A Cooperative Detection Model Based on Artificial Neural Network for VANET QoS-OLSR Protocol

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***Abstract*—In this paper, we address the problem of detecting misbehaving vehicles in Vehicular Ad Hoc Network using (VANET QoS-OLSR), Quality of Service-Optimized Link State Routing protocol. VANET QoS-OLSR is a clustering protocol that is able to increase the stability of the network while maintaining the QoS requirements. However, in this protocol, vehicles can misbehave either by under-speeding or over-speeding the road speed limits after clusters are formed. Such misbehavior leads to a widely disconnected network, which raises the need for a detection mechanism. The majority of the existing detection mechanisms are non-cooperative in the sense that they are based on unilateral judgements, which may be untrustworthy. Others employ cooperative detection scheme with evidence-based aggregation techniques such as the Dempster-Shafer (DS) which suffers from the (1) instability when observations come from dependent sources and (2) absence of learning mechanism. To overcome these limitations, we propose a cooperative method using Artificial Neural Network (ANN), which is able to (1) aggregate judgments and prevent the unilateral decisions, and (2) benefit from the previous detection experience by continuous learning. Simulation results show that our model improves the detection probability and reduces the false alarms rate.**

***Index Terms*—VANET, Artificial Neural Network, Cooperative Detection, Reputation, Misbehaving Vehicles.**

I. Introduction

Vehicular Ad Hoc Networks (VANET) [14] [8] [13] [5] will play an important role in the future of communication, especially in emergency cases of accidents and crimes to link police cars and ambulances. VANET is a special class of Mobile Ad Hoc Networks (MANETs) that is characterized by high mobility of vehicles. To cope with this mobility,(VANET QoS-OLSR) [10] is a clustering protocol that has been proposed to maintain the stability of the network without sacrificing the QoS requirements. In this protocol, a QoS function composed of a combination of several mobility and performance metrics such as velocity, residual distance, bandwidth , and connectivity is proposed. This function is used to elect the cluster-heads and select the Multi-Point Relays (MPRs) that are responsible for connecting clusters by forwarding the messages to the other clusters. Nonetheless, the selected MPRs may misbehave after clusters formation either by under-speeding the minimum road speed limit or over-speeding the maximum limit. This misbehavior leads to several negative implications on the network such as (1) decreasing the network's stability, and (2) increasing the clusters disconnections, which raises the need for a detection mechanism to detect these misbehaving MPRs. Some of the existing mechanisms are non-cooperative, which may lead sometimes to untrustworthy decisions because of the unilateral judgements. Moreover, the recently proposed approach based on Dempster-Shafer (DS) [11], [12] suffer from the (1) instability when observations come from dependent sources, and (2) absence of learning mechanism. To address these problems and detect these misbehaving MPRs, we propose a cooperative detection mechanism using Artificial Neural Networks. ANN are computer programs that process information in a way simulating the human brain neural functionality. It is made of hundreds of neurons or processing elements (PE) arranged in an input layer, an output layer and several hidden layers. In the context of the problem we are addressing, the ANN is used to analyze the collected observations from all the watchdogs [9] for detecting the misbehaving vehicles. Each vehicle plays the role of watchdog to overhear its one-hop away MPR. Before using the Neural Network, a back-propagation learning algorithm is used to train the network and adjust neurons' weights. In summary, we are proposing a cooperative detection technique based on Artificial Neural Network to detect the misbehaving MPRs. Our technique is able to:

- Aggregate the watchdogs' observations to come up with a final cooperative judgment.
- Benefit from the previous detections experience by the continuous learning.
- Improve the detection probability and reduce false alarms.

Simulation results show that the use of ANN produces high probability of detection and low false alarms compared to the DS model used as a benchmark.

II. Related Work

This section briefly reviews the prior work of misbehaving nodes detection and ANN-based detection mechanisms.

