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Pollution Reduction and Carbon Reduction in Mixed Traffic Flow Environments under the Influence of LCI for Energy Consumption Analysis

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ABSTRACT
The accelerated progression of urbanisation has emerged as a pivotal factor in the escalating issue of global warming, with automobile exhaust emissions assuming a central role in this context. This phenomenon underscores the growing prominence of energy consumption and environmental pollution as critical concerns. To promote the healthy development of green and sustainable transportation systems, this study analyses the impact of lane change intention (LCI) on reducing pollution and carbon in mixed traffic flow. The study proposes a traffic energy consumption model to analyse the impact of LCI on vehicle energy consumption in a mixed traffic flow environment. The model combines the collaborative adaptive cruise control (CACC) strategy to explore energy consumption in a multidimensional mixed traffic environment. The results showed that vehicles with LCI in mixed traffic flow had an average energy consumption increase of 7.65% compared to vehicles driving normally. When the vehicle adopted CACC, it could effectively alleviate the increase in energy consumption caused by LCI. Vehicles with the LCI and applying CACC only increased their energy consumption by an average of 4.84%, a decrease of 2.81% compared to those without cruise control. In summary, the research on pollution reduction and carbon reduction in mixed traffic flow environments under the influence of LCI for energy consumption analysis provides support and reference for the sustainable development of green transportation.

KEYWORDS
collaborative adaptive cruise control; LCI; energy consumption; green transportation; mixed traffic flow.

1. INTRODUCTION

In modern society, the rapid pace of urbanisation and infrastructure development is expanding transportation networks to more regions, creating new challenges for managing traffic and reducing environmental impacts [1]. At the same time, the severity of global climate change is pushing governments and international organisations to find effective solutions to reduce greenhouse gas emissions and mitigate their effects. The transportation sector, a major contributor to both air pollution and carbon emissions, plays a crucial role in this effort [2]. Managing traffic conditions more efficiently while achieving pollution and carbon reduction (PCR) has become a significant challenge for many governments [3]. Advancements in transportation technology, coupled with increased public environmental awareness, have led to a growing interest in PCR strategies within the transportation field. Many scholars are now focusing on optimising traffic flow to reduce energy consumption, improve vehicle efficiency and minimise emissions [4]. Research on vehicle energy consumption analysis (VECA) has emerged as a critical area, with methods being developed to assess and optimise energy use in traffic systems. For instance, Ullah et al. proposed a machine learning-based technique to improve the accuracy of energy consumption predictions in vehicles, providing a foundation for more sustainable transportation systems. As the significance of traffic flow management and energy conservation efforts increases, the integration of these research efforts becomes imperative to achieve long-term sustainability goals.

Some scholars have conducted relevant research on VECA. The machine learning algorithm-based technique proposed by Ullah et al. aimed to test the performance of extreme gradient enhancement and mild gradient enhancement machines for the problem of VECA. This method could effectively improve the accuracy of automotive energy consumption prediction [5]. Dai et al. established a method combining carbon dioxide emission analysis to address the issue of fossil fuel consumption during vehicle operation. It could effectively extract the characteristics of vehicle energy consumption (VEC) changes by combining dynamic conventional minimum quartile testing for analysis [6]. Manimutu et al. proposed an artificial intelligence-based modelling method for analysing the energy consumption of commercial vehicles, which used embedded devices supported by the internet of things for data collection. This method could effectively analyse VEC [7]. Farghali et al. developed a method combining VECA to analyse the energy consumption differences between electric vehicles (EVs) and fossil fuel vehicles in response to the energy crisis. This method could effectively provide strategies for energy conservation [8]. Nishanthy et al. analysed the cost of EVs and the sensitivity of energy consumption to new energy vehicles, addressing the issue of VEC. This method could effectively provide high-quality data reference for transportation energy conservation [9].

At present, mainstream traffic management methods require data as support, but existing technologies often face challenges in computational efficiency and accuracy when dealing with large-scale and multi-modal traffic flows [10-11]. VECA is a key link in evaluating and optimising traffic energy consumption (TEC) [12]. Vehicles powered by different materials exhibit different energy consumption behaviours during operation, and the characteristics of the materials also affect the energy management mode of the vehicle. The impact of lane change intention (LCI) on traffic flow is a complex problem that involves multiple factors such as driver behaviour decisions and dynamic changes in the traffic environment. LCI is often accompanied by rapid acceleration, deceleration or changes in driving speed, which can lead to increased energy consumption. In theory, fluctuations in traffic flow caused by lane change behaviour lead to an increase in the power demand of vehicles, which consumes more energy. Vehicular traffic characterised by frequent lane changes can lead to fluctuations in the velocities of vehicles in adjacent lanes. This instability in traffic flow can result in frequent accelerations and decelerations, thereby increasing energy expenditure. Some scholars have conducted relevant research on LCI during vehicle operation. Zhang et al. conducted a questionnaire analysis on the reasons for the impact of LCI and analysed the impact of illumination on lane selection by drivers with different experiences. This method could effectively utilise regression models to predict lane-changing behaviour (LCB) [13]. Zhang et al. developed a method that combines LCI analysis to explain the driver's decisions and trust when changing lanes from a tactical perspective, and to analyse the correlation between the situation and the decision, specifically for level driving tasks. This method could effectively provide a reference for driving tasks [14]. Ahmed et al. proposed a method combining trajectory recognition to analyse driver LCB, using critical crossing time and unit distance lane changing amount as analysis indicators. This method could effectively analyse the LCB of drivers [15]. Gan et al. proposed a method based on vehicle trajectory data to analyse the impact of distance between vehicles and lane changes on vehicle speed in merging areas. This scheme could effectively analyse the movement of vehicles [16]. Li et al. designed a method based on lane change recognition for vehicle cruise control. By adding simulation datasets and utilising variable weight linear quadratic optimal control for optimisation, it has been proven that it can effectively improve the control effect of vehicles [17].

