# Data fusion for a forecasting link state indicator in VANETs

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***Abstract*—Due to their lack of assessment mechanisms of link quality in VANET environments, routing protocols do not deal efficiently with highly volatile links. One way to fill this gap would be to anticipate links breakages with new route computation. Currently available link quality indicators are not sufficiently responsive to consider forecasting. In this paper we present a novel predictive link quality indicator that is based on the OFDM decoding steps into the PHY layer. The events generated by these steps are threated by a data fusion algorithm. The resulting link quality indicator presents interesting forecasting characteristics and is suitable for a cross-layer usage in routing protocols.**

## I. Introduction

Due to their mobility and topology changes, Vehicular Ad-hoc NETworks (VANETs) experience frequent link breakages. Many researches dedicated to VANETs focus on the subject of discovering and maintaining a reliable path. Particularly, routing protocols mechanisms are widely studied and many propositions are made to face up link breakage due to channel volatility [1]. Each one tries to adapt itself to handle with.

As the propagation channel cannot be controlled, there is no solution to avoid or eliminate link disruption in communication between vehicles. Abboud et al. [2] proposed an analysis of the communication link lifetime that shows how determinant it is on the network performance. Many recent works propose to anticipate the failures before they happen in order to adapt their process [3] [4] [5] [6]. For example, Cherif el al. [6] proposed a routing protocol that can switch from the currently used route to a new one depending on a Lagrange interpolation of the Signal to Noise Ratio (SNR) and MAC overhead. Results show performance improvements but simulations are conducted under the two ray ground propagation model, which is only accurate in a free of obstacles environment. To detect forthcoming link breakage, previous cited works follow a common way: they compute a link state indicator that is able to inform upper layers about link degradation. Link state is computed by taking into account different events at different levels of the networking stack. As we will see it in the next section, the indicators can be classified in three categories.

In this paper, we propose a new computing method of a link state indicator that allows to forecast link disruption. In [7], Gabteni et al. present a method to compute relevant metrics from the PHY layer that we used in this work. This indicator is computed at the receiver side and uses both received and unreceived (from the Media Access Control layer point of view) packets regardless to the type of the packet. The indicator we propose relies on OFDM (Orthogonal Frequency Division Multiplexing) decoding events and uses a Dempster-Shafer data fusion mechanism to make breakage prediction. To the best of our knowledge this work is a novel contribution that mix physical layer decoding events and data fusion together to provide a link state indicator for link state forecasting.

This paper is organized as follow. Section II presents the related work to predictive link state indicators. Section III details our contribution: a forecasting link state indicator based on internal OFDM wifi decoding events and using Dempster-Shafer data fusion. Section IV presents the simulation environment and states of the impact of the propagation model on the results. Section V concludes the paper.

## II. Related works

The computation of a wireless link quality indicator takes usually place at the Media Access Control (MAC) layer, because it is the lowest layer networkers have access to. This is also the last place a packet is seen as a suite of bytes without modulation, coding and other transmission related process.

As the goal of a link is to carry packets, it is obvious to compute a link quality metric at the MAC layer by considering the packet delivery ratio (PDR) over this link. So the basic idea to produce a link-quality metric is to observe the packet reception during a certain period of time, and to produce from this observation an expected packet delivery ratio (ePDR) that gives an idea on what could be the PDR in the future (i.e. the next packet(s) emission). In fact, in wireless communication, due to the volatility of the wireless channel, the simple observation of the PDR is not enough for qualifying the link quality [4] [5]. Therefore, the determination of a link quality indicator should be reinforced by additional measurements or even replaced by other indicators that are linked to the PDR. In [4], Baccour et al. classified the link quality metrics into hardware and software based indicators. The former are related to the wireless channel and provided by the physical (PHY) layer that are the reception signal strength intensity (RSSI), the signal to noise ratio (SNR), the 802.15.4 link quality information (LQI) and the 802.11n channel state information (CSI). The latter are computed from higher level information like the expected count transmission (ETX) [5] packet reception rate based (PRR based), etc. To be adapted to the volatility of wireless links, quality metrics should be both reactive to follow link behavior, accurate to provide a representation of the link quality and stable to avoid rapid fluctuation between several states.

