Improving Road Safety by Blockchain-based Monetization of Driver Behavior

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Abstract

The transportation system places a top priority on driving safety. Most drivers on the road and their actions determine how safe it is to drive. Speed, hard braking, abrupt accelerations, and other aggressive driving behaviors are some of the main safety-compromising elements that could jeopardize human life in the event of a fatality. We presented a driver incentive model that ranks and rewards the driver's daily behavior in order to increase the safety of drivers and other road users. These rewards will come in the form of cryptocurrency tokens. We also examined the cooperative driving (or platooning) scenario. Road safety is improved by connecting two or more cars together by utilizing vehicular communication technologies. The leader is crucial as it manages the platoon, establishes communication between vehicles, and performs platoon maneuvers namely Join, Merge, Leave, and Split. As the leader of the platoon has multiple responsibilities than followers, our model rewards more incentives to the leader than followers. This digital monetization method is accomplished by secure transactions using blockchain.

Key Words: Cooperative driving, platooning, ranking, monetization, blockchain technology.

1 Introduction

Aggressive driving has become a global issue as per World Health Organization (WHO), Global status report on the road safety 2018 [3] and Centers for Disease Control and Prevention (CDC), Global Road Safety 2020 [18]. As per WHO [5] nearly 1.3 million people die each year on the world's roads. According to the United States, the National Highway Traffic Safety Administration (NHTSA) [1], aggressive driving is defined as "an individual commits a combination of moving traffic offenses so as to endanger other persons or property". Aggressive driving is a factor in 49% of all fatal motor vehicle crashes, according to the NHTSA, Traffic Safety Facts 2019 [49].

In addition, as stated by NHTSA [4] speeding is the leading aggressive driving behavior which accounts for 17.2% fatal crashes in 2019. It also defines that accidental difficulties to others on road are caused by aggressive driving [1]. The aggressive driving includes but not limited to speeding [6, 48], rapid acceleration or deceleration [15], sudden lane change [28] etc.

For some drivers, aggressive driving is a dysfunctional habit which can jeopardize other drivers on the road. This behavior can be fun on the spur of the moment for the driver but is uncomfortable for other road users which can cause fatal situations. To mitigate unsafe driving, various law enforcement strategies have been placed. When combined with public awareness outlets, it's been shown to be effective in reducing unsafe driving patterns.

Cooperative driving uses vehicle-to-vehicle and infrastructure-to-vehicle wireless communication system and [40] emphasizes the technology aids in the interchange of data gathered from other cars that is impossible to obtain via on-board sensors. The Advanced Transportation Technology (PATH) project in California [45] first proposed the idea of cars traveling together on the road in 1980. Cooperative driving can improve the driving experience on the road by relieving the driver from some of the driving obligations. Traditional sensor based Adaptive Cruise Control (ACC) isn't enough for cooperative platooning, instead Cooperative Adaptive Cruise Control (CACC) should be considered. CACC broadcasts information such as speed, acceleration, and distance through wireless communication. By allowing CACC, the distance between vehicles can be minimized by following closely, improving both safety and fuel efficiency . The focus on cooperative driving or platooning has increased globally in recent years because of the potential it holds in road transportation mainly focusing on automated and mixed traffic. Truck platooning [8, 29], and CACC [46] were prominent examples of cooperative driving, which focused on minimizing inter-vehicular distance by obeying the "Three Second Rule" safety rule [52].

Having a good leader for a platoon is really crucial in forming, maintaining, and improving safety. There are a lot of methods in electing a platoon leader. [47] proposed an incentive based strategy using blockchain to elect a leader who is the best for the safety of the platoon. The other way is through voting [10] to elect the platoon leader. Some other methods may be through scoring and ranking the drivers based on the everyday driving and the driver with the best rank can only initiate platoon formation. Our inspiration is drawn from the ranking method. We added an incentive or monetization

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factor for selecting a platoon leader based on rank. When a driver of a vehicle drives everyday there will be a rank assigned to the driver performance and the driver with the best rank can become a platoon leader and other drivers will be followers. To encourage more drivers to be platoon leaders, a monetization system is required that is fair for all members. This digital monetization is implemented by the usage of a smart contract in blockchain technology that holds users to a higher level of behavior, which is promising in this regard. This smart contract establishes what constitutes acceptable behavior and prevents users from breaking that standard.

