Vehicle as a Resource for Continuous Service Availability in Smart Cities

Moayad Aloqaily[1], Ismaeel Al Ridhawi[2], Burak Kantraci[3], Hussein T. Mouftah[3]
[1]Systems and Computer Engineering Department, Carleton University, Ottawa, ON, Canada, MoayadAloqaily@cunet.carleton.ca
[2]College of Engineering and Technology, American University of the Middle East (AUM), Egaila, Kuwait, Ismaeel.Al-Ridhawi@aum.edu.kw
[3]School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada, {Burak.Kantarci; Mouftah}@uottawa.ca

Abstract— **The Smart City vision is to improve quality of life and efficiency of urban operations and services while meeting economic, social, and environmental needs of its dwellers. Realizing this vision requires cities to make significant investments in all kinds of smart objects. Recently, the concept of smart vehicle has also emerged as a viable solution for various pressing problems such as traffic management, drivers' comfort, road safety and on-demand provisioning services. With the availability of on-board vehicular services, these vehicles will be a constructive key enabler of smart cities. Smart vehicles are capable of sharing and storing digital content, sensing and monitoring its surroundings, and mobilizing on-demand services. However, the provisioning of these services is challenging due to different ownerships, costs, demand levels, and rewards. In this paper, we present the concept of Smart Vehicle as a Service (SVaaS) to provide continuous vehicular services in smart cities. The solution relies on a location prediction mechanism to determine a vehicle's future location. Once a vehicle's predicted location is determined, a Quality of Experience (QoE) based service selection mechanism is used to select services that are needed before the vehicle's arrival. We provide simulation results to show that our approach can adequately establish vehicular services in a timely and efficient manner. It also shows that the number of utilized services have been doubled when prediction and service discovery is applied.**

Index Terms—**cloud computing, location prediction, mobility, service availability, quality of experience.**

I. Introduction

With the evolving nature of the smart city environment, smart objects have risen as inseparable components of such an environment [1]. The transformation of a city into a smart form requires the integration of all these objects into a smart system. This concept is becoming more popular and of a great value due to the fact that current cities are suffering (in terms of, for example, pollution, resources, and energy) and a new solution is desperately needed.

Automotive technology is evolving very rapidly and the emerging applications of vehicular cloud computing and on-demand service provisioning have been developed in recent years [2]. On-demand transportation services (e.g., ride-hailing, carpooling, and/or public transit) are converging with the disruptive vehicular technology of electrification, wireless connectivity, and autonomous capability to create a low-carbon transportation system for cities over the next 25 years.

Thus, smart vehicles are no longer a stand-alone smart concept but rather key enablers for smart city environments. Smart vehicles are equipped with supplementary on-board gear to enable on-demand services for vehicle occupants and surrounding environments. It is expected that more than 1.2 billion smart vehicles will be connected to each other globally, to the infrastructure (cloud) and/or to their surroundings through either built-in or brought-in communications technologies [3].

A smart city retrieves and communicates information from surrounding environments and stores it to the internet cloud. As a key enabler of smart cities, the vehicular cloud (i.e. smart vehicles) is a development domain very rapidly expanding. The main goal of the vehicular cloud is to offer vehicular communication technologies and infrastructures for the vehicles to communicate with other parties, among themselves and with the cloud [4]. To date, two standards have been implemented: IEEE 802.11.p and IEEE 1609. With the aid of these two standards and the collaborative research, ideas, and expertise in this domain, smart vehicles are classified as of the most important components of the smart city [5]. By utilizing smart vehicle technology and connecting smart cities with automotive technology, smart vehicles would be a great source of information and service for smart cities. This paper aims to meet this objective by employing a Smart Vehicle as a Resource (SVaaR) solution for providing continuous service availability in the smart city.

An SVaaR in the smart city will be used for the purposes of sensing, storing, computing, infotainment,

978-1-5386-3531-5/17/$31.00 ©2017 IEEE

and/or mobilizing services. However, the provision of these services and the availability of such great resources will be challenging due to different ownerships, costs, demand levels, requesters and players, and different rewards. Thus, in this paper, we introduce a solution that provides continuous vehicular services by predicting the future location of vehicles and preparing/utilizing the requested services ahead of time.

The remainder of the paper is organized as follows. Related work is presented in Section II. Section III covers the problem and solution overview. The location prediction model and QoE game model will be discussed in IV and V respectively. Numerical results are presented and discussed in Section VI. Finally, we conclude the paper in Section VII.

