ESTIMATION OF $CO_2$ EMISSIONS CONSIDERING THE DECISIONS OF MULTIPLE DRIVERS WITHIN CAR-FOLLOWING MODELS

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ABSTRACT

Decisions made by the drivers on the road have a significant impact on the traffic, as well as on their vehicular emissions. Simple decisions such as accelerating at a yellow traffic signal can alter the dynamics of traffic flow and engine operating points. Especially in cities, these decisions, cumulatively, can impact large complex systems like transportation network. For example, these can lead to unstable conditions such as traffic congestion or high concentration of emissions. In order to reduce these impacts, it is necessary to understand the drivers’ decisions, their influence on other vehicles, and the resulting impacts on emissions. This need drives the main objective of this paper, which is, to understand the relationships between the drivers decisions and vehicular $CO_2$ emissions. In this paper, we model the drivers’ decisions by introducing a utility function for each driver in a micro-transportation model. Our hypothesis is that drivers have their own safe distance not only over front headway but also on rear headway. This usually happens when the driver chooses to change from acceleration to deceleration phases. We also propose a non-linear driver model to quantify the risk attitude of a driver based on factors such as age, experience, time of journey and the number of occupants. The Full Velocity Difference Method (FVDM) represents the traffic characteristics including speed, position, and vehicle acceleration at a traffic signal better than other car-following models. Hence, FVDM is used in our simulations. Numerical simulations show that a risk prone person results in a greater fuel consumption compared to the risk averse person. Simulation results also show that decisions made by a lead vehicle can be influenced by the follower vehicles properties such as speed and position and vice versa. The results show how driver decisions can alter the vehicular $CO_2$ emissions. The proposed model is a step towards developing a decision support tool, which can help drivers in reducing $CO_2$ emissions.

Keywords: Car following models, Decision Making, Tailgating, Non-linear Driver Model

1 Introduction

Air Quality Index (AQI) is a value which indicates the air pollution in a given area. Many government agencies measure this data to analyze and forecast the air pollution and its effect on health. Road vehicles are one of the main contributors to air pollution. At the same time, road transportation plays a major role in the economic development.

This calls for technologies which can decrease emissions and increase the performance of vehicle. Battery powered, electric powered vehicle technologies are gaining popularity because they do not emit emissions. However, till date, most of the vehicles are powered by internal combustion engines (ICE) due to their better performance characteristics. In the recent past, many technologies such as Diesel Particulate Filter (DPF), Lambda Sensor, Selective Catalytic Reduction (SCR) were introduced to reduce emissions.

Usually the operation of an ICE is based on lot of parameters such as fuel quality, air-fuel ratio, environmental conditions, engine load, engine speed etc. In other words, several factors influence vehicular emissions. Currently, ICES are calibrated such that the emissions are least for certain set of operating conditions. However, in a real scenario, the operation of engine is entirely in the hands of a driver. This calls for challenging tasks such as real-time engine optimization to augment the performance of ICE. Tasks like these are also finding their applications in other types
of powered vehicles as well. In electric vehicles (like gogoro), researchers are trying to explore such techniques in order to improve the riding experience.

Another undesired outcome of road transportation is accidents. Unfortunately, in most of the cases, these are attributed to human error. Features like Cruise Control, Advanced Cruise Control and Forward Collision Warning were introduced in modern cars to decrease the work load on the driver. In spite of these features and safety regulations, still many accidents lead to causalities and property loss. We believe that the above mentioned features find their maximum usage only in particular traffic scenarios. From this discussion, it can be understood that driver plays an important role in road transportation (both emissions and accidents). This lays the foundation for our research on studying the driving behavior and its effect on emissions.

Road transportation is analyzed using traffic simulation models. These can be broadly classified as Microscopic and Macroscopic models. Macroscopic models deal with the traffic flow and congestion on an aggregate scale. Whereas, microscopic models simulate individual vehicle movements by considering properties such as position, speed and acceleration. Most of these models consider that all drivers behave in a similar way.

Microscopic models have increasingly gained interest in recent years and plenty of algorithms and software were developed as a result. A few examples are AIMSUN, CORSIM, PARAMICS. The microscopic models in these softwares depend on speed, acceleration, and spacing between the lead and follower vehicles. Based on this information, vehicle position is estimated.

A driver can control a car mainly in two ways. He/she can use the accelerator pedal or brake, or can turn the steering wheel. The usage of steering wheel is not considered since lane changing is out of the scope for this paper. Therefore, we are restricting our study to a single lane.

In a single lane, drivers involve in making decisions of choosing either accelerator pedal or brake pedal (in vehicles with automatic powertrain). These decisions are vulnerable to a multiple of traffic scenarios. These traffic scenarios can be classified into two groups based on the position of the vehicle in front. In free flow traffic i.e., vehicle in the front is very far off, drivers’ decisions are purely based on his/her preferred distance to the next car, and will keep this as often as possible. This behavior is shown in both congested and uncongested scenarios.

This discussion illustrates the importance of including the driver model in the car following models to develop driver assistance systems. In this paper, we make a modest first step to include the driver model and decision making model (using a utility function of the driver) into the Full velocity Difference Method (FVDM) and study the impact of different driving behavior on CO₂ emissions.

2 Literature Survey

The research in microscopic traffic models (Car following models) started in the early 1950s. Since then, there were various theories proposed which try to estimate the velocity of a follower vehicle based on its leader vehicle. Some of the popular models are the Gazis-Herman-Rothery model (GHR) [2], the Collision Avoidance Models (CA) [3], the Linear Model [5], the Optimal Velocity Model (OVM) [Bando et al. [1]], Psychophysical models and Fuzzy Logic Models [6].