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A. *Misbehaving Vehicles Detection*

To detect misbehaving vehicles, authors in [11] used a two-phase model that is able to motivate nodes to behave cooperatively during clusters formation, and detect misbehaving nodes after forming the clusters. Once selected, cluster-heads and MPRs collect virtual money, which is added to their reputation points. Each node can benefit from the network according to its reputation ratio. This has the advantage of motivating the vehicles to behave cooperatively in order to increase their benefits from the network's resources. To detect misbehaving nodes, the authors proposed a cooperative watchdogs monitoring mechanism. Each node plays the role of watchdog to track its neighbor MPR. However, since watchdogs may be selfish themselves, a cooperation algorithm based on Dempster-Shafer theory is used to aggregate the judgments. This method suffers from the instability when the same watchdog gives more than one opinion over time. In addition, the DS method doesn't benefit from the previous detection experience which is considered as a waste of huge amount of data. In [7], Tit-for-Tat associates the motivation mechanisms with the reputation concept. To benefit from a larger set of services, nodes seek to increase their reputation values by cooperating with more reputable nodes. However, this strategy suffers from many problems such as neglecting the cases of collisions and high mobility that may affect the monitoring process. Moreover, it restricts the decision of cooperation to the local relation between each pair of nodes. It also leads to stop the cooperation among nodes. In [9], Marti et al. included the pathrater and the watchdog concepts into the Dynamic Source Routing (DSR) protocol [6]. Their method consists of preventing the detected misbehaving node from forwarding packets Rather than punishing them. According to this method the misbehaving nodes are requited according to their behavior while their packets continue to be transmitted by others, which is considered as waste of resources. Overall, each of these approaches have one or more disadvantage that may limit their efficiency such as: limited transmission power, ambiguous collision, non-cooperative monitoring, instability, false alarms, and not benefiting from the previous detections.

B. *Artificial Neural Network utility in attacks detection*

The artificial neural networks are usually used in classification and pattern recognition, prediction and modeling. In [15], authors used ANN in VANET application to classify alert messages as spurious alert or valid alert messages. They used a two layer filter, coarse filter and fine filter. The coarse filter uses the digital signature verification, the time validation, geographic location validation and support from Road Side Units (RSUs). If the coarse filter cannot classify the alert message independently, it uses the fine filter, which is necessary in most situations. It uses a back propagation neural network to classify behavior patterns, which taking into account the neighbors' support. Before using the Neural Network, a back-propagation learning algorithm is used to train the network and adjust neurons' weights using samples in a training set. These samples come from historical alert reports organized as feature vectors. They used a two layer multilayer perceptron. Layer '0' is the input layer formed from 4 neurons: (1) The distance between event spot and sender, (2) distance between receiver and sender, (3) sender's current speed, and (4) sender's reputation. Layer '1' is the hidden layer formed of 8 neurons; Layer '2' is the output layer formed of 1 neuron 'The event-trustworthiness'. This method shows the efficiency of the neural network in the misbehaving detection. However, it suffers from the unilateral decisions and non-cooperative monitoring.

III. Background

Artificial Neural Networks are computer programs simulating the way in which a human brain processes information. An ANN is formed from hundreds of neurons or processing elements (PE), arranged in an input layer, an output layer and several hidden layers. Each PE has a weight, a transfer function and an output. During training, processing elements' weights are optimized until the error is minimized and the network reaches the specified level of accuracy.

A. *Processing Phase*

As its name indicates, the multilayer perceptron (MLP) is an artificial neural network model formed from several layers. Conventionally, the input layer is 0, thus a three layers Multi-Layer Perceptron [2] takes the form shown in Figure 1. The output of each neuron is equal to the transfer function $F(x)$ applied to the variable x, where x is equal to the sum of the neuron's inputs multiplied by their weights.

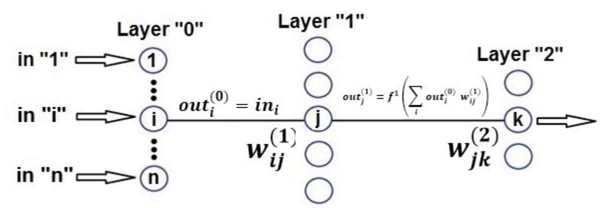


Fig. 1: Architecture of 3 layer MLP

B. *Training Phase*

Before using the ANN we have to train it until the error is minimized. MLP uses the back-propagation learning technique [3] to train the network. In the training phase, a set of vectors collected from real data or generated by a convenient simulator is employed. Learning occurs in the perceptrons by changing the connections' weights to minimize the error in the output compared to the expected result according to each training vector.

IV. Misbehaving Vehicles Detection Using the ANN Method

In this section, we will explain how to use the artificial neural network to detect the misbehaving nodes. First we explain the clusters formation, the nodes motivation, and the utility of the watchdogs, to finally reach the cooperation using the neural network.

