Fair Distributed Congestion Control with Transmit Power for Vehicular Networks

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***Abstract*—We model the problem of beaconing congestion control as a *Network Utility Maximization (NUM)* transmit power allocation problem. We propose a distributed congestion control algorithm by transmit power adaptation called FCCP, which allows to dynamically select the appropriate fairness notion. Our results show that FCCP converges to the close proximity of the optimal value both in static and dynamic multihop scenarios while keeping the channel load at the desired level.**

I. Introduction

Vehicular communications based on wireless technologies are the foundations for innovative applications in traffic safety, driver-assistance, traffic control and other advanced services which will make up future Intelligent Transportation Systems (ITS). Cooperative inter-vehicular applications rely on the exchange of broadcast single-hop status messages, called *beacons*, among vehicles on a single control channel [1]. Beacons are transmitted periodically, at a fixed or variable *beaconing rate*. In addition, vehicles exchange other messages on the control channel such as emergency messages, transmitted when a dangerous situation is detected. *Channel congestion due to beaconing activity* occurs when the aggregated load on the wireless channel due to periodic beacons may limit or prevent the transmission of other types of messages. Control schemes are required to prevent this situation and several alternatives are available: adapting either the beaconing rate, the transmission range, the data rate, the carrier sense threshold or a combination of some of them [2]. The goal is to keep the channel capacity used by beacons under a Maximum Beaconing Load (MBL) to ensure that the remaining capacity is available to event-based messages.

In addition, *fairness* must be guaranteed as a safety requirement since beacons are used to provide vehicles with an accurate estimate of the state of their neighbors [2]. Consequently, no vehicle should be allocated arbitrarily less resources than its neighbors, under the constraints imposed by the available capacity. However, several notions of fairness can be defined, and in most of them there is a trade-off between fairness and efficiency [3]: more fairness results usually in a less efficient use of the shared resource. But, since in general, the quality of the state information [2] depends on using a high beaconing rate, reducing the efficiency is detrimental to safety. Thus, using an inadequate notion of fairness implies not simply wasting resources but also has a negative influence on the safety of the users. In conclusion, in vehicular networks it is necessary not only to provide fairness but also to be able to *select the appropriate fairness notion*.

In a previous paper [4] we modeled the congestion control as a *Network Utility Maximization (NUM)* rate allocation problem. This approach, as shown in [5], also ensures that they converge to a formally well-defined fair rate allocation. That is, the particular (concave) shape of the utility function of the vehicles is related to the different notions of fairness induced globally, the so-called (α, ω)-fairness allocations. Therefore, the shape of the utility function can be selected in order to enforce a particular type of fairness, such as proportional fairness ($\alpha = 1$), or max-min fairness ($\alpha \to \infty$). In a related work [6], we extended the model by considering the possibility of transmitting beacons with multiple powers simultaneously. Although transmit power was introduced in the distributed congestion control framework, bringing additional flexibility, we did not actually control it explicitly. That is, the only controlled variable was the beaconing rate.

In this paper, we focus on transmit power control (TPC) exclusively. That is, we assume the beaconing rate is dynamically set by the application and we select the transmit power that keeps the channel congestion under the desired limit, while maximizing the utility. This type of control is more suitable when it is preferable to let the application freely determine the beaconing rate (within the allowable limits), such as when it is generated by vehicle dynamics [1], [7]. In order to incorporate transmit power, we have to assume a propagation model: a path loss and Nakagami-m fading model is chosen. This model is very general and by selecting the m parameter it spans a variety of multipath distributions such as one-sided Gaussian (m=0.5), Rayleigh (m=1) or non-fading AWGN channel (m $\to \infty$). Although such a general fading model makes the problem not convex in general, with an appropriate change of variable it can be transformed into an equivalent convex problem.

We first review related works in section II. In section III we formulate the NUM TPC model and propose a distributed algorithm which solves it. Results are discussed in section IV before concluding in section V.

