Effects of Car Following Safety Parameters on Battery Electric Vehicles’ Power Consumption

Mojolaoluwa Ladipo-Obasa
mojola17@gwmail.gwu.edu
Department of Civil and Environmental Engineering
Center for Intelligent Systems Research
Traffic and Networks Research Laboratory
The George Washington University
Exploration Hall
20101 Academic Way
Ashburn, Virginia 20147

Claire E. Silverstein*
csilvs@gwmail.gwu.edu
Department of Civil and Environmental Engineering
Center for Intelligent Systems Research
Traffic and Networks Research Laboratory
The George Washington University
Exploration Hall
20101 Academic Way
Ashburn, Virginia 20147

Samer H. Hamdar
hamdar@gwu.edu
Department of Civil and Environmental Engineering
Center for Intelligent Systems Research
Traffic and Networks Research Laboratory
The George Washington University
Exploration Hall
20101 Academic Way, Room 201-I
Ashburn, Virginia 20147
Phone: (202) 994 6652
Fax: (202) 994 0127

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Effects of Car Following Safety Parameters on Battery Electric Vehicles’ Power Consumption

M. Ladipo-Obasa, C. E. Silverstein*, S. H. Hamdar

ABSTRACT

With the ever-present need to reduce fuel consumption and emissions, battery electric vehicles are expected to become more prominent on roadways. While these vehicles alleviate pollution, they still require electricity from charging stations. In order to gauge how much energy battery electric vehicles require, this paper looks into the relationship between car-following safety and power consumption. Car-following safety is quantified using the acceleration Prospect Theory-based model. Consumed power is calculated using a modified “power requirement predictor” model suggested in 2013. Tested safety-related parameters in the car-following model include driver sensitivity to losses or gains in speed, driver relative weight of losses compared to gains in speed, driver collision weighting function, driver uncertainty of leading vehicle’s velocity, and driver sensitivity to surrounding environment. The three types of vehicles utilized to investigate the effects of parameters on power consumption and were selected based on their popularity among electric vehicle consumers: 2015 Nissan Leaf, 2015 Tesla Model S, and 2015 BMW i3 base. Simulations are conducted by having the leader vehicle follow the Urban Dynamometer Drive Schedule and therefore compelling the following vehicle to employ urban environment accelerations. Each originally calibrated safety parameter is changed through an elaborate sensitivity analysis. Results show that the driver’s sensitivity to the surrounding environment and the corresponding risk-taking attitudes (e.g. relative weight of speed gains compared to speed losses) impact the required power; however weighing rear-end collision related losses does not have a significant effect on the urban driving style and the corresponding required power.

Keywords: battery electric vehicles, car-following, prospect theory, power consumption, safety
1.0 INTRODUCTION

Energy plays a fundamental role in the functioning of society. Today, the major sources of energy are fossil fuels such as coal, petroleum (oil), and natural gas, which account for 82% of the energy fed into the U.S. Energy grid (1). Although fossil fuels have been paramount to society’s progress and transformation, other “cleaner” resources are necessary due to the increase in the average temperatures of the Earth’s atmosphere and oceans caused by greenhouse gas emissions (2).

The transportation sector is one of the biggest contributors to greenhouse emissions. In 2013, it utilized 28% of the total U.S. energy (3) and accounted for 27% of the nation’s total greenhouse gas emissions (2). Among the various modes of transportation available, light duty vehicles (a category that includes passenger cars, light trucks and motorcycles) is responsible for the most greenhouse gas emissions. So far, the transportation sector has implemented several measures to curb its consumption such as increasing the fuel economy of vehicles through the Corporate Average Fuel Economy program (4) as well as promoting eco-driving, benefits of carpooling, use of public transit and use of electric vehicles. According to the U.S. Department of Energy, vehicles contribute to air pollutants and greenhouse gases either on a direct basis or well-to-wheel basis (5). Unlike their traditional counterparts, pure electric vehicles (EV), also known as battery electric vehicles (BEVs), typically have lower emissions because they have zero tailpipe emissions and only affect the atmosphere through the source of electric power (5).

This characteristic along with BEVs proven energy efficiency in traffic congestion conditions (6), offers major environmental gains. It is anticipated that the EV market share will comprise up to 7% of light duty vehicles by 2020 due to vehicle appeal, consumer demand, government influence, and benefits to the economy (7).

