Modeling Task Capability in Full Velocity Differential Model

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***Abstract*—Car following (CF) models formally explain acceleration behavior of drivers. Historically, human factors are not considered in CF models. Attention is a very critical human factor. Drug use, panic, fear, or anger may negatively affect attention and consequently driving behavior. In the recent years, researchers have focused on modeling of CF behavior considering human factors as an outcome of research by traffic psychologists and engineers. These observations make clear that integration of human factors into car following models is necessary to develop a more realistic depiction of CF maneuvers under intricate driving situations. In complex driving situations, it is important to measure the dynamic interaction of driving task demand and ability of driver to handle the task at hand. The basic idea of Task Capability Interface (TCI) model is to incorporate task difficulty and task demand within a framework which gives the detailed account of their influence on one another. Task demand and capability plays a key role in decision making. TCI model has earlier been used to improve two traditional CF models namely Gipps' model and Intelligent Driver Model (IDM). The enhanced models are referred as TD-Gipps model and TD-IDM. There is another model namely Full Velocity Differential Model (FVDM). Unlike its predecessors, FVDM doesn't suffer from unrealistic acceleration and deacceleration. But FVDM has not been enhanced using TCI model. In this work, FVDM has been enhanced to incorporate TCI model. The enhanced model namely TD-FVDM has been verified by comparing it with TD-Gipps using simulation-based experiments. The enhanced proposed model reproduces acceleration behavior as intended.**

Keywords—traffic flow modeling, driver behavior modeling, car following model, task capability, task demand, IDM, Gipps, FVDM

I. Introduction

Transportation ensures delivery of goods and services. It heavily relies on means of transportation, among these modes of transportation, road transportation is very important. But road transportation is very complex system, mainly due to number of agents e.g. drivers, pedestrians, traffic infrastructure. Overtime, the system has become a sociotechnical system. For sustainable growth of the current world, effective management of this system is very much required.

Effective management of transportation is only possible by adapting scientific method. Scientific method would help to enhance comprehension of the system and to design interventions. Computational modeling and simulation is a way to conduct scientific enquiry. It has been heavily employed to formally represent and model traffic flow [1]. Simulation of such models helps in performing what-if analysis which are prohibitive to be evaluated in real world.

Dynamics of traffic flow depends on behavior of individual drivers constituting the traffic flow. Accurate representation of traffic flow is done by modeling of behavior of individual driver on microscopic scale. Generally, driver behavior is further divided in car following or acceleration behavior and lane change behavior [2]. The current study focuses on car following models. Existing literature suggests that under different set of assumptions numerous car following models are proposed. However, it is quite evident that these models represent idealistic behavior of driver which is far away from realistic behaviour. As human drivers are prone to errors. This abstraction on macroscopic scale may not be a problem, however such models cannot represent individual drivers or a specific demography [3], [4].

Recent studies have identified and bridged this gap by modeling human factors into excising car following models. As It is important that the CF modeling should encompass human factors to attain more realistic results in complex driving situations. Due to significance of the human factors in context of the CF behavior, CF models should be enhanced considering research outcomes of both engineering and psychological studies to bridge gaps and inconsistences in existing driver behavior model. Driving decisions and driver's performance are hugely influenced by task difficulty. Existing CF models are enhanced to simulate driving behavior, these models are enhanced by integrating task capability model to simulate driving behavior with divided attention or workload [4].

This line of scientific enquiry will be extremely fruitful in the field of transportation research, particularly in microscopic models. As these models can predict driving behavior on more granular level . To contribute towards this, in an existing car-following model namely Full Velocity Difference Model (FVDM) task capability interface model has been incorporated. Where task capability is ability to handle a task.

Driving performance is negatively impacted by human imperfections. Road crashes are thought of as compared to other things, infrequent events. Because in most of the cases drivers are vigilant of the possible risk and to avoid possible hazardous situation they take compensatory actions, this behavior is generally known as risk compensation [3]. For instance, an exhausted driver might consider to choose a less swarmed and blocked route or may drive more gradually. If driver's ability has not been fully and appropriately recognized and the driver's actions are not accounted for risky situations (e.g. after heavy drinking; when the driver is under pressure to reach the destination within an inhibited period) then chances of collision increases. Driving job demand may go well beyond driver's driving ability under the said conditions. Subsequently, any sudden change in the driver's surrounding conditions may cause a collision [5].

