A Fuzzy Full Velocity Difference Model Based on Driver’s Perception Characteristics

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The perception characteristics of drivers greatly vary with the status of traffic flow. To designate the vehicle trajectory more accurately, a driver’s perception headway coefficient is introduced, and a fuzzy full velocity difference (FVD) model is proposed in this paper. Consistent with the control theory, the stability conditions of the improved model are derived. Through the fuzzy control method, the input and output items of the control rule are constructed, respectively. The genetic algorithm is operated to calibrate the model parameters of timid and aggressive drivers. Eventually, the effectiveness of the model is verified by simulations. The research results show that, with the decrease of driver’s perception headway coefficient, the stability range of the traffic flow gradually increases, which is beneficial. Additionally, the average root means square percentage errors (RMSPE) values of the full velocity difference (FVD) model, the intelligent driver model (IDM), and the proposed model are, respectively, 0.312, 0.308, and 0.213. Compared with IDM and FVD models, the proposed model can accurately describe the local velocity variations and determine the car-following behavior of the human driving vehicle better.

1. Introduction

The uninterrupted traffic flow in urban expressways exhibits many complex phenomena, such as traffic congestion, fleet dispersion, and traffic wave propagation [1–5]. Hence, researchers have proposed various models to explore the mechanism evolving the traffic flow. Since the microscopic traffic flow models can represent the operation details of the traffic system, they are often used to simulate the process of driving. As a typical microscopic traffic flow model, the car-following model can explain the complex traffic phenomena from the perspective of dynamics based on the relationship between relative velocity and the headway of adjacent vehicles [6]. Newell [7] claimed that the velocity of a vehicle was directly related to its headway and so proposed a simple and practical model. Bando et al. [8] found out that Newell’s model had an issue during acceleration and deceleration and therefore proposed the classic optimal velocity (OV) model. Helbing and Tilch [9] showed that the OV model had the speed lag issue in the vehicle starting phase, so they considered the negative velocity difference and proposed a general force (GF) model. However, the analysis of the measured data revealed that the headway in the GF model was less than the safety threshold and the rear vehicles would not slow down when needed. Thus, Jiang et al. [10] proposed the full velocity difference (FVD) model to address these issues. Based on the OV model framework, researchers have explained the relationships between the changes of micro-parameters and the traffic flow state from a microlevel perspective [11–15].

In order to highlight the driver characteristics, researchers introduced more subjective factors into the car-following model to explore the influence of driver behavior characteristics on the model performance. Considering the driving characteristics specific to freeway car-following, Sun et al. [16] analyzed three car-following models calibrated for different driving styles. Gazis et al. [17] proposed that the driver’s sensitivity would decrease with the increase of
headway. Andersen [18] introduced the perception threshold concept in the car-following model to define the driver’s perception range. Wang et al. [19] established an improved model based on the driver’s perception characteristics, but the perception headway that they defined was fixed, which did not conform to the actual situation. The introduction of subjective factors, such as memory effect [20], aggressiveness [21], and expected velocity [22], deepened the research on driver’s perception characteristics. The driver, while driving the vehicle, often judges the movement of the vehicle based on their experience. However, the same vehicle state may stimulate different feelings under different traffic flow conditions [23]. Since the fuzzy control can effectively describe the driver’s subjective perception, such as low velocity and large headway, it can be introduced into the car-following model to describe the driver’s perception characteristics. Chakroborty and Kikuchi [24] were first to explain the human driving process. In addition, the driver’s perception headway is introduced and a fuzzy FVD model is proposed in this paper. Then, based on the control theory, we provide the stability conditions of the traffic flow system.

2. The Car-Following Model


Although the existing literature above have studied the driver behavior characteristics and the fuzzy control, these models still have the following shortcomings: (1) It is assumed that a driver perceives the headway, but the dynamic relationship between the perception headway and the vehicle state has not been discussed. (2) The existing fuzzy control methods disregarded the internal relationships between the parameters, which made it difficult to analyze the models in terms of mathematics and dynamics.