As a result of such increase in market share, there is a need to investigate the BEV engine performance in terms of required power under a variety of traffic conditions and the corresponding safety implications. To do so, microscopic traffic simulation may be used (8)(9)(10)(11)(12) since it is able to capture interactions between drivers as a function of different behavioral (e.g. perception, desired speed) and mechanistic (e.g. maximum acceleration/deceleration, vehicular size) characteristics. Accordingly, the objective of this research is to investigate the relationship between safety in driving behavior and BEV required power through microscopic traffic simulation.

To be able to accomplish the aforementioned objective, the trajectory, velocity, and acceleration of a car-following vehicle, which responds to the behavior of its leader, is recorded. The behavior of the leader is regulated by the EPA’s Urban Dynamometer Driving Schedule (UDDS) (13), which is intended to recreate driving conditions in an urban environment. The position, velocity, and acceleration/deceleration values from the simulations are then used to calculate respective forces acting on the vehicle. Calculation of the power consumption is done based on a modified “power requirement predictor” (PRP) model suggested in 2013 (14). On the other hand, the Prospect Theory (PT)-based microscopic car-following model is utilized to evaluate the safety of driving behavior through five quantifiable safety-related parameters (15).

Through variation of these parameters, the authors are able to observe the power required by different drivers and determine if the “safest” drivers are in fact the most environmentally friendly (i.e. consume less power). As a benchmark, the obtained values are compared to those obtained by using the Intelligent Driver Model (IDM). It has previously been suggested that this model is able to simulate “autonomous” vehicles (16). In other words, the lowest “human driver”
required power (obtained by the PT model) is compared to that of “autonomous” vehicles (represented by IDM).

The structure of this paper is closely related to the research approach presented in the previous paragraph. Section 2 presents a brief literature review that discusses battery technologies adopted in BEVs and microscopic acceleration models that can be “linked” to the corresponding power and energy consumption models. Section 3 presents the resulting modeling approach (both the power requirement model and the car-following models) and the vehicle types used in the simulation. The simulation set-up is then offered in Section 4. Section 5 provides the numerical results and the corresponding analysis. Finally, Section 6 presents the concluding remarks and the future research needs.

2.0 LITERATURE REVIEW

The limitation of the energy storage system for BEVs has led to the development of several battery technologies, which are lighter and cheaper than their predecessors (17)(18)(19). Lithium-ion (Li-ion) batteries appear to be the preferred BEV batteries (6). It should be noted that all of the battery technologies must enable the vehicle to meet a specified range so as to easily achieve the power requirement for a specified acceleration performance, grade ability, and top cruising speed of the vehicle (20). Given the above findings and since the authors are focusing on existing widely used technologies, the vehicles analyzed in this paper are all assumed to be equipped with lithium-ion batteries.

There are many types of microscopic acceleration models that may be used to compute electric vehicles’ power consumption. Some are stimulus-response models (8)(21)(22)(23), while others are safe-distance models (24)(25)(10). These model categories display limitations in the ability to reproduce both accurate traffic dynamics and realistic acceleration/deceleration values. In 2000, Treiber et al. (11) developed a continuous-in-time model called Intelligent Driver Model (IDM) that can model hysteresis effect and complicated traffic states. The choice between acceleration and deceleration is determined by the vehicle’s desired speed, and its leader’s position and speed. IDM’s influencing factors are desired velocity, safe time headway, maximum acceleration, desired deceleration, acceleration exponent, jam distances, and vehicle length. This model has been used to “mimic” autonomous driving movement (16) but lacks the cognitive dimension/parameters that can shed some light into the safety and the risk-taking attitudes in driving behavior. Prospect Theory, developed by Kahneman and Tversky, seeks to provide an alternative account of individual decision-making in risky situations (26). This theory was expanded for its application to microscopic traffic modeling by (15). The PT-based model realistically demonstrates a driver’s decision-making process in many scenarios due to its inclusion of risk perception and risk-taking behavior as cognitive elements. The vehicle’s acceleration rate is determined by considering the safety-related parameters of sensitivity of the driver’s confidence in taking risks and driving experience, desire to gain or lose speed, subjective probability of getting into a collision and the subjective losses involved. In comparison to the previously discussed models, this model can be viewed as more inclusive and human behavior-oriented as a result of its ability to allow and learn from the occurrence of collisions, and the lack of restriction on maximum allowable deceleration and acceleration rates imposed on drivers (25). Accordingly, the PT-based model will be used in this paper along with the IDM model for cross-comparative assessment.

