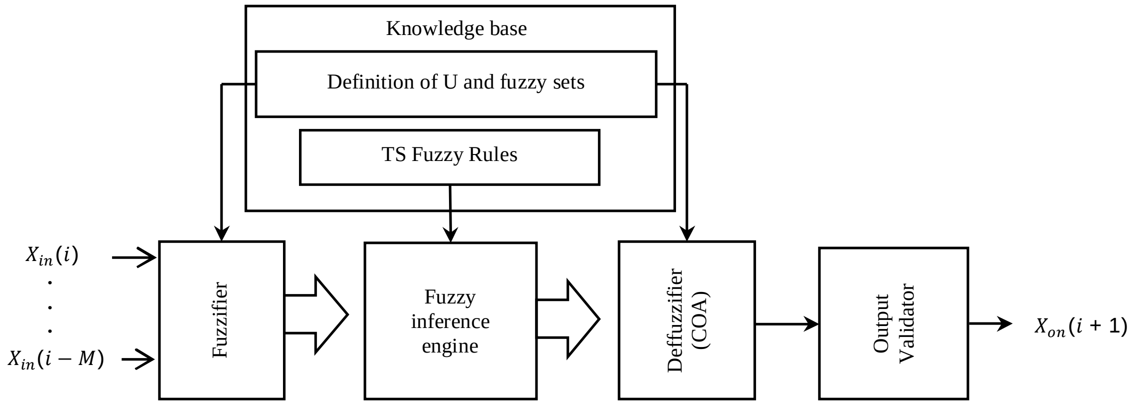

Fig. 2: Proposed Fuzzy Predictor

C. *Proposed Sensing Strategy*

LBT time slot is divided into two phases: the sensing phase with T_s time duration and transmission phase with T_d time duration. The length of sensing phase T_s is directly related to sensing methods adopted because it affects the accuracy of sensing. In this paper, a perfect sensing method is assumed. So, issues related to sensing method are not answered. The sensing strategydefines the structure of LBT slot and defines the time when CR senses.

On CR perspective, longer transmission phase duration T_d is desired, since it gives CR an opportunity to transmit more time. But, longer transmission time T_d results in more interference time to PU. Higher interference time is intolerable by PUs. Interference time to PUs is reduced by having shorter transmission phase duration T_d. But, the shorter the transmission phase duration T_d, the higher is the frequency of sensing which results in higher number of quite periods. During quite periods, CR does not transmit data. Hence, the higher the frequency of quite periods the shorter time available for CR transmission. The challenge here is how CR can have higher time for transmission as the same time keep short interference time to PU.

The proposed way to increase transmission time is to avoid unnecessary quite periods. Unnecessary quite periods are those periods in which the sensing result is the same as prediction result. Note that if the prediction algorithm is perfect i.e. 100 % error free then, there is no need for sensing. This is possible because the sensing result will agree with predicted result. For unnecessary quite periods CR is 100% sure that the sensing result is equal to the predicted result. In this paper, slots with unnecessary quite periods are called sure slots to emphasize that the predictor is 100% sure of the result.

The main challenge for avoiding unnecessary quite period is how to be sure of the prediction result in the presence of error. Here, error of the PFP is assumed not to exceed Maximum Absolute Error (MAE) encountered during training phase. This MAE can be used to determine sure slots. In other words, one can assume the PFP as a measuring device with accuracy equals to the maximum absolute error. So, at the worst case, any prediction may differ from actual value by MAE. With this assumption, any slot with CSI satisfying the following condition is considered as sure slot.

$$(C + |E_{max}|) \le CSI_{CAV(1)}(2) \le (CAV(2) - (C + |E_{max}|), \; 1 \le C < (\tfrac{CAV(2)}{2} - |E_{max}|) \text{eqn. (4)}$$

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where, E_{max} is the MAE of the PFP, $CAV(2)$ is the predicted length of idle slots. $CSI_{CAV(1)}$ is the current or updated status of the best channel. The selected channel is used for CR data transmission. The difference between $CSI_{CAV(1)}(2)$ and $CAV(2)$is that the former is the predicted length of a particular cycle while the latter is the current or updated status of channel. C is a positive safety constant introduced for safety. This constant is included because error is undeterministic.

