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Cognitive radio based connectivity management for resilient end-to-end communications in VANETs

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ABSTRACT

VANET has attracted a good deal of attention owing to its wide range of important applications. VANET is a special kind of mobile ad hoc network, in which most of the nodes are spatio-temporally volatile fast-moving vehicles. Hence, it is extremely difficult to provide resilient end-to-end communications in VANET, although it is a cornerstone for the wider deployment of VANET applications. In VANET, the network and upper layers often fail due to frequent link disruptions caused by the highly dynamic environment. In view of this, we propose MOCA, a *M*echanism for c*O*nnectivity management in *C*ognitive vehicul*A*r networks, which make use of cognitive radio (CR) technology, to overcome frequent link disruptions and achieve greater resilience for end-to-end data delivery. MOCA benefits from the flexibility and adaptability of CR, which opportunistically accesses the best available licensed channel frequencies. The selection of the best available links is determined by values from *observable* parameters related to channels and nearby vehicles, such as bit error rate (BER), node speed and driving direction, as well as on the unique application requirements. As the VANET environment can be highly dynamic, MOCA carries out a periodic re-evaluation of the quality of the available channels. Our simulation results show that MOCA outperforms all the other representative alternatives in the literature in terms of throughput and jitter. To the best of our knowledge, MOCA is the first application-independent strategy to provide VANET with resilient end-to-end communications.

1. Introduction

Vehicular ad hoc networks (VANETs) have attracted considerable attention as their deployment will significantly enhance our daily experience of driving. VANET consists of on-board units (OBUs) installed in vehicles and roadside units (RSUs) deployed alongside urban roads/highways, which is a means of facilitating both vehicle-to-vehicle (V2V) communications and vehicle-to-infrastructure (V2I) communications [1]. For instance, with this new networking technology, drivers on a highway will be able to find out about the traffic situation ahead, take precautionary measures, and avoid serious accidents which would otherwise be unforeseen.

In the literature, there are many important applications of VANETs, which are related to safety, mobile healthcare and entertainment, and require end-to-end communication channels with a high degree of resilience as a key enabler of safety [2]. Unfortunately, VANET is a special kind of mobile ad hoc networks, since most of the nodes are spatio-temporally in volatile fast-moving vehicles [1]. They are prone to network failures, such as frequent communication link disruptions caused by various factors, such as severe interference, interceptions, hidden terminal problems, radio channel fading, selfish behavior, and frequent topology changes caused by highly mobile nodes [3]. Hence, network failures have become a rule rather than an exception [4], and a high degree of network resilience is required to support VANET applications and ensure optimum reliability in V2V and V2I communications [2,5].

Over the years, there have been several attempts in the literature to improve the efficiency of data delivery in various kinds of wireless networks, such as wireless sensor networks, mobile ad hoc networks and VANETs [3,6–9]. These approaches have mainly concentrated on the management of resources, mobility, and/or message dissemination to improve network throughput, and this may improve the reliability of VANETs as well. However, as

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their main concern is with connectivity management for the sake of greater efficiency, generally speaking, these existing schemes would not be an effective way of improving resilience (i.e. the ability of the network to maintain its total throughput when there is node and link disruption [10]); having reliability feature as one of its main attributes. These approaches are generally constrained by the fact that they can only use unlicensed frequency bands (defined by the current IEEE 802.11p protocol specifications) that are becoming increasingly overused because of the popularity of portable devices. Being restricted to employing only unlicensed frequencies has led to the use of programmable technologies, such as cognitive radio, so that advantage can be taken from their flexibility [11–13].

Cognitive radio (CR) technology allows unlicensed users (secondary users – SUs) to access licensed frequency bands (of primary users – PUs) opportunistically. As an emerging technology, CR is becoming popular and is now being applied to vehicular networks, largely due to its ability to solve the serious problem of wireless network capacity and exhaustion in unlicensed network frequency bands, such as WiFi [11]. When employing this strategy, CR evaluates the available channels on the basis of the physical characteristics which can affect the reliability of the channels – such as received residual signal strength (RSS), interference, and bit error rate (BER) – and can thus ensure that the most reliable ones are selected. This study investigates the capacity of CR to improve the resilience of VANET communications. Encouraged by the fact that CR has a number of readily-available functionalities for dealing with dynamic physical environments, we attempt to use CR to improve the resilience of end-to-end V2V and V2I communications in VANETs in accordance with the requirements of the applications.

This article proposes MOCA, as a **M**echanism for c**O**nnectivity management in **C**ognitive vehicul**A**r networks. MOCA is able to exploit the high degree of flexibility and adaptability which are provided by CR and access licensed frequency bands opportunistically with the aim of achieving communications resilience. Within the framework of MOCA, each node (*on board unit* – OBU – in the vehicle or *roadside unit* – RSU) can individually operate with the list of available channels along with the information from nearby vehicles, such as speed and driving directions. Following this, each node periodically evaluates the quality of the available channels as well as predicting what it will be in the near future, without any need to keep a record of previous states. Thus, it can take swift action to prevent a sudden disruption of communication links, and establish stable end-to-end communications to meet the particular requirements of the applications.

