Modeling of Individual Differences in Car-following Behaviour of Drivers

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***Abstract*—Car-following models microscopically express acceleration behavior of an individual driver. There are many car-following models each with its own assumptions. Among these car-following models, Intelligent Driver Model (IDM) has been used and cited extensively by research community. All the models including IDM have been developed with engineering perspective i.e. to reproduce perfect acceleration behavior. This study focuses on development of a humanistic car-following model. We have identified humanistic parameters that have been modeled in IDM from mathematical formulation of the model. In its existing form, parameters of IDM could be assigned arbitrary values from a prescribed range to define different driver profiles. This way, theoretically, infinite driver profiles could be created many of which does not exist in real. Literature of traffic psychology suggests that there are few dominant classes of drivers, which exhibit certain behavioral patterns. These dominant classes are characterized with the help of human personality. In our study, we have modeled a relationship between model of human's personality profile namely Big Five Factors (BFF) and parameters of IDM. The enhanced model let us reproduce individual differences in driving behaviors. The proposed model has been verified using computer simulation to investigate whether proposed humanistic car-following model produce desirable results or not. The proposed car-following model would be able to help in simulating driving behavior of an individual given that personality profile of that individual is known.**

Keywords—car-following; modeling; simulation; personality profile; humanistic characteristics; individual differences

I. Introduction

Computational modeling and simulation have widely been used to solve various research questions related to driving and transportation [1]. But understanding and modeling of differences in human driving behavior of individuals is relatively less addressed [2]. Understanding and modeling of human driving behavior is extremely important due to following two reasons.

- Realistic/humanistic traffic simulation/prediction
- Interpretation of driving behavior through models

Successful transition of human driven cars to fully autonomous vehicles is also dependent on reliable models of human drivers. As, autonomous cars would also need models of human behaviors to gauge effects of maneuvering in context where surrounding vehicles are still being driven by humans. To predict behaviors of surrounding drivers, to make better decisions such models are required so that autonomous vehicle may reproduce and predict human driving behavior. In this regard, understanding and modeling of differences in human driving behavior of individuals has a pivotal role.

Human driving behavior is a complex phenomenon as it involves route selection, acceleration, lane change, steering, gear, and pedal control. Modeling of all these aspects of driving activity is important, however, acceleration behavior has been widely modeled due to its critical nature and frequency of engagement i.e. acceleration control is most critical and frequent decision while driving a vehicle. In literature, models of acceleration behavior are referred as car-following models. There are many car-following models, each with its own assumptions, among these car-following models, Intelligent Driver Model (IDM) has been used and cited extensively by researchers.

In our study, to develop a humanistic car-following model, IDM has been used. The humanistic parameters that have been modeled in IDM are identified from mathematical formulation of the model. In its existing form, parameters of IDM could be assigned a numeric value in a prescribed range, consequently, theoretically, infinitely many driver profiles could be generated by assigning arbitrary values to these parameters. However, literature of traffic psychology suggests that there are few classes of drivers or certain types of driving profiles. These profiles exhibit behavioral patterns. As per literature, these driver classes could be characterized by human personality. In other words, there are few types of personalities of drivers, these personalities exhibit certain behavioral pattern while driving.

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In our study, a relationship between personality profile and IDM parameters has been modeled. So that IDM may reproduce individual differences in driving behaviors. To do so, Big Five Factor (BFF) model of personality has been used as a measure of personality. Further, the most common driver personality classes or types based on BFF has been generated and their observable behaviors (acceleration) have been studied with the help of computer simulations. Through computer simulations, the proposed humanistic car-following model of car-following behavior has been verified whether our model reproduces pattern in driving behavior as it is reported in traffic psychology literature or not. It has been verified that it produces desirable results. The proposed humanistic car-following model could be used to simulate driving behavior of an individual driver given that personality profile of the driver is known.

Remaining of the paper distributed in several sections including background of the problem which provides historical perspective, state-of-the-art modeling techniques and related work which has helped us in developing our model. The background section is followed by our methodology, design of experiments, discussion on results, conclusion, and future work.