Equation 4's use lies on scheduling of sensing which helps to avoid miss detection and wrong detection. CR main intention is to avoid wrong detection because PU are interference intolerant. Therefore, idle slots subjected to eqn (4) are sensed. The pseudo code of proposed sensing strategy is:

Step 1: schedule sensing only if the current slot does satesfy(eqn. 4)

1. **If**$(C + |E_{max}|) \leq CSI_{CAV(1)}(2) \leq (CAV(2) - (C + |E_{max}|)$
2. **Schedule** sensing action on the next slot

Step 2: skip sensing if the current slot lies on the sure slot

3. **Else if** $(C + |E_{max}|) < CSI(2) < (CSI_{predicted}(2) - (C + |E_{max}|)$
4. **No** scheduling
5. **End if**

where, C is the safety constant and $E_{max}$is the MAE of the PFP.The main aim of the proposed sensing strategy is to keep short LBT slot structure and avoids unnecessary quite periodsto increase the transmission time of CR. unnecessary quite periods are determined by eqn (4). Avoiding unnecessary quite periods reducesthe energy required for sensing.

IV. SIMULATION RESULTS

A. *PFP Accuracy Test*

PFP is a universal predictor that can be applied for any time series prediction problems. Therefore, the accuracy of PFP is tested using Mackey-Glass time series data. The MG time series is chaotic time series which makes it universally acceptable representation of nonlinear oscillations of many physiological processes [31]. It is widely used for testing the performance of prediction models [32], [33], [34]. The MG time series is the solution of the differential equation:

$$\frac{dx(t)}{dt} = \frac{\alpha x(t-\tau)}{1+x^{10}(t-\tau)} - \beta x(t) \qquad \text{eqn. (5)}$$

To obtain time series value at integer points, fourth-order Rung-Kutta method is used with time step size of 0.1. The initial conditions are set to:

$$\tau = 17\,, \alpha = 0.2 \; and \; \beta = 0.1$$

Input-output is constructed using embedded theorem. The retardation of the time for chaotic time series is described as [35]:

$$X(t) = [x(t-(E_m-1)t_d), \dots, x(t-t_d), x(t)] \qquad \text{eqn. (6)}$$

where, $X(t)$ is the embedded vector, $x(t)$ is the value of the sequence at time t, $t_d$denotes retardation of the time and $E_m$denotes the embedding dimension. The embedded vector $X(t)$ is used to predict sequence value at $x(t+v)$, where v is the prediction step.Simulation parameters are$v = 1,\; t_d = 1 \; and \; E_m = 4$. The embedded vector will be:

$$X(t) = [x(t-(E_m-1)t_d), \dots, x(t-t_d), x(t)]$$

A total of 1000 data are selected for simulation from $x(124) \; to \; x(1123)$. The first 500 data are selected for training and remaining half for testing. Input output data has the form:

$$x(t-3), x(t-2), x(t-1), x(t), x(t+1) \; where \; t = 124 - 1123$$

PFP involves initialization of random numbers. Different result is obtained for different runs. To account such effects i.e. initialization of parameters, the performance of PFTSP is evaluated using performance testing algorithm discussed in [36]:

First the proposed algorithm is trained and then tested multiple times. For every training run i of training algorithm, Mean Error $E(i)$ and Standard Deviation $Std(i)$ are obtained for N test data as follows [36]:

$$E(i) = \frac{1}{N}\sum_{j=1}^{N}(Y_p^i(j) - Y(j)) \qquad \text{eqn. (7)}$$

$$Std(i) = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(Y_p^i(j) - Y(j))^2} \qquad \text{eqn. (8)}$$

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where, $Y^i(j)$is the j^{th}output obtained by the i^{th}run and $Y(j)$ is thej^{th}actual output. The performance evaluation algorithm is [36]:

1. **For** i=1 to M
2. **Train** the system using training data set
3. **Test** system using test data set
4. **Calculate** the mean prediction error E(i) using eqn. (7)
5. **Calculate** the standard deviation std(i) using eqn. (8)
6. **Next** i

Based on the above algorithm, the following performance metrics are defined [35]:

- The Timeliness

The Timeliness is given by global mean of all the M values of$E(i)$:

$$Timeliness = \bar{E} = \frac{1}{M}\sum_{i=1}^{M} E(i) \qquad \text{eqn. (9)}$$

where, M is the number of runs, and $E(i)$ is Mean Error at run i. The perfect predictor score is $Timeliness = 0$. For small value of Timeliness the probability to have a prediction close to real value is significant. On the contrary, if the Timeliness value is high, the probability to have a wrong prediction is very high.

