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# Development of parametric eco-driving models for fuel savings: A novel parameter calibration approach

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ABSTRACT

The existing conventional traffic flow models aims to simulate human-driven following vehicles in real world. In this era of emerging transport solutions, controlling or intervening traffic flow to achieve high fuel efficiency along with good driving safety and travel efficiency becomes a reality. As such, it is worth exploring the possibility of developing eco-driving models to optimise vehicle movements for fuel consumption minimisation, while maintaining safety and efficiency. In this study, we propose a modified genetic algorithm (GA) based calibration method that enables the calibrated parametric traffic flow (car following) models to simulate or control vehicles in an eco-driving manner. By developing a novel objective function for the GA method based on the widely-used VT-Micro fuel consumption model, the proposed method can calibrate model parameters towards improving fuel efficiency. Besides, by subtly using heavy fuel consumptions as a surrogate index to represent low travel efficiency or dangerous driving strategies, the modified GA method with the novel objective function can guide the calibrated model towards achieving complete eco-driving requirements. Experimental simulation results further indicate that traffic flow models calibrated by the modified GA-based method can also alleviate traffic disturbances and oscillations in a more effective manner.



## 1. Introduction

Microscopic traffic flow models, also known as microscopic car following models, describe how vehicles are following one another on roadways, which are the foundation of microscopic traffic flow theories and are of great significancy with regard to the development of adaptive cruise control (ACC) systems (Jiang et al., 2001; Yu et al., 2019). The majority of existing car following models consists of continuous mathematical functions and can be categorized as conventional parametric car following model, as compared to car following models built on novel technologies such as machine learning based car following models or cell automata car following models (Treiber and Kesting, 2013b). Despite of numerous studies on the developments and applications of conventional car following models (Gipps, 1981; Bando et al., 1995; Treiber et al., 2000; Jiang et al., 2001; Sangster and Rakha, 2014; Fadhloun and Rakha, 2020; Xu et al., 2021), the potentials of these car following models are yet to be fully tapped. To be specific, since conventional models with multiple mathematical equations would

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inevitably include some model parameters that needs to be calibrated before the models can be used, the performances and capabilities of the models would largely lie on the adopted calibration method as well as the quality of the calibration data. However, regardless of using different calibration data, the majority of current approaches for calibrating car following models will drive the model parameter values towards best fitting the calibration data which usually comprises following-the-leader field data (Kesting and Treiber, 2008; Chen et al., 2010; Punzo et al., 2012, 2014; Wang et al., 2012; Treiber and Kesting, 2013a). As a result, most calibrated conventional car following models are only good at simulating or predicting real following vehicles, which is equivalent to well reproduce human driver behaviours. Yet these calibrated models may not be capable of simulating or controlling the following vehicles to solve various traffic challenges that human drivers are hard to handle.

The calibration of conventional car following models is a branch of nonlinear optimization problems. The current approaches for solving nonlinear optimization problems would normally adopt objective function(s) to quantitively measure the optimization objective (e.g. cost, profit, prediction error and so on) that needs to be maximized or minimized subject to specified constraints. As for calibrating parameters for conventional car following models, the objective functions adopted by the majority of existing calibration approaches (e.g. genetic algorithm approach by Kesting and Treiber (2008), least square errors approach by Treiber and Kesting (2013a) and so on) measure the errors between the actual gap/speed/acceleration of a real following vehicle and the predicted gap/speed/acceleration of a model-driven following vehicle, with an aim to minimize such errors through the calibration process. In other words, the behaviours of real manually-driven following vehicles are used as the benchmarks for measuring the performance and fitness degree of a particular calibrated car following model. Therefore, the final calibrated models do have the potential to reproduce real followers.

On the other hand, eco-driving has become an increasingly popular technological topic in the background of reducing Greenhouse Gas (GHG) emissions to protect environment (Barkenbus, 2010). In a brief word, eco-driving refers to a way of driving that emphasizes better fuel efficiency while still maintaining sound driving safety and acceptable travel efficiency, which can be achieved by several manners including applying more moderate accelerations/decelerations and anticipating traffic flow and signals (Barkenbus, 2010). A number of automobile manufacturers such as Toyota, Honda and so on have already implemented different levels of eco-driving technologies into the ACC systems. Meanwhile, in the discipline of traffic engineering, various efforts on developing eco-driving technologies have also been made and one can refers to a number of technical reviews such as Alam and McNabola (2014), Taiebat et al. (2018), Huang et al. (2018) for more details. It is also worth mentioning that Mintsis et al. (2020) even paid special attentions to achieve dynamic eco-driving in the vicinity of signalized intersections.

However, as illustrated before, current car following models calibrated by existing approaches are not necessarily good choices for addressing specified traffic challenges such as improving fuel efficiency to achieve eco-driving. This is because model parameters calibrated based on actual manually-driven vehicle (MV) data may also introduce extra uncertainties caused by human drivers' errors, physical limits, or selfishness (non-cooperativeness) into the model, which will inevitably compromise the performances of the calibrated model.

To enable car following models to better address traffic challenges that human drivers are hard to handle, one common approach is to modify and optimize the structures or stimulus–response logics of conventional car following models. A good example is a modified Intelligent Driver Model proposed by Zhou et al. (2017a) that can improve the efficiencies of freeway ramp merging, which is an optimized variant of the widely-used Intelligent Driver Model (Treiber et al., 2000). Nonetheless, to the best of our knowledge, very few studies have paid attentions to improving car following models to better address traffic challenges through modifying the model calibration method, rather than changing the model structure or logics (which can be very complicated). To bridge this gap, this study aims at introducing a novel objective function for a widely-used genetic algorithm (GA) based calibration method (Kesting and Treiber, 2008) in order to enable the calibrated car following models to improve fuel efficiency while still maintain driving safety and travel efficiency. Accordingly, even without any model structure/logic modifications, conventional car following models calibrated by this modified GA-based approach can enable the following vehicles to drive in an eco-driving manner, which provides traffic researchers an effective way to simulate eco-driving vehicle platoon and analyses its properties and features.

The rest of this paper is organized as follows. Section 2 introduces in details the proposed GA-based calibration method with a modified objective function. Section 3 calibrates two widely-used conventional parametric car following models using both the modified GA approach and the original GA approach respectively. Section 4 comprehensively compare the performances of the same car following model calibrated by both approaches to validate the effectiveness of the modified GA-based calibration method. Section 5 further discusses about the scope of the proposed calibration method and concludes the study.

## 2. A genetic-algorithm based model calibration approach with novel objective function

To find a possibly optimal solution (a set of possibly optimal model parameter values) for an equation-based, parametric car following model, Kesting and Treiber (2008) propose an effective calibration method which resort to the genetic algorithm (Goldenberg, 1989) as a solution search heuristic. Assume there are $X$ unknown parameters in a car following model $M$, the detailed workflow of a typical GA-based calibration method is organized as follows:

- Define a wide but reasonable value range (serve as the parameter constraints) for each of the $X$ model parameters from which the optimal value for each parameter will be generated. This can greatly reduce the calibration complexity and enable the calibration method to converge faster towards the optimal parameter values.
- Initialize a population of $N$ individuals, each of which is a set of $X$ parameter values randomly generated from their respective value ranges. The $N$ individuals (parameter sets) form the first generation of the genetic algorithm.
- In each generation (iteration):
  1) Calculate the average trajectory prediction error of car following model $M$ under each of the $N$ individuals of the current generation based on a pre-defined objective function. The goal of the GA-based calibration method is to find an individual (a set of model parameter values) that can minimize such errors. Details of the adopted objective function and how the errors for each individual are calculated are illustrated separately in a later paragraph;
  2) Stochastically select $N-1$ pairs of individuals from the current population based on their average trajectory prediction errors: individuals with lower errors will possess higher probabilities of being selected and vice versa. The $N-1$ pairs of selected individuals correspond to $N-1$ parents in a genetic context. This step ensures that individuals with better genes are always more likely to be chosen as the parents to yield next-generation individuals so that individuals in each generation would gradually evolve and produce lower and lower trajectory prediction errors;
  3) Produce one next-generation individual from each selected parental pair through a stochastic crossover action: each parameter value in the next-generation individual is inherited from one of its two parental individuals in a stochastic manner. A total of $N-1$ next-generation individuals will be produced;
  4) For each of the $N-1$ next-generation individuals, there is a small chance described by a mutation probability $Pb_m$ that one of its parameters will mutate and get a random new value. As for which of the $X$ parameters in a next-generation individual would mutate, each of the parameters will share the same mutation probability $\frac{1}{X}$;
  5) Keep the individual that achieves the lowest errors (the best-performed one) in the population of current generation to the next generation without any changes.
  6) By implementing the above actions, a next generation of $N$ individuals will be finally yielded from the current population, making the population of each generation remains stable and unchanged.
- The calibration process will go through numerous generations and will terminate in either of the two conditions:
  1) A pre-specified number of generations is evaluated;
  2) The lowest error achieved by the best-performed individual in a generation has reached below a pre-specified error threshold, which means the calibration process has converged.

