Distributed Transmit Power Control for Beacons in VANET

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Abstract: In vehicle to vehicle communication, every vehicle broadcasts its status information periodically in its beacons to create awareness for surrounding vehicles. However, when the wireless channel is congested due to beaconing activity, many beacons are lost due to packet collision. This paper presents a distributed congestion control algorithm to adapt beacons transmit power. The algorithm is based on game theory, for which the existence of the Nash Equilibrium (NE) is proven and the uniqueness of the NE and stability of the algorithm is verified using simulation. The proposed algorithm is then compared with other congestion control mechanisms using simulation. The results of the simulations indicate that the proposed algorithm performs better than the others in terms of fairness, bandwidth usage, and the ability to meet the application requirements.

1 INTRODUCTION

In Vehicular Ad hoc NETworks (VANETs), vehicles periodically broadcast Basic Safety Messages (BSMs), also known as beacons, to inform other vehicles of their status such as position, speed, and acceleration. The performance of safety applications is dependent on how precisely a vehicle knows the status of its neighbouring vehicles thus, it is very important that enough beacons from each vehicle reaches its neighbours. In dense vehicular traffic, many beacons become lost due to packet collision. Thus, considerable efforts have been made to limit the channel usage to around 0.65 (ideally with a range between 0.4 and 0.8), so that the number of successfully delivered messages are maximised (Fallah, Huang et al. 2011). The proposed approaches are generally based on reducing the rate (Bansal, Kenney et al. 2013, Kim, Kang et al. 2014, Egea-Lopez, Pavon-Marino 2016) or range (Egea-Lopez, Alcaraz et al. 2013, Torrent-Moreno, Mittag et al. 2009) or both rate and range (Huang, Fallah et al. 2010) of BSMs. This paper specifically focuses on transmission range or power control.

The problem of beacon's power control is presented as a non-cooperative game. It is proven the Nash Equilibrium (NE) exists for the game and that the NE regarding appropriate range of the parameters is unique and stable. An algorithm is presented to find the equilibrium point in a distributed manner. The current approach differs from previous works in this area for two main reasons: First, the fairness is obtained whiteout exchanging information between nodes, which results in bandwidth saving. The fairness in this protocol is obtained based on the fairness concept of the NE. Second, weighted fairness in power allocation is achieved which is useful to meet application requirements (Sepulcre, Gozalvez et al. 2010). Some safety applications require that the status of vehicles be disseminated longer distances thus, assigning the same power to vehicles with different requirements cannot meet this goal.

Like other beacon power control approaches for VANET (Egea-Lopez, Alcaraz et al. 2013, Torrent-Moreno, Mittag et al. 2009), it is assumed that there is no power restriction and every node transmits its beacons with the maximum allowed power level. When there is congestion in the network, vehicles reduce their power level to prevent BSM loss due to collision.

The remaining of this paper is organized as follows. Section 2 introduces the non-cooperative power control game. Section 3 discusses the NE's existence and its uniqueness and stability and presents a distributed algorithm for power control. Selection of the parameters of the algorithm is presented in Section 4. The simulation results and performance evaluation and comparison with other approaches are presented in Section 5. Section 6 concludes the paper.

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2 NON-COOPERATIVE POWER CONTROL GAME

Let $\mathcal{G} = \{\mathcal{N}, \{\mathcal{P}_i\}_{i\in\mathcal{N}}, \{\mathcal{F}_i\}_{i\in\mathcal{N}}\}$ denotes the Non-cooperative Power Control (NPC) game, where $\mathcal{N} = \{1, \dots, N\}$ is the set of players (vehicles), and $\mathcal{P}_i$ is the set of possible beaconing powers for player i . $\mathcal{P}_i$ is called the strategy set of player i and the power $p_i \in \mathcal{P}_i$ is called the strategy of player i. Each player selects its strategy independently. The vector $\mathbf{p} = (p_1, p_2, \dots, p_N) \in \mathbf{P}$ shows the selected power of all the players, where $\mathbf{P} = \prod_{i=1}^{\mathcal{N}} \mathcal{P}_i$. $\mathcal{F}_i$ is the payoff function of player i and is indicated as $\mathcal{F}_i(\mathbf{p}) = \mathcal{F}_i(p_i, \mathbf{p}_{-i})$, where $\mathbf{p}_{-i}$ denotes the vector consisting of the beacon powers of all the players except the ith player.