In this section we provide an analysis on the most often used/proposed wireless link quality estimation techniques. We arrange them into three categories relating to the information that they take into account. Additionally, for each of them we analyze the associated computing technique.

### A. Signal to Noise Ratio based estimators

The Signal to Noise Ratio (SNR) is a metric that is widely used to estimate link quality [3]. As this information results from the correct reception of a packet, this metric is only available when the packet is correctly received. This excludes all the packets that are rejected for insufficient ratio. The method used to predict link disruption is based on statistical analysis and suffers from insufficient discrimination. This means that good link state and intermediate link state overlaps and do not allow to discriminate one state from another [4]. Furthermore, SNR based estimators only consider packets received successfully at the MAC layer which lead to an overoptimistic indicator. They do not take into account dropped packets with errors at the PHY layer.

### B. Packet reception based estimators

Several estimators are based on statistical techniques that use packets reception as metric. For example, Expected Transmission Count (ETX) [5] anticipate link failure based on the combination of both forward and backward packet reception rate. Another example is Window Mean Exponential Weighted Moving Average (WMEWMA) [4] that combines recent and older packet reception rate. Other estimators are based on a qualitative approach instead of a quantitative one. An example is Short Term Link Estimator (STLE) [8] that considered links as reliable as long as three consecutive packets are received successfully. Another one is Holistic Packet Statistics (HoPS) [9] that combines short term and long term deviation with trends information. However, all of these indicators only consider packets received successfully at the MAC layer, their reactivity decreases with the link volatility [10] [11].

### C. PHY layer based estimators

Metrics used to anticipate link disruption presented on section II.A and II.B only use successfully received packets at the MAC layer and do not take into account packets that are dropped at the PHY layer. Techniques that use these metrics missed all information gathered at the PHY layer. In order to use these crucial data, new estimators have emerged based on PHY layer metrics. Three of these techniques are [7], [11], [12]. They use the packet decoding process to compute a link quality estimator. The packet is analyzed at the bit level and the dropped packet, because of decoding errors, are also taken into account in the estimation algorithm. Results of these works show a high reactivity when compared to other techniques.

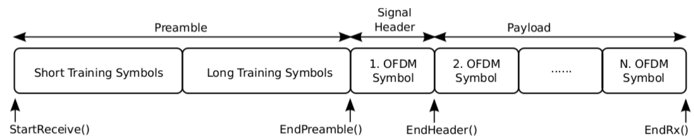


Fig. 1. OFDM decoding events.

## III. Cross-layer data fusion indicator

The contribution of this paper is the use of the OFDM events into a data fusion algorithm in order to create an accurate link quality estimator for VANETs. As showed in Fig. 1, we use the preamble decoding error event, the EndRx decoding error event and the RxPhyOk event as data sources for the data fusion technique. The first are intermediate OFDM decoding stages while the last is the OFDM packet successful decoding event. These information are gathered in a buffer for each sender-receiver link. This decoding technique gives events at the PHY layer that can be used and combined for link failure prediction. An efficient method to combine these information is the data fusion.

This section first presents in a detailed manner the OFDM events provided by the PHY layer, and specifically those used in this paper. Then, the data fusion technique principle is presented. Finally, our indicator based on the data fusion of collected OFDM events is detailed.

### A. OFDM decoding events

The IEEE 802.11p PHY layer uses the OFDM coding/decoding technique, including all the signal processing at the bit level, that can be splitted into decoding phases. As shown in figure 1, packet reception is composed of four events: StartReceive, EndPreamble, EndHeader and EndRx. The first event is the reception of the first bit of a packet. The received signal power must be greater than the energy detection threshold or else the packet will be discarded. The second condition for the success of the first decoding event is that the reception state should not be busy. When all that conditions are met, then the preamble reception starts. The second decoding event is the preamble reception process. The reception state should not be busy while the detected signal should have an SNR greater than 4 dB. If so, the EndHeader decoding event is scheduled. The third decoding event is used to know modulation, coding, length and parity check of the data. The reception state should once again not be busy. Information found in the header should be plausible or else the EndRx event will not be scheduled. During the EndRx event, the data are finally decoded by signal demodulation and error correction. This is done just before the scrambler module rearranges the bits in their original condition. During this process, the initial channel estimation is applied to all the OFDM samples. When data are decoded successfully the RxPhyOk decoding event occurs.

