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TruMan: Trust Management for Vehicular Networks

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Resumo

À medida em que computadores tornam-se menores e mais poderosos, a possibilidade de integrá-los a objetos do cotidiano é cada vez mais interessante. Ao integrar processadores e unidades de comunicação sem fio a veículos, é possível criar uma rede veicular ad-hoc (VANET), na qual carros compartilham dados entre si para cooperar e criar ruas mais seguras e eficientes. Uma solução descentralizada ad-hoc, que não depende de infraestrutura pré-existente, conexão com a internet ou disponibilidade de servidores, é preferida para que a latência de entrega de mensagens seja a mais curta possível em situações críticas. No entanto, assim como é o caso de muitas novas tecnologias, VANETs serão um alvo de ataques realizados por usuários maliciosos, que podem obter benefícios ao afetar condições de trânsito. Para evitar tais ataques, uma importante característica para redes veiculares é gerenciamento de confiança, permitindo que nós filtrem mensagens recebidas de acordo com valores de confiança previamente estabelecidos e designados a outros nós. Para gerar esses valores de confiança, nós usam informações adquiridas de interações passadas; nós que frequentemente compartilham dados falsos ou irrelevantes terão valores de confiança mais baixos do que os que aparentam ser confiáveis. Este trabalho propõe um modelo de gerenciamento de confiança no contexto de trajetos diários, utilizando o *Working Day Movement Model* como base para a mobilidade de nós. Este modelo de movimentação permite a comparação entre VANETs e redes sociais tradicionais, pois é possível observar que pares de veículos podem se encontrar mais de uma vez em diversos cenários: por exemplo, eles podem pertencer a vizinhos ou colegas de trabalho, ou apenas tomar rotas similares diariamente. Através de repetidos encontros, uma relação de confiança pode ser desenvolvida entre um par de nós. O valor de confiança resultante pode também ser usado para auxiliar outros nós que podem não ter uma relação desenvolvida entre si. O algoritmo proposto é baseado em um já existente, que foi desenvolvido para redes centralizadas e focado em modelos ad-hoc estáticos; o algoritmo anterior será adaptado para servir uma rede descentralizada e dinâmica, que é o caso de VANETs. Usando valores de confiança existentes, um grafo direcionado é modelado, no qual arestas representam a relação de confiança entre os pares de nós. Então, componentes do grafo são formados, de forma que nenhum par de nós em um componente tenha uma relação de confiança negativa. Um algoritmo de coloração de grafo é usado no grafo de componentes resultantes e, usando os resultados de coloração, é possível inferir quais nós são considerados maliciosos pelo consenso da rede. Espera-se que o algoritmo completo final seja rápido, para que ele possa ser executado frequentemente, e permita que nós mantenham um modelo da rede ao seu redor indicando quais nós vizinhos podem ou não ser confiados.

Palavras-chave: redes veiculares, gerenciamento de confiança, identificação de nós maliciosos.

Abstract

As computers become small and powerful, the possibility of integrating them into everyday objects is ever more appealing. 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 doesn't 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. This movement model allows the comparison of VANETs to traditional social networks, because it can be observed that pairs of vehicles are likely to meet more than once in several scenarios: for example, they can belong to neighbors or work colleagues, or simply take similar routes every day. Through these repeated encounters, a trust relationship can be developed between a pair of nodes. The resulting trust value can also be used to aid other nodes which might not have a developed relationship with each other. The proposed algorithm is based on a previously existing one, which was developed for centralized networks and focused on static ad-hoc models; the previous algorithm will be adapted to serve a decentralized and dynamic network, which is the case of VANETs. Using existing trust values, a directed graph is modeled in which edges represent the trust relationship between pairs of nodes. Then, graph components are formed in which no pair of nodes within a single component has a negative trust relationship. A graph coloring algorithm is used on the resulting components graph and, using the coloring results, it is possible to infer which nodes are considered malicious by the consensus of the network. The complete algorithm is expected to be fast, so it can be executed frequently, and will allow nodes to maintain a model of the surrounding networks indicating which neighboring nodes can be trusted or not.

Keywords: vehicular networks, trust management, malicious node identification.

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List of Acronyms

DTN	Delay-Tolerant Network
GPS	Global Positioning System
LTE	Long-term Evolution
MANET	Mobile Ad-hoc Network
WDM	Working Day Movement Model
OBU	On-Board Unit
RSU	Road-Side Unit
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VANET	Vehicular Ad-hoc Network
WAVE	Wireless Access in Vehicular Environments

Lista de Símbolos

δ	Network density (see subsection 5.4.1).
ρ	Transmission range.
η	Number of nodes in a network.
α	Area of a simulation.
π	The constant pi.

Chapter 1

Introduction

As computers grow in power and shrink in size, more aspects of everyday life can be enhanced by adding processing units to common devices. While many of these applications focus on conveniences, such as home automation [McCole, 2016] (the collection of connected and smart devices is dubbed the Internet of Things or IoT [Morgan, 2014]), the integration of computers with other objects and devices can also be important to save time and save lives [Real-Time Innovations, 2014]. One way of achieving this is by adding computers and wireless transmitters to vehicles — such as cars, buses, and trains — so they can share data which may increase traffic efficiency or reduce the chance of accidents [Saini et al., 2015].

In 2013, an estimated 1.25 million people lost their lives due to traffic accidents globally [World Health Organization, 2013]. While this number has greatly reduced over the past decades [Johnson, 2010] thanks to better safety features (seat belts, air bags, ABS, etc.) and stronger laws (drunk driving, motorcycle helmets, speed limits, etc.), it may still rise as a major cause of death in the years to come [World Health Organization, 2015], so further actions are necessary. Furthermore, as the car population increases, congestions consume ever more time of the daily commuter, peaking at over 100 hours per year for the residents of Los Angeles, CA [INRIX, 2017].

Smart vehicles and vehicular networks are ways that technology can aid both of the aforementioned problems. Through the use of sensors and wireless communications, these vehicles are able to avoid accidents by alerting distracted drivers [Lee et al., 2004], or by knowing in advance another vehicle's position and speed [Hafner et al., 2011]. By communicating, they can also collaborate to offer driving and route suggestions, therefore reducing the possibility of traffic jams [Knorr et al., 2012].

When dealing with safety or traffic-efficiency applications, it is crucial that network communications occur with low latency (approximately 100 milliseconds [CAMP Vehicle Safety Communications Consortium, 2005]). Current cellular technology, such as LTE, could be used to connect vehicles to the Internet, but the delay added by the transmission would make safety applications unfeasible or unreliable [Mangel et al., 2010]. Cellular connections also have other problems: the connection would require an active subscription with a carrier; the connection

depends on available infrastructure; the wireless frequency would be shared with phones and other mobile devices, increasing the possibility of interference and congestion; server-side issues could impact the vehicles' communications.

For these reasons, ad-hoc solutions are preferred over centralized ones. An ad-hoc network is one that has no reliance on pre-existing infrastructure (such as routers or access points) [Wu and Stojmenovic, 2004]. Instead, each node is able to communicate directly with others and a routing protocol allows for messages to be forwarded until they reach their destinations. Every time a node wants to send a message and the recipient is not a direct neighbor, it must choose which nearby node is the most likely one to get the message to its destination. Routing techniques can use either the network's topology or geographical coordinates [Saini et al., 2015] to choose which node should be the next hop.

These issues — the additional safety and efficiency as well as the low-latency communications — can be tackled through the use of a vehicular ad-hoc network (VANET), in which vehicles share data amongst themselves without relying on external devices, an Internet connection or server availability. Neighboring vehicles can share their position and velocity data at high frequencies, allowing, for example, for autonomous vehicles to plan a platooning approach to traffic [Amoozadeh et al., 2015]. In the case of a collision or other event, nearby nodes can broadcast alerts, which other nodes pick up and forward [Li and Wang, 2007]. That way, an alert can travel long distances in little time, allowing approaching vehicles to safely slow down or pick alternative routes.

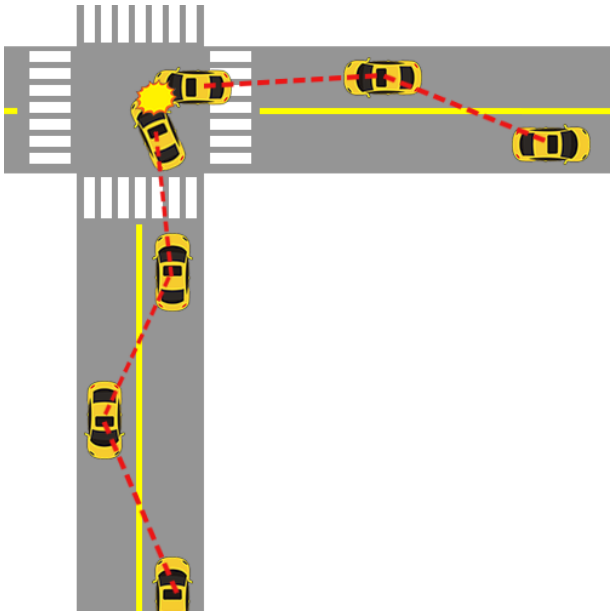


Figure 1.1: Propagation of a collision alert in a VANET

As is the case with most new technologies, VANETs are expected to be a notable target of attacks for a diversity of reasons [Isaac et al., 2010]. A local malicious user might alter the data his or her vehicle broadcasts in order to manipulate traffic conditions, while remote attackers could invade vehicles' computers and obtain partial control of the network [Garip et al., 2015].

These attacks can vary from time-consuming annoyances to life-threatening, so it is important that real-world implementations of vehicular networks are prepared to handle them.

In ad-hoc networks, one way to mitigate a number of attacks is through each node using data collected from previous experiences to filter out incoming messages that seem to be malicious, incorrect, or irrelevant. A node's degree of confidence that some data is correct and useful is called *trust*. For instance, in the example of a single malicious user broadcasting false data, nodes receiving these messages can use their own sensors to verify whether or not the data was correct, and update the *trust value* of the sender vehicle. In case the trust value of a sender is too low, a receiver node can choose to ignore the data contained in a message, as it concluded that the sender is not trustworthy. Trust allows for better cooperation of nodes in a network, since incorrect messages might be detected and discarded.

Furthermore, once nodes form their own opinions about others, they can propagate pre-existing trust values when necessary. For example, if two nodes are not direct neighbors and do not have any pre-existing trust information about each other, they can ask intermediary nodes for their opinions on the other node [Wang et al., 2009]. The management of trust values (i.e. how one node acquires and updates trust values) and the use of these values to derive further information (such as designating nodes as malicious or not) is called *trust management* [Ma et al., 2011]. The effective use of trust management allows for the detection of malicious, misbehaving or faulty nodes in the network, and for such information to be shared amongst the benign participants. Throughout this document, trust and trust management may be used interchangeably.

While the detection of incorrect nodes and/or messages is an important aspect of security and safety in vehicular networks, it does not address all of the problems. Trust solutions are not viable without a solid identity verification scheme, for instance, since nodes would not be able to form trust opinions without being sure of the others' identities (these schemes often use a Public Key Infrastructure [Wasef et al., 2010]). They also do not address issues such as driver and passenger privacy when using the facilities of a VANET. Furthermore, cryptography must be used in order to guarantee that the secrecy of messages is not violated. Therefore, trust and trust management must be viewed as an important aspect of vehicular ad-hoc networks, but not as a definitive solutions to all of the related concerns.

In order to study the implications of trust in vehicular networks, it is interesting to first take a closer look at trust in other kinds of networks. VANETs are a subset of technological networks, therefore it is useful to consider how the Internet or other ad-hoc networks handle trust. Furthermore, VANETs contain several features often found in social networks, which can be directly tied to how nodes form and develop trust relationships with each other.

The study of networks is tied to graph theory, since graphs are a useful way to generate models of networks, and therefore many concepts of the two fields overlap. Mathematical, computational and statistical concepts developed for graphs can be translated to be useful for a

variety of different types of networks. Therefore, this document utilizes notation from graph theory in order to represent various kinds of networks.

This work introduces TruMan, a trust management solution for vehicular networks. TruMan combines solutions to two classic graph theory problems, strongly connected components and graph coloring, in order to provide an efficient approach to identifying malicious nodes in a dynamic and decentralized network. This is based on a previously existing algorithm, called MaNI [Vernize et al., 2015], which is limited to centralized networks.

In order to function in a dynamic and decentralized environment, TruMan takes advantage of features that allow the development of trust relationships between members of the network. Since there is no unifying agent supervising the network, trust relationships are built over time, as nodes move around the network and meet other nodes.

These features are discovered by tracing analogies with social networks. There might be groups of nodes which meet each other with a predictable frequency and at predictable intervals, for example vehicles which belong to family members, neighbors or work colleagues. By considering such features, TruMan allows the formation of strong trust relationships, which in turn facilitate the discovery of malicious members of the network.

The remainder of this document is organized as follows. Chapter 2 explains the broad study of complex networks and the importance of trust in technological and social networks. Then, chapter 3 goes into details regarding VANETs and the importance of trust solutions in the field, presenting previous studies made on the subject. Chapter 4 describes the goals of TruMan, its underlying hypothesis and the work done to achieve those goals, as well as the previously existing algorithms which form parts of TruMan. Next, chapter 5 explains the tools used to validate TruMan's functionality and presents the results of the experiments that were performed. Finally chapter 6 presents the final thoughts on the project and concludes this document.

Chapter 2

Complex Networks

Complex networks can describe many systems which are observed in nature and society through a collection of *vertices* (or *nodes*) and *edges* [Newman, 2010]. They can be comprised of palpable components (such as computers and cables), somewhat abstract entities (such as the World Wide Web's collection of webpages and URLs), or both (like the people and relationships that form a social network).

Complex networks are generally divided into four categories [Newman, 2010]:

1. **Technological Networks** are grids purposefully engineered to provide services to consumers and/or citizens. The primary examples of these networks are the Internet, the telephone network, power grids, transportation and delivery networks. A commonly studied type of technological network are Mobile Ad-hoc Networks (MANETs). Although not of widespread use, MANETs can provide a way to create a network without pre-existing infrastructure, as long as each device is equipped with the proper hardware and software. Trust issues in technological networks and MANETs are detailed in section 2.2. VANETs, which are special types of MANETs, are introduced in chapter 3, along with several details regarding trust in those types of networks.