Every vehicle transmits its beacons with a power between 1 and 100 mW (Kenney 2011). Thus, the strategy set of vehicle i is $\mathcal{P}_i = [1, 100]$. A higher power is desired because the beacon is disseminated over larger distance thus, it creates higher awareness under normal conditions. But high power has a negative effect on awareness in congested situations. Therefore, the desirable payoff function would yield lower payoff with the same power in situations with high levels of congestion. To fulfil this goal, the pay-off function is modeled as the difference between a utility function $(U_i(p_i))$ and a price function $(J_i(p_i, \mathbf{p}_{-i}))$. Accordingly, the payoff for player i is as follows:

$$\mathcal{F}_i(p_i, \mathbf{p}_{-i}) = U_i(p_i) - J_i(p_i, \mathbf{p}_{-i})$$
$$= u_i \ln(p_i) - c_i\, p_i\, CBR_i(\mathbf{p}) \quad (1)$$

where u_i and c_i are positive parameters, $\ln(.)$ is natural logarithm, and $CBR_i(\mathbf{p})$ is the channel busy ratio that player i senses, and it is a function of all the players' power level.

The first term in the payoff function is called utility, it is an increasing function of BSM power level. A logarithmic function has been selected as utility because it is increasing and has nice concavity properties. The second term ($c_i\, p_i\, CBR_i(\mathbf{p})$), is the price function. Which indicates that a user should pay more price at higher congestions. This term is a function of CBR because CBR is a good indicator of successful information dissemination in VANET (Fallah, Huang et al. 2011); high CBR results in poor inter-vehicle awareness. The price function becomes larger in scenarios with higher levels of congestion, yielding a lower payoff.

$\nabla_i \mathcal{F}_i(\mathbf{p}) = \frac{\partial \mathcal{F}_i(\mathbf{p})}{\partial p_i}$ is the marginal payoff of player i. The vector of marginal payoffs of all the players is given as

$$\nabla \mathcal{F}(\mathbf{p}) = \left(\nabla_1 \mathcal{F}_1(\mathbf{p}), \nabla_2 \mathcal{F}_2(\mathbf{p}), \dots, \nabla_N \mathcal{F}_N(\mathbf{p})\right)^T \quad (2)$$

and its Jacobian as $G(\mathbf{p})$.

For $CBR_i(\mathbf{p})$, the mathematical model developed in (Chen, Jiang et al. 2011), given below, is used.

$$CBR_i(\mathbf{p}) = \sum_{j=1}^{N} h_{ij}\, r \quad (3)$$

where

$$h_{ij} = T_{frame} \times \frac{\Gamma\left(m, \frac{mC_{Tt}}{\Omega_{ij}}\right)}{\Gamma(m)} \quad (4)$$

$$\Omega_{ij} = \frac{p_j\, \lambda^2}{(4\pi)^2\, d_{ij}^{\gamma}} \quad (5)$$

$\Gamma(.)$ is gamma function, $\Gamma(.,.)$ is upper incomplete gamma function, C_{Tt} is the threshold power level of carrier sense, p_i is beacon transmit power of player i, d_{ij} is the distance between jth and ith players, r is the beaconing frequency, m is Nakagami fading parameter, λ is the wavelength, γ is the path loss exponent, and T_{frame} is the time required to send a BSM packet.

