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A cooperative route choice approach via virtual vehicle in IoV ☆

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ABSTRACT

Popular navigation services are used by drivers both to plan out routes and to optimally navigate real time road congestion in internet of vehicles (IoV). However, the navigation system (such as GPS navigation system) and apps (such as Waze) may not be possible for each individual user to avoid traffic without creating congestion on the clearer roads, and it might even be that such a recommendation leads to longer aggregate routes. To solve this dispersion, in this paper, we first apply a concept of virtual vehicle in IoV, which is an image of driver and vehicle. Then, we study a setting of non-atomic routing in a network of m parallel links with symmetry of information. While a virtual vehicle knows the cost function associated with links, they are known to the individual virtual vehicles choosing the link. The virtual vehicles adapt the cooperation approach via strategic concession game, trying to minimize the individual and total travel time. How much benefit of travel time by the virtual vehicles cooperating when vehicles follow the cooperation decisions? We study the concession ratio: the ratio between the concession equilibrium obtained from an individual optimum and the social optimum. We find that cooperation approach can reduce the efficiency loss compared to the non-cooperative Nash equilibrium. In particular, in the case of two links with affine cost functions, the concession ratio is at most 3/2. For general non-decrease cost functions, the concession ratio is at most 2. For the strategic concession game, the concession ratio can approach to 1 which is a significant improvement over the unbounded price of anarchy.

1. Introduction

Optimal route choice not only can decrease the travel time for drivers, but also can solve or reduce the traffic congestions [1,2], particularly in metropolitan areas. To provide an optimal route, most navigation systems (such as Google Maps) and traffic apps (such as Waze) are used by drivers both to plan out routes and to optimally navigate real time road congestion [3].

Navigation systems and traffic apps calculate the best route taking into account real-time traffic flow data, as well as historic data to predict traffic flow [4]. For example, Google Maps calculates the current traffic condition using both real-time data from anonymous GPS-enabled device users and historic traffic data to provide optimal routes [3]. Waze collects aggregate traffic information in areas of interest and so can take real time traffic conditions, which are incalculable to individual drivers, into account when computing optimal route recommendations [4].

Despite this, drivers may still not satisfy the recommendations of the route from navigation systems and traffic apps. And the recommendations always not consider the possible for each individual driver to avoid traffic without creating congestion on the clearer roads, and it might even be that such a recommendation leads to longer aggregate routes.

Consider a simplistic example according to [4]. Suppose that a thousand drivers want to route from city Source to city Destination, which is reachable from Source through two parallel roads. The travel time in each of these roads depends on whether or not an accident has occurred. Specifically, suppose that in each of these roads, in the absence of accidents, each driver's trip takes $n/1000$ hours, where n is the number of driver on the road (e.g., if half of the drivers take a road with no accident, then the travel time of each driver is half an hour). However, if an accident occurs, then the road becomes clogged, and each driver's trip takes one $2n/1000$ hours, independently of the number of drivers on the road. Suppose that an accident occurs on each road with some probability p, which is known to all drivers, but whether or not an accident has occurred on a given road is unknown. Now, we analyze the travel time expectation of each driver cloud spend in different cases [5]:

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Case 1: If there is no any real-time traffic information exist, then each driver would choose a road random. To a first order approximation, we assume that the exactly half of drivers would take each road. In this case, the travel time expectation can be obtained easily, i.e. $3p(1-p)/2$.

Case 2: If there is exist navigation system or traffic app, suppose that each driver can knows exactly which road has had an accident, and can route each driver to his individually optimal. In this case, in every situation except one where no accident occurs on either road, each driver would spend two hours on the road. The travel time expectation of each driver is $2p(1-p)$ which is larger than Case 1.

Case 3: Now suppose that each driver not only knows which road has had an accident, and also can negotiate with others to choose road cooperatively. In this case, a part of drivers would choose the road which has had accident. Assuming n drivers chooses the accident road, then the travel time expectation of each driver can be obtained, i.e., $(6n^2 - 4000n + 2 \times 10^6)p(1-p)/10^6$.

Taking a closer look at this example, we observe that Case 2, in which each driver chooses the road selfishly, maybe is the worst selection, even is worse than Case 1. This implies recommendations form the navigation systems and traffic apps may not decrease the travel time for driver, and even lead to a new traffic congestion. In Case 3, it is same as Case 2 when $n = 0$, or is same as Case 1 when $n = 500$. For the Case, we know that the travel time expectation of each driver is the least when $n = 1000/3$, that is say the socially optimal routing when drivers cooperate to choose the road. Hence, drivers cooperate with each other can optimal the travel time.

According to the above analysis, we know drivers choose road cooperatively can optimal socially welfare. However, drivers always cannot know others choices in reality, and they also cannot negotiate with each other when they choose the route.

