Chapter 4

Game-Theoretic Models for Vehicular Networks

Dusit Niyato, Ekram Hossain, and Mahbub Hassan

Contents

4.1 Introduction

An intelligent transportation system (ITS) integrates information, computer, and telecommunication technology to enhance the safety, efficiency, and pleasantness of road transportation. ITS applications include both safety-related (e.g., emergency message communication) and non-safety-related (e.g., road traffic condition, pollution monitoring, remote vehicle diagnostics, and infotainment) applications. These applications can be supported through vehicle-to-infrastructure (V2I) and/or vehicle-to-vehicle (V2V) communications based on different wireless technologies. In a V2I communication scenario, the onboard unit (OBU) in a vehicle communicates with the infrastructure (i.e., roadside base station or RBS). In a V2V communication scenario, OBUs in the vehicles communicate with each other directly. Also, V2I and V2V communications can be integrated to improve the efficiency and flexibility of data transmission in a vehicular networking environment. Different wireless technologies such as the 3G cellular wireless, mobile broadband wireless access (MBWA), wireless local area network (WLAN), and dedicated short-range communication (DSRC) technologies can be used in a vehicular network. Wireless access protocols for these different technologies, however, need to be optimized for a vehicular network considering its unique characteristics (e.g., high mobility of vehicle) and specific quality of service (QoS) requirements of ITS applications.

For wireless access by OBUs, many conflicting situations arise in a vehicular network. For example, several OBUs may competitively access the radio channel to connect to an RBS. The OBUs are generally rational to maximize their own benefits. However, the benefit of one OBU depends not only on its own action (i.e., strategy) but also on the actions of other OBUs. Game theory is a set of mathematical tools used to analyze the conflicting situations involving multiple agents (i.e., players). The players are rational (or of self-interest) to strategically maximize their own benefits (i.e., payoffs). The players decide to perform actions according to their received payoffs. The payoff of one player is a function of its own action and the actions of other players. To obtain the optimal strategy of each OBU in a vehicular wireless access environment, noncooperative game theory can therefore be applied. Besides, there are situations where the vehicles may cooperate with each other for information sharing through V2V communications. Cooperative game models can be used to model such V2V communication scenarios and obtain the optimal wireless access methods for the OBUs. In this chapter, we present several game-theoretic models that can be used as a basis to design optimal wireless access methods for V2I and/or V2V communications in a vehicular networking environment. For each game model, the motivation, system model, formulation, and some selected numerical examples are presented. At the beginning, we provide an overview of the different ITS applications that can be supported by vehicular networks and the basics of V2I and V2V communications. A brief introduction to the different game models considered here followed by the different conflicting situations, which are modeled by these games, is then presented.

The rest of this chapter is organized as follows: Section 4.2 presents an overview of the different ITS applications and V2I/V2V communications scenarios in vehicular networks. Section 4.3 introduces several game models and the different conflicting situations that can be modeled by using these games. A noncooperative game model is presented in Section 4.4 for truthful dissemination of road traffic information by OBUs in a V2V communications scenario. For V2I communications, a game model is presented in Section 4.5 for bandwidth auction among OBUs at an RBS. A stochastic game model for competitive wireless access for streaming data through V2I communications is presented in Section 4.6. A game model is presented in Section 4.7 for transmission rate control of traffic sources to the mobile routers (i.e., vehicles) for delay-tolerant vehicular telematic applications using V2I communications. Again, for a V2V scenario, a bargaining game model is discussed in Section 4.8 for peer-to-peer (P2P)-based data transfer. For applications involving both V2V and V2I communications, a hierarchical game model is presented in Section 4.9 where the vehicles form clusters and the limited radio bandwidth is shared among the vehicles in a heterogeneous wireless access environment. Extensions of these game models are discussed in Section 4.10. Finally, Section 4.11 concludes the chapter.

4.2 ITS Applications and Vehicular Networks

4.2.1 ITS Applications

Vehicular networks support data transfer among moving vehicles and fixed infrastructure for various ITS applications as follows:

- *Public safety applications:* These ITS applications aim to increase the safety in transportation systems, for example, to reduce the number of vehicle collisions and accidents. The collision warning system [1–4] can avoid vehicle crashes. For example, a vehicle detecting obstacle on the road can broadcast this information to other vehicles so that drivers can react properly and timely.
- *Traffic management applications:* These applications aim to improve the traffic flow on the roads, which can reduce the travel time, congestion, transportation cost, and accident. A vehicle or an RBS can monitor the local traffic conditions. This information is then passed to other vehicles so that the optimal route can be chosen to minimize the travel time [5,6]. Also, traffic lights can be scheduled according to the traffic load condition to minimize congestion.
- *Driver support applications:* These applications aim to provide useful information including traffic, road, and weather condition to the drivers [7]. Drivers can retrieve these information from the RBSs. The road conditions (e.g., water on the road, repairing bridge, or bumps) can

also be proactively reported to the drivers in advance. This type of application is referred to as vehicular telematics applications [8,9]. Also, they include applications to collect highway tolls and parking payments automatically. In other applications, the repair and maintenance data can be collected and remotely reported to the vehicle service centers.

- *Infotainment applications:* These applications aim to enhance the pleasantness of the road journey for passengers. Voice and instant messaging can be communicated among moving vehicles. Web access, video, and multimedia streaming can be provided through the RBSs [10,11].

4.2.2 Communication Scenarios in Vehicular Networks

Different types of communication scenarios, namely, V2I, V2V, and hybrid communications, can be identified in vehicular networks to support different types of ITS applications (Figure 4.1). In V2I communications, data are transferred between vehicles and fixed infrastructure (e.g., RBS or gateway), which is connected to the public network (e.g., Internet). Alternatively, the vehicles can communicate with each other directly. This is referred to as V2V communications. V2V communications can involve either single-hop or multihop transmissions. In single-top communication, the OBU in a vehicle transmits data directly to the other vehicles. On the other hand, in multihop communication, data from the source vehicle can be relayed by other vehicles to the destination. In a hybrid scenario, V2V and V2I communications are integrated (Figure 4.2). In one such scenario, data from a vehicle are transmitted to an RBS. Then, the RBS relays these data to the destination vehicle [12]. This is referred to as infrastructure-based relay approach. In another scenario, data from the source vehicle are relayed through multiple vehicles to the infrastructure (i.e., RBS) [13]. This is referred to as vehicle-to-vehicle-to-infrastructure (V2V2I) [14] or vehicle-based relay approach.

Two major communication scenarios in vehicular networks, that is, V2I and V2V scenarios, are discussed next.

4.2.3 Vehicle-to-Infrastructure Communications

In V2I communications, vehicles transmit and/or receive data from the infrastructure (i.e., RBS, access point, or gateway). For traffic management and driver support applications, a vehicle can monitor the road and traffic condition, and then report the information to the ITS servers residing in the external network connected with the RBS. Also, a vehicle can download the road and traffic

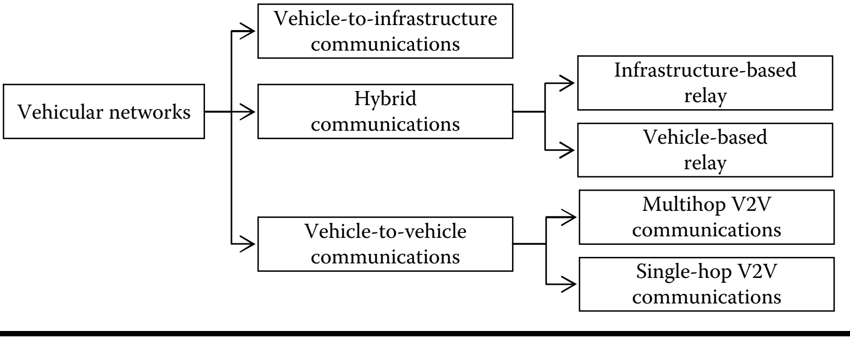


Figure 4.1 Communication scenarios in vehicular networks.

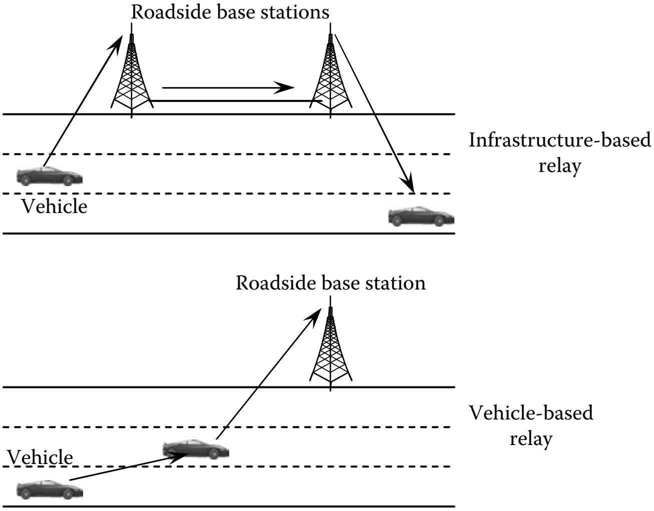


Figure 4.2 Infrastructure-based and vehicle-based relay communications in a vehicular network.

information from the ITS servers via roadside access point. V2I communication can also be used for infotainment applications. Passengers can access Internet and download video and multimedia streaming data during the journey.

V2I communications can be based on the traditional cellular wireless technology [15] and/or mobile broadband wireless access (MBWA) such as IEEE 802.16e technology [16]. For short-range V2I communications (e.g., from a vehicle to an RSB installed in traffic light post), IEEE 802.11 WLAN technology can also be used [17]. A feasibility study and comparison between using IEEE 802.16 and IEEE 802.11 technologies for V2I communications were presented in Chou et al. [18]. It was observed that although IEEE 802.16 can provide larger coverage for wireless access, the delay could be higher due to the complicated network structure and access protocol.

However, since the IEEE 802.11 standard was not designed for high mobility wireless access environment, it lacks of the proper mobility management functionalities. Therefore, DSRC standard/IEEE 802.11p has been introduced specifically for vehicular networks, which has similar physical and medium access control (MAC) layer specifications as the IEEE 802.11 [19]. An experimental study on using IEEE 802.11p for V2I communications was presented in Xiang et al. [20]. DSRC can be used in many ITS applications such as for transferring real-time safety-critical data [21], exchanging logistic information [22], and performing traffic control [23,24]. In Jonsson and Bohm [25], a collision-free MAC mechanism was introduced as an enhancement to the IEEE 802.11p standard for safety-critical and real-time V2I communications. To ensure that the delay-sensitive data are transmitted before deadline, a prioritization mechanism based on the vehicle's position and road traffic intensity was presented. With this protocol, the QoS requirements for the application can be met, while at the same time, the network throughput can be improved. In Jhang and Liao [26], the IEEE 802.11 DCF (distributed coordination function) protocol was enhanced for V2I communications to support collaborative and opportunistic data forwarding between vehicles. A new transmission technique based on cooperative diversity was applied in Ilhan et al. [27] for V2I communications to gain higher transmission rate.

Wireless access by the vehicles in a V2I communication scenario depends on the bandwidth demand of the vehicles, the availability of the bandwidth at the corresponding RBSs, locations of the vehicles, and vehicle mobility. The limited available bandwidth of the V2I link to an RBS needs to be shared among multiple vehicles. The bandwidth demand of a vehicle can be determined from the application's QoS requirement and the mobility of the vehicle. For example, for infotainment type of applications, a vehicle can download data in advance (i.e., pre-fetch) when wireless connectivity is available to RBSs to avoid service outage due to buffer underrun effect while the vehicle is on the road. The bandwidth sharing becomes a challenging issue when each vehicle has self-interest to maximize its own benefit. In a competitive wireless access environment, each of the vehicles will compete to obtain as much bandwidth as possible to meet its communication requirement in a short period of time (e.g., due to fast mobility). Game theory can be applied to analyze competitions among vehicles.

4.2.4 Vehicle-to-Vehicle Communications

In V2V communication scenarios, vehicles transmit data to each other directly without the use of any infrastructure. Due to direct transmission, the communication delay is much smaller than that for V2I communications. Therefore, V2V communication is suitable for real-time ITS applications such as collision warning and avoidance applications. For traffic management and driver support applications, road traffic information can be forwarded to the far-away vehicles to avoid congestion and to let the drivers be prepared for the road and weather conditions. For infotainment applications, voice and video conferences among users in moving vehicles can be supported using V2V communications [28]. Also, P2P applications such as file exchange/sharing can be supported in vehicular environment through V2V communications [29].

V2V communications form the basis of a vehicular ad hoc network (VANET), which is a special class of mobile ad hoc network (MANET) [30]. The mobility of vehicular nodes in a VANET is based on vehicle movements [31] rather than the random way point mobility model as adopted for many MANETs [32]. For V2V communications in a VANET, the specific requirements of ITS applications have to be taken into account.

