Chapter 3

Resource Optimization in Cognitive Radio Networks

3.1 Introduction
This chapter presents the review of various optimization techniques employed in resource allocation problems. Basic concepts of constrained optimization, mathematical programming, integer/combinatorial optimization, genetic programming and game theory are introduced. As game theory has been proved to be appropriate for analyzing CRNs, and hence it is presented in detail. After introducing preliminaries and fundamental components of game theory, different game models are discussed. Relevance of game theory for CRN is presented and detail literature survey of applications of game theory for resource allocation is undertaken.

3.2 Optimization Techniques
Resource allocation is a broad issue covering wide range of problems. Therefore, a variety of optimization tools are employed. Though convex optimization is used in communication system design, many resource allocation problems are nonlinear and nonconvex in nature. The channel allocation problems are modeled as integer, combinatorial or both. Dynamic optimization becomes important under time-varying conditions. When cooperation among different users is considered, game theory can be employed to find optimal solution and strategy. Thus, single optimization tool is not available to solve all resource-allocation problems at once.
3.2.1 Constrained Optimization

The design of communication system in order to achieve a given objective (maximize/minimize a cost function) subject to various resource constraints. This type of problems is called constrained optimization which often appears in the multicarrier systems [12]. The general formulation is given as

$$\min_{\mathbf{x} \in \Omega} f(\mathbf{x}), \quad (3.1)$$

subject to \{ $g_i(\mathbf{x}) \leq 0$, for $i = 1 \ldots m$

$$h_j(\mathbf{x}) = 0, \text{ for } j = 1 \ldots l$$

where $\mathbf{x}$ is a parameter vector for optimizing resource allocation, $\Omega$ is the feasible range for the parameter vector, and $f(\mathbf{x})$ is the optimization goal matrix, objective goal, or utility function that represents performance or cost. The equality and inequality constraints are represented by $g_i(\mathbf{x})$ and $h_j(\mathbf{x})$. The optimization process finds the solution $\bar{\mathbf{x}} \in \Omega$ that satisfies all equality and inequality constraints. For an optimal solution, $f(\bar{x}) \leq f(x)$, $\forall x \in \Omega$.

If the objective and constraints functions are all linear, the problem is called linear programming (LP) and the global optimal point is easy to be found. Simplex algorithm is one of the most popular LP algorithms. Since the LP problem having a solution must have an optimal value that falls on the boundary of the feasible region, the algorithm starts with a given initial solution and moves to the neighboring vertex that best improve the objective function value. These movements are performed until obtaining the optimal point.

When the optimization problem is convex, global optimal solution is equal to local optimal point. LP problem is a special kind convex optimization problem. Different methods can be used to find the global optimal point. For the unconstrained convex problem, gradient and Newton's method are the known ones. Gradient method (also called gradient ascent method) moves from an initial feasible point towards the optimal value by updating
iteratively the current optimization variables' values in the direction of the gradient. Although the gradient method is simple and it guarantees locating the optimal point (if exists), it has slow convergence. Newton’s method normally converges faster than the gradient method but it requires computing the Hessian of the objective function. Newton’s method is used to find the roots of the equation in one or more dimensions by approximating the objective function at a given point by a quadratic function and takes a step towards the maximum of that quadratic function.

In a constrained convex optimization problems, projected gradient algorithm, interior point method, and ellipsoid method can be applied. In projected gradient algorithm, the search direction is projected into the subspace tangent to the active constraints. Ellipsoid method generates a sequence of ellipses inside the feasible set whose volumes decreases at each iteration to enclose the maximum of the convex function. Ellipsoid method is used in low-dimensional problem due its poor performance in large ones. Interior point method is a search algorithm that adds a penalty to the objective function when the search point approaches the boundary of the feasible set.

If the objective function or some of the constraints are non-linear, the optimization problem is called non-linear programming (NLP) problem. Interior point method, simulated annealing and genetic algorithm are widely employed to perform the global optimization in NLP [12]. The name of simulated annealing is inspired from the annealing process in metallurgy which consists of heating and control cooling of a material increase the size of the crystals. In simulated annealing, the current solution is replaced by a new nearby random solution generated according to pre-defined distribution.