3 THE NASH EQUILIBRIUM OF THE GAME

According to theorem 1 in (Rosen 1965), if the strategy spaces of the players are convex, closed and bounded, and each player's payoff function is concave in its own strategy, an equilibrium point exists. The payoff functions (1) are twice differentiable, and their first and second derivatives are:

$$\frac{\partial \mathcal{F}_i}{\partial p_i} = \frac{u_i}{p_i} - c_i\, CBR_i(\mathbf{p}) \quad (6)$$

$$\frac{\partial^2 \mathcal{F}_i}{\partial^2 p_i} = -\frac{u_i}{{p_i}^2} < 0 \quad (7)$$

The second derivative of $\mathcal{F}_i$ is always negative, which means that the payoff functions are concave and at least one Nash Equilibrium exists. It is worth noting that $\mathrm{CBR_i}(\mathbf{p})$ is independent of $\mathrm{p_i}$ because considering (4), $\mathrm{d_{ii}}=0$ thus, $\frac{\Gamma(\mathrm{m},\frac{\mathrm{mC_{Tt}}}{\Omega_{\mathrm{ij}}})}{\Gamma(\mathrm{m})}=1$.

In NPC, $-\mathrm{G}(\mathbf{p})$ is an $\mathrm{N}\times\mathrm{N}$ matrix with diagonal elements:

$$\mathrm{g_{ii}}=-\frac{\partial^2\mathcal{F}_\mathrm{i}}{\partial^2\mathrm{p_i}}=\frac{\mathrm{u_i}}{\mathrm{p_i}^2} \tag{8}$$

and off-diagonal elements:

$$\mathrm{g_{ij}}=-\frac{\partial^2\mathcal{F}_\mathrm{i}}{\partial\mathrm{p_i}\,\partial\mathrm{p_j}}=\frac{\mathrm{c_i\,r\,T_{frame}}}{\Gamma(\mathrm{m})}\frac{\partial\,\Gamma\left(\mathrm{m},\ \frac{\mathrm{mC_{Tt}}}{\Omega_{\mathrm{ij}}}\right)}{\partial\mathrm{p_j}}$$

$$=\frac{\mathrm{c_i\,r\,T_{frame}}}{\Gamma(\mathrm{m})}\times\frac{(\mathrm{k_{ij}})^\mathrm{m}}{\mathrm{p_j}^{\mathrm{m+1}}}\,\mathrm{e}^{-\frac{\mathrm{k_{ij}}}{\mathrm{p_j}}}\quad \mathrm{i}\neq\mathrm{j} \tag{9}$$

where

$$\mathrm{k_{ij}}=\frac{\mathrm{mC_{Tt}}(4\pi)^2\,\mathrm{d_{ij}^{\gamma}}}{\lambda^2} \tag{10}$$

Localizing the eigenvalues of $-\mathrm{G}(\mathbf{p})$ using analytical methods, if not impossible, is very difficult. In such conditions, numerical-based or simulation-based techniques are used (Alpcan, Basar et al. 2005), to ensure the uniqueness and stability of the system. In the next sections, simulation in high density scenarios is used, to show the stability of the system under the gradient method. However first in the next paragraph it is justified that it is very likely that $-\mathrm{G}(\mathbf{p})$ has positive eigenvalues.

To derive the condition for the uniqueness of the equilibrium easier, we assume that all the players have the same c_i and apply the Gershegorin theorem for the positivity of eigenvalues over column jth. Thus, we have:

$$\frac{\mathrm{u_j}}{\mathrm{p_j}^2}>\frac{\mathrm{c\,r\,T_{frame}}}{\Gamma(\mathrm{m})}\sum_{\substack{\mathrm{i=1}\\ \mathrm{j\neq i}}}^{\mathrm{N}}\frac{(\mathrm{k_{ij}})^\mathrm{m}}{\mathrm{p_j}^{\mathrm{m+1}}}\,\mathrm{e}^{-\frac{\mathrm{k_{ij}}}{\mathrm{p_j}}} \tag{11}$$

