Abstract: In recent years, game theory has emerged as a promising approach to solving the power control problem in wireless networks. Many of the power control techniques in cognitive radio networks use Game theoretic approach to maintain Quality of Service (QoS) of communication and interference free communication. Earlier non-cooperative game model for controlling power has some lameness as it does not take account of effect of primary user on cognitive user and hence each cognitive user gets penalty based on the same cost factor without considering fairness. Thus, transmit power of cognitive users is too low and hence the QoS of communication for cognitive users decreases significantly. Recent approaches based on fairness pricing while designing cost factor. Such non-cooperative game model fair cost function used the complete information game method in order to adjust cognitive user’s power parameters dynamically based on the power and location parameters of other cognitive users and primary users. Cost function in such algorithm represents the fairness as the interference of the primary users and other cognitive users are evaluated using different cost factors while considering the channel condition and the distance from the current cognitive user to the base station. The algorithm based on fairness pricing factor ensures the system stability and benefit maximization of each cognitive user by making the transmit power to reach a steady state with iteration.

Keywords— power control; cognitive radio; game theory; SNR; cost function; fairness pricing.

I. INTRODUCTION

1.1 Cognitive Radio Networks and its necessity

In recent years, increasing dependence on diverse wireless technologies has brought a huge demand for extra bandwidth. This increasing demand for wireless services causes spectrum scarcity problem and hence it needs to be used efficiently.

In traditional approach of fixed spectrum allocation to authorized networks has leads to spectrum shortage for newly Increasing requirements of high rated data services and on the other hand the allotted spectrum not being used by the licensed users continuously [1]. The recent studies by the Federal Communication Commission’s (FCC) on spectrum allocation policy have shown that large portions of the licensed bands remain unused for as much as 90% of the time [2]. This problem of spectrum scarcity inspired a new direction of possible solutions. The new concept cognitive radio proposed by Joseph Mitola is put forward to solve this contradiction by detecting and accessing idle spectrum in order to improve the spectrum utilization to meet the growing demands [3].

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learn from the environment and then adapts its internal states to statistical variations in the incoming RF stimuli by making corresponding changes of certain operating parameters? Thus, a full cognitive radio task can be divided into three parts viz. radio environment analysis (outside world and inside world); channel estimation (state estimation and capacity prediction); resource management (power control and spectrum allocation) [4].

1.2 Power control in cognitive radio

Power control is one of the key technologies for cognitive radio network (CRN) communication which is used to solve the power allocation problem when cognitive radio and authorized users share the spectrum simultaneously to ensure the interference free communication with smaller transmit power [5]. Power control can decrease the user transmit power in order to reduce interference and improve the system capacity and communication effectively. Hence the research on power control algorithm is always a core issue of radio resource management (RRM).

Currently, the research is going on two types of power control algorithm viz. centralized power control and distributed power control. As compared to centralized power control, the distributed power control does not require a large scale data management and uses the present carrier interference radio measurement and transmission power and hence needs very little information. Distributed power control issue in multiuser environment chooses transmitting power level of n users in the premise of not violating the interference temperature and in limited spectrum holes in order to maximize the joint data transmission rate [6].

The main challenge to cognitive communication is to make balance between the conflicting goals of minimizing the interference to the primary users and maximizing the performance of the secondary user [7]. If the transmit power is too low that the received signal to interference (SIR) cannot reach the threshold and the whole communication gets failed. Due to these conflicting goals, a game theoretic approach for power control provides a best solution.

1.2.1 Differences between Competitive Optimality Water-Filling Algorithm and Distributed Water-Filling Algorithm

Two information theoretic procedures for transmit-power control in a two-user DSL environment, competitive optimality power control water-filling, or rate-adaptive water-filling and distributed power control water-filling, or power-adaptive water-filling. In competitive optimality water-filling algorithm, users compete to maximize achievable data rates by adjusting their power allocation subject to fixed power constraints. All users competitively adjust their transmit power over available frequency bands, or spectrum holes, until they reach equilibrium known as the Nash equilibrium. At Nash equilibrium, each player’s strategy is the best response to the other players” strategies. Conversely, distributed power control water-filling aims at minimizing transmission power subject to the constraint imposed by fixed target rates. The system ultimately converges to equilibrium when the set of target data rates are achieved. Although some research papers on iterative water-filling algorithm favor the competitive optimality procedure and multiuser cognitive radio networks perform optimally when the network structure is distributed.

