Abstract: Smart grid is widely considered to be a next generation power grid, which will be integrated with information feedback communications. However, smart grid communication technologies are subject to inefficient spectrum allocation problems. Cognitive radio networks can solve the problem of spectrum scarcity by opening the under-utilized licensed bands to secondary users. In this paper, adaptive cognitive radio spectrum sensing and sharing algorithms are developed for smart grid environments. Simulation results are presented to demonstrate the effectiveness of the proposed scheme in comparison with other existing schemes.

Index Terms: Biform game, cognitive radio (CR) networks, cooperative spectrum sensing, egalitarian bargaining model, evolutionary game theory, smart grid.

I. INTRODUCTION

Smart grid has become a global concern as the next generation power grid. A crucial factor to realize smart grid features is timely access to meter data via reliable communication infrastructure. Therefore, two-way feedback communication plays an important role in smart grid; it directly affects the performance of the whole system. To accommodate the growth of the numbers and types of data, a significant challenge for the future smart grid is to ensure a large amount of bandwidth. Therefore, a key point in the success of smart grid technology is how to reduce the communication expenses as well as saving transmission bandwidth. Recently, many advanced wireless technologies are being investigated to be used for the communication layer of smart grid [1], [2].

Cognitive radio (CR) is a new technique for wireless communications to improve the utilization of radio spectrum [3], [4]. In the CR networks, unlicensed users (i.e., secondary users (SUs)) are allowed to sense and temporarily access the unused bands originally allocated to the licensed users (i.e., primary users (PUs)) when the PUs are inactive. For the accurate detection of idle spectrum bands, spectrum sensing is a crucial technology. Among spectrum sensing methods, cooperative sensing is an efficient and promising technique to obtain more trustable sensing results. This approach has been shown that sensing performance can be greatly improved [3], [4].

Nowadays, the main idea of game theory has emerged as an effective way of designing this CR management process. Game theory is a field of applied mathematics that provides an effective tool in modeling the interaction among independent decision makers. In 1996, Brandenburger and Stuart introduced the fundamental notion of the biform game to shape the competitive environment in a favorable way. It is a hybrid noncooperative-cooperative game model to formalize the two-stage decision problem [5], [6]. The first stage is the noncooperative component of a biform game. Each player chooses a strategy to maximize his expected payoff while regarding a subsequent effect of the chosen strategies on the second stage. The second stage is the cooperative component to model the resulting competitive environment. In this stage, players form a coalition to generate a surplus, which is shared fairly and optimally. Therefore, an actual payoff is realized after the second-stage game. Recently, it has been proven that the biform game model is efficient when it is applied to a business strategy [5], [6].

Motivated by the above discussion, we design a new biform game model for smart grid system. To support the fast growing demand, we present a biform game based CR communication algorithm, which is mainly motivated to use the unlicensed bandwidth while ensuring the need of explosive data traffic. At the first stage, SUs estimate the current network condition and adaptively form clusters for the cooperative spectrum sensing. Clusters are made up according to the non-cooperative game model. At the second stage, the detected idle spectrum is shared based on the cooperative bargaining model. The main feature of the proposed scheme is to maximize spectrum efficiency while ensuring the sharing fairness. Under dynamically changing network environments, SUs compete or coordinate with each other in order to maximize their payoffs. Therefore, the proposed biform game approach is suitable to get a globally desirable network performance.

Recently, several CR management schemes have been presented for the next generation communication system. The dynamic cooperative spectrum sensing (DCSS) scheme in [7] is an evolutionary game-theoretical scheme for distributed cooperative sensing over cognitive radio networks. By employing the theory of evolutionary game, the DCSS scheme modeled the interactions between selfish users in cooperative sensing and developed a distributed learning algorithm that can help the secondary users approach their optimal strategy with only their own payoff history. The group-based cooperative spectrum sensing (GCSS) scheme in [8] is a cooperative spectrum sensing algorithm for multiband, where a number of clusters are formed to sense a small portion of the multiband. The SUs belonging to the same cluster cooperatively sense the presence of PU in the narrowband. Based on the sensing results of SUs in a channel, the GCSS scheme assigned some of SUs to the channel which they can sense confidently. Compared to these schemes [7], [8], the proposed scheme attains better performance for CR network.
systems.