2. **Social Networks** are formed of relationships between people, or groups of people. These relationships can be familiar, friendships, acquaintance, etc. For the purposes of this work, the most relevant type of relationship is that of trust. The details surrounding trust relationships in social networks are shown in section 2.1.

3. **Information Networks** are the ones in which nodes are pieces of data or information and the edges are the connections between those pieces. Often, information networks are directly associated with technological or social networks. For instance, while the World Wide Web is an information network (in which the nodes are webpages and the edges are the links that users click on to navigate), it relies on the Internet, as it contains the physical infrastructure that makes the web possible. Online social networks can also be classified as information networks, since their nodes are actually information about people rather than

the people themselves. Trust in information networks can be observed in some instances, like peer-to-peer networks, although its usages are not relevant for this work.

4. **Biological Networks** are the networks found in nature. Their nodes can be chemicals, cells, animals, groups of lifeforms, and more. An example is the brain, which contains a neural network formed by neurons; connections in the network represent signals that are sent from one neuron to another. Another instance of biological networks are food chains, categorized as ecological webs. Species of animals are the nodes, while the predation of other species form the edges. In biological networks, it is difficult to clearly define trust, since nodes may not have any sort of awareness or intelligence (such as cells or proteins). Regardless, the study of trust in biological networks is not relevant for this proposal.

In most networks, trust can be a useful tool to aid the security and safety of its members. Therefore, the study of the concept and applications of trust is an important part of the study of networks.

Trust is a concept studied in fields such as psychology and economics, with specific definitions. In complex networks, under the perspective of computer science, it is a measure of one entity's confidence that another will behave properly and provide valid and/or meaningful data [Sherchan et al., 2013]. What follows is the basis of how a network can be modelled using a graph and how a trust model can be applied to it.

Consider an undirected graph $G = (V, E_G)$, which models one complex network of any kind. The vertices are the members of the network (computers, humans, etc.) and each edge represents a pair of vertices' ability to exchange data freely. This graph represents the network's *topology*, that is, the basic structure of the network. Then, there is also a directed graph $T = (V, E)$, called a *trust graph*. T contains the same vertices as G, although its edges represent the degree of trust (or opinion) each node has towards another.

There are two main ways to describe the edges in E: they can be binary, either existing when there is trust or not otherwise, or they can hold a specific trust value within a certain range. In some cases, an edge $a \to b$ with value 0 indicates lack of trust, meaning a has no reason to trust b. In others, it indicates *negative trust*, meaning a has reason to believe b is malicious.

Since G and T represent different types of information, the shape of T is not necessarily similar to that of G, even though they share the same vertices. For instance, two people can have contact with each other (therefore sharing an edge in G) but not maintain a trust relationship (therefore not sharing an edge in T), thus altering the layout of the trust graph compared to the network topology.

In the following two sections of this chapter, trust is further explained in the contexts of social and technological networks. Both types of network can be fitted into the model above, but contain distinct features that demand closer examination. Furthermore, features of both are relevant when analyzing network structure and trust graphs for vehicular networks, which are expanded upon in chapter 3.

2.1 Trust in Social Networks

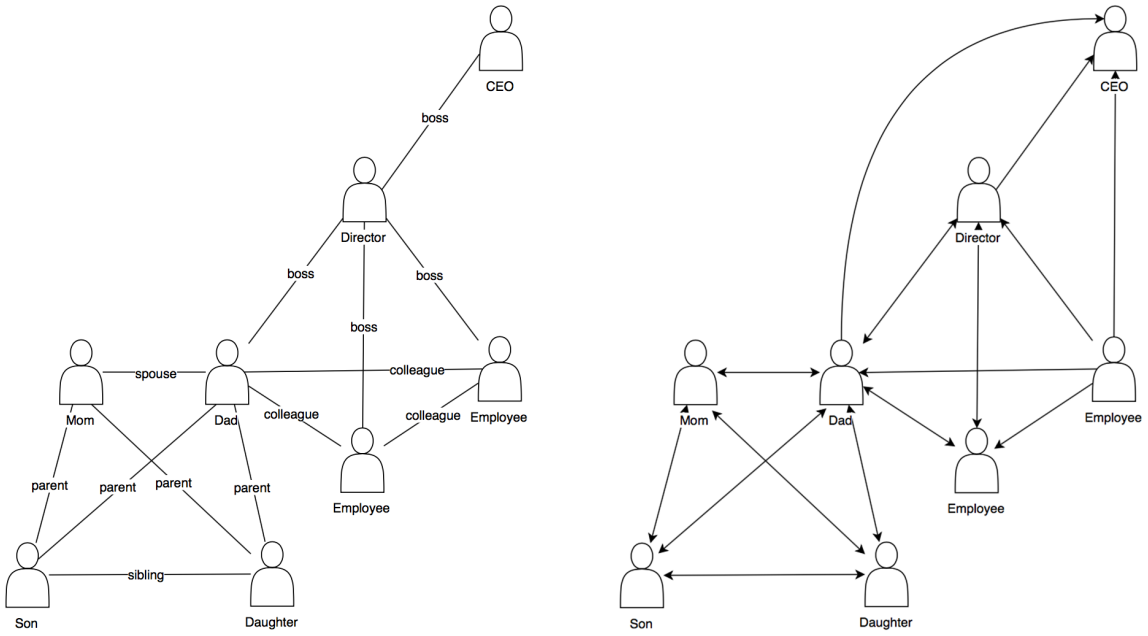
There are two types of social networks: real-world ones formed by relationships between people, and online ones that attempt to abstract the former into a digital environment. Examples of the first one are all around, present in any family, workplace, school or group of friends [Newman, 2010]. Online social networks started by connecting people who already knew each other and giving them an additional form of interaction (analogous to what telephones and email did before), but, today, it is not unusual for people to form relationships with others whom they have only met online.

In a traditional social network, it is simple to perceive how trust is relevant and how it works, since trust relationships between people are used on a daily basis to make decisions. When adapted to a digital environment, these social relationships can be used to automatically increase the relevance of certain information. For instance, upon reading an online review for a certain product, a user will be more likely to accept the review's conclusion if it was written by a close friend than if it were written by a stranger. Social trust is a way of estimating how much a certain recommendation will lead to a positive outcome [Golbeck and Hendler, 2006].

The absence of trust or the presence of distrust have consequences as well. Both in the real world and online, information which comes from a stranger is received with uncertainty; there is no reason to trust the sender, so the data itself must be analyzed and compared to other sources in order to judge whether or not it may be trusted. When one person actively distrusts another (that is, the person believes the other is malicious or uninformed), receiving data from the untrustworthy source will be actively avoided. In online social networks, for example, one user can "block" another in order to avoid seeing anything from the other.

Social networks also have the property of carrying trust from one relationship to another: information shared by a close friend of a person might be considered almost as trustworthy as some collected by the person him or herself. Therefore, it is possible to model social trust relationships as a graph, in which nodes represent people and edges represent a certain degree of trust [Newman, 2010]. Expanding on that property, there is the concept friends of friends [Boissevain, 1974]. If, for example, nodes a and b have mutual trust and are considered friends, then it is reasonable to assume that some of a's trust for b carries over to other nodes that enjoy mutual trust with b. In other words, a friend of a friend can be considered more trustworthy than the average stranger. This property is similar, although not identical, to transitivity, since trust is diminished for each extra step an origin node needs to reach a destination, and there is also the possibility that one node distrusts another even if they share a mutual friend. Naturally, social trust is not commutative (a trusting b does not imply that b trusts a).

In general, social networks' topology and trust graphs are mostly static. Although friendships are formed and ended frequently (i.e. the topology is dynamic), those connections do not disrupt the general shape of the network, because members of the network will usually have other friends whose relationships remain stable. Even if a certain person's trust integrity



(a) Topology graph (b) Trust graph

Figure 2.1: Example of a topology graph and a trust graph in a social network.

is compromised due to a specific incident, that person's friends are not necessarily deemed untrustworthy, preserving part of the trust graph. While positive trust is often tied to the social topology, it is not always the case: one example is two work colleagues who may have a professional relationship, but wouldn't trust each other on other matters; another is the trust people place in authority figures without necessarily having met. Figure 2.1 shows an example of a small social network containing a family and an office.

In section 4.2, the argument is made that VANETs can be considered social networks in several occasions and how this can be used to develop trust in vehicular networks.

2.2 Trust in Technological Networks

In conventional technological networks, such as the Internet, trust is defined and applied quite differently from social networks since, generally, it is very centralized through services that offer security to users. Examples of this can be an IP filtering scheme to avoid distributed denial of service (DDoS) attacks or web browser extensions that block requests to domains in a blacklist; a central agent, be it a hosting provider or the extension's publisher, must maintain and update a list of untrustworthy IP addresses or domains. This means that, in the context of the Internet, trust is often derived from a secondary source: end users and their computers can't be expected to maintain their own blacklists, so they rely on external parties which may provide these lists along with other security services. Similarly, when a user visits an e-commerce website, they must have some degree of trust on the website or the vendor; in this case as well, third-party services are used to certify the legitimacy of the transaction, based on feedback from other customers.

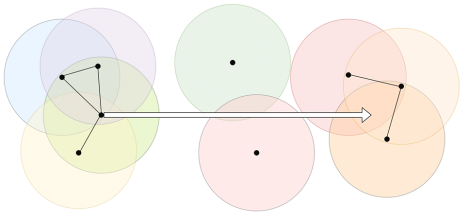
While the centralized trust solutions above serve their purpose on the security and privacy of Internet users, they would be too slow to be viable in a dynamic ad-hoc network, which cannot rely on a back-end infrastructure to distribute those lists. The most common instance of mobile ad-hoc networks, or MANETs, is using mobile devices, such as smartphones, being carried by humans. Although these networks are dynamic, their mobility is relatively low in relation to the wireless range of the devices — if two people are walking in opposite directions, their phones may communicate for several seconds before they leave each other's range. Trust solutions for MANETs can use this property to their advantage, since it allows one node to test another and check several of the messages sent between them.

Ad-hoc networks require a decentralized approach to trust management; each member of a network has its own opinions about other members, and these opinions can change over time. For these opinions to be generated and updated, two nodes must have had previous contact with each other, or derive trust from a third, intermediary, node. Hence, there is the correlation between the trust graph and the topology graph of the network. Since MANETs are dynamic, the graph that represents a network's topology is frequently changing and, with that, the opportunities to create and update trust relationships also changes. In networks in which nodes can meet more than once, it might be valuable to store information from previous encounters to use in the future, although this process can be too slow or resource-consuming to be viable in certain devices; by doing this, the trust graph maintains edges between nodes that are no longer connected in the topology.

Another important aspect of trust in ad-hoc networks is that information is, generally, uncertain and incomplete [Baras and Jiang, 2005]. That is, since nodes form their own model and opinions of the surrounding network, it is unlikely that this data will be certain and accurate with reality. For this reason, it is also possible to use data gathered by neighboring nodes to complement the model. This data itself is subject to the trust evaluation of the neighbors, but it is crucial to better approximate the trust values of other nodes. Incompleteness is an inherit trace of MANETs, since it is entirely possible for nodes to be too distant to communicate, and only occasionally come into contact.

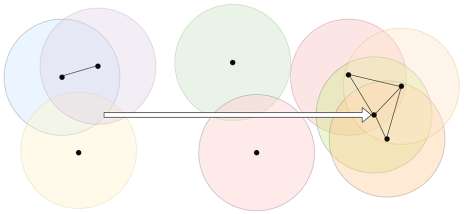
Finally, MANETs must consider the processing and battery limitations of the devices that integrate it. Nodes may disable wireless communications to save power and therefore become uncooperative, or it may be too slow to be a reliable source of information.

There are few examples of MANETs implemented for consumer devices. Two examples are networks created to quickly share data between devices using Wi-Fi or Bluetooth [Krochmal et al., 2014], or ones that allow for multiplayer gaming sessions amongst multiple nearby devices [Sasaki and Kuwahara, 2011]. In both cases, there is no need for a complicated system-level trust model, since those activities involve active participation from the users wielding the device (that is, the user chooses whether or not to communicate with other devices); rather, the trust relationship occurs socially amongst the users themselves.

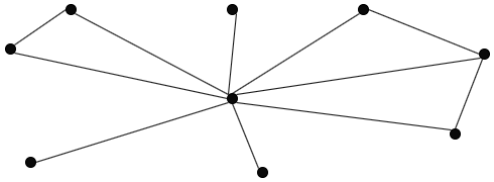


(a) Initial topology and trust graph

(b)



(c) Final topology graph



(d) Final trust graph

Figure 2.2: Example of the changes node mobility causes to the topology and trust graphs.

Figure 2.2 is an example highlighting the difference between the topology graph and the trust graph. The topology graph changes as one node moves across the network, with edges being added and removed as nodes move into and out of each other's ranges. The trust graph, however, is constantly being built, maintaining past relationships even if the nodes are no longer in communication range.

Naturally, VANETs are an instance of MANETs and therefore share some of the same features. However, the topology of vehicular networks is very different from standard ad-hoc networks, and possible trust solutions are accordingly also distinct.

Chapter 3

Vehicular Ad-hoc Networks

Today, most premium vehicles come equipped with hardware that allow for connectivity features; it is expected that, by 2022, many standard vehicles will also come with such features built-in, accounting for a substantial share of the automotive industry's revenue [Viereckl et al., 2016]. Although these features can be useful tools to aid drivers, reducing traffic and risk of accidents, they are merely a gateway to the long-term goal of truly autonomous vehicles, which might become a reality within the next decade; many automakers and technology companies have laid out their plans for the upcoming years [Stewart, 2016]. However, the proper functioning and utility of both connected and fully autonomous vehicles rely on technologies, protocols and applications that allow for the fast communication between vehicle's on-board computers.

Vehicular ad-hoc networks, which are a special instance of MANETs, are a much-studied solution to the problems in the way of smart and autonomous vehicles. In these networks, all nodes are related to traffic; they can be vehicles equipped with on-board computers, or stationary units placed near roads. By quickly sharing data with neighboring vehicles, without the need of an Internet connection, smart vehicles can alert their drivers of important road conditions [Barba et al., 2012], while autonomous vehicles can synchronize their movements to maximize traffic throughput [Amoozadeh et al., 2015].