MOCA examines deterministic and probabilistic criteria such as channel information, vehicle speed, and expected node mobility, to evaluate the resilience of the available channels. Since VANETs are dynamic, the criteria used in the channel (connectivity) selection may have different degrees of importance over a period of time. Thus, we designed MOCA so that the importance of each criterion varied in accordance with the situation, which means that it is more adaptable, proactive, and suited to a dynamic VANET environment (since this feature is the main value of MOCA). Finally, by carrying out simulations, we were able to compare the average performance of MOCA with an existing representative alternative from the literature – the TFRC-CR protocol [8] – in the same conditions as in an urban environment. The TFRC-CR protocol is essentially designed to select channels that conform to network conditions, and we show that MOCA outperforms it in terms of throughput and jitter.

This paper proceeds as follows. Section 2 describes related works. Section 3 outlines the system model. Section 4 presents the new mechanism for connectivity management in vehicular networks (MOCA). Section 5 evaluates the performance of MOCA through simulated experiments. Section 6 concludes this article and makes suggestions for future work.

2. Related works

The problem of network-failure resilience and its correlated concepts (such as survivability and fault-tolerance) have been addressed in a number of studies in the last few years, within the context of wireless ad hoc networks. The causes of these failures include the following: hardware/software faults, operator errors, malicious or selfish attacks, and natural disasters [10,14,15]. In a nutshell, when an attempt is made to tackle the problem of resilience in wireless ad hoc networks, the main focus is on connectivity management restoring a physical topology [14], providing redundancy [16,17] or applying technologies that can opportunistically use radio spectrum frequency [15]. Although these previous works have made some improvements, very few of them address resilience in vehicular ad hoc networks [18], but rather, tend to focus on specific types of applications, such as video streaming [1,19] or user authentication [20]. Furthermore, owing to the frequent topology changes in VANETs, network-failures in terms of link disruptions must be considered the rule rather than the exception in the design of protocols for these networks, and for this reason require further study in the literature.

Since reliability is an attribute of resilience, many works were found in the literature that investigate this with regard to vehicular ad hoc networks. The required level of communication reliability depends on the kind of application, which can be classified as either general or driving-safety-related. In the case of the applications in the first category (including cooperative games and video broadcasting), communication reliability is not a critical issue, despite the fact that resilience is important for them too in certain applied contexts, - for instance, disaster assistance. In contrast, with regard to applications in the second category, (such as the cooperative forward collision warning, pre-crash sensing/warning, curve speed warning, left-turn assistance and hazardous location notification), communication reliability is a significant issue [3]. In recent years, a number of studies have investigated how to improve the quality of data delivery in VANETs, particularly in terms of throughput and latency, by making use of mobility prediction, routing, resource management and channel selection [21–24]. However, most of these approaches have failed to give priority to end-to-end communication reliability, or consider how it can support resilience.

The work in [6] takes as its criterion the average length of time in which a pair of nodes is within communication range of each other and employs this to select the best next hop node to provide Quality of Service (QoS). However, the approach is centralized and lacks a timely mechanism for regular updates or a re-evaluation of channel quality which are necessary in a highly dynamic VANET environment to ensure reliable end-to-end communications. In seeking to provide QoS and network stability, the routing protocol based on QoS-OLSR [7] carries out a clustering of VANET nodes on the basis of their mobility. The protocol employed an ant-inspired model for this purpose. However, as VANETs are highly sensitive to the mobility and density of nodes, the protocol incurs a very high network overhead to maintain the groups of nodes, which adversely affects the reliability of the data delivery.

CR technology has been introduced as a promising means of solving the problem of capacity exhaustion resulting from highly congested unlicensed frequencies such as those allocated to WiFi [11]. It allows unlicensed users (SUs) to opportunistically access licensed frequency bands (e.g. those allocated to cellular networks) when licensed users (PUs) are not transmitting data [5]. CR employs mechanisms to detect the absence of primary users nearby, as well as select the best available licensed frequencies [5]. One

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representative work, the TFRC-CR protocol [8], uses the activity information of the PUs to allow the SUs to randomly select available channels and then use the channels they prefer. However, TFRC-CR is only designed to operate within a predetermined area as it uses the records of a limited number of primary users. As a result, TFRC-CR is not suited to the highly dynamic VANET environment where the nodes often change their location.

The SURF protocol [9] selects channels based on their degree of quality. This value is calculated for each channel by taking into account the activities of the associated primary users and the density of the nodes competing for the channel. In situations where this value suggests that an erroneous estimate has been made, SURF relies on future decisions. SURF achieves this by choosing a better channel which has a greater number of nodes. However, as the number of nodes that use a channel increases, the competition for the channel becomes more fierce and as a result, those applications which are sensitive to delay may not be satisfied with this approach. The traffic prediction shows the likely conditions in the near future. In the context of VANETs, predicting traffic helps in the selection of channels. Thus, the reliability prediction procedure assists in managing the channel selection since it satisfies the different requirements and purposes of the nodes [22,25]. However, until now, prediction has not been employed to help in channel selection by seeking to improve reliability in data delivery.

