A Game Theoretic Framework for Cognitive Radio Networks Using Adaptive Channel Allocation Spectrum

Md. Mostafizur Rahman

Islamic University, Kushtia, Bangladesh

***Abstract*—** *In this research, we propose a game theoretic framework to investigate the behavior of the cognitive radio networks for distributed adaptive channel allocation. We illustrate two separate objective functions for spectrum sharing games, which capture the benefit of selfish users and cooperative users, respectively. Based on utility definition for cooperative users, we determine that the channel allocation problem can be formed as the potential game, and converges to a deterministic channel allocation Nash equilibrium point. Alternatively, no regret learning implementation is proposed for both scenarios. Also, it is pointed to have similar performance with the possible game when cooperation is expected, but with a higher variability beyond users. The no regret learning formulation is beneficial to accommodate selfish users. Non-cooperative learning games have very low overhead for information interchange in the network. We point that cooperation-based spectrum sharing protocol improves the overall network performance at expense of an extended overhead needed for information exchange.*

***Keywords*— Spectrum Etiquette, Adaptive Channel Allocation, Cognitive Radio, Game Theoretic Framework.**

I. INTRODUCTION

With new paradigm shift in the FCC's spectrum management policy [3] that generates opportunities for new, more competitive, reuse, cognitive radio technology sets the foundation for deployment of smart flexible networks that cooperatively adjust to increase the overall network performance. The cognitive radio terminology was invented by Mitola [15], and introduces to a smart radio which has the powers to sense the external conditions, learn from the past, and make intelligent judgments to adjust its transmission parameters according to the current state of environment. The possible participation of cognitive radios to spectrum sharing and an initial framework for precise radio protocol have been discussed in [16]. According to the suggested protocol, the users should adopt to the environment, determine the radio temperature of the channels and determine the interference contributions on their neighbors. Based on these measures, the users should respond by changing their transmission parameters if some other users may require to use the channel. While it is obvious that this behavior improves cooperation between cognitive radios, the behavior of networks of cognitive radios working distributed resource allocation algorithms is limited well known.

As cognitive radios are really autonomous agents that are absorbing their environment and optimizing their performance by changing their transmission parameters, their interactions can be modeled utilizing a game theoretic framework. In this framework, the cognitive radios are the players and their performances are the selection of different transmission parameters and new transmission frequencies, which change their own performance and the performance of neighboring players. Game theory has been widely applied in micro economics, and only recently has received attention as a useful mechanism to design and analyze distributed resource allocation algorithms. So, the spectrum sharing problem was analyzed in [7] that based on a game model among providers using bargaining strategies. In [7], the bound of price of anarchy was investigated under the assumption that users are uniformly distributed, or every AP uses same transmission power. Some game theoretic models for cognitive radio networks were conferred in [18], which has recognized potential game formulations for power control, call admission control and interference delay in cognitive radio networks. The convergence conditions for different game models in cognitive radio networks were studied in [19].

In this research, we propose a game theoretic framework of adaptive channel allocation problem for cognitive radios. Our current research assumes that radios can estimate the local interference temperature on different frequencies and can improve by optimizing the information transmission rate for a given channel quality using adaptive channel coding and by possibly changing to a different frequency channel. The cognitive radios' decisions depend on their perceived utility associated with each possible action. We introduce two different utility definitions, which indicate the amount of cooperation enforced by the spectrum sharing protocol. We design adaptation protocols based on both potential game formulation and no regret learning algorithms. We investigate the convergence properties of the proposed adaptation algorithms and tradeoffs involved.

II. SYSTEM MODEL

The cognitive radio network consists of a set of N transmitting-receiving nodes, consistently distributed in the square region of dimension $D* \times D*$. We assume that the nodes are either fixed or moving slowly (slower than the convergence time for the recommended algorithms). Fig. 1 shows lines to join the transmitting node to its intended receiving node. The nodes contain the spectrum availability and decide on the transmission channel.

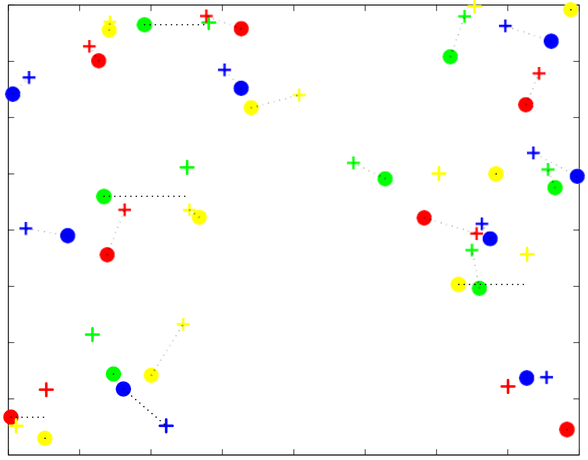

FIG. 1. Snapshot of nodes' positions and network topology

We assume that there are K frequency channels used for transmission, with $K < N$. By distributive choosing a transmitting frequency, the radios effectively form a channel reuse distribution map with decreased co-channel interference. The transmission link property can be characterized by a required Bit Error Rate (BER) target, which is particular to the given application. An equivalent SIR point requirement can be determined by the modulation type and amount of channel coding. The Signal-to-Interference Ratio (SIR) estimated at the receiver *j* associated with transmitter *i* can be represented as:

$$SIR_{ij} = \frac{p_i G_{ij}}{\sum_{K=1,K\neq 1}^{N} p_k G_{kj} I(k,j)} \tag{1}$$

where p_i is transmission power at transmitter i, tt_{ij} is the link gain among transmitter i and receiver j. Also, $I(i, j)$ is interference function characterizing the interference produced by node i to node j. Analyzing (1), we observed that to maintain a certain BER constraint the nodes can adjust at both physical and network layer level. At the network level, the nodes can reduce the interference by selecting the transmission channel frequency. At the physical layer, power control can reduce interference for a feasible system, results in all users meeting their SIR constraints. Alternatively, target SIR requirements can be modified (reduced or increased) by using different modulation levels and various channel coding rates. For example, adaptation at the physical layer, we have assumed that for fixed transmission power level, software defined radios enable nodes to adjust their transmission rates and the required SIR targets by changing the amount of channel coding for a data packet. For our simulation, we have assumed that all users have packets to transmit at all the times.

TABLE 1
Code Rates of Reed-Muller Code RM (1, *m*) and Sir Requirements for Target BER=10^{-3}

m	Code Rate	SIR (dB)
2	0.75	6
3	0.5	5.15
4	0.3125	4.6
5	0.1875	4.1
6	0.1094	3.75
7	0.0625	3.45
8	0.0352	3.2
9	0.0195	3.1
10	0.0107	2.8

Multiple users are allowed to transmit at the same time over a shared channel. We assume that users in the network are identical, which means they have an identical action set and identical utility purposes associated with the possible actions. The BER specification selected for simulations is 10−3, and we assume the use of a Reed-Muller channel code RM (1, m). In table 1, we confer the coding rate sequences and the identical SIR target requirements used for our simulations [13].

III. A GAME THEORETIC FRAMEWORK

Game theory depicts a set of mathematical tools produced for the purpose of analyzing player's interactions in the decision processes [8]. It can be used to predict the result of the interactions and to identify optimal strategies for the players. The main elements of a simple game (strategic and rational), their set of actions or decisions and a set of preference connection associated with every action tuple (usually measured by means of the utility function).

In particular, we can show our channel allocation problem as a result of a game, in which the players are communicating channel and their preferences are associated with quality of the channels. The quality of the channels is determined by the cognitive radios by measurements on separate radio frequencies. We show our channel allocation problem as a normal form game, which can be mathematically described as $\Gamma = N, \ S_i \ i \in N, \ U_i \ i \in N$, where N is the finite set of players (decision makers who choose a particular channel to transmit), and Si is the set of policies associated with player i (channels which could be selected by i). We define $S = S_i, \ i \ N$ as strategy space, and $U_i : S \ R$ as the set of utility purposes that the players associate with their strategies. For every player i in game Γ, the utility function Ui is a function of si, the strategy chosen by player i, and of the current policy profile of its opponents: $s{-}i$. The utility of user i in our channel allocation game can be counted as the reward received by user i from the network depending on the channel it selects, si, and on the other users' preferences, $s{-}i$. We will explain shortly how the choice of the utility function affects the outcome of the game. In explaining the outcome of the game, as players make decisions independently and are determined by the other players' decisions, we are involved to determine if there exists a convergence point for adaptive channel selection algorithm, from which no player would deviate anymore, i.e. Nash equilibrium. If equilibrium strategy profile is deterministic, a pure strategy Nash equilibrium survives. For finite games, even if pure strategy Nash equilibrium does not exist, a mixed approach Nash equilibrium can be observed (equilibrium is defined by a set of probabilities assigned to pure strategies).

While it becomes apparent from the above discussion, the performance of the adaptation algorithm depends significantly on selection of utility function which characterizes the preference of a user for a particular channel. The choice of the utility function is not unique. It must be chosen to have physical meaning for the particular application, and also have appealing mathematical properties that will guarantee equilibrium convergence for the adaptation algorithm. We have proposed two different utility functions that capture the channel quality and the level of cooperation and fairness in sharing the network resources.

3.1 Utility Function

The utility function (U1) we propose accounts for the case of a "selfish" user, which values a channel based on level of the interference perceived on that particular channel. We denoted P=$[p_1, p_2, \ldots p_N]$ as transmission powers for the N radios, S=[s1,s2,...,sN] S=$[s_1, s_2, \ldots s_N]$ as the strategy profile and $f\,(s_i, s_j)$ as interference function:

$$f(S_i, S_j) = \begin{cases} 1 & if\ S_i = S_j, transmitter\ j\ and\ i\ choose\ the\ same\ strategy\ (same\ channel) \\ 0 & \text{otherwise} \end{cases}$$

This choice of utility function requires a minimal amount of information for the adaptation algorithm, namely interference measurement of a particular user on the different channels. The second utility function accounts for the interference seen by a user on a particular channel and the interference this particular choice will create to neighboring nodes. The complexity of algorithm implementation will increase for the particular case, as the algorithm will need probing packets on a common access channel for the measuring and estimating the interference a user will create to neighboring radios. The above-defined utility functions characterize a user's level of cooperation and support a selfish and cooperative spectrum sharing etiquette, respectively.