Several current efforts to make VANETs viable in cities are centered around the IEEE 802.11p standard, also called Wireless Access in Vehicular Environments (WAVE) [Jiang and Delgrossi, 2008]. Among other aspects of the wireless technology, the WAVE standard describes two types of nodes for vehicular networks: on-board units (OBUs) and road-side units (RSUs). On-board units are computers placed within each vehicle which monitor the vehicle's data and are able to communicate with other nodes using wireless signals. Road-side units are placed in static locations near roads; they may also have wired interfaces with other RSUs and the Internet, so it is possible to use them as anchor points for Internet access for passing vehicles. When referring to the communication between two OBUs, the term vehicle-to-vehicle (V2V) communication is used [Yang et al., 2004]; when both an OBU and an RSU are involved, it is called vehicle-to-infrastructure (V2I) communication [Chou et al., 2009]. Although this nomenclature is important to understand other studies on the subject of VANETs, this study does

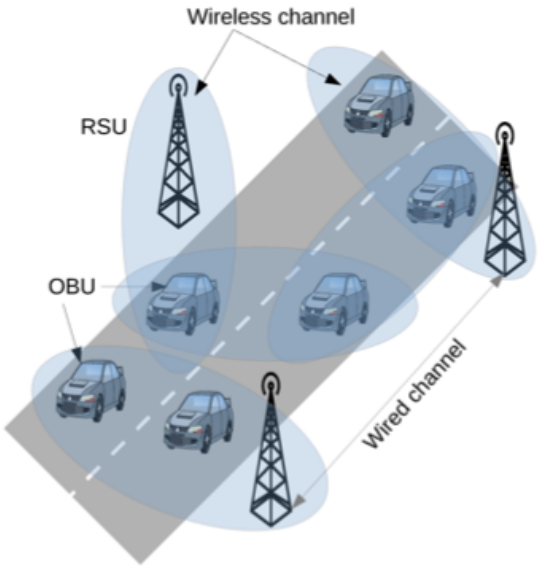


Figure 3.1: Basic elements of a VANET: OBUs and RSUs. [Saini et al., 2015]

not consider RSUs and focuses only on vehicles themselves as nodes, so references to VANETs and vehicular networks are exclusively tied to V2V communications.

In traditional networks (ad-hoc or not), routing protocols usually use the topology to choose where to forward packets; in other words, the primary metric used is the number of hops required to reach the destination. This metric is not as useful in vehicular networks, since the high mobility causes the topology to change frequently. Instead, most VANET routing protocols use geographical coordinates to forward packets [Saini et al., 2015], that is, the physical distance between two nodes is used as the primary metric. The implication is that, even if a packet requires more hops to reach its destination, it will always be traveling the generally correct direction.

As expected for a new technology being introduced, vehicular communications can become an appealing target for malicious users and attackers. These are some examples of possible issues in a VANET:

1. Vehicles with faulty GPS modules, speedometers or other sensors. If a vehicle is broadcasting incorrect data (perhaps unknowingly) because of a hardware or software fault, it can be a serious hinderance to efficiency and safety applications. It might behaving appropriately according to protocol, but the data it sends is not reliable [Isaac et al., 2010].

2. Vehicles might be deliberately broadcasting false data. In this case, there might be a specific purpose (by either the vehicle's driver or a remote attacker), like altering traffic or even cause an accident [Golle et al., 2004].

3. Attackers with control of several vehicles can propagate junk data in an attempt to flood the network, causing a distributed denial of service (DDoS) attack. Alternatively, the data propagated might have some reasoning behind it, like lying about road conditions in order to divert traffic [Garip et al., 2015].

4. Instead of sending data, some vehicles might try to eavesdrop on others' communications. The hop-based routing protocols used in VANETs facilitate this, since any node can be asked to be a hop. If the intermediary node is malicious, it may attempt to extract data contained in messages or refuse to forward them. Related to this, there is the Sybil attack [Isaac et al., 2010], in which a node lies about its position in order to seemingly alter the physical topology of the network and be chosen as a hop [Leinmüller et al., 2005].

5. Malicious vehicles may use signal jammers or other devices in order to affect other vehicles' sensors and communications [Isaac et al., 2010]. That can cause other vehicles to broadcast incorrect data, therefore obfuscating the origin of the attack.

6. A malicious user or remote attacker can monitor messages shared across the network in an attempt to stalk one specific vehicle [Isaac et al., 2010].

Each of these possible attacks requires a unique approach, though there are some broader ways to help the security and safety of VANET users. Trust, as is described in section 3.2, can be an important feature in vehicular networks, especially when attempting to filter out malicious or incorrect messages. It does not, however, avoid all possible attacks, such as a signal jammer or stalking. Rather, different mechanisms must be explored in order to avoid most problems.

3.1 Special properties of VANETs

VANETs feature several unique properties which distinguish them, and the behavior of its members, from other types of networks [Yousefi et al., 2006]. Some of these properties include:

1. Rapidly changing topology. Since the nodes are vehicles, they move frequently and at relatively high speeds. Each node's wireless communications also have a certain range, so the other nodes within that range (and, therefore, network neighbors) can change very quickly.

2. Node mobility is constrained to a pre-existing grid of roads. Within those roads, nodes usually travel in predictable directions according to local laws and historical data. The spaces in the grid, like city blocks, provide a challenge to communication both because of distance and because buildings can cause obstructions to radio transmissions.

3. VANETs are prone to fragmentation, since a gap in the network topology can make two parts of it unable to communicate with each other. Combined with the property above, this fragmentation can appear and disappear frequently, depending on the node density.

4. Due to the changing topology and possible disconnection, connection with distant nodes is not reliable. Therefore, the effective diameter of the network is relatively small for important applications.

5. Compared to devices like smartphones, vehicles have no notable power constraints.

6. In certain locations and/or moments, large vehicle density results in a large-scale network, since there are many nodes concentrated in a relatively small space.

7. The topology is susceptible to driver behavior. First, this means the topology can occasionally change in unpredictable ways. Second, contents of a message sent through the network can alter the driver's behavior and therefore change the topology.

Some of these properties provide advantages or disadvantages when developing trust models for vehicular networks, although all of them must be considered.

3.2 Trust in VANETs

Like in other types of networks, the proper functioning of a VANET depends on the reliability of the vehicles (nodes) which participate in it. If a node is malicious or faulty, it can spread incorrect data that may compromise the network's utility. Once the concept of VANETs was established, researchers have been attempting to predict ways in which malicious users might use the network to their advantage. Examples include triggering false alarms about inexistent accidents, lying about the average speed in a road to make it less desirable for others, and falsifying geolocation data to exploit location-based routing algorithms. Therefore, the concept of trust must be established in the vehicular network context, allowing for nodes to judge the validity of information transmitted by others and share those conclusions with other nodes.

There is an important distinction between a malicious node and a faulty one; both of them may be sharing false data, but for different reasons and with different consequences. For example, a malicious node may lie about its location in order to make routing protocols use it [Leinmüller et al., 2005], in order to try to store or alter messages, while a faulty GPS module may cause an accident because its position data was incorrect. However, that distinction can be hard to make, because a close inspection is necessary to determine whether the incorrect data is erratic or deliberate. Since both types of nodes are problematic to the proper functioning of a network, malicious and faulty nodes can be treated as the same in a trust model.

In general, trust management solutions for VANETs use *data-oriented trust*, *entity-based trust*, or a combination of the two. The solutions that use data-oriented trust (or *data-centric trust*) [Raya et al., 2008] focus on validating messages instead of entities. This is important when vehicles share messages about a specific event, such as a collision, which must be quickly validated by neighbors and distributed to other nodes within a relevant area. In this scenario, vehicles sharing the same road might be complete strangers to each other, and therefore would not have any trust relationship, so neighboring nodes must decide if a message is true by its contents and by other nodes' observations of the event. On the other hand, when dealing with frequent messages which contain basic information such as geolocation and speed (used for traffic-diminishing

solutions), it is too costly to judge each individual message. Therefore, *entity-based trust* becomes more appealing, since benign nodes can quickly identify a malicious node and isolate it from the network. Within entity-based trust, there are also two often-used methods of establishing trust: first, there is *role-based trust*, which is the static trust of pre-authenticated vehicles such as police units; second, there is *experience-based trust*, which is built through previous encounters shared between pairs of nodes. The model proposed in this work utilizes entity-based and experience-based trust, as it is based on the possibility of nodes meeting more than once and, therefore, being able to form a long-term trust relationship with each other.

3.3 Desired properties for VANET trust models

The analysis of related work is based on [Zhang, 2011], which proposes eight desired properties for a trust management model for VANETs. In this section, these properties are briefly described.

1. Decentralized trust establishment: nodes must be able to form their own trust values about other nodes without the aid of an Internet connection or centralizing agents. Nodes may or may not use information from other trustworthy nodes to build trust values (in other words, trust might be transitive).

2. Coping with sparsity: the model still functions when there are few nodes populating the network. Due to the dynamic nature of vehicular networks, it is possible that nodes will find themselves with few other nodes in range. In such scenarios, a trust model should be able to establish trust even if there are few neighbors with whom to share data.

3. Event/task and location/time dynamics: the model reacts to different situations depending on what, where and when events happen. The event or task dynamics involve managing different situations in different ways. Messages can carry different types of alerts, and not all of them need to be addressed with the same urgency. A message about a nearby crash, for example, requires a much quicker reaction than one about an upcoming change in weather; malicious nodes that broadcast false information about critical events are especially important to detect. Similarly, in order to satisfy location and time dynamics, nodes might behave differently according to where and when certain messages are received. To do this, messages about events must contain timestamp and geolocation data attached; nodes close to the event in space and in time could be considered more trustworthy. Furthermore, by attaching timestamp data to messages, it is possible to age information, allowing the model to consider only data that is recent enough to be relevant.

4. Scalability: the model can work on very large networks at high speeds. This is very important in vehicular networks, since, at certain times or locations, there might be a very large number of vehicles very close to one another. In the case of a model that allows transitive trust, a high volume of nearby vehicles can be advantageous because it allows nodes to share a lot of recent data with each other.

5. Integrated confidence measure: allows nodes to estimate how useful the output of the algorithm is. Along with the information of whether or not a node *a* trusts *b*, there should also be information regarding *how sure a* is of its trust in *b*. Generally, a higher confidence measure is the result of more and/or better evidence.

6. System level security: requires authentication of nodes participating in the network. There should be an infrastructure in place in order to avoid identity falsification from potentially malicious nodes as well as verifying which node is the sender of a given message.

7. Sensitivity to privacy concerns: avoids eavesdropping and stalking by malicious nodes. A message should only be received by the nodes it was meant for, avoiding eavedropping of its contents. Additionally, it should not be possible to track the activity of a node based on the messages it sends.

8. Robustness: the model's resistance to attacks. There are already some studied attacks for vehicular networks, such as the Sybil Attack, Newcomer Attack and Betrayal Attack. Models must show that they function in the event of such attacks.

3.4 Existing trust models for VANETs

Several models have been proposed to solve the problem of trust in vehicular networks. In this section, the most relevant ones are described, considering the time in which they were proposed, the advantages they bring and their contributions to later study. None of them provide a complete solution, but serve as pieces of a puzzle that is still incomplete. Many trust management solutions for VANETs have been proposed over the years, such as [Patwardhan et al., 2006], [Gerlach, 2007], [Raya et al., 2008], [Huang et al., 2010], [Ding et al., 2013], [Haddadou et al., 2013], [Liu et al., 2016], [Kerrache et al., 2016]. There are also some review and/or survey articles on the subject of VANET trust models, such as [Zhang, 2011], [Ma et al., 2011], [Zhang, 2012], [Mejri et al., 2014], [Soleymani et al., 2015] [Sengar, 2016], and [Dwivedi and Dubey, 2016].

[Dotzer et al., 2005] is one of the earliest examples of VANET trust models, establishing a system called VARS, based on the reputation of nodes and messages throughout the network. The authors use what they call *opinion piggybacking*, which means that, for each hop between the origin and the destination of an event-related message, the forwarding node appends its opinion of the message's contents and the message's sender. In other words, when a node *a* receives a message about a certain event from *b*, it calculates a new opinion considering it rebroadcasts the message to other nearby nodes, but with its own opinions about the event and about node *b* attached. This process adds credibility to a message through validation by nodes in a decentralized fashion. It combines aspect of data- and entity- based trust, since nodes share their opinion of the data as well as their opinion of the sender. An interesting observation is setting higher trust values for certain vehicles based on their familiarity with the region (vehicles that reside in a given city may have more experience with certain types of events than newcomers). However,

opinion piggybacking has its own share of problems. First, it allows forwarding nodes to access (at least some of) the contents of a message so it can form an opinion on it, diminishing privacy; a malicious forwarding node could even attempt to alter those contents. Second, since each new opinion appended to the message considers the previously appended opinions, the first nodes to forward the message to have a substantially greater impact over the final opinion than the later ones. Finally, there is an issue with scalability, since appending new information to a message on each hop may add a significant overhead to the transmission. Additionally, the authors provide little to no experimentation or proof that their approach would be sound in a real-world network.

The model proposed in [Minhas et al., 2010] uses several criteria to judge whether or not a received message is trustworthy. First, nodes are classified by their roles and previous experience with them. Roles are used for vehicles which should be more trustworthy than the average: government official cars, traffic report vans, buses, cabs, etc. 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. The model considers both role-based trust and experience-based trust; although the work proposed here does not use role-based trust, the authors provide a useful method of calculating and updating an experience-based trust value, which might be used or adapted. However, their 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 [Chen et al., 2010], 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; furthermore, 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 trust model in [Park et al., 2011] takes advantage of daily commutes. In this article, the focus is on the early stages of VANETs, in which a very small percentage of vehicles are equipped with OBUs. To make trust viable in such a scenario, the authors rely on RSUs to store reputation information from passing vehicles. Each vehicle must have an "Agent RSU", which is in charge of storing and sharing that vehicle's trust data to other passing vehicles and connected

RSUs. It must also keep the data updated when the vehicle approaches it again. To make this viable, the properties of daily commutes are used: it is assumed that the vehicle is near its Agent RSU with reasonable frequency because it is located within the driver's home-to-work route. The main problem with this model is that it relies on the presence of frequent RSUs, which might not always be viable. It also does not make it clear what should happen when a vehicle stops using a route or does not have a daily predictable path (it does, however, handle occasions in which a vehicle chooses an alternate route or is absent for some days such as weekends and holidays).