This paper is organized as follows. Section II presents the proposed algorithms in detail. In Section III, performance evaluation results are presented along with comparisons with the DCSS and GCSS schemes proposed in [7] and [8]. Through simulation, we show the ability of proposed scheme to achieve high accuracy and promptness in dynamic network environments. Finally, concluding remarks are given in Section IV.

II. PROPOSED SPECTRUM MANAGEMENT ALGORITHM

In this section, the proposed spectrum management algorithms are explained in detail. To reach a desirable system performance, the CR spectrum is sensed and shared based on the biform game model. This approach can be concluded to be an effective solution for the adaptive CR spectrum management in smart grid communications.

A. Non-Cooperative Game based Spectrum Sensing Algorithm

The main concept of smart grid is the employment of intelligent two-way communication networks. Therefore, a key determining factor is timely access to meter data via an effective communication infrastructure. However, in harsh smart grid environments, communication infrastructure can provide limited bandwidth, which causes the spectrum scarcity problem. Nowadays, CR is recognized as a promising technology for bandwidth scarcity. To share the CR network spectrum, the first task is to correctly sense the PUs’ activities. Therefore, the accuracy of sensing reports from SUs is critical to the CR network performance. However, the required sensitivity is very demanding since any individual SU may face fading and shadowing effects.

To overcome these problems, cooperative spectrum sensing approach has been studied as a promising solution to improve the probabilities of detection and reduce the false alarm [7], [8]. In this approach, all SUs should be separated into a few clusters and some SUs, which are clustering together, cooperatively sense a small portion of the multiband. Each SU in each cluster performs local spectrum sensing independently and this sensing information is sent to the cognitive base station (CBS), which makes a final decision to control the usage of the CR spectrum.

In this paper, we design a new cooperative spectrum sensing algorithm to provide reliable and effective service. We follow the system model [8] where there are \( M \) SUs and \( K \) PUs; the multiband spectrum consists of \( K \) non-overlapping narrowband channels and each of them is used by each PU [8]. The multiband \( (\mathcal{F}) \) composed of narrowbands \( \{f^a : a \in \{1, 2, \ldots, K\}\} \) is given by

\[
\mathcal{F} = \bigcup_{a=1}^{K} f^a
\]

where \( K \) is the number of PUs. Traditionally, multiband spectrum is divided into many narrowbands, which may carry data, independently. There should be no overlap among narrowband channels. Multiple cognitive SUs form a cluster to jointly access a narrowband and SU clusters do not interfere with each other. Each SU in a cluster can use only one narrowband at a time and each narrowband channel cannot be multiplexed by different SU clusters. In the proposed algorithm, there can be \( K \) different SU clusters to the utmost. The set \( (\mathcal{C}) \) of clusters are defined as follows [8]

\[
\mathcal{C} = \bigcup_{a=1}^{K} C^a \text{ where } C^p \cap C^q = \emptyset \text{ and } ||\mathcal{C}|| \leq K.
\]

The SU in \( C^a \) cluster cooperatively sense the particular \( a \)th narrowband (i.e., the \( a \)th PU band). Based on the sensing data from multiple SUs in each cluster, the decision about the spectrum idleness is made collaboratively. The sensed idle spectrum band is temporarily allocated to a specific SU in its cluster. Therefore, cooperative spectrum sensing becomes effective when SU clusters are formed adaptively. In the proposed sensing algorithm, the fundamental concept of evolutionary game is adopted to form clusters.

Evolutionary game is a well-known non-cooperative game model and has been developed in biological sciences in order to explain the evolution of genetically determined social behavior. The payoffs in evolutionary game model depend on the actions of the co-players; strategies with high payoff will spread within the entire populations of players [9]. We practically apply the evolutionary game model to the clustering problem without much deviation from its original form. Each SU, as a non-cooperative game player, can constantly adapt the strategy (i.e., cluster selection) based on the evolutionary learning mechanism.

