Towards Intelligent Tuning of Frequency and Transmission Power Adjustment in Beacon-based Ad-Hoc Networks

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Abstract: This paper presents a genetic-based approach to determine optimal values of frequency and transmission power in beacon-based ad-hoc networks. The approach has been evaluated through simulations, and it has demonstrated to be more efficient than a dynamic control of frequency and transmission power, with reduction of up to 73% in packet collisions and with reduction of packet losses of up to 63% in an urban scenario. The approach and the results presented in this paper represent our initial efforts towards a more efficient control of beacon frequency and transmission power, which can exploit the benefits of a genetic-based approach but that can be applied in runtime in practical scenarios.

1 INTRODUCTION

Intelligent transportation systems (ITSs) refer to the integration of information and communication technologies with transport infrastructures. The goal is to design novel applications to enhance road safety and traffic efficiency (Maimaris, 2016). To this end, modern vehicles are equipped with multiple sensors such as global positioning system (GPS) receivers, proximity sensor, cameras, among others. These sensors are used for different applications such as parking assistance, lane keeping, pedestrian detection. In this regard, information exchange among vehicles is essential to expand the scope of these applications. However, in order to provide information to each vehicle, especially those that are not in the field of vision of drivers, it is of paramount importance the design of timely efficient dissemination approaches.

A prominent approach to message dissemination relies on the deployment of vehicular *ad hoc* networks (VANETS). In a VANET, the vehicles are equipped also with On-Board Units (OBUs) and air interfaces allowing the information exchange via either vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication paradigms (Fazio, 2013; Reis, 2014). VANETs operate on the dedicated short-range communication (DSRC) spectrum at 5.9 GHz to be used exclusively for V2V and V2I communications (Zhu, 2003). DSRC relies on several standards designed for vehicular communications, including the IEEE 802.11-OCB1 operation mode, formerly known as IEEE 802.11p (IEEE, 2016), which defines physical (PHY) and medium access control (MAC) layers for Wireless Access in Vehicular Environments (WAVE) (IEEE, 2017).

VANETs can be considered as a subset of mobile *ad-hoc* networks (MANETs), but they have specific characteristics that distinguish them (Dorronsoro, 2014) in terms of topology changes, low link availability, communication paradigms, etc. An open research challenge in VANETs is how to provide cooperative knowledge among vehicles, which in turn is a basic requirement of multiple applications of road safety and traffic management. This cooperative knowledge is built upon the periodic exchange of messages called beacons, which contain important data, about the status of the vehicle, such as position, speed, and acceleration (ETSI, 2014). The beaconing process, allows the receiver vehicles to create a Local Dynamic Map (LDM) based on surrounding environment information, which is essential for the proper performance of cooperative awareness applications, which also require high reliability and low delays. However, the wireless cooperation between vehicles is a challenging

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problem due to a large amount of dynamic data. In a VANET, the problem becomes more stringent due to the mutual interferences (Cailean, 2014).

It is worth noting that, while a fixed beacon transmission rate can easily increase the channel load and saturate the network, especially in scenarios with high vehicle density (Schmidt, 2010), a reduction of the beacon transmission rate may result in a reduction of quality and freshness of the information (Jiang, 2008). Consequently, the position errors can impact the proper performance of cooperative safety applications, which rely on real-time accurate information. In this context, the Vehicle Safety Communications Consortium (CAMP, 2005), specifies 10 beacon/s as the minimum beacon rate required by several cooperative safety applications, while others can demand up to 50 beacons/s.

