Mode Selection in UAV-aided Vehicular Network: an Evolutionary Game Approach

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***Abstract*—In vehicular networks, safety-related applications require ultra high transmission reliability. An unmanned aerial vehicle (UAV) aided vehicular network is explored to enhance the reliability, where UAVs provide additional communication resources for vehicles. In this scenario, three communication modes are available for vehicles, i.e. vehicle to base station (V2B), vehicle to vehicle (V2V), and vehicle to UAV (V2U). The transmission reliability highly depends on the selection of communication modes under different channel conditions and resource constraints, and thus the key issue is to appropriately select optimal communication modes to achieve the best reliability. In this paper, a mode selection approach based on evolutionary game is proposed in UAV-aided vehicular network, and an evolutionarily stable strategy is obtained. With the proposed algorithm, the proportion of vehicles in different communication modes can converge quickly to the evolutionary equilibrium where no vehicle has an incentive to change its communication mode. Numerical results show that our proposed algorithm exhibits a fast and controllable convergence and achieves higher transmission reliability with lower cost of resource utilization, compared with the selfish and random selection schemes.**

I. Introduction

Vehicular networks provide communication capability for vehicles and infrastructures, enabling various vehicular safety-related applications [1]. Thereupon, the 3rd Generation Partnership Project (3GPP) working group asserts that ultra-high reliability is required for supporting safety-related and fully automated driving vehicular applications [2]. However, neither conventional dedicated short range communication (DSRC) [3] nor LTE-based vehicle-to-everything (V2X) communication [4] can fully satisfy the reliability requirement in vehicular networks at current stage. DSRC mainly suffers from severe collisions while LTE networks can only provide limited spectrum resources without inherent support for V2V communication.

On the other hand, deploying Unmanned Aerial Vehicles (UAVs) for Intelligent Transportation System (ITS) is becoming a reality [5]–[7]. In [7], the authors analyze the scenario where the UAV provides communication services for vehicles and the connection probability as a function of the UAV altitude is derived. One of the key features is that the UAV has more Line of Sight (LoS) connections. Also it has flexible deployment and adjustable mobility. Therefore, the UAVs can be used for traffic offloading and potentially reduce the interference in terrestrial communication systems, and thus enhance the quality of service (QoS) for vehicular communications.

In UAV-aided vehicular network, it is crucial to select a proper communication mode, including vehicle to base station (V2B), vehicle to vehicle (V2V), and vehicle to UAV (V2U). There exist some works on mode selection problem in heterogeneous networks [6]–[9]. The work in [8] provides an evolutionary game model for dynamic network selection in heterogeneous wireless network. Population evolution based and reinforcement learning based algorithms are proposed to solve this problem. In [9], a mode selection problem for user access in fog radio access network is also modeled as an evolutionary game, showing better performance than the maximum-rate based access algorithm. Note that these papers provide game-based approaches for network selection in terrestrial networks, but the following distinct features in UAV-aided vehicular network are not exploited. The existence of LoS connection probability and frequent vehicular channel variations complicate the reliability analysis. Also, the costs of spectrum resources in terrestrial network and UAV network are different, which distinguishes this problem from other network selection problems. Therefore, approaches from above mentioned works are not suitable for mode selection problem in UAV-aided vehicular network.

In this work, we first present the system model for UAV-aided vehicular networks, based on which the reliability analysis is conducted for different communication modes. Also, the closed-form expressions of reliability defined as the successful transmission probability are derived based on stochastic geometry. Then, the mode selection problem is modeled as an evolutionary game and the interactions among vehicles are analyzed through replicator dynamics. Furthermore, an evolutionary mode selection algorithm is proposed to obtain the evolutionarily stable strategy. Numerical results show that our proposed algorithm exhibits a fast and controllable convergence and achieves better performance than other selection benchmark schemes.