The novelty of the paper is that the driver’s perception characteristics are introduced based on fuzzy control method, which makes the model more accurate to simulate the human driving process. In addition, the driver’s perception characteristics are dynamic and can adapt to the complex and changeable traffic flow environment.

Based on the above considerations, the driver’s perception headway is introduced and a fuzzy FVD model is proposed in this paper. Then, based on the control theory, we provide the stability conditions of the traffic flow system. Finally, we calibrate the relevant parameters and verify the fitting effect between the fuzzy FVD model and the real traffic flow by simulations.

\[
\frac{dv_n(t)}{dt} = \sum_{j=1}^{r} \omega_j (v_n(t), \Delta x_n(t)) \left[ a \left[ V(\beta_{n,j} \Delta x_n(t)) - v_n(t) \right] + y (v_{n+1}(t) - v_n(t)) \right] = \sum_{j=1}^{r} h_j (v_n(t), \Delta x_n(t)) \left[ a \left[ V(\beta_{n,j} \Delta x_n(t)) - v_n(t) \right] + y (v_{n+1}(t) - v_n(t)) \right] ,
\]
where \( \omega_j(v_n, \Delta x_n) = \prod_{k=1}^2 M_k^j(v_n, \Delta x_n) \) and \( \omega_j(v_n, \Delta x_n) \geq 0 \), \( M_k^j(v_n, \Delta x_n) \) is the membership of each fuzzy set, \( h_j(v_n, \Delta x_n) = \omega_j(v_n, \Delta x_n)/\sum_{j=1}^{r} \omega_j(v_n, \Delta x_n) \), with \( \sum_{j=1}^{r} \omega_j(v_n, \Delta x_n) > 0 \), \( h_j(v_n, \Delta x_n) \geq 0 \), and \( \sum_{j=1}^{r} h_j(v_n, \Delta x_n) = 1 \).

### 3. Model Stability Analysis and Parameter Calibration

#### 3.1. Stability Analysis

To analyze the stability of the fuzzy FVD model, the stability of the transportation system is explored using cybernetics, and its stability conditions are derived. For the car-following model with a homogeneous traffic flow, when all vehicles achieve the optimal velocity, the traffic flow reaches a steady state. The dynamics equation of this situation can be given as

\[
\begin{align*}
\frac{d\Delta x_n(t)}{dt} &= v_{n+1}(t) - v_n(t).
\end{align*}
\]

If the driver’s perception headway is ignored, the steady-state traffic flow becomes

\[
\begin{bmatrix}
v_n(t) \\
\Delta x_n(t)
\end{bmatrix}^T = \begin{bmatrix} v_0 \\ V^{-1}(v_0) \end{bmatrix},
\]

where \( v_0 \) is the steady-state velocity of the traffic flow.

According to the fuzzy FVD model, there is a mismatch between the driver’s perception of headway and the actual headway. When the actual headway is \( \Delta x_n(t) \), the driver will determine the optimal velocity of the vehicle based on the perception headway \( \beta_{n,j} \Delta x_n(t) \). It is assumed that the leading vehicle in the queue is not constrained or affected by other vehicles, and its velocity is constant at \( v_0 \). Thus, the steady state of the traffic flow considering the drivers’ perception headway can be expressed as

\[
\begin{bmatrix}
v_n(t) \\
\beta_{n,j} \Delta x_n(t)
\end{bmatrix}^T = \begin{bmatrix} v_0 \\ V^{-1}(v_0) \end{bmatrix}.
\]

By linearizing the error system in (5), the following equation can be obtained:

\[
\begin{align*}
\frac{d\delta v_n(t)}{dt} &= \sum_{j=1}^{r} h_j(v_n, \Delta x_n) \alpha \left[ \beta_{n,j} \Delta x_n(t) \Lambda - \delta v_n(t) \right] + \gamma (\delta v_{n+1}(t) - \delta v_n(t)), \\
\frac{d\delta \Delta x_n(t)}{dt} &= \delta v_{n+1}(t) - \delta v_n(t).
\end{align*}
\]

where \( \delta v_n(t) = v_n(t) - v_0 \), \( \delta \Delta x_n(t) = \Delta x_n(t) - V^{-1}(v_0) \), and \( \Lambda = \frac{dV(\Delta x_n(t))}{d\Delta x_n(t)} \big|_{\Delta x_n(t)=V^{-1}(v_0)} \).

