Dynamic Programming-Based Energy Optimization for Pure Electric Commercial Vehicles with Predictive Cruise Control

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Reducing energy consumption and carbon emissions while effectively utilizing automotive resources is a crucial task for both the country and the automotive industry. To achieve this goal, this study employs the Dynamic Programming algorithm to optimize the control of pure electric commercial vehicles' driving process, thereby reducing their energy consumption. With the objective function of minimizing energy consumption and the constraints of vehicle power performance and economy, a simulation platform is built to analyze the driving energy consumption of pure electric commercial vehicles under typical working conditions. The experiment verified the effectiveness and feasibility of the driving energy consumption control strategy based on the Dynamic Programming algorithm. The results showed that compared with the traditional PID control method, the improved Dynamic Programming algorithm saved 1.63%, 4.56%, 7.19%, and 4.63% of the power under the conditions of uphill, downhill, first uphill then downhill, and first downhill then uphill, respectively. Compared with traditional Dynamic Programming algorithms, the improved algorithm saved power by 0.49%, 3.23%, 6.68%, and 2.36%, respectively. Compared to normal driving, the optimized-speed tracking reduced total energy consumption by 23.56%, while energy consumption during constant-speed driving decreased by 6.62%. This indicates that the proposed energy consumption control strategy for pure electric commercial vehicles can achieve the goal of reducing driving energy consumption. The proposed driving energy consumption control strategy for pure electric commercial vehicles aims to plan the vehicle's driving speed, enabling it to travel on a reasonable speed track, and ultimately reducing driving energy consumption while improving driving economy.

Povzetek: Opisana je strategija za zmanjšanje porabe energije pri električnih tovornih vozilih z uporabo algoritma dinamičnega programiranja in prediktivnega tempomata. Model optimizira porabo energije v različnih pogojih vožnje, izboljšuje gospodarnost ter zmanjšuje emisije, kar prinaša trajnostne rešitve v transportni industriji.

1 Introduction

Pure Electric Commercial Vehicles (PECVs), as the emerging green vehicles, have advantages such as zero emissions, low noise, and low cost compared to traditional fuel vehicles [1, 2]. With the rapid development of PECVs, their economy and power have gradually attracted the attention of the industry and consumers. At present, research on vehicle energy conservation mainly focuses on the following four aspects. (1) Improve engine performance, enhance transmission performance, and reduce body weight and air resistance. (2) Improve driving economy. (3) Improve and develop intelligent transportation management systems such as electronic toll collection and electronic navigation. (4) Promote the development of new energy technologies, mainly focusing on the development of pure electric and hybrid vehicles [3, 4]. Regarding the control of energy consumption in PECVs, industry scholars focus on reducing Driving Energy Consumption (DEC) by optimizing the vehicle power system structure, improving motor efficiency, and enhancing vehicle control strategies [5]. This study proposes a DEC control strategy based on a Dynamic Programming (DP) algorithm to address the issues of PECVs in DEC control. A mathematical model for automobile energy consumption is established, and the DEC of automobiles under different operating conditions is analyzed. The optimization of the engine operating points is achieved by considering the energy consumption requirements of vehicles under different working conditions and the overall power performance requirements of the vehicle, resulting in DEC optimization. Finally, the verification of this strategy through simulation experiments provides a theoretical basis for the development of DEC control strategies for PECVs.

This study combines DP and model predictive control to implement a hierarchical control strategy for commercial vehicle predictive cruise control. The contribution of this study lies in this combination of addressing the computational complexity and real-time issues of DP. By establishing the corresponding objective function and constraint and adopting a limited time domain optimization control strategy, the road slope information can be used to enable the vehicle to drive economically within the permissible speed range. It achieves energy savings and reduces consumption while meeting the longitudinal speed-tracking performance of commercial vehicles. Additionally, it ensures a certain level of riding comfort.

The paper conducts research through four parts. Part 1 is a review of the current research status of the application of DP algorithm in vehicle DEC control. Part 2 is the DEC study of PECVs based on DP algorithm. Part 3 is performance validation of the proposed system. Part 4 is the conclusion.

2 Related works

DP algorithms typically have low time complexity and are suitable for large-scale problems. Compared to some complex algorithms, the implementation of the DP algorithm is relatively simple, so many scholars have researched it. Chen et al. developed an adaptive DP optimization method to improve the safety performance and endurance of battery systems. It simplified the theoretical analysis of reminder error by using a quadratic local expansion method to replace existing nonlinear numerical functions and replaced traditional static networks with long short-term memory neural networks. Through verification, this method could not only avoid overcharging and over-discharging but also limit the charging and discharging capacity of the battery within the set range [6]. To achieve effective regulation of train air conditioning, Xie et al. proposed a two-level control strategy of "decision layer control layer", which means that at the decision layer, DP is applied to the temperature inside the carriage to reduce the energy consumption of the air conditioning system. At the control layer, the fuzzy PID algorithm was used to adjust the designed temperature, so that the temperature inside the carriage tended to be consistent with the design value. Compared to switch controllers, this strategy saved 30.2% of energy [7]. Fiori et al. presented a model for electric vehicle energy consumption that accounts for input uncertainty. They also developed a framework for global and regional sensitivity analysis of energy consumption models. The authors applied this framework to identify the inputs that contribute the most to the variance of simulated energy consumption and recovery, as well as the input values that result in average or extreme model outputs. The results showed that the model tended to overestimate the average power consumption and underestimate the average recovery [8]. Xu et al. proposed a power optimization method for waste heat recovery systems based on the DP algorithm. It obtained the optimal power generation law through machine learning algorithms and applied a reduced order model based on single-state eigen orthogonal decomposition and Galerkin projection to DP under transient conditions to improve its operational efficiency. For transient operating conditions, the DP algorithm was used to obtain the optimal operating conditions, significantly increasing the recovery rate from 66.5% to 97.2% [9]. Hou et al. proposed an off-road DP method that can balance solution accuracy and speed to address the issues of hydrogen economy and system efficiency in hybrid electric vehicles. This method analyzed the impact of different discrete step sizes of state variables on the results and selected a discrete step size that can ensure algorithm accuracy and reduce calculation time, proving the accuracy of the optimization results [10].

Reducing the DEC of PECVs not only reduces energy consumption but also lowers pollutant emissions. Zhang et al. established a model for extended-range electric vehicles based on their energy consumption under different driving conditions, addressing the issue of driving range for electric vehicles. The model obtained energy consumption under different operating conditions, and the results of the micro gas turbine showed that the MGT model has high accuracy. The error between simulation values and experimental values was less than 2%, and the error between speed and turbine inlet temperature was less than ±3% [11]. Ren et al. proposed an optimal path planning and speed control strategy for the motion planning of unmanned ground vehicles in different driving environments. The DP method was used to convexate the channel constraints in the obstacle avoidance path pre-selection and re-planning and optimize the longitudinal motion and steering Angle control at the prediction and control level. Finally, the feasibility and performance of the proposed strategy were verified by numerical experiments [12]. He et al. proposed a real-time energy-aware ecological driving control strategy to optimize energy consumption and meet the needs of ecological driving. They established a longitudinal driving dynamics model and an energy consumption model for the entire vehicle, and then constructed the optimal control problem with the maximum driving distance and the shortest driving time as objective functions, respectively. This method could perceive the remaining battery level of the battery pack in real-time, and achieve ecological driving with the maximum driving distance and the shortest driving time [13]. Pan et al. have developed a novel hybrid DC prediction model that utilizes algorithms such as principal component analysis and K-means clustering to establish driving cycles suitable for different cities. Then, using the hybrid DC prediction method, the problem of traditional rolling prediction not being able to accurately predict vehicle speed was solved. Finally, by establishing a DC state transition matrix, the vehicle speed prediction during starting, the range of the vehicle, and energy conservation and consumption reduction were achieved [14].