We can rewrite (11) as:

$$\frac{\mathrm{u_j}}{\mathrm{c}}>\frac{\mathrm{r\,T_{frame}}}{\Gamma(\mathrm{m})}\sum_{\substack{\mathrm{i=1}\\ \mathrm{i\neq j}}}^{\mathrm{N}}\frac{(\mathrm{k_{ij}})^\mathrm{m}}{\mathrm{p_j}^{\mathrm{m-1}}}\,\mathrm{e}^{-\frac{\mathrm{k_{ij}}}{\mathrm{p_j}}} \tag{12}$$

The minimum of $\Gamma(\mathrm{m})$ is about 0.8 and happens for $m\approx 1.4$. For any m less than 1 or greater than 2, $\Gamma(\mathrm{m})$ is greater than 1. Regarding the exponential term with negative power, the term $\frac{\frac{(\mathrm{k_{ij}})^\mathrm{m}}{\mathrm{p_j}^{\mathrm{m-1}}}\mathrm{e}^{-\frac{\mathrm{k_{ij}}}{\mathrm{p_j}}}}{\Gamma(\mathrm{m})}$ always has small value. With the nominal beaconing rate of 10Hz and the average beacon size of 500 byte and data rate of 6 Mbit/s, $\mathrm{r\ T_{frame}}=\frac{8\times500}{6\times10^6}=6.6\times10^{-3}$. Thus, the right-hand side of (12) should be a small number even for a large number of vehicles (N); then by selection of appropriate values for parameters u_j and c ($\frac{\mathrm{u_j}}{\mathrm{c}}$ larger than the right-hand side of (12)), we can be sure that the condition for the uniqueness and stability of the Nash equilibrium is met. Besides, the derived condition (12) is a sufficient condition for the uniqueness of the NE, which means even if this condition is violated still the algorithm might be stable.

The gradient method has been used, finding the NE in a distributed manner; thus, in NPC, every vehicle updates its beacon power, according to the gradient method, as follows.

$$\frac{\mathrm{dp_i}}{\mathrm{dt}}=\frac{\partial\mathcal{F}_\mathrm{i}}{\partial\mathrm{p_i}}=\frac{\mathrm{u_i}}{\mathrm{p_i}}-\ \mathrm{c_i}\,\mathrm{CBR_i}(\mathbf{p}) \tag{13}$$

Algorithm 1 shows the NPC mechanism.

Algorithm 1. Beacon's power updates based on gradient method

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1. Every node measures CBR
2. Update the beacon power as

$$p_i=\left[p_i+\frac{u_i}{p_i}-c_iCBR_i(\boldsymbol{p})\right]_{p_{min}}^{p_{max}}$$

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p_{max} and p_{min} are 100 mW and 1 mW, respectively (Kenney 2011). As Algorithm 1 shows, every vehicle updates its BSM power, according to the locally measured CBR in each iteration of the algorithm, and vehicles do not communicate their information.

4 SELECTION OF THE PARAMETERS

As discussed before, the purpose of the NPC is to control the CBR around 0.65 (according to (Fallah, Huang et al. 2011) between 0.4 and 0.8); thus, simulations are run, in order to find the appropriate values for u_i and c. For this purpose, OMNeT++ as network simulator and SUMO as mobility generator have been used. The simulation parameters are summarized in Table 1.

Table 1: Simulation Parameters.

Parameter	Value
Thermal Noise	-100 dBm
Carrier Sense Threshold	-90 dBm
MAC Protocol	IEEE 802.11p
Carrier Frequency	5.89 GHz
Bit Rate	6 Mbps
Beacon Size	500 Byte
Beacon Rate	10 Hz
Sampling Time	500 msec
Propagation Model	Nakagami m = 2.0
N_{max} (SBCC-N)	98.3
C_{max} (SBCC-C)	0.65

Simulations were run for a scenario of a track with three lines and a total number of vehicles N= 396 vehicles, with a homogeneous distribution. Figure 1 shows that by increasing c, the CBR is controlled at a lower level and vehicles tend to use less power. The increase of u has the reverse effect. The Figure also shows that for c=20 and u=300, the CBR is controlled around the desirable level 0.65. Thus, these values are used to compare our algorithm with SBCC-N and SBCC-C (Egea-Lopez, Alcaraz et al. 2013); however, later it is shown that vehicles can change their u parameter individually, in order to meet their application requirements, while they do not need to communicate their parameter with other vehicles and the algorithm works properly and is stable.

