Generalized Nash Equilibrium approach for radio resource sharing and power allocation in vehicular networks

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Abstract

The enabling technology of vehicular networks for Intelligent Transportation Systems (ITS), smart cities and autonomous driving, offers promising on-board services such as road-safety, easy navigation, comfort driving and infotainment. These services can co-exist simultaneously in the system. One challenging issue is to provide the different quality of service (QoS) requirements adequate to each service. This may not be an easy task because of the constrained factors characterizing these networks (e.g., growing number of connected vehicular devices, wireless communications, etc.). In this paper, we investigate the radio resources allocation problem to match different QoS requirements in terms of data rate whilst reducing the interference ratio. We first proposed a radio allocation model that aims to maximize the data rate and minimize the transmission power for all users. However, since not all vehicles use services that require high data rates, it will be more efficient to consider different required data rate for each user. Hence, we develop an efficient model for transmission power allocation that aims to reduce the interference ratio while providing the data rate required by each user. The proposed model is based on Generalized Nash Equilibrium (GNE) game where the users compete to acquire the radio resources. We proposed also two water-filling algorithms to solve the spectrum allocation game during Vehicle-to-Vehicle (V2V) communication over multiple channels. The extensive simulations have shown that our model can satisfy the users regarding different.

Keywords: Vehicular networks; radio resource allocation; spectrum sharing, water-filling algorithms; Generalized Nash Equilibrium GNE; game theory

1. Introduction

The advent of vehicular technology will offer efficient services that ease the life of road users. Vehicular networks have emerged as a key component of intelligent transportation systems. These networks allow an efficient information sharing and dissemination between vehicles and infrastructures for a wide range of applications. Some of these applications, such as road safety and driving assistance, need high quality of service requirements for V2V communications as well as ultra-low latency and high reliability. There are two major modes for V2V communications: Dedicated Short Range Communications (DSRC), and cellular based vehicular communications [1, 2]. DSRC is supported by some standards including the IEEE 802.11p amendment for Wireless Access Vehicular Environment (WAVE). Cellular based vehicular communications, called C-V2X, allow vehicles to communicate with each other over cellular networks such as Long Term Evolution (LTE) [3] and 5G new radio (5G NR).

Both of these V2V communication modes have their respective advantages and limitations when they are adopted in vehicular environments. Thus, Heterogeneous Vehicular Networks (HVNs) have been proposed to combine the benefits of the two communication modes and mitigate their drawbacks. In this type of networks, using either DSRC or C-V2X mode depends on the application requirements (e.g., latency, throughput, data rate, etc.). However, due to wireless communication nature, even HVNs suffer from a wide range of impairments such as interferences, path loss, shadowing, fading, jamming, etc. To deal with these issues, radio resources (e.g., frequency bands, transmission power, time slot, ...) should be optimally allocated. Moreover, since V2V users have to share the medium with cellular users, the resource allocation and transmission scheduling strategies influence considerably the system performance. Using underlay scheme, V2V users and regular cellular ones can exploit the same cellular band at the same time. Hence, the spectrum utilization is improved. In the overlay scheme, a portion of the cellular spectrum is allocated to V2V transmission, which means that both V2V and conventional cellular communications are carried out in a separate frequency bands. Nevertheless, the resource allocation faces serious challenges due to:

- High dynamic mobility of vehicles that needs different requirements in terms of time-frequency resources to face the impairments.

- Wide range of services (e.g., multimedia entertaining, video conference, safety applications, etc.) with different QoS requirements in terms of reliability, latency, and data rates. Moreover, some of these requirements may be contradictory and hence we need to find a tradeoff between them.

- Growing number of vehicle communication devices. These devices have different hardware characteristics which affects their communication capabilities under different channel and network conditions.

In this context, we study the problem of power control and channel allocation for V2V communication through cellular C-V2X technology. The V2V mode permits vehicles to communicate directly, bypassing the eNodeB, using a licensed frequency band. C-V2X communication is proven to achieve large coverage, high data rates, high capacity, superior QoS, and multi-cast/broadcast support [4]. We investigate the use of Game Theory [5], in particular Generalized Nash Equilibrium (GNE) game, for efficient transmission power allocation and control. Unlike many other non-cooperative games where players behave independently, the GNE model is more suited for power control in a spectrum sharing context since the feasible strategies' set of each player depends on all other players' strategies.

The rest of this paper is organized as follows: Section 2 overviews the existing approaches for radio resource allocation in vehicular networks. In Section 3, we describe the system model, and formulate the problem as a constrained optimization problem. A Generalized Nash Equilibrium model as well as two water-filling algorithms for transmission power control are proposed in Section 4. Section 5 is dedicated to the performance evaluation and simulation results, and finally Section 6 concludes the paper.