Collaborative adaptive cruise control (CACC) can to some extent reduce the increase in energy consumption caused by improper driver operation [18]. In this study, an innovative approach is proposed that combines LCI with vehicle-following behaviour analysis, while also incorporating the concept of individual driver spaces. This method aims to develop a comprehensive traffic flow energy consumption analysis framework that considers multiple energy types and driving control modes. By integrating these factors, the study seeks to provide valuable technical support for traffic management, optimise energy efficiency, reduce emissions and improve overall traffic flow sustainability. This study mainly consists of four sections. Section 1 mainly designs research techniques for TEC under the influence of LCI in mixed traffic flow environments (MTFE). Section 2 is performance testing and application analysis of research methods. Section 3 summarises and discusses the experimental results, and compares them with other studies. Section 4 summarises the entire text.

Table 1 – Table of abbreviations

Abbreviation	Full form
LCI	Lane change intention
CACC	Collaborative adaptive cruise control
VECA	Vehicle energy consumption analysis
VEC	Vehicle energy consumption
TEC	Traffic energy consumption
PCR	Pollution and carbon reduction
EV	Electric vehicle
VSP	Vehicle specific power
MEC	Multi-dimensional energy consumption
HRST	High-resolution simulation technology for energy consumption and emissions in transportation
IVHS-Estimator	Intelligent vehicle highway systems-estimator
ECI	Energy consumption intensity

2. TEC UNDER THE INFLUENCE OF LCI IN MTFE

This section will use MTFE as the background to construct a TEC research model that combines driver LCB analysis. By combining the car following model and individual driver space, the model is optimised to generate accurate TEC analysis results, which can provide a reference for PCR strategy formulation.

2.1 A TEC model based on LCI impact

Transportation is one of the primary sources of energy consumption in current society. Studying TEC can help with sustainable development and provide data and technical support for energy conservation and environmental protection [19]. LCI greatly affects the driving mode and control strategy of vehicles, and correspondingly affects the power consumption performance of vehicles [20, 21]. This study constructs a TEC model built on the impact of LCI and analyses the TEC of vehicles. When conducting VECA, it is necessary to first obtain data on the vehicle and driving area. This study uses high-altitude drone images and satellite images as data sources and processed unstructured data, as shown in *Figure 1*.

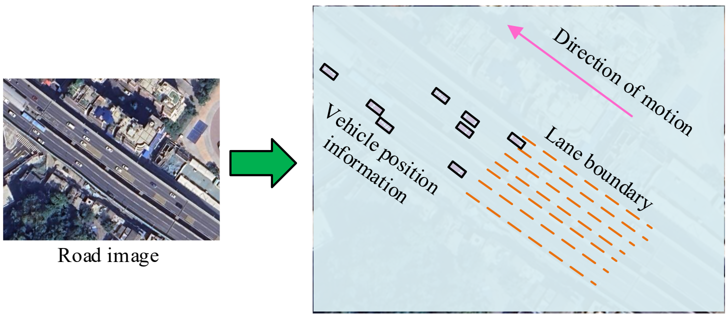


Figure 1 – Unstructured data processing

In *Figure 1*, during the processing of unstructured data, Matlab's image recognition system is used to distinguish the road boundaries and vehicle positions in the image. After obtaining the vehicle position, multiple continuous images are collected to analyse the vehicle's movement direction, speed, speed changes and changes in the mutual position relationship between different vehicles. Lanes with lane numbers and vehicles with complete information are retained. This study establishes a system of influencing factors on motor VEC based on traditional energy consumption models, as shown in *Figure 2*.

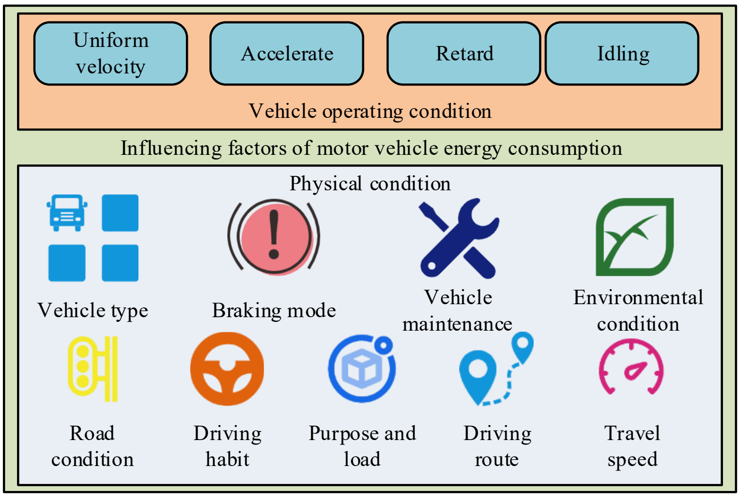


Figure 2 – System of influencing factors of motor VEC

Figure 2 outlines the factors influencing motor VEC, categorised into physical conditions and operating conditions. The operating conditions include four driving modes: uniform velocity, acceleration, deceleration and idling. These modes play a critical role in determining the vehicle's energy efficiency during different driving scenarios. The influencing factors include vehicle type, braking mode, vehicle maintenance, road conditions, driving habits, load, driving routes, environmental conditions and travel speed. Each of these factors can either increase or decrease the energy consumed by a vehicle, depending on the specific conditions and behaviours involved. In the context of the entire study, this figure supports the development of a comprehensive model for VECA that accounts for multiple variables impacting energy efficiency. By analysing these factors, the study provides a more holistic approach to understanding and managing energy consumption in mixed traffic flows, with an emphasis on optimising traffic flow and promoting sustainable green transportation practices. To reduce the difficulty of obtaining computational data, this study selects vehicle specific power (VSP) to evaluate the vehicle's power performance and energy consumption. VSP represents the real-time traction force per unit mass of a vehicle, which can be calculated by examining the rolling resistance and aerodynamic resistance of the vehicle, as shown in *Equation 1*.