The player’s payoff is defined as the amount of actually transmitted bits by using CR technique. Therefore, the utility function for player \( i \) \( (U_i, s.t., i \in \mathcal{C}^a) \) with strategy \( s \) \( (s \in \{1, 2, \ldots, K\}) \) is given in [10] and [11] as follows

\[
U_i(s) = \frac{W}{p_i} \log_2 \left( 1 + \frac{\gamma_i(\mathcal{F})}{\Omega} \right) \Psi_s,
\]

where \( \Psi_s = 1 \), if \( k \)th PU band is allocated to the player \( i \)

\[
\Psi_s = 0, \text{ otherwise}
\]

and

\[
\gamma_i(\mathcal{F}) = \frac{p_i h_{ii}}{\sigma_i + \sum_{j \neq i} p_j h_{jj}}
\]

where \( W \) is the PU channel bandwidth and \( \gamma_i(\mathcal{F}) \) is the SINR of player \( i \), respectively [10], [11], \( p_i \) is the power level of player \( i \) to sense the \( k \)th PU band. The goal of each player is to maximize his own payoff by selecting a specific strategy where \( \max_s: U_i(s) \rightarrow \mathcal{A}, s \in \mathcal{A} = \{1, 2, \ldots, K\} \) and \( \mathcal{A} \) is the set of PUs [12].

During the evolutionary game, players learn how to select their strategies like as a tournament play where losing strategies are eliminated and winning strategies remain. Therefore, players have a chance to reconsider the current strategy and react to maximize the expected payoff. In the jargon of evolutionary game theory, the equilibrium strategies of players are called evolutionary stable strategies (ESS) and the changing rate of the players’ selection is defined as replicator dynamics (RD) [11], [13]. When a player chooses a strategy, it can change the current network environment and triggers reactions by other players. After making further changes among players, this interaction mechanism gradually leads the network system into a stable
state. The RD describes the evolution in the proportion of each strategy to reach an equilibrium; a specific strategy evolves at a rate equal to the difference between the payoff of that strategy and the average payoff of the whole population [11], [13].

Each player has the same strategy space, denoted by \( \mathcal{A} = \{1, 2, \cdots, K\} \). If the payoff of strategy \( s (s \in \mathcal{A}) \) is small compared to other strategies, the selection probability for strategy \( s \) decreases in proportion to the expected payoff reduction. Therefore, the desirable strategy that will improve player’s payoff is more likely to be selected. To maximize their expected payoffs, players iteratively change their current strategies and repeatedly interact with other players. In this paper, we try to derive the ESS from the RD, especially by exploring different actions, adaptively learning during the strategic interactions, and approaching the best response strategy under changing conditions. Using the RD, players can try different strategies and learn a better strategy through strategic interactions. Since a rational player should choose a strategy more often if that strategy brings a relatively higher payoff, a new strategy updating process can be developed with the RD [11], [13].

To represent the RD for the cluster formation problem, let \( x_s (s \in \mathcal{A}) \) be the probability to select the \( s \) strategy; strategy \( s \) means to join the \( s \)th cluster and sense the \( s \)th narrowband. \( \mathcal{X} \) is the \( K \)-dimensional vector \( (x_1, \cdots, x_K) \) and \( \dot{x}_s \) stands for the variation of \( x_s \), which is the RD for strategy \( s \). \( J (s, k) \) is denoted by the expected payoff for a player using strategy \( s \) when it encounters a player with strategy \( k \) and \( J (s, \mathcal{X}) \) is the payoff for a player using strategy \( s \) when it encounters the rest of other players whose strategies are distributed in \( \mathcal{X} \), which can be expressed like as \( \sum_{j \in \mathcal{A}} (J (s, j) x_j) \) [11], [13]. Finally, the RD is defined as

\[
\dot{x}_s = x_s \left( J (s, \mathcal{X}) - \sum_j x_j J (j, \mathcal{X}) \right)
\]

\[
= x_s \left( \sum_j x_j J (s, j) - \sum_j \sum_k x_j J (j, k) x_k \right)
\]

(4)

where \( \dot{x}_s \) is the current estimated RD value for the strategy \( s \). By using (4), each player maintains two variables, \( J (s, \mathcal{X}) \) and \( \dot{x}_s \), which are the basis for the next strategy decision. Under all possible network scenarios, players learn how to perform well by interacting with other players and dynamically select the best PU band. Therefore, without any impractical rationality assumptions, players can modify their strategies in an effort to maximize their own goals.

B. Cooperative Game based Spectrum Allocation Algorithm

With the spectrum sensing technique, spectrum allocation is also important part for the CR network management. Traditionally, bargaining solution, which is a famous cooperative game theoretic concept, is an effective tool to solve resource allocation problems; it is a map that assigns a fair and optimal solution to a given cooperative game. In 1977, Kalai and Myerson developed the egalitarian bargaining solution (EBS). Among various bargaining solutions, the main feature of the EBS is a monotonicity with respect to expansions of the feasible set without using Nash’s axiom of independence of scale of utility. Therefore, unlike other bargaining solutions, the egalitarian solution enjoys even stronger monotonicity requirements while satisfying independence conditions [14], [15]. To ensure fairness among multiple SUs, we adopt the EBS to develop the spectrum allocation algorithm.

