

TrustPH: Trustworthy Platoon Head Selection considering Cognitive Biases to enhance Secure Platooning in Intelligent and Connected Vehicles

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Abstract—Vehicle platooning is a well-known technique utilized in intelligent and connected vehicles, where a platoon head is responsible to safely lead and guide a group of user vehicles. Platoon head selection can be optimized for various objectives, such as efficiency, safety, and security. This work considers a reputation system based approach to enhance the trustworthiness of platoon head selection while maintaining existing security requirements. The selection of a platoon head is based on the analysis of historical data, collected during previous trips among all participating user vehicles. To enhance trustworthiness, we propose the TrustPH framework, in which cognitive biases in the feedback scores, provided by user vehicles, are examined and the scores are adjusted accordingly. To evaluate TrustPH, a number of datasets are generated including different scenarios of cognitive bias and malicious behavior in user vehicle scoring. The obtained results demonstrate the effectiveness of TrustPH in ignoring cognitive biases in the platoon head selection process while ensuring that certain types of malicious scores are removed.

Index Terms—vehicle platooning, platoon head, cognitive bias, trustworthy, security, malicious vehicles, reputation systems

I. INTRODUCTION

Under cooperative driving, a number of vehicles are grouped together into a single group to enhance traveling quality, traffic throughput, and road safety [1]–[3], [9]. This collaborative Intelligent and Connected Vehicle (ICV) model is referred as vehicle platooning and has the capability to make vehicles accelerate or brake in a collaborative manner. Vehicle platooning typically consists of a platoon head vehicle leading a set of user vehicles [4], [10], [12]. A platoon head's role is crucial as it is responsible to guide user vehicles safely to their destination. Therefore, it controls the speed and maintains a minimum safe distance between all user vehicles to avoid possible fatalities [5]. To fulfill this, the platoon head communicates and gathers data from all the user vehicles via Vehicle-to-Vehicle (V2V) communication, and it also exchanges data with Road Side Units (RSUs) via Vehicle-to-Infrastructure (V2I) communication. Apart from the safety requirements, security is a growing challenge in vehicle platooning, which needs to be considered explicitly [8], [11].

Several works have been proposed to select a secure and trustworthy platoon head. Hu et al. [8] present an iterative trust-based filtering algorithm to filter out possible malicious feedback scores from user vehicles in order to select a

secure platoon head. The consequent work of Toor et al. [11] provides an improvement on the computational complexity of [8], but does not consider further the trustworthiness or security of the approach. The game theory-based framework presented by Chen et al. in [6] presents a cyber-physical-social approach to motivate user vehicles in order to act as platoon heads in a collaborative manner. The work in [6] considers several social metrics such as the number of common friends, common social interests, and social interactions. In [8] and [11], the social parameter is not explicitly considered. Instead, uncertainty, in general, is modeled using Dirichlet and Beta distributions. Contrary to these previous works, the proposed approach incorporates social behavior in user vehicles' feedback scores by considering certain behavior based on cognitive biases of the users, which can affect their scores and, hence, the selection of the platoon head.

In general, cognitive biases are systematic patterns of deviation from the norm which stem from belief, decision-making and behavioral biases, memory biases, or other social biases. In this work, we consider social cognitive biases, which result in biased and/or unfair scoring in reputation-based systems [7]. In particular, we consider three different types of biased scoring behavior: (i) *optimistic* behavior, where a user tends to consistently give higher scores than other users in the same group with the same experience, (ii) *pessimistic* behavior, where a user tends to consistently give lower scores than other users in the same group with the same experience, and (iii) *inconsistent* behavior, where a user's scores have high variability with respect to the scores of other relevant users.

This work considers a reputation system based approach to select a platoon head among the available candidate platoon heads. After completing a trip, platoon user vehicles provide feedback to score the platoon head vehicle's performance. The feedback is stored in a central server and used for future platoon head selections [3]. Typically, reputation systems analyse historical data collected during previous trips among participating vehicles based on which reputation score for each candidate platoon head is computed. The candidate platoon head with the highest reputation score is selected to lead the platoon.

