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Research Article

Optimized speed control for electric vehicles on dynamic wireless charging lanes: An eco-driving approach

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ABSTRACT: As the adoption of Electric Vehicles (EVs) intensifies, two primary challenges emerge: limited range due to battery constraints and extended charging times. The traditional charging stations, particularly those near highways, exacerbate these issues with necessary detours, inconsistent service levels, and unpredictable waiting durations. The emerging technology of dynamic wireless charging lanes (DWCLs) may alleviate range anxiety and eliminate long charging stops; however, the driving speed on DWCL significantly affects charging efficiency and effective charging time. Meanwhile, the existing research has addressed load balancing optimization on Dynamic Wireless Charging (DWC) systems to a limited extent. To address this critical issue, this study introduces an innovative eco-driving speed control strategy, providing a novel solution to the multi-objective optimization problem of speed control on DWCL. We utilize mathematical programming methods and incorporate the longitudinal dynamics of vehicles to provide an accurate physical model of EVs. Three objective functions are formulated to tackle the challenges at hand: reducing travel time, increasing charging efficiency, and achieving load balancing on DWCL, which corresponds to four control strategies. The results of numerical tests indicate that a comprehensive control strategy, which considers all objectives, achieves a minor sacrifice in travel time reduction while significantly improving energy efficiency and load balancing. Furthermore, by defining the energy demand and speed range through an upper operation limit, a relatively superior speed control strategy can be selected. This work contributes to the discourse on DWCL integration into modern transportation systems, enhancing the EV driving experience on major roads.

KEYWORDS: dynamic wireless charging (DWC), electric vehicle (EV), eco-driving, speed control, load balancing

1 Introduction

Road transport is responsible for the lion's share of fossil fuel consumption and carbon emissions within the global transportation matrix (Chai et al., 2016; Ehsani et al., 2016). Addressing critical global challenges, such as climate change and the energy crisis, calls for a paradigm shift towards a sustainable road transport system. In this context, Electric Vehicles (EVs) emerge as a beacon of hope, rapidly gaining traction and popularity (He et al., 2022; Liu et al., 2022a; Zhang et al., 2022). Yet, the adoption curve of EVs is somewhat tempered by persistent user concerns, notably the vehicle's range (Ahasan et al., 2022; Ruan and Lv, 2022; Zhang et al., 2021b) and the inherent charging latency (Aljehane and Mansour, 2022; Boddapati et al., 2022; Ji et al., 2022).

Drivers' range anxiety can be alleviated by the emerging Dynamic Wireless Charging (DWC) technology, which uses a charging infrastructure embedded under the road surface to transmit power to the vehicle's inductive pickup assembly while the vehicle is moving to provide charging for a moving electric vehicle. It does not require the EV to stop while it is charging, which can reduce the travel time for charging technologies on the move (He et al., 2020; Kim et al., 2019). DWC lanes can be considered charging stations when a high demand for EVs that need to be charged. Thus, DWC technology will promote the use of electric vehicles and significantly change the development of the road transportation sector. For those keen on real-world applications, DWC is not just a concept confined to research papers. Several industrial applications have been pioneered across the globe. Recently, an Israeli technology company, ElectReon, has completed the deployment of its dynamic wireless charging system on 1.65 km (1.02 miles) of public roads on the Swedish island of Gotland (Radu, 2022). Also, in other countries and regions, electric vehicles are operating on roads using DWC technology, for example, the Qualcomm Halo DEVC in France (Hilton, 2017) and the OLEV tram installed in the Grand Park in Seoul, Republic of Korea (Jang et al., 2016). In Fig. 1, we highlight some of the trailblazing initiatives: Bombardier's PRIMOVE System, Qualcomm's Halo DEVC, KAIST's OLEV tram system, and notable applications from Chinese cities like Nanning, Suzhou, and Changchun.

According to He et al. (2020), the application of DWC lanes was mainly analyzed in inner city areas. However, with the advancement of battery technology, the charging demand for EVs often occurs in inter-city trips. In DWC lanes, EVs need to

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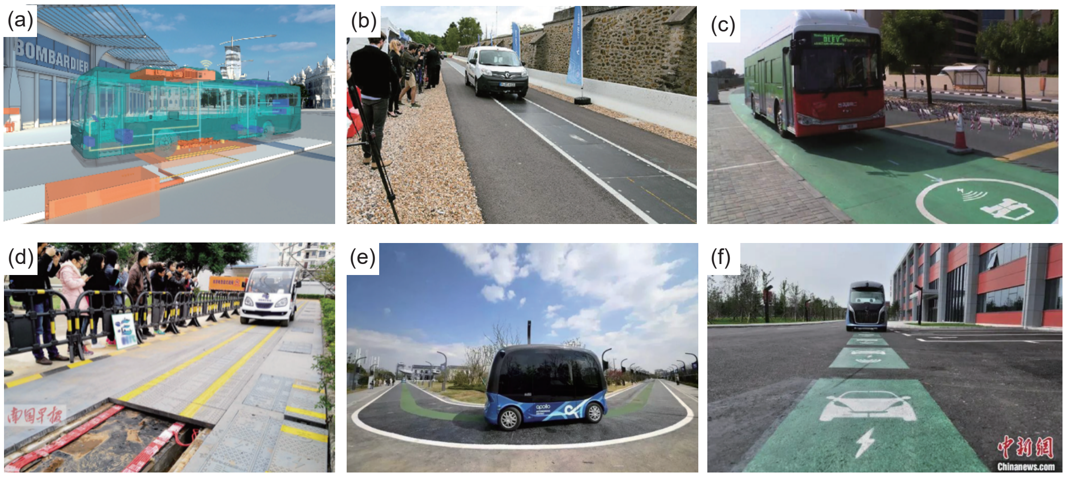

Fig. 1 Test and applications: (a) Bombardier, PRIMOVE (Bombardier, 2023); (b) Qualcomm Halo DEVC (Hilton, 2017); (c) KAIST OLEV (Khaleej, 2020); (d) Nanning, China (Tan et al., 2022); (e) Suzhou, China (Hawkins, 2023); (f) Changchun, China (Changchun International Automobile City (CIAC), 2023).

increase their state of charge (SoC) at low speeds over a limited DWC section. However, slowing down on the freeway is not acceptable for vehicles. The limited number of freeway service areas and varying service rates make it impractical to build more charging stations. This can result in piles of unused stations due to random power demand, leading to long queues at some stations while others have no electric vehicles being charged. This study proposes a solution to the problem by introducing a DWC lane. Electric vehicles in need of charging can drive into the DWC lane to increase their SoC. This helps avoid long queues at charging stations and also predicts the queues at stations. The DWC lane also allows the power demand to be uniformly distributed in time and space.