3.2 A Potential Game Formulation

In the previous section, we have presented the choice of utility functions based on physical meaning. However, in order to have excellent convergence properties for adaptation algorithm we have to ensure that these functions possess certain mathematical properties. There are some types of games that have been shown to converge to Nash equilibrium when a best response adaptive strategy is employed. In what follows, we point that for the U2 utility function, we can express an exact potential game, which concentrates to a pure strategy Nash equilibrium solution. Characteristic of a potential game is the existence of a possible function that exactly reflects any single change in the utility function of any player. The possible function models the information associated with the improvement paths of a game instead of the exact utility of the game [17].

An exact possible function is defined as a function

$$P: S \rightarrow R, if\ for\ all\ i, and\ s_i, s'_i \epsilon S_i,$$

If a possible function can be defined for a game, the game is an accurate potential game. In exact potential game, for a change in operations of a single player, the change in the possible function is equal to the value of the improvement deviation. Any potential game in which players practices sequentially converges to a pure strategy Nash equilibrium that maximizes the potential function [17]. For our earlier formulated channel allocation game with the utility function U2, we establish an exact potential function to be

$$Pot(S) = Pot(s_i, s_{-i}) =$$

$$\sum_{i=1}^{N}(-\frac{1}{2}\sum_{j=1,j\neq 1}^{N} p_j G_{ij} f(s_j, s_i) - \frac{1}{2}\sum_{j=1,j\neq 1}^{N} p_i G_{ji} f(s_j, s_i)) \tag{2}$$

The function in (2) actually reflects the network utility. It can be recognized that the potential game property ensures that an increase in individual users' utilities contributes to an increase of the overall network utility. We show that this section holds only if users take actions sequentially, following the best response strategy.

Hence, to guarantee convergence for the spectrum allocation game, either a centralized or a distributed scheduler should be expanded. In an ad hoc network, the latter solution is better. To this end, we propose random access for decision making in which each user is strong with probability p_a = 1/N. More pointedly, at the beginning of each time slot, each user flips a coin with probability p_a , and, if successful, produces a new decision based on the current values for the utility functions for each channel; unless, the user takes no new action. We perceive that the number of users that attempt to share each channel can be ascertained from channel listening as we will detail shortly. The suggested random access ensures that on ordinary exactly one user makes determinations at a time, but of course has a nonzero possibility that two or more users take actions simultaneously. We have discovered experimentally that the convergence of the game is robust to this happening: when two or more users simultaneously choose channels, the potential capacity may temporarily decrease (decreasing the overall network production) but then the upward monotonic course is re-established.

The proposed potential diversion detailing necessitates that clients ought to have the capacity to assess the competitor channels' utility capacity U2. To give all the data important to decide U2, we propose a flagging convention dependent on a three-way handshake convention. The flagging convention is fairly like the RTS-CTS bundle trade for the IEEE 802.11 convention, yet expected as a call confirmation reservation convention, instead of a parcel get to reservation convention. At the point when a client needs to settle on a choice on choosing the best transmission recurrence (another call is started or ended, and the client is fruitful in the Bernoulli preliminary), such a handshaking is started. As opposed to the RTS-CTS reservation system, the flagging parcels, START, START CH and ACK START CH (END, ACK END) in our convention are not utilized for conceding transmission for the impacting clients, but instead to quantify the impedance segments of the utility capacities for various frequencies and to help with registering the utility capacity. The flagging parcels have a twofold job: to declare the activity of the present client to choose a specific channel for transmission, and to fill in as examining bundles for obstruction estimations on the chose channel. The flagging bundles are transmitted with a settled transmission control on a typical control channel. To streamline the examination, we expect that no crashes happen on the normal control channel. As we referenced previously, the union of the adjustment calculation was tentatively appeared to be powerful in impact circumstances. For better recurrence arranging, it is alluring to utilize a higher transmission control for the flagging parcels than for the transmitted bundles. This will allow clients to become familiar with the potential interferers over a bigger region. For our reproductions, we have chosen the proportion of transmitted powers among flagging and information parcels to be equivalent to 2. We take note of that the U2 utility capacity has two sections: an) a proportion of the obstruction made by others on the ideal client, Id and b) a proportion of the impedance made by the client on its neighbors' transmissions, Io. The initial segment of U 2 can be assessed at the getting hub, while the second part must be evaluated at the transmitter hub. As such, the tradition requires that both transmitter and beneficiary tune in to the control channel and each keep up a data table on all frequencies, like the NAV table in 802.11. In what pursues, we diagram the means of the convention. Convention steps:

1) Bernoulli trial for p_a
   if 0, listen to common control channel; *break*. if 1, go to 2)
2) Transmitter sends START packet that includes current estimates for interference created to neighboring users on all possible frequencies, $I_o(f)$ (this information is computed based on the information saved in the Channel Status Table);
3) Receiver computes current interference estimate for user $I_d(f)$, determines $U2(f) = -I_d(f) - I_o(f)$ for all channels, and decides on the channel with highest U 2 (in case of equality, the selection is randomized, with equal probability of selecting channels);
4) Receiver includes newly selected channel information on a signaling packet START CH which is transmitted on the common channel;
5) Transmitter sends the ACK START CH which acknowledges the decision of transmitting on the newly selected frequency and starts transmitting on newly selected channel;
6) All the other users (transmitters and receivers) heard the START CH and ACK START CH packets update their Channel Status Tables (CST) accordingly.

We take note of that when a call closes, just a two-way handshake is required (END, ACK END) to report the arrival of the channel for that specific client. After hearing these finish of-call flagging bundles, all transmitters and beneficiaries refresh their CSTs as needs be. We can see that an alternate duplicate of the CST ought to be kept at both the transmitter and the beneficiaries (CST t and CST r, separately). The passages of each table will contain the neighboring clients that have asked for a channel, the channel recurrence, and the evaluated connection gain to the transmitter/recipient of that specific client (for CST r and CST t, separately).

The proposed potential diversion structure has the preferred standpoint that a balance is achieved quick if a best reaction dynamic is pursued, yet requires significant data on the impedance made to different clients and extra coordination for successive updates. We note, be that as it may, that the successive updates strategy likewise settles the potential clashes which may happen after getting to the normal control channel. The potential amusement detailing is reasonable for planning a helpful range sharing manner, however can't be utilized to dissect situations including narrow minded clients, or situations including heterogeneous clients (with different utility capacities relating to various QoS prerequisites). In the accompanying segment, we present an increasingly broad plan approach, in light of no-lament learning strategies, which reduces the previously mentioned issues.

3.3 Φ-No-Regret Learning for Dynamic Channel Allocation

While we appeared in the past segment that the amusement with the U2 utility capacity fits the structure of a correct potential diversion, the U1 work comes up short on the vital symmetry properties that will guarantee the presence of a potential capacity. So as to break down the conduct of the narrow-minded client's amusement, we resort to the execution of adjustment conventions utilizing lament minimization learning calculations. Learning calculations decide probabilistic methodologies for players by thinking about the historical backdrop of play. A learning calculation is described by two stages: investigating and misusing [9]. In the investigating stage, the players endeavor to locate the best activities by investigating the whole space of activities. This is accomplished by choosing all activities with a non-zero likelihood. The misusing stage job is to build the determination likelihood of fruitful methodologies. This sort of learning calculations has customarily been portrayed by lament estimates, for example, outside and inner lament, and were not identified with balance ideas. Outside lament is characterized as the contrast between the adjustments accomplished by procedures endorsed by the given calculation and the settlements gotten by playing some other settled arrangement of choices in the most pessimistic scenario. Inward lament is characterized as the contrast between the settlements accomplished by the systems endorsed by the given calculation, and the adjustments that could be accomplished by a re-mapped arrangement of these procedures. On the off chance that the result contrast approaches zero, the calculation is said to show no-lament.

All the more as of late, thinks about have been performed to relate the execution of the lament minimization calculations to diversion theoretic equilibria [10]. All the more explicitly, in [10], a progressively broad class of no-lament learning calculations called Φ-no-lament learning calculations were appeared to be identified with a class of equilibria named Φ-equilibria. For this class of learning calculations, Φ decides the arrangement of techniques against the present play ought to be thought about. A learning calculation is said that fulfills Φ-no-lament, if no lament is experienced by playing as the learning calculation endorses, as opposed to playing as indicated by any change of the calculation's play, described by the parts of Φ. No-external regret and no-internal mourn learning estimations are exceptional examples of Φ-no-mourn learning count. It is showed up in [10] that the observational spread of play of Φ-no-lament calculations joins to a lot of Φ-equilibria. It is additionally demonstrated that no-lament learning calculations can possibly learn blended methodology (probabilistic) equilibria, and that the most secure diversion theoretic arrangement idea to which the Φ-no-lament learning calculations merge is the connected harmony. We take note of that a Nash harmony is anything but an essential result of any Φ-no lament learning calculation [10]. We propose a substitute answer for our range sharing issue, in view of the no-outer lament learning calculation with exponential updates, proposed in [4].

$$w_i^{t+1}(s_i) = \frac{(1+\beta)^{U_i^t(s_i)}}{\sum_{s_i' \epsilon S_i}(1+\beta)^{U_i^t(s_t')}}$$

A formal evidence for the intermingling of this learning calculation is difficult to give. In [11], in view of reproduction results, it is demonstrated that the above learning calculation unites to a Nash harmony in amusements for which an unadulterated methodology Nash balance exists. In this work, we likewise appear by recreations that the proposed channel designation no-lament calculation con-borderlines to an unadulterated procedure Nash harmony for agreeable clients (utility U2) and to a blended technique balance for childish clients (utility U1).