The concept of spectral efficiency which establishes a relationship between the service charge and the channel bandwidth, was outlined in [26]. The algorithm makes it possible to predict the service charge at a future time based on the information of the users' requirements and is thus able to ensure compliance with QoS requirements. The authors employed an optimization technique for access control and restricted the channel bandwidth. However, the algorithm does not allow a reliable channel decision to be made that is acceptable to dynamic environments. Moreover, it does not use any metric that satisfies the conditions of dynamic environments, such as node density and mobility in the channel.

Generally speaking, a decision based on insufficient information leads to a lack of confidence. This also applies to the channel selection mechanism that concerns us here. In view of this, it is highly desirable to obtain as much relevant information as possible to make a better choice. Information about the performance of the channels and the users' requirements is important when selecting the best channels. However, other representative information can assist in addressing questions such as mobility and the dynamics of nodes, in particular, information about the behavior of nodes for connectivity and the channel selection mechanism.

Thus, this system allows greater connectivity assurance and reliability-based decision-making. Unlike existing approaches, MOCA is able to provide a dynamic prediction of channel quality, by advising what changes are required when the current channel is in a poor position to meet the QoS requirements of each node application. Hence, MOCA considers the features of node mobility, together with the efficient management of drivers and channels. Owing to the dynamic nature of the environment, these criteria have independent values at every moment. As a result, MOCA has learning parameters and considers their importance at every moment.

3. System model

It is defined a vehicular network consisting of a set $\Lambda = \{1, 2, 3, \ldots, n\}$ of nodes/secondary users (On Board Units – OBU, in the vehicles, or Roadside Units – RSU), with cognitive radio (CR) capabilities, i.e. equipped with pairs of cognitive transmitters/receivers that can make use of one of these channels when it is not occupied with a primary user. Each vehicle is provided with its own position in a local urban road (by GPS). Λ is the set of node identities in the network. Each node i can sense and operate within its own set of orthogonal frequency channels denoted by Ξ_i, in which $N_i = |\Xi_i| < \infty$ is called its sensible channel number. We do not assume there is a universal channel set for all the nodes since their sensible frequency channels are mapped to a set of channel indices in the same way. Each node i has its own channel labeling function then it can assign each frequency channel in Ξ_i, a channel index chosen from its channel label set $\mathbb{N}_{N_i} = \{0, 1, 2, 3, \ldots, N_i - 1\}$. The elements of the label set are called $\mathbb{N}_{N_i}$ channel indices.

Each given channel $c \in \Xi_i$ has a maximum capacity of BW_c. Moreover, each channel displays different physical characteristics depending on various factors, such as interference, signal-to-noise (SNR) and the bit error rate (BER), that are involved when transmitting data. Furthermore, these characteristics affect the performance of the channel. In VANETs, the characteristics of each channel may change significantly over a period of time [5] as a result of node mobility. Hence, these factors should be noted when selecting a suitable channel that can satisfy the requirements of an application, especially one that requires end-to-end reliability.

This work adopts the popular setting in which the RSUs are fixed, whereas each OBU follows the mobility pattern of the speed of the vehicle, which is represented by a continuous state stochastic model $S(t)$. Each pair of nodes (i and $j \in \Lambda$) is kept distant from each other by $D_{ij}(t)$, in a continuous stochastic process, and the distance between the same nodes in the future instant of observation $t + 1$ can be estimated by the formula $D_{ij}(t + 1)$. We assume that there is no distinction between $D_{ij}(t)$ and $D_{ji}(t)$. Moreover, it can be assumed that the neighbor nodes periodically exchange beacon messages to inform others about their position and speed.

The network supports different kinds of applications, which means that these applications can be classified as safety driven (e.g. able to give warnings of accidents and issue emergency alerts) and non-safety driven (e.g. they depend on cooperative games and multimedia sharing). However, within each group, the applications may have different requirements, particularly in terms of bandwidth, throughput and delay. The idea is kept generic in this work by categorizing the applications into *a* fixed classes each of which has its own requirements with regard to reliability in data delivery. We assume that these classes can be defined offline, which means that on the basis of the requirements of the applications, it is possible to select the best channels for each of them.

4. Mechanism of connectivity management for resilient cognitive vehicular networks

In this section, we provide a detailed description of MOCA, the mechanism designed for channel selection. This is undertaken by a *typical OBU* (a SU - node i) by making a prediction of the channel state for $t + 1$ and attempting to meet the application requirements to achieve a high degree of reliability in data delivery.