Upon the completion of the above calibration process, one can simply adopt the parameter value set that achieves the lowest average trajectory prediction error in the last generation as the model parameters for the target car following model $M$.

It is easy to conclude that for a typical GA-based calibration approach, the fitness degree of a particular individual is represented by the average trajectory prediction error of the car following model $M$ under that parameter set. Given that the mixed error measure function is a combination of the relative error measure and absolute error measure and will not overestimate errors in most cases (Kesting and Treiber, 2008), it is also adopted as the objective function of the GA-based calibration method to calculate the average trajectory prediction error of each individual when compared to the real follower trajectories, which is shown below in Eq. (1).

$$F_{mix}\left[\Delta x^{sim}\right] = \sqrt{\frac{1}{\langle\left|\Delta x^{real}\right|\rangle}\langle\frac{\left(\Delta x^{sim}-\Delta x^{real}\right)^2}{\left|\Delta x^{real}\right|}\rangle} \tag{1}$$

where expression $\langle\cdot\rangle$ means the temporal average value of the variable over the entire time duration and $|\cdot|$ refers to the absolute value of the variable. $x$ refers to the position of the following vehicle at a specific time step such that $\Delta x^{sim}$ denotes the predicted space headway at the same time step and $\Delta x^{real}$ denotes the corresponding real space headway. $F_{mix}\left[\Delta x^{sim}\right]$ refers to the trajectory prediction error in predicting a single following vehicle. To obtain the average trajectory prediction error, one simply needs to calculate $F_{mix}\left[\Delta x^{sim}\right]$ for each follower in the calibration dataset and take the average of them.

Nonetheless, as illustrated in Section 1, conventional car following models calibrated by the current GA-based approach or other existing approaches are not necessarily suitable choices for improving fuel efficiency due to the introduction of extra uncertainties caused by various limits of human drivers during the calibration process. Therefore, to enable the calibrated car following models to better improve fuel efficiencies of following vehicles while still maintaining driving safety and acceptable travel efficiency so that eco-driving can be achieved, we attempt to modify the current GA-based calibration method by 1) introducing the average instantaneous fuel consumption of vehicle as the surrogate index for measuring the fitness degree of a model parameter set and 2) use the widely-used VT-Micro fuel consumption model (Ahn et al., 2002) as the core part of the proposed objective function to calculate such instantaneous fuel consumption. The details of the modified objective function are listed below:

$$e_{vt}(\dot{x}(t),\ddot{x}(t)) = \exp\left\{\sum_{i=0}^{3}\sum_{j=0}^{3}K_{ij}(\ddot{x}(t))\left(\lfloor\dot{x}(t)\rfloor_{0km/h}^{120km/h}\right)^{i}\left(\lfloor\ddot{x}(t)\rfloor_{-5km/h/s}^{13km/h/s}\right)^{j}\right\} \tag{2}$$

$$e(\dot{x}(t),\ddot{x}(t),\Delta x(t)) = \begin{cases} e_{penalty} : if \begin{cases} \dot{x}(t) < 0 \\ or \\ \dot{x}(t) > v_{limit} \\ or \\ \Delta x(t) - l > max(\Delta x_{max}, \dot{x}(t) \times hw_{max}) \\ or \\ \Delta x(t) - l < max(\Delta x_{min}, \dot{x}(t) \times hw_{min}) \end{cases} \\ e_{vt}(\dot{x}(t),\ddot{x}(t)) : otherwise \end{cases} \tag{3}$$

$$e_{avg} = \langle e(\dot{x}(t),\ddot{x}(t),\Delta x(t))\rangle \tag{4}$$

Eq. (2) is the VT-Micro model that calculates the instantaneous fuel consumption ($liters/s$) of a vehicle at time $t$ based on the instantaneous speed $\dot{x}(t)$ and acceleration $\ddot{x}(t)$. $K_{ij}(\ddot{x}(t))$ is a coefficient whose value depends on the sign of instantaneous acceleration $\ddot{x}(t)$. To be consistent with previous studies including Zhou et al. (2019) and Ma et al. (2017); Qu et al., 2020, the values of $[K_{ij}(\ddot{x}(t))]_{i,j=0,1,2,3}$ are simply adopted the same as those in Ma et al. (2017). Besides, it is worth noting that the truncation of speed and acceleration may cause slight underestimation of fuel consumption.

In addition, considering that the GA-based approach with the modified objective function should enable the calibrated car following models to not only reduce fuel consumptions, but also maintain driving safety and travel efficiency at an acceptable level, a step function described by Eq. (3) is further introduced, in which the final instantaneous fuel consumption $e(\dot{x}(t),\ddot{x}(t),\Delta x(t))$ at time $t$ is determined by the result $e_{vt}(\dot{x}(t),\ddot{x}(t))$ of VT-Micro model in most cases except the following:

- Current speed (unit: $m/s$) of the following vehicle is smaller than 0 or larger than a pre-specified speed limit $v_{limit}$, which strongly contradicts the basic driving safety requirement;
- Current net gap[1] $\Delta x(t) - l$ of the following vehicle is smaller than the minimum safe net gap defined by the larger value of a minimum safe net space headway $\Delta x_{min}$ and a minimum safe time headway $hw_{min}$, which contradicts driving safety requirement as well;
- Current net gap $\Delta x(t) - l$ is larger than the maximum allowable net gap defined by the larger value of a maximum allowable net space headway $\Delta x_{max}$ and a maximum allowable time headway $hw_{max}$. This contradicts the requirement of maintaining an acceptable travel efficiency since keeping a too large net gap will definitely sacrifice travel efficiency.

Therefore, when encountering the above three situations, instead of taking the result of VT-Micro model, Eq. (3) will adopt a fixed heavy punishment defined by $e_{penalty}$ as the final instantaneous fuel consumption of the following vehicle at time $t$. In other words, the dangerous or unwanted performance of a calibrated car following model in the fields of driving safety and travel efficiency will be represented by an extremely high instantaneous fuel consumption so that parameter set leading to such situations will be gradually eliminated through multiple generations during the calibration process. At last, Eq. (4) is introduced to calculate the average instantaneous fuel consumption $e_{avg}$ of the car following model with a specific parameter set over all times. The obtained $e_{avg}$ will be the new surrogate index to measure the fitness degree of a parameter set.

Eqs. (2)–(4) comprise the complete objective function proposed in this study. By replacing the average trajectory prediction error in the current GA-based calibration method with the average instantaneous fuel consumption calculated by Eqs. (2)–(4) combined while keeping all other parts of the calibration method unchanged, the modified GA-based approach can easily calibrate parameters of conventional parametric car following models towards achieving lower fuel consumptions while maintaining driving safety and acceptable travel efficiency. Thus, it makes it possible to achieve certain level of eco-driving by simply using existing car following models (tap more potentials of existing car following models).

## 3. Calibrations of two conventional car following models

In this section, we attempt to calibrate conventional car following models using both the original GA-based method and the modified GA-based method respectively against the same calibration dataset in order to compare and validate whether the proposed calibration approach do outperform the original approach in enabling the following vehicles to achieve the aforementioned eco-driving requirements.

Two conventional, equation-based car following models that output accelerations are thus adopted: 1) the confined Full Velocity Difference (c-FVD) car following model proposed by Yu et al. (2019), and 2) the Intelligent Driver Model (IDM)

[1] $\Delta x$ refers to the space headway and $l$ refers to the average vehicle length taking as 5 m.

proposed by Treiber et al. (2000). Given that the details of car following models are beyond the scope of this study, we would directly introduce the parameters that need to be calibrated in both car following models while one could refer to the corresponding papers for more details regarding model structures, applications, and performances.

For the c-FVD model, it is developed based on the popular FVD car following model (Jiang et al., 2001) by introducing a dynamic acceleration confinement term to further ensure that under no circumstances will the model produce any overreacted maneuvers. As for finalizing the c-FVD model, there are a total of 12 parameters that needs to be determined: the first 6 parameters ($\tau$, $\lambda$, $V_1$, $V_2$,$l_{int}$ and $\beta$) are inherited from the original FVD model and are used to generate the original predicted acceleration based on inputs; the other 6 parameters ($a_{cap}$, $a_{max}$, $d_{cap}$, $d_{max}$, $r^+$ and $r^-_{ini}$) are used by the dynamic acceleration confinement term of the c-FVD model to further control the rationality of the predicted acceleration. To scale down the calibration complexities of c-FVD model without compromising the calibration quality, we decide to only calibrate the first 6 model parameters ($\tau$, $\lambda$, $V_1$, $V_2$,$l_{int}$ and $\beta$) which directly determines how the accelerations of following vehicles are generated based on current vehicle/traffic conditions. By contrast, we directly adopt the values from Yu et al. (2019) for the other 6 model parameters since their values are mainly decided by the physical performance limits of vehicles and common practices of drivers, both of which do not vary a lot in different calibration data.