This study plans to incorporate this human factor into a car following model namely FVDM. The study is inspired by recent efforts in which task capability interface model has been fused and incorporated into existing car following models [4].

II. Background

The background section has been separated in three subsections. First theory of task capability has been presented. After that mathematical formalization has been presented. At the end several applications of task capability interface model have been discussed.

A. Task-Capability Interface (TCI) Model

In Task capability interface (TCI) model, task capability and task demand has interdependencies. A driver's capability is considered a function of driver's traits such as education, skills, knowledge, driving training and reaction time towards a task difficulty. Whereas task difficulty depends upon environmental conditions, visibility, time of the day and vehicle qualities such as power staring and engine power.

The theory behind the TCI model is task difficulty homeostasis. Task difficulty homeostasis explains relationship between difficulty of driving sensed by the driver and driver's capability. It states that drivers handle a given situation by modifying control factors such as car speed and headway [6]. For example, if the task difficulty is higher than driver's capability then drivers tend to slow down to drop the level of task difficulty within the controlled limit, for instance driving in swear climate conditions such as haze, snow or rain drivers alter their speed. Similarly, if driving is boringly simple then the drivers tend to increase speed of the vehicle to make the task relatively harder like driving on an almost straight freeway. It is also observed that the same task could be difficult for one driver and relatively easier for the other driver depending upon their capability level and desired headway.

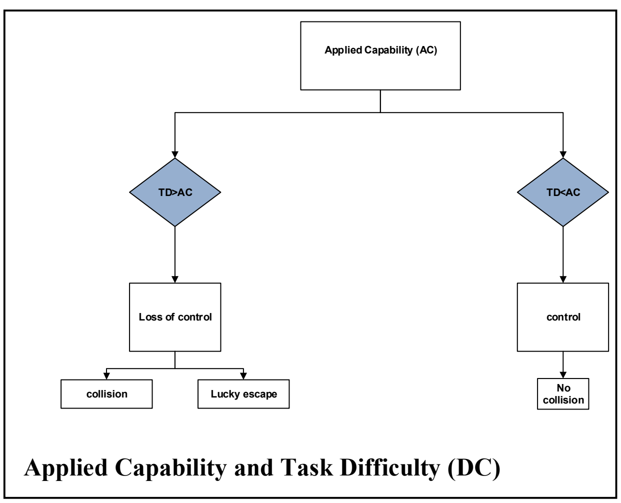

Fig. 1 Relationship between driver's capability and task demand

B. Formulation of Task Difficulty

TD_n describes the task difficulty perceived by a driver from its environment on a point in time as represented in Fig. 1. It is directly proportional to the velocity which represented by V_n. It is inversely proportional of the spacing from the leading vehicle which represented by S_n. The effect of spacing S_n is coupled with driver's risk appetite which is represented by δ_n. Driver's response time is represented τ_n and γ is the sensitivity parameter which is utilized to model the driver's sensitivity towards difficulty of the task. Formal mathematization of task difficulty is presented in Eq. (1).

$$TD_n = \left(\frac{V_n(t-t'_n)}{(1-\delta_n)S_n(t-\tau_n)}\right)^{\gamma} \qquad \textbf{(1)}$$

In literature, the task difficulty homeostasis theory is utilized to incorporate task difficulty into car following models. Aaccording to this theory if TD_n=1, it means that the driver has the capability to handle the task at hand. Whereas if TD_n>1then the driver doesn't have capability to handle the task at hand and driver should consider easing the task at hand by decreasing the velocity or/and increasing the distance from the leading vehicle. On the other hand, if TD_n<1 then the driver is at ease and the driver may consider making the task at hand difficult a bit by increasing its velocity or decreasing the distance from the leading vehicle [6].

Until recently, there was no notion of task difficulty in car following models. Recently, some of the traditional car following models have been extended to incorporate task difficulty. In following section, application of task difficulty on exiting car following models has been examined in detail.

C. Applications of Task Difficulty Model

Recently, task difficulty has been incorporated in Intelligent Driver Model (IDM) and Gipps model. Following subsections discuss application of task difficulty on IDM and Gipps model.