Table 1: Summary of literature review

Author	Research method	Results
Chen et al. [6]	Adaptive DP based on long- and short-term memory neural networks	Vehicle energy consumption is reduced by 15% to 20%
Xie et al. [7]	"Decision level - control level" two-level control strategy	Energy savings of 30.2% compared to switching controllers
Fiori et al. [8]	An electric vehicle energy consumption model considering input uncertainty	Compressor energy consumption and thermal management system energy consumption were reduced by 5.71% and 4.37%, respectively
Xu et al. [9]	Power optimization of waste heat recovery system based on DP algorithm	The recovery rate increased from 66.5% to 97.2%
Hou et al. [10]	The DP of the distance walk takes into account both the solution precision and the solution speed	Efficiency is 5%-10% higher than induction motor
Zhang et al. [11]	Energy saving analysis of extended range electric vehicle based on micro gas turbine	Range increased from 73 km to 128 km
Ren et al. [12]	The channel constraints in obstacle avoidance path pre-selection and rerouting are optimized by using DP method	Achieve a 3% fuel saving effect without sacrificing the average speed
He et al. [13]	A real-time energy sensing eco-driving control strategy	Energy consumption is reduced by 1.9% to 4.0%
Pan et al. [14]	Hybrid DC prediction method	The energy saving rate is about 5%
Nie et al. [15]	Energy saving speed planning for autonomous electric vehicles based on reinforcement learning	It can save 2% to 5% under different working conditions
Proposal	Improved DP algorithm	Compared with the traditional DP algorithm and the conventional PID algorithm, it saves 1%-2% and 1-7.5% more energy consumption, respectively

Nie et al. proposed a collaborative optimization strategy to address the adverse effects of uncertainty and lateral stability of complex traffic conditions on vehicle online speed planning and energy management. The strategy utilized gradient-based model predictive control and fast projection gradient method to calculate the safe optimal speed sequence. The energy management strategy based on the adaptive equivalent energy consumption minimization strategy of power ratio was adopted for energy allocation. The results showed that this strategy could obtain a safe and optimal speed sequence on curves [15].

Table 1 shows that the DP algorithm can achieve better results in vehicle energy consumption optimization. The incline of the road exerts a gravitational force on the vehicle, either impeding its forward motion or providing a driving force, which in turn affects the vehicle's braking force. Sloped driving thus typically has a deleterious effect on the condition of the vehicle. However, most current methods are based on trajectory optimization to reduce energy consumption and limit the travel radius of the owner. Therefore, according

to the work needs and objectives of the speed planning system, the overall structure of the speed planning system is determined and the perfect process of speed planning is established. The DP algorithm is applied to transform the ramp-driving process of PECV into a mathematical problem, and the ramp-driving speed optimization model is established.

3 Design of DEC control scheme for PECVs

This study first completes the establishment of basic theoretical models, including the overall architecture of control strategies and the longitudinal dynamics model of vehicles. Subsequently, the research on the objective function establishment and solution algorithm for multi-objective programming problems in this experiment is completed.

3.1 Overall design and vehicle mass modeling

The advancement of new energy vehicle technology has made PECVs an important component of new energy vehicles, with extensive applications in urban logistics, urban passenger transportation, and other fields [16]. However, as a hybrid electric vehicle with multiple power sources, PECVs have always been one of the main challenges in the development of new energy commercial vehicles due to their DEC. This study is based on high-precision electronic maps and GPS positioning technology and implements a new predictable DEC control system. The main architecture is shown in Figure 1. The vehicle position and slope information of the road ahead obtained through GPS are combined with the reference vehicle speed set by the driver, and this data is transmitted to the upper controller. This controller is based on a predictive energy-saving control model for a constructed vehicle, combined with the DP algorithm, to obtain the optimal reference speed running trajectory. The obtained trajectory is used as the set speed benchmark for the lower-level controller. The lower-level controller solves Multi-objective Optimization (MOO) problems based on the slope information of the road ahead and the set performance function to plan the vehicle's speed reasonably.

This experiment mainly studies the longitudinal performance of PECVs, and models the longitudinal degrees of freedom and mechanical characteristics of the entire vehicle through analysis. Commercial vehicles achieve energy conservation and consumption reduction by optimizing the driving force and selecting the optimal gear for variable speed driving under different working conditions. In the time domain, a car with a mass of m passes through a short period T_s on a slope with a tilt angle of θ. T_s is very small, so it can be assumed that the acceleration during this process will not change. The force situation of the PECVs particle model is shown in Figure 2.

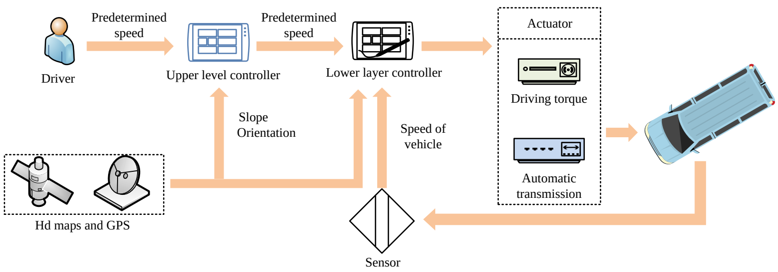


Figure 1: DEC control system architecture of PECVs

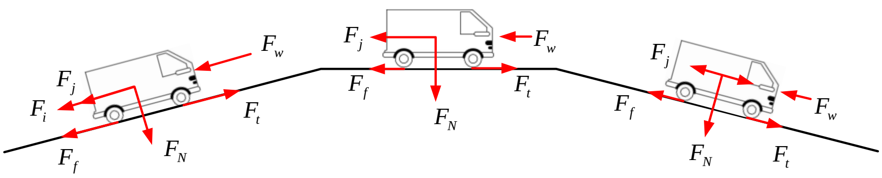


Figure 2: Stress on the particle model of PECVs

According to Newton's second law, the vehicle force balance, equation (1), is obtained.

$$F_t\left(F\right)=F_f+F_w+F_i+F_j \qquad (1)$$

In equation (1), F_t represents the driving force. F represents braking force. F_f represents rolling resistance. F_w represents air resistance. F_i represents the slope resistance. F_j represents acceleration resistance. To balance the complexity and accuracy of the model, a simple assumption and simplification have been made for the longitudinal dynamic characteristics of the entire vehicle: lateral and vertical movements are not considered, only longitudinal movements of the vehicle are considered. Under normal driving conditions, the vehicle does not consider tire sliding or deformation of the drive shaft. The vehicle has no transmission and is symmetrical on both sides. Substituting the calculation equations in equation (1) yields equation (2).

$$\frac{T_m i_0 \eta_T}{r}(F) = mgf\cos\theta + \frac{1}{2}C_D A\rho v^2 + mg\sin\theta + \delta m\frac{dv}{dt} \tag{2}$$

In equation (2), T_m represents the motor torque. i_0 represents the transmission ratio of the main reducer. η_T represents the mechanical efficiency of the vehicle's transmission system. r represents the rolling radius of the wheel. g represents gravitational acceleration. f represents the rolling resistance coefficient. C_D represents the air resistance coefficient. A represents the windward area of the vehicle. ρ represents air density. δ represents the conversion factor for the rotational mass of the vehicle. v represents the driving speed.