DWC presents promising economic advantages, including the reduction of fuel costs, enhanced convenience and range for EV users, and decreased reliance on conventional fuel-powered vehicles (Bi et al., 2019; Liu and Song, 2017). These factors collectively contribute to the commercialization prospects of DWC technology. Moreover, the transformative potential of DWC technology in the EV industry and sustainable energy sector may lead to the implementation of government subsidies and policies (Lazzeroni et al., 2021; Majhi et al., 2022). These measures could include financial assistance, tax incentives, or direct subsidies aimed at supporting businesses and consumers in adopting DWC technology. The advantages of DWC technology are contingent upon ensuring a reliable charging efficiency. Concurrently, attention must be given to reducing travel time and implementing appropriate load balancing measures to prevent an excessive concentration of vehicles in specific charging areas. Such concentration could result in decreased charging efficiency and increased queue time. To achieve the optimal application experience of DWC technology, it is imperative to contemplate the interrelated issues of charging efficiency, travel time reduction, and load balancing. In this context, the implementation of a vehicle speed control strategy assumes a pivotal role. When charging a vehicle using DWC, it is important to control the speed of the vehicle to ensure a safe and efficient charging process (Yang et al., 2022). In addition, the vehicle's speed can also impact the energy utilization efficiency, traffic efficiency (He et al., 2023), and charging process time of DWC, which ultimately affects the EV's mileage (Li et al., 2022; Zheng et al., 2022). This study has developed a nonlinear mixed-integer programming method to determine the speed trajectory for the corresponding DWCL lane, in order to address the issue of vehicle speed control in the DWC lane. The technique ensures optimal energy use efficiency and reduces mileage anxiety by regulating the speed of vehicles in the DWC lane. This study does not plan to assign electric vehicles from the freeway to the DWCL lane, which is the upper-level problem within the scope of this study. In the results of this paper, the efficiency of the traffic flow, the charging demand of the driver, and the load pressure of the DWC lane are simultaneously optimized by a carefully designed control.

In this study, we proposed a load-balancing eco-driving strategy for autonomous electric vehicles in charging lanes with DWC lanes, aiming to satisfy the different charging demands of EVs. In addition, the load pressure to the DWC lanes, as well as the traffic system, is considered. Note that reducing the load pressure on the traffic system is equivalent to alleviating traffic congestion. The contributions of this study are listed below.

1) An eco-driving speed control approach was developed specifically for EVs operating on DWCLs. This strategy seeks to bolster charging efficiency and the duration of effective charging, offering a potential avenue for enhanced in-transit charging while prioritizing both safety and efficiency.

2) Through the formulation of three objective functions—minimizing travel time, maximizing charging benefits, and achieving a balanced load—a comprehensive optimization framework was established. Integral to this framework was the incorporation of the vehicle's longitudinal dynamics as a physical model for calculating EV energy consumption. The various examined control strategies showcased their unique strengths in balancing load distribution with energy consumption considerations.

3) The study furnishes valuable insights into the plausible integration of DWCLs within modern transportation infrastructures. This perspective suggests a roadmap to augment the EV driving experience on highways, possibly alleviating the well-documented concerns of range anxiety.

The technical route presented in Fig. 2 illustrates the progression of the research, which delineates the systematic process of developing a load-balancing eco-driving speed control strategy. It encompasses key steps such as establishing an accurate EV's battery model, formulating an objective function based on travel time, energy consumption, and load balance, deriving and scrutinizing multiple control strategies, selecting the most superior speed control approach, and ultimately crafting a bespoke eco-driving strategy that incorporates longitudinal dynamics. By adhering to this methodological framework, researchers and

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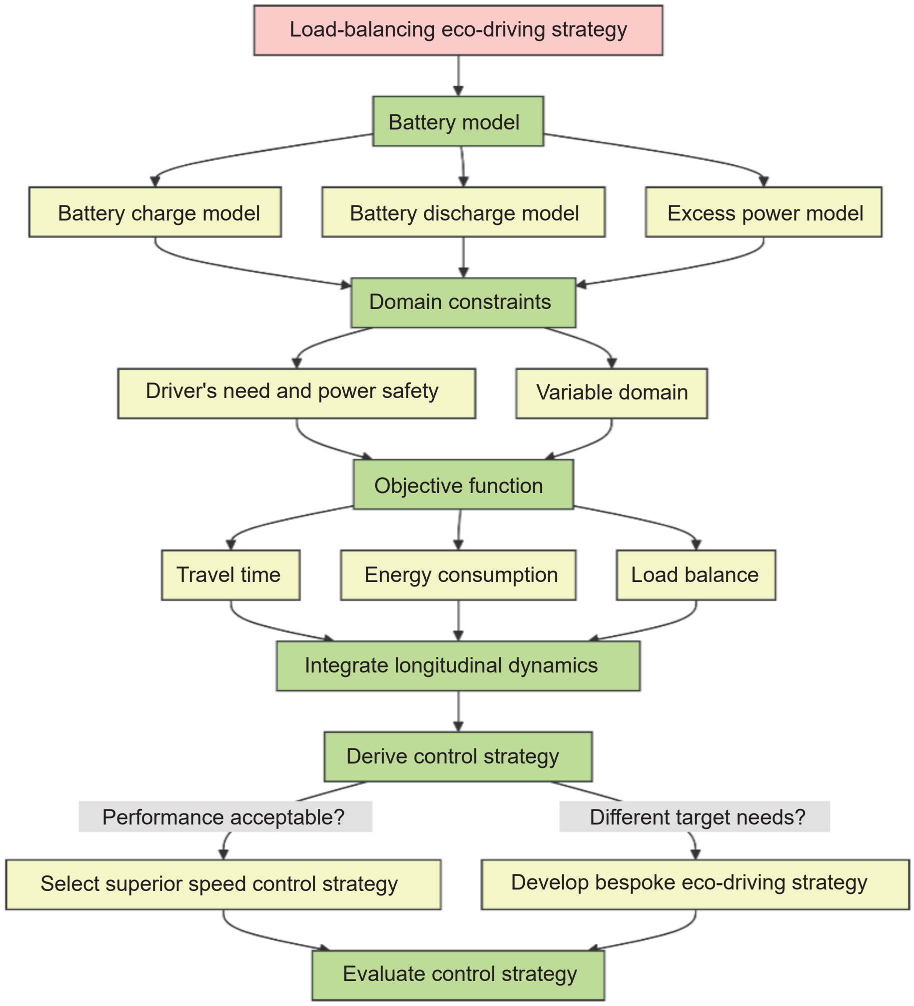