Over the time, the usage of the GHR model depreciated because of contradictory findings in the literature. Among the models mentioned above, the Gipps Model [3] gained popularity, and it is being used in many commercial software such as IN-TRAS and CARSIM. Brackstone and McDonald [4] stated that its widespread usage can be attributed to its ease of calibration.

Another class of car following models is based on the relative velocities and headways. In 1995, Bando et al. [1] presented a car following model called Optimal Velocity Model (OVM). However, the results showed unrealistic acceleration and deceleration when compared with the real traffic data. So, Helbing and Tilch [7] modified OVM by adding a term on the right hand side of the OVM. They called it as the General Force Model (GFM). The results from GFM gave acceptable acceleration levels but other important characteristics such as delay time of the car motion was larger than the expected values. The results from GFM showed that this delay time is around 2s whereas, Bando et al. [1] in his experiments, observed that this delay time is of the order 1s.

Later, Jiang et al. [8] proposed Full Velocity Difference Method (FVDM) to overcome the limitations of GFM and OVM. A comparison of the velocity and acceleration profiles generated by these models are shown in Figure 1 and Figure 2 respectively. FVDM is explained in detail in Section 3 and it is used as the starting point in our research. Unfortunately, driver behavior is not considered in all these models.

The fundamental work of Michaels [9] formed the basis for the construction of driver behavior models. He proposed that relative velocity is perceived through the changes in the visual angle subtended by the vehicle ahead. Drivers have a threshold for this angle and will choose to decelerate until they can no longer perceive any relative velocity. Cassidy and Windover [10] coined a term called “driver memory” which defines that a driver has his/her own preferred distance ahead to the next car, and will keep this as often as possible. This behavior is shown in both congested and uncongested scenarios.

Greaves and Ellison [11] investigated the links between personality traits, self reported behavior and actual speeding behavior. In their study they found that human factors such as time of day, number of co-passengers affect the speeding behavior. Surprisingly, it was noticed from the GPS data, that many drivers unknowingly cross the speed limit more often in a residential area. Speeding is an act of aggressive driving. So, we need to include these kind of internal factors while modeling the driver behavior.

Taylor [12] proposed that drivers attempt to maintain a con-
stant level of anxiety while driving and Fuller [13] corroborated this theory and came up with a task-capability interface model to describe the interaction between demand and capability while driving. Our driver model is built on Fuller’s model and this is further discussed in detail in Section 4.1.

Brackstone and McDonald [4] believed that these driver behavior models suffered acceptance since they need to be validated on an individual basis. With the recent developments in machine learning strategies, we believe that it is possible to calibrate these models on an individual basis. In fact, Wang et al. [14] developed a prototype based on driver characteristics and showed that self learning algorithm of driver’s pedal deflection is effective. However, it was reported that this self learning approach is limited to a few of the driver characteristics.

Aggressive drivers’ tend to do actions such as cutting off, speeding, tailgating etc while driving. And such actions are responsible for a number of road accidents [15]. This discussion reveals the importance of capturing such kind of tendencies in a micro transportation model. So, we introduce driver model into FVDM to differentiate between aggressive, neutral and conservative drivers. Earlier Tang et al. [16] used this approach and analyzed the effect of aggressive driving on emissions. Later in this paper, we compare our model with Tang et al.’s model [16] in Section 4.2 and show the necessity of non-linearity in the driver models. To the best of our knowledge, tailgating is not considered in the existing car following models. In this paper, we integrate a utility function with FVDM so that the decisions taken by the lead vehicle can be accommodated when he/she is being tailgated.

The decisions made by the drivers (say acceleration) may lead to higher amount of emissions. These vehicular emissions are one of the major contributors to the air pollution. Among all, $\text{CO}_2$ emissions is a greenhouse gas and it is also related to the fuel consumption. So, it becomes an interesting case to study the influence of driver’s attribution on $\text{CO}_2$ emissions. There are many existing statistical models to estimate the emissions based on parameters such as vehicle’s instantaneous speed, acceleration, tractive power, air-fuel ratio etc. However, car following models are based on vehicle’s speed and acceleration. So, models such as VT-Micro model, Afotey et.al’s emission model [17] can only be used. In this paper, we use afotey et.al’s emission model [17] to study each vehicle’s exhaust emissions.

2.1 Assumptions

The following are the assumptions made in most of the existing car-following models:

1. All drivers react in a particular pattern to a stimulus based on the front headway
2. Drivers make rational decisions which implies that drivers avoid collisions and do not violate traffic regulations.
3. The vehicles are in a single lane and hence, there is no chance of overtaking one another.

In recent times, Many researchers( [11], [16]) are posing questions about the validity of the first assumption. We also believe that driver’s response to front headway varies among drivers. Hence, we introduced a driver model. We also introduced a decision making model to accommodate the choices made by the driver.

2.2 Structure of the Paper

Of the existing car following models, we chose FVDM as the basis for our work. In Section 5 we discuss this model in detail and describe the advantages of this method over others. In FVDM, decision making process of a driver is not considered. In this paper, we model the decision making process of a driver by defining a utility function. In Section 4.2 this utility function is discussed. Numerical simulations for different traffic scenarios are discussed in Section 5. Two different traffic situations are considered where driver’s attribution and tailgating effect can be observed. These situations can result in different forms of decisions which result in different amounts of vehicular emissions ($\text{CO}_2$). These are also discussed in Section 5.

3 Full Velocity Difference Method (FVDM)

Car following models can be categorized into two major theories. The first category of models assumes that the vehicles maintain legal safe distances (e.g. [3]) while the second category assume the vehicles maintain legal velocities (e.g. [11]). The Full Velocity Difference Model (FVDM) is one such model which falls into the latter category. In this paper, we use this type of model for our analysis and this section describes the reasons for choosing FVDM among other car following models.