In this regard, defining the beacon communication parameters that can meet the requirements of all applications for all potential scenarios is a very complex task, since the beacon requirements depend on application type (Sepulcre, 2011a) and vehicular context (Sepulcre, 2011b). Therefore, it is essential to define the most relevant metric for safety-critical applications. In this sense, in previous work (Bolufé, 2017; Ortega, 2018) we proposed the position error as the priority metric, due to its impact on the timely detection of potentially dangerous situations. More specifically, in (Bolufé, 2017), we proposed an algorithm that dynamically adjusts the beacon rate based on vehicle movement status. This approach was experimentally evaluated in (Ortega, 2018), using test bed equipment for vehicular communications. The objective of these previous works is twofold. On the one hand, these previous works assess the dynamic adjusting of the beacon rate to achieve a target position error, that can meet the requirements of cooperative safety applications. On the other hand, driven by the vehicle movement status, the approach adjusts the transmit power considering the channel load and the beacon rate with the aim of reducing packet collisions.

More recently, in (Bolufé, 2018), we propose the use of a novel joint power & rate control distributed algorithm in cooperative vehicular networks. Simulation results show that the dynamic control of beacon transmission rate limits the average position error, and the use of maximum transmit power leads to an increase of packet collisions. However, the joint power & rate control allows reducing the packet collisions. Although the approach in (Bolufé, 2018) outperforms other beaconing strategies in terms of a trade-off between the main performance metrics, we believe that the fine-tuning, by evolutionary algorithms, of this joint power & rate control will allow obtaining better results.

This paper presents our initial efforts toward intelligent tuning of frequency and transmission power adjustment in beacon-based VANETs. This paper presents an approach to exploit the benefit of genetic algorithms in the setting of beacon rate and power transmission parameters. More specifically, the contributions of this work are as follows:

- We propose the use of genetic algorithms (GA) to search for beacon rate and power transmission parameters that outperform other approaches in terms of packet losses, packet delivery, and number of collisions.
- To the best knowledge of the authors, this study presents the first reference to the use of GAs in the beaconing process.

This paper is organized as follows. Section 2 presents the state of the art. Section 3 presents the baseline approach to adapt beacon rate and power transmission parameters. Section 4 presents our initial approach towards intelligent control of rate and power transmissions. Section 5 presents simulation results. Section 6 concludes the paper.

2 STATE OF THE ART

Adaptive beacon techniques have been the subject of research since the last decade, all in all, assuming simplified scenario conditions. The main goal of these techniques is to adapt the beacon rate and power effectively considering the channel load and specific application requirements. To address this problem, different adaptive beacon strategies have been proposed (Shah, 2016; Zemouri, 2014; Sepulcre, 2016; Aygun, 2016). These strategies combine the control of beacon rate and transmission power, according to the channel load and specific application requirements. In (Zemouri, 2014) the transmission rate is adapted to meet the channel requirements in terms of collision rate and channel busy ratio (CBR), while the transmit power is adjusted according to the required awareness level. In the algorithm of Sepulcre et al. (Sepulcre, 2016), the packet rate of each vehicle is set according to the minimum beacon rate required by each application and it is set according to the required packet reception rate at the application warning distance. The algorithm, of Aygun et al. (Aygun, 2016), adapts the transmit power in order to reach a desired awareness ratio at the target distance while adjusting the beacon rate to limit the current channel busy ratio. However, all these approaches do not consider the vehicle movement status and the vehicular traffic dynamics, factors that affect the system performance.

Optimization methods can be broadly classified into two main classes: exact and approximate (Talbi, 2009). On one hand, exact methods ensure finding the optimal solution to the optimization problem. However, their complexity and high computational demand are not suitable to tackle real-world optimization problems. Alternatively, evolutionary algorithms (EAs), which are population-based metaheuristics, allow obtaining acceptable solutions in a reasonable time (Dorronsoro, 2014). EAs have been widely used in many scientific domains such as ad-hoc networking (Reina, 2016). Depending on the execution mode, the EAs can be deployed in VANETs following an off-line or an on-line approach. While off-line approaches help to search for the best suitable parameters configuration, a special care must be taken in highly dynamic scenarios. On the other hand, online approaches are expected to adapt their behavior (i.e., find the best parameter solutions) during runtime.

