A Study of the Modified Microscopic Model Incorporating Weather Effect and Cooperative Behavior

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A study of the modified microscopic model incorporating weather effect and cooperative behavior

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Highlights:

- Incorporating the pulling and bad weather effects is a new addition to our proposed model of alleviating traffic instability.
- The pulling effect of the focal car relieves the restless follower by maintaining the gap.
- The bad weather effect is related to the driver's visibility while driving the vehicles.
- Analytical analysis of linearity has been carried out to assess our model's validation.
- The findings of the modified model are plausible and efficient in reducing traffic unrest.

Abstract

With advancements in science and technology, weather is not controlled by human mechanisms and disrupts various aspects of societal life. Especially in bad weather, traffic flow dynamics are severely affected. To address this issue, we develop a modified traffic model that mitigates traffic instability by building on the conventional full velocity difference (FVD) model and incorporating factors such as pulling effect and bad weather. These properties were previously absent in the FVD model, which exhibits internal traffic noise affecting the dynamics of traffic systems. To examine our proposed model, we conduct a linear stability analysis to capture the neutral stability conditions, dividing the area into three realms: stable, unstable, and metastable. Our findings demonstrate that the new model significantly outperforms the FVD model in eliminating traffic instability, offering a robust solution to maintaining stable traffic flow considering challenging weather.

PACS numbers: Theory and modeling; computer simulation, 87.15. Aa; Dynamics evolution, 87.23kg

Keywords: Pulling effect; Linearity; Bad weather effect; Microscopic model; Driver's visibility.

1. INTRODUCTION

Transportation engineering is one of the most thought-provoking research fields for potential researchers, with traffic congestion being today's buzzword. With the advancement of civilization, sciences, and technology, transportation demand is rising every moment. To mitigate this demand, we must incorporate many factors, such as the number of vehicles, road space, drivers, urbanization, etc. In the meantime, some models have been put forward for traffic flow dynamics, and some approximate solutions have also been found to alleviate this hazard. The traffic specialists studied several types of traffic models and classified them into microscopic and macroscopic categories. Considering some phenomena, researchers innovated empirical microscopic models [1-5], macroscopic models [6-8], cellular models [9-12], gas kinetic models [13-15], and lattice hydrodynamic models [16-18]. We focused on the car-following models from these established models, which are easily grasped due to the analytical and numerical investigations and exhibit traffic congestion from a microscopic standpoint. The optimal velocity model (OVM) [19] is a well-established model that has some inconsistencies, such as high acceleration and deceleration compared to field data, which is unacceptable. To overcome the OVM discrepancies, Helbing and Tilch [20] invented a traffic flow model named the generalized force model (GFM), which showed better agreement with empirical data and the number of parameters only two comparing the OVM. Subsequently, to release this intricacy, considering positive velocity differences, a more realistic and acceptable traffic model called the FVD model was derived by the eminent researchers Jiang et al. [21], which is the most reliable and effective model in traffic flow dynamics till now. The FVD model addressed the mentioned inconsistencies in the OVM and GF models, uncovering a new research avenue for emerging researchers. The horn effect is accumulated by Tang et al. [22-23], with the OVM extending equilibrium velocity in the case of moderate density and the car-following situations. From a macroscopic viewpoint, Hossain et al. [24] investigated the horn effect and found positive outcomes. Md. Z. Hosen et al. [25] introduced a new feature combining pulling and pushing effects in the car-following and continuum models to address traffic instability. H. Tan et al. [26] put forward a lattice hydrodynamics model considering the bad weather effect on phase transitions.

The manuscript is organized as follows: Section 2 discusses well-established traffic flow models and our proposed model formulation. Section 3 explains linearity, which derives neutral stability conditions, while conclusions are drawn in Section 4.