As for IDM, it can produce collision-free car following behaviours as well as a self-organized characteristic so that the model can reproduce smooth traffic flow and simulate bottleneck congestions (Zhou et al., 2017a). There are 6 model parameters to be calibrated in the IDM as well: $v_0$, $T$, $a$, $b$, $\delta$, $s_0$.

To enable a fair performance comparison between the same model calibrated by different approaches, we adopt the same calibration dataset for all calibrations in this study. The calibration dataset consisting of 10 stable following-the-leader data samples (10 pairs of leader–follower data pairs) are stochastically selected from either the US 101 dataset or the I-80 dataset from the NGSIM program (FHWA, 2008). Same as previous studies such as Yu et al. (2019) and Zhou et al. (2017b), the raw trajectory data of all adopted data samples are pre-processed using a symmetric exponential moving average filter (Thiemann et al., 2008) with a smoothing width of 0.5 s, which eliminates mutated and false position values in the field data and smooths the trajectories of both real leaders and followers. After that, the smoothed speed or acceleration values at each time step are obtained from the first or second order finite differentiations of the corresponding position (trajectory) values. By doing so, the quality of the calibration dataset is effectively improved. Besides, the updating/simulation/prediction interval of the two car following models are both set as 0.1 s, which is consistent with the scan interval of the NGSIM data. During the calibration process of both calibration methods, only the complete trajectory/speed/acceleration data of the leader and the initial boundary conditions of the following vehicle are given while the complete trajectory and movements of the following vehicle are simulated by the car following model with specific parameter set. At last, as an important baseline to judge the calibration results, the average speeds of leading/following vehicles of all adopted data samples are calculated and the results range between $35km/h$ and $70km/h$.

Before the start of the calibration, the values of all hyper-parameters in both calibration approaches are reasonably determined as shown below in Table 1.

At last, as was introduced in the beginning of Section 2, the first two steps of both GA-based calibration methods is to initialize the parameter values of each individual for the first generation, which requires us to firstly define a wide but reasonable value range to serve as the constraints for each of the model parameters in c-FVD model or IDM. To enable both car following models to be calibrated under fair conditions, the parameter value ranges and constraints for similar parameters (e.g. maximum free-flow speed) in both car following models are designed as the same, all of which are listed as below.

**For c-FVD model:**

- The relaxation time $\tau$ is in the range of $[0.1, 4]s$;
- The sensitivity parameter $\lambda$ is in the range of $[0.1, 3]s^{-1}$;
- $V_1 > 0m/s$ , $V_2 > 0m/s$;
- The maximum free-flow speed $V_1 + V_2$ is in the range of $[15, 35]m/s$;
- The interaction length $l_{int}$ is in the range of $[0.1, 80]m$;
- The unitless parameter $\beta$ is in the range of $[0.1, 6]$;
- $V_1 + V_2 \tanh(-\beta) < 0$ since every vehicle should at least stop when its net space headway $(\Delta x - l)$ becomes $0m$, which can be easily derived from the Optimal Velocity function in the c-FVD model.

**Table 1**
Hyper-parameter values for the modified GA-based calibration method (unit: $v_{limit}$ – $m/s$, $\Delta x$ – $m$, $hw$ – $s$, $e_{penalty}$ – $litres/s$). The first three parameter values are also used by the original GA-based calibration method.

| *Max iterations* | *Population* | $Pb_m$ | $v_{limit}$ | $\Delta x_{max}$ | $hw_{max}$ | $\Delta x_{min}$ | $hw_{min}$ | $e_{penalty}$ |
|---|---|---|---|---|---|---|---|---|
| 300 | 4000 | 0.1 | 33.33 | 20 | 4 | 1 | 0.6 | 2 |

**For IDM:**

- The desired free-flow speed $v_0$ is in the range of $[15, 35]m/s$;
- The safe time headway $T$ is in the range of $[0.1, 4]s$;
- The maximum acceleration $a$ is in the range of $[0.1, 3.5]m/s^2$;
- The desired deceleration $b$ is in the range of $[0.1, 3.5]m/s^2$;
- The acceleration exponent $\delta$ is in the range of $[1, 10]$;
- The minimum jam distance $s_0$is in the range of $[0.1, 10]m$.

The calibration results of both car following models under different calibration approaches are presented in Tables 2 and 3, respectively.

## 4. Comparisons of calibrated model performances and validations of the proposed calibration approach

In this section, we attempt to comprehensively compare the two c-FVD models (the two IDMs) determined by both calibration methods in order to validate the effectiveness of the modified GA-based calibration method. All the experimental simulation tests in this section is conducted in a single-lane scenario without lane changes.

### *4.1. Model performance comparisons in simulating a single following vehicle*

Firstly, the performances of the two c-FVD models (the two IDMs) in simulating/controlling a single following vehicle are tested and compared. Given that the accumulated fuel consumption of a vehicle in a longer period tends to be a more stable value that can better represent the fuel consumption level of a car following model, we decided to initialize a virtual leading vehicle which travels for 10 minutes (6000 time steps) with random acceleration/deceleration maneuvers, whose details are listed as follows:

- The initial speed of the leader is $15m/s(54km/h)$;
- The initial acceleration of the leader is $0m/s^2$;
- The leader starts driving from the position of 30 m, enabling an initial space headway of 30 m for the immediate following vehicle;
- For every 10 time steps (every 1 s), an acceleration variation value will be stochastically generated according to a Gaussian distribution with mean value 0 and standard deviation 0.5. The variation value will then be added to the current acceleration of the leader to reproduce a real leading vehicle with random but continuous acceleration/deceleration maneuvers;
- Accelerations of the leader will always be truncated within the range of $[-3.41, 3.41]m/s^2$, which is consistent with both the range in NGSIM datasets and the deceleration values used in determining the stopping sight distance (Contributors, 2015; Fambro et al., 1997);
- Acceleration of the leader at current time step will be auto-adjusted if it will make the vehicle to reach a new speed at the next step that is out of the range $[0, 20]m/s$ ($[0, 72]km/h$). This is to ensure that the speed profile of the leader is consistent with those of real leaders in the calibration dataset.

  Correspondingly, the initial boundary condition for the following vehicle is set as:

- The initial speed of the follower is $15m/s(54km/h)$;
- The initial acceleration of the follower is $0m/s^2$;

**Table 2**
Calibrated parameter values for the c-FVD model.

| FVDM parameter | $T$ | $\lambda$ | $V_1$ | $V_2$ | $l_{int}$ | $\beta$ |
|---|---|---|---|---|---|---|
| Values by modified GA method | 3.703 | 0.557 | 1.882 | 18.393 | 42.135 | 0.106 |
| Values by original GA method | 3.999 | 0.721 | 14.318 | 20.681 | 24.419 | 0.859 |

**Table 3**
Calibrated parameter values for the IDM.

| IDM parameter | $v_0$ | $T$ | $a$ | $b$ | $\delta$ | $s_0$ |
|---|---|---|---|---|---|---|
| Values by modified GA method | 19.898 | 1.288 | 2.671 | 3.057 | 2.643 | 1.216 |
| Values by original GA method | 34.995 | 1.259 | 1.491 | 1.226 | 9.998 | 2.212 |

- The follower starts driving from the position of 0 m, enabling an initial space headway of 30 m or an initial time headway of 2 s.

A total of 10 tests are conducted for the two c-FVD models as well as the two IDMs. To justify the capability of the modified GA-based method in enabling eco-driving, we still use the VT-Micro model defined by Eq. (2) to calculate the fuel consumptions of the follower while adopt the inverse time-to-collision (iTTC) (Balas and Balas, 2006) to measure driving safety risks of the follower. In addition, the travel efficiency of the follower can be easily described by its total travel distance given that the travel time of the follower is fixed as 10 minutes. The iTTC of a following vehicle is described by the following equation:

$$iTTC = \int_t \max\left[0, \frac{-\dot{\Delta x}(t)}{\Delta x(t) - l}\right] dt \tag{5}$$

where $-\dot{\Delta x}(t)$ refers to the approaching rate of the following vehicle while $\Delta x(t) - l$ is the net space headway.

The comprehensive results of the 10 tests are listed below in Tables 4 and 5.