A. VANET QoS-OLSR Protocol

To increase the network's stability and decrease the link failures, the VANET QoS-OLSR clustering protocol was proposed in [10]. In this protocol, a QoS function composed of a combination of several mobility and performance metrics such as velocity, residual distance, bandwidth , and connectivity is proposed. This function is used to elect the cluster-heads. Thereafter, an Ant Colony Optimization (ACO) derived algorithm is proposed to select the optimal Multi-Point Relay (MPR) nodes in terms of QoS and stability.

B. Nodes Motivation

To motivate nodes to work cooperatively, an incentive model has been proposed in [11]. In this model, cluster-heads and MPRs receive virtual money in the form of reputation after being elected. This reputation is used later in the network's resources distribution process. In this paper, we adopt the same incentive model to build the reputation values of the vehicles.

C. Watchdogs Judgment

To detect misbehaving vehicles, watchdogs are needed to track the MPRs and make judgments on their behaviors. Each node will play the role of watchdog where nodes can overhear their neighbor MPR. When the MPR sends a message, the watchdogs that maintain a buffer of recently sent packets will overhear this communication, compare the message to their buffers' contents to see if there is a match and decide if this MPR is misbehaving or cooperating.

D. Judgments aggregation using Artificial Neural Network

During monitoring, the watchdog itself can be misbehaving and can give fake judgments. To overcome this problem, we proposed a cooperative detection algorithm Figure 2 based on the ANN method to combine all the watchdogs judgments and reach finally the global final judgment on the MPR in question. After making the decision, each watchdog sends its judgment to its cluster-head, as 1 indicating that the charged MPR is cooperating, and 0 indicating that the MPR is misbehaving. The cluster-head aggregates these opinions and uses them with the nodes' reputations as inputs to the ANN. First, it assigns 1 for cooperative opinion and -1 for misbehaving opinion. Then, it multiplies each decision by the related watchdog's reputation, and uses it as an input for the neural network, to collect finally the cooperative judgment on the output of the ANN, which is "0" for misbehaving and 1 for cooperative judgment. To fix the number of the neural networks' inputs, we use a fixed number of the positive most significant watchdogs' judgments and negative most significant judgments according to the number of networks nodes, together with their reputations as inputs to the neural network. If the number of watchdogs is lower than the number of fixed inputs, we assign 0 to the remaining inputs as a none significant judgment.

E. Artificial Neural Network's Parameters

An Artificial Neural Network is identified by four parameters: the input layer, hidden layer, output layer and transfer functions that link the layers to each others. These parameters are explained in Table I.

