Reputation-based User Vehicle Assignment in Intelligent and Connected Vehicle Platoons

Subham Datta*, Panagiota Nikolaou†, Maria K. Michael*

*KIOS Research and Innovation Center of Excellence & Department of Electrical and Computer Engineering
University Of Cyprus, Nicosia, Cyprus,

†KIOS Research and Innovation Center of Excellence & University of Central Lancashire Cyprus, Pyla, Larnaca, Cyprus

{sdatta01, nicolaou.panayiota, mmichael}@ucy.ac.cy

***Abstract*—Vehicle platooning is a promising and emerging framework in intelligent transportation systems. Recent works consider reputation-based approaches for head selection in single platoons, in order to optimize safety and security. When a large number of user vehicles having the same destination want to benefit from platooning, several platoons need to be formed. To this end, user vehicles are allocated to different platoons, with each platoon being led by a platoon head. To ensure necessary network bandwidth and latency, the number of user vehicles between the newly formed platoons must be balanced. However, an arbitrary assignment of user vehicles in platoons can bias the future selection of the platoon heads in such reputation-based approaches. This work considers reputation-based platooning systems and proposes an optimal approach to balance the number of user vehicles in platoons while at the same time ensures fairness in the reputation score of platoon heads. A mixed-linear integer programming formulation is proposed, which provides an optimal allocation of the user vehicles in platoons based on the above objectives. The approach is validated using multiple synthetically generated datasets using 14 different input parameters. The obtained results demonstrate the optimality of the proposed method while achieving significant time performance speedups (∼ 140x on average) when compared to a brute-force exhaustive method.**

Keywords–vehicle platooning, vehicle assignment, trustworthy systems, reputation systems, fairness

I. Introduction

With the rapid advancement in Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication technologies, Intelligent and Connected Vehicles (ICVs) can communicate with each other and with the road infrastructures to enhance road safety [1]. In intelligent transportation systems, the benefits of ICVs can be further improved with the promising framework of vehicle platooning [2]. In vehicle platooning, there are two types of vehicles: a platoon head and a set of user vehicles. The platoon head guides the user vehicles to their destination, and it is responsible for controlling the speed and maintaining a safe distance between the user vehicles [3]. However, the number of user vehicles that a platoon head can lead is limited, as user vehicles must maintain a maximum distance (∼ 300m) from the platoon head in order to to ensure reliable communication [4], [5]. Furthermore, all user vehicles must communicate with the platoon head in real-time to share important information such as speed, road information, and live location [6]. Thus, high demand for network bandwidth can result in communication delays [7], which can potentially lead to fatalities. When a large number of user vehicles with the same destination require platoon services, multiple platoons need to be formed and guided by distinct platoon heads.

When forming one or more platoons, reputation-based approaches can be used to select the platoon head vehicle(s) [8]–[10]. In such frameworks, each user vehicle provides feedback at the end of each trip to rate the performance of its platoon head. This feedback is used to calculate the reputation score of future candidate platoon heads, in subsequent trips. Any head selection algorithm requires as an input a set of viable platoon heads. Similarly, when assigning user vehicles to platoons, a set of viable user vehicles per platoon must be available.

For the problem of user vehicle assignment in multiple platoons, which we consider in this work, the first requirement is to provide balanced platoons with respect to the number of user vehicles in each platoon. Moreover, the assignment of user vehicles in each balanced platoon is crucial in order to maintain fairness in the reputation-based system [11]. A reputation system is called fair if every agent receiving feedback (i.e., a score) has an equal opportunity to receive trustworthy feedback [12]. In the considered system, these agents correspond to the platoon heads, which receive feedback scores from the user vehicles. These feedback scores are used to calculate the reputation score of platoon heads. A random assignment of user vehicles in a platoon cannot guarantee a fair reputation score for the platoon head, as this is derived from the user vehicle's cumulative feedback scores, which may contain individual biased or untrustworthy user vehicle scores. Therefore, balancing the trustworthiness of the feedback of the assigned user vehicles provides fairness among the reputation scores of the leading vehicles.

