TruMan: Trust Management for Vehicular Networks

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***Abstract*—By integrating processors and wireless communication units into vehicles, it is possible to create a vehicular ad-hoc network (VANET), in which cars share data amongst themselves in order to cooperate and make roads safer and more efficient. A decentralized ad-hoc solution, which does not rely on previously existing infrastructure, Internet connection or server availability, is preferred so the message delivery latency is as short as possible in the case of life-critical situations. However, as is the case with most new technologies, VANETs will be a prime target for attacks performed by malicious users, who may benefit from affecting traffic conditions. In order to avoid such attacks, one important feature for vehicular networks is trust management, which allows nodes to filter incoming messages according to previously established trust values assigned to other nodes. To generate these trust values, nodes use information acquired from past interactions; nodes which frequently share false or irrelevant data will have lower trust values than the ones which appear to be reliable. This work proposes a trust management model in the context of daily commutes, utilizing the Working Day Movement Model as a basis for node mobility. The results prove to be accurate and efficient, thanks to the low complexity of the algorithms constituting the trust model.**

I. Introduction

Within the next few years, a substantial share of new vehicles will come equipped with networking features [1]. These features will allow vehicles to quickly share data with other nearby devices and can be useful tools to reduce traffic and the risk of accidents. Over 1 million people lose their lives to traffic accidents every year [2], so solutions to improve road safety are crucial for modern life. By quickly sharing data with neighboring vehicles without the need of an Internet connection, smart vehicles can alert their drivers of important road conditions [3], while autonomous vehicles can synchronize their movements to maximize traffic throughput [4].

The communication stardard for vehicular communication is the IEEE 802.11p or Wireless Access in Vehicular Environments (WAVE) [5]. It describes two types of nodes for vehicular networks: on-board units (OBUs) and road-side units (RSUs). Communication between two OBUs is called vehicle-to-vehicle (V2V) communication, while communication between an OBU and an RSU is called vehicle-to-infrastructure (V2I) communication. This study focuses only on V2V scenarios, and therefore, any references to Vehicular ad-hoc networks (VANETs) and their nodes refer exclusively to vehicles with on-board units.

As is expected for new technologies, vehicular communications can become an appealing target for malicious users and attackers. Some issues that could be exploited in such network include: vehicles with faulty sensors [6]; vehicles broadcasting false data [7]; a flood of false data to generate a distributed denial of service (DDoS) scenario or to divert traffic [8]; eavesdropping on other vehicles' communications, signal jamming or stalking [6].

Each of these problems require specific solutions, although there are ways of making the network safer in general. One way is taking advantage of the concept of trust between network members. By having nodes remember previous interactions with one another, it is possible for them to build trust relationships and avoid those attacks that involve the spread of false data. Trust solutions for VANETs are generally classified into data-oriented trust, which emphasizes the contents of a message, and entity-based trust, which emphasizes the sender of a message.

This work proposes a new and improved entity-based trust model to compute the trust between any pair of nodes in a vehicular network. Using the proposed trust model, nodes in a vehicular network are able to identify which other nodes might be malicious. Since the network is dynamic, nodes acquire more knowledge as time passes and the algorithm's results become more precise, taking advantage of social properties of VANETs [9] [10] to build strong relationships between frequently connected nodes. Simulations demonstrate that nodes are able to correctly identify more than 95% of nodes in the network (malicious or not). Obviously, the algorithm correctness depends upon the velocity of the nodes, the frequency of the information exchange between them and the running time, i.e. the longevity, of the algorithm.

The remainder of this paper is organized as follows. Section IV shows some examples of existing trust models for vehicular networks and the trust model for static networks that served as basis for this one; section II explains the algorithms used to develop the trust model; section III shows the simulations which validate the usefulness of the trust model; and section V presents closing thoughts on the project.

II. Understanding the algorithm

The objective of the Truman trust model is to allow nodes to infer whether or not other nodes in the network are malicious. The algorithm that dictates the trust model runs continuously,

with iterations happening in preset intervals. In every iteration, a node collects information from its neighbors and runs a combination of algorithms to detect malicious nodes in the known network. This information is maintained in a directed graph $T = (V, E)$, in which V is the set of known vertices and E is the set of trust relationships between pairs $u, v \in V$. Graph T is known as the *trust graph*.