It is easy to derive from Tables 4 and 5 that for both car following models, when compared to the model calibrated by the original GA-based method, the same model always performs much better in fuel efficiency when it is calibrated by the modified method with Eqs. (2)–(4) as the objective function. To be specific, in all the 10 tests with different leader movement profiles, the modified GA-based method enables both c-FVD model and IDM to control the following vehicle to drive in a more fuel-efficient way because the average fuel consumption per $km$ in all tests are reduced for at least 10.24% (at least 10.24% fuel efficiency improvement) without any exceptions. And the average fuel efficiency improvements across all 10 tests for both c-FVD model and IDM are very similar and are identified as 11.73% and 12.29%, respectively.

Despite of the stable fuel efficiency improvements, models calibrated by the modified GA-based method also presents a highly-acceptable travel efficiency since in all 10 tests, the follower controlled by the fuel-efficient c-FVD model (calibrated by the modified GA-based method) travels almost the same distance as the followers controlled by the normal c-FVD model (calibrated by the original GA-based method). This can be further proved by the fact that the average travel distance of the 10 followers controlled by the fuel-efficient c-FVD model is about 5932$m$ while that is 5947$m$ for the followers controlled by normal c-FVD model, which indicates a negligible difference. The same conclusion on travel efficiency can be easily drawn for the 10 IDM tests from Table 5. In other words, the modified GA-based calibration method achieves significant improvement in fuel efficiency almost without sacrificing travel efficiency.

Now we take a look at driving safety issues. For the 10 c-FVD tests (Table 4), the average iTTC result of the followers by the fuel-efficient c-FVD model (29.750) is significantly lower than that of the followers by the normal c-FVD model (36.139). Given that iTTC index is proportional to safety risks, the above result indicates that the modified GA-based method also enables car following models to drive in a safer (lower risk) way. The above is further supported by the fact that the average space headway produced by the fuel-efficient c-FVD model (32.411$m$) is much larger than that of the normal c-FVD model (19.934$m$). Nonetheless, considering that 1) the average speeds of the followers controlled by both c-FVD models are only about 10$m/s$ such that even the average time headway produced by the normal c-FVD model still reaches around 2 s; 2)

**Table 4**
Performance comparisons of two c-FVD models calibrated by modified GA method and original GA method respectively in simulating a single following vehicle. Note: In the rest of the tables and figures, the c-FVD model calibrated by the modified GA method is described as the fuel-efficient c-FVD model yet the c-FVD model calibrated by the original GA method is described as the normal c-FVD model.

| Test No. | | **Test 1** | **Test 2** | **Test 3** | **Test 4** | **Test 5** | **Test 6** | **Test 7** | **Test 8** | **Test 9** | **Test 10** | **Avg Value** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Total time steps (0.1 $s$ per step) | | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | |
| Normal c-FVDM | Total fuel consumption ($l$) | 1.126 | 0.935 | 1.164 | 0.977 | 1.029 | 1.029 | 1.122 | 1.072 | 1.067 | 1.018 | **1.054** |
| | Total iTTC | 34.769 | 40.019 | 36.506 | 33.076 | 37.373 | 35.730 | 39.359 | 33.462 | 36.029 | 35.063 | **36.139** |
| | Total travel distance ($m$) | 6396 | 5086 | 6220 | 5599 | 5644 | 6123 | 6113 | 6479 | 5794 | 6017 | **5947** |
| | Avg headway ($m$) | 20.858 | 17.809 | 20.568 | 19.204 | 19.332 | 20.326 | 20.320 | 21.128 | 19.694 | 20.104 | **19.934** |
| | Min headway ($m$) | 5.458 | 5.492 | 5.669 | 6.245 | 6.107 | 5.543 | 5.827 | 5.657 | 6.089 | 6.036 | **5.812** |
| | **Avg fuel cost per *km*** | **0.176** | **0.184** | **0.187** | **0.175** | **0.183** | **0.168** | **0.184** | **0.165** | **0.184** | **0.169** | **0.177** |
| Fuel-efficient c-FVDM | Total fuel consumption ($l$) | 0.984 | 0.833 | 1.002 | 0.875 | 0.907 | 0.913 | 0.980 | 0.942 | 0.935 | 0.902 | **0.927** |
| | Total iTTC | 27.101 | 35.138 | 30.227 | 26.755 | 31.372 | 29.451 | 31.543 | 27.992 | 28.669 | 29.250 | **29.750** |
| | Total travel distance ($m$) | 6380 | 5068 | 6199 | 5583 | 5643 | 6111 | 6088 | 6479 | 5767 | 6001 | **5932** |
| | Avg headway ($m$) | 35.151 | 28.392 | 33.589 | 30.043 | 30.558 | 33.746 | 32.805 | 35.802 | 31.134 | 32.896 | **32.411** |
| | Min headway ($m$) | 6.705 | 5.521 | 5.5166 | 6.645 | 6.328 | 5.880 | 6.284 | 5.737 | 6.107 | 5.997 | **6.072** |
| | **Avg fuel cost per *km*** | **0.154** | **0.165** | **0.162** | **0.157** | **0.161** | **0.149** | **0.161** | **0.145** | **0.162** | **0.150** | **0.156** |
| **Fuel efficiency improvement** | | **12.38%** | **10.52%** | **13.63%** | **10.24%** | **11.88%** | **11.10%** | **12.30%** | **12.11%** | **11.97%** | **11.21%** | **11.73%** |

**Table 5**
Performance comparisons of two IDMs calibrated by modified GA method and original GA method respectively in simulating a single following vehicle. Note: In the rest of the tables and figures, the IDM calibrated by the modified GA method is described as the fuel-efficient IDM while the IDM calibrated by the original GA method is described as the normal IDM.

| Test No. | | **Test 1** | **Test 2** | **Test 3** | **Test 4** | **Test 5** | **Test 6** | **Test 7** | **Test 8** | **Test 9** | **Test 10** | **Avg Value** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Total time steps (0.1 $s$ per step) | | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | 6000 | |
| Normal IDM | Total fuel consumption ($l$) | 1.109 | 0.923 | 1.103 | 0.992 | 1.007 | 1.015 | 1.092 | 1.019 | 1.022 | 1.006 | **1.029** |
| | Total iTTC | 34.374 | 34.819 | 37.179 | 34.146 | 38.965 | 33.667 | 39.087 | 33.996 | 35.998 | 34.117 | **35.635** |
| | Total travel distance ($m$) | 6387 | 5081 | 6216 | 5595 | 5643 | 6122 | 6077 | 6478 | 5791 | 6016 | **5941** |
| | Avg headway ($m$) | 27.865 | 22.468 | 27.001 | 22.382 | 24.199 | 23.971 | 25.925 | 26.308 | 24.109 | 22.893 | **24.712** |
| | Min headway ($m$) | 7.204 | 7.182 | 7.182 | 7.184 | 7.184 | 7.182 | 7.182 | 7.182 | 7.182 | 7.183 | **7.185** |
| | **Avg fuel cost per *km*** | **0.174** | **0.182** | **0.178** | **0.177** | **0.178** | **0.166** | **0.180** | **0.157** | **0.176** | **0.167** | **0.173** |
| Fuel-efficient IDM | Total fuel consumption ($l$) | 0.947 | 0.814 | 0.958 | 0.866 | 0.888 | 0.882 | 0.962 | 0.913 | 0.910 | 0.874 | **0.901** |
| | Total iTTC | 39.769 | 41.477 | 42.297 | 39.547 | 45.167 | 39.934 | 45.224 | 39.167 | 42.015 | 40.503 | **41.510** |
| | Total travel distance ($m$) | 6385 | 5077 | 6203 | 5590 | 5644 | 6123 | 6086 | 6479 | 5770 | 6014 | **5937** |
| | Avg headway ($m$) | 30.760 | 24.777 | 28.840 | 24.926 | 25.947 | 28.942 | 27.768 | 31.513 | 26.755 | 28.173 | **27.840** |
| | Min headway ($m$) | 6.269 | 6.220 | 6.217 | 6.297 | 6.262 | 6.216 | 6.220 | 6.222 | 6.249 | 6.225 | **6.240** |
| | **Avg fuel cost per *km*** | **0.148** | **0.160** | **0.155** | **0.155** | **0.157** | **0.144** | **0.158** | **0.141** | **0.158** | **0.145** | **0.152** |
| **Fuel efficiency improvement** | | **14.56%** | **11.70%** | **12.97%** | **12.66%** | **11.83%** | **13.10%** | **12.03%** | **10.41%** | **10.55%** | **13.08%** | **12.29%** |

the minimum space headways in all tests for both c-FVD models are always larger than the vehicle length of $5m$, we can simply conclude that the c-FVD models calibrated by both approaches can both enable the following vehicle to drive in a very safe manner, while the modified GA-based calibration method does lead to even better safety results.