The longitudinal dynamics model of a car can reflect the relationship between various forces and its motion state during operation [17]. PECVs can obtain real-time vehicle speed and motor torque through the local area network of the vehicle controller. The transmission ratio, wheel radius, air resistance coefficient, and windward area of the main reducer are already known parameters. The rolling resistance coefficient, road slope, and other parameters are dependent on the road condition. In this study, quality estimation is the input of the ramp speed planning system, and it is believed that road parameters can be obtained through high-precision electronic maps and other means. However, to improve the applicability of the quality estimation model, it is considered that these two parameters are unknown. Therefore, equation (2) can be rewritten as equation (3).

$$\begin{cases} \dot{v} = \dfrac{T_m i_0 \eta_T}{\delta m r} - \dfrac{1}{2\delta m} C_D A\rho v^2 - R \\ R = \dfrac{g}{\delta}\left(f\cos\theta + \sin\theta\right) \end{cases} \tag{3}$$

In the longitudinal dynamic's equation of a vehicle, v represents the time variation of the vehicle's motion state. However, m and the road related parameter R are unknown, so these three parameters are selected as the system state parameters. The rolling resistance coefficient remains relatively constant under the same road conditions, despite changes in slope angle. The mass estimation process is also relatively quick, taking into account factors such as the vehicle's constant mass and rolling resistance coefficient. Therefore, assuming that R remains basically unchanged, the differential equation of the system can be obtained as shown in equation (4) below.

$$\begin{cases} \dot{v} = \dfrac{T_m i_0 \eta_T}{\delta m r} - \dfrac{1}{2\delta m} C_D A\rho v^2 - R \\ \dot{R} = 0 \\ \dot{m} = 0 \end{cases} \tag{4}$$

Equation (4) is discretized and state noise is added to obtain the state equation of the system. In the observation equation of the system, only the vehicle speed can be observed by the bus in the local area network of the onboard controller. After considering the observation noise, equation (5) is obtained.

$$x = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_k \\ m_k \\ R_k \end{bmatrix} + V_k \tag{5}$$

In this model, the state equation of the system is nonlinear, while the observation equation of the system is linear. When using the extended Kalman filtering method, the first step is to perform partial differentiation on each parameter of the system, and then calculate its Jacobian matrix, as shown in equation (6).

$$J_f = \begin{bmatrix} 1 - \dfrac{\Delta t C_D A v}{\delta m} & \Delta t\left(\dfrac{C_D A\rho v^2}{2\delta m} - \dfrac{T_m i_0 \eta_T}{\delta m^2 r}\right) & -\Delta t \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

Then, according to equations (3) to (5), the initial values and relevant parameters are determined, and the extended Kalman filtering algorithm is used to achieve real-time estimation of the vehicle mass.

3.2 Vehicle speed planning and predictive cruise control strategy

DP algorithm is a typical type of nonlinear programming method. Due to its global optimality, the DP method is widely used to solve multi-stage decision optimization problems and is also regarded as a validation standard for the accuracy of other algorithms. The core idea is "reverse optimization, forward solution". This approach breaks down the original multi-stage decision problem into several sub-problems, which are then solved iteratively in reverse order to obtain a sequence of optimal solutions for the multi-stage problem [18].

Figure 3 briefly illustrates the basic principle of the DP algorithm. In practical engineering, local optimal control problems can be transformed into multi-stage decision problems. To break it down into multiple sub-problems (or stages). The endpoint of each sub-problem is two adjacent sets of states, each containing a finite number of partitioned state variables, each of which can take a value within a certain interval. A series of states composed of multiple states, obtained by solving the optimal control problem, is the most effective series of control sequences, which is the optimal solution to the optimal control problem.

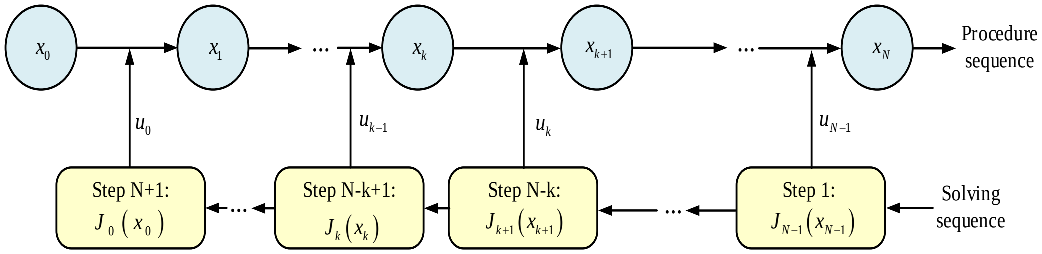


Figure 3: Schematic diagram of DP algorithm principle

The predictive cruise control system aims to optimize the speed set by the driver and reduce electrical energy consumption, achieving economical driving while keeping the following speed constant. The DEC control of PECVs is a MOO problem. The objective function includes speed tracking indicators and electricity economy indicators [19, 20].

Based on the slope information of the road ahead, future road conditions can be predicted and vehicle speeds can be planned reasonably. Additionally, the conversion between potential energy and kinetic energy can be utilized to reduce unnecessary braking and select the optimal gear to reduce fuel consumption. The economic index J_E of electric energy is given by equation (7).

$$J_E = E_t(k)\Delta t \quad (7)$$

In equation (7), $E_t(k)$ represents the electric energy consumption rate of commercial vehicles. The system does not limit the speed range, but allows the speed of commercial vehicles to change within a certain range of reference speeds set by the driver. However, the magnitude of this change is not completely fixed, but adjusted by controlling the weight coefficients in the algorithm. The speed tracking index J_v is given by equation (8).

$$J_v = \kappa_1 \left(v(k) - v_{ref}\right)^2 \Delta t \quad (8)$$

In equation (8), κ_1 represents the weight coefficient and v_{ref} represents the predetermined vehicle speed. When commercial vehicles are driving at a constant speed, their speed tracking performance, electric energy efficiency, comfort, and safety factors mutually affect and constrain each other. Therefore, to obtain the optimal cruise control system, it is necessary to collaborate and optimize multiple performance indicators. By adding up the weights of each indicator, a comprehensive performance indicator function that can achieve optimal comprehensive performance is obtained. The comprehensive performance indicator function that needs to be minimized is given by equation (9).

