GSS-VC: A Game-theoretic Approach for Service Selection in Vehicular Cloud

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***Abstract*—Vehicular Cloud Computing (VCC) exploits resources at vehicles, such as computing, storage and internet connectivity to provide services for applications supporting different ITS (Intelligent Transportation System) services. Current Vehicular Cloud (VC) systems allow Consumer Vehicles (CVs) to discover and consume offered services by nearby mobile cloud servers (vehicles). However, to consume the required services, the CVs must first select the most suitable service provider, given that each of providers is characterized by specific features, limitations and prices. To the best of our knowledge, no work to date addresses the critical question of how to select the best provider fitting the quality of services and costs requirements of the consumer vehicles. Similarly, Provider Vehicles (PVs) should adjust the provided services' features and prices under certain conditions such as the rate of consumers' requests which makes this issue even harder. In this paper, we propose GSS-VC as a new distributed game theory-based approach to manage the service provisioning in vehicular cloud. Our approach takes into account the benefit of each player and allows the CVs to find the most suitable PV based on the probability interaction between them. Simulation results are carried out using urban mobility model and illustrate the effectiveness of the proposed approach to answer the raised questions: what is the best condition under which the CVs may request the PVs for services? and how to select the best service with respect to the CV preferences? Results from extensive simulations on up to $1,500$ vehicles show that GSS-VC is a an efficient and reliable service selection scheme while achieving high QoS.**

***Keywords*—Vehicular Cloud, Provider Vehicles, Consumer Vehicles, Service Selection, Game Theory.**

I. Introduction

Over the last decade, the wide deployment and evolution of cloud-based solutions have motivated research community to study the benefits of migrating to other cloud-inspired environments, such as Vehicular Clouds (VCs) [1] [2] [3]. Recently, Vehicular Cloud (VC) has emerged as a new landscape of mobile cloud computing, aiming to provide wide-range of on-demand applications, including, weather information, road conditions, parking availability, advertisements, storage of videos or music files [4] [5].

A smart vehicles can act as a client of a service as well as a provider, thanks to the many available on-board resources including powerful computers, sensors, radar devices and wireless communication devices allowing it to perform relatively high computing and storage. Therefore, such advanced in-vehicle resources enable provider vehicles to offer a variety of services ranging from Network as a Service (NaaS) to provide Internet access to other vehicles, STorage as a Service (STaaS) for vehicles that may need additional storage to run their applications, going through COoperation as a Service (COaaS) to perform a specific task such as vehicle health monitoring, to INformation as a Service (INaaS) and ENtertainment as a Service (ENaaS) [4] [6] [7].

We rely on a VC system model and architecture to, on one hand, allow Provider Vehicles (PVs) to rent out their services and resources to other vehicles, and, at the same time, enable Consumer Vehicles (CVs) to discover and consume PVs' services. VCs can be operated in; (i) a stationary mode, say for parked vehicles to offer their services in a cloud environment [1] [3]. Such examples are traffic jams, vehicles parked at an airport or any other parking lot. (ii) On the move mode, a rather challenging case where vehicles offer their services while moving.

However, It is an issue for consumer vehicles to discover provider vehicles, aquire information about the offered services, and request them for services of interest, given different PV can offer services which differ in quality and cost. The CVs must first select the most adequate provider in order to consume the required service, given that each provider has specific features, limitations and prices. However, to the best of our knowledge, no work to date addresses the critical question of *how to select the best PV which meets the requirements of the Consumer Vehicle (CV) in terms of Quality of Service (QoS) and costs*? Specially, with the mobility and intermittent connectivity of vehicles impacting the obtained QoS, thus, resulting in an increased latency as well as reduced reliability. Another challenge is that the PVs should adjust the provided services' features and prices based on both, the offered QoS parameters, and the external cloud conditions such as the rate of CVs' requests which is challenging to address in a highly dynamic vehicular network.

In this paper, we model the interaction between CVs and PVs in a vehicular cloud network by enabling CVs to select the best PVs, and vice-versa, allowing PVs to gain appropriately from the CVs based on their QoS and costs. To do so, we propose GSS-VC, a Game theory-based approach for Service Selection in Vehicular Cloud, as a new distributed game-theoretic approach to manage on-demand service provisioning in vehicular clouds. GSS-VC takes into account the gains and costs of both, the consumer and the provider vehicle in order to obtain Nash Equilibrium as the solution between the CVs and PVs. Additionally, it considers key QoS parameters such as the data throughput and delay for successful responds to CV requests as well as their incurred cost of service provisioning. Results from extensive simulations on up to $1,500$ vehicles show that GSS-VC is a an efficient and reliable service selection scheme while achieving high QoS. The contribution of this paper are as follows:

- We propose GSS-VC as the first distributed model of inter-vehicle relation for service provisioning in a vehicular cloud, catering the challenge of mobility and intermittent connectivity.
- We exploit game-theory to consider jointly the QoS parameters and costs for both, service provider as well as consumer vehicles towards a Nash-Equilibrium as a solution.
- We validate the proposed GSS-VC by performing extensive simulations using up to $1,500$ vehicles, 180 road in a $9\ km^2$ area where each road is of $1\ km^2$.