$$V = v_n(t)\left(1.1\dot{v}_n(t) + 9.81g_d + 0.132\right) + \left(3.02\times10^{-4}\right)v_n^3 t \tag{1}$$

In *Equation 1*, V represents VSP. g is the percentage slope of the road. $v_n(t)$ and $\dot{v}_n(t)$ are the driving speed and acceleration of the vehicle. On the basis of VSP, partitioning is carried out to evaluate the fuel consumption level of the vehicle, as shown in *Equation 2*.

$$F_{fuel} = \gamma \cdot \tilde{V}^{0.42} \tag{2}$$

In *Equation 2*, F_{fuel} is the instantaneous fuel consumption level during vehicle operation. γ is the vehicle coefficient obtained based on the comprehensive physical performance of the vehicle itself. $\tilde{V}$ is the VSP partition in which it is located. The electric VEC during movement is different from that of gasoline vehicles. EVs use batteries as energy storage media. At present, the batteries used in EVs are mainly lithium-ion materials [22]. The positive electrode of lithium-ion batteries generally uses lithium cobalt oxide materials or nickel cobalt aluminium oxide materials, which have good cycling stability. The negative electrode material generally uses graphite [23]. Lithium-ion solid electrolytes have good thermal stability, releasing a large amount of energy when EVs climb hills and recovering some energy when going downhill. This study analyses the energy consumption of EVs using car traction, as shown in *Equation 3*.

$$Pt = M\dot{v}_n(t)v_n(t) + Mgv_n(t)\sin\theta + 0.5C_d A\rho_{air}v_n^3(t) + MgCr\cos\theta v_n(t) \tag{3}$$

In *Equation 3*, Pt is the total traction force of the car. g is the gravitational constant. M is the weight of the car. θ represents the angle of the road. A is the surface area of the windward surface of the vehicle. Cr is the rolling resistance coefficient. ρ_{air} represents air density. C_d is the traction coefficient. LCI mostly comes from scenarios where the driver is dissatisfied with the driving situation and then accelerates, decelerates and changes lanes, and these scenarios mainly come from vehicle following [24-25]. The basic car following model established for analysing TEC is shown in *Figure 3*.

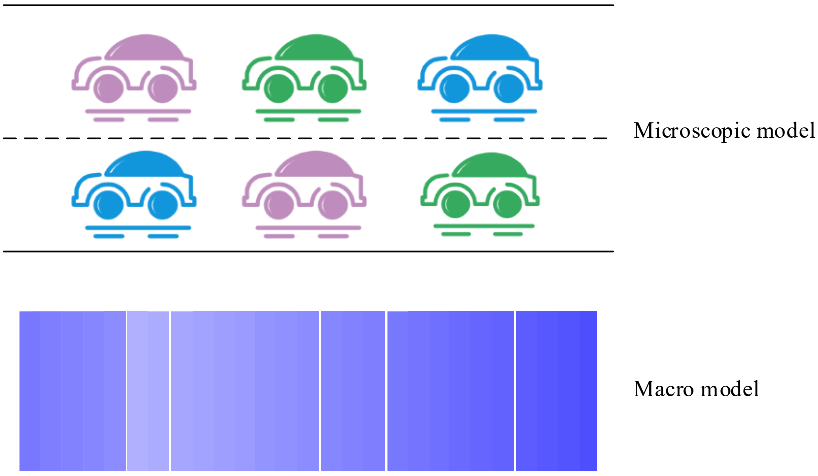


Figure 3 – Basic car following model

In *Figure 3*, the car following model is divided into two aspects: macro and micro. On a macro level, the traffic flow environment is compared to a liquid, and on a micro level, it focuses on observing individual vehicles in the traffic flow. The macro model expression is shown in *Equation 4*.

$$\frac{\partial \rho}{\partial t}+\frac{\partial}{\partial x_n}\left(\rho V\left(\rho\right)\right)=0 \tag{4}$$

In *Equation 4*, t is the time. ρ represents the number of vehicles per unit distance. x_n is the length of the analysed road segment. $V(\rho)$ is the relationship between velocity and density. The variables in the macro model constantly change in time and space, forming clusters of traffic flow. The expression of the microscopic model is shown in *Equation 5*.

$$\frac{dv_n\left(t\right)}{dt}=f\left(x_n\left(t\right),v_n\left(t\right),\Delta v_n\left(t\right)\right) \tag{5}$$

In *Equation 5*, $v_n(t)$ and $x_n(t)$ are the speed and displacement distance of the n-th vehicle at the corresponding time. $\Delta v(t)$ represents the speed difference between the n-th vehicle and the vehicle ahead at the corresponding time. In the basic car following model, the driving situation of the vehicle is analysed, and the vehicle LCI data are extracted and analysed for corresponding TEC.

2.2 The impact of multi-dimensional MTFE on TEC

With the development of intelligent driving technology and various automotive power technologies, the traffic flow environment has become complex and diverse [26-27]. To analyse TEC more accurately and provide support for PCR, this study analyses TEC from the perspective of multidimensional MTFE. When driving a vehicle, the driver's psychological cognition and decision-making are related to individual space, and the individual space during the driving process is centred around the vehicle body, as shown in *Figure 4*.