Congested roadways are linked to longer commute, lower fuel economy, and a higher risk of motor vehicle collisions. We could save a lot of travel time if we could reduce commuting times by a fraction of a second. One solution to the traffic problem is cooperative driving, also known as platooning [14]. Vehicles in a platoon communicate using an ad-hoc network or other communication protocols. These communication channels allow platoons to drive close to each other while maintaining a safe distance. A platoon of vehicles will have a leader who will interact with the platoon followers while managing the platoon and overseeing maneuvers. The platoon leader is in charge of speed, lane changes, braking, and so on, while the follower vehicles are in charge of following the leader vehicle.

To help improve the driving behavior, Demerit points system [35] and Driver Feedback systems [34] were used extensively. In recent times, driver credit or scoring systems were also introduced to enhance the road behavior. To further enhance the behavior of the drivers, we put forward a ranking framework along with monetization using the blockchain. The inspiration for ranking is drawn from credit bureaus [37, 32]. These credit bureaus put together the credit reports and credit scores of potential individuals that can borrow from lenders or government. The credit bureaus decide the creditworthiness of an individual just from a score. In the proposed system, a simulated driving dataset is generated. Significant features are extracted from the dataset and driver behavior is analyzed for assigning a rank for the driver. Based on the driving rank, the driver is monetized with Driver Safety Reward (DSR) tokens and the transactions are stored on a blockchain network along with driver attributes.

The contributions of this paper are organized as follows: Literature Survey on Driver behavior, Ranking Systems, Cooperative Platooning and Blockchain are discussed in Section 2. Section 3 presents the Monetizing of Driving Behavior including Platooning. Implementation of the simple test network to simulate the storing in Blockchain is elaborated in Section 4. Finally, Section 5 talks about Conclusion and future directions.

2 Literature Review

An *Aggressive* driver is defined as an individual who commits road traffic offenses and put others at risk. The attributes that contribute to driving aggressiveness are speeding, acceleration, braking etc. The authors in [25] proposed a method to detect driver aggressiveness on a vehicle based on visual and sensor features. A Support Vector Machine (SVM) classifier is used to classify those feature vectors in order to detect aggressiveness. This paper [21] states that hurriedness is the primary cause for speeding. They conducted a driving simulated study recruiting thirty-six drivers. The drivers in a hurry drove with higher speeds, accelerated faster, decelerated faster, made tight turns, accelerated faster after red lights, left smaller gaps between vehicles, were more likely to pass a slow vehicle.

Driving behavior plays a major role in improving the road safety. Lately, with the advancements in smart devices and Internet of Things (IoT) [11, 12], the sensors generate huge amounts of data. The data that can be extracted but not limited to speed, braking, accelerations, trip distance, accelerometer, magnetometer, gyroscope information etc. This rich data can be used to analyze and classify driving behavior patterns. In [19] they monitored the driving behavior from the collected set of experimental data to detect the accelerations, brakings and lane-changing behavior while providing constructive audio feedback to the driver. In paper [7] they exploited the demerit point system in Denmark. They introduced a point-recording scheme to record the drivers behavior to a non-monetary penalty method. Based on the driving behavior the responses are stored and demerit points are assigned to their driving licenses. Depending on the number of demerit points piled, drivers with more demerit points reduced the frequency of committing traffic offenses by 9–34%. The authors in [17] proposed a driving profile platform called SenseFleet, to detect risky driving events using smartphone sensors to identify driving maneuvers. A representative score for a driver was accurately detected using real-time information by applying the Fuzzy Logic Systems.

Ranking is a way to give credit for a safe driving behavior. The authors in [51] proposed a Driving Safety Credit system inspired by credit scoring in financial security field, and designed a scoring method using driver's trajectory data and violation records. Initially they extracted driving habits, aggressive driving behaviors and traffic violation behaviors from driver's trajectories and traffic violation records. Later, they trained a classification model to filter out irrelevant features and scored each driver with selected features. In order to accurately identify abnormal driving behavior, the authors in the paper [30] proposed different abnormal driving behavior recognition algorithms. They obtained the data from OBD terminal that combines acceleration changes and behavior. The model combines the driving data of the driver, takes the proportion of abnormal driving behavior as the evaluation index, and uses the entropy weight method and the analytic hierarchy process to obtain the index weight. The model can analyze and evaluate the driving behavior of the driver and give a score for driver's behavior.