Output from the microscopic traffic models are used as input for the selected polynomial power requirement model. In this model, elements such as traffic scenarios and regulations, the
vehicle’s state, the driver behavior, and road conditions are essential for required power calculation (27). Although this power model does not account for the power gains due to regenerative braking or the loss due to auxiliary units, motors, and braking, it is applied in lieu of other power models (28)(29)(31)(31)(32) because it fully incorporates the forces that are pertinent to the proposed experimental setup and operates with publicly accessible data. The way that the selected model works is first, the position, velocity, and acceleration data from the microscopic traffic models are used to calculate the forces due to acceleration, aerodynamics, load related to steepness, and rolling resistance. Then, force values are combined to determine the power requirement.

3.0 MODELING APPROACH
Based on the findings of Section 2, this section offers the details of the techniques used to model the power requirement of the BEVs and the two car-following models used in simulation. The vehicles to represent light-duty BEVs in this study are: 2015 Nissan Leaf, 2015 Tesla Model S and 2015 BMW i3. These models were selected due to popularity among consumers (33) and ease of observation of the changes in power consumption with variation in driving conditions. The parameters of each vehicle that pertains to this study are available in Table 1.

3.1 Car-Following Models
The modeling of required engine power of a battery electric vehicle under the effects of changing safety parameters can only be realized with the availability of location, velocity, and acceleration information of the vehicles at each time step. This is achieved by the adoption of the PT-based car-following model developed by Hamdar et al. (15) and IDM developed by Treiber et al. (11). The PT-based model obtains acceleration from probability analysis of the driver’s cognitive process when confronted with risky alternatives, while the IDM derives acceleration based on the desired acceleration and braking decelerations induced by the front vehicle. The following subsections (Sections 3.1.1 and 3.1.2) are intended to introduce the parameters associated with each car-following model. A full discussion of the models may be found in the corresponding literature.

3.1.1 Prospect Theory-based Model
The PT-based model uses the drivers’ perception, judgment, and anticipation in recreating the vehicular behavior in response to traffic flow. The acceleration value function is calculated as:

$$U_{PT}(a_n) = \frac{w_m+(1-w_m) [tanh(\frac{a_n}{a_0})+1]}{2} \left[ \frac{(\frac{a_n}{a_0})^\gamma}{1+(\frac{a_n}{a_0})^\gamma} \right]^\gamma$$  \hspace{1cm} (1)

Where $U_{PT}$ = the acceleration value function, $a_0$ = the normalization parameter, $a_n$ = the variable acceleration, $\gamma$ = the sensitivity exponent that indicates the sensitivity of drivers towards gains or losses in travel times (speeds), and $w_m$ = the relative weight of losses in comparison to gains.

Assuming that the driver does not get involved in a rear-end collision; the desired acceleration will prompt a gain in $U_{PT}$. However, if there is a collision the calculation of disutility is defined as:

$$U(a_n) = (1 - p_{n,i})U_{PT}(a_n) - p_{n,i}w_c k(v, \Delta v)$$  \hspace{1cm} (2)
Where \( p_{n,t} \) = the subjective crash probability based on the standard deviation of the assumed future velocity of the leader represented by \( \alpha \) (i.e. greater \( \alpha \) indicated greater uncertainty), \( w_c = \) the crash weighting function that is lower for drivers who are more likely to take a higher risk, and \( k(v, \Delta v) = \) the crash seriousness term (assumed to be 1 at this stage).

The process of choosing acceleration is stochastic in nature and is captured through the logistic functional form in the following equation:

\[
f(a_n) = \begin{cases} 
\frac{e^{(\beta_{PT} \times t \times (a_n))}}{\int_{a_{min}}^{a_{max}} e^{(\beta_{PT} \times t \times (a))} da}, & a_{min} \leq a_n \leq a_{max} \\
0, & \text{otherwise}
\end{cases}
\] (3)

Where \( f(a_n) = \) the probability function, \( \beta_{PT} = \) the sensitivity of the driver’s choice to total utility.