Fig. 2 Technical route of load-balancing eco-driving speed control strategy.

practitioners can effectively optimize the performance and efficiency of eco-driving systems.

2 Literature review

Wireless power transfer (WPT) technology is an emerging technology to realize electric vehicle charging. It is an energy transfer method that achieves electrical energy from the power source to load without direct electrical contact (Jiang et al., 2012; Mohamed et al., 2020; Wen et al., 2019) and is mainly classified into three types: static wireless charging (SWC), dynamic wireless charging (DWC), and quasi-dynamic/static wireless charging (QDWC). SWC and DWC modes are defined by whether the vehicle is charged at non-zero speed, while QDWC mode can charge an electric vehicle when it is stationary or DWC technology enables wireless charging of EVs by transmitting electrical energy from a management unit located outside the road to a transmitting coil buried below the road surface, using the phenomenon of magnetic induction (Theodoropoulos et al., 2015). Specifically, when the coil is energized, a magnetic field is generated. When the electric vehicle is driven on the wireless charging section, the receiving coil inside the vehicle generates an induced current by cutting the magnetic induction lines. This current is then transmitted through a circuit to the battery system, thus completing the wireless charging process.

The history of DWC technology can be traced back to the late 1970s. In 1997, a team of researchers at Oakland University made a breakthrough in the application of wireless charging technology to electric vehicle charging and developed the world's first wirelessly charged bus in collaboration with the Konstant, Germany. This was followed by the development of the first working prototype of wireless charging for electric vehicles by a team of researchers at the University of California, Berkeley, USA. Although DWC has many benefits, its commercialization and industrialization has not been successful. This is due to issues such as high costs, safety concerns, and low charging efficiency. To address these problems, numerous studies have suggested optimization strategies for factors like charging time, lane selection, driving speed control, and energy transfer efficiency. Chen et al. (2016) proposed a UE model for the user equilibrium problem to describe the equilibrium traffic distribution after deploying charging lanes in the network. Liu et al. (2021) investigated the optimal location and tariff of dynamic wireless charging sections for electric vehicles to minimize the total social cost within a given budget. The main problem of the traffic system is to design energy-optimal wireless charging speed control by guiding the vehicle travel speed and rated charging voltage (Gong et al., 2018; Tan et al., 2019). Zhang et al. (2021a) designed the location, power, and length of DWC lanes and proposed an eco-driving strategy for electric, connected, and autonomous vehicles to reduce the cost and range of vehicle trips near signalized intersections. Na et al. (2018) proposed a problem to minimize the energy consumption of charging devices by determining the movement paths and efficient charging points of mobile chargers and proved that the problem is NP-hard. Yassine et al. (2019) proposed a game-theoretic approach to optimize the efficiency of wireless charging on the move taking into account traffic congestion.

DWC systems suffer from a supply-demand imbalance (Green and Guha, 1995; Hörcher and Graham, 2018; Huang et al., 2021). To solve this problem, many researchers have tried to shift the demand from peak periods to low-peak periods to balance the supply and demand in the system. For example, pricing strategies are often used in public transportation systems to alleviate congestion problems (De Palma and Lindsey, 2011). In network theory, load balancing is used to distribute network traffic to multiple servers to achieve optimal utilization of resources (Bourke, 2001). From the perspective of load balancing, many researchers have adopted similar strategies to address the supply-demand imbalance in DWC systems. Freire et al. (2010) integrated renewable energy generation into an electric vehicle charging strategy to optimize grid load balancing. Liu et al. (2022b) used the concept of load balancing to design a single-agent deep reinforcement learning model to optimize vehicle dispatching in a ride-hailing system. It is important to note that when roads and energy supply are considered as multiple servers (multiple charging stations, lanes, and road segments), changes in traffic demand are closely related to load balancing. Therefore, two load balancing scenarios need to be considered in the charging lanes charges problem, i.e., load balancing of different charging stations and load balancing of each DWC segment in charging lanes. The focus of this study is on the latter. Table 1 summarizes the strategies and targets employed in previous literature for load balancing and optimizing traffic efficiency.

This study proposes a speed control of EVs in charging lanes with a model framework that discretizes the road segment and time. The travel time, net energy input, and load balancing in each DWC segment are considered in the speed control. The remainder of this paper is organized as follows. In Section 3, we present the formulation and analysis of the model of the traffic system and discuss extensions to our transportation model. In Section 4, we conduct numerical tests in a case study, and then we provide a conclusion in Section 5.

3 Problem statement

This study proposes a scheme to address EV drivers' range anxiety on a long trip on the highway with charging lanes. And the vehicle's speed control in charging lanes is planned in this study. In the highway system, EVs should wait for a long time in the nearby charging station. Alternatively, they can drive into the DWCL lane to increase their SoC and then search for a charging station with a short waiting time. There may exist one or several charging lanes between two charging stations, and vehicles with different charging demands (which is dependent on the operation of administration in central control or the decision of drivers) can be guided or controlled into different charging lanes to make the total system efficient.

This study focuses on a more detailed problem, that is, the speed control of EVs in charging lanes. In the charging lanes, the EV's speed should be carefully planned to make the load pressure on the DWC lanes modest. In addition, the travel time on charging lanes should be reduced, otherwise, some vehicles will waste time on the charging lanes.