Similar findings can be derived from Table 5 for the 10 IDM tests: the average space headway produced by the fuel-efficient IDM ($27.840m$) is also larger than that of the normal IDM ($24.712m$) while the minimum space headways in all tests for both IDMs are always larger than the typical vehicle length. The only difference from the c-FVD test results is that the average iTTC result of the followers by the fuel-efficient IDM (41.510) is higher than that of the followers by the normal IDM (35.635), which is merely caused by the fact that the calibrated net minimum jam distance $s_0 = 1.216m$ for the fuel-efficient IDM while $s_0 = 2.212m$ for the calibrated normal IDM (see Table 3) such that the actual minimum space headway kept by fuel-efficient IDM ($6.240m$, including leading vehicle length of $5m$) is slightly smaller than that of normal IDM ($7.185m$, see Table 5). Nonetheless, given that the IDM is calibrated by field data with medium/low average vehicle speed (no more than $20m/s$ or $72km/h$), a standstill net gap of more than $1.240m$ is already sufficiently safe and reasonable. Therefore, we can still conclude that both IDMs can enable safe following behaviours in all the tests.

To conclude, when simulating a single vehicle following a speed-changing leader, car following models calibrated by the proposed GA-based method do enable the following vehicle to achieve a higher fuel efficiency while maintaining good driving safety and travel efficiency. In other words, the proposed GA-based method does enable conventional car following models to simulate/control vehicles in a more eco-driving manner. There are mainly two reasons why the proposed calibration method can achieve the above:

- It encourages more moderate accelerations and decelerations while discourages large speeds by tuning down the parameter value of 'maximum free-flow speed' (and adjusting other parameter values) in the car following models during calibration process, which is proved by model calibration results in Tables 2 and 3;
- It encourages to keep relatively larger space headways when the traffic is smooth so that the movement of the following vehicles is also smoother with less sudden accelerations or decelerations (drives in a more relaxed way), which can be supported by the predicted average space headways listed in Tables 4 and 5, as well as the plots in Figs. 1 and 2. In the two figures, the trajectory, space headway, speed, and acceleration profiles of the follower simulated by both c-FVD models in Test 1 are plotted, in which the follower controlled by the fuel-efficient c-FVD model (blue dashed line) indeed keeps a larger yet still reasonable space headway (corresponds to an average time headway of around 3.3 s) when the traffic is smooth and unblocked. This is also proved by Fig. 2 (a) and (b) since whenever the leader speed increase towards or reaches each crest (see the crests in Fig. 2 (b)), the space headway kept by the fuel-efficient c-FVD model is always larger than the space headway kept by the normal c-FVD model (see the corresponding crests in Fig. 2 (a)).

### *4.2. Model performance comparisons in simulating vehicle platoon*

Secondly, the performances of the two c-FVD models (the two IDMs) in simulating/controlling a vehicle platoon following a speed-changing vehicle are tested and compared. We still adopt the same configuration for the leading vehicle and the

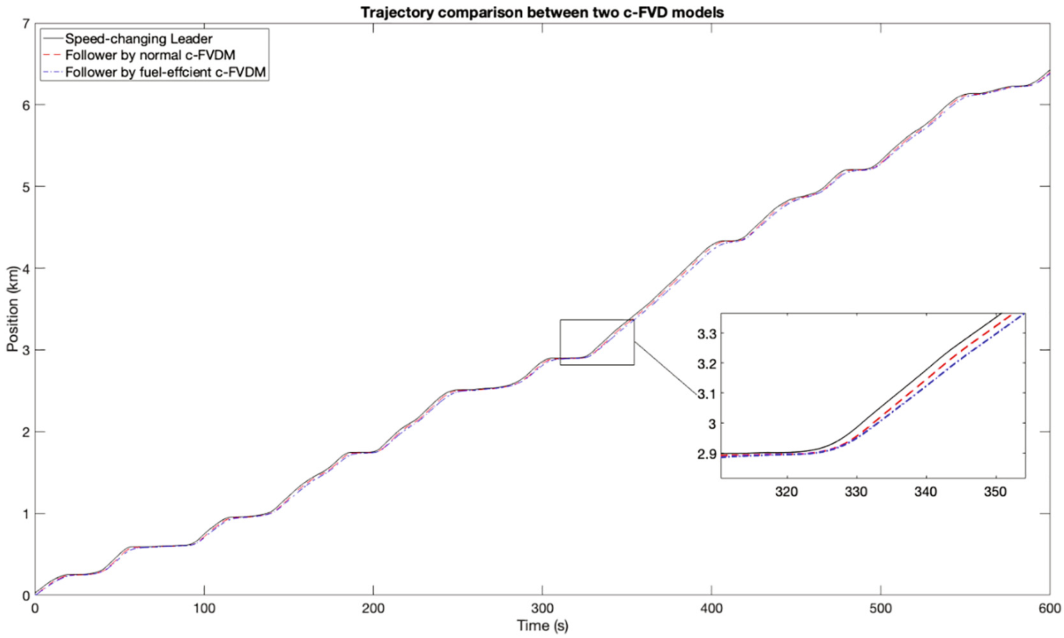


**Fig. 1.** Simulated follower trajectory comparison of two c-FVD models.

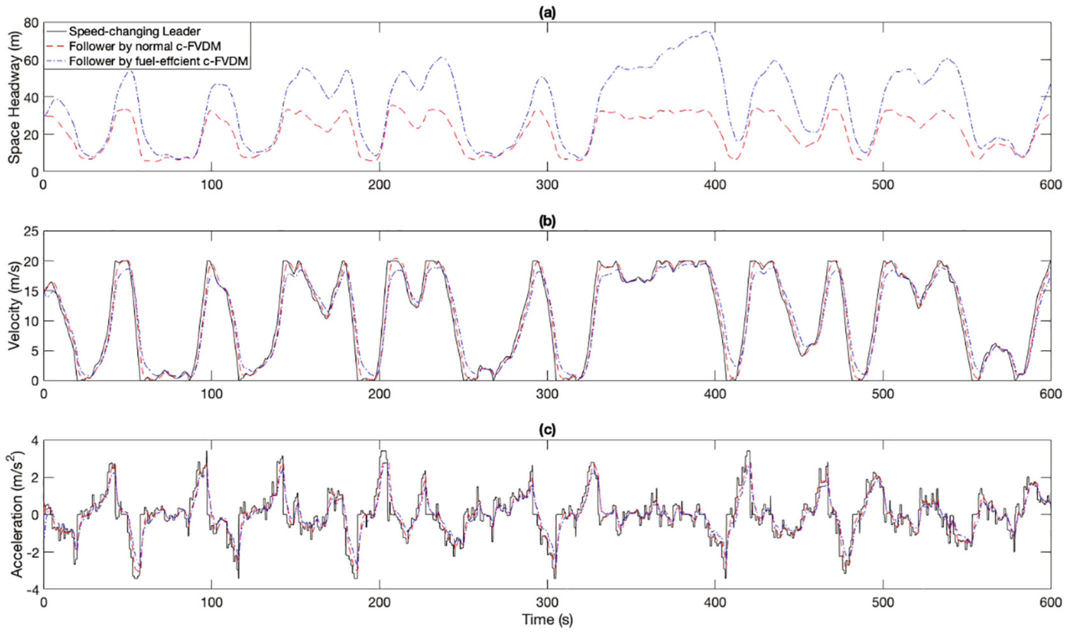


**Fig. 2.** Simulated follower status comparison of two c-FVD models: (a) space headways, (b) speeds, and (c) accelerations.

same initial boundary conditions for all the following vehicles: the leading vehicle will still travel for 10 minutes with stochastic accelerations decided by a Gaussian distribution; a simulated following vehicle with an initial speed of $15m/s$ will be added to the road whenever the space headway between the last vehicle on road and the origin point exceeds 30 m. A total of 50 following vehicles are created and all four calibrated car following models (two c-FVD models and two IDMs) are tested. The comprehensive results of the test are listed below in Tables 6 and 7.