- The Precision

The Precision is given by the global mean of all the M values of $Std(i)$:

$$Precision = \overline{Std} = \frac{1}{M}\sum_{i=1}^{M} Std(i) \qquad \text{eqn. (10)}$$

where, $Std(i)$ is standard deviation of each running test i. The perfect score, $Precision = 0$. For a small value of the Precision, the probability to have predictions grouped together is significant. On the contrary, if the Precision value is high, the predictions are dispersed.

- The Repeatability

The Repeatability in terms of $E(i)$and $Std(i)$is given as:

$$Repeatability = \frac{\sigma(Std)+\sigma(E)}{2} \qquad \text{eqn. (11)}$$

where, $\sigma(Std)$ and $\sigma(E)$ represents the standard deviation of the M values of $E(i)$ and $Std(i)$ values respectively.

$$\sigma(std) = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(\overline{std} - std(i)\right)^2} \qquad \text{eqn. (12)}$$

$$\sigma(E) = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(\bar{E} - E(i))^2} \qquad \text{eqn. (13)}$$

The perfect score is $Repeatability = 0$. This parameter shows how close the different values of $E(i)$ and $std(i)$ are grouped or clustered together. Repeatability reveals dispersion of $E(i)$ and $std(i)$ values. For small values of $\sigma(std)$ and $\sigma(E)$, it means that at each running time i, the model gives same performance on test set. Repeatability parameter reveals random initialization influence of some learning parameters. The training process is completely repeatable for small values of Repeatability.

- The Accuracy

The Accuracy is obtained from the above three parameters and it gives a global appreciation of the predictor. Accuracy is given as:

$$Accuracy = \frac{1}{Repeatability+Timeliness+Precision} \qquad \text{eqn. (14)}$$

If a model has a good $Timeliness$, $Precision$ and is completely Repeatable, then the prediction given by that model is very close to real data. The prediction confidence is very high. A big value of the Accuracy parameter gives a great confidence of prediction. PFP is tested by the above algorithm. 30 test runs are performed for evaluation. Fig. 3 shows the difference between real MG time Series data and the predicted time series data. The table next to Fig. 3contains the Timeliness, Precision, Repeatability and Accuracy of PFP along with the score of a perfect predictor. The score of PFP shows that it has high Timeliness, Precision, and Repeatability.

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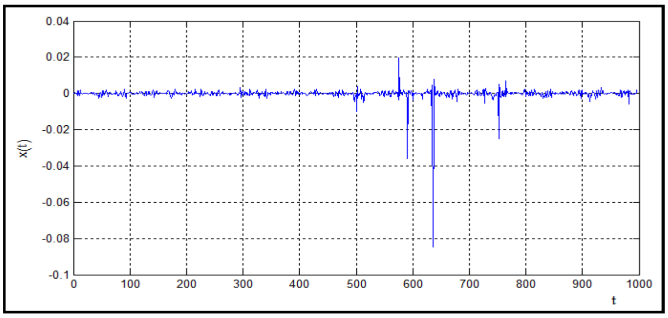

Fig. 3: Prediction error of PFP for MG time series data

Table 1: Performance of the Proposed Fuzzy Predictor

Metrics	PFP	Perfect predictor
Timeliness	3.1892×10^{-4}	0
Precision	2.1753×10^{-5}	0
Repeatability	1.2051×10^{-6}	0
Accuracy	2925.0472	∞

B. *FPBOSA Performance Test*

In wireless environment, two classes of PUS traffic patterns are distinguished [8]. The first case is deterministic patterns where PUs (e.g. radar transmitter) is assigned a fixed time slot for transmission. The second type of traffic pattern is the stochastic pattern. In stochastic pattern the traffic data can only be described in statistical terms. The model parameters of stochastic traffic data vary slowly and, therefore, lend themselves to on line estimation using historical data. For simulation, stochastic traffic pattern is considered.