II. Related Work

ETSI standards [8] define a framework for decentralized congestion control (DCC) in the control channel, which can

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accommodate a variety of controls such as transmit power, message rate or receiver sensitivity. TPC is discussed in [2], [9], [10], [11]. In [9] we proposed a transmit power control that linearly adjusts the average carrier-sense range to keep the desired number of neighbors in range. However, fairness was not considered. D-FPAV [10], on the contrary, aims at inducing a max-min fairness allocation in a distributed way. In comparison, with our proposal any induced fairness notion, included max-min, can be selected with the α parameter. A major problem of D-FPAV is that nodes have to exchange two-hop neighbor position information piggybacked in beacons, which introduces an excessive overhead. In order to overcome it, DVDE/SPAV [10] estimates vehicle density around every node and exchanges it in a constant-size histogram of the density. With our approach, only the weight, a single number, has to be additionally exchanged which introduces very little overhead. Finally, in [11] authors propose to randomly set the transmit power. While this procedure improves an awareness quality metric, no guarantees can be provided with respect to the channel congestion.

Joint power and rate control [12], [13], [14] has also been considered. However, none of those proposals attempt to actually control *both* transmission variables jointly, in the sense that the values of transmit power and rate are completely determined by the algorithm. Instead, the minimum required values are set by the application and the available excess of capacity is then controlled by heuristically adjusting *only one of the variables*. Our proposal is also compatible with this approach: Each vehicle can dynamically set its beaconing rate according to its quality of service requirements and independently set a minimum transmit power. Our algorithm then assigns a higher power which complies with the MBL constraint.

III. Fair Distributed Congestion Control with Transmit Power

In this section we model the transmit-power based congestion control problem as a convex optimization problem. We first discuss the propagation model we use. Afterwards we formally formulate the general problem which is not convex, then transform the problem into convex form and propose a distributed algorithm for its solution.

Propagation and fading model. Let us assume that a vehicle transmit with power p over a fading channel with path loss attenuation. Then, the power received at a distance d from a transmitter is $p\mathbf{F_o}/l(d)$, where $l(d)$ is a path loss attenuation model and $\mathbf{F_o}$ is some fading random variable (r.v.) with mean 1. Equivalently, we include the power in a new random variable $\mathbf{F} = p\mathbf{F_o}$.

We consider a general Nakagami-m model [15] for fading, so the received power follows a gamma distribution, with shape parameter m and scale parameter μ. Therefore, the pdf of the r.v. $\mathbf{F}$ is $f_{\mathbf{F}}(x) = \frac{(\mu x)^{m-1}\mu e^{-\mu x}}{\Gamma(m)}$, where $\Gamma(x)$ is the *gamma function*, and $\mu = \frac{m}{p}$ to obtain an average power of p. The fading intensity is given by the parameter m, a lower value implies more severe fading conditions. We use a one-slope path loss model $l = Ad^{\beta}$, where $A = (\frac{4\pi f}{c})^2$, f is the carrier frequency and β is the *path loss exponent*.

With this model, the probability p_r that the received power at a point at distance d from a transmitter is above the sensitivity of the receiver S is:

$$
\begin{aligned}
p_r(m,p) &= Pr(\mathbf{F} > SAd^{\beta}) = \\
&= 1 - F_{\mathbf{F}}(SAd^{\beta}) = \frac{\Gamma(m, \frac{SAd^{\beta}m}{p})}{\Gamma(m)}
\end{aligned} \tag{1}
$$

where $\Gamma(m,x)$ is the *upper incomplete gamma function*. From now on, to simplify notation, we define $K_{ij} = SAm(d_{ij})^{\beta}$, where d_{ij} is the distance between vehicle i and j. Note that $K_{ij} = K_{ji}$. To avoid confusions with the power variable, we refer to the probability as $p_r(m,p) = f(m, K_{ij}/p)$.

A. Problem formulation

Let V be a set of vehicles in a vehicular network. Each vehicle $v \in V$ can select a transmit power $p_v \in [p_v^{min}, p_v^{max}]$ mW for each beacon transmission. To avoid channel congestion we want to limit the total rate received by each vehicle to a *Maximum Beaconing Load* (MBL) of C beacons/s. Since we also want to maximize the effective beaconing rate in a fair way, we use α-fair utility functions U_v as

$$
U_v(x) = \begin{cases} w_v x & \text{if } \alpha = 0 \\ w_v \log x & \text{if } \alpha = 1 \\ w_v \frac{x^{1-\alpha}}{1-\alpha} & \text{if } \alpha > 0, \alpha \neq 1 \end{cases} \tag{2}
$$

so that the optimal solutions the NUM problem are also (w,α)-fair [5]. The w_v values can be used to achieve weighted fairness, but in the following we consider all vehicles equal and set them to 1. Any required fairness notion can be enforced by setting the α parameter.