$$\begin{cases} J = \sum_{k=0}^{N-1} L\left[x(k), u(k), k\right] + \varphi\left[x(N), N\right] \\ L\left[x(k), u(k), k\right] = E_t(k)\Delta t + \kappa_1\left(v(k) - v_{ref}\right)^2 \Delta t \\ \varphi\left[x(N), N\right] = \kappa_2\left(v(N) - v_{set}\right)^2 \end{cases} \quad (9)$$

In equation (9), N represents the number of grid divisions. κ_2 represents the weight coefficient. v_{set} represents the speed set by the driver. $\left(v(N) - v_{set}\right)^2$ represents the terminal punitive indicator. By determining the weight coefficients of each objective, the multi-objective model can be transformed into a single objective model, thereby adjusting the weights of the multi-objective programming problem. The core of this method is to reasonably determine the weight coefficient to reflect the importance of different goals. The independent weight coefficient method is used to determine the weight of each index according to the collinearity between each index and other indicators. Given an indicator item $X_\kappa \in \{X_1, X_2, \ldots, X_m\}$, if the complex correlation coefficient between indicator X_κ and other indicators is larger, it indicates that the collinearity relationship between indicator X_κ and other indicators is stronger. The easier it is to be represented by the linear combination of other indicators, the more repetitive information it is, and the smaller the weight of this indicator should be. That is, if the complex correlation coefficient R between indicator X_κ and other indicators is larger, the weight of the indicator is smaller. The R is expressed as equation (10).

$$R = \frac{\sum(x-\bar{x})(\hat{x}-\bar{x})}{\sqrt{\sum(x-\bar{x})^2 \sum(\hat{x}-\bar{x})^2}} \quad (10)$$

The reciprocal of R is taken as the score, and then normalized to get the weight system. Predicting cruise control for commercial vehicles is not a random process, but requires applying certain constraints to the various state variables and control variables of the system. Assuming the maximum engine speed is $\omega_{\min}$ and the minimum engine speed is $\omega_{\max}$, the engine speed constraint is given by equation (11).

$$\omega_{\min} \le \omega(k) \le \omega_{\max} \quad (11)$$

The predictive cruise control system allows the vehicle to change within a given speed range, but if the reference speed is exceeded, it will have a certain impact on the vehicle. For example, if the speed is too fast, it can lead to vehicle speeding or safety accidents, while if it is too low, it can cause an extension of travel time, resulting in a decrease in traffic efficiency. The expression for velocity constraint is given by equation (12).

$$v_{set} - v_{down} \le v(k) \le v_{set} - v_{up} \quad (12)$$

In equation (12), v_{down} and v_{up} respectively represent the limits of the allowed downward and upward variations in the actual driving speed. Business vehicles are generally equipped with several gears to optimize their power, economy, and shifting smoothness. Multiple gears can allow drivers to choose gears that are more energy-efficient and have better power, but gears are also limited by speed. At a certain speed, not every gear can meet certain limits. The constraint conditions that the allowed gear $G(k)$ needs to meet are shown in equation (13).

$$G(k) = \left\{ G(k) \middle| \omega_{\min} \frac{\pi r_w}{30 i_f v(k)} \le i_g(G(k)) \le \omega_{\max} \frac{\pi r_w}{30 i_f v(k)} \right\} \quad (13)$$

If the engine speed is $\omega(k)$, the maximum output torque of the engine is $T_{\max}(\omega(k))$, and the minimum is $T_{\min}(\omega(k))$. The constraint of the system's engine torque is given by equation (14).

$$T_{\min}(\omega(k)) \le T(\omega(k)) \le T_{\max}(\omega(k)) \quad (14)$$

The transmission can only switch to adjacent gears. If the shifting command is defined as $u_g(k)$, $\{-1,0,1\}$ represents downshift, hold, and upshift respectively, then the corresponding shifting constraint is given by equation (15).

$$u_g(k) \in \{-1,0,1\} \quad (15)$$

In multi-variable systems, model predictive control is a method that can be controlled through optimal methods. The schematic diagram of the solving mechanism for model predictive control is shown in Figure 4. It consists of three parts: model, prediction, and control. The three parts are connected by constructing a mechanism model or a data-based model that describes the motion state of the controlled object. This allows for predicting the future of the controlled object. Subsequently, a judgment is made and control behaviors are outputted with the objective of achieving the optimal solution.

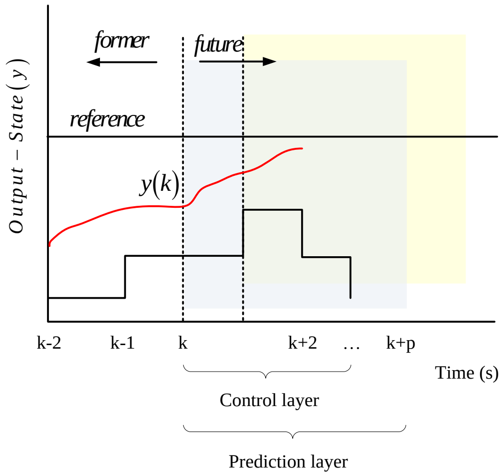


Figure 4: Schematic diagram of solving mechanism of model predictive control

Grid discretization is an important step in applying DP methods to solve continuous problems. The magnitude of its dispersion directly affects the overall optimal solution result. When solving the same problem, using a smaller mesh can accelerate the calculation speed of the DP algorithm, but there is a significant deviation between its calculation results and the actual optimal value. As the number and density of grids increase, the error between the calculation accuracy of the DP method and the true value will become smaller, but the calculation speed will be greatly reduced, and the calculation time will grow exponentially. To strike a balance between computational speed and accuracy, it is necessary to choose the appropriate grid dispersion.

The entire journey is divided into parts N to obtain time $N+1$. Each moment includes the vehicle state of displacement, speed, and gear, i.e. $x(k)=\left[s(k)\quad v(k)\quad G(k)\right]^T$, as shown in Figure 5. If the starting point offset of commercial vehicles is 0, then the distance from the starting point to the current point of the commercial parking space movement can be determined. Similarly, the speed of commercial vehicles can also be discretized into equation (16).

$$V_k=\{v_{\min},v_{\min}+\sigma,v_{\min}+2\sigma,v_{\max}\} \quad (16)$$

In equation (16), V_k represents the discrete interval. For each discretized speed, a finite number of gears can be selected based on limitations such as torque and speed. This study completes the selection of the above parameters by comparing the simulation results under different mesh densities.