5 PERFORMANCE EVALUATION

The same scenario in the previous section; the track with length 1000 m and N= 396 vehicles; with c=20 and u=300 is used to compare NPC algorithm with SBCC-N and SBCC-C (Egea-Lopez, Alcaraz et al. 2013). Figure 2 shows power and CBR for the vehicles in the scenario; as it is evident, NPC is fairer in power allocation. The Jain Index (Jain, Chiu et al. 1984) for allocated power for SBCC-N and SBCC-C and NPC are 0.57, 0.83 and, 0.98, respectively, which indicates NPC is fairer than the others. This Figure also shows that the CBR over the track has more fluctuations with SBCC-N than the other algorithms do. In addition, the functionality of SBCC algorithms relies on the exchange of excess information in beacons; every vehicle should include its transmit power in its beacons. Thus, NPC is better, in terms of bandwidth usage too.

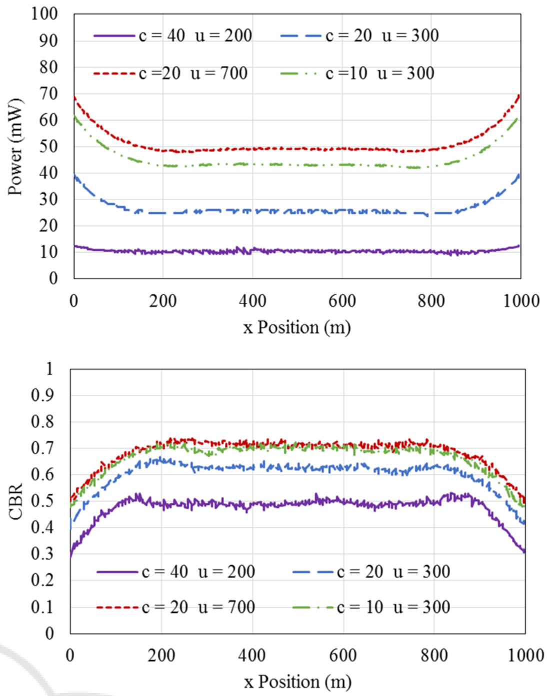

Figure 1: Beacon power and CBR for a 1000 m track with three lines and homogenous distribution of 396 vehicles, for different values of u and c parameters.

To show the stability of the algorithm and the uniqueness of the NE in a scenario with a higher number of vehicles, the next scenario is selected so that there are 850 vehicles randomly distributed, over a track with a length of 1400 m and with six lines. The scenario has been repeated with different initial values of power for vehicles: when all the vehicles have an initial power 1 mW, 100 mW and when every vehicle has a random initial power between 1 and 100 mW. For all the conditions, NPC converges to the same level of power and CBR, which indicates the uniqueness and stability of the algorithm.

Figure 3 shows the power and CBR for this scenario, for the three algorithms. It is clear that NPC is much fairer in terms of power allocation than SBCC algorithms and that CBR is smoother along the track. NPC achieves fairness because NE is unique and at the NE point, players with the same payoff function will have the same power. If there is no fairness at the equilibrium point, some vehicles can change their strategy unilaterally to obtain higher payoff, and this is in contradiction with the NE point concept.