2. MODEL

Considering the traffic flow complexity, some models have been developed by researchers to address this issue. Among the pioneers in this field, Bando et al. [19] proposed the optimal velocity model (OVM) to calibrate the car-following model for a single lane without overtaking. The governing equation is described as follows:

$$v_n'(t) = a\left[V\left(\Delta x_n(t)\right) - v_n(t)\right] \tag{1}$$

where $\Delta x_n(t)$ is the headway distance between the focal and preceding cars, $V(\bullet)$ is the optimal velocity function depending on headway, a is the driver's constant sensitivity; $v_n(t)$ is the velocity of the n^{th} car at time t. Investigating this model, some inconsistencies have been found such as high acceleration and unrealistic deceleration, which are irrelevant to our real-life traffic flow dynamics. To address the deficiencies of the OVM, Helbing and Tilch [20] presented an improved generalized forced (GF) model, described below:

$$\begin{aligned} v_n'(t) &= a\left[V\left(\Delta x_n(t)\right) - v_n(t)\right] \\ &+ \lambda \Delta v_n(t) H(-\Delta v_n) \end{aligned} \tag{2}$$

where $H(x) = \{0,\ x < 0 \text{ and } 1,\ \text{x} \geq 0$ is the Heaviside function, $\Delta v_n(t) = v_{n+1}(t) - v_n(t)$ is the velocity difference between the focal and preceding cars λ represents the sensitivity different from a, and other symbols retain their previously defined meanings. The GF model did not exhibit good results compared with empirical traffic field data. In this continuation, Jiang et al. [21] introduced the Full Velocity Difference (FVD) model, which employs a positive velocity difference instead of a negative one. Their findings demonstrated highly efficient results, showing a strong correlation between their empirical and actual traffic flow data. The equation of motion of the FVD model is given by:

$$v_n'(t) = a\left[V\left(\Delta x_n(t)\right) - v_n(t)\right] + \lambda \Delta v_n(t) \tag{3}$$

where all symbols have the same meaning interpreted above and this model is widely recognized as a standard, well-acceptable, and realistic representation of the traffic flow dynamics.

Considering the abovementioned discussion and based on the FVD model [21], we propose a modified traffic flow model governed by the equation:

$$\begin{aligned} v_n'(t) &= a[\eta . p \cdot V_F\left(\Delta x_n(t)\right) + \eta .(1-p) \cdot \\ & V_{Fpull}\left(\Delta x_{n-1}(t)\right) - v_n(t)] + \eta . \lambda . \Delta v_n(t) \end{aligned} \tag{4}$$

where η is the bad weather effect related to driver's visibility, p is the weighted parameter of the Optimal Velocity (OV) function $V_F(\Delta x_n(t))$ describing the forward-looking effect; *(1-p)* presents the backward-looking effect termed the pulling effect of the focal car to the follower OV function $V_{Fpull}(\Delta x_{n-1}(t))$; a indicates the driver's sensitivity, and h_c is the safety distance. Here $V_F(\Delta x_n(t))$ signifies the forward effect depending on the headway distance ($x_n(t)$) between the focal and preceding vehicles. When the headway gap is larger between the focal and follower vehicles, that is, $\Delta x_{n-1}(t) > h_c$, the focal car decelerates its speed to reduce this gap and retains the standard headway distance to pull the follower. Consequently, the follower does not become aggressive or disappointed due to the large distance or suddenly not being inspired to accelerate at high speed, which may cause accidents. In this formulation, $p>0.5$ due to real perspective. The two types of OV functions can be defined in the following functions [19-25]:

$$\begin{aligned} V_F\left(\Delta x_n(t)\right) &= (v_{max}^F)/2.[tanh\left(\Delta x_n(t) - h_c\right) \\ &+ tanh\left(h_c\right)] \end{aligned} \tag{5}$$

$$\begin{aligned} V_{Fpull}\left(\Delta x_{n-1}(t)\right) &= (-v_{max}^{Fpull})/2.[tanh\left(\Delta x_n(t) - h_c\right) \\ &+ tanh\left(h_c\right)] \end{aligned} \tag{6}$$

in our proposed model, the behavior exhibits unstable and constant on the other hand; h_c is the safety distance. Let $v_{max}^F = 2$ and $v_{max}^{Fpull} = 1$ are the maximum speeds of the forward and pulling effects of the vehicles in the free flow state. The optimal velocity functions demonstrate the behavior depicted in the following graph. Fig. 1 illustrates the forward-looking effect with a red line and the