Yu’s work on distributed power control water-filling algorithm in [21] has inspired the application of the iterative water-filling algorithm to the problem of cognitive radio transmit-power control in some research papers.

In [18] and [23], Haykin proposed distributed water-filling algorithm for multiuser cognitive radio environment and developed useful mathematical notations to characterize the cognitive radio channel properties. In [24], Liao et al. have shown the characteristics of power control game for two users.
sharing two channels by water-filling strategy, first, as a cooperative and then, as a non-cooperative game. The results indicated that if the players are irrational, they will both choose to cooperate, and a channel each will be allocated until the end of the finite stage. Otherwise, if the players are rational they will adopt competition and allocate power on both channels and thus obtain maximum payoffs.

In [25], Laufer and Amir have shown certain condition when the iterative water-filling procedure was suboptimal due to the occurrence of what is known as the Prisoners Dilemma in game theoretic papers. They proposed a modified version of the algorithm, which was shown to perform optimally.

**1.2.2 Comparison between No-External Regret and No-Internal Regret Learning Algorithm**

In [20], Greenwald et al. defined two important regret variations, namely external regret and internal regret. An example of external regret is the concept of “boosting” as explained by Freund and Schapire in [26], which refers to the process of training a machine to accurately make predictions by a combination of logical deductions from history. An example of internal regret, on the other hand is the concept of “regret-matching” as espoused by Gordon in [22]. Regret-matching is the probability distribution over the actions of a player, proportional to the regrets for having not played the other possible action sets. While the concept of boosting is limited because the predictions are inaccurate because they are chosen from a small discrete set of hypothesis, the advantage of regret-matching is based on the fact that the algorithm derives from procedures that adaptively adjust to accuracy over time.

In [19], Hart and Mas-Colell shown that correlated equilibrium can be attained by a procedure of play called “regret-matching”. This work has inspired the application of no-regret to the problem of cognitive radio power control in some research papers. The procedure of regret-matching leading to correlated equilibrium was applied for distributed access point selection in a wireless network and distributed opportunistic spectrum access for cognitive radio networks. However, a modified version of the regret-matching learning algorithm explained in [28], where each player only needs to know his own realized payoffs and actions.

**1.2.3 Conditions for the Implementation of Distributed Power-Control Scheme**

In the distributed settings, there is no centralized server or moderator and each user controls its transmit power by itself using only local information. Distributed power control avoids the signaling bottlenecks and information overhead associated with having users communicate with a centralized manager. However, the problems with the distributed power-control scheme are due to the severe non-cooperation of the secondary users and the interference from the transmit power of the all distributed secondary users being above the interference temperature threshold. The problem of non-cooperation can be solved by the use of game theoretic concepts, while the problem of interference can be solved by the use of distributed algorithms.

In [29], Neel and Reed modeled a low-complex autonomous distributed channel assignment algorithm based on game theory. They have shown by simulations that if the algorithm is applied to cognitive radio networks, each node derives the same utility from the available spectrum. The nodes then decide on the maximization of their utility, subject to the actions of their neighbors.

In [30], a distributed joint coordination and power control algorithm, regarded as Joint Coordination and Power Control (JCPC) algorithm, is proposed to maximize the system capacity of secondary users in a cognitive radio network. The JCPC algorithm works by allocating transmission power to all secondary users in the network.
In [31], Qian et al. proposed a distributed cognitive radio network aided by a “genie” placed near the primary receiver to monitor the interference level and inform the secondary users when the interference level caused by their opportunistic activities becomes too high or above the interference temperature limit.

In [32], the authors propose a non-cooperative power control game via linear pricing. The outcome of the game results in a Nash equilibrium that is efficient, but unfair to the cognitive radio users. In [33], the authors defined a power control algorithm and a new pricing function with interference temperature constrains to control the network’s power consumption in a distributed cognitive radio network game model.

The Nash equilibrium is identified as the outcome of the game with optimal power allocation policy. Though the game was measured to guarantee some extent of fairness for the users, the Nash equilibrium is not considered as an efficient solution concept for stochastic games, due to the fact that it is based on only local information available to users. The efficiency of the system can significantly be improved when users are made to have information about the environment and other users.

In [34], Maskery et al. proposed a game theoretic approach to opportunistic spectrum access. In the model, Carrier Sense Multiple Access is used with an adaptive concept known as “regret-tracking” to capture the activities of every user in the network. The game converges to correlated equilibrium and each radio learns to respond optimally to its environment.