3.2.2 Mathematical Programming

In mathematics, the optimization problem is expressed as:

given: a function \( f: A \to R \) from a certain set \( A \) to the real numbers
sought: an element $x_0$ in $A$ such that $f(x_0) \leq f(x), \forall x \in A$ (minimization) or such that $f(x_0) \geq f(x) \forall x \in A$ (maximization)

Typically, $A$ is a certain subset of Euclidean space $R^n$, often specified by a set of constraints, equalities and inequalities that the members of $A$ have to satisfy. The elements of $A$ are called feasible solutions. The function $f$ is called an objective function, or cost function. A feasible solution that maximizes or minimizes the objective function is called an optimal solution. The domain $A$ of $f$ is called the search space, and the elements of $A$ are called feasible solutions. This formulation of optimization problem is also called as mathematical programming.

**Linear Programming**

Problems where objective function $f$ is linear and the set $A$ is specified using only linear inequalities, are well-formulated by linear programming techniques. This method is widely used in improving network performance of different users using the same radio resources.

- **Convex Programming:** When the constraints and the optimization goals are convex or linear, convex programming is useful.
- **Nonlinear Programming:** Nonlinear programming studies the general case in which the objective function or the constraints or both contain nonlinear parts.
- **Dynamic Programming:** In some situations, the optimization strategy is based on splitting the problem into smaller sub-problems or considers the optimization problems over time.

**3.2.3 Integer/Combinatorial Optimization**

When the value of any of the optimization variables is restricted to be integer, the problem is called integer programming problem. In this category of problems, there are no optimality conditions that can be checked to declare that a given feasible solution is optimal. Relaxation and decomposition method is one of the ways of solving the integer programming problems.
this method, the complicated constraints are removed from the constraints set by forming a new suboptimal problem that is easier to solve. The suboptimal problem is solved repetitively until the optimal value is found [131]. The branch-and-bound method is another technique to solve the integer programming problems. This method tries to avoid the enumeration of all the possible solutions of the problem by eliminating the unfeasible or dominated solutions. The branching is used to cover the feasible region by smaller sub-regions while the bounding is used to exclude the solutions dominated by previous computations.

Combinatorial optimization problems are the problems of choosing the best combination out of all possible combinations. Most combinatorial problems are formulated as integer problems. In wireless networking and resource allocation, integer/combinatorial problems are analyzed with the efficient allocation of the limited resources to meet the desired objectives. In this case some of the variables are restricted to be integral. Constraints on basic resources such as modulation, channel allocation, and coding rate restrict the possible alternatives that are considered feasible. For example, in 3G cellular networks, discrete processing gains of different codes give users different bandwidths for transmission. Allocation of different time-slots to different users in WLAN and allocation of distinct time-frequency slots to the admitted users can be well solved by integer programming. Thus, integer programming is more often used in wireless industrial applications.

### 3.2.4 Genetic Algorithms

Genetic algorithms are class of evolutionary algorithms inspired by the evolution biology. It starts by constructing a population of a group of random candidate solution (called individuals). The fitness of this population is evaluated and multiple individuals are selected based on their fitness and modified to form a new population. The process is repeated until the terminating condition is met.
3.2.5 Game Theory

Recent advancements in the technology have led to a persistent need for novel analytical frameworks that can be suited to tackle the variety of technical challenges accompanying the present and next generation wireless challenges. As a result, in recent years game theory has been emerged as an important tool for the design of communication networks.

In communication networks scenario, multiple users share common resources such as power, bandwidth, time, and space. Future wireless networks needs to incorporate decision-making rules and techniques so as to operate efficiently and meet the user's need in terms of communication services (e.g. ubiquitous internet access, heterogeneous networks, video streaming over mobile networks etc). Conventional approaches of radio resource sharing are based on static network environment. In dynamic network environment, users have different requirements and goals. Hence, this cognitive interaction process can be well-modeled and analyzed by game theory.

Game theory was first introduced by J. V. Neumann and O. Morgenstern in 1944. Game theory has been widely used as an analysis method in economics [28]. Along with economics and biology, game theory has been introduced used as a tool to design cognitive radio and adhoc networks. The specific areas of communication networks, where game-theoretic tools are used include power control, congestion control, networking and sensing.