This model can also be extended for cooperative platooning. The first platooning simulator that was developed was Hestia [22]. This simulator is used for simulating various scenarios using sensors but its drawback is that it doesn't execute the platooning maneuvers and does not simulate traffic scenarios. In paper [20], the researchers tried to simulate the mixed traffic scenarios using SUMO [31] and were unsuccessful. They implemented a car following model based on CACC to simulate inter-vehicle communication.

The researchers in [27] mainly focused on analyzing the communication effects using the platooning simulator. In [50] paper, they manually simulated the mixed traffic scenarios and tested the simulator to study the consequences of CACC on traffic.

There are different simulation tools that are available in platooning discipline. The PLEXE [44] simulation tool is a platooning extension for SUMO [31] which is open-source and is available to the community. This simulation tool has different CACC car-following models to experiment. The wireless communication protocols are available for simulating the formation and platoon management. Mixed traffic scenarios are available to use and implement platooning maneuvers. The authors in paper [24], developed a simulator to implement platooning maneuvers such as to join an existing platoon and merge two platoons. In paper [10], the authors developed a state-of-the-art simulator based on VENTOS [9] which uses SUMO. PERMIT [36] is a tool which simulates platooning maneuvers like join, merge, leave, and split which is built on Plexe [44].

One way to store the details of driver behavior digitally and securely is through *Blockchain Technology* [39]. It can be defined as decentralized, distributed, encrypted, immutable, trust-free, digital ledger system. Bitcoin [38] and Ethereum [2] are the decentralized peer-to-peer digital currencies that are the most popular examples that rely on blockchain technology. In the paper [41], a new blockchain model was implemented to regulate the traffic offense using demerit points. Smart contracts were used as a conditional filter. These smart contracts store driver offense's demerit points,fines collected, and penalty information including revocation of driver license. A user interface was provided for a traffic officer to input the driver's offense and drivers can check the offense. The evaluation shows that the smart contracts are executed properly as compared to real regulations.

Currently, to our knowledge only few researchers are working on effectively combining the benefits of blockchain technology with the platooning technology to better understand the usefulness. The authors in paper [43] used blockchain as a medium in transportation. They achieved the communication between vehicles in platoon and blockchain public key infrastructure by securely using hardware-based side channels. In [16], they decreased the blockchain transaction validation time, and verified the vehicle identity. The authors in [23], emphasized on using blockchain with platooning to share information securely and rapidly. In [33] paper, the authors build a reputation system based on blockchain for anonymous vehicles. The authors in [26] implemented a leadership incentives mechanism based on blockchain technology for heterogeneous and dynamic platoons.

In this study, existing research such as demerit point system, feedback models, and scoring methods for driving aggressiveness can be further extended by introducing monetization. The driver is offered test crypto tokens and these transaction details along with driver attributes are stored on a blockchain network.

3 Our Approach

This methodology consists of two variations for monetizing the driving behavior one without cooperative platooning and other with it. The main difference between these two forms are what simulation tool is used for fetching the required data and earnings.

3.1 Simulation of Urban Mobility (SUMO)

Using ***Simulation of Urban Mobility (SUMO)*** [13], a road network is built and random traffic is generated. Many characteristics need to be taken into consideration to represent the road network environment. However, we mainly focused on the few performance factors such as Speed, Acceleration, Braking, and Over Speed Limit (OSL). An XML formatted dataset is extracted by running the simulator. From this raw XML dataset, necessary features like Driver ID, and Speed are extracted. Different driver behavioral attributes like the number of sharp decelerations are calculated based on speed. A driving regulatory rule stating that reducing speed of 6mph ($2.5m/s$) in one second is considered as a sharp brake is used as a baseline for calculating the count of the sharp braking. Similarly, the number of sharp accelerations is also determined. Another law states that representing the posted speed limit (max speed limit + 7mph) is being used to compute the over speed feature. By repeating the above process, random driver behaviors are collected each day. Once the features are being prepared in the features extraction phase, a rank is assigned to the driver considering aforementioned features. The driver behavior is captured for 17 drivers over 4 days. The generated data is used for analysis of driver behavior detailed more in [42]. The entire architecture of the above process is detailed in Figure 1.

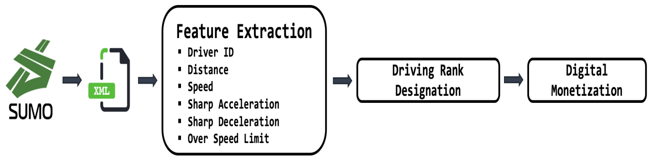

Figure 1: SUMO methodology

3.2 Driver Scoring Model

The driver scoring model takes the parameters from section 3 to rank the driver. The following are the steps that need to be followed to score the driver.