MOCA proactively and periodically assesses the quality of the near-future channel based on *observable* parameters related to mobility, channel performance, and the relative driving direction. These three kinds of parameters are representative of VANETxvt's characteristics, i.e. mobility is related to network dynamism; channel performance depends on the features of the wireless links; and the driving direction supplements the estimates of changes in the network topology. We also consider the use of parameters related to mobility, for example *vehicular speed*, to support a mechanism where the dynamic features in the vehicular network can be used as input; driving direction parameters, such as *distance* and *vehicular speed*, assist in estimating the new distance between two nodes. There are also parameters related to channel performance, for instance *SNR* and *BER*. These provide information to the cognitive radio and enable it to determine the quality of the channel and

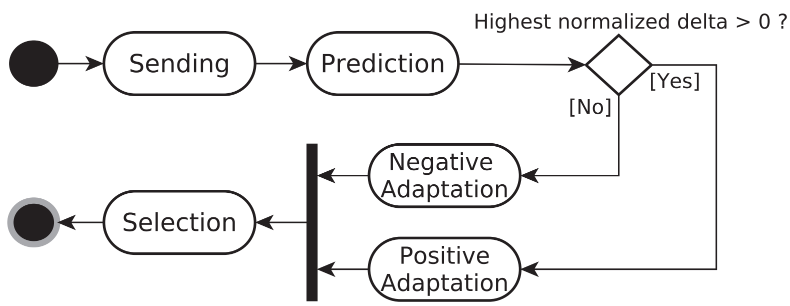

Fig. 1. Steps for channel selection in MOCA.

make decisions about whether to tune in to another channel, if the quality of the channel is not sufficient to support a certain class of application. Due to the dynamic nature of VANETs, the parameters may have a different degree of importance over time. Hence, MOCA dynamically adapts the weights of each parameter periodically. In practice, this is made possible through the flexibility provided by CR technology.

As shown in Fig. 1, MOCA follows five key stages : (a) sending spectrum information, (b) prediction, (c) classification, (d) adaptation (positive and negative), and (e) selection. The network observations and channel sensing are carried out just before the beginning of each cycle. Hence, before each employed parameter is selected, the question is raised about whether it is viable to collect its value at the beginning of each cycle without delaying the whole process. The time period between an observation made at t and the next observation made at $t+1$, is a Δ. Hence, all the MOCA stages must be completed when the window of duration is equal to Δ. In the following subsections, we discuss the details of each step and how the collected values of the parameters are employed. First of all, MOCA receives information about the spectrum characteristics. On the basis of these, it is possible to predict the levels of channel quality and compare them. After that, an adaptation procedure is triggered and the best channel is defined.

4.1. Spectrum sensing

All the N_i channels are sensed during the $T_{sense} \ll \Delta$ to obtain a full awareness of spectrum usage and the existence of primary users in a geographical area. The aim is to ensure that the channel sensing is as passive as possible, and thus prevent it from causing interference or collisions between the nodes. There are different types of spectrum sensing methods such as geolocation and database, the use of beacons, and local spectrum sensing for cognitive radios. A survey of spectrum sensing methods is conducted by Yucek and Arslan [27]. This work adopts the multidimensional spectrum sensing approach, similar to [15]. Although spectrum sensing is generally understood as measuring the spectral content of a signal or measuring the radio frequency energy [27], the multidimensional spectrum sensing approach obtains different features in multiple dimensions. This is achieved by collecting signals that can provide information regarding modulation, waveform, bandwidth, carrier frequency, and other factors. In this study, we believe that there are no sensing errors and plan to address this question in a future work.

The parameters related to mobility, channel performance and relative driving direction are also observed in this stage and their values are collected. With regard to mobility, MOCA makes use of information about the position and speed obtained from the vehicle. On the question of the channel performance, each node receiver measures the SNR and BER. In the case of the relative driving direction, MOCA makes use of information regarding the relationship between speed and distance of travel between two nodes. The SNR parameter compares the level of a desired signal with the amount of background noise, i.e. signals in a communication channel that are unrelated to the information being transmitted and can reduce the throughput of the channel. The signal-to-noise ratio, bandwidth, and channel capacity of a communication channel are connected by the Shannon–Hartley theorem [28]. The basic method employed for measuring SNR entails comparing the received signal and noise levels for a known signal level [29]. The BER parameter is calculated by comparing the transmitted sequence of bits with the received bits and counting the number of errors [30,31]. BER can be defined as the ratio of the number of bits received in error to the number of total bits received. This measured ratio is affected by many factors including: signal-to-noise, distortion, and jitter [30].

4.2. Prediction

In VANETs, the prediction of channel quality helps in selecting the channel. This procedure shows which channels have enough resources to meet the application requirements in a future instant $t+1$ and at the same time, issues a warning about the quality of the channel at the current instant t. The prediction anticipates possible problems regarding connectivity and allows changes to be made in the channel with best quality. The prediction aims to forecast future situations on the basis of current or historical information, i.e. from $(t-1)$ [32]. Owing to the uncertainty of the VANETs, connectivity may be unavailable when the channel quality is degraded. MOCA avoids this issue by using the prediction of channel quality estimated based on previously sensed information.