DSRC can be used for V2V communications. In Kukshya and Krishnan [33] an experimental study was conducted to measure the performance of this protocol. In a multihop V2V communication scenario, routing is important for relaying data over multiple vehicles from source to destination. In Chen et al. [34] a routing protocol was proposed, which takes the driving information of the vehicles into account. For data forwarding, the routing metric combines hop count with vehicle speed, which results in smaller delay. In Kwon et al. [35] an on-demand unicast routing protocol was proposed. This protocol is composed of route search, establishment, and maintenance mechanisms optimized to achieve the best performance in terms of reachability while minimizing the signaling overhead.

Note that a comprehensive survey on inter-vehicle communication protocols and related ITS applications specifically based on V2V communications can be found in Willke et al. [36].

4.3 Game Theory for Designing Vehicular Networking Protocols

4.3.1 Game Models

The following game models can be used to model and analyze different conflicting situations in a vehicular network.

- *Noncooperative game:* In a noncooperative game [37], the players make decisions and perform actions independently to maximize their own payoffs. In general, a noncooperative game model is described by a set of players, a set of actions for each player, and the corresponding payoff, which is a function of actions of all players. A noncooperative game can be played by the players with either complete or incomplete information. In a complete information game, each player knows the available actions and preferences (i.e., *types*) of all other players. On the other hand, in an incomplete information game, each player knows only the probability distribution of the *type* of other players [37]. A player can decide and perform its action deterministically or randomly. The former is referred to as a pure strategy in which one specific action is chosen. The latter is referred to as a mixed strategy in which the probability distribution of all available actions is determined. For a noncooperative game, Nash equilibrium is one of the most widely used solutions. This Nash equilibrium ensures that none of players will change its action to achieve a better payoff given that all other players stick to using their Nash equilibrium actions. In short, at the Nash equilibrium, none of the players has any motivation to deviate.
- *Stochastic game:* Similar to a noncooperative game, in a stochastic game [38], players are noncooperative and they select actions such that their payoffs are maximized. However, in a stochastic game, the players are characterized by their states (e.g., payoff of a player is a function of its state and action). The state transitions are random and may possess the Markov property. Therefore, each player optimizes its policy (i.e., mapping of local state to the action) given the policies of other players. The solution of a stochastic game is generally referred to as constrained Nash equilibrium.
- *Evolutionary game:* An evolutionary game models the decision-making process of a population (i.e., group) of players [39]. Unlike a noncooperative game, in an evolutionary game, these players possess the property of bounded rationality in which the rationality of a player is limited by the available information. Therefore, a player may not be able to make decision to maximize its payoff directly. Alternatively, a player will evolve over time by gradually adjusting its action so that the payoff is maximized. The typical solution of an evolutionary game is the evolutionary equilibrium. At this equilibrium, the population stops evolving.
- *Cooperative game:* Players in a game can cooperate to achieve better payoffs compared to that with noncooperation. If the players are cooperative, a cooperative game model can be used to obtain an efficient and fair solution for all players. The most common type of cooperative game is the bargaining game [40] in which the players can negotiate on the solution. The most popular solution concept for a bargaining game is the Nash bargaining solution (NBS) which provides both fairness and efficiency (due to Pareto optimality). Two other solution concepts are Kalai-Smorodinsky solution (KSS) and Egalitarian solution (ES) [41].

4.3.2 Conflicts in Vehicular Networks

In a vehicular network, different entities (e.g., vehicles and roadside base stations) have different objectives that could be conflicting with each other. A few examples of these conflicting situations are provided in the following.

- *Broadcasting true road traffic information:* Road traffic information can be exchanged among vehicles so that they can choose their optimal routes to the destination. However, a selfish vehicle can minimize its travel time by propagating false traffic information. If other vehicles believe this false information, they will deviate from using the same route as that of the selfish vehicle. A conflicting situation arises here between the selfish and the non-selfish vehicles. A selfish vehicle has to decide whether it should broadcast true traffic information or not, and a regular vehicle should decide whether it should trust the received traffic information or not. A noncooperative game can be formulated to obtain the Nash equilibrium strategies for the vehicles [42].

- *Bandwidth allocation among vehicles by the RBS:* RBSs are typically deployed at selected locations (e.g., bus stops or traffic lights) to provide wireless access to the passengers in the vehicles (e.g., buses). When a vehicle moves into the coverage area of an RBS, the vehicles/users download and cache data. When the vehicle moves out of the coverage area of the RBS, the cached data is used by the users, for example, to playout streaming data. When there are multiple vehicles connected to an RBS, the OBUs in these vehicles compete for bandwidth to download data from the RBS. An auction mechanism can be used for bandwidth allocation by the RBS among vehicles. A competitive bidding strategy has to be determined for each vehicle (i.e., OBU) so that its utility is maximized. This situation can be analyzed by using a noncooperative game model for which the Nash equilibrium can be obtained as the solution of the bidding prices of the OBUs [43].
- *Location-aware wireless access for data streaming:* Vehicular users with streaming applications (e.g., infotainment applications) download and cache data from RBSs deployed at the different locations. The network service provider (NSP) can adjust the price of wireless connectivity for vehicles based on the total demand at the different locations of the RBSs. Therefore, each vehicle has to determine the optimal location-aware wireless access policy such that the application QoS requirement (i.e., buffer underrun probability for a streaming application) is met while the cost of wireless connectivity is minimized. With the buffer state and location of each vehicle, a stochastic game model can be formulated to obtain the constrained Nash equilibrium for data downloading policy [44].
- *Data transfer from sources (e.g., telematic sensors) to mobile routers:* For delay-tolerant vehicular telematic applications, vehicles can be used as mobile routers to transfer data from the telematic sensors (i.e., data sources) to the destination (i.e., data sink) connected with the RBSs. However, due to the limited buffer space, a mobile router selectively receives data from different sources. Therefore, the sources have to compete with each other to upload data to the mobile routers. In this case, the sources can optimize their transmission rates such that their utility (which is a function of the end-to-end throughput and the cost of wireless connectivity) is maximized. A noncooperative game can be formulated to obtain the Nash equilibrium of transmission rates of data sources [45].
- *P2P data transfer in vehicular networks:* Peer-to-peer (P2P) file sharing protocols can be used in vehicular networks to transfer large amount of data among vehicles through V2V communications. In such a case, each vehicle has an objective to maximize the amount of data received from other vehicles within a limited connection time. To reach a fair and efficient solution of data exchange among moving vehicles, a bargaining game can be formulated [29].
- *V2I and V2V communications in cluster-based heterogeneous vehicular networks:* In a heterogeneous vehicular network, vehicular nodes (i.e., OBUs) can use different wireless technologies to communicate with the RBSs and other nodes. A vehicular node has to determine whether it should become a cluster head with a direct connection to RBS or become a cluster member and let the cluster head relay the data to the RBS or another vehicle (in the same cluster or in a different cluster). If the vehicular node chooses to become a cluster head, it has to determine the competitive price to be charged to its cluster members. On the other hand,

if the vehicular node chooses to become a cluster member, it has to select the cluster head to relay its data to the RBS or to another cluster. For cluster heads, a noncooperative game can be formulated and solved to obtain the Nash equilibrium price to be charged to the cluster members. For the cluster members, an evolutionary game can be formulated to obtain the equilibrium solution on cluster head selection [46].

In the following, the details of the game models will be presented, which have been developed to analyze the aforementioned conflicting situations.

4.4 Game-Theoretic Modeling of Selfish Behavior in Vehicular Networks

Vehicles can exchange road traffic information among each other to help the drivers to identify road congestion [47], obtain optimal driving route [48], and improve traffic safety [49]. This is known as cooperative driving. To support cooperative driving, the OBU in a vehicle collects and propagates collected local road traffic information (e.g., location and speed of vehicle) to other vehicles using V2V communications based on WiFi radio. However, since the vehicles want to reach the destination as fast as possible, the OBUs can be programmed to broadcast false information about road traffic (i.e., cheating). In [42], this selfish behavior of vehicles in broadcasting road traffic information was studied. A noncooperative game model was formulated and the Nash equilibrium of the game was obtained.

4.4.1 Selfish Behavior of an OBU to Maximize Its Utility

The objective of a selfish OBU is to maximize its own utility, which is defined as the average duration of journey on the road. Since this objective can be achieved by removing congestion on the road, the OBU can broadcast false information in the network. With falsified information about high congestion condition in a certain route, the other vehicles will refrain from taking the same route.

While a regular OBU (i.e., naive OBU) will collect road traffic information (e.g., from local measurement or from other OBUs) and send it to other OBUs, the selfish OBU will perform differently. First, a selfish OBU calculates the shortest path from the origin to the destination. Then, for any road that is not in the route of the selfish OBU, the true information will be broadcast. However, for all roads that are in the route of the selfish OBU and have not been traveled by this selfish vehicle yet, a high congestion condition will be broadcast.

Simulation results show that a selfish vehicle can achieve a smaller delay compared to that of a regular OBU using the same or a different route (Figure 4.3). Note that a selfish vehicle gains benefit from reporting false information only after the second round of journey. Since in the first round, the regular OBUs have not received the false information yet, they do not deviate from the old route as the selfish vehicle wants.

A noncooperative game can be formulated to obtain the equilibrium strategies for selfish vehicles and regular vehicles. In this game, the *players* are selfish OBUs and regular OBUs. A selfish OBU broadcasts the duration it takes to travel on a certain road. Since this duration information could be false, the selfish OBU randomly chooses the value between the thresholds T_{slf} and $T_{\max}$ from an inverse geometric distribution, where $T_{\max}$ is the maximum duration. This threshold can be chosen to be $T_{\mathrm{avg}} \leq T_{\mathrm{slf}} \leq T_{\max}$, where T_{avg} is the true average duration. The *payoff* of the selfish

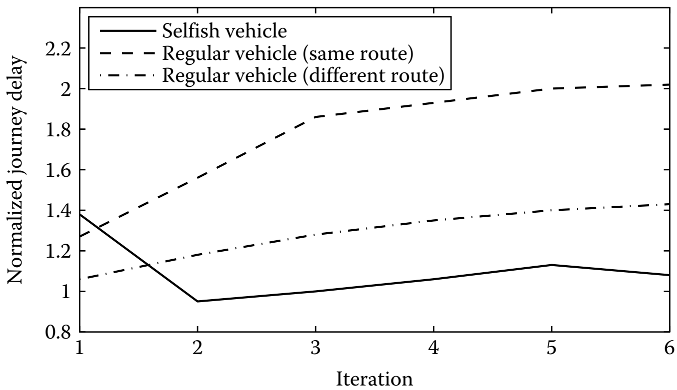


Figure 4.3 Normalized average delay for different vehicles.

OBU is the time duration of journey from origin to destination. Since the regular OBU knows that there could be false information in the network, it will ignore the received information if the broadcast information on duration of travel on a road is higher than the threshold T_{ign} for $T_{\text{avg}} \leq T_{\text{ign}} \leq T_{\text{max}}$. The *strategies* of the selfish and regular OBUs are the values of thresholds T_{slf} and T_{ign}, respectively.

If the duration information broadcast by the selfish OBU is higher than or equal to threshold T_{ign} of regular OBU, it will not gain any benefit, and its payoff is zero. In contrast, if it is lower than the threshold T_{ign}, the selfish OBU will gain a positive benefit. For a regular OBU, if the false duration broadcast by the selfish OBU is accepted, the payoff of a regular OBU will be negative. Otherwise, the regular OBU will gain positive benefit. Therefore, the payoffs of selfish and regular OBUs (i.e., U_{slf} and U_{reg}, respectively) can be defined as follows:

$$U_{\text{slf}}(T_{\text{slf}}, T_{\text{ign}}) = \begin{cases} 0, & T_{\text{slf}} \geq T_{\text{ign}} \\ T_{\text{slf}} - T_{\text{avg}} + 1, & T_{\text{slf}} < T_{\text{ign}} \end{cases} \tag{4.1}$$

$$U_{\text{reg}}(T_{\text{ign}}, T_{\text{slf}}) = \begin{cases} T_{\text{ign}} - T_{\text{avg}}, & T_{\text{slf}} \geq T_{\text{ign}} \\ T_{\text{slf}} - T_{\text{ign}}, & T_{\text{slf}} < T_{\text{ign}}. \end{cases} \tag{4.2}$$

The Nash equilibrium for selfish and regular OBUs is defined, respectively, by T^*_{slf} and T^*_{ign}, where $U_{\text{slf}}\left(T^*_{\text{slf}}, T^*_{\text{ign}}\right) \geq U_{\text{slf}}\left(T_{\text{slf}}, T^*_{\text{ign}}\right)$ and $U_{\text{reg}}\left(T^*_{\text{ign}}, T^*_{\text{slf}}\right) \geq U_{\text{reg}}\left(T_{\text{ign}}, T^*_{\text{slf}}\right)$. This Nash equilibrium is found to be $\left(T^*_{\text{slf}}, T^*_{\text{ign}}\right) = (T_{\text{avg}}, T_{\text{avg}})$ for which none of the selfish and regular OBUs will change its strategy to improve its payoff. This Nash equilibrium can be proved to be unique. However, the Nash equilibrium solution is inefficient since the selfish OBU cannot gain any benefit (i.e., payoff is zero as $T^*_{\text{slf}} = T^*_{\text{ign}} = T_{\text{avg}}$). Also, since the regular OBU will ignore all the information with the duration larger than or equal to the average duration, it is unable to detect the false information in the network.