- Calculate the total trip distance and scale using min-max normalization.
- Over speed limit (OSL) percentage is computed using total trip distance and Over Speed Limit (OSL) count.
- The Acceleration Percentage (AP) and Deceleration Percentage (DP) are computed.
- Define the weights for above three parameters as 60% for Deceleration, 30% for Acceleration and 10% for OSL.

- Compute the score using weighted average.

$$Score = \frac{0.3 * AP + 0.6 * DP + 0.1 * OSL}{100}$$

- The weighted average is scaled between 1-5 as referred in Table 1.

Table 1: Score rating

Rank	Rating
5	Excellent
4	Very Good
3	Good
2	Bad
1	Very Bad

3.3 Monetization Heuristic

An earning rate scale is defined depending on the rank calculated from subsection 3.2. The Table 2 shows the earning rates.

Table 2: Monetization

Score	Earning Rate
5	0.15
4	0.12
3	0.09
2	0.03
1	0.01

Using scaled total distance (S_{dis}) and earning rate (ER) from above, total test tokens to be credited in the Rinkeby driver wallet is determined by the following formulation.

$$E_{tokens} = S_{dis} * ER$$

Following subsections explain the above methodology including the cooperative platooning.

3.4 Simulation with PERMIT and Feature Extraction

PERMIT [36], an open source platooning simulator based on SUMO and its platooning extension PLEXE. With PERMIT, Merge, Join, Leave and Split maneuvers can be performed. *Merge* is a maneuver in which two platoons join to form one platoon. *Join* refers to joining one vehicle into an existing platoon. *Leave* maneuver is when a car exits the current platoon. *Split* refers to dissolving one single platoon into two platoons. By using the PERMIT, we simulated all these maneuvers. This provides the data required which are (1) number of cars, and (2) distance traveled for evaluating the earnings with platoon for a driver. The model for the Simulation with Platooning is shown in the Figure 2.

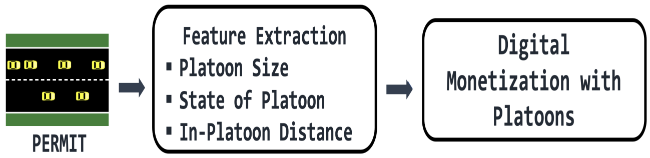

Figure 2: Permit system methodology

3.5 Digital Monetization with Platoons

With the features extracted from the previous step, we formalized the earnings (er_d) for the driver as summation of the earnings achieved while he drove in platoons (er^{in}) and earnings achieved while driving outside the platoon (er^{out})

$$er_d = er^{in} + er^{out} \tag{1}$$

Because different maneuvers can exist inside the platoon, we decomposed the earning offered inside the platoon into addition of earnings during join(P^{er}_{join}) and leave(P^{er}_{leave}) maneuver.

$$er^{in} = P^{er}_{join} + P^{er}_{leave} \tag{2}$$

However, the er^{out} is calculated as product of previous day earnings rate (ER_{d-1}) which determined by the Driving Rank Designation Model and distance travelled by the driver outside the platoon(d^{out}).

$$er^{out} = ER_{d-1} * d^{out} \tag{3}$$

As mentioned earlier that a platoon leader will have a little favor by this model due to his responsibilities, join and leave maneuvers are calculated using two different equation one representing Leader and other Follower in the platoon.

Join Maneuver For every platoon, driver joined on a particular day, and for all the states in each platoon, calculate the product of the average of the States of the platoon(S_i) and the sum of the previous earning rate of the driver(ER_{d-1}) and $n\delta$. The State(S_i) is defined as the product of the Length of Platoon(L_i) at state i and distance travelled inside the platoon(d_i^{in}). Here the term $j\delta$ is the additional incentive for the leader of the platoon. It represents the summation of the balancing factor over the number of cars joined in the platoon. The balancing factor δ is used to control the amount of incentive the driver will be provided during the platoon. We assigned it as 0.01.

$$P^{er}_{join}(L) = \sum_{p=1}^{w}\sum_{i=1}^{n} S_i * (ER_{d-1} + j\delta) \tag{4}$$

The difference between leader and follower is there will be no additional incentives for follower. Instead, only the balancing factor is added to the previous day earning rate(ER_{d-1}). Platoon follower doesn't require length of the platoon. So, it just uses the distance travelled in each state.