The rest of the paper is organized as follows. In section II, we provide the system model and reliability analysis. In section III, the evolutionary game model for mode selection

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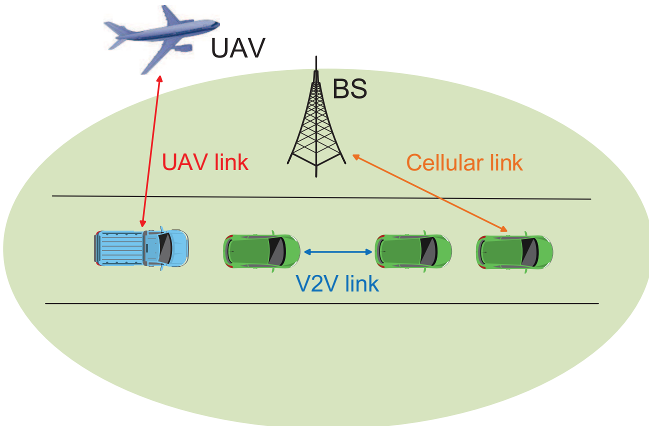

Fig. 1. UAV-aided vehicular network.

problem and corresponding evolutionary mode selection algorithm are introduced. The numerical results are presented and discussed in section IV. Finally, the paper is concluded in section V.

II. System Model

A. UAV-aided Vehicular Network

As shown in Fig. 1, we consider an UAV-aided vehicular network, where both the UAV and terrestrial Base Station (BS) can provide broadband wireless coverages for vehicles. A coverage segment of finite length is considered and is denoted as the set $\mathcal{D}_{\mathrm{r}} = \{r \in \mathbb{R} \mid 0 \leq r \leq D\}$, where the BS is positioned at the center of the segment. The distribution of vehicles on the road is modeled by one-dimensional homogeneous Poisson point process (H-PPP) with intensity λ_v. Considering a vehicle with the demand to access the Internet, three types of accessing nodes are available, including the UAV, the terrestrial BS, and neighboring vehicles that have already connected to the Internet. Thus there exist three types of communication modes in this heterogeneous network architecture, described as follows:

1) ***Cellular Communication (V2B)*** In this mode, the vehicles transmit data packets to the BS directly using cellular resources.
2) ***Vehicle-to-Vehicle Communication (V2V)*** In this mode, the vehicles directly transmit data packets to neighboring vehicles sharing spectrum resources with cellular users. The reuse of resources can improve the spectrum efficiency but will complicate the interference management.
3) ***UAV Communication (V2U)*** In this mode, the vehicles can transmit data packets to the UAV using dedicated spectrum resources orthogonal with the cellular spectrum. Due to the costly maintenance of a flying UAV, as well as the limitation of dedicated spectrum resources, the cost of using UAV communications is much higher than cellular communications.

In this model, it is assumed that the UAV links will not suffer any interference due to the channel orthogonality while there exists interference among cellular links and V2V links. We also assume that each vehicle transmits data packets independently with probability P_c, and thus the distribution of the transmitters follows a thinning PPP with intensity $P_c\lambda_v$.

B. Channel Models

We assume that the small-scale fading of V2V links follows Rayleigh fading with unit mean. Then the channel gain between vehicle i and vehicle j is

$$h_{i,j} = g_{ij} A d_{ij}^{-\alpha_V}, \tag{1}$$

where g_{ij} denotes the small-scale fading and $g_{ij} \sim \exp(1)$, A is a constant, α_V is the path loss exponent, d_{ij} is the distance between vehicle i and vehicle j. Because vehicles distribute according to H-PPP, d_{ij} follows exponential distribution with parameter λ_d.

Accordingly, the signal to interference plus noise ratio (SINR) of the link between vehicle i and vehicle j is

$$\gamma_{ij} = \frac{P_v h_{i,j}}{\sum\limits_{k \in \Phi_I, k \neq i} P_v g_{kj} A d_{kj}^{-\alpha_V} + N_0}, \tag{2}$$

where P_v denotes the transmit power, N_0 is the noise power, Φ_I is the set of interfering vehicles.

Similarly, the channel gain between vehicle i and the BS is

$$h_{i,B} = g_{iB} A d_{iB}^{-\alpha_B}, \tag{3}$$

where d_{iB} is the distance between vehicle i and the BS, which is assumed to be uniformly distributed. Then the SINR between vehicle i and the BS can be expressed as

$$\gamma_{iB} = \frac{P_v h_{i,B}}{\sum\limits_{k \in \Phi_I, k \neq i} P_v g_{kB} A d_{kB}^{-\alpha_B} + N_0}. \tag{4}$$

