Artificial Neural Network Classifier for Network Traffic Load in Vehicular Ad-hoc Networks

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***Abstract*—Machine learning algorithms are used in many computing systems due to their abilities to learn the conditions of a computer system without being explicitly programmed. In particular, these algorithms have a great potential to be exploited in Vehicular Ad-hoc Networks (VANETs) because these networks have very dynamic topologies and also very dynamic traffic loads. In fact, since each node or vehicle in the VANET has a process unit, we can use the existing VANET architecture to develop machine learning-based algorithms to exploit their benefits. In this work, we present the design of an Artificial Neural Network (ANN) classifier that enables VANET vehicles to determine the Communication Network Traffic Load scenario by means of evaluating three key metrics of the MAC layer protocols in VANETs, namely, the Channel Busy Ratio (CBR), the Normalized Broadcast Received (NBR), and the Normalized Times Into Back-off (NTIB). The ANN classifier will eventually be part of a Context-aware System designed for improving the dissemination of safety messages. Our ANN Classifier has been implemented and validated through simulations, whose results demonstrate that it provides an accuracy of success classification of 98% for low density scenarios and a success classification of 94% for high density scenarios.**

***Index Terms*—Artificial Neural Networks (ANN), Vehicular Ad-hoc Networks (VANETs), Machine Learning, Vehicular Simulation.**

I. Introduction

The use of machine learning algorithms on vehicular ad-hoc networks is increasing every day, with varied applications to improve the exchange of information and knowledge in both safety and non-safety scenarios. For example, in [1] the authors work on a misbehavior detection mechanism based on artificial neural networks. The goal of the approach is to detect driver misbehavior that could affect the performance of safety applications. On the other hand, in [2] the authors use machine learning algorithms to develop reliable traffic control management techniques powered with IoT (Internet of Things) technology. Another interesting research is presented in [3], where the authors propose a traffic accident detection approach based on a random forest classifier.

Many application in Vehicular Ad-hoc Networks (VANETs) need to be reliable, in particular safety applications need a good performance in terms of packets delivery and end-to-end delay; however, the network communication conditions in these scenarios are very dynamic. For this purpose, we need to determine efficiently the state of the network to use this information for different applications.

In this work, we present the design of an Artificial Neural Network (ANN) classifier that can provide support in the classification block of a Context-aware System for improved dissemination of safety messages in VANETs, which was previously developed and presented in [4]. For this purpose, we gather non-direct measurements from the MAC layer protocol at each node or vehicle in a simulated VANET environment. Then, we make use of a training model to classify different network traffic scenarios depending on the levels of communication network loads of the nodes.

II. Methods

First, in order to lay down the concepts of our approach, we simulate a realistic urban intersection of Santiago City with different levels of vehicular density and networks configurations. Nonetheless, the concepts presented in this work are not restricted to the mentioned intersection; instead, they can be applied to any urban intersection. We use the bidirectional simulator framework VEINS [5] because of its capabilities to simulate the mobility of the vehicles at intersections and the exchange of information between them, using realistic models for the signal propagation, and the MAC layer protocols to communicate among VANET nodes (i.e., the vehicles).

In Figure 1a we show the simulated scenario running under SUMO simulator which provides mobility to each vehicle following realistic patterns. In Figure 1b we show a view from the OMNeT++ network simulator. In the figure, one safety message, also known as beacon, is transmitted via broadcast and disseminated to neighboring vehicles. In the simulations we use the standard IEEE 802.11p technology for wireless communications among the network nodes. The intersection scenario is simulated with different configurations of the following network parameters:

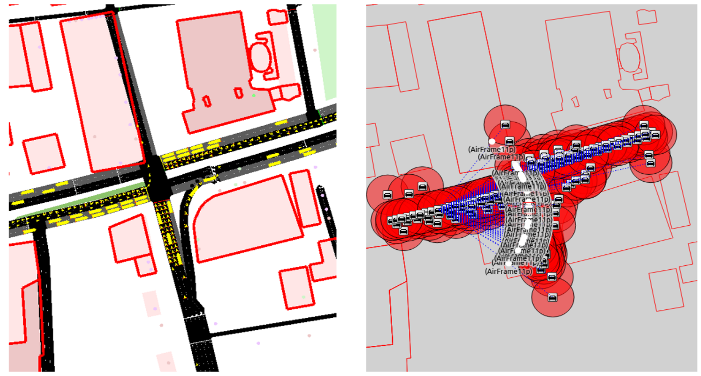
- *Beaconing frequency* varying between 2 Hz and 10 Hz. These messages carry mandatory information for the operation of safety applications: position, velocity, and acceleration of the vehicle.
- *Wave Service Advertisement messages (WSA)* which are turned on/off at a frequency of 1 Hz. These messages

are included to simulate background traffic on the network corresponding to various on-route services (i.e., additional traffic from safety applications). They are an additional load to the channel, on top of the regular beaconing exchange that operates permanently.

We identify each scenario with a Network Traffic Load (NTL) label as it is shown in table I (left part).

TABLE I: Network traffic loads definition

Network traffic load (NTL)	Beacon frequency	WSA
1	2 [Hz]	off
2	10 [Hz]	off
3	10 [Hz]	on



(a) Simulation's view from SUMO. (b) Simulation's view from OMNet++.

Fig. 1: Simulation Scenarios.