The reminder of this paper is organized as follows. The related work is discussed in Section II. In Section III, we describe the proposed game-based approach dealing with the interactions between PVs and CVs. Section IV presents the numerical results with their appropriate analysis. Finally, Section V concludes the paper along some insights into future directions.

II. Related Work

The service selection problem is widely studied in cloud computing where existing approaches can be categorized into two groups; (i) MCDM-based (Multiple Criteria Decision Making) techniques which consist of the comparison of several service providers by evaluating and aggregating their quality criteria [9] [10] [11]. The most popular MCDM techniques used for the selection problem are Analytic Hierarchy Process/Analytic Network Process (AHP/ANP), outranking, MAUT, and Simple Additive Weighting (SAW) [8]. (ii) Optimization-based techniques which find the best services for the clients, which maximize or minimize one or several criteria. Several optimization techniques are applied to resolve the service selection problem such as dynamic programming, integer programming, greedy algorithm, etc [12] [10] [13].

As a specific class of Cloud Computing, the Mobile Cloud Computing (MCC) combines Cloud Computing and wireless networks such as 3G and Wi-Fi [14] [15]. The goal is to offload high computation tasks from resource limited mobile devices to the distributed cloud environments. However, wireless network characteristics, users mobility and the resources limits in terms of computational power and battery consumption introduce new complexities in order to satisfy QoS needs of mobile users. Proposed works in this context address the challenge of how the mobile users can efficiently make use of cloud service by optimizing the resource utilization and their QoSs [14] [15] [16].

Although the above studies shed the light on how to select the most suitable cloud service, they can not be directly applied in the high mobile vehicular cloud in which the topology of the network varies fast over time due to the high mobility of vehicles which may affect services' QoS such as the latency and the reliability.

In vehicular cloud context, as we mentioned before, proposed works focus on systems and architectures which aim at facilitating service discovering and consuming operations [3] [4] [6] [7] [8] [9] [10] [11]. To manage on-demand service provisioning, the authors in [17] [18] propose a negotiation system between provider and consumers. This system assumes a network of static vehicles and it is based on negotiation interaction through a trusted third party which is also in charge to control misbehavior of participants and to guarantee the payment operation. However, this system requires n x n x n communication model and hence it includes more delay which has a significant impact since the consumers in this systemare charged by the amount of time the service is used. In conclusion, there exists no successful solution, to the best of our knowledge, to solving the service selection problem in vehicular clouds, while vehicles are on the move, thus catering high mobility and intermittent connectivity.

III. GSS-VC: A FULLY DISTRIBUTED APPROACH

Service selection of a CV requires wireless connections with all PVs which may offer the desired service. For a better balance of offer and demand, service selection scenario requires the interaction between the most important actors, CV and PV. In this section, we formally study this interaction by the use of a game theory that represents one of the most important tools for studying behaviors and strategies of interacting actors. The main idea of the proposed game model is that the two sides of the system (PV and CV) should have a monetary gain by participating in service selection operation. We first describe the proposed model that involves the major characteristics of PV (i.e. offered service features such as response time and service price) and the CV request (i.e. the service required). We then provide the payoff matrix related to PV and CV. We finally predict the behavior of both PV and CV based on the Nash equilibrium concept [19].

A. *Game Description*

In our approach, we consider two players representing the main actors in the service selection scenario: Players = $\{$PV, CV$\}$. The CV can perform two actions which are consuming a service from the PV or not, this will depend on both the QoSs and the price proposed by the PV. Besides, the PV has also two actions which are offering the service to the CV or not. It is clear that the CV prefers to have good quality resource at a low price whereas PV will define the price based on its QoSs. Therefore, both, CV and PV will choose the appropriate action in order to maximize their respective gain. When no player can increase its own gain, there will be a stable state, achieved with a help of a Nash Equilibrium which we used to determine the future behaviors of both players. In our approach, we represent each service by a number of data packets which must be exchanged between a PV and a CV with respect to the service type. We consider four PVs' quality parameters for the service selection problem:

1) **Data Throughput** (q_{DTH}): the q_{DTH} represents the number of delivered data packets in a given time period by a PV and it is measured in data packets per second.
2) **Successful Execution Ratio** (q_{SER}): it is the probability that a CV's request is correctly responded by

a PV within the maximum expected time. The q_{SER} value is calculated as, $q_{SER} = \frac{N(s)}{K}$, where $N(s)$ is the number of times that a PV's service s has been successfully consumed, and K is the total number of invocations for the service s.