The authors of [Huang et al., 2014] take special note of two characteristics from social networks that can also be found in many VANET trust models: *information cascading* and *oversampling*. That is, information reported by a number of original nodes (i.e. the ones that witnessed an event) may be diluted as nodes that forward it append their own opinions on the matter. An algorithm is proposed to diminish that effect by assigning higher weights to the opinions of origin nodes and lower weights to others. However, the authors conclude that the optimal scenario is to assign no weight at all to forwarding nodes, therefore allowing each node to form an opinion based only on the original nodes' reports. Furthermore, the authors are quick to dismiss the validity of entity-based trust, instead opting for a pure data-oriented approach. Although it is true that data-oriented trust is efficient for events, which is what their model is based on, it is not ideal for sharing data quickly and frequently. When a collision or other major incident occurs, it is useful to judge each message on its own, since not all members of the network will have existing trust relationships with each other. However, when sharing location and velocity data several times per second, it is not reasonable to expect that each message will be analyzed so carefully; rather, it makes sense to form an opinion about the sender of the message and use the resulting trust value to choose which messages are relevant or not.

The Attack-Resistant Trust Management Scheme (ART) from [Li and Song, 2016] proposes to resist three types of attacks: simple attacks, in which malicious nodes do not cooperate with the network; bad-mouth attacks, in which malicious nodes perform simple attacks but also share false information about benign nodes; and zig-zag attacks, in which nodes vary their behaviour from benign to malicious in order to be harder to detect. It works in two main steps: data gathering and malicious node detection. For data gathering, it uses the Dempster-Shafter theory of evidence, which establishes *belief* and *plausibility* values, both real numbers ranging from 0 to 1. The former refers to the amount of evidence indicating the truthfulness of a hypothesis (for example, a node sending false data corroborates the hypothesis of it being malicious), while the latter is 1 minus the amount of evidence that supports the possibility of the hypothesis being false. These evidences are acquired through observations by a node and through data received from other nodes. The resulting probability is the basic trust value, which is stored in a trust vector (a series of trust values regarding other nodes). The malicious node detection step uses a Cosine-based metric to compare two nodes' trust vectors. When two nodes share similar opinions about other nodes, they will consider each other trustworthy. The downside of this model is that each step is mathematically costly, requiring several intensive calculations in order to achieve its

Table 3.1: Properties of the related work

Property	1	2	3	4	5	6	7	8
[Dotzer et al., 2005]	✓	-	✓	-	-	-	✓	-
[Minhas et al., 2010]	✓	✓	✓	✓	✓	✓	✓	-
[Chen et al., 2010]	✓	✓	✓	✓	✓	✓	-	-
[Park et al., 2011]	-	-	-	-	-	✓	✓	✓
[Huang et al., 2014]	✓	-	✓	✓	✓	-	-	-
[Li and Song, 2016]	✓	-	-	-	✓	-	-	✓
[Chen and Wang, 2017]	-	✓	-	✓	-	✓	✓	-

goals. This likely increases the complexity of the algorithm, which is not detailed by the authors. Because of this, it is uncertain how the model would scale to large networks, while it might also underperform in small networks in which there is little evidence to collect.

The authors of [Chen and Wang, 2017] 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 in which mobile 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.

Table 3.1 shows how well each studied trust model satisfies the eight properties described in section 3.3. The numbers used in the table are the same ones from section 3.3. This analysis shows that, although several previously proposed trust models provide reasonable solutions to the trust management problem, all of them have issues in terms of correctness, completeness or efficiency, indicating that the problem is not yet truly solved.

Chapter 4

TruMan

This work introduces an efficient solution to trust management in dynamic networks such as VANETs. In order to make this possible, it is necessary to identify features in VANETs that show that nodes can share a long-term relationship, as is the case for social networks. Through these long-term relationships, it then becomes feasible for nodes to store trust data and share it with other nodes. By combining a node's own opinions about familiar nodes and trust information received from its neighbors, it is possible to create a model of the surrounding network. This model includes a trust graph, showing the trust relationships between pair of nodes, which can then be used in conjunction with other algorithms in order to classify nodes as correct or malicious.

In this chapter, the reasoning behind TruMan and details of how it works are presented. First, it is shown how vehicles can form long-term relationships and trust one another in a similar way to social networks. Then, two algorithms are introduced: Tarjan's strongly connected components algorithm [Tarjan, 1972] and an efficient algorithm for graph coloring [Mittal et al., 2011]. Next, the Malicious Node Identification Algorithm (MaNI) [Vernize, 2013] is explained, because it is the work that suggests the usage of strongly connected components and graph coloring for malicious node detection. Finally, TruMan itself is detailed, showing how it combines features from existing algorithms and adapts them to a dynamic environment, enabled by the social properties found in vehicular networks.

4.1 Goals

Building from the foundation set by MaNI [Vernize, 2013], TruMan strives to enable efficient trust management in highly dynamic networks such as VANETs. In addition to efficiency, it is desirable that the trust model is both simple to understand and to implement, making it appealing for real-world usage.

Furthermore, the desired properties of a VANET trust model described in [Zhang, 2011] (explained in detail in section 3.3) were considered, so TruMan attempts to fulfill or enable as many of those properties as possible.

4.2 Social Networks and VANETs

Some proposed trust models for vehicular networks, such as [Huang et al., 2014], state that the likelihood of two nodes meeting each other twice is too low to be relevant. However, it stands to reason that, throughout the course of several days, many drivers take similar routes at similar times of day (e.g. to commute to work) and, therefore, their vehicles are in similar locations each day. Additionally, many cities rely on main roads to serve as backbones to their traffic, meaning there is a high density of vehicles on those roads during rush hours. Since that is true for a notable percentage of a city's fleet, it can also be assumed that those vehicles may frequently encounter each other during their commute. While two vehicles that share a commute route may not be direct neighbors every day, they are likely to be relatively close to each other most days, meaning few hops separate them in the ad-hoc network. Furthermore, certain pairs of vehicles are bound to be within communication range of each other nearly every day. Examples of these include vehicles whose owners are neighbors or coworkers. Such vehicles' trust relationship should become steady over time and, in the case of positive trust, they can use each other's information to learn more about other nodes in the network.

Most cities also have one or more types of mass transit systems (buses or trains). Those vehicles can also be part of a VANET and communicate with private cars. Buses share the same roads as cars, but instead of having specific destinations, they travel a predefined route during the whole day, usually tied to a tight schedule. Trains travel on rails, so their contact with cars is less frequent, but it can also happen on railroad crossings; they travel long distances in relatively short amount of time, which helps the dissemination of data in a VANET. In the same way that cars have a high probability of meeting more than once during their commutes, it is also very likely that they meet the same buses and/or trains frequently.

In [Cunha et al., 2013], [Cunha et al., 2014b], and [Cunha et al., 2014a], the authors attempt to find features usually attributed to social networks in vehicular networks. By using a data set from the city of Zurich, Switzerland, they show that some metrics, such as clustering coefficient and number of encounters, have peaks during the rush hours. They note that, during rush hours, the diameter of the graph decreases to around 6 hops; additionally, the frequency of total encounters between pairs of nodes in the network increases during those hours. Although the authors do not quantify the encounters between specific pairs of nodes, these numbers support the idea that daily commutes do indeed cause vehicular networks to exhibit social network features.

4.3 Tarjan's strongly connected components algorithm

The use of Tarjan's strongly connected components algorithm [Tarjan, 1972] 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 is 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).

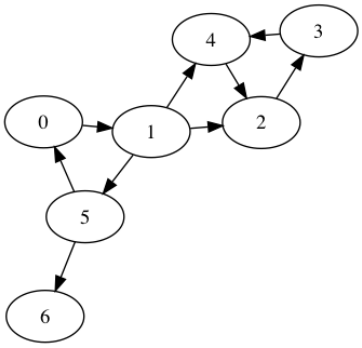
Each node has two attributes assigned to it during the execution of the algorithm: $index$ is used to number the nodes in the order they are visited, while $lowlink$ is the lowest indexed node reachable from each node. In the implementation used, $index$, $lowlink$, $count$ and $stack$ are global variables accessed from every call of the function. $index$ and $lowlink$ are arrays indexed by unique node identifiers, $count$ is an integer and $stack$ is a last-in-first-out data structure.

In the call that visits a node u, the algorithm must loop through each node v trusted by u (that is, $u \rightarrow v$ 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.

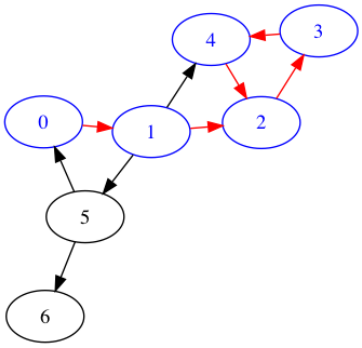
The number of components is, at most, $|V|$: in a worst-case scenario, each node is placed into its own component. The complexity of the algorithm is $O(|V| + |E|)$ for a graph $T = (V, E)$. Algorithm 1 shows the general structure of Tarjan's algorithm [Tarjan, 1972].

Figure 4.1 illustrates the execution of Tarjan's algorithm. The algorithm starts from node 0, with $index[0] = 0$ and $lowlink[0] = 0$. With a depth-first search, the algorithm traces the path $0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 2$. Since node 2 has already been visited and nodes 4 and 3 have no further outgoing edges, $lowlink[4]$ and $lowlink[3]$ receive the value 2 and the function calls return back to the first visit of node 2. At this point, nodes 2, 3 and 4 all have 2 as the smallest reachable index and, therefore, they form a strongly connected component.

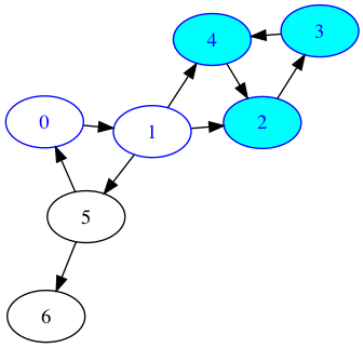
Continuing from node 1, the algorithm traces $1 \rightarrow 5 \rightarrow 0$, but stops there since node 0 has already been visited. Continuing from node 5, the algorithm traces $5 \rightarrow 7$. Node 7 has no outgoing edges, so it forms a strongly connected component by itself. Once the function calls return to node 0, a strongly connected component is formed with nodes 0, 1, and 5, since they all have 0 as their $lowlink$ value.



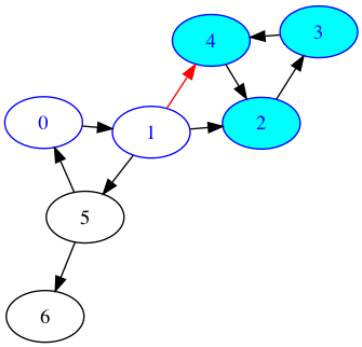
(a) Initial graph.



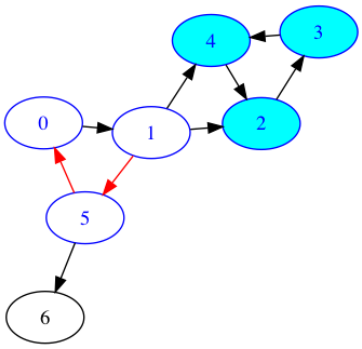
(b) The search follows the path $0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 2$.



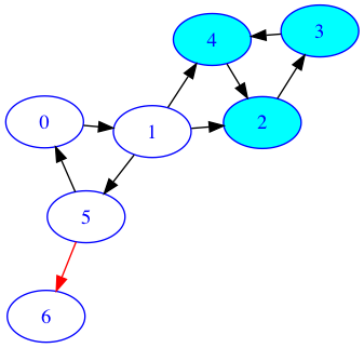
(c) Since $lowlink[2] = 2$, nodes 2, 3 and 4 are added into a component.



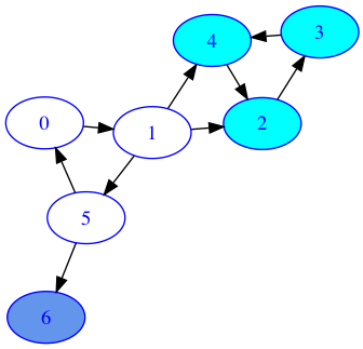
(d) The search follows the path $1 \rightarrow 4$, but node 4 has already been visited.



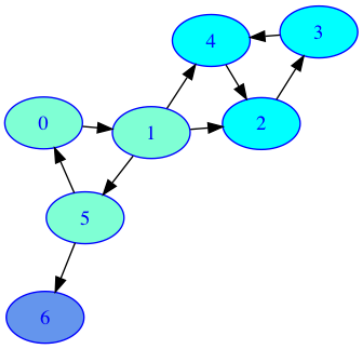
(e) The search follows the path $1 \rightarrow 5 \rightarrow 0$.



(f) The search follows the path $5 \rightarrow 6$.



(g) Node 6 does not have outgoing edges and is added to a component.



(h) The algorithm returns to 0 and, since $lowlink[0] = 0$, adds 0, 1 and 5 to a component.

Figure 4.1: Example of an execution of Tarjan's strongly connected components algorithm.