In this regard, EAs have been employed in optimization processes to finding optimum topology in MANETs (Reina, 2016) as well as to optimize the deployment of Road Side Units (RSUs) to maximize the coverage (i.e., number of vehicles covered) in a given area (O. Dengiz, 2011). More specifically, in (Galaviz-Mosqueda, 2016), the authors proposed a component-based methodology using GAs for the membership functions tuning problem for broadcasting protocols in VANETs. Other recent examples of the use of GAs in VANETs are on optimizing the topology connectivity (Dorronsoro, 2009), realistic vehicular mobility models (Seredynski, 2012), optimize routing protocols (Toutouh, 2012), and optimizing broadcasting (Jafer, 2016; Jafer, 2017).

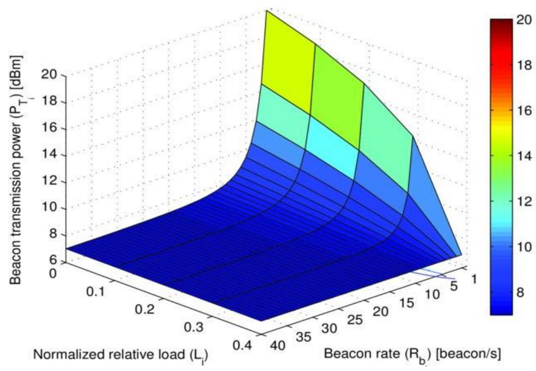


Figure 1: P_{Ti} as a function of L_i and R_{bi}, according to (2).

From the aforementioned ideas, it is clear that genetic algorithms have been applied for optimizing different parameters in VANETs and MANETs. However, to the best knowledge of the authors, this study presents the first reference to the use of GAs in the beaconing process.

3 DYNAMIC CONTROL OF TRANSMISSION PARAMETERS

This section aims to describe the Dynamic Control of Beacon Transmission Rate and Power (DC-BTR&P) algorithm developed in (Bolufé, 2018). Due to its enhanced performance, the DC-TR&P algorithm will be used as the baseline approach for intelligent tuning of transmission rate and power (described in Section 4).

The DC-BTR&P approach adjusts the beacon transmission parameters to meet the position accuracy requirements of cooperation aware applications. DC-BTR&P is capable of adapting to the vehicular traffic dynamics and to the vehicle movement status reducing interferences guaranteeing the vehicle's minimum warning range. The DC-BTR&P algorithm uses the position error as a priority metric due to its impact on vehicular systems ability to detect and mitigate potentially dangerous traffic situations in real-time. The beacon rate is computed by the vehicle n_i as a function of its velocity (v_i) and acceleration (a_i) expressed as:

$$a_i I_{b_i}^2 + 2\left(v_i + a_i t_D\right) I_{b_i} + 4\left(v_i t_D - \overline{E_i}\right) = 0 \quad (1)$$

, where I_{bi} is the beacon interval of n_i (equivalent to the inverse of beacon transmission rate R_{bi}); t_D is the transmission delay, which is equal for all vehicles by assuming beacons of the same size and equal data rate; and $\bar{E}_i$ is the average position error computed by surrounding vehicles. Once the beacon rate has been set, DC-BTR&P adapts the beacon transmit power according to the relative channel load and the preset beacon rate, in order to decrease packet collisions. The beacon transmit power is adjusted by n_i using the expression (2).

$$P_{T_i} = P_{T_{\min}} + \left(P_{T_{\max}} - P_{T_{\min}}\right)\left(1 - \frac{L_i}{L_o}\right) R_{b_i}^{-\beta} \quad (2)$$

, where PT_{min} is the transmit power required by n_i to generate a minimum warning range, P_{Tmax} is the maximum transmission power allowed, L_o is the normalized critical channel load, L_i is the normalized relative channel load on n_i and β is the weight factor, which controls the impact of the beacon rate on the transmission power. L_i is computed considering the impact of multiple transmitters, and the distance to each neighbor vehicle. It should be noted that (2) controls the beacon transmission power between minimum and maximum transmit power values, being $P_{Ti} = P_{Tmin}$ for $L_i = L_o$, and $P_{Ti} = P_{Tmax}$ for $L_i \approx 0$ and $R_{bi} = 1$ beacon/s. Figure 1 shows the transmit power according to the normalized relative channel load and beacon transmission rate, with $P_{Tmin} = 7$ dBm, $P_{Tmax} = 20$ dBm, $L_o = 0.4$, and $\beta = 2$. Note that the transmit power decreases when the normalized relative channel load or/and the beacon transmission rate increases, while a minimum warning range is guaranteed.

