

Modelling and simulation of autonomous train operation based on a car-following model

Guangyi Ma(马广义) and Keping Li(李克平)
Citation: Chin. Phys. B, 2025, 34 (**10**): 104502. DOI: 10.1088/1674-1056/adf17b
http://cpb.iphy.ac.cn; http://iopscience.iop.org/cpb

What follows is a list of articles you may be interested in

Effect of speed humps on instantaneous traffic emissions in a microscopic model with limited deceleration capacity

Yu-Chen Hu(胡宇晨), Qi-Lang Li(李启朗), Jun Liu(刘军), Jun-Xia Wang(王君霞), and Bing-Hong Wang(汪秉宏)
Chin. Phys. B, 2024, 33 (**6**): 064501. DOI: 10.1088/1674-1056/ad2608

Efficient control of connected and automated vehicles on a two-lane highway with a moving bottleneck

Huaqing Liu(刘华清) and Rui Jiang(姜锐)
Chin. Phys. B, 2023, 32 (**5**): 054501. DOI: 10.1088/1674-1056/acb918

A stochastic two-dimensional intelligent driver car-following model with vehicular dynamics

Hong-Sheng Qi(祁宏生) and Yu-Yan Ying(应雨燕)
Chin. Phys. B, 2023, 32 (**4**): 044501. DOI: 10.1088/1674-1056/ac8f3c

Traffic flow of connected and automated vehicles at lane drop on two-lane highway: An optimization-based control algorithm *versus* a heuristic rules-based algorithm

Huaqing Liu(刘华清), Rui Jiang(姜锐), Junfang Tian(田钧方), and Kaixuan Zhu(朱凯旋)
Chin. Phys. B, 2023, 32 (**1**): 014501. DOI: 10.1088/1674-1056/ac9369

A modified heuristics-based model for simulating realistic pedestrian movement behavior

Wei-Li Wang(王维莉), Hai-Cheng Li(李海城), Jia-Yu Rong(戎加宇), Qin-Qin Fan(范勤勤), Xin Han(韩新), and Bei-Hua Cong(丛北华)
Chin. Phys. B, 2022, 31 (**9**): 094501. DOI: 10.1088/1674-1056/ac65f8

Modelling and simulation of autonomous train operation based on a car-following model

Guangyi Ma(马广义) and Keping Li(李克平)†

School of Systems Science, Beijing Jiaotong University, Beijing 100044, *China*

(Received 26 December 2024; revised manuscript received 13 July 2025; accepted manuscript online 18 July 2025)

The growing demand for capacity has prompted the rail industry to explore next-generation train control systems, such as train autonomous operation control systems, which transmit real-time information between trains with the help of train-to-train communication. The communication delay affects the operation of the system. In addition, the train monitors real-time traffic information through on-board sensors. However, no measurement can be perfect, including sensors, which are affected by factors such as railway geometry and weather conditions. The sensor detection error is uncertain, resulting in multiple information uncertainties. Therefore, this paper proposes a train-following model based on the full velocity difference model by considering multiple information uncertainties and communication delay time to describe the autonomous operation of the train under a train autonomous operation control system. Based on this train-following model, a stability analysis and numerical simulation of train traffic flow are carried out. The results show that when the velocity measured by the sensor is smaller than the real velocity or the headway monitored by the sensor is greater than the real headway, the delay will increase and continue to propagate and accumulate backward, resulting in blockage. Otherwise, the opposite occurs. These findings suggest that the effects of multiple information uncertainties are two-sided, depending on the degree of uncertainty of velocity information and headway information. In addition, communication delay time has little effect on train flow and delay.

Keywords: car-following model, train autonomous operation control system, communication delay time, multiple information uncertainties

PACS: 45.70.Vn, 94.20.Xa, 43.60.Dh

DOI: 10.1088/1674-1056/adf17b **CSTR:** 32038.14.CPB.adf17b

1. Introduction

With the booming development of urban rail transit at home and abroad and the increasing demand for operational capacity of rail transport lines, infrastructure managers are faced with a huge challenge to continuously expand the capacity of existing networks. In addition to deploying new rail networks to accommodate higher train speeds and capacities there is also a need to minimize train intervals and increase capacity and volume on existing lines.[1] Train operation control systems, as the core for ensuring the safety and efficiency of train operation, have become an important breakthrough point for railways to further enhance and meet operational demands. A train control system centered on the train is a hot topic, encompassing train-to-train communication and train autonomy technology; it is also known as a train autonomous operation control system.