In summary, for exchanging road traffic information, a vehicular network is vulnerable to the misbehavior of a selfish vehicle. The selfish behavior of vehicles can degrade the performance of the network. Consequently, game-theoretic incentive mechanisms can be designed to prevent such misbehaviors.

4.5 Bandwidth Auction Mechanism for Wireless Access for V2I Communications

For infotainment applications, OBUs can pre-fetch data from RBSs [50,51] which are deployed at the selected locations (e.g., bus stops in Figure 4.4). Due to the sporadic wireless connectivity along the route, the OBUs have to ensure that sufficient amount of data is cached, which can be used when wireless connectivity is not available (i.e., when the vehicle is on the road). When there are multiple vehicles at the same location, an auction mechanism can be used for bandwidth sharing among vehicles [43]. In Akkarajitsakul and Hossain [43], a game-theoretic bandwidth auction mechanism was developed to solve the conflict among vehicles to share the wireless bandwidth to connect to the RBS. In this model, the auctioneer and the bidders are the RBS and the vehicles, respectively. A vehicle can adjust its bidding strategy such that its utility is maximized.

4.5.1 Model for Bandwidth Auction

Let us consider one RBS that is connected with the Internet (Figure 4.4). When a vehicle moves into the coverage area of the RBS, the OBU can connect to the RBS and download data from the Internet. When the vehicle moves out of the coverage area of the RBS, the OBU uses the cached data in the buffer. The total available bandwidth to connect to RBS is denoted by B, which is shared among N vehicles. Vehicle i submits the bid defined as $d_i = (q_i, p_i)$ to the RBS, where q_i is the total required amount of bandwidth, and p_i is price per unit of downloaded data [52]. Given the bids from all vehicles, the amount of allocated bandwidth to vehicle i is obtained from

$$b_i = \min\left(q_i, \frac{p_i}{\sum_{j=1}^{N} p_j} B\right). \tag{4.3}$$

4.5.2 Game Formulation of Bidding Strategy

The bandwidth allocated to one vehicle will depend not only on its own bid but also on the bids from other vehicles. Therefore, each vehicle will optimize its bid such that its utility is maximized. Given this conflicting situation, a noncooperative game for sharing the bandwidth at the RBS can be formulated as follows: The *players* of this game are the vehicles connecting to the RBS. The *strategy* is the bidding price, that is, p_i. The *payoff* is the utility, which is defined as follows:

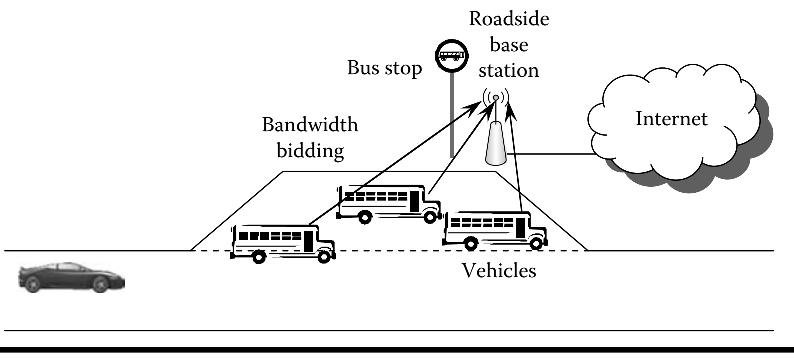


Figure 4.4 System model of bandwidth auction for bandwidth allocation among vehicles.

$$\mathscr{U}_i(p_i, \mathbf{p}_{-i}) = \mathscr{V}_i(b_i(\mathbf{b})) - \mathscr{C}_i(b_i(\mathbf{b}), p_i) \tag{4.4}$$

where
- $\mathbf{p}_{-i}$ is the vector denoting the bidding prices of all vehicles except vehicle i
- $\mathbf{b}$ is the vector of bids from all vehicles
- $\mathscr{V}_i(b_i(\mathbf{b}))$ is the valuation function
- $\mathscr{C}_i(b_i(\mathbf{b}), p_i)$ is the cost function defined as $\mathscr{C}_i(b_i(\mathbf{b}), p_i) = b_i p_i$

The valuation function is defined as follows:

$$\mathscr{V}_i(b_i) = t_{\text{on},i}\alpha \log(1 + \gamma b_i) + \mathscr{S}(t_{\text{out},i}) \tag{4.5}$$

where
- $t_{\text{on},i}$ is the time interval during which the vehicle is connected to the RBS
- α and γ are the constants of the logarithmic utility function of allocated bandwidth b_i
- $\mathscr{S}(t_{\text{out},i})$ is the user's satisfaction as a function of the time interval t_{out} during which there is no cached data for the user (i.e., service is interrupted)

In other words, t_{out} is the time duration during which there is not enough cached data in the buffer. This satisfaction is defined as follows:

$$\mathscr{S}(t_{\text{out},i}) = 1 - \frac{1}{1 + \exp(-\mu(t_{\text{out},i} - \beta))} \tag{4.6}$$

where μ and β are constants. The best response of vehicle i can be defined as follows:

$$\mathscr{B}_i(\mathbf{p}_{-i}) = \arg\max_{p_i} \mathscr{U}_i(p_i, \mathbf{p}_{-i}). \tag{4.7}$$

Then, the Nash equilibrium is given by

$$p_i^* = \mathscr{B}_i\left(\mathbf{p}_{-i}^*\right) \tag{4.8}$$

where $\mathbf{p}_{-i}^*$ is the vector of Nash equilibrium of bidding prices of all vehicles except vehicle i.

For two vehicles, Figure 4.5 shows the utility (i.e., payoff) of vehicle 1 given the varying bidding prices. When the bidding price of this vehicle increases, the payoff first increases, since the RBS allocates more bandwidth to this user. However, at a certain point, the utility decreases since the cost becomes higher than the benefit. Therefore, an optimal bidding price can be obtained such that the maximum utility is achieved. This is referred to as the best response of the vehicle. Also, when the other vehicle changes its bidding price (e.g., from $p_2 = 1$ to $p_2 = 2$), this best response changes accordingly.

Figure 4.6 shows the best response of two vehicles under different bidding prices. When one vehicle increases its bidding price, the best response for the other vehicle will also be to increase the bidding price. The Nash equilibrium is located at the point where the best responses intersect.

In summary, an auction mechanism can be applied to determine the allocated bandwidth among multiple vehicles according to their demands. Since the vehicles are rational to maximize their own payoffs, the Nash equilibrium of the bidding strategy (i.e., bidding price) can be obtained from a noncooperative game formulation.

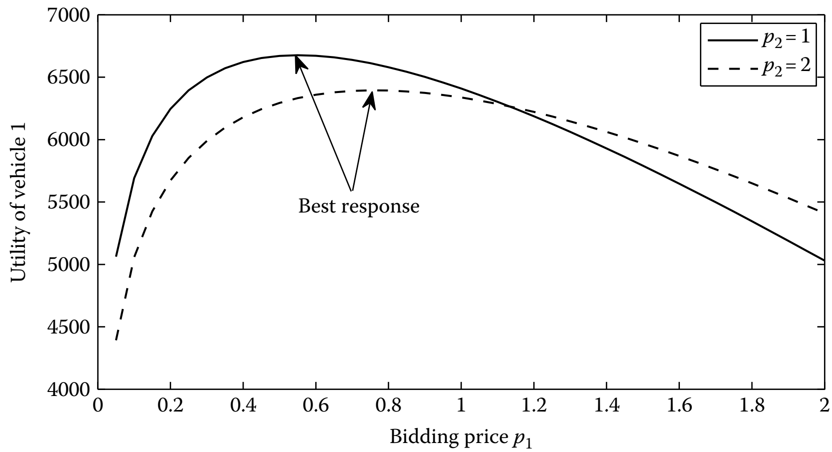


Figure 4.5 Utility of a vehicle under different bidding prices.

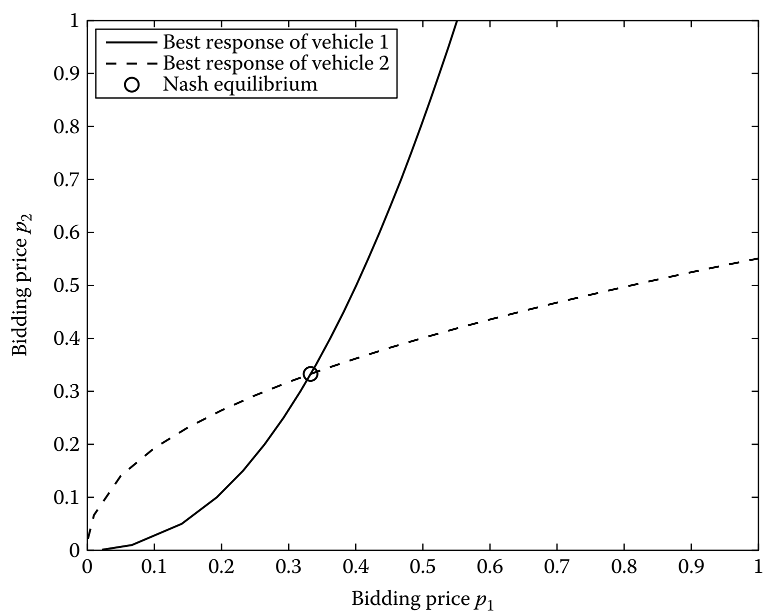


Figure 4.6 Best responses of two vehicles under different bidding prices.

4.6 Stochastic Game Model of Location-Aware Competitive Wireless Access for Data Streaming over V2I Communications

Data streaming is one of the major ITS applications, which relies on V2I communication to download data from Internet servers to the users in moving vehicles. In Niyato et al. [44] the problem of competitive wireless access for data streaming over V2I communications was modeled considering multiple RBSs, locations of those RBSs, mobility of the vehicles, QoS requirements for

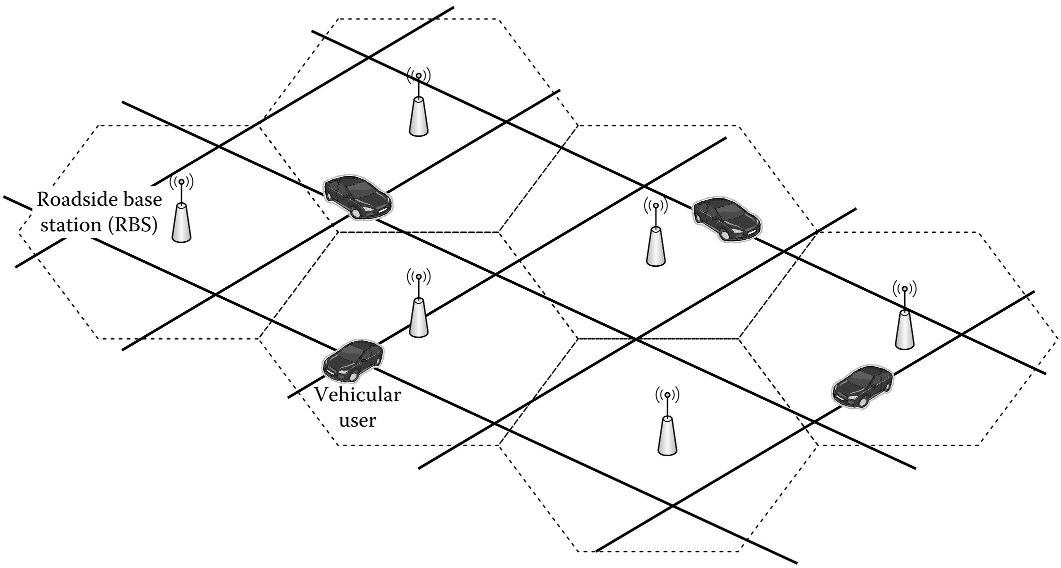


Figure 4.7 Example of service area of competitive wireless access for data streaming over V2I communications.

the streaming application (e.g., buffer underrun probability), and the cost of wireless connectivity. This buffer underrun probability denotes the probability that the data in the streaming buffer in the OBU of a vehicle are less than the demand from streaming application.

A streaming application scenario similar to that in Mancuso and Bianchi [53] is considered for a particular service area (Figure 4.7). This service area is composed of a set of locations denoted by $\mathbb{L}$ where wireless access is available through RBS $l \in \mathbb{L}$. All RBSs are assumed to belong to the same network service provider (NSP). The cost of wireless access through an RBS in a particular location depends on the total demand from all vehicles served by that RBS in that location. There are N vehicles in this service area. For vehicle $i \in \{1, \ldots, N\}$, the mobility is modeled by a transition matrix $\mathbf{M}_i$. The element $M_i(l, l')$ of this matrix $\mathbf{M}_i$ represents the probability that the vehicle changes its location from l to l'.