Each edge $(u, v) \in E$ stores a value between 0 and 1 which represents the degree of trust u has for v. This value is called the *opinion* of u about v. At the start of the execution, edges have value 0.5; this value increases when nodes have positive interactions and decreases otherwise. A threshold $0 < h < 1$ is used to define the minimum weight for an edge to be considered positive, meaning that the origin node trusts the destination node.

After collecting information from other nodes, Truman performs two steps: (i) it divides the network graph into strongly connected components using Tarjan's strongly connected components algorithm; (ii) it uses a graph coloring algorithm as a heuristic to determine which nodes to trust or not.

The detailed descriptions of both algorithms are below, followed by the complete process of each iteration of the Truman trust model.

A. Tarjan's strongly connected components algorithm

The use of Tarjan's strongly connected components algorithm [11] is an important aspect of Truman's efficiency. This allows a large graph to be abstracted into a smaller one, which therefore reduces the input for further steps. Given a directed graph $T = (V, E)$, a strongly connected component is defined as a group of nodes in which, for any pair of nodes $u, v \in V$, there exists a path from u to v and a path from v to u. For the purposes of trust management, this definition is extended to accept only paths of edges with weight above a predetermined threshold h. Every node of the input graph T must belong to a component.

The algorithm works by performing a depth-first search, adding nodes to a stack as they are visited. If two nodes are present on the stack, then there is a path from the first node to the second one (in the order they were added to the stack). Each node has two attributes assigned to it during the execution of the algorithm: $index$ is used to number the nodes in the order they are visited, while $lowlink$ is the lowest indexed node reachable from each node.

In the call that visits a node u, the algorithm must loop through each node v trusted by u (that is, $u \to v$ exists and has value greater than h). If node v has not yet been visited, the algorithm is called for v. The $lowlink$ of u is then calculated as the smallest value between $lowlink[u]$ and $lowlink[v]$, because any node reachable from v is also reachable from u. After the loop, if $lowlink[u]$ is equal to $index[u]$, it means that u is the lowest indexed node reachable from itself and that it is the root of a component. Therefore, nodes must be popped from the stack until u is found. Each node popped, including u, is a member of a strongly connected component.

The number of components is, at most, $|v|$: in a worst-case scenario, each node is placed into its own component.

Algorithm 1 shows the general structure of Tarjan's algorithm [11]. The complexity of the algorithm is $O(|V| + |E|)$ for a graph $T = (V, E)$.

With the results of Tarjan's algorithm, an undirected component graph $C = (V', E')$ is formed. Each $v' \in V'$ is the abstraction of one component identified by Tarjan's algorithm, while the edges $e' \in E'$ are edges from T between nodes that do not belong in the same component.

Algorithm 1 Tarjan's strongly connected components algorithm

```
1:  function TARJAN(vertex u)
2:      index[u] = count
3:      lowlink[u] = count
4:      count ← count + 1
5:      push u to stack
6:      for v in neighbors of u  do
7:          if weight of u → v < h then
8:              continue
9:          if index[v] = −1 then    // v has not been visited
    yet
10:             Tarjan(v)
11:         lowlink[u] ← min(lowlink[u], lowlink[v])
12:     if lowlink[u] = index[u] then
13:         repeat   // unstack nodes until u is found
14:             pop w from stack
15:             add w to component
16:         until w = u
```

B. Graph coloring with minimum colors

The algorithm proposed in [12] is an efficient approach to graph coloring. Graph coloring is one of the possible heuristics used to detect malicious nodes after the generation of the component graph using Tarjan's algorithm. Out of the tested heuristics, it presents the best results, so it has been chosen as the heuristic for the trust model.

It has been mathematically proven that any planar graph can be colored with at most four colors [13], but discovering the smallest number of colors necessary to color an arbitrary graph (called the graph's chromatic number) is an NP-hard problem [14]. In [12], the authors propose to color a graph using the minimum possible amount of colors. Although they do not prove that their algorithm always uses the smallest possible amount of colors, the output is always a correct coloration and the algorithm is nevertheless efficient. The complexity of the algorithm is $O(|E'|)$ for a graph $C = (V', E')$. As a comparison, the classic DSATUR algorithm for graph coloring has complexity $O(|V'|^2)$ [15].