II. Related Work

The Vehicle as a Resource (VaaR) concept has been proposed previously by the authors in [6]. In addition to introducing VaaR, the authors also enumerated different services that a smart vehicle could provide, indicating that a smart vehicle could be a significant service provider in a variety of situations and demonstrate an illustrative scenario supporting the viability of VaaR.

The authors in [5] proposed an architecture (i.e. Car4ICT) for making cars the main ICT resource in smart cities. Car4ICT gives the users the opportunity to offer and request services. The vehicles components are the central part of their proposed architecture. A proof of concept based simulation has been presented showing that service discovery is fast and reliable even under poor communication circumstances. The work is indeed promising; however, one area of concern is that the architecture appears to be centralized as specific entities within the architecture are in charge of service discovery and of routing data between users. In addition, the services identifications are insufficient in such mobile environment. In [7], the authors extend Car4ICT architecture to interconnect smart cities and rural areas. This extension increases the number of available services and makes the connecting link between smart cities more resilient in the event of infrastructure failures. To this end, the authors in [8] experimentally investigated the performance of the Car4ICT architecture by providing a prototype to emulate multiple vehicles on a few machines.

Location-based discovery services, incentives mechanisms, and context-awareness are also needed for the success of the proposed integration. The authors in [9] proposed a context-aware and location-based service discovery protocols for vehicular networks and its variant. The proposed solution is clustered-based and shows a 20% success rate comparing to other solutions (e.g. Vehicular Information Transfer Protocol [10]).

III. Problem And Solution Overview

This paper incorporates a Trusted Third Party (TTP) cloud entity and QoE game model that was introduced earlier in [11] and [12] which acts as a mediator between Smart Vehicular nodes (SV) and Service Providers (SP) and handles all communication with the SP. TTPs are well-known profitable commercial organizations that provide and sell service to users. TTPs thus provide an abstraction layer between the vehicular service users and providers and will simplify the process of resource discovery and selection in a smart city.

Continuous service availability has become an essential part of mobile users' daily lives. With the rise of smart vehicles, continuous service availability provides a wide range of services such as traffic management and road safety. Additionally, on-demand applications such as multimedia streaming and content sharing between vehicular nodes has become a widely accepted vehicular service. Although most vehicles have only recently become acquainted with 'all-time' network connection, some are starting to pose more and more stringent service quality demands on service providers. User satisfaction (QoE) can be achieved through the use of TTP nodes.

Vehicles can either be service providers or service requestors. Location Prediction uses a prediction engine based on the Dempster-Shafer theory [13] and relies on contextual information such as user schedule, tasks, interests, and location history to predict future user locations. Details pertaining to the prediction module are discussed in Section IV. The location prediction module is incorporated within the TTP Service Mediator module found in TTPs. Additionally, service discovery, selection, and TTP negotiations are found in the TTP service mediator module which relies on a collaborative game-theory approach where TTPs play the roles of buyers and sellers at the same time; buying from the SPs (or SVs) and selling to the SVs. Details pertaining to service discovery and selection are discussed in Section V.

IV. Location Prediction Model

To predict a smart vehicle user's future location, the method requires access to essential contextual parameters such as user schedule, tasks, interests, activities, current location, and location history. Such context will be used to generate hypotheses and bodies of evidence which will be used to determine future high dense spots.

Evidence extraction is applied on four types of parameters (user interests, schedule constraints, tasks, and location history). For each, a frame of discernment Θ is generated from all potential future destinations:

$$\Theta = \{O_i : O_i \epsilon O\} \tag{1}$$

where O represents the target locations of a user. Hypothesis construction for each context parameter is performed as follows:

For each evidence based on an interest, a group of hypotheses is constructed such that:

$$H_j^{(i)} = \{O_K : O_K \in \Theta \mid C_j^i \in C_o(O_K)\} \quad (2)$$

where $C_j^{(i)} = \{c_1^{(i)}, c_2^{(i)}, \dots, c_n^{(i)}\}$ is the set of characteristics related to an interest i, and C_o represents a function of a set of characteristics for destination location O_K. A belief mass value m is associated with $H_j^{(i)}$ such that:

$$m\left(H_j^{(i)}\right) = \frac{1}{n} \quad (3)$$

For each piece of evidence based on a user's schedule constraint, a group of hypotheses is constructed such that:

$$H_j^{(S)} = \left\{O_K : O_K \in \Theta \mid \begin{pmatrix} t(O_C, O_K) + t(O_K, O_S) \\ \leq j \times \frac{t_s}{n} \end{pmatrix}\right\} \quad (4)$$

where O_c is the vehicle's current location, and $t(O_C, O_K)$ is the time that it takes the user's vehicle to go from O_C to O_K. O_s represents the location of the earliest scheduled appointment and t_s the time left before the scheduled appointment takes place. A belief mass value m is associated with $H_j^{(s)}$ such that:

$$m\left(H_j^{(s)}\right) = \frac{1}{n} \quad (5)$$

For each evidence based on a user's task, a group of hypotheses is constructed such that:

$$H_j^{(t)} = \{O_K : O_K \in \Theta \mid C_j^t \in C_o(O_K)\} \quad (6)$$

A belief mass value m is associated with $H_j^{(t)}$ such that:

$$m\left(H_j^{(t)}\right) = \frac{1}{n} \quad (7)$$

For each piece of evidence based on a user's vehicle location history, a weighted sum of the fraction of time a vehicle has spent in the previous L locations are obtained, such that:

$$O_K = \sum_{l=0}^{L} \left(\frac{T(O_l)}{T(O_K, O_L)}\right) f^l \quad (8)$$

where $T(O_l)$ is the time spent in location l and $T(O_K, O_L)$ is the time duration required to go from the previous l location to the target destination K. f^l, $0 \leq f^l \leq 1$, is a forgetting weight factor that is used to give more significance for recent visited locations such that:

$$\sum_{l=0}^{L} f^l = 1 \quad (9)$$

$$f^0 > f^1 > f^2 > \dots > f^L \quad (10)$$

where the most recent and oldest services are indexed by $l = 0$ and $l = L$, respectively. A group of hypotheses is then constructed such that:

$$H_j^{(l)} = \{O_K : O_K \in \Theta \mid C_j^l \in C_o(O_K)\} \quad (11)$$

A belief mass value m is associated with $H_j^{(l)}$ such that:

$$m\left(H_j^{(l)}\right) = \frac{1}{n} \quad (12)$$

Finally, each pair of hypothesis-belief mass is combined using the Dempster-Shafer rule of combination (13) to produce a list of candidate future locations.

$$m_i \oplus m_j\,(C) = \frac{\sum_{X \cap Y = C \neq 0} m_i(X)\, m_j(Y)}{1-K} \quad (13)$$

$$K = \sum_{X \cap Y = \emptyset} mi(X) mj(Y) \quad (14)$$

where X and Y are all the possible subsets of belief mass values for a particular interest, the denominator $1 - K$ is a normalization factor, and C is the set of characteristics for a related interest. A belief value (15) associated with each candidate location A is produced, describing the degree of support for each.

$$Bel\,(A) = \sum_{C \mid C \subseteq A} m(C) \quad (15)$$

The location with the highest belief value (16) is chosen as the vehicle's predicted future location.

$$\mathrm{D} = \arg_{\mathrm{A} \epsilon \Theta}\left(\max\left(\mathrm{Bel}(\mathrm{A})\right)\right) \quad (16)$$

Predicted vehicle locations will trigger the TTPs to negotiate on service provisioning for vehicles that are currently being served and ones that will be served in the future at different cloud service areas.

V. QoE Game Model

QoE methodology can be considered as the most appropriate solution for vehicular cloud service provisioning. It has been used widely and with different applications (e.g. video streaming [14]). QoE improves sharing services among vehicular cloud networks. It will enable service providers to improve resource utilization by incorporating information and feedback from various vehicle drivers and thereby deliver improved service quality. In our previous work [11]-[12], a game theory model to manage on-demand service provisioning in a vehicular cloud has been proposed. A QoE framework to provide several vehicular cloud services in a vehicular cloud at low cost, with the least possible revealed information and minimal service latency has been implemented as well. A rating measure to quantify the reputation of each service provider and their available services based on overall level of satisfaction of the provided services is also implemented according to (17).