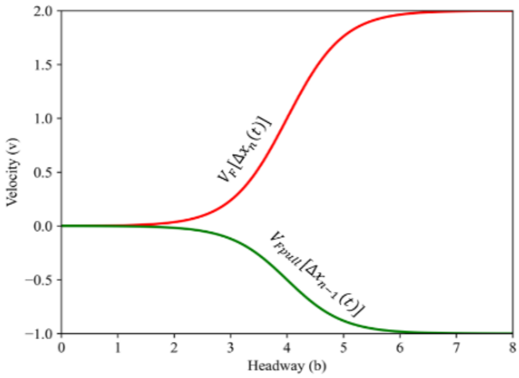


Fig. 1: The forward and pull optimal velocity functions representation for headway-velocity.

3. LINEARITY ANALYSIS

Linear stability analysis is a powerful tool in mathematics and transportation system engineering. It is used to examine the stability of traffic flow patterns. Here, we use this to investigate the stability of uniform flow of the car-following model which is interpreted in equations (4), (5), and (6). The steady-state flow can be described as vehicle movement with fixed headway b with forward, bad weather, and pull effects. Hence, for uniform flow, the steady state solution is given:

$$x_n^0(t) = bn + [\eta.p.V_F(b) + \eta.(1-p).V_{Fpull}(b))]t \quad \text{and} \quad b = L/N \tag{7}$$

where L denotes the length of the road assuming cyclic boundary conditions and the total number of cars is N. Let us consider the perturbed solution $y_n(t)$, indicating a small breach from the steady-state solution $x_n^0(t)$: $x_n(t) = x_n^0(t) + y_n(t)$ and $y_n(t) = x_n(t) - x_n^0(t)$

(8)

From (10/8) we have, $\dot{y}_n(t) = \dot{x}_n(t) - \dot{x}_n^0(t)$,

$$\ddot{y}_n(t) = \ddot{x}_n(t)$$

$$\Delta y_n(t) = y_{n+1}(t) - y_n(t) \tag{9}$$

In that case, $v_n(t)$ can be written as:

$$v_n(t) = \dot{x}_n^0(t) + \dot{y}_n(t) = \eta.p.V_F(b) + \eta.(1-p).V_{Fpull}(b) + \dot{y}_n(t) \tag{10}$$

$\Delta x_n(t)$ can be written as:

$$\Delta x_n(t) = x_{n+1}(t) - x_n(t) = b + \Delta y_n(t) \tag{11}$$

$\Delta v_n(t)$ can be written as:

$$\Delta v_n(t) = v_{n+1}(t) - v_n(t) = \Delta\dot{y}_n(t)$$

and $v_{n+1}(t) - v_n(t) = \dot{y}_{n+1}(t) - \dot{y}_n(t)$ (12)

pulling effect with a green line, highlighting their comparative characteristics. Both lines start from 0 when their headway distance is in initial. As the headway increases, the forward-looking rises, while the pulling effect falls. The maximum velocity for the forward is considered 2, and for the pulling, it is 1, since the forward is typically greater than other effects in the real sense.

Considering

$$\dot{x}_n^0(t) = \eta.p.V_F(b) + \eta.(1-p).V_{Fpull}(b) \tag{13}$$

From (1), We have

$$y_n''(t) = a[\eta.p.V_F'(b)\Delta y_n(t) + \eta.(1-p).V_{Fpull}'(b) \Delta y_{n-1}(t) - y_n'(t)] + \eta.\lambda.\Delta y_n'(t) \tag{14}$$

Where,

$\Delta y_n(t) = y_{n+1}(t) - y_n(t), (t) V_F'(b) = dV_F(\Delta x_n)/d\Delta x_n|_{\Delta x_n(t)=b}$,

$V_{Fpull}'(b) = dV_{Fpull}(\Delta x_{n-1})/d\Delta x_{n-1}|_{\Delta x_{n-1}(t)=b}$