A train autonomous operation control system is an advanced and applied development of a train automatic control system, and represents a new trend in the development of train control systems, featuring environmental perception and self-adaptation capabilities. The main difference between the two types of control system is that a train autonomous operation control system relies on communication technology to achieve direct communication between trains and is based on on-board intelligence, while in a train automatic control system communication is between trains and the ground and depends on external instructions. A train autonomous operation control system is based on train self-discipline to realize autonomous train operation paths, autonomous train protection and autonomous train operation adjustments. Among these, train safety autonomous operation is a key part that needs to be studied in depth.[2]

Due to the complexity and nonlinearity of train-tracking operations under a train autonomous operation control system it is difficult to establish an accurate mathematical model for comprehensive analysis so computer simulation is an ideal research method. The car-following model is an important traffic simulation model that can simulate various traffic phenomena in real traffic, such as stop-and-go.[3–7] Helbing and Tilch[8] found that the optimal velocity model would experience excessive acceleration and unrealistic deceleration, and proposed a general force model. On the basis of the general force model, Jiang *et al.*[9] considered the influence of positive velocity difference and deduced the full velocity difference model. Li *et al.*[10] proposed a new train flow model based on the car-following model which considered the distance between the train heads and the safe stopping distance. Based on the op-

†Corresponding author. E-mail: kpli@bjtu.edu.cn

© 2025 Chinese Physical Society and IOP Publishing Ltd. All rights, including for text and data mining, AI training, and similar technologies, are reserved.

timal velocity model, Ye *et al.*[11] introduced the train cruise mode to reduce train energy consumption. Corman *et al.*[12] developed a series of railway traffic dynamics models based on velocity stochastic processes, extending the car-following model to specific railway constraints. Saidi *et al.*[13] introduced a new train-following model that can accurately capture the interactions among trains and predict delays based on the spacing between adjacent trains. The results show that this model can accurately reflect train operating conditions under both normal and interrupted conditions. Up to now, most the research on the car-following model has focused on the analysis and discussion of road traffic problems and has rarely been used to study rail traffic. In fact, the car-following model is more suitable for the simulation of rail transit, because in rail transit the action between trains is one way and the current train only reacts to the incentive effect from the train in front, all of which meet the assumptions of the car-following model.

Under a train autonomous operation control system, the train can realize direct communication between trains by means of train-to-train communication. Due to factors such as thermal noise, contention, multipaths and signal blocking, train-to-train communication time can be delayed. Seo *et al.*[14] put forward a macroscopic and dynamic model of urban rail transit that considers delay and congestion. Quaglietta *et al.*[1] proposed a novel train-following model considering communication delay that captures the operating state and corresponding transitions of trains operating under virtual coupling. Bai *et al.*[15] investigated the coordinated control problem of multi-car high-speed train systems in the presence of unknown communication delays. Considering the inertia lag of servo motors, a third-order nonlinear control model was constructed to capture the dynamic characteristics of trains during actual operation. Guo *et al.*[16] proposed an online optimization method based on particle swarm optimization for virtual coupling in train-to-train communication considering the uncertainty delay. The results showed that the proposed method significantly reduces the impact of uncertainty delay on virtual coupling. Based on the above analysis, study of the impact of communication delay on train traffic flow is an important consideration in the development of a train autonomous operation control system.

In real traffic, the movement of the vehicle is subject to many uncertainties, such as the weather, the judgment of the driver, the needs of the passengers and sensor detection errors, which can lead to uncertainties in multiple items of information. Li *et al.*[17] developed a novel car-following model considering the historical velocity information uncertainty to better describe real traffic. In order to research the effect of uncertainty in velocity information on traffic flow, Zhang *et al.*[18] put forward an extended optimal velocity model for a cooperative driving system. Zheng *et al.*[19] proposed a stochastic model considering spacing information uncertainty for mixed traffic flow in Lagrangian coordinates. Based on the level of uncertainty of multiple information items, Li *et al.*[20] established a generalized model to describe the dynamics of vehicles under the influence of sensor detection errors. Ye *et al.*[21] put forward an extended optimal velocity model for trains to research the stability of the car-following model considering the constraint of uncertain factors. Blanco-Castillo *et al.*[22] developed an ecological driving model to design efficient driving instructions that can adapt to the uncertainty of climatic conditions. Fuzzy numbers were used to model the uncertainties in temperature, air pressure and wind speed. Tang *et al.*[23] explored the optimization problem of emergency resource scheduling for major railway emergencies under the influence of multiple uncertainties. They also took into account the impacts of uncertainties such as resource demands, reserves and transportation costs. Traffic information is also a necessary prerequisite for the train to operate under a train autonomous operation control system. However, due to errors of sensor detection and information transmission, the accuracy of traffic information cannot be guaranteed. Therefore, the accuracy of traffic information is also an important consideration in the development of a train autonomous operation control system.