The main contributions of this paper are the following:

- A new cognitive bias analysis algorithm is proposed for the type of biases discussed above, which enhances

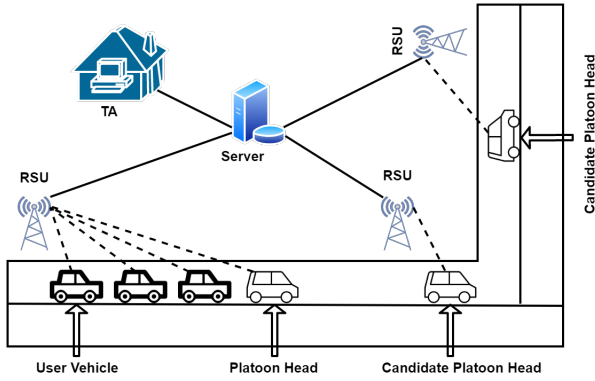


Fig. 1: VANET System Model for Platooning

the overall trustworthiness in the selection of a platoon head. The algorithm is based on a proposed faith score model to adjust biased scores where appropriate, or remove all together untrustworthy vehicles.

- A secure reputation system scheme for vehicle platooning similar to that in [8] is considered, however, attacker vehicles are distinguished from vehicles with cognitive bias but not necessarily malicious scores. In the case a vehicle is identified as an attacker, all of its scores are dropped from consideration.
- A parameterizable dataset generator with 12 input parameter has been developed to evaluate the proposed TrustPH framework, and multiple datasets based on different bias and attack scenarios have been derived.
- TrustPH is validated using the generated datasets and is compared with existing works to demonstrate its effectiveness in improving the accuracy and robustness when the considered biases are taken under consideration, as proposed in this work.

The rest of the paper is structured as follows. Section II discusses the considered system model and major definitions. Section III presents the proposed framework, along with the new algorithm for cognitive bias identification and calculation of the reputation score of a candidate platoon head. Section IV discusses the newly generated datasets used to evaluate the proposed framework. The obtained experimental results are presented and discussed in Section V, which also provides comparison with the related state of the art. Section VI concludes the paper and discusses future directions.

II. SYSTEM MODEL AND DEFINITIONS

A. System Model and Problem Definition

The system model considered in this work is a Vehicular Ad hoc NETWORK (VANET) model consisting of a Trust Authority (TA), multiple Road Side Units (RSU), a central server, a set of platoon head vehicles, a set of candidate platoon head vehicles, and a set of user vehicles as shown in Figure 1. The TA administrates the VANET system and registers the server, the RSUs, and the participating vehicles in the network. RSUs are placed to specific distances on the road to facilitate uninterpreted communication. The user

TABLE I: Historical Database with user vehicle feedback scores and platoon heads reputation scores in previous trips

PH Vehicle	Trip ID	User Vehicle	Feedback	Reputation Score
ph_1	Tr_1	v_1	$F_{Tr_1}^{v_1}$	Rep_1
		v_2	$F_{Tr_1}^{v_2}$	
	Tr_2	v_1	$F_{Tr_2}^{v_1}$	
		v_7	$F_{Tr_2}^{v_7}$	
ph_2	Tr_3	v_1	$F_{Tr_3}^{v_1}$	Rep_2
		v_2	$F_{Tr_3}^{v_2}$	
		v_4	$F_{Tr_3}^{v_4}$	
		v_5	$F_{Tr_3}^{v_5}$	
	Tr_6	v_2	$F_{Tr_6}^{v_2}$	
		v_3	$F_{Tr_6}^{v_3}$	
...
ph_{n-ph}	Rep_{n-ph}
	Tr_j	
		v_i	$F_{Tr_j}^{v_i}$	

vehicles that participate in a platoon provide their feedback score to an RSU after the completion of a trip, using a V2I communication. Then, the RSU forwards the user vehicle feedback to the server which computes the reputation score of the platoon head vehicle. In the model there are also several candidate platoon heads that are ready to act as platoon heads in upcoming trips in the case that they will be selected. When a platoon is formed, the RSU selects the platoon head that has the highest reputation score among all the candidate potential platoon heads. This work focuses on the selection of a trustworthy and secure platoon head from on-the-road candidate platoon heads before the beginning of a new trip. The selection is based on a reputation approach, estimated by using historical data.

B. Historical Database

To estimate the reputation score, a global database is needed to keep historical data related to the platoon heads and the trips they led in the past, as shown in Table I. The database is updated each time a group of user vehicles complete a trip and submit their feedback scores.