To study this question, in this paper, we first utilize a vehicle agent-based [6] in Edge and cloud to help drivers negotiate with others called virtual vehicle (VV) [7]. Suppose each driver has a corresponding VV, and it has the parts of driver's knowledge which can replace the driver to make decision in cloud.

Then we consider a bargaining routing approach [8] to optimal the travel time to solve the cooperative problem. In this game, we set a source node, a target node, and m parallel links, known to all players. The players (who know the others' strategy) decide which route to take, and incur the travel cost realized on their route. Because the VV may exist selfish behavior and we cannot inextricably compel VV to cooperate with others. However, if there has any benefit from the cooperation, the VVs may willing cooperate with others to decrease the cost. In this paper, we restrict attention to bargaining policies which performed by VVs themselves – that is, policies that induce an equilibrium in which all VVs are best off by perform the strategic concession game [9]. Our contributions can be summarized as follows.

- First, we have detailed the composition and architecture of VV. We have constructed the VV that encompasses both a vehicle and its driver, and we have extended the architecture of VV.
- Second, we have shown a revelation principle, which implies that restricting attention to bargaining policies is without loss of generality. And we also have quantified the efficiency loss in this setting using the concession ratio, which is the ratio between the concession equilibrium and the socially optimal one. Clearly, the Nash equilibrium of the non-cooperative game can always be obtained to implementing the full-information by VVs. Therefore, the mediation ratio is always bounded from above by the price of anarchy (PoA) [10].
- Finally, we have shown that if all cost functions are affine, then the concession ratio is at almost $3/2$ for the case of two parallel links, and is almost at $(2m-k)/2(m-k)$ for the case of m parallel links with k accident links. For general (non-decreasing) cost functions, we show that the concession ratio for m parallel links is at almost 2.

The rest of this paper is organized as follows. In Section 2, we introduce the virtual vehicle, and describe the basic knowledge of strategic concession game. The affine cost function case of concession ratio is analyzed in Section 3. In Section 4, the con-cession ration in general cost function is presented. Finally, we conclude in Section 5.

2. Related work

To solve the cooperative routing problem, several approaches were designed which can be divided into two categories.

The first category of approaches aims to keep user equilibrium and focus on social optimum. These approaches plan and fastest path to users via computing the predicted travel time (PPT) of road segments. In the previous works, the PPT is related in Greenshield's model [11] with anticipated traffic volume (ATV). Such as Yamashita et al. [12] used this model to design the Passage Weight heuristic which can be generated the contribution of each planned path towards ATV. Wilkie et al. [13] first assumes that the traffic volume is stochastic which determined by both historical traffic and previously assigned traffic, then they used a similar model to relate PTT and ATV except to solve the cooperative routing problem. Another approach [14] is proposed to compute a few alternatives based on real-time traffic and then route the car to the path with the shortest PTT based on encounter prediction. Some other studies focus on social optimum, whose objective is minimizing the average travel time of a group users not the individual travel time. Jindal and Bedi [15] proposed a parallel preemptive algorithm to reduce the average queue length resulting in decrease of overall waiting time, which use the Compute Unified Device Architecture by harnessing the power of Graphical Processing Units in the implementation. Bosch et al. [16] proposed an approach to handle a routing request by searching a path minimizing the total PTT of all previous assigned drivers. Based on Board of Public Roads flow-delay model, Lim et al. [17] proposed an approach via computing a few route candidates based on real-time traffic and investigating the mutually timing influence of users' route choices to optimize the total travel time. In the paper, the proposed algorithm was evaluated using the taxi trajectory data in Singapore [18]. Besides, some approaches choose routes are not reference to PPT but some heuristic functions. Such as Pan et al. [19] proposed an approach to plan and choose first-k shortest paths (KSPs) using several heuristics based on previously assigned traffic. To balance the traffic volume distribution, EBkSP algorithm in this paper first computes the KSPs according to real-time traffic, and then chooses the route with the least popularity. In this category of approaches, the personal intends are not considered so that drivers may not satisfy the recommendations.

The other category is using the online social networking services to route cooperatively. Toyota integrates the short message social media into the vehicle's dashboard, and the driver can obtain the route information of others. Stephen et al. [20] presents a framework for vehicular social networks where people who are physically adjacent to each other construct a periodic virtual social relation. This is an integration of social and vehicular networks whose goal is to virtually build a community for commuters. In this works, the authors built a voice chatting system over vehicular social networks, named RoadSpeak, which can be used by daily driving commuters or a group of people who are on a commuter bus or train. Similarly, NaviTweet uses the same way to calculate the navigator's route with driver's preferences via posting and listening to traffic related voice tweets. The app Caravan Track [21] has been designed for a group of vehicles, which allow drivers to share vehicle and route information in this group. Caravan Track allows members in a same group to track one another's specific entities such as location, speed and direction. Waze is another popular navigation app which uses crowdsourcing to provide real-time routing and traffic information along with functions to improve and edit the map itself. Here, social networks are used to send predefined push button messages stating incidents like the degree of traffic, police speed traps or accidents. For this category of approaches, the social information is used in the calculation of the best route. However, the route recommendations also not accommodate human preference factors to the route selection.