### 3.1.2 Intelligent Driver Model

Unlike the PT-based model, IDM does not account for the mental process involved in decision-making (i.e. physics based model). This model computes acceleration through restriction set in place by different parameters. The acceleration function is calculated as:

\[
\frac{dv}{dt} = a \left[ 1 - \left( \frac{v}{v_0} \right)^\delta - \left( \frac{s^*(v, \Delta v)}{s} \right)^2 \right]
\] (4)

Where \( \frac{dv}{dt} = \) acceleration chosen by the driver, \( a = \) acceleration, \( v = \) velocity, \( v_0 = \) desired velocity when driving on a free road, \( \delta = \) acceleration exponent, \( \Delta v = \) relative speed difference between leading and following vehicle, \( s^* = \) desired gap between leading and following vehicle, \( s = \) actual gap between leading and following vehicle.

The desired gap \( s^* \) is set by the following equation:

\[
s^*(v, \Delta v) = s_0 + \max \left[ 0, \left( vT + \frac{v \Delta v}{2ab} \right) \right]
\] (5)

Where \( s_0 = \) minimum bumper-to-bumper distance to the leading vehicle, \( v = \) velocity, \( T = \) desired safety time headway when in a car-following scenario, \( \Delta v = \) relative speed difference between leading and following vehicle, \( a = \) acceleration, \( b = \) braking.

### 3.2 Power Model

The power requirement model (14) calculates the required power for the engine of BEVs during varying traffic conditions fed through the aforementioned acceleration models (Section 3.1). The total power requirement \( P_{total} \) function is calculated as:

\[
P_{total} = F_a \ast v + F_{air} \ast v + F_c \ast v + F_r \ast v
\] (6)

\[
F_a = m \ast a
\] (7)

\[
F_{air} = \frac{1}{2} \ast \rho_{air} \ast C_d \ast A \ast v^2
\] (8)
\[ F_c = m \cdot g \cdot \sin(\theta) \]  
(9)

\[ F_r = m \cdot g \cdot K_r \]  
(10)

\[ A = W \cdot H \cdot 0.85 \]  
(11)

Where \( F_a \) = force due to acceleration, \( F_{air} \) = aerodynamic force, \( F_c \) = a load related to steepness, \( F_r \) = rolling resistance, \( v \) = velocity (m/s), \( m \) = vehicle mass (kg), \( a \) = acceleration (m/s²), \( \rho_{air} \) = density of air at sea level at a temperature of 15°C, \( C_d \) = drag coefficient of vehicle, \( A \) = frontal area of vehicle (m²); that is the product of a vehicle’s width (W), height(H) and a coefficient of 0.85 (32), \( g \) = acceleration due to gravity (9.81 m/s²), \( \theta \) = theta, and \( K_r \) = rolling resistance coefficient.

In order to adhere to the UDDS urban environment simulation scenario, the road is assumed to be level (\( \theta = 0 \)) and at sea level (zero altitude and air density is 1.2256 kg/m³).

Additionally, the road is surfaced with asphalt that has a rolling resistance coefficient of 0.07.

The parameters used in the study are indicated in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>2015 Nissan Leaf S</th>
<th>2015 Tesla Model S</th>
<th>2015 BMW i3 (base)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Mass (m) [kg]</td>
<td>1476.897</td>
<td>2190.851</td>
<td>1269.605</td>
</tr>
<tr>
<td>Drag coefficient (( C_d ))</td>
<td>0.28</td>
<td>0.27</td>
<td>0.29</td>
</tr>
<tr>
<td>Height (W) [m²]</td>
<td>1.770</td>
<td>1.963</td>
<td>1.778</td>
</tr>
<tr>
<td>Width (H) [m²]</td>
<td>1.549</td>
<td>1.435</td>
<td>1.575</td>
</tr>
</tbody>
</table>

4.0 EXPERIMENTAL SETUP

In this section, the UDDS schedule and the definitions of the PT model safety parameters are provided. Such definitions dictate the corresponding values adopted in the simulation set-up presented afterwards.

4.1 The Urban Dynamometer Driving Schedule

The Urban Dynamometer Driving Schedule (UDDS) defines the leading vehicle’s driving pattern in terms of length and time of simulation, along with a velocity profile (13). By providing the leading vehicle with the UDDS, car-following behavior is prompted in the subsequent vehicle. This schedule, commonly known as the “LA4”, is a reflection of driving conditions within a city in the U.S. and is part of a series of tests performed on light duty vehicles at the National Vehicle and Fuel Emissions Laboratory. In addition, the cycle covers a distance of 7.45 miles in 1,369 seconds with frequent stops and an average speed of 19.59 mph.