The energy detection threshold event is not significant for our purpose as packets without sufficient energy cannot identify their emitter. Moreover, as header is small compared to preamble and data, header events do not occur frequently contrary to preamble events. So, in this work, we focus only on preamble events instead of header ones. We will make use of the preamble decoding error event, the EndRx decoding error event and finally the RxPhyOk decoding event.

### *B. Data Fusion technique*

Previous section presented the OFDM events that may be combined together to give an estimation of the link quality. The information combination is a challenging task as events may provide inappropriate data. To overcome this challenge, data fusion techniques may be used. This section describes these techniques from the Dempster-Shafer Theory basics [13] [14] to our link state indicator in details.

Data fusion techniques does not depend on a particular application and may be used with respect to the theory regardless of the input data's [15] [16] including VANET simulations [17]. It requires 3 main steps which are modeling and estimation of the imperfections, combination of the heterogeneous information and application of an algorithm to take a decision. This approach helps to determine the best information regarding its redundancy and to provide then a reliable link estimator.

The first step of the theory of belief functions [13] [14] models the belief level, called frame of discernment and formalized on a finite set $\mathrm{d}$ that one has in a defined event. This belief is defined through functions, named mass functions $\mathrm{m}$ that are defined in [0; 1] and which verify that the sum of all mass functions is 1. To develop a complete system, a refinement of the belief mass modeling and estimation has to be done. Indeed, to determine mass functions the frame of discernment (1) and the referential subset (2) must be defined first.

$$\Theta = \{d_1, d_2, \dots, d_n\} \tag{1}$$

$$2^{\Theta} = \{\varnothing, \{d_1\}, \{d_2\}, \{d_1, d_2\}, \{d_1, d_3\}, \{d_2, d_3\}, \{d_1, d_2, d_3\}, \dots, \Theta\} \tag{2}$$

Then, mass functions are written with equation 3:

$$m \,:\, 2^{\Theta} \to [0,1]\,, \sum_{A \subseteq 2^{\Theta}} m(A) = 1 \tag{3}$$

In the theory of belief function, the degree of belief supporting a proposition and not committed to any subset of the chosen proposition is taken into account. The combination operator is the second step and the core of the data fusion because information are gathered and regrouped at this step. The operator must be chosen wisely as it has a direct impact on the fusion results. The most straightforward combination operator and the one we used in this work is the conjunctive one which is associative and commutative for independent metrics (4).

$$m(A) = \sum_{A_1 \cap A_2 \cap \dots A_m = A} \prod_{j=1}^{p} m_j(A_j) \tag{4}$$

The Dempster operator is based on intersection, that is why discordant sources are interpreted as conflict $\mathrm{m}_{\cap}^{\Theta}(\varnothing)$. Indeed, Shafer normalized the combination of masses and defined the Demster operator $\oplus$ which is an orthogonal sum operator (5).

$$\begin{cases} m_{1\dots p}^{\oplus}(A) = k \bullet m_{1\dots p}^{\cap}(A) \\ m_{1\dots p}^{\oplus}(\varnothing) = 0 \end{cases} \tag{5}$$

where k :

$$k = \frac{1}{1 - m_{1\dots p}^{\cap}(\varnothing)}$$

An important element of the data fusion process is the conflict management that can be done using four types of solutions, namely: redistribution, discounting, combination operators, or source of information. In this work we used the redistribution method that equally normalize the conflict on masses whatever the conflict level. The final step in the data fusion process is the decision. It consists in the selection of the most relevant solution depending of the combination results. The decision criterion selected in this work is a simple heuristic decision based on comparison between masses. If $\mathrm{m(A)} > \mathrm{m(B)}$ then $\mathrm{m(A)}$ is selected. If $\mathrm{m(B)} > \mathrm{m(A)}$ then $\mathrm{m(B)}$ is selected.