The following information, which is collected in a distributed manner, is gathered from the MAC layer protocol of each vehicle, as input to the ANN classifier during our simulations:

- Channel Busy Ratio (CBR): is the time during which the channel is busy (i.e., sending packets) in a time interval. This metric is used by the CSMA/CA protocol and it is calculated with Equation (1) as follows:
$$CBR = \frac{t_{busy}}{t_{interval}}, \tag{1}$$
in this case $t_{interval} = 1$ s.
- Normalized Times Into Back-off (NTIB): it is the number of times that the MAC layer based on CSMA/CA protocol does not transmit because the channel is busy within a time window of 1 s.
- Normalized Broadcast Received (NBR): it is the number of received broadcast packets from other vehicles in a time window of 1 s.

In order to process the above data we use MATLAB® and the Neural Networks Toolbox^{TM} [6]. Based on preliminary evaluations with different configurations of the supervised neural network, varying the numbers of neurons in the hidden layer, and the number of hidden layers, we took the decision to employ the architecture shown in Figure 2. We then took the data and ran a few examples in the Classification Learner App that provides MATLAB®; the mentioned application provides different kinds of classifiers (e.g., random forest, support vector machine, and nearest neighbour algorithms, among others) but the chosen neural network showed to have a better performance in terms of success classification.

We collected $5,000$ samples on the low density scenario and up to $10,000$ samples on the high density scenario. We divided the data-set as follows: 65% of the total data for the training set, 15% of the data for validation, and the remaining 20% of the data for test set.

III. Results

In the low density scenario, the results show a 98.9% of success classification (see Figure 3a), and for the first class (i.e. $NTL = 1$) the 100% of the test data was successfully classified. The second and third classes have a mayor level of confusion between them. In the high density scenario, the results show a 94.5% of success classification (see Figure 3b), and similar performance for the confusion inter-classes. These results demonstrate that the classifier is a good tool for identifying the different network traffic loads from indirect and distributed measurements of the behavior of the MAC protocol at each vehicle.

Contrary to intuition, for the highest density scenario, which has a greater number of samples because there are more vehicles at the intersection scenario, the performance of the classifier is worse than in the lower density scenario. This could be explained because the metric NBR could be biased by possible packet collisions in the communications network. As well as the other metrics could be in saturation levels which makes the discrimination between classes 2 and 3 more difficult.

IV. Contribution

The main contribution of our work is to design an ANN classifier that can discriminate different degrees of network traffic load in the VANETs, which in turn can be exploited in favour of different safety and non-safety applications developed in the context of Intelligent Transportation Systems. In particular, we can say that this classifier will be pivotal for the development of a context-aware dissemination mechanism for safety applications in VANETs. In the future work, this classifier could be improved to discriminate other levels of traffic in the network, as well as to extend its operation in scenarios of different topologies. Future applications of the classifier are in the adaptive transmission algorithms or other applications that depend on the network scenario, because for these algorithms, to be aware of the context is key to improve their performance.

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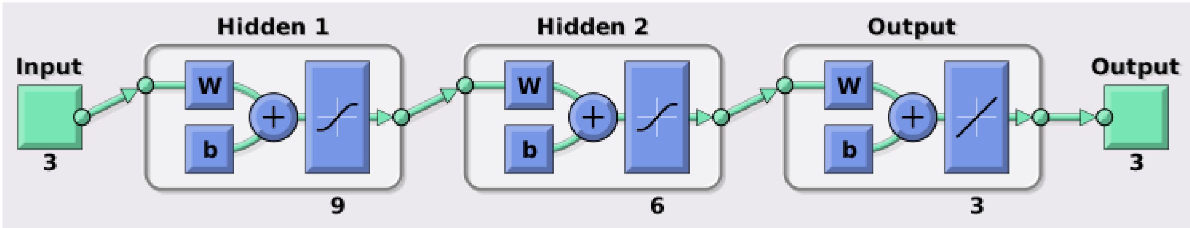

Fig. 2: Neural Network Architecture.

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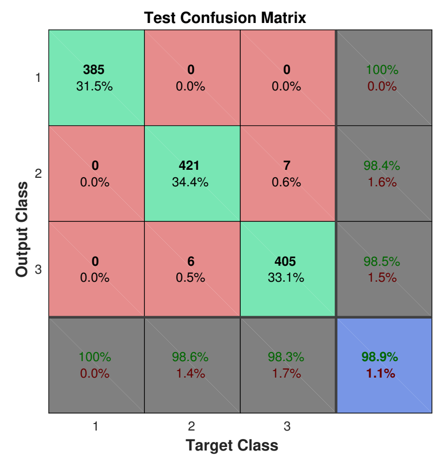
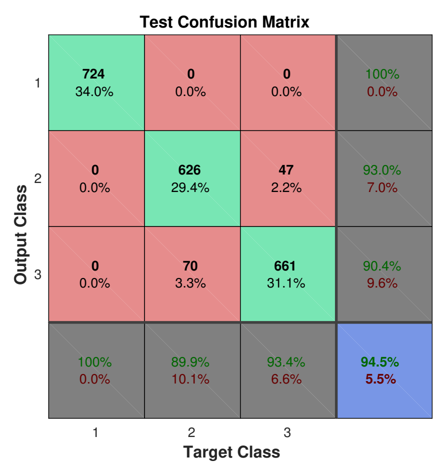


(a) Confusion matrix for low density scenario.



(b) Confusion Matrix for high density scenario.

Fig. 3: Results