Dynamic wireless power transfer system for electric-powered connected and autonomous vehicle on urban road network

Qingyun Liu1 | Simon Hu1,2 | Panagiotis Angeloudis3 | Yibing Wang2 | Lihui Zhang2 | Qiang Yang4 | Yongfu Li5

1 School of Civil Engineering, ZJU-UIUC Institute, Zhejiang University, Haining, China
2 Institute of Intelligent Transportation Systems, College of Civil and Engineering and Architecture, Zhejiang University, Hangzhou, China
3 Department of Civil and Environmental Engineering, Imperial College London, London, UK
4 College of Electrical Engineering, Zhejiang University, Hangzhou, China
5