In conclusion, few of the current train-following models can take into account the factors that influence the dynamics of trains. As a result, it is difficult to accurately describe the motion situation of other trains in train-following mode under a train autonomous operation control system. A train autonomous operation control system relies on on-board intelligence and makes use of communication technology to enable direct communication between trains. It represents a leap from automation to intelligence and represents the trend of development of future train control systems. When a train runs under a train autonomous operation control system the on-board controller obtains information about the adjacent train through direct train-to-train communication, but when receiving the running status of the adjacent train the information transmission time will be delayed. At the same time, when acquiring its own state information, because its own sensor is easily affected by the railway geometry or weather state, the detection error will fluctuate, resulting in uncertainty about acquisition of its own state information, which not only directly affects the normal operation of the train but also indirectly affects the operation of other trains through train-to-train communication. The train autonomous operation control system is still in the experimental and development stage. Previous research mainly focused on the framework and structure, and there are few relevant theoretical studies. Our research mainly involves theoretical mathematical modeling, analysis of model stability and in-depth exploration of train flow characteristics. Therefore,

a train-following model based on the full velocity difference model is developed to describe train autonomous operation under a train autonomous operation control system and considers the uncertainties of multiple information and communication delay time. The linear stability of the train-following model during train tracking is analyzed. In addition, a train-tracking model is numerically simulated to simulate the autonomous operation state of the train under the train autonomous operation control system and to grasp the evolutionary characteristics of train flow and its influencing factors. This saves a lot of the cost of a train operating experiment, improves work efficiency, has important practical significance and provides theoretical support for the development of train autonomous operation control systems. The main contributions of this study are as follows. (1) Under the train autonomous operation control system, a train-following model based on the full velocity difference model is developed, which takes into account the uncertainties in multiple information items and communication delay time. (2) The uncertainty in multiple information items includes uncertainty of velocity information and of position difference. It can better describe the evolution of train flow under the train autonomous operation control system. (3) The linear stability of the train-following model during train autonomous operation is analyzed. The train-following model is numerically simulated to simulate the autonomous operation state of the train under the train autonomous operation control system, and to grasp the evolutionary characteristics of train flow and its influencing factors.

2. Model and methodology

2.1. Dynamical modeling

The train autonomous operation control system is based on train-to-train communication and train self-regulation, and is characterized by an autonomous train path, autonomous train protection and autonomous train adjustment. It grafts the trackside core control functions of the traditional communication-based train control system to the train, and highly integrates the train operation control system with the vehicle network control, traction and braking systems to reduce the amount of trackside equipment, optimize the system architecture, effectively reduce the transmission delay of communication of train control information, improve control accuracy, shorten the train-tracking interval and greatly improve operational efficiency. In addition to saving construction costs and operation and maintenance costs, the train is significantly improved in terms of safety, intelligence, efficiency and economy.

When a train runs under a train autonomous operation control system, the on-board controller obtains information about adjacent trains through direct train-to-train communication, but a delay in the information transmission time occurs when receiving the running status of adjacent trains. At the same time, when acquiring its own state information, because its own sensor is easily affected by railway geometry or the weather state, the detection error will fluctuate, leading to uncertainty when obtaining its own state information. Therefore, considering the above factors, a train-following model based on the car-following model under the train autonomous operation control system is proposed to simulate the train autonomous operation process. We construct the general framework of train flow based on the train operation mode under the autonomous operation control system of the train

$$\frac{\mathrm{d}v_n(t)}{\mathrm{d}t} = f(pv_n(t),\ qs_n(t-\tau),\ p\Delta v_n(t-\tau)), \tag{1}$$

where $v_n(t)$ is the velocity of train n, and $s_n(t)$ and $\Delta v_n(t)$ represent the position difference and velocity difference of the $(n-1)$th train and the nth train, respectively, p and q represent the degree of uncertainty of velocity information and position difference information, respectively, which are affected by the size of sensor detection errors. The degree of uncertainty about velocity difference and that of velocity information are classified into the same category. The reason for this is that the velocity difference of any train is calculated based on the velocity information of the current train and the adjacent train ahead of it. τ is the time delay of train-to-train direct communication signal transmission.