$$QoE = \alpha.D + \beta.P + \gamma.I \;\mid\; \alpha + \beta + \gamma = 1 \quad (17)$$

where D, P and I represent the service latency, price and information revealed (Privacy), respectively. As shown, the sum of the coefficients in the equation equals one. QoE components are obtained via feedback from previously provisioned vehicles in a vehicular cloud and formulated according to a weighted combination of the three key factors. Each participant describes their overall satisfaction of the service by providing a 1 to 10 rating value where 10 denotes excellent and 1 denotes the worst experience. QoE reputation value for each service provider is presented to guide service requesters with their selection. The framework has shown great improvements to service cost, service latency, and drivers' privacy. However, unbalance in the service distribution among potential service providers (game players) appears. A cooperative decision-theoretic approach to formulate the interaction among vehicular cloud on the requested services by players has been formalized and optimized in [12].

Dynamic interaction among vehicular cloud providers and mainly service providers have been accomplished by using a Game Engine Service Management (GESM) model. GESM guarantees efficient and fair services/resource distribution across service providers or requesters by acquiring all service providers' information including resources, available services, currently involved requesters, service charges, computation capabilities, game participants, game events, and QoE reputation values for each service.

Given a system with a number of requested services and available resources, the potential participants can be clustered into sellers and buyers. Sellers are capable of providing different types of services to a different number of buyers. Each one of them has their own QoE reputation value for each type of different services, as follows, QoE $= \{\, QoE_{VD}, QoE_{SP}\}$. Let$S\ and\ B\ \rightarrow\ \mathbb{R}$ denote the sets of sellers and buyers, respectively, given that $S\ and\ B$ are the total number of sellers and buyers in the game. A sub-set of $S\ and\ B$ are produced, namely, $S'and\ B'$, which represent the group of sellers who possess the requested services/resources by the buyers. Each seller, S', provides a number of services defined by the following set, $R = \{1, 2, 3, \dots, r\}$, where r is the total number services. Each seller $s_i \in S$ has a service r_s^i available to provide to a buyer $b_j \in B$ who is actively seeking this service, r_b^j. $X^i(j)$ is the total number of services provided from seller i to buyer j.

In order to balance the load of the requested services from the buyers to the sellers and provide fairness in distrusting services among service providers, GESM module ensures that all service providers are equally loaded depending on their system capacity and resource availability. Let $R_{QoE}(n) = \left[R_{QoE_1}^{r_1} + R_{QoE_2}^{r_2} + \cdots + R_{QoE_n}^{r_n}\right]$ denote the vector of summation of resources. Thus, our constructed resources function is:

$$\Phi(\mathrm{R}) = \left[\mathrm{X^i(j)} * \log\left(\sum_{n=1}^{N} \mathrm{R}_{\mathrm{QoE_n}}^{\mathrm{r_n}}\right)\right] - \left(\mathrm{T_r^i(j)}\right) \tag{18}$$

where $T_r^i(j)$ is the total number of third parties used between seller i and buyer j to request a service r.

VI. Simulation Results

Our simulations were conducted using NS-3 to test our proposed predictive TTP-based vehicular service acquisition approach where services are acquired and provided through TTP mediators against an original approach where services are acquired directly from the service providers and thus vehicular nodes must negotiate with SPs directly without TTP intervention. Different scenarios have been adopted using four service providers (SP1, SP2, SP3, and SP4), three trusted third-party nodes (TTP1, TTP2, and TTP3) and up to 50 vehicular nodes (SV1 – SV50) placed randomly in the environment. A Destination-Sequenced Distance Vector Routing (DSDV) protocol on the IEEE 802.11.p vehicular communication stack was employed with 1024 byte packets. The data rate is set at 2Mb/s at 204GHz bandwidth frequency.

The two tested approaches are evaluated using three metrics: service delay, price, hit ratio, and a number of services discovered. Delay is the end-to-end latency required for an SV to receive the requested service from the SP or SV via the TTP. The price represents the service usage cost per time unit. Number of services discovered is the accumulated number of services discovered either by SVs or TTPs. Hit ratio is the ratio of the services retrieved from the TTP in the cloud service area where a SV was predicted to be available in at a future time point over the total of number of services requested using the location prediction technique.

Three resource discovery and selection techniques were tested, namely: the proposed predictive TTP-based vehicular service acquisition approach (P-TTP), the original non-predictive TTP approach introduced in [12] (TTP), and a direct service acquisition approach (Direct) that does not incorporate a TTP in the model, where SVs directly search for the fittest SP and acquire service directly.

