A Topological Approach to Secure Message Dissemination in Vehicular Networks

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Abstract—Secure message dissemination is an important issue in vehicular networks, especially considering the vulnerability of vehicle-to-vehicle message dissemination to malicious attacks. Traditional security mechanisms, largely based on message encryption and key management, can only guarantee secure message exchanges between a known source and destination pairs. In vehicular networks, however, every vehicle may learn its surrounding environment and contributes as a source, while in the meantime, acting as a destination or a relay of information from other vehicles, and message exchanges often occur between "stranger" vehicles. This makes secure message dissemination against malicious tampering much more intricate. For secure message dissemination in vehicular networks against insider attackers, who may tamper the content of the disseminated messages, ensuring the consistency and integrity of the transmitted messages becomes a major concern which the traditional message encryption and key management-based approaches fall short to provide. However, it is challenging for a vehicle to distinguish which message is true when the messages received from multiple nearby vehicles are conflicting. In this paper, by incorporating the underlying network topology information, we propose an optimal decision algorithm that is able to maximize the chance of making a correct decision on the message content, assuming the prior knowledge of the percentage of malicious vehicles in the network. Furthermore, a novel heuristic decision algorithm is proposed that can make decisions without the aforementioned knowledge of the percentage of malicious vehicles. The simulations are conducted to compare the security performance achieved by our proposed decision algorithms with that achieved by the existing ones that do not consider or only partially consider the topological information to verify the effectiveness of the algorithms. Our results show that by incorporating the network topology information, the security performance can be much improved. This paper sheds light on the optimum algorithm design for secure message dissemination.

Index Terms—Vehicular networks, security, message dissemination, decision algorithm.

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I. INTRODUCTION

VEHICULAR networks, with the assistance of dedicated short-range communication (DSRC) [1] and LTE technology, enable safety and non-safety information sharing among vehicles and infrastructure through vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications, and therefore are conductive to improving road safety, enhance traffic efficiency and increase comfort and convenience to drivers and passengers [2]–[4]. On the other hand, accompanying these benefits brought along by vehicular network applications is the urgent security issue that should be addressed. Specifically, considering the vulnerability of V2V communications, message dissemination in vehicular networks is susceptible to malicious attacks, e.g., malicious vehicles who may spread false messages, tamper or drop the received messages [5] to disrupt delivery of authentic messages. These attacks in vehicular networks could potentially result in catastrophic consequences like city-wide traffic congestion, traffic crash, even loss of lives, and therefore are significant security threats to transportation systems that must be thoroughly investigated before vehicular networks can sbe deployed.

Vehicular network security design should guarantee authentication, non-repudiation, information integrity, and in some specific application scenarios, confidentiality, to protect the network against attackers [6]. Conventional security mechanisms, largely based on message encryption and key management [7], [8], are effective to guarantee message integrity against outsider attackers, however fall short of protecting the integrity of disseminated messages when there exist insider attackers who possess valid certificates that can pass the authentication process conducted by the certification authorities [9], [10].

To keep the network message dissemination secure against insider attackers, the trustworthiness of each vehicle and the integrity of their transmitted messages are of great importance. Different from traditional security settings, in vehicular networks, information collection and dissemination are mainly conducted by distributed vehicles due to the limited number of road side infrastructure attributable to the high deployment cost, and also the unreliable nature of a centralized data base. Quite often, information may be generated by or received from a vehicle that has never been encountered before. Moreover, the vehicular network topology is constantly changing considering that both V2V and V2I connections

may emerge opportunistically. These unique characteristics may render the entity-based trust establishment approach, conducted at each vehicle by monitoring their instantaneous neighbors' behavior, futile in vehicular networks because it is challenging to maintain a stable reputation value for an unknown and fast-moving vehicle. Furthermore, safety-related vehicular network applications usually require vehicles to respond quickly to the received messages [11]. In such cases, determining the integrity of the disseminated messages is of greater importance than the malicious vehicle detection. Therefore, decision algorithms based on data consistency and integrity check emerge, e.g., [12]–[16]. However, when a vehicle receives conflicting messages from different nearby vehicles, it is not straightforward to assess which message is true if focusing on data only while ignoring the underlying network topology information that tells where these messages come from. Indeed, messages coming from different paths can be correlated when the these paths share some common nodes. For instance, multiple false messages may result from the same malicious vehicle shared by multiple paths. Therefore, taking the underlying topological information into consideration is essential and beneficial when designing decision algorithms for vehicles to conduct data consistency check.

In this paper, we consider vehicular networks containing insider malicious vehicles that may tamper the content of messages to disrupt their successful delivery. We are interested in investigating topology-based decision algorithms to keep vehicles from being misguided by false messages. To the best of our knowledge, this is the first work that takes the underlying topology information into consideration when checking the consistency of messages for secure message dissemination. Our results shed insight on the optimum decision algorithm design for vehicular networks to improve security performance.

The novelty and major contributions of this paper are summarized as follows:

1) By utilizing the underlying network topology information, we propose two message decision algorithms to cope with the issue of message inconsistency caused by insider malicious vehicles in the network.

2) The proposed optimum decision algorithm is able to effectively help a vehicle maximally make a correct decision on the content of the message when receiving conflicting messages, and the proposed heuristic decision algorithm enables a vehicle to make a decision purely based on topology information.

3) Simulation results show that both our proposed algorithms outperform existing decision algorithms that do not consider or only partially consider the topological information in terms of secure message dissemination in vehicular networks.

The rest of this paper is organized as follows: Section VI reviews related work. Section II introduces the system model and the problem formation. The optimum decision algorithm and the heuristic decision algorithm are presented in Section III and Section IV respectively. In Section V, we conduct simulations to validate the effectiveness of our proposed

decision algorithms and discuss their insight. Section VII concludes this paper.

II. SYSTEM MODEL AND PROBLEM FORMATION

In this section, we first introduce the system model, including the network model, message dissemination model, and the attack model. Then, we give a rigorous description of the research problem addressed in this paper.

A. Network and Message Dissemination Model

We consider a vehicular network where each vehicle has a unique ID number that is registered in certification authority to represent its identity, and vehicles cannot forge their own or other vehicles' ID numbers. That is, we assume all vehicles are legitimate vehicles that have passed the authentication process conducted by the certification authority [13], [15].

Specifically, consider that there is a vehicle in the network (termed as the source vehicle) intending to deliver a message about the road condition to inform other vehicles further away. The road condition information can be abnormal situations, e.g., congestion, hazardous road conditions such as traffic accident, slippery road, etc., or normal situation, e.g., uncongested traffic. We assume that the content of message takes value from $\{0, 1\}$, and 1 represents abnormal road condition and 0 represents normal road condition. When the source vehicle sends the source message m_0 on road condition, it will also send the location information applied to the road condition along with message m_0, to help other vehicles in the network make a better route choice. It is worth noting that the road situation can also be described as a multi-variable vector and these variables can be correlated [13], e.g., one such variable can be traffic congestion state and another can be accident state. We denote the content of message on road condition transmitted by the source vehicle, which represents the actual road condition, by m_0, $m_0 \in \{0, 1\}$. Other vehicles do not know the true value of m_0 a priori.

The message is forwarded from the source vehicle in a broadcast and multi-hop [17], [18] manner to other vehicles with the help of relay vehicles. Relay vehicles can be any vehicle along the message propagation path. Each time when a relay vehicle receives a message from its neighbor, it will forward the message. That is, when a relay vehicle gets the same message several times (from different neighbors), it will forward as many times as it receives the message. Multi-path forwarding makes it challenging for the attackers to influence all message forwarding paths [12], therefore helps to improve the message security. When a vehicle transmits the message on road condition to other vehicles, it transmits its identity information, i.e., ID number, along with the message. This is commonly adopted in vehicular network applications and can be achieved by some standard signature approach [2], [19]. Using this, any vehicle in the network is able to obtain an integrity-protected path list that records the relay vehicles of the corresponding received message on road condition.