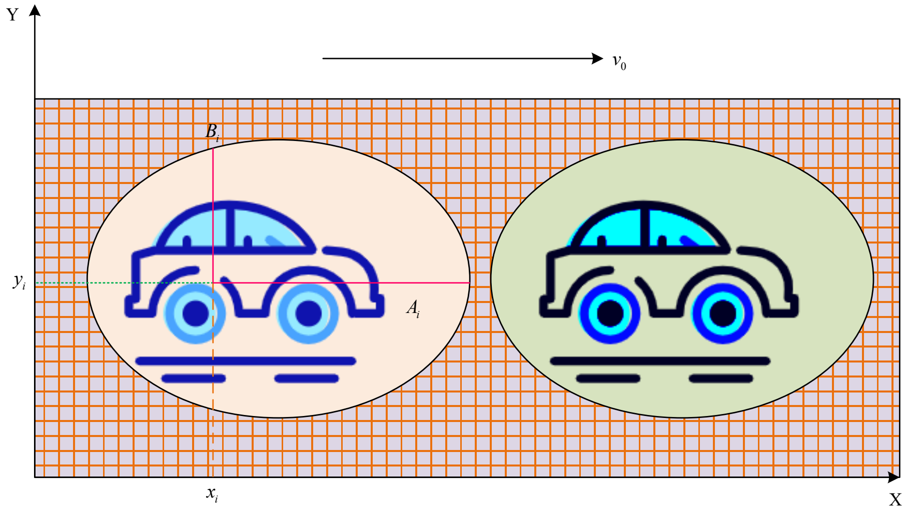


Figure 4 – Individual space of driving and following process

In *Figure 4*, while driving, the driver has the maximum individual space judgement towards the front, with the vehicle slightly smaller on both sides and the smallest towards the rear. The overall individual space is enclosed in a shape similar to an egg in front of a trendy car. The expression of individual spatial boundaries established in this study is shown in *Equation 6*.

$$S_i(t) = \begin{cases} \dfrac{(x - x_i(t))^2}{A_i(t)^2} + \dfrac{(y - y_i(t))^2}{B_i(t)^2} \le 1, x \ge x_i(t) \\ \dfrac{(x - x_i(t))^2 + (y - y_i(t))^2}{B_i(t)^2} \le 1, x < x_i(t) \end{cases} \tag{6}$$

In *Equation 6*, $S_i(t)$, $x_i(t)$, and $y_i(t)$ are the individual spatial boundaries, horizontal axis positions, and vertical axis positions of the vehicle i at the corresponding time. A_i and B_i represent the distance between the vehicle i and the front or side of the vehicle. x and y are the boundary points corresponding to the horizontal and vertical axis positions of the vehicle i at the corresponding time. The formula for the analytical model of vehicle following behaviour in combination with individual space is shown in *Equation 7*.

$$\begin{cases} s_1 = s_0 + v_0 (T_s + \Delta T) + \dfrac{v_0 \Delta v}{2\sqrt{ab}} \\ \dot{v} = a \left[1 - \left(\dfrac{v_0}{v_f} \right)^4 - \left(\dfrac{s_1}{h - l} \right)^2 \right] + \varepsilon c_i \end{cases} \tag{7}$$

In *Equation 7*, $\dot{v}$ is the acceleration of the vehicle while it is in motion. a is the upper limit of acceleration. l represents the length of the vehicle body. v_f is the speed of free flow in traffic flow. s_1 is the driver's expected distance. T_s represents a safe headway. b is the ideal deceleration. ΔT represents the corrected value of the headway. ε is a lateral utility parameter. c_i is the distance at which the vehicle intrudes into the individual space on both sides. The energy density of different materials varies, with gasoline and diesel typically having a higher energy density than lithium-ion materials. However, during work, the thermal efficiency of gasoline and diesel is lower than that of lithium-ion material batteries [28-29]. To unify the energy consumption units of electric and fuel vehicles when analysing energy consumption, this study uses coal equivalent value as the unified unit, as shown in *Equation 8*.

$$\begin{cases} C_{fuel} = \dfrac{\sum_t F_{fuel}\kappa_{fuel}}{10} \\ C_{ele} = \dfrac{\sum_l F_{ele}\kappa_{ele}}{10} \end{cases} \tag{8}$$

In *Equation 8*, C_{fuel} and C_{ele} are the energy consumption per 100 kilometres of the fuel vehicle section and EV section. F_{ele} is the unit distance energy consumption of EVs. κ_{fuel} and κ_{ele} are the coal conversion coefficient of gasoline and electricity. In the adaptive cruise control environment, there is feedback information from the preceding vehicle. This study introduces feedback coefficients to construct the expression of vehicle constraints in mixed traffic flow, as shown in *Equation 9*.

$$\dot{v}_n(t) = a\left[1-\left(\frac{v_n(t)}{v_f}\right)^4 - \left(\frac{s_0 + v_n(t)T + \frac{v_n(t)\Delta v}{2\sqrt{ab}}}{h_n(t)-l}\right)^2\right] + r\dot{v}_{n-1}(t) \tag{9}$$

In *Equation 9*, r represents the feedback coefficient of the front vehicle. This study comprehensively constructs a multi-dimensional MTFE VEC calculation formula, as shown in *Equation 10*.

$$C_s = \sum_d \left\{ mn\left[(1-p)C_1 + pC_2\right] + (1-m)n\left[(1-p)C_3 + pC_4\right] \right\} \tag{10}$$

In *Equation 10*, C_s is the total energy consumption intensity (ECI) of the road section. m represents the proportion of EVs. p is adaptive cruise control penetration rate. The lane-changing model of the front vehicle, which is constructed by extracting the influencing factors of LCI from the microscopic model, is shown in *Figure 5*.

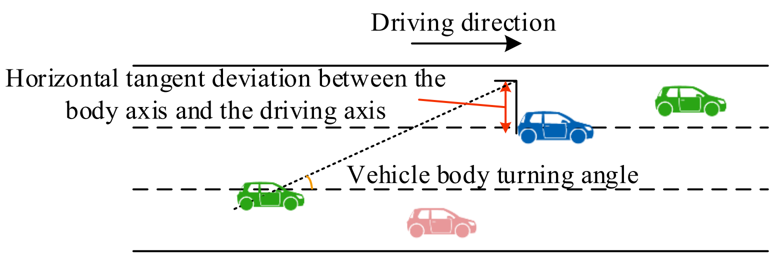


Figure 5 – Front car changing lane model

In *Figure 5*, when the front vehicle changes lanes, as the direction of the vehicle changes, the axis of the vehicle body will create an angle with the axis of the road. The larger the angle generated, the deeper the degree of LCI, causing a local deceleration in the rear traffic flow. Lateral intrusion in individual space will promote an increase in vehicle speed. This study improves the acceleration calculation formula for vehicles, as shown in *Equation 11*.