Algorithm 2 shows the general structure of the graph coloring algorithm [12] [16].

A limitation of this algorithm is that the edges must be sorted according to node indexes beforehand. It does not matter which nodes get assigned which indexes, but once they

are assigned those numbers, the algorithm must follow the edges in numerical order. This is demonstrated in [16].

Algorithm 2 Graph coloring with minimum colors

```
1: function COLORING(graph G)
2:     color all nodes of G with 0
3:     d → 0
4:     for e = (u, v) in edges of G do
5:         if u and v have the same color then
6:             if color[v] = d then
7:                 d → d + 1
8:             color[v] → d
```

C. The Truman algorithm

Truman is based on the MaNI algorithm [17], which suggested the use of Tarjan's algorithm and the graph coloring algorithm used here. However, MaNI was developed for static networks such as social networks, and is executed by an external supervising agent (i.e. outside of the network), making it unsuitable for a vehicular network.

In order to work with dynamic networks, the Truman algorithm runs iterations at predetermined intervals. Furthermore, the algorithm runs in a decentralized fashion, meaning each node in the network runs its own instance of the algorithm. Each node starts knowing information only about itself and maintains its own abstraction of the network surrounding it. Every node u stores a model of the network in the form of a static, connected and directed trust graph $T = (V, E)$, in which V is the set of nodes u is aware of and E is the set of trust relationships (opinions) u knows about between members of V. Since each node has its own model and the model changes over time, there is a $T_i^u = (V_i^u, E_i^u)$ for every node u and iteration i.

At first, the node is collecting and organizing information. A prerequisite of this step is a test that correctly classifies a neighboring node as benign or malicious. There are several ways to perform such a test, but a study between these methods is out of the scope of this paper. Every time a neighboring node v is tested as benign, the trust graph T_{i-1}^v is merged into u's trust graph. After this, a new T_i^u is formed, which is then used for the following steps.

After the collection of data, T_i^u is separated into strongly connected components using Tarjan's algorithm [11]. For each node in a component, there is a path formed by edges of weight higher than the threshold h to each other node in the same component. In other words, within a single component, all nodes trust one another directly or indirectly; nodes that do not satisfy this condition are separated into different components. Each of these components becomes a node of a component graph $C_i^u = (V_i'^u, E_i'^u)$.

The creation of C_i^u simplifies the remaining computation. Since each vertex $v' \in V_i'^u$ is a component of T_i^u in which all nodes trust each other, for the purposes of identifying malicious nodes, all nodes within each of those components can be treated as the same. They can either be benign nodes which legitimately trust one another, or malicious nodes colluding with each other. After the formation of C_i^u, a heuristic is used to classify the nodes as benign or malicious.

In this study, the coloring heuristic is used to classify nodes, which uses the algorithm described in subsection II-B [12], although other heuristics may be considered. After running the graph coloring algorithm with graph C_i^u as input, the color whose nodes in C_i^u represent the most nodes in T_i^u is classified as correct, and all others are classified as malicious. Once this information from C_i^u is brought back to graph T_i^u, it is trivial to label the nodes in T_i^u as either benign or malicious based on their components' classifications.

The complexity of the whole algorithm can be calculated by adding the most costly operations involved. As discussed above, Tarjan's algorithm has a complexity of $O(|V|+|E|)$ (for the trust graph T), while the graph coloring algorithm has a complexity of $O(|E'|)$ (for the component graph C). The most costly part of the algorithm is the graph merge operation that happens between trusted nodes. The complexity of the graph merge algorithm is $O(|E|)$ for each neighbor a node has in an iteration; this number is at most $|V|$. The total complexity of Truman is therefore $O(|V| + |E|) + O(|E'|) + O(|V| \times |E|)$. Since $|O'| \leq |E|$ and $|V| + |E| \leq |V| \times |E|$, the complexity can be simplified to $O(|V| \times |E|)$.