One of the key features of V2U channels is the probability of occurrence for Line of Sight (LoS) connection, which is given by [10]

$$P_{LoS}(\theta) = \frac{1}{1 + a\exp(-b[\theta - a])}, \tag{5}$$

where a and b are the environment parameters which are related to the area of the buildings, the density of the buildings, the heights of the buildings and corresponding distributions, θ is elevation angle between the UAV and ground vehicles, which is related to the altitude of the UAV. Then, the probability of Non Line of Sight (NLoS) connection is

$$P_{NLoS}(\theta) = 1 - P_{LoS}(\theta). \tag{6}$$

Accordingly, the channel gain between vehicle i and the UAV is expressed as [7],

$$h_{i,u} = \begin{cases} \eta_{LoS} A d_{iu}^{-\alpha_U}, & \text{LoS connection}, \\ \eta_{NLoS} A d_{iu}^{-\alpha_U}, & \text{NLoS connection}. \end{cases} \tag{7}$$

where η_{LoS} and η_{NLoS} are the shadow fading component which are assumed to follow Gamma distribution [11], d_{iu} is the distance between vehicle i and the UAV, α_U is the path loss exponent for V2U channels. Due to the large coverage, UAVs are sparsely deployed and the distance between two UAVs is long enough to neglect the interference. In addition, without the interference from terrestrial cellular networks, the SINR of V2U channels can be expressed as

$$\gamma_{iU} = \frac{P_v h_{i,U}}{N_0}. \tag{8}$$

C. Reliability Analysis

We consider a time-slotted system, where the positions of vehicles and the channels can be regarded fixed in each time slot, but will change among different slots. Our goal is to improve the transmission reliability, which is defined as the probability that the SINR of the receiver is larger or equal to a predefined SINR threshold β. The proportion of vehicles that transmit data packets through V2U communications is denoted by $x_{_U}(t)$. In this case, for V2V communications, the successful transmission probability can be derived as follows:

Theorem 1: In a given time slot t, if vehicle i directly transmits data packets to vehicle j, the successful transmission probability is

$$\begin{aligned} P_{V2V}(x_{_U}(t), d_{ij}) =& \exp\left(-\frac{\beta N_0}{P_v A d_{ij}^{-\alpha_V}}\right) \\ & \cdot \exp\left(\frac{-P_c[1-x_{_U}(t)]\lambda_V \beta^{\frac{1}{\alpha_V}} d_{ij}\pi}{\alpha_{_V}\sin(\frac{\pi}{\alpha_{_V}})}\right). \end{aligned} \tag{9}$$

proof: See appendix A.

In (9), the first term on the right hand side represents the successful transmission probability without any interference, while the second one can be interpreted as the degradation factor caused by interference. If $x_{_U}(t)$ increases which means that more vehicles choose to use V2U links, the interference among V2V links and V2B links will decrease, and thus the successful transmission probability of V2V links will increase.

For V2B links, the reliability analysis is similar to V2V links so that we can skip over the details. For V2U links, the channel condition is separated into two groups. In this case, the successful transmission probability is derived as follows:

Theorem 2: Given the position of the UAV, if vehicle i transmits data packets to the UAV through V2U communications, the successful transmission probability is

$$\begin{aligned} P_{UAV}(d_{iu}) =& P_{LoS}(\theta)\left(\frac{\Gamma(A_{los}, \frac{C}{B_{los}})}{\Gamma(A_{los})} - \frac{\Gamma(A_{nlos}, \frac{C}{B_{nlos}})}{\Gamma(A_{nlos})}\right) \\ & + \frac{\Gamma(A_{nlos}, \frac{C}{B_{nlos}})}{\Gamma(A_{nlos})}, \end{aligned} \tag{10}$$

where $\Gamma(\cdot)$ and $\Gamma(\cdot,\cdot)$ are Gamma function and upper incomplete Gamma function respectively, A_{los}, B_{los}, A_{nlos} and B_{nlos} are environment parameters for LoS connection and NLoS connection respectively, C is given by

$$C = \frac{\beta N_0}{P_v A d_{iu}^{-\alpha_U}}. \tag{11}$$

proof: See appendix B.

Theorem 2 indicates that the successful transmission probability of V2U communications highly depends on the position of the UAV. On the one hand, the path loss increases as the UAV altitude increases. Even so, the successful transmission probability will not necessarily decrease. It is because that, on the other hand, a higher probability of LoS connection will be reached as the UAV altitude increases.