### *C. Predicting communication losses using data fusion*

In the proposed link failure prediction process, we make use of a data fusion technique based on the belief functions theory (Algorithm 1). We choosed to describe our system and confidence with mass functions. A criterion $\mathrm{d_{ij}}$ is required to be able to match pairs of objects in a defined frame, i.e. $\mathrm{X_i}$ (preamble error) and $\mathrm{Y_j}$ (reception error). The criterion should be defined for all objects sets and the corresponding mass functions, i.e. $\mathrm{m_{ij}}$. Low values of the criterion go along with the association between $\mathrm{X_i}$ and $\mathrm{Y_j}$ named $\mathrm{m_{ij}(n)}$ (the probability of not losing communication), whereas high values go along with its contrary $\mathrm{m_{ij}(z)}$ (the probability of losing communication). The remaining ignorance is $\mathrm{m_{ij}}(\Theta)$. Thus, mass functions are defined by equation 6 :

$$\begin{cases} \mathrm{m_{ij}(n)} = \alpha_{\mathrm{ij}} = \alpha \exp^{-\gamma \mathrm{d} \beta_{\mathrm{ij}}} \\ \mathrm{m_{ij}(z)} = \beta_{\mathrm{ij}} = \alpha(1 - \exp^{-\gamma \mathrm{d} \beta_{\mathrm{ij}}}) \\ \mathrm{m_{ij}}(\Theta) = \gamma_{\mathrm{ij}} = 1 - \alpha_{\mathrm{ij}} - \beta_{\mathrm{ij}} \end{cases} \tag{6}$$

where $0 < \alpha < 1$ is the confidence degree in the association. According to Denoeux [15], $\gamma \epsilon \mathrm{R}^*$ and $\beta \epsilon \mathrm{N}^*$ can be fixed to a low value. The mass modeling and estimation, that represent the confidence of the system, have been defined for both preamble and EndRx decoding error events with a maximum fixed to seven. This maximum corresponds to seven consecutive errors at the PHY layer that characterize a packet loss at the MAC layer (due to the seven retransmissions restriction of MAC layer). Figure 2 shows the mass functions of respectively preamble and reception errors. As an increase of the number of errors events is a sign of a probable link failure, the mass functions have been tuned with the hypothesis of maximum probability of disconnection in this case. Indeed, in this work $\mathrm{d_{ij}} = 7$ while $\gamma = 1$. Moreover $\alpha = 0,9$ and $\beta = -0,7$ for the preamble mass function, and $\alpha = 0,9$ and $\beta = -0,35$ for the reception mass function. The fluctuation between error events and RxPhyOk events was computed as the ignorance and it has been fixed to 10% at minimum. The more the fluctuation increases, the more the ignorance increases. The operator chosen for the fusion is the conjunctive one, and the conflict management is done by redistribution. Finally, the decision of the fusion algorithm has been chosen this way : when $\mathrm{m_{ij}(z)} > \mathrm{m_{ij}(n)}$ then $\mathrm{m_{ij}(z)}$ is selected,

**Data**: OFDM reception events.
**Result**: Link state indicator.
**if** *Preamble decoding error event, or reception decoding error event or reception event* **then**
  compute $\mathrm{m_{ij}}(\mathrm{n})$;
  compute $\mathrm{m_{ij}}(\mathrm{z})$;
  compute $\mathrm{m_{ij}}(\Theta)$;
  **if** $\mathrm{m_{ij}}(\mathrm{z}) > m_{ij}(n)$ **then**
    Link failure state;
  **else**
    Link connected state;
  **end**
**end**