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
```

4.4 Graph coloring with minimum colors

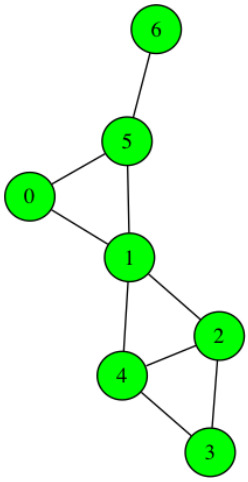
Graph coloring is one of the possible heuristics suggested by MaNI to detect malicious nodes after the generation of the component graph using Tarjan's algorithm. Out of the tested heuristics, it presents the best results, so it has been chosen as the heuristic for TruMan.

The process of graph coloring consists of giving each node a label (represented by a color) so that no two neighboring nodes share the same color. This problem has been studied in Computer Science since, at least, 1972 [Karp, 1972] and has been studied as a classic mathematics problem for even longer [Kempe, 1879]. It has been proven mathematically that any planar graph can be colored with at most four colors [Appel et al., 1976], but discovering the smallest number of colors necessary to color an arbitrary graph (called the graph's chromatic number) is an NP-hard problem [Sánchez-Arroyo, 1989].

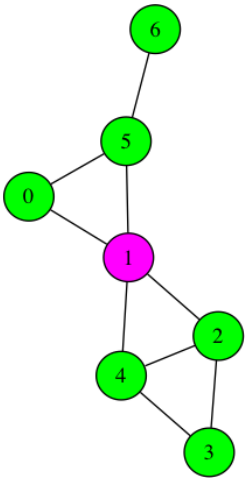
In [Mittal et al., 2011], the authors present an efficient approach to graph coloring using the minimum possible amount of colors. Although they do not prove that their algorithm always uses the smallest possible amount of colors, the output is always a correct coloration and the algorithm is nevertheless efficient. For the purposes of trust management, it is not necessary to prove that the coloring algorithm's output uses the minimum possible number of colors.

The complexity of the algorithm is $O(|E'|)$ for a graph $C = (V', E')$. As a comparison, the DSATUR algorithm for graph coloring has complexity $O(|V|^2)$ [Brélaz, 1979]. Algorithm 2 shows the general structure of the graph coloring algorithm [Mittal et al., 2011].

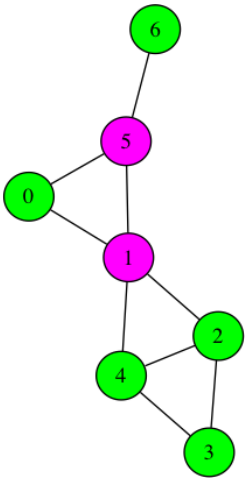
A limitation of this algorithm is that the edges must be sorted according to node indexes. It doesn't matter which nodes get assigned which indexes, but once they are assigned those numbers, the algorithm must follow the edges in numerical order. This is demonstrated in [Vernize, 2013].



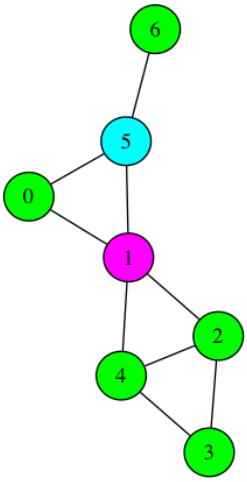
(a) Initial graph with all nodes labeled 1. $d = 1$ (green).



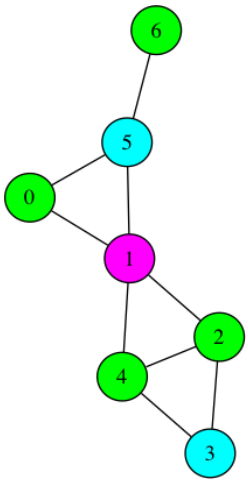
(b) Edge $(0, 1)$ is checked and node 1 gets a new color. $d = 2$ (magenta).



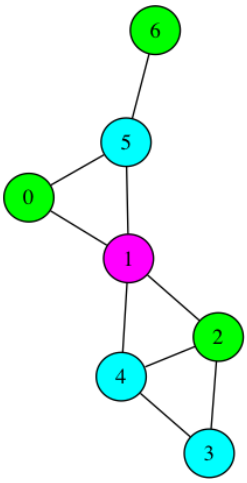
(c) Edge $(0, 5)$ is checked and node 5 gets the current value of d.



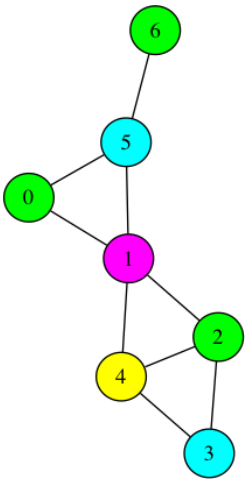
(d) Edge $(1, 5)$ is checked and node 5 gets a new color. $d = 3$ (cyan).



(e) Edge $(2, 3)$ is checked and node 3 gets the current value of d.



(f) Edge $(2, 4)$ is checked and node 4 gets the current value of d.



(g) Edge $(3, 4)$ is checked and node 4 gets a new color. $d = 4$ (yellow).

Figure 4.2: Example of an execution of the graph coloring with minimum colors algorithm.

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
```

Figure 4.2 illustrates the execution of the graph coloring algorithm. It is notable how the algorithm takes few iterations to fully color the graph. However, it is also possible to observe that the result does not use the minimum amount of colors. By coloring node 4 as cyan and node 3 as magenta, the sample graph could have been colored with only three colors instead of four. As described above, this is not a problem for the usage of the algorithm in TruMan.

4.5 Malicious Node Identification Algorithm

The basis of TruMan is the Malicious Node Identification Algorithm (MaNI) proposed in [Vernize et al., 2015], which suggests the use of strongly connected components and graph coloring for malicious node detection. This article presents a malicious node identification scheme based on strongly connected components and graph coloring. The model is proposed for complex networks in general, but is not suited for VANETs because it is designed only for static networks. Furthermore, the algorithm is executed by a global observer which has information about the complete network.

The input graph $T = (V, E)$ is a static, connected, and directed graph containing all trust relationships in the network. Such relationships are binary, so there are no varying degrees of trust: either one node trusts another completely (edge value is 1), or it distrusts the other completely (edge value is 0). The relationships are also directed, meaning that if the value of $A \rightarrow B$ is 1, $B \rightarrow A$ is not necessarily 1.

The process for identifying malicious nodes within T is as follows:

First, T is separated into strongly connected components using Tarjan's algorithm [Tarjan, 1972], which is described in detail in section 4.3. In each of these components, all nodes are connected by edges of value 1. In other words, within a single component, all nodes trust one another; nodes connected by edges of value 0 are separated into different components. Each of these components becomes a node of a component graph $C = (V', E')$.

The creation of the graph C simplifies the remaining computation. Since each node of C is a vertex $v' \in V'$ and each vertex v' is a component of T 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 one. They can either be benign nodes which legitimately trust one another, or

malicious nodes colluding with each other. After the formation of C, one or more heuristics can be used to classify the nodes as benign or malicious.

In the experiments performed by the authors of MaNI, the coloring heuristic shows the most promising results, identifying a high ratio of the malicious nodes in the network. The coloring heuristic uses a graph coloring algorithm, such as DSATUR [Brélaz, 1979] or the algorithm detailed in section 4.4. Other heuristics were experimented with, but were either less effective in detecting malicious nodes, provided too many false positives, or were not efficient enough.

After running a graph coloring algorithm with graph C as input, the color whose nodes in C represent the most nodes in T is classified as correct, and all others are classified as malicious. Once this information from C is brought back to graph T, it is trivial to label the nodes in T as either benign or malicious based on their components' classifications.

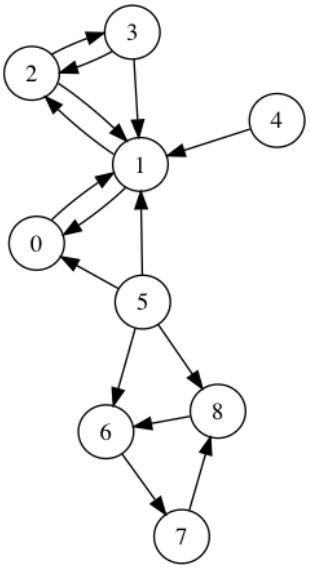
Two types of experiments were made in each network: first, all malicious nodes inverted the edge weights leading to their neighbors; second, malicious nodes randomly inverted or not the weights. In the first scenario, the results show excellent precision in most networks, detecting nearly every malicious node. Experimenting with the second scenario, the results are less precise, however still promising: with up to 20% of malicious nodes in the network, the error rate is under 7%, while with the worst case, 50% of the network being malicious, the error rate is approximately 15%.

The authors suggest running the algorithm repeatedly after removing the malicious nodes from the network. By doing this a small number of times, nearly all malicious nodes are detected by it even when randomly changing edge weights.

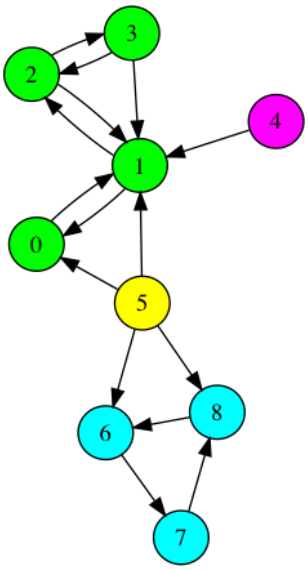
Figure 4.3 illustrates the execution of the MaNI algorithm. With the starting graph T, whose edges represent the trust relationships between nodes, Tarjan's strongly connected component algorithm is executed. Figure 4.3(b) shows nodes colored according to their placement in a strongly connected component. The strongly connected components form a graph C according to edges present in T. In Figure 4.3(c), component 0 is the one containing node 5; component 1 contains nodes 6, 7 and 8; component 2 contains nodes 0, 1, 2 and 3; and component 3 contains node 4. The graph coloring with minimum colors algorithm is executed on C, producing the coloration shown in Figure 4.3(d). Finally, each node in T is colored according to which color its component received in C. The color with the most nodes is deemed benign, while the others are considered malicious.

4.6 The TruMan algorithm

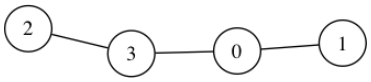
TruMan is based on the MaNI algorithm [Vernize et al., 2015], which suggested the use of Tarjan's algorithm and the graph coloring algorithm. However, MaNI was developed for static networks such as social networks, and is executed by an external supervising agent (i.e. outside of the network), making it unsuitable for a vehicular network.



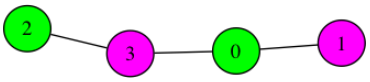
(a) Initial graph T.



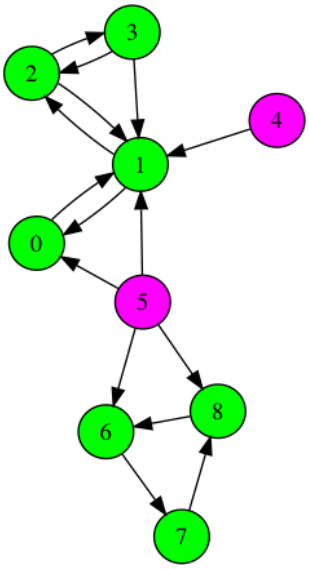
(b) Tarjan's algorithm is used to identify the strongly connected components.



(c) The graph C is formed from the components of T.



(d) The coloring algorithm is used to label the nodes of C.



(e) The colors from C are used to label nodes in T as correct or malicious.

Figure 4.3: Example of an execution of the MaNI algorithm.

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 representation of the network in the form of a static, connected and directed trust graph $T^u = (V^u, E^u)$, in which V^u is the set of nodes node u is aware of and E^u is the set of trust relationships (opinions) u knows of between members of V^u. Since each node has its own network representation and it 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 collects and organizes 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 beyond the scope of this paper. Every time a neighboring node v is tested as benign, the value of $u \rightarrow v$ increases. Additionally, node u performs an union between its trust graph and v's trust graph, forming a new graph $T_i^u = T_{i-1}^u \bigcup T_{i-1}^v$, which is used for the remaining steps. Algorithm 3 shows the basic interaction between two nodes, while algorithm 4 details the steps of the graph union.

Algorithm 3 Interaction between two nodes

```
1:  function INTERACTION(node u, node v)
2:      if v ∉ T^u then
3:          add v to T^u
4:          add u → v to T^u
5:          T^u(u → v).trustvalue = 0.5
6:          T^u(u → v).timestamp = now
7:      u tests v
8:      if v is benign then
9:          T^u(u → v).trustvalue increases
10:         Union(T^u, T^v)
11:     else
12:         T^u(u → v).trustvalue decreases
```

Algorithm 4 Graph union

```
1:  function UNION(graph T^u, graph T^v)
2:      for a → b in edges of T^v do
3:          if a ∉ T^u then
4:              add a to T^u
5:          if b ∉ T^u then
6:              add b to T^u
7:          if a → b ∉ T^u then
8:              add a → b to T^u
```

After the collection of data, T_i^u is separated into strongly connected components using Tarjan's algorithm [Tarjan, 1972], although the implementation of the algorithm slightly differs

from the one used in MaNI. Since MaNI uses binary trust, Tarjan's algorithm only checks whether edges have value 0 or 1; in TruMan, each edge stores a trust value $t \in [0, 1]$.Therefore, a threshold h is defined so Tarjan's algorithm can consider only edges represent a significant trust relationship when forming strongly connected components. So, 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. Each of these components becomes a node of a component graph $C_i^u = (V_i'^u, E_i'^u)$.

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.

The coloring heuristic is used to classify nodes, which uses the algorithm described in section 4.4 [Mittal et al., 2011], 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 the classifications of their components.

In a network in which malicious nodes are a minority (under 50%), it is expected that the benign nodes will form components with large numbers of nodes, because these benign nodes will share their networks with each other and it is easy to form trust paths between pairs of benign nodes. Malicious nodes, on the other hand, do not send their own networks of false information to benign nodes, and might not always trust other malicious nodes, causing them to become isolated in small strongly connected components (in some cases, these contain a single malicious node). The result is that most benign nodes become members of a small number of large components; when the component graph is colored, these components are likely to receive the same color, because two benign components are never adjacent. Because of this, the coloring heuristic works as a classification method.

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

1. Node u checks which are its neighbors (nodes within its communication range). New discovered nodes and new formed edges are added to T_i^u. Edges are created with weight 0.5.

2. Node u tests all 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 performs a union with T_{i-1}^u and T_{i-1}^v, establishing 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.

4.6.1 Information aging

In order to make TruMan resistant to attacks, it is necessary to age the information nodes store about the network, so old information does not affect the identification of malicious nodes.

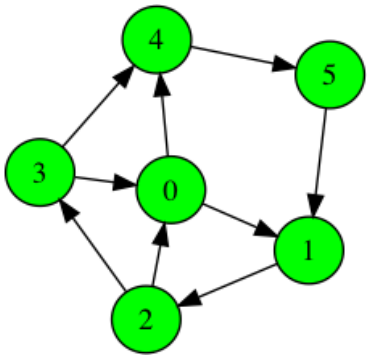
To do this, each edge stores a timestamp value s in addition to the trust value t. When two nodes u and v interact with each other, the edge $u \rightarrow v$ in T_u stores the timestamp s, which is set according to node v's internal clock.