Suppose, $y_n(t) = e^{(ikn+zt)} \Rightarrow \dot{y}_n(t) = ze^{(ikn+zt)}$

$$\Rightarrow \ddot{y}_n(t) = z^2 e^{(ikn+zt)} \tag{15}$$

$$\Delta y_n(t) = y_{n+1}(t) - y_n(t) = e^{(ikn+zt)}(e^{ik} - 1) \tag{16}$$

$\Delta\dot{y}_n(t) = \dot{y}_{n+1}(t) - \dot{y}_n(t) = ze^{(ikn+zt)}(e^{ik} - 1)$,

and $y_{n-1}(t) = e^{ikn+zt}.e^{-ik}$ (17)

Substituting (8) to (17) into (14), we then obtain

$$z^2 = a[\eta.p.V_F'(b)(ik + (ik)^2/2) + \eta.(1-p). V_{Fpull}'(b)(ik - (ik)^2/2) - z_1(ik) - z_2(ik)^2] + \eta.(\lambda z_1(ik) + \lambda z_2(ik)^2).(ik + (ik)^2/2) \tag{18}$$

Suppose $e^{ik} = 1 + ik + (ik)^2/2$, and

$$z = z_1(ik) + z_2(ik)^2 + \ldots.. \tag{19}$$

Substituting this value into (18) and comparing the coefficients of (ik) and $(ik)^2$:

$$z_1 = \eta.p.V_F'(b) + \eta.(1-p).V_{pull}'(b) \tag{20}$$

$$z_1^2 = a.\eta.p.V_F'(b)/2 + a.\eta.(1-p). V_{Fpull}'(b)/2 - az_2 + \eta.\lambda.z_1$$

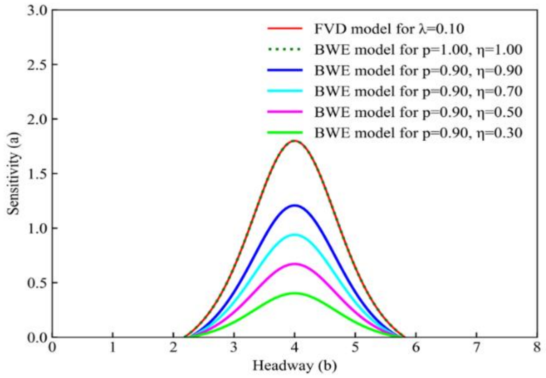
$$\Rightarrow z_2 = 1/a.[-[\eta.p.V_F'(b) + \eta.(1-p).V_{Fpull}'(b)]^2 + \eta.\lambda.[\eta.p.V_F'(b) + \eta.(1-p).V_{Fpull}'(b)]] + \eta.p.V_F'(b)/2 - \eta.(1-p).V_{Fpull}'(b)/2 \tag{21}$$

Letting $z_2 = 0$, we have the neutral stability conditions:

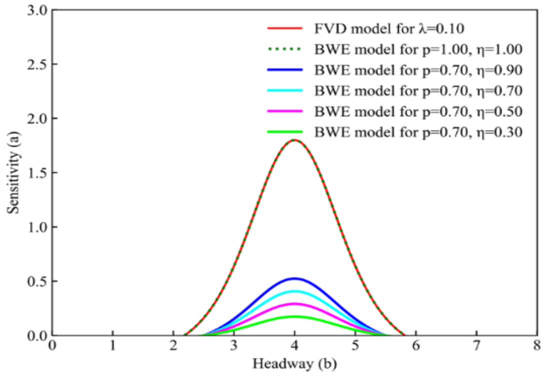
$$a = (2.\eta.[p.V_F'(b) + (1-p).V_{Fpull}'(b)]^2 - 2.\eta. \lambda[p.V_F'(b) + (1-p).V_{Fpull}'(b)]) /(p.V_F'(b) - (1-p).V_{Fpull}'(b)) \tag{22}$$

If $p = \eta = 1$ in (22) termed as the conventional FVD model [21].