The general transmit power optimization problem becomes

$$
\mathbf{G-P}: \quad \max_{p_v} \sum_{v} U_v(p_v) \tag{3a}
$$

subject to:

$$
\sum_{v'} r_{v'} f(m, K_{vv'}/p_{v'}) \leq C \quad \forall v \in V \tag{3b}
$$

$$
p_v^{min} \leq p_v \leq p_v^{max} \quad \forall v \in V \tag{3c}
$$

The objective function (3a) maximizes the sum of the utilities as functions of the transmit power. Constraints (3b) ensure that the beaconing load measured by a vehicle is below the MBL: The aggregated beaconing load on the channel locally measured by a vehicle includes its own beaconing rate plus the beaconing rate of neighbor vehicles multiplied by the probability of receiving a beacon from them, $r_{v'} f(m, K_{vv'}/p_{v'})$, which is a function of the distance to and the power used by the neighbor. Notice how the sum extends to all the vehicles in the network, because with a Nakagami-m channel model there is a probability of receiving beacons from neighbors at any arbitrary distance. Conversely, there is a chance of not receiving beacons from close neighbors. In that case, the channel is effectively not occupied since the received power is below the sensitivity due to fading. Due to this stochastic nature of the process, occasionally the load will exceed the MBL. Therefore, constraints (3b) actually ensure that the *average* load measured by every vehicle is below the MBL. They are the average if we assume a binomial distribution with parameter $q = f(m, K_{ij}/p)$ for the number of successfully received beacons and neglect the changes of distance in vehicles during the measurement period (250 ms), which is reasonable. Let us remark that the beaconing rate r_v is not a decision variable of the problem, that is, it is externally set, and that the application can change its value at each measurement period. The algorithm simply adapts to it.

Finally, constraints (3c) keep the variables within the allowed limits. The lower value is determined typically by the standards or by applications in order to enforce some quality of service requirements. Let us also remark that each vehicle can independently and dynamically set its own values.

Problem $\mathbf{G}-\mathbf{P}$ (3) is not convex in general, but it can be transformed to convex form. We discuss it and reformulate the problem in the next subsection.

B. Equivalent convex problem

The convexity of the probability of reception function $f(m, K_{ij}/p)$, depends on the values of its arguments in general. Fortunately, the following change of variable $\frac{1}{p} = y^{\frac{1}{m}}$ makes the function $f(m, K_{ij} y^{\frac{1}{m}})$ strictly convex for $m > 0$ for all $y \geq 0$, as can be checked by computing $f''(y)$. With this change we obtain a convex set of constraints.

Now, with the above change of variable, the utility function of a vehicle becomes $U(p) = U(y^{-\frac{1}{m}}) = \frac{(y^{-\frac{1}{m}})^{1-\alpha}}{1-\alpha}$. Computing $U''(y)$ we get that this function is concave for $\alpha \geq m+1$, that is, we have a concave problem only for certain fairness notions, a common situation. For instance, for Rayleigh propagation ($m = 1$) we cannot obtain a proportional fairness ($\alpha = 1$) allocation and have to induce a stronger fairness notion (at least $\alpha = 2$). Let us note that this is not a severe limitation, since realistic channels show strong fading ($m \leq 1$) even at short distances [15].

Let us also remark that we are directly maximizing the transmit power, while the usual goal is to maximize some *awareness*-related metric, as a function of the power. For instance, to maximize the inverse of the average inter-beacon reception time (IRT) at a target distance d_o, which is $rf(m, K_o/p)$. However, the objective function $U_v = \frac{(rf(m,K_o/p))^{1-\alpha}}{1-\alpha}$ is not concave even after the change of variable. Therefore, we have decided to optimize the transmit power as a way to indirectly minimize the average IRT.