B. Attack Model

Vehicles in the network can be classified into two categories: *normal vehicles,* which behave normally and

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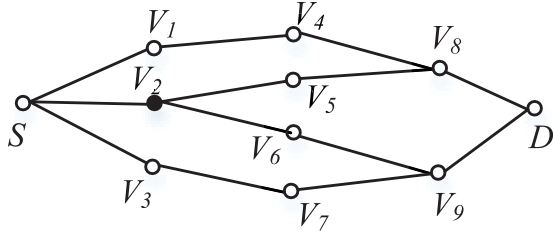
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Fig. 1. An illustration of a vehicular network when there exists a malicious vehicles V_2 who would tamper the content of message. Specifically, S is the source vehicle, D is the destination vehicle, and vehicles between them are relay vehicles. There are four paths ($S-V_1-V_4-V_8-D$, $S-V_2-V_5-V_8-D$, $S-V_2-V_6-V_9-D$, and $S-V_3-V_7-V_9-D$) that deliver the source message from S to D. Therefore, out of the four copies of messages received by D, two copies are incorrect as there are two paths containing the malicious vehicle V_2.

will forward the received message without any alteration, and *malicious vehicles*, which may tamper the received message. It is assumed that vehicles cannot forge their own or other vehicles' ID numbers, and the path list transmitted along with the message is protected by signature approach. Therefore, malicious vehicles can only tamper the content part of the message, but cannot tamper the path list record. Malicious vehicles are uniformly and randomly distributed in the system with proportion p. It follows that the probability of a vehicle being a malicious vehicle is p, independent of the event that another distinct vehicle is a malicious vehicle.

We assume that the source vehicle is normal and only relay vehicles may be malicious. We acknowledge there is possibility that the source vehicle can be malicious, and it is also an important scenario when investigating the vehicular network message security issue. In this paper, our main focus is to design a topological approach to address the message inconsistency issue resulted from the message dissemination process. Therefore, we assume the source vehicle is normal, and only relay vehicles can be malicious. We will leave the work that removes this assumption as our future work. Besides, we assume the normal vehicles do not know which vehicles are normal or malicious. On the other hand, we consider the most unfavourable situation for secure message dissemination in vehicular networks that malicious vehicles not only know which vehicles are malicious, but also are capable of communicating with each other via back channels of infinite bandwidth [20]. That is, we assume malicious vehicles collaborate with each other and they also know what the correct message m_0 transmitted by the source vehicle is. Therefore, if a malicious vehicle receives the correct message, it will tamper it to the incorrect one, i.e., different from message m_0; and if it receives the incorrect message, it will directly forward it to others. This implies that as long as a message is relayed by at least one malicious vehicle, the message would be incorrect. Fig. 1 gives a simple example of message dissemination process when there are insider attackers in the network.

C. Problem Formation

Now we give a detailed description of the research problem considered in this paper.

We consider that there is a vehicle, which is several hops away from the source vehicle, trying to make a decision on the message content when it receives several copies of message, and we call it the destination vehicle. Note that the destination vehicle can be any vehicle along the message dissemination path. From the time instant the destination vehicle receives the first message, it waits time period T to receive more messages before making a final decision. T characterizes the response time requirement on the decision, and a larger T potentially allows the vehicle to receive more messages. We will discuss its impact on the integrity of the decision later in the simulation. Let k be the number of message received by a destination vehicle during its waiting time period T and let n be the number of relay vehicles that participate in relaying the k copies of message from the source vehicle to the destination vehicle. In the following analysis, we regard k and n are known to the destination vehicle, which can be readily obtained from the received messages. Consequently, the network being considered has n relay vehicles and k paths between the source vehicle and the destination vehicle. Other nodes who do not participate in the relay have little impact and hence can be ignored.

Denote the k messages on road condition received by the destination vehicle by M_i, $i = 1, 2, ...k$, $M_i \in \{0, 1\}$. As each message on road condition is transmitted together with a specific delivery path from the source vehicle to the destination vehicle, we number the corresponding paths by $L_1, L_2, ...L_k$. In addition, we number the relay vehicles by $V_1, V_2, ...V_n$. A vehicle V_i may belong to one or more paths.

Note that due to the existence of malicious vehicles who may tamper the content of the message, the k copies of message on road condition received by the destination vehicle can be in conflict instead of being consistent with each other. Furthermore, with the potential existence of some shared relay vehicles in different paths, the k messages received from k different paths may not be independent. These correlations are all contained in the information of message dissemination paths. Therefore, we construct a topology matrix to represent the underlying network topological correlation. Specifically, based on the path information derived from the received messages, the destination vehicle can readily construct a $k \times n$ topology matrix B, where each row represents a path, each column a node (vehicle), and the (i, j)-th entry B_{ij} being an indicator whether vehicle V_j belongs to path L_i:

$$B_{ij} = \begin{cases} 1, & \text{if vehicle } V_j \text{ belongs to path } L_i \\ 0, & \text{else} \end{cases} \quad (1)$$

In this paper, we are interested in designing decision algorithms for the destination vehicle to improve the chance of a correct decision on the content of the disseminated message against attacks from malicious vehicles by utilizing the underlying network topology information. Denote by d, $d \in \{0, 1\}$ the final decision on the content of message made by the destination vehicle. If the decision is the same as the source message, i.e., if $d = m_0$, we say the destination vehicle makes a correct decision, otherwise we say it makes an incorrect decision. We use the probability of correct decision,

denoted by P_{succ}, as the performance metric to measure the secure message dissemination performance, and P_{succ} can be formally defined as follows:

$$P_{succ} = \Pr(d = 1, m_0 = 1) + \Pr(d = 0, m_0 = 0) \qquad (2)$$

In the following two sections, we will propose two decision algorithms to improve the message security performance in vehicular networks by utilizing the underlying network topology information. First, we will propose an optimum decision algorithm that maximizes the probability of correct decision P_{succ} based on Bayes decision theory, assuming the percentage of malicious vehicles in the network is known. A detailed implementation of the algorithm will be provided to illustrate how a destination vehicle makes the decision on the message content according to this prior knowledge and the network topology information. Then, we will introduce a heuristic decision algorithm based on the Maximum Likelihood Estimation. This heuristic decision algorithm will enable a vehicle to make a decision when receiving conflicting messages purely based on network topology information, without the need for knowing the percentage of malicious vehicles, which can be difficult to estimate in some circumstances. Therefore, the heuristic algorithm is easier to implement in practice.

III. Optimum Decision Algorithm

In this section, we propose a decision algorithm aims to optimize the secure message dissemination performance in terms of maximizing the probability of correct decision P_{succ}, that is,

$$\max \; P_{succ}, \qquad (3)$$

where P_{succ} is given by (2).

In the following, we will first present the optimum decision algorithm followed by a detailed proof to prove its optimality, and then we will introduce its detailed implementation and discuss its limitation in practical realization.

A. Optimum Decision Algorithm

The following theorem summarizes the optimum decision algorithm to maximize P_{succ}.

Theorem 1: Consider that a destination vehicle receives k copies of messages $M_1 = m_1, M_2 = m_2, ...M_k = m_k$. Given the prior knowledge of the probabilities that the occurrence of abnormal event of interest, e.g., traffic congestion, are $P_1 = Pr(m_0 = 1)$, and $P_0 = 1 - P_1 = Pr(m_0 = 0)$, which can be estimated from empirical knowledge [21], the optimum decision algorithm that leads to (3) can be shown as follows:

$$d = \begin{cases} 1, & \dfrac{Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)}{Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)} > \dfrac{P_0}{P_1} \\ 0, & \dfrac{Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)}{Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)} < \dfrac{P_0}{P_1}, \end{cases} \qquad (4)$$

and when $\frac{Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)}{Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)} = \frac{P_0}{P_1}$, d is randomly chosen from 0 and 1 with equal probability.

Proof: As introduced in [22] and [23], the objective of a binary Bayes decision problem is to minimize the expectation of the decision cost, denoted by $U(d, m_0)$. Let U_{ij}, $i = 0, 1$,

$j = 0, 1$, represents the cost of declaring the final result $d = i$ when actually the source message $m_0 = j \neq i$, and U_{ij} can be negative to represent the benefits of making a correct decision. As a ready consequence of the total probability theorem, the expectation of the decision cost $U(d, m_0)$ can be expressed as follows:

$$U(d, m_0) = \sum_{i=0}^{1} \sum_{j=0}^{1} U_{ij} \Pr(d = i, \; m_0 = j). \qquad (5)$$

When assuming $U_{01} > U_{11}$ and $U_{10} > U_{00}$, which is reasonable considering the cost of making an incorrect decision is usually larger than that making a correct decision, the optimum decision algorithm that minimizes the expectation of the decision cost made by the destination vehicle given its k copies of received message $M_1 = m_1, M_2 = m_2, ...M_k = m_k$, is given by [23]:

$$d = \begin{cases} 1 & \dfrac{\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)}{\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)} > \dfrac{P_0(U_{10} - U_{00})}{P_1(U_{01} - U_{11})} \\ 0, & \dfrac{\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)}{\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)} < \dfrac{P_0(U_{10} - U_{00})}{P_1(U_{01} - U_{11})}, \end{cases} \qquad (6)$$

where $\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)$ are the two conditional probabilities of the occurrence of event $M_1 = m_1, M_2 = m_2, ...M_k = m_k$, which characterize the correlations between received messages. Besides, when a tie occurs, namely, when $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)} = \frac{P_0(U_{10}-U_{00})}{P_1(U_{01}-U_{11})}$, d is randomly chosen to be 0 or 1 with equal probability.