3.1 Eco-driving strategy in a charging lane for EVs

For the convenience of readers, we list some notations frequently used in this study in Table 2. The DWCL lane consists of S segments, and each segment is indexed by $S \in \mathcal{S}$ ($|\mathcal{S}| = S$). We assume that the length of each segment is common and denoted by l. We use w_s to record whether a DWC lane is laid on segment s or not. If it is, $w_s = 1$, otherwise, $w_s = 0$.

Consider a battery of vehicles that need to be charged is controlled or guided, which is recorded in set $\mathcal{U}$. A specific vehicle is indexed by $u \in \mathcal{U}$. We use $\mathrm{SoC} \in [\mathrm{SoC}_{\min}, \mathrm{SoC}_{\max}]$ to denote the vehicle's state of charge. $\mathrm{SoC}_{u,0}$ is the initial SoC of vehicle u and $\mathrm{SoC}_{u,s}$ is the SoC of vehicle u at the beginning of segment s. A vehicle shares only one trip in this study. Thus, the trip is also indexed by u. We use c_{u,s_u^+} and t_{u,s_u^+} to denote the initial battery capacity and departure time for trip u, respectively, where s_u^+ ($s_u^+ \in \mathcal{M}$) is the departure location for the trip u.

3.2 Assumptions

The administrator then faces an optimization problem to operate and manage each vehicle's motion and decision to improve the DWC system. To facilitate the optimization model, we adopt the following assumptions in the investigated problems.

Assumption 1. The acceleration is consistent in each segment. We assume that the vehicle's acceleration in each segment has no change to reduce the dimension of the optimization problem. Notice that the assumption is reasonable when the length of the segment is not long, and the vehicle's velocity can also vary to improve the total performance of the DWC system.

Assumption 2. All vehicles share the same battery properties.

Assumption 3. The road elevation and temperature are consistent, and the influence of the charging rate caused by slope inclination and temperature change are not taken into account. In the short term, the temperature and slope can be seen as fixed and the slope is an exogenous variable dependent on the topological structure of the road. The temperature may change within a day, but we can discretize the operation time into several time intervals, in which the temperature has little change in each time interval.

Table 1 Comparison of various strategies

Ref.	Strategy	Target
Chen et al. (2016)	User equilibrium model	User equilibrium problem
Liu et al. (2021)	Logit-based stochastic user equilibrium model	Optimal locations and electricity prices
Zhang et al. (2021a)	W-eco-driving control strategy	Decrease the total energy consumption and increase traffic efficiency
Yassine et al. (2019)	Game-theoretic approach	Optimize the efficiency considering traffic congestion
Freire et al. (2010)	Vehicle-to-grid charge strategy	Optimize grid load balancing
Liu et al. (2022b)	Single-agent deep reinforcement learning model	Optimize vehicle dispatching in a ride-hailing system
He et al. (2014)	Network equilibrium model	Minimize the trip times and costs without running out of charge
Aljehane and Mansour (2022)	Deep learning with metaheuristic optimization strategy	Optimal allocation of renewable energy sources and charging stations

Table 2 Summary of notations

Notation	Description
Set	
$\mathcal{U}$	Set of EV index, and $\mathcal{U} := \{1, 2, \ldots, U\}$
$\mathcal{S}$	Set of discrete route segment, $\mathcal{S} := \{1,2, 3, \ldots, S\}$
Parameter	
u	Index of EV, $u \in \mathcal{U}$
s	Index of segment, $s \in \mathcal{S}$
w_s	$= 1$ when the segment s is a wireless charging segment, $= 0$ otherwise
c_{u,s_u^+}	Initial battery capacity for vehicle trip character index u
t_{u,s_u^+}	Departure time for vehicle trip character index u
s_u^+	Departure location for vehicle trip character index u
s_u^-	Destination location for vehicle trip character index u
SoC	State of charge for electric vehicle
$\text{SoC}_{\max}$	Maximum state of charge
$\text{SoC}_{\min}$	Minimum state of charge
l	Distance per segment
C_u	Battery capacity for vehicle u
P_s	Lane use penalty for segment s
Variable	
$x_{u,s}$	$= 1$ when the DWC lane in segment s is selected by vehicle u, $= 0$ otherwise
$v_{u,s}$	Continuous variables, initial speed for vehicle u at segment s
$a_{u,s}$	Continuous variables, acceleration for vehicle u at segment s
$\text{SoC}_{u,s}$	SoC of vehicle u at the beginning of segment s
$p_{u,s}^+$	Continuous variables, EV battery power charging of vehicle u at segment s
$p_{u,s}^-$	Continuous variables, EV battery power consuming of vehicle u at segment s
$E_{u,s}^-$	Continuous variables, the energy consumption of vehicle u at segment s
$\Delta_{u,s}$	Continuous variables, EV battery input power of vehicle u at segment s
$p_{u,s}^e$	Continuous variables, amount of excess power for vehicle u at segment s

Assumption 4. On a charging link, an EV driver can choose his or her travelling speed between a maximum currently allowable speed and a minimum speed limit. Assumption 4 is the same as an assumption in Chen et al. (2016). More detailed explanations can be found in Chen et al. (2016). The assumption is reasonable with the cooperation of connective and autonomous vehicles (Qu et al., 2022).

3.3 Model related to the electric vehicle's battery

The models of the battery's discharging and charging are proposed in Section 3.3.1.

3.3.1 Battery charge/discharge model

When an electric vehicle runs on a DWC lane, the variation of its actual energy storage is dependent on its energy consumption and charging. To simplify the model, we use $p_{u,s}^-$ to represent the average value of the u-th vehicle's energy consumption power in the m-th segment, and use $p_{u,s}^+$ to represent the average value of the u-th vehicle's charging power in the s-th segment. Then, the n-th vehicle's energy storage is formulated as

$$c_{u,s} = c_{u,s_u^+} + \sum_{i=s_u^+}^{s-1} \Delta_{u,i} \quad u \in \mathcal{U}, s \geq s_u^+ \tag{1a}$$

$$\Delta_{u,s} = \frac{2l}{v_{u,s} + v_{u,s+1}} + E_{u,s}^- \quad u \in \mathcal{U}, s \in \mathcal{S} \setminus \{S\} \tag{1b}$$

Discharge model: The discharge model of the EV's battery, also known as the energy consumption model, consists of the energy consumption for rolling resistance, road slope resistance, acceleration resistance, and wind resistance (Chang et al., 2014). The energy consumption model adopted here is a physical model based on vehicle longitudinal dynamics from the reference (Wang et al., 2015).