Now, let us assume that \( \bar{\beta}_{n,j} = \sum_{j=1}^{r} h_j(v_n, \Delta x_n) \beta_{n,j} \). Hence, (8) can be rewritten as

\[
\begin{align*}
\frac{d\delta v_n(t)}{dt} &= \left\{ \bar{\beta}_{n,j} \Delta x_n(t) \Lambda - \delta v_n(t) \right\} + \gamma (\delta v_{n+1}(t) - \delta v_n(t)), \\
\frac{d\delta \Delta x_n(t)}{dt} &= \delta v_{n+1}(t) - \delta v_n(t).
\end{align*}
\]
3.2. Parameter Calibration

3.2.1. Data Processing. We extract the vehicle trajectory on the US101 highway in the NGSIM dataset to calibrate the fuzzy FVD model parameters and verify the fitting effect between the model and the real vehicle data. Based on the data filtering rules proposed by Xiao et al. [27], we select the space-time trajectories of 10 adjacent vehicles in the left lane as shown in Figure 1.

The Laplace transform of the above-given equation is

\[ \begin{cases} sV_n(s) - V_n(0) = \alpha \overline{\beta}_{n,j} \Delta x_n(s) \Lambda - \alpha V_n(s) + \gamma (V_{n+1}(s) - V_n(s)), \\ s \Delta x_n(s) - \Delta x_n(0) = V_{n+1}(s) - V_n(s) \end{cases} \]

which can be expressed in matrix form as

\[ \begin{bmatrix} V_n(s) \\ \Delta x_n(s) \end{bmatrix} = \begin{bmatrix} s \alpha \overline{\beta}_{n,j} \Lambda & 1 \\ 0 & s + \alpha \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \begin{bmatrix} V_{n+1}(s) \\ 1 \end{bmatrix} d(s) \]

(11)

and Taylor’s expansion of which is

\[ G(s) = \frac{\gamma s + \alpha \overline{\beta}_{n,j} \Lambda}{s^2 + \alpha \overline{\beta}_{n,j} \Lambda + \sigma + s^2} \]

(12)

and

\[ G(s) = \frac{\gamma s + \alpha \overline{\beta}_{n,j} \Lambda}{s^2 + \alpha \overline{\beta}_{n,j} \Lambda + \sigma + s^2}. \]

(13)

Based on the stability theory, when \( d(s) \) is stable and \( G(s)_{\infty} \leq 1 \), the traffic flow is stable and so no congestion will occur. Hence, the ace of \( G(s)_{\infty} \leq 1 \) is written as

\[ |G(s)|^2 = |G(-j\omega)G(j\omega)| = \frac{(\alpha \overline{\beta}_{n,j} \Lambda)^2 + (\gamma)^2 \omega^2}{(\alpha \overline{\beta}_{n,j} \Lambda - \omega^2)^2 + (\alpha + \gamma)^2 \omega^2} \leq 1. \]

(14)

Thus, the stability condition can be described as

\[ \omega^2 - 2\alpha \overline{\beta}_{n,j} \Lambda + \alpha^2 + 2\alpha \gamma \geq 0, \]

(15)

which can be further simplified as

\[ \alpha \geq 2 \overline{\beta}_{n,j} \Lambda - 2\gamma. \]

(16)

Incorporating \( \overline{\beta}_{n,j} = \sum_{i=1}^{r} h_i (v_n, \Delta x_n) \beta_{n,i,j} \) into (16) gives the following stability condition:

\[ \alpha \geq 2 \sum_{j=1}^{r} h_j (v_n, \Delta x_n) \beta_{n,j} \Lambda - 2\gamma. \]