(a-1)



(a-2)



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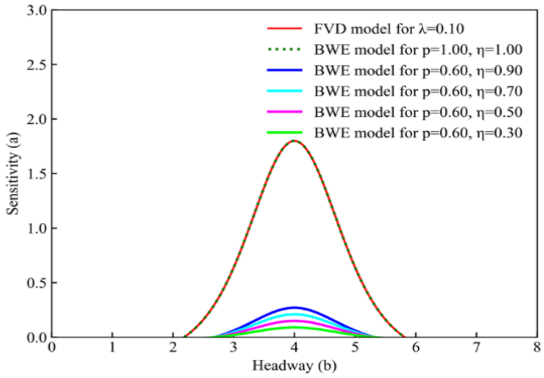
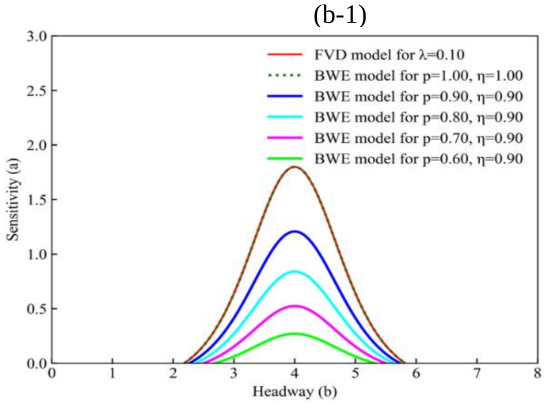
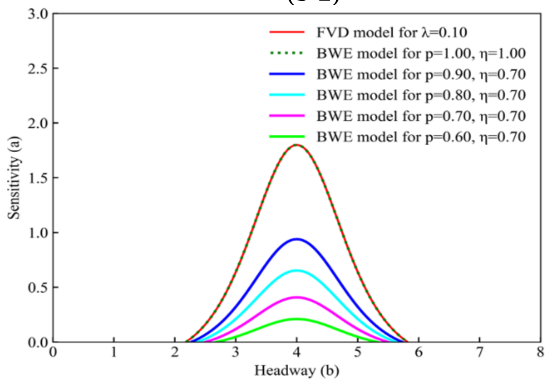


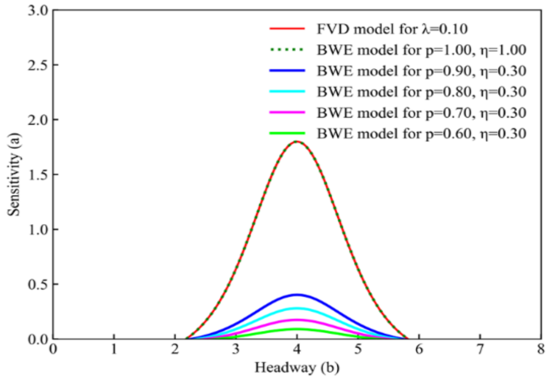
(b-1)



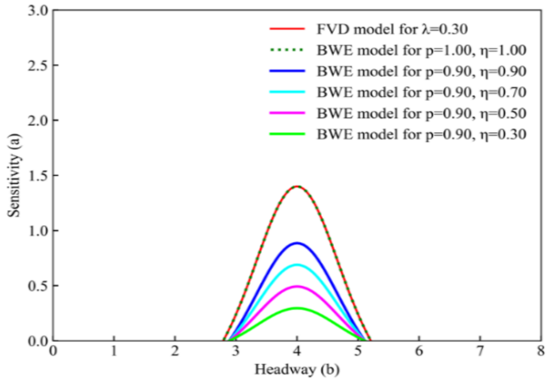
(b-2)