$$\dot{v}_n(t) = a\left[1-\left(\frac{v_n(t)}{v_f}\right)^4 - \left(\frac{s_0 + v_n(t)T + \frac{v_n(t)\Delta v}{2\sqrt{ab}}}{h_n(t)-l}\right)^2\right] + r\dot{v}_{n-1}(t) + \alpha Z\left(v_n(t)\right) - \beta\frac{d}{dt}\theta_n(t) \tag{11}$$

In *Equation 11*, $Z(v_n(t))$ is the lateral distance function of the vehicle body. α is the utility parameter of lateral distance. $\theta_n(t)$ is the car body turning angle function. β is the turning angle utility parameter of the vehicle body. The front distance that interferes with the vehicle's turning angle is set, and the time derivative is used to obtain the rate of change in the vehicle's turning angle, as shown in *Equation 12*.

$$\frac{d}{dt}\theta_n(t) = -\frac{b_n}{\left(h_n(t)-l\right)^2}h'_n(t) \tag{12}$$

In *Equation 12*, $h_n(t)$ is the distance between the front of the vehicle n at the specified time. b_n represents the horizontal tangent deviation between the body axis and the driving axis. The analysis framework of the impact of multidimensional MTFE on TEC is shown in *Figure 6*.

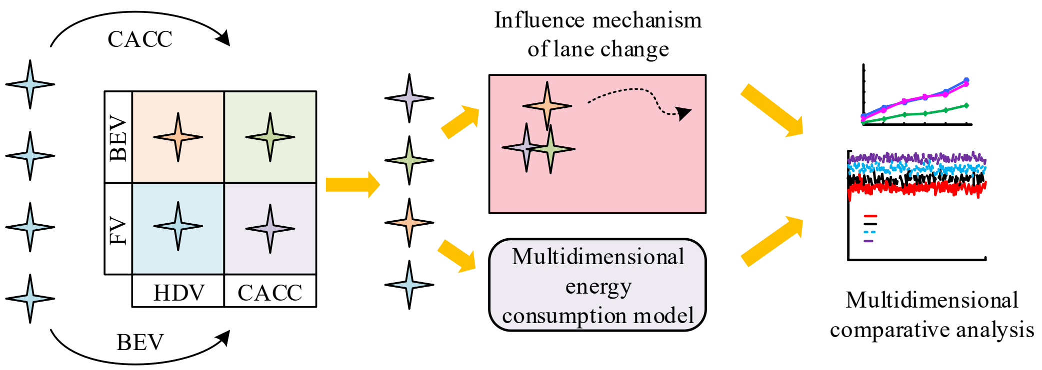


Figure 6 – Analytical framework for the influence of multi-dimensional MTFE on TEC

In *Figure 6*, the framework for analysing the influence of multi-dimensional MTFE on TEC is presented. The research method sets up two types of energy consumption: fuel vehicles and EVs, considering both manual driving and CACC. By combining different vehicle types and control modes, a multi-dimensional energy consumption model is constructed, and the influence of lane-changing mechanisms is extracted. These factors are analysed separately and compared across multiple dimensions to study the impact of LCI and traffic flow status on energy consumption. Ultimately, this analysis helps optimise road layout and traffic strategies, effectively reducing congestion and vehicle-following behaviour, thereby achieving the goal of PCR.

3. ANALYSIS OF TEC UNDER THE INFLUENCE OF LCI IN MTFE

This section will analyse the performance and effectiveness of research methods from two perspectives: simulation analysis and application experiments. The calculation time and vehicle speed propagation calculation effect of the method are tested using simulation scenarios, and the TEC in actual scenarios is analysed in practical application environments.

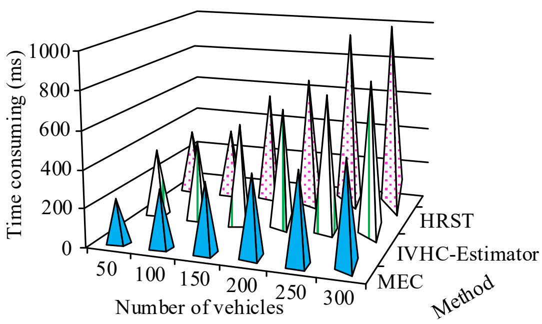
3.1 Simulation analysis of the TEC model

To analyse the energy consumption analysis method of the design, this study sets up a simulated traffic scenario with six lanes in both directions to simulate and analyse the TEC model. In the simulation process, the driver's subjective intention is simulated by the automatic driving system. *Table 2* shows the model parameters.

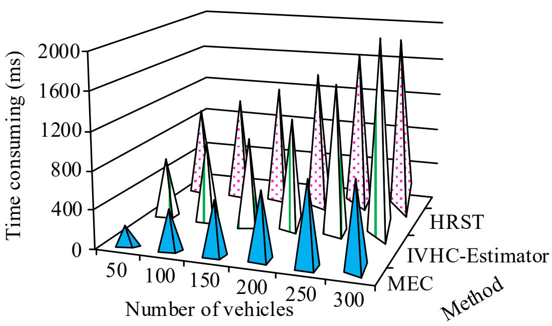
Table 2 – Simulation traffic scenario model parameters

Argument	Parameter unit	Parameter value
Maximum acceleration	2.5	m/s^2
Maximum deceleration	3	m/s^2
Free flow velocity	33.4	m/s^2
Corrected the headway	The value is based on the normal distribution probability	\
Lateral distance utility function	0.0051	\
Lateral migration utility function	8.5	\
Standard body length	5	m
Minimum stopping distance	1	m
The maximum body offset distance	1.5	m

When analysing, the research method is referred to as multi-dimensional energy consumption (MEC), and compared with intelligent vehicle highway systems-estimator (IVHS-Estimator) and high-resolution simulation technology for energy consumption and emissions in transportation (HRST). A section of road with a length of 2,000 m is established as the short scene, and a section of road with a length of 10,000 m is set as the long scene. Both the short scene and the long scene have convergence and diversion nodes. *Figure 7* shows the results of testing the energy consumption analysis time of different methods.