By following our proposed learning adjustment process, clients figure out how to pick the recurrence channels which expand their prizes through continued playing of the amusement. For the instance of childish clients, the measure of data required by this range sharing calculation is negligible: clients need to quantify the obstruction temperature at their in-tended collectors (work U1) and to refresh their loads for channel determination in like manner, to support the channel with least impedance temperature (break even with transmitted forces are expected). We take note of that the no-lament calculation in (8) necessitates that the loads are refreshed for every conceivable system, including the ones that were not played at the time. The reward acquired if different activities had been played can be effectively assessed by estimating the obstruction temperature all things considered. For the instance of helpful clients, the data expected to figure 2 is like the instance of potential amusement detailing. We take note of that, while the learning calculation does not require successive updates to unite to a harmony, the measure of data trade on the regular control channel expects coordination to keep away from impacts. One conceivable way to deal with lessening the measure of flagging is keep up the entrance plot proposed in the past area, which would guarantee that by and large just a single client at any given moment will flag changes in channel designation.

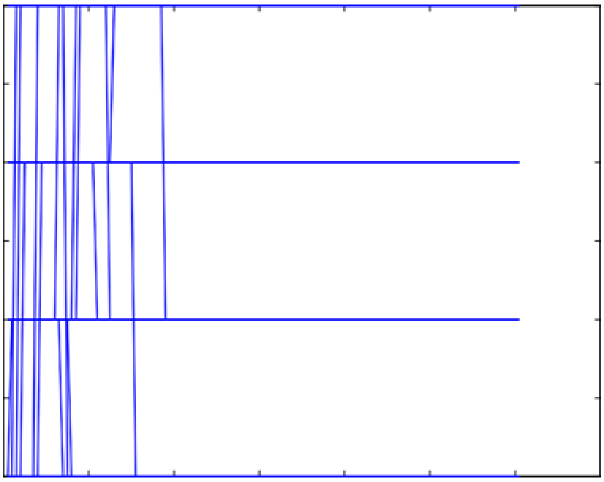

FIG. 2. Potential game: convergence of users' strategies

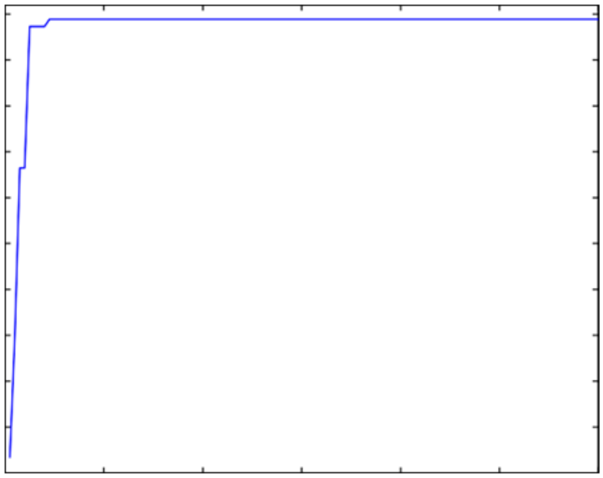

FIG. 3. Evolution of potential function

We initially delineate the intermingling properties of the proposed range sharing calculations. We can see that for agreeable diversions, both the potential amusement plan, just as the learning arrangement meet to an unadulterated system Nash harmony (Figures 2, 4, and 10). In Figure 3, we outline the adjustments in the potential capacity as the potential diversion advances, and it very well may be seen that to be sure by distributivity enhancing their utility, the clients emphatically influence the general utility of the system, which is approximated by the potential capacity. Paradoxically, the narrow-minded clients' learning procedure unites to a blended methodology balance, as it tends to be found in Figures 8 and 9.