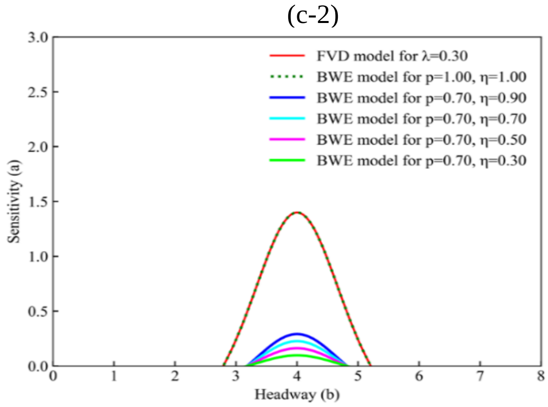
(b-3)



(c-1)



(c-2)



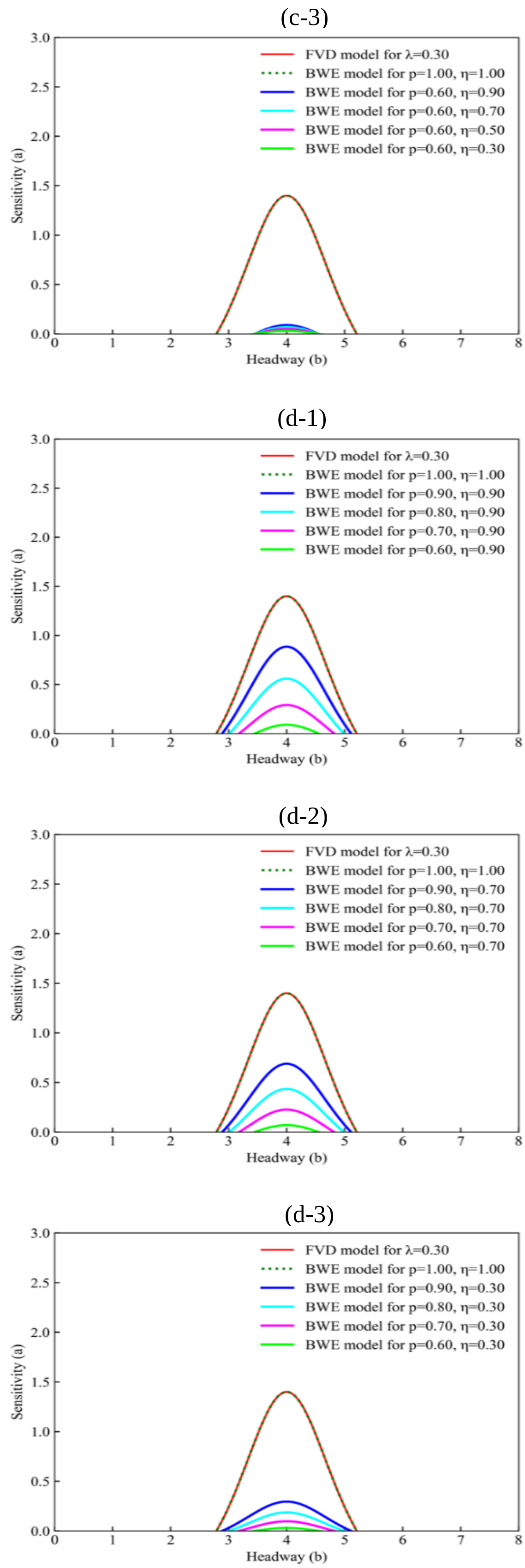


Fig.2: Neutral stability of headway-sensitivity profiles for different parameter values of p and η with $\lambda = 0.1, 0.3$.

A comparative analysis of our proposed traffic model for parameter values p and η are analyzed from a headway versus sensitivity perspective based on neutral stability conditions. The neutral stability curves divide into three realms: stable, unstable, and metastable, which are shown in four panels such as (a-1) to (a-3) and (b-1) to (b-3) for λ=0.1; (c-1) to (c-3) and (d-1) to (d-3) for λ=0.3. From the first panel (a-1) to (a-3), the forward-looking effect is kept fixed, while the bad weather effect η=*0.90, 0.70, 0.50, 0.30* decreases, indicating improved visibility effect and increased traffic stability. Consequently, decreasing the forward-looking effect *p=0.90, 0.70, 0.60*, indicating the pulling effect increases. In the second panel (b-1) to (b-3), the weighted parameters *p=0.90, 0.80, 0.70, 0.60* decreases, the pulling effect increases simultaneously. The bad weather effect η=*0.90, 0.70, 0.30* remains fixed, enhancing traffic flow due to the increased pulling effect. The decreasing bad weather effect demonstrates that driver visibility increases. The remaining panels (c-1) to (c-3) and (d-1) to (d-3) for λ=0.3 illustrate similar behaviors to the first two panels. From the four panels' discussion, decreasing the pulling and bad weather effects demonstrate overall the metastable