FVDM is an extension of Optimal Velocity Model (OVM). The acceleration of a vehicle according to OVM is given by

$$\frac{dv_{n+1}}{dt} = k[V(s) - v_{n+1}(t)] \quad (1)$$

Where, $k$ is the sensitivity and $V(s)$ is the velocity that driver’s prefer. $v_{n+1}(t)$ represent the speed of $n+1$ vehicle at a time $t$. Helbing and Tilch [7] calibrated this model with real traffic data and found the optimal velocity to be as follows:

$$V(s) = V_1 + V_2 \times \tanh(C_1 \times (s - lc) - C_2) \quad (2)$$

Here, $s$ represents the headway (distance between two vehicles), $V_1$ and $V_2$ represent traffic parameters and $lc$ is the length of the vehicle. The values of the optimized parameters are $V_1 = 6.95 m/s$, $V_2 = 7.91 m/s$, $C_1 = 0.13 m^{-1}$, $C_2 = 1.57$. In Section 6 we consider $C_1$ to be function of driver’s attributes such as biological characteristics, acquired characteristics and human factors and use it to estimate the driver’s capability.

Jiang et al. [8] proposed FVDM by introducing relative speed between the lead vehicle and follower vehicle in determin-
ing the velocity that the driver prefer. Their model is as follows:

\[
\frac{dv_{n+1}}{dt}(t) = k[V(s) - v_{n+1}(t)] + \lambda \Delta v
\]  

(3)

Where, \( \lambda \) is a step function defined as follows,

\[
\lambda = \begin{cases} 
  a, & s \leq s_c \\
  b, & s > s_c 
\end{cases}
\]

(4)

where, \( a, b \) and \( s_c \) are taken as \( 0.5 \, s^{-1}, 0 \, s^{-1}; 100 \, m \) respectively.

The velocity and acceleration profiles of the follower vehicle for the models (OVM, GFM, FVDM) discussed in the Section 2 are plotted in Figures 1 and 2 respectively. It can be observed that, the OVM results in unrealistically high acceleration when compared to real traffic conditions (please refer the Figure 2). The acceleration measured using GFM is realistic but it suffers a huge time delay to accelerate. FVDM represents the traffic flow properties of the vehicles such as position, velocity, and acceleration more accurately than others. However, FVDM assumes that each vehicle obeys a common equation of motion. This is not true in real scenarios since all the vehicles are not operated by the same driver. Hence, we introduce driver model and decision making model into FVDM. These are elaborated in the following sections.

4 Description of the Proposed Model

Every driver has his/her own driving style \([16]\) and hence it is not appropriate to describe the vehicle motion by a common equation of motion. Through our model, we attempt to address this drawback in car following models.

It is well known from the literature on psychology that the driver’s decisions are primarily influenced by personality traits, the task demand and driver capability\([11], [13]\). Fuller \([13]\) argued that feedback regarding the difficulty of the driving task is relevant in the decision making loop rather than the risk of collision. Our driver model is based on this fundamental assumption.

4.1 Driver Model

Many researchers tried to model the driver behavior using simulators as well as on-road experiments in real conditions\([4], [11], [18]\). One of the important results of these studies was that there exists a strong relationship between personality traits (risk aversion, risk proneness etc.) and driving behavior. Greaves and Ellison \([11]\) also observed that the driving behavior dictates the decisions that drivers make while driving \([11]\) in their experiments. In this section, we introduce the driver model and the decision making model and integrate these with FVDM.

Fuller \([13]\) proposed that the task difficulty is considered to be inversely proportional to the difference between task demand and driver capability. Driver capability is measured based on biological characteristics such as reaction time and acquired characteristics such as skills arising out of experience in driving. The driver capability thus measured is vulnerable to a host of human factor variables such as fatigue, drowsiness, time of day etc. In other words, human factors can reduce the task capability of the driver. So, please note that the capability measured through these characteristics helps us in determining the upper limit of driver capability for a particular driver.

On the other hand, task demand is primarily determined by the speed of the vehicle. Other elements that influence task demand are road and environmental conditions such as visibility, camber angle, potholes on the road. Operational features of the vehicle such as information display, control characteristics such as Electronic Stability Programme (ESP) and anti-lock braking system (ABS) also influence the task demand. In our model, without loss of generality, we assume that all the vehicles are equipped with same hardware and are operated under same external conditions. Hence, we restrict the task demand to be dependent only on speed.
We realize that driver capability can vary among drivers. To address this, biological factors such as age is considered. In the literature [19], it is well known that a large portion of accidents around the world are caused by young and novice drivers. Hence, we treat young adults to be more aggressive than adult and old drivers. We also realize that driver capability can vary at different times for the same driver. So, we consider aspects such as the time of day and number of occupants. In the current model, we assume that age and experience in driving have a predominant effect on driving behavior over other factors such as time of day and number of occupants.

It is a well-known phenomenon that driving style can momentarily change temporarily due to traffic disturbances and the drivers return to their original driving style after the disturbances disappear [10]. We simulated the actions of a risk prone driver (tailgating) as a traffic disturbance. This will be discussed in detail in Section 5. Internal factors like emotions and influence of alcohol can change the driving style. These are considered to be out of the scope for this paper.