[37] and [38] conduct spectrum measurements on Paging band $(928 - 948\ MHz)$ located at global Positioning System (GPS) latitude$42°16'94''\ N$and longitude $71°48'29''\ W$. For a PU channel having bandwidth of $20\ KHz$. [42] and [43] conclude that the off duration of PU in the paging band follows an exponential distribution with mean λ_{off}:

$$f(t_{off}; \lambda_{off}) = \begin{cases} \lambda_{off} e^{-\lambda_{off} t_{off}}, & t_{off} \geq 0 \\ 0 & t_{off} < 0 \end{cases} \qquad \text{eqn. (15)}$$

Similarly, the on duration of PU follows exponential distribution with mean λ_{on}:

$$f(t_{on}; \lambda_{off}) = \begin{cases} \lambda_{on} e^{-\lambda_{on} t_{on}}, & t_{on} \geq 0 \\ 0 & t_{on} < 0 \end{cases} \qquad \text{eqn. (16)}$$

The other important observation is that PUs traffic pattern shows periodicity of one day [12]. Hence, CR can learn previous day PU traffic characteristics to predict the current day.Consider a CR that uses four PU channels opportunistically located on the above location(global Positioning System (GPS) latitude$42°16'94''$ Nand longitude$71°48'29''$ W).This means that the on and off duration of PUs traffic follows exponential distribution given in eqn. 15 and eqn. (16). CR, in fact, can use more than 4 channels but for the purpose of detail analysis 4 PU channels are selected.

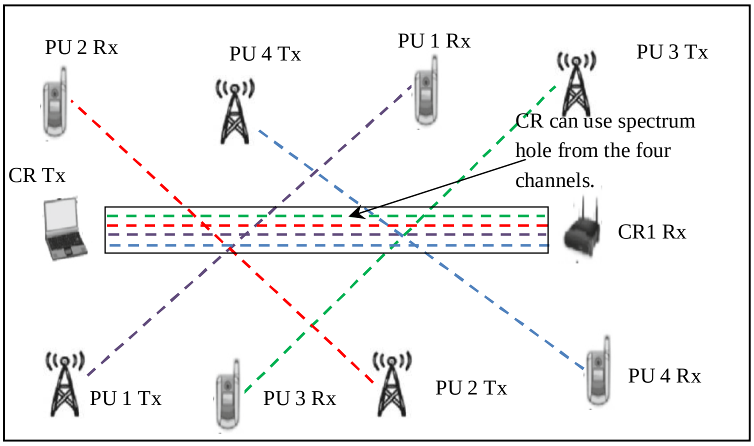

Fig. 4: Simulation scenario

Table 2: PU channel statistics

Metrics	λ_{on}	λ_{off}	λ_{off}	ρ
PU 1	21	9	0.7	
PU 2	12	8	0.6	
PU 3	15	15	0.5	
PU 4	12	18	0.4	

where, λ_{on} is mean on time of PU channel; λ_{off} is mean off time of PU channel and ρ is the traffic intensity given by $\frac{\lambda_{on}}{\lambda_{on}+\lambda_{off}}$.

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Fig. 4 shows the whole simulation scenario.Table 2 contains on and off values for these 4 PU channels. CR has the knowledge of history of the four PU traffic. A total of 7200 slots are considered for the simulation. The FPBOSA performance is tested using the probabilities of miss detection, wrong detection and throughput.

- Probability of miss detection and wrong detection

Probability of miss detection measures probability of missing available spectrum hole, while probability of wrong detection measures probability of causing interference to PUs. Table 3 on the next page shows simulation result of probability of miss detection and wrong detection, if the CR uses each channel for transmission.The probability of miss detection for all channels is below 0.12, the result implies that CR discovers at least 88% of the available spectrum hole. The probability of wrong detection is below 0.08 for all channels. This means that CR interferes with PU less than 8% of operating time.