2. Related Work

In literature, there are many interesting works dedicated to resource allocation in vehicular networks. In [6, 7], graph interference aware resource allocation algorithms have been proposed. The optimization objective of the model proposed in [6] is the maximization of the sum rate with low computational complexity; while in [7], the authors aim to improve the connectivity of vehicular communications using a connectivity index. In [8], the authors exploit geographical information to propose a joint resource allocation and power control for reliable D2D enabled vehicular communication while considering fading channel information. To meet different QoS requirements, queuing dynamics are also presented. Mei et al. [9] investigated dynamic Minimal Cut Sequences (MCS) while allocating the radio bands and the transmit power to guarantee reliability and latency. In [10], the authors presented a resource allocation scheme that supports V2X communications in a D2D-enabled cellular system. The main objective is to maximize the sum of ergodic capacity of V2I links while respecting the delay requirements of V2V links. A bipartite matching algorithm is combined with effective capacity theory to solve the problem. The work in [11] proposes a resource allocation scheme based on a semi-Markov decision process for a vehicular cloud computing system. Lin et al. [12] aims to minimize the serving latency by optimally allocating the available bandwidth to four types of services in a vehicular fog computing system. A Lagrangian algorithm is proposed to solve the problem and give the sub-optimal solutions. Then, a second algorithm for an optimal solution selection is presented and analyzed. In [13], the authors modeled the resource sharing in heterogeneous vehicular networks as a non-cooperative game with correlated equilibrium. They first proposed an incentive mechanism for encouraging macrocells to share spectrum resource with vehicle users. Then, they presented a game theoretical strategy optimization algorithm based on regret-matching and derived the correlated equilibrium solution. Finally, they proposed a power control heuristic for further mitigating the inter road side units' interferences in the non-cooperative game based resource allocation.

Liu *et al.* [14] proposed dynamic virtual resource allocation in 5G vehicular communication networks with mixed SCMA/OFDMA. They used SCMA

(Sparse Code Multiple Access) and full-duplex to reduce the transmission latency and improve the spectrum efficiency for V2V communications. For vehicular-to-infrastructure (V2I) communications, OFDMA and half- duplex technologies are adopted for traffic efficiency information transmission and entertainment content transmission. A virtual resource allocation approach is proposed. It applies a priority mechanism to ensure the successful transmission of road safety information. In [15], a spectrum and power allocation scheme is presented with the aim to maximize the sum ergodic capacity of V2I links, while guaranteeing reliability and latency requirements of V2V links. The optimization of the spectrum reusing pattern is achieved by addressing a polynomial time solvable bipartite matching problem. Based on slowly varying large-scale fading channel information, the approach proposed in [16] introduces a reliability and latency aware resource allocation that maximizes the throughput of vehicular-to-network (V2N) links. A deep reinforcement learning based resource allocation for V2V communications applied to both unicast and broadcast scenarios is proposed in [17]. The simulation showed that the proposed approach satisfies the latency constraints on V2V links while minimizing the interference to V2I communications.

Some of the previous research works (i.e., from [6] to [17]), have not thoroughly considered QoS requirements of each V2V user. Generally, these works aims to improve the spectrum allocation of vehicular system as a unit without considering each user individually. For instance, the maximization of the sum data rate may lead to inefficient and unfair rate distributions among the V2V users even if the global sum rate is maximized. It would be more interesting to focus on the satisfaction of each user as well as the whole system in such a competitive environment.

In this paper, we focus on efficient control and allocation of transmission power that ensure a desired data rate for each V2V pair with an optimal transmission power. Hence, we propose a transmission power allocation model using game theory for V2V communication in C-V2X based vehicular network. A generalized Nash equilibrium game model is introduced to distribute and control the transmit power of V2V pairs over dedicated channels. The presented game aims to determine an efficient power distribution that guarantees the required data rate and minimize transmit power for each user.

3. System Model and Problem Formulation

We consider a vehicular network with multiple vehicular users as depicted in Fig. 1. We consider an urban environment where vehicles move with low speed. The velocity limitation is guaranteed by low in countries. For instance, in France, the vehicles speed cannot exceed the threshold of 50 km/h in urban zones, and this threshold is reduced to 30 km/h in some zones such as residential and school neighborhoods. The V2V users are considered by pairs, each consisting of a transmitter and a receiver. We denote by $\mathcal{N}$ and $\mathcal{K}$ ($N = |\mathcal{N}| > K = |\mathcal{K}|$) the sets of V2V pairs and channels, respectively. In this model, each vehicle communicates with its corresponding receiver over the K channels. The radio resource allocation is performed at the beginning of each Transmission Time Interval (TTI).

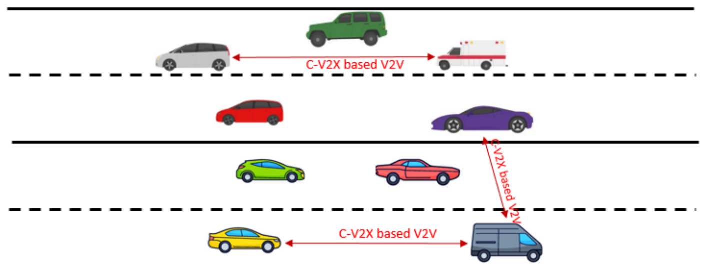

Figure 1: The system model of the vehicular network.