4.2 Safety Parameters Definition

Since the lead vehicle’s driving pattern is determined by the UDDS cycle, the PT-based model and IDM are used to stimulate the driving behavior of the following vehicle. The PT-based model safety-related parameters that are altered are the following: driver uncertainty of leading vehicle’s velocity \( \alpha \), driver sensitivity to surrounding environment \( \beta_{PT} \), driver sensitivity of losses or gains \( \gamma \), driver collision weight parameter \( w_c \), and the driver’s relative weight of travel time losses compared to gains \( w_m \). The responsiveness of each of these parameters to acceleration is discussed in detail in (12) and briefly presented below.
To begin, $\alpha$ represents the uncertainty involved with estimating the lead driver’s acceleration pattern. An increase in the value of $\alpha$ will give rise to more uncertainty due to a wider acceleration distribution function. This situation may suggest a dangerous driving environment, where braking is much more frequent and following vehicle drivers have a broader range of deceleration selection. $\beta_{PT}$ is the represents variability that may be associated with driver experience. A driver with a greater $\beta_{PT}$ value can be described as experienced and more comfortable with his or her surroundings. A driver’s desire to achieve a specific velocity or to avoid collision is indicated with $\gamma$. The assignment of a low $\gamma$ value may represent an increase in driver anxiety, which limits the acceleration choice range. When $\gamma$ exceeds a certain threshold, acute braking is observed. The collision weight parameter $w_c$ characterizes the aggressiveness of a driver in near collision scenarios. Increasing or decreasing this parameter value appears not to yield significant acceleration changes due to an inclination among drivers to evaluate the losses in near-collision situations. On the contrary, $w_m$ symbolizes the risk-averseness of a driver and serves as a weighting factor for negative utility. A high value may correspond to a driver’s reluctance to take chances on the roadway, possibly increasing the likelihood of congestion and decreasing the variation of the acceleration choice process.

### 4.3 Simulation Scenarios

The PT-based model simulates the UDDS and first employs typical values for the safety-related parameters based upon the calibration results of NGSIM data and the detailed review in (15). For the simulation of the effects of the typical values, three runs that represent each BEV are conducted. In addition to these initial runs, the simulations for every parameter variation are executed, while the other parameters are held constant at their typical calibrated values. During each run, the selected parameter is changed based on the multipliers of 0.2, 0.4, 0.6, 0.8, 1.2, 1.4, 1.6, 1.8 and 2.0 of the typical value. The maximum acceleration, desired velocity, minimum gap and the acceleration normalizing factor are assigned the following values: $4 \text{m/s}^2$, $30 \text{m/s}$, $3 \text{m}$, and $1 \text{m/s}^2$ due to the calibration in (15).

Table 2, obtained from (35), displays all of the parameter values to be used for each execution of the simulation. The cells labeled “co” for collision, will not be considered in this study because such parameter values result in collision formation and do not allow for the UDDS completion. This table reveals that the lead and following vehicles are involved in collisions at the lowest value of $\alpha$ and higher values of $\gamma$. Collisions (co) may occur at the $\alpha$ 0.2 multiplier because the acceleration range is limited, making it difficult to react in a safe manner to sudden actions by the lead vehicle. Additionally, collisions may occur at the higher $\gamma$ values due to the non-linearity emphasis on gains in the driving time as opposed to losses, risky-collision inducing behavior.

After the simulations using the variations in the safety-related parameters are conducted, the parameter values that are associated with the lowest total power requirement are combined for another simulation. Results from these simulations, which look at the safety of human driving patterns, are then compared to simulation results from IDM. The IDM simulation is conducted using parameter values that are calibrated to represent autonomous vehicles, or vehicles that drive themselves from. The free acceleration exponent, desired time gap, jam distance, maximum acceleration, and desired deceleration are $4$, $1.5 \text{s}$, $2 \text{m}$, $1.4 \text{m/s}^2$, and $2.0 \text{m/s}^2$, respectively (36).
TABLE 2: Typical and multiplied values of the PT-based model parameters for simulation (35)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Multiplier</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Typical Values)</td>
<td>1.0</td>
</tr>
<tr>
<td>Velocity Uncertainty Variation Coefficient, $\alpha$</td>
<td>0.1215</td>
</tr>
<tr>
<td>Exponent of PT Utility, $\gamma$</td>
<td>0.3754</td>
</tr>
<tr>
<td>Collision Weighing Factor, $wc$</td>
<td>95938.4</td>
</tr>
<tr>
<td>Weighing Factor for the Negative Utility, $wm$</td>
<td>4.4954</td>
</tr>
</tbody>
</table>