region and stability increase. So, our proposed model enhances traffic flow stability by incorporating bad weather and pulling effects, demonstrating significant improvements compared to the conventional FVD model.

4. CONCLUSIONS

In this study, we investigate a modified traffic flow model incorporating bad weather and pulling effects, expanding upon the conventional FVD model to address traffic instability from a microscopic perspective. To illustrate our model, we define a bad weather effect and introduce two optimal velocity functions that capture their real-world behaviors. The pulling demonstrates the cooperation of the focal vehicle with its followers. At the same time, the bad weather effect accounts for reduced the driver's visibility, indicating a positive impact on traffic flow dynamics. We examine our proposed model validation utilizing the linear stability property from both mathematical and graphical points of view, deriving the neutral stability curves that distinguish stable, unstable, and metastable regions. The findings of our work are plausible, captivating, and efficient in mitigating the instability of traffic flow dynamics.

Our next plan is to extend this model to a macroscopic scale in future studies through nonlinear analysis and numerical simulations in detailed explanations. Despite some limitations in this modified model related to parameters that will be explored thoroughly in the next plan, the findings of our proposed model are both captivating and realistic.

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REFERENCES

[1] Tanimoto, J. Traffic Flow Analysis Dovetailed with Evolutionary Game Theory. In: Tanimoto, J., Ed., Fundamentals of Evolutionary Game Theory, and Its Applications, Vol. 6, Springer 2015, Tokyo, 159-182.https://doi.org/10.1007/978-4-431-54962-85

[2] Nagatani, T. Modified KdV Equation for Jamming Transition in the Continuum Models of Traffic. Physica A: Statistical Mechanics and its Applications 1998, 261,599-607. https://doi.org/10.1016/S0378- 4371(98) 003471

[3] Hossain MA, Tanimoto J. A dynamical traffic flow model for cognitive drivers' sensitivity in Lagrangian scope. Sci Rep 2022; 12. https: //doi.org/10.1038/s41598-022- 22412-9.

[4] Tang TQ, Huang HJ, Shang HY. An extended macro traffic flow model accounting for the driver's bounded rationality and numerical tests. Phys A Stat Mech Its Appl 2017; 468:322–33. https://doi.org/10.1016/j.physa.2016.10.092.

[5] Tanimoto J, An X. Improvement of traffic flux with the introduction of a new lane-change protocol supported by Intelligent Traffic System. Chaos, Solitons and Fractals 2019; 122:15. https://doi.org/10.1016/j.chaos.2019.03.007.

[6] Newell G.F. Nonlinear Effects in the Dynamics of Car Following. Oper Res 1961; 9:209–29. https://doi.org/10.1287/opre.9.2.209.

[7] Li X, Cui J, An S, Parsafard M. Stop- and-go traffic analysis: Theoretical properties, environmental impacts, and oscillation mitigation. Transp Res Part B Method 2014; 70:319–39. https://doi.org/10.1016/j.trb.2014.09.014.

[8] Tian J, Treiber M, Ma S, Jia B, Zhang W. Microscopic driving theory with oscillatory congested states: Model and empirical verification. Transp Res Part B Method 2015;

[9] Jiang R, Jin CJ, Zhang HM, Huang YX, Tian JF, Wang W, et al. Experimental and empirical investigations of traffic flow instability Transp Res Part C Emerg Technol 2018; 94:83–98. https://doi.org/10.1016/j.trc.2017.08.024.