Recall the four parameters that were introduced by Helbing and Tilch [7] while calibrating the optimal velocity. Of these, \(V_1\) and \(V_2\) are representative of the allowable speeds in a given traffic situation and we assume \(C_1\) and \(C_2\) to represent the driver’s capability. Earlier in this section, we assumed that task demand is a function of speed. In other words, as the relative velocity between the vehicles (leader and follower) increases, the difficulty to maintain the same front headway distance increases. From Fuller’s Model [13], we note that task difficulty is inversely related to driver capability. A simple sensitivity analysis of \(C_1\) and \(C_2\) shows that the influence of \(C_2\) is comparatively minimal on \(V(s)\). Hence, we chose \(C_1\) to represent the driver capabilities and \(C_2\) is assumed to be constant for simplicity.

\[ C_1 = f(age, experience, timeofday, #occupants) \] (5)

\(C_1\) is treated to be a function of biological characteristics such as age and acquired characteristics such as experience. Since young drivers are more aggressive than old drivers, we conclude that aggression has a negative relation with age. Experience in driving improves the procedural knowledge and enables he/she to predict on how the traffic scenarios develop. So, we feel that as the experience of a driver increases, they tend to be more cautious of their surroundings. Hence, aggression in driving reduces with age and experience.

Greaves and Ellison [11] found that speeding has a relation with the time of day and the number of occupants. Since, speeding is an act of aggressive driving, we included these in the calculation of \(C_1\). In their study they found that people showcase speeding behavior more often at night times and weekends. Also, speeding is highest when driven alone. It decreases when there are one or two co-passengers and increases again when there are more than three passengers. These observations need to be considered while determining \(C_1\).

We intend to use machine learning strategies to determine the nature of this function (on individual basis) defined in eq 5. Our intent here is to identify the necessary (or tangible) parameters (biological, human factors and acquired characteristics) and integrate such a model with FVDM. To demonstrate the necessity of a driver model, we consider \(C_1\) to be a simple arithmetic combination of all the factors. From now on, \(C_1\) will be referred as \(C_1^{tot}\) and it is calculated as below

\[ C_1^{tot} = C_1^{age} + C_1^{experience} + C_1^{timeofday} + C_1^{#occupants} \] (6)

The factors considered in eq 5 are linearly scaled from 0.01 to 0.4. This approach results in reasonable headway distances when compared with the experimental data [18].

For a given driving task, the difficulty is determined by the range of values that \(C_1\) can take. Let the lower bound and upper bound of this range be \(C_1^{low}\) and \(C_1^{high}\) respectively. Any value higher than \(C_1^{high}\) implies that driver capability is more than the task demand. Please note \(C_1^{tot}\) is proportional to acceleration of the vehicle. So, higher value of \(C_1^{tot}\) implies that the driver is capable of driving at higher acceleration than the nominal and vice versa for values below \(C_1^{low}\). In other words, the value of \(C_1^{tot}\) represents the risk attitude of the driver.

### 4.2 Decision Making Model

In Section 2, we concluded that the existing car following models do not account for the decisions made by the driver. Drivers make decisions at multiple levels ([20], [21], [22]). For example, the decisions on the selection of routes and time of the journey. These are made at a strategic level. While maneuvering, decisions are made at a tactical level. Within the scope of this paper, we consider only the acceleration and deceleration phases while maneuvering, i.e., decisions only at a tactical level.

Typically, drivers fall into one of the following personality traits: risk averse, risk prone and risk neutral. In the Section 4.1 we have seen that factors such as age and experience play an important role in defining the driver’s attribution towards risk. In real traffic, the permutation of these drivers in a single lane is unpredictable. Hence, the cumulative effect of the decisions made by all these drivers is highly variable. This variability in decisions affects the traffic flow and the \(CO_2\) emissions and this makes the analysis of a transportation network interesting and challenging.

Let us consider a scenario where there are two vehicles in a single lane. The first vehicle is termed as lead vehicle and the second vehicle is termed as follower vehicle. Assume that both of the vehicles are at a red traffic signal. For argument sake, consider the first driver to be risk averse and second driver to be risk prone. As it turns green, the velocities of both these vehicles increase. The risk prone driver will maintain a lesser front headway compared to the expected rear headway of a risk averse driver. Due to this, there is a possibility of influencing the decisions of one driver on another. Such actions can alter the emissions and
the traffic flow. Hence, inclusion of a decision making model is important in car following models.

4.2.1 Tailgating In simple terms, following the lead vehicle too closely is termed as tailgating. It is recognized as an act of aggressive driving behavior. Many government agencies (23) define tailgating as following less than 2-3 seconds behind the lead vehicle. In other words, if the lead vehicle passes a point on the road, and its follower passes the same point in under 2-3 seconds, then the follower is said to be tailgating the lead vehicle. Glendon (24) reported from their experiments that young drivers are most likely to tailgate when compared to older people. So, for our study, we chose risk prone drivers (young drivers) to tailgate their lead vehicle and a threshold of 2s is used for the detection of tailgating.

In this paper, we assume that all the drivers are rational decision makers. So, they try to avoid (both rear and front) collisions with other vehicles. However, the safe distance to avoid a collision differs among the drivers. At times, this can trigger changes in the driving behavior. For example, when the lead vehicle is being tailgated, the lead vehicle would like to avoid high deceleration. For example, at an yellow traffic signal, drivers tend to accelerate or maintain the same speed until they cross the traffic signal. Please note that the drivers are not violating any traffic signal here. This particular case is discussed in detail in the Section 5. To the best of our knowledge, tailgating is not including in the car following models. And we feel that it is necessary to model the interactions of vehicles in traffic. So, we introduce tailgating into FVDM.

Tailgating can happen at very low speeds as well. However, it might not have an appreciable impact on driver’s decisions. So, we choose a lower bound (V_{tailgate}) above which, drivers recognize that they are being tailgated.

4.2.2 Utility Function of a Driver Recall that, in this paper, we are considering the decisions only at a tactical level i.e., maneuvering in a single lane. In other words, drivers decide on acceleration or deceleration. Please note that lane changing is not considered here.