Then, when node u interacts with another node w in the future, u's opinion of v comes with the timestamp attached, so w has the information to know how much time has passed since the interaction between u and v happened. Once w performs the graph merge procedure with T_u and T_w, but T_w already has an edge $u \rightarrow v$ stored, it checks the two timestamps and only updates the edge if the incoming information is more recent than what is already stored. Since the timestamp is always set to the destination node of the edge, it can be used for comparison regardless of which nodes handled the information. Algorithm 5 shows how the union function was changed to accommodate timestamps and information aging.

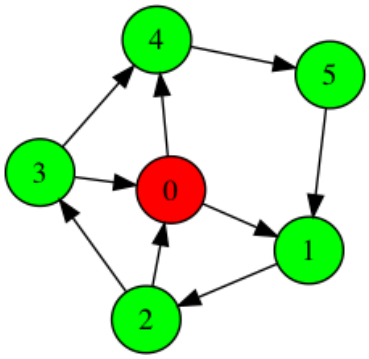
Algorithm 5 Graph union with timestamps

```
1:  function UNION(graph T^u, graph T^v)
2:      for a → b in edges of T^v do
3:          if a ∉ T^u then
4:              add a to T^u
5:          if b ∉ T^u then
6:              add b to T^u
7:          if a → b ∉ T^u then
8:              add a → b to T^u
9:          else
10:             s_0 ← T^u(a → b).timestamp
11:             s_1 ← T^v(a → b).timestamp
12:             if s_1 is more recent than s_0 then
13:                 T^u(a → b).trustvalue ← T^v(a → b).trustvalue
14:                 T^u(a → b).timestamp ← T^v(a → b).timestamp
```

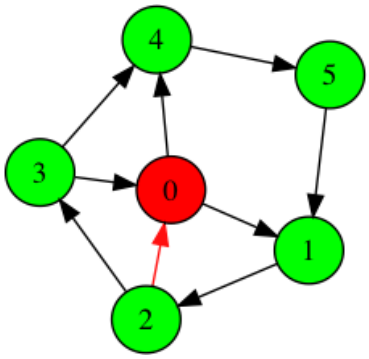
For example, when u interacts with v on and establishes that v is benign, it creates the edge $u \rightarrow v$ with $t \geq 0.5$ and $s = s_0$, where s_0 is the timestamp of the moment in which the interaction occurred according to v. Then, when w interacts with u and establishes that u is benign, it receives network information from u, including the edge $u \rightarrow v$. Since w didn't have that edge in its graph before, it is added maintaining the original timestamp s_0. Later, when w



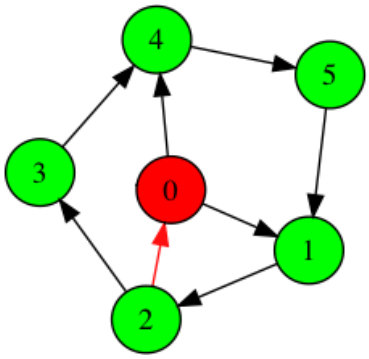
(a) All nodes are benign and belong to the same strongly connected component.



(b) Node 0 becomes malicious, but still belongs to the component.



(c) Node 2 updates its opinion of node 0, identifying it as malicious.



(d) 3's opinion becomes too old and is discarded.

Figure 4.4: Example of what happens when a node becomes malicious.

interacts with u again or with another trustworthy node that recently interacted with u, it receives information about the edge $u \rightarrow v$ again. If this new information includes the timestamp s_1 which is more recent than s_0, w updates its own graph so that the edge $u \rightarrow v$ stores the new timestamp and the new trust value.

Furthermore, after each iteration, nodes go through the edges they have stored and discard the ones that are too old. This is done by setting a maximum age m for edges; once a edge is older than m, it is discarded. A low value for this setting allows for faster detection of converted nodes, however also increases the likelihood of good information being thrown away (therefore increacing the likelihood of false positive detections).

Information aging is necessary because, when a node converts from benign to malicious, old information might still indicate that it is benign, as shown in Figure 4.4. Immediately after node 0 becomes malicious, it is still part of a benign strongly connected component, because there are paths from every other node to 0, and from 0 to every other node. Some time later, node 2 interacts with 0 again and identifies it as malicious; other nodes that interact with 2 will receive that updated information. However, the outdated edge $3 \rightarrow 0$ keeps 0 in the component, since other nodes trust 3 and 3 still hasn't updated its own opinion of 0. Once that edge is old enough, it is discarded and node 0 is correctly identified as malicious by all other nodes.

4.6.2 Complexity

The complexity of TruMan must calculated for each iteration executed and each node in the network. It can be estimated by adding the complexity of most costly operations involved, which are: (i) Tarjan's algorithm, (ii) the graph coloring algorithm, and (iii) the graph union process. Tarjan's algorithm and the graph coloring algorithm are executed once per iteration on each node of the network. The graph union, however, is executed once every time a neighboring node shares information. Each neighbor shares information once per iteration, so the complexity of the graph union procedure is multiplied by n_i^u, the number of neighbors node u has during iteration i.

Therefore, the general complexity equation for each node and each iteration is as follows:

$$TruMan = Tarjan + Coloring + (Union \times (n_i^u))$$

As discussed above, Tarjan's algorithm has a complexity of $O(|V| + |E|)$ and is executed on graph T. Meanwhile, the graph coloring algorithm has a complexity of $O(|E'|)$ and is executed on graph C. The complexity of the graph merge algorithm is $O(|E|)$ and, in a worst-case scenario, n_i^u is at most $|V|$ (every node in the network is a neighbor), resulting in a total complexity of $O(|V| \times |E|)$ for a whole iteration. The total complexity of each iteration of TruMan is, therefore:

$$O(|V| + |E|) + O(|E'|) + O(|V| \times |E|)$$

However, $|E'| \leq |E|$ is always true, because the graph C is a reduction of graph T. Furthermore, $|V| + |E| \leq |V| \times |E|$ is also true, except for the irrelevant scenarios of $|V| \leq 1$ or $|E| \leq 1$.

Therefore, the complexity can be simplified to: $O(|V| \times |E|)$.

Chapter 5

Evaluation

In order to validate TruMan's functionality and efficiency, several simulations were executed, attempting to replicate real-world scenarios. This chapter includes all information relevant to these simulations, including the tools used, the chosen movement model, the parameters and methodology, and the results.

5.1 SNAP library

The simulations necessary to validate the project require a robust library to handle graph data structures. The Stanford Network Analysis Platform (SNAP) library [Leskovec, 2016] was chosen primarily because it is memory efficient. The simulations require multiple graphs that share the same set of nodes (because each node in the network has its own knowledge of the surrounding network), and the SNAP library uses pointers to nodes and edges, saving memory by not having to duplicate the entire data structure. It is written in C++, but, for these simulations, the Snap.py Python library was used.

5.2 The ONE Simulator

The Opportunistic Network Environment simulator [Keränen et al., 2009] [Keränen, 2015] is a Delay-Tolerant Network simulator, used in this study to generate mobility patterns used as input for simulations. It was chosen for the simulations of TruMan primarily because it already includes integration with the Working Day Movement Model.

The ONE Simulator comes with a usable map of the city of Helsinki, Finland, so the city was chosen as the map for the simulations of TruMan.

In order to use data from the ONE simulator as input for TruMan, a new report module had to be created for it. The `AdjacencySnapshotReport` module creates a report consisting of all adjacencies in the network every x number of simulated seconds. That is, at a given timestamp t, all pairs of nodes that are within communication range of each other are added

to the report. This report is then used as input to TruMan, which uses the adjacencies to build the topology graph for each iteration of the algorithm. The `AdjacencySnapshotReport` module has been submitted to the ONE repository as a pull request [Greca, 2017].

5.3 Working Day Movement Model

Most VANET trust models use the Random Waypoint mobility model for simulations, i.e. each node has an origin point, chooses a random location, gets to that location, then chooses another random location and goes there, and so forth. While this model is efficient for testing trust protocols, it doesn't truly represent vehicle mobility in the real world.

To make use of the properties described in section 4.2, it is important to choose a mobility pattern that properly represents the way vehicles move on a daily basis in the real world. Therefore, the Working Day Movement Model [Ekman et al., 2008] (WDMM) is useful. The model, developed for use in Delay-Tolerant Network (DTN) simulations, includes many of the features that are necessary to simulate the daily movement of a vehicular network.

As the name implies, the Working Day Movement Model abstracts people's movement from their homes to their offices and back. Each node has a home and a workplace and they need to travel back and forth between those locations on a daily basis. Occasionally, nodes can also go to other locations for leisure. As mentioned above, many drivers have routes they travel on daily, so the Working Day Movement Model is a reasonably accurate representation of daily movement in a city.

5.3.1 Original model

The Working Day Movement Model was developed for Delay-Tolerant Networks in which network members are devices (such as smartphones) carried by people. Therefore, the Working Day model represents not only people's movements inside their cars, but also within their offices, walking on foot, or riding a bus.

The model proposed by the authors makes use of several other models for specific tasks. The main mobility model places devices in the network and sets their destinations. Within it, five submodels are used:

1. The **home activity submodel** describes what devices do at night, within their owners' homes. No movement is modeled. Devices can belong to relatives or neighbors, and therefore share the same home location.

2. The **office activity submodel** describes the devices' movement routines within their owners' offices. Devices can move to other locations within the office (such as meeting rooms) and such movement is modeled. Devices whose owners are coworkers share the same office space.

3. The **evening activity submodel** is responsible for mobility outside the devices' owners' standard routines. Devices can be carried by people who meet at certain locations (such as restaurants) and spend a few hours with friends.

4. The **transport submodel** shows how devices move around the city. It includes another tier of submodels, responsible for modeling three different types of transportation: walking, driving, and riding a bus. People who own cars always use them, while the others can decide to walk or ride a bus depending on the distance between the origin and destination and the available bus stops. The walking and driving submodels represent similar types of movement, although at different speeds, while the bus submodel follows cyclical routes and can take or deliver passengers at bus stops.

5. The **map** represents the city in which the simulation runs. Its streets constrain the movement of devices, and all homes, offices and meeting spots must be within the map boundaries. The map can be divided into districts, which increases what the authors define as *locality*. It is possible to configure how many people work in the same district where they reside; devices carried by these people rarely leave their district. People who reside and work in different districts allow information to spread across different parts of the network by carrying their device with them.

5.3.2 Adaptation for a vehicular simulation

By thinking of these submodels for vehicles instead of people, it becomes apparent that the frequency and length of encounters between members of the network are similar in both instances. If two vehicles belong to family members or neighbors, they likely spend most of the night within communication distance, while coworkers' cars spend the office hours close by. Cars can also meet each other frequently if their drivers are friends who go out together after work. In the vehicular case, there is an added layer of encounters: cars can communicate frequently with buses and other cars that take the same route daily, even if their drivers are complete strangers.

To adapt the Working Day Movement Model to a VANET environment, a few changes had to be made so the network members are vehicles instead of people (or the devices they carry). Rather than altering the model itself, all of these changes were implemented as parameters for the model. The changes are as follows:

1. The office activity submodel no longer needs to model movement within the office and can be identical to the home submodel. In both, a node can move a small amount once after reaching the office or home, to simulate parking. This was done by setting the `officeSize` parameter to 1, so vehicles do not move around while their drivers are at work.

2. The walking submodel needs to be disabled, since all nodes are cars. By setting the `ownCarProb` parameter to 1, mobility is always done by car.

3. While the bus submodel could be used for a vehicular simulation, this was not used in this evaluation.

One important topic raised in the Working Day Movement Model article is the use of two metrics for a movement model: *inter-contact times* and *contact duration*. Inter-contact time is the average time it takes for two nodes to meet repeatedly in the network. For example, two vehicles who belong to neighbors might have an inter-contact time of about 12 hours, since that is how long they are apart before connecting again. Meanwhile, the contact duration is the time nodes spend connected when they do meet. In the case of the two vehicles owned by neighbors, the contact duration might also be about 12 hours, while their owners are at home and leave the vehicles close to each other.

The choice of the Working Day Movement Model for evaluations is more strongly related to inter-contact times. For reasons explained in **??**, relatively short inter-contact times is important for TruMan's functionality. Contact duration time is an important metric to measure how much data can be exchanged during each encounter, although, for this evaluation, it was not considered.

5.4 Simulation parameters and methodology

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 [Keränen et al., 2009] was used in conjunction with the Working Day Movement Model [Ekman et al., 2008], which provides a strong similarity with vehicle movement in real life.

Snapshots of the network were taken every 10 simulated seconds using the `AdjacencySnapshotReport` module for the ONE simulator. However, a few experiments showed that it was not necessary to run iterations of TruMan that frequently; therefore, iterations run at an interval of 100 simulated seconds and only use one tenth of the snapshots saved.

Table 5.1: Simulation parameters

Parameter	**Value**
Duration	86400 seconds
Work day length	28800 seconds
Std. dev. departure time	7200 seconds
Node velocity	7 to 10 m/s
Simulation area	14,689,750 m^2
Number of nodes	150 (WDMM) + 10 (random)
Office size	1

Most of the parameters for the ONE simulator were taken from the article detailing the Working Day Movement Model [Ekman et al., 2008]; the most important parameters are shown

in Table 5.1. The simulation ran for 86400 seconds (24 hours), with a work day length of 28800 seconds (8 hours) and a standard deviation of departure time of 7200 seconds (2 hours). Nodes move between 7 and 10 m/s in an area of approximately 14.7 km^2 based on a section of the map of Helsinki. There is a total of 160 nodes, 150 of which follow the Working Day Movement Model, and 10 that follow the random waypoint mobility model to simulate vehicles that do not follow daily patterns. 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 and travel by car. Aside from the office size parameter, 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. The transmission range of nodes varies from simulation to simulation, for reasons explained in subsection 5.4.1.

5.4.1 Network Density

The communication range of nodes varies 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 chapter 5). It is calculated using the transmission range of the nodes (ρ), the amount of nodes (η), and the total area of the simulation (α, in m^2).

The coverage of a single node is the circumference around it formed by the transmission radius. This is divided by two to compensate for overlapping circumferences, then 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. The network density formula is as follows:

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

For example, in a simulation with ρ = 30m, the calculation is as follows:

$$\delta = \frac{\frac{30^2\pi}{2} \times 160}{14.689.750} = 0.0154$$

In Table 5.2, a few densities for different values of ρ, η and α are shown. Simulations for TruMan have densities between 0.0017 (ρ = 10m) and 0.0428 (ρ = 50m).