3) **Execution duration** (q_{ED}): defined as the expected delay in seconds between the moment when a request is sent and the moment when the results are received. It is calculated as $q_{ED} = T_{Process}(s) + T_{Trans}(s)$, meaning that the q_{ED} of a service s is the sum of the processing time ($T_{Process}$) and transmission time (T_{Trans}). We note that the T_{Trans} is determined according to the required quantity of service s by a CV and the PV's Data throughput.
4) **Execution Price** (q_{EP}): The service price which we represent as the price per data packet.

B. Payoff Matrix

In this subsection, we present the payoff matrix of the game between the CV and PV (see TABLE I), where p and $1-p$ are the probabilities with which the PV decides an action if it is offering or not offering a service. Similarly, q and $1-q$ are the probabilities with which the CV player decides whether it is consuming or not consuming the service.
The payoff equation of each player is as follows:

$$X_{11} = N * q_{EP} - (q_{ED} + q_{SER}), \tag{1}$$

$$Y_{11} = N - (q_{ED} + N * q_{EP} + q_{SER}), \tag{2}$$

$$X_{12} = -N * q_{EP}, \tag{3}$$

$$Y_{12} = -M * N, \tag{4}$$

$$X_{21} = \begin{cases} 0, & Busy \\ -L * N * q_{EP} & Otherwise, \end{cases} \tag{5}$$

$$Y_{21} = -N, \tag{6}$$

$$X_{22} = 0, \tag{7}$$

$$Y_{22} = 0, \tag{8}$$

where,

- N: is the number of required data packets by the CV which represents the service s.
- M: is the number of unsuccessful attempts to deliver a service to the CV. The PV accepts to deliver the service but the CV refuses to consume.
- L: is the number of times that the PV rejects CV's demand. The CV wants to consume but the PV refuses to offer it.

In order to have normalized payoffs, each quality parameter (variable) is standardized with no unit. Hence, each payoff equals to a score with no unit. For example, the price of a service q_{EP} is normalized by a standardized price Max(q_{EP}) (i.e. q_{EP}=(Real(q_{EP}) / Max(q_{EP})).

TABLE I: Payoffs Matrix of both palyers PV and CV.

PV / CV	Consuming	Do not consume	
Offering	(X_{11}, Y_{11})	(X_{12}, Y_{12})	p
Do not offer	(X_{21}, Y_{21})	(X_{22}, Y_{22})	$1-p$
	q	$1-q$	

TABLE II: Simulation Parameters.

Parameters	Values
Simulation Time	1000 s
Simulation Area	9 x 9 km^2
Transmission Range	500 m
Data Throughput	[1, 5] packets/s
Vehicles speed	Up to 70 km/h
Consumer vehicles Density (CD)	[300-1500] vehicles
PVs density (P)	1/4, 1/3, and 1/2 of CD
Execution Price	[10, 100]$
Request Rate	[1-5] Requests
Maximum number of offered services per PV	3 Services
Maximum number of requested services per CV	2 Services

We describe below the set of strategies that could occur between the PV and the CV.

- **Strategy combination (Offering & Consuming)**
In this case, the PV offers its service and the CV decides to consume it. X_{11} represents PV's gain, which is equal to the number of sent data packets multiplied by the price of each packet. On the other hand, this PV's gain is affected by both the execution duration which is a negative criteria, i.e. the lower the value the higher the quality, and the successful execution ratio which is a positive criteria, i.e. the higher the value the higher the quality. The gain of the CV Y_{11} relies on the received service in terms of data packets. This gain is affected by the service price, the execution duration, and the successful execution ratio.
- **Strategy combination (Offering & Do not consume)**
In this case, the PV wants to sell its service to the CV, but this latter doesn't buy (i.e. does not consume). The CV may refuse to consume because it is not satisfied by the PV's QoS or it had consume from another PV. Here, X_{12} represents the failure of PV in selling service to the CV, which is the number of sent data packets multiplied by the price of each packet. In this case, the CV will be penalized by multiplying its gain by the number of times that it has refused to consume from PV. This is represented by Y_{12}.
- **Strategy combination (Do not offer & Consuming)**
In this case, the CV wants to consume, but the PV decides not to sell (i.e. do not offer). The PV does not deliver because it is occupied (offers its service to another CV). If it is not the case, the PV will be penalized. This penalty is represented by X_{21} and Y_{21} represents the consuming failure of the CV.
- **Strategy combination (Do not offer & Do not consume)**
In this case, both PV and CV gains will be null since both neither deliver nor consume the service.