In utility theory literature, it is well known that rational people make decisions based on their preference structure (25). Here, the alternatives in the preference structure are front headway (\(\Delta x_f\)) and rear headway (\(\Delta x_r\)). The utility function (\(U\)) based on this preference structure will depend on the vehicle properties such as speed, position, acceleration of their own vehicle as well as neighboring vehicles. Our hypothesis is, when accelerating, drivers pay attention to their front headway more compared to their rear headway (\(U(\Delta x_f) > U(\Delta x_r)\)) and vice versa when decelerating the vehicle. In this paper, we considered the utility function of a driver to be as follows:

\[
U(\Delta x_f) = \alpha x_f
\]

where \(\alpha\) and \(\beta\) are constants.

It is well known that drivers tend to accelerate or decelerate if the change of their neighboring vehicles crosses a threshold (or safe distance) (9). We understand that this threshold varies among drivers and it is dependent on their personality trait. The threshold for acceleration based on front headway is considered in the conventional models. But, the threshold for rear headway while decelerating is not considered in the existing models. This is important to model a driver’s decisions especially while being tailgated. So, we felt the need for the inclusion of this into FVDM. We chose the tailgating definition by Glendon (24) as the threshold (V_{tailgate}) over which the driver’s pay attention to their rear headway while decelerating.

4.3 Integration of Driver Model and Decision-Making Model with FVDM

From the above discussions, we propose that drivers prefer to have a certain threshold (safe distance) for front headway and rear headway. However, the utility of these distances can vary for different traffic conditions and for different drivers. The current FVDM cannot accommodate this change of utility function of a driver. So, we introduce two parameters \(\alpha\) and \(\beta\) in the FVDM model to capture these changes. \(\alpha\) represents the weight factor for front headway and \(\beta\) represents the weight factor for rear headway. The values of \(\alpha\) and \(\beta\) are chosen such that \(\alpha > \beta\) when accelerating and \(\alpha < \beta\) when decelerating.

\[
V(s) = V1 + V2 * \tanh(C1^s * (\alpha x_f + \beta x_r - l_c) - C2)
\]

\[
\frac{dv_{n+1}}{dt} = k * [V(s) - v_{n+1}(t)]
\]

Please note that eq (10) is same as eq (1). The inclusion of driver model and decision making model are included in eq (9) which determines an optimal velocity of a driver based on his age, experience, headway etc.

4.4 Comparison of the Proposed Model with Tang et al.’s Model (16)

In the recent past, attention to the behavior of individual vehicles in a transportation network has increased. Many researchers have tried to integrate micro-simulation models with the real driving behavior models and now, it has become an important branch of research in transportation domain. In our opinion, the work of Tang et al. (16) is closely related to the nature of our work. Hence, we took their work as the bench-mark model. Tang et al. (16) assumed that expected headway is linearly related to driver’s attribution and is given by the following equa-
\[ \Delta x_c(t) = (1 + r)\max\{h_{c,\text{stop}}, v_n(t)t_w - \frac{(v_n(t))^2}{2a_{n,\text{min}}} \]  
\[ + \frac{(v_n-1(t))^2}{2a_{n-1,\text{min}}} + h_{c,\text{stop}} \} \]  

Where \( r \) is the index for the driver’s attribution and \( h_{c,\text{stop}} \) is the \( n^{th} \) driver’s front headway distance when \((n-1)^{th}\) vehicle stops. \( v_n \) is \( n^{th} \) vehicle’s speed. \( t_w \) is the \( n^{th} \) driver’s reaction time when \((n-1)^{th}\) vehicle stops. \( a_{n,\text{min}} \) is the \( n^{th} \) vehicle’s maximum deceleration.

\( r \) is chosen to be a random number between \((-0.15, -0.05)\) for a risk prone person, and a risk averse driver’s \( r \) is chosen to be again a random number but within the interval of \((0.05, 2)\). A value of zero is taken in case of risk neutral driver. We chose the extreme values and plotted the velocity of a vehicle with its front headway in Figure 3. It is evident that the nature of these curves is linear and we believe this is not true with the realistic scenarios.

Our hypothesis is that a risk prone driver maintain a constant front headway at lower velocities. He/She slowly increase their front headway with increase in the velocity of the vehicles. Whereas, risk averse drivers will increase their headway even at lower velocities. Please note that this rate of change of headway is comparatively large for risk averse drivers. Another major characteristic of a risk averse driver is that, beyond a certain velocity, he/she prefers not to accelerate even if the vehicle has a sufficient front headway. We believe that the driver’s response to the headway needs to include these characteristics. So, we feel that the driver model should possess a non-linear nature [10].

From Figure 3, it can be observed that the features discussed in the Section 4 are captured by our model. The intent of this paper is to describe the importance of the non-linear characteristics of the driver into car following models.

### 4.5 Impact on Vehicular Emissions

It is clear that every driver has his/her own style of driving i.e. choice of speed, headway (front and rear) etc. This influences in different usage of accelerator pedal position which results in different vehicular emissions. Among emissions (\( NO_x, CO_2, CO, HC, PM \)), in this paper, we are interested in \( CO_2 \). A number of statistical models were developed to estimate \( CO_2 \) emissions. These models are based on the instantaneous speed and acceleration of the vehicle.

Afotey et al. [17] proposed a statistical vehicle tailpipe emissions for \( CO_2 \) of a passenger car. Based on the data collected, they built an emission model using velocity, acceleration and an interaction term for both arterial and highway roads. It was concluded that this arterial model represents a good trade-off between accuracy and ease of use. The \( CO_2 \) emissions are given by

\[ CO_2 = 0.867 + 0.011 \times V + 1.17 \times a + 0.21 \times V \times a \]  

where,

- \( CO_2 \) = Carbon dioxide emissions in grams per second.
- \( V \) = the vehicle velocity in miles per hour (mph).
- \( a \) = the vehicle acceleration in mph per second.