As a comparison, the city of São Paulo (Brazil) has a fleet of over 8 million vehicles [Detran SP, 2017] in an area of 1,521.11 km^2 [Instituto Brasileiro de Geografia e Estatística, 2016], and thus has a density of 0.8884 at ρ = 10m, a much higher value than what is necessary for a satisfactory performance of the algorithm. Table 5.3 shows the densities of a few major cities around the world, using ρ = 10m for all of them. All data is taken from local government

Table 5.2: Simulation densities

Range (ρ)	**Nodes** (η)	**Area** (α)	**Density**(δ)
10 m	160	14,689,750	0.0017
30 m	160	14,689,750	0.0154
50 m	160	14,689,750	0.0428
100 m	160	14,689,750	0.1604
150 m	160	14,689,750	0.3609
200 m	160	14,689,750	0.6416

sources regarding the number of licensed vehicles in each city; these numbers do not include vehicles from the larger metropolitan areas that surround these cities.

Table 5.3: Calculated densities of major cities

City (country)	**Nodes** (η)	**Area** (α)	**Density** (δ)
Helsinki (FI)	250,000 [Helsinki, 2011]	214,250,000 [NLSF, 2018]	0.1833
São Paulo (BR)	8,603,239 [Detran SP, 2017]	1,521,110,000 [IBGE, 2016]	0.8884
New York (US)	2,162,349 [NY DMV, 2016]	777,934,030 [US Census, 2017]	0.4366
Los Angeles (US)	8,050,850 [CA DMV, 2016]	1,213,820,883 [US Census, 2017]	1.041
Tokyo (JP)	3,159,455 [Statistics Japan, 2017]	2,191,000,000 [Tokyo MG, 2017]	0.2265
London (UK)	3,091,393 [UK DfT, 2016]	1,572,100,000 [GLA, 2011]	0.3089

Simulations of TruMan were performed with densities as low as 0.0017, a value much lower than even the real world density of Helsinki, which is a city with relatively few vehicles for its size. It can be expected that the model will perform even better in real-world scenarios in cities with even higher densities, which is common, as exemplified by Table 5.3.

5.5 Results

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

- The X axis shows the results of sequential iterations, ranging from 0 to 8639 in most cases;
- The Y axis shows a percentage of all nodes in the network, ranging from 0 to 100;
- The blue line represents the percentage of nodes detected out of the complete network;
- The magenta line is the percentage of malicious nodes in the network (ground truth);

- The green line represents the nodes correctly identified as malicious (true positives);
- When present, the cyan line represents the undetected malicious nodes (false negatives);
- The red line represents the benign nodes incorrectly identified as malicious (false positives);
- The lines represent average values between all benign nodes on the network, while the colored regions represent the standard deviation present in the data.

It is expected that the results are very inconsistent at the beginning of the simulations, since nodes are still building their models of the network and have relatively little information to use.

Figure 5.1 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 range allows the algorithm to produce better results. At ρ = 10m and δ = 0.0017, a large amount of time is spent with only about half of malicious nodes being accurately identified. Results with ρ = 30m and δ = 0.0153 are better, but still less than ideal; during this simulation, there were more false positive detections happening, although it was still a small amount. At ρ = 50m and δ = 0.0427, results are solid before the 2000th iteration of the algorithm, since at that point over 90% of the network has been acknowledged by most nodes. The amount of false positive detections is extremely low, and, by the end of the simulation, all benign nodes have identified 100% of malicious nodes.

Figure 5.2 and Figure 5.3 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, although there is still a small amount of false positive detections. At 40%, a small part of malicious nodes are yet to be detected and the standard deviation is larger overall. At 50%, as expected, the results are inconsistent as the network is completely split between benign and malicious nodes; at this point, the network is considered completely compromised. True positive and false positive detections are often inverted, because whenever there are more malicious nodes than benign one in a certain node's network model, the algorithm will classify the malicious ones as correct. The amount of malicious nodes also affects how quickly nodes are able to acquire information about the network, since nodes do not trust information from malicious neighbors.

All simulations were performed with trust threshold h = 0.5, except for the ones in Figure 5.4, performed to demonstrate the impact of different threshold values. The plots illustrate that there is not a significance change in results depending on the different thresholds. The results are slightly better at h = 0.7, however not in a significant way. It still takes over 8000 iterations to detect all malicious nodes and there are still some false positive detections.

Figure 5.5 shows the execution of the algorithm over the course of 7 days. Most malicious nodes are identified by the end of the first day, before iteration 9000. However, not all nodes have finished building their model of the network and therefore there are still a number

of false positive detections occurring. Around iteration 20000, all nodes finish building their models and the false positive detection rate drops to an insignificant amount.

Figure 5.6 and Figure 5.7 show how TruMan reacts to one node converting from benign to malicious. These were the only simulations to consider information aging. Here, several different values for the maximum age, m, were tested. For the simulation, information timestamps are set as the iteration in which they were added to the graph ($s \leftarrow i$), and the age is calculated as the difference between the current iteration and the timestamp ($age \leftarrow i - s$). With $m = 10$, information is discarded too quickly, resulting in highly imprecise results. Starting with $m = 250$, results are reasonable, and the additional malicious node is detected approximately 250 iterations after it converts. With higher values such as $m = 1000$, detection takes longer, but not much else changes. When the value is very high, like in the case of $m = 5000$, the extra malicious node is not detected by the end of one simulated day.

5.6 Satisfaction of desired properties

Eight desired properties for VANET trust models were presented in section 3.3. Here, TruMan's ability to satisfy each property is evaluated, ending with a final comparison between TruMan and previously proposed trust models for VANETs.

1. Decentralized trust establishment: TruMan is built from the ground up for decentralized systems. Nodes form their own abstractions of the network and the model does not rely on a central observer.

2. Coping with sparsity: The experiments using low density values demonstrate that TruMan works in reasonably sparse networks. Since nodes carry information from previous interactions, the model can also work on temporarily isolated parts of the network.

3. Event/task and location/time dynamics: Aside from the time-related information used for information aging, dynamics were not used in the simulations presented here. However, TruMan can be extended to consider event, task, location and time dynamics when managing trust.

4. Scalability: Due to the low complexity of the algorithms used in the model, TruMan is highly scalable, as it does not incur substantial pressure on the vehicles' on-board units. It has also been demonstrated that iterations of the algorithm do not need to run very frequently in order to detect malicious nodes with high accuracy — once every ten seconds is more than enough.

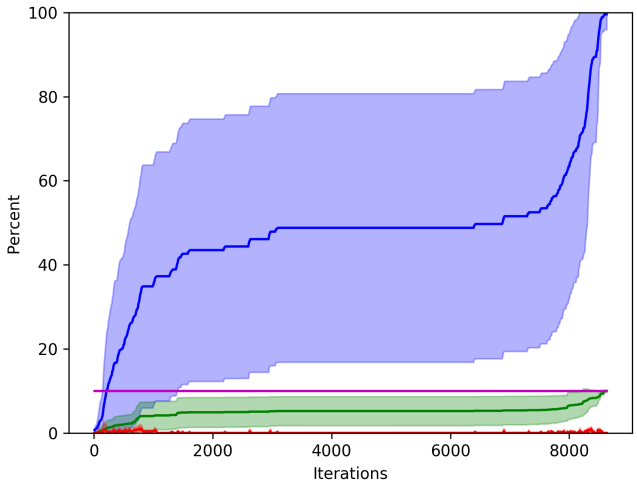
5. Integrated confidence measure: Since nodes using TruMan store trust values as a number between 0 and 1 that increase or decrease the more nodes interact (i.e. the more evidence they gather), this value can be used as a confidence measure of the opinion. Setting the threshold h to a value closer to 1 makes it unlikely that untrustworthy nodes will be incorrectly labeled as correct.

6. System level security: A public-private key solution can be used to verify message integrity. This has not been considered in evaluations of TruMan. However, it can be included as a separate security model during the transmission of messages.

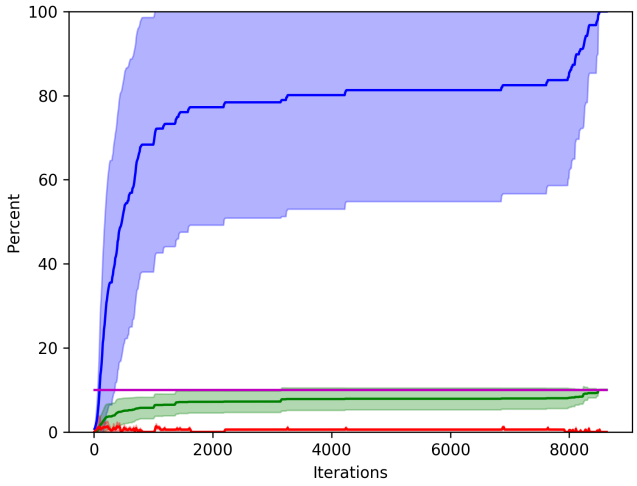
7. Sensitivity to privacy concerns: TruMan has not been designed with this in mind, as it requires that nodes maintain a constant identity the whole time. However, this does not inhibit other types of privacy protection, which can be implemented in addition to TruMan.

8. Robustness: the model's resistance to attacks. TruMan satisfies this property. Malicious nodes are quickly and accurately identified, making it difficult for them to perform attacks. Experiments show that, when fewer than 50% of nodes in the network are malicious, TruMan performs as expected. Collusion attacks must be performed by more than half of the entire network, in which case the network is considered compromised. Furthermore, since nodes take into consideration experiences from several trustworthy nodes, a malicious node that occasionally behaves correctly can still be identified. Experiments with information aging show that it is possible to detect nodes that suddenly become malicious, although further experimentation with known attacks is still necessary.

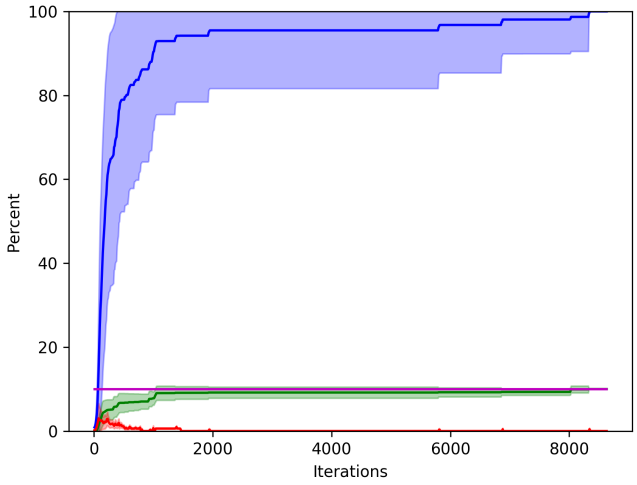
Finally, it is worth noting that, considering the scale of the problem, TruMan's cost is very low without sacrificing completeness and correctness. The model satisfies or permits most of the desired properties of a trust model with low computational complexity, making it viable for real-world use.



(a) ρ = 10m.

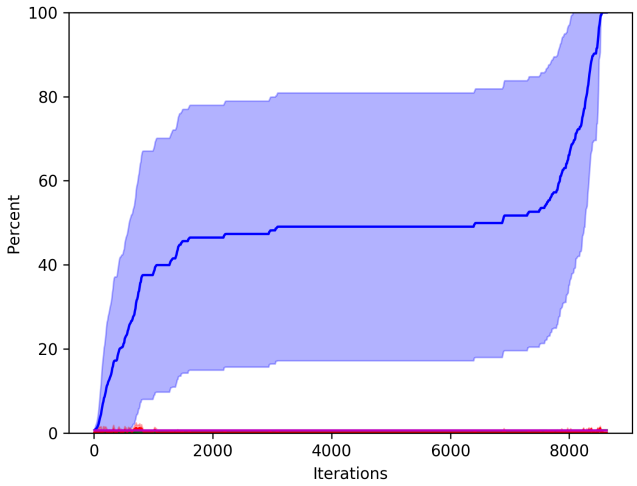


(b) ρ = 30m.

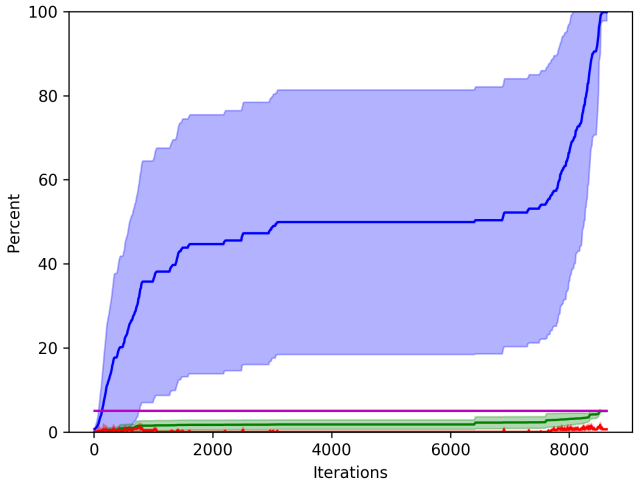


(c) ρ = 50m.

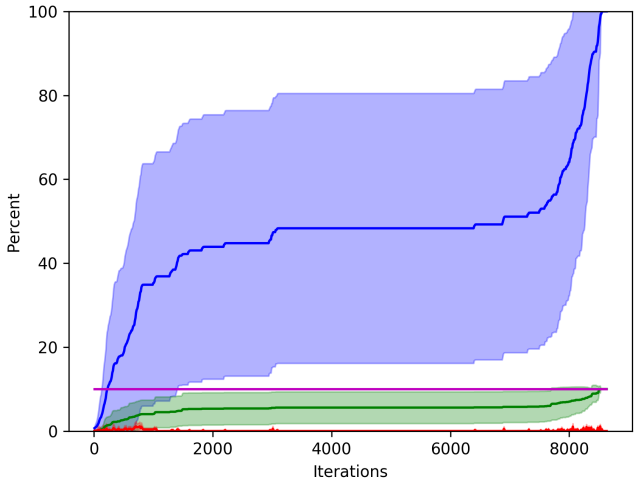
Figure 5.1: Simulation with 10% malicious nodes and varying values of ρ.



(a) 1% malicious.