Let TR be a set of trips with the total number of n_{tr} trips in the database so that $TR = \{Tr_1, Tr_2, Tr_3, \dots, Tr_{n_{tr}}\}$, and V be the set of all the unique vehicles with a total number of n_v vehicles in the system so that $V = \{v_1, v_2, v_3, \dots, v_{n_v}\}$. Let PH be the set of platoon heads with the total number of n_{ph} so that $PH = \{ph_1, ph_2, ph_3, \dots, ph_{n_{ph}}\}$. If a user vehicle $v_i \in V$ participates in a platoon service with a platoon head $ph_k \in PH$ in a trip $Tr_j \in TR$, the user vehicle gives a feedback $F_{Tr_j}^{v_i} (\in [0, 1])$. The reputation score for each platoon head is denoted as Rep_i for a platoon head ph_i .

C. Platoon User Vehicles Definitions

In the proposed framework, the database is updated at the end of each new trip Tr_i . Let C denote the set of all user

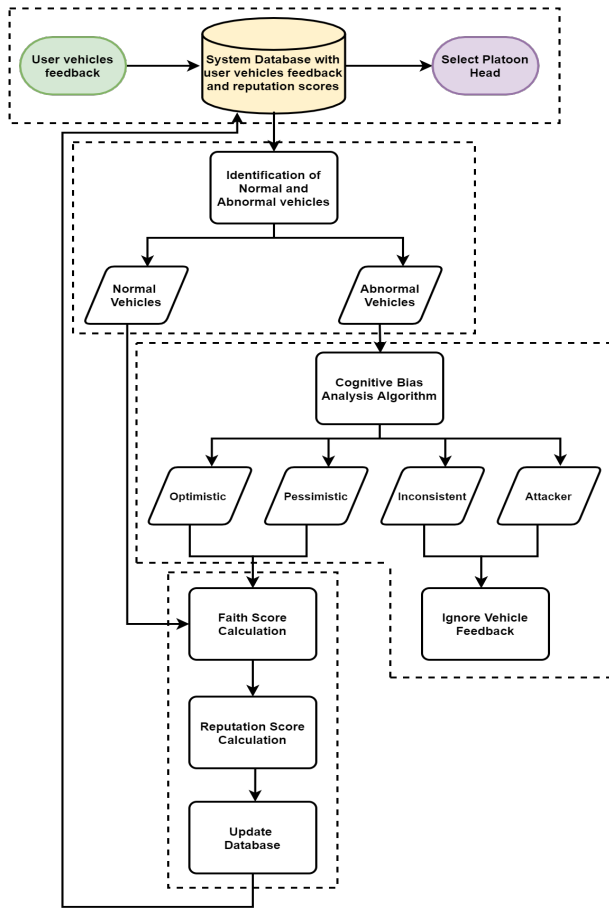


Fig. 2: TrustPH framework for platooning

vehicles participating in Tr_i . After Tr_i is completed and all user vehicles feedback is collected, the reputation scores of platoon head vehicles in the database are updated. All platoon heads for which some user vehicle $v_j \in C$ appears in previous trips for these heads, are considered. This is done in order to maintain up-to-date reputation scores for all platoon heads, based on the collective knowledge and analysis done of the provided feedback. Hence, biased or untruthful feedback is identified and adjusted accordingly to derive up-to-date and trustworthy reputation scores for relevant platoon head vehicles. To facilitate this process, user vehicles are identified using the following categories:

Definition 1 - Normal Vehicle: A vehicle $v_i \in V$ is considered as normal if v_i consistently provides truthful and unbiased feedback score. A normal vehicle is trustworthy. The set of all normal vehicles is denoted by NV .

Definition 2 - Abnormal Vehicle: A vehicle $v_i \in V$ is considered as abnormal if $v_i \in V \setminus NV$. An abnormal vehicle can be untruthful or biased. The set of all abnormal vehicles is denoted by UV .

Definition 3 - Optimistic Vehicle: A vehicle $v_i \in UV$ is considered as optimistic if v_i consistently provides truthful but biased feedback score which is higher than the feedback score provided by normal vehicles within the same trip and

experience. The set of optimistic vehicles is denoted by OV .

Definition 4 - Pessimistic Vehicle: A vehicle $v_i \in UV$ is considered as pessimistic if v_i consistently provides truthful but biased feedback score which is lower than the feedback score provided by normal vehicles within the same trip and experience. The set of pessimistic vehicles is denoted by PV .

Definition 5 - Inconsistent Vehicle: A vehicle $v_i \in UV$ is considered as inconsistent if v_i provides feedback scores with large variance with the feedback scores provided by normal vehicles within the same trip and experience. The feedback is considered inconsistent but not necessarily malicious. The set of inconsistent vehicles is denoted by IV .