Our objective is to maximize the information rate of each V2V pair $n \in \mathcal{N}$. Notice that for each transmitter, increasing its power at any frequency increases its own data rate. However, this increases this user's interference into other users' communications and is, therefore, detrimental to other users' transmissions. Thus, the system design must consider the tradeoff among the data rates of all users. For example, it is not enough to consider just the maximization of the sum rate, because it does not guarantee a minimal data rate for any one user.

Let $p_n = [p_n^1, \dots, p_n^K]$ denotes the transmit power vector of n over channel k, the received SINR of n over k-th channel is expressed as:

$$\gamma_n^k = \frac{p_n^k g_{nn}^k}{\sum_{m \neq n \in \mathcal{N}} p_m^k g_{nm}^k + \sigma^k}, \tag{1}$$

where g_{nn}^k, g_{nm}^k and σ_n^k denote the power channel gains, and the variance of Gaussian noise over channel k, respectively. The SINR is considered as the most critical parameter for the QoS as it directly affects the throughput and the bit error rate. The maximum data rate of n is obtained by:

$$R_n(p_n, p_{-n}) = \sum_{k=1}^{K} \log_2(1 + \gamma_n^k) \tag{2}$$

where $p_{-n} = [p_1, \dots, p_{n-1}, p_{n+1}, \dots, p_N]$ represents the transmit power vector of all the users except for user n.

The sum-rate optimal power allocation is often the one that assigns high data rates to some users and low data rates to other users, creating inherent unfairness. Thus, our model must reflect the trade-off between the benefit (i.e., the data rate) and the cost (i.e., the total power over K channels) as well as fairness. Therefore, the optimization problem for each V2V pair n is defined as:

$$P1 : \max_{p_n} \frac{R_n}{\sum_{k=1}^{K} p_n^k} \tag{3}$$

s.t.

$$\sum_{k=1}^{K} p_n^k \leq p_{max}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N} \tag{4}$$

$$\gamma_n^k \geq \gamma_{min} \tag{5}$$

The utility function is quasi-concave, therefore, the optimal solution $p_n^* = \{p_n^{k*}\}_{k=1}^{K}$, for any fixed and non-negative p_{-n}, exists and is unique as shown in [19].

Proposition 1. *Given the power vector p_{-n}, the user n's optimal solution for problem P1 is given by*

$$p_n^k = \begin{cases} p_n^{\overline{k}*}, & \text{if } k = \overline{k} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

with $\overline{k} = arg \min_k p_n^{k*}$, where p_n^{k*} denotes the transmission power of user n to achieve the optimal SINR γ^* over channel k, or p_{max} if γ^* is not achievable. γ^* is the unique positive solution of

$$\gamma \frac{\partial R_n}{\partial \gamma} = R_n \tag{7}$$

If in addition to the two constraints of P1, we add the following constraint:

$$\sum_{n \in \mathcal{N}} p_n^k \leq P_{MAX}, \forall k \in \mathcal{K} \tag{8}$$

which means that the sum of the power allocated to all the users cannot exceed a predefined threshold. Then, the unique optimal solution can be obtained using the geometric Water-Filling algorithm proposed in [20].

It is worthy to mention that the objective function is particularly suitable for wireless systems with energy constraints as minimizing the transmission power means minimizing the energy consumed by the transmission process.

Although problem P1 guarantees a tradeoff between the maximization of the data rate and the minimization of transmission power (reduction of interference ratio), it may not be the best spectrum allocation strategy for all users since some of them does not require high data rates. It will be better for these users to use lower transmission power to achieve desired data rates than maximize the data rate in the cost of using more power. In the next section, we propose a second model that aim to minimize the transmission power whilst achieving the desired data rate of each user. We opt for the game theory to propose an efficient solution for competitive spectrum allocation. Hence, we reformulate the channel allocation and power control problem as a generalized Nash equilibrium game, where the strategy of each player depends on the other players' strategies since the SINR of a user depends on the other users' transmit powers.

4. Power Control Game

In this section, we describe the Generalized Nash Equilibrium Problem (GNEP) model for radio resource allocation and power control problem.

4.1. Generalized Nash Equilibrium Game Formulation

In the standard non-cooperative game, it is usually assumed that the feasible set of the game is composed of full Cartesian product of the individual strategy sets; it is assumed that players can only affect the utilities of other players but not their feasible sets. However, in many real-world problems, such as those of radio resources allocation, each player's strategy set may depend on the strategies of other players. This leads to the introduction of the generalized Nash game, or the generalized Nash equilibrium problem (GNEP for short) defined as a n-person non-cooperative game with non-disjoint strategy sets.

Using the concepts of GNEP, we introduce the power control game as $\mathcal{G} = \left\{\mathcal{N}, \mathcal{P}_n(p_{-n})_{n\in\mathcal{N}}, u_n(.)_{n\in\mathcal{N}}\right\}$, where $\mathcal{P}_n(p_{-n})$ and $u_n(.)$ represent the set of player n's feasible strategies and the payoff function, respectively. The players are the V2V pairs Unlike P1, where each user tries to maximize the data ratio whilst minimize the transmission power; in this game, each player compete against other players by choosing the strategy that minimizes his transmission power whilst ensuring a minimum desired achievable data rate. This data rate is chosen by the user itself among the achievable data rates in the system. Hence, the strategy set is defined as:

$$\mathcal{P}_n(x_{-n}) \triangleq \{p_n \in \mathbb{R}_+^N | R_n(p_n, p_{-n}) \geq R_n^*\} \tag{9}$$

where R_n^* denotes the minimum information rate desired by user n. In the following, we consider the vector $R^* = R^{*\,N}_{n\,n=1}$ as the rate profile.