In order to carry out detailed theoretical analysis and numerical simulation, the full velocity difference model is used to describe the traffic flow dynamics of trains under the train autonomous operation control system. Therefore, the traffic flow dynamics of trains is designated as

$$\frac{\mathrm{d}v_n(t)}{\mathrm{d}t} = \alpha\left[V(qs_n(t-\tau)) - pv_n(t)\right] + kp\Delta v_n(t-\tau), \tag{2}$$

where α is the sensitivity parameter, k represents the velocity difference adjustment parameter and V is the optimal velocity of the train.

In this model, the formula for the optimal speed of subsequent trains in the train following process under the train autonomous operation control system is

$$V(qs_n(t-\tau)) = \frac{v_{\max}}{2}\left[\tanh\left(V(qs_n(t-\tau)) - h_{\mathrm{c}}\right) + \tanh\left(h_{\mathrm{c}}\right)\right]. \tag{3}$$

Due to the complexity of the situation when the train enters the station, when the station is occupied by the front train, the tracking speed of the subsequent train is still carried out according to the up formula, and when there is no train in the station the optimal speed of the approaching train is

$$V(qs_n(t-\tau)) = \frac{v_{\max}}{2}\left[\tanh(V(qs_n(t-\tau))\right.$$

$$-(pv_n(t)\cdot pv_n(t))/(2a_b))$$
$$+\tanh((pv_n(t)\cdot pv_n(t))/(2a_b))\big], \quad (4)$$

where $v_{\max}$ is the maximum speed, h_c is the safe distance and a_b is the maximum deceleration.

2.2. Stability analysis

The linear stability method is a widely used analytical tool in traffic flow research; it is used to study the dynamic stability of traffic systems, especially under the influence of long-wave disturbances. By linearizing the differential equations of the system, this method can derive the critical conditions that lead to instability in traffic flow, such as changes in traffic density, speed or control parameters that trigger congestion or fluctuations. However, the limitation of linear analysis is that it mainly focuses on the linearized disturbance behavior and may not fully capture nonlinear effects or short-wave instabilities. Nevertheless, linear stability analysis is considered to be an effective tool for studying traffic flow and the dynamic characteristics of similar systems due to its mathematical simplicity and insight into the overall behavior of the system. For a detailed discussion on stability analysis methods for general car-following models refer to Refs. [24–26], which provide mathematical derivations and in-depth analyses of practical applications.

In this paper, we extend the linear stability method from traditional traffic flow to train flow, and investigate the stability of train flow operation for trains under an autonomous operation control system. Train flow differs significantly from traffic flow in terms of dynamic characteristics, such as train operation being constrained by fixed tracks and signal systems, and coupling between trains is usually achieved through automatic control systems rather than the driver's reactions. Therefore, we adjusted the framework of linear stability analysis to be applicable to the autonomous operating scenario of trains. Specifically, we established a dynamic model of train movement and analyzed the response characteristics of trains to external disturbances during autonomous operation. By linearizing the train motion equations and introducing small disturbances, we derived the sufficient conditions for stability of train flow. Given that the initial state is stable, the distance between all trains is s^{e}, the train speed is v^{e} and $f(v^{\mathrm{e}}, s^{\mathrm{e}}, 0) = 0$ is satisfied. δv_n and δs_n are set to represent small deviations in speed and distance around the stationary state, $v_n = v^{\mathrm{e}} + \delta v_n$, $s_n = s^{\mathrm{e}} + \delta s_n$. By a first-order Taylor expansion of Eq. (1), we obtain

$$\begin{aligned}\frac{\mathrm{d}\delta v_n(t)}{\mathrm{d}t} &= f(v^{\mathrm{e}}, s^{\mathrm{e}}, 0) + f_n^v p\delta v_n(t) + f_n^s q\delta s_n(t-\tau)\\ &\quad + f_n^{\Delta v} p\delta\Delta v_n(t-\tau), \quad (5)\\ \frac{\mathrm{d}\delta v_n(t)}{\mathrm{d}t} &= f_n^v p\delta v_n(t) + f_n^s q\delta s_n(t) + f_n^{\Delta v} p\delta\Delta v_n(t)\end{aligned}$$
$$-\tau f_n^s q\frac{\mathrm{d}\delta s_n}{\mathrm{d}t} - \tau f_n^{\Delta v} p\frac{\mathrm{d}\Delta v_n}{\mathrm{d}t}, \quad (6)$$

where $f_n^v = \partial f/\partial v_n$, $f_n^s = \partial f/\partial s_n$, $f_n^{\Delta v} = \partial f/\partial\Delta v_n$.