So, with the aforementioned change of variable, the convex form of the power control problem is

$$\mathbf{C}-\mathbf{P}: \quad \max_{y_v} \sum_v \frac{(y_v^{\frac{-1}{m}})^{1-\alpha}}{1-\alpha} \tag{4a}$$

subject to:

$$\sum_{v'} r_{v'} f(m, K_{vv'} y_{v'}^{\frac{1}{m}}) \leq C \quad \forall v \in V \tag{4b}$$

$$(p_v^{max})^{-m} \leq y_v \leq (p_v^{min})^{-m} \quad \forall v \in V \tag{4c}$$

C. Dual decomposition

In order to find a decentralized algorithm to solve problem $\mathbf{C}-\mathbf{P}$ (4) we use a dual decomposition. We first form the Lagrangian function L of (4a) relaxing the constraints (4b):

$$L(\lambda, y_v) = \sum_v \left(\frac{(y_v^{\frac{-1}{m}})^{1-\alpha}}{1-\alpha} - r_v (\sum_{v'} \lambda_{v'} f(m, K_{v'v} y_v^{\frac{1}{m}}) \right) + \\ + C \sum_v \lambda_v \tag{5}$$

where $\lambda_v \geq 0$ are the Lagrange multipliers (prices) associated with the relaxed constraints. The Lagrange dual is the maximum value of the Lagrangian over the domain of the variables. That is, given a set of non-negative prices λ

$$g(\lambda) = \max_{(p_v^{max})^{-m} \leq y_v \leq (p_v^{min})^{-m}} L(\lambda, y_v) \tag{6}$$

And the dual problem is:

$$\min_{\lambda \geq 0} g(\lambda) = \min_{\lambda \geq 0} \left\{ \max_{(p_v^{max})^{-m} \leq y_v \leq (p_v^{min})^{-m}} L(\lambda, y_v) \right\} \tag{7}$$

Since the objective function in (4a) is concave, for $\alpha \geq 1$, and the Slater condition holds, it has the *strong duality property* and the Karush-Kuhn-Tucker (KKT) conditions characterize its optimum solution [16]. Then, it can be shown that the dual problem (7) has a unique set of optimum link prices λ^* such that the associated rates are the optimal solution of the original problem (4). The dual approach to solve the power-rate allocation problem consists of iteratively finding the dual optimal prices λ^* using a subgradient-based algorithm, as a mean to in parallel obtain the optimum power p_v^* allocation. In next subsection we develop this scheme: At each iteration vehicles exchange their prices λ_v with their one-hop neighbors and use them as input to the optimization problem (6) which can be solved autonomously by each vehicle with its local information.

D. Distributed algorithm

In this section, we propose FCCP (Fair distributed Congestion Control with Transmit Power), an algorithm that solves problem (7) in a distributed way. Let us note that there are three main steps: first vehicles collect the prices from one-hop neighbors, next compute the gradient of (6) and update their prices and then solve the *local* optimization problem (6). There are several alternatives to solve the latter: we propose to use a gradient projection algorithm that provides a quick convergence to the optimal solution. In Algorithm 1 we describe the main procedure while in Algorithm 2 we describe the local gradient projection.

Algorithm 1 - Fair Distributed Congestion Control with Transmit Power (FCCP).

At $k = 0$, set initial vehicle price λ_v^0 and power via $p^0 = y_v^{-\frac{1}{m}}$
Then, at each time k:
Step 1. Each vehicle v receives the prices of all the neighbor vehicles $\lambda_{v'}^k$.
Step 2. Each vehicle updates its own price λ_v^{k+1} according to: $\lambda_v^{k+1} = \left[\lambda_v^k + \gamma\left(\sum_{v'} r_{v'} f(m, K_{vv'} y_{v'}^{\frac{1}{m}}) - C\right)\right]^+_{\lambda_v \geq 0}$
Step 3. Each vehicle computes y_v^{k+1} as the result of execution of Algorithm (2): $y_v^{k+1} = LGP(\lambda_{v'}^k, y_v^k, r_v)$
Transmit with power $p^{k+1} = (y_v^{k+1})^{-\frac{1}{m}}$

Algorithm 2 - Local Gradient Projection with diminishing step size.

```
procedure LGP(λ_v, y, r)
    y^1 = y, i = 1
    repeat
        y^{i+1} = [y^i + ε(i)∇L_{y_v}(y^i)]^+_{(p_v^{max})^{-m} ≤ y ≤ (p_v^{min})^{-m}}
        i = i + 1
    until |∇L| = 0
    return y^{i+1}
end procedure
```

Where we use the notation $[x]_X^+$ to denote the orthogonal projection with respect to the Euclidean norm of a vector onto the convex set X, that is, $[x]_X^+ = \arg\min_{z \in X} ||z - x||_2$.