$$P^{er}_{join}(F) = \sum_{p=1}^{w}\sum_{i=1}^{n} d_i * (ER_{d-1} + \delta) \tag{5}$$

Leave Maneuver During the leave maneuver, for the leader, instead of the number of cars joined(j), number of cars left(l)

is considered. Additionally, there will be a penalty if a car leaves the platoon before travelling η miles. In other words, earnings for the followers will start only after travelling η miles. The overhead incurred by changing the structure of the platoon while on the move is the main reason for penalty. Here we considered $\eta = 10$.

$$P^{er}_{leave}(L) = \sum_{p=1}^{w} [\sum_{i=1}^{n} S_i * (ER_{d-1} - l\delta) + penalty_w] \tag{6}$$

where,

$$S_i = L_i * d_i^{in} \tag{7}$$

$$penalty = \begin{cases} (d^{in} - \eta) * \delta, & \text{if } d^{in} < \eta \\ 0, & \text{otherwise} \end{cases}$$

All the notations used in the model are summarized in the Table 3. To ensure the safety on the road, drivers with rank less than four cannot act as platoon leaders.

Table 3: List of Notations

Symbol	Definition
er_d	Earnings of particular day
er^{out}	Earnings outside of the platoon
er^{in}	Earnings inside of the platoon
ER_{d-1}	Earning rate of previous day
d^{out}	Out-platoon distance
n	Number of cars in a platoon
j	Number of followers in the platoon in join maneuver
l	Number of cars left the platoon in leave maneuver
δ	Balancing factor
η	Penalty factor
S	State-of-platoon
L_i	Length of the platoon at state i
d^{in}	In-platoon distance at state S
w	Number of platoons a driver travelled
$P^{er}_{join}(L)$	In-platoon earnings with join maneuver of leader
$P^{er}_{join}(F)$	In-platoon earnings with join maneuver of follower
$P^{er}_{leave}(L)$	In-platoon earnings with leave maneuver of leader

3.6 Storing in Blockchain

For secure transaction of the crypto tokens, the extracted data from the feature extraction step is stored in a blockchain technology. Features stored are driver ID, current earnings, rank designated for the driver, over speed limit count, distance traveled, number of sharp accelerations, number of sharp decelerations, number of platoons he joined, platoon leader activity and earning date. The above architectures can be simplified into one single architecture as shown in Figure 3.

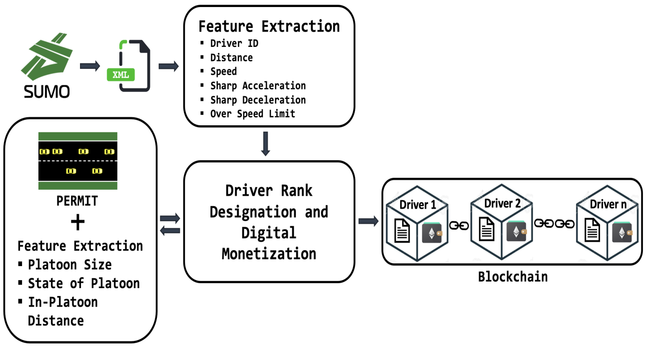

Figure 3: Methodology

4 Driver Safety Reward (DSR) Implementation

Upon the extraction of the features from the SUMO simulator and assigning a rank to the driver based on the driving, driver behavioral characteristics are stored in a blockchain [39]. Each block in the chain consists of the attributes such as driver ID, distance traveled, number of sharp breaking, sharp accelerations, exceeded speed limit count, rank, earnings, and earning date. While inserting a block into the blockchain, the driver's DSR wallet will be credited with the certain number of DSR test tokens which can only be used for vehicular purposes.

In a case considering a platoon (platoon size of 6), PERMIT is used for implementing join and leave maneuvers. With the data from the PERMIT and the above formulation, we calculated the earnings for a leader and a follower in both scenarios.

For implementation, a Rinkeby test network is used as our ethereum network. Two smart contracts one for tokenization, the other for storing driver record were deployed on Rinkeby Etherscan network. Tokenization contract will initially approve the driver record contract with certain limit of driver DSR test tokens and transfer few DSR test tokens to the driver record contract. Now, the driver record will be able to credit the DSR test tokens to the assigned drivers based on the ranking to their wallet.