As can be easily observed from Table 6, while all four sample followers (the 1st, 10th, 30th, 50th followers) in the platoon controlled by the fuel-efficient c-FVD model have achieved obvious fuel efficiency improvements when compared to the corresponding followers in the platoon controlled by the normal c-FVD model, the improvements made by vehicles in the

**Table 6**
Performance comparisons of two c-FVD models calibrated by modified GA method and original GA method respectively in simulating a vehicle platoon.

| *ith* Follower | | **Follower 1** | **Follower 10** | **Follower 30** | **Follower 50** |
|---|---|---|---|---|---|
| Total time steps (0.1 *s* per step) | | 6000 | 6000 | 6000 | 6000 |
| Normal c-FVDM | Total fuel consumption (*l*) | 1.140 | 0.985 | 0.806 | 0.704 |
| | Total iTTC | 30.534 | 16.595 | 11.442 | 8.158 |
| | Total travel distance (*m*) | 7070 | 6842 | 6414 | 5990 |
| | Avg headway (*m*) | 22.572 | 22.640 | 22.740 | 22.986 |
| | Min headway (*m*) | 6.522 | 9.635 | 10.923 | 12.080 |
| | **Avg fuel cost per *km*** | **0.161** | **0.144** | **0.126** | **0.117** |
| Fuel-efficient c-FVDM | Total fuel consumption (*l*) | 1.003 | 0.659 | 0.557 | 0.491 |
| | Total iTTC | 23.520 | 5.749 | 1.532 | 1.047 |
| | Total travel distance (*m*) | 7053 | 6699 | 6074 | 5363 |
| | Avg headway (*m*) | 38.072 | 34.857 | 34.256 | 33.748 |
| | Min headway (*m*) | 7.896 | 14.333 | 20.008 | 18.911 |
| | **Avg fuel cost per *km*** | **0.142** | **0.098** | **0.092** | **0.092** |
| **Fuel efficiency improvement** | | **11.78%** | **31.65%** | **27.01%** | **22.01%** |

**Table 7**
Performance comparisons of two IDMs calibrated by modified GA method and original GA method respectively in simulating a vehicle platoon.

| *ith* Follower | | **Follower 1** | **Follower 10** | **Follower 30** | **Follower 50** |
|---|---|---|---|---|---|
| Total time steps (0.1 *s* per step) | | 6000 | 6000 | 6000 | 6000 |
| Normal IDM | Total fuel consumption (*l*) | 1.124 | 1.039 | 0.856 | 0.755 |
| | Total iTTC | 33.268 | 21.321 | 14.760 | 10.820 |
| | Total travel distance (*m*) | 7069 | 6807 | 6417 | 6010 |
| | Avg headway (*m*) | 28.196 | 23.330 | 22.878 | 22.856 |
| | Min headway (*m*) | 7.182 | 7.681 | 8.804 | 9.848 |
| | **Avg fuel cost per *km*** | **0.159** | **0.153** | **0.133** | **0.126** |
| Fuel-efficient IDM | Total fuel consumption (*l*) | 0.976 | 0.732 | 0.600 | 0.536 |
| | Total iTTC | 38.645 | 14.654 | 4.677 | 2.635 |
| | Total travel distance (*m*) | 7066 | 6767 | 6390 | 5880 |
| | Avg headway (*m*) | 32.947 | 25.699 | 24.813 | 24.534 |
| | Min headway (*m*) | 6.250 | 8.153 | 9.891 | 12.340 |
| | **Avg fuel cost per *km*** | **0.138** | **0.108** | **0.094** | **0.091** |
| **Fuel efficiency improvement** | | **13.17%** | **29.18%** | **29.63%** | **27.48%** |

middle or rear of the platoon (up to 31.65% improvement in fuel efficiency) are significantly higher than that of the first follower (11.78%). In addition, although the iTTCs representing safety risks are keeping reducing towards the end of the platoon for both c-FVD models, the reducing degree of iTTC in the fuel-efficient c-FVD platoon is much more significant such that the iTTC of the 50th follower in the normal c-FVD platoon (8.158) is about 8 times the iTTC for the 50th follower in the fuel-efficient c-FVD platoon (1.047). In other words, the last follower in the fuel-efficient c-FVD platoon is driving in a much safer manner with much lower safety risks. By contrast, while the travel distance for the 50th follower in the fuel-efficient c-FVD platoon (5363$m$) is indeed smaller than that of the 50th follower in the normal c-FVD platoon (5990$m$), this is already the maximum sacrifice on travel efficiency among all vehicles and is only measured as $-10.47\%$. If we further measure travel efficiencies of both platoons by calculating traffic flow at the reference point of 5000$m$ (see the crosslines in Fig. 3 (a) and (b)), one can find that for the normal c-FVD platoon, it takes around 519$s$ for the leading vehicle and all 50 following vehicles to pass the reference point, which corresponds to a throughput of 354vehs/h. By contrast, all 51 vehicles in the fuel-efficient c-FVD platoon take 570$s$ to pass the reference point with a throughput of 322vehs/h. Hence, the platoon travel efficiency sacrifice of the fuel-efficient platoon is measured as $-9.04\%$, which is indeed smaller than the travel efficiency sacrifice of the last vehicle ($-10.47\%$). Thus, it can be fully compensated by the substantial improvements in fuel efficiency and driving safety.

At last, by referring to Table 7, one can easily find that the performance comparison between two IDM platoons present almost the same results and findings as the comparison between two c-FVD platoons, yet the maximum sacrifice on travel efficiency for the fuel-efficient IDM is even smaller and only measured as $-2.16\%$ (5880 m vs. 6010 m for the last vehicles in both IDM platoons).

Therefore, the modified GA-based calibration method indeed enables the calibrated car following models to achieve eco-driving, especially achieve substantial improvements in both fuel efficiencies and driving safeties, in a platoon level.

Since the overall performance improvements of fuel-efficient IDM (compared to normal IDM) is highly similar to the overall improvements of fuel-efficient c-FVD model (compared to the normal c-FVD model), we will only present several plots regarding the comparison test results between the two c-FVD models for further illustration purposes. Fig. 3 plot the respective trajectories of the platoon controlled by the two c-FVD models while Fig. 4 plot the tendency curves for average fuel consumptions, iTTCs, and travel distances of all 50 following vehicles in the two c-FVD vehicle platoons. Both figures

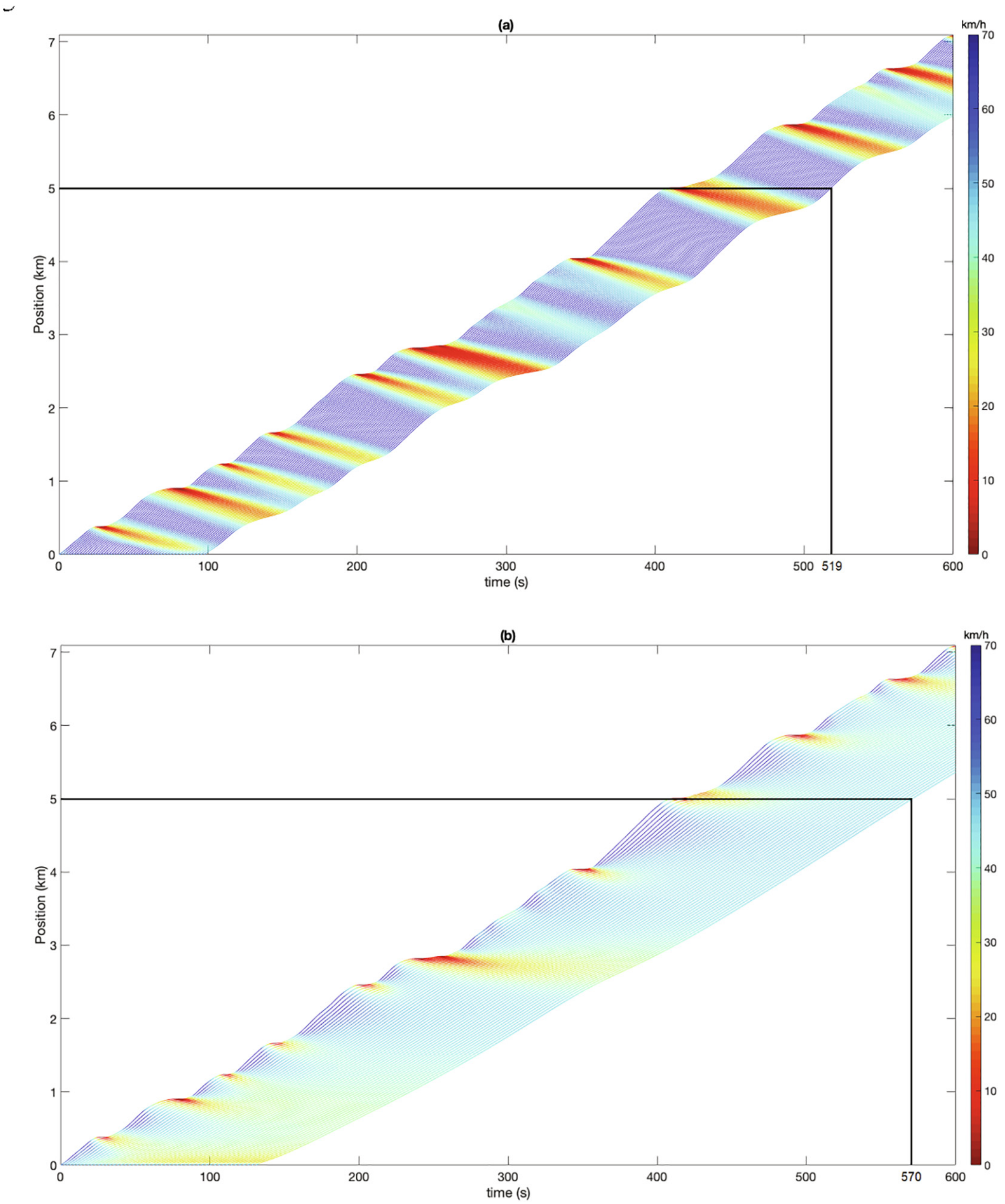


**Fig. 3.** Simulated platoon trajectory comparison of two c-FVD models: (a) normal c-FVD platoon, and (b) fuel-efficient c-FVD platoon.

strongly support our above findings drawn from Tables 6 and 7. Moreover, Fig. 3 (b) also clearly shows that the traffic oscillations (disturbances) originated from the first leading vehicle has been dissipated very effectively in the platoon controlled by the fuel-efficient c-FVD model while this is not the case for platoon controlled by the normal c-FVD model (Fig. 3 (a)), which indicates that the fast dissipation of oscillations is positively correlated to the implementations of eco-driving strategy. In fact, both eco-driving and oscillation accommodation are the results of a more relaxed driving strategy in which space headways between vehicles are relatively larger than usual while the frequencies and degrees of sudden accelerations/decelerations are relatively lower than usual, which are exactly the direction towards which the modified GA-based calibration method changes the parameter values for a car following model.