In summary, every node u runs the following steps in each iteration to detect malicious nodes in the network:

1) Node u checks who are its neighbors (nodes within its communication range). Newly discovered nodes and newly formed edges are added to T_i^u. Edges are created with weight 0.5.
2) Node u tests all of its neighbors to discover which ones can be directly trusted or not. New trust values are computed for the edges using the average between the previous value and either 1 (if the neighbor is trustworthy) or 0 (otherwise).
3) If a neighbor v is trustworthy, u merges T_{i-1}^v into T_i^u.
4) Tarjan's algorithm is executed to identify the strongly connected components of T_i^u, resulting in a component graph C_i^u.
5) The graph coloring algorithm is executed on C_i^u and nodes are classified as benign or malicious.

III. Results

In order to test the Truman trust model, simulations were made using an implementation of the algorithm in Python. To generate the input graphs with node mobility, the ONE simulator [18] was used in conjunction with the Working Day Movement Model [19], which provides strong similarity with vehicle movement in real life. Snapshots of the network were taken every 10 simulated seconds, and these snapshots were used as input for the algorithm.

Most of the parameters for the simulator were taken from the article detailing the Working Day Movement Model [19]. Different parameters are shown in Table I. Since this simulation is for vehicles instead of pedestrians, there are no buses in the model and every node is guaranteed to own a vehicle

TABLE I: Simulation parameters

Parameter	Value
Duration	86400 seconds
Work day length	28800 seconds
Std. dev. departure time	7200 seconds
Node velocity	7 10m/s
Simulation area	approximately 14km^2
Number of nodes	150 (WDMM) + 10 (random)

and travel by car. The parameters regarding offices, meeting spots and shopping were kept intact. A small part of nodes move randomly to simulate vehicles that do not follow daily patterns.

A. Network Density

The communication range of nodes vary from 10m to 50m, to illustrate the impact of different network densities. The network density (δ) is a value which abstracts the volume and frequency of connections in a vehicular network by estimating how much of the environment is covered by the network. For Truman, higher densities yield better results, since nodes can construct and update their models of the network faster (this is demonstrated in subsection III-B). It is calculated using the transmission range of the nodes (σ), the amount of nodes(η), and the total area of the simulation(α).

The coverage of a single node is the circumference around it formed by the transmission radius; this is multiplied by the number of nodes in the network to estimate the maximum coverage area. Finally, the value is divided by the total area of the environment. formula is as follows:

$$\delta = \frac{\frac{\sigma^2 \pi}{2} \times \eta}{\alpha}$$

Simulations shown here have densities that varying between 0.001 (10m range) and 0.04 (50m range). As a comparison, the density of São Paulo was calculated as 2.24 with 10m range, a value much higher than what is necessary for a satisfactory performance of the algorithm.

B. Simulations

To improve readability, all figures in this section follow the same format:

- X axis shows the results of sequential iterations, ranging from 0 to 8639;
- Y axis shows a percentage of all nodes in the network, ranging from 0 to 100;
- Blue line represents the percentage of nodes detected out of the complete network;
- Magenta is the percentage of malicious nodes in the network (ground truth);
- Green represents the nodes correctly identified as malicious (true positives);
- Cyan represents the undetected malicious nodes (false negatives);
- Red represents the benign nodes incorrectly identified as malicious (false positives).

Figure 1 shows the results of simulations running with 10% of nodes acting maliciously, with communications range varying from 10m to 50m. It is possible to see how the increase in the communication range allows the algorithm to converge much sooner, taking over 8000 iterations with 10m range and achieving solid results at just over 1000 iterations with 50m range.

Figure 2 and **??** show the variation of results for different amounts of malicious nodes in the network. By the end of one day, the algorithm is able to detect all malicious nodes when they are up to 30% of the network. At 40%, a small part of malicious nodes are yet to be detected. At 50%, as expected, the results are inconsistent the network is completely split between benign and malicious nodes; at this point, the network is completely compromised. The amount of malicious nodes also affects convergence of the algorithm, since nodes do not trust information from malicious neighbors.

Figure 3 shows the execution of the algorithm over the course of 7 days. Most malicious nodes are identified by the end of the first day; in the following iterations, the algorithm finishes building the network model and sorts out remaining false negative or false positive results. After iteration 20000, the results are completely consistent.