In [27], Han proposed a distributed protocol based on an adaptive learning algorithm for multiple secondary users using only local information. The distributive users adjust their transmit power probabilities over the available channel and their actions converge towards correlated equilibrium.

1.3 Game theoretic approach in CRN

Game theory is a branch of applied mathematics that provides models and tools for analyzing situations where multiple rational agents interact to achieve their goals. The classic book ‘The Theory of Games and Economic Behavior’ by John von Neumann and Oskar Morgenstern published in 1944 laid the first foundations for the research field of game theory, which now has numerous application in economics, social science, engineering and recently computer science. The treatment of game theory is very comprehensive and complete. In communications engineering, game theory is often used for distributed resource management algorithms as they are naturally autonomous and robust. Examples of applications of game theory in wireless communications include transmission or power control, pricing, flow and congestion control, and load balancing.

The greatest feature of game theory is that it can provide mathematical basis for strategies with different scenarios and ultimately achieves the algorithm convergence. The concept of Nash equilibrium has made it possible to find the optimal solution of steady state [8].

Game models generally divided into two type viz. cooperative games and non-cooperative games. In cooperative games all players are concerned about the overall benefits and they are not so worried about their own personal benefit and hence players fully cooperate with each other in order to achieve the highest possible overall benefit. In non-cooperative games every user is mainly concerned about his personal payoff and therefore all its decisions are made competitively and moreover selfishly.

The choice of the model depends on the problem and its characteristics. The power control problem in a cognitive radio has resemblance with game model. The power control problem in a cognitive radio has resemblance with game model. The player’s payoff is a function of her own SIR and the player’s SIR is a function of her own transmit power of the other players in the cell when a player increases her
own power level which will cause increase her own SIR but will decrease the SIR of all other players.

For a fixed SIR, the players prefer lower power levels to higher ones and for a fixed power level, players prefer higher SIR to lower SIR. Usually a game theory model includes three elements viz. Decision maker \((N)\); Action space \((P)\); Utility set \((U)\). Thus with \(N\) cognitive users and single base station, the game model is defined as \(G = [N, P, U]\). \(N = \{1, 2, \ldots, N\}\) is the player in the game model, it represents the cognitive radio user in the system. \(P = \{p_1, p_2, \ldots, p_N\}\) is the action space, it represents the user’s transmission power strategy space in the cognitive radio system. \(U = \{U_1, U_2, \ldots, U_N\}\) is the utility function set, it represents utility function of all users in the system.

In the game process, if there is a strategy set which can satisfy the condition [4]. \(\forall j \in N, U_j(p_j, p_{-j}) \geq U_j(\bar{p}_j, p_{-j})\) and \(\bar{p}_j \in P\) can be considered as Nash equilibrium (NE) point where \(p_j\) the power of user \(j\) is and \(p_{-j}\) is the power vector which contains power of all users except \(j\). At this point the model has reached a state where no user can increase his utility function and all utility functions have reached a stable state [4].

1.3.1 Static Game vs. Stochastic Game

Static game framework has been used to compute the Nash equilibrium power allocation policies in cognitive radio networks. Different from a dynamic game where players make sequence of decisions, a static game is one in which all players make decisions one time simultaneously, without knowledge of the strategies of other players. A distributed asynchronous iterative water-filling algorithm is used to compute the Nash equilibrium power allocation policy of such a system using static game theoretic approach.

Most games considered in wireless communication systems to date are static games. Stochastic dynamic game theory is an essential tool for cognitive radio systems as it is able to exploit the correlated channels in the analysis of decentralized behaviors of cognitive radios. The concept of a stochastic game, first introduced by Lloyd Shapley in early 1950s, is a dynamic game played by one or more players. The elements of a stochastic game include system state set, action sets, transition probabilities and utility functions. It is an extension of the single player Markov Decision Process (MDP) to include the multiple players whose actions all impact the resulting payoffs and next state. A switching control game is a special type of stochastic dynamic game where the transition probability in any given state depends on only one player. It is known that the Nash equilibrium for such a game can be computed by solving a sequence of Markov decision processes.