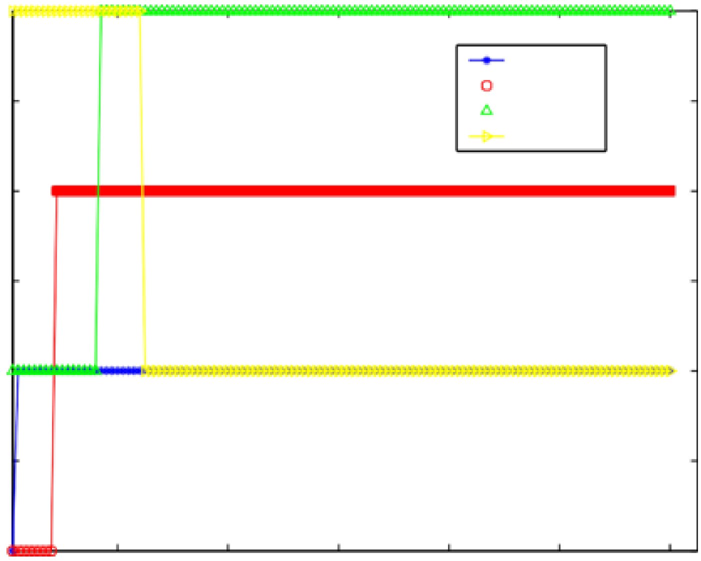

FIG. 4. Potential game: strategy evolution for selected arbitrary users

We consider the accomplished SIRs and throughputs as execution measures for the proposed calculations (versatile coding is utilized to guarantee a certain BER focus, as recently clarified in Section II). We consider the normal execution per client just as the fluctuation in the accomplished execution (reasonableness), estimated regarding change and CDF. We first give results for the potential diversion-based calculation. The decision of the utility capacity for this diversion implements a specific level of decency in dispersing system assets, as it very well may be found in figures 5, 6, 7 and 8. Figures 5 and 6 show the SIR accomplished by the clients on every one of the 4 distinct channels for introductory and last assignments, separately. We can see the SIR enhancement for the clients that at first had a low execution, in spite of the fact that it comes to the detriment of a slight punishment in execution for clients with an at first high SIR. It very well may be found in Figure 7 that at the Nash harmony point, the quantity of clients having a SIR beneath 0 dB has been decreased.