Observe that, because of rate constraints, the set of feasible strategies $\mathcal{P}_n(p_{-n})$ and utility function u_n of each player depend on all players' strategies, which are collectively denoted by the vector p_{-n}.

Player n's strategy is denoted by p_n and his utility function u_n depend on all players' strategies, which are collectively denoted by the vector $p = [p_1, \ldots, p_N]$. Player n's strategy set $\mathcal{P}_n(p_{-n})$ is dependent of the other players' strategies, which are denoted by $p_{-n} := (p_1, \ldots, p_{n-1}, p_{n+1}, \ldots, p_N)$. For every fixed but arbitrary vector (I.,e., strategy) p_{-n}, player n solves the following optimization problem for his own decision vector p_n:

$$\min_{p_n} u_n(p_n, p_{-n}) = \sum_{k=1}^{K} p_n^k \tag{10}$$

subject to

$$p_n \in \mathcal{P}_n(p_{-n}) \tag{11}$$

Let $\mathcal{P}(p) := \mathcal{P}_1(p_{-1}) \times \ldots \times \mathcal{P}_N(p_{-N})$ denotes the Cartesian product of the strategy sets of all players. The corresponding equilibrium for the GNEP $\mathcal{G} = \left\{\mathcal{N}, \mathcal{P}_n(p_{-n})_{n\in\mathcal{N}}, u_n(.)_{n\in\mathcal{N}}\right\}$ can be defined as follows:

Definition 1. *A tuple of strategies $p^* := (p_n^*)_{n=1}^N \in \mathcal{P}(p^*)$ is called a generalized Nash equilibrium of the GNEP if*

$$u_n(p_n^*, p_{-n}^*) \leq u_n(x_n, p_{-n}^*), \forall p_n \in \mathcal{P}_n(-n) \tag{12}$$

hold simultaneously for all players $n = 1, \ldots, N$.

The optimal solution $p_n^* = \{p_n^{k*}\}_{k=1}^K$, for any fixed and non-negative p_{-n}, exists and is unique. This solution is the well-known water-filling power allocation:

$$p_n^* = WF_n(p_{-n}) \tag{13}$$

where the water-filling operator $WF_n(.)$ is defined as:

$$[WF_n(p_n)]^k \triangleq \left(\lambda_n - \frac{\sum_{m \neq n \in \mathcal{N}} p_m^k g_{nm}^k + \sigma_n^k}{g_{nn}^k}\right)^+, k \in \mathcal{K} \tag{14}$$

with $(x)^+ \triangleq \max(0, x)$ and the water level λ_n is a constant chosen so that the rate constraint $R_n(p_n^*, p_{-n}) = R_n^*$ is met. The $WF_n(.)$ operator selects the strategy that minimize the utility function u_n while achieving the minimum data rate.

The solutions of the game $\mathcal{G}$, if they exist, form the generalized Nash equilibria that satisfies the following condition: A feasible strategy $p^* = (p_n^*)_{n \in \mathcal{N}}$ is a GNE of the game $\mathcal{G}$ if and only if it satisfies the following nonlinear system:

$$p^* = WF_n((p_n), \forall n \in \mathcal{N} \tag{15}$$

Given the above system, the questions that we need to answer are: i) does a solution exist for any rate profile?, ii) if it exists, is it unique?, and iii) how can this solution be reached in a distributed way?

4.2. Existence and Uniqueness of GNE

We start by providing sufficient conditions for the existence of a nonempty and bounded solution set of Nash equilibria. Then, we consider the uniqueness of the GNE.

Given the rate profile $R^* = (R_n^*)_{n=1}^N > 0$, we define the Z-matrix (i.e., a matrix where its off-diagonal entries are all non-positive) $Z_k(R^*) \in \mathbb{R}^{N \times N}$ as follows:

$$Z_k(R^*) \triangleq \begin{pmatrix} g_{11}^k & -(e^{R_1^*} - 1)g_{12}^k & \ldots & -(e^{R_1^*} - 1)g_{1N}^k \\ -(e^{R_2^*} - 1)g_{21}^k & g_{22}^k & \ldots & -(e^{R_2^*} - 1)g_{2N}^k \\ \vdots & \vdots & \ddots & \vdots \\ -(e^{R_N^*} - 1)g_{N1}^k & -(e^{R_N^*} - 1)g_{n2}^k & \ldots & g_{NN}^k \end{pmatrix} \tag{16}$$