In modern passenger cars, the engine control unit (ECU) ensures that there is no fuel flow when the accelerator pedal is not pressed. So, when the driver presses the brake, the ECU ensures that there will be no additional fuel flow into the engine chamber and hence \( CO_2 \) emissions can be safely considered to be zero when decelerating. In Section 5, we use this model to estimate \( CO_2 \) during acceleration and at constant speeds (based on the velocity and acceleration profiles generated our micro-traffic simulation model).

### 5 Simulations

In this section, we explore the impacts of the driver’s attitude towards risk on his/her decision making process and their combined effect on \( CO_2 \) emissions. Simulations are run for two different cases at a traffic signal. Section 5.1 provides the description of these traffic situations that are used for the simulations. In Section 5.2, we discuss the influence of driver’s attribution towards the choice of the headway distance. And Section 5.3 analyzes the influence of these choices on the motion of neighboring vehicles (the influence of risk prone driver on the risk averse driver).
Previously many researchers considered the situation at a traffic signal (7, 8, 15) for simulations purposes. Hence, we also use a similar scenario to compare our results with the existing literature. The values of the parameters, we use in these simulations, are taken from [7]. All the parameters used in our model are listed in Table 1 with their respective values except α and β. α and β are described in the Section 5.3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_1$</td>
<td>Traffic Parameter</td>
<td>6.75 m/s</td>
</tr>
<tr>
<td>$V_2$</td>
<td>Traffic Parameter</td>
<td>7.91 m/s</td>
</tr>
<tr>
<td>$l_c$</td>
<td>length of the car</td>
<td>5 m</td>
</tr>
<tr>
<td>$\Delta x_f$</td>
<td>front headway</td>
<td>7.4 m</td>
</tr>
<tr>
<td>$\Delta x_r$</td>
<td>rear headway</td>
<td>7.4 m</td>
</tr>
<tr>
<td>$\Delta t$</td>
<td>Time step</td>
<td>0.05 s</td>
</tr>
<tr>
<td>$t_g$</td>
<td>Duration of green signal</td>
<td>15 s</td>
</tr>
<tr>
<td>$t_y$</td>
<td>Duration of yellow signal</td>
<td>5 s</td>
</tr>
<tr>
<td>$t_r$</td>
<td>Duration of red signal</td>
<td>10 s</td>
</tr>
<tr>
<td>$TS_1$</td>
<td>Case 1: Traffic Signal Location</td>
<td>22.2 m</td>
</tr>
<tr>
<td>$TS_2$</td>
<td>Case 2: 1st Traffic Signal Location</td>
<td>44.4 m</td>
</tr>
<tr>
<td>$\beta$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_r$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$V_f$</td>
<td>$V_{tailgate}$</td>
<td>20 mph</td>
</tr>
</tbody>
</table>

5.1 Traffic Signal

We assume that the drivers are rational decision makers. In other words, they do not violate traffic signals and avoid collisions (both front and rear-end). We assume that driver’s tend to accelerate when the traffic light is green and stop when the traffic light is red. However, the situation in yellow falls into a conditional clause. It is recommended to slow down and stop if the traffic situation allows to do it safely [23].

Decelerating a vehicle safely depends not only on its own speed/acceleration but also on the neighboring vehicles. We believe that the utility function of headways (front and rear) plays an important role in the driver’s decisions especially at a yellow traffic signal. Based on the rationality assumption, the drivers intend to decelerate at a yellow signal. However, some situations may arise in traffic which influences the driver to deviate from deceleration. Later in this section, we describe such situations and show that the driver in the following vehicle can influence the lead vehicle. In all our simulations, we consider the traffic light is in green from 0s to 15s, 15s to 20s in yellow and then followed by red.

The formation of vehicles at a traffic signal is as follows. Each car starts from rest, with a headway of 7.4m (both front and rear). All the vehicles are assumed to be of the same length (5m). In our study, we broadly classify the simulations into two categories. In Case 1, we show the effect of driver’s attribution towards risk on the headway in car following models. In this case, only one traffic signal is considered. There are N (say 3) vehicles in a single lane waiting at a traffic signal. The location of the traffic signal is at 22.2m from the 3rd vehicle.

In Case 2, there are N (say 6) vehicles in a single lane, waiting at a traffic signal for it to turn green. The first traffic signal and the second traffic signal are located at 44.4m and 140m from the 6th vehicle respectively. For simplicity, consider that both of these traffic lights operate at the same time. In other words, the time duration for each signal is same for both.

After 15s, at the first traffic signal, when it turns yellow, the drivers that have not crossed the first traffic signal yet, must decide whether to continue forward or to stop. We consider that this decision is based on the location of the vehicle with respect to the first traffic signal. When the light turns red, since the drivers are assumed to be rational i.e., they do not violate traffic rules, we assume that the vehicles (that have not crossed the traffic signal) will come to a stop without any collisions. The pictorial representation of the initial conditions discussed here is summarized in Figure 4. Please note that the location of the first traffic signal is calibrated such that tailgating influences driver’s decisions.

In both the cases, we consider two scenarios: Scenario 1 where all the drivers have similar attitude towards risk (say risk averse) and Scenario 2 where all the drivers are have similar attribute towards risk except one (say risk prone). Both these scenarios are listed in Table 2 for more clarity. Numerical simulations of the model described in Section 4 are run in Matlab. Euler Forward Difference Method (26) is used to discretize this model (Eq. 5-6) i.e,
\[ v_n(t + \Delta t) = v_n(t) + \Delta t \frac{dv_n(t)}{dt} \] (13)

\[ x_n(t + \Delta t) = x_n(t) + v_n(t)\Delta t + \frac{1}{2} \frac{dv_n(t)}{dt}(\Delta t)^2 \] (14)

Where, \( v_n(t) \), \( x_n(t) \) represents the speed and the position of the \( n \)th vehicle at a time \( t \).