Definition 6 - Attacker Vehicle: A vehicle $v_i \in UV$ is considered as an attacker if it provides untruthful and malicious feedback. The set of attacker vehicles is denoted by AV . Different types of attacks can be considered to identify an attacker vehicle. The focus of this work is on cognitive bias identification, while maintaining a secure reputation system. Hence, without any loss of generality, we consider three different types of attacks: *badmouth*, *ballot – stuff*, *on – off* feedback attack examined in [8] and ensure that bias is distinguished from possible malicious behavior.

III. PROPOSED TRUSTPH FRAMEWORK

This section introduces TrustPH, a framework for classifying user vehicles and updating the reputation scores of relevant platoon head vehicles. This process is executed upon completion of a trip and the collection of the feedback scores from all user vehicles participating in the trip. The flowchart of TrustPH is shown in Figure 2. The framework consists of three main processes: identification of the normal (NV) and abnormal (UV) vehicles, analysis of the user vehicles cognitive bias to further classify the abnormal (UV) vehicles, calculation of the reputation scores of relevant platoon head vehicles based on the faith score of vehicles in $NV \cup OV \cup PV$.

A. Identification of Normal and Abnormal Vehicles

When a platoon trip is completed, reputation scores need to be re-calculated and updated in the database. In order to do this, the framework first identifies normal and abnormal vehicles from the set of all user vehicles that participated in the trip. The identification process filters out all the vehicles that exhibit any abnormal behaviour, in order to consider them for further exploration. Such an identification process can be handled by existing approaches, such as the one proposed in [8] where an iterative filtering algorithm is utilized to filter out malicious vehicles.

Let the set of all the user vehicles which completed some trip be denoted by $C \subseteq V$. By applying the identification process for C , we derive $C' \subseteq C$ that contains all the abnormal vehicles, which are further analysed and classified.

Algorithm 1: Cognitive Bias Analysis Algorithm

Input: Set of abnormal vehicles C'

Output: Sets of biased vehicles $OV \cup PV$ and
untrustworthy vehicles $IV \cup AV$

```
1 for ( $\forall v_i \in C'$ ) do
2   if ( $MF_{v_i} \leq MT_{Low} \vee MF_{v_i} \geq MT_{High}$ ) then
3     if ( $SDF_{v_i} \geq LT_{STD} \vee SDF_{v_i} \geq HT_{STD}$ )
4       then
5         for  $\forall F_{v_i} \in Tr_j$  do
6           if ( $MF_{v_i} \geq MT_{High} \wedge F_{v_i}^{Tr_j} \leq$ 
7              $MT_{High}$ )  $\vee$ 
8             ( $MF_{v_i} \leq MT_{Low} \wedge F_{v_i}^{Tr_j} \geq$ 
9                $MT_{Low}$ ) then
10               $Count = Count + 1$ 
11            end
12          end
13          if ( $Count \leq N_{v_i}$ ) then
14            Add  $v_i$  to  $OV \cup PV$ 
15          else
16            Add  $v_i$  to  $IV \cup AV$ 
17          end
18        else
19          Add  $v_i$  to  $OV \cup PV$ 
20        end
21      else if ( $SDF_{v_i} > T_{Trip} \wedge SDT_{v_i} > T_{Trip}$ ) then
22        Add  $v_i$  to  $IV \cup AV$ 
23      end
24    end
25  end
```

B. Cognitive Bias Analysis Algorithm

The pseudocode of the second process of TrustPH is shown in Algorithm 1, which is applied on C' set derived during the previous process. The aim of this algorithm is to distinguish user vehicles according to their cognitive biases into optimistic, pessimistic, or inconsistent. Vehicle not classified as biased are identified as attack vehicles.

Let F_{v_i} be the set that contains all the feedback scores of a user vehicle v_i , MF_{v_i} is the mean of all the feedback scores given by a user vehicle v_i , SDF_{v_i} is the standard deviation of all the feedback scores given by a user vehicle v_i and SDT_{v_i} is the standard deviation of all the feedback scores given by all the vehicles for the trips that v_i participated. All the user vehicles that satisfy the condition $MF_{v_i} \leq MT_{Low}$, are added to the OV set, where all the user vehicles that satisfy the condition $MF_{v_i} \geq MT_{High}$, are added to the PV set.

MT_{Low} and MT_{High} denote the mean feedback threshold values for optimistic and pessimistic vehicles, respectively. These values are picked randomly for the experiment. The SDF_{v_i} is compared with LT_{STD} and HT_{STD} that denote the standard deviation threshold values for the optimistic and pessimistic vehicles, respectively.