TABLE III: The five top selected Provider vehicles in each time period.

Ranking	Off-peak Time				Mid-peak Time				On-peak Time			
	CV ID	PV ID	Consuming Probability (q)	Offering Probability (p)	CV ID	PV ID	Consuming Probability (q)	Offering Probability (p)	CV ID	PV ID	Consuming Probability (q)	Offering Probability (p)
1	287	34	0.86	0.53	698	467	0.77	0.58	309	100	0.65	0.75
2	502	122	0.86	0.53	23	529	0.77	0.58	119	1391	0.65	0.75
3	129	98	0.86	0.53	176	190	0.76	0.59	1487	609	0.64	0.77
4	398	213	0.85	0.55	239	96	0.76	0.59	765	419	0.63	0.79
5	1100	387	0.85	0.55	004	702	0.76	0.59	901	200	0.63	0.79

C. Nash Equilibrium

The utility of Nash Equilibrium (NE) is to predict the future behavior of the PV and the CV and determine the permanent state, i.e. each player has an interest in performing the same action. We use the NE to determine the stage when both PV and CV do not change their actions, which are respectively offering and consuming.

Theorem 1: There is a mixed strategy NE $\{PVplayer$ (Offering, $p*$), $CVplayer$ (Consuming, $q*$)$\}$ in which the PV chooses Offering action when the probability $p > p*$ and the EV chooses Consuming action when $q > q*$.

Proof:

The mixed strategy of the PV is defined as follows: $P = (p, 1 - p)$, and the expected payoffs of the CV for playing Consuming action or not are:

- U_{CV}(Consuming) $= Y_{11} * p + Y_{21} * (1 - p) = p * (Y_{11} - Y_{21}) + Y_{21}$
- U_{CV}(Do not consume)$= Y_{12}*p+Y_{22}*(1-p) = p*Y_{12}$

The CV will play Consuming action when U_{CV}(Consuming)$>$ U_{CV}(do not consume). Therefore, we have:

- $p > p*$ where $p* = \frac{-Y_{21}}{Y_{11}-Y_{21}-Y_{12}}$ with $0 < p* <= 1$

The mixed strategy of the CV is defined as follows: $Q = (q, 1 - q)$, and the expected payoffs of the PV for playing Offering action or not are:

- $U_{PV}(Offering) = X_{11} * q + X_{12} * (1 - q) = q * (X_{11} - X_{12}) + X_{12}$
- U_{PV}(Do not offer)$= X_{21} * q + X_{22} * (1-q) = X_{21} * q$

The PV will play Offering action when U_{PV}(Offering)$>$ U_{PV}(do not offer). Therefore, we have:

- $q > q*$ where $q* = \frac{-X_{12}}{X_{11}-X_{12}-X_{21}}$ with $0 < q* <= 1$

As a result, we conclude that when the Consuming action probability of the CV is above $q*$ and the Offering action probability of the PV is above than $p*$, both players do not change their actions.

■

IV. PERFORMANCE EVALUATION

In this section, we present the simulation experiments that we performed to evaluate our GSS-VC approach.

A. Simulation Setup and Parameters

To validate GSS-VC, we use OMNet++ network simulator [20], which provides infrastructure and tools for writing wired and wireless simulations, and used SUMO mobility simulator [21] to generate the vehicles mobility traces that we inputted to OMNet++. We use a Manhattan-based map of 9x9 km^2 where there are 180 roads of 1 km and 16 junctions. The main parameters of our simulation are shown in TABLE II. We vary the Consumer vehicles Density (CD) between 300 and 1500, where three values of PVs density are considered: one fourth, one-third, and one-half of each level of CD. We intend to evaluate the performance of GSS-VC in terms of; 1) the efficiency of the service selection in choosing the best provider and maximizing the service gain of the consumers, 2) the latency of the service selection in reducing the service selection delay, and 3) the reliability of the service selection in increasing the successful execution ratio of the service.

During the simulation, each CV plays the game with all PVs present in its vicinity. It selects then the PV with which it reaches the highest consuming probability (q). We choose the following metrics to evaluate our approach:

1) **Probability Convergence (PC)**: In order to be more realistic and to study the probability interaction between PVs and CVs, we simulate our approach in three different time periods; off-peak times where the service demand is low (for instance, at night), mid-peak times where the service demand is medium and on-peak times when we have a huge demand of vehicular cloud service, for example, during congestion.
2) **Average Service Delay (ASD)**: measures time delay before a consumer receives the requested service from the service provider. This metric is used to evaluate the delay generated by game model.
3) **Service Gain (SG)**: It represents the CVs' gain after they consume desired services from selected PVs'. For all schemes, we compute the CVs' gain using Y_{11} which relies on the received service in terms of data packets, PVs' prices, the execution duration, and the successful execution ratio. We then normalized this value with respect to the top identified services' QoSs and prices.
4) **Successful Execution Ratio (SER)**: it measures the rate of CVs' requests are being correctly responded by selected PVs within the maximum expected time.