3.3 Preliminaries of Game Theory

As technology of cognitive radios aim to utilize spectrum intelligently, users should be adaptive to the communication environment and accordingly adapt the operating parameters.

Traditional methods of resource management are moreover static in nature whereas in cognitive networks users employ cognition cycle. They have an ability to observe, learn and act to optimize performance. User mobility, time-varying nature of channels, and traffic variations continuously change the
Radio environment. Reallocation of resources is very difficult in traditional methods. As users are from different authorities and have different requirements and goals, they compete with each other. In this scenario, game theory can be effectively used.

The collaboration between the users can give the optimum solution by analyzing different strategies of individual users. This fact lead to development of cooperative game theory. J. Nash developed a new criterion, known as Nash Equilibrium (NE) [12] which determines the stability of game. Before Nash, Von Neumann and Morgenstern [12] defined the criterion which as specific to zero-sum games. Important concepts in game theory such as repeated games, Shapely value, etc. were developed during 1950. In 1960s, stability conditions were refined.

It can be seen that the SUs in CRNs sense the spectrum and take intelligent decisions on the use of spectrum and other parameters. Also, SUs may behave selfishly as there is no incentive to cooperate. Such type of selfish networks can be studied from game-theoretic perspective as discussed below:

Game structures can be used to model spectrum sharing and sensing between PUs and SUs. Game-theoretical principles can lead to solutions to this sharing games.

The optimality criteria is well exhibited in game theory. As seen before, spectrum sharing problem is very difficult to solve as many times it is a multi-objective optimization problem. There are different equilibrium criteria defined in the game theory for different situations.

In the case of distributed control, self-organized approach is necessary. Using local information, dynamic spectrum sharing can be performed. Concepts in non-cooperative game theory can be utilized to determine the optimal solution.
3.3.1 Components of Game Model

A strategic-form game model is denoted by where,

\[ S \] is a finite set of players;
\[ A_i \] is a set of actions for each player \( i \);
\[ u \] is a payoff/utility function and \( \rho \), which measures the outcome for player \( i \) determined by the actions of all players.

CR can have variable power levels and rates, variety of channel and source coding parameters etc. These are mapped as components of the action space in a CR game.

Utility function for each player is provided by cognitive radio’s goal and the arguments. Valuations for utility functions are taken from the outputs of cognitive radios observation and orientation steps. Each cognitive users goals and performance metrics are the components of utility function. As CR adapts the transmission environment, utility function is updated.

Figure 3.1 shows an illustration of how different components in the cognitive radio cycle can be mapped in to game. Utility function assigns a numerical value to each possible outcome. If the utilities are higher, function is more desirable. In wireless scenario, players may prefer outcomes that give lower bit error rates, higher signal to noise ratio (SNR), and lower power consumption. But in real environment, these goals will be in conflict.

![Fig. 3.1 Components of Cognitive Game](image-url)
One of the most challenging aspects of game theory is to model these preferences optimally. Game theory is more appropriate in the scenario where we can reasonably expect decisions of one player to impact decisions of other players.

### 3.3.2 Nash Equilibrium

Nash equilibrium (NE) is the most commonly used stable solution concept in game theory specifically applied in the non-cooperative game. In this case, each user tries to maximize his/her own benefit and selects the optimal strategy to maximize his/her utility function.

**Definition 3.1.** A Nash equilibrium of a strategic game \( \langle S, (A_i), (U_i) \rangle \) is a profile \( a^* \in A \) of actions such that for every player \( i \in N \) we have

\[
u_i(a^*_i, a^*_i) \geq u_i(a_i, a^*_i) \quad (3.2)\]

for all \( a_i \in A_i \), where \( a_i \) denotes the strategy of player \( i \) and \( a_{-i} \) denotes strategy of all players other than player \( i \).

Above definition shows that any player can't improve his/her utility by a unilateral decision that deviates from NE.