II. Background

Background has been divided in four parts. First part provides information on exiting microscopic car following models. After that, IDM has been discussed. The trailing section discusses incorporation of human factors in IDM. In our work, BFF of model of personality has been used to incorporate human individuality in IDM, therefore, BFF has been discussed in context of driving activity. After that, discussion on exiting gaps in the literature has been presented.

A. Car-following models

In computational transportation literature, many microscopic car-following models have been proposed. These models could be broadly categorized in three classes, namely, time continues models, intreated graph models and cellular automata models. Intelligent Driver Model (IDM) [3], Optimal Velocity Model (OVM) [4] and Full Velocity Difference Model (FVDM) [5] are time continuous models. Gipps Model [6] and Krauss Model [7] are iterated graph models. Whereas, Nagel-Schreckenbreg (NaSch) Model [8] and Kerner-Klenov-Wolf (KKW) Model [9] are based on cellular automata approach. However, practitioners and scientists have shown significantly more interest in IDM primarily due to its elegance (simplicity) and computational robustness.

B. Intelligent Driver Model (IDM)

IDM is a microscopic model to exhibit intelligent driving behavior [10]. The said model is selected due to its ability to simulate several types of traffic breakdowns with empirically measured boundary conditions. This model is computationally robust and all model parameters have a reasonable interpretation. The model has applications in modeling microscopic acceleration and deceleration behavior for various agents and hence can be used to monitor and interpret smaller details of a traffic situation. Equation (1) presents mathematical formulation of IDM.

$$\alpha_{mic}(s, v, \Delta v) = a\left(1 - \left(\frac{v}{v_0}\right)^{\delta} - \left(\frac{s^*(v, \Delta v)}{s}\right)^2\right) \qquad (1)$$

$$s^*(v, \Delta v) = s_0 + \max\left(0, vT + \frac{v\Delta v}{2\sqrt{ab}}\right) \qquad (2)$$

The acceleration function presented in equation (1) is defined in terms of $\alpha_{mic}(s, v, \Delta v)$ where s is distance of current vehicle from leading vehicle, v is velocity of current vehicle and Δv is difference between velocity of current vehicle and velocity of leading vehicle. Here current vehicle depicts the vehicle whose acceleration behavior is determined by equation (1). The function gauntness displacement on desired velocity v_0 ensuring that the current vehicle would not collide with leading vehicle. The acceleration function in equation (1) relies on function $s^*(v, \Delta v)$ which is presented in equation (2). The function controls free flow and leading vehicle acceleration dynamics of the current vehicle. Brief description of the model parameters is stated below.

- Desired velocity is referred by v_0. It is the velocity on which the vehicle would drive in free flow, when there is no obstacle. It may change depending on length of vehicle i.e. a truck's desired velocity might be less than that of a car. Also, an aggressive young driver might want to reach a higher maximum velocity than an old/calm driver.
- Safe time headway is referred by T. It is the time in which current vehicle would collide with leading vehicle. Aggressive drivers may have low T whereas careful drivers may have a high value of T. All the various modes can be simulated by changing this single parameter.
- Maximum acceleration is referred by a.
- Desired deceleration is referred by b.
- Acceleration exponent is referred by δ. Decrease in acceleration is controlled by acceleration exponent when the subject vehicle reaches desired velocity.

C. Incorporation of Human Factors in IDM

According to literature of computational transportation research, mechanized and human drivers are different from each other in following aspects [10].

- Reaction time
- Estimation errors
- Spatial anticipation
- Multi-input signals
- Context sensitivity
- Finite perception threshold
- Courtesy, cooperation

IDM do support controlling/delaying reaction time, estimation errors, finite perception threshold and courtesy through its paraments. It is worth noting that by setting values of parameters within prescribed range, theoretically, infinitely many different driver profiles could be generated, however, these profiles would not be meaningful as traffic psychology suggest that there are certain types or classes of drivers which shows certain behavioral patterns [11]. Hence, to realistically simulate vehicular traffic, these driver classes should not be ignored while modeling the driver population.

D. Human Factors and Driving Behaviour

Literature of traffic psychology suggests that there are many human factors which effects driving behavior. TABLE I. presents list of human factors along with literature references that are found to effect driving behavior.