To assess the performance of GSS-VC, we compared it with two other service selection schemes: (i) Neutral scheme [18], it is a simple selection scheme in which a consumer vehicle selects the first available provider vehicle without any QoS as-

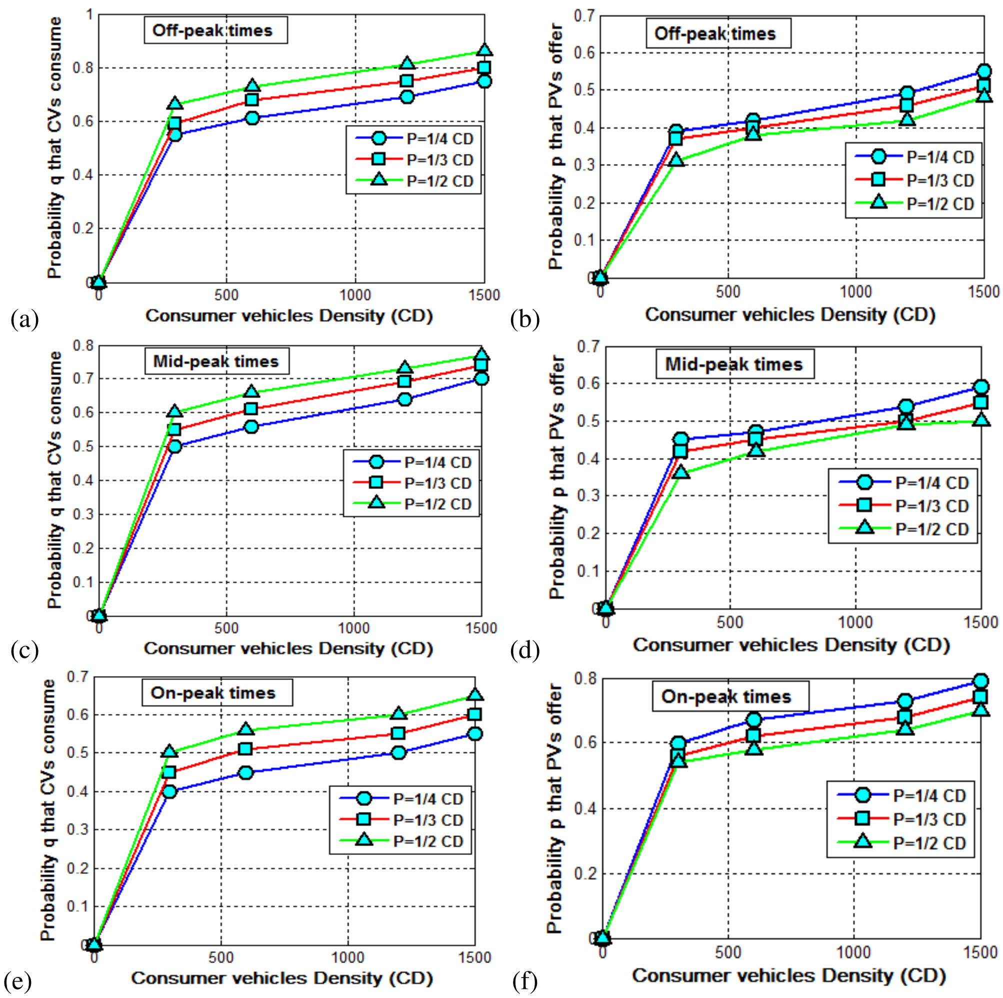

Fig. 1: Probabilities convergence in different time periods.

pects. (ii) The Negotiation-based service selection [17] which uses QoS-awareness, and manages a competition between provider and consumer vehicles through trusted third parties. This scheme is comprised of three main actors: consumer vehicles, provider vehicles and trusted vehicles as trusted third parties. So, at receiving a service request, the trusted vehicles are responsible for the negotiation the services and for the search of the best price. To be fair in our simulation and since these schemes are proposed for static vehicular cloud, we adopt them to be executed while vehicles are on the move.