**Condition 3.1.** A strategic game \( \langle S, (A_i), (U_i) \rangle \) has a Nash equilibrium if, for all \( i \in S \), the action set \( A_i \) of player \( i \) is a nonempty compact convex subset of a Euclidian space, and the payoff function \( U_i \) is continuous and quasi-concave on \( A_i \).

In above definition, it is implicitly assumed that players only take certain specific strategies, called as pure strategies. Also, there may be the case where the players’ strategies are probabilistic. In such situation, Mixed Strategy Nash equilibrium concept is formulated to reach to stable solution.

### Uniqueness of Equilibrium

A unique equilibrium condition gives the optimum allocation and hence the performance of CRN is optimum. Optimally selecting design parameters of the game, it is possible to predict and define behavior of PUs/SUs to enable
spectrum sharing at the equilibrium. Uniqueness of NE holds only for certain cases. For example, in the case of strictly convex nature of utility function, there exists a unique equilibrium.

The NE work outs the best strategy such that all the other players also stick to their equilibrium strategy. It is a challenging task to determine the NE in case of distributed systems. The players may use their observations and adjust their strategies iteratively till convergence is achieved. If the game has certain structure, for example potential games, convergence of NE is achieved.

**Definition 3.2.** A game \( (S, (A_i), (U_i)) \) is a potential game if there is a potential function \( P: A \rightarrow R \) such that one of the following conditions holds. The game is an exact potential game if the first condition holds, and an ordinal potential game if the second condition holds.

1. \( P(a_i, a_{-i}) - P(a'_i, a_i) = U_i(a_i, a_{-i}) - U_i(a'_i, a_{-i}) \) for any \( i \in S, a \in A, \) and \( a'_i \in A_i \)
2. \( \text{sgn}(P(a_i, a_{-i}) - P(a'_i, a_i)) = \text{sgn}(U_i(a_i, a_{-i}) - U_i(a'_i, a_{-i})) \) for any \( i \in S, a \in A, \) and \( a'_i \in A_i \) where \( \text{sgn}(.) \) is the sign function.

From above it is clear that if all players take better strategies, game will lead to an NE that maximizes the potential function. This is because any player who chooses better strategy, given current strategy of all other players, steps towards improvement in value of potential function.

### 3.3.3 Pareto Optimality

In case of more than one equilibrium in the game, it is necessary to observe their performance and decide optimal equilibrium. If the players have conflicting interests with each other, increase in one player's pay-off may decrease other's. This condition makes it difficult to attain optimality.

Weighted sum of individual pay-offs can be compared to in order to define the optimality. This converts multi-objective problem to single-objective one. More appropriate solution is to define Pareto optimality. It is a payoff profile
that no strategy can make at least one player better off without making any other player worse off.

### 3.3.4 Correlated Equilibrium

In this case, players can observe the public signal and select their strategies accordingly. All players adopt recommendations and no player would deviate from the recommended strategy, game has attained correlated equilibrium.

### 3.4 Different Game Models

Different game models used in wireless communication are discussed below.

#### 3.4.1 Standard Function

Cellular networks used Standard Function for power control [133]. Increased transmitted power increases interference and harms to other users. Also selfish users try to pursue high utility by increasing their transmitted power. Therefore, conventional power control can be defined as a non-cooperative power control game (NPG).

NPG has a unique equilibrium, if best response strategy is a standard function of variable that represents the user’s action [124]. In [125] cooperative cognitive CRN is considered where SUs serve as cooperative relays for the PUs. This gives opportunity to SUs to access the wireless channel. The achievable rate minus payment defines utility of SUs. Users maximize this utility by appropriately selecting price.

#### 3.4.2 Pricing Game Model

Pricing is introduced to improve the efficiency of the NE of non-cooperative games in CRNs as selfish network users will be guided to a more efficient operating point [136].

Pricing can be viewed as the cost of the resources a SU receives, or the cost of harm the this user imposes on other users, in terms of performance degradation, revenue deduction, or interference. System efficiency reduces as
the selfish network users only optimize their own performance. In addition, their aggressive behavior degrades the performance or QoS of all the other users in the network.

Efficient pricing mechanism motivates selfish users to compete for the network resources more efficiently. This increases the benefits of all the users and also revenue of entire network is increased. For example, Linear pricing which increases monotonically with the transmit power of a user has been widely adopted.