4 INTELLIGENT CONTROL OF BEACON TRANSMISSION RATE AND POWER

This section firstly provides an overview of fundamental concepts of GAs. Then, we elaborate on the integration of GAs towards providing intelligent tuning of frequency and power parameters in a beacon-based ad-hoc networking scenario.

4.1 Fundamentals of GAs

The genetic algorithm is based on the evolution process of living beings. In which, over generations, the populations evolve following the principles of natural selection (the survival of the fittest) postulated by Darwin. This algorithm was proposed by Goldberg and Holland in 1998 (Goldberg, 1998).

The baseline procedure of a GA is depicted in Fig. 2. The initial population is randomly created as a set of candidate solutions, where an objective function is used a fitness measure. Based on this fitness, the better individuals (solutions) have a higher probability to be selected to the next generation by applying *recombination* and *mutation*. The recombination process is applied to two selected individuals (parents), resulting in two new solutions. On the other hand, the mutation process is applied to one individual and it results in one new solution. Therefore, by applying recombination and mutation processes, the algorithm produces a set of new solutions, called children. Based on their fitness, these children compete for a place in the next generation. This procedure can be iterated until a solution is found or a previously set of generations limit is reached.

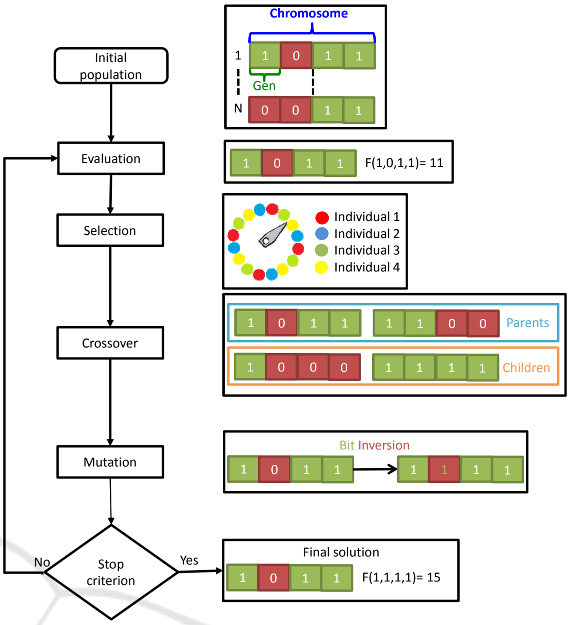


Figure 2: General scheme of a genetic algorithm.

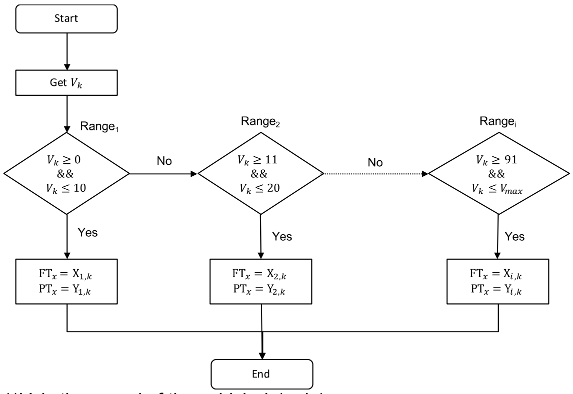
4.2 GA-based Control of Beacon Transmission Rate and Power (GA-BTR&P)

This section presents our initial GA-based Transmission Rate and Power (GA-BTR&P) control approach. GA-BTR&P adjusts the transmission rate and power at once, taking into account deterministic rules based on the vehicle travel speed. For this purpose, we performed a discretization of the travel speed values in 10 possible ranges, which are shown in Table 1. It should be mentioned that the V_{max} value is the maximum possible travel speed of a

Table 1: Ranges of the travel speeds for deterministic rules.