The proposed methodology provides optimal user vehicle assignment, leading to balanced and fair platoons. To achieve this, a mixed-linear integer programming (MILP) formulation is proposed, which takes the user vehicle feedback scores as an input to properly assign user vehicles under platoons such that: (i) the number of user vehicles per platoon is as balanced as possible, and (ii) the average faith score among user vehicles per platoon across all platoons is also balanced. The faith score is calculated based on the current and historical feedback scores of a user vehicle in prior trips, and provides an adjustment of the feedback score in terms of trustworthiness. In this manner, the reputation score of platoon heads is calculated appropriately, based on fair user vehicle faith scores.

In particular, the main contributions of this work are:

- A new MILP formulation is proposed to maintain balance and fairness in the reputation system when assigning viable user vehicles to multiple platoons. The approach is optimal and, to the best of our knowledge, unique in reputation-based frameworks for ICVs.
- To properly evaluate the proposed framework, we created four synthetic datasets with 14 parameterizable inputs, keeping in mind real-world driving environments.
- Our approach is compared with a brute-force exhaustive optimal algorithm and a non-optimal random assignment of user vehicles. Results show that the MILP approach always finds the optimal solution while requiring significantly lower execution times (140x speedup on average) than the brute-force exhaustive approach. Furthermore, the random assignment approach is shown to be significantly inferior in terms of fairness, justifying the need for the proposed systematic approach.

The rest of the paper is structured as follows. We discuss the related works and system architectural model along with a brief background on relevant reputation-based systems for platooning in Section II and III. Section IV presents the objectives and the proposed MILP formulation. The details about the synthetic datasets used are explained in Section V. The obtained experimental results are presented in Section VI. Section VII concludes the paper.

II. Related Work and Background

Existing works in reputation-based platooning systems only focus on the selection of platoon heads [8]–[10]. Ying et al. in [9] proposed an approach for platoon head election in an opportunistic autonomous vehicle platoon (OAVP) model with an incentive mechanism to motivate vehicles to participate in the head election process. Hu et al. in [10] proposed an iterative filtering algorithm to filter out malicious feedback and select a reliable platoon head. However, all these works do not consider cognitive biases in user vehicle's feedback. The work in [8] considers such biases and proposes a cognitive bias analysis algorithm to differentiate cognitive biases from malicious feedback before calculating the reputation score of the platoon head candidates. However, the assignment of user vehicles in different platoons is not considered.

Contrary to previous works, the purpose of this work is, given a set of selected (viable) platoon heads and a set of user vehicles that are traveling together to form balanced platoons while maintaining the fairness of the reputation system by appropriate assignment of user vehicles in each platoon. The proposed approach works complementary to the reputation-based platoon head selection algorithms of [8], [10], which can provide the necessary input set of platoon heads. Even though [8], [10] consider single platoon head selection, the extension to multiple head selection is trivial, as explained in Section III.B.

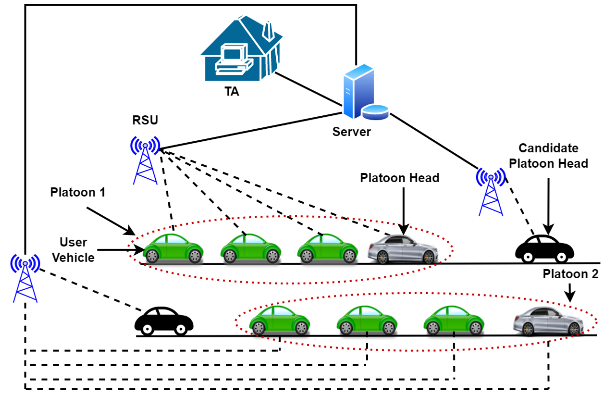

Fig. 1: Platoon System Model

III. System Model

A. System Model

The proposed work considers a Vehicular Ad Hoc NETwork (VANET) model for vehicle platooning. Our model consists of several Road Side Units (RSUs), a central server, a Trust Authority (TA), a set of platoon head vehicles, a set of candidate platoon head vehicles, and a set of user vehicles as shown in Fig. 3. To achieve high platooning performance, the communication is relied on a number of RSUs [13]. Moreover, to enhance seamless communication, the RSUs are typically deployed uniformly. After completing a trip, user vehicles rate their leading platoon head by sending feedback to the closest RSU. The RSU forwards the feedback scores ([0, 1]) to the central server, which stores the scores in a historical database and computes the cumulative faith score for user vehicles over multiple trips (based on historical and new feedback scores) [8]. When a number of user vehicles travelling together to the same destination need to form platoons, the RSU, with the help of the server, selects a number of platoon heads based on different algorithms [8], [10] from the available candidate platoon heads. Each platoon head will lead a number of user vehicles within the platoon and the RSUs with the help of the central server under the trust authority must assign the viable user vehicles under each platoon using some criteria.