In addition, Fig. 5 plot the curves of the space headway, speed, and acceleration for the 30th follower in the two vehicle platoons controlled by the two c-FVD models, respectively. One can easily observe that when compared to the 30th follower controlled by normal c-FVD model, the same follower controlled by the fuel-efficient c-FVD model goes through much

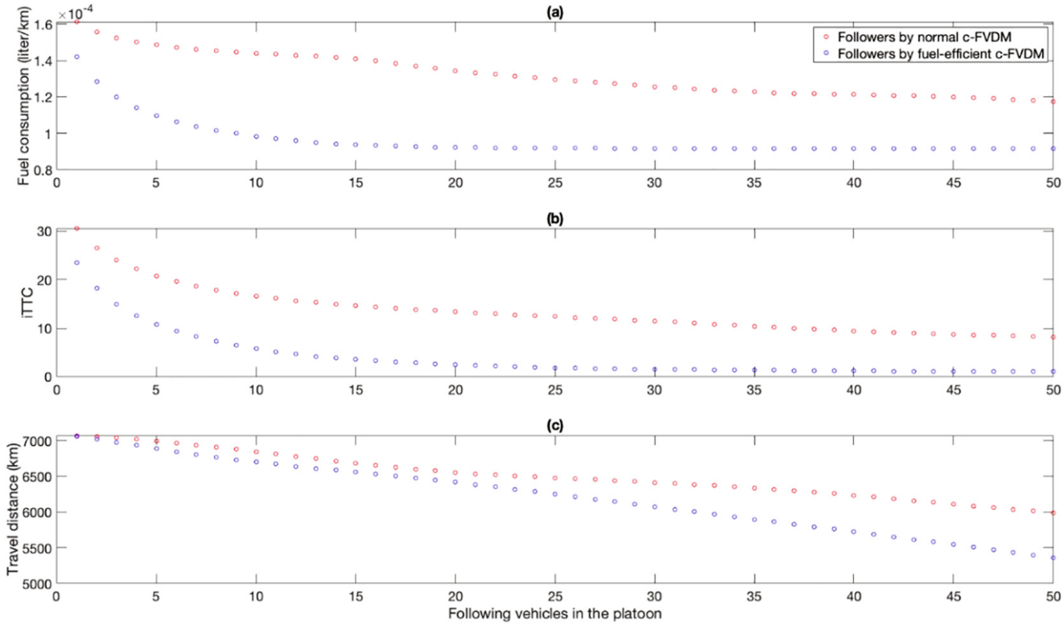


**Fig. 4.** Simulated platoon status comparison of two c-FVD models: (a) fuel consumptions, (b) iTTCs, and (c) travel distances.

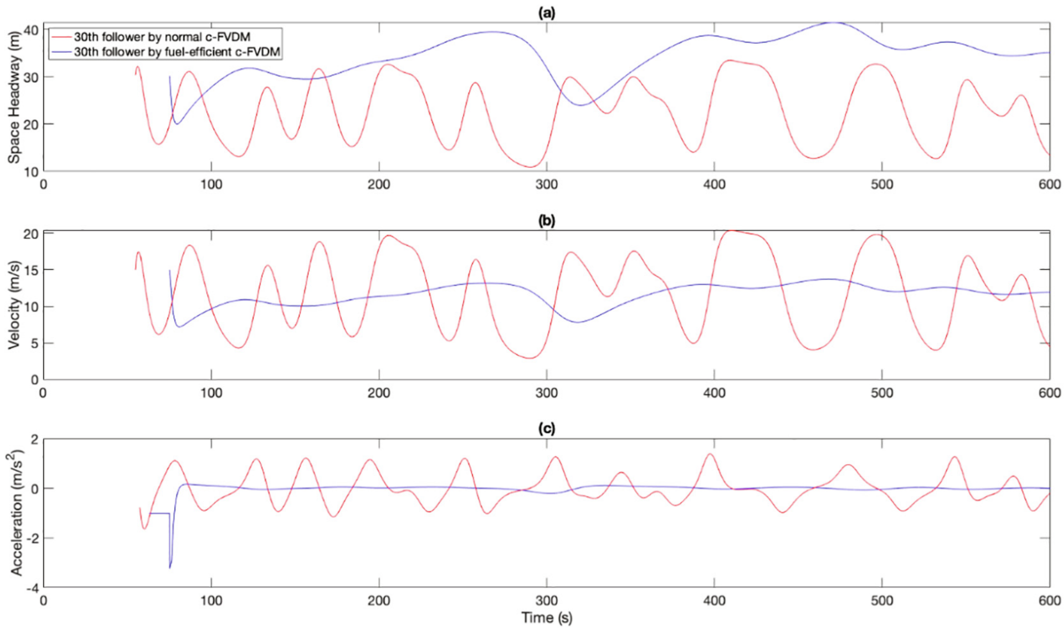


**Fig. 5.** Performance comparison of the 30th followers in two vehicle platoons controlled by two c-FVD models respectively: (a) space headways, (b) speeds, and (c) accelerations.

smaller fluctuations in all three curves, which is a result of 1) the use of the fuel-efficient c-FVD model to drive this vehicle in a more relaxed way, 2) the effective dissipation of oscillations by preceding vehicles further enabling this vehicle to move forward in a smoother traffic condition without much need for large speed changes so that eco-driving can be achieved even more easily.

To summarize, the modified GA-based calibration method does enable the calibrated car following models to better achieve eco-driving and oscillation dissipations simultaneously when simulating/controlling a platoon of vehicles.

### 4.3. Model performance comparisons as per driving safeties under urgent scenario

At last, we attempt to test and validate whether car following models calibrated by the modified GA-based method can still avoid accidents in urgent scenarios by generating very strong but reasonable decelerations.

We define a very urgent scenario which is highly similar with the one used in both Zhao and Gao (2005) and Yu et al. (2019) to carry out the test. The details are defined as follows: Two successive vehicles are initially moving forward with an identical speed of $20m/s$ and a space headway of just $30m$ (net gap $25m$), then the leader begins to decelerate with an extremely strong deceleration of $-5.5m/s^2$ until it totally stops. We need to verify whether the c-FVD model and IDM calibrated by the modified GA-based method can control the follower to fully stop before rear-end collision happens. The space headways, speeds, and decelerations of the follower simulated by two c-FVD models are displayed in Fig. 6 while those of the follower simulated by two IDMs are presented in Fig. 7, respectively.

First, as can be observed from Graph (a) of both figures, the followers simulated by all four calibrated car following models successfully stops before accidents happen because the final space headways are all larger than the average vehicle length of 5m. Yet the final space headways produced by the two fuel-efficient car following models (blue dashed line) are indeed slightly smaller than those of the two normal car following models (red dashed line), which indicates that the modified GA-based calibration method that can achieve eco-driving does not compromise too much the car following models' deceleration capabilities in urgent scenario and can still ensure high-level safety. More specifically, from Graph (c) of both figures we can find that the maximum decelerations generated by both the fuel-efficient c-FVD model and fuel-efficient IDM are indeed slightly smaller than those generated by the two normal models because the modified GA-based method encourages more moderate acceleration or deceleration maneuvers. Yet the two fuel-efficient car following models still successfully produce a set of considerably strong decelerations (up to about $-4.5m/s^2$) to stop the following vehicle in time. Accordingly, the proposed modified GA-based calibration method has the capability to cope with very urgent scenarios like the one above. Finally, it is worth noting that for even worse scenarios, a car following model calibrated by the proposed calibration approach may not be able to fully avoid an accident. However, the same would possibly happen to the same model calibrated by other approaches as well since the capability of a car following model to handle specific extreme situations is more related to the model structure/logics than the way to calibrate it.