Speed Range (*i*)	**Vehicle speed (V_k)**
1	0 - 10 km/h
2	11 - 20 Km/h
3	21 - 30 Km/h
4	31 - 40 Km/h
5	41 - 50 Km/h
6	51 - 60 Km/h
7	61 - 70 Km/h
8	71 - 80 Km/h
9	81 – 90 Km/h
10	91 - V_{max} Km/h

vehicle (V_k) during a given simulation. The Fig. 3 shows the GA-BTR&P flow diagram to obtain the values of frequency FT_x and power transmission PT_x of the vehicle k (veh_k).



**V_k is the speed of the vehicle k (veh_k)

Figure 3: Deterministic & rule-based definition of frequency and power transmission values.

The GA-BTR&P approach considers the range of the travel speed to determine the values of frequency $X_{i,k}$ and power transmission $Y_{i,k}$, for the i speed range of vehicle k (veh_k). It is important to mention that the values of the variables $X_{i,k,}$ and $Y_{i,k}$ are determined (i.e. optimized) with the genetic algorithm. For this reason, we propose the encoding presented in Fig. 4 for the vehicles. Each vehicle is represented by a set of 20 variables: 10 related to the frequency and 10 related to the power transmission. We consider one variable of frequency and one variable of power transmission for each range i of vehicle speed presented in Table 1.

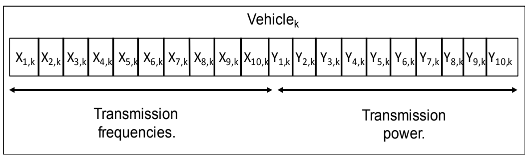


Figure 4: Proposed vehicle encoding.

Each population individual is represented by a set of k vehicles, where k is the total number of vehicles in the scenario as it is graphically shown in Figure 5. It should be mentioned that each vehicle consists of a set of 20 variables (see vehicle encoding in Fig. 4).

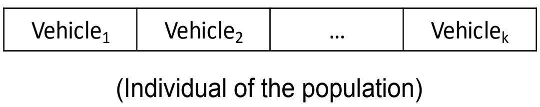


Figure 5: Proposed individual encoding.

In order to lay down the concepts of our GA-based approach, we make use of a simulation platform where the GA-based approach can iterate and refine (i.e. optimize) the values for transmission rate and power. For this purpose, we use the OMNet++ simulation platform, although our approach can be applied to other platforms. Figure 6 represents the optimization scheme for k vehicles where each vehicle has 20 candidate variables, 10 for transmission power transmission and 10 for beacon rate (see encoding in Fig. 4). The performance of each population individual (i.e. the set of k*20 variables) is evaluated through OMNet++ simulations. The performance of each population individual is evaluated in an urban mobility scenario for which the optimization procedure is executed. In each simulation (i.e. evaluation), the number of packet collisions is used to calculate the fitness value. A lower number of collisions represents a greater fitness value of the population individual. Each evaluation of the population individual is followed by the selection, recombination, and mutation processes of the genetic algorithm until the stop criterion is met. At the end of the evolutionary process, the best parameters of frequency and transmission power for each speed range of each vehicle are obtained for a given urban mobility scenario.