From (5), when assuming the cost of making a correct decision is 0 and making an incorrect decision is 1, namely, by assuming $U_{00} = U_{11} = 0$ and $U_{01} = U_{10} = 1$, we have:

$$\begin{aligned} U(d, m_0) &= \Pr(d = 0, m_0 = 1) + \Pr(d = 1, m_0 = 0) \\ &= 1 - P_{succ}. \end{aligned} \qquad (7)$$

It follows that a minimization of the expectation of the decision cost, is equivalent to a maximization of the probability of correct decision, namely, we have

$$\min \; U(d, m) \iff \max \; P_{succ} \qquad (8)$$

Therefore, the optimum decision algorithm for the optimization problem (3) is exactly the decision algorithm that provides a solution to the classical Bayes decision problem in a special case, shown as (4), which finalize the proof. ∎

Remark 2: It can be seen from (4) that, given the probabilities of the occurrence of an event of interest, P_0 and P_1 respectively, the decision on $d = 1$ or $d = 0$ depends on the ratio $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)}$. That is, given a set of received messages $M_1 = m_1, M_2 = m_2, ...M_k = m_k$, the destination vehicle need to calculate the probability that the event $M_1 = m_1, ...M_k = m_k$ occurs if the true message m_0 is 1, denoted as $\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 1)$, and the probability that the event occurs if the true message m_0 is 0, denoted as $\Pr(M_1 = m_1, ...M_k = m_k | m_0 = 0)$, respectively. A decision on d is then made by comparing the value of $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)}$ and $\frac{P_0}{P_1}$. Therefore, calculation of the

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two probabilities is the crucial part of implementing the algorithm, and will be detailed in the following subsection.

In summary, the optimum decision algorithm for the destination vehicle to maximally make a correct decision on the message content works as detailed in Algorithm 1, where the details of calculating the two terms $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$ will be given in the following subsection.

Algorithm 1 Optimum Decision Algorithm

INPUT: $M_1, M_2, ...M_k, P_0, P_1, p$
OUTPUT: d
begin

  1) Construct the topology matrix B based on the paths information derived from the received k messages;
  2) Calculate $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$ according to (12) and (13) respectively, given the network topology information and the prior knowledge on the proportion of malicious vehicles in the network;
  3) **If** $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)} > \frac{P_0}{P_1}$ **then** $d = 1$;

    elseif $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)} < \frac{P_0}{P_1}$ **then** $d = 0$;

    else then d is randomly chosen to be 0 or 1 with equal probability;

  end

end

B. Algorithm Implementation

In this part, we will introduce the detailed implementation of the proposed optimum decision algorithm. As discussed in Remark 2, the first step is to calculate the two probabilities $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$ as they are prerequisite to obtaining the final decision d.

The main idea behind the calculation of $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$ is as follows. We classify vehicles into three different types based on the paths they belong to. We call a vehicle a *Type 0* (or *Type 1*) vehicle if it only belongs to paths that deliver messages with content 0 (or 1) to the destination vehicle, and a vehicle is a *Type 2* vehicle (if any) if it belongs to at least one path that delivers message with content 0 and another path that delivers message with content 1 to the destination vehicle. That is a Type 0 vehicle only belongs to paths that deliver consistent messages 0; a Type 1 vehicle only belongs to paths that deliver consistent messages 1; while a Type 2 vehicle belong to paths that delivers inconsistent messages. Therefore, by separating the paths according to the delivered message contents, the conclusion readily follows that given $m_0 = 1$, all the Type 1 and Type 2 vehicles are normal vehicles, meanwhile malicious vehicles only exist

among Type 0 vehicles. Then, by listing and analyzing all the different combination of malicious vehicles among the Type 0 vehicles, we can obtain the result of our target conditional probability $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$. The idea of calculating $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$ is totally the same.

In the following, we will first demonstrate the method of constructing topology matrix B based on the above idea, and then calculate the two probabilities $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$ respectively. Without loss of generality, we assume that among the k copies of messages $M_1 = m_1, ...M_k = m_k$ received by the destination vehicle, there are exactly k_1, messages with content 1 and the other $k - k_1$ messages with content 0. Note that $k_1 = 0$ and $k_1 = k$ are both trivial cases implying no conflict in the received messages so that the decision is straightforward, therefore we only consider the case when $0 < k_1 < k$.

1) Constructing the Topology Matrix B: Specifically, recall the definition of the topology matrix given in (1), that each row corresponds to a path and each column corresponds to a vehicle. Based on the idea discussed above to calculate the probabilities $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$, we re-arrange the network topology matrix B in the following form:

$$B = \begin{bmatrix} B_1 & B_{s_1} & \mathbf{0} \\ \mathbf{0} & B_{s_0} & B_0 \end{bmatrix}, \qquad (9)$$

where B_1, B_0, B_{s_1} and B_{s_0}, if exist, are non-zero matrices, and $\begin{bmatrix} B_1 & B_{s_1} & \mathbf{0} \end{bmatrix}$ is a $k_1 \times n$ sub-matrix corresponding to the paths that deliver messages with content 1 to the destination vehicle, and $\begin{bmatrix} \mathbf{0} & B_{s_0} & B_0 \end{bmatrix}$ is a $(k - k_1) \times n$ sub-matrix corresponding to the paths that deliver messages with content 0 to the destination vehicle. Besides, the columns of B_1 and B_0 correspond to vehicles that only belong to paths that deliver messages with content 1 and that deliver messages with content 0 to the destination vehicle respectively, i.e., Type 1 vehicles and Type 0 vehicles respectively. The columns of sub-matrix $\begin{bmatrix} B_{s_1} \\ B_{s_0} \end{bmatrix}$ correspond to all the Type 2 vehicles. Assume that the number of Type 1 and Type 0 vehicles are n_1 and n_0 respectively, $0 \leq n_1 + n_0 \leq n$, and the number of Type 2 vehicles is $n_2 = n - n_1 - n_0$. It follows that matrices B_1 and B_0 are of size $k_1 \times n_1$ and $(k - k_1) \times n_0$ respectively, and the matrix $\begin{bmatrix} B_{s_1} \\ B_{s_0} \end{bmatrix}$ is of size $k \times (n - n_1 - n_0)$.

It is worth noting that the above arrangement of columns and rows of matrix B corresponds to a re-numbering of vehicles and paths and it does not change the underlying topology in terms of paths information. Besides, the sub-matrix B_1 can be non-existent if $n_1 = 0$, i.e., when the paths that deliver messages 0 to the destination vehicle contains all the n vehicles in the network. Under this circumstance, $B = \begin{bmatrix} B_{s_1} & \mathbf{0} \\ B_{s_0} & B_0 \end{bmatrix}$. Similarly, the sub-matrix B_0 (or $\begin{bmatrix} B_{s_1} \\ B_{s_0} \end{bmatrix}$) can also be non-existent when $n_0 = 0$ (or $n_2 = 0$).

2) Calculation of $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$: In this part,

we show the method of calculating the two conditional probabilities $\Pr\left(M_1 = m_1, ...M_k = m_k | m_0 = 1\right)$ and $\Pr\left(M_1 = m_1, ...M_k = m_k | m_0 = 0\right)$ using the constructed topology matrix B. The following two theorems summarize the results.