Let $\delta v_n(t) = V\mathrm{e}^{\mathrm{i}wn+\lambda t}$ and $\delta s_n(t) = S\mathrm{e}^{\mathrm{i}wn+\lambda t}$, where V and S are constants. By using $\mathrm{d}s_n/\mathrm{d}t = v_{n-1} - v_n$ we get

$$S = V\frac{\mathrm{e}^{-\mathrm{i}w}-1}{\lambda}. \quad (7)$$

By plugging Eq. (7) into Eq. (6), we get the following equation:

$$\begin{aligned}&\lambda^2 - \lambda(f_n^v p + f_n^{\Delta v} p(1-\mathrm{e}^{-\mathrm{i}w})\mathrm{e}^{-\lambda\tau})\\ &-f_n^s q(1-\mathrm{e}^{-\mathrm{i}w})\mathrm{e}^{-\lambda\tau} = 0. \quad (8)\end{aligned}$$

If λ is the solution of the equation and its real value is $\mathrm{Re}(\lambda) \le 0$, the system is stable. It is clear that $w = 0$, $\lambda = 0$ is a solution to Eq. (8). We need to analyze λ as w changes. For this, let us expand λ into $\lambda = \mathrm{i}w\lambda_1 + w^2\lambda_2 + \cdots$, where λ_1 and λ_2 are real parameters. Substituting this expansion into the equation, the exponential terms are expanded to second order and the first $\vartheta(w)$ and second $\vartheta(w^2)$ terms are set to zero. After quite a long algebraic calculation, we get

$$\begin{aligned}\vartheta(w) &= 0, \quad \lambda_1 = \frac{f_n^s q}{f_n^v p}, \quad (9)\\ \vartheta(w^2) &= 0,\\ \lambda_2 f_n^v p &= -\lambda_1^2 + f_n^s q\left(\frac{1}{2} + \lambda_1\tau\right) + \frac{f_n^s q}{f_n^v} f_n^{\Delta v}\\ &= -\left(\frac{f_n^s q}{f_n^v p}\right)^2 + f_n^s q\frac{1}{2} + f_n^s q\frac{f_n^s q}{f_n^v p}\tau + \frac{f_n^s q}{f_n^v} f_n^{\Delta v}. \quad (10)\end{aligned}$$

Since $f_n^v \le 0$, $f_n^{\Delta v} \le 0$ and $f_n^s \ge 0$, so $\lambda_1 \le 0$. Hence, when $\lambda_2 \le 0$, the traffic is stable, and we get

$$-\left(\frac{f_n^s q}{f_n^v p}\right)^2 + f_n^s q\frac{1}{2} + f_n^s q\frac{f_n^s q}{f_n^v p}\tau + \frac{f_n^s q}{f_n^v} f_n^{\Delta v} \ge 0. \quad (11)$$

By defining $V_e' = -f_n^s/f_n^v$, we further get

$$-qv_e' - \frac{1}{2}p^2 f_n^v + f_n^v pqV_e'\tau - f_n^{\Delta v} p^2 \ge 0, \quad (12)$$

where $f_n^v = -\alpha$ and $f_n^{\Delta v} = k$.

Thus, the stability condition becomes

$$\alpha \ge \frac{2V_e' q + 2kp^2}{p^2 - 2V_e' pq\tau}. \quad (13)$$

In addition, the Fourier method can also be used for the novel model. Compared with the above method, the results are the same. However, the above method is more general, more engineering-oriented and more flexible. It is stronger in handling time delays and high-order expansions, and is particularly suitable for analyzing the stability issues of the train flow system in the context of train autonomous control. It is especially applicable to systems with complex multi-variable structures.

3. Numerical simulation

To evaluate the performance of the train-following model in an autonomous train control system, numerical simulations are conducted to simulate the longitudinal motion characteristics of multiple trains on a single-track line with a single station. The longitudinal motion of each train is modeled using Eq. (1). The performance parameters of all trains in the system are the same, there is a total of five trains, the maximum speed of the train is 10, the length of the train is 140 and the maximum acceleration and deceleration speed is 1. The train-following model in this paper is built under open boundary conditions, setting the length L of the monorail, and the boundary conditions are as follows: assuming that the departure time interval of trains is $T_g = 50$, when the time interval of the previous train leaving the starting point is T_g one train will immediately depart from the starting point, and the new train will immediately run according to the proposed model. When the train reaches position L, the train is free to exit the terminal.