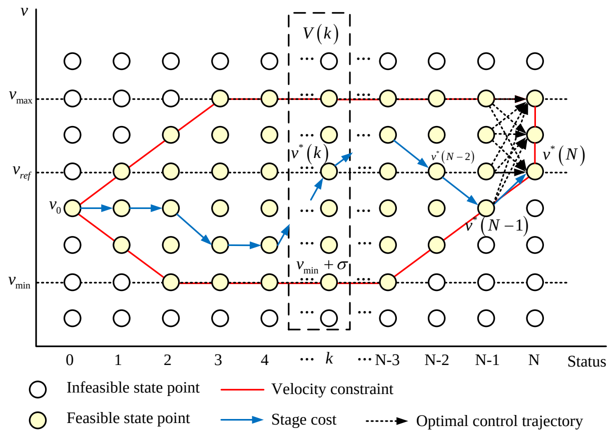


Figure 5: Schematic diagram of DP solution process

4 Simulation analysis of energy consumption control during vehicle operation

To verify the effectiveness of the designed DP-based DEC control strategy, simulation analysis was conducted on the DEC data of the vehicle model under typical operating conditions. This study built a simulation model of the vehicle model in MATLAB/Simulink and set three different operating conditions in the simulation model to compare the effectiveness of the proposed system.

4.1 Analysis of vehicle uphill and downhill working conditions

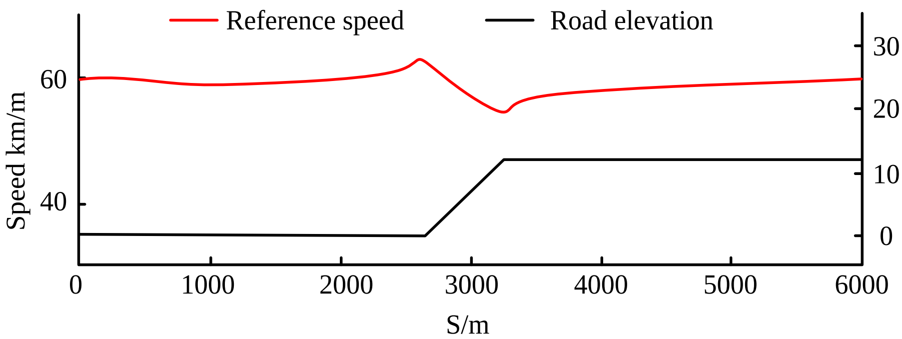
The total length of the simulated virtual road is 6500m, and the driving distance of the vehicle is 5500m. Table 2 shows all the parameter settings of vehicle. Uncertainty represents the evaluation of the magnitude range of the measured truth value. The uncorrectable part of the error range represents the dispersion of the measured value. Observation error is the difference between the measured result and the measured true value, indicating the degree to which the measured result deviates from the true value. The observation error of the experimental data is 1%, and the relative uncertainty is in the range of [-1%, 1%].

The vehicle is a PECV, and the parameters in Table 2 are all actual vehicle data. Firstly, the ramp modeling collects the vehicle's ramp driving data. Then, the motion travel between the beginning of one idle state and the beginning of the next idle state during the running of the vehicle is regarded as a short travel. Next, the feature parameters of each divided short stroke are calculated. The feature parameters include velocity, acceleration, and slope angle. Principal component analysis is used to construct the principal component score matrix. Finally, the short-stroke clustering results are obtained and the candidate driving conditions with the lowest average relative error are taken as the driving conditions of urban ramps. There are 4 types of virtual typical ramps, including uphill, downhill, concave, and convex slopes. The four types of virtual ramps are constructed using the sine function, and the average slope is 6%.

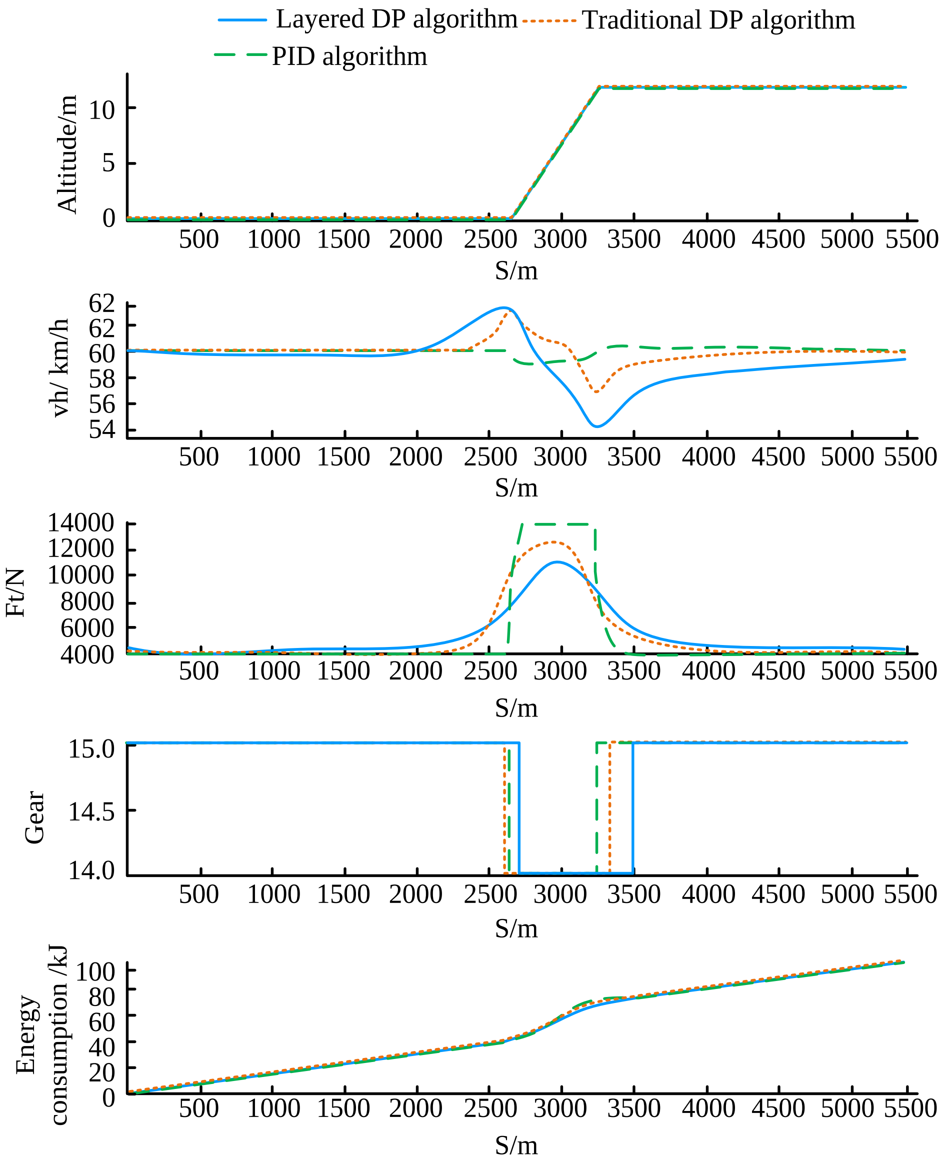
Table 2: Parameter settings

Parameter name	Parameter value
Vehicle mass	3340 kg
Initial velocity state	45 km/h
Velocity state minimum	30 km/h
Velocity state maximum	60 km/h
Minimum allowable acceleration	-3 m/s^2
Allowable maximum acceleration	3 m/s^2
Distance phase partition interval	25 m
Speed state interval division interval	1 km/h

The simulated slope is set between 2600-3200 meters, with a 3% uphill slope. The simulation results are shown in Figure 6. Commercial vehicles using the DP control algorithm accelerate in advance before going uphill, which results in a slower speed compared to the original deceleration during the actual uphill process, and the speed will also change up and down from the reference speed. This means the degree of speed deviation has been controlled. The speed of a car controlled by PID is constant before going uphill, but gradually decreases when going uphill, resulting in a greater change in speed during full uphill compared to the previous two methods. The proposed DP algorithm combines the long-term optimization of the DP algorithm with the real-time correction of model predictive control, overcoming the limitation that model predictive control is only suitable for short-term optimization. As a result, lower torque fluctuations and smoother driving have been achieved, with greater energy-saving potential. Under this operating condition, the improved DP algorithm achieves a power saving rate of 1.63% compared to the traditional PID control method.