## 5. Further discussions and conclusion

The majority of microscopic traffic flow (car following) models, especially conventional parametric models, usually consist of one or more mathematical equations with some unknown parameters. Thus, the performances and capabilities of these parametric car following models would largely lie on the quality of the calibration data and how the model parameters

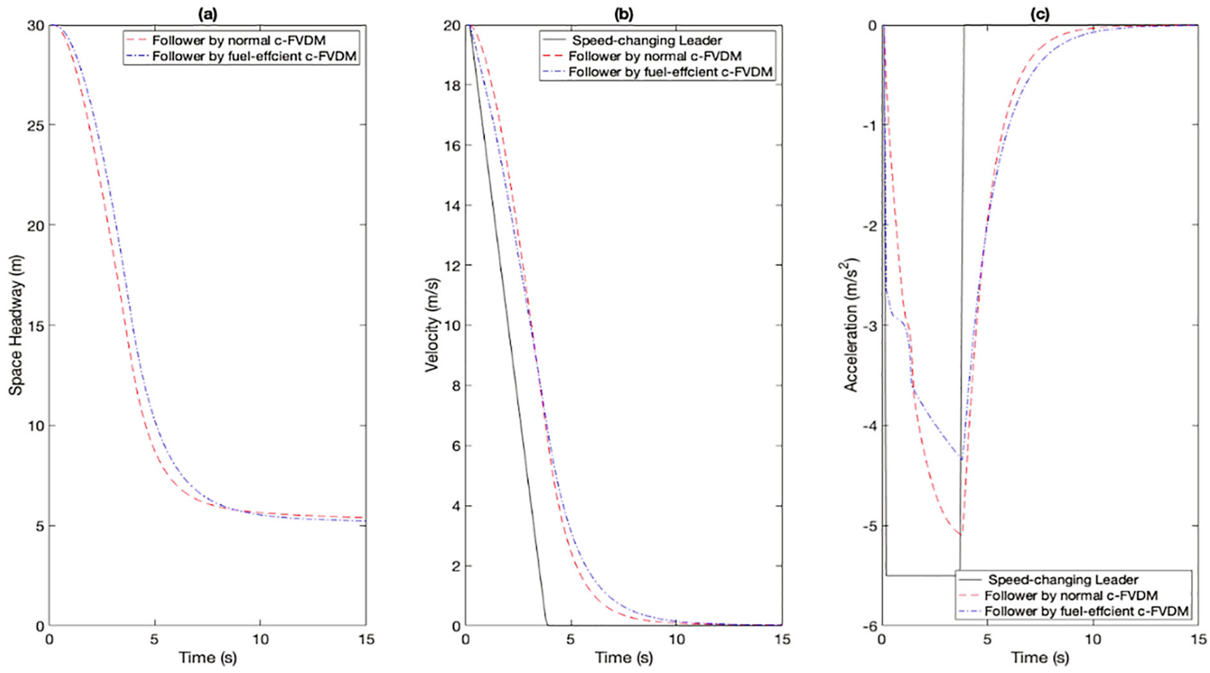


**Fig. 6.** Test results of a follower simulated by two c-FVD models respectively under an urgent traffic scenario: Comparison of (a) space headways, (b) speeds, and (c) accelerations.

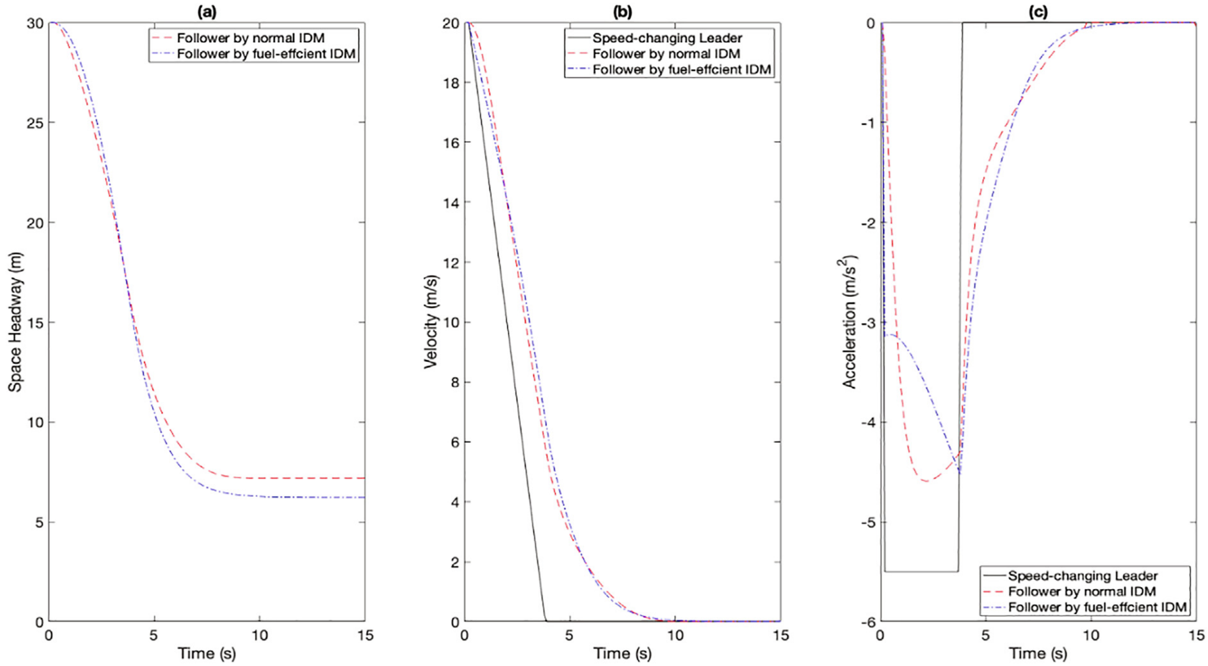


**Fig. 7.** Test results of a follower simulated by two IDMs respectively under an urgent traffic scenario: Comparison of (a) space headways, (b) speeds, and (c) accelerations.

are calibrated. However, regardless of different calibration data, the majority of current approaches for calibrating parametric models will drive the model parameters towards best fitting following-the-leader field data. Thus, these calibrated models tend to excel at predicting human-driven following vehicles. Yet they may not be capable of simulating or controlling the following vehicles to solve various traffic challenges that human drivers are hard to handle, e.g. to achieve high fuel efficiency along with good driving safety and travel efficiency, which is known as eco-driving strategy.

In this study, we propose a modified genetic algorithm (GA) based calibration method that enables the calibrated car following models to simulate or control vehicles in the eco-driving mode. By developing a novel objective function for the GA method based on the widely-used VT-Micro fuel consumption model, the modified GA-based method can calibrate model parameters towards reducing fuel consumptions. In addition, by subtly using heavy fuel consumptions as a surrogate index to represent low travel efficiency or dangerous driving strategies, the proposed objective function can guide the calibration method to drive the calibrated model towards simultaneously achieving high fuel efficiency, good driving safety, and acceptable travel efficiency, which corresponds to achieving eco-driving. Experimental simulation results further indicate that parametric car following models calibrated by the modified GA-based method can also alleviate traffic disturbances and oscillations in a more effective manner.

Despite of all the above great advantages of the modified GA-based calibration method, it is still worth noting that the time complexity of this calibration method is very low, which can easily take a normal computer several hours to complete one calibration process. However, the low computational efficiency is an inherent feature of all GA-based calibration method that is hard to overcome, which is caused by the fact that in the genetic algorithm, the population $N$ of each generation, the maximum allowable generations/iterations $g_{max}$, and the size (total time steps) of the calibration dataset $s_{data}$ need to be sufficiently large in order to enable better calibration results (better convergence). Given that the time complexity of a typical GA-based calibration method is $O(Ng_{max}s_{data})$ if producing a single output by the car following model based on a specific parameter set is regarded as the basic operation, it is easy to understand why the GA-based method is so time costly when all the three values are sufficiently large[2].

Therefore, one meaningful future research direction extended from this study is to modify the objective functions for other types of optimization/calibration approaches such as the least square errors (LSE) method to validate whether similar performance improvements can be achieved with higher calibration efficiencies. In addition, in this study, given that the modified GA-based calibration method adopt the 10 following-the-leader data samples (leader in each sample has limited time steps) used by the original method as the calibration dataset in order to enable a fair performance comparison, another future research direction is to use a single artificial leader sample (such as the practices in Section 4) which travels for longer time steps as the calibration dataset so that the modified calibration method may converge to better results.

[2] In this study, $N$, $g_{max}$, and $s_{data}$ are 4000, 300, and 3500 (approx.), respectively.

## Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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