In this work, we focus on the assignment of user vehicles to the preselected platoon heads for multiple platoons at the beginning of a trip, in such a way that the number of user vehicles controlled by each platoon head is balanced and the fairness of the reputation score among the platoon heads in the reputation system is preserved. As explained in Section I, the problem of platoon control is complementary to reputation systems and out of scope in this work.

B. Reputation-Based Platoon Head Selection

Previous works in [8], [10] focus on the selection of a single platoon head in a vehicle platooning system. The selection of a platoon head is based on the analysis of historical data collected during previous trips among all participating user vehicles. The work in [8] in particular considers and identifies cognitive biases in user feedback scores and adjusts such scores accordingly in order to maintain fairness in the reputation scores of viable platoon heads. After completing a trip, a cognitive bias analysis algorithm analyzes the given feedback and identifies certain biases while distinguishing them from malicious behavior. Biased feedback is readjusted, while feedback identified as unreliable or possibly malicious is removed from the system. The readjustment is done based on the collective feedback of user vehicles identified as normal (neither biased nor malicious). Following the bias analysis and feedback readjustment, the *faith score* per user vehicle across all previous trips is recalculated. The faith score is the most crucial parameter for user vehicles in the reputation system. It represents the reliability and trustworthiness of the feedback given by user vehicles. Finally, using the calculated faith score of user vehicles, the *reputation score* is computed for each potential platoon head. When forming multiple platoons, the platoon heads are selected using the same approach. For example, if k platoons are required to be formed, then k viable platoon heads with the highest reputation score are selected to lead the platoons. The reader is referred to [8] for additional details regarding the computation of faith score for user vehicles and the selection of platoon heads based on the reputation score.

IV. Proposed Methodology and Objectives

This section introduces the proposed formulation for user vehicle assignment under different platoons in order to ensure balancing and fairness between the different platoons. Let the set of all user vehicles be denoted by $N = \{n_1,\ n_2, ..., \ n_\eta\}$, with $|N| = \eta$. Also, let the set of platoon heads for different platoons be denoted by $P = \{p_1,\ p_2,\ p_3, ...,\ p_k\}$, where $|P| = k$ is the number of platoon heads. In the case of multiple platoons, each platoon head in P leads one platoon. Moreover, each user vehicle in N must be assigned to exactly one platoon. In this work, we assume that all user vehicles in N are viable for any platoon, i.e., can be led by any platoon head. The problem can be easily extended to distinct viable user vehicle sets per platoon head.

A mixed-linear integer programming (MILP) formulation is proposed, which focuses on the fair and optimal assignment of user vehicles in N under platoon heads in P. Specifically, if we want to form k platoons, the user vehicle set N is partitioned and assigned to k platoon heads that lead the platoons. Moreover, each user vehicle needs to be assigned to a single platoon led by some platoon head $p_j \in P$. Since any user vehicle in N is a viable choice for any platoon head, it is assigned to any platoon. However, each platoon needs to satisfy the following conditions:

- The number of user vehicles per platoon is balanced in order to avoid biases in reputation systems and communication delays.
- The average faith score of the user vehicles in each platoon is as close as possible in order to maintain fairness in the reputation system.

To better understand the considered problem, Fig. 2 illustrates two different scenarios (random, optimal) of user vehicle assignment. Before the start of user vehicle assignment, we