To estimate LT_{STD} and HT_{STD} threshold values the following formulas are used:

$$LT_{STD} = \frac{\sum_{\forall v_i \in OV} \sigma(F_{v_i})}{|OV|} \quad (1)$$

$$HT_{STD} = \frac{\sum_{\forall v_i \in PV} \sigma(F_{v_i})}{|PV|} \quad (2)$$

Furthermore, T_{Trip} is the threshold value for the standard deviation for all the feedback scores for all the trips that v_i participated. To calculate T_{Trip} , the following formula is used:

$$T_{Trip} = \frac{\sum_{\forall v_i \in NV} \sigma(F_{v_i})}{|NV|} \quad (3)$$

Another important parameter in the algorithm is the N_{v_i} . This parameter determines the number of fluctuations of all the feedback given from a specific vehicle. Thus, to estimate the number of feedback fluctuations for a vehicle v_i , we estimate N_{v_i} :

$$N_{v_i} = T_N^{v_i} * NF_{v_i} \quad (4)$$

where $T_N^{v_i} = [0, 1]$ is the fluctuation threshold for the user vehicle v_i and NF_{v_i} is the total number of feedback of the user vehicle v_i . In the case that the number of the fluctuations are above a specific threshold then the vehicle v_i is determined as inconsistent. In our work, we allow a percentage of fluctuations $T_N^{v_i} = [0, 1]$ for each user vehicle. The proposed algorithm identifies the set of $OV \cup PV$, and the set of $IV \cup AV$. All the feedback scores in $IV \cup AV$ are ignored from the calculation of the reputation scores, whereas the feedback scores in $OV \cup PV$ are adjusted to remove the bias.

C. Faith and Reputation Score Calculation

The feedback scores of the normal (N), optimistic (OV) and pessimistic (PV) user vehicles are used to estimate faith scores and reputation scores. Faith score is the cumulative, adjusted (where necessary) score of a user vehicle v_i , computed based on all the feedback scores of v_i for all the trips in which it has participated.

The formula used to calculate the faith score $FS_{v_i} (\in [0, 1])$ for a user vehicle v_i is as follows:

$$FS_{v_i} = \frac{1}{\gamma_o} \sum_{j=1}^{|I_{v_i}|} \frac{A_{Tr_j}}{F_{Tr_j}^{v_i}} \gamma_s \quad (5)$$

where A_{Tr_j} is the average number of the feedback given by the normal vehicles in trip Tr_j , $F_{Tr_j}^{v_i}$ denotes the feedback of a user vehicle v_i for the trip Tr_j , γ_s is the cumulative feedback of v_i , γ_o is the sum of cumulative feedback of v_i , and I_{v_i} has all the trip ids that a user vehicle v_i participated.

The faith score is then used to estimate the reputation score of platoon head vehicles in the database, to determine the trustworthiness of relevant platoon heads after the completion of a trip. Relevant platoon heads include the head of the trip, as well as heads that have previously led any of the user

TABLE II: Input Parameters for Dataset Generation Program

Parameters	Description	Single-Biased Datasets	Multi-Biased Datasets			
		Validation Dataset Group	Dataset 1	Dataset 2	Dataset 3	Dataset 4
V_U	Total number of unique vehicles	50	100	200	50	100
PH	Total number of platoon head	[10, 11]	[6, 8]	[12, 20]	[10, 20]	[15, 20]
T_{PH}	Number of trips under each platoon head	[5, 10]	[8, 14]	[25, 40]	[25, 40]	[10, 15]
V_T	Number of vehicles under each trip	[5, 25]	[10, 20]	[15, 30]	[15, 30]	[10, 20]
T_G	Percentage of high quality trips	0.8	0.8	0.8	0.8	0.8
T_M	Percentage of medium quality trips	0	0.15	0.15	0.15	0.15
T_B	Percentage of low quality trips	0.2	0.05	0.05	0.05	0.05
V_{OV}	Percentage of optimistic vehicles	0.1, 0.2, 0.3, 0.4	0.1	0.1	0.1	0.25
V_{PV}	Percentage of pessimistic vehicles	0.1, 0.2, 0.3, 0.4	0.1	0.1	0.2	0.25
V_{IV}	Percentage of inconsistent vehicles	0.1, 0.2, 0.3, 0.4	0.1	0.1	0.1	0.1
T_N	Percentage of fluctuations in vehicles feedback	0	[0, 0.4]	[0, 0.5]	[0, 0.3]	[0, 0.4]
V_{AV}	Percentage of attacker vehicles	0	0.05	0.05	0.1	0.1