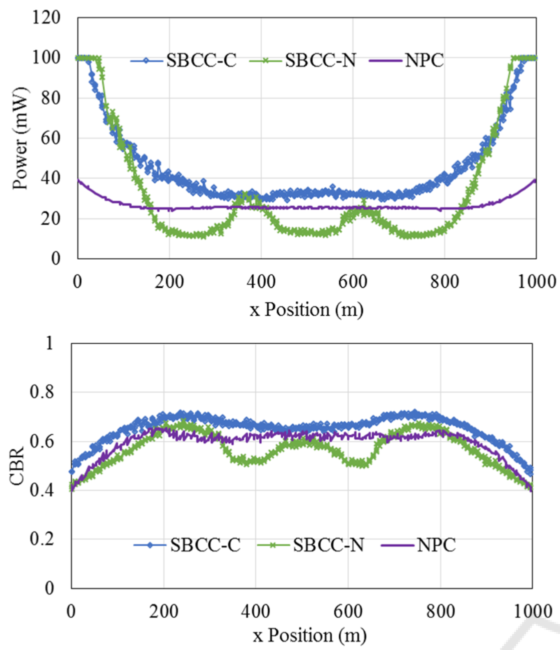

Figure 2: Beacon power and CBR for the algorithms.

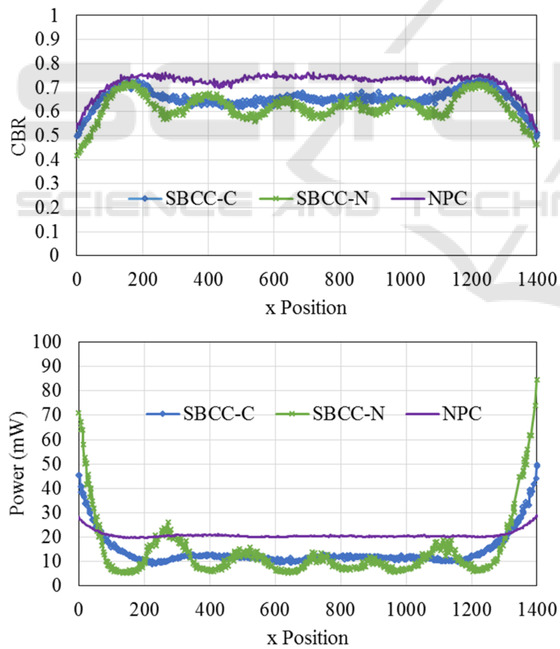

Figure 3: Beacon power and CBR for a 1400 m track with six lines and random distribution of 850 vehicles.

In SBCC algorithms, vehicles require to compute average power used by neighboring nodes. They also estimate channel parameters such as path loss component and shape parameter in Nakagami fading model. In SBCC-N the number of neighboring vehicles should be estimated too. Because different vehicles might estimate different values for above mentioned parameters, unfairness happens in beacon power.

Figure 4 shows the changes in power against iteration of the algorithms, for a vehicle at a position almost middle of the track (almost x=700) for NPC with the three different initial conditions and also for SBCC-N and SBCC-C. It is observed that NPC converges in less than ten iterations of the algorithm.

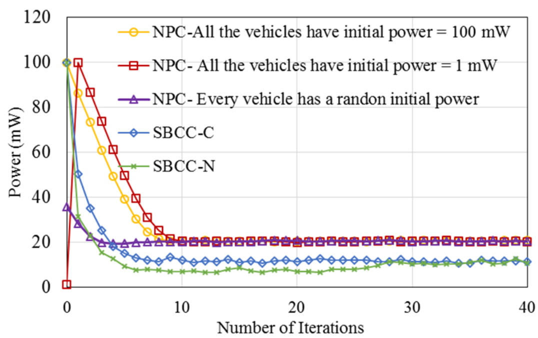

Figure 4: Beacon power changes versus the iteration of the algorithms for a 1400 m track, with six lines and a random distribution of 850 vehicles.