IV. Related work

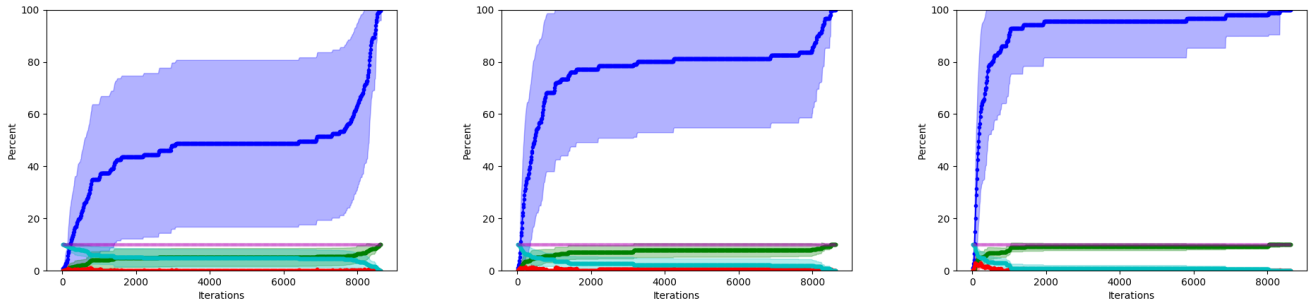
Several models have been proposed to solve the problem of trust in vehicular networks. The analysis of related work is based on [20], which proposes eight desired properties of a trust management model for VANETs. In the first part of this section, these properties are described with an assessment of whether or not Truman satisfies their conditions. Then, some of the most relevant models are described, considering how well they satisfy the desired properties and Table II shows how they compare with Truman.

A. Desired properties

The first property is *decentralized trust establishment*, which means nodes must be able to form their own trust values about other nodes. Nodes may or not use information from other trustworthy nodes to build trust values. Truman satisfies this as it is built from the ground up for decentralized systems.

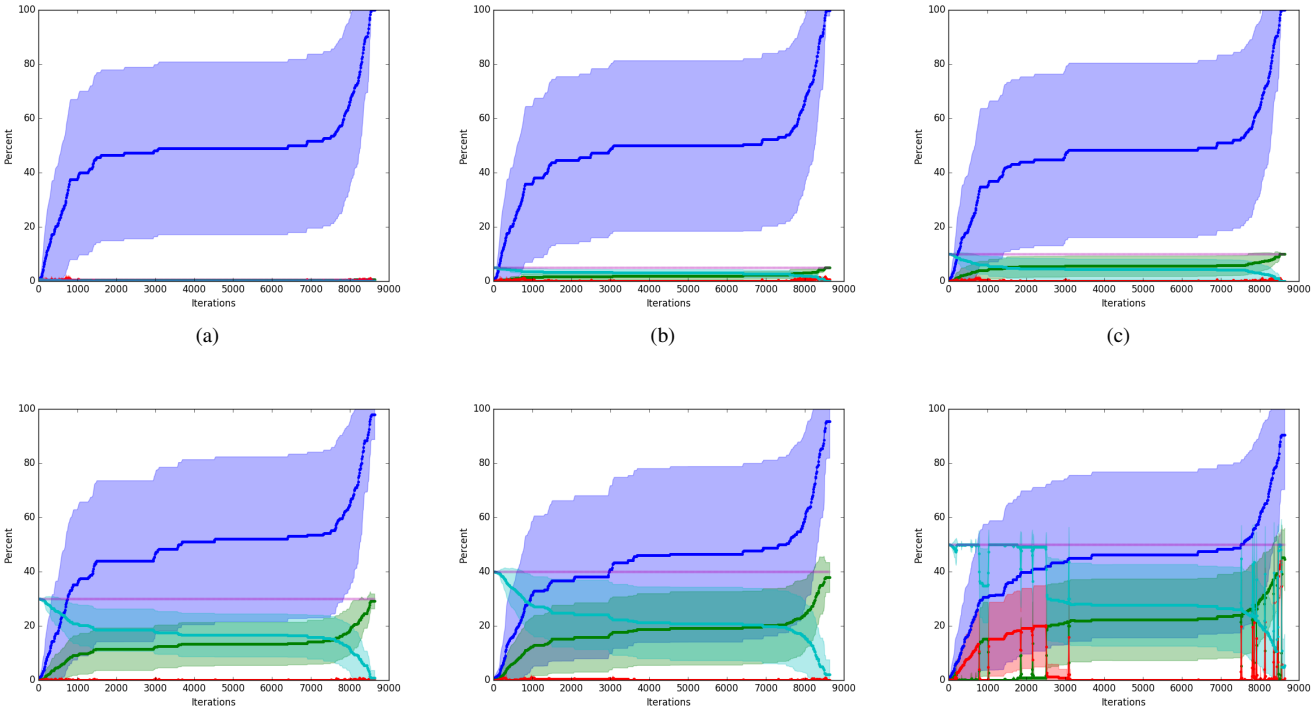
The second is *coping with sparsity*, meaning the model still functions when there are few nodes populating the network. The experiments using low density values demonstrate that Truman works in reasonably sparse networks. Due to its decentralized nature, it can also work on isolated chunks of the network.