[10] Tanimoto J, Nakamura K. Social dilemma structure hidden behind traffic flow with route selection. Phys A Stat Mech Its Appl 2016; 459:92–9. https://doi.org/10.1016/j.physa.2016.04.023.

[11] Hossain MA, Tanimoto J. A microscopic traffic flow model for sharing information from vehicle to vehicle by considering the system time delay effect. Phys A Stat Mech Its Appl 2022;585. https://doi.org/10.1016/j.physa.2021.126437.

[12] Nagel K, Schreckenberg M, Nagel K, Schreckenberg M. A cellular automaton model for freeway traffic to cite this version:cellular. J Phys I 1992; 2:2221–9. https://doi.org/10.1051/jp1:1992277.

[13] Ge HX, Lv F, Zheng PJ, Cheng RJ. The time ependent Ginzburg-Landau equation for the car-following model considering anticipation-driving behavior. Nonlinear Dyn 2014; 76:1497–501. https://doi.org/10.1007/s11071-013-1223-y.

[14] Jiang R, Hu M Bin, Zhang HM, Gao ZY, Jia B, Wu QS. On some experimental features of car- following behavior and how to model them. Transp Res Part B Method 2015; 80:338–54. https://doi.org/10.1016/j.trb.2015.08.003.

[15] Tang TQ, He J, Yang SC, Shang HY. A car following model accounting for the driver's attribution. Phys A Stat Mech Its Appl 2014; 413:583–91. https://doi.org/10.1016/j.physa.2014.07.035.

[16] Y.K.D. Sun, Lattice hydrodynamic traffic flow model with explicit drivers ' physical delay, (2013) 531–537. https://doi.org/10.1007/s11071-012-0679-5.

[17] T. Wang, Z. Gao, J. Zhang, A new lattice hydrodynamic model for two-lane traffic with the consideration of density difference effect, (2014) 27–34.https://doi.org/10.1007/s11071-013-1046-x.

[18] T. Nagatani, Jamming transition in a two-dimensional traffic flow model, 59 (1999) 4857–4864.

[19] Bando M, Hasebe K, Nakayama A, Shibata Xagoya University A, Sugiyarna JY. Dynamical model of traffic congestion and numerical simulation, Phys. Rev.E., 1995;1035–1042, http://dx.doi.org/10.1103/PhysRevE.51.1035.

[20] Helbing D, Tilch B. Generalized force model of traffic dynamics. vol. 58. 1998. https://doi.org/10.1103/Phys RevE.58.133.

[21] Jiang R, Wu Q, Zhu Z. Full velocity difference

model for a car-following theory. Phys Rev E Stat Physics, Plasmas, Fluids, Relat Interdiscip Top 2001;64:4. https://doi.org/10.1103/PhysRevE.64.017101
[22] Hossain MA, Tanimoto J. Diverse reactivity model for traffic flow dynamics in Eulerian scope. Nonlinear Dyn 2023;111:17369–78. https://doi.org/10.1007/s11071-023-08734-x.
[23] Tang TQ, Li CY, Wu YH, Huang HJ.Impact of the honk effect on the stability of traffic flow. Phys A Stat Mech Its Appl 2011; 390:3362–8. https://doi.org/10.1016/j.physa.2011.05.010.
[24] Hossain MA, Tanimoto J. The “backward-looking” effect in the continuum model considers a new backward equilibrium velocity function. Nonlinear Dyn 2021;106: 2061–72. https://doi.org/10.1007/s11071-021-06894-2.
[25] Z. Hosen, A. Hossain, J. Tanimoto, Traffic model for the dynamical behavioral study of a traffic system imposing push and pull effects, Phys. A Stat. Mech. Its Appl. 645 (2024)129816. https://doi.org/10.1016/j.physa.2024.129816.
[26] H. Tan, C. Yin, G. Peng, Impact of the visibility effect on phase transitions in lattice hydrodynamic model under the bad weather traffic environment, Chinese J. Phys. 89 (2024) 46–55. https://doi.org/10.1016/j.cjph.2024.01.035.