The prediction requires consistent information to ensure that it is efficient. Hence, MOCA uses **local node information** related to mobility, channel performance, and relative driving direction to calculate the quality of the channel. MOCA avoids using the channel when it tends to be of a low quality or is unable to meet the future expectations of the applications. Thus, MOCA suggests alternative channels for the near future (instant $t+1$), which can assist in meeting the requirements of the applications.

The quality of a channel c is calculated separately by each node, by means of the Eq. (1), where c means the channel being evaluated and t is the instant of the observation. $Q_c(t+1)$ indicates the prediction in the quality of the channel that is a function of normalized values $Mob(t)'$, $Ch_c(t)'$, and $Dir(t)$, respectively, the current mobility (Eq. (2)), the capacity of the channel (Eq. (7)), and relative node direction (Eq. (9)). These criteria have been chosen to assess the quality of the channel because they have a direct influence on connectivity. Their values are normalized in the interval from 0 to 1 and no attempt is made to predefine which normalization method should be employed. An example of a normalization method that can be employed is outlined by Nasser et al. [33] and Yan et al. [34]. Note that each of these components is pondered by weights α, β, and γ, (as will be explained in the next sections),

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namely, $\alpha + \beta + \gamma = 1$.

$$Q_c(t+1) = \alpha \times Mob(t)' + \beta \times Ch_c(t)' + \gamma \times Dir(t)' \quad (1)$$

To obtain $Q_c(t+1)$, MOCA first calculates the predictions of mobility ($Mob(t)$), channel performance ($Ch_c(t)$), and relative direction ($Dir(t)$) by Eqs. (2), (7), and (9), respectively. Eq. (2) predicts the mobility of the nodes at the observed instant t. $Mob(t)$ has as input the value of the present average distance between a node i and its neighbors j, $\overline{D_{ij}(t)}$ and the future expected average distance $\overline{D_{ij}(t+1)}$ between i and its neighbors j. In this way, $Mob(t)$ uses the ratio between $\overline{D_{ij}(t)}$ and $\overline{D_{ij}(t+1)}$.

Initially, the distance $D_{ij}(t)$ is calculated by Eq. (3) between a node i and each neighbor j individually. Then the average of these distances is calculated. Although the general idea involves following a radio propagation model as an aid in calculating the distance between two antennas, MOCA employs the Friis equation [35] to estimate $D_{ij}(t)$, since it is one of the fundamental equations in antenna theory. With regard to the Friis equation, it should be noted that owing to the dynamic characteristics of VANETs, this must be modified since the antenna polarization may not match. This modification involves multiplying the basic Friis equation by a Polarization Loss Factor (PLF). The distance $D_{ij}(t)$ is calculated by a derivation of the modified equation.

$$Mob(t) = \overline{D_{ij}(t)} / \overline{D_{ij}(t+1)} \quad (2)$$

$$D_{ij}(t) = Friis(t) \quad (3)$$

The calculation of $D_{ij}(t+1)$, Eq. (4) is based on the equation for rectilinear motion with uniform acceleration [36]. It considers as input the average speed $\overline{S_i(t)}$ and acceleration $A_i(t)$ of the node i. By means of Eq. (5), the average speed $\overline{S_i(t)}$ is calculated by measuring the average between the current speed $S_i(t)$ and speed experienced in the previous moment $S_i(t-1)$. Owing to the highly dynamic nature of VANET topologies, longstanding historical information about the speed and acceleration of nodes is not necessary.

$$D_{ij}(t+1) = \overline{S_i(t)} + 1/2 \times A_i(t) \times t^2 \quad (4)$$

$$\overline{S_i(t)} = (S_i(t) + S_i(t-1))/2 \quad (5)$$

$$S_i(t-1) = S_i(t) \quad (6)$$

$$Ch_c(t) = BW_c \times log_2(1 + SNR(t+1)) \quad (7)$$

$$SNR(t+1) = Friss(\overline{D_{ij}(t)}) \quad (8)$$

$$Dir(t) = \psi \times S(t)' + \phi \times \overline{D_{ij}(t)}' \quad (9)$$

Eq. (7) predicts the channel quality and is based on Shannon's equation. It employs as input the results of Eq. (8), which indicates the prediction of the future $t+1$ channel capacity. Eq. (8) is calculated by a variation of the Friis equation. The BW_c variable is the maximum capacity of the channel. Moreover, Eq. (9) makes an accurate prediction by employing metrics such as current speed and the current distance between the vehicles (Eq. (3)). The value of $S(t)$ is obtained from information about the GPS location and thus $S(t)'$ is its normalized value. In the same way, $\overline{D_{ij}(t)}'$ is the normalized value of $\overline{D_{ij}(t)}$ in the range between 0 and 1. The weights ψ and ϕ in Eq. (9) control, respectively, the influence of speed and distance during time. This means that these weights can be adjusted to aid drivers to maintain reliable connectivity with other nodes, and give greater emphasis to vehicle control.