TABLE III: Threshold values for parameters that are used on cognitive bias analysis algorithm for all the multi-biased datasets

Parameters	Dataset 1	Dataset 2	Dataset 3	Dataset 4
MT_{Low}	0.5	0.5	0.5	0.5
MT_{High}	0.5	0.5	0.5	0.5
LT_{STD}	0.1521	0.1456	0.1189	0.1181
HT_{STD}	0.1019	0.1208	0.1177	0.1274
T_{Trip}	0.0852	0.0855	0.0915	0.0893
$T_N^{v_i}$	0.1	0.2	0.1	0.1

vehicles of the trip. The reputation score Rep_k for a platoon head vehicle ph_k is calculated using the following equation:

$$Rep_k = \frac{\sum_{Tr_j} \sum_{v_i} FS_{v_i} \cdot F_{Tr_j}^{v_i}}{\sum_{Tr_j} (\sum_{v_i} FS_{v_i} \cdot F_{Tr_j}^{v_i})} \quad (6)$$

where $Tr_j \in AT_k$. AT_k is the set of all the trip IDs for the platoon head ph_k . After the calculation of the reputation score, the database is updated.

IV. DATASET GENERATION

Due to the lack of real-world data related to user vehicle feedback, we have developed a dataset generator program to evaluate our proposed framework. The dataset generator consists of 12 input parameters as shown in Table II. The input parameters PH , T_{PH} and V_T use a range of input values, and the generator is responsible to output a specific value between that range. Inspired by real-life, on-road situations, the dataset generator includes three types of trips which are determined based on the average feedback given by the normal vehicles for a specific trip : high-quality trips, medium quality trips, and low-quality trips. High quality trips have a high feedback average, medium quality trips have medium feedback average and low-quality trips have low feedback average.

To evaluate our proposed framework, we have generated 16 different datasets split into two main categories: the single-biased datasets, and the multi-biased datasets, as shown in Table II. The single-biased datasets consist of a group of 12 sub-datasets that are used only for validation

of the cognitive-biased algorithm. Specifically, each dataset from the single-biased datasets has only a single bias, either optimistic or pessimistic or inconsistent. All the other parameters used for the single-biased datasets remain the same for all the 12 datasets as shown in Table II. Particularly, each of the single-biased datasets includes 50 unique vehicles, 74 trips, 10 platoon heads, and 1140 total feedback. On the other hand, the multi-biased datasets are used for evaluation of the reputation score under different scenarios presented in Section V. The input values used for each dataset in the multi-biased datasets are as follows: dataset 1 includes 100 unique user vehicles, 68 trips, 6 platoon heads, and 1033 total feedback scores, dataset 2 includes 200 unique user vehicles, 662 trips, 20 platoon heads, and 14926 total feedback scores, dataset 3 includes 50 unique vehicles, 228 trips, 18 platoon heads, and 3359 total feedback scores and finally, dataset 4 includes 100 unique vehicles, 250 trips, 19 platoon heads, and 3692 total feedback scores. The use of small and large datasets is to evaluate the scalability of the TrustPH framework. All the other input values for each parameter of each dataset are presented in Table II.

The percentages of pessimistic vehicles (V_{PV}) and optimistic vehicles (V_{OV}) for each dataset, shown in Table II, are estimated using normal distribution based on the mean and standard deviation of the normal vehicles feedback scores. Table III depicts all the threshold values that are used to evaluate the cognitive bias analysis algorithm for the multi-biased datasets.

V. EVALUATION RESULTS

A. Cognitive Bias Analysis Algorithm Results

In this analysis, we explore how the cognitive bias analysis algorithm affects the reputation scores for the three cognitive biased categories by using all the 12 single-biased datasets.

Figure 3 shows an exploration of the reputation scores of optimistic vehicles (OV), pessimistic vehicles (PV), and inconsistent vehicles (IV) for different percentages. In the following results, we compare our proposed framework's