In [126], joint power control and spectrum allocation is performed using a network-user hierarchy model that consists of spectrum manager, service provider and end users for dynamic spectrum leasing. End users trade off the achievable data rate and the spectrum cost through transmission power control while optimizing their payoff. Linear functions of spectrum access cost and transmission power are used to define a pricing term. This game can result in a efficient power control.

CRNs are maximized for revenue while ensuring incentive compatibility to users. Service provider charges each user a certain amount of payment for each unit of the transmitting power on the uplink channel in wide-band CRNs for revenue maximization, while ensuring incentive compatibility for the users.

In [127], authors further emphasize that most existing pricing techniques, for example, a linear pricing function with a fixed pricing factor for all users, can usually improve equilibrium by shifting it closer to the Pareto optimal point. However, they may not be (Pareto) optimal, and not suitable for distributed implementation, since they require global information. Hence, a user-dependent linear pricing function that drives the NE close to the Pareto optimal point is proposed [128], through analysis of the Karush–Kuhn–Tucker conditions. Proposed spectrum management can be implemented in a distributed way as optimal pricing factor for a link only depends on its neighborhood information,
Depending upon the specific game, more sophisticated nonlinear pricing function can also be designed. In an underlay spectrum sharing problem, SUs’ transmission is constrained by the interference temperature limit (ITL). In deriving the NE of a game, players are assumed to define their strategies independent of the others’. When they no longer do so, for instance, following the recommendation of a third party, efficiency of game outcome can be significantly improved.

### 3.4.3 Cooperative Games

In cooperative games, network users have an agreement on how to fairly and efficiently share the available spectrum resources. Two important classes of cooperative spectrum sharing games are bargaining games and coalitional games. Bargaining games are discussed below and coalitional games are presented in Chapter 4 in view of spectrum sensing.

**Bargaining Games**

In this game individual users have opportunity to reach to a mutually beneficial agreement. Approval of player for the game is mandatory in this game as individual players have conflicts of interest.

Though there are other models such as the strategic approach with a specified bargaining procedure, Nash’s axiomatic model has been widely applied to CRNs.

Bargaining games have been applied to CRNs where cooperation among players is possible and fairness is an important concern. Nash Bargaining Solution (NBS) is applied to allocate frequency-time slots in an efficient and fair way. Initially, payoffs with disagreement are determined. The symmetry axiom implies that all players are equal in the bargaining game; this condition may not be true in case of prioritized users.

For example, in power allocation game consisting of PUs and SUs [126], different values of utility functions are set to PUs and SUs because PUs have the priority to use spectrum resources in CRNs. Heterogeneous wireless
users, the disagreement point in the NBS objective function is replaced by the threat made by individual players.

Finding NBS needs global information which is not always available. A distributed implementation is proposed in [130] where users adapt their spectrum assignment to approximate the optimal assignment through bargaining within local groups. It belongs to category of the NBS, because objective is to maximize the total user throughput which is equivalent to maximizing the product of user payoffs. Neighboring players adjust spectrum band assignment for better system performance through one-to-one or one-to-many bargaining. In addition, a theoretic lower bound is derived to guide the bargaining process.

Power allocation with similar approach is done in [130] where power allocation strategy is iteratively updated using only local information. In this game, players allocate power to channels and their payoffs are the corresponding capacity.

Each player sequentially adjusts the strategy, and it is proved that the iterative process is convergent. Although it is not sure whether it converges to the NBS, it is demonstrated that the convergence point is closer to the true NBS.

The concept of the NBS can also be applied to games without explicit bargaining. For example, the NBS is used to find how to split payment among several users in a cognitive spectrum auction in, where auctioneer directly set the NBS as price to each player, and they will be ready to accept because the NBS is an equilibrium.

