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# DSRBT - Driving Safety Reward based on Blockchain Technology

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**Abstract**

The driver safety is given an utmost importance in the Transportation system. Road safety is mostly dependent on the all driver's on road and their behavior. Aggressive driving behavior such as speed, braking, accelerations etc are some of the major factors contributing to the safety which can jeopardize human lives if a fatality occurs. To improve the safety of drivers and other road users, we proposed a framework which ranks and rewards the driver's behavior for each day in crypto tokens. Existing frameworks emphasizes on analyzing or ranking the behavior, however monetizing driver's behavior will improve the driver's discipline. A randomized simulated traffic is used to extract the both friendly and aggressive driving patterns and provide test crypto tokens based on them.

## 1 Introduction

Aggressive Driving has become a global issue as per World Health Organization (WHO), Global status report on road safety 2018 [1] and Centers for Disease Control and Prevention (CDC), Global Road Safety 2020 [2]. As per WHO [3] nearly 1.3 million people die each year on the world's roads. According to Unites States, the National Highway Traffic Safety Administration (NHTSA) [4], 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 [5].

In addition, as stated by NHTSA [6] 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 [4]. The aggressive driving includes but not limited to speeding [7, 8], rapid acceleration or deceleration [9], sudden lane change [10] etc.

For some drivers, aggressive driving is a dysfunctional habit which can jeopardize other drivers on 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 the unsafe driving, various law enforcements and strategies have been placed. When combined with public awareness outlets, it's been shown to be effective in reducing unsafe driving patterns. To help improve the driving behavior, Demerit points system [11] and Driver Feedback systems [12] 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 [13, 14]. 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 is organized as follows: Section 2 elaborates about the different driving behavior, ranking systems, and storage on blockchain network. Section 3 provides an overview of the implemented methodology. Section 4 describes the simulation setup, analysis, scoring model, and monetization heuristic. Section 5 explains the implementation of Driver Safety Reward (DSR). Section 6 presents conclusions and future work.

## 2 Literature Survey

An *Aggressive* driver is defined as an individual who commits road traffic offences and put others at risk. The attributes that contribute to driving aggressiveness are speeding, acceleration, braking etc. [15] proposed a method to detect drive 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 [16] states that hurriedness is the primary cause for speeding. They conducted a driving simulated study recruiting thirty-six drivers. The drivers in 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) [17, 18], the sensors generates 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. [19] 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. [20] 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 [21] 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 [22] 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 paper [23] 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.

*Blockchain Technology* [24] can be defined as decentralized, distributed, encrypted, immutable, trust-free, digital ledger system. Bitcoin [25] and Ethereum [26] are the decentralized peer-to-peer digital currencies that are most popular examples that rely on blockchain technology. In the paper [27], a new blockchain model was implemented to regulate the traffic offence using demerit points. Smart contracts were used as a conditional filter. These smart contracts store driver offence's demerit points,fines collected, and penalty information including revocation of driver license. A user interface was provided for traffic officer to input the driver's offence and drivers can check the offence. The evaluation shows that the smart contracts are executed properly as compared to real regulations.

To improve the safe driving behavior, existing research focuses on demerit point systems, feedback models, and scoring methods for driving aggressiveness to our knowledge. These models can be further extended introducing monetization based on the driving behavior.

# 3 Our Approach

This section presents the entire overview of the proposed framework as shown in the figure 1. This methodology put forward 6 steps, namely: (1) SUMO Simulation (2) Exporting Dataset (3) Feature Extraction (4) Driving Rank Designation (5) Digital Monetization (6) Blockchain.

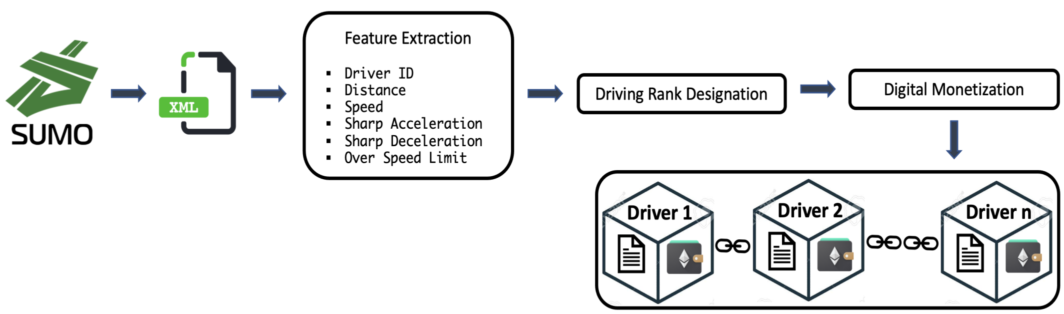



Figure 1: DSRBT System Methodology

Using Simulation of Urban Mobility (SUMO) [28], 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 number of sharp deceleration 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 baseline for calculating the count of the sharp braking. Similarly, 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 which each treated as a different day. Once the features are being prepared in the Features extraction phase, a rank is assigned to the driver considering aforementioned features as explained in Section 4.4.