TABLE I. HUMAN FACTORS HAVING IMPACT ON DRIVING

Human Factor	***Reference***
Personality	[12][13][14][15][16][17][18][19]
Age	[20][21][22][23]
Anger	[21][24][25]
Distraction	[15][16][26]
Gender	[22][23]
sociodemographic profile and criminal history	[17][18]
Mental stress	[27][28]
Time and social pressure	[29]
Parenting and driving intention	[14]
Response time, preferences and habits	[30]
Temporal heterogeneity	[31]
Executive control	[19]

In literature, human personality and its impact on driver behavior has extensively been studied and the literature suggests that personality may help in predicting and revealing behavioral pattern of drivers [11]. As per literature, human drivers may be divided in three major classes according to their personality, which shows distinctive behavioral patterns. These classes are named as resilient, overcontrolled and under-controlled drivers. In our study, we have incorporated personality in IDM. We have also verified our model with the help of computer simulation whether enhanced IDM exhibit behavioral patterns as per theory of traffic psychology or not. In our work, we have used BFF model of personality which has been briefly explained in following section.

E. Big Five Factor (BFF) Model of Personality

In psychology, human personality is represented using different ways however BFF is considered de-facto in personality computing, here personality computing refers to use of personality in computing applications [32]. The BFF model comprise of five broad dimensions or factors. These five factors could be computed through a test or could also be inferred using indirect cues. These traits are referred as OCEAN. A summary of the factors and their constituent traits are explained in following bullets in order of their occurrence in the acronym form (OCEAN).

- Openness to experience: Appreciation for art, emotional intelligence, adventure loving, innovative ideas, curiosity, and wide exposure.
- Conscientiousness: An inclination towards being organized and responsible, act dutifully, aim for achievement, and prefer planned activity rather than spontaneous behavior.
- Extraversion: Energy, positive emotions, sociability, enjoying company of others, and talkativeness.
- Agreeableness: An inclination towards being kindhearted and cooperative rather than suspicious, competitive, and aggressive.
- Neuroticism: An inclination towards experiencing unpleasant emotions easily, such as anxiety, anger depression, and vulnerability.

As described in [11], the human drivers can be broadly classified into three personality classes which are explained as under.

- Resilient: Situation dependent person, generally well-adjusted and seems to function well in all situations.
- Over-Controlled: Calm and peaceful, less adventurous, co-operative, and polite.
- Under-Controlled: Rash and open to adventure, non-co-operative.

F. Conclusion

Literature suggests that there are many humanistic factors which impacts driving behavior. Exiting mainstream car-following model are developed with engineering perspective rather than humanistic perspective. IDM is a car-following model which has modeled few humanistic characteristics. But values of those parameters could be assigned in infinitely many ways. In our work, we have modeled relationship between prominent driver personality classes and parameters of IDM. In following section, computational formulation of the model has been presented.

III. METHODOLOGY

Methodology section has been divided in two sub-sections. First section presents correlation between each personality factor with IDM parameters. The section discuses personality characteristics and their positive or negative impact on all the IDM parameters. The second part presents correlation of IDM parameters with OCEAN of each driver class. Here driver class revers to resilient, over-controlled and under-controlled drivers.

A. Correlations

A set of positive and negative co-relations among OCEAN traits and humanistic parameters of IDM has been modeled. These relationships correspond to the findings of traffic psychology [11]. These correlations have been depicted in TABLE II. + sign shows a positive correlation and – sign shows a negative correlation among corresponding BFF trait and MOBIL parameter.

TABLE II. IDM PARAMETRS AND PERSONALITY CO-RELATION

	IDM Parameters				
BFF	v_0	T	a	b	δ
O	+	-	+	+	-
C	-	+	-	-	+
E	+	-	+	+	-
A	-	+	-	-	+
N	+	-	+	+	-

Justification of each correlation have also been discussed separately in following sections.