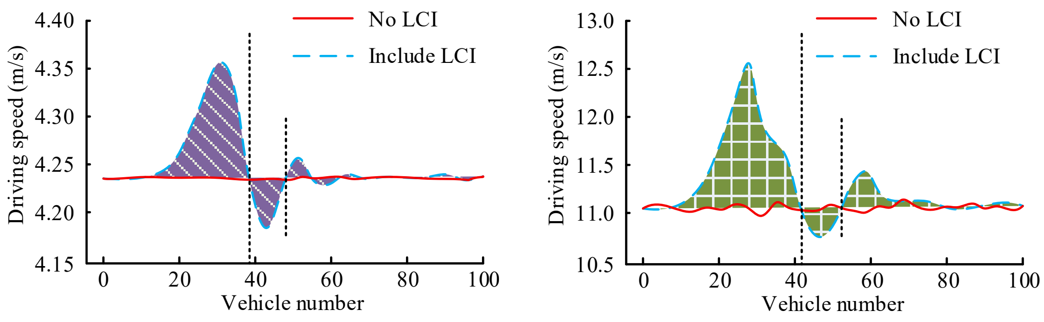
(a)



(b)

Figure 7 – Energy analysis time consuming: a) short scene; b) long scene

In *Figure 7*, when analysing the TEC, the analysis time of different methods increases with the growth of the quantity of vehicles in the scene. *Figure 7a* shows that in a short scenario, the time consumption of MEC remains below 200 ms when the number of vehicles is 50, and below 600 ms when the number of vehicles increases to 300. In *Figure 7b*, the difference in time consumption between different methods is greater in long scenes compared to short scenes. The time required for HRST to reach 300 vehicles in the scene is 1,800 ms. The time consumption of MEC remains below 200 ms when the number of vehicles is 50, and below 900 ms when the number of vehicles increases to 300. This indicates that the research method has a higher analysis speed when conducting calculations. The total number of vehicles in the scene is set to 100. By using research methods to extract two scenarios, the vehicle speed propagation situation at the 180th second is shown in *Figure 8*.



(a) *(b)*

Figure 8 – Analysis of vehicle speed propagation: a) short scene; b) long scene

In *Figure 8*, MEC is able to analyse the speed propagation of vehicles without and with LCI in both short and long scenes. *Figure 8a* shows that in a short scenario, with LCI included, the speed of the traffic flow at the beginning and end is the same. There are significant fluctuations in the velocity of the traffic flow in the front and middle sections, showing a situation where one section of the vehicle is fast, one section of the vehicle is slow, and one section of the vehicle is fast. The fastest vehicle speed can reach 4.36 m/s. In *Figure 8b*, in a long scenario, without LCI, the vehicle's speed is maintained at a level of 11.0 m/s, with a fluctuation range of no more than 0.2 m/s. When including LCI, the maximum speed of some traffic flow is 12.6 m/s, which is significantly higher than the speed at the beginning and end of the traffic flow. The analysis results of MEC on vehicle speed propagation are in line with the trend of real traffic conditions. This indicates that the research method can effectively analyse the speed propagation of vehicles, thereby providing reliable data for traffic flow energy consumption analysis.

3.2 Energy consumption analysis under multi-dimensional MTFE

To further confirm the effectiveness and performance of the research method, a section of road with vehicles entering the Poisson distribution during actual operation is selected for practical application, and the obtained data are all real data. The width of the road lane is 3.75 metres, and the initial speed of the vehicle is 10 m/s. The results of analysing the road energy consumption corresponding to different proportions of fuel vehicles on the road are shown in *Figure 9*.

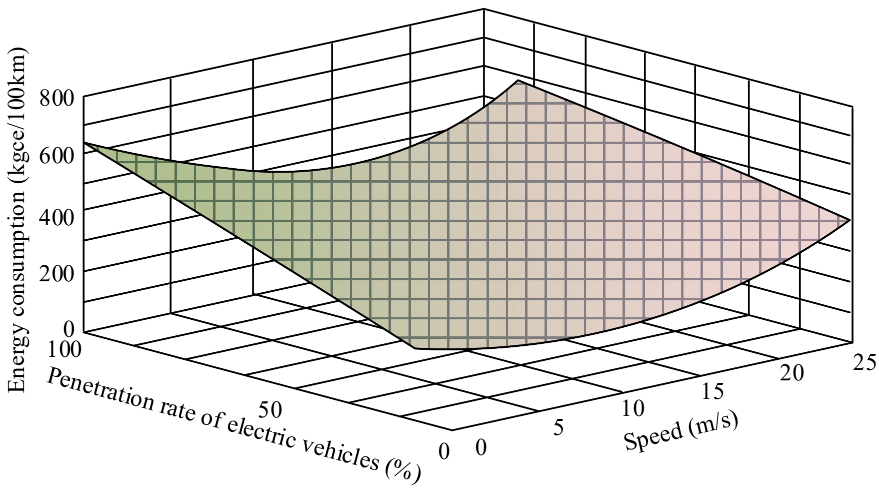


Figure 9 – Road energy consumption corresponding to the proportion of fuel vehicles

In *Figure 9*, under different fuel vehicle ratios, MEC shows that as the penetration rate of EVs in traffic flow increases from 0% to 100%, the cumulative energy consumption (CEC) per 100 km changes. The CEC of mixed traffic flow is not only affected by driving speed but also negatively correlated with the penetration rate of EVs. This means that the lower the proportion of EVs in the traffic flow, the higher the overall energy consumption of the traffic flow. When the penetration rate reaches 100%, that is, all vehicles are EVs, driving at a speed of approximately 9.5 m/s can achieve the lowest ECI, which is 191.23 kgce/km. As the penetration rate of fuel vehicles increases, the economic speed gradually increases from 9.5 m/s, until the economic speed reaches its highest point at 14.4 m/s when the penetration rate is 0%. The research method effectively outputs the road energy consumption corresponding to different proportions of fuel vehicles. *Figure 10* shows the analysis of road energy consumption in different mixed-traffic scenarios.