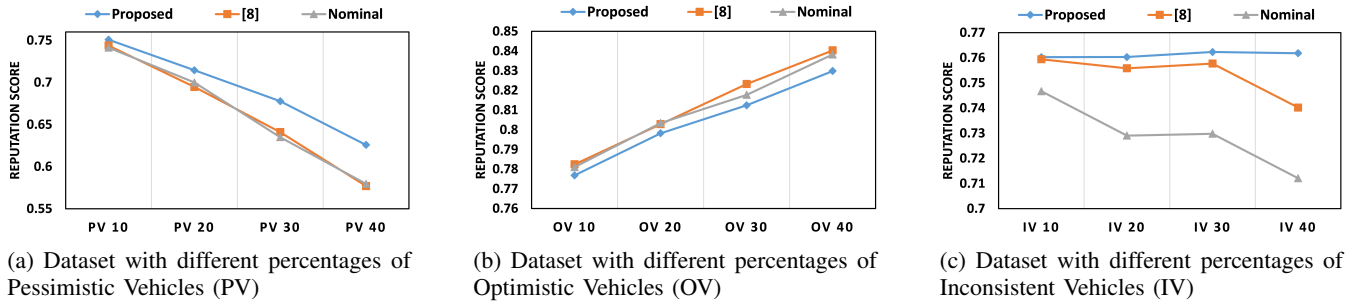


Fig. 3: Reputation Score for different cognitive biased user vehicles using Validation Dataset Group

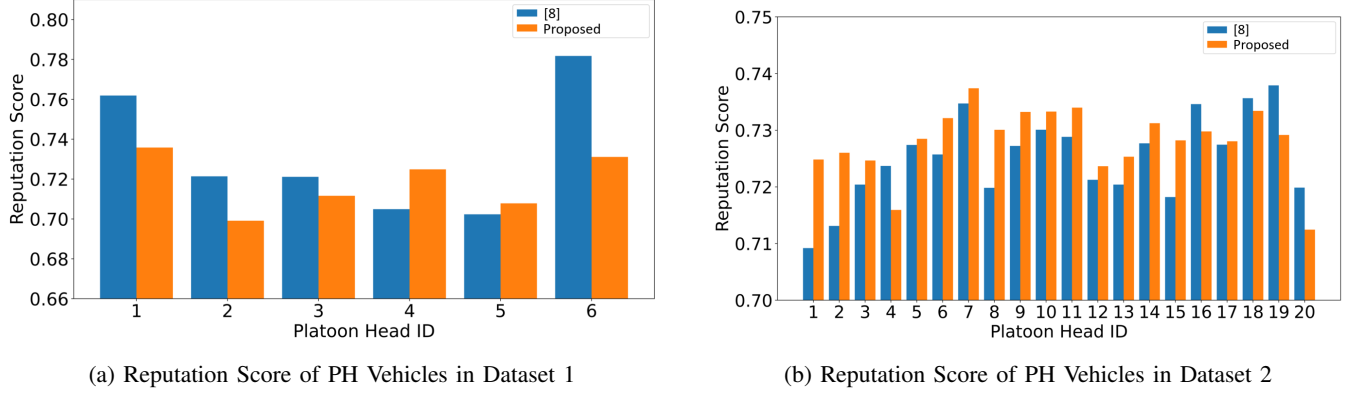


Fig. 4: Platoon Head (PH) Selection with [8] and proposed frameworks for Dataset 1 and Dataset 2

reputation score (TrustPH) with the reputation score estimated from the work in [8] and with a reputation score derived from a nominal approach. The work in [8] removes only the attacker user vehicle's feedback scores, whereas the nominal approach is the baseline where there are no adjustments or removals. Figure 3(a) shows how different percentages of *PV* affect the reputation scores for all the three approaches. In order to evaluate the single-bias for *PV*, we do not add any percentage of *OV* and *IV* or attacker vehicles. Figure 3(a) clearly shows that the proposed approach has a higher reputation score than the other two approaches. Figure 3(b) presents how different percentages of *OV* affect the reputation scores for all of the three approaches. The reputation score of the proposed approach is lower than the other two approaches for all the *OV* percentages. Finally, Figure 3(c) shows the reputation scores for different percentages of *IV*. In this case, we can see that the proposed approach gives a higher reputation score because when we detect an inconsistent vehicle, we remove all of the feedback given by that vehicle. The removal of all the inconsistent user vehicle's feedback leads to higher reputation score as only normal and adjusted optimistic and pessimistic vehicles remain in the set.

B. Platoon Head Selection

We compare the TrustPH with the work in [8] as both use the same architecture. For this analysis we run Dataset 1 and Dataset 2 of the multi-biased datasets. Figure 4(a) presents the reputation score for all the candidate platoon heads for

Dataset 1, and Figure 4(b) shows the reputation scores for all the candidate platoon heads in Dataset 2. As the Figure shows, the platoon head with the highest reputation score is different in the two approaches. Specifically, the work in [8] selects PH6 as the next platoon head, while TrustPH selects PH1 in Dataset 1, whereas in Dataset 2, the work in [8] selects PH19 while TrustPH selects PH7. The different selection happens because the work in [8] does not take into account the impact of the cognitive bias of the user vehicles.