In the next experiment, it is indicated how NPC can assign different power levels to vehicles with different application requirements. In the proposed power control algorithm, every vehicle can adjust its u parameter to meet its application requirement. For example, when there is a traffic jam in one side of a highway and there is free flow on the other side, it is desired that vehicles with higher speed will have higher power. Such a scenario has been simulated in the next experiment. In the scenario, there is a traffic jam on one side of a highway, so vehicles are static. On the other side of the highway, vehicles move with speeds of 10, 15 or 20 m/s. Every vehicle adjusts its u parameter proportional to its speed, as follows.

$$u_i = 50 * [v_i]_4 \tag{14}$$

where v_i is the speed of the vehicle. Thus, for example, the utility factor for static vehicles would be 50×4=200 and, for vehicles with 10 m/s speed it would be 50×10=500. Figure 5 shows that for vehicles far enough from the edges of the scenario, the vehicles with higher speeds use higher power for beaconing and the CBR is controlled. This could be explained in this way that, at equilibrium point:

$$\frac{\partial \mathcal{F}_i}{\partial p_i} = \frac{u_i}{p_i} - c_i \, CBR_i(\mathbf{p}) = 0 \tag{15}$$

thus,

$$p_i = \frac{u_i}{c\,CBR_i(\mathbf{p})} \qquad (16)$$

The vehicles i and j at the same x position sense the same CBR; so:

$$\frac{p_i}{p_j} = \frac{u_i}{u_j} = \frac{[v_i]_4}{[v_j]_4} \qquad (17)$$

Thus the allocated power is proportional to the speed of vehicles. In other words, the NPC algorithm has per vehicle parameter u_i that every vehicle can change it without communicating it with other vehicles to meet its application requirement. Besides, it is seen that there is fairness in power amongst the vehicles that have the same application requirement (in this example the same speed). The parameter u_i could be a function of acceleration, deceleration….. so that the vehicles which are in a status that needs to have a longer beaconing range, can obtain this by adjusting their u_i parameter, while the CBR is controlled at the desired level.

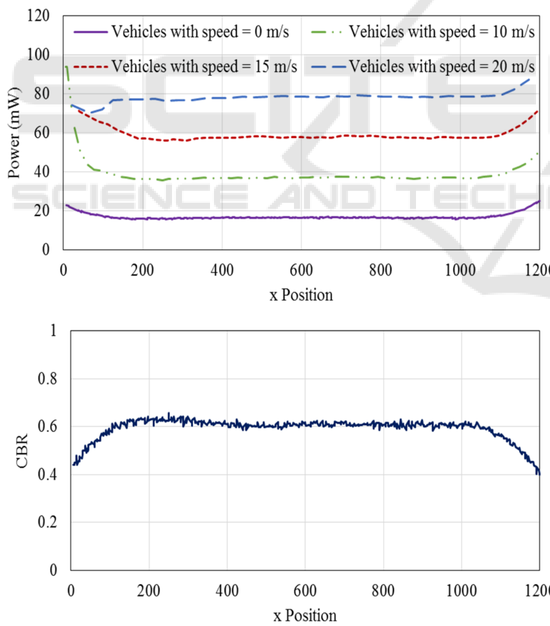

Figure 5: Beacon power and CBR for a 1200 m track, with vehicles which have different speeds of 0, 10, 15 and 20 m/s.

6 CONCLUSION

A distributed algorithm for congestion control, by adapting BSM power for VANET, was proposed. The algorithm is based on non-cooperative game theory and it was indicated that it has unique NE for a large number of vehicles. The algorithm was compared with other power control algorithms and it was indicated that it performs much better in terms of fairness and band width usage. In addition, NPC can meet the application requirements; it has per vehicle parameter so that every vehicle can obtain appropriate power for its requirement by adapting them, while congestion is controlled.

In very dense traffic situations, vehicles might be required to reduce both their beacon power and rate. ETSI DCC proposes a joint beacon rate and power control mechanism. However, several researches have revealed that ETSI DCC suffers unfairness and oscillation (Kuk, Kim 2014, Autolitano, Campolo et al. 2013, Marzouk, Zagrouba et al. 2015). A joint beacon rate and power control mechanism that does not suffer such problems is the subject of the future work.

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