The model is built in a reverse way, and it can calculate the energy consumption for a given speed profile. Let continuous variables $p_{u,s}$ denote the EV battery power consumed by vehicle u at segment s. The battery power consumption $p_{u,s}$ is given in Eq. (2):

$$p_{u,s}^- = (F_r + F_g + F_a + F_{\text{air}}) \cdot v + P_{\text{Loss}} \tag{2a}$$

$$F_r = f_r mg \cos\alpha \tag{2b}$$

$$F_g = mg \sin\alpha \tag{2c}$$

$$F_{\text{air}} = \frac{1}{2}\rho C_d A v^2 \tag{2d}$$

$$F_a = \left(m + \frac{4J_w}{r^2} + \frac{J_m}{r_d^2 r^2}\right) a \tag{2e}$$

where a and v denote the instantaneous acceleration and velocity of the vehicle, respectively; F_r denotes the rolling resistance force; F_g denotes the force originating from the road slope; F_{air} is the air resistance force; F_a denotes the acceleration force; P_{Loss} denotes the vehicle powertrain loss, which determines in the dynamometer test; A is the front area of the vehicle; ρ is the air density; C_d is the coefficient of air resistance; α is the road slope; J_w is the wheel inertia, J_m is the motor inertia; r_d is the gear reduction ratio.

It should be noted that the trajectories of vehicles should satisfy the vehicle's kinematics, i.e.,

$$a_{u,s} = \frac{v_{u,s}^2 - v_{u,s-1}^2}{2l} \qquad u \in U, s \in S \setminus \{S\} \tag{3}$$

Then, the vehicle's energy consumption for vehicle u in segment s can be formulated as

$$E_{u,s}^- = \left(\frac{1}{4}\rho C_d A l + \frac{1}{2}m_{eq}\right) v_{u,s+1}^2 + \left(\frac{1}{4}\rho C_d A l - \frac{1}{2}m_{eq}\right) v_{u,s}^2 + f_r mgl - \frac{2lP_{Loss}}{v_{u,s+1} + v_{u,s}} \quad u \in U, s \in S \setminus \{S\} \tag{4}$$

Charge model: We adopt a simple model to describe the charging rate of EVs as Eq. (5)

$$p_{u,s}^+ = p_c \qquad u \in U, s \in S \tag{5}$$

Equation (5) indicates that the charging power is constant, which is also adopted by He et al. (2014).

3.3.2 Excess charging power

For the operation feasibility, we do not permit the vehicle to enter or quit in the internal link of a designed segment. Thus, the vehicle should finish the charging process but not leave the DWC lane in a segment. To describe the property, we define a continuous variable $p_{u,s}^e$ as the amount of excess power on segment s for vehicle/trip u. As shown in Fig. 3, the green curve illustrates the current battery power in each charging segment, and the vehicle stops charging and maintains when the battery is fully charged or reaches the value of $\mathrm{SoC_{max}}$.

Based on the definition of $p_{u,s}^e$, we present it as Eq. (6):

$$p_{u,s}^e = \begin{cases} 0, \Delta_{u,s} \le C_u(\mathrm{SoC_{max}} - \mathrm{SoC}_{u,s}) \\ \Delta_{u,s} - C_u(\mathrm{SoC_{max}} - \mathrm{SoC}_{u,s}), \\ \qquad \Delta_{u,s} \ge C_u(\mathrm{SoC_{max}} - \mathrm{SoC}_{u,s}) \end{cases} \qquad u \in \mathcal{U}, s \in \mathcal{S} \tag{6}$$

3.4 Domain constraints

Driver's need and power safety: Before driving into the DWC lane, each vehicle or driver has a charging need for having enough energy storage to finish the rest of the trip. We use the variable $c_{u,\min}$ to record the u-th vehicle's needs when they leave the DWC

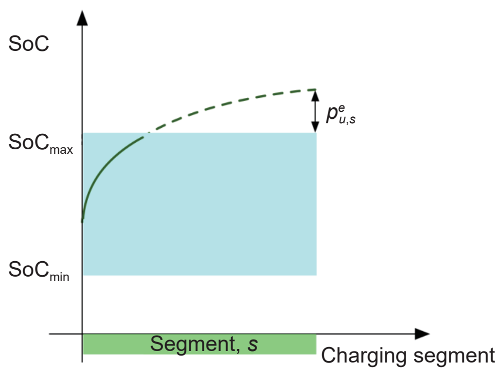

Fig. 3 Diagram of excess power.

lane. For safety purposes, the vehicle's SoC is not allowed to exceed the maximum value of the setting. Thus, the following constraint should be satisfied.

$$c_{u,\min} \le c_{u,s} \quad u \in \mathcal{U} \tag{7a}$$

$$c_{u,s} \le \mathrm{SoC_{max}} \quad u \in \mathcal{U}, s \in \mathcal{S} \tag{7b}$$

Equation (7a) states that the energy storage of each vehicle after charging should meet the energy demand to finish the following trip task. Equation (7b) indicates that the power storage of a vehicle cannot exceed the maximum value of SoC.