(17)

3.2. Parameter Calibration

3.2.2. Fuzzy Rules Determination. Before parameter calibration, the fuzzy set division of input and output variables needs to be determined. Here, we refer to the fuzzy set division method proposed by Qiu et al. [25] adopting the form of membership function combining the triangle type and the ladder type to fuzzify the vehicle velocity, headway, and perception headway coefficient. The vehicle velocity \( v_n(t) \) has three fuzzy sets, namely, VS, VM, and VB, where VS refers to lower velocity, VM denotes moderate velocity, and VB signifies higher velocity. The headway \( \Delta x_n(t) \) has four fuzzy sets, namely, HS, HMS, HMB, and HB, where HS refers to smaller headway, HMS denotes medium-to-small headway, HMB signifies medium-to-large headway, and HB means larger headway. The driver’s perception headway coefficient \( \beta_{n,j} \) contains three fuzzy sets, namely, PS, PM, and PB, where PS refers to a smaller coefficient value, PM denotes a moderate coefficient value, and PB signifies a larger coefficient value.

In this paper, through the analysis of NGSIM data, the fuzzy rules under different speeds and headways are determined. The results show that both aggressive and timid vehicles comply with the following rules: when the headway
is small and the driving velocity is low, $\beta_{n,j}$ is the smaller coefficient value; when the headway is large and the driving velocity is low, $\beta_{n,j}$ is the larger coefficient value; if the headway is small and the driving velocity is high, then $\beta_{n,j}$ is the smaller coefficient value. In addition, under the same conditions, compared with timid drivers, aggressive drivers have a larger value of $\beta_{n,j}$. Based on the above analysis, 12 fuzzy rules are given in Table 1.

### 3.2.3 Parameter Calibration

Parameter calibration can be regarded as a self-learning process for the car-following model. Alternatively, it can be considered as an optimization problem to find the optimal parameter values, which will be used when simulating the human driver process. Since the fuzzy control rules are introduced in the model to determine the perception characteristics of human drivers, it is difficult to calibrate a large number of parameters directly. As the genetic algorithms can deal with extremely complex problems that are hard to solve with traditional methods, this paper adopts the method proposed by Hao et al. [26] to deal with the membership function parameters. First, a large number of parameters in the range of $[-1, 1]$ are randomly generated for each variable, and then they are fuzzified using the corresponding fuzzy sets. Next, each variable is assigned with a serial number for chromosome encoding. Finally, the variables are standardized by their respective maximum values, and the range is converted to $[-1, 1]$.

#### 3.2.4 Contrast Model

To better show the performance of the fuzzy FVD model, we chose the IDM and the FVD as the comparison models and genetic algorithms to calibrate the parameters of the models [26]. The IDM is one of the typical car-following models of a human-driven vehicle. It considers the expected velocity of the vehicle and the expected headway. The IDM can be expressed as follows [28]:

$$a_n(t) = \left(\frac{v_n(t)}{\bar{v}_n(t)}\right)^\beta \left(\frac{\bar{s}_n(t)}{\bar{v}_n(t)}\right)^2,$$

(18)

$$\bar{s}_n(t) = \bar{s}_{jam} + \frac{s_{jam}(t)}{\bar{v}_n(t)} \frac{v_n(t)}{\bar{v}_n(t)} + v_n(t) \times \bar{T}_n(t) - \frac{v_n(t) \times \Delta \bar{v}_n(t)}{2 \times \sqrt{a_{\text{max}}^{(n)} \times a_{\text{comf}}^{(n)}}}$$

(19)