Equilibrium and Learning a major breakthrough in game theory was due to John Nash when he introduced the solution concept of Nash equilibrium in the early 1950’s. A strategy combination constitutes Nash equilibrium if each agent’s strategy is optimal against other agent’s strategies. As a result, at Nash equilibrium agents have no motivation to unilaterally deviate from their strategies. Nash equilibrium plays an essential role in analysis of conflict and cooperation in economics and social sciences. However, Nash equilibrium suffers from limitations, such as non-uniqueness, loss of efficiency, non-guarantee of existence. In game theory, a correlated equilibrium is a solution concept which is more general than the Nash equilibrium and is defined as each player in a game chooses his action according to his observation of the value of a signal. A strategy assigns an action to every possible observation a player can make. If no player would deviate from the recommended strategy, the distribution is called a correlated equilibrium. Compared to Nash equilibria, correlated equilibria offer a number of conceptual and computational advantages, including the facts that new and sometimes more “fair” payoffs can be achieved, that correlated equilibria can be computed efficiently for games in standard normal form, and that correlated equilibria are the convergence notion for several natural learning algorithms.
1.3.2 Stochastic optimization Algorithms

Stochastic optimization algorithms are widely used in electrical and computer engineering to recursively estimate the optimum of a function or its root. The first papers on the stochastic approximation methods are those by Robbins and Monro and Kiefer and Wolfowitz in the early 1950’s. The well-known Least Mean Squares (LMS) adaptive filtering algorithm is a simple example of a stochastic approximation algorithm with a quadratic objective function.

In tracking applications, the step size of a stochastic approximation algorithm is chosen as a small constant. For such constant step size algorithm, one typically proves weak convergence generated by the stochastic approximation algorithm. Weak convergence is a generalization of convergence in distribution to a function space. The weak convergence analysis of stochastic approximation algorithms with Markovian noise has been pioneered by Kushner. It was demonstrated in the 1970’s that the limiting behavior of a stochastic approximation algorithm can be modeled as a deterministic ordinary differential-equation (ODE). This is the basis of the so-called ODE method for convergence analysis of stochastic approximation algorithms. In wireless networks, as there are usually underlying dynamics (e.g., a correlated fading channel) or factors that can only be measured in noise such as expected system throughput, stochastic approximation algorithms play an important role in optimization.

1.4 Scope of the paper

The following text summarizes the advantages of the non-cooperative game model based on fairness pricing algorithm over the non-cooperative game model based on unfair pricing algorithm. Many literatures have designed different utility function for different users using non-cooperative game theory according to the difference of user’s performance and the target utility function so as to reduce the user’s break probability and improve the system transmission rate. In some literature, different utility function for user and base station and connect the two utility functions with throughput which effectively controlled the transmit power of each user and improved the throughput [9]. The non-cooperative Power control Game model based on Pricing (NPGP) model discussed in literature [10] does not take account of the impact of primary user on the cognitive user while designing the SNR function which causes the problem if very low transmit power from the cognitive user and hence Quality of Service (QoS) of communication gets affected adversely.

Thus, to overcome this problem, literature [9] have designed a new cost function based on the principle of fairness while designing the SNR cost function. In this algorithm, the current cognitive user not responds to other cognitive user’s strategy choice and each user cannot increase its benefit by adjusting its transmit power, so other user’s benefit does not decreased.

II. Power Control Algorithms based on Non-Cooperative Game Model

2.1 Algorithm based on unfair pricing

The NE point of the non-cooperative game model without pricing factor is not a Pareto optimal solution and in such a model, all users want to enlarge their own utility by increasing their own power and neglect the other user’s utility value. Thus it does not provide the efficient maximal solution [4].

In order to overcome this problem, literature [4] provides a utility function based on pricing factor. The pricing factor in the utility bounds the users from increasing their power infinitely. After adding the pricing factor (c), gradually increase it until the model provides the optimal solution. Choosing a proper utility function is essential to solve the power control problem in cognitive radio system. Literature [4] defined the utility function as the number of information bits received per Joule of energy.
Assuming the length of the information bits in a packet is \( L \) bits, increases to \( M \) bits after channel coding, the transmission rate \( R \) b/s over a spread spectrum bandwidth of \( W \) (Hz), the signal to noise ratio \( (S/N)_j \) at the receiver of terminal \( j \) can be expressed as [4],

\[
S/N_j = r_j = \frac{W}{R} \frac{h_j p_j}{\sum_{i \neq j} h_i p_i + \sigma^2}
\]

where the ratio \( W/R \) denotes the processing gain of the spread spectrum system, \( p_i \) and \( p_j \) are the transmit powers of user \( i \) and \( j \) respectively, \( h_i \) and \( h_j \) are the path gain from user \( i \) to base station and user \( j \) to base station respectively and \( \sigma^2 \) denotes the background noise at the receiver.