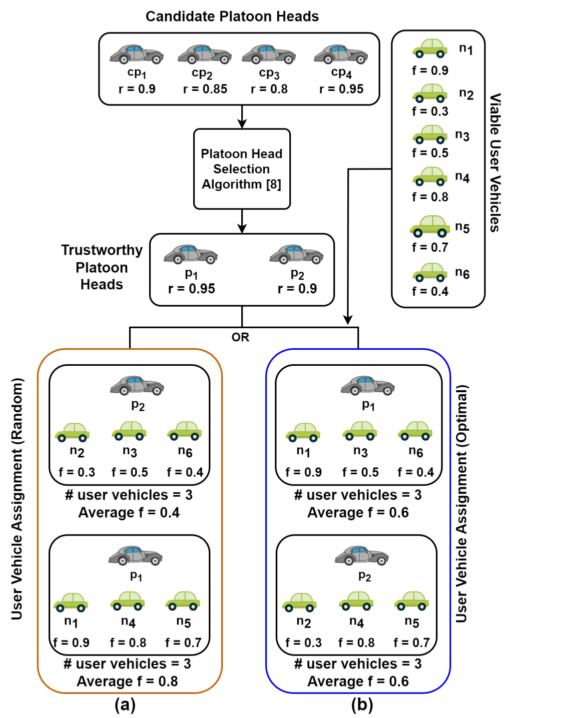

Fig. 2: An example of (a) Random and (b) Optimal Assignment of User Vehicles in each platoon

select trustworthy and secure platoon heads (P) from the candidate platoon head set (CP) using a platoon head selection algorithm [8] as shown in Fig. 2. The selection of platoon head is based on the reputation score (r) calculation which takes into account the faith scores (f) and feedback given by the participating user vehicles as defined in [8]. In this example, the number of preselected platoon heads (k) is 2, and the number of user vehicles (η) is 6. The task is to partition and assign the user vehicles from N into two platoons, led by two different platoon heads p_1 and p_2. As Fig. 2 (a) shows, if the assignment is done randomly, the average faith score of user vehicles for each platoon can deviate greatly, favoring platoon head p_1 in this case. Additionally, the random assignment negatively impacts the reputation score of p_2 and reduces the chances of getting selected as platoon head for future trips. Additionally, Fig. 2 (b) shows how the average faith score of user vehicles is comparable among the two platoons (identical in this case) when an optimal approach is used to ensure fair user vehicle assignment.

All the parameters and variables used in the formulation are presented in TABLE I. The inputs of the model are: the user vehicle set N, the available platoon head set P, and the faith score of every user vehicle, $f_{n_i}\ \forall\ n_i \in N$. The first objective is to balance the number of user vehicles in each platoon by using $\lfloor \eta/k \rfloor = q$. Additionally, we use $\eta \% k = r$ to indicate if the user vehicles can be equally allocated in k platoons. If $r = 0$, all the platoons can be perfectly balanced by assigning exactly q user vehicles in each platoon. On the other hand, if $r \neq 0$, then $(P - r)$ platoons will need to be assigned with q user vehicles each, and the remaining r

TABLE I: Description of Parameters used in MILP

Parameters	Description
N (input)	Set of user vehicles
P (input)	Set of platoon heads
f_{n_i} (input)	Faith score of user vehicle $n_i \in N$
η	Total number of user vehicles in N
k	Total number of platoon heads in P
x_{ij}	Binary variable; 1 if user vehicle $n_i \in N$ is led by a platoon head $p_j \in P$, 0 otherwise.
y_j	Number of user vehicles in a platoon led by platoon head $p_j \in P$
y_{min}	Minimum number of user vehicles among all platoons
y_{max}	Maximum number of user vehicles among all platoons
tf_{p_j}	Total faith score of a user vehicle partition in a platoon led by head $p_j \in P$
$A_{f_{p_j}}$	Average faith score of a user vehicle partition in a platoon led by head $p_j \in P$
$A_{f_{min}}$	Minimum average faith score among all platoons
$A_{f_{max}}$	Minimum average faith score among all platoons

platoons will be assigned with $(q+1)$ user vehicles each. The number of user vehicles in a platoon led by platoon head $p_j \in P$ is denoted as y_j. Moreover, variables y_{max} and y_{min} are used to calculate the maximum and minimum number of user vehicles among all k platoons. Hence, we achieve the first objective of balancing the number of user vehicles among the platoons by minimizing the difference between the number of user vehicles $(y_{max} - y_{min})$ in all platoons.

The second objective is to maintain the average faith score of user vehicles per platoon as close as possible. Each user vehicle $n_i \in N$ has its own faith score denoted by f_{n_i}. Furthermore, we denote the total faith score of user vehicles in a platoon led by a platoon head p_j by tf_{p_j}. Variable $A_{f_{p_j}}$ computes the average faith score of user vehicles assigned to a platoon led by platoon head p_j. Finally, the minimum and maximum average faith score among all user vehicle partitions assigned to different platoons are denoted as $A_{f_{min}}$ and $A_{f_{max}}$, respectively. In order to achieve the second objective, we minimize the differences between the average faith scores of user vehicle partitions in different platoons $(A_{f_{max}} - A_{f_{min}})$.