In the above formulas, $a_{\text{max}}^{(n)}$ is the maximum acceleration or deceleration of vehicle $n$, $a_{\text{comf}}^{(n)}$ is the comfortable acceleration of vehicle $n$, $v_n(t)$ is the velocity of vehicle $n$, $\bar{v}_n(t)$ is the expected velocity, $\Delta \bar{v}_n(t)$ is the velocity difference between vehicle $n$ and the adjacent vehicle $n+1$, $s_{jam}(t)$ is the headway, $\bar{s}_n(t)$ is the expected headway, $\bar{s}_{jam}$ and $s_{jam}$ are, respectively, the minimum headways of vehicles under congested and

### Table 1: Fuzzy rules of fuzzy FVD model.

<table>
<thead>
<tr>
<th>VS</th>
<th>VM</th>
<th>VB</th>
</tr>
</thead>
<tbody>
<tr>
<td>HS</td>
<td>PS</td>
<td>PS</td>
</tr>
<tr>
<td>HMS</td>
<td>PM</td>
<td>PM</td>
</tr>
<tr>
<td>HMB</td>
<td>PB</td>
<td>PM</td>
</tr>
<tr>
<td>HB</td>
<td>PB</td>
<td>PM</td>
</tr>
</tbody>
</table>

Now, assume that the first-generation population was 100, and they were randomly generated. For each time step, the acceleration, velocity, position, and headway of the vehicle at the current moment were used as the input for the next time step. After the simulation, the fitness of each chromosome was calculated, where the fitness was expressed by the mean square error of the simulated and the actual accelerations. Here, the genetic algorithm was used to iteratively calculate the model until the convergence. $V_{1712}$ has 597 pairs of samples, and the mean square error of acceleration after the convergence of the genetic algorithm is 0.48. Tables 2 and 3 show the results of parameter calibration, where Table 3 particularly focuses on the horizontal axis values of the characteristic points of the membership function. The membership function is generated by adding the corresponding vertical axis coordinate values. Figure 2 illustrates the membership function of the fuzzy set of velocity variables, which is marked with different line types and colors. The membership function setting method of other variables is similar to this. $V_{1720}$ has 597 pairs of samples, and the mean square error of acceleration after the convergence of the genetic algorithm is 0.64. Tables 4 and 5 show the results of parameter calibration.
Table 2: Calibration results of driver and traffic flow parameters for $V_{1712}$.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\alpha$</th>
<th>$L_{n-1}$</th>
<th>$\gamma$</th>
<th>$V_1$</th>
<th>$V_2$</th>
<th>$C_1$</th>
<th>$C_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>0.14 s$^{-1}$</td>
<td>4.66 m</td>
<td>0.52 s$^{-1}$</td>
<td>2.93 m/s</td>
<td>7.11 m/s</td>
<td>0.19</td>
<td>3.30</td>
</tr>
</tbody>
</table>

Table 3: Calibration results of the fuzzy set for $V_{1712}$.

<table>
<thead>
<tr>
<th>Fuzzy set</th>
<th>Velocity set</th>
</tr>
</thead>
<tbody>
<tr>
<td>VS</td>
<td>0.00</td>
</tr>
<tr>
<td>VM</td>
<td>5.07</td>
</tr>
<tr>
<td>VB</td>
<td>8.12</td>
</tr>
<tr>
<td>HS</td>
<td>6.43</td>
</tr>
<tr>
<td>HSM</td>
<td>20.83</td>
</tr>
<tr>
<td>HMB</td>
<td>25.57</td>
</tr>
<tr>
<td>HB</td>
<td>34.51</td>
</tr>
<tr>
<td>PS</td>
<td>0.95</td>
</tr>
<tr>
<td>PM</td>
<td>1.21</td>
</tr>
<tr>
<td>PB</td>
<td>1.35</td>
</tr>
</tbody>
</table>

4. Simulation Results and Discussion

4.1. Stability Results. Following the above-given conditions of (17), the stability of the traffic flow is determined by the driver's sensitivity $\alpha$, the perception headway coefficient $\beta_{n,j}$, and the feedback coefficient of velocity difference $\gamma$. Based on the calibration results of the optimal velocity function, the relevant parameters are determined as follows: $V_1 = 2.9$ m/s, $V_2 = 7.08$ m/s, $C_1 = 0.15$ m/s, $C_2 = 3.32$ m/s, $L_{n-1} = 4.57$ m, and $\gamma = 0.73$ [25]. These parameters are incorporated into (17), and the stability of the traffic flow is calculated for different values of $\beta_{n,j}$. Figure 3 shows the calculation results, where the stable area of the traffic flow is above the curve, and the unstable area is just below.

