1. Introduction

Car-following models are fundamental in transportation engineering and traffic flow theory, offering insights into the dynamics of individual vehicles within traffic. These models simulate how a driver responds to the vehicle ahead, typically by relating acceleration to factors such as current speed, following distance, and speed difference. The core concept, rooted in the stimulus-response framework (Chandler et al. (1958); Gazis et al. (1961)), suggests that a driver's acceleration is influenced by their immediate environment and personal sensitivity.

The evolution of car-following models began in the 1950s (Pipes (1953)), with the Gazis-Herman-Rothery (GHR) model being one of the earliest, emphasizing reaction time and speed difference (Chandler et al. (1958); Herman et al. (1959)). Despite its simplicity, the GHR model assumes uniform driver behavior, which can overlook variations in responses. Subsequent enhancements, such as the introduction of a memory function (Lee (1966)) and accounting for multiple vehicles (Herman (1959)), sought to address these limitations. Alternative approaches focus on maintaining safe following distances rather than just speed differences. Gipps' model (Gipps (1981)) is a notable example, prioritizing safe stopping distances over speed. Bando's Optimal Velocity Model (OVM) (Bando et al. (1995)) introduced the idea of drivers adjusting their speed to an optimal velocity based on headway, although it can produce unrealistic acceleration rates under certain conditions (Helbing and Tilch (1998)). The Full Velocity Difference Model (FVDM) (Jiang et al. (2001)) was developed to address these issues by incorporating drivers' reactions to speed differences.

Psycho-physical models, such as Wiedemann's model (Wiedemann (1974)), integrate driver perceptions and divide driving scenarios into distinct regimes. While this model offers a detailed understanding of driver behavior, it relies on predefined thresholds that may oversimplify the fluidity of real driving (Saifuzzaman and Zheng (2014)). The Intelligent Driver Model (IDM) (Treiber et al. (2000)) stands out for its comprehensive approach, incorporating both desired speed and following distance to determine acceleration. IDM is versatile across different driving regimes, providing smooth transitions and clear physical interpretations for each parameter (Treiber and Kesting (2013b)). This model has become a cornerstone in modern car-following theory due to its ability to accurately simulate complex driving behaviors.

2. Methodology

To calibrating the car-following models and simulate the behaviors, the IDM model is chosen and recommended for the following reasons:

1). Comprehensive Consideration of Driver Behavior: IDM incorporates both the driver's desired speed and desired following distance to determine the acceleration rate, taking into account factors such as current speed, speed difference, minimum safe following distance, and maximum acceleration. This model has demonstrated its versatility across various following regimes, offering smooth transitions between them.

2). Parameter Interpretability and Flexibility: Each parameter in the IDM can be associated with a distinct aspect of driver behavior and has a clear physical meaning. One of the advantages of the IDM is its ability to represent a wide range of driving styles by adjusting its parameter values.

3). Realistic Accelerating Behaviors: When simulating accelerating behavior, the IDM generates realistic acceleration rates than other car-following models, avoiding the unrealistic values that can sometimes be produced by alternative models.

Table 1: Typical Values of Parameters for Highway

Parameter	Typical Value
v_0	120 km/h
T	1.0 s
s_0	2 m
a	1.0 m/s^2
b	2.5 m/s^2

2.1. Intelligent Driver Model

The IDM can be expressed as follows:

$$\frac{dv_n}{dt} = a[1 - (\frac{v_n}{v_0})^\delta - (\frac{s^*(v_n, \Delta v_n)}{s_n})^2] \tag{1}$$

The free accelerating term $a[1 - (\frac{v_n}{v_0})^\delta]$, governs the acceleration of the vehicle. Here, a represents the maximum acceleration, and v_0 denotes the vehicle's desired speed. Given an unobstructed path for a stationary vehicle, the vehicle would first accelerate at the rate of a, and the acceleration gradually decreases as the speed increases. Such reduction is controlled by the exponent term δ, and the vehicle would not exceed its desired speed. In accordance with the IDM author's recommendation (Treiber and Kesting (2013b)), this paper assigns the value of 4 to δ.