**Algorithm 1:** Link state indicator simplified algorithm.

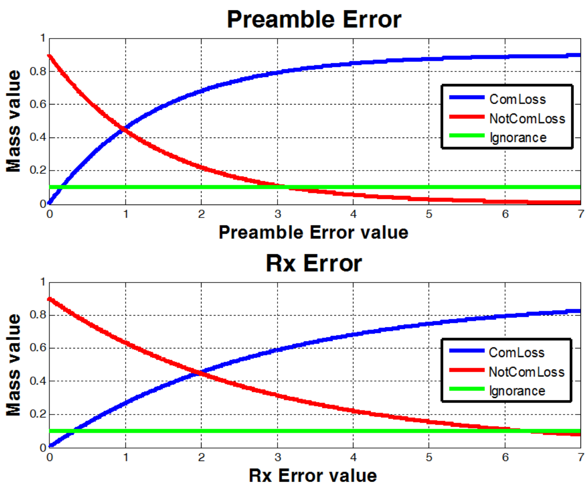


Fig. 2. Mass functions.

whereas when $\mathrm{m_{ij}}(\mathrm{n}) > \mathrm{m_{ij}}(\mathrm{z})$ then $\mathrm{m_{ij}}(\mathrm{n})$ is selected. To clarify, a link error is detected only when the probability of losing communication becomes stronger than the probability of not losing communication. In the rest of this paper the mass function $\mathrm{m_{ij}}(\mathrm{z})$ will be noted $\mathrm{m}(\mathrm{ComLoss})$ and $\mathrm{m_{ij}}(\mathrm{n})$ will be noted $\mathrm{m}(\mathrm{NotComLoss})$.

## IV. Simulation

In this section, the simulation environment is depicted and the importance of the propagation model is highlighted. Then, our results are presented and analyzed to show the effectiveness and accuracy of the data fusion based indicator.

### *A. Simulation environment*

The impact of the channel modeling is a crucial issue in VANETs and many research highlight the need of realistic channel modeling [1] [18] [24]. The probability of successful packet reception is impacted by the radio propagation environment, link failure and interference from other transmissions. Many previous works already show how wave propagation affects the link quality [19] [25] [26] [27].

Most research relies on simulations to prove the strength of their proposal. However, sometimes, they do not take into account any environment into the propagation channel model which can produce biased and rather optimistic results. In order to be realistic, a propagation model needs to consider path loss, fading and shadowing effects. For this reason, in this paper the SUMO generator [20] is used to create realistic VANET mobility while PhySimWifi [21] is used in combination with the NS-3 simulator [22] to model realistic network communications. The propagation model used in this paper is a Line-of-Sight Obstruction model from [23] that we implemented into the PhySimWifi model. It is a statistical model that represents the high fluctuation of the channel in urban VANETs scenarios and it has two advantages: it is easy to implement and it gives realistic results. Thus, while permitting a complete 802.11p OFDM implementation, the use of these software combined together helps to simulate VANETs in a realistic manner.

TABLE I
Simulation parameters

| Paramter | Value |
|---|---|
| Network simulator | NS-3 |
| Simulated time | 80 seconds |
| Number of nodes | 2 |
| Simulation area | 2500m*2500m |
| MAC layer | 802.11p |
| Propagation model | PhySimWifi |
| Bit rate | 6 Mb/s |
| Tx power | 20 dBm |
| Mobility simulator | SUMO |
| Speed | Up to 15m/s |

Our main objective is to show the effectiveness of the fusion data technique. The decoding process is the same for every packets, so simulations were run in a simple 2 nodes environment because we do not want to take into account interferences due to collision with other packets at first. We know that the more the number of packets, the more collision will happened causing a reduction of the delivery ratio, but decoding process and data fusion based on it remains unchanged.

Simulations represent the situation that may occur during VANET scenarios. We focus on two particular situations to prove the robustness of our data fusion indicator: a situation of intersection where link failures happen, and a situation of following vehicles with or without link failures. In the intersection situations, the speed of vehicles is constant and several speeds were tested from 3m/s to 15m/s. In the following vehicles situations, the speed of vehicles is variable and so is the distance between vehicles (from 60m to 210m). All intersection situations give a link failure while only half of the following situations give one (this depends on the distance and the statistical channel model). Table I summarizes parameters.