Our goal is to maximize the transmission reliability of all vehicles as well as considering the cost of resource utilization. The selection decision of each vehicle will influence the transmission probability of other vehicles. The interactions and competitions among vehicles are highly dynamic, because a vehicle needs to make the best choice based on the choices of other vehicles, rather than the selfish choice. Traditional optimization approaches can also be used to solve this problem. However, obtaining the optimal result with a large number of vehicles is time consuming and global information of the whole network is required. Therefore, game theory is suitable for solving this problem, leading to an adaptive mode selection scheme which demands for lower signaling overhead.

III. Evolutionary Game Model

In this section, we model the transmission mode selection problem by using an evolutionary game [12]. In contrast to traditional game, where single player makes best decision based on other players' behavior in order to reach the Nash Equilibrium, evolutionary game extends the model with the concept of population in which the players adopt the same strategy. The players can change their factions, i.e. the strategies, and the proportions of different populations gradually evolve to achieve the Evolutionary Equilibrium where no player has an incentive to change its strategy.

A. Game Formulation

The transmission mode selection problem in UAV-aided vehicular network can be formulated as an evolutionary game as follows:

1) ***Players*:** The players are the vehicles that can select different communication modes.
2) ***Strategies*:** The set of strategies for all players can be denoted by $\mathcal{S} = \{U, V, B\}$, where U, V, B represent the selection of V2U communications, V2V communications and V2B communications respectively.
3) ***Populations*:** The population is the set of players that choose the same strategy.
4) ***Population State*:** The population state is the proportion of players that choose different strategies, which can be denoted by a vector $\mathbf{x} = [x_{_U}, x_{_V}, x_{_B}]$, where x_i represents the proportion of players that choose strategy i ($i \in \mathcal{S}$). Alternatively, $\mathbf{x}$ can be interpreted as *Mixed Strategy*, which means that players choose strategy i with probability x_i ($i \in \mathcal{S}$).
5) ***Payoff*:** The payoff is the net utility that players can obtain when choosing a specific strategy, and it depends

on the transmission reliability and the cost of resource utilization.

For a given population state $\mathbf{x}$, the payoff function of a player who selects strategy U is

$$\pi_{U}(\mathbf{x}) = k_u P_{UAV}(\mathbf{x}) - q_u x_{U}, \tag{12}$$

where $k_u P_{UAV}(\mathbf{x})$ is the utility of transmission reliability. $P_{UAV}(\mathbf{x})$ is the average successful transmission probability over the distance distribution of V2U links and k_u is the linear coefficient, $q_u x_U$ is the resource utilization cost which is proportional to x_U. Similarly, the payoff function of a player who selects strategy B is

$$\pi_{B}(\mathbf{x}) = k_b P_{V2B}(\mathbf{x}) - q_b x_{B}. \tag{13}$$

Generally, we have $q_u > q_b$, because the spectrum resource is more scarce in UAV network.

Due to the resource reuse for V2V communications, the cost of V2V communications is set to be free. Hence, the payoff function of a player who selects strategy V is

$$\pi_{V}(\mathbf{x}) = k_v P_{V2V}(\mathbf{x}). \tag{14}$$

Accordingly, For a given population state $\mathbf{x}$, the average payoff of all players can be obtained by

$$\pi(\mathbf{x}) = \sum_{\forall i \in \mathcal{S}} x_i \pi_i(\mathbf{x}). \tag{15}$$

B. Evolutionarily Stable Strategy (ESS)

Evolutionarily stable strategy is defined as the solution of the evolutionary game [13]. We can comprehend this concept in the perspective of Mixed Strategy. When the evolutionary game reaches the evolutionary equilibrium, all involved players adopt the evolutionarily stable strategy, which is denoted by $\mathbf{x}^*$. That means no individual has an incentive to change its strategy for a higher payoff. To evaluate the stability of the evolutionary stable strategy, some invaders that adopt different mixed strategy which is denoted by $\mathbf{y}$ ($\mathbf{y} \neq \mathbf{x}^*$) are considered. The proportion of the invaders is denoted by a small value $\omega \in (0, 1)$. Hence after the invasion, the population state will change to $(1-\omega)\mathbf{x}^* + \omega\mathbf{y}$. We can say that $\mathbf{x}^*$ is evolutionary stable only if the following inequality holds

$$\pi_{\mathbf{x}^*}[(1-\omega)\mathbf{x}^* + \omega\mathbf{y}] > \pi_{\mathbf{y}}[(1-\omega)\mathbf{x}^* + \omega\mathbf{y}]. \tag{16}$$

Thus the payoff of a player playing $\mathbf{x}^*$ must be strictly greater than the payoff of a player playing $\mathbf{y}$. In consequence the invaders will gradually die off over time and the whole population will adopt the evolutionarily stable strategy $\mathbf{x}^*$ after the evolution process.