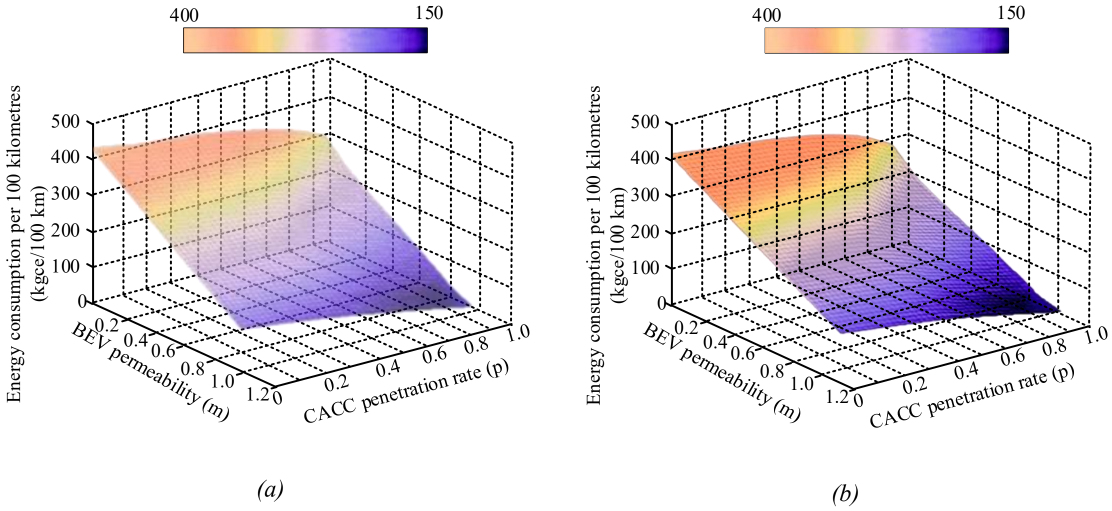


Figure 10 – Road energy consumption in mixed scenarios of different traffic flows: a) no LCI; b) included LCI

In *Figure 10*, MEC generates corresponding road energy consumption analysis results in different mixed-traffic scenarios. *Figure 10a* shows that in traffic control scenarios without LCI, the energy consumption of traffic flow is affected by the proportion of CACC and fuel vehicles. As the proportion of EVs and CACC vehicles increases, the ECI continuously decreases, reaching a minimum of 119 kgce/km. In *Figure 10b*, in the traffic flow scenario with LCI, the overall ECI of the traffic flow is higher compared to the scenario without LCI, but the trend of ECI changes is consistent. The ECI of the road reaches a maximum of 400 kgce/km and a minimum of 131 kgce/km. This indicates that the research method can effectively analyse road energy consumption in different mixed-traffic scenarios, and LCI will to some extent hinder the PCR of traffic. Overall, vehicles with lane-changing intentions in MTFE have an average energy consumption increase of 7.65% compared to normal driving vehicles. Vehicles with the intention of changing lanes and applying CACC at the same time only see an average increase of 4.84% in energy consumption, which is 2.81% lower than those without using CACC. *Figure 11* shows the analysis accuracy of the research method.

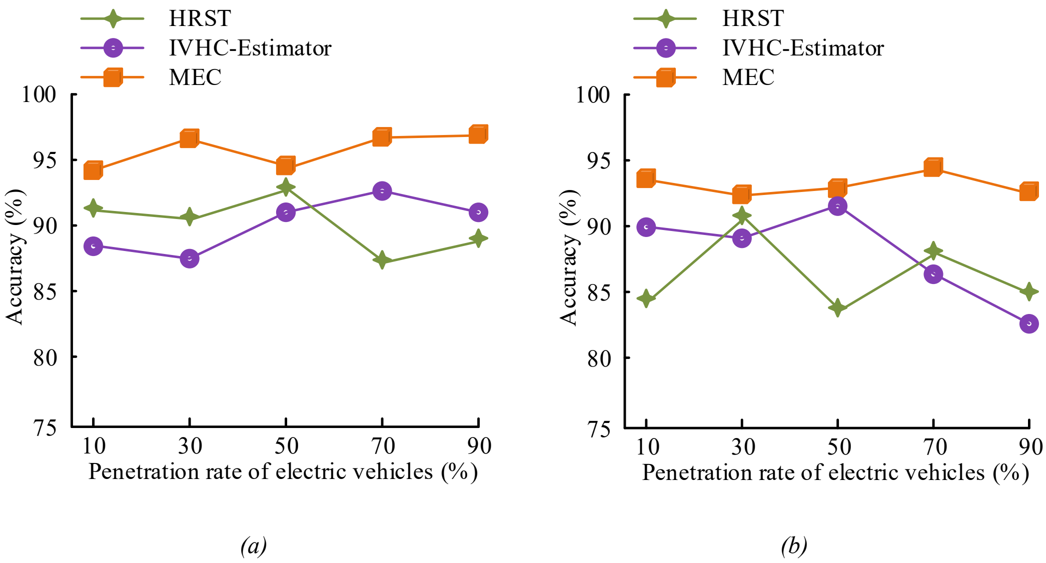


Figure 11 – Accuracy of energy consumption calculation: a) no LCI; b) included LCI

In *Figure 11*, the accuracy of energy consumption calculations for different methods fluctuates within a certain range. *Figure 11a* shows that in the traffic scenario without LCI, HRST achieves the highest calculation accuracy of 92.5% when the proportion of EVs reaches 70%. The calculation accuracy of MEC is the lowest point at 94.2% when the proportion is 10%. The calculation accuracy reaches 96.6% when the proportion is 90%. In *Figure 11b*, in the traffic scenario with LCI, the calculation accuracy of HRST and IVHS-Estimator shows a significant decline compared to the traffic scenario without LCI, and the fluctuation range is larger. The calculation accuracy of MEC is at its lowest point when the proportion is 30%, maintaining above 92.3%. The highest calculation accuracy is achieved when the proportion is 70%, reaching 94.5%. This indicates that the research method has better accuracy in energy consumption analysis and can provide more accurate data for PCR.