In addition, there are some approaches are proposed based on agent [22]. Agent-based transportation systems allow distributed subsystems collaborating with each other to perform traffic control and management based on real-time traffic conditions [23]. There are two main existing solution categories for mitigating the huge traffic congestion loss based on agent. One is the dynamic optimization of traffic light phases [24]. Another solutions category is vehicular route assignment using shortest path finding algorithms [25,26]. For example, the well-known vehicle navigation systems (e.g., Google Navigation) can calculate "the fastest" route based on the current traffic conditions to reduce the travel time for a specific journey. However, there are two issues in present works. One is only few vehicles can coordinate with each other in present approaches, such VANETs, which cannot solve the widely-area traffic jam due to lack of real-time trafic. Another is focus on the coordination between vehicles and traffic infrastructure (e.g., traffic lights), but they cannot control each vehicle accurate to coordinate.

In this paper, we address the challenges of cooperative routing problem based on vehicle agent-based approach, virtual vehicle, which has a parts of driver's knowledge and can replace the driver to make decision in cloud. In this approach, VVs adapt the strategic concession game to negotiate with each other.

3. Model and preliminaries

3.1. Virtual vehicle

VV is the image in cyber space (such as cloud) of the human and vehicle in physical space. This image includes the features and characteristics of human and vehicle. VV embodies the microcosmic behavioral features of driver and vehicle during the driving. And VVs can interact directly with each other in cyber space by providing traffic service and sharing sensing data coordinately, which can solve the bottleneck of communication in physical space.

Like the agent bridge the gap between cyber and physical [27], the VV can make decisions to replace driver, and have the detailed of driver information: preferences (such as which lane the driver is likely to select) and route plans are together considered as driver's behavior.

3.1.1. The composition of VV

Since the proposed VV should make decisions to replace driver, it needs detailed driver information: preferences (such as which lane the driver is likely to select) and route plans are together considered as driver's behavior. In order to effectively describe and obtain the personalization navigation, we construct the VV that encompasses both a vehicle and its driver as shown in Fig. 1. Form the figure, the same vehicle with different drivers can form different VVs, similarly, different vehicles with the same driver can form different VVs. The VV has the artificial intelligence which

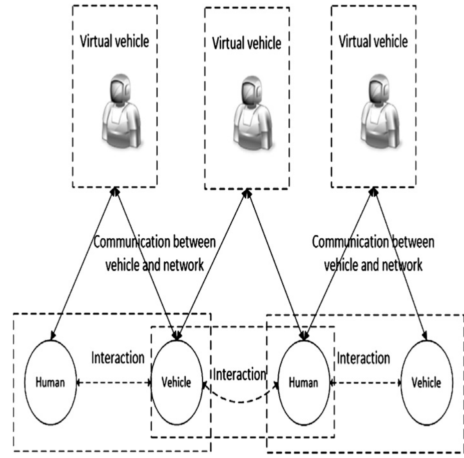

Fig. 1. The composition of VV.

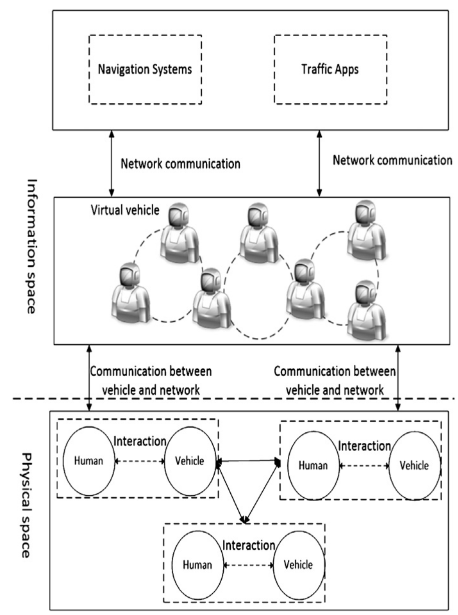

Fig. 2. The IoV architecture based on VV.

can make decision according to the dynamic traffic information, Therefore, each virtual vehicle only corresponds one combination of driver vehicle. VVs can both locally sense data and directly access social network data and physical sensor data from the cloud. And it can communicate with the corresponding human and vehicle through the existing telecommunication systems, such as LTE. Navigation systems and traffic apps can connect with VVs through the network communication in cloud.