The vehicle has a finite proxy buffer of length X packets to store the downloaded streaming data. The packet retrieval process from the proxy buffer is modeled by a batch Markovain process. The transition probability matrix for the packet departure process from the proxy buffer is given by $\mathbf{D}_i^{(d)}$ for $d \in \{0, 1, \ldots, D\}$ departing packets, where D is the maximum batch size. In this case, if the number of packets in the proxy buffer is less than the demand from the streaming application, the playout of streaming data will be interrupted. The corresponding performance measure is the buffer underrun probability, which has to be maintained below a threshold $E_{\max}$. The OBU in vehicle i obtains wireless access to the RBS at location l using bandwidth u_i. A connection fee or price $\mathscr{P}(\overline{u})$ is charged to the vehicle per unit of bandwidth, which is a function of total bandwidth demand from all vehicles, where $\overline{u} = \lim_{t\to\infty} \sup(1/t) \sum_{t'=1}^{t} \sum_{i=1}^{N} u_i(t')$, and $u_i(t')$ is the bandwidth used by vehicle i at time t'.

4.6.1 Stochastic Game Formulation

Given the states of the vehicles (i.e., location, buffer size, and packet departure rate), a stochastic game model can be formulated [54]. The *players* of this game are vehicles. The *state space* of player

i is $\mathbb{S}_i$, which is defined as follows:

$$\mathbb{S}_i = \{(\mathcal{L}, \mathcal{X}, \mathcal{D}); \mathcal{L} \in \mathbb{L}, \mathcal{X} \in \{0, 1, \ldots, X\}, \mathcal{D} \in \{1, \ldots, H\}\} \tag{4.9}$$

where
- $\mathcal{L}$ is the location of the vehicle
- $\mathcal{X}$ is the number of packets in the buffer
- X is the maximum buffer size
- $\mathcal{D}$ is the phase of packet departure (i.e., due to playout of streaming data)
- H is the maximum number of phases

Let $\mathbb{S} = \prod_{n=1}^{N} \mathbb{S}_i$ denote the global state space (i.e., state space of all players), where $\prod$ is the Cartesian product. The *strategy* of each player is the action to request u_i units of bandwidth from RBS at each location. The action space of vehicle i is defined as $\mathbb{U}_i(s_i) = \{0, 1, \ldots, U\}$, where $s_i \in \mathbb{S}_i$. An action $u_i \in \mathbb{U}_i(s_i)$ corresponds to the amount of bandwidth to be used by vehicle i. The state transition probability matrix of player i is denoted by $\mathbf{P}_i(u_i)$, which depends on action u_i. The *payoff* of a player is the long-term average cost of wireless access. The constraint for a player (i.e., a vehicle) is to maintain the buffer underrun probability below or equal to threshold $E_{\max}$.

The strategy of a vehicle can be expressed as the wireless access policy. The stationary policy π_i of vehicle i defines the probability of performing an action in a given state. Let $\nu(\mathbb{U}_i(s_i))$ denote the probability distribution for a discrete set of actions $\mathbb{U}_i(s_i)$ given state $s_i \in \mathbb{S}_i$. The stationary policy for state s_i is defined as $\pi_i(\cdot|s_i) \in \nu(\mathbb{U}_i(s_i))$. We can also define $\boldsymbol{\pi}_i$ as a set of stationary policies for vehicle i, that is, $\pi_i \in \boldsymbol{\pi}_i$. In short, vehicle i will choose action u_i with probability $\pi_i(u_i|s_i)$ if the state of the vehicle is s_i. Then $\boldsymbol{\pi} = \prod_{i=1}^{N} \boldsymbol{\pi}_i$ denotes a set of stationary multi-policies, that is, the policies of all vehicles.

The policy of a vehicle is to be optimized such that the cost of wireless access is minimized and the QoS constraint is met. For this, the long-term average cost $\mathscr{J}_{C,i}(\pi)$ and long-term QoS performance measure (i.e., buffer underrun probability) $\mathscr{J}_{E,i}(\pi)$ for vehicle i are defined as follows:

$$\begin{aligned} \mathscr{J}_{C,i}(\pi) &= \lim_{t\to\infty} \sup \frac{1}{t} \sum_{t'=1}^{t} E_\pi \left(\mathscr{C}_i(\mathcal{S}_{t'}, \mathcal{U}_{t'}, \pi)\right) \\ \mathscr{J}_{E,i}(\pi) &= \lim_{t\to\infty} \sup \frac{1}{t} \sum_{t'=1}^{t} E_\pi \left(\mathscr{E}_i(\mathcal{S}_{t'}, \mathcal{U}_{t'}, \pi)\right). \end{aligned} \tag{4.10}$$

$\mathcal{S}_{t'} \in \mathbb{S}$ is the global state, and $\mathcal{U}_{t'} \in \mathbb{U}$ is the actions of all vehicles at time t', where $\mathbb{U} = \prod_{i=1}^{N} \mathbb{U}_i$. $E_\pi(\cdot)$ in (4.10) denotes an expectation over the stationary multi-policy $\pi \in \boldsymbol{\pi}$. These long-term cost and buffer underrun probability measures are defined as functions of the stationary multi-policy π. $\mathscr{C}_i(s_i, u_i, \pi)$ and $\mathscr{E}_i(s_i, u_i, \pi)$ for $s_i \in \mathbb{S}_i$ and $u_i \in \mathbb{U}_i$ are the immediate cost and immediate buffer underrun probability functions, respectively, which are functions of local state s_i. The immediate cost function is defined as follows:

$$\mathscr{C}_i(s_i, u_i, \pi) = \omega \mathscr{E}_i(s_i, u_i, \pi) + \mathscr{P}(\overline{u}) u_i. \tag{4.11}$$

A constrained Markov decision process (CMDP) can be formulated for each vehicle as follows:

$$\text{Minimize:} \quad \mathscr{J}_{C,i}(\pi) \tag{4.12}$$

$$\text{Subject to:} \quad \mathscr{J}_{E,i}(\pi) \le E_{\max} \tag{4.13}$$

where

multi-policy π can be defined as $\pi = (\pi_{-i}|\pi_i)$

π_{-i} is the multi-policy of all vehicular users except vehicular user i

In this optimization problem, each vehicle can optimize its own policy π_i. The policy of one vehicle will affect the cost of other vehicles.

The constrained Nash equilibrium is considered to be the solution of this game. To obtain this constrained Nash equilibrium, first the feasibility condition for a multi-policy is defined. The multi-policy π is feasible if π satisfies $\mathscr{J}_{E,i}(\pi) \leq E_{\max}$. The multi-policy π is feasible if π is feasible for all $i = \{1, \ldots, N\}$. Then multi-policy π^* is the constrained Nash equilibrium if for each vehicle $i = 1, \ldots, N$ and for any $\tilde{\pi}_i$, the condition

$$\mathscr{J}_{C,i}(\pi^*) \leq \mathscr{J}_{C,i}(\tilde{\pi}) \tag{4.14}$$

is satisfied for feasible multi-policy $\tilde{\pi} = (\pi_{-i}|\tilde{\pi}_i)$.

The optimization problem defined in (4.12) and (4.13) can be solved to obtain the *best response policy* $\pi_n^\star$ of vehicle i given the multi-policy π_{-i} of other vehicles. This best response policy can be obtained by formulating and solving an equivalent linear programming (LP) problem. Let $\phi(s_i, u_i)$ denote the stationary probability that the vehicle takes action u_i when the local state is s_i. The LP problem corresponding to the optimization formulation in (4.12) and (4.13) can be expressed as follows:

$$\text{Minimize} \sum_{(s_i,u_i)\in\mathbb{K}_i} \mathscr{C}_i(s_i, u_i, \pi)\phi(s_i, u_i) \tag{4.15}$$

$$\text{Subject to} \sum_{(s_i,u_i)\in\mathbb{K}_i} \mathscr{E}(s_i, u_i)\phi(s_i, u_i) \leq E_{\max} \tag{4.16}$$

$$\sum_{u_i\in\mathbb{U}_i} \phi\left(s_i', u_i\right) = \sum_{(s_i,u_i)\in\mathbb{K}_i} P\left(s_i'|s_i, u_i\right)\phi(s_i, u_i) \tag{4.17}$$

$$\sum_{(s_i,u_i)\in\mathbb{K}_i} \phi(s_i, u_i) = 1, \quad \phi(s_i, u_i) \geq 0 \tag{4.18}$$

for $s_i' \in \mathbb{S}_i$, where $P\left(s_i'|s_i, u_i\right)$ is the probability that the state changes from s_i to s_i' when action u_i is taken. This probability is the element of matrix $\mathbf{P}_i(u_i)$. $\mathbb{K}_i = \{(s_i, u_i); s_i \in \mathbb{S}_i, u_i \in \mathbb{U}_i(s_i)\}$ is the local set of state-action pairs for vehicle i. The objective and the constraint defined in (4.15) and (4.16) correspond to those in (4.12) and (4.13), respectively.

Let $\phi^*(s_i, u_i)$ denote the optimal solution of the LP problem defined in (4.15) through (4.18). The best response policy $\pi_i^\star$ is a randomized policy, which can be uniquely mapped from the optimal solution of the LP problem as follows:

$$\pi_i^\star(u_i|s_i) = \frac{\phi^*(s_i, u_i)}{\sum_{u_i'\in\mathbb{U}_i} \phi^*\left(s_i, u_i'\right)} \tag{4.19}$$

for $\sum_{u_i'\in\mathbb{U}_i} \phi^*\left(s_i, u_i'\right) > 0$. Otherwise, the action $u_i = 0$ is chosen. The optimal solution $\phi^*(s_i, u_i)$ can be obtained by using a standard method for solving LP.

4.6.2 Constrained Nash Equilibrium

To obtain the solution (i.e., constrained Nash equilibrium), the stationary probabilities for the different states are required. The stationary probability for the vehicle to be in state s_i is denoted by $q_i^\pi(s_i)$ for $s_i \in \mathbb{S}_i$. This probability can be obtained by solving the following set of equations:

$$\left(\vec{\mathbf{q}}_i^\pi\right)^T \mathbf{P}_i^\pi(\cdot) = \left(\vec{\mathbf{q}}_i^\pi\right)^T, \quad \left(\vec{\mathbf{q}}_i^\pi\right)^T \vec{\mathbf{1}} = 1 \tag{4.20}$$

where

$\vec{\mathbf{q}}_i^\pi = \left[\cdots \; q_i^\pi(s_i) \; \cdots\right]^T$

$\vec{\mathbf{1}}$ is a vector of ones

$\mathbf{P}_i^\pi(\cdot)$ is the transition probability matrix for vehicle i when the multi-policy π is applied

The following iterative algorithm can be used to obtain the constrained Nash equilibrium.

```
Initialize multi-policy π
repeat
    for i = 1, ..., N do
        J_{C,i} = 𝒥_{C,i}(·, π) {Compute the stationary cost}
        Given multi-policy π, the stationary probability vector q_i^π is obtained from (4.20)
        Obtain the best response policy π_i^⋆ by solving the LP problem defined in (4.15)–(4.18)
        given multi-policy π and stationary probability q_i^π
        Update the multi-policy π = (..., π_i^⋆, ...)
    end for
until max |J_{C,i} − 𝒥_{C,i}(·, π)| < ϵ.
```

ϵ is the threshold used in the termination criterion of the algorithm (e.g., $\epsilon = 10^{-6}$). The constrained Nash equilibrium is obtained as $\pi^* = \left(\pi_1^\star, \ldots, \pi_i^\star, \ldots, \pi_N^\star\right)$.

4.6.3 Numerical Examples

Figure 4.8 shows the convergence of the iterative algorithm to obtain the constrained Nash equilibrium policy for two vehicles. In particular, the amount of bandwidth allocated to two vehicles

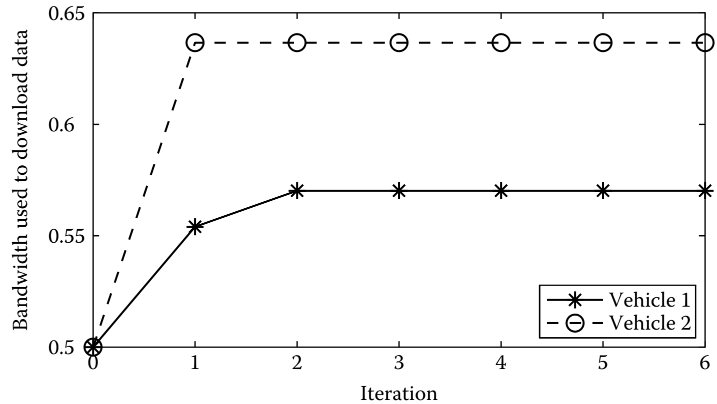
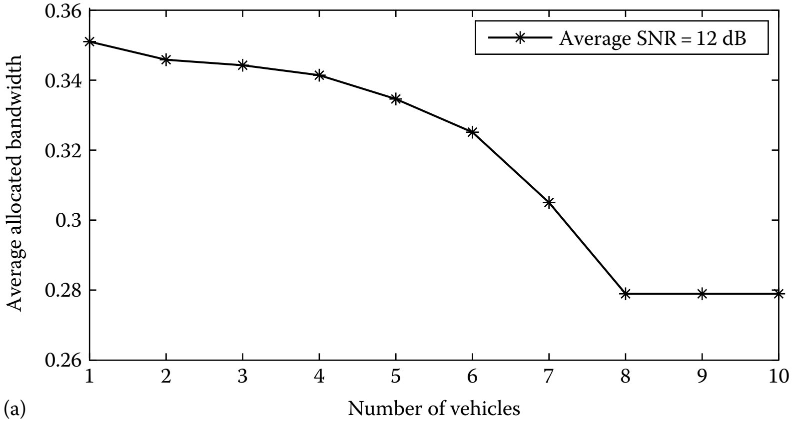


Figure 4.8 Convergence of the optimal wireless access policy adopted by a vehicle.