4. DISCUSSION

By constructing a TEC model, this paper analyses the impact of LCI on VEC in TMTFE and discusses the energy consumption in a multi-dimensional mixed traffic environment combined with the CACC strategy. The research results showed that in mixed traffic flow, the average energy consumption of vehicles with LCI increased by 7.65% compared with normal-driving vehicles. The average energy consumption of vehicles with CACC could effectively alleviate the increase caused by LCI, and the average energy consumption increased by only 4.84%, which was 2.81% lower than that of vehicles without cruise control. A distinguishing feature of this study is its comprehensive consideration of the interaction between lane change behaviour and vehicle-to-vehicle behaviour, which is a novel contribution within the field. Additionally, it offers technical assistance for traffic management by constructing a road traffic flow energy consumption analysis method that encompasses multiple energy forms and driving control modes. For example, Mohseni et al. improved the accuracy of VEC prediction through machine learning algorithms, and the study further verified the effectiveness and practicability of the model through simulation analysis and application experiments in actual traffic scenarios [21]. In addition, the study also analysed the energy consumption performance of vehicles with different energy types in the mixed traffic flow and found that with the increase of the penetration rate of EVs in the traffic flow, the overall energy consumption showed a downward trend. This echoes the study of Akbari et al. on the energy consumption sensitivity of new energy vehicles, which further confirms the potential of EVs in energy conservation and emission reduction [22]. The results obtained in this study are similar to those obtained by Jafari et al., both of which prove that energy type and vehicle driving mode greatly affect transportation energy consumption [23].

However, there are some limitations to the study. First of all, there may be differences between the simulation scenario used in the research and the actual traffic environment, and future research needs to be verified under a wider range of actual traffic conditions. Secondly, the research mainly focuses on the analysis of energy consumption under normal traffic conditions, and the change of energy consumption under abnormal conditions such as sudden accidents has not been considered, which needs further discussion in future research. Finally, although the research has made some achievements in the accuracy of energy consumption analysis, there is still room for improvement in the generalisation ability and real-time performance of the model. To overcome these shortcomings, future research can be optimised and improved from the following aspects. The first is to expand the range of simulated and experimental traffic scenarios, including different types of roads and traffic conditions. The second is to consider the influence of abnormal conditions such as traffic accidents on energy consumption to improve the robustness of the model. The third is to use more advanced data processing technology to improve the real-time accuracy of energy consumption analysis. Through these improvements, the methods studied are expected to provide more comprehensive and in-depth support for the sustainable development of green transportation systems.

5. CONCLUSION

In this study, a TEC research method was designed to address the complexities of analysing TEC in MTFE, particularly under the influence of LCI. The study processed unstructured data from various sources, establishing a system of factors that affect motor VEC, and used these data to analyse both conventional and electric VEC. Key findings of this research include the observation that LCI significantly impacts the energy consumption of vehicles in mixed traffic environments. Specifically, vehicles with LCI exhibited a 7.65% increase in energy consumption compared to those driving without such intentions. This increase in energy consumption is primarily attributed to changes in vehicle speed, acceleration and deceleration, which disrupt the flow of traffic and lead to greater energy expenditure. The utilisation of CACC led to a mitigated increase in energy consumption, with a recorded rise of only 4.84%. This outcome underscored the efficacy of adaptive systems in addressing inefficiencies stemming from human driving behaviours. The research method proved highly effective, maintaining an analysis time of less than 900 ms, even when the number of vehicles increased to 300 in large traffic scenarios. This suggests that the method is well-suited for analysing energy consumption in both small and large-scale traffic environments. Additionally, the study found that traffic flow with LCI generally exhibited higher energy consumption compared to flow without LCI, underscoring the negative impact of unpredictable lane changes on energy efficiency. Through further analysis of road energy consumption in different MTFE scenarios, the study established that the integration of CACC and the increasing penetration of EVs into the traffic flow can significantly reduce overall energy consumption. The research demonstrated a decrease in energy consumption as the proportion of EVs in the traffic flow increased, which suggests that transitioning to EVs can substantially reduce the carbon footprint of the transportation sector. The study also highlighted the effectiveness of the proposed research method in accurately calculating energy consumption, achieving the highest calculation accuracy of 96.6% in traffic scenarios without LCI. This demonstrates the efficacy of the proposed method for implementation in real-world traffic management systems.

While the results of this study provide valuable insights, there are several areas for further exploration and development. The study primarily focused on normal traffic conditions, and future research should expand to analyse how abnormal conditions, such as traffic accidents or sudden disruptions, influence energy consumption. Understanding the impact of such events is crucial for enhancing the robustness and real-time adaptability of energy consumption models. Additionally, the study relied on simulations and did not fully consider the complexities of real-world traffic environments. Future research should involve more diverse and real-world traffic scenarios to better validate the proposed models. The incorporation of more detailed data on road conditions, driver behaviour and traffic density will further enhance the accuracy and applicability of energy consumption analysis. Another important direction for future research is the integration of external factors that can affect driving behaviour, such as weather conditions, infrastructure types and regulatory measures. These factors are likely to have significant effects on both energy consumption and traffic flow dynamics. By considering these external influences, it will be possible to develop more comprehensive and adaptable traffic management strategies.

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