In the simulation, we set the system $L = 10000$ and the iteration time to $T_s = 2000$. A station is set in the middle of the system, that is, in this simulation system the position of the station is $l = 5000$. When the train enters the station, it must stop for a certain period of time T_d before leaving the station, where T_d is called the station residence time. Due to the great difference between train operation and road vehicle operation, for example the range of acceleration of a vehicle on the road is large and the change in speed can be fast, while the range of acceleration during train operation is small, and considering the safety and comfort of the operation the rate of change of acceleration is also small. Therefore, the parameter k in the model is set to 0.01. The safety distance $h_c = 200$ is set, and the train running data are recorded after the train running simulation.

This numerical simulation was achieved through programming in MATLAB software, integrating the train-following model. The calculation was completed on a portable computer equipped with an AMD 3.20 GHz CPU and 16 GB RAM. Post-processing was carried out using MATLAB to generate time–distance curves for each train column under different conditions, thereby evaluating the performance of the train-following model.

3.1. The impacts of uncertainty in headway information and velocity information

In this part, we mainly study the impacts of uncertainty in headway information and velocity information on train flow. The position information for all vehicles on the track is obtained when the uncertainty parameters of the headway information and of the velocity information are used and other running control parameters are unchanged. Figures 1 and 2, respectively, show the time–space diagrams at different headway information uncertainty values q and velocity information uncertainty values p between $t = 0$ and $t = 1000$. Figures 1(a)–1(d) correspond to $q = 0.9$, 0.95, 1 and 1.05, with the fixed values $p = 1$, $\tau = 0$ and $T_d = 40$, while figures 2(a)–2(d) correspond to $p = 0.9$, 0.95, 1 and 1.05, with the fixed values $q = 1$, $\tau = 0$ and $T_d = 40$.

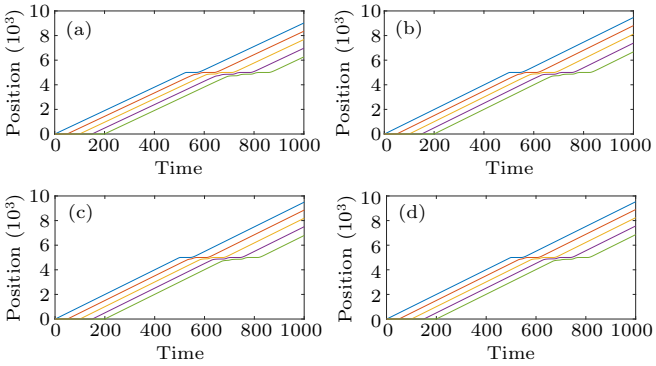


Fig. 1. Time–space diagrams for all trains with different values of headway information uncertainty.

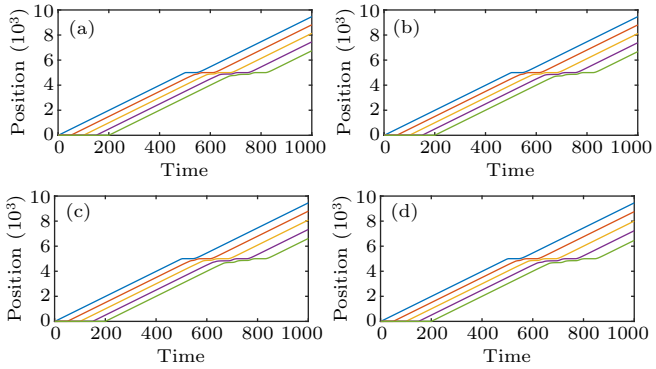


Fig. 2. Time–space diagrams for all trains with different values of velocity information uncertainty.

When the departure interval is fixed, the traffic density on the track is unchanged, and the slowing down and stopping of the train in front of it does not restrict the operation of the subsequent train and is not affected by the uncertainties in headway information and velocity information. Before the train enters the station, the dynamic characteristics of the train running near the station are extremely complex, requiring constant acceleration and deceleration. In this part, although the stopping time of the train remains unchanged, due to the influence of uncertainty about headway information and velocity information, the running time of the interval will also change. It can be clearly seen from Figs. 1 and 2 that the front train slows down in front of the station and stops, and the subsequent train is forced to slow down and wait for the station, thus causing the delay to spread backward and accumulate continuously. With an increase in headway information uncertainty or a decrease in velocity information uncertainty, the interval running time of trains increases, and the train delay propagates backward and accumulates continuously, and vice versa. In other words, when the measured speed of the train is

less than the true speed, or the detected headway of the train is greater than the true headway, the train interval running time increases, creating delays and spreading, otherwise the opposite occurs. This is because it is affected by the detection error of its own sensor, even if the stop time is unchanged. It can be seen that uncertainties in headway information and velocity information have an important impact on train autonomous operation, especially at a station.