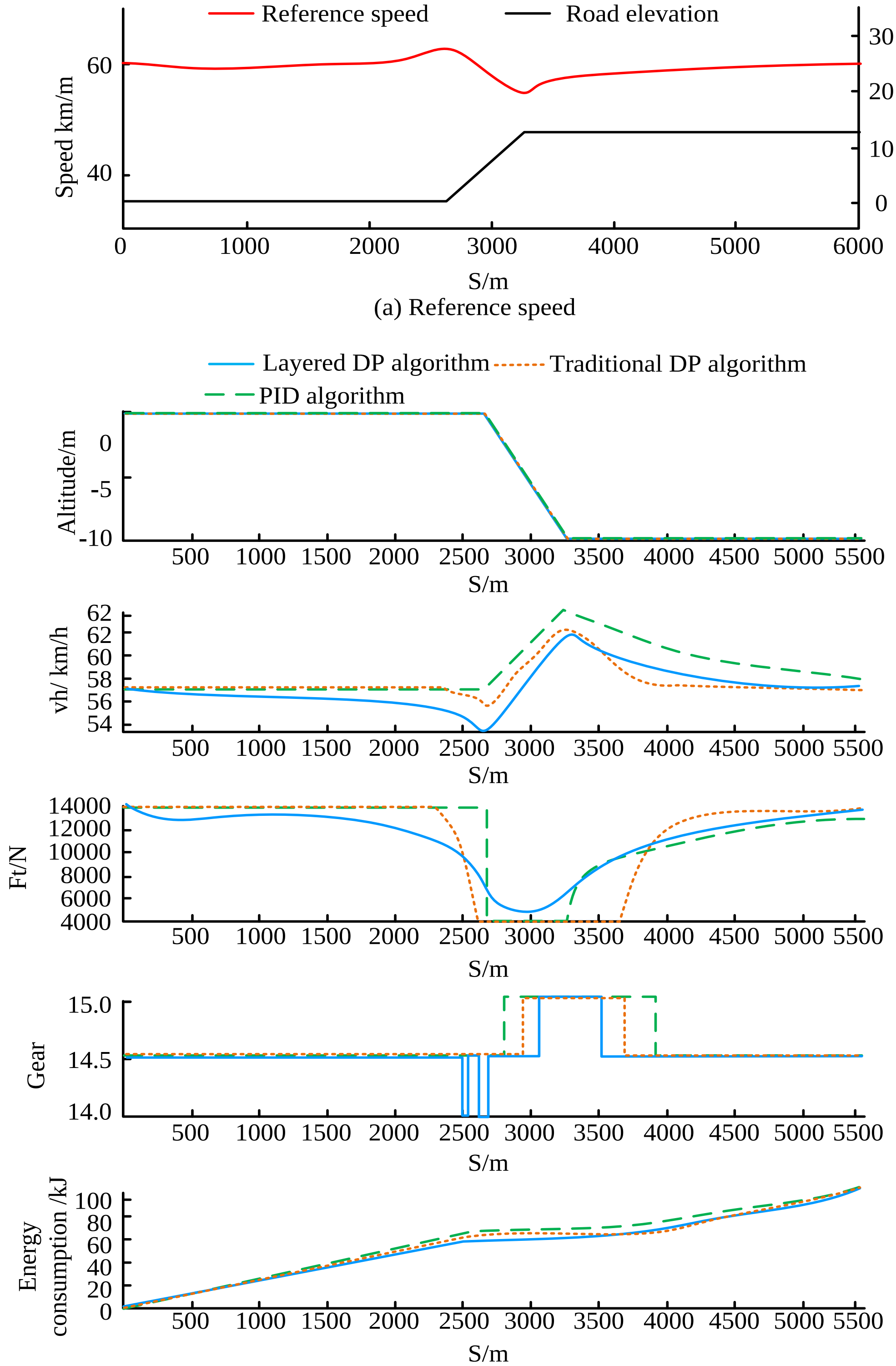


(a) Reference speed



(b) Algorithm comparison

Figure 6: Comparison diagram of co-simulation of uphill road



(a) Reference speed

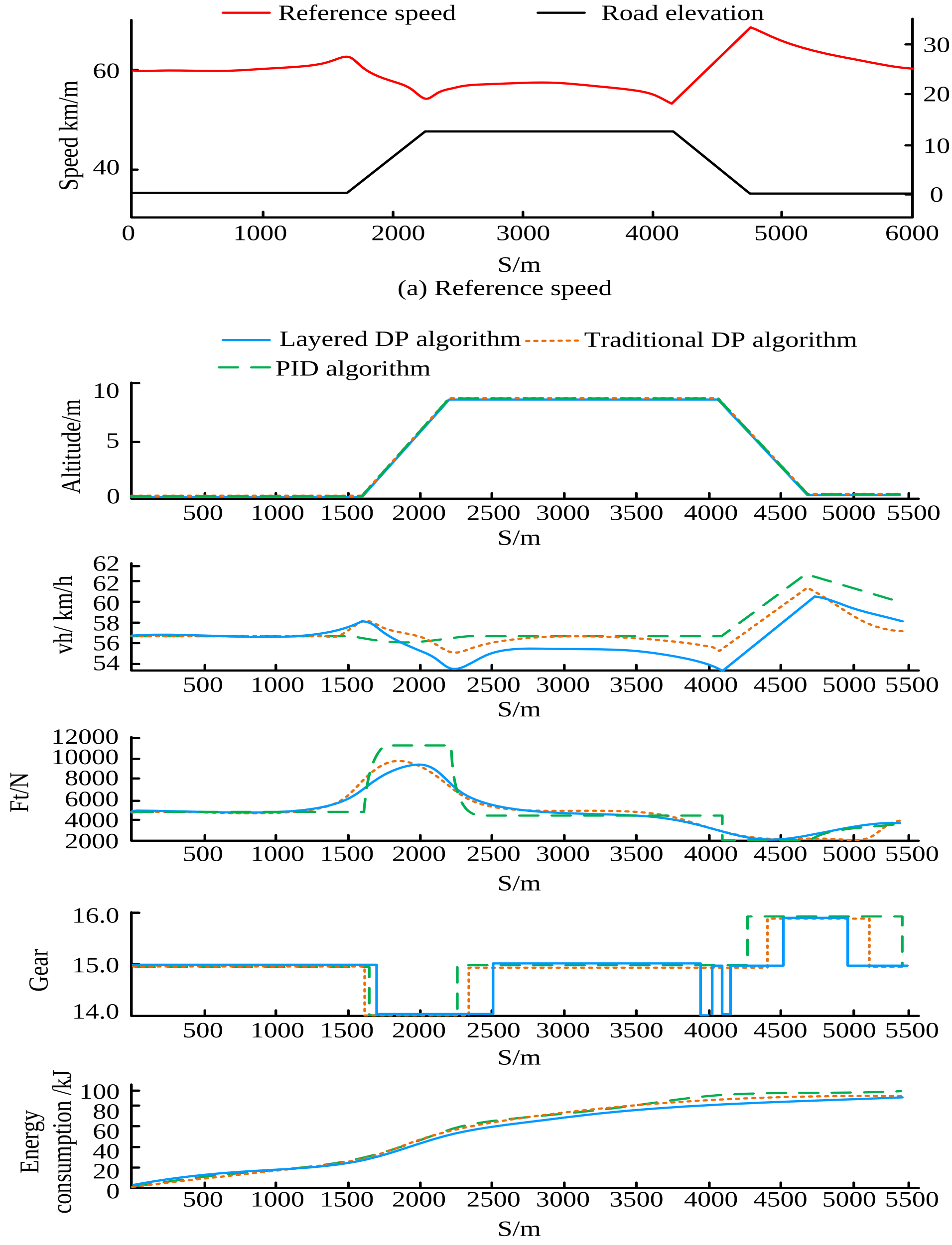
(b) Algorithm comparison

Figure 7: Comparison of downhill road co-simulation

Figure 7 shows the result of a downhill slope of -3% on the 2600–3200-meter section. Commercial vehicles using the DP algorithm will also slow down in advance before going downhill. Therefore, in the actual downhill process, the speed of the car is slightly slower than the initial growth rate, and the speed varies between the increase and decrease of the reference speed, indicating that the degree of speed deviation has been controlled.

The speed of a car controlled by PID is constant before going downhill, and gradually accelerates when going downhill, resulting in significant changes in the speed of the car. This system has lower torque fluctuations and higher energy-saving potential. Under this operating condition, compared to conventional PID control, the traditional DP algorithm can save about 3.23% of electricity, while the improved DP algorithm can save 4.56%.

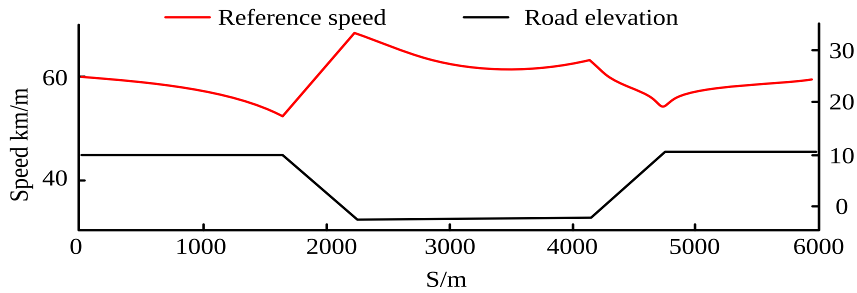
Figure 8 shows the simulation results of uphill and downhill roads (uphill first, then downhill), with a 3% uphill condition set for the 1700–2300-meter section and a -3% downhill condition set for the 4200–4800-meter section. Commercial vehicles controlled by the DP algorithm accelerate before going uphill and decelerate before going downhill. Therefore, when going downhill, the increase in car speed is smaller than before, and the degree of speed deviation is also