3.1.2. The IoV architecture based on VV

We describe the IoV architecture based on VV as shown in Fig. 2. In the architecture, VV can communicate with the corresponding human and vehicle through the existing telecommunication systems [28,29], such as LTE. In the information space, navigation systems and traffic apps can connect with VVs through the network communication.

VV can interact with other VVs, navigation systems and traffic apps in the cloud, where it is not limited by communication and computation resources. VV can obtain big-picture real-time traffic data, both sensed locally and from the cloud; by interacting with other VVs, VVs can predict other drivers' behavior and proactively work to plan a route. VVs for driverless vehicles can make decisions about path planning and about interaction with other vehicles; VVs for common vehicles can help drivers make decisions by mining other drivers' behavior. By obtaining social and sensor data directly from the cloud to learn, and by actively communicating with other VVs, the VV can coordinate with others to select a best route for driver. In other words, the VV acts like a brain, allowing a physical vehicle and driver to interact and coordinate with others in the cloud; the physical vehicle behaves like an actuator on the road, acting upon directions from the VV. Control actually happens at the virtual level, in the cloud, instead of at the physical level, on the road.

VVs in cloud can obtain full-information including traffic information and other VVs decisions from the navigation systems and traffic apps. Hence, VVs can cooperate with each other to achieve a concession equilibrium via strategic concession game, and they can choose a more suitable route for driver.

3.2. Preliminaries

Let $N = 1, 2, ..., n$ be the set of players, which are the VVs in this paper. A nonatomic unit of flow must be passed from a source node to a sink node through a parallel links network on a set of links $L = 1, 2, ..., m$, and each link can be chosen by an arbitrarily player. Hence, each player has m strategies denoted by $x_i \in 1, 2, ..., m$, the aggregate decisions of all VVs yield a feasible flow, $X = (x_1 x_2 ... x_n)$. From the example describe in Section 1, we know that each vehicle's travel time is decided by all vehicles choices, and the cost function of VV i can be denoted by $\varphi_i(x) = \varphi_i(x_i, ..., x_i, ..., x_n)$. The social cost of a given tuple of cost functions and flow is given by $cost(X) = \sum_{i=1}^{n} \varphi_i(x)$. We consider a Strategic Concession Game (SCG) in which VVs have incomplete information regarding the cost function on the link. We call all games that follow the description above, SCG, and focus on the concession model.

In non-cooperative game, there exists Nash Equilibrium (NE) when all players denoted $(x_1^{NE}, x_2^{NE}, ..., x_n^{NE})$, such as in the example described in Section 1, the travel time expectations are two NEs in Case 1 and Case 2, respectively. Let $S_j \in [0, x^{NE}]$, $j \in 1, 2, ..., n$ denotes the discount of player j from its NE. Then the concession principle is that player i executes concession if its discount satisfies:

$$S_i = \begin{cases} \alpha_i S_j, & \text{if } \alpha_i S_j \le x_i^{NE}; \\ x_i^{NE}, & \text{if } \alpha_i S_j > x_i^{NE}. \end{cases} \tag{1}$$

where $\alpha_i \in R$ denotes the offer from player i.

We further endow the game with an informed, benevolent VVs who observe the realization of cost functions before any flow is routed, and can communicate with each other. Hence, all players can execute the SCG to achieve a new equilibrium via communication. However, players how make decision in SCG? What principles players should be obeyed? The following we discuss the detail of SCG principles [30].

Principle 1. The offer from player i has more attractive than all other players, i.e., for $\forall j(\neq i) \in \{1, 2, ..., n\}$, if

$$\frac{\alpha_i S_j / x_i^{NE}}{S_j / x_j^{NE}} > \frac{\alpha_j S_i / x_j^{NE}}{S_i / x_i^{NE}} \Leftrightarrow \alpha_i \frac{x_j^{NE}}{x_i^{NE}} > \alpha_j \frac{x_i^{NE}}{x_j^{NE}} \Leftrightarrow \alpha_i > \alpha_j \left(\frac{x_i^{NE}}{x_j^{NE}} \right)^2.$$

Principle 2. We say a player is winner if its offer has more attractive other players. If the player i is a winner, other players must receive the offer α_i. Hence, the aim of other player $j(\neq i) \in \{1, 2, ..., n\}$ is choose the maximum S_i when the winner i gives the offer α_i. And when the player j making concession, the player i must reduce its discount, i.e., $S_i = \alpha_i S_j$.