Hence, combining both objectives, the proposed MILP formulation minimizes the sum of the differences between the cardinality and the average faith score among user vehicles in different platoons:

$$Minimize\ \{(y_{max} - y_{min}) + (A_{f_{max}} - A_{f_{min}})\}$$

Subject to the following constraints (3) - (8):

$$\sum_{p_j \in P} x_{ij} = 1,\ \forall\ n_i \ \in\ N \tag{1}$$

The binary variable x_{ij} denotes if a user vehicle is already assigned to a platoon or not. Thus, if $x_{ij} = 1$, the user vehicle $n_i \in N$ is assigned to a platoon led by platoon head $p_j \in P$. Otherwise, it is equal to 0. By setting the binary variable x_{ij} to 1, we ensure that each user vehicle belongs to exactly one platoon.

The following ensures that the number of user vehicle in each platoon is balanced:

$$\sum_{n_i \in N} x_{ij} = y_j,\ \forall\ p_j \ \in\ P,\ q \leq y_j \leq (q+1) \tag{2}$$

$$y_{min} \leq y_j \leq y_{max},\ \forall\ p_j \ \in\ P,\ q \leq y_j \leq (q+1) \tag{3}$$

Variable y_j counts the number of user vehicles in each platoon. The maximum and minimum number of user vehicles among all user vehicle partitions is computed using y_{max} and y_{min} and the number of user vehicles y_j needs to be within this range. Due to (4) and (5), the number of vehicles in each platoon always remains between q and $(q+1)$.

We calculate the total faith score tf_{p_j} of a platoon led by a platoon head p_j by summing the faith scores of user vehicles belonging to that platoon. This needs to be done for all platoons, hence:

$$\sum_{n_i \in N} f_{n_i} * x_{ij} = tf_{p_j},\ \forall\ p_j \ \in\ P \tag{4}$$

The average faith score, $A_{f_{p_j}}$, is computed by dividing the total faith score (tf_{p_j}) with the total number of user vehicles in a platoon led by a platoon head p_j (y_i). We calculate the average faith score for all the platoons by:

$$\frac{tf_{p_j}}{y_j} = A_{f_{p_j}}, \forall\ p_j \ \in\ P,\ q \leq y_j \leq (q+1) \tag{5}$$

Finally, the maximum and minimum average faith score among platoon heads in P is calculated using $A_{f_{max}}$ and $A_{f_{min}}$:

$$A_{f_{min}} \leq A_{f_{p_j}} \leq A_{f_{max}},\ \forall\ p_j \ \in\ P \tag{6}$$

V. Synthetic Dataset Generation

In order to evaluate the proposed approach, we generated four different datasets by enhancing the in-house automated dataset generator of [8]. Each new dataset contains 14 parameterizable inputs, as shown in TABLE II. The values of the input parameters were based on currently acceptable platooning models.

Datasets include parameters such as the initial number of user vehicles (V) before applying the cognitive bias analysis algorithm in [8], the number of platoon heads (k) in the current trip, the number of trips (T_k) and user vehicles (V_T) under each platoon head for all the previous trips. The number of user vehicles (η) is derived after the biased and malicious users vehicles are removed from V ($\eta \leq V$) using the cognitive bias analysis algorithm of [8]. Based on the average feedback given by the normal vehicles, the trips are classified into three categories: high, medium, and low-quality trips to denote quality of each trip. The input parameters T_H, T_M, T_L represent the percentage of high, medium, and low-quality trips. The expected average feedback for each of these three categories is regulated by the parameters AL, AM, and AH. Normal distributions are used to generate more realistic datasets according to the quality of the trip based on the