Table 3: Probabilities of miss and wrong detection

Channel	Probability of miss detection	Probability of wrong detection
Channel 1	0.0422	0.0180
Channel 2	0.1125	0.0790
Channel 3	0.0563	0.0628
Channel 4	0.0357	0.0534

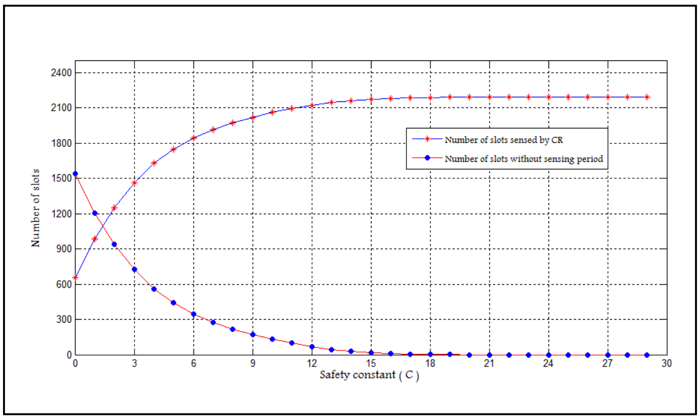

Fig.5: Number of slots with and without sensing phase for PUs channel 1 for different C values.

- Throughput

The number of packets received is dependent on the time available for transmission. If more time available, more data is transmitted. For this reason, Throughput can be defined in terms of available time for transmission as:

$$Throughput = \frac{Total\ idle\ time\ discovered\ for\ transmission}{Total\ actually\ available\ time\ for\ transmission} \quad \text{eqn. (17)}$$

When CR discovers all available time, then $Throughput$ is equals to one. However, CR cannot use all time for transmission because of quite periods. This results in values less than one. Throughput is maximized by avoiding unnecessary quite periods using Proposed Scheduling Algorithm. Equation (4) assumes CR has the knowledge of the maximum absolute error (E_{max}) of fuzzy predictor. (E_{max}) is determined from training data. C is the safety constant to be determined by the CR user. The choice of safety constant (C) affects the number of avoided quite periods, so is throughput. To illustrate the effect of safety constant on the number of avoided quite periods, consider the case where CR use only PU channel 1. Fig 5 simulates the effect of C on the quite periods. For safety constant greater than 15, almost all idle slots are sensed. This is because, for higher values of C the condition (eqn.4) is violated. For safety constants less than 2 the number of unsensed slots is greater than that of the number sensed slots. This means that more quite periods are avoided for smaller safety constant. C = 2 can be selected as typical value of safety constant where CR has appropriate safety and avoid quite periods. At this value, the number of sensed slots is equal to 985 out of 2191 idle slots. In general, higher safety constant reveals that CR doesn't trust the prediction so that more safety is needed. Consequently, the number of slots that need to be sensed increases, while that that of unsensed slots decreases.

The above simulation shows that, in order for CR to achieve high throughput, C, the safety constant, should be selected to lower values. This is true for all remaining channels though minor difference on Fig 5. From total N idle slots M slots are sensed. The remaining N-M idle slots are without sensing phase.So, the whole duration of the slot is used for transmission. The achievable throughput calculated using (17) is reduced to:

$$Throughput = \frac{M(T-t)+T(N-M)}{NT} \quad \text{eqn. 18}$$

Where, t is duration of sensing phase. Table 4 on next page contains simulation result of the number of sensed and sure slots for safety constant $C = 2$ along with calculated Throughput. Assuming a unit sensing energy is required to sense a

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slot. The number of energy needed for sensing by the CR is equal to the number of slots sensed. Hence, the required sensing energy for each channel is M.

Table 4: Throughput of the four channels

Channel	M	N	Throughput
Channel 1	1253	2191	$1-\frac{0.5719t}{T}$
Channel 2	1936	2968	$1-\frac{0.6523t}{T}$
Channel 3	1306	3838	$1-\frac{0.3403t}{T}$
Channel 4	1489	4319	$1-\frac{0.3448t}{T}$

Table 5: Reduction insensing energy

Channel	SE for $\mathbf{CR_{fuzzy\_predict}}$	SE for $\mathbf{SE_{CR_{sense}}}$	% SE reduction
Channel 1	1253	7200	82.5972
Channel 2	1936	7200	73.1111
Channel 3	1306	7200	81.8611
Channel 4	1489	7200	79.3194

C. *FPBOSA Performance Improvement*

- Throughput Improvement

Consider two devices $CR_{fuzzy\_predict}$, a device that uses FPBOSA and CR_{sense}, a device that relies on sensing to discover spectrum hole. The main purpose here is to examine the improvement gained by using FPBOSA. For the basic CR device all slots are sensed. Therefore, the number of quite period is equal to total available idle slots. Throughput, using eqn. 18, is equal to $1-\frac{t}{T}$for all channels, where, t is duration of sensing phase. Throughput for FPBOSA is given in Table 4. For all channels the Throughput of FPBOSA is greater than the basic CR device.