Theorem 3: Consider that a destination vehicle receives k copies of message $M_1 = m_1, M_2 = m_2, ...M_k = m_k$, and among which k_1 messages are with content 1 and the other $k - k_1$ messages are with content 0, $0 < k_1 < k$. Conditioned on the source message $m_0 = 1$, the conditional probability of the occurrence of event $M_1 = m_1, ...M_k = m_k$ can be calculated as follows:

$$
\begin{aligned}
&Pr\left(M_1 = m_1, ...M_k = m_k | m_0 = 1\right) \\
&= \begin{cases} (1-p)^{n-n_0} \cdot \left[\displaystyle\sum_{i=1}^{n_0} a_i \cdot p^i (1-p)^{n_0-i}\right], & n_0 > 0 \\ 0, & n_0 = 0, \end{cases}
\end{aligned}
\tag{10}
$$

where n_0 is the number of vehicles that only belong to paths that deliver messages with content 0 to the destination vehicle, i.e., the number of Type 0 vehicles in the network, and a_i, $i = 1, 2, ...n_0$ is the number of combinations that contain exactly i malicious Type 0 vehicles leading to the occurrence of event $M_1 = m_1, ...M_k = m_k$.

Proof: When $n_0 = 0$, there are no Type 0 vehicles in the network, which implies that the paths that deliver messages with content 1 to the destination vehicle contain all the n vehicles in the network, and the topology matrix $B = \begin{bmatrix} B_1 & B_{s_1} \\ \mathbf{0} & B_{s_0} \end{bmatrix}$. Under this circumstance, conditioned on the source message $m_0 = 1$, when the event that k_1 messages are with content 1 occurs, all the n vehicles in the network should be normal vehicles. It follows that the event that the other $k - k_1$ messages are with content 0 occurs with probability 0. Therefore, we have $\Pr\left(M_1 = m_1, ...M_k = m_k | m_0 = 1\right) = 0$ when $n_0 = 0$.

When $n_0 > 0$, from the topology matrix B, we can conclude that if the matrix $\begin{bmatrix} B_{s_1} \\ B_{s_0} \end{bmatrix}$ exists, then the corresponding Type 2 vehicles should be all normal vehicles. Observing that there is no possibility for two paths sharing the same malicious vehicle to deliver different contents. Therefore, malicious vehicles exist either among Type 1 vehicles or among Type 0 vehicles.

Given the source message $m_0 = 1$, all the Type 1 vehicles should be normal vehicles. Malicious vehicles can only exist among Type 0 vehicles. Besides, the malicious Type 0 vehicles should be able to compromise all the $k - k_1$ paths (corresponding to the sub-matrix $\begin{bmatrix} \mathbf{0} & B_{s_0} & B_0 \end{bmatrix}$) to cause the occurrence of the event that all the $k - k_1$ paths delivering messages with incorrect content 0. Therefore, any combination of malicious vehicles should satisfy the follows condition: by implementing element-wise *union* on their corresponding columns in sub-matrix B_0, i.e., implementing element-wise Boolean operation *OR* on them, the result should be a column with each entry be 1.

Note that the number of malicious type 0 vehicles can be any integer within $[1, n_0]$. We denote by event e_i that randomly choosing i columns from sub-matrix B_0 and then

conducting element-wise union operation to them, there results a column with each entry being 1. Denote by a_i, $i = 1, 2, ...n_0$ the total number of combinations that event e_i occurs. Therefore, we have

$$
a_i = \sum_{j=1}^{z_i} I \left(\text{event } e_i \text{ occurs}\right),
\tag{11}
$$

where $z_i = \binom{n_0}{i}$, and $I(x)$ is an indicator function that $I(x) = 1$, when x is true; otherwise $I(x) = 0$.

It then follows from the combination theory [24] that :

$$
\begin{aligned}
&\Pr\left(M_1 = m_1, ...M_k = m_k | m_0 = 1\right) \\
&= (1-p)^{n-n_0} \cdot \left[\sum_{i=1}^{n_0} a_i \cdot p^i (1-p)^{n_0-i}\right],
\end{aligned}
\tag{12}
$$

where the first part corresponds to the probability that the k_1 paths deliver messages with correct content 1, so that all the $n - n_0$ vehicles contained in these k_1 paths are therefore normal vehicles; and the second part is the probability that the $k - k_1$ paths deliver messages with incorrect content 0, which summing up all the probabilities of different malicious vehicle combinations. ∎

Theorem 4: Consider that a destination vehicle receives k copies of message $M_1 = m_1, M_2 = m_2, ...M_k = m_k$, and among which k_1 messages are with content 1 and the other $k - k_1$ messages are with content 0, $0 < k_1 < k$. Conditioned on the source message $m_0 = 0$, the conditional probability of the occurrence of event $M_1 = m_1, ...M_k = m_k$ can be calculated as follows:

$$
\begin{aligned}
&Pr\left(M_1 = m_1, ...M_k = m_k | m_0 = 0\right) \\
&= \begin{cases} (1-p)^{n-n_1} \cdot \left[\displaystyle\sum_{i=1}^{n_1} b_i \cdot p^i (1-p)^{n_1-i}\right], & n_1 > 0 \\ 0, & n_1 = 0, \end{cases}
\end{aligned}
\tag{13}
$$

where n_1 is the number of vehicles that only belong to paths that deliver messages with content 1 to the destination vehicle, i.e., the number of Type 1 vehicles in the network, and b_i, $i = 1, 2, ...n_1$ is the number of combinations that exactly i malicious Type 1 vehicles leading to the occurrence of event $M_1 = m_1, ...M_k = m_k$.

Denote by event e_i' that randomly choosing i columns from sub-matrix B_1 and then conducting element-wise union operation to them, there results a column with each entry be 1. Denote by b_i, $i = 1, 2, ...n_1$ the total number of combinations that event e_i' occurs. Then we have

$$
b_i = \sum_{j=1}^{z_i'} I \left(\text{event } e_i' \text{ occurs}\right),
\tag{14}
$$

where $z_i' = \binom{n_1}{i}$. Therefore, this theorem can be readily proved following the same method as that used in the proof of Theorem 3, and hence is ignored.

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CHEN *et al.*: TOPOLOGICAL APPROACH TO SECURE MESSAGE DISSEMINATION IN VEHICULAR NETWORKS
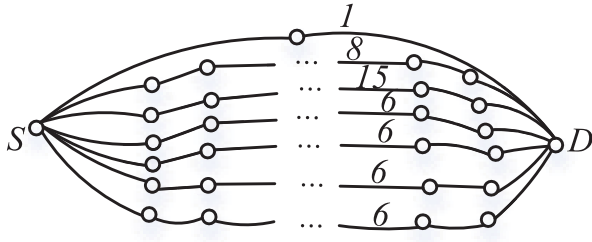
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Fig. 2. An illustration of a vehicular network that contains 7 independent paths from the source vehicle to the destination vehicle, each path containing 1, 8, 15, 6, 6, 6, 6 vehicles respectively.
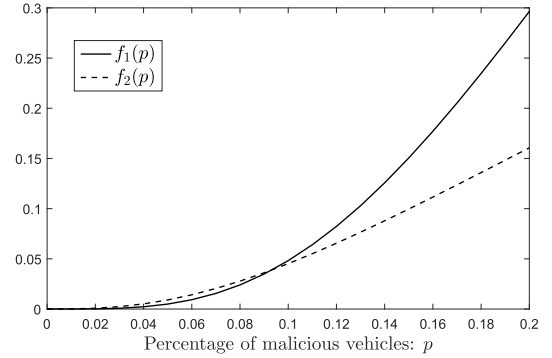

Fig. 3. An illustration to show that the percentage of malicious vehicles is indispensable in implementing the optimum decision algorithm to achieve an accurate decision result.

C. Discussion

From the analysis in Section III-B, we can see that the value of n_0, n_1, and a_i, $i = 1, 2, ...n_0$ in (10), b_i, $i = 1, 2, ...n_1$ in (13) can be obtained from the network topology matrix. That is, when the k received messages $M_1 = m_1, ...M_k = m_k$, and the network topology is given, the value of n_0, n_1, a_i, $i = 1, 2, ...n_0$, and b_i, $i = 1, 2, ...n_1$ are all determined. However, the exact values of $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)$ and $\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)$, shown also in (10) and (13), also depend on the proportion of malicious vehicles p in the network, which usually, is not easy to be obtained or estimated as a prior knowledge. In the following, we use a simple example to show the dependency on p of the proposed optimum decision algorithm.

Consider a network that contains a total of 7 independent paths from the source vehicle to the destination vehicle. The first three paths, containing 1, 8 and 15 vehicles respectively deliver messages with content 1 to the destination vehicle, and the other four paths, containing 6 vehicles each, deliver messages with content 0 to the destination vehicle. See Fig. 2 for an illustration.