B. Results and Discussions

The objective of our simulation study is to find answers to the fundamental question: *when and how the CVs may select the best service*? TABLE III shows the five top selected provider vehicles and the corresponding consuming and offering probabilities, during the three time periods (off-peak, mid-peak and on-peak times). We observe that the consuming probability may reach up to 0.86 in off-peak time. This value decreases to 0.77 and 0.65 in mid-peak and on-peak times, respectively. On the other hand, the offering probability is increasing from 0.53 in off-peak time to 0.58 and 0.75 in mid-peak and on-peak times, respectively. These results are also confirmed in Fig. 1 which can be justified by the fact that from off-peak to on-peak times, the service demand increases, which causes an increase in the selling price proposed by the PVs. Therefore, these latter can increase their prices especially when the number of consumers is important in order to increase their gain. Hence, the PVs have more interest to offer their services during on-peak periods than during off-peak hours. In addition, the decrease of the consuming probability from off-peak to on-peak times is also due to the increase in demand, which induces the increase in price. This will oblige the consumers to consume their services with minimum amount as possible during these periods or sometimes not to charge. We notice also that the offering probability decreases and the consuming probability increases as we increase the providers' density (P). The presence of more PVs in the network implies that the CVs have likelihood to find the most suitable PVs, causing the probability p to decrease (cf. Figure 1-a, 1-b, 1-c) and the probability q to increase (cf. Fig 1-d, 1-e, 1-f).

In order to consume with less cost and maximize their profit, it is a good strategy to encourage CVs consuming during off-peak times at the night for instance. So, the PVs have to choose the right pricing policy to balance between offer and demand.

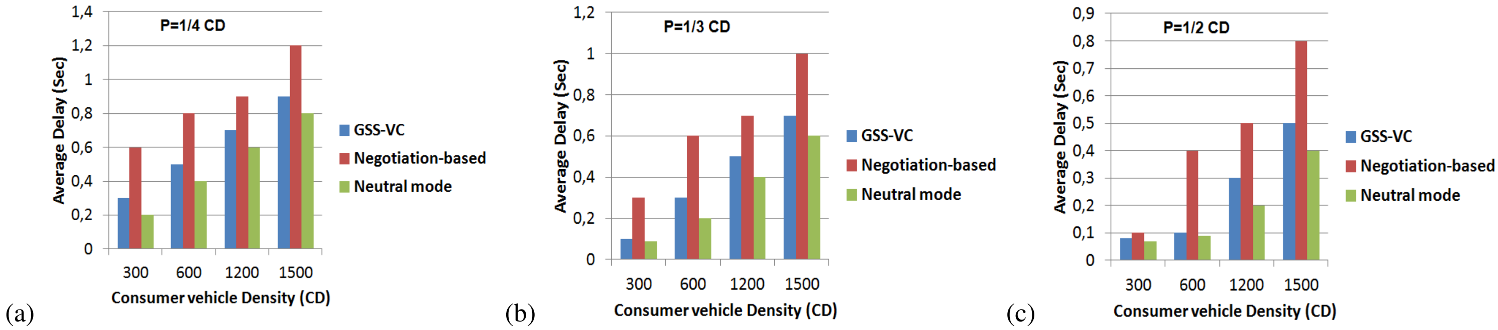

Fig. 2: Average service delay comparison between GSS-VC, Negotiation-based and Neutral mode, during on-peak times while varying both the consumer and the PV densities.