In step 2 of Algorithm 1 to update the price we use the fact that, given a set of prices λ, a subgradient of the dual function g, $G \in \partial g$, evaluated at λ is given by

$$G(\lambda) = \sum_{v'} r_{v'} f(m, K_{vv'} y_{v'}^{\frac{1}{m}}) - C, \quad \forall v \tag{8}$$

With Algorithm 2 we solve the local problem (6) by executing a gradient-descent algorithm. In this case, given the set of prices λ, collected from neighbors at each step, the gradient ∇L of $L(\lambda, y_v)$ is

$$\nabla L_{y_v}(y_v) = \frac{\partial L(\lambda, y_v)}{\partial y_v} =$$

$$= -\frac{y_v^{\frac{\alpha-1}{m}-1}}{m} + r_v \sum_{v'} \lambda_{v'} (K_{v'v})^m e^{-K_{v'v} y_v^{\frac{1}{m}}}, \quad \forall v \tag{9}$$

Let us remark that:

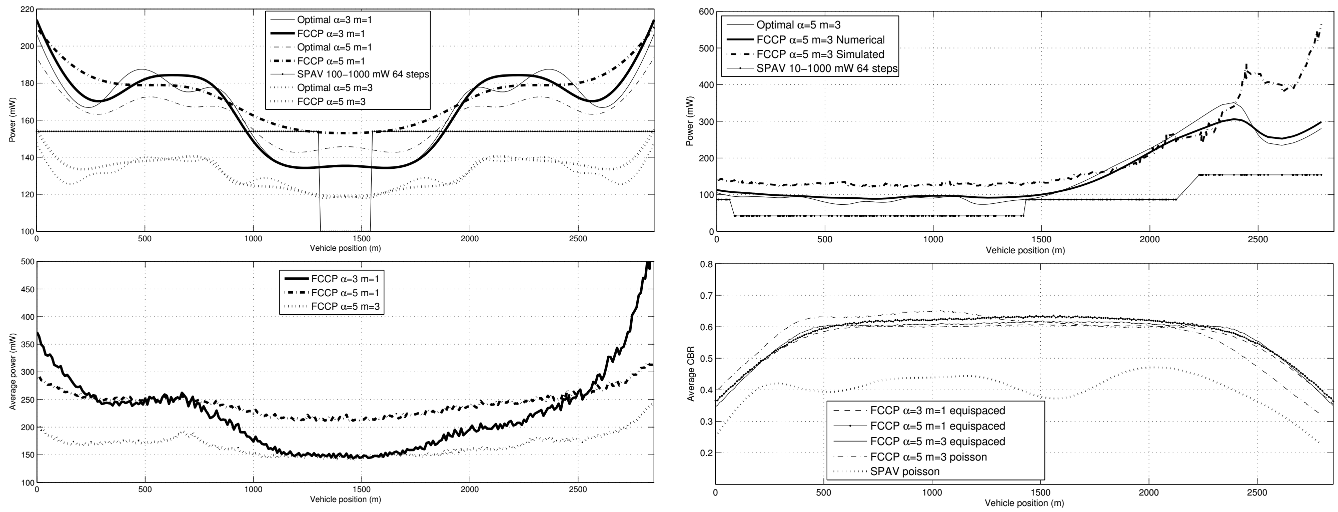
- To compute its price in step 2 in Algorithm 1, a vehicle compares its perceived congestion with the MBL. It can be done directly by measuring the Channel Busy Ratio (CBR), since in absence of collisions, the sum in the subgradient expression (8) coincides with the CBR. When collisions occur the theoretical CBR slightly overestimates the real one [9]. Measurements are taken during a sample period (T_s), which corresponds to the time between algorithm iterations. The only additional information to be included in a beacon is the current price (λ_v).
- The radio channel fading (m) and pathloss parameters (β) can be estimated from measurements as in [9].
- From the above expression is clear that to compute its power with Algorithm 2 a vehicle only needs to know its own beaconing rate and the collected prices from its one-hop neighbors. To compute the $K_{vv'}$, we use the position information included in beacons and assume that the sensitivity S is the same for all the vehicles.
- For the sake of numerical stability it is better to use power values in W, instead of mW.
- For Algorithm 2 we use a variant of a Jacobi algorithm with diminishing stepsize, $\epsilon(i) = \frac{\epsilon}{i|\nabla^2_{y_v}|}$. Any other choice of diminishing stepsize converges to the optimal solution, though possibly with different speed.