The IDM works by letting the vehicle accelerate on the desired acceleration. It penalizes the desired acceleration considering the desired velocity and desired distance. As the vehicle reaches towards the desired speed the acceleration is penalized similarly when the distance from leading vehicle reaches desired distance acceleration is penalized to avoid collision. Mathematical formulation of the model is presented in Eq. (2) and Eq. (3).

$$a_n(t) = a_n^{max}\left[\left(1-\frac{V_n(t)}{\tilde{V}}\right)^{\beta} - \left(\frac{\tilde{S}_n(t)}{S_n}\right)^{2}\right] \qquad \textbf{(2)}$$

$$\tilde{S}_n(t) = S_n + V_n(t)\tilde{T}_n - \frac{V_n(t)\,\Delta V_n(t)}{\sqrt[2]{a_n^{max}\,a_n^{comf}}} \qquad \textbf{(3)}$$

In Eq. (3), a_n is acceleration produced by the IDM models. a_n is considered function of $V_n$current velocity of the subject vehicle, ΔV_n difference of the velocity from the leading vehicle and S_n distance from the leading vehicle. Whereas $\tilde{V}$ desired velocity, S_n desired distance in meters, $\tilde{T}_n$ desired time headway, a_n^{max} desired acceleration, a_n^{comf} desired deceleration and β acceleration exponent and tunable parameters of the model [7]. To enhance the model to incorporate the task difficulty, interaction between $\tilde{S}_n$ desired collective distance from the leading vehicle and TD_n

has been modeled. The enhanced model has been presented in Eq. (4).

$$a_n(t+\tau'_n) = a_n^{max}\left[1-\left(\frac{V_n(t)}{\tilde{V}_n}\right)^{\beta}-\left(\frac{\tilde{S}_n(t)*TD_n(t+\tau'_n)}{S_n(t)}\right)^2\right] \quad (4)$$

The Gipps model separately handles the acceleration and deceleration, in contrast to the IDM, it computes velocity instead of the acceleration. Mathematical formulation of the Gipps model is presented in Eq. (5), (6) and (7).

In Gipps model, V_n refers to the current speed of the subject vehicle, ΔX_n denotes to the space between the subject vehicle and leading vehicle, and V_{n-1} refers to the velocity of leading vehicle. These three variables are input of the model, whereas other variables are parameters of the model. These tunable parameters include $\tilde{V}_n$ desired velocity, S_n stand-still minimum space, L length of the car, $\tilde{a}_n$, $\tilde{b}_n$ are the desired acceleration and deceleration individually, τ_n is modified reaction time which vary from one driver to another [8], [9]. The model has been enhanced by modeling interaction of task difficulty with acceleration and declaration component of the model in Eq. (6) and (7). The enhanced model has been presented in Eq. (8), (9), (10), (11) and (12).

Both the extended model namely TD-IDM and TD-Gipps have been verified using simulation-based experiments. Both models demonstrate driving behavior under load. Both models have also been validated against human subjects in a virtual reality-based experiments. FVDM is considered numerically more stable than its predecessor models as in some scenarios the previous models may produce unrealistic acceleration and deceleration. Therefore, in this paper FVDM has been extended to incorporate notion of task difficulty.

III. Methodology

In methodology section, first formal formulation of FVDM is presented and discussed. After that incorporation of task difficulty has been discussed and its mathematical formulation has been presented.

A. *Full Velocity Difference Model*

Full velocity difference model (FVDM) is enhanced form of previous models namely optimal velocity model (OVM) and generalized force model (GFM). This model is an enhancement over past models as it covers more aspects of car following regime than others. OVM was predicated on the conception of optimal velocity that each car has its optimal velocity based on the distance from the next vehicle but there are some major issues with OVM as the model was prone to come across unrealistic deceleration and very high acceleration [10]. Its mathematical formulation is presented in Eq. (13).

FVDM equation is divided into four parts where λ is sensitivity, s is desire headway which enables the value of λ. K is the sensitivity constant equals to 0.41 s^{-1}, $V(s)$ is optimal velocity of the driver's preference, V_m is the max velocity. Ɵ is the Heaviside function whose purpose is to convert its input to 0 or 1 using a threshold. This function enables the model to switch mode between acceleration and deceleration. $\lambda\Theta(\Delta V)\Delta V$ Controls the acceleration and $\lambda\times\Theta(-\Delta V)\Delta V$ controls the deceleration of the subject vehicle, it is presented in Eq. (10).