Referring to [21], the game $\mathcal{G}$ admits a nonempty and bounded solution set if $Z_k(R^*)$ is a P-matrix $\forall k \in \mathcal{K}$. A matrix is called P-matrix if every principal minor is positive. Moreover, any GNE p^* is defined as:

$$\begin{pmatrix} p_1^{k*} \\ \vdots \\ p_N^{k*} \end{pmatrix} \leq \begin{pmatrix} \overline{p}_1^k \\ \vdots \\ \overline{p}_N^k \end{pmatrix} \triangleq (Z_k(R^*))^{-1} \begin{pmatrix} \sigma_1^k(e^{R_1^*}-1) \\ \vdots \\ \sigma_N^k(e^{R_N^*}-1) \end{pmatrix}, k \in \mathcal{K}. \tag{17}$$

As a proven in [22] and [23], sufficient conditions for $Z_k(R^*)$ to be P-matrices are

$$\sum_{m \neq n} \frac{\overline{g}_{nm}^k}{\overline{g}_{nn}^k} \frac{d_{nn}^\beta}{d_{nm}^\beta} < \frac{1}{e^{R_n^*}-1}, \forall m \in \mathcal{N}, \forall k \in \mathcal{K} \tag{18}$$

where $\overline{g}_{nm}^k = g_{nm}^k d_{nm}^\beta$ denotes the normalized channel gain. d_{nm}^β represents the distance between n and m; β is the path-loss exponent.

The interpretation of these conditions is as follows: Given the channels and the data rates, the GNE exists if the interference ratio is small, which means the vehicular pairs are sufficiently far apart and the distance between them is beyond a minimum distance.

To provide the conditions of the uniqueness of the GNE, we define the matrix $B_k(R^*) \in \mathbb{R}^{N \times N}$ as follows:

$$[B_k(R^*)]_{nm} = \begin{cases} e^{-R_n^*}, & \text{if } n = m \\ e^{-R_n^*}.\alpha_{nm}^{max}, & \text{otherwise} \end{cases} \tag{19}$$

where

$$\alpha_{nm}^{max} = \max_{k \in \mathcal{K}} \left(\frac{g_{nm}^k}{g_{mm}^k} . \frac{\sum_{m' \neq m} g_{mm'}^k \overline{p}_{m'}^k + \sigma_m^k}{\sigma_n^k} \right) \tag{20}$$

Assuming that the solution set is nonempty and bounded, if $B_k(R^*)$ is a P-matrix, then the GNE of the game $\mathcal{G}$ is unique as proven in [21]. However, as for the existence of GNE, its uniqueness depends on the interference level.

4.3. Water-Filling algorithms

In this section, we introduce two distributed iterative water-filling algorithms to solve the problem P2. In the distributed solving, each user chooses its optimal strategy independently while perceiving the other users as interferences.

4.3.1. Sequential Water-Filling Algorithm

The proposed sequential iterative water-filling algorithm (IWFA) is an instance of the Gauss-Seidel approach [24] by mapping solution (13). In this algorithm, each user sequentially and locally measures the interference-plus-noise power level over the K channels and water-fill based on this level as described in Algorithm 1

When *number_iterations* tends to ∞, IWFA converges linearly to the unique GNE of the game $\mathcal{G}$, if the conditions of existence and uniqueness hold [21]. This means that the convergence is guaranteed if the level of interferences level is not too high. However, despite the fact that IWFA has low complexity, it may suffer

Algorithm 1 Sequential iterative water-filling algorithm

$p_n^{(0)}$=random(non-negative);

for $i = 0$ to *number_iterations* **do**

$$p_n^{(i+1)} = \begin{cases} WF_n(p_{-n}^{(i)}), & \text{if } i+1 \bmod N = n \\ p_n^{(i)}, & \text{otherwise} \end{cases} \quad \forall n \in \mathcal{N}; \tag{21}$$

end for

from high convergence delay when the number of users becomes large. Since each user measures the SINR power level over the K channels and water-fill using this level, the complexity is $O(K \times N)$.

4.3.2. Simultaneous Water-Filling Algorithm

As an alternative of IWFA, we propose a simultaneous water-filling algorithm (SWFA) to reduce the convergence delay. This algorithm is an instance of Jacobi algorithm, where the users update their power strategies simultaneously using the interference level of the previous iteration as described in Algorithm 2

Algorithm 2 Simultaneous water-filling algorithm

$p_n^{(0)}$=random(nonegative),$\forall n \in \mathcal{N}$;

for $i = 0$ to *number_iterations* **do**

$$p_n^{(i+1)} = WF_n(p_{-n}^{(i)}), \forall n \in \mathcal{N}; \tag{22}$$

end for

When *number_iterations* tends to ∞, SWFA converges linearly to the unique GNE of the game $\mathcal{G}$, if the conditions of existence and uniqueness hold [21]. Moreover, it converges faster than IWFA with the same low complexity even with a large number of users.

5. Performance Evaluation

To evaluate the performance of the proposed scheme, we perform extensive simulations. We consider an area with V2V users randomly distributed. Table 1 shows the simulation parameters. We compare the proposed scheme to an approach that aims to maximize the data rate of each user without considering the minimization of the transmission power (Max data rate approach).