controlled. However, commercial vehicles using the PID algorithm have no significant changes before going uphill and downhill, maintaining the same speed. As the uphill speed declines, the downhill speed continues to rise, resulting in a more pronounced alteration in the vehicle's velocity during the ascent and descent phases when compared to the initial two methods. Under this operating condition, compared to conventional PID control, the traditional DP algorithm can save about 6.68% of electricity, while the improved DP algorithm can save 7.19% of electricity.



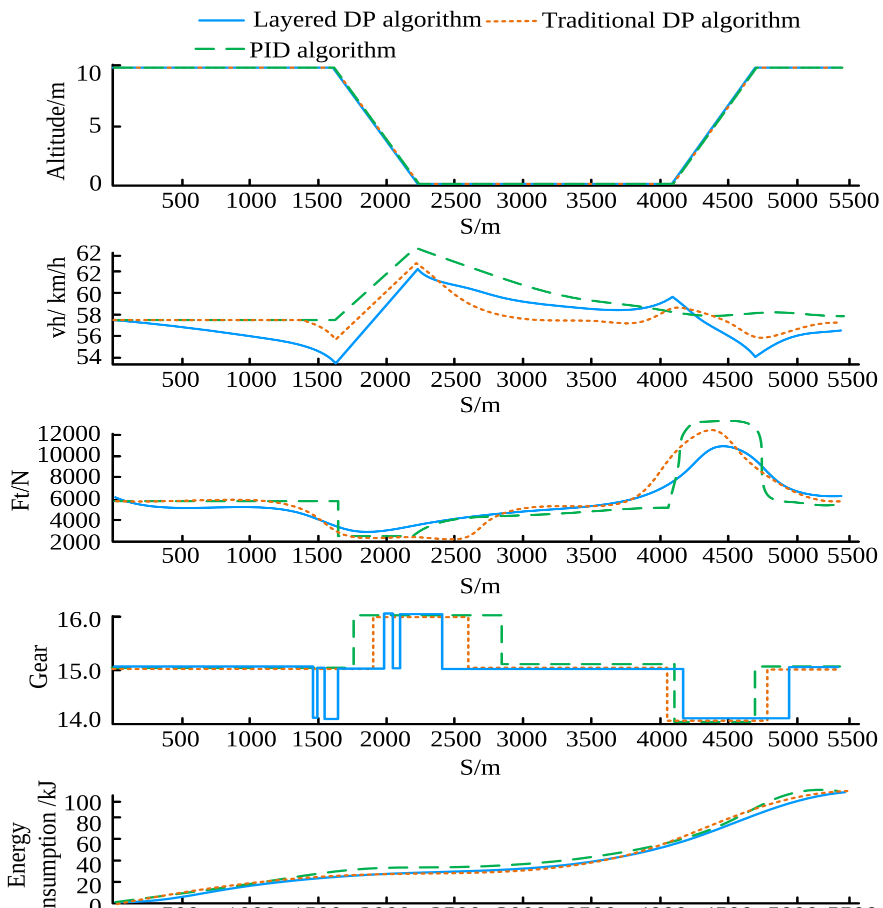
(b) Algorithm comparison

Figure 8: Comparison diagram of co-simulation of uphill and downhill roads (uphill first then downhill)

Figure 9 shows the comparison results of uphill and downhill roads (downhill first, then uphill), where the 1700–2300-meter section is set as a -3% downhill condition, followed by a 3% uphill condition in the 4200–4800-meter section. Commercial vehicles controlled by the DP algorithm slow down before going downhill and accelerate before going uphill. Therefore, when the car is uphill, the increase in speed will decrease and the deviation in speed will be controlled. Commercial vehicles using the PID algorithm maintain a constant speed before going downhill and uphill, gradually increasing speed while going downhill but decreasing speed when going uphill. This results in a greater change in the speed of the car during the entire uphill process compared to the first two methods. Under this operating condition, compared to conventional PID control, the traditional DP algorithm can save about 2.36% of electricity, while the improved DP algorithm can save 4.63%.