3.2. The impact of communication delay time

In this section we mainly research the influence of communication delay time on train flow. By adjusting the communication delay time, the position information for all vehicles on the track is obtained. Figure 3 shows the time–space diagrams for all trains at different communication delay times. Figures 3(a)–3(d) correspond to $\tau = 0$, 1, 2 and 3, respectively. The remaining parameters remain the same ($p = q = 1$, $T_{\rm d} = 40$). As can be seen from Fig. 3, when the departure distance of trains is large, the operation of trains is not affected, train flow is in a free flow state and the deceleration and stopping of the train in front will not affect the operation of subsequent trains. When the trains enter the station, the trains interact with each other, and the influence is obvious. The communication delay time has a relatively minor influence on train delay. This is because during the stop time the distance traveled forward by the preceding train is slightly less than the safety distance, thus having a relatively small impact. Once the safety distance is reached, the train could move forward freely.

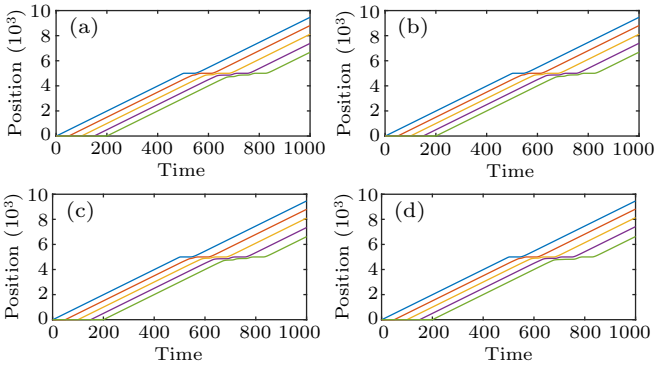


Fig. 3. Time–space diagrams for all trains with different communication delay times.

3.3. The impact of different station residence times

In this section we study the effect of train station residence time on train flow. Figure 4 shows the time–space diagrams for all trains at different station residence times. The station residence time is increased from 30 to 45, with an increase of 5 each time, corresponding to Figs. 4(a)–4(d), respectively. The other parameters are $q = p = 1$ and $\tau = 0$. As can be seen from Fig. 4, the longer the train stops at the station, the greater the delay caused to subsequent trains, showing a certain blocking characteristic. This is because when the departure interval is fixed the traffic density on the rail line is unchanged; when the station residence time is increased the subsequent train can only queue outside the station to wait. Under train renewal rules, delays spread backwards and accumulate. In this case, the train delay can be alleviated by increasing the departure interval and reducing the traffic density on the track line. It can be seen that the station residence time has a great impact on train operation. This result also shows that the train-following model can effectively show the phenomenon of delay in train operation.

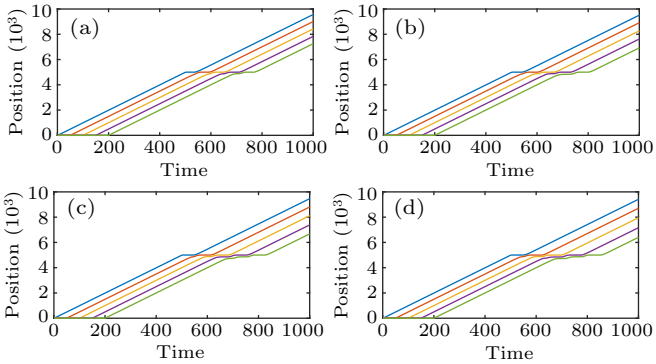


Fig. 4. Time–space diagrams for all trains with different station residence times.