Once the rank of the driver is computed, earnings for that day is evaluated, above mentioned driver behavioral characteristics are stored in Rinkeby ethereum test network for testing proposed monetization model. To the crypto wallet of the driver, certain DSR test tokens are credited based on the driver rank and distance travelled.

# 4 Simulation and Analysis

To simulate the road system we used Simulation of Urban Mobility (SUMO) [28] software as a simulation tool. SUMO simulation suite is an open source, portable, light, and has packages (network importing and demand modeling components) to continuously generate traffic simulation. When using SUMO simulator one thing to remember is it being multimodal [29] we can use different vehicles that are part of transportation (human or goods). It's independent and microscopic, meaning that on a road network the vehicles generated have their own route and travel individually. SUMO is a time discrete (one second duration is the default time step), collision free, and space continuous system.

## 4.1 Simulation Setup

Initially, a simple road circuit is built with different road characteristics like stop signs, traffic signals, and lane changes. Cars are generated with equidistant default departure time stamps and an end time. The driver behavior is captured for 17 drivers over 4 days. The generated data is used for the implementation of the framework.

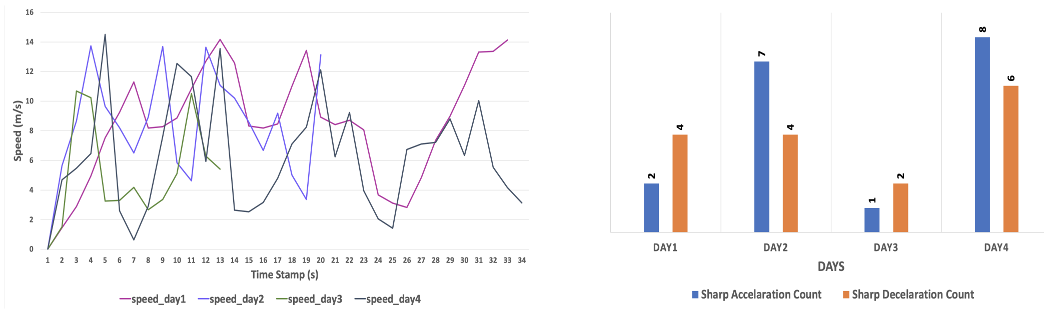
SUMO uses Krauss car following model for generating the cars in the trips by default. Krauss car following model was developed by Stefan Krauss in 1997 [30] which is revised to create the default car following model. The default parameters of krauss model are vehicleClass (vClass) defines the vehicle type, minimum Gap (minGap) assigns the gap between one vehicle to an other, acceleration (accel), deceleration (decel), maximum Speed (maxSpeed), and Tau ($\tau$) is the headway reaction time as shown in table 1.

| **vClass** | **minGap** | **accel** | **decel** | **maxSpeed** | $\tau$ |
|---|---|---|---|---|---|
| Passenger Car | 2.5m | $2.6\,\mathrm{m/s^2}$ | $4.5\,\mathrm{m/s^2}$ | 200km/h | 1 |

Table 1: Car Following Model Vehicle Type Parameter Defaults

## 4.2 Analysis of Driver Behavior

The figure 2a represents one of the driver's speed pattern for 4 days. As stated in section 3 if the vehicle accelerates or decelerates 6mph (2.5 $m/s$) in one second, it is marked as sharp acceleration or deceleration. Additionally, if the vehicle exceeds 7mph (3.12 $m/s$) than speed limit it is considered as over speed limit. It can be observed from the figure 2a that driver is aggressive in terms of speed at least one particular time on all days. Moreover, the driver attempted sharp acceleration from 5.1 $m/s$ to 13.8 $m/s$ on day 2 between time stamp 11s and




(a) Driver Speed Pattern for each day (b) Aggressive Behavior of Driver

Figure 2: Driver Behavior Patterns

12s. The driver also accounted for sharp braking on day 4 from 13.6 $m/s$ to 2.8 $m/s$ between time stamp 13s and 14s.

The figure 2b represents the total number of sharp accelerations and brakings of a driver over the period of 4 days. On day 3 the total number of aggressiveness is 3 and on day 4 it's 14. From this we can observe that the rank will be better on day 3 than day 4.

## 4.3 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.
- Defined 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 2.

## 4.4 Monetization Heuristic

An Earning Rate scale is defined depending on the rank calculated from subsection 4.3. The table 3 shows the earning rates.

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.