We first illustrate the impact of the number of V2V communications at the same time on the power and data rate at the equilibrium. We compare the transmit power of two users U1 and U2 with different QoS requirements. The desired data rates of U1 and U2 equal 10 Mbps and 2 Mbps, respectively using the proposed GNE approach and max data rate approach. As Fig. 2 shows, with

Table 1: Simulation Parameters

Parameter	**Value**
Area	1 km x 1 km
Number of V2V pairs	[10..100]
Required data rate	From 1 Mbps to 10 Mbps
Number of channels	16
Max V2V communication distance	200 m
Maximal transmit power	30 dBm
Thermal noise power density	-115 dBm/Hz

a small number of V2V users, the users can achieve the desired data rate with a low power level as the interference ratio is small. When the network density increases, the uses are obliged to increase their transmit powers to overcome the interferences. However, although the data rate is multiplied by 5, the minimal power to achieve 10 Mbps is less than the double of that to achieve 1 Mbps.

With the aim to maximize the data rate with the only constraint to not exceed the allowed maximal power, the two users U1 and U2 achieve high data rates, as depicted by Fig.3, by using high levels of power even that they need lower rates. Unfortunately, not all the users need these high rates. This allocation approach results that some users are allocated more resources than they need while others are still starving and cannot achieve the required QoS. The data rates as well as the transmission powers decrease as the number of V2V pairs increases because of the interferences. It is obvious that the users need to adjust their power to minimize the interference level and reach the maximum possible data rates at the equilibrium. However, using max rate approach, the two users U1 and U2 cannot achieve the required data rates since as all the users try to maximize their data rates regardless their required rates. The loss is heavier for U1 who needs 10 Mbps and obtain only 1.75 Mbps. In the proposed approach, user U2 maintains the desired rate, while U2's data rate decreases slightly and is still above 7 Mbps even with 100 vehicular pairs.

To evaluate the efficiency of power control allocation, we define the efficiency metric as $\frac{min(required\_rate, achieved\_rate)}{power}$ (measured in Mbps/W). Fig. 4 depicts how the number of communications influences the efficiency of the spectrum allocation of the compared approaches. From the figure, it is clear that the efficiency of all the approaches decreases with a larger number of users due to the interference factor and the smaller set of feasible allocation strategies. However, the proposed GNE approach outperforms the max rate approach and is still way better than it even when the network becomes denser. This reflects the importance of the allocation method that consider different desired data rates that achieves different QoS requirements.

To show that the proposed GNE based allocation approach outperforms the

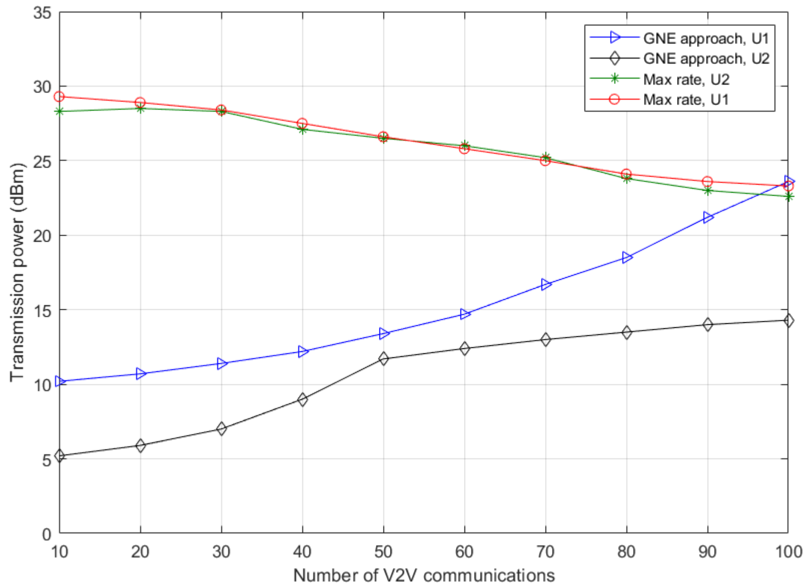

Figure 2: Impact of the number of V2V communications on the transmit power.

allocation based on data rate maximization, we evaluate the packet delivery ratio. Fig. 5 depicts that the Max data rate approach offers slightly better results with small number of vehicles. When the network becomes denser, the packet delivery ratio decreases quickly because of collisions and interferences. With our proposed approach, the obtained results are close to those offered by the first approach when the number of vehicles is small. Moreover, the gap between the results of the two approaches becomes wider with the increasing number of vehicles as shown by the figure. Even if the packet delivery ratio decreases in the power minimization based approach, it is still above 80% with 100 users, which is much better than the ratio obtained by Max data rate approach.

We then evaluate the convergence speed of the two water-filling alternatives. We compare two scenarios: with 10 users and with 20 users. We consider a desired data rate of 1 Mbps for the two scenarios. As shown by Fig. 6 and as expected, the simultaneous algorithm SWFA converges quicker than the iterative algorithm IWFA. When the number of vehicle pairs increases, the difference between the convergence speeds becomes more important. This can be explained by the fact that the users update their power allocation strategies sequentially in IWFA, which means that each user must wait for all the strategies to be updated.