C. Variations on the selection of platoon head

To approach the cognitive bias aspect in [8], they derive a threshold value ($C_{threshold}$) that determines the variation between the feedback provided by a vehicle v_i for a trip Tr_j and the average feedback scores for that trip. When the feedback score of a vehicle v_i overcomes this threshold, the feedback is ignored from the calculation of the reputation score. By doing this, they provide a simple way to model the aspect that the feedback scores given by the participated vehicles may be untruthful.

Figure 5 shows an exploration of different $C_{threshold}$ values for Dataset 3 and Dataset 4. The labels above the points in each line indicate the selected platoon head id for each approach. We can observe that when $C_{threshold}$ changes, the selection of the platoon head and the reputation scores change in [8] where after 0.5 it converges to the proposed platoon head selection for Dataset 3 while after 0.7 in Dataset 4, whereas the proposed approach selects the same platoon head for all the $C_{threshold}$ s. Figure 5

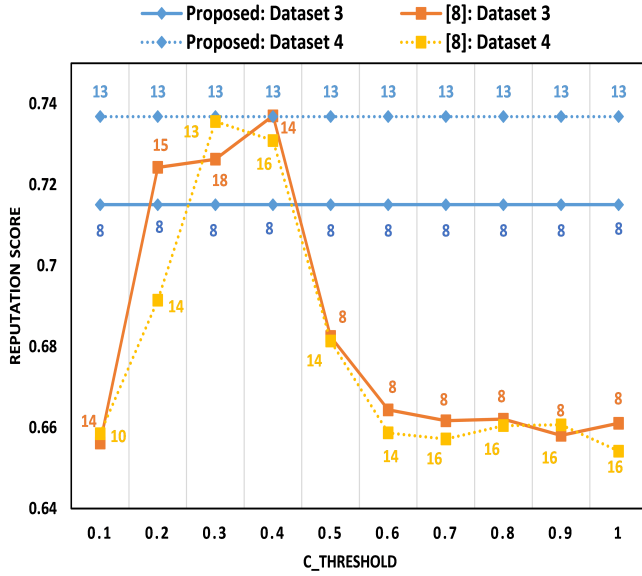


Fig. 5: Impact of $C_{threshold}$ variation on reputation score

TABLE IV: Percentage of attacker vehicles feedback scores ignored by proposed approach and the approach in [8], for all the multi-biased datasets

	Total number of feedback scores	Feedback scores ignored by [8]	Feedback Scores ignored by Proposed
Dataset 1	1033	8.89%	14.3%
Dataset 2	14926	15.05%	19.43%
Dataset 3	3359	25.13%	26.28%
Dataset 4	3692	33.23%	34.26%

clearly indicates that the work in [8] struggles to pick a good $C_{threshold}$ and thus the selection of platoon head is based on the exploration of the appropriate $C_{threshold}$ value before making any platoon head selection.

D. Analysis of the Attacker vehicles

We present in Table IV the percentages of the ignored feedback scores only for attacker vehicles. Table IV shows that the proposed approach ignores a higher percentage of feedback scores from the total number of scores because when TrustPH detects an attacker vehicle, it ignores all the feedback scores given by that user vehicle for all the trips in order to reduce the probability of any type of malicious activity in the future. In contrast, [8] removes only the detected malicious feedback scores and not all the feedback scores given by the attacker vehicles. Hence, the scores ignored in [8] are a subset of the scores ignored in the proposed approach.

VI. CONCLUSION

This paper proposes TrustPH, a cognitive bias analysis framework to select a trustworthy vehicle in secure platooning systems. A reputation system is considered, in which user vehicles provide feedback scores for each participating trip. The selection of a platoon head is decided based on

reputation scores which are derived based on historical data from previous trips. Trustworthy but biased user feedback scores are identified and adjusted by the proposed approach, in order to enhance the trustworthiness in the selection of future platoon head vehicles. Furthermore, biased feedback behavior is distinguished from malicious behavior, and the impact of each type of behavior is reflected in the computation of reputation scores. The obtained experimental results, derived based on a number of synthetically generated historical datasets, demonstrate the effectiveness of the proposed approach in identifying the considered biases, and enhancing the platoon head selection process. Future work will concentrate on identifying additional biases in single as well as multiple platoon head systems.

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