In the proposed work, just like TD-Gipps, task difficulty has been incorporated in FVDM. The acceleration component of the FVDM has been divided by the TD_n and declaration component is being multiplied by the TD_n, as it was done to enhance Gipps model. Mathematical formulation of TD-FVDM is presented in Eq. (14).

$$V_n(t+\tau_n) = \min\{V_{a,n}(t+\tau_n), V_{b,n}(t+\tau_n)\} \quad \textbf{(5)}$$

$$V_{a,n}(t+\tau) = V_n(t) + 2.5\tilde{a}_n\tau_n\left(1-\frac{V_n(t)}{\tilde{V}_n}\right)\left(0.025+\frac{V_n(t)}{\tilde{V}_n}\right)^{\frac{1}{2}} \quad \textbf{(6)}$$

$$V_{b,n}(t+\tau_n) = \tilde{b}_n\tau_n + \sqrt{\tilde{b}_n^2\tau_n^2 - \tilde{b}_n\left[2(\Delta X_n(t) - L_n - S_n) - V_n(t)\tau_n - \frac{V_{n-1}(t)^2}{\tilde{b}_n}\right]} \quad \textbf{(7)}$$

$$V_n(t+\tau'_n) = \max\{V_{d,n}(t+\tau'_n), \min\{V_{a,n}(t+\tau), V_{b,n}(t+\tau_n), V_{c,n}(t+\tau'_n)\}\} \quad \textbf{(8)}$$

$$V_{a,n}(t+\tau) = V_n(t) + 2.5\frac{\tilde{a}_n\tau_n}{TD_n(t+\tau'_n)}\left(1-\frac{V_n(t)}{\tilde{V}_n}\right)\left(0.025+\frac{V_n(t)}{\tilde{V}_n}\right)^{\frac{1}{2}} \quad \textbf{(9)}$$

$$V_{b,n}(t+\tau_n) = \tilde{b}_n\tau'_n TD_n(t+\tau'_n) + \sqrt{(\tilde{b}_n\tau'_n)^2 - \tilde{b}_n\left[2(\Delta X_n(t) - L_n - S_n) - V_n(t)\tau'_n - \frac{V_{n-1}(t)^2}{\tilde{b}_n}\right]} \quad \textbf{(10)}$$

$$V_{c,n}(t+\tau'_n) = V_n(t) + a_n^{max}\tau'_n \quad \textbf{(11)}$$

$$V_{d,n}(t+\tau'_n) = max\{0, V_n(t) + b_n^{max}\tau'_n\} \quad \textbf{(12)}$$

$$\frac{dv_{n+1}}{dt} = K[V_m - V_{n-1}(t) + K[V(s) - V_m] + \lambda\times\Theta(-\Delta V)\Delta V + \lambda\Theta(\Delta V)\Delta V \quad \textbf{(13)}$$

$$\frac{dv_{n+1}}{dt} = K[V_m - V_{n-1}(t) + K[V(s) - V_m] + \lambda\Theta(-\Delta V)\Delta V * TD_n(t+\tau'_n) + \frac{\lambda\Theta(\Delta V)\Delta V}{TD_n(t+\tau'_n)} \quad \textbf{(14)}$$

In the next section a comparison between TD-Gipps and TD-FVDM has been presented. Here it is worth mention that unlike IDM, in Gipps, acceleration and declaration has been modeled separately, in that regard, the Gipps model is structurally more like FVDM as FVDM also models both components separately.

IV. Model Varification

Simulation based verification has been performed for TD-Gipps model as well as TD-FVDM. Verification has been performed to evaluate enhancement of the respective models. The models have been compared in low, equal, and high task difficulty situations. Except task difficulty, all other exogenous and indigenous variables are taken as constant in acceleration and declaration scenarios so that effect of task difficulty interfacing could be observed. It is expected that if the task difficulty is greater than 1 so that the TD enabled model should produce less acceleration than the normal model and if the task difficulty is lesser than 1 then the TD enabled model should suggest higher acceleration than the normal model.

Interaction of Gipps model with task difficulty has been presented in Fig. 2 and Fig. 3 in acceleration and deceleration context respectively.