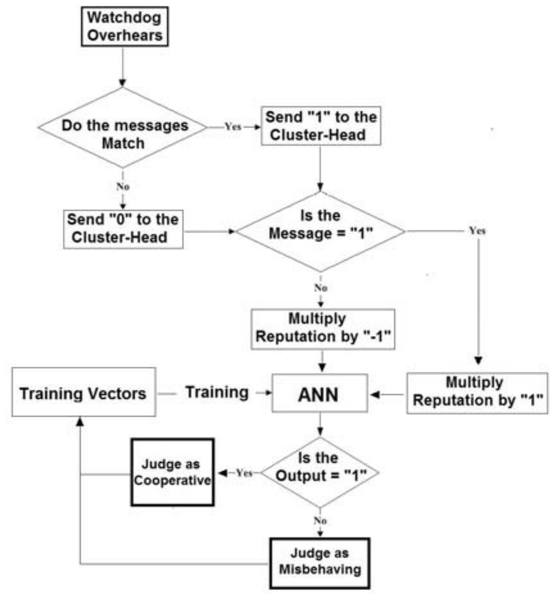


Fig. 2: Aggregation Algorithm

V. Illustrative Example

In this section, we will discuss an example of a cooperative judgment on a misbehaving MPR using the ANN. We begin first by training the neural network using more than 1000 vectors generated by the matlab simulator with a percentage of misbehaving nodes varying from 10 % to 50 %. During the training phase, the neurons' weights are changed until reaching optimal values to generate the expected outputs according to each training vector. Consider now a cluster containing 7 vehicles having the characteristics as shown in Figure 3. We have to make a cooperative decision on the behavior of the MPR (node 1) using the judgments of the watchdogs (nodes 2 .. 7). Consider that the MPR is misbehaving, and the cluster-head is at the same time a watchdog. The watchdogs will monitor the behavior of the MPR, and detect that it is misbehaving. Then watchdogs 2, 5 and 7 are cooperative watchdogs. As shown in the second phase of our algorithm Figure 2 they will judge that the MPR is misbehaving by sending "0" to the cluster-head. The watchdogs 4 and 6 are misbehaving watchdogs so they will judge that the MPR is cooperative by sending 1 to the cluster-head. The cluster-head will aggregate all judgments, add its own judgment, and assemble them in 2 sets. The first containing the positive judgments, and the second containing the negative judgments. Afterwards, it will sort each set according to the watchdogs' reputations, and multiply the reputations of the negative judgments by "-1". Then, as shown in Figure 4, it will use them as inputs to the neural network. When applying the neural network, each neuron's output will be equal to the transfer function $F(x)$ applied to the variable x, where x is equal to the sum of the neuron's inputs multiplied by their weights as shown in Figure 1. After applying the neural network, the output neuron will be equal to "0" indicating that the charged MPR is a misbehaving MPR. Finally we expel this MPR from the network and add this detection as a training vector to increase the ANN experience.

TABLE I: Artificial Neural Network Parameters

ANN Parameters
Let define:
Ni = Number of input layer's neurons
Nh = Number of hidden layer's neurons
No = Number of output layer's neurons
F(x) = Transfer Function
Input layer's neurons
1 Ni: The number of neurons in the input layer is equal to the number of watchdogs needed, it's proportional to the number of nodes.
Hidden layer's neurons
2 Nh: The number of neurons in the Hidden layer is set according to the empirical equation: Nh=$\sqrt{(Ni+No)}+l$, l between 1 and 10
Output layer's neurons
3 No: The number of neurons in the output layer is equal to one and indicates the final judgment.
Transfer Function
4 F(x) = tansig(x) = 2/(1+exp(-2x))-1

VI. Simulation

To simulate the different scenarios, we used MATLAB [4] network simulator and the VanetMobisim [1] traffic simulator. VanetMobisim is a simulator that allows us to define the network's features such as velocity, position, number of nodes and destination.

A. Simulation Parameters

We define a simulation area of $900 \times 600\ m^2$, a set of nodes from 50 to 100 nodes, a transmission range of 300m, and a multi-lane highway topology. The VanetMobisim simulator generates a file containing the necessary parameters to simulate the proposed method using MATLAB. The simulation parameters are summarized in Table II.

TABLE II: Simulation Parameters

Parameter	Value
Aggregation models	Artificial Neural Network
Number of Nodes	50,60,70,80,90 and 100
Percentage of misbehavior	10%, 20%, 30%, 40% and 50 %
Transmission Range	300 m
topology	Multi-lane highway
initial Reputation	100
Minimum speed	60 km/h
Maximum speed	120 km/h

The number of nodes used to simulate the detection model varies from 50 to 100 nodes and the number of misbehaving nodes varies from 10% to 50%. For 0% misbehaving nodes there is no need for detection since all the vehicles are cooperative. Similarly, for 50% misbehaving nodes, there is no need for detection since the majority of the nodes will be misbehaving. They can form new clusters and resume the networking functions again.

B. Simulation Results

In this section, we reveal the efficiency of our detection scheme in terms of the percentage of misbehaving nodes and the number of nodes.

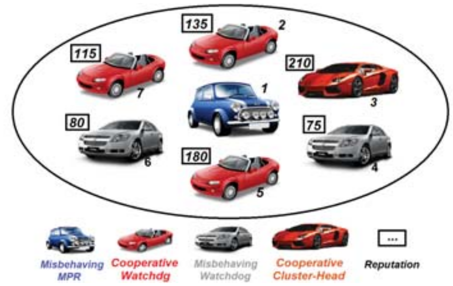


Fig. 3: Vehicles Characteristics

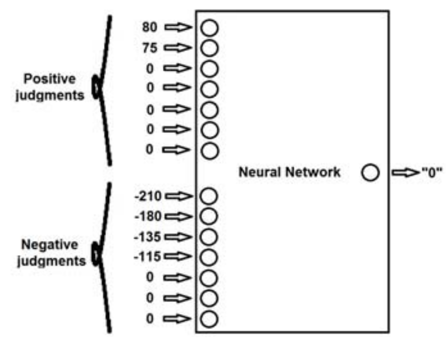
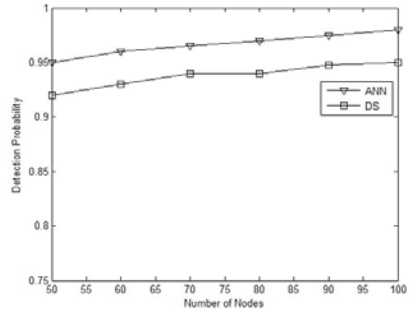