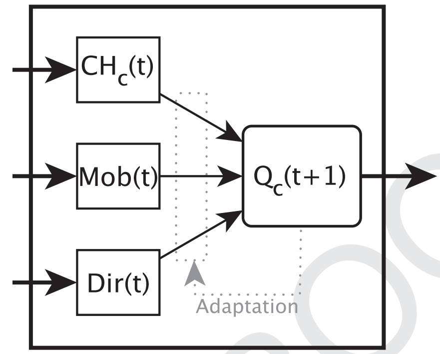

Fig. 2. Adaptation of parameters.

4.3. Adaptation

Owing to the dynamic nature of VANETs, the parameters related to mobility, channel performance and relative driving direction can have different levels of importance over a period of time. Fig. 2 shows that the adaptation feature uses the values of these parameters as input for the prediction of the quality of the channel $Q_c(t+1)$. Thus, MOCA controls the weights of these parameters to predict the channel quality at each moment.

It is assumed that each parameter has a significance level α, β, and γ as expressed in Eq. (1). Initially, all the criteria have the same importance value, which is approximately 33%. However later, this degree of significance can change because of the network conditions calculated by Eqs. (2), (7), and (9). Thus, this equation analyzes how far the predictions of current and previous states can be attained when a possible dynamic performance is expected by the channel.

At the moment, it is necessary to know the most influential parameters. This can make it possible to calculate δs for each of the parameters related to the following: mobility, channel performance and relative driving direction. The driving-force behind this is the approach adopted in neural networks [37]. These δs are the result of the difference between the current state (at t) and the previous state (at $t-1$). Hence there is a need to keep a historical record of the states, and not just the immediately preceding one. After this, these δs are normalized between [0, 1]. During the normalization, each δs is divided by the sum of all the δs which means that the highest normalized value indicates what is currently the most influential parameter.

The node evaluates the δs values and, on this basis, it is able to decide whether or not to update the weight parameters. If the highest normalized δs is positive, the weight of the most influential parameter is increased by the difference between the normalized value of the highest δ and the second highest parameter. However, if this δs is negative, it reduces the weight of the most influential parameter by the difference between the normalized value of the highest δ and the second highest parameter. The other parameters have a uniform weight redistribution of 1 minus the sum of the weights employed in the two most influential parameters. Q4

4.4. Selection

Since the i node knows the available channels, MOCA ranks them in relation to their $Q_c(t+1)$. The highest is the $Q_c(t+1)$ value, and the best is the channel quality. Once the channels have been arranged in descending order, MOCA maps the best channel for the application class data request transmission. Once a channel has been selected, the node continually assesses the quality of the channel and predicts its status in the near future.

5. Evaluation

This section conducts a performance evaluation of MOCA through simulations in NS-2.31. The results from MOCA were compared with the results from TFRC-CR [8]. Before comparing the results, the implementation of the TFRC-CR protocol was validated under the same conditions employed by the authors in [8]. TFRC-CR is a representative spectrum management proposal that aims to provide end-to-end communication. It was selected so that its performance could be compared with that of MOCA, because they share some of the most significant features addressed in this work, such as its ability to adapt to the use of the spectrum, which could not be found in related works. In addition, there are related works that address the question of reliability and even resilience; however, these only concern certain kinds of applications, and this is not one of the objectives of MOCA.

The evaluation scenarios varied and the parameters **number of nodes** in the network ranged between 100, 300, and 500. This variation in the number of nodes is evidence of the network density, which is a significant feature of vehicular ad hoc networks since it can characterize the environment in which the network is embedded - such as high density for urban areas and low density for non-urban areas. The nodes follow the pattern in the Manhattan Grid mobility model [38], including the source and destination of each connection, within an area of 1000 m $\times$ 1000 m. The Manhattan Grid mobility model was employed to simulate realistic VANET scenarios [39,40]. The scenario comprises interconnecting streets and avenues designated as 10m $\times$ 10m.

Each node is equipped with a radio interface and has an omni-directional antenna with a transmission range of 250 m. The speed of the nodes can vary between 2 and 12 m/s with a probability of velocity change of 20%, and probable pause in movement of 50%. With regard to PUs, their activities follow a Poisson distribution of 50% (whether active or inactive). The coverage range of the PUs is 300 m. The SUs are not allowed to operate in the coverage range of an active PU.