The number of transmissions necessary to receive a packet correctly is random variable \( k \). If all transmissions are statistically independent then \( k \) is a geometric random variable with probability mass function and its expectation value is [4]

\[
E(k) = 1/P_c.
\]

From all these assumptions, the expression for \( Q \) defined as below [4],

\[
Q(k)= \begin{cases} \frac{P_c}{1-P_c} & k=1,2,3,\ldots; \\ 0 & \text{Others} \end{cases}
\]

Assuming the delay time of \( M/R \) seconds each time and the transmission power of the cognitive user \( j \) is \( P_j \) watt, the total delay time is \( kM/R \) seconds and the total power consumed is [4]

\[
E[k] P_j M/R = P_j M/[R. P_c].
\]

Thus, the utility function can be expressed as follows [4],

\[
U = \frac{E[\text{Benefit}]}{E[\text{Energy cost}]} = \frac{LR P_c}{M P_j} (b/J)
\]

The equation (3) has a mathematical anomaly in its formulation. For all modulation schemes, in the case of transmission power \( P_j = 0 \), receiver tries to make a guess for the values of the \( M \) bits per packet and all users set their bits with power zero and only wait for the bits to come and guess its value which is called a degenerating solution.

To avoid this problem, considering the channel to be AWGN channel, \( f(r_j) \) has the same property as \( P_c \) for \( \langle f(\infty) = 1 \) at the point \( p \to \infty \) and \( f(0) = 0 \) at the point \( p = 0 \). Thus, the modified utility function can be expressed as [4],

\[
U = u_j(p_j, p_{-j}) = \frac{LR}{M P_j} f(r_j)
\]

Where \( f(r_j) \) is the efficiency function which is based in \( S/N_j \). The maximum utility occurs at a power level for which the partial derivation of \( U \) with respect to \( p \) is zero. Therefore,

\[
\frac{\partial U_j}{\partial p_j} = \frac{LR}{M P_j^2} \left( r_j \frac{df(r_j)}{dr_j} - f(r_j) \right) = 0
\]

And so the necessary condition is

\[
r_j \frac{df(r_j)}{dr_j} - f(r_j) = 0
\]

Thus, the user’s utility function value is not determined only by its own transmission power but also by other user’s transmission power. The pricing factor in NPGP algorithm defined in literature [4] as,

\[
C_j(p_j, p_{-j}) = c_p j
\]

The modified utility function expressed as [4],

\[
u_j^c(p_j, p_{-j}) = u_j(p_j, p_{-j}) - C_j(p_j, p_{-j})
\]

Substituting the equations (7) and (8) into the equation (4), final expression of the utility function can be written as,

\[
u_j(p_j, p_{-j}) = \frac{LR}{M P_j} f(r_j) - c P_j
\]

Literature [4] provides a simulation results under different situations. It shows that in the NPGP model, other user’s utility decreases if any other user wants to increase his own power and affected user increases his power eventually and all users’ power is enlarged. It
also shows that the improved algorithm with pricing factor has a better performance than the algorithm without a pricing factor. It also shows that the utility function value of the user decrease with increase in distance between the user and the base station.

Fig. 2 NPGP algorithm flow chart

2.2 Algorithm based on fairness pricing

The aim of Non-cooperative Power control Game via Fairness Pricing (NPGFP) algorithm is that in the premise of no effect on the primary users, each cognitive user can make the strategy choice to maximize the benefit according to other user’s strategy information and meanwhile, the strategy set composed by the chosen strategy needs to get equilibrium.

Literature [9] shows that how each cognitive user achieves its maximum benefit in case of knowing other user’s strategy information and at the same time every user reaches the Nash equilibrium.

Assume the system with $N$ cognitive users, $M$ primary users, $K$ available channels and channel bandwidth $W$ for each cognitive user. Let $P_{ik}$ and $P_{jk}$ respectively represents the transmit power of the cognitive user $i$ and $j$ on the channel $k$. $g_{ii}$ represents the channel gain of cognitive user $i$ from the transmitter to the receiver. $h_{ml}$ represents the channel gain from primary user $m$ to cognitive user $i$ and $\sigma^2$ is the random noise.

Thus, the receiver’s SNR of the $i^{th}$ cognitive user can be defined as [9],

$$Y_{ik} = \frac{p_{ik}g_{ii}}{\sum_{j=1,j\neq i}^{N} p_{jk}g_{jj} + \sigma^2 + \sum_{m=1}^{M} p_{mk}h_{ml}}$$  \hspace{1cm} (10)

Where $g_{ii} = \alpha / d_{ii}^b$, $\alpha$ is a constant with value 0.097 called gain factor, $\theta$ is the attenuation factor and $d_{ii}$ is the distance between the current cognitive users to the cognitive base station. The interference affects to cognitive user shown in the denominator of equation (10) indicates the interference from other cognitive users, the noise interference and the interference from the primary users. Hence, interference can be evaluated objectively and comprehensively.