According to (10) and (13), we have:

$$\Pr(M_1 = M_2 = M_3 = 1, M_4 = ... = M_7 = 0|m_0 = 1)$$
$$= (1-p)^{1+8+15} \cdot \left[1 - (1-p)^6\right]^4$$
$$= (1-p)^{24} \cdot \left[1 - (1-p)^6\right]^4, \tag{15}$$

and

$$\Pr(M_1 = M_2 = M_3 = 1, M_4 = ... = M_7 = 0|m_0 = 0)$$
$$= (1-p)^{6\times4} \cdot [1-(1-p)]\left[1-(1-p)^8\right]\left[1-(1-p)^{15}\right]$$
$$= (1-p)^{24} p \left[1 - (1-p)^8\right]\left[1 - (1-p)^{15}\right]. \tag{16}$$

Therefore,

$$\frac{\Pr(M_1 = M_2 = M_3 = 1, M_4 = ... = M_7 = 0|m_0 = 1)}{\Pr(M_1 = M_2 = M_3 = 1, M_4 = ... = M_7 = 0|m_0 = 0)}$$
$$= \frac{1 - (1-p)^6}{p\left[1 - (1-p)^8\right]\left[1 - (1-p)^{15}\right]} \tag{17}$$

Let

$$f_1(p) = 1 - (1-p)^6 \tag{18}$$

and

$$f_2(p) = p\left[1 - (1-p)^8\right]\left[1 - (1-p)^{15}\right], \tag{19}$$

and plot them with different values of p, see Fig. 3 for an illustration. We can see that the value of $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)}$ depends on the percentage of malicious vehicles in the network. Specifically, it is shown in Fig. 3 that when p is smaller than a threshold, e.g., $p_{th} = 0.092$ in this case, the value of $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)} = \frac{f_1(p)}{f_2(p)}$ is smaller than 1, while when p is larger than the threshold, the value of $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)} = \frac{f_1(p)}{f_2(p)}$ is larger than 1, and will further increase with an increase of p. Therefore, given the network topology, the optimum decision based on (4) relies on the value of p. This illustrates that the value of p is indispensable in adopting the optimum decision algorithm to achieve an accurate decision result.

IV. HEURISTIC DECISION ALGORITHM

As discussed in the Section III-C, the implementation of the optimum decision algorithm proposed in the last section relies on prior knowledge of the percentage of malicious vehicles p in the network, which is usually not easy to be obtained or estimated. In this section, to eliminate the dependence on p, we propose a heuristic decision algorithm for the destination vehicle to make a decision when receiving conflicting messages purely based on network topology information only.

The heuristic decision algorithm is derived from the principle of Maximum Likelihood Estimation [25], which can be described as follows:

$$d = \begin{cases} 1, & \frac{\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)}{\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)} > 1 \\ 0, & \frac{\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 1)}{\Pr(M_1 = m_1, ...M_k = m_k|m_0 = 0)} < 1, \end{cases} \tag{20}$$

where $M_1 = m_1, ...M_k = m_k$ are the k messages received by the destination vehicle, m_0 is the source message and d is the decision made by the destination vehicle. When $\frac{\Pr(M_1=m_1,...M_k=m_k|m_0=1)}{\Pr(M_1=m_1,...M_k=m_k|m_0=0)} = 1$, d is randomly chosen to be 0 or 1 with equal probability.

Based on the received messages $M_1 = m_1$, $M_2 = m_2$, ..., $M_k = m_k$ and the path information obtained from messages, the method of constructing the topology matrix B is the same as introduced in Section III-B, i.e., $B = \begin{bmatrix} B_1 & B_{s_1} & \mathbf{0} \\ \mathbf{0} & B_{s_0} & B_0 \end{bmatrix}$.

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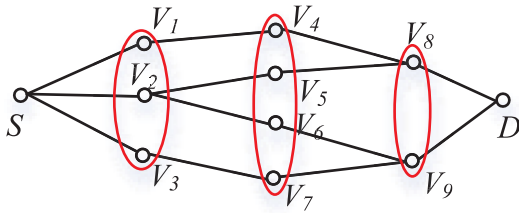IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS

Fig. 4. An illustration to show the malicious cut sets and minimal malicious cut sets of a network.

Therefore, by combining (10), (13) and (20), it is ready to have $d = \begin{cases} 0, & n_0 = 0 \\ 1, & n_1 = 0 \end{cases}$, and when $n_0 > 0$ and $n_1 > 0$,

$$
\begin{aligned}
&\frac{\Pr(M_1 = m_1, ... M_k = m_k | m_0 = 1)}{\Pr(M_1 = m_1, ... M_k = m_k | m_0 = 0)} \\
&= \frac{(1-p)^{n-n_0} \cdot \left[\sum_{i=1}^{n_0} a_i \cdot p^i (1-p)^{n_0-i}\right]}{(1-p)^{n-n_1} \cdot \left[\sum_{i=1}^{n_1} b_i \cdot p^i (1-p)^{n_1-i}\right]} \\
&= \frac{\sum_{i=1}^{n_0} a_i \cdot \left(\frac{p}{1-p}\right)^i}{\sum_{i=1}^{n_1} b_i \cdot \left(\frac{p}{1-p}\right)^i}.
\end{aligned}
\tag{21}
$$

Recall that both sub-matrix $\begin{bmatrix} B_1 & B_{s_1} & \mathbf{0} \end{bmatrix}$ and $\begin{bmatrix} \mathbf{0} & B_{s_0} & B_0 \end{bmatrix}$ correspond to a sub-network of the considered network and the common nodes shared by the two sub-networks (if any) can not be malicious vehicles. Therefore, when considering the potential malicious vehicle combinations, we avoid these common nodes and only focus on the sub-matrix B_1 and B_0. Specifically, we regard the network corresponding to sub-matrix B_1 and B_0 as networks that each row represents a complete path and each column represent a vehicle, denoted by T_1 and T_0 respectively. In the following, with a twist use of the vertex-cut [26] terminology from graph theory which defines a vertex set whose removal would disconnect the graph, we define *malicious cut set*, *size* of a malicious cut set, and *minimal malicious cut set* of a network in this paper, and demonstrate that the parameter a_i, $1 \le i \le n_0$ and b_i, $1 \le i \le n_1$ in (21), which was defined in (11) and (14), are exactly the number of malicious cut sets with size i of the network T_0 and T_1 respectively.

Definition 5: A *malicious cut set* of a network is a combination of vehicles, where if all vehicles in the set are malicious vehicles all paths of the network can be compromised. The *size* of a malicious cut set is the number of vehicles contained in the set. A *minimal malicious cut set* is a malicious cut set with the smallest size.

It is worth noting that the network may have multiple malicious cut sets and multiple minimal malicious cut sets. Consider the network shown in Fig. 4 for an example. Vehicle sets $\{V_1, V_2, V_3\}$, $\{V_4, V_5, V_6, V_7\}$, and $\{V_8, V_9\}$ (to name a few) are all malicious cut sets of the network, and a minimal malicious cut set is the malicious cut set $\{V_8, V_9\}$ with size 2. Therefore, to compromise all paths of this network, the minimum number of malicious vehicles needed is 2.

Based on Definition 5, if a vehicle set is a malicious cut set, then each path of the network contains at least one vehicle

belongs to this set. Recall that a_i (or b_i) represents the number of combinations that randomly choosing i columns from sub-matrix B_0 (B_1) and then conducting element-wise union to them, there results a column with each entry be 1. That is, a_i (or b_i) represents the number of combinations that by choosing i vehicles from Network T_0 (or T_1) to form a vehicle set, each path of network T_0 (or T_1) contains at least one vehicle belongs to this set. Therefore, a_i, $1 \le i \le n_0$ and b_i, $1 \le i \le n_1$ are exactly the number of malicious cut sets with size i of the network T_0 and T_1 respectively.

According to the properties of malicious cut sets, it can be readily obtained that $a_i = 0$ if $a_{i+1} = 0$, and $a_{i+1} > 0$, if $a_i > 0$. Similarly, we have $b_i = 0$ if $b_{i+1} = 0$, and $b_{i+1} > 0$, if $b_i > 0$.