In Fig. 7, we compare the power allocation process delay of the proposed SWFA algorithm to an existing game- theoretic approach [13]. We can notice

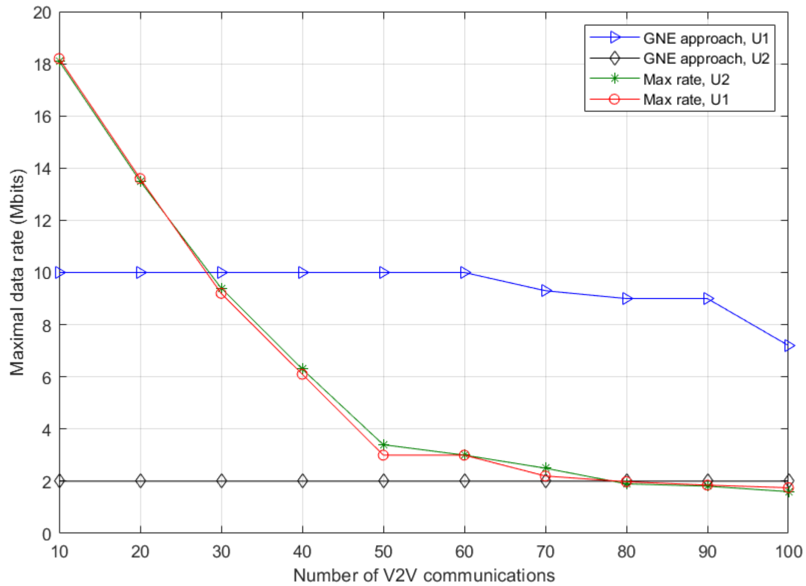

Figure 3: Impact of the number of V2V communications on the data rate.

that the SWFA delay increases slightly with the number of communications contrarily to the other approach where the delay increases quickly. The gap between the delays generated by the two approaches becomes wider and wider with the number of users. The low delays generated by SWFA is the consequence of the simultaneous execution of the water-filling by all the users.

Finally, Table 2 gives a comparison of the proposed GNE approach to some of existing power allocation approaches in terms of main objective, used method, and complexity.

6. Conclusion

The exploitation of C-V2X technology may improve the different QoS requirements for V2V communication in vehicular networks. However, sharing the spectrum between multiple interfering V2V users with different QoS requirements may be very challenging. In this paper, we have investigated the topic of radio resource and power allocation in vehicular networks. We first have proposed a model that aims to find a tradeoff between the maximization of data rate and minimization of transmission power for each user. However, since vehicles use different services with different QoS requirements in terms of data rate, it would be better to develop an optimization model adapted to different data rate requirements. Hence, we have proposed of non-cooperative game model where the users try to achieve their desired data rate with the minimum

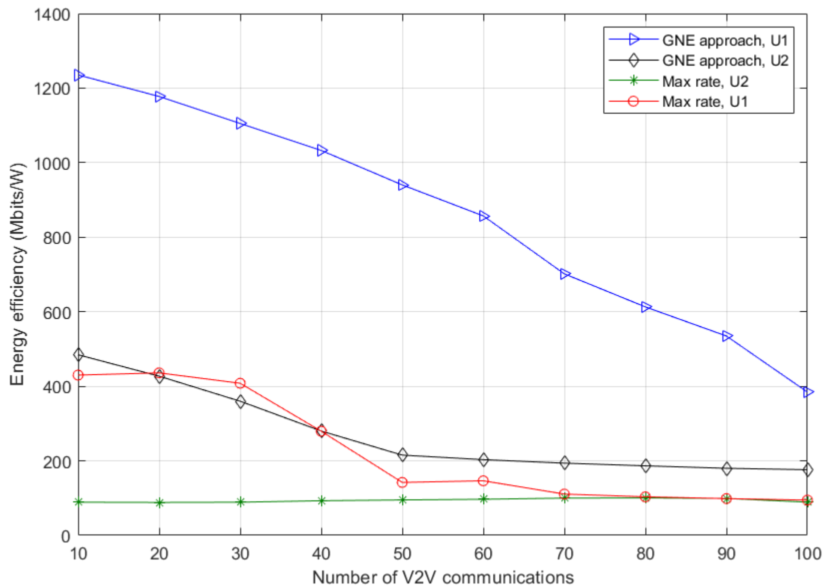

Figure 4: Energy efficiency vs. the number of V2V communications

transmission power while competing for radio resources. We have formulated the power allocation problem as a Generalized Nash Equilibrium (GNE) game where the transmit power distribution strategies' set of each player depends on the strategies of all the other players. Then, we have demonstrated the existence and uniqueness of Nash equilibrium under certain conditions. Moreover, we have presented two distributed water-filling algorithms that solve the problem with low complexity in a totally distributed manner. These algorithms have been proved to converge to the Nash equilibrium. The simulation results have shown that the proposed scheme can satisfy the V2V users regarding their desired data rate, while minimizing their transmit powers. As a future work, we intend to investigate the impact of vehicles' velocity on the QoS requirements in C-V2X based vehicular networks.