TABLE II: Input Parameters for Generated Datasets

Parameters	Description	D1	D2	D3	D4
V	Total number of initial user vehicles	20	20	30	20
k	Total number of platoon heads	[2, 5]	[2, 5]	[2, 5]	[2, 5]
T_k	Number of trips under each platoon head	[10, 15]	[10, 15]	[10, 15]	[10, 15]
V_T	Number of vehicles under each trip	[10, 15]	[10, 15]	[10, 15]	[10, 15]
T_H	Percentage of high quality trips	0.8	0.8	0.8	0.8
T_M	Percentage of medium quality trips	0.1	0.1	0.1	0.1
T_L	Percentage of low quality trips	0.1	0.1	0.1	0.1
AL	Low quality trip average feedback	[0, 0.4]	[0, 0.4]	[0, 0.4]	[0, 0.4]
AM	Medium quality trip average feedback	[0.4, 0.7]	[0.4, 0.7]	[0.4, 0.7]	[0.4, 0.7]
AH	High quality trip average feedback	[0.7, 1]	[0.7, 1]	[0.7, 1]	[0.7, 1]
T_{SD}	Standard deviation for trips	[0, 0.1]	[0, 0.1]	[0, 0.1]	[0, 0.1]
V_B	Percentage of vehicles with biases	0.2	0.3	0.3	0.4
T_U	Percentage of uncertainty in vehicles feedback	[0, 0.1]	[0. 0.1]	[0, 0.1]	[0, 0.1]
V_M	Percentage of malicious vehicles	0.75	0.5	0.5	0

TABLE III: Output Parameters of Experimental Datasets

Parameters	D1	D2	D3	D4
Total number of user vehicles (η)	5	10	15	20
Total number of trips	65	59	64	65
Total number of feedback in the dataset	789	724	775	795

average feedback. In order to provide more realistic datasets, we included a percentage of uncertainty in the vehicle's feedback (T_U), which adds more deviations to the original feedback given by the user vehicles. The values in TABLE II are used as input to the cognitive bias analysis algorithm that removes malicious feedback and re-adjusts feedback of biased user vehicles. TABLE III shows the remaining number of user vehicles (η), the total number of trips, and feedback for each dataset that is used in the user vehicle assignment problem.

VI. Experimental Results and Discussion

A. User Vehicle Assignment Results

This section presents user vehicle assignment results along with the CPU execution time that is needed for the assignment. The experimental results are presented in TABLE IV for all the datasets in TABLES II and III. Specifically, for each dataset, we experimented with a number of platoon heads from $k = 2$ to 5, resulting in a total of 16 unique dataset instances. Depending on the value of k, we show the total number of possible ways (combinations) the user vehicles can be assigned to the different platoons. Out of all the possible combinations, the objective is to find an optimal combination. An optimal combination represents balanced platoons with the smallest standard deviation (SD) value of the average faith score among all possible combinations. Due to the lack of existing comparable works, we implemented an optimal brute-force exhaustive (BF/E) method which explores the entire search space and all the possible combinations in order to find the optimal combinations as well as a random assignment method for demonstrating the effectiveness and validating the optimality of the proposed MILP approach. TABLE IV presents our results. Columns 1 and 2 lists the total number of user vehicles and platoon heads considered in each dataset instance, respectively. The number of platoon head also represents the number of platoons need to be formed. Column 3 reports the total number of possible user vehicle assignment combinations per dataset instance. This number grows exponentially very quickly when the numbers of user vehicles and platoon heads increase, demonstrating the complexity of the considered problem.

Column 4 reports the standard deviation of the average faith score among all user vehicle partitions in platoons, denoted by $SD(A_{f_{p_j}}),\ p_j \in P$, which is the same in both the BF/E approach and the proposed MILP approach and, hence, validates the optimality of the proposed formulation. The same metric, $SD(A_{f_{p_j}})$ is reported for the random assignment approach. In this case, up to 1000 combinations were randomly selected and the one with the smallest $SD(A_{f_{p_j}})$ was kept. We repeated the random approach 20 times and report the average among the smallest $SD(A_{f_{p_j}})$ for the 20 runs in column 5. The random assignment is implemented in order to show the possible results that can be achieved when restricting the search space. It can be clearly observed that a random approach for this problem is far from an optimal result for realistic sizes of user vehicles (between 15-20 vehicles). We provide further discussion on this in subsection VI.B.

The CPU time required by the two optimal approaches, BF/E and proposed MILP-based, is given in columns 6 and 7, respectively. Column 8 reports the significant performance advantage of the proposed approach, showing the significant speedup (x) achieved with respect to the BF/E approach. On average, the proposed method achieves $\sim$ 140x speed up. All the approaches have been developed using Python, the Gurobi solver [14] was used to derive the MILP solutions, and all approaches were run on an HP PC (Intel(R) Core(TM) i5-8265U CPU @ 1.60GHz, 8 GB RAM). When utilizing a more powerful central server (as shown in Fig. 1) execution times of the proposed approach are expected to reduce even further.