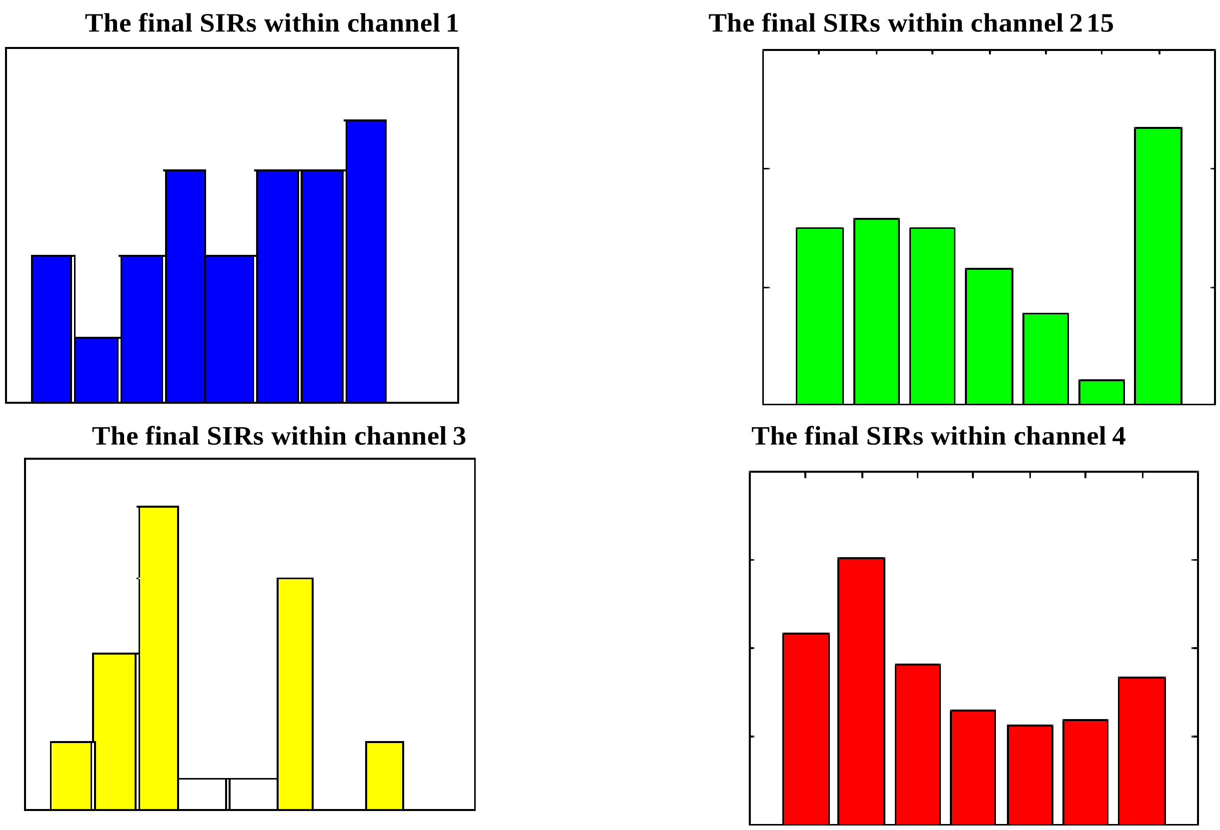

FIG. 5 & 6. Potential Game: SIRs at final channel assignment

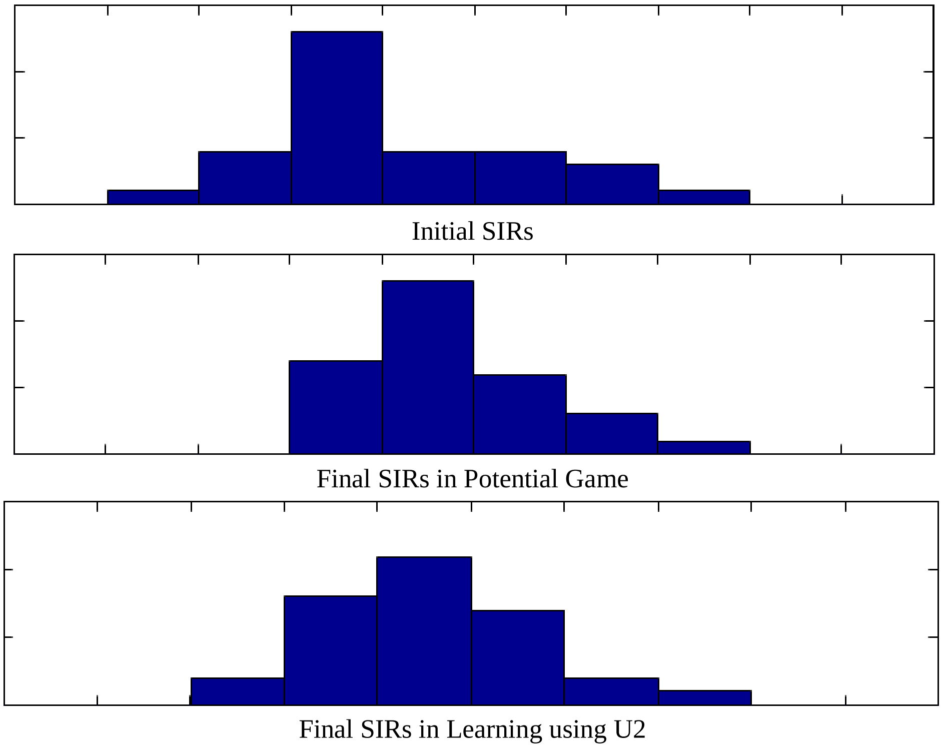

FIG. 7. SIRs histogram. Initial Channel Assignment vs. Final Channel Assignment

Moreover, Figure 8 demonstrates that the level of clients who have a SIR underneath 5 dB diminishes from 60% to about 24%, to the detriment of a slight SIR decline for clients with a SIR more prominent than 12.5 dB. The benefit of the potential amusement is delineated in Figure 9, as far as the standardized feasible throughput at every beneficiary. For the underlying channel task, 62% of the clients have a throughput under 0.75. At the balance, this portion is decreased to 38%. Total standardized throughput upgrades for the potential amusement definition are outlined in Table 2. Our reproduction results indicate fundamentally the same as exhibitions for the learning calculation in agreeable situations with the potential diversion plan. Figures 7 demonstrate the underlying and last task for this calculation, just as the accomplished.

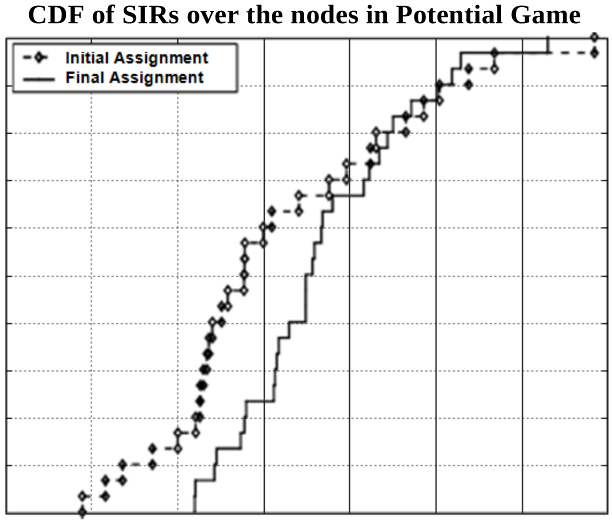

FIG. 8. CDF for the achieved SIRs. Initial Channel Assignment vs. Final Channel Assignment

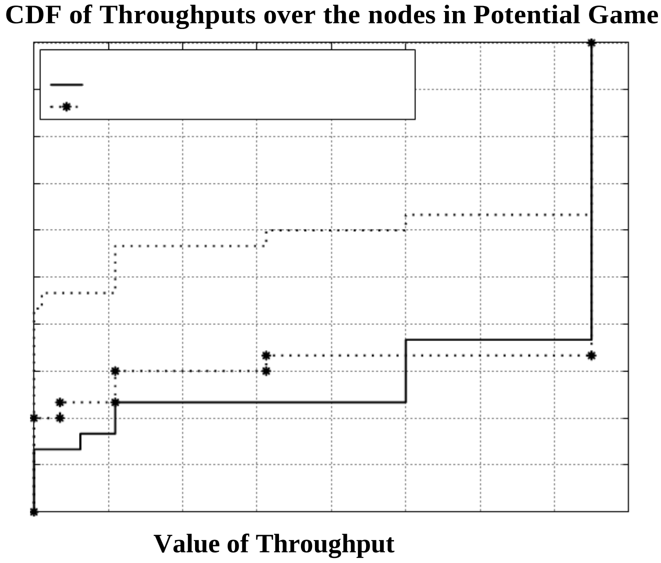

FIG. 9. CDF for the achieved throughputs. Initial Channel Assignment vs. Final Channel Assignment

SIRs after combination for all clients in the system. As far as reasonableness, the learning calculation performs somewhat more regrettable than the potential amusement plan (Figure 9). In any case, despite the fact that the balance point for learning is unique in relation to that of the potential diversion, the two calculations accomplish close throughput execution (Table 2).