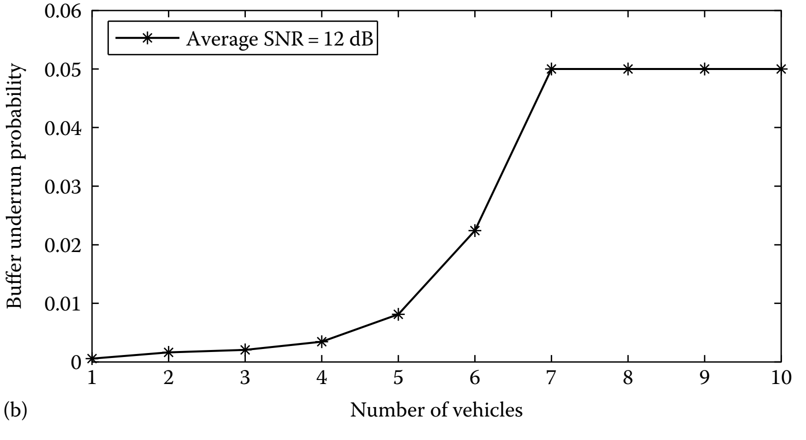
in each iteration is shown. Clearly, from an initial policy, the algorithm converges rapidly to the equilibrium (e.g., in less than five iterations).

Figure 4.9a and b show the amount of bandwidth and buffer underrun probability under different number of vehicles competing in a service area. When the number of vehicles increases, a larger bandwidth demand results in a higher price per unit of bandwidth. In this case, the cost of wireless access for a vehicle can be minimized by reducing the amount of allocated bandwidth (Figure 4.9a), which results in a higher buffer underrun probability. Nonetheless, due to the QoS requirement considered in the stochastic game formulation, the buffer underrun probability is bounded at $E_{\max} = 0.05$ even with increasing number of vehicles (Figure 4.9b). Similarly, the amount of allocated bandwidth reaches a constant value, which is sufficient to maintain the buffer underrun probability at the threshold $E_{\max}$.

In summary, if the price of wireless access through RBSs is adjusted dynamically by the NSP, the vehicles have to optimize their wireless access policy given its buffer state and location. This situation can be modeled as a stochastic game in which the states of the vehicles are independent of each other. Given the QoS requirement (i.e., maximum buffer underrun probability), the constrained Nash equilibrium can be obtained as the solution of this stochastic game.



(a)



(b)

Figure 4.9 (a) Amount of bandwidth and (b) buffer underrun probability under different number of vehicles.

4.7 Rate Control in Vehicular Delay-Tolerant Networks

In a delay (or disruption)-tolerant vehicular network (VDTN), the telematic sensors (or data sources) rely on the mobility of the vehicular nodes (i.e., mobile routers) to carry the data and forward it to the sink [45] (Figure 4.10). Each traffic source and sink is connected to an RBS. When the mobile router (i.e., vehicle) moves into the transmission range of the RBS to which the traffic source is connected to, the traffic source transmits the data packet to the mobile router. The data are stored in the buffer of the mobile router when it travels. Once the vehicle moves into the transmission range of the RBS the sink is connected to, the mobile router transmits data in its buffer to this RBS. However, since the resources in a mobile router are limited (i.e., buffer size is finite), which are shared among multiple traffic sources, the performance (i.e., end-to-end throughput) of one traffic source depends not only on its own transmission rate but also on that of each of the other sources. For example, if one source transmits at a high data rate, the buffer of the mobile router will be full, and, hence, when it moves to other sources, data from the other sources cannot be stored and consequently their performances will degrade. A noncooperative game can be developed to obtain the equilibrium transmission rates of the traffic sources to the mobile router.

4.7.1 System Model of a VDTN

A set of locations, denoted by $\mathbb{L}$, is considered. At each location, there is a stationary node, which acts as either a traffic source or a sink (Figure 4.10). The data packets at traffic source i need to be delivered to sink i'. There is no direct connection between any traffic source and data sink. Therefore, the packets from traffic sources are delivered to the sink with the help of mobile routers. A mobile router may visit different locations in $\mathbb{L}$ randomly at a random speed. When the mobile router visits the location of traffic source i, this traffic source transmits the data packet (destined to sink i') to the mobile router. However, the mobile router can decide to accept or reject the incoming packet from the traffic source. This decision of the mobile router depends on the current buffer status and the importance of the packet. Once the mobile router travels and visits the corresponding

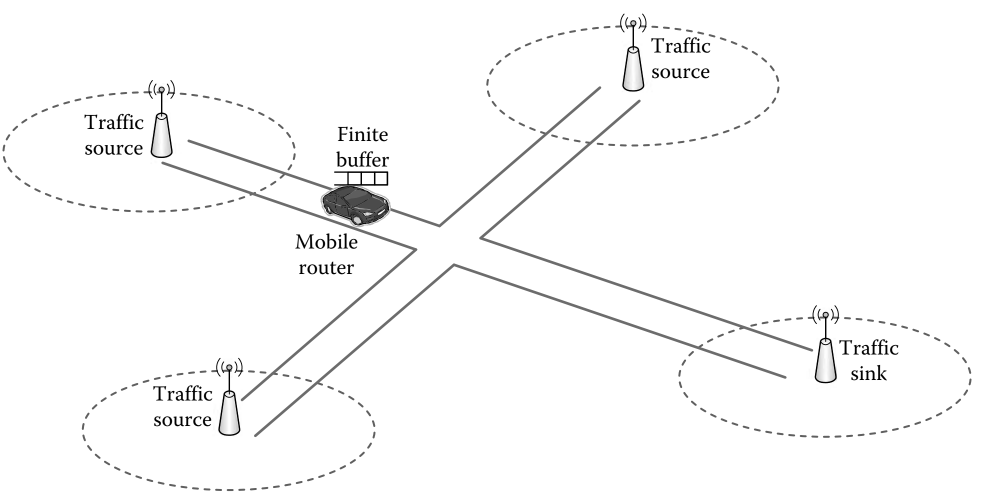


Figure 4.10 Example of a vehicular delay-tolerant network with three traffic sources and one sink.

sink i', the packet is transmitted by the mobile router to the sink. There is no strict delay constraint for packet delivery from a traffic source to the sink in this network.

Let the transmission rate of source i to sink i' be denoted by λ_i. The end-to-end throughput of source i received from the mobile router is denoted by $\tau_i(\boldsymbol{\lambda})$, where $\boldsymbol{\lambda}$ is a vector of transmission rates of all sources. The end-to-end throughput of each traffic source is a nondecreasing function of the transmission rate of the corresponding source.

4.7.2 Noncooperative Game Formulation for Rate Control of Traffic Sources in a VDTN

A noncooperative game model for rate control of the traffic sources in a VDTN can be formulated as follows: The *players* of this game are the traffic sources. The *strategy* of each traffic source is the transmission rate denoted as λ_i for source i. The *payoff* is the utility defined as follows:

$$\mathscr{U}_i(\lambda_i, \boldsymbol{\lambda}_{-i}) = w_i \tau_i(\boldsymbol{\lambda}) - c_i \lambda_i \tag{4.21}$$

where

w_i and c_i are the weight of the throughput and the cost of transmission rate, respectively
$\boldsymbol{\lambda}_{-i}$ is a vector of the transmission rates of all sources except source i

The Nash equilibrium of the noncooperative game is a set of strategies λ_i^* with the property that no traffic source can increase its payoff by choosing a different transmission rate, given other sources' transmission rates $\boldsymbol{\lambda}_{-i}^*$. That is,

$$\mathscr{U}_i\left(\lambda_i^*, \boldsymbol{\lambda}_{-i}^*\right) \geq \mathscr{U}_i\left(\lambda_i, \boldsymbol{\lambda}_{-i}^*\right) \quad \forall i. \tag{4.22}$$

The Nash equilibrium can be obtained from the best response of each traffic source. This best response is defined as an optimal set of strategies of a particular source given the strategies of other sources. The best response of traffic source i, as defined in the following, can be obtained numerically.

$$\lambda_i^* = \mathscr{B}_i(\boldsymbol{\lambda}_{-i}) = \arg\max_{\lambda_i} \mathscr{U}_i(\lambda_i, \boldsymbol{\lambda}_{-i}). \tag{4.23}$$

The Nash equilibrium is considered to be the solution of the following optimization formulation, which minimizes the difference between the strategy of traffic source i and its best response:

$$\text{Minimize} \sum_{i=1}^{N} \left|\lambda_i - \mathscr{B}_i\left(\boldsymbol{\lambda}_{-i}\right)\right|. \tag{4.24}$$

The Nash equilibrium is located at the point where the objective function is zero.

In a centralized decision-making scenario, the traffic sources can be cooperative to maximize the total utility, which is defined as follows:

$$\mathscr{T}(\boldsymbol{\lambda}) = \sum_{i=1}^{N} \mathscr{U}_i(\lambda_i, \boldsymbol{\lambda}_{-i}) \tag{4.25}$$

An optimization problem can be formulated to obtain the optimal strategy as follows:

$$\boldsymbol{\lambda}^* = \arg\max_{\boldsymbol{\lambda}} \mathscr{T}(\boldsymbol{\lambda}). \tag{4.26}$$

Again, the optimal strategy can be obtained by using numerical method.

4.7.3 Numerical Examples

The payoffs (i.e., utility) of two traffic sources, which compete to transmit their packets to the sink through the mobile router, are shown in Figure 4.11. As the packet transmission rate increases, the utility first increases. However, at a high transmission rate, the buffer at the mobile router becomes congested. Therefore, the packet blocking probability increases, which results in a lower utility. The packet transmission rate of each source that yields the highest utility is defined as the best response given the packet transmission rates of other sources.

The best responses of sources 1 and 2 are shown in Figure 4.12. As one source increases its packet transmission rate, the other source has to decrease its transmission rate in order to achieve the highest utility. Since the buffer of the mobile router becomes congested when one source increases its packet transmission rate, the other source has to reduce its packet transmission rate to avoid high cost due to packet blocking. Therefore, the best response of each source decreases as the packet transmission rate of other source increases. For noncooperative sources, the point at which the best responses of all sources intersect is the Nash equilibrium.

Figure 4.13 shows the total utility of two traffic sources. As expected, as both sources increase their packet transmission rates, the total utility first increases and then decreases at a certain point due to the congestion at the mobile router. The point that yields the maximum total utility is the optimal strategy of both sources. This optimal strategy (which is obtained by global optimization) is different from the Nash equilibrium. This result indicates that the Nash equilibrium of the packet transmission rates cannot maximize the total utility.

In summary, in a VDTN, there is no end-to-end path from traffic sources to the sinks, and the data are transferred by the mobile routers. Since the buffer size at a mobile router is limited, the traffic sources have to optimize the data transmission rates to the mobile router. A noncooperative game can be formulated to obtain the Nash equilibrium of the transmission rates.

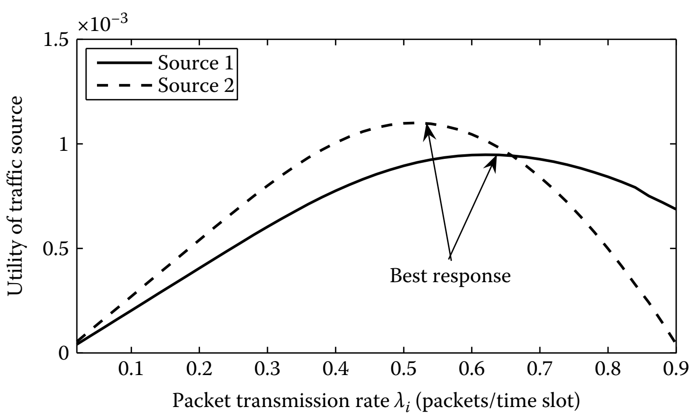


Figure 4.11 Utility of the traffic sources under different packet transmission rates.