Variable domain: The decision variables, including $x_{u,s}$, $v_{u,s}$, $a_{u,s}$ have their domain according to their definitions and the performance of the vehicle. In summary, these variables are constrained by Eq. (8):

$$x_{u,s} \in \{0,1\} \quad u \in \mathcal{U}, s \in \mathcal{S} \tag{8a}$$

$$v_{\min} \le v_{u,s} \le v_{\max} \quad u \in \mathcal{U}, s \in \mathcal{S} \tag{8b}$$

$$a_{\min} \le a_{u,s} \le a_{\max} \quad u \in \mathcal{U}, s \in \mathcal{S} \tag{8c}$$

3.5 Objective function

The load-balancing eco-driving strategy intends to reduce vehicle's energy consumption and travel time provided that each vehicle's charging demand is satisfied, and the traffic system, as well as the DWC system, is load-balancing (no traffic congestion and no much pressure on the DWC system). We conclude these objectives with Eq. (9):

$$F_1 = \sum_{u \in \mathcal{U}, s \in \mathcal{S}} \frac{l}{v_{u,s}} \tag{9a}$$

$$F_2 = \sum_{u \in \mathcal{U}, s \in \mathcal{S}} (p_{u,s}^e - \Delta_{u,s} w_s x_{u,s}) \tag{9b}$$

$$F_3 = \max_{s \in \mathcal{S}} \left\{ \sum_{u \in \mathcal{U}} w_s x_{u,s} \right\} \tag{9c}$$

In the above objectives, Eq. (9a) is the total travel time for vehicles running on the DWC lane. Reducing the travel time when all vehicles have enough energy storage can also avoid the stack of vehicles in the DWC lane. Equation (9b) is the additive inverse of energy storage variation, and minimizing it indicates that the vehicle can be charged as much as possible within a reasonable velocity range. Equation (9c) represents the loading pressure on the DWC lane. We should reduce the value of F_3 to improve the lifetime of the DWC service.

4 Numerical test

4.1 Parameters, scenarios, and metrics

In this section, some numerical tests conducted to verify the effectiveness and efficiency of the speed control. The total length of the DWCL lane is $L = 5$ km, and the length of each segment is $l = 500$ m. The case when the power demand is huge is not considered. Also, the speed is in the range of [10 m/s, 20 m/s] to meet the condition of Assumption 4. The constant power of the DWC lane is set as $p_c = 90$ kW, the same in He et al. (2014). The parameters related to the discharging of EVs are the same in

Chang et al. (2014).

Four cases tested in this section are set based on the objective function in Section 2. To simplify, we named the four cases Case A, Case B, Case C, and Case D. Case A, Case B, and Case C are the speed control problem considering F_1, F_2, F_3, respectively. And the fourth case considers the three objectives together, i.e., $F = \alpha F_1 + \beta F_2 + \gamma F_3$.

The following metrics are proposed to compare the performances of the speed control in different scenarios:

● Average travel time (ATT) is the travel time's mean value for all vehicles that through the DWCL lane.

● Average energy consumption per kilometer (AECpk) is the average energy consumption's mean value for all vehicles that through the DWCL lane.

● Maximum power-out time (MPOT) is the maximum value of the power output for all segments when the EVs in a planning period are all serviced.

4.2 Fundamental test

We conduct a fundamental test when the speed of the vehicle should be in a range of [10 m/s, 20 m/s]. While this range of speeds may fall short of conventional highway standards, they can still result in significant time savings compared to stopping for recharging, thereby providing tangible benefits for vehicle owners. To mitigate the negative impact of relatively low charging speeds on traffic flow, judicious network planning and road design strategies can be explored. These include situating charging sections in areas with lower speed limits, such as ramp zones, and introducing dedicated slow lanes for charging purposes alongside regular lanes (Chandra et al., 2022; Chen et al., 2016; Liu and Song, 2018; Ushijima-Mwesigwa et al., 2018; Wang et al., 2023). As battery technology and wireless charging continue to advance, future reductions in charging time may facilitate faster passage through charging lanes. The methodologies proposed in this study will remain applicable for speed planning considerations at that juncture. The demand for energy input is [7.2 kW·h, 9.6 kW·h] and the number of vehicles that should be charged is 121. Each vehicle corresponds to a combination of the two integer values from the ranges of SoC and velocity. The hardware configuration used in our research includes an Intel Core i7 CPU with a clock speed of 2.2 GHz. We utilized MATLAB to invoke Gurobi and conducted the simulation process on a personal computer. The vehicle velocity trajectories are sequentially planned according to their entry order into the system. Utilizing MATLAB on a personal computer, each vehicle's trajectory can be planned in under one second, resulting in a total optimization time of 71 s for 121 vehicles.

We present the overall performances of the four cases in Table 3. The control in Case A and Case B was always adopted in traditional eco-driving strategies, which aim to reduce the total (or average) travel time and energy consumption. The control in Case C tries to reduce the maximum value of the charging time of segments, which can avoid or postpone the damage of the DWC lane caused by prolonged use and overload.

Even though the control in Case C can reach the "load balancing", the energy consumption is greater than the controls in Case A and Case B. To make a tradeoff between load balancing and the vehicle's energy consumption, the control in Case D is proposed. The weight parameters utilized in Case D are $\alpha = 10$, $\beta = 1$, and $\gamma = 10$, that is, $F = 10F_1 + F_2 + 10F_3$. It should be noted that due to the inherent variance in the dimensions of the three objectives, the absence of weighting would unduly diminish the significance of objectives with smaller numerical values. At present, the weight parameters employed have not undergone meticulous optimization; rather, they have been approximated to ensure a comparable magnitude across all objectives. Nonetheless, in practical industrial applications, it is advisable to tailor weights according to specific requirements or employ appropriate normalization or standardization techniques to address the inherent discrepancies in the objective dimensions. The properties of the control in Case D are concluded:

Table 3 Metrics of the controls in four cases

Case	ATT (s)	AECpk ((kW·h)/km)	MPOT (h)
A	354.887	0.472	1.323
B	487.938	0.419	1.678
C	356.539	0.492	1.204
D	375.895	0.458	1.284

• Compared with the control in Case A, the control in Case D increases ATT by 5.92%, but decreases AECpk by 2.97% and reduces MPOT by 2.95%.

• Compared with the control in Case B, the control in Case D increases AECpk by 9.31% but reduces ATT by 23% and reduces MPOT by 23.48%.

• Compared with the control in Case C, the control in Case D increases MPOT by 6.64% and ATT by 5.43%, but reduces AECpk by 6.91%.

The results of the comparison from the aggregate perspective seem to suggest that the control in Case C is the best. However, the aggregate results cannot prove the microscopic behaviours of vehicles with the control in Case C are also the best. To illustrate the microscopic performance, we presented the average speed and energy consumption for each segment in Figs. 4 and 5.