3.4.4 Stochastic Games

In the games discussed so far the players are assumed to have the constant game stage i.e. game and the players’ strategies does not depend on the current state of the network. This situation is not true in a cognitive radio network where the spectrum opportunities and the surrounding radio
environment keep changing over time. The different game-theoretic models can be summarized in Fig. 3.2

![Fig. 3.2 Summary of Game-theoretic Models](image)

Stochastic games are more appropriate, in order to study the cooperation and competition behaviors of cognitive users in a dynamic environment. A stochastic game is an extension of Markov Decision Process (MDP) [132] by considering the interactive competition among different agents.

From the literature it can be observed that game theory has been widely adopted for CRNs by designing the strategies of PUs and SUs. Still there are many research challenges that require to be addressed.

**Defining a proper Utility/Pay-off Function**

Utility function indicates objective that a player wants to achieve at the end of the game. For games in CRNs, different utility functions have been chosen for different problem settings: utility function in auction games or spectrum trading, is mostly defined as net profit, i.e. gain from using spectrum minus cost of holding spectrum band. Also, they may not be directly related to spectrum trading. Widely used adopted utility function is usually a simple (often concave) function containing one or more QoS metrics, such as throughput/rates/capacity, delay, or error probability.

Review reflects that a lot of real-world constraints and situations are largely ignored while choosing a simple utility function. For instance, many
researchers have chosen the cost term in the utility function as a linear function of the transmit power. However, the cost of the transmit power may depend on the specific device/user and the remaining power level. It is probably not linear for transmit power. Even a linear function can roughly capture the cost, if the gain term (e.g., a function of some QoS metric) in the utility function is in another unit rather than power unit, how to choose the weight of the linear function to balance the gain and the cost still remains a problem. Therefore, it is important to choose a meaningful utility function that can precisely characterize players’ objectives.

3.5 Resource Allocation using Game Theory

With the growing demand for wireless services of higher QoS (data rate, latency, coverage, etc), the need for more efficient schemes to provide better utilization of the limited available resources such as spectrum becomes inevitable. The wireless service providers need to support the large number of users with flexibility in their QoS requirements. During the network planning stage, operators decide the number and locations of network devices such as BS and relays to be deployed based on the demand of users’, transmission environment and other factors. How to utilize the radio resources in the most effective and efficient way is one of the most important objectives of Radio Resource Management (RRM). The effectiveness is to provide the user the satisfactory quality of service and the efficiency to increase the revenue of the network service providers.

Spectrum Sharing Schemes

Spectrum sharing schemes are classified as open spectrum sharing and licensed spectrum sharing. Unlicensed spectrum bands is referred to as open spectrum sharing while spectrum sharing among the SUs and PUs in licensed spectrum bands is referred to as licensed spectrum sharing. Figure 3.3 shows model for spectrum sharing games. In cognitive radios, game-theoretic solutions can be used to solve spectrum sharing in unlicensed band and licensed band.
Spectrum allocation can be based on two independent approaches; Centralized and Distributed. In a centralized approach, a central controller is aware of the channel conditions and transmission parameters of SU. In the fast fading environment and specifically in the ad-hoc networks, it is difficult to implement a centralized system. Distributed approach doesn't require knowledge of channel state information of PU.

In [126], a joint power control and admission control was proposed such that the priority of PU should be maintained. Beamforming strategy is used in [30] to solve a problem of resource allocation. A number of distributed resource allocation strategies have been proposed in the literature. In [34], a potential game model of joint channel selection and power allocation is formulated. It is shown that the distributed sequential play converges to a Nash Equilibrium point and quickly satisfy the interference constraint. Game theoretic Max-Logit Learning Approaches are used for Joint base station selection and resource allocation. The exact potential game is proposed to maximize the throughput.

Some of the previous works try to resolve the resource allocation challenge using game theory. As discussed in [133], the spectrum allocation is addressed by both cooperative and non-cooperative approaches. The following describes examples of works for both cooperative and non-

Fig. 3.3 Model of Spectrum Sharing Games
cooperative game approaches. First, non-cooperative approach is investigated where players play the game independently. A single strategy can be chosen for all players or each player chooses its own strategy. The objective is to maximize the overall utility function of all players. In [134], authors propose a decentralized approach where each radio estimates the spectrum conditions based on its history, and choose the allocation that maximizes his/her utility in a non-cooperative game. They demonstrate that the proposed model converges after a number of iterations.