5.0 NUMERICAL RESULTS

From Figure 1, it is evident that the engine of the Tesla Model S demands the most power at 177.081 kW, followed by the Nissan Leaf with 119.977 kW and 103.497 kW by BMW i3. The similar patterns observed in both the velocity vs. time and power vs. time graphs shows that a vehicle’s power requirement is influenced by velocity and acceleration. Therefore, positive acceleration demands more power and vice-versa. Sections of the graph with constant velocity appear to correspond with peaks in required power. Since all three vehicles have the same velocity and acceleration data, required power trends are the same. However, differences exist between the vehicle types in terms of magnitude of required power because of variances in weight and other vehicle specifications.
FIGURE 1: Required engine power of the three representative vehicles under typical parameters, as well as velocity patterns for snapshot times of 500 s to 800 s and 950 s to 1200 s.
FIGURE 2: Total power of the three representative vehicles when varying the 5 safety parameters in the acceleration model.
The power consumption in relation to the PT model safety related parameters are presented in Figure 2. As discussed in Section 4, an increase in \( \alpha \) leads to the expansion of the acceleration distribution. However, in Figure 2a such increase is shown to require less power. This could possibly be a result of the adoption of a conservative driving style that utilizes less power due to the uncertainty in the preceding vehicle’s behavior (a more conservative driving style over-estimating the collision probability). Likewise, the required power peak at the 0.4 multiplier of \( \alpha \) indicates that driver confidence promotes a sense of control up to a certain threshold, which is observed through the power requirement results. This same trend is observed with experienced drivers in Figure 2b, where familiarity with surroundings and traffic conditions prompts slight increases in power requirement until a specific parameter value. The presence of a large difference in required power from the 0.2 to 0.4 multiplier of \( \beta_{PT} \) suggests that a difference between levels of inexperience among drivers is significant. An upward trend in Figure 2c shows that as drivers value gains over losses, they require more power in their driving episodes. Unlike the other parameters, the relationship between the collision weight parameter and required power appears to be insignificant, with almost no differences in power requirement as seen in Figure 2d. A reason for such uniformity could be due to a greater importance of this parameter in near-collision situations that are not within the scope of this study. Higher \( w_m \) values appear to require more power in Figure 2e due to driver risk averseness and willingness to use extreme braking to avoid collisions.

A comparison of the power required by the standard PT-based model along with the variations in the safety-based parameters that required the least amount of power and the Intelligent Driver Model is found in Table 3. This table shows that “autonomous” vehicles are more power efficient due their smoother driving characteristics. Total required power was also computed for the “optimal” PT-based model, created by combining the five safety parameters values yielded the minimum total required power during each parameter variation. These parameter values and their corresponding power demand are also presented in Table 3. For each representative vehicle, it is apparent that the total power demand from the “jointly-optimized” parameters is greater than the same measurement for simulations with typical and individually optimized safety parameters. Results indicate that insights into the safety parameters cannot be equated with a low power demand for a battery electric vehicle. Safety seems to have many dimensions (i.e. risk attitude, collision weight, speed relative weight, experience, uncertainty …etc.) and being conservative in all safety related dimensions may reduce collisions but does not necessarily lead to an “environmentally friendly” traffic condition in terms of required power.
TABLE 3: Minimum total power required by the three representative vehicles for each model and parameter