Define

$$
r_0 = \min\{i : a_i > 0\}, \quad 1 \le r_0 \le n_0
\tag{22}
$$

and

$$
r_1 = \min\{i : b_i > 0\}, \quad 1 \le r_1 \le n_1,
\tag{23}
$$

the smallest integer that satisfies $a_i > 0$ and $b_i > 0$ respectively. Therefore, r_0 is the size of the minimal malicious cut set of network T_0, and a_{r_0} is the number of minimal malicious cut sets of network T_0. Similarly, r_1 is the size of the minimal malicious cut set of network T_1, and b_{r_1} is the number of minimal malicious cut sets of network T_1. This follows that

$$
\begin{aligned}
\frac{\Pr(M_1 = m_1, ... M_k = m_k | m_0 = 1)}{\Pr(M_1 = m_1, ... M_k = m_k | m_0 = 0)} &= \frac{\sum_{i=r_0}^{n_0} a_i \cdot \left(\frac{p}{1-p}\right)^i}{\sum_{i=r_1}^{n_1} b_i \cdot \left(\frac{p}{1-p}\right)^i} \\
&\approx \frac{a_{r_0} \left(\frac{p}{1-p}\right)^{r_0}}{b_{r_1} \left(\frac{p}{1-p}\right)^{r_1}},
\end{aligned}
\tag{24}
$$

where the first step is obtained from the fact that $a_1 = a_2 = ... a_{r_0-1} = 0$, $a_{r_0} > 0$, and $b_1 = b_2 = ... b_{r_1-1} = 0$, $b_{r_1} > 0$, and the second step is obtained by only keeping the first item of both the numerator and denominator. Considering the fact that when p is small, the probability that there are $i+1$ malicious vehicle in the network is much smaller than the probability that there are i malicious vehicles in the network, therefore, this approximation is quite accurate.

Note that when p is small, we have $\frac{p}{1-p} \ll 1$. Therefore, when $r_0 \ne r_1$, whether the value of $\frac{a_{r_0}\left(\frac{p}{1-p}\right)^{r_0}}{b_{r_1}\left(\frac{p}{1-p}\right)^{r_1}}$ shown as (24) is larger than 1 is dominantly determined by the value of $r_0 - r_1$. Specifically, when $r_0 < r_1$, we have $\left(\frac{p}{1-p}\right)^{r_0-r_1} \gg 1$. In this case, the coefficient $\frac{a_{r_0}}{b_{r_1}}$ plays marginal role and therefore $\frac{a_{r_0}\left(\frac{p}{1-p}\right)^{r_0}}{b_{r_1}\left(\frac{p}{1-p}\right)^{r_1}} > 1$; when $r_0 > r_1$, we have $\left(\frac{p}{1-p}\right)^{r_0-r_1} \ll 1$, and therefore $\frac{a_{r_0}\left(\frac{p}{1-p}\right)^{r_0}}{b_{r_1}\left(\frac{p}{1-p}\right)^{r_1}} < 1$. On the contrary, when $r_0 = r_1$, whether the value of $\frac{a_{r_0}\left(\frac{p}{1-p}\right)^{r_0}}{b_{r_1}\left(\frac{p}{1-p}\right)^{r_1}}$ is larger than 1 would heavily

depend on the value of the coefficient $\frac{a_{r_0}}{b_{r_1}}$. Consequently, we have

$$\frac{\Pr\left(M_1 = m_1, \ldots M_k = m_k | m_0 = 1\right)}{\Pr\left(M_1 = m_1, \ldots M_k = m_k | m_0 = 0\right)} \approx \frac{a_{r_0}\left(\frac{p}{1-p}\right)^{r_0}}{b_{r_1}\left(\frac{p}{1-p}\right)^{r_1}}$$

$$\begin{cases} > 1, & r_0 < r_1 \\ < 1, & r_0 > r_1 \\ = \frac{a_{r_0}}{b_{r_1}}, & r_0 = r_1, \end{cases} \quad (25)$$

which shows that to compare the values of $\Pr(M_1 = m_1, \ldots M_k = m_k | m_0 = 1)$ and $\Pr(M_1 = m_1, \ldots M_k = m_k | m_0 = 0)$, we only need to compare the values of r_0 and r_1, namely, the size of minimal malicious cut set of network T_0 and T_1 when $r_0 \neq r_1$, or the value of a_{r_0} and b_{r_1}, namely, the number of minimal malicious cut sets of network T_0 and T_1 when they have the same size of minimal malicious cut set.

From Menger's Theorem [26], the size of the minimal vertex-cut whose removal would disconnect two non-adjacent vertices, is equal to the maximum number of vertex-independent paths between these two non-adjacent vertices. Therefore, it can be concluded that the size of minimal malicious cut set of a network is also equal to the maximum number of node-disjoint paths in the network between the source vehicle and the destination vehicle. Therefore, r_0 and r_1 are also the numbers of maximum number of node-disjoint paths exist in network T_0 and T_1 respectively. Note that calculating the maximum number of vertex-disjoint paths from source to destination is a special case of finding the maximum flow problem by setting every vertex capacity 1 [26]. Therefore, the values of r_0 and r_1 can be readily obtained by existing maximum flow algorithms, e.g., introduced in [26]–[28]. When $r_0 = r_1$, a_{r_0} and b_{r_1} can be obtained by exhaustive search algorithm according to their definitions given by (11) and (14).

In summary, by combining (20) and (25), the decision rule of our proposed heuristic algorithm can be shown as

$$d = \begin{cases} 1, & (r_0 < r_1) \; or \; (r_0 = r_1, \; a_{r_0} > b_{r_1}) \\ 0, & (r_0 > r_1) \; or \; (r_0 = r_1, \; a_{r_0} < b_{r_1}), \end{cases} \quad (26)$$

and when $r_0 = r_1$, and $a_{r_0} = b_{r_1}$, d is randomly chosen from 0 and 1 with equal probability.

Remark 6: It is worth noting that in the above analysis, the network with a topology matrix B_1 may not be unique. For instance, a topology matrix $B = \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ can correspond to both networks shown in Fig. 5. However, the malicious cut sets of the networks with different topology remain the same as there is a one-to-one correspondence between each malicious cut set and a combination of columns from the topology matrix that an element-wise union of them resulting in a column with each entry being 1. That is, as long as networks have the same topology matrix B, they would have the same malicious cut sets. Therefore, the network T_1 (or T_0) corresponding to the same sub-matrix B_1 (or B_0) may not unique, however it does not affect their malicious cut sets analysis.
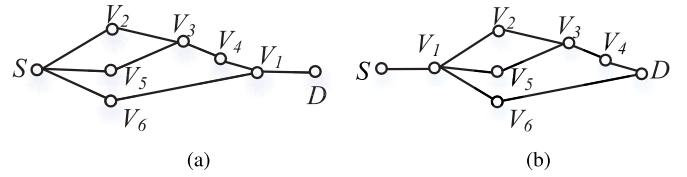

Fig. 5. An illustration of two networks that have the same topology matrix. (a) Network 1. (b) Network 2.

Remark 7: The implication of the heuristic decision algorithm (26) can also be explained straightforwardly as follows. Given two networks that deliver conflicting message contents, by removing the common nodes shared by these two networks and regarding each path after the removal of the common nodes as a new complete path, there results in two new independent networks that deliver conflicting message contents. Therefore, decision can be made by comparing the robustness of the two new networks. Note that a smaller size of the minimal malicious cut set of a network implies a less number of minimal malicious vehicles are required to compromise that network, and consequently, a higher probability to deliver incorrect messages. Therefore, the decision will always be chosen as the message delivered by the network with a lower probability to be compromised.

From (26), we can see that the decision result is now entirely determined by the network topology, and is independent of the proportion of malicious vehicles in the network. That is, the proposed heuristic decision algorithm is purely topology-based so that is easy to be implemented in practice. In summary, the heuristic decision algorithm works as detailed in Algorithm 2.

V. SIMULATION AND DISCUSSION

In this section, we conduct simulations based on real traffic data to establish the validity of the decision algorithms proposed in Section III and Section IV, as well as to demonstrate the application of our proposed algorithms in a real life situation to indicate their usefulness. We utilize the real traffic data collected by inductive loop detectors in Taipei city, including 1-minute averaged vehicular speed passing each loop detector, and the volume, i.e., the number of vehicles, passing the corresponding loop detectors during this 1 minute, to model real life traffic. Specifically, we choose the traffic data at 17:00 pm (peak hour, the traffic is congested) on the road segment, named Jianguo North Road, covered by 6 loop detectors (labeled by 'Loop 1' to 'Loop 6'), to build the considered vehicular network for our simulation. See Fig. 6 for an illustration. The interval distance between two consecutive loop detectors are 700m, 550m, 300m, 280m, and 240m respectively. Vehicles are moving in the direction from Loop 6 to Loop 1. We assume that at the specific minute we focused on, vehicles located between two loop detectors move at the same constant speed, the same as the average speed passing the next loop during this minute. For instance, we approximately regard vehicles located between Loop 1 and Loop 2 at 17:00pm travel at the same constant speed as the average speed vehicles passing Loop 1 at 17:00 pm.