In the proposed model, \( K \) PUs and \( M \) SUs are involved in a spectrum sharing process. Therefore, \( A^{\{1\cdots K\}, 1\cdots M} \) can represent the cluster formation of SUs; it is a Boolean table of \( K \) lines and \( M \) columns [14], [15].

\[
A^{\{1\cdots K\}, 1\cdots M} = \begin{pmatrix}
A_{1,1} & A_{1,2} & \cdots & A_{1,M} \\
\vdots & \vdots & \ddots & \vdots \\
A_{K,1} & A_{K,2} & \cdots & A_{K,M}
\end{pmatrix}
\]

(5)

\( A^{\{1\cdots K\}, 1\cdots M} \) contains at most one element, which has 1, per column. If \( A_{k,i} = 1 \), it can say that the \( i \)th SU \( (1 \leq i \leq M) \) is an element belonging to the \( k \)th cluster \( (1 \leq k \leq K) \) to sense the \( k \)th spectrum band. The EBS attempts to grant equal gain to players. In other words, it is the point which maximizes the minimum payoff among SUs in each cluster. Formally, in the cluster \( k \), the allocation resulting from EBS (\( E_{A_k} (A^*) \)) is defined as follows [14], [15]

\[
E_{A_k} (A^*) = \max_{1 \leq i \leq M} \min_{i \in C^k} \left\{ \int_{t_c}^{t_{i,s}} I_B (k) dt \right\} \]

\[
\left( t_{c} - t_{i,s} \right)
\]

(6)

where \( I_B (k) \) is the \( k \)th cluster idle band, which is allocated for the player \( i \). \( t_{i,s} \) is the start-time when the player \( i \) joins to the \( k \)th cluster. \( t_c \) is the current times of system operations. Therefore, the time period \( t_c - t_{i,s} \) is the sensing duration of \( k \)th band from the player \( i \). In each cluster, this allocation mechanism is executed in a distributed manner. Based on the social choice theories and welfare economics, EBS based spectrum allocation mechanism can be defined metaphorically as the welfare of the “unhappiest” or least “well-off” user in the system [14], [15].

C. The Main Steps of Proposed Scheme

In the proposed CR management scheme, both non-cooperative and cooperative game models have been applied to spectrum sensing and allocation algorithms. This biform game approach is an effective way to control the CR spectrum. At first stage, SUs are clustered to jointly sense the same PU’s presence. Each SU will act selfishly by pursuing as high an individual payoff as possible. Therefore, non-cooperative game approach is suitable for the cluster formation problem. The developed clustering procedure is designed based on the evolutionary game theory. This model offers a more realistic model for players with bounded rationality. During the evolutionary game, players have a chance to reconsider the current strategy and react to maximize the expected payoff. To implement our distributed learning algorithm, there is a little communications overhead. However, it is a controllable overhead for practical implementations. At second stage, the key issue is how to allocate the idle frequency band among SUs in each cluster. Cooperative bargaining solutions strive to understand the interplay between an efficient and a fair allocation. The problem of spectrum allocation in each cluster can be mapped into a bargaining game. In this work, spectrum allocation mechanism is developed according to the Egalitarian bargaining solution. This approach fairly
distributes the idle spectrum to each SU. The main steps of the proposed spectrum sensing and allocation algorithms are given next.

**Step 1:** At the initial iteration \((n = 0)\), the selection probability for each strategy is equally distributed. \((x_i(n) = 1/|\mathcal{A}|, \forall i\) where \(|\mathcal{A}|\) is the number of strategies, i.e., \(\mathcal{A} = \{1, 2, \ldots, K\}\). This starting guess guarantees that each player enjoys the same benefit at the beginning of the game.

**Step 2:** Each SU player selects a PS band \((f^i \in \mathcal{F}\) and \(i \in \mathcal{A}\)) according to the current selection probability.

**Step 3:** In each cluster, the sensed idle band is allocated according to (6). This allocation mechanism is executed in a distributed manner.