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

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

Table 2: Score Rating

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

Table 3: Monetization

## 5 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 behavioural characteristics are stored in a blockchain [24]. Each block in the chain consists of the attributes such as driverId, distance travelled, number of sharp breaking, sharp accelerations, exceeded speed limit count, rank, earnings, earning date. While inserting a block to the blockchain, driver's DSR wallet will be credited with certain number of DSR test tokens which can only be used for vehicular purposes.

For implementation, a Rinkeby test network is used as our ethereum network. Two smart contracts one for tokenization, 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 3a, 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 are credited into "Driver_1" account as shown in the figure 3b. Moreover, driver data can be retrieved from the network using defined method. Both transaction logs can be seen in table 4 and 5.

## 6 Conclusion and Future Work

To encourage the safe driving practices, we proposed a methodology to quantify and monetize the driver's behavior. A random dataset with 17 drivers over 4 days is generated using SUMO simulation software and extracted aggressive driving features from it. From the extracted features, we analyzed the aggressive driving patterns and driver scoring model was presented.

| insertRecord Log | |
|---|---|
| hash | 0xc74************9d314e |
| from | 0x651************7f1d9a |
| to | driverRecord.insertRecord(address,string,uint256,uint256, uint256, uint256,uint256,uint256,string)<br>0x4ABc************49544b |
| gas | 279203 gas |
| transaction cost | 279203 gas |
| hash | 0xc74************d314e |
| input | 0xb12************00000 |
| decoded input | "address driverAddress": "0x44************6A147",<br>"string driverId": "Driver_1",<br>"uint256 distance": "120",<br>"uint256 sharpBreaking": "1",<br>"uint256 sharpAcc": "0",<br>"uint256 overSpeedLimit": "0",<br>"uint256 rank": "4",<br>"uint256 earnings": "2000000",<br>"string earningDate": "12-3-2021" |

Table 4: insertRecord Log

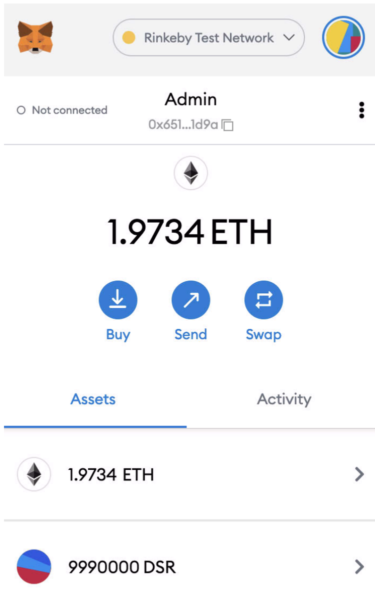
| getDriverInfo Log | |
|---|---|
| decoded input | "string driverId": "Driver_1" |
| decoded output | "0": "tuple(address,string,uint256,uint256,uint256,uint256, uint256, uint256,string):<br>0x44659c35594C9149C872F5813526fde5A8b6A147,<br>driver1,120,1,0,0,4,2000000,12-3-2021" |

Table 5: getDriverInfo Log

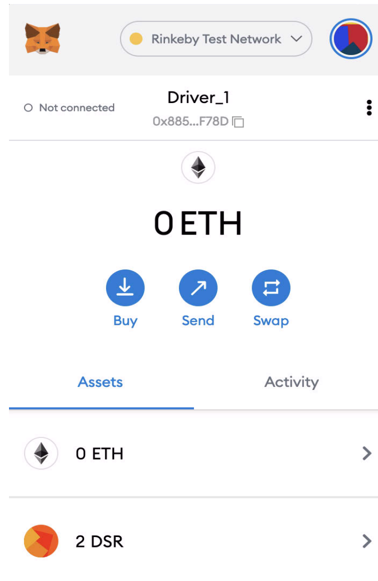
The score is measured on a scale from 1-5 (1 being Very Bad - 5 being Excellent). In addition to that a Reward based system was proposed where crypto tokens were awarded provided the rank (these earned DSR test tokens are not to be exchanged for currency). This transaction data along with the driver properties are entered in a decentralized Rinkeby Test network for ease of access by the different end points. Currently, we considered some of the key parameters in testing the framework. 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. This framework can be extended to a platoon environment to improve the road usage and cooperative driving.

## References

[1] World Health Organization. Global status report on road safety 2018. https://www.who.int/publications-detail-redirect/9789241565684.




(a) Admin




(b) Driver

Figure 3: Wallet

[2] Centers for Disease Control and Prevention. Globalroadsafety. https://www.cdc.gov/injury/features/global-road-safety/index.html, Dec 2020.

[3] World Health Organization. Road traffic injuries. https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries.

[4] National Highway Traffic Safety Administration. Aggressive driving chapter 1: Introduction. https://one.nhtsa.gov/people/injury/research/aggressionwisc/chapter_1.htm.

[5] National Highway Traffic Safety Administration. Traffic safety facts 2019. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813141, 2021.