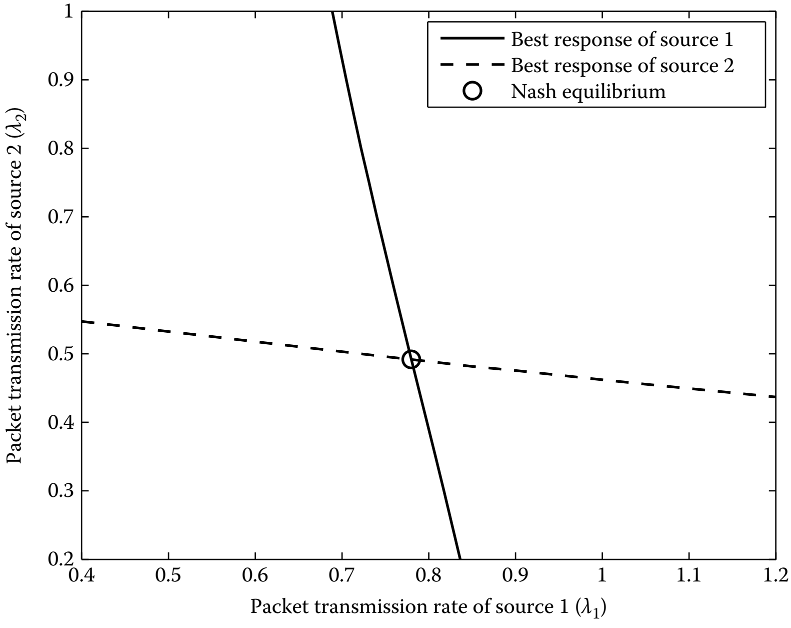


Figure 4.12 Best responses and Nash equilibrium transmission rates of traffic source 1 and source 2.

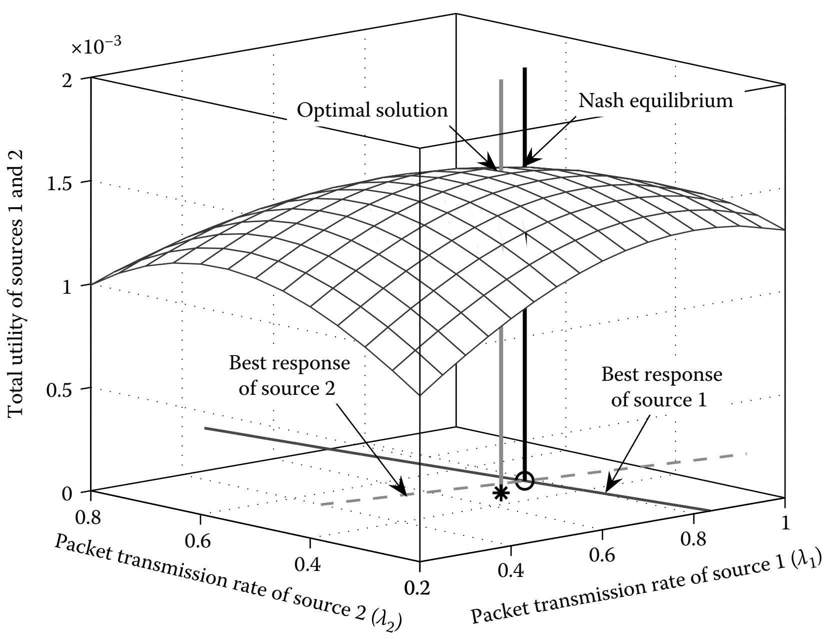


Figure 4.13 Total utility of traffic source 1 and source 2, and locations of Nash equilibrium strategy and optimal strategy.

4.8 Bargaining of P2P-Based Data Transfer in Vehicular Networks

P2P is a distributed network architecture in which resources (e.g., data) can be shared among multiple peers efficiently. In P2P file sharing, a file is fragmented into multiple chunks. These chunks are distributed and stored on a number of nodes in the network. When a user requests for the file, instead of downloading from a single server, the user can download the data chunks from multiple sources. Therefore, P2P file sharing can improve not only the speed but also the reliability (due to the redundant copies of the file). The concept of P2P file sharing (e.g., BitTorrent) has been applied to bulk data transfer in vehicular networks [55,56].

4.8.1 System Model of P2P-Based Data Transfer in Vehicular Networks

In Shrestha et al. [29] a P2P-based data transfer model over vehicular networks was considered. An example scenario is shown in Figure 4.14, where RBS 1 wants to transfer data to the vehicles in lane B, and RBS 2 wants to transfer data to the vehicles in lane A. However, since the file size is large and the duration during which the vehicle will be in the transmission range of an RBS is small, RBS 1 and RBS 2 cannot transmit the entire file at once to the vehicles in lanes B and A, respectively. Therefore, the RBSs transmit the data chunks to the vehicles in the opposite lanes. In this case, RBS 1 and RBS 2 first transmit the data chunks to the vehicles in lanes A and B, respectively. Then, on the road, these vehicles in lanes A and B exchange the data when they pass each other. In this way, a large file can be distributed to multiple vehicles efficiently.

In Shrestha et al. [29] wireless access in vehicular environment (WAVE) technology (i.e., IEEE 802.11p) was considered for data exchange among passing vehicles. The wireless propagation was modeled by a two-ray ground reflection model. Adaptive modulation was used for data transmission among vehicles. The file to be shared is divided into L chunks with the same size, and a vehicle needs to receive all chunks. The weight of chunk k is denoted by $w(k)$. The number of chunks c that can be transmitted within t_0 is defined as $c \leq Bt_0/M$, where B is the transmission rate.

The utility of vehicle i is defined as the sum of weights for the set $\mathcal{I}_i$ of chunks that vehicle i currently has, that is,

$$U_i = \sum_{k \in \mathcal{I}_i} w_i(k). \tag{4.27}$$

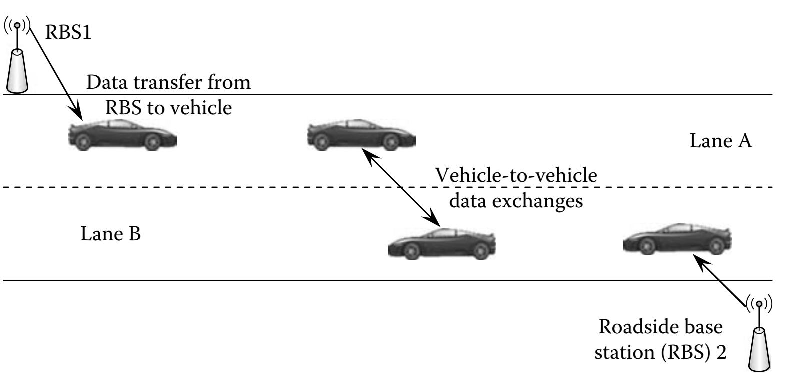


Figure 4.14 System model of P2P-based data transfer in a vehicular network.

This utility function corresponds to the user's satisfaction gained from an application-specific data chunk. For vehicle i and vehicle j, if each has some chunks that the other does not have, they will exchange these data chunks. For two vehicles, the bargaining problem can be stated as follows:

$$\text{Maximize} \quad \mathscr{F}(U_i, U_j) \tag{4.28}$$

$$\text{Subject to} \quad \sum_{k \notin \mathcal{I}_i, k \in \mathcal{I}_j} 1 + \sum_{l \notin \mathcal{I}_j, l \in \mathcal{I}_i} 1 \leq n_{i,j} \tag{4.29}$$

where

$n_{i,j}$ is the maximum number of data chunks that can be exchanged within the time period t_0
This time period t_0 is the duration when two vehicles are in the transmission range of each other
$\mathscr{F}(\cdot, \cdot)$ is a function that represents the social welfare

4.8.2 Bargaining Game among Vehicles

In [29], three fairness criteria for bargaining among vehicles were considered. First, the NBS [41] for a two-player game was considered. The definition of NBS is given in the following.

Definition 4.1 Nash Bargaining Solution Define $\mathcal{U}$ as the feasible region, $\mathbf{U}$ as the utility vector after users' bargaining, and $\mathbf{U}^0$ as the utility vector before the negotiation (i.e., disagreement point). $\phi(\mathcal{U}, \mathbf{U}^0)$ is the NBS that maximizes the product of utility from both players as follows:

$$\phi(\mathcal{U}, \mathbf{U}^0) = \arg \max_{\mathbf{U} \geq \mathbf{U}^0, \mathbf{U} \in \mathcal{U}} \prod_{i=1}^{2} \left(U_i - U_i^0\right). \tag{4.30}$$

Under six general conditions shown in [41], the NBS is a unique solution.

Then, the Kalai-Smorodinsky solution (KSS) and the Egalitarian solution (ES) are considered. These solutions require having the restricted monotonicity property defined as follows:

Definition 4.2 Restricted Monotonicity If $\mathcal{V} \subset \mathcal{U}$ and $H(\mathcal{U}, \mathbf{U}^0) = H(\mathcal{V}, \mathbf{U}^0)$ then $\phi(\mathcal{U}, \mathbf{U}^0) \geq \phi(\mathcal{V}, \mathbf{U}^0)$, where $H(\mathcal{U}, \mathbf{U}^0)$, called the *utopia point*, is defined as

$$H(\mathcal{U}, \mathbf{U}^0) = \left[\max_{\mathbf{U} > \mathbf{U}^0} U_1(\mathbf{U}) \quad \max_{\mathbf{U} > \mathbf{U}^0} U_2(\mathbf{U})\right] \tag{4.31}$$

Definition 4.3 Kalai-Smorodinsky Solution Let Λ be a set of points on the line containing $\mathbf{U}^0$ and $H(\mathcal{U}, \mathbf{U}^0)$. $\phi(\mathcal{U}, \mathbf{U}^0)$ is the KSS, which can be expressed as follows:

$$\phi(\mathcal{U}, \mathbf{U}^0) = \max \left\{ \mathbf{U} > \mathbf{U}^0 \,\middle|\, \frac{1}{\theta_1}\left(U_1 - U_1^0\right) = \frac{1}{\theta_2}\left(U_2 - U_2^0\right) \right\} \tag{4.32}$$

where $\theta_i = H_i(\mathcal{U}, \mathbf{U}^0) - U_i^0$. The solution is in Λ.

Definition 4.4 Egalitarian Solution $\phi(\mathcal{U}, \mathbf{U}^0)$ is the ES, which can be expressed as follows:

$$\phi(\mathcal{U}, \mathbf{U}^0) = \max\left\{\mathbf{U} > \mathbf{U}^0 \,\middle|\, U_1 - U_1^0 = U_2 - U_2^0\right\}. \tag{4.33}$$

From (4.32), the KSS assigns as the bargaining solution the point in the boundary of a feasible set that intersects the line connecting the disagreement point and the utopia point. From (4.33), the ES assigns as the bargaining solution the point in the feasible set where all players achieve maximal equal increase in utility relative to the disagreement point.

4.8.3 Data Exchange Algorithm

To exchange data among vehicles, the following algorithm is executed.

1: **repeat**
2: *Neighbor Discovery*: Investigate the neighbor in the transmission range with the best channel and with the packets which are most beneficial.
3: *Negotiation*: Vehicles exchange information of available data packets and their weights.

- The expected number of transmitted packets $c_{i,j}$ between vehicle i and vehicle j is computed for a certain transmission duration t_0.
- Assume that vehicle i initiates the negotiation by sending a message containing information about its available packets to vehicle j.
- After receiving this information, vehicle j checks whether it has data packets of interest in vehicle i or not.
- Vehicle j replies with a message containing information about the needed packets from vehicle i and their weights.
- Information about the data packets available at vehicle j is piggybacked with this message and sent back to vehicle i.

4: *Bargaining*: The solution of the bargaining game is obtained.
5: *Data Transmission*: Exchange packets to the other vehicle.
6: *Adaptation*: Monitor the channel and adjust modulation and coding rate accordingly.
7: **until** Both vehicles have similar packets or the channel becomes bad.

In Step 4, the bargaining solution is obtained from the following algorithm.

Determine weights of available packets k from vehicles $i \in \{1, 2\}$ (i.e., $w_i(k) \in \mathcal{I}_i$), transmission rate between vehicles i and j (i.e., $c_{i,j}/t_0$) where $i \neq j$.
Sort packets according to their weights, i.e., $w_i(1) > \cdots > w_i(k) > \cdots > w_i(\langle \mathcal{I}_i \rangle)$, where $\langle \mathcal{I}_i \rangle$ gives the number of elements in set $\mathcal{I}_i$.
Define the set of number of transmitted packets by vehicles i and j as $\left\{(c_i, c_j) : c_i = \{0, \ldots, c_{i,j}\}, c_j = c_{ij} - c_i\right\}$. $U_i(n)$ can be obtained based on (4.27), i.e., $U_i(n) = \sum_{k=1}^{n} w_i(k)$.
if Nash solution **then**
Obtain solution in terms of $\left(c_i^*, c_j^*\right) = \arg\max_{(c_i, c_j)} \left(U_i(c_i) - U_i^0\right) \times \left(U_j(c_j) - U_j^0\right)$.
else if Kalai-Smorodinsky solution **then**
Define normalized utility $\hat{U}_i(c_i) = \frac{1}{\theta_i}\left(U_i(c_i) - U_i^0\right)$, where $\theta_i = \max_{c_i\{0,\ldots,c_{i,j}\}} U_i(c_i) - U_i^0$.
$\left(c_i^*, c_j^*\right) = \arg\min_{(c_i, c_j)} \left|\hat{U}_i(c_i) - \hat{U}_j(c_j)\right|$.

else if Egalitarian solution **then**

  The solution is obtained from $\left(c_i^*, c_j^*\right) = \arg\min_{(c_i,c_j)} \left| \left(U_i(c_i) - U_i^0\right) - \left(U_j(c_j) - U_j^0\right) \right|$.

end if

$\phi(\mathcal{U}, \mathbf{U}^0) = \left(U_i\left(c_i^*\right), U_j\left(c_j^*\right)\right)$

The number of packets to be transmitted by vehicles i and j is given by $\left(c_i^*, c_j^*\right)$, respectively.