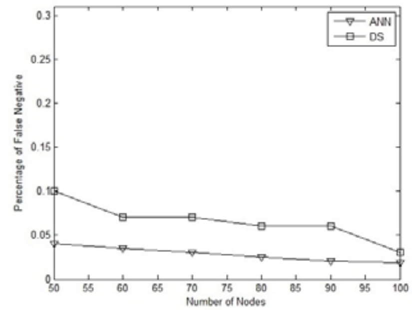
Fig. 4: Artificial Neural Network Architecture

1) Detection in terms of the number of nodes: To show the efficiency of the ANN method, we simulated the detection ratio and the percentage of false negative in terms of the number of nodes by varying the number of vehicles from 50 to 100 nodes, with 10% misbehaving nodes. When the number of nodes increases, the number of watchdogs of each MPR will increase too, which will lead to more precision in the detection. The simulation results show that the detection ratio is increasing when augmenting the number of nodes to reach 0.98 with 100 nodes as shown in Figure 5.a, and the percentage of false negative is decreasing to reach 0.05 with 100 nodes as shown in Figure 5.b.

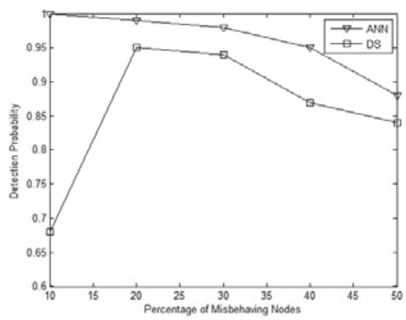
2) Detection in terms of the percentage of misbehaving nodes: To illustrate the efficiency of our algorithm, we simulated the detection ratio and the percentage of false negative in terms of the percentage of misbehaving nodes by varying it from 10% to 50% with a fixed number of nodes equal to 100. When the percentage of misbehaving nodes augments, the number of misbehaving watchdogs augments, the false alarm rate increases and the probability of detection decreases. The results also reveal that the detection ratio is decreasing slowly when augmenting the percentage of misbehaving nodes to reach 87% detection with 50% misbehaving nodes as shown in Figure 5.c, and the percentage of false alarms is increasing slowly to reach 15% with 50% misbehaving nodes as shown in Figure 5.d.



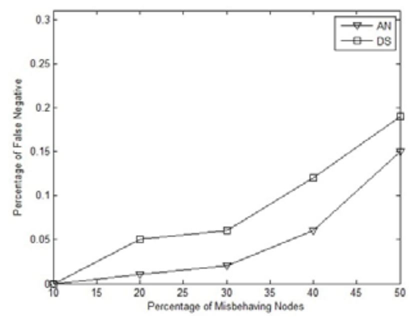
(a) Detection rate according to the number of nodes



(b) False alarms rate according to the number of nodes



(c) Detection rate according to the percentage of misbehavior



(d) False alarms rate according to the percentage of misbehavior

Fig. 5: Simulation Results According to the Number of Nodes and the Percentage of Misbehavior.

VII. Conclusion

In this work, we address the problem of detecting misbehaving nodes in Vehicular Ad Hoc Networks. A vehicle is considered as misbehaving when it over-speeds or under-speeds the rode speed limits. The majority of current approaches are based on unilateral decisions. Others employ a cooperative scheme and use evidence-based models to aggregate the different observations. However, these models suffer from the (1) instability when using dependent sources, and (2) absence of learning mechanism. To improve the probability of detection and decrease the false alarm rate we proposed a cooperative detection algorithm based on the Artificial Neural Network method. The advantages of the proposed model are (1) using a cooperative monitoring process, and (2) benefiting from the previous detection experience by employing continuous learning. Simulation results show that our detection model is performing better then the DS in terms of probability of detection and false alarm ratio. Our scheme augments the detection probability up to 98% with 100 nodes and decreases the false negative to approximately 3%.

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