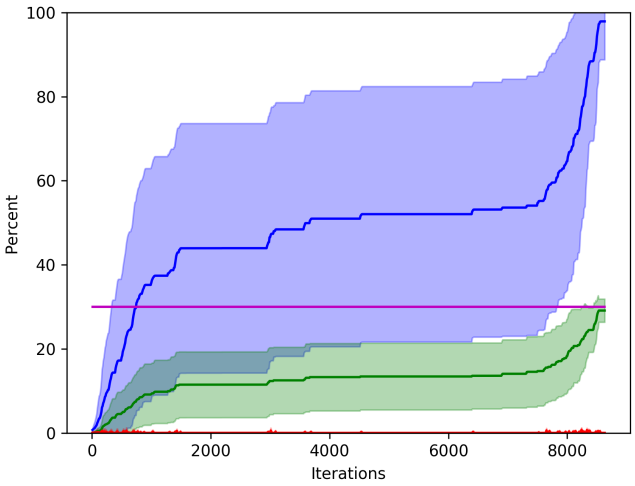


(b) 5% malicious.

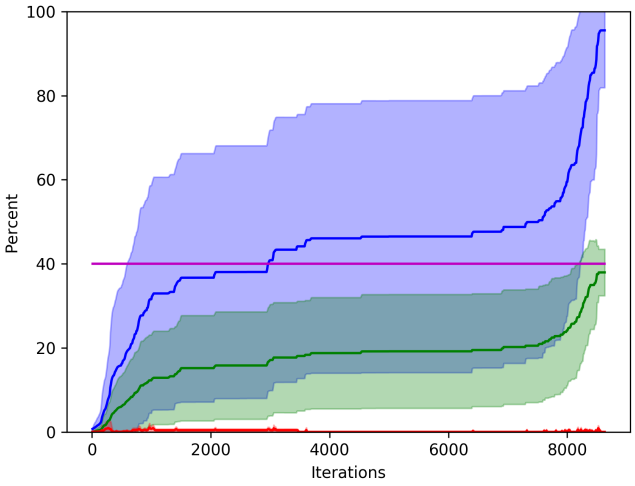


(c) 10% malicious.

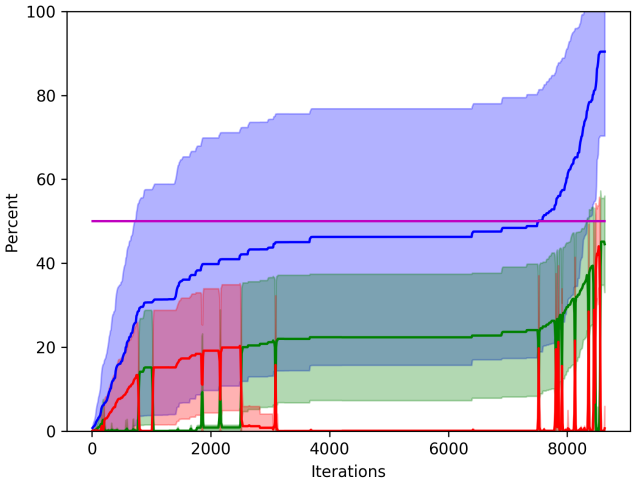
Figure 5.2: Simulation with ρ = 10m and varying percentages of malicious nodes (1/2).



(a) 30% malicious.

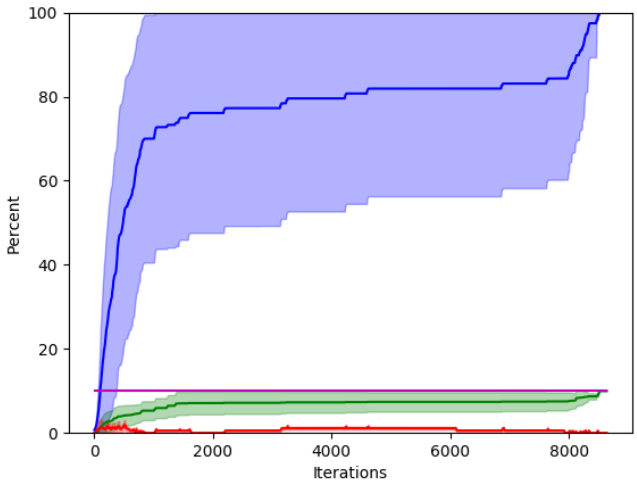


(b) 40% malicious.

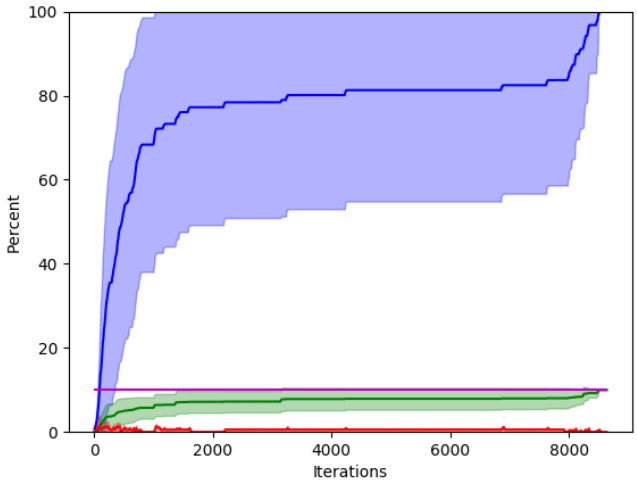


(c) 50% malicious.

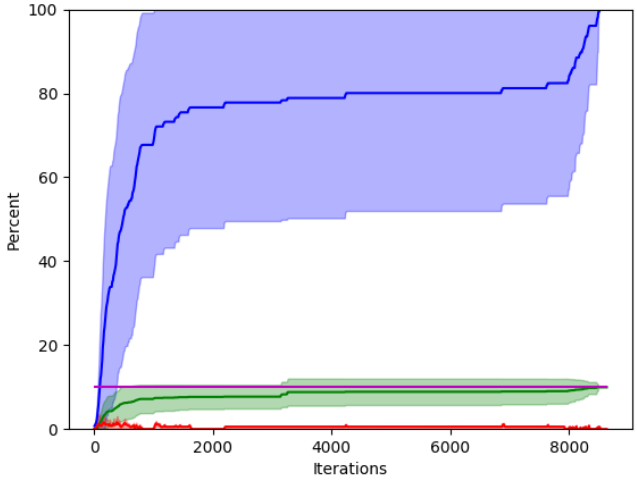
Figure 5.3: Simulation with ρ = 10m and varying percentages of malicious nodes (2/2).



(a) $h = 0.3$.



(b) $h = 0.5$.



(c) $h = 0.7$.

Figure 5.4: Simulation with 10% malicious nodes, $\rho = 30$m and varying values of h.

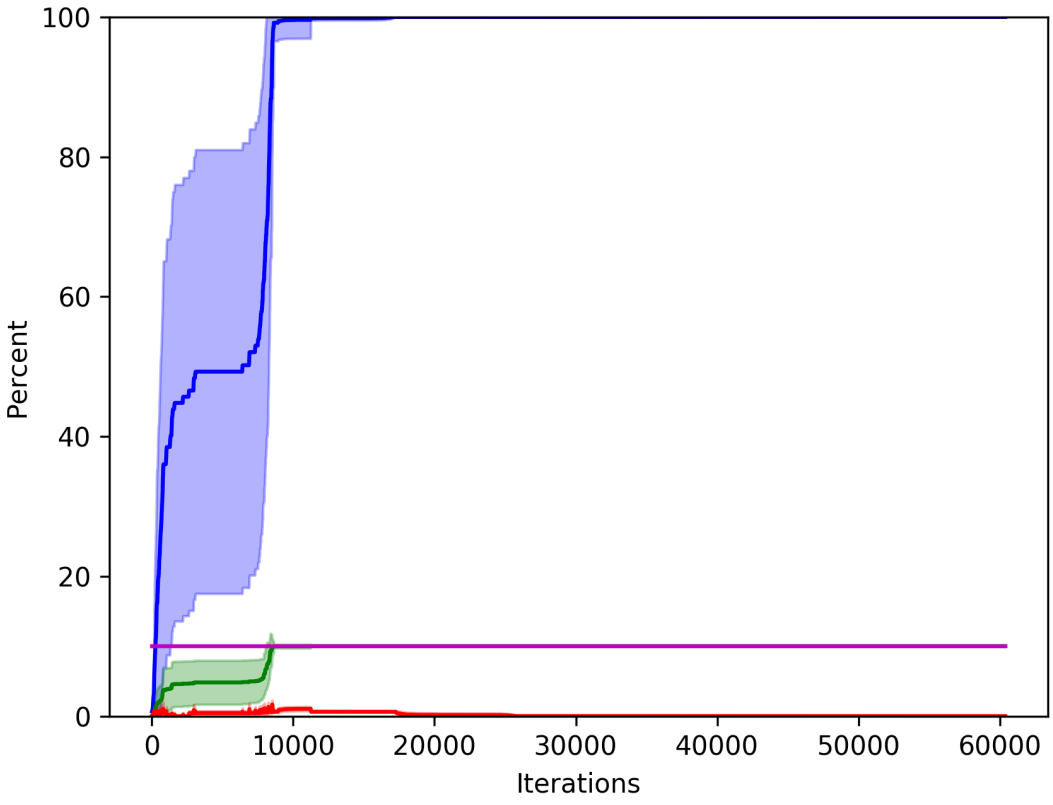
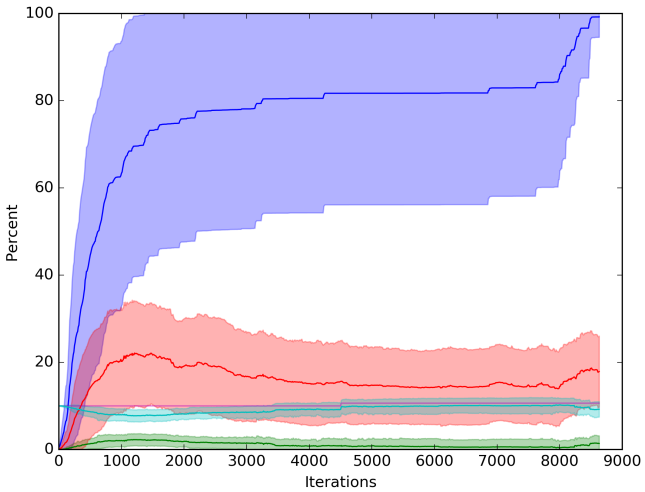
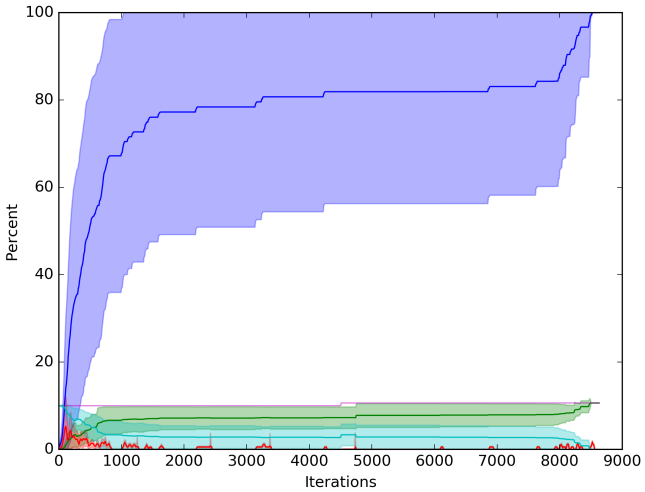


Figure 5.5: 7 days scenario: 10m range and 10% malicious nodes.

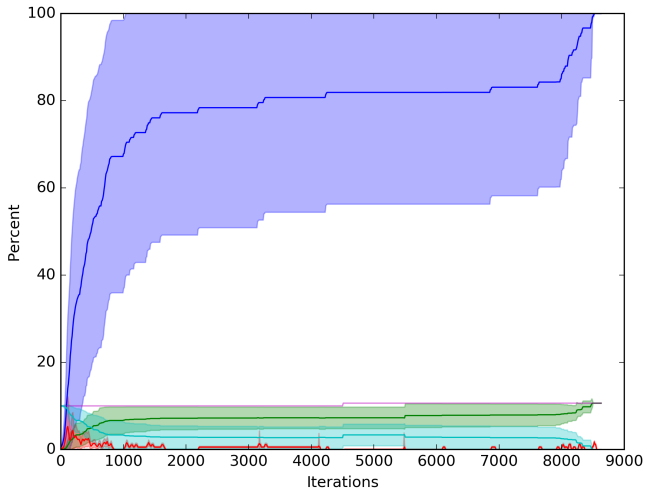


(a) $m = 10$.

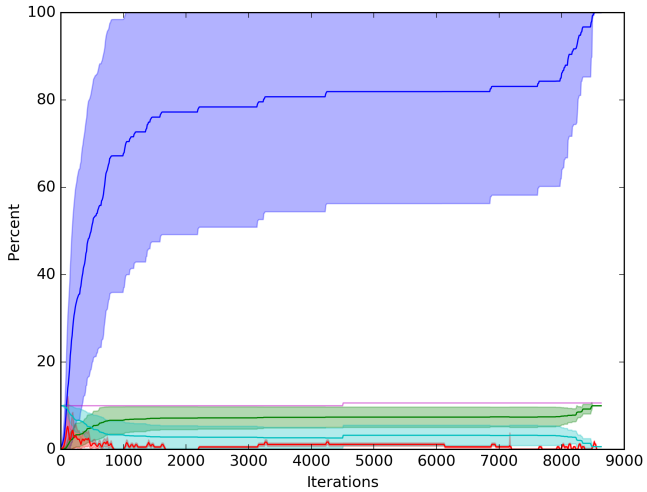


(b) $m = 250$.

Figure 5.6: Simulation with information aging, with different maximum age values (1/2).



(a) $m = 1000$.



(b) $m = 5000$.

Figure 5.7: Simulation with information aging, with different maximum age values (2/2).

Chapter 6

Conclusion

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 previously proposed algorithms in order to generate fast and accurate results.

As nodes travel across the network and collect more data from neighbors, 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 nodes can be simplified into a much smaller one. Using a simple graph coloring algorithm, most malicious nodes stand out by having different colors 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 very tiny 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. Future work includes the extension of the proposed model to use V2I communications.

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