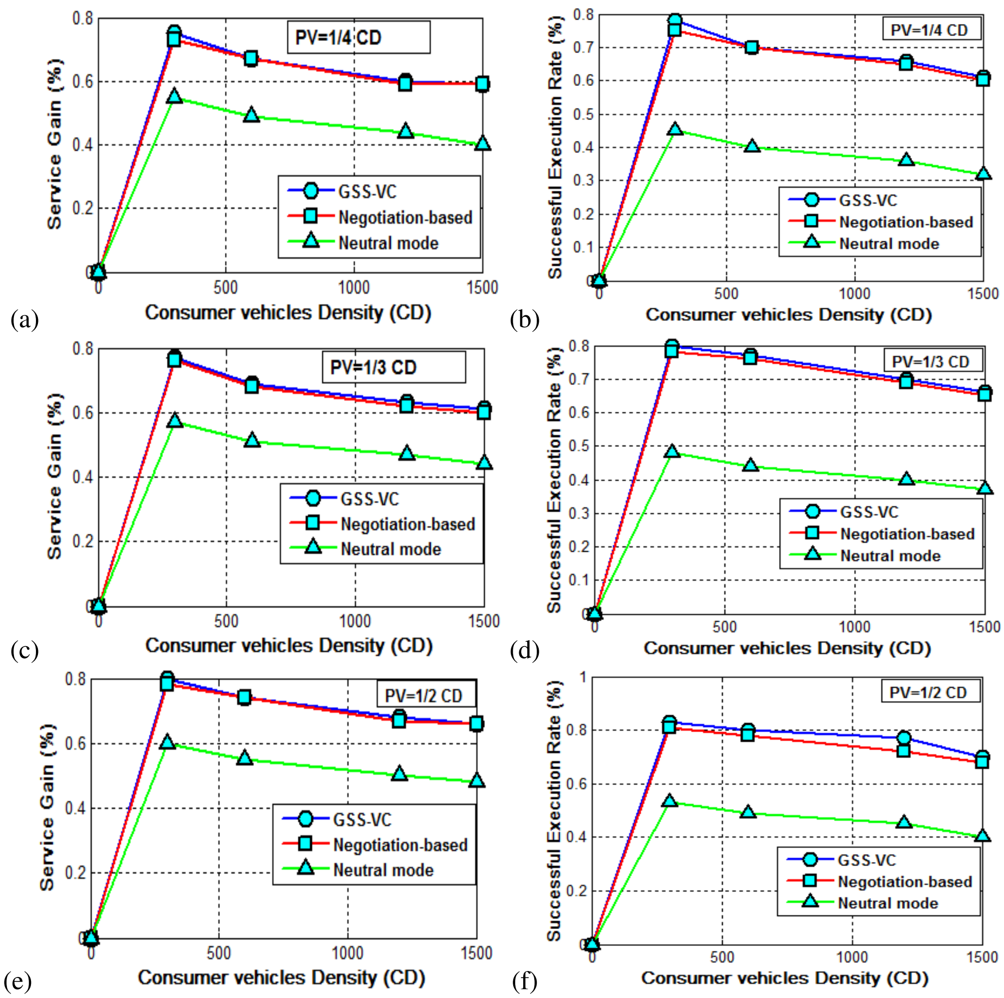

Fig. 3: Service gain and Successful Execution Ratio comparison between GSS-VC, Negotiation-based and Neutral mode, during on-peak times while varying both the consumer and the PV densities.

Fig. 2 depicts the Average Service Delay (ASD) of GSS-VC, Negotiation scheme and Neutral mode while varying both consumer and provider densities. It shows that Neutral mode achieves a low ASD compared to the other schemes. The Neutral mode selects the first available nearby service provider to handle a consumer request while the consumers must first play a game or negotiate with the providers in GSS-VC and Negotiation-based schemes, respectively. However, the latency introduced in GSS-VC and Negotiation-based schemes improves the service gain and the successful execution ratio compared to the Neutral mode (cf. Fig. 3). In addition, we remark that the ASD increases as we increase the Consumer Density (CD) which can be justified by the increasing number of requester vehicles when CD increases. Nevertheless, it decreases (ASD) as we increase the provider density (P). The presence of more providers implies that a consumer has a likelihood of being answered by these PVs, causing ASD to decrease.

Fig. 3 compares the gain and the successful execution ratio of the services between GSS-VC, Negotiation-based and Neutral mode. As we can see, both GSS-VC and Negotiation-based schemes generate almost the same performances which are higher than that of the Neutral mode. As we mentioned before, a consumer vehicle in the Neutral mode selects the first available nearby service provider. As the provider's QoSs and prices are unpredictable, a consumer can find a provider with lower QoSs and higher price which reduces both the gain and the successful execution ratio of the requested service. On the other hand, GSS-VC and Negotiation-based are QoSs aware and a service provider should propose an acceptable and reasonable offer to the consumer if he wants to provide the service. For instance, the service gain in our scheme (GSS-VC) is determined with respect to the received service in terms of data packets, service price, the execution duration, and the successful execution ratio. We also notice that the gain and the successful execution ratio of the services decrease when we increase the CD and they increase as we increase the PVs density (P). As explained for Fig. 2, these results are mainly due, on one hand, to the increasing number of requester vehicles when CD increases which causes the gain and the successful execution ratio of the services to decrease, on the other hand, to the presence of more providers which causes the gain and the successful execution ratio of the services to increase.

Therefore, we can deduce that GSS-VC enables consumer vehicles to select the most suitable provider vehicles and at the best moment thanks to its game-based model. When compared to the other schemes, we also deduce that GSS-VC improves: (i) the **efficiency** of the service selection in terms of choosing the best provider and the obtained service gain. (ii) The **latency** of the service selection in terms of the service delay. (iii) The **reliability** of the service selection in terms of successful execution ratio.

V. Conclusion and Future work

In this paper, we proposed a new distributed service selection scheme for vehicular cloud called GSS-VC. GSS-VC focuses on the interaction between consumers and providers in vehicular cloud in order to enable consumers selecting the best providers. To study this interaction, we formulated a game model and with the help of the Nash Equilibrium (NE), we evaluate the interaction probability between CVs and PVs for three time periods (off-peak, mid and on peak times). We validated the performance of GSS-VC throughout simulation experiments and have compared them with those of Neutral mode and Negotiation-based schemes. The simulation results show that GSS-VC enables consumer vehicles to select the most appropriate provider vehicles as it improves the efficiency, the latency and the reliability of the service selection operation. As future work, we aim to secure the service selection process in order to deal with rational/selfish providers which indicate untrustworthy QoSs and prices.