4.8.4 Numerical Examples

Figure 4.15 shows the transmission rate (i.e., packets/second) between two vehicles using the IEEE 802.11p radio. As two vehicles approach each other (Figure 4.14), the transmission rate becomes higher due to the shorter distance and hence closer transmission range. Note that the flat line on the top of the curve occurs when the highest transmission rate of IEEE 802.11p is used (i.e., transmission mode 11 with 64QAM and coding rate 7/8 is used). We observe that the vehicles with slower speed have longer duration for data transmission.

The different solutions of the bargaining game (i.e., Nash, KSS, and ES) are shown in Figure 4.16. Here, U_1 and U_2 denote the utilities of vehicles in the different lanes. The three solutions along with the Pareto optimal solutions under different transmission rates between two vehicles are shown. The Nash solution is located where $\max(U_1 \times U_2)/U_1$ intersects the Pareto-optimal rates (which is concave). Here, Nash solution, ES, and KSS are located at the different points on the Pareto-optimal utility line.

The rate of vehicles entering the highway is varied, and the utility of the vehicles under different bargaining solutions is shown in Figure 4.17. As expected, when the traffic intensity increases, the utility of the vehicles increases, since there is higher probability that most of data chunks will be exchanged. Different bargaining solutions yield different average utility.

In summary, with P2P-based data transfer in a vehicular network, moving vehicles exchange and collect data chunks from each other. With the different weights of the data chunks and limited connectivity period between vehicles, the exchange has to be performed in a fair and efficient fashion. A bargaining game model can be used to model this situation and various solution concepts (i.e., Nash, KSS, and ES) can be applied.

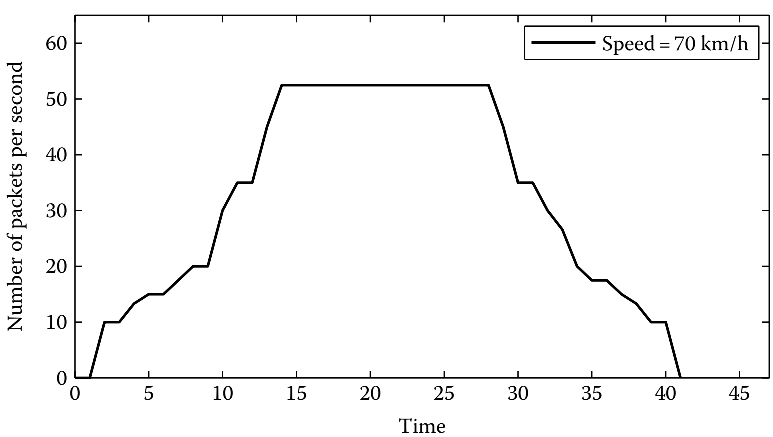


Figure 4.15 Transmission rate between two vehicles.

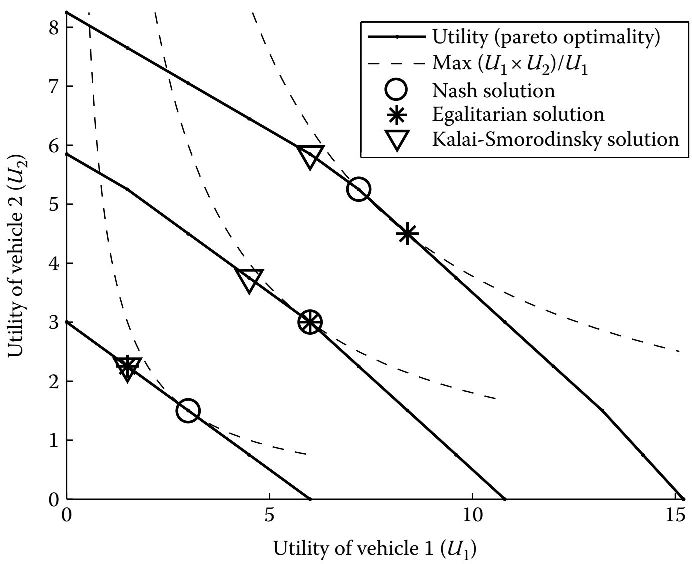


Figure 4.16 Utility, Pareto optimality, and bargaining solutions.

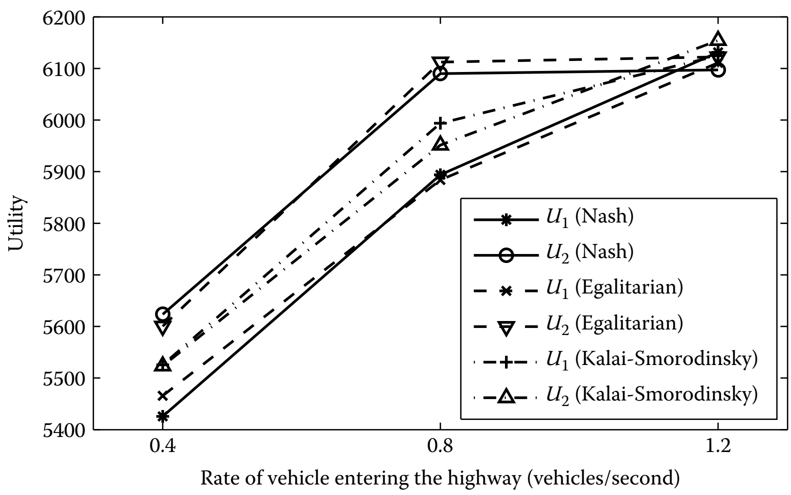


Figure 4.17 Average utility of vehicles under different bargaining solutions.

4.9 V2I and V2V Communications in Cluster-Based Heterogeneous Vehicular Networks

Heterogeneity will be one of the most important features in the next generation mobile communication networks. In such a network, multiple wireless access technologies will be integrated to provide seamless and high-speed wireless connectivity to the mobile users. A heterogeneous wireless access system based on the integration of IEEE 802.11-based WLAN and IEEE 802.16- or WiMAX-based MBWA can be used in a clustered vehicular network to support V2I and V2V communications

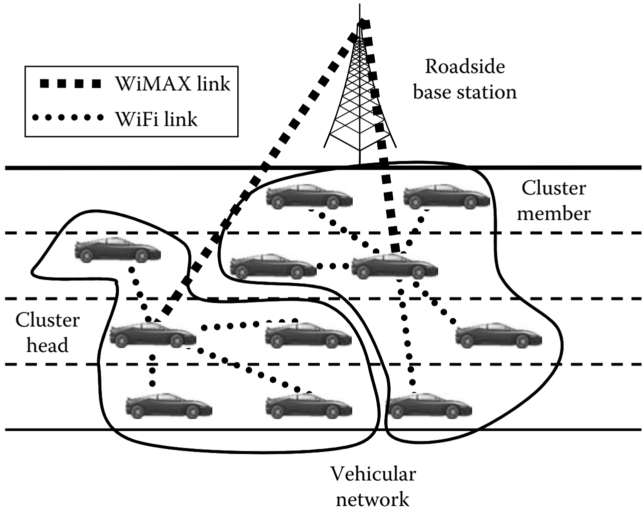


Figure 4.18 Heterogeneous vehicular network with integrated WiFi–WiMAX access.

efficiently [42]. With the clustering structure, IEEE 802.11-based WLAN is used for communications among vehicles (i.e., cluster head and cluster member) while IEEE 802.16-based MBWA is used for communications between vehicle (i.e., cluster head) and the RBS (Figure 4.18). In this section, a game model for such heterogeneous vehicular network proposed in [46] is discussed.

A clustered vehicular network is considered with rational vehicular nodes that have self-interest to maximize their own utilities [42]. A vehicular node has to decide whether to become a cluster head or a cluster member. A cluster head connects to the RBS using WiMAX radio interface. It receives data from cluster members using the WiFi radio interface. A cluster head charges a price to a cluster member to relay its data to the RBS. If a vehicular node decides to become a cluster member, it has to select the cluster head to transmit data to. If a vehicular node decides to become a cluster head, this node has to choose a price to be charged to the cluster member. To obtain these decisions, a hierarchical game model can be formulated by incorporating both networking and economic (i.e., pricing) aspects.

4.9.1 System Model of a Clustered Heterogeneous Vehicular Network

Consider a cluster-based transmission strategy in a vehicular network with N vehicular nodes moving in the same direction (Figure 4.18). Each of these N nodes is equipped with a dual-mode WiFi/WiMAX transceiver. All vehicular nodes need to communicate through the RBSs. Vehicular nodes can form clusters consisting of cluster heads and cluster members. Let n_g denote the number of cluster heads (i.e., number of clusters). The number of cluster members associated with cluster head i is denoted by $n_{c,i}$. The bandwidth on a WiMAX link is B_b bps. This link is shared among $1 + n_{c,i}$ nodes (a cluster head and its members). Each of the vehicular nodes is allocated with a logical WiMAX link with bandwidth $b_i = B_b/(1 + n_{c,i})$ bps. Let B_c denote the aggregated bandwidth on all WiFi links associated with a cluster head. Therefore, the end-to-end bandwidth is $b_i^{(ee)} = \min(B_b/(1 + n_{c,i}), B_c/n_{c,i})$ bps. The RBS charges P_b monetary units (MUs) to cluster

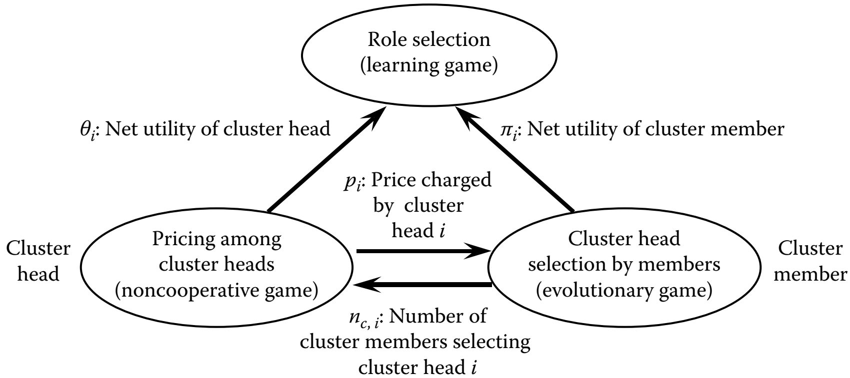


Figure 4.19 A hierarchical game model for vehicular nodes in a heterogeneous vehicular network.

head for WiMAX link with bandwidth B_b bps. Cluster head i offers relay service to the associated cluster members and charges each of its members price $p_i < P_b$ MUs.

Each vehicular node needs to make a two-level decision (Figure 4.19). In the first level, a vehicular node decides whether to be a cluster member or a cluster head. In the second level, a cluster member determines its cluster head, and the cluster head determines its competitive price. Every vehicular node is interested in maximizing its own net utility, which is defined as follows:

$$\mathcal{N}(b, p, r) = \mathcal{U}(b) - p + r \tag{4.34}$$

where

$\mathcal{U}(b)$ is the utility for bandwidth b

p is cost

r is revenue (for cluster head)

The utility is given by the following concave logarithmic function:

$$\mathcal{U}(b) = u_1 \log(1 + u_2 b) \tag{4.35}$$

where u_1 and u_2 are the parameters of the function [57]. This utility function is used to compute the benefit (i.e., net utility) of a vehicular node to become a cluster head or a cluster member.

4.9.2 Decision Making by a Vehicular Node

Given the hierarchical game model shown in Figure 4.19, in the first level, each vehicular node applies a *learning game* to determine its role (as a cluster member or as a cluster head). In the second level, a cluster head applies a *noncooperative game* to obtain the competitive price, while a cluster member uses an *evolutionary game* for cluster head selection. These game models can be analyzed by using backward induction.

4.9.2.1 Cluster Member Decision—Select a Cluster Head

For a cluster member, to select a cluster head, an evolutionary game [58] is applied. Here, each cluster member observes the prices broadcast by the cluster heads periodically. Each cluster member computes the expected net utility and selects the cluster head that yields the highest net utility. The net utility depends on both price and bandwidth in which this end-to-end bandwidth depends on the decision of other cluster members selecting the same cluster head. Therefore, all cluster members iteratively choose a cluster head. After reaching the equilibrium, the net utility will remain unchanged over the rest of the adaptation interval.