Fig. 1 depicts the average delay encountered when adopting the three techniques. Results show that the proposed P-TTP technique outperforms the other two with a maximum average delay reduction of up to 7.2 ms (31.7% reduction). Although it can also be seen from the figure that the direct resource discovery and selection method outperforms the original TTP solution, it is worthy to note that the direct method does not receive the most optimal service experience (QoE) in most cases. On the contrary TTP and P-TTP receive the best service experience results. P-TTP outperforms TTP due to its capability of having the service ready in the location where the vehicle is predicted to be in, while in the TTP approach SVs will need to request the service once they arrive at a particular destination.

The second experiment focuses on the cost of acquiring services from SPs using the three-different service discovery and selection techniques. Fig. 2 depicts the results and shows that the P-TTP method outperforms the other two methods. Due to the excessive time gained by predicting the location of SVs at a future time point, the game-based service selection method will determine the optimal service experience with a reduced cost. A total reduction of 4 price units is achieved when adopting the P-TTP over the TTP approach (14.8% reduction) and a reduction of 21 price units when adopting the P-TTP over the direct service selection solution (77.7% reduction).

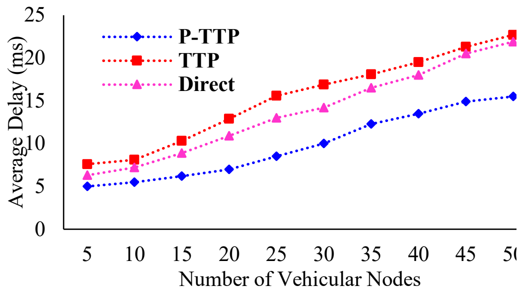

Fig.1. Average delay experienced by vehicular nodes using three different service discovery and selection techniques.

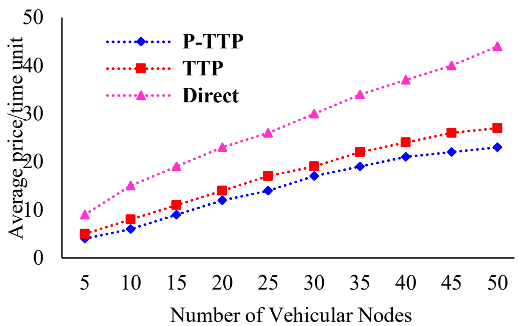

Fig.2. Average cost affixed on vehicular nodes using three different service discovery and selection techniques.

The third experiment focuses on the service hit ratio. Fig. 3 clearly shows that the direct approach will always end up with having a 100% hit ratio. This is due to the fact that since SVs are directly requesting service from SPs, SVs will always commit to a particular service after agreeing with the SPs. On the contrary, the TTP and P-TTP approach will not always end up with a 100% hit ratio. This is due to having the TTP negotiate with many SPs and end up with selecting only one particular service from a SP. This decrease in hit ratio can be clearly seen in the P-TTP approach, where SV future locations are predicted and service negotiation through TTPs are initiated before SV arrival. Some location predictions might end up not being accurate and thus service acquisition is not initiated. Although a decrease in hit ratio is seen in the P-TTP approach, other performance metrics clearly show that the QoE gains outperform the losses.

Fig. 4 outlines the number of services discovered using the proposed technique. The adopted approach shows that the total number of services discovered is more than doubled when compared to the TTP technique. Services are not only discovered in the current cloud service area but also discovered in other cloud services areas where SVs are predicted to be in at a future time point. This service discovery is achieved through the collaboration with other TTPs. The direct approach shows that service discovery is limited to the SV node's capability of discovering services through direct negotiation with SPs. Undoubtedly, this limitation is due to constrained awareness of the available SPs in the cloud service area and the services they offer. By adopting a TTP approach, SVs will be made aware of the available services through the TTPs which have complete awareness of all available services in the environment.

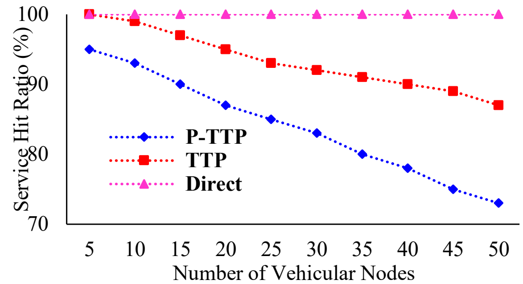

Fig.3. Service hit ratio experienced using three different service discovery and selection techniques.