4. Conclusion

In this study, a train-following model has been put forward based on the full velocity difference model for simulating a train autonomous operation process; it not only considers the influence of communication delay time but also the influence of multiple information uncertainties. Multiple items of information measured by the sensors are inconsistent with the real information. The linear stability of the train-tracking model during train tracking is analyzed. The results show that multiple information uncertainties have dual effects, which are both beneficial and harmful, depending on the degree of uncertainty about the velocity information and headway information. Specifically, in the train-tracking operation, the train is not affected by multiple information uncertainties and communication delay times, but at the station, when the velocity of the train monitored by the on-board sensor is less than the actual velocity, or the headway monitored by the on-board sensor is greater than the actual headway, train flow will be delayed and the backward propagation will increase the interval running time. In addition, the results will be reversed when the velocity of the train detected by the on-board sensors is greater than the actual velocity, or the headway detected by the on-board sensors is less than the actual headway. Communication delay times have little effect. In addition, the different stopping times of trains have a great influence on train flow. When the departure interval is fixed, the longer the stopping time of

the trains the greater the train delay. This provides theoretical support for the development of a train autonomous operation control system. In the future, when train autonomous operation control systems are applied in practice, actual train flow data will be collected from the real system and used to further verify the validity of the model. Furthermore, by integrating stochastic processes and taking into account the differences in train operating performance and train types, a more in-depth study will be conducted on heterogeneous train flows in complex scenarios such as multiple stations.

Acknowledgements

This work was supported by Beijing Natural Science Foundation (Grant No. L231009), the National Natural Science Foundation of China (Grant No. 72288101), and the Fundamental Research Funds for the Central Universities (Grant No. 2022JBZY017).

References

[1] Quaglietta E, Wang M and Goverde R M P 2020 *J. Rail Transport Pla.* **15** 100195
[2] Qing J Q, Lei C J and Liang B 2021 *Control Inf. Technol.* **472** 95
[3] Tan H T, Lu G Q, Wang Z J, Hua J and Liu M M 2024 *Simul. Model. Pract. Th.* **136** 102991
[4] Wang W J, Ma M H, Liang S D, Xiao J C and Yuan N T 2024 *Proc. Inst. Mech. Eng. D* **238** 1639
[5] Liu Z L, Yan M D and Zuo L 2025 *Phys. A* **660** 130357
[6] Peng G H, Luo C L and Tan H L 2025 *Chin. J. Phys.* **94** 789
[7] Wang S A, Shang M F, Levin M W and Stern R 2023 *Transport. Res. C* **146** 103967
[8] Helbing D and Tilch B 1998 *Phys. Rev. E* **58** 133
[9] Jiang R, Wu Q S and Zhu Z J 2001 *Phys. Rev. E* **64** 017101
[10] Li K P, Guan L J and Gao Z Y 2009 *Chin. Phys. B* **18** 2200
[11] Ye J J, Li K P and Jin X M 2013 *Chin. Phys. B* **22** 120206
[12] Corman F, Trivella A and Keyvan-Ekbatani M 2021 *Transport. Res. C* **128** 103167
[13] Saidi S, Koutsopoulos H N, Wilson N H M and Zhao J H 2023 *Transport. Res. C* **148** 104037
[14] Seo T, Wada K and Fukuda D 2017 *Transportation Research Board 96th Annual Meeting*, January 8–12, 2017, Washington D.C., The United States
[15] Bai W Q, Dong H R, Zhang Z X and Li Y D 2021 *IEEE Intell. Transp. Syst.* **23** 4331
[16] Guo Y X, Pei X, Luo X and Hou T G 2023 *IEEE Intell. Transp. Syst. Mag.* **15** 49
[17] Li S, Wang T, Cheng R J and Ge H X 2020 *Math. Probl. Eng.* **2020** 9546012
[18] Zhang G, Sun D H, Zhao M, Liao X Y, Liu W N and Zhou T 2018 *Phys. A* **505** 1008
[19] Zheng F, Liu C, Liu X, Jabari S E and Lu L 2020 *Transport. Res. C* **112** 203
[20] Li S, Zhou B and Xu M 2023 *Appl. Math. Model.* **123** 790
[21] Ye J J, Li K P and Jiang X D 2015 *Math. Probl. Eng.* **2015** 230616
[22] Blanco-Castillo M, Fernandez-Rodriguez A, Fernandez-Cardador A and Cucala A P 2022 *Sustainability* **14** 8645
[23] Tang Z P, Li W D, Zhou S Y and Sun J P 2023 *Appl. Sci.* **13** 4432
[24] Wilson R E and Ward J A 2011 *Transp. Planning Technol.* **34** 18
[25] Ngoduy D 2015 *Commun. Nonlinear Sci. Numer. Simulat.* **22** 420
[26] Ngoduy D and Li T L 2021 *Transportmetrica A* **17** 878