A number of 100 simulations was carried out, with a duration of 600 s each, in order to demonstrate the benefits of MOCA. The results showed a confidence interval of 95%. MOCA was evaluated by metrics related to data delivery reliability, connectivity, and energy costs. The metrics for data delivery are the **Packet Delivery Ratio (PDR)** and **jitter**. PDR is calculated as the average number of packets received at the destination node times the total number of packets sent from the source node. Jitter is the variation of delay in delivering packets end-to-end. Connectivity related metrics are **connectivity duration** and the **number of channel changes**. Connectivity duration is the total amount of time when the node is connected, whereas the number of channel changes represents how many times the node needed to select and use a new channel. **Energy costs** represent the percentage of consumed energy, and is calculated by the ratio between the average of the final amount of energy consumed in the nodes at the end of the simulation period and the average of the initial energy in the nodes at the beginning of the simulation. Although VANETs do not have energy constraints, energy costs are an important indicator of the overhead resulting from MOCA and how much of the vehicle resource is used, and gives an idea of the trade-off between the number of observable parameters used and the consumption of node resources. Table 1 summarizes the simulation parameters.

Table 1
Simulation parameters.

Parameters	Value
Area	1000 x 1000 m
Grid of streets and avenues	10, 10
Number of vehicles	100, 300, 500
Area of the vehicle transmission	250 m
Number of transmitters in the vehicle	1
Velocity	2, 12 m/s
Probability of velocity change	0.2
Stopping probability	0.5
Maximum probability to be stopped	0.5
Numbers of PUs	11
Sensing and transmission time	0.5 s
Prediction time of MOCA	1 s
PUs activity (Poisson distribution)	0.5

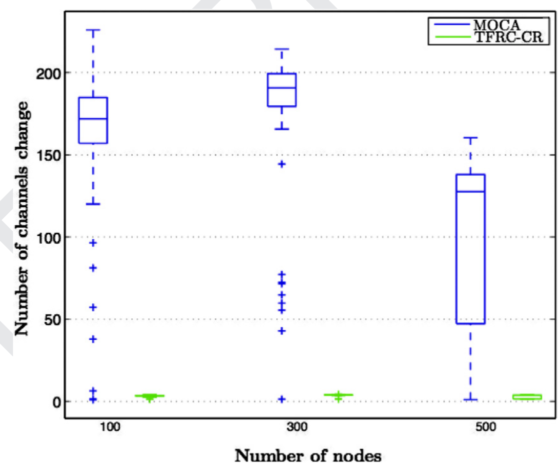

Fig. 3. Number of channel changes.

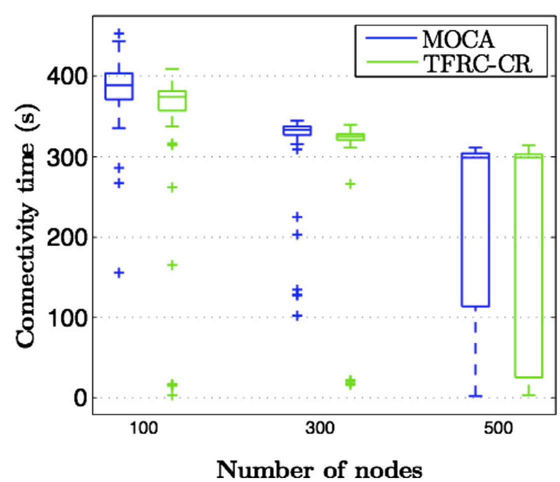

Fig. 4. Connectivity time.

5.1. Results

Fig. 3 shows the effects of increasing the number of nodes in the network (as represented by the network density) for the number of channel changes carried out. It should be noted that MOCA has a number of channel changes, on average, 60 times more than TFRC-CR. This large number of changes occurs because MOCA evaluates the current conditions of the channels, while also attempting to predict their conditions for the next cycle of the mechanism. Furthermore, by observing the increase in the network density, it is also possible to confirm a higher statistical dispersion in the number of changes of the selected channel. In parallel with the number of changes in the selected channel, there was an analysis of the connectivity time (or connectivity duration). The higher the network density, the greater the competition for channel use resulting from an increase in statistical dispersion for the duration of the connectivity , (as shown in Fig. 4). In all the cases, MOCA

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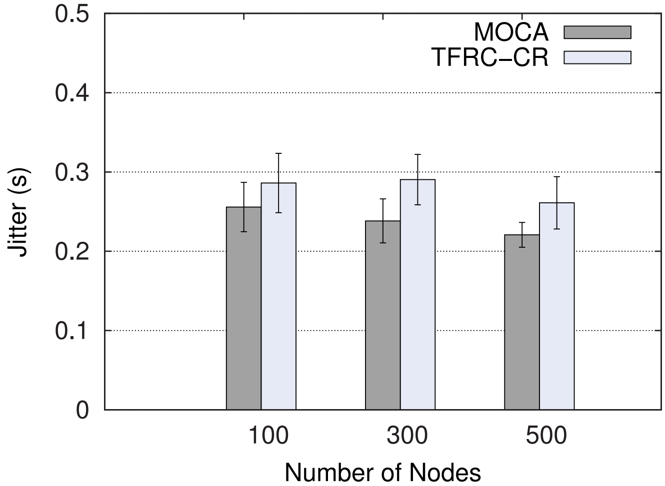

Fig. 5. Jitter (s).