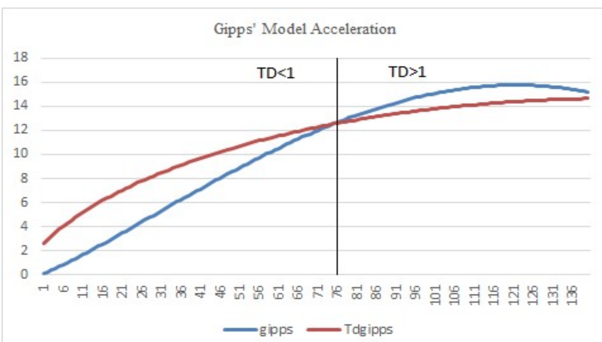

Fig. 2 Gipps and TD-Gipps in acceleration context

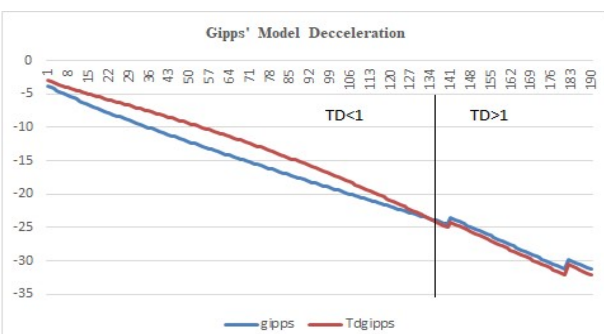

Fig. 3 Gipps and TD-Gipps in deacceleration context

Interaction of FVDM with task difficulty has presented in Fig. 4 and Fig. 5 in acceleration and deceleration context respectively.

The Enhanced FVDM produce behavioral dynamic as per expectation. The enhanced models produce same amount of velocity when task difficulty is zero, it is worth noticing that task difficulty is equal to 1 is shown by a horizontal black line. When the task difficulty is less than 1, the enhanced model produces higher velocity and when the task difficulty id greater then 1, the enhanced model produces lower velocity in comparison to the simple model.

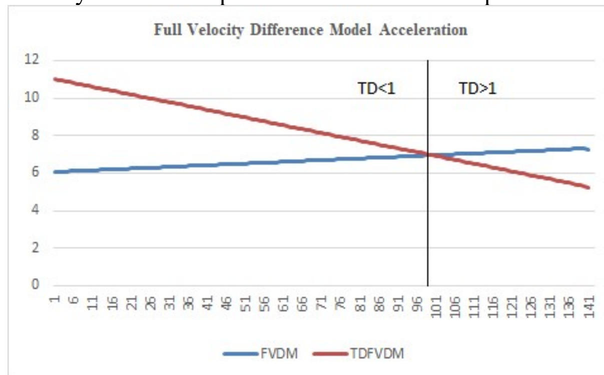

Fig. 4 FVDM and TD-FVDM in acceleration context

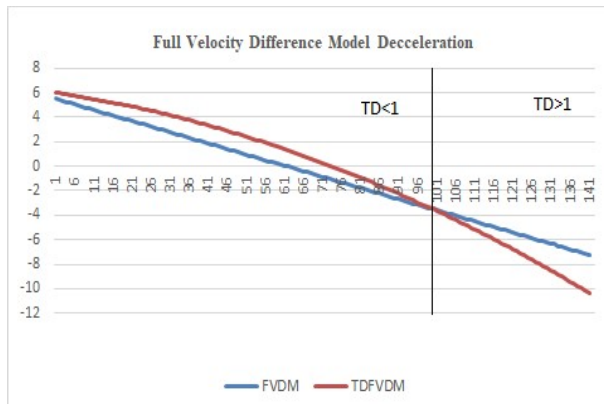

Fig. 5 FVDM and TD-FVDM in deceleration context

V. Conclusion

Existing car following models are conceived with engineering perspective i.e. to produce idealistic acceleration behavior. Therefore, these models are not accurate representation of car following behavior of human driver. Recently, this issue has been addressed by introducing notion of task difficulty in existing car following models. IDM and Gipps are considered de-facto car following models. Both models have been enhanced to carry the notion of task difficulty. Another model namely FVDM is considered numerically more stable than its successor models. The model has been enhanced to incorporate task difficulty in same manner. The simulation-based verification confirms the modeling assumption of the enhanced model. It is concluded that the enhanced TD-FVDM can reproduce car following behavior in both acceleration and deacceleration context in low and high task difficulty.

VI. Future Work

It is intended to perform equilibrium analysis on TD-FVDM to guarantee that the model is stable for all the endogenous or exogenous variables. It is also intended to perform exhaustive comparative study between TD-IDM, TD-Gipps and TD-FVDM. TD-IDM and TD Gipps are validated through human subject-based experiments by exposing several driving tasks with varied difficulty to real human beings with the help of virtual reality-based traffic situation. Similarly, the proposed TD-FVDM would be validated against human subjects using virtual reality-based experimentation setup by exposing several driving tasks with varying difficulty.

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