Principle 3. If $\alpha_i \frac{x_j^{NE}}{x_i^{NE}} = \alpha_j \frac{x_i^{NE}}{x_j^{NE}}$ for all $j(\neq i) \in \{1, 2, ..., n\}$, the player i is the winner if it satisfies, for $\forall j(\neq i) \in \{1, 2, ..., n\}$, it has $\left\{U_i^W(\alpha_i), U_j^L(\alpha_i)\right\} \ge \left\{U_i^W(\alpha_j), U_j^L(\alpha_j)\right\}$, where

$$U_i^W(\alpha_i) = \varphi_i(x_1^{NE}, ..., x_i^{NE} - \alpha_i S_j(\alpha_i), ..., x_j^{NE} - S_j(\alpha_i), ..., x_n^{NE}),$$
$$U_j^L(\alpha_i) = \varphi_j(x_1^{NE}, ..., x_i^{NE} - \alpha_i S_j(\alpha_i), ..., x_j^{NE} - S_j(\alpha_i), ..., x_n^{NE}).$$

Otherwise, select another player as the winner via random device.

Principle 4. If the offer α_i from the winner i satisfies $U_i^W(\alpha_i) < U_i^L(\alpha_i \left(\frac{x_j^{NE}}{x_i^{NE}}\right)^2)$, the player j can replace i to be a new winner. If player j does that, it can select an arbitrary α_i^P if its satisfies $U_i^W(\alpha_j^P \left(\frac{x_j^{NE}}{x_i^{NE}}\right)^2) \le U_i^L(\alpha_j^P)$.

Principle 5. If $\alpha_i^m > \alpha_i^0$, and player i give the discount offer α_i^s, then player j has a right to be a winner via selecting an offer α_j^P which satisfies $U_i^L(\alpha_j^P) \ge \min\left\{U_i^W(\alpha_i^s), U_i^L(\alpha_i^s \left(\frac{x_j^{NE}}{x_i^{NE}}\right)^2)\right\}$. Or player i to be the winner and its offer α_j^Q is selected by player j which satisfies $U_i^W(\alpha_i^Q) \ge U_i^W(\alpha_i^s)$. For $i, j \in \{1, 2, ..., n\}$, $i \neq j$, α_i^0 and α_i^m can be described as follows.

$$\alpha_i^0 = \max\left\{\alpha_i \in R^+ | U_i^W(\alpha_i) = U_i^L(\alpha_i \left(\frac{x_j^{NE}}{x_i^{NE}}\right)^2)\right\},$$

$$\alpha_i^m = \arg\max_{\alpha_{i \ge} \alpha_i^0} \left\{U_i^W(\alpha_i)\right\}.$$

In those principles, the Principle 1 and 2 defined a player how to be a winner, and Principle 3 limits the benefits between winner and loser. Otherwise, Principle 4 and 5 can prevent the hostile offer.

Each VV can be able to use his knowledge of cost realizations to maximum the benefit, but he cannot compel VVs to take his advice. Hence, VVs can perform SCG with each other to achieve a concession equilibrium (CE).

Definition 1. Given an aggregate offer $\Lambda = \{\alpha_1, \alpha_2, ..., \alpha_n\}$, if there is no player change its offer and all players agree the present benefit, we say the $\Lambda = \{\alpha_1, \alpha_2, ..., \alpha_n\}$ is a concession equilibrium (CE).

Obviously, there may more than one CE in SCG due to the CE is decided the offer of winner. As we shall soon show, in some cases the unconstrained social optimal flow cannot be implemented as a CE. To measure the difference from the optimal solution, we introduce the concession ratio (CR), defined as the ratio of the expected costs of CE flow and the globally optimal flow.

Definition 2. Give a CE $\Lambda = \{\alpha_1, \alpha_2, ..., \alpha_n\}$, suppose the corresponding decisions $X = (x_1 x_2 ... x_n)$, the concession ratio (CR) with respect to is defined as:

$$CR(\Lambda) = \frac{E_\Lambda[cost(X)]}{E[cost(X_{optimal})]}.$$

The globally optimal decisions known by all VVs, but they may not make that decision due to some VVs cannot obtain a satisfactory benefit, but the optimal can be calculated according to the full information of VVs and flow. Hence, we can use the CR to measure the difference between SCG and other approaches. To understand our approach more convenience, we show several more properties of our models:

Lemma 1. *In the non-cooperative games, if the decisions of all players are NE, and the CR is not the optimal, then if players cooperate and perform a SCG, a new CE can be achieved, and the CR cloud be better than NE.*

Proof. Assume the NE is $X^{NE} = (x_1^{NE} x_2^{NE} ... x_n^{NE})$, $CR(X^{NE}) > CR(X_{optimal})$. Then, players perform SCG and players give the offers. According to the Principle 1, 2 and 3, there is a winner and other players would calculate their offer, until achieve a CE which implies the benefits of players are increased. Hence, the globally cost could be decreased, and the CR decrease □

From the Lemma 1, we know that the globally of CE from the SCG is better than NE from non-cooperative games. In the SCG, players may give the different offers, and the discounts vary from different players, hence there exists more than one CE in a same CE, and we have the following results.