An evolutionary game for cluster head selection is formulated as follows: The *players* are the cluster members. The *population* is the group of all cluster members. The *strategy* of a cluster member is the selection of a cluster head. The *payoff* of a cluster member is the net utility. Each cluster member decides to join one of n_g clusters [59] which maximizes its net utility. In this evolutionary game, let x_i denote the proportion of cluster members selecting a cluster head i, where $\sum_{i=1}^{n_g} x_i = 1$. The evolutionary equilibrium is defined as a point where no strategy can lead to a change in the proportion of cluster members x_i. This evolutionary equilibrium satisfies the following condition:

$$\dot{x}_i = x_i (\pi_i - \overline{\pi}) = 0 \tag{4.36}$$

where
$\pi_i = \mathcal{N}(b_i, p_i, 0)$ denotes the payoff of each cluster member selecting cluster head i
$\overline{\pi}$ denotes the average payoff of n_c cluster members

Since the proportion x_i ceases to change at the evolutionary equilibrium, the number of cluster members associated with cluster head i, $n_{c,i} = x_i(N - n_g)$, ceases to change. At this point, the net utility of each cluster member becomes constant.

4.9.2.2 Cluster Head Decision—Set Competitive Price

A rational cluster head aims at setting price to attract cluster members and maximize its net utility. While a high price repels cluster members, leading to low revenue, a low price attracts cluster members, which may cause congestion. A noncooperative game is formulated to obtain this competitive price. This game can be described as follows: The *players* of this game are cluster heads. The *strategy* of a player is the price. The *payoff* of a cluster head is the net utility defined as

$$\theta_i = \mathcal{N}(b_i, P_b, n_{c,i} p_i) \tag{4.37}$$

where $n_{c,i}$ is the total number of cluster members selecting cluster head i. The Nash equilibrium is considered to be the solution of this noncooperative game at which none of the cluster heads would unilaterally change its strategy to improve its payoff θ_i.

4.9.2.3 Role Selection for Vehicular Nodes

Then, the decision of a vehicular node to choose its role (i.e., as cluster member or as cluster head) is analyzed. Since becoming a cluster member or a cluster head will yield different payoffs (π_i and θ_i, respectively), a vehicular node chooses its role so that its net utility is maximized. The role selection takes the following factors into account. A cluster head pays expensive WiMAX service fee; however, it achieves high data rate and earns revenue from traffic relaying for other nodes. A cluster member pays a cheap traffic relaying fee, but it cannot earn revenue from reselling the service. If there are few cluster heads in the network, each cluster member will obtain only small fraction of end-to-end bandwidth. In this case, the cluster member will switch its role to become a cluster head and earn revenue by relaying traffic. Since the net utility of each node is a private information, vehicular nodes choose their role by learning. The algorithm for role selection is as follows:

A vehicular node randomly chooses to become a cluster head or a cluster member
loop
    A vehicular node observes its net utility (i.e., θ_i or π_i if the node decides to be cluster head or cluster member, respectively).
    if node is a cluster head **then**
        Update $\tilde{\theta}_i = (1 - \alpha_i)\tilde{\theta}_i + \alpha_i \theta_i$
        if $\tilde{\theta}_i < \tilde{\pi}_i$ **then**
            Cluster head switches back to become a cluster member. {Becoming a cluster member yields a higher net utility}
        else
            Cluster head randomly becomes a cluster member with small rate ρ (e.g., $\rho = 10^{-3}$) {Learns by trying}
        end if
    else
        Update $\tilde{\pi}_i = (1 - \alpha_i)\tilde{\pi}_i + \alpha_i \pi_i$
        if $\tilde{\pi}_i < \tilde{\theta}_i$ **then**
            Cluster member switches to cluster head {Becoming a cluster head yields a higher net utility}
        else
            Cluster member randomly becomes a cluster head with small rate ρ. {Learns by trying}
        end if
    end if
end loop

Note that $0 < \alpha_i < 1$ is the learning rate of node i.

This role selection algorithm can be modeled as a learning game as follows: The *players* are the vehicular nodes. The *strategy* of a player is to become either a cluster head or a cluster member. The *payoff* is the net utility of a node. The solution of this learning game is an equilibrium where none of the vehicular nodes has any motivation (i.e., no improvement in its payoff) to switch its role. This equilibrium can be obtained analytically by formulating a finite discrete-state and continuous-time Markov chain.

4.9.3 Numerical Examples

Figure 4.20 shows the number of cluster members selecting different cluster heads at the evolutionary equilibrium. With $n_g = 3$ and $n_c = 30$, the prices of cluster heads 2 and 3 are $p_2 = 1$ and $p_3 = 1.5$, respectively, while that of cluster head 1 is varied. When price p_1 of cluster head 1 increases, the number of cluster members selecting this cluster head 1 decreases. At the same time, the number of cluster members selecting cluster heads 2 and 3 increases.

Figure 4.21 shows the net utility of two cluster heads under different prices (i.e., strategies). Clearly, there is an optimal price to maximize the net utility of each cluster head. This price is referred to as the best response. The Nash equilibrium prices of all cluster heads are located where all best responses intersect. At this Nash equilibrium, none of the cluster heads will change its price to improve its net utility.

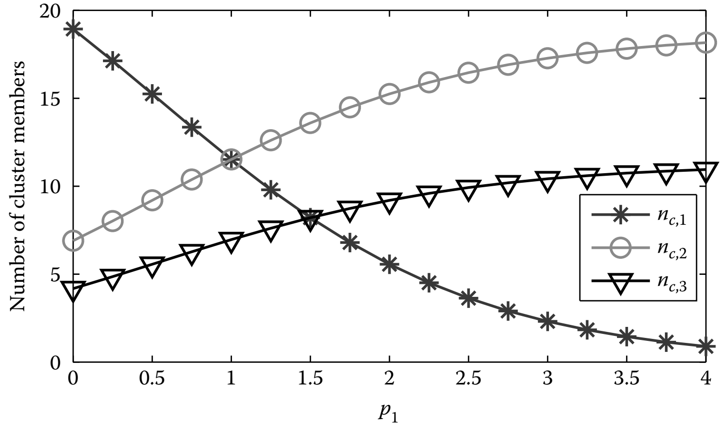


Figure 4.20 Number of cluster members selecting three cluster heads under different price.

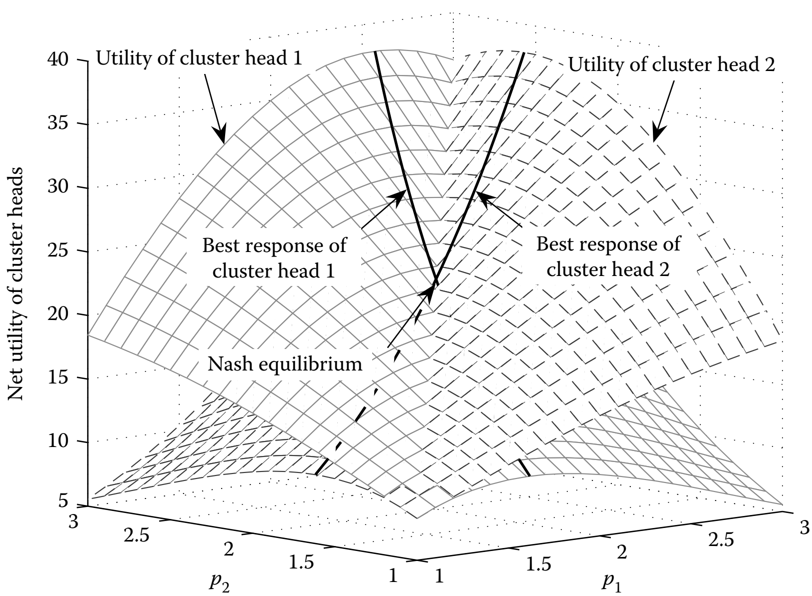


Figure 4.21 Net utility of cluster heads under varied price p_1.

Figure 4.22 shows the net utility of cluster head and cluster member given different number of available cluster heads in the vehicular network. As the number of cluster heads increases, the net utility of a cluster head decreases, since the number of cluster members as well as revenue per cluster head decreases. Conversely, the net utility of a cluster member increases as the number of cluster heads increases—this is due to the larger share of end-to-end bandwidth and lower relaying fee charged by the cluster heads (due to higher degree of competition). It is observed that there is a point where the net utilities of cluster head and cluster member are identical. This is the equilibrium of the learning game since none of the vehicular nodes can improve the net utility by changing the role. This equilibrium can be reached by the role selection algorithm.

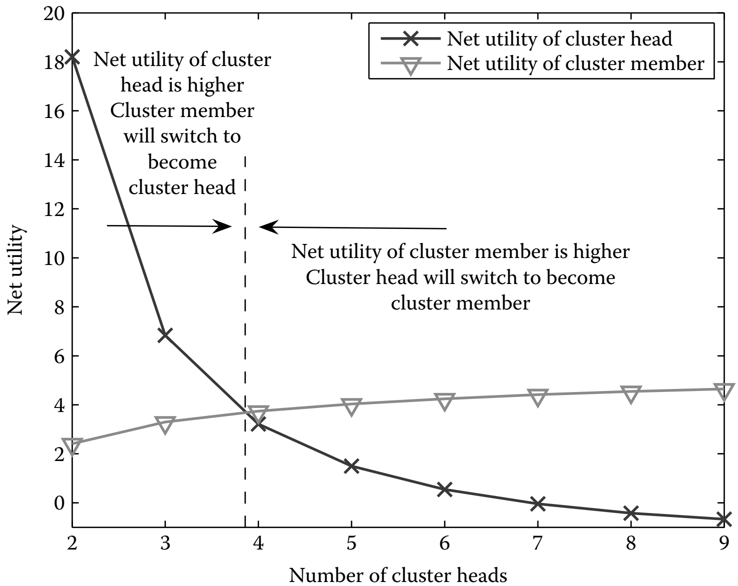


Figure 4.22 Net utility of cluster head and cluster member.

In summary, with heterogeneous wireless access in a vehicular network, different wireless technologies (e.g., IEEE 802.11 WiFi and IEEE 802.16 WiMAX) can be integrated to improve the efficiency of data transfer through V2I and V2V communications. Also, the vehicles can form clusters for better network scalability. For such a clustered vehicular network, a distributed decision-making framework would be required. A hierarchical game model can be formulated to realize this distributed decision framework to obtain decisions on role selection between cluster head and cluster member, the competitive price of a cluster head, and cluster head selection by a cluster member.

4.10 Extensions of the Game Models and Related Research Issues

The different game models described earlier in the context of different V2I and V2V communication scenarios can be extended considering several practical network design issues as described in the following.

- *Decision making of vehicular nodes under incomplete information as Bayesian games:* In a vehicular network, complete information to select a strategy or action may not be available to a vehicular node. For example, the bandwidth demand of multiple vehicles sharing the same RBS is a private information. In a P2P scenario, the weight of the data packets to be exchanged among vehicular nodes may not be known in advance. Therefore, to achieve the optimal strategy in such an environment, game models based on incomplete information (e.g., Bayesian noncooperative game) need to be formulated and solved (e.g., to obtain Bayesian Nash equilibrium).
- *Decision making of vehicular nodes in a dynamic environment and repeated games:* It may be common that the vehicles competing or cooperating for wireless access in a vehicular

network will interact repeatedly. For example, vehicles can bid for the bandwidth from different RBSs at the different points in time. In this case, the dynamics of decision making has to be modeled through dynamic and repeated games with an objective to achieve the optimal long-term decision (e.g., subgame perfect equilibrium).

- *Hierarchical decision making of vehicular nodes and leader–follower games:* In a vehicular network, there could be an entity (i.e., leader) that makes a decision and executes the corresponding action before others (i.e., followers). For example, the transport service provider (e.g., bus operator) reserves the bandwidth from network service provider (NSP). Then, the vehicles bid for the available bandwidth from the transport service provider. In this case, the leader will make decision to maximize its payoff given that the followers make their best decisions. A hierarchical game model such as a Stackelberg game can be used to obtain the solution (e.g., Stackelberg equilibrium).
- *Coalition among vehicular users and coalitional games:* To efficiently utilize the radio resources in a vehicular network, coalitions can be formed among vehicles. For example, given different mobility patterns, the vehicles can share the wireless access at the different RBSs efficiently by forming coalitions such that the cost for wireless access is minimized while the QoS requirements are satisfied. A coalition game model [60] can be applied whose solution is given by the *core*. This core ensures that none of the vehicles will deviate from the current coalition to improve its payoff.

4.11 Conclusion

In this chapter, applications of several game theory models to solve decision-making problems in vehicular networks have been discussed. First, an overview of the different communication scenarios in a vehicular network and several ITS applications, which can be supported through vehicular networks, have been presented. Examples of several different conflicting situations that arise for wireless access in a vehicular networking environment have been discussed, and the game theory tools to model these conflicts have been introduced. The details of these game models from the perspectives of the different communication scenarios have been presented along with representative numerical illustrations. To this end, several extensions of these game models have been outlined.

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