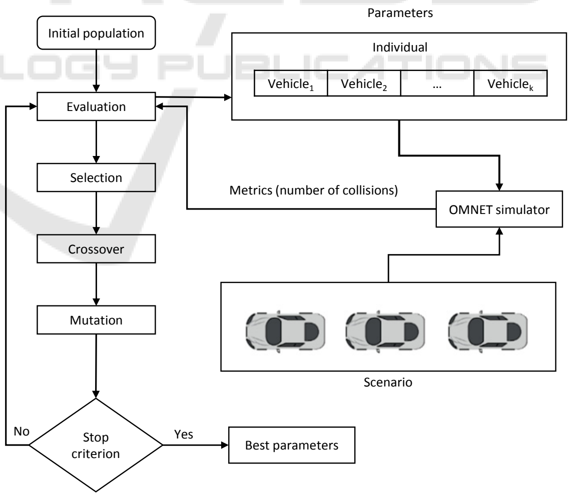


Figure 6: GA-based simulation platform.

5 SIMULATION RESULTS AN TECHNICAL DISCUSSION

This section compares the performance of the baseline DC-BTR&P algorithm with our GA-based

Transmission Rate and Power (GA-BTR&P) control approach.

5.1 Simulation Setup

Our simulations are intended to evaluate the performance of the above approaches to disseminate cooperative knowledge. The simulations were performed considering a scenario with a grid-shaped square of five streets on each side. The square has sixteen blocks of 200m per side. Each street is crossed by a car with the direction shown in Fig. 7. The maximum speed of the vehicles was set to 100km/h, with an acceleration and deceleration of 2 m/s^2 and 4.5 m/s^2 respectively. The simulation parameters are summarized in Table 2.

Table 2: Simulation parameters.

Parameter	Value
Map shape	grid
Number of streets	5 x 5
Dimensions	0.8 km x 0.8 km
Maximum speed	100 km/h (27.8 m/s)
Acceleration	2 m/s^2
Number of vehicles	10
Vehicle travel time	≈ 80 sec

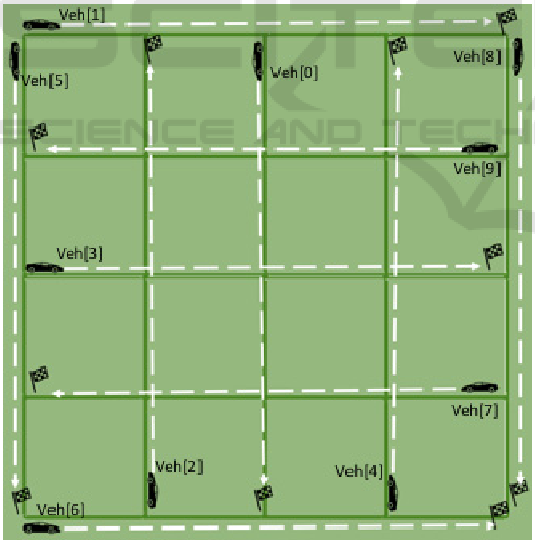


Figure 7: Simulation map with directions of vehicles.

5.2 Comparative Results

This section compares the performance of the DC-BTR&P and GA-BTR&P approaches. Namely, we evaluate their performance in terms of number of collisions and packet delivery, which in turn are representative parameters that allow for efficient cooperative knowledge. Table 3 shows the performance of the transmission rate and power parameters defined by both, the DC-BTR&P and GA-BTR&P approaches.

Table 3: Performance comparison for cooperative knowledge.

Metric	DC-BTR&P	GA-BTR&P
Packets Sent	4051	4052
Lost packets	49	18
Delivery effectiveness	98.79%	99.55%
Number of collisions	48	13

In more detail, Table 4 shows the actual values of the vehicles in our simulations for each metric. The results demonstrate that our GA-based approach can reduce the number of collisions up to a 73% and the packet losses can be reduced up to a 63% in this urban scenario. These results demonstrate that the performance of a dynamic allocation of beacon transmission rate and power certainly can be enhanced with the use of an intelligent approach, i.e. based on a genetic algorithm. Nevertheless, there are important aspects that need to be considered regarding these partial conclusions. These are discussed in the next section.

Table 4: Values produced for each vehicle in simulations.