Lemma 2. *In the SCG, there may exist K CEs $\{CE_1, ..., CE_k\}$, for an arbitrary CE_i, $i = \{1, 2, \dots, k\}$ with the corresponding aggregate decisions X_i, and the CR satisfies*

$$CR(X_{optimal}) \le CR(X_i) < CR(X^{NE}).$$

From the Lemma 1, we know $CR(X_i) < CR(X^{NE})$. According to the Principle 4 and 5, there is no any player can provide a hostile offer, hence the decisions cannot be better than the globally optimal decisions, then the results of Lemma 2 can be obtained.

4. Affine cost function

In the full-information case, VVs in same link have same travel time, if the cost functions in each link only decided by the number of VVs affine cost function in this paper, i.e., the cost functions in a no accident road is n/N, and with accident road is $2n/N$. We show that the concession ratio bounded away from the PoA in the case of two links, and for any fixed number of links. We begin with the case of two parallel links.

Proposition 1. *The CR of SCG with affine cost function on two links is at most* 3/2.

Proof. Consider N VVs in the full-information case with two links with the accident probability p in each link, and link 1 has an accident, the cost functions of the two links is $\varphi_1(X_1) = (2\sum_{X_1} 1)/N$ and $\varphi_2(X_2) = (\sum_{X_2} 1)/N$, then the NE of non-cooperative game is $X^{NE} = \{x_i^{NE} | x_i^{NE} = 2p(1-p), i = 1, 2, ..., N\}$. Then, all VVs perform the SCG and give the offers $\Lambda = \{\alpha_1, \alpha_2, ..., \alpha_n\}$. Because of the offer of VV should make the all benefits of players increasing, there must exist at least one VV changes its selection. Assume the player 1 is winner, then according to the Principles 3 of SCG, others should compute their benefits and make a new decision. Since their benefits increase, they must agree with the concession, then the cost could be less than the X^{NE}. According to definition of CR, we have

$$CR(X) = \frac{(6n^2 - 4Nn + 2N^2)p(1-p)/N^2}{(4/3)p(1-p)},$$

where n denote the number of players which selection the link 1. Since the Principle 4 and 5 limited the hostile offer, hence the benefits should be higher than NE, in other words the cost should decrease and we have:

$$CR(X) = \frac{(6n^2 - 4Nn + 2N^2)p(1-p)/N^2}{(4/3)p(1-p)} \le \frac{2p(1-p)}{(4/3)p(1-p)} = \frac{3}{2}. \qquad \square$$

VVs know all other VVs' decisions and the accident information, the SCG can be performed if there are VVs willing concession, then all VVs can decrease the cost. From Proposition 1, the bound of CR in SCG can be obtained, i.e., in the full-information case with the affine cost function, the CR in SCG has the upper bound 3/2 and the lower bound 1.

Proposition 2. *The CR of SCG with affine cost function on two links can achieve at 1, if all VVs has no any selfish behavior and seek to maximize their benefit cooperatively.*

Proof. The main objective of SCG is that player maximize its benefit via concession from the NE. In the non-cooperative games, players not always satisfy the benefits in the case of NE, such as the Case 2 in the example in Section 1. If all players willing to cooperate with each other, then the SCG can be performed. From the offers $\Lambda = \{\alpha_1, \alpha_2, ..., \alpha_n\}$, assuming player i is the winner, then we have

$$U^L(\alpha_i) = \varphi(x_1^{NE} - s_1(\alpha_i), ..., x_i^{NE} - \alpha_i \prod_{j=1, j\neq i}^{N} s_j(\alpha_i), ..., x_N^{NE} - s_N(\alpha_i)),$$

$$U_i^W(\alpha_i) = \varphi_i(x_1^{NE} - s_1(\alpha_i), ..., x_i^{NE} - \alpha_i \prod_{j=1, j\neq i}^{N} s_j(\alpha_i), ..., x_N^{NE} - s_N(\alpha_i)).$$

Since the benefit only decided by the VVs' decisions, and there only two selections for VVs, hence the benefit can be described as follows.

$$U^L(\alpha_i) = \frac{w_1(x_1^{NE} - s_1(\alpha_i)) + \dots + (x_i^{NE} - \alpha_i \prod_{j=1, j\neq i}^{N} s_j(\alpha_i))}{N} + \frac{\dots + w_N(x_N^{NE} - s_N(\alpha_i))}{N},$$

where $w_j \in \{0, 1\}$, and $w_j = 1$ denotes VV i and VV j have the same decision, otherwise $w_{ji} = 0$. Then the first order of benefit is:

$$\frac{\partial U^L(\alpha_i)}{\partial S_j} = \frac{w_j - \alpha_i \prod_{k=1, k\neq i, k\neq j}^{N} s_k(\alpha_i))}{N} = 0, \quad j(\neq i) \in \{1, 2, \dots, N\}.$$