C. Replicator Dynamics

In the evolutionary game, the population with “good” strategy will spread out during the evolution by replicating. Replicator dynamics is used to describe the evolution process, which can capture the variations of the population state.

In this work we assume that vehicles are able to switch to any other transmission mode with constant switching cost, denoted by C_s. Increasing the number of vehicles choosing V2V communications can reduce the cost of resource utilization, but it will also increase the interference among vehicles leading to lower transmission reliability. If more vehicles switch to V2U modes, the traffic burden of V2V and V2B communications will be released. However the vehicles should pay more prices for the costly resources. In the evolution process, a vehicle prefers to switch to a mode that provides higher payoff especially when its received payoff is lower than the average. In time slot t, the replicator dynamics can be defined as

$$\dot{x_i}(t) = \mu x_i(t) \left\{\pi_i[\mathbf{x}(t)] - \pi[\mathbf{x}(t)]\right\}, \forall i \in \mathcal{S}, \tag{17}$$

where μ is a parameter that controls the speed of population state evolution. Note that the growth rate of the population state depends on the current state as well as the difference between the payoff of a specific strategy and the average payoff.

D. Evolutionary Mode Selection Algorithm

To obtain the ESS of the mode selection problem, we propose an evolution algorithm based on the replicator dynamics, as shown in Algorithm 1.

Algorithm 1 Evolution Algorithm for Mode Selection

1: Initialization: all vehicles randomly select a transmission mode i, $i \in \mathcal{S} = \{U, V, B\}$
2: **for** each vehicle **do**
3: Calculate the received payoff $\pi_i(\mathbf{x}), i \in \mathcal{S}$ based on current population state
4: Send the payoff information to the BS
5: **end for**
6: The BS calculates the average payoff $\pi(\mathbf{x})$ and broadcasts the feedback to all vehicles
7: **for** each vehicle **do**
8: **if** $\pi(\mathbf{x}) - \pi_i(\mathbf{x}) > C_s$ **then**
9: Randomly switch to the transmission mode j with probability $\mu\frac{\pi(\mathbf{x})-\pi_i(\mathbf{x})}{\pi(\mathbf{x})}$, where $\pi_j(\mathbf{x}) > \pi(\mathbf{x})$, $j \neq i$, and $j \in \mathcal{S}$
10: **end if**
11: **end for**
12: Repeat from step 2 to step 11 until convergence

We can observe that the BS plays as the centralized controller because it can always provide available access. The BS collects global information from all vehicles within its coverage and return the processing results through broadcasting. A vehicle makes switching decision depending on the difference between the current payoff and average payoff of all vehicles. Only when the payoff increment is larger than the switching cost, the vehicle will probably switch its communication mode. We define a switching probability $\mu\frac{\pi(\mathbf{x})-\pi_i(\mathbf{x})}{\pi(\mathbf{x})}$ to control the speed of strategy adaption and to avoid from falling in local optimal results.

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Description
P_v	0.5 W	Vehicle transmit power
A	-30 dB	Path loss constant
P_c	0.1	Channel access probability
α_B	3 dB	Path loss exponent for V2B link
α_U	2 dB	Path loss exponent for V2U link
N_0	-104 dBm	Noise power
β	3 dB	SINR threshold

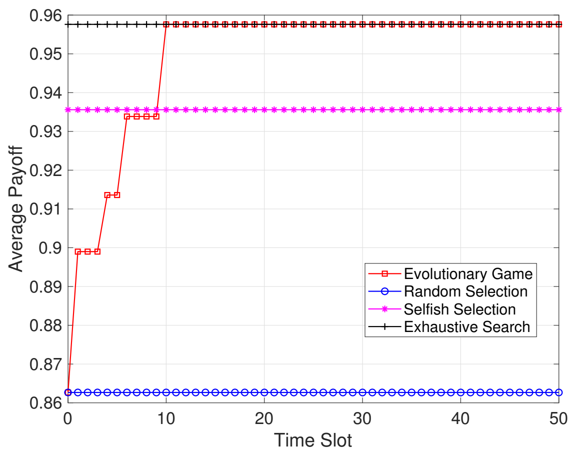

Fig. 2. Average payoff with different mode selection strategies.