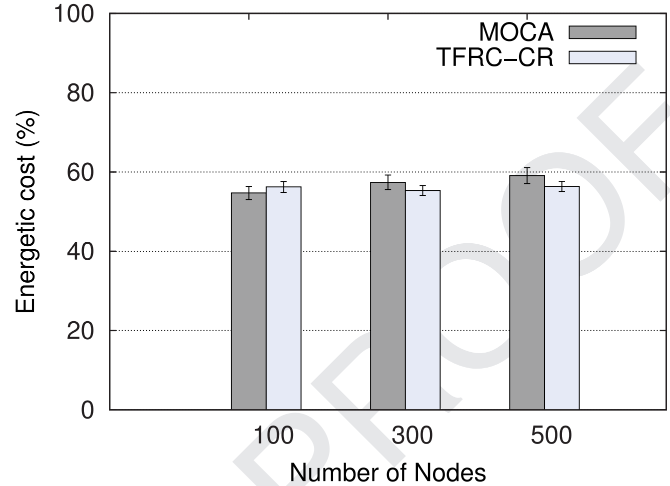

Fig. 7. Computational cost in terms of energy consumption.

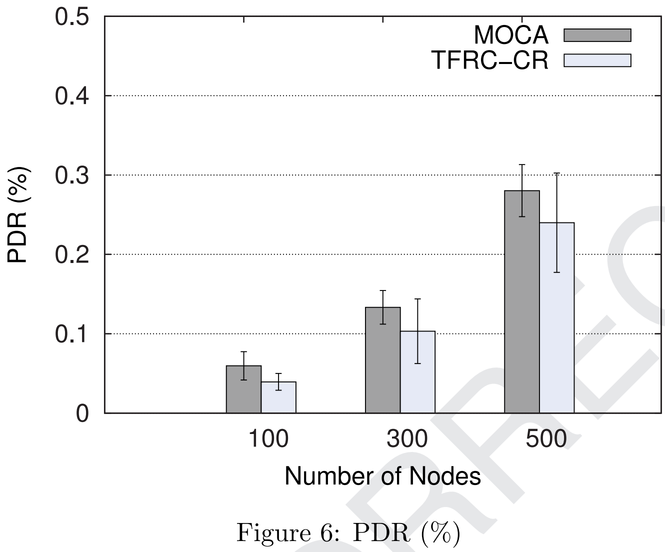

Fig. 6. PDR (%).

resulted in a longer connectivity. This factor also benefits PDR and jitter, since they tend to have better results when MOCA is employed.

For a better analysis of these two metrics, a discussion has been included which compares them with the results for PDR and jitter. Fig. 5 shows jitter in terms of a variation in network density (number of nodes). In the scenario with 300 nodes, MOCA shows jitter as 12% lower than when jitter is produced by TFRC-CR. Denser scenarios involve a high competition for channel usage. This means that these scenarios may have greater signal noise, adding uncertainty about channel conditions. MOCA reduced the time needed to change the channel because of the selections and predictions procedures. TFRC-CR shows a high standard deviation value, because the channel selection is carried out in a random manner.

Fig. 6 shows the results obtained from correlating PDR and network density (represented by the number of nodes). In the scenario with 300 nodes, MOCA achieves a 12% higher PDR than TFRC-CR. By increasing the network density, MOCA showed that the channel selection avoids a degradation of channel quality and reduces competition between those who use them.

Fig. 7 shows the analysis of energy costs. MOCA reduced in 3%, on in average, energy costs when it was employed. This is a result of the lower number of channel changes needed to give priority to the channel with better quality and the number of parameters considered in the mechanism. The larger the number of nodes, the greater is the competition for using the channels. As a result, the channel quality varies as the uncertain conditions of the network during the channel selection procedure. Thus, MOCA increases the amount of channel switching required to establish which channels have a higher quality and are able to improve resilience in connectivity. However, despite using a larger number of parameters than TFRC-CR, the energy costs for both mechanisms are very similar. The reason for this is that the nodes in MOCA employ local values for the parameters, that they would normally have already to evaluate the channel quality. Moreover, this requires 'extra work' in contrast with TFRC-CR which only involves the calculation of the quality of the channel and the new values for the weights.

6. Conclusion

This article has examined MOCA, a mechanism for cOnnectivity management in cognitive vehiculAr networks. MOCA manages the connectivity between pairs of nodes in vehicular networks, and is able to benefit from the flexibility provided by cognitive radio technology to make an improvement in the reliability of data delivery. Moreover, MOCA makes use of information from vehicles, such as speed and driving direction, as well as that obtained from application requirements to manage connectivity. The mechanism was compared with a representative approach from the literature carried out in urban scenarios. The evaluation results demonstrated that MOCA can significantly enhance connectivity in vehicular cognitive networks and outperformed the other approach in terms of throughput and jitter. In future work, our intention is to examine an advanced approach to correlate the channels and the QoS and QoE requirements from the application and the influence of other parameters in predicting the behavior of channels. In addition, an attempt will be made to employ an advanced radio propagation model, including a model for urban areas.

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