A proof of the convergence of the algorithm is not provided due to lack of space. In the next section we show by simulation and numerical results the convergence in static and dynamic scenarios.

IV. Results

In this section we test the validity of our algorithm and assumptions, The simulations have been implemented with the OMNET++ framework and its inetmanet-2.2 extension [17]. This library implements a realistic propagation and interference model for computing the Signal to Interference-plus-Noise Ratio (SINR) and determining the packet reception probabilities, considering also capture effect. The MBL has been set to 3.6 Mbps, which is 60% of the available data rate of 6 Mbps. We use a beacon size of 500 bytes plus 76 bytes of MAC and physical headers, which results in a maximum channel capacity of $C = 781.25$ beacons/s. Table I summarizes the rest of common parameters, used unless another value is explicitly mentioned in the text. All the simulations have been replicated 10 times with different seeds. Since the radius of the 90% confidence interval are below 1% we do not plot them to avoid cluttering the figures.

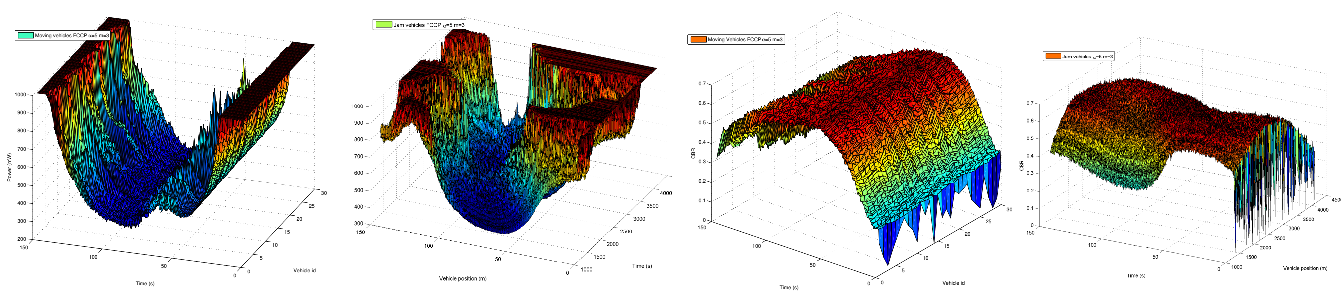
Static scenarios. We first test a static multihop scenario where vehicles do not move, which allows us an accurate control of the vehicle interactions. The results of FCCP are compared with those of SPAV [10]. For FCCP we set the same minimum and maximum power for all the vehicles, [10,1000] mW. For SPAV we use both 10 and 100 mW for minimum power and 64 power steps. Vehicles are either equally spaced with distance 10 m along a 2850 m long line or randomly positioned with poisson distribution with mean 10 m. Finally, we execute numerically FCCP with a Java program as an *ideal* scenario without MAC or other effects, to validate it, and simulate a more realistic *not ideal* MAC with collisions, capture effect and SINR evaluation.



(a) Equispaced vehicles. Fairness notions. Numerical vs simulation. Top: Numerical ideal MAC. Bottom: Realistic simulation.

(b) Top: Power vs position for randomly placed vehicles with Poisson distribution. Numerical and simulated. Bottom: CBR for equispaced and poisson with a simulated realistic MAC.

Fig. 1. Power and CBR vs vehicle position in a multihop static scenario. 286 vehicles are equally spaced with distance 10 m (equispaced) or randomly placed with a poisson distribution with an average of 10 m. For FCCP, $\gamma = 10^{-4}$ and $\gamma = 10^{-3}$ was used for $\alpha = 3$ and $\alpha = 5$ respectively.