$$s^*(v_n, \Delta v_n) = s_0 + max(v_n T + \frac{v_n \Delta v_n}{2\sqrt{ab}}, 0) \tag{2}$$

$$\Delta v_n = v_n - v_{n-1} \tag{3}$$

$$S_n = x_{n-1} - l_{n-1} - x_n \tag{4}$$

On the other hand, the vehicle's decelerating process is regulated by the braking term $(\frac{s^*(v_n,\Delta v_n)}{s_n})^2$, where $s^*(v_n, \Delta v_n)$ represents vehicle's desired gap and s_n is the actual gap as shown by Equations 2 - 4. The term $s_0 + v_n T$ denotes the vehicle's desired following distance at the steady state. Here, the minimum gap, s_0, represents the space gap between the standstill vehicles, T is the time gap that the driver aims to maintain while in motion. The dynamic term $\frac{v_n \Delta v_n}{2\sqrt{ab}}$, symbolizes the driver's response to the speed difference Δv_n based on its own comfortable deceleration b. Typical parameter values for highway traffic are shown in Table 1.

2.2. Calibration Setup

Calibration of a car-following model involves choosing an appropriate optimization algorithm, a goodness-of-fit (GoF) function, and a measure of performance (MoP). In this study, the Genetic Algorithm (GA) is chosen for parameter calibration due to the complexity of the models. GA, a heuristic nonlinear optimization algorithm inspired by biological evolution, has proven to be an effective and reasonable method for calibrating various car-following models (Kesting and Treiber (2008), Chen et al. (2010), Punzo et al. (2012), Punzo et al. (2021)). Furthermore, the combination of MoP and GoF can significantly influence the effectiveness of the calibration process. (Punzo et al. (2021)) pointed out that the spacing outperforms speed and acceleration when serve as the MoP at most cases. Thus, As shown by Equations 5, this study adopts the commonly used combinations for calibration: RMSE of spacing (Yu et al. (2016), Park et al.

(2019), Rhoades et al. (2016)). A lower GoF value indicates a more precise simulation.

$$RMSE(s) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}[s_i(t) - \widetilde{s}_i(t)]^2} \tag{5}$$

where $s_i(t)$ represents the observed spacing of the ith vehicle at time t, and $\widetilde{s}_i(t)$ correspond to the simulated spacing.

To ensure that the calibrated parameters of the IDM remain within a realistic range, their boundaries are defined as follows: The time gap T is set between [0.1, 3] seconds and the minimum spacing s_0 is limited to [1, 5] meters. The maximum acceleration is restricted to [0.1, 4] m/s^2, which correlates with a maximum acceleration rate of 4 m/s^2 (equivalent to 0-100km/h in 6 seconds), while the comfortable deceleration boundary is set at [0.1, 9] m/s^2. The upper limit of the desired velocity v_0 is set to 33.6 m/s (120km/h). Regarding the lower limit, it should be noted that this limit must exceed the highest velocity value observed in the dataset, a detail often overlooked in other studies. This is a critical consideration because if the actual velocity exceeds v_0, the power of 4 applied in the $(\frac{v_n}{v_0})^4$ can induce an excessively large deceleration. It is important to remember that v_0 in the IDM is primarily designed for modeling acceleration and is not intended to handle deceleration scenarios Treiber and Kesting (2013b). In this study, the parameters for executing the GA for calibration are as follows: the GA will run for a maximum of 500 generations, with each generation consisting of a population of 200. The mutation rate is set to 0.05. For the sake of computing intensity, the sampling rate employed in this study is 0.2s which has been deemed sufficient for calibrating the car-following model (Treiber and Kesting (2013a)).

In addition, it should be noted that aside from calibration settings, the quality of data can significantly impact the calibration results when a single trajectory is used to emulate driving behaviors. The effectiveness of a training dataset depends more on its quality than on its sheer volume (Treiber and Kesting (2013a)). A trajectory that includes only a stop-and-go scenario is insufficient for calibrating the desired speed, as it lacks the corresponding condition. Therefore, verifying the dataset's completeness is a crucial step before calibration.

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