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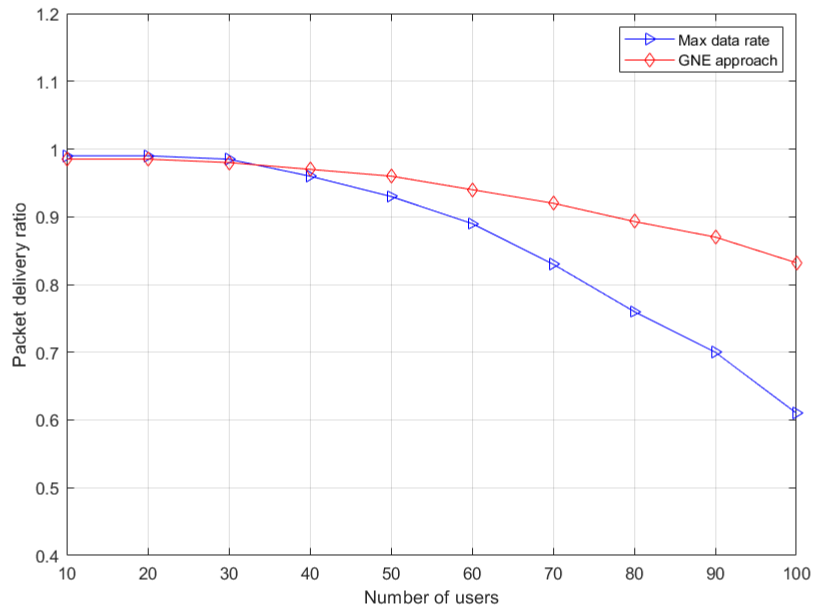

Figure 5: Packet delivery ratio versus the number of vehicles

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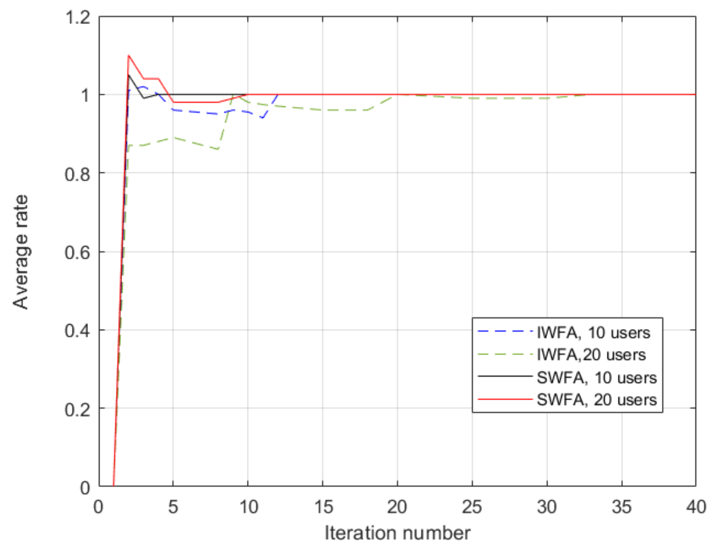

Figure 6: Convergence speed of IWFA and SWFA

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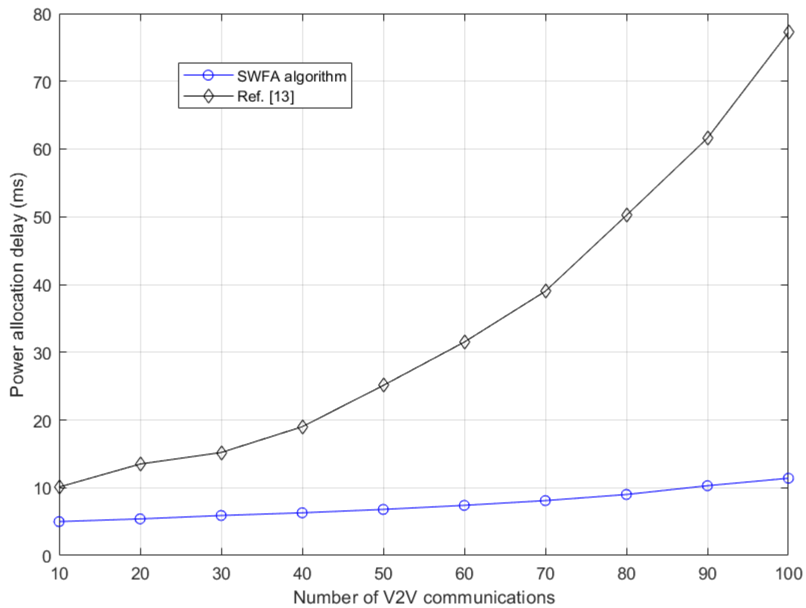

Figure 7: Power allocation delay SWFA

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Table 2: Comparison between power allocation approaches

Approach	**Main objective**	**Method**	**Complexity**
[6]	maximize the sum rate	Graph theory	Low
[7]	Improve the connectivity	Graph theory	Low
[8]	maximize the ergodic capacity	Geographical information	–
[17]	maximize the sum rate	Deep reinforcement learning	very high
[12]	minimize the latency	Lagrangian algorithm	high
[13]	maximize the overall data rate	Game theory	high
Proposed GNE approach	minimize the power and achieve the different QoS requirements in terms of data rates	Game theory and water-filling algorithms	very low

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