In literature [9], cost function is designed with higher fairness based on the SNR. The cost function has two characteristics that the interferences of the primary users and other cognitive users evaluated using different cost factors as well as the distance and the channel condition from the current cognitive user to the base station are considered. According to the distance and channel quality, the penalty is decided. Thus, the cost function designed as [9],

$$C_{ik} = \alpha_{ik} \frac{p_{ik}g_{ii}}{\sum_{j=1,j\neq i}^{N} p_{jk}g_{jj}} + \beta_{ik} \frac{p_{ik}h_{ik}}{\sum_{m=1}^{M} p_{mk}h_{mk}}$$  \hspace{1cm} (11)

The first term in equation (11) represents the interference of the other cognitive users caused by the $i^{th}$ cognitive user and the second term represents the interference of the primary users caused by the $i^{th}$ cognitive user. The terms $\alpha_{ik}$ and $\beta_{ik}$ are the cost factors and defines the reciprocal of the distance between the current cognitive user and other cognitive users and the reciprocal of the distance between the current cognitive user and other primary users respectively. Thus, the fairness in cost function has been implemented.

The literature [11] have defined the utility function of NPGP model as
where $R$ is the transmission rate.

Putting the values of equation (10) and (11) into the utility function of the NPGP model, new utility function forms as below:

$$U_{ik}^{SNR}(p_{ik}) = \frac{R}{p_{ik}} \left( \frac{1}{1 + \exp(10 - \gamma_{ik})} - C_{ik} \right)$$

The equation (13) represents the utility function based on SNR cost function and referred as NPGFP model.

After certain number of iterations in NPGFP game model algorithm, the utility function of every cognitive user has got maximization. If any user changed it’s transmit power caused to reduce its own or other cognitive user’s benefit. Meanwhile, system reaches the steady state and the transmit power of each cognitive user represents the Nash equilibrium solution set.

Literature [9] also defines throughput as an important performance index factor for whole communication system besides SNR and utility function. The throughput of the $i^{th}$-cognitive user expressed in literature [68] as below,

$$T_i = W \sum_{k=1}^{K} \log(1 + \gamma_{ik})$$

For all other cognitive users, it can be expressed as below,

$$T_{-i} = W \sum_{k=1}^{K} \sum_{j=1}^{N} \log \left( 1 + \frac{P_{Red,n}}{\sum_{j=1}^{N} P_{ij} + P_{ij}^{2} + \sum_{k=1}^{K} P_{mk,n}} \right)$$

Hence, the total throughput of the system is shown is following equation,

$$T_{total} = \sum_{i=1}^{N} (T_i + T_{-i})$$

Simulation result in literature [9] have shown that the throughput in case of fairness pricing based power control game model increases around 11% as compared to the unfair model. This happens due to the increase in transmit power in fairness pricing game model in order to achieve higher SNR.

III. CONCLUSION

In this review paper, we provided a broad overview of game theory and its applications to the research on power control in cognitive radio networks. Various power control algorithms developed by different researchers have explained. This paper provides an overview of the most recent practical implementations in controlling power in cognitive radio using game theory.

Finally, paper explored the two algorithms based on non-cooperative game model to control power in cognitive radio networks. The simulation results given in the literature [4] shows that the NPGP algorithm improves the performance parameters of the communication system considerably as inclusion of the pricing factor. However, the NPGP model does not take into the consideration of the impact of the interference from the primary user on the cognitive users while designing the SNR function which cause the problem of very low transmit power.

The NPGFP algorithm provided fairness while designing the SNR cost function. Compared to the NPGP algorithm, the NPGFP algorithm does provide better system throughput as well as stability and
iteration number. However, the simulation results given in literature [9] proved that as the number of user increases, the transmit power cannot converges to stable value. Increase in transmit power of NPGFP model to obtain higher SNR also causes the interference to the other cognitive and primary users which increases penalty value. Thus, there is no real increase in user’s benefit.

In this review paper, solutions to the problem of transmit power control in cognitive radio networks have been approached from the perspective of game theory. The NPGP algorithm and the NPGFP algorithm have been reviewed and represented in sufficient theoretical details.

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