B. Fairness Balance Score Comparison

In this section, we introduce the Fairness-Balance Score (FBS) metric for comparison between the random assignment and the proposed optimal (MILP) method. The fairness balance score is an efficiency metric that indicates how fair and balanced the solution is. When FBS is close to 0, the assignment tends to be more fair and balanced. We define FBS as the sum of the standard deviation of the number of user vehicles among all platoons $SD(y_i)$ and the standard deviation of the average faith scores among all platoons, $SD(A_{f_{p_j}})$:

$$FBS = SD(y_j) + SD(A_{f_{p_j}}),\ \forall\ p_j\ \in\ P \tag{7}$$

TABLE IV: Vehicle assignment results of proposed MILP approach, brute-force exhaustive (BF/E), and random approach

Datasets: # User Vehicles	# Platoon Heads / Platoons	# Combinations	SD($A_{f_{p_j}}$) among all platoons: Optimal Assignment (Proposed & BF/E)	SD($A_{f_{p_j}}$) among all platoons: Random Assignment	CPU time (in sec): BF/E	CPU time (in sec): Proposed	Speed Up (x)
D1: η = 5	k = 2	10	0.04409500	0.04409	4.02	0.03	111.80
	k = 3	15	0.11054400	0.110544	4.82	0.05	87.78
	k = 4	10	0.11585900	0.11585	5.14	0.07	72.39
	k = 5	1	0.25691000	0.25691	2.09	0.15	13.75
D2: η = 10	k = 2	126	0.00184430	0.00185	3.69	0.72	5.12
	k = 3	2100	0.00516080	0.00622	3.93	1.12	3.50
	k = 4	6300	0.00488030	0.00725	8.18	1.89	4.30
	k = 5	945	0.01716640	0.01729	6.39	2.13	3.00
D3: η = 15	k = 2	6435	0.00000920	0.00001	4.50	2.27	1.98
	k = 3	126126	0.00822680	0.25969	27.00	6.01	4.49
	k = 4	2627625	0.01204870	0.89968	357.00	86.84	4.11
	k = 5	1401400	0.02806140	0.39861	200.00	97.00	2.06
D4: η = 20	k = 2	92378	0.00000034	0.00018	15.31	1.76	8.69
	k = 3	66512160	0.00153187	0.96152	8843.00	13.72	644.53
	k = 4	488864376	0.00239016	1.12578	71283.00	339.00	210.27
	k = 5	2546168625	0.00710542	1.59374	398496.00	374.00	1065.49
Average			0.03848960	0.36245			140.20

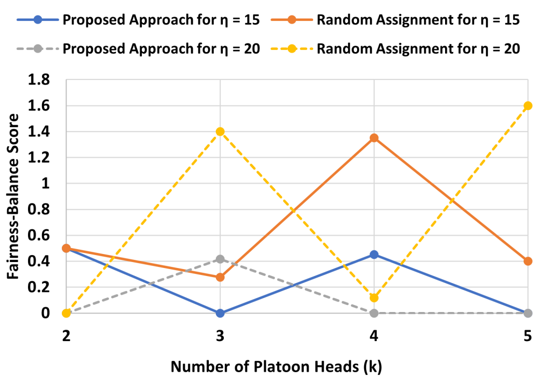

Fig. 3: Fairness-Balance Score (FBS) comparison between Optimal and Random Assignment Methods

In Fig. 3, we compare the proposed MILP method with the random assignment method for the more realistic sizes of user vehicles (between 15-20 vehicles). Fig. 3 clearly indicates that a random approach will not be able to provide acceptable solutions when the problem is scaled up for larger platoons. This is observed for all the datasets.

VII. Conclusion

This paper proposes a reputation-based, fairness-aware approach for the optimal assignment of user vehicles for different platoons with the same destination. A set of platoon heads is selected to form the platoons based on the reputation score. The assignment of user vehicles to different platoons is a crucial step towards a balanced and fair reputation system. The proposed MILP-based approach provides a systematic and elegant way to balance user vehicles and ensures similar average faith scores in platoons. The experimental results demonstrate the effectiveness and efficiency of the proposed approach in obtaining optimal user vehicle assignments while satisfying the necessary constraints of balanced and fair platoons. Future work will concentrate on security threats and mitigation approaches in reputation-based platooning systems.

VIII. Acknowledgement

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