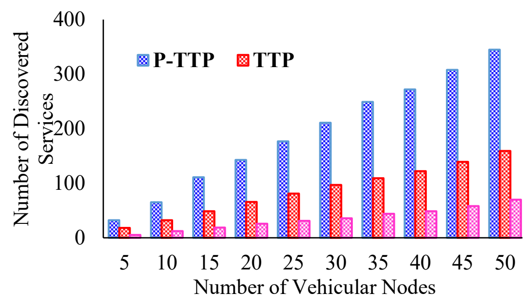

Fig.4. Number of services discovered using three different service discovery and selection techniques.

VII. CONCLUSION

This paper has introduced the concept of Smart Vehicle as a Service (SVaaS) to provide continuous vehicular services in smart cities. The solution relies on a location prediction mechanism to determine a vehicle's future location. Once a vehicle's predicted location is determined, a QoE-based service selection mechanism is used to select services that are needed before the vehicle's arrival. Simulation results show that our approach can adequately establish vehicular services in a timely and efficient manner. In future work, we are will implement the solution using real-time data collected from smart car sensors and test the solution against this data.

REFERENCES

[1] S. Distefano, N. Banerjee, and A. Puliafito, "Smart Objects, Infrastructures, and Services in the Internet of Things," International Journal of Distributed Sensor Networks, vol. 12, no. 2, p. 8642512, 2016.

[2] F. Emura, et. al. "Automotive Technologies for Smart Cities and their Global Deployment," Hitachi Review, vol. 63, no. 2, 2014.

[3] NavigantResearch, “How Connectivity, Autonomous Technology, On-Demand Mobility, and Vehicle Electrification Will Transform Global Passenger Transportation,” Transportation Outlook: 2025 to 2050, 2016.

[4] M. Soyturk, et. al., “From vehicular networks to vehicular clouds in smart cities,” in Smart Cities and Homes, M. S. Obaidat, Eds. Boston: Morgan Kaufmann, 2016, pp. 149–171.

[5] O. Altintas, et. al., “Making cars a main ICT resource in smart cities,” 2015 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), 2015, pp. 582–587.

[6] S. Abdelhamid, H. S. Hassanein, and G. Takahara, “Vehicle as a resource (VaaR),” IEEE Network, vol. 29, no. 1, pp. 12–17, 2015.

[7] F. Hagenauer, et. al., “Interconnecting Smart Cities by Vehicles: How feasible is it?,” 35th IEEE Conference on Computer Communications (INFOCOM 2016), 2016, pp. 788–793.

[8] F. Hagenauer, et. al., “Cars as the Base for Service Discovery and Provision in Highly Dynamic Networks,” in 35th IEEE Conference on Computer Communications (INFOCOM 2016), Demo Session, 2016, pp. 358–359.

[9] K. Abrougui, A. Boukerche, and R. W. N. Pazzi, “Design and evaluation of context-aware and location-based service discovery protocols for vehicular networks,” IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 3, pp. 717–735, 2011.

[10] M. D. Dikaiakos, et. al., “Location-Aware Services over Vehicular Ad-Hoc Networks using Car-to-Car Communication,” IEEE Journal on Selected Areas in Communications, vol. 25, no. 8, pp. 1590–1602, 2007.

[11] M. Aloqaily, B. Kantarci, and H. T. Mouftah, “Multiagent/Multiobjective Interaction Game System for Service Provisioning in Vehicular Cloud,” IEEE Access: Advances in Vehicular Clouds, vol. 4, no. 1, pp. 3153–3168, 2016.

[12] M. Aloqaily, B. Kantarci, and H. T. Mouftah, “Fairness-Aware Game Theoretic Approach for Service Management in Vehicular Clouds,” IEEE 86th Vehicular Technology Conference, 2017.

[13] I. Al Ridhawi, M. Aloqaily, A. Karmouch, and N. Agoulmine, “A location-aware user tracking and prediction system,” in Information Infrastructure Symposium, GIIS’09. Global, 2009.

[14] M. Aloqaily, B. Kantarci, and H. T. Mouftah, “Vehicular clouds: State of the art, Challenges and Future Directions,” 2015 IEEE Conference on Applied Electrical Engineering and Computing Technologies (AEECT), pp. 1–6.