On the other hand, cooperative approach is investigated in [135] where players can form coalitions or sub-groups in order to maximize their profits. Two models are based on cooperative game theory. The first one, proposes an allocation of multiple available channels to single SU. The proposed model minimizes the conflicts due to the allocation of each user and maximizes the overall allocation of all users. The second model allocates only one channel to each SU. For that purpose, the availability of channels and their signal energy are used as reward functions in this model. Both models try to achieve Nash equilibrium using a cooperative game model while maximizing the overall allocation of all users.

Authors in [136] propose to use a cooperative approach in spectrum sensing and wonder on how to collaborate. For that purpose, they propose an evolutionary framework based on evolutionary game theory. The idea is that users should find the best cooperation strategy by learning on strategies interaction between users and pay-off history of each user. On the other hand, there are benefits of cooperation and a cooperative model can be used for overlay approach and underlay approach. A comparison is made between cooperation in the overlay approach and the underlay approach which is not a cooperative approach and conclude that the overlay approach is better than the underlay approach in terms of SINR, outage and interference temperature. The proposed model used a potential game.
3.6 Resource Allocation for Multimedia Applications

In CRN, spectrum efficiency is improved significantly by allowing unlicensed SUs to opportunistically obtain spectrum resources from licensed PUs, and thus can effectively reduce increasing pressure on network due to the rapid growth of wireless multimedia services. To provide both spectrum utilization and fairness, cooperative local bargaining is proposed by Cao and Zheng [37]. Minimum spectrum allocation to each user is assigned by using local bargaining concept. Reinforcement-learning-based spectrum-sharing scheme is used by Jiang et al. [38] to increase efficiency of rate allocation. CR users can learn through interactions and assess the success level of a particular action. Zheng and Cao [39], considered non cooperative intra-network spectrum sharing. An opportunistic spectrum management scheme is proposed where users allocate channels based on their observations of interference patterns and neighbors.

Dynamic game model between multiple PUs in CRNs can be used. PUs using Bertrand model game each other and then achieve the best price ultimately. In literature [137], authors present secondary users utility function and compete for bandwidth through non-cooperative game. Utility function [138] is defined in terms of system throughput and achieves the maximum system throughput ultimately through price and spectrum competition. Method of joint power and rate control mechanism is proposed in [139]. Based on the control of secondary users transmit rate, the method limits their power reasonable to reduce interference on the primary user. Power interference threshold of secondary users is set. Within allowable interference range, the secondary users game mutually, such that the final utility function is maximum.

Authors in [140], propose method based on microeconomics. It introduces layering the users according to different service, and then allocates the spectrum dynamically on the basis of different hierarchy. Sub-layer users can perceive upper levels users spectrum, and sharing bandwidth with them. This
method not only ensures the upper levels’ traffic needs, but also improves the spectrum efficiency. Different methods and strategies discussed above do not explicitly consider the secondary user's traffic characteristics. Video services such as video conferencing, Internet TV, etc gradually increase. Compared to traditional data services, these video services are significantly different, such as that video service need consider the delay sensitive, user’s subjective visual experience and so on. So the video traffic cannot simply use the conventional method of data service to allocate the bandwidth.

Cross-layer optimization strategies have been proposed as a solution for improving the performance of video over wireless applications. Since video over cognitive networks require seamless communication in the dynamic spectrum access environment, game-theoretic techniques are more suitable for the spectrum allocation.

3.7 Discussion

This chapter emphasized on different optimization methods used for the resource allocation. Basic concepts of constrained optimization, mathematical programming, integer/combinatorial optimization, genetic programming and game theory are introduced. From review, it is understood that game theory can is an effective tool to handle the problem of resource allocation in multimedia applications. Detail overview of game theory is undertaken. We classified game-theoretic research contributions as cooperative and non-cooperative spectrum sharing, spectrum trading and mechanism design, and stochastic spectrum sharing games. For each class, fundamental concepts and properties and their applications in CRN are discussed.

The study shows that there is a large scope to develop more efficient utility functions to improve the performance of CRN specially for multimedia applications. It is observed that parameters of multimedia data are not introduced significantly in the utility functions developed so far.