**Step 4:** Based on the individual self-interest, players re-estimate each strategy’s selection probability according to the RD. For each player, the \(n\)th RD of the strategy \(s\) is obtained as

\[
x_s(n+1) = x_s(n) \left( \sum_j x_j(n)J(s,j) - \sum_j \sum_k x_j(n)J(j,k)x_k(n) \right)
\]

(7)

**Step 5:** When the change of RD is within a pre-defined minimum bound \((\epsilon)\), this change can be negligible. Otherwise, proceeds to step 2 for the next iteration. This iterative feedback procedure continues until network system reaches to an efficient equilibrium state.

**Step 6:** If all players do not change their current strategy, they remain the same cluster. All SUs have converged to the ESS.

**Step 7:** Constantly, the system is self-monitoring the current network situation. When the change of RD is larger than \((\epsilon)\), it can re-trigger the cluster formation procedure; proceeds to step 2 for the next iteration.

### III. PERFORMANCE EVALUATION

In this section, the effectiveness of the proposed scheme is validated through simulation. The assumptions implemented in simulation model are as follows.

- System performance measures are plotted as a function of time period, and the performance measures obtained on the basis of 50 simulation runs.
- There are 10 PUs (i.e., \(K = 10\)) and 50 SUs (i.e., \(M = 50\)).
- A narrow sub-band size in the multiband spectrum is 128 kbps.
- The pre-defined minimum bound \((\epsilon)\) is defined as 0.1.
- Performance criteria obtained through simulation are spectrum efficiency, SU’s payoff, fairness and network throughput, etc.
- Spectrum efficiency is defined as the percentage of spectrum that is being consumed by network service.
- SU’s payoff is the normalized value for total accrued data transferred by using CR technique.
- Network throughput is also a normalized value, which is measured as the ratio of the successfully serviced data amount to the total generated data amount.

- Fairness is defined as an equitable transmission rate for different individual SUs in a cluster.

In order to effectively control the spectrum sharing problem in cognitive radio networks, a number of schemes have been developed. In this section, we compare the performance of the proposed scheme with two recently published schemes: the DCSS scheme [7] and GCSS scheme [8]. Fig. 1 shows the normalized SU payoff for all the schemes. From the SUs’ point of view, the total accrued data transferred by using CR technique is a very important factor. Usually, SU payoff is assumed as a major QoS satisfaction factor. The curves in Fig. 1 present that the normalized SU payoff of proposed scheme is better than the other schemes. In Fig. 2, the comparison of the network throughput is presented. In cognitive radio system, SUs are allowed to temporally occupy the idle spectrum which PUs do not use. When PUs come back to use, SUs try to find other idle spectrum. If SUs cannot find out an idle spectrum hole, these ongoing call connections are forcibly terminated. Once a call is completed, the total transmission rate of that call is considered to be gained by network throughput. However, no gain is accrued for terminated calls in the middle of call connections. As simulation time goes on, the number of terminated calls increases. Therefore,
question. Due to this reason, we adopt the CR technique to develop a new smart grid communication algorithm. In this paper, adaptive CR spectrum sensing and sharing algorithms are developed for smart grid communications. To implement the cognitive radio technique, we design the biform game model to effectively control the scarce bandwidth resource. Due to the self-regarding game model feature, the proposed scheme effectively adapts to current communication conditions and approximates an optimal network performance under dynamically changing smart grid environments.

IV. SUMMARY AND CONCLUSIONS

As an effective solution for bandwidth scarcity, CR network is recognized as a promising technology to address the above the network throughput is decreased with the time. Based on the adaptive online spectrum allocation strategy, the proposed scheme improves the performance significantly better than the other schemes.

Fig. 3 shows the spectrum efficiency of each scheme. The proposed scheme is designed to concentrate on the effectiveness of CR system. Therefore, we can avoid spectrum waste due to adaptive spectrum sharing; it is profitable for the spectrum efficiency. All the schemes have similar trends. However, under various service operation time, the spectrum efficiency of the proposed scheme is better than the other schemes.

Fig. 4 indicates the network fairness of each scheme. In this paper, the network fairness is defined based on the Jain’s fairness index [16]. According to the Egalitarian bargaining approach, the proposed scheme makes the network system adaptable in order to achieve a balanced spectrum allocation. Therefore, the proposed scheme can maintain the excellent network fairness. This feature is highly desirable for the multi-user CR network.

REFERENCES