As we recently referenced, the learning calculation for narrow minded clients does not prompt an unadulterated procedure Nash balance channel designation. In Figure 8 we outline the union properties for a discretionarily picked client, which unite to a blended procedure portion: chooses channel 1 with likelihood 0.575 or channel 3 with likelihood 0.425. The developments of the loads for every one of the clients in the system are appeared in Figure 9. We think about the execution of the proposed calculations for both agreeable and non-helpful situations.

TABLE 2
SIR AND NORMALIZED THROUGHPUT OF ALL USERS AT INITIAL AND FINAL CHANNEL ASSIGNMENT

	Total Normalized Throughput
Initial	9.4
Final (Potential Game)	16.5
Final (Learning U2)	15.3

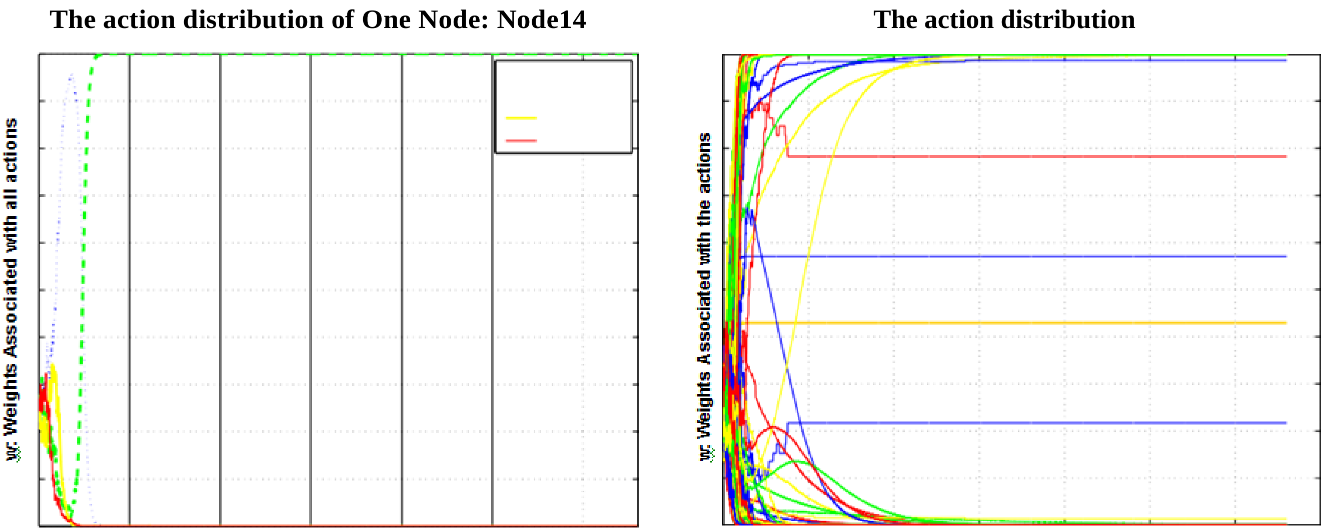

FIG. 10. No-regret learning for cooperative users: weights distribution evolution for an arbitrary user

The execution estimates considered are the normal SIR, normal throughput per client and absolute normal throughput for the system. Toward the start of each availability, each client will either pick a similar balance channel for transmission (in helpful diversions with unadulterated procedure Nash harmony arrangements), or will pick a channel to transmit with some likelihood given by the blended technique balance (for example getting the hang of utilizing U1). In the irregular channel designation plot, each client picks a channel with equivalent likelihood from a pool of four channels.

IV. CONCLUSION

In this work, we have examined the plan of channel sharing decorum for intellectual radio systems for both helpful and non-agreeable situations. Two distinct plans for the channel distribution amusement were proposed: potential diversion definition, and no-lament learning. We demonstrated that all the proposed range sharing strategies merge to a channel portion harmony, in spite of the fact that an unadulterated methodology assignment can be accomplished just for agreeable situations. Our recreation results have demonstrated that the normal execution as far as SIR or reachable throughput is fundamentally the same as for both learning and potential diversion definition, notwithstanding for the instance of narrow-minded clients. In any case, regarding decency, we demonstrated that both participation and allotment methodology assume imperative jobs. While the proposed potential amusement detailing yields the best execution, its pertinence is constrained to helpful situations and huge learning about neighboring clients is required for the usage. On the other hand, the proposed no-lament learning calculation is appropriate for non-helpful situations and requires just an insignificant measure of data trade. This work speaks to an initial phase in understanding the range sharing issue for psychological radio systems. In future work, we will stretch out the proposed answers for location increasingly handy situations, for example, the instance of clients with unequal forces, control-controlled systems, just as the instance of heterogeneous clients, described by various utility capacities.

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