[6] Insurance Information Institute. Facts and statistics on aggressive driving. https://www.iii.org/fact-statistic/facts-statistics-aggressive-driving.

[7] National Highway Traffic Safety Administration. Speeding. https://www.nhtsa.gov/risky-driving/speeding.

[8] Stephen Stradling, Michelle Meadows, and Susan Beatty. Characteristics of speeding, violating and thrill-seeking drivers. In *International Conference on Traffic and Transport Psychology, Bern*, 2000.

[9] Prashant Shridhar Bokare and Akhilesh Kumar Maurya. Acceleration-deceleration behaviour of various vehicle types. *Transportation research procedia*, 25:4733–4749, 2017.

[10] Xin-Gang Li, Bin Jia, Zi-You Gao, and Rui Jiang. A realistic two-lane cellular automata traffic model considering aggressive lane-changing behavior of fast vehicle. *Physica A: Statistical Mechanics and its Applications*, 367:479–486, 2006.

[11] Arif Mehmood. Evaluating impact of demerit points system on speeding behavior of drivers. *European Transport Research Review*, 2(1):25–30, 2010.

[12] Andreas A Malikopoulos and Juan P Aguilar. An optimization framework for driver feedback systems. *IEEE Transactions on Intelligent Transportation Systems*, 14(2):955–964, 2013.

[13] Margaret J Miller. *Credit reporting systems and the international economy.* Mit Press, 2003.

[14] Inessa Love and Nataliya Mylenko. *Credit reporting and financing constraints*, volume 3142. World Bank Publications, 2003.

[15] Omurcan Kumtepe, Gozde Bozdagi Akar, and Enes Yuncu. Driver aggressiveness detection via multisensory data fusion. *EURASIP Journal on Image and Video Processing*, 2016(1):1–16, 2016.

[16] Cole D Fitzpatrick, Siby Samuel, and Michael A Knodler Jr. The use of a driving simulator to determine how time pressures impact driver aggressiveness. *Accident Analysis & Prevention*, 108:131–138, 2017.

[17] Kevin Ashton et al. That 'internet of things' thing. *RFID journal*, 22(7):97–114, 2009.

[18] Luigi Atzori, Antonio Iera, and Giacomo Morabito. The internet of things: A survey. *Computer networks*, 54(15):2787–2805, 2010.

[19] Mohamed Fazeen, Brandon Gozick, Ram Dantu, Moiz Bhukhiya, and Marta C González. Safe driving using mobile phones. *IEEE Transactions on Intelligent Transportation Systems*, 13(3):1462–1468, 2012.

[20] Kibrom A Abay. How effective are non-monetary instruments for safe driving? panel data evidence on the effect of the demerit point system in denmark. *The Scandinavian Journal of Economics*, 120(3):894–924, 2018.

[21] German Castignani, Thierry Derrmann, Raphaël Frank, and Thomas Engel. Driver behavior profiling using smartphones: A low-cost platform for driver monitoring. *IEEE Intelligent transportation systems magazine*, 7(1):91–102, 2015.

[22] Wenfu Wang, Yao Yang, An Chen, and Zhijie Pan. A scoring method for driving safety credit using trajectory data. In *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, pages 558–565. IEEE, 2019.

[23] Tianshi Liu, Guang Yang, and Dong Shi. Construction of driving behavior scoring model based on obd terminal data analysis. In *2020 5th International Conference on Information Science, Computer Technology and Transportation (ISCTT)*, pages 24–27. IEEE, 2020.

[24] Michael Nofer, Peter Gomber, Oliver Hinz, and Dirk Schiereck. Blockchain. *Business & Information Systems Engineering*, 59(3):183–187, 2017.

[25] Satoshi Nakamoto. Bitcoin: A peer-to-peer electronic cash system. https://bitcoin.org/bitcoin.pdf.

[26] Ethereum. Ethereum whitepaper. https://ethereum.org/en/whitepaper/.

[27] Aditya Pradana, G Sing, Y Kumar, and A Mohammed. Blockchain traffic offence demerit points smart contracts: Proof of work. *International Journal of Advanced Computer Science and Applications*, 9(11), 2018.

[28] Michael Behrisch, Laura Bieker, Jakob Erdmann, and Daniel Krajzewicz. Sumo–simulation of urban mobility: an overview. In *Proceedings of SIMUL 2011, The Third International Conference on Advances in System Simulation*. ThinkMind, 2011.

[29] Daniel Krajzewicz, Georg Hertkorn, Christian Rössel, and Peter Wagner. Sumo (simulation of urban mobility)-an open-source traffic simulation. In *Proceedings of the 4th middle East Symposium on Simulation and Modelling (MESM20002)*, pages 183–187, 2002.

[30] Stefan Krauss. Microscopic modeling of traffic flow: Investigation of collision free vehicle dynamics. 1998.