**TABLE 2**: Snapshot of different situations considered in the simulations

<table>
<thead>
<tr>
<th>Scenario #</th>
<th>Case 1</th>
<th>Case 2</th>
</tr>
</thead>
<tbody>
<tr>
<td># of vehicles (N)</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td># Traffic Signals</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Driver Type</td>
<td>Same</td>
<td>Different</td>
</tr>
<tr>
<td>Vehicle Type</td>
<td>Same</td>
<td>Same</td>
</tr>
<tr>
<td>Traffic Conditions</td>
<td>Same</td>
<td>Same</td>
</tr>
</tbody>
</table>

Recall that in Section 4.1, we discussed that risk attitude of a driver is determined based on the value of \( C_{1tot} \), \( C_{1low} \) and \( C_{1high} \). For the traffic situations discussed here (both Case 1 and Case 2), the values for \( C_{1low}, C_{1high} \) are chosen to 0.2 and 0.3 respectively. Please refer Table 3 for the classification scheme of the drivers.

**5.2 Case 1: Influence of Driver’s Attribution**

Let us consider a situation where there are three drivers waiting at a traffic signal at 09:00 AM. Assume the ages of these drivers to be 80, 80, 16 respectively and there are no co-passengers in the vehicle. As soon as the traffic signal turns green, the first vehicle is free to accelerate. However, the motion of the remaining vehicles is influenced by their neighboring vehicles. The velocity profiles of these vehicles using original FVDM (i.e., without driver and decision making models) are shown in the Figure 5. Recall that, driver’s attribution is not accounted for in the original FVDM model. So, the velocity profiles of these vehicles which are shown in Figure 6 are different from the previous case.

**FIGURE 5**: Case 1, Scenario 1: Velocity profiles with all risk averse drivers

is 16 year old driver and possesses a risk prone character. So, he/she has a tendency to follow his/her lead vehicle very closely. This results in a comparatively lower front headway for the third driver unlike the second driver. So, the velocity profiles of these vehicles which are shown in Figure 6 are different from the previous case.

**FIGURE 6**: Case 1, Scenario 2: Velocity profiles with all risk averse drivers except one

In order to show the effect of driver’s attribution, we chose the extreme combinations i.e., second driver is 80 year old (risk averse) and the third driver as 16 year old (risk prone). The idea behind this simulation is to accommodate the variation of choices

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**TABLE 3**: Classification Scheme for Drivers

<table>
<thead>
<tr>
<th>Value of ( C_{1tot} )</th>
<th>Risk Attitude of Driver</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_{1low} ) ( \leq 0.2 )</td>
<td>Risk Averse</td>
</tr>
<tr>
<td>( 0.2 &lt; C_{1tot} \leq 0.3 )</td>
<td>Risk Neutral</td>
</tr>
<tr>
<td>( C_{1tot} &gt; 0.3 )</td>
<td>Risk Prone</td>
</tr>
</tbody>
</table>

---
for the headway distances among different drivers. This variation in the following distances can influence the traffic flow and exhaust emissions.

We use Afotel et al.’s [17] emission model for the estimation of the CO$_2$ emissions. The cumulative value of CO$_2$ emissions for all the vehicles considered in Scenario 1 and Scenario 2 are shown Figure [7]. It can be observed that the cumulative value of CO$_2$ emissions for the first two vehicles remain same in both the scenarios. This is expected since they are risk averse in both the scenarios. Whereas, the cumulative emissions from the vehicle #3 in these scenarios are 199 and 201 gms respectively. This difference is mainly due to the introduction of driver’s attribution in Scenario 2. Hence, we conclude that the CO$_2$ emitted by the risk prone driver is higher compared to risk averse driver. Tang et al. [16] also concluded that risk prone drivers consume more fuel than risk averse drivers.

![Figure 7: Case 1: Cumulative CO$_2$ emissions for Scenario 1 and Scenario 2](image)

5.3 Case 2: Influence of Tailgating and Personality Traits

From Section 4.3 we understood that drivers make decisions based on their neighboring vehicles, traffic conditions etc. In this section, we simulate certain conditions through which the influence of neighboring vehicles can be seen on driver’s decisions. Here, the influence of a risk prone driver on the driving behavior of his/her lead vehicle is shown. It is also possible that a risk averse driver can influence the driving behavior of his/her following vehicle. In this paper, we analyze the first case since it has more implications on vehicular emissions.

Assume that there are 6 vehicles waiting at a traffic signal at 09:00 AM. Also assume that there are no co-passengers in these vehicles. Now, consider a scenario (scenario 1) where all the drivers have same attribution towards risk (say risk averse). Simulations are run with the conditions described in Section 5.1 using original FVDM. The velocity profiles of these vehicles are plotted in Figure [8]. It is evident from these velocity profiles that the first three vehicles cross the second traffic signal while the rest decelerate and stop.

![Figure 8: Case 2, Scenario 1: Velocity profiles with all risk averse drivers](image)

Now let us consider another scenario (scenario 2) where one of them is risk prone. We understand that the choice of which driver among the 6 drivers has an influence on the results. In order to show the influence of tailgating, we assume that the Driver #5 is risk prone.