The results in Figs. 4 and 5 reveal that the speed and energy consumption in each segment for Case C fluctuates in the widest range. Despite the assumption in Assumption 4, reducing the speed fluctuation always benefits the traffic system. Even though the variances of speed and energy consumption are the smallest in Case B, the charging time in this case is too high, which will bring damage to the power grid.

4.3 Extension tests

To test the effectiveness of the four controls, we conducted more numerical tests. The charging demand of vehicles and the speed range in the DWCL lane are changed. The results of the extension tests are concluded in Tables 4–6.

The above tables convey the following information:

• The control in Case A: It has a good performance in travel time-saving. It has a good performance in energy consumption saving when the vehicle's energy demand is high (8.8–9.6 kW·h). The reason is that the vehicles do not need to make a tradeoff between the charging time in different segments and energy consumption. It also has a good performance in load balancing when the vehicle's energy demand is low (7.2–8.0 kW·h) and the required speed is relatively low (10–13.3 m/s).

• The control in Case B: It has a tremendous advantage over other controls when the energy-related metric is of most interest to drivers.

• The control in Case C: It has a good performance in energy consumption and travel time when energy demand is high (8.8–9.6 kW·h). The performance of this control is relatively poor when energy demand is low.

• The control in Case D: It has better performance than the control in Case D on travel time and energy consumption

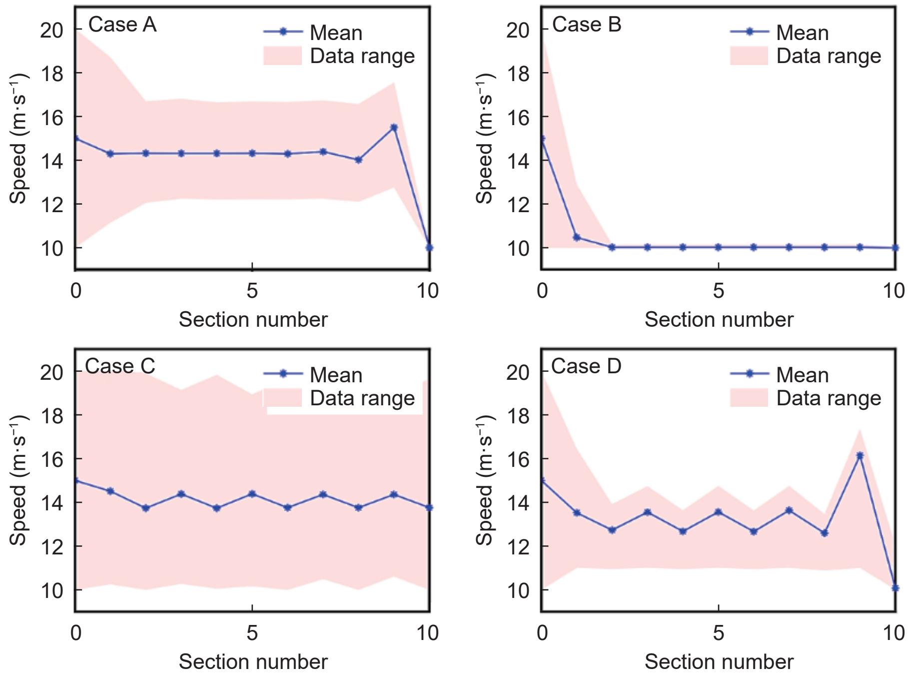

Fig. 4 Average speed in each section for the four cases.

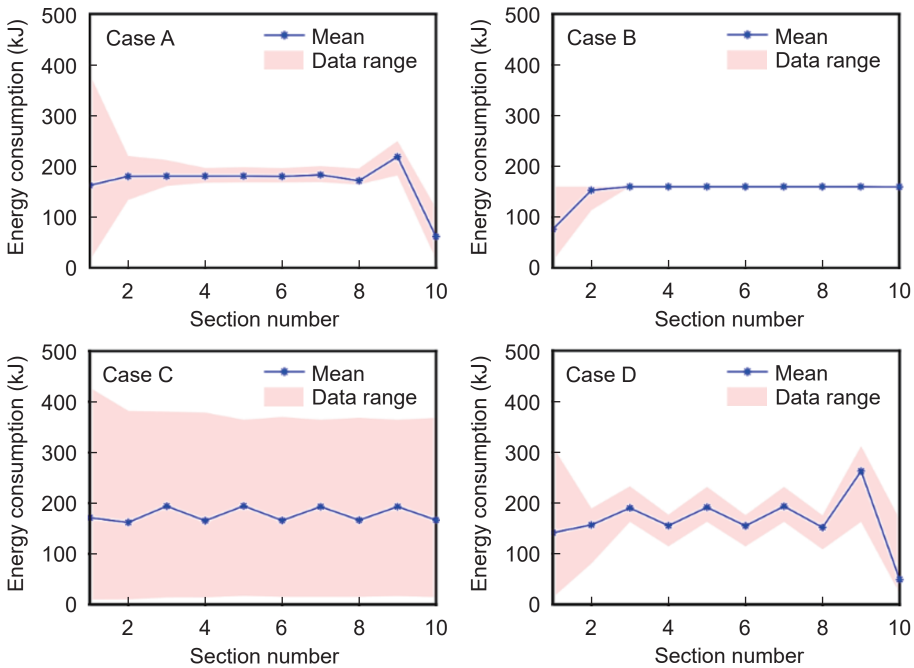

Fig. 5 Average energy consumption in each section for the four cases.