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Algorithm 2 Heuristic Decision Algorithm

INPUT: $M_1...M_k$

OUTPUT: d

begin

1) Construct the topology matrix B based on the path information derived from the received k messages;
2) Based on the constructed topology matrix B, calculate r_0 and r_1 using the minimum cut algorithm;
3) **If** $r_0 < r_1$ **then** $d = 1$

    elseif $r_0 > r_1$ **then** $d = 0$

    else calculate a_{r_0} and b_{r_1} based on their definition given by (11) and (14);

    if $a_{r_0} > b_{r_1}$ **then** $d = 1$

    elseif $a_{r_0} < b_{r_1}$ **then** $d = 0$

    else d is randomly chosen to be 0 or 1 with equal probability

    end

    end

end

Fig. 6.   Target road segment.

We assume the source vehicle is exactly located at the location of Loop 1 when it detects the congestion at its location, and it would like to disseminate the congestion information to other vehicles moving towards the congestion area. Therefore, messages are disseminated in the direction from Loop 1 to Loop 6, which is opposite to the traveling direction of vehicles. Vehicles communicate with their neighbors adopting the unit disk model [17], [29] with a transmission range $r_0 = 250$m [30]. Each relay vehicles in the network has a probability p to be a malicious vehicle.
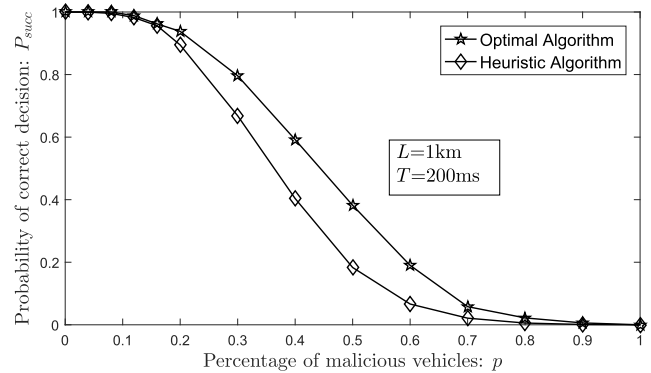
Fig. 7.   A comparison of the probabilities of correct decision achieved by the optimum decision algorithm proposed in Section III, and by the heuristic decision algorithm proposed in Section IV.

We focus on a destination vehicle located at a distance L from the source vehicle, and track the probability of correct decision made by the destination vehicle. From the time instant the destination vehicle receives the first message reporting road condition, it waits a fixed time period T to receive more number of messages before it starts to make a decision. The per-hop transmission delay is assumed to be $\beta = 4$ms [30].

At each simulation, a topology matrix B can be constructed based on the underlying network topology. Therefore, given the malicious vehicle distribution and the topology information, the content of the k messages $M_1, M_2, ...M_k$ received by the destination vehicle is determined. The destination vehicle then makes a decision given the received messages and the derived underlying topology information according to our proposed decision algorithms at each simulation. The decision result can be either correct or incorrect. The simulation is repeated 5000 times and the proportion of the correct decision, i.e., the probability of correct decision, is plotted.

In the following, we first compare our proposed two decision algorithms, and then we study the effects of topology information, and some performance-impacting parameters on the algorithms. The performance-impacting parameters including the proportion of malicious vehicle in the network, the choice of waiting time by the destination vehicle before it starts to make the decision.

A. Comparison of the Two Proposed Algorithms

In this part, we compare the message security performance achieved by the two proposed decision algorithms to provide insight on the optimum decision algorithm design for secure message dissemination.

Fig. 7 compares the probability of correct decision achieved by the proposed optimum decision algorithm (labeled as Optimum Algorithm) and by the proposed pure topology-based heuristic decision algorithm (labeled as Heuristic Algorithm) respectively. It is shown that when the percentage of malicious vehicles in the network is small, e.g., when $p < 0.15$ in this case, the message security performance achieved by the optimum decision algorithm is only slightly better than the performance achieved by the heuristic decision algorithm.

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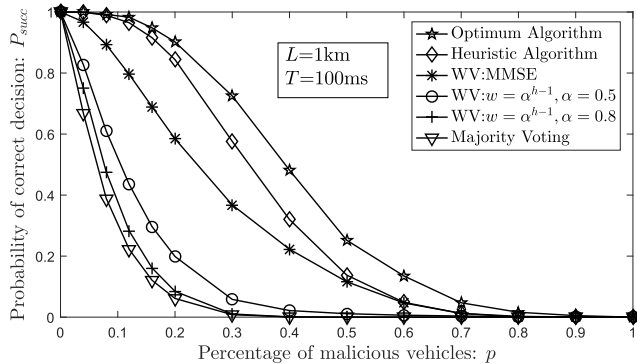

Fig. 8.   A comparison of the probability of correct decision achieved assuming our proposed algorithms and that achieved assuming other existing weighted voting algorithms.
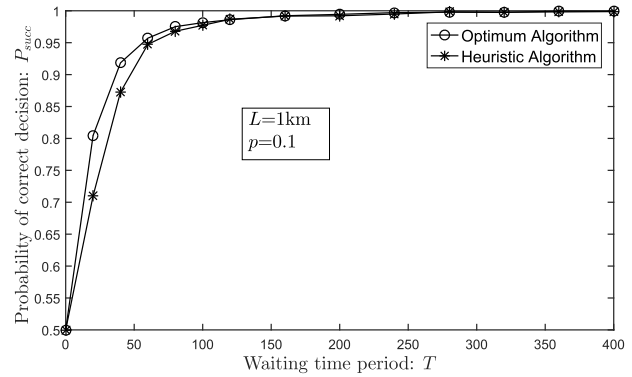

Fig. 9.   An illustration of the relationship between the probability of correct decision and the waiting time period the destination vehicle waits before it starts to make a final decision by adopting the proposed two algorithms respectively.

This implies that the heuristic decision algorithm, that purely based on network topology information and easily to be implemented in practice, is sufficient to achieve a high message security performance for vehicular networks.

B. Impact of Topology Information

To evaluate the effectiveness of our proposed algorithms that takes the underlying topology information into consideration, we compare the security performance, in terms of the probability of correct decision made by the destination vehicle, achieved by our proposed algorithms described by Algorithm 1 and 2 respectively, with that achieved by existing weighted voting algorithms like the weighted voting algorithm proposed in [23] (labeled with WV: MMSE) that considers partial correlation between messages, the weighted voting algorithm proposed in [14] (labeled with WV: $w \propto \alpha^{h-1}$) that does not consider the underlying topology information causing the correlation between messages, and the majority voting (a special case of weighted voting by assigning identical weights to each vote) that totally ignores the underlying topological correlation. Specifically, the weighted voting algorithm proposed in [23] set weight to each message as $w_i = \sum_{j=1}^{k} C_{ij}^{(-1)} \left(\sum_{r,j=1}^{k} C_{rj}^{(-1)} \right)^{-1}$, where C is the error covariance matrix whose (i, j)th entry is defined by the error covariance between message M_i and message M_j, calculated by $C_{ij} = E\left[(M_i - m_0)(M_j - m_0)\right]$. C^{-1} is the inverse matrix of the error covariance matrix C, and $C_{ij}^{(-1)}$ is the (i, j)th entry of the matrix C^{-1}. The weighted voting algorithm proposed in [14] simply assigns weight to each message as $w_i = \frac{\alpha^{h_i-1}}{\sum_j \alpha^{h_j-1}}$, where $\alpha \in (0, 1)$ is a weighting factor to reduce the oversampling impact caused by messages generated from the same source and h_i is the number of hops travelled by the ith message from the source to the destination.

It can be seen in Fig. 8 that both our proposed algorithms outperform the weighted voting algorithms proposed in [14] and [23] and the majority voting algorithm, which demonstrates that our algorithms taking into account topology information and correlation between different copies of message are

able to effectively improve the robustness of vehicle networks against attacks from malicious vehicles.