As seen, when the headway is less than 0.5 m or greater than 8.5 m, the traffic flow is stable. Adversely, when it is between 0.5 m and 8.5 m, the traffic flow is unstable. As parameter $\beta_{n,j}$ decreases, the stable interval of the traffic flow gradually increases. Hence, a smaller perception of headway is conducive to the stability of the traffic flow. In other terms, it is easier to stabilize the traffic flow by adjusting the driver's perception headway.

4.2. Vehicle Trajectory Results. To further verify the feasibility of the proposed fuzzy FVD model, the acceleration, velocity, and position of the adjacent preceding vehicle at each time step and the same parameters together with the headway of the following vehicle at the initial moment are treated as inputs to simulate the vehicle trajectories. It should be noted that the distance mentioned in this paper refers to the length between the current position of the vehicle and the starting point of the road. In addition, it is assumed that the adjacent vehicles on the actual road are represented by the preceding vehicle and the following vehicle, respectively.

Figure 4 shows the actual and the simulated trajectories of the parameter calibration vehicles $V_{1712}$ and $V_{1720}$. It can be seen from Figure 4(a) that the IDM and the fuzzy FVD models can roughly simulate the trajectory trends of aggressive drivers after calibration. Compared to the actual data, the simulation trajectory of the IDM is conservative, especially in the period of 485 s–515 s. The error between the actual and the simulated headways first decreases and then increases, leading to poor fitting accuracy. In contrast, FVD could not simulate the trajectory realistically because the gaps between the preceding vehicle and the follower are less than zero in the periods of 469.2 s–474.7 s for vehicle $V_{1712}$. Noncongested conditions, $\bar{T}_n(t)$ is the expected time headway, and $\beta$ is the model parameter.

After the genetic algorithm converges, the mean square errors of $V_{1712}$ and $V_{1720}$ in the IDM model are calculated as 1.57 and 2.21, respectively. Table 6 lists the specific parameter calibration results of the two vehicles.

The mean square errors of $V_{1712}$ and $V_{1720}$ in the FVD model are calculated as 1.61 and 2.25, respectively. Table 7 lists the specific parameter calibration results of the two vehicles.

Table 4: Membership function graph of the velocity fuzzy sets.

Figure 2: Membership function graph of the velocity fuzzy sets.

Table 5: Calibration results of the fuzzy set for $V_{1720}$.

<table>
<thead>
<tr>
<th>Fuzzy set</th>
<th>Velocity set</th>
</tr>
</thead>
<tbody>
<tr>
<td>VS</td>
<td>0.00</td>
</tr>
<tr>
<td>VM</td>
<td>4.42</td>
</tr>
<tr>
<td>VB</td>
<td>7.38</td>
</tr>
<tr>
<td>HS</td>
<td>6.92</td>
</tr>
<tr>
<td>HSM</td>
<td>16.74</td>
</tr>
<tr>
<td>HMB</td>
<td>21.5</td>
</tr>
<tr>
<td>HB</td>
<td>30.31</td>
</tr>
<tr>
<td>PS</td>
<td>0.75</td>
</tr>
<tr>
<td>PM</td>
<td>0.84</td>
</tr>
<tr>
<td>PB</td>
<td>0.92</td>
</tr>
</tbody>
</table>
especially when the velocity stop phenomenon occurs. Besides, between 480 s and 515 s, the actual vehicle has great acceleration, deceleration, and a speed maintenance process, but the IDM model and FVD model could not describe this phenomenon. The speed change trend of the fuzzy FVD model is similar to that of the real vehicle, which can accurately describe the local speed fluctuation and solve the problem of the poor fitting effect of the IDM in the case of large speed shock.