<table>
<thead>
<tr>
<th>Vehicle Type</th>
<th>Nissan</th>
<th>Tesla</th>
<th>BMW</th>
</tr>
</thead>
<tbody>
<tr>
<td>PR for Typical PT-based Model Parameters (kW)</td>
<td>53,474</td>
<td>76,010</td>
<td>47,303</td>
</tr>
<tr>
<td>PR for IDM Model (kW)</td>
<td>24,715</td>
<td>32,592</td>
<td>22,884</td>
</tr>
<tr>
<td>PR for PT-based Model with Optimized Parameters (kW)</td>
<td>62,471</td>
<td>89,165</td>
<td>55,113</td>
</tr>
<tr>
<td>Minimum PT-based Model PR with alpha = 0.2431 (kW)</td>
<td>51,898</td>
<td>73,740</td>
<td>45,920</td>
</tr>
<tr>
<td>Minimum PT-based Model PR with $\beta_{PT} = 1.2326$ (kW)</td>
<td>47,970</td>
<td>67,376</td>
<td>42,759</td>
</tr>
<tr>
<td>Minimum PT-based Model PR with Gamma = 0.1501 (kW)</td>
<td>49,618</td>
<td>70,341</td>
<td>43,967</td>
</tr>
<tr>
<td>Minimum PT-based Model PR with $W_c = 19187.7$ (kW)</td>
<td>52,344</td>
<td>74,307</td>
<td>46,342</td>
</tr>
<tr>
<td>Minimum PT-based Model PR with $W_m = 1.7982$ (kW)</td>
<td>53,199</td>
<td>75,551</td>
<td>47,086</td>
</tr>
</tbody>
</table>

After studying the results microscopically (at the individual parametric level), additional preliminary analysis was performed to compare how the PT-based model safety parameter variations and IDM affect traffic macroscopically at the fundamental diagram level. Separate simulations of 50 vehicles along a two-lane 7,000 m roadway that included a deceleration of the lead vehicle in the right hand lane of $2 \text{ m/s}^2$ for 1,000 m (to create a bottleneck scenario) were run for three different scenarios. The three scenarios include the PT-based model with the typical safety-related parameter values, the PT-based model with $\beta_{PT}$ equal to 1.2326 and the rest of the safety-related parameters set at their typical values, and IDM using its typical parameter values. The PT-based model with the lower $\beta_{PT}$ value was selected because it improves the model leading to the most significant decrease in power consumption. As shown in Figures 3a and 3b, the typical safety-related parameters for the PT-based model produce a flow-density graph with lower capacity and more congestion than the same model with a lower $\beta_{PT}$ value. Even though an increase in $\beta_{PT}$ represents a more experienced driver, it can also imply that the driver is also more impatient. Since the scenarios include a slowdown in traffic, the higher value of $\beta_{PT}$ (from the typical PT-based model parameters shown in Figure 3a) could indicate that the braking is more severe and therefore can lead to fewer throughputs and more congestion than the lower value as seen in Figure 3b. Furthermore, Figure 3c shows that IDM produces the most stable traffic and highest capacity of the three tested scenarios. This is a reasonable based on the lower reaction times of autonomous vehicles in comparison to human drivers. When comparing the power requirement results from Table 3 and Figure 3, the lower the power requirement, the more stable the traffic and the higher the roadway capacity. However, such conditions may be only achieved through a level of automation removing the human errors representing a less safe driving environment.
FIGURE 3: Flow vs. density for traffic comparison
6.0 CONCLUSION
This paper considers the impact of different driving patterns represented through variation of the PT-based model safety-related parameters and IDM on the power demand of three popular battery electric vehicles. Evaluation of power requirement results shows that driver sensitivity and weighting of gains vs. losses, as well as driving experience have more of an effect on power requirement than driver collision weighting and driver uncertainty. In addition, it appears that less power is required for autonomous vehicles as modeled using IDM than for the adjusted PT-based model. It is important to note that being conservative in all driving safety dimensions does not result in the safest driving episode. $\beta_{PT}$ appears to be the most significant safety-related parameter when varied alone in terms of power consumption reduction, but when it is adjusted with the other parameters it does not appear to improve throughput. Furthermore, results indicate that even when drivers behave in a safe manner on the roadway, they do not necessarily drive in an environmentally friendly way or allow for more capacity and stability on roadways.

Future work will involve the testing of more driving scenarios with car-following and lane-changing that go beyond the UDDS to include highway driving. Heterogeneity in driving episodes along with more traffic dynamics in terms of wave propagation should also be investigated. Moreover, further analysis of traffic stability and congestion will be explored through means that extend past the basic scattering of flow-density data points. The computation of a BEV’s power requirement will be extended to assess the impact of regenerative braking as well. Efforts will also be made towards the application of an eco-drive algorithm, which uses a feedback system to minimize the total power demand.

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7.0 REFERENCES


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