Then there are *event/task and location/time dynamics*, which is how the model reacts to different situations depending on what, where and when events happen. Although this has not been used in the simulations in this paper, Truman can easily be extended to receive time and location dynamics as long as nodes store the geolocation and timestamp data when it acquires new information.



(a) (b) (c)

Fig. 1: Simulation with random nodes, 10% malicious and range of (a) 10m, (b) 30m and (c) 50m.



(a) (b) (c)

(d) (e) (f)

Fig. 2: Simulation with random nodes, range of 10m and (a) 1%, (b) 5%, (c) 10%, (d) 30%, (e) 40% or (f) 50% malicious.

The fourth desired property is *scalability*, meaning the model can work on very large networks at high speeds. Due to the low complexity of the algorithms used in the model, Truman can be highly scalable, as it does not put substantial pressure on the vehicles' on-board units. It has also been demonstrated that iterations of the algorithm do not need to run extremely frequently in order to detect malicious nodes with high accuracy.

The fifth is an *integrated confidence measure*, a value that allows nodes to estimate just how useful the output of the algorithm is. Since nodes using Truman store trust values as a number between 0 and 1, this value can be used as a confidence measure of the opinion. The closer it is to 1, the higher the chance that it is accurate.

The sixth is *system level security*, which requires authentication of nodes participating in the network. This has not been used in simulations of Truman, but can be included as a separate security model during the transmission of messages.

The seventh is *sensitivity to privacy concerns*, which avoids eavesdropping and stalking by malicious nodes. Truman has not been designed with this in mind, but it doesn't inhibit privacy protection, however it does require that nodes cannot be completely anonymous — there must be some way of identifying the same node over time.

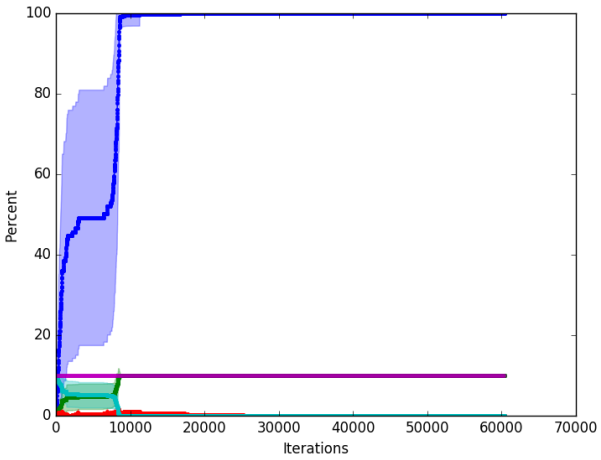


Fig. 3: Simulation with random nodes, range of 10m and 10% malicious during 7 days.

Finally, there is *robustness*, which is the model's resistance to attacks. Truman satisfies this as malicious nodes are usually identified quickly and accurately, making it difficult for them to perform attacks.

B. Comparison with other trust models

For the Malicious Node Identification Algorithm (MaNI) proposed in [17], the authors present a malicious node identification scheme based on strongly connected components and graph coloring. The model is proposed for complex networks in general, but is designed only for static networks and the algorithm relies on a global observer which has information about the complete network. It is, however, very efficient thanks to the classification of nodes into components and the usage of a fast heuristic. The usage of strongly connected components and coloring serve as basis for Truman, which is expanded to work on distributed and dynamic networks such as vehicular networks.