(a) Reference speed



(b) Algorithm comparison

Figure 9: Comparison diagram of co-simulation of uphill and downhill roads (First down, then up)

Compared to traditional DP algorithms, improved DP algorithms can save 1%-2% more electricity (Table 3). This method is more efficient because it can process and utilize slope information more quickly. Compared to conventional PID algorithms, this method can save about 1%-7.5% of electrical energy, and the average vehicle speed under typical operating conditions is relatively similar. While ensuring the efficiency of vehicle operation, it can significantly improve the fuel economy of the vehicle.

From the average total DEC values of three experiments in each of the three groups, compared to normal driving, the total energy consumption of optimized speed tracking decreases by 23.56%, while the DEC at constant speed decreases by 6.62% (Table 4). The simulation results indicate that the proposed PECVs ramp driving speed planning can achieve the goal of reducing DEC.

Table 3: Summary of simulation results

Road type	Algorithm	Average speed [km/h]	Travel time [s]	Energy saving rate
	PID	60.12	324.13	/
Uphill	Traditional DP	59.63	324.02	0.49%
	Improved DP	59.21	329.45	1.63%
	PID	62.31	309.45	/
Downhill	Traditional DP	60.47	319.82	3.23%
	Improved DP	59.68	324.91	4.56%
	PID	62.38	315.74	/
First up, then down	Traditional DP	60.49	319.84	6.68%
	Improved DP	59.22	327.38	7.19%
	PID	63.78	308.19	/
First down, then up	Traditional DP	61.68	319.47	2.36%
	Improved DP	60.94	323.16	4.63%

Table 4: Experimental results of vehicle speed trajectory

Experiment	Serial number	Total DEC (kJ)	Average value (kJ)
	1	10362	
Normal driving	2	9845	9814.00
	3	9235	
	1	7963	
Constant speed	2	8175	8033.33
	3	7962	
	1	7485	
Optimized speed	2	7496	7501.67
	3	7524	

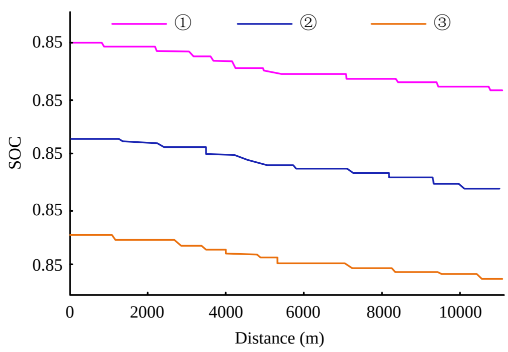


Figure 10: SOC changes corresponding to three constant speed trajectories

The change of battery State of Charge (SOC) when the driver drives three times at a constant speed on the selected road is shown in Figure 10. The experimental battery SOC is reduced by 0.32 for the three times of constant speed driving. The constant speed is controlled by the driver, resulting in a lower overall speed. This reduces the work required to overcome driving resistance, leading to a lower total DEC compared to normal driving.

5 Results and discussion

The study focused on the slow development of PECVs due to the range limit. To address this challenge, a strategy was proposed to reduce the DEC by planning the ramp driving speed. This approach aimed to achieve two key objectives: reducing the slope DEC and avoiding the excessively high temperature of the downhill brake. Additionally, the study conducted a detailed analysis of the speed planning of PECVs on ramps. The simulation results of speed optimization to reduce DEC under four virtual typical ramp conditions showed that compared with constant speed cruise control, the economic speed trajectory of PECV could reduce DEC on the ramp in both regenerative and non-regenerative braking states. There are two points of principle. First, through the lower speed in the uphill stage, the vehicle can overcome the driving resistance and do less work, thereby reducing the DEC. The second point is to make full use of the gravitational potential energy of the vehicle during the downhill process, decelerate before the downhill, accelerate during the downhill, and decelerate again after the downhill. Given this, the motor driving torque demand before and after the downhill can be reduced, thus reducing the DEC [21].

The simulation results of vehicle speed optimization under virtual long downhill road conditions to reduce brake temperature rise showed that, compared with constant speed cruise control, the safe vehicle speed trajectory could reduce the brake temperature rise during downhill driving under two conditions: whether regenerative braking is possible or not. The safe speed trajectory converted the gravitational potential energy of the vehicle into kinetic energy, consumed the work to overcome resistance, and recovered braking energy. As a result, the gravitational potential energy converted into thermal energy during the downhill process was reduced [22, 23]. The experimental results of economic speed track verification showed that the actual speed track obtained by the driver according to the economic speed cue had the same change trend and characteristics as the economic speed track. This can reduce the work to overcome the resistance and utilize the downhill gravitational potential energy in the uphill stage. The driver's economic speed track followed the total DEC, which reduced energy consumption by 23.56% compared with normal driving and reduced energy consumption by 6.62% compared with constant speed driving. It shows that the speed planning of PECV on the ramp can achieve the goal of reducing DEC.

6 Conclusion

This study aims to develop a PECV predictive cruise layered control system with advantages such as efficiency and economy to minimize electrical energy consumption and improve endurance within the allowable speed range. This study used a reference speed planning algorithm based on the DP algorithm in the upper layer and a speed tracking algorithm based on predictive cruise control in the lower layer to optimize the speed trajectory and control actions of commercial vehicles. The effectiveness and superiority of the developed algorithm in vehicle driving economy have been demonstrated through testing under different working conditions. The results showed that under uphill conditions, the improved DP algorithm achieved a power saving rate of 1.63% compared to the traditional PID control method. In downhill conditions, the improved DP algorithm saved 4.56% of electricity. Under the conditions of uphill and downhill, the traditional DP algorithm could save about 6.68% of electricity compared to conventional PID control, while the improved DP algorithm could save 7.19% of electricity. Compared to conventional PID control, the traditional DP algorithm saved approximately 2.36% of electricity in downhill and uphill conditions. The improved DP algorithm saved 4.63%. The comparison results greatly demonstrate that the algorithm has a good effect on improving the operational economy of PECVs. This experiment was conducted offline and failed to verify the real-time performance of the model. In the future, real-time data processing can be carried out based on the way of data flow, that is, the data arrive in a continuous stream and are processed and analyzed immediately. It emphasizes the real-time processing ability of infinite data flow, considering the design of data order, window processing, state management, etc., to carry out more perfect and effective experiments.

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