Table 4 ATT for different speed ranges and charging demand for four cases (Unit: s)

Speed (m/s)	Charging demand (kW·h)	Case A	Case B	Case C	Case D
	8.8–9.6	393.24	497.74	394.25	398.35
10.0–13.3	8.0–8.8	361.96	497.74	363.22	396.44
	7.2–8.0	330.95	497.74	333.40	397.77
	8.8–9.6	392.52	491.17	393.81	393.59
13.3–16.6	8.0–8.8	361.22	491.17	362.74	371.60
	7.2–8.0	330.19	491.17	331.76	365.35
	8.8–9.6	391.65	481.73	392.95	392.15
16.6–20.0	8.0–8.8	360.34	481.73	362.10	365.12
	7.2–8.0	329.30	481.73	331.76	358.49

Table 5 AECpk for different speed ranges and charging demand for four cases (Unit: kW·h)

Speed (m/s)	Charging demand (kW·h)	Case A	Case B	Case C	Case D
10.0–13.3	8.8–9.6	0.4711	0.4399	0.4790	0.4711
	8.0–8.8	0.4891	0.4399	0.5006	0.4761
	7.2–8.0	0.5137	0.4399	0.5308	0.4758
13.3–16.6	8.8–9.6	0.4529	0.4236	0.4702	0.4538
	8.0–8.8	0.4705	0.4236	0.4917	0.4682
	7.2–8.0	0.4948	0.4236	0.5163	0.4700
16.6–20.0	8.8–9.6	0.4313	0.4046	0.4474	0.4316
	8.0–8.8	0.4486	0.4046	0.4737	0.4461
	7.2–8.0	0.4725	0.4045	0.5062	0.4503

Table 6 MPOT for different speed ranges and charging demand for four cases (Unit: h)

Speed (m/s)	Charging demand (kW·h)	Case A	Case B	Case C	Case D
10.0–13.3	8.8–9.6	1.418	1.681	1.328	1.346
	8.0–8.8	1.331	1.681	1.225	1.341
	7.2–8.0	1.245	1.681	1.128	1.345
13.3–16.6	8.8–9.6	1.424	1.681	1.328	1.34
	8.0–8.8	1.336	1.681	1.219	1.264
	7.2–8.0	1.248	1.681	1.115	1.244
16.6–20.0	8.8–9.6	1.431	1.675	1.341	1.353
	8.0–8.8	1.341	1.675	1.229	1.259
	7.2–8.0	1.251	1.675	1.119	1.235

when charging demand is high. When the vehicle's speed is high, the travel time is extremely close to the travel time for Case A.

4.4 Discussion

This study proposes a new solution to direct electric vehicles that need to be charged to drive DWCL lanes at a controlled speed. It should be noted that the main content, i.e., the controls of vehicles in the DWCL lane, is a piece of the puzzle of the energy management system on the highway with the DWCL lane. The results in this study are essential for constructing the whole energy management system. We present the following explanations:

1) When using the energy management system on the highway with DWCL lanes, a group of vehicles will be designated to a specific charging lane. Once assigned, controlling the speed of these vehicles can be viewed as a separate issue by limiting their speed. As a result, this study's model is a part of the energy management system.

2) This study provides valuable insights into how to allocate vehicles to different charging lanes based on their charging demands and speed intervals. By selecting the appropriate speed control, vehicles can be batched together and directed to the same charging lane. If vehicles are not allocated efficiently, causing high pressure on the DWC lane and low efficiency, the speed control should be re-evaluated.

5 Conclusions

As the global transition towards sustainable transportation accelerates, EVs stand out as pivotal players offering significant reductions in carbon emissions and fossil fuel dependency. Despite their promise, inherent challenges related to charging efficiency, driving range, and infrastructure integration remain. This study embarked on addressing these challenges by presenting a load-balancing eco-driving strategy designed for autonomous EVs navigating on DWCLs.

In this study, a mathematical programming approach has been proposed to identify optimal speed controls for EVs. Four distinct control strategies considering various objectives, such as travel time, energy consumption, and load balancing, have been derived. The results of numerical tests indicate that a comprehensive control strategy, which considers all objectives, achieves a minor sacrifice in travel time reduction while significantly improving energy efficiency and load balancing. This study contributes concise comparisons between different considerations incorporated within the objective functions. Importantly, the findings highlight that controls with differing objectives exhibit dominant ranges in energy demand and speed. By determining the energy demand and speed range through an upper operation limit, a relatively superior speed control strategy can be selected.

At the heart of our investigation was the bespoke eco-driving speed control strategy for EVs on DWCLs, emphasizing enhanced charging efficiency and extended effective charging duration. Through this, EVs could harness the full spectrum of continuous charging benefits while upholding safety and efficiency. A trio of objective functions was meticulously formulated, providing a panoramic perspective of the challenge: curtailing travel time, amplifying charging benefits, and ensuring a balanced DWCL load. This multifaceted approach was enriched by weaving in the vehicle's longitudinal dynamics, offering an accurate physical model for EV energy consumption. Our deep dive into various control strategies unearthed the unique strengths and nuances of each, particularly in striking a balance between load distribution and energy consumption.

Our results showcased that a strategy that synergised all objectives, struck a harmonious balance, making only a slight concession in travel time but yielding substantial improvements in energy efficiency and load balancing. Additionally, our findings illuminate the path for the seamless integration of DWCLs into the modern transportation tapestry. By facilitating continuous on-the-move charging on arterial highways, DWCLs hold the potential to redefine the EV driving narrative, addressing and possibly eliminating the prevailing range of anxiety concerns. Looking to the horizon, the future beckons further exploration into the intricate interplay between vehicle allocation, speed control, and DWCL efficiency.

As EV adoption scales, understanding and optimizing this dynamic will be critical. We envisage delving deeper into the energy management ecosystem of highways featuring DWCLs, aiming to craft strategies that further elevate the EV user experience. Furthermore, within the related research field, the impact of charging time on the lifetime of DWC lanes remains uncertain. Once this relationship is established, it will enable the reformulation of the speed control problem by imposing constraints on the utilization of each DWC segment. In addition, we will consider the demand prediction (Lin et al., 2023), microscopic behaviors (Cao et al., 2023; Shen et al., 2023) of vehicles to investigate the DWC planning and optimization in depth, and make the optimization to be practical with large model (Liu et al., 2023; Qu et al., 2023).

Replication and data sharing

The data and code are withheld due to confidentiality requirements and can be obtained by contacting the corresponding author upon request.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contributions

The authors confirm their contribution to the paper as follows: study conception and design: Lingshu Zhong, Mingyang Pei; data collection: Lingshu Zhong, Ho Sheau En; analysis and interpretation of results: Ho Sheau En, Lingshu Zhong, and Mingyang Pei; draft manuscript preparation: Lingshu Zhong, Mingyang Pei, and Tao Wang. All authors reviewed the results and approved the final version of the manuscript.

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