IV. NUMERICAL RESULTS

In this section, the performance of proposed mode selection evolution algorithm is evaluated. The basic simulation parameters are listed in Table I.

Fig. 2 shows the evolution process of average payoff with different mode selection strategies. In this simulation, the number of vehicles is set to 10. Note that the exhaustive search strategy always achieves optimal value, but intolerable complexity is introduced especially when the numbers of vehicles are large. In selfish selection strategy, the vehicles will always choose the communication mode with the highest payoff without considering the actions of other vehicles. As shown in this figure, the average payoff of evolutionary game strategy keeps increasing and eventually reaches the highest value after several iterations, while selfish selection strategy obtains an sub-optimal result and random selection strategy has the worst one. This result indicates that the mode selection strategy obtained by the proposed algorithm can achieve optimal value with much lower computing complexity and performs better than selfish and random mode selection strategies. Actually, the evolutionary mode selection strategy trades for the reliability improvement at the expense of iteration delay.

The evolution of proportions for each population with different mode selection strategies is shown in Fig. 3. We can see that, during the evolution process, the proportions will eventually converge to the evolutionary equilibrium where no player chooses to deviate from its strategy. Moreover, the

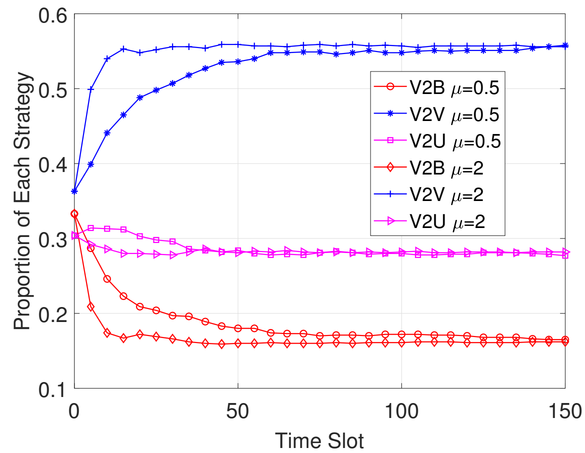

Fig. 3. Convergence of the population proportion with evolutionary mode selection algorithm.

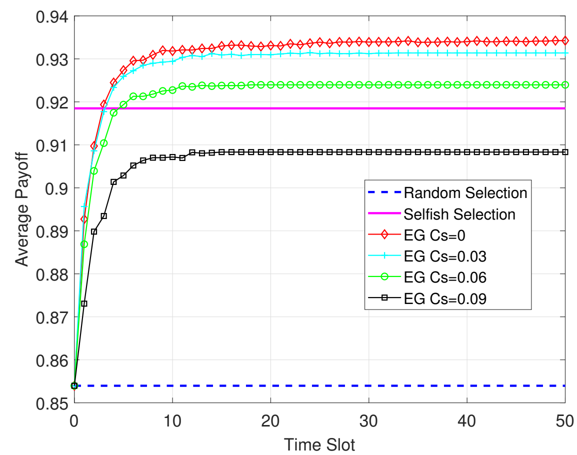

Fig. 4. Average payoff with different switching cost.

proportion of the population selecting V2B communications has the lowest value indicating that V2B communications has a low priority in mode selection strategy. This is because V2U communications provide much better performance by using dedicated resources while V2V communications is cost free due to the resource reuse. Additionally, as shown in Fig. 3, the speed of convergence is controlled by the parameter μ. The proposed algorithm with a higher value of μ will lead to faster convergence in evolution process. However, if μ is set too large, the result will fall in local optimal.

The influence of switching cost is also investigated, as shown in Fig. 4. As can be seen, the performance of evolutionary mode selection algorithm highly depends on the value of the switching cost. The optimal average payoff decreases as the switching cost increases, while the global optimal result can only be obtained when the switching cost equals to zero. When the switching cost is high enough ($C_s = 0.09$ as illustrated), the selfish selection strategy even performs better.