For illustration, the tokenization contract generated the 10000000 (10^7) DSR test tokens and approved the data record to spend those. The contract transfers 10000 DSR test tokens to data record for further assigning them to the drivers. As shown in Figure 4, the MetaMask represents 9990000 ($0.999 * 10^7$) DSR test tokens in the admin wallet. After inserting the data record into the Rinkeby test network, 2 DSR test tokens and 26 DSR test tokens are credited into "Driver_1" account as shown in the Figure 5. Moreover, driver data can be retrieved from the network using defined method. Both transaction logs can be seen in Tables 4 and 5.

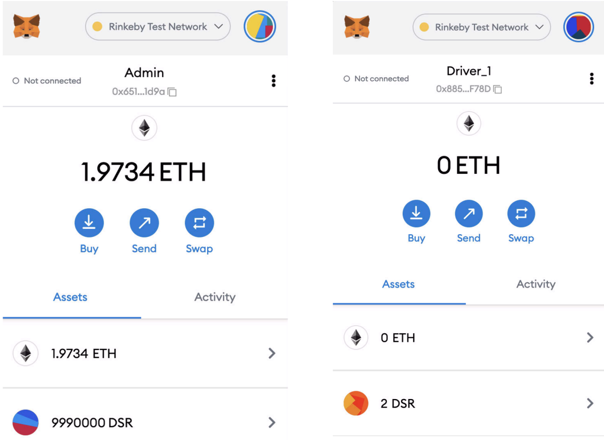

Figure 4: Admin and Driver Wallet without platooning

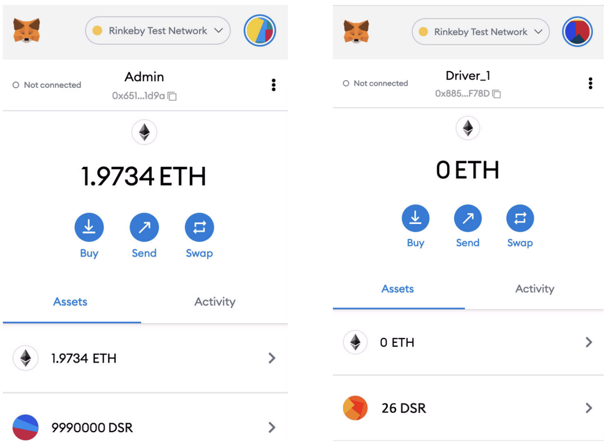

Figure 5: Admin and Driver Wallet with platooning

5 Conclusion and Future Work

To encourage safe driving practices, we proposed a methodology to quantify and monetize the driver's behavior along with platooning. This system considers the different maneuvers in platoon namely Join, Leave, Merge, and Split. Simulation tools SUMO and PERMIT were used. Based on the observed driving behavior from the aforementioned tools, the aggressive driving patterns and driver scoring model were presented. The score is measured on a scale from 1-5 (1 being Very Bad - 5 being Excellent). In addition to that a reward based system was proposed where crypto tokens were awarded provided the rank (these earned DSR test tokens are not to be exchanged for currency). This transaction data along with the driver properties are entered in a decentralized Rinkeby Test network for ease of access by the different end points. We would also like to extend this framework considering the other parameters like cornering, weather, time of the day, age, gender while using real time dataset.

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Table 4: insertRecord Log

insertRecord Log	
hash	0xe74************5c835a
from	0x651************9d4b7d
to	driverRecord.insertRecord(address,string,uint256,uint256, uint256, uint256,uint256,uint256, uint256,uint256,string) 0x4ABc************49554b
gas	278003 gas
transaction cost	278003 gas
hash	0xe74************5c835a
input	0xb12************00010
decoded input	"address driverAddress": "0x44************6A147", "string driverId": "Driver_1", "uint256 distance": "200", "uint256 sharpBreaking": "1", "uint256 sharpAcc": "0", "uint256 overSpeedLimit": "0", "uint256 totalPlatoonsJoined": "2", "uint256 platoonLeader": "0", "uint256 rank": "4", "uint256 earnings": "2000000", "string earningDate": "06-24-2022"

Table 5: getDriverInfo Log

getDriverInfo Log	
decoded input	"string driverId": "Driver_1"
decoded output	"0": "tuple(address,string,uint256, uint256,uint256,uint256, uint256, uint256,uint256,uint256,string): 0x44659c35594C9149C872F5813526fde5A8b6A147, driver1,200,1,0,0,2,0,4,2000000,06-24-2022"

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