1) Desired Velocity (v_0)

- Openness leads to risky driving behavior, thus an increase in openness may lead to increase in v_0.
- Conscientiousness leads to following rules thus such a person would maintain a low value of desired velocity. It is negatively related to traffic risk taking.
- Extraversion leads to higher level of energy hence over speeding may be seen in drivers with higher values of extraversion.
- Agreeableness is negatively related to traffic violations, thus increase in agreeableness means decrease in maximum desired velocity.
- Neuroticism is significantly related to risk taking. Thus, an increase in value of this trait leads to high value of maximum velocity.

2) Safe Time Headway (T)

- Openness leads to risky driving behavior, thus an increase in openness leads to decrease in T.
- Conscientiousness leads to following rules thus such a person would maintain a greater value of T. It is negatively related to traffic risk taking.
- Extraversion leads to positive energy leading to a risky behavior and hence a decrease in T.
- Agreeableness is negatively related to traffic violations and represents a trusting nature, thus increase in agreeableness means increase in safety time headway.
- Neuroticism is significantly related to risk taking. Thus, an increase in this trait leads to low values of safety time headway.

3) Maximum Acceleration (a)

- Openness leads to risky driving behavior, thus an increase in openness leads to increase in maximum acceleration.
- Conscientiousness leads to following rules thus such a person would maintain a small value of maximum acceleration.
- Extraversion leads to higher level of energy hence an increase in maximum acceleration is expected from drivers who have higher extraversion.
- Agreeableness is negatively related to traffic violations and represents a trusting nature, thus increase in agreeableness means decrease in maximum acceleration.
- Neuroticism is significantly related to risk taking. Thus, an increase in the value of this trait leads to high values of acceleration.

4) Maximum Deceleration (b)

- Openness leads to risky driving behavior, thus an increase in openness leads to increase in maximum deceleration.
- Conscientiousness leads to following rules thus a person with high values would maintain a low value of maximum deceleration.
- Extraversion leads to positive energy and hence rapid increase in deceleration.
- Agreeableness is negatively correlated to traffic violations and depicts a trusting nature, thus increase in agreeableness means decrease in deceleration.
- Neuroticism is significantly related to risk taking. Thus, an increase in this trait leads to high values of deceleration.

5) Acceleration Exponent (δ)

- Openness leads to risky driving behavior, thus an increase in openness indicates a rapid acceleration/deceleration hence a lower value of δ as stated in [10].
- Conscientiousness leads to following rules thus a person with high values would maintain a relatively high value of δ i.e. a constant increase in acceleration.
- Extraversion leads to positive energy and hence rapid increase in acceleration indicating lower values of δ.
- Agreeableness is negatively correlated to traffic violations and depicts a trusting nature, thus increase in agreeableness means a constant increase in acceleration hence a large value of δ.
- Neuroticism is significantly related to risk taking. Thus, an increase in this trait leads to exponential (rapid) acceleration/deceleration and hence a low value of δ.

B. Mapping Devised for Each Personality Class

TABLE III. TABLE IV. and TABLE V. presents correlations between OCEAN traits and humanistic aspects for each personality class namely and respectively resilient, over-controlled and under-controlled drivers. When devising the tables, biasness caused by mood swings or environmental changes has not been considered.

The tables define the relations in terms of a scale where L indicates low, M indicates medium and H indicates high values for the respective parameter with respect to range of values of OCEAN traits, which make a person fell into a particular class, as defined by [11].

1) Resilient

These drivers are characterized as follows.

- Low scores in N
- Above average in O, C, E, and A.

TABLE III. MAPPING OF BFF AND IDM PARAMETERS FOR RESILIENT DRIVER

	IDM Parameters				
BFF	v_0	T	a	b	δ
O	M	M	M	M	M
C	M	M	M	M	M
E	M	M	M	M	M
A	M	M	M	M	M
N	L	H	L	L	H

Since O, C, E, and A have above average scores, so they take medium values for all the parameters. As N has low scores for resilient people, thus they won't have a very high v_0. Their safety time headway would be high because a low value in N implies a low level of risk taking. The values for a and b would be low as low value of N means less risky behavior. A large value of δ means a constant increase in acceleration which is why their delta would be high.