### *B. Simulation results*

Each set of results is presented within 2 graphs: one to show decoding errors and the other to show data fusion indicator. Each one depends on time. There are 3 indications that help to read graphs: 2 crossed lines that respectively represent the first packet lost at the physical layer and then at the network layer, and a continuous line that represents

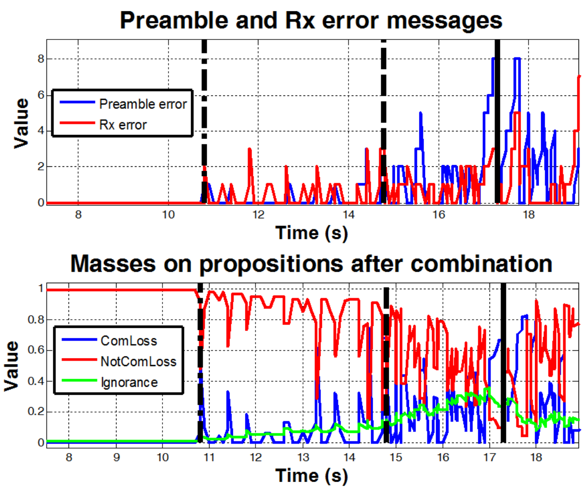


Fig. 3. Intersection situation result.

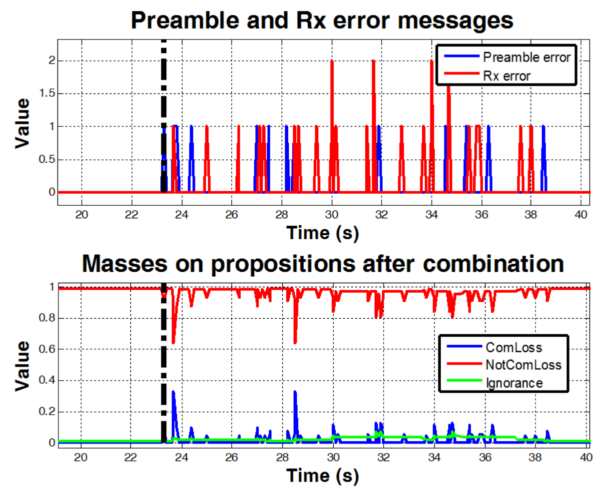


Fig. 4. Following vehicle without failures result.

TABLE II
AVERAGE PREDICTION TIME

| Speed of vehicles (m/s) | Detection time (seconds) |
|---|---|
| 3 | 8.6 |
| 5 | 5.53 |
| 9 | 4.15 |
| 13 | 2.29 |
| 15 | 1.31 |

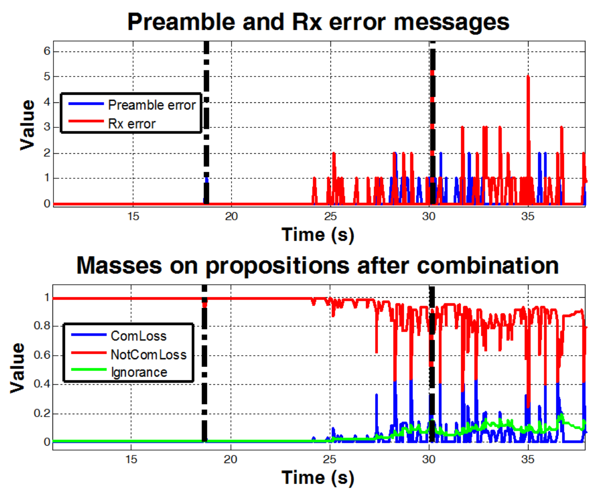


Fig. 5. Following vehicle with failures result.

the total disconnection state (no packets can be received). The indicator works properly when it is able to detect link failure after the first crossed line and before the second one. Figure 3 depicts results of the data fusion indicator in the case of a typical intersection situation. On the upper graph, from 0s to 10.8s there are no decoding errors. This shows the communication is not perturbed during the first 10.8 seconds and all packets send are fully received. Then the first loss at the physical layer occurs and errors start to increase until the communication is broken. At 13.3s, on can see on the lower graph that the mass communication loss probability (ComLoss) of the indicator become greater than the mass not communication loss probability (NotCommLoss), the decision criteria is reached. Finally, 1s later at 14.8s, the first packet is lost at the network layer : the link between nodes is broken. In this scenario, our indicator had correctly detected the link failure before it happened. We tested 50 cases of intersection situations and the indicator worked properly in all of them. Moreover the detection time is influenced by the speed of vehicles. The higher the speed of vehicles is, the lower the prediction time is. When vehicles move at high speed, the channel is more versatile and link failures may appear suddenly which explain why the prediction time is very dependent of the speed of vehicles. Table II depicts the average prediction time of the indicator.