Figure 6 shows the actual and the simulated trajectories of the parameter validation vehicles \( V_{1735} \) and \( V_{1742} \). Overall, the headway of the IDM is relatively conservative compared to the real data. Especially in the periods of 480 s–490 s and 500 s–515 s, the headway error has a large-scale divergence phenomenon. Thus, it is difficult to simulate the real car-following process accurately with the IDM model. Similar to Figure 4, the vehicle trajectory of the FVD model has a large error with the actual trajectory and cannot simulate the running process of the vehicle well. In contrast, the vehicle trajectory of the fuzzy FVD model is consistent with the real data most of the time. Although there is a certain deviation between the actual and simulated data in some cases, it resides in an acceptable range. Besides, the simulation vehicle of the fuzzy FVD model has relatively constant headway with the adjacent preceding vehicle. Hence, it has strong stability, and the traffic flow system will not tend to diverge due to frequent speed disturbance. In conclusion, the simulation results of the fuzzy FVD are consistent with the real vehicle trajectory, so the model can be used to describe the car-following process.

To further investigate the fitting precision, we analyze the error of the fuzzy FVD model. Considering that the trajectory of the vehicle is closely related to its velocity and headway, we choose the root mean square percentage errors (RMSPE) used in the works of Wang et al. [29] and Zhu et al. [30] to characterize the fitting error of the model as follows:

\[
E_{\text{RMSPE}} = \sqrt{\frac{\sum_{i=1}^{N} (s_i^\text{sim} - s_i^\text{obs})^2}{\sum_{i=1}^{N} (s_i^\text{obs})^2}} + \sqrt{\frac{\sum_{i=1}^{N} (v_i^\text{sim} - v_i^\text{obs})^2}{\sum_{i=1}^{N} (v_i^\text{obs})^2}},
\]

where \( E_{\text{RMSPE}} \) is mean of the RMSPE, \( N \) is the total number of data samples, \( s_i^\text{sim} \) and \( s_i^\text{obs} \) are, respectively, the simulated and the actual headways of sample \( i \), and \( v_i^\text{sim} \) and \( v_i^\text{obs} \) are, respectively, the simulated and the actual velocities of sample \( i \).

Table 8 shows the RMSPE values of some calibrated vehicles. As seen, the RMSPE of the fuzzy FVD is under 0.25, and the overall fitting effect is better than the IDM and the

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### Table 6: Calibration results of \( V_{1712} \) and \( V_{1720} \) in the IDM model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( V_{1712} )</th>
<th>( V_{1720} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_{\text{max}}^{(n)} )</td>
<td>5.46 m/s²</td>
<td>6.2 m/s²</td>
</tr>
<tr>
<td>( a_{\text{comf}}^{(n)} )</td>
<td>3.68 m/s²</td>
<td>6.02 m/s²</td>
</tr>
<tr>
<td>( v_n(t) )</td>
<td>19.26 m/s</td>
<td>13.63 m/s</td>
</tr>
<tr>
<td>( s_{\text{jam}}^{(n)} )</td>
<td>8.73 m</td>
<td>7.69 m</td>
</tr>
<tr>
<td>( s_2^{(n)} )</td>
<td>0.52 m</td>
<td>0.30 m</td>
</tr>
<tr>
<td>( T_n(t) )</td>
<td>0.59 s</td>
<td>0.47 s</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.79</td>
<td>0.49</td>
</tr>
</tbody>
</table>