V. Conclusion

In this paper, the evolutionary game is exploited to solve the mode selection problem in UAV-aided vehicular network, where each vehicle has three communication modes, including V2B, V2V, and V2U. The reliability performance of different communication modes is analyzed which acts as the metric to guide the mode selection of each vehicle. An evolution algorithm for mode selection problem is proposed, with which the population state can converge to the evolutionary equilibrium where no vehicle has an incentive to change its strategy. Numerically, at evolutionary equilibrium, all vehicles achieve the highest payoff which means that all vehicles achieve best transmission reliability while considering the cost of resource utilization. Also, the average payoff keeps increasing during the evolution process and the evolutionarily stable strategy obtained by our proposed algorithm exhibits a better performance under small switching cost compared to the benchmark mode selection schemes.

Appendix

A. Proof of Theorem 1

According to the definition of successful transmission probability, we can get

$$\begin{aligned} P_{V2V}(x_U(t), d_{ij}) &= \Pr\left\{ g_{ij} \geq \frac{\beta(I_v+N_0)}{P_v A d_{ij}^{-\alpha_V}} \right\} \\ &\overset{(a)}{=} \mathbb{E}\left[\exp\left(-\frac{\beta(I_v+N_0)}{P_v A d_{ij}^{-\alpha_V}} \right) \right] \\ &= \exp\left(-\frac{\beta N_0}{P_v A d_{ij}^{-\alpha_V}} \right) \\ &\quad \times \mathbb{E}\left[\exp\left(-\frac{\beta I_v}{P_v A d_{ij}^{-\alpha_V}} \right) \right], \end{aligned} \tag{18}$$

where (a) follows from the exponential distribution of g_{ij} (i.e. $g_{ij} \sim \exp(1)$), and we take the expectation over the interference I_v. Then, we have

$$\begin{aligned} &\mathbb{E}\left[\exp\left(-\frac{\beta I_v}{P_v A d_{ij}^{-\alpha_V}} \right) \right] \\ =&\mathbb{E}_{\Phi_I}\left\{ \prod_{\Phi_I} \mathbb{E}_g \left[\exp\left(-\frac{\beta g d_{kj}^{-\alpha_V}}{d_{ij}^{-\alpha_V}} \right) \right] \right\} \\ \overset{(b)}{=}&\exp\Bigg\{ -(1-x_U)P_c\lambda_V \\ &\times \mathbb{E}_g \left\{ \int_0^\infty \left[1-\exp\left(-\frac{\beta g x^{-\alpha_V}}{d_{ij}^{-\alpha_V}} \right) \right] \mathrm{d}x \right\} \Bigg\} \\ \overset{(c)}{=}&\exp\left(\frac{-P_c(1-x_U)\lambda_V \beta^{\frac{1}{\alpha_V}} d_{ij}\pi}{\alpha_V \sin(\frac{\pi}{\alpha_V})} \right), \end{aligned} \tag{19}$$

where (b) follows from the probability generating functional (PGFL) of PPP, (c) follows from the equation (3.21) in [14]. Finally, Theorem 1 can be proofed by substituting (19) into (18).

B. Proof of Theorem 2

According to the definition of successful transmission probability and law of total probability, we can get

$$\begin{aligned} P_{UAV}(d_{iu}) =& \Pr\{\gamma_{iU} \geq \beta \mid LoS\} P_{LoS}(\theta) \\ &+ \Pr\{\gamma_{iU} \geq \beta \mid NLoS\} P_{NLoS}(\theta), \end{aligned} \tag{20}$$

then

$$\begin{aligned} \Pr\{\gamma_{iU} \geq \beta \mid LoS\} &= \Pr\left\{ \eta_{LoS} \geq \frac{\beta N_0}{P_v A d_{iu}^{-\alpha_U}} \right\} \\ &\overset{(d)}{=} \frac{\Gamma(A_{los}, \frac{C}{B_{los}})}{\Gamma(A_{los})}, \end{aligned} \tag{21}$$

where (d) follows from the Gamma distribution of η_{LoS}, C is given by

$$C = \frac{\beta N_0}{P_v A d_{iu}^{-\alpha_U}}, \tag{22}$$

similarly, the expression of $\Pr\{\gamma_{iU} \geq \beta \mid NLoS\}$ can be obtained. Finally, Theorem 2 can be proofed by substituting (6), (21) and (22) into (20).

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