C. Impact of the Percentage of Malicious Vehicles

Fig. 8 reveals the relationship between the probability of correct decision P_{succ} and the percentage of malicious vehicles in the network, p. It can be seen that the probability of correct decision made by the destination vehicle decreases to its minimum value $P_{succ} = 0$ when the proportion of malicious vehicles in the network is larger than a certain threshold. Beyond that threshold, a further increase in p has little impact on the security performance. Specifically, as shown in Fig. 8, when p is small, the security performance achieved assuming the optimum decision algorithm decreases with an increase of p; however, when p increases beyond a certain threshold, a further increase in p has no impact on the security performance. This can be explained by the fact that the more malicious vehicles in the network, the more tampered copies of message will be delivered, and therefore a lower chance for the destination vehicle to make a correct decision regardless of what algorithm it adopts. Furthermore, when the number of malicious vehicles in the network reaches a certain threshold, most of the message dissemination paths will be compromised. In this case, the destination vehicle will totally misguided by the incorrect messages and the message security performance approaches its minimum value $P_{succ} = 0$.

D. Impact of the Waiting Time Period

As mentioned in Section II-C, the waiting time period T the destination vehicle waits before it starts to make a decision is an important parameter that should balance the trade-off between the response time requirement and the integrity of the decision. Therefore, in this part, we study the impact of the waiting time period T on the security performance assuming the two proposed algorithms, under different traffic densities.

Fig. 9 demonstrates the relationship between the probability of correct decision, P_{succ}, and the waiting time period T the destination vehicle waits before it starts to make a decision, assuming our two proposed algorithms respectively,

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TABLE I

APPROACHES FOR SECURE MESSAGE DISSEMINATION IN VEHICULAR NETWORKS

Approach	Description	Ref.	Advantages	Disadvantages
Entity-centric approach	Assess each vehicles' trustworthiness level	[31] [32] [33] [34]	Helpful to filter out malicious vehicles	Not suitable for vehicular networks with dynamic network topology
Data-centric approach	Check the consistency of data	[12] [13] [14] [15] [16]	Helpful to filter out false data	May cause oversampling issues when data is highly correlated
Combined approach	Assess each vehicles' trustworthiness level, and also check data consistency	[35] [36]	Helpful to filter out both malicious vehicles and false data	Algorithms may be too complicated to implement in practice
Our approach	Check the consistency of data by considering underlying network topology information	-	Significantly improve vehicular network message security performance, and easy to implement in practice	The optimum decision algorithm requires a prior knowledge on the percentage of malicious vehicles

and gives insight into the choice of waiting time by the destination vehicle. Importantly, we can see that for both algorithms, a larger number of waiting time is beneficial to the secure message dissemination because a longer waiting time potentially implies a larger number of received messages. This consequently, brings more information on the underlying network topology, and therefore leads to a more robust result of the data consistency check. However, when T increases beyond a certain threshold T_{th}, e.g., $T_{th} = 100ms$ when adopting the proposed optimum decision algorithm, a further increase in T has marginal (less than 3%) impact on the probability of correct decision. This is due to the fact that when T is larger than a threshold, the marginal return brought by waiting a longer time to the security performance is diminishing.

VI. RELATED WORK

For secure message dissemination in vehicular networks against insider malicious vehicles, the trustworthiness of each vehicle and the integrity of each transmitted message are two major factors need to be considered. Accordingly, three misbehavior detection schemes are commonly adopted to help prevent the disseminated messages from being tampered: entity-centric misbehavior detection scheme, data-centric misbehavior detection scheme, and a combined use of both. In the following, we will review works on these three schemes separately.

Entity-centric misbehavior detection schemes are commonly conducted at each vehicle by monitoring their instantaneous neighbors' behavior to assess their trustworthiness level, so as to filter out malicious vehicles. In [31], Gazdar *et al.* proposed a dynamic and distributed trust model based on the use of a Markov chain to evaluate the evolution of each vehicle's trust value. In [32], Ahmed *et al.* proposed a trust framework to identify malicious nodes in the network by evaluating the trust value of each vehicle, and the trust includes node trust and recommendation trust. In [33], motivated by the job market signaling model, Haddadou *et al.* proposed a distributed trust model for vehicular ad hoc networks (VANETs) that is able to gradually detect all malicious nodes as well as boosting the cooperation of selfish nodes. In [34], Sedjelmaci and Senouci proposed a lightweight intrusion detection framework with the

help of a clustering algorithm to overcome the challenges of intermittent and ad hoc monitoring and assessment processes caused by the high mobility and rapid topology change in vehicular networks.

Data-centric misbehavior detection schemes focus on the consistency check of the disseminated data to filter out false data. In [12], Dietzel *et al.* indicated that redundant data forwarding paths are the most promising technique for effective data consistency check in a multi-hop information dissemination environment, and proposed three graph-theoretic metrics to measure the redundancy of dissemination protocols. In [13], Raya *et al.* proposed a framework for vehicular networks to establish data-centric trust, and evaluated the effectiveness of four data fusion rules. In [14], Huang *et al.* firstly demonstrated that information cascading and oversampling adversely affect the performance of trust management scheme in VANETs, and then proposed a novel voting scheme that takes the distance between the transmitter and receiver into account when assigning weight to the trust level of the received data. In [15], Zaidi *et al.* proposed a rogue node detection system for VANETs utilizing statistical inference techniques to determine whether the received data are authentic. In [16], Radak *et al.* applied a so-called cautious operator to deal with data received from different sources to detect dangerous events on the road. Their adopted cautious operator is an extension of the Demper-Shafer theory that is known to be superior in handling data coming from dependent sources.

A combined misbehavior detection scheme makes use of both the trust level of vehicles and the consistency of received data to detect misbehaving vehicles and filter out incorrect messages. Works adopting the combined scheme are limited. In [35], Dhurandher *et al.* proposed a security algorithm using both node reputation and data plausibility checks to protect the network against attacks. The node reputation value is obtained by both direct monitoring and indirect recommendation from neighbors, to detect misbehaving vehicles; and the data consistency check is conducted by comparing the received data with the sensed data by the vehicle's own sensors. In [36], Li and Song proposed an attack-resistant trust management scheme to evaluate the trustworthiness of both data and vehicles in VANETs. They adopted the Dempster-Shafer theory to

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combine the data received from different sources, and then used this combined result to update the trust value of vehicles for misbehavior detection.

In summary, all the aforementioned works on protecting vehicular networks from insider attackers either focused on node trust model establishment and management to detect misbehaving nodes in the network, or focused on methods to assess data from different sources to check their consistency, but did not take the underlying network topological information into consideration. Our work distinguishes from theirs in that we focus on the received data itself, and utilize the underlying network topology information to design the decision algorithms for vehicles to check data consistency so as to maximally protect the authenticity of the disseminated messages. Concisely, Table I provides a comparative summary of approaches in the related work and our proposed approach.

VII. Conclusions

By utilizing underlying network topology information, this paper proposed two decision algorithms - the optimum decision algorithm and a heuristic decision algorithm - to address the issue of message inconsistency caused by insider malicious vehicles that would tamper the content of disseminated messages in the network. The proposed optimum decision algorithm is able to effectively help a destination vehicle maximally make a correct decision on the content of message, given the network topology information and the prior knowledge of the percentage of malicious vehicles in the network. The proposed heuristic decision algorithm further enables a vehicle to make a decision based on network topology information only and without the need for knowing the percentage of malicious vehicles which can be difficult to estimate in some circumstances, at a modest cost in performance. Therefore, the heuristic algorithm is easier to implement in practice. Simulations based on real traffic data were conducted to evaluate the effectiveness of two algorithms. It was demonstrated that the heuristic decision algorithm is able to achieve a security performance close to that achieved by the optimum decision algorithm, especially when the percentage of malicious vehicles is small. By comparing the two proposed algorithms with existing algorithms that do not consider the underlying topological information or only partially consider message correlation, it was shown that the proposed algorithms greatly outperform existing ones. Moreover, the impact of some key parameters on the performance of the proposed algorithms was discussed, including the percentage of malicious vehicles, and the waiting time the destination vehicle waits before making a final decision. A deeper insight revealed in our work is that messages coming from redundant paths are not equal and messages coming from diversified and independent paths carry more information than those from correlated paths. In this sense, we consider our work is just a first step towards the big direction of harnessing the network topology information to improve the vehicular network security. In the future, we would like to utilize more traveling information of vehicles in the network, like location, speed, direction, .etc, to design a more comprehensive topological approach, so as to further improve the vehicular network security.

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