- Improvement in Spectrum Utilization (SU)

$CR_{fuzzy\_predict}$ discover spectrum hole by PFP, while CR_{sense} senses a random channel at each slot. Both $CR_{fuzzy\_predict}$ and CR_{sense} device involve random numbers. Consequently, at each simulation run, different results are obtained. To account for such variation, simulation is performed 30 times. Theaverage of this 30 runs is then used, to determine the improvement.

$$Average\ SU \ = \frac{1}{30}\sum_{run=1}^{30} SU\ (run) \qquad \text{eqn. (19)}$$

where, SU is given by:

$$SU = \frac{Number\ of\ idle\ slots\ descovered}{Actually\ avalable\ number\ of\ idle\ slots} \qquad \text{eqn. (20)}$$

Average SU for $CR_{fuzzy\_predict}$ = 95.6344 %

Average SU for CR_{sense} = 84.2704 %

Using the above average values, the improvement is calculated as:

$$SU_{imp}(\%) = \frac{SU_{CR_{fuzzy_{predict}}} - SU_{CR_{sense}}}{SU_{CR_{sense}}} * 100 = \frac{95.6344 - 84.2704}{84.2704} * 100 = 13.4852\%$$

One can see that by using FPBOSA, spectrum utilization is increased by 13.4852% .

- Improvement in Sensing Energy

CR_{sense} device senses each slot for detecting spectrum hole. Hence, the sensing energy for CRsense is given by:

$$SE_{CR_{sense}} = Total\ no\ of\ slots * Unit\ sensing\ energy \qquad \text{eqn. (21)}$$

Assuming, a unit sensing energy for a slot, then the total sensing energy is equal to the total number of simulation slots. $SE_{CR_{sense}} = 7200$. Since simulation is performed for a total of 7200 slots. For$CR_{fuzzy_predict}$ device the required sensing energy is shown in Table 4 (column labeled M). Reduction in sensing energy is calculated as:

$$SE_{red}(\%) = \frac{SE_{CR_{sense}} - SE_{CR_{fuzzy\_predict}}}{SE_{CR_{sense}}} * 100$$

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where, $SE_{CR_{sense}}$is sensing energy of basic CR device and $\mathrm{SE}_{\mathrm{CR}_{\mathrm{fuzzy_predict}}}$is sensing energy required by the proposed algorithm. The achieved sensing energy reduction is shown in Table 5.The minimum improvement is 73.1111 %. This large reduction in sensing energy is achieved by the proposed scheduling algorithm.

V. CONCLUSION AND FUTURE WORK

The main problems existed related to scheduling spectrum sensing are sensing overhead and structure of a slot. Predictions of PUs traffic reduce sensing overhead. This is possible by not sensing busy predicted PUs channel.A good predictor is characterized by high accuracy to reduce miss detection and wrong detection, provide extra additional information beside status of a slot and has lesscomputational complexity to reduce prediction overhead. FPBOSA is proposed to meet these criterions.

In FPBOSA, CR gain information about the best and back up channels and residual idle slots by using CSI and CAV. To reduce miss detection and wrong detection fuzzy predictor is proposed. The PFP is tested using MG Time series data which is abenchmark data to test performance of prediction algorithms. PFP is compared with perfect predictor using MG time series data. As Table 1 shows, PFP has accuracy of 2925.0472.

Back to the problem of slot structure: Scheduling algorithm, which decreases interference time of PUs at the same time increasing throughput of CRs, is proposed. The proposed scheduling algorithm uses MAE of PFP to avoid unnecessary quite periods.

The performance improvement against basic CR device is simulated. The result shows the FPBOSA improves throughput, Improves spectrum utilization by at least 13.485 % and reduces sensing energy by at least 73.1111 %.

FPBOSA and scheduling algorithm can be used to develop cognitive MAC layer. The development of cognitive MAC layer is an interesting future work. The output of FPBOSA i.e. CAV can be used to provide extra information for higher layer protocols. For instance it can be used by the MAC layer to adjust the data rate in advance. Examining and verifying such cases is left as future work.

Prediction on CR is not restricted to spectrum usage. Hence, the PFP can be used to predict transmission rate, data rate and other CR reconfigurable parameters.

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