The model proposed in [21] uses several criteria to judge whether or not a received message is trustworthy. First, nodes are classified by their roles, used for vehicles which should be automatically trustworthy (i.e. police cars). Nodes also store their experience each time an event message is received (if one neighboring node reported an event which did not turn out to be true, its trust value is reduced). Additionally, messages have higher reliability when their senders are closer in time and space to the reported event. When several messages about the same event are received, a node can either choose the n most trustworthy senders, according to the priority (fewer chosen nodes means a faster, but less precise, decision), or compute the majority opinion of the messages according to each sender's trust value. However, the model relies only on direct interaction between pairs of nodes, so no form of indirect trust (that is, trust values received from other nodes) is considered.

In [22], the authors propose to evaluate messages utilizing a cluster-based trust model. By separating nodes into clusters with their geographical neighbors, it is possible to efficiently distribute the evaluation of messages using previously formed opinions. When a node sends a message, one node in the cluster (the leader) must aggregate the other nodes' opinions on that message. Afterward, the message is only forwarded to another cluster if that aggregate opinion is above a certain threshold; additionally, nodes that receive the message only act upon it if the overall trust on it is above another threshold, which can be different according to the nature of the message. However, it is unclear how the model behaves when the network is too sparse to form relevant clusters, neither do the authors inform how the aforementioned thresholds are decided. Furthermore, maintaining clusters in a highly dynamic network is a costly job and, if the cluster leader itself is malicious, all the information from that cluster becomes untrustworthy.

The ART model proposed in [23] is similar to Truman in the sense that there are two main steps: data gathering and malicious node detection. It uses the Dempster-Shafter theory of evidence to merge data coming from other nodes. Then, it uses a Cosine-based metric to compare two nodes' trust vectors (a series of opinions regarding other nodes). However, these steps require several intensive calculations, which greatly increases the complexity of the algorithm. The authors present no details on how the model deals with sparsity, dynamics, scalability, security and privacy.

The authors of [24] propose a cloud-based solution for a trust model, which requires an Internet-based global trust manager. This has the advantage of simplifying properties such as handling sparsity and scalability, but also makes the system slower in general, especially in situations when cellular communication is slow or unreliable. It also makes the system prone to attacks, since the whole system collapses if the global trust manager is attacked.

Finally, it is worth noting that, aside from MaNI, none of the mentioned related work presents complexity calculations for their algorithm. Considering the scale of the problem, Truman's cost of $O(|V| \times |E|)$ is very low without sacrificing quality. The model still satisfies or permits most of the desired properties of a trust model, making it viable for real-world use.

TABLE II: Properties of Truman and related work

Property	Truman	[16]	[21]	[22]	[23]	[24]
Decentralized	✓	-	✓	✓	✓	-
Sparsity	✓	-	✓	✓	-	✓
Dynamics	✓	-	✓	✓	-	-
Scalability	✓	✓	✓	✓	-	✓
Confidence	✓	✓	✓	✓	✓	-
Security	✓	-	✓	✓	-	✓
Privacy	-	-	✓	-	-	✓
Robustness	✓	-	-	-	✓	-
Efficiency	✓	✓	-	-	-	-

V. Conclusion

While malicious nodes can diminish the usefulness of vehicular networks, the concept of trust as applied in VANETs is a powerful tool for those seeking to reduce the spread of false information as much as possible. In this paper, a new trust model for vehicular networks was presented, which combines the efficiency of previous algorithms in order to generate fast and accurate results.

As nodes travel across the network and collect more data from neighbor, they are able to form an abstraction of the network which can be used to detect malicious nodes. By placing nodes into strongly connected components, a network containing a large amount of node can be simplified into a much smaller one. And, using a simple graph coloring algorithm, most malicious nodes stand out by having colors different than the majority of nodes. This allows for a low complexity approach to malicious node identification in a dynamic network.

The experiments show that vehicles within a network can form a sufficient model of the network in around one day, and by then they are also able to detect nearly every malicious node in the network, with a small amount of false positives. As the network changes in shape, nodes acquire more information and are able to make even more accurate classifications of malicious nodes around them.

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