To solve the above equations, we have $\alpha_j/\alpha_i = 1$ if player j has the same selection with player i, and $\alpha_j/\alpha_i = (2\sum_{X_1} 1)/(\sum_{X_2} 1)$ if player j has different selection with player i. When the final equilibrium achieved, then the discount can be obtained $s(\alpha_j) = \frac{2\alpha_j x_j^{NE}}{\alpha_j + 2\alpha_j}$, and $x_j^{NE} = 2p(1-p)$, we have $s(\alpha_j) = \frac{4}{3}p(1-p)$. According to the definition of CR, the CR is 1 and the proof is finish. □

From Proposition 2, the optimal equilibrium can achieve and each player can obtain the maximum benefits when all players willing cooperate in the full-information case. In other words, VVs can minimize their travel time cooperatively, and the social cost also cloud be achieved.

Now we complement this positive result by a negative one, showing that when m is large. For each link, the cost functions in a no accident road is n/N, and with accident road is $2n/N$. Before presenting the results of m is large, we introduce a helpful lemma.

Lemma 3. *Consider N VVs with m links, if there is a link has an accident, VVs can select a link random in the full-information case. In the non-cooperative games, there only exist one NE, i.e.,* $x^{NE} = mp(1-p)^{m-1}$.

In the non-cooperative games, each VV knows the traffic information. They will choose a link random in the rest $m-1$ links, then the N VVs cloud be distribute in $m-1$ links uniformly. Then, assume the i link has an accident, the NE can be calculated:

$$x^{NE} = \binom{m}{1}\left(\sum_{L/i}\frac{N/(m-1)}{N}\frac{N}{m-1}\right)p(1-p)^{m-1}$$
$$= \frac{m}{m-1}p(1-p)^{m-1}.$$

We are now ready to present our negative result, by constructing an affine SCG to observe the number of links how impacts the CR.

Proposition 3. *The CR of SCG with affine cost function is irrelevant with the number of links, and the CR also is at most* $\frac{2m-1}{2(m-1)}$.

According to the Lemma 3, we can obtain the NE of non-cooperative games in the full-information case. Then, we can calculate the optimal equilibrium, i.e., $2/3mp(1-p)^{m-1}$, similar with Proposition 1, we have

$$CR(X) \le \frac{\frac{m}{m-1}p(1-p)^{m-1}}{\frac{2m}{2m-1}p(1-p)^{m-1}} = \frac{2m-1}{2(m-1)}.$$

Now, we extend the one accident link to accident links, and the results of the general case of affine cost function can be described as follows.

Theorem 1. *For the m links with* $k(\le m)$ *accident links, N VVs perform the SCG with affine cost function, the value of CR is limited in the range of* $\left[1, \frac{2m-k}{2(m-k)}\right]$.

Proof. In the SCG, each VV willing cooperative to obtain maximum benefit which implies the minimum travel time in our considering case. According to Proposition 2, we know that VV can make the best decision to cooperate with each other, and the optimal decisions can be obtained when all VVs make the best the decision. Hence, the minimum of CR is 1 according to its definition. Similar with the proof of Proposition 2, we can calculate the expected costs of each VV as follows:

$$\binom{m}{k}\frac{((2m-k)(\frac{n-Nk}{(2m-k)})^2 - \frac{2k(m-k)N^2}{(2m-k)})p^k(1-p)^{m-k}}{k(m-k)p^k(1-p)^{m-k}N^2},$$

then the optimal costs is $\binom{m}{k}\frac{2}{2m-k}$. In the non-cooperative games, we can obtain the NE is $\binom{m}{k}\frac{1}{m-k}$. According to the definition of CR and the Lemma 2, the maximum of CR is $\frac{2m-k}{2(m-k)}$. □

5. General cost function

As established in the previous section, when the cost functions are restricted to the set of affine functions, the MR in m links with k accident links can be converged the optimal cost.

In this section, we discuss the MR in case of general cost function. For the cost function, we know the travel time cannot decrease with the number of vehicles increasing in a road, hence the general cost function must be a non-decrease function. Then, we show the results has some difference with the affine cost function case. Before presenting the results, we fist introduce a definition of partition.

Definition 3. For the m links and with k accident links, assume the cost functions of m links are $c_1 \le c_2 \le \ldots \le c_m$, we can divide the m links into l sets $L_1, L_2, \ldots, L_l$ such that:

- The links i, j in the same set if $c_i(n) = c_j(n)$, n denotes the number of VVs;
- For arbitrary two sets L_i and L_j, $i \ne j$, they satisfy $L_i \cap L_j = \emptyset$;
- For $c_i \in L_h$ and $c_j \in L_k$, if $h < k$, $c_i(n) < c_j(n)$.

Note that the link in same set has same cost function, and VVs cloud choose the links of L_l random in non-cooperative game, hence the NE could be $c_1(N\backslash|L_1|)$, $|L_1|$ denotes the number of links in L_l.