(a) Time evolution of power for moving vehicles.

(b) Time evolution of power for vehicles in jam.

(c) Time evolution of CBR for moving vehicles.

(d) Time evolution of CBR for vehicles in jam.

Fig. 2. Time evolution of power and CBR in a multihop dynamic scenario. FCCP with $\alpha = 5$, $m = 3$ and $\gamma = 10^{-4}$.

TABLE I
COMMON PARAMETERS FOR SIMULATIONS

Parameter	Value
Pathloss exponent (β)	2.5
Data rate (V_t)	6 Mbps
Sensitivity (S)	-92 dBm
Frequency	5.9 GHz
Noise	-110 dBm
SNIR threshold	4 dB
Beacon size (b_s)	500 bytes
Beaconing rate (r_v)	10 beacons/s
Power range ($[p_v^{min}, p_v^{max}]$)	[10, 1000] mW

In Fig. 1(a) we plot the results for the power allocation versus the position on the road of the vehicles. To compare, we also plot the optimal allocations calculated by solving exactly the optimization problem $\mathbf{C}-\mathbf{P}$ (4) with Wolfram Mathematica. Ideal results in Fig. 1(a).Top show that FCCP tracks closely the optimal allocation after 100 iterations, with $T_s = 250$ ms, that is 20 s. The average powers for the simulated scenario in Fig. 1(a).Bottom are higher than the numerical results because, as we discussed before, FCCP uses the measured CBR as input, which is different from the ideal one in (8). In fact, it makes FCCP correctly adapt to the actual channel load: the average measured CBR keeps close to the MBL in the simulated scenarios, as can be seen in Fig. 1(b).Bottom. Moreover, they show that it is not necessary to converge to the optimal value to keep the CBR below the MBL. Fig. 1(a) also illustrates how FCCP can control the induced fairness notion: increasing α the optimal allocation becomes flatter as it tends to max-min fairness, trading efficiency by fairness [3]. SPAV, aiming at max-min fairness, results in an even flatter allocation with suboptimal results. Finally, in Fig. 1(a) we also show how for a more moderate fading ($m = 3$) the power is decreased, because fewer packets are lost due to fading and so the average channel occupation is higher. Fig. 1(b) allows to compare the results for a less homogeneous scenario, with nodes randomly placed according to a Poisson distribution. Again, FCCP converges to the close proximity of the optimal allocation in numerical and simulated tests.

Although not shown here, our tests also reveal that, if possible, *it is preferable to use higher values of* α, since it improves the stability and speed of convergence of the algorithm.

Dynamic scenarios. In this test we simulate a highway with a cluster of moving vehicles approaching and passing a traffic jam in the other direction. The jam is simulated with a static set of 285 vehicles randomly placed with poisson distribution with mean 10 m. The moving vehicles start 1000 m before the jam with constant speeds uniformly distributed between 26 and 32 m/s. The beaconing rate used by each moving vehicle is proportional to its speed, between 8.125 and 10 beacons/s. The beaconing rate of the vehicles in the jam is randomly selected with uniform distribution between 4 and 6 beacons/s. In Figs. 2(a) and 2(b) we have plotted the time evolution of FCCP, showing how it quickly adapts the power to the congestion situation and recovers the maximum one as soon the congestion is over for both moving and static vehicles. The particular power allocation of the scenario may not be specially clarifying, but the time evolution of the CBR shown in Figs. 2(c) and 2(d) demonstrates that it keeps the CBR at the MBL threshold most of the time, except for brief periods of adaptation when the moving vehicles enter the range of the jam ones.

V. Conclusion

In this paper we model the congestion control as a *Network Utility Maximization (NUM)* transmit power allocation problem. We propose a distributed algorithm, called FCCP that solves the optimization problem. Different notions of fairness can be induced globally and dynamically by setting the α parameter. Our results show that FCCP converges to the close proximity of the optimal value both in static and dynamic multihop scenarios while keeping the CBR at the desired level. Joint power-beaconing rate control, where both beaconing rate and transmit power are simultaneously adapted is left as future work.

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