References

[1] H. T. Mouftah and B. Kantarci, *Communication Infrastructures for Cloud Computing: Design and Applications*. IGI Global, 2013.

[2] Z. Sanaei, S. Abolfazli, A. Gani, and R. Buyya, "Heterogeneity in mobile cloud computing: Taxonomy and open challenges," *IEEE Communications Surveys Tutorials*, vol. 16, no. 1, pp. 369–392, 2014.

[3] A. u. R. Khan, M. Othman, S. A. Madani, and S. U. Khan, "A survey of mobile cloud computing application models," *IEEE Communications Surveys Tutorials*, vol. 16, no. 1, pp. 393–413, First 2014.

[4] M. Whaiduzzaman, M. Sookhak, A. Gani, and R. Buyya, "A survey on vehicular cloud computing," *Journal of Network and Computer Applications*, vol. 40, pp. 325 – 344, 2014.

[5] J. A. Khan and Y. Ghamri-Doudane, "Saving: socially aware vehicular information-centric networking," *IEEE Communications Magazine*, vol. 54, no. 8, pp. 100–107, 2016.

[6] M. Gerla, "Vehicular cloud computing," in *Ad Hoc Networking Workshop (Med-Hoc-Net), 2012 The 11th Annual Mediterranean*, June 2012, pp. 152–155.

[7] M. Abuelela and S. Olariu, "Taking vanet to the clouds," in *Proceedings of the 8th International Conference on Advances in Mobile Computing and Multimedia*, ser. MoMM '10. New York, NY, USA: ACM, 2010, pp. 6–13. [Online]. Available: http://doi.acm.org/10.1145/1971519.1971522

[8] T. E, *Multi-criteria decision making methods: a comparative study*. Springer, 2000.

[9] R. Karim, C. Ding, and A. Miri, "An end-to-end qos mapping approach for cloud service selection," in *2013 IEEE Ninth World Congress on Services*, June 2013, pp. 341–348.

[10] Z. Zheng, X. Wu, Y. Zhang, M. R. Lyu, and J. Wang, "Qos ranking prediction for cloud services," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 6, pp. 1213–1222, June 2013.

[11] P. Saripalli and G. Pingali, "Madmac: Multiple attribute decision methodology for adoption of clouds," in *2011 IEEE 4th International Conference on Cloud Computing*, July 2011, pp. 316–323.

[12] J. Yang, W. Lin, and W. Dou, "An adaptive service selection method for cross-cloud service composition." *Concurrency and Computation: Practice and Experience*, vol. 25, no. 18, pp. 2435–2454, 2013.

[13] C. W. Chang, P. Liu, and J. J. Wu, "Probability-based cloud storage providers selection algorithms with maximum availability," in *2012 41st International Conference on Parallel Processing*, Sept 2012, pp. 199–208.

[14] E. Cuervo, A. Balasubramanian, D.-k. Cho, A. Wolman, S. Saroiu, R. Chandra, and P. Bahl, "Maui: Making smartphones last longer with code offload," in *Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '10. New York, NY, USA: ACM, 2010, pp. 49–62.

[15] M. V. Barbera, S. Kosta, A. Mei, and J. Stefa, "To offload or not to offload? the bandwidth and energy costs of mobile cloud computing," in *2013 Proceedings IEEE INFOCOM*, April 2013, pp. 1285–1293.

[16] M. R. Rahimi, N. Venkatasubramanian, S. Mehrotra, and A. V. Vasilakos, "On optimal and fair service allocation in mobile cloud computing," *IEEE Transactions on Cloud Computing*, vol. PP, no. 99, pp. 1–1, 2016.

[17] M. Aloqaily, B. Kantarci, and H. T. Mouftah, "Multiagent/multiobjective interaction game system for service provisioning in vehicular cloud," *IEEE Access*, vol. 4, pp. 3153–3168, 2016.

[18] ——, "An auction-driven multi-objective provisioning framework in a vehicular cloud," in *2015 IEEE Globecom Workshops (GC Wkshps)*, Dec 2015, pp. 1–6.

[19] T. Alpcan and L. Pavel, "Nash equilibrium design and optimization," in *2009 International Conference on Game Theory for Networks*, May 2009, pp. 164–170.

[20] "Omnet++ network simulation framework." [Online]. Available: http://www.omnetpp.org/

[21] "Sumo, simulation for urban mobility." [Online]. Available: http://sourceforge.net/apps/mediawiki/sumo