![Figure 9: Velocity profiles with all risk averse drivers except Driver #5](image)

One of the virtues of a risk prone driver is that they tend to tailgate their lead vehicle. In other words, here Driver #4 is being tailgated by Driver #5. For an easy classification, tailgating is broken into three states: 0, 1, and 2 (refer to the Figure [10]). Tailgating state 0 implies that the driver is not being tailgated. Tailgating state 1 implies that he/she is being tailgated but the driver does not pay attention since he is accelerating his/her vehicle. Tailgating state 2 implies that driver is being tailgated during his/her deceleration and driver pays attention to the rear headway.
From Figure[10] it is clear that the Driver #5 tailgates Driver #4 during the green and yellow states of the traffic signal. This happens since Driver #5 displays risk prone behavior. Recall that Driver #4 is risk averse. Driver #4 does not pay attention to rear headway while accelerating i.e., traffic signal is in green (0-15s). However, when the traffic signal turns yellow (15s), he/she decides to decelerate (at this moment, Driver #4 has enough headway to the second traffic signal location). During deceleration, he/she looks back and watches the rear headway. In other words, he/she is changing his/her utility function. He/she realizes that his/her vehicle is being tailgated. In order to avoid a read-end collision, he/she tries to maintain a sufficient rear headway with Driver #5. Beyond a critical point, he/she decides to accelerate instead of decelerating to avoid a read-end collision and crosses the signal before the traffic light turns red.

The results of the velocity profiles in this simulation are displayed in Figure[9]. An interesting observation is that the deceleration rates of Driver #5 is higher than Driver #4. In other words, Driver #5 responds to the actions of Driver #4 effectively. Still, Driver #4 chooses to accelerate since his/her choice of ”safe distance” is higher than Driver #5’s. So, it can be concluded that these actions are primarily influenced by the Driver #5’s actions and Driver #4’s attribution towards risk. The change in the utility function of Driver #4 is plotted in Figure[11]. Please note that Driver #4 or Driver #5 are not violating any traffic regulations in this scenario.

We understand that the values of $\alpha$ and $\beta$ play a prominent role and they need to be calibrated on individual basis. In this paper, our intentions are to show the effects of changes in utility functions on vehicle and traffic properties. Hence, simple values of $\alpha = 1$ and $\beta = 0$ during acceleration and while decelerating $\alpha = 0$ and $\beta = 1$ are chosen.

These decisions impact the emissions released by the vehicles. The cumulative $CO_2$ emissions for Case 2 Scenario 2 are displayed in Figure[12]. It is evident that the $CO_2$ emissions from Driver #4 and Driver #5 are comparatively higher than others. The increase in emissions from Driver #4 can be primarily attributed to the influence of risk prone driver on risk averse driver. The huge amount of emissions from Driver #5 can be attributed to his/her driving behavior (risk prone).

In both of these cases, we primarily simulated the risk attitude of a driver based on age and experience. The importance for other factors such as time of day and number of occupants is not included here for brevity.

### 6 Future Work

In the current model, the driver model ($C_{1}^{\text{tot}}$) is considered to be influenced by a specific set of parameters and needs to be calibrated for each traffic situation. To avoid this laborious work, we foresee to implement machine learning strategies to determine the nature of $C_{1}^{\text{tot}}$. In the past, Wang et al. [14] developed a longitudinal driving assistance system based on machine learning techniques and integrated with ACC and FCW. According to Wang et al. [14] this method is effective in capturing the important driving characteristics. However, due to the large variability

![Figure 10: Case 2, Scenario 2: Tailgating states of the Driver #4](image)

![Figure 11: Velocity profiles with driver behavior model in FVDM](image)

![Figure 12: Case 2: Cumulative $CO_2$ emissions for Scenario 1 and Scenario 2](image)
of the driver’s state of mind and the effect of dynamic road and traffic environments, some questions are still unanswered.

The accelerator pedal position and steering torque are the strong indicators of driving style. Many researchers earlier (e.g. [11]) relied on GPS data to measure the acceleration, position and velocity of the vehicle. Radars were used to measure the headway. And, including the steering torque can reveal more insights in the lane changing behavior of the driver. More than this, machine learning strategies can open up possibilities of optimizing the engine in real time based on driver behavior and traffic conditions.

We also plan to include weather conditions such as rain and fog since modern vehicles are being equipped with these sensors. Greaves and Ellison [11] in their research concluded that temporal spatial and situational elements of driving can be extracted from the speeding data. So, impact of road conditions can be derived from this. Including all of these factors along with appropriate machine learning strategies, we believe that it is possible to develop driver assistance systems at moderate speeds as well. We also believe that such systems can be included in driverless vehicles to improve the driving pleasure.

7 Closing Comments

Although the existing car following models represent significant traffic properties, there is a growing consensus among researchers that these are still far from reality. The basic reason behind this is that the vehicle’s motion cannot be defined by a single equation of motion. Drivers play a vital role in this, and their capabilities and style of driving are complex in nature and differ at different times for the same driver.

This paper attempts to integrate the driver model (along with the decision making model) into the Full Velocity Difference Model (a car following model). It is assumed that drivers’ decisions are dependent on their utility functions. Usually, preference structure remains the same for an individual. However the utilities of the attributes may vary based on human factors, traffic conditions and environmental conditions etc. In this paper, we considered two situations (all drivers are alike (say risk averse) and all drivers are alike except one (say risk prone)). Numerical simulations are run for such scenarios and they show how the risk prone person influences the driving characteristics of the risk averse driver. The impact on CO2 emissions is also studied. Results show that a risk prone person consumes comparatively more fuel than a risk averse person. However, the model presented in this paper has the following limitations:

1. The parameters considered in the driver model varies from driver to driver. These values needs to be calibrated on an individual basis.
2. Our analysis is based on the numerical results. We did not compare these with real data.
3. Weightage factor for age and experience in driving are given higher preference compared to the weightage factor from time of the day and number of occupants.
4. Our analysis is primarily focused on age and experience in both cases. Analysis of other factors such as time of day, number of occupants is not included here for brevity.

Acknowledgments

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REFERENCES

characteristics”.  