Metric / Vehicle	Packets Sent		Packets lost		Number of collisions	
	DC BTR&P	**GA BTR&P**	**DC BTR&P**	**GA BTR&P**	**DC BTR&P**	**GA BTR&P**
Veh[0]	396	396	3	2	3	1
Veh [1]	397	397	1	0	1	0
Veh [2]	396	396	3	0	3	0
Veh [3]	432	432	5	2	5	2
Veh [4]	395	395	13	3	12	2
Veh [5]	398	398	1	1	1	0
Veh [6]	398	398	1	1	1	0
Veh [7]	420	421	15	6	15	5
Veh [8]	397	397	2	0	2	0
Veh [9]	422	422	5	3	5	3
TOTAL	***4051***	***4052***	***49***	***18***	***48***	***13***

5.3 Technical Discussion

The results presented in Section 5.2 are encouraging, they demonstrate that there is still a reasonable margin to enhance the performance of the DC-BTR&P by means of an intelligent approach. Moreover, there are important aspects that deserve special attention in this respect.

On the one hand, the DC-BTR&P approach is a distributed beaconing algorithm that performs transmission frequency (*Ftx*) and transmission power (*Ptx*) adjustments in each vehicle. In the implementation of this algorithm, each vehicle calculates the *Ftx* according to its speed and the average position error limit perception of its neighbors. Then the transmitter vehicle calculates the probability of successful reception of its neighbors and with the *Ftx* already calculated, the *Ptx* of the same vehicle is calculated. Before sending a beacon, each vehicle makes these calculations to minimize the average position error (dynamically adjusting the *Ftx*) and to reduce the number of collisions (by adjusting the *Ptx*).

On the other hand, the GA-BTR&P approach uses a genetic algorithm to find in each vehicle, the best values of *Ftx* and *Ptx* to achieve a reduction in the number of collisions in the scenario for the speed ranges of each vehicle. Nevertheless, this approach has to execute a number of iterations, which in turn makes it computationally expensive so that, it difficult to be applied to practical scenarios. A trade-off solution that can exploit the benefits of our GA-BTR&P approach in favor of a fast and more efficient version of the DC-BTR&P approach will be the basis of our future work.

6 CONCLUSIONS AND FUTURE WORK

This paper has presented our initial steps towards intelligent tuning of frequency and transmission power adjustment in beacon-based ad-hoc networks. A genetic-based beacon control has been proposed and simulation results have demonstrated that an intelligent-based approach can outperform a dynamic control in terms of a number of collisions (with reductions up to 73%) and packet losses (with reductions up to 63%) in our urban simulation scenario. Nevertheless, this advantage can be considered relative, as an intelligent-based approach like the one described in this paper can be computationally prohibitive for real scenarios due to time constraints. In this regard, we are currently developing a trade-off solution, where the genetic-based approach can be used to produce values of frequency and transmission power that can take into account a target average error together with the number of collisions. This way, the genetic algorithm can be used to produce a regression-based polynomial function that could be used to estimate the beacon frequency for a given vehicle speed, which in turn could be used by the DC-BTR&P approach to produce frequency values to enhance its performance closer to the performance of the GA-BTR&P approach but in runtime.

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APPENDIX I. GLOSSARY OF ACRONYMS

Channel Busy Ratio (CBR)
Dedicated Short-Range Communication (DSRC)
Dynamic Control of Beacon Transmission Rate and Power (DC-BTR&P)
European Telecommunications Standards Institute (ETSI)
Evolutionary Algorithm (EA)
Genetic Algorithm (GA)
Genetic Algorithm-based Transmission Rate and Power (GA-BTR&P)
Global Positioning System (GPS)
Local Dynamic Map (LDM)
Mobile Ad-hoc Networks (MANETs)
On-Board Units (OBUs)
Physical Layer (PHY)
Road Side Units (RSUs)
Transmission Frequency (Ftx)
Transmission Power (Ptx)
Vehicle-to-Infrastructure (V2I)
Vehicle-to-Vehicle (V2V)
Vehicular Ad-hoc Networks (VANETS)
Wireless Access in Vehicular Environments (WAVE)