Above table presents value of all the model parameters under the influence of each OCEAN trait. However, IDM accepts one value of each of the parameter. Hence an aggregation scheme is required. In our work, we have taken average of all the value of a parameter to calculate aggregated value of the parameter. More sophisticated approaches could be used such as using different probability distribution for low, medium, and high values of each personality trait and later applying weighted average to aggregate all the values of parameter to compute value of the parameter.

2) Over-Controlled

These drivers are characterized as follows.

- High scores in N and C
- Low scores in E and O
- Average scores in A

TABLE IV. MAPPING OF BFF AND IDM PARAMETERS FOR OVER-CONTROLLED DRIVER

	IDM Parameters				
BFF	v_0	T	a	b	δ
O	L	H	L	L	H
C	L	H	L	L	H
E	L	H	L	L	H
A	M	M	M	M	M
N	H	L	H	H	L

Average Scores in A indicates medium values for all parameters. High scores in N means a risky behavior thus it would tend the over controllers towards high values of v_0, a and b whereas low values of T and δ. Low scores in E, O and high scores in C implies a risk free and cautious behavior. Thus, a low value of v_0, a and b whereas a high value of a δ indicating a responsible and controlled behavior. All the values of each parameter would be aggregated to compute one value for each parameter.

3) Under-Controlled

These drivers are characterized as follows.

- Above average scores in N and O
- Low scores in C and A
- Average scores in E

TABLE V. MAPPING OF BFF AND IDM PARAMETERS FOR UNDER-CONTROLLED DRIVER

	IDM Parameters				
BFF	v_0	T	a	b	δ
O	H	L	H	H	L
C	H	L	H	H	L
E	M	M	M	M	M
A	H	L	H	H	L
N	H	L	H	H	L

Average Scores in E indicates medium values for all parameters. Low scores in C, A and above average scores in N and O indicates a risky and anti-social behavior thus implying high values of v_0, a and b and low values for T and δ.

IV. EXPERIMENTS DESIGN

A lane closure i.e. a simple road with a bottleneck is modeled to verify Humanistic IDM. A set of agents belonging to each personality class were generated to identify how each of the personality class behaves under same circumstances. Throughout the simulation, trajectory data was logged at every timestep of the simulation. The logged data has multiple dimensions such as acceleration, time, velocity, distance, and lane number. The experimental setup is presented in Fig. 1.

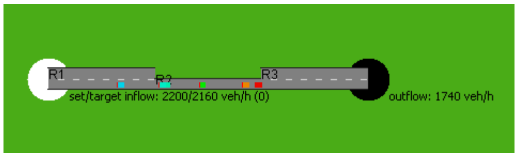

Fig. 1. Experimental Setup

To simulate the experimental setup Multi-model Open-source Vehicular-traffic Simulator (MovSim) has been used [33]. MovSim is primarily based on Java technology. The free and open-source simulator also uses Apache Maven as build automation tool. The simulator expects two different XML files as input. One of the XML is an OpenDRIVE XML file with extension XODR. OpenDRIVE is an industry standard specification to express road infrastructure such as topology, number of lanes and physical properties such as width and length of roads. The other file is xProject file with extension XPRJ. XPRJ file carries information about traffic population i.e. traffic models to be used and their respective parameters. MovSim generates logs of simulation which carries road, lane, longitudinal position, velocity, acceleration, and clock-time for each vehicle on each time step of the simulation. These results could be used to study dynamics of the simulated vehicular traffic.

V. RESULTS

Velocity graphs are drawn for all personality classes separately using velocity and time. Graph depicted in Fig. 2, Fig. 3 and Fig. 4 presents velocity-time graphs for the three personality classes. The graphs depict the velocity of drivers belonging to a specific class as well as the trend of velocity in their route completion. The velocity curves going back to x-axis indicate that cars decreased their speed due to some blockage in their way and were unable to change lane until the simulation got finished.