### Table 7: Calibration results of \( V_{1712} \) and \( V_{1720} \) in the FVD model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( V_{1712} )</th>
<th>( V_{1720} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.16 s⁻¹</td>
<td>0.21 s⁻¹</td>
</tr>
<tr>
<td>( L_{\text{av}-1} )</td>
<td>4.54 m</td>
<td>5.38 m</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>0.49 s⁻¹</td>
<td>0.62 s⁻¹</td>
</tr>
<tr>
<td>( V_1 )</td>
<td>3.02 m/s</td>
<td>2.76 m/s</td>
</tr>
<tr>
<td>( V_2 )</td>
<td>7.32 m/s</td>
<td>4.89 m/s</td>
</tr>
<tr>
<td>( C_1 )</td>
<td>0.13</td>
<td>0.64</td>
</tr>
<tr>
<td>( C_2 )</td>
<td>3.46</td>
<td>9.71</td>
</tr>
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</table>

---

The simulation results of the fuzzy FVD model are in relatively good agreement with the actual data. In particular, the simulated trajectories in the periods of 475 s–485 s and 500 s–515 s almost coincide with the actual trajectories. As seen in Figure 4(b), the IDM model is not ideal for the simulation results of the trajectory of conservative drivers. Similar to Figure 4(a), the traffic flow state drastically changes during the period of 485 s–515 s, and it is difficult for the vehicle simulated by the IDM to maintain a stable headway with the preceding vehicle. The FVD model cannot simulate the trajectory of vehicle 1720 well, especially between periods of 466.6 s–485.2 s. Furthermore, for the fuzzy FVD model, although the simulated headway is larger than the actual distance in the period of 455 s–475 s, it can often simulate the driving trajectory of timid drivers well.
Figure 4: The actual and simulated trajectories of parameter calibration vehicles. (a) $V_{1712}$. (b) $V_{1720}$.

Figure 5: The actual and simulated velocities of parameter calibration vehicles. (a) $V_{1712}$. (b) $V_{1720}$.

Figure 6: The actual and simulated trajectories of parameter validation vehicles. (a) $V_{1735}$. (b) $V_{1742}$. 
FVD model. Moreover, the average RMSPE values of FVD, IDM, and fuzzy FVD models are, respectively, 0.312, 0.308, and 0.213, which further validates that the proposed fuzzy FVD has good fitting precision.

5. Conclusions

This paper introduces the driver’s perception headway and suggests a fuzzy FVD model. Based on the control theory, the stability of the fuzzy FVD model is analyzed, and the stability conditions of the model are set. A fuzzy control rule is constructed which takes velocity and headway as input and perception headway coefficient as output through the fuzzy control method. Based on the NGSIM data, the genetic algorithm was operated to calibrate the FVD model, IDM, and fuzzy FVD model parameters, and the model was verified by simulation.

The results show that, with the decrease of perception headway coefficient, the traffic flow stability area increases gradually, which is conducive to the stability of traffic flow. The introduction of parameter $β_{n,j}$ allows the fuzzy FVD model to more accurately describe the local velocity fluctuations, besides solving the problem of the poor fitting effect of the IDM and FVD models when the speed changes sharply. The RMSPE of the fuzzy FVD model stays under 0.25, while its average value is around 0.213, which further verifies the applicability. Although the proposed fuzzy FVD model can improve the accuracy of trajectory fitting, there is still room for improvement. In future research, we will add auxiliary driving equipment to vehicles and introduce more road information to achieve stable regulation of traffic flow.

Data Availability

The data used to support the findings of this study are available from https://data.transportation.gov/Automobiles/Next-Generation-Simulation-NGSIM-Vehicle-Trajectory/8e8c7f-6jqj.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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### Table 8: Fitting precision of car-following models.

<table>
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<tr>
<th>Number</th>
<th>Preceding vehicle</th>
<th>Following vehicle</th>
<th>IDM</th>
<th>FVD</th>
<th>Fuzzy FVD</th>
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<tr>
<td>1303</td>
<td>1304</td>
<td>0.319</td>
<td>0.324</td>
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<td>1155</td>
<td>1159</td>
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<td>1048</td>
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<td>0.242</td>
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<tr>
<td>846</td>
<td>850</td>
<td>0.324</td>
<td>0.330</td>
<td>0.201</td>
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<tr>
<td>Average value</td>
<td>0.308</td>
<td>0.312</td>
<td>0.213</td>
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### References