As a conclusion from these results, one can say that the indicator is able to predict link failures in an urban context a few seconds before they really happened at high speed and up to ten seconds at low speed. To check the robustness of the indicator we test it in another situation: following vehicles. Figure 4 depicts results of the data fusion indicator in a typical case of following vehicles without link failures. As one can see on the upper graph, during the entire communication the link between nodes only encounter a few losses at the physical layer without any repercussion on the network layer (there are no more than 7 consecutives errors). The fusion indicator combines all decoding errors information but it never found a probability of link failure greater than the probability of communication which is fine. Thus, when there are no or few channel perturbations, the link indicator also works properly. Figure 5 depicts results of the data fusion indicator in the case of following vehicles with link failures. At 28s, the mass communication loss probability (ComLoss) of the indicator become greater than the mass not communication loss probability (NotCommLoss), and so the decision criterion is reached. 2s later, at 30s, the first data packet is lost at the network layer. The indicator is, once again, able to detect a link failure that is going to happen between nodes a few second before it actually occurs. Yet, this indicator based on decoding errors

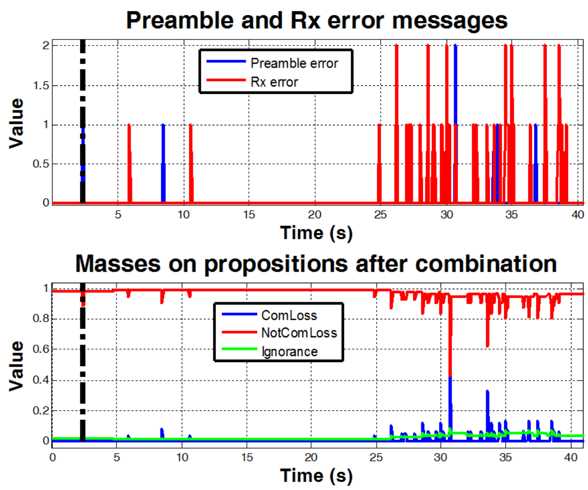


Fig. 6. Following vehicle with false positive result.

has a limit which is false positives predictions that occurs when there are high perturbations of the propagation channel without packet loss at the NET layer thanks to the MAC layer. Figure 6 illustrates this. On this particular scenario, there are no packet loss at the network layer because of the MAC layer retransmissions but there is a high perturbation of the propagation channel. These perturbations influence the fusion algorithm and the decision criteria is reach at 30.5s. The prediction of link failure is wrong in this situation. However, this false positive is very suitable to give information about the perturbation that occurs at the physical layer. This may be a vital information for routing protocols in order to choose one route over another.

Thus, in all tested situations, the link indicator detected broken links before they occurs and it may also give an alert for versatile links even if they remain connected. This makes it a pessimistic link indicator which is very suitable for routing protocols because it always give a precious information about the channel propagation even in case of false positive prediction. Any link that is detected by the fusion based indicator is encountering packet loss at the physical layer and should be avoided if possible. Finally, all of the results show that the indicator can detect all link failure before they really happened at the NET layer. The more the speed increases, the more the indicator reacts quickly. Moreover, false positive predictions indicate versatile links and confirm the robustness of the indicator.

## V. Conclusion

In this paper we have presented a cross-layer data fusion predictive indicator based on OFDM decoding process. Simulation results show that the indicator is effective, accurate and robust for the simulated situations. The next step is to integrate the indicator to a routing algorithm to improve its performances. We planned to add more information to the data fusion algorithm in order to improve the prediction delays.

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