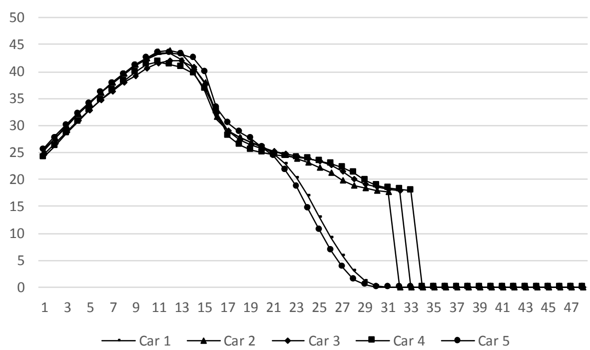

Fig. 2. Velocity graph of resilent drivers

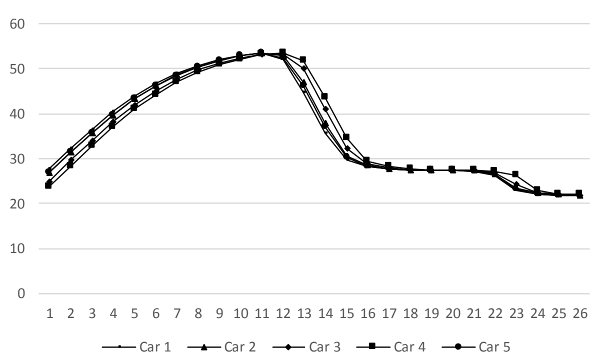

Fig. 3. Velocity graph of over-controled drivers

The graphs indicate that under-controlled reach highest speed than other two classes and with resilient in middle and over-controlled on the last place. These results are in accordance with the experiment and conclusion deduced in [11], that over-controlled have less tendency of over speeding and breaking rules whereas under-controlled have highest tendency of getting involved in a risky driving.

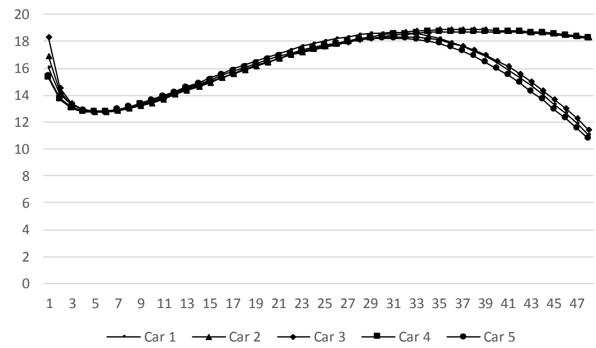

Fig. 4. Velocity graph of under-controlled drivers

The velocity graphs also show a similar trend that over-controlled and resilient drivers, as it shows patterns and smoothness when they accelerate or decelerate and they do not change lane often, thus they also apply less brakes. The sharp curves in acceleration time graph of under-controlled drivers indicate that they rapidly increase speed or apply brake and this phenomenon is repeated.

VI. CONCLUSION

As the world is moving towards automated completion of various phenomenon and the scarcity of resources indicate that only a proper and best suited plan be implemented for any real-world problem, which justifies the utility of computer simulation. The use of traffic simulation dates back to 1955 when D.L. Gerlough published his dissertation "Simulation of freeway traffic on a general-purpose discrete variable computer" at the University of California, Los Angeles [34]. Standing firm on a solid foundation of traffic simulation, we have proposed a mapping between human personality and traffic parameters.

The results carried out by the experiments indicate that the driver model created by the personality-parameter mapping worked as assumed and produced results in accordance with the empirical study carried out by the experts of traffic psychology.

Though, there are outlier points and exceptions, which are interesting instances in their own and should be investigated thoroughly. The personality biased/colored simulation is a step forward in comparison to the randomly created diversity in simulated driver population. It may be useful to depict traffic scenarios more realistically, which otherwise would not be possible.

VII. FUTURE WORK

The experiment was conducted using a simple two-lane road with a bottleneck in the center that led towards the traffic jam. To conduct a better and more diverse experiment, complex infrastructure of roads with various lanes could be simulated, which would help in verification of model in diverse situation. Various driver types could be mixed and simulated at once to study their mutual effect on each other. The devised conversion tables are using a fuzzy scale of low, medium, high values. The model itself could be used to infer personality of drivers by tuning the model against their driving log or profile. Once this model is validated the model could be used to investigate driving pitfalls in driving behavior of each driver class.

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