Lemma 4. *Let* $c_1, c_2, \ldots, c_m$ *be a cost functions than can be divided into a partition* $L_1, L_2, \ldots, L_l$. *In the SCG with N VVs, let* $n_1, n_2, \ldots, n_m$ *be the optimal number of VVs in the corresponding links, and let* $\sum_{i=1}^{m} c_i(n_i) = \gamma$. *Then* $\sum_{i=1}^{m} n_i c_i(n_i) \le \gamma N/|L_1|$.

Proof. Since $n_1, n_2, \ldots, n_m$ are the optimal number of VVs in links, hence we have

$$n_i c_i(n_i) = n_j c_j(n_j), \forall i, j \in \{1, 2, \ldots, m\}.$$

According to the definition of partition, the cost functions satisfy $c_1 \le c_2 \le \ldots \le c_m$, hence $n_1 \ge n_2 \ge \ldots \ge n_m$. Then, we have follow result:

$$\sum_{i=1}^{m} n_i c_i(n_i) \le \sum_{i=1}^{m} n_1 c_i(n_i),$$
$$\sum_{i=1}^{m} n_i c_i(n_i) \le n_1 \sum_{i=1}^{m} c_i(n_i) = n_1\gamma.$$

Besides, in the NE of non-cooperative game, the number of VVs in each link of L_l is $N/|L_1|$. Since the n_l is the number of VVs in each link of L_l in the optimal case, hence $n_1 \le N/|L_1|$. □

In the full-information case, VVs cooperate with each other to decrease the cost using SCG. When VVs perform the SCG, they will calculate the discount according to the offers, then they exchanged their offers until achieve a CE, and we use the CR to measure the CE referred to its definition. For the CR with the non-decrease cost function case, we have the following result.

Theorem 2. *For the m links with* $k(\le m)$ *accident links, N VVs perform the SCG with non-decrease cost function* $c_1, c_2, \ldots, c_m$, *and assume it can be divided into a partition* $L_1, L_2, \ldots, L_l$. *Then, the upper bounds of CR can be limited in* $\left[\max\left\{1, \frac{|L_1|}{m}\right\}, 2\right]$.

Proof. In the non-cooperative game, the NE is $c_1(N\backslash|L_1|)$, and according to the Lemma 4, then we have

$$CR_{\max} = \frac{c_1 (N \backslash |L_1|)}{\left(\sum_{i=1}^{m} n_i c_i(n_i)\right)/N} \geq \frac{c_1 (N \backslash |L_1|)}{\gamma N |L_1| / N},$$

$$CR_{\max} = \frac{|L_1| c_1 (N \backslash |L_1|)}{\gamma} \geq \frac{|L_1| c_1 (N \backslash |L_1|)}{m c_1 (n_1)} \geq \frac{|L_1|}{m}.$$

According to the SCG, VVs make discounts $d_1, d_2, ..., d_m$ to achieve a new CE, and we have $c_1 (N \backslash |L_1|) = c_1 (n_1) + d_1$. Then, we have

$$CR_{\max} = \frac{c_1 (N \backslash |L_1|)}{\left(\sum_{i=1}^{m} n_i c_i(n_i)\right)/N} = \frac{N c_1 (N \backslash |L_1|)}{m n_1 c_1 (n_1)}$$
$$\leq \frac{N c_1 (N \backslash |L_1|) + m n_1 d_1}{m n_1 (c_1 (n_1) + d_1)},$$
$$CR_{\max} \leq \frac{N}{m n_1} + \frac{d_1}{c_1 (n_1) + d_1}.$$

Since $c_1 = \min\{c_1, c_2, ..., c_m\}$ and $n_i c_i(n_i) = n_j c_j(n_j)$, hence $n_i \geq N/m$, then

$$CR_{\max} \leq \frac{N}{m n_1} + \frac{d_1}{c_1 (n_1) + d_1} \leq \frac{N}{mN/m} + 1 = 2.$$

From the definition of CR, we know that $CR \geq 1$, hence we have CR can be limited in $\left[\max\left\{1, \frac{|L_1|}{m}\right\}, 2\right]$. □

6. Conclusion

In this paper, we first apply a concept of virtual vehicle in IoV, which is an image of driver and vehicle, to solve the optimal route choice problem when drivers willing cooperate with each other. We study a class of strategy concession game with parallel-links routing in which VVs have incomplete information about the costs of the links and other VVs decisions. We define the concession ratio: the ratio between the concession equilibrium arising from cooperation recommendations and the social optimum, which is always bounded from above by the PoA. We find that the concession ratio is at most 3/2 for two links with affine cost functions, the concession ratio is at most 2 for general non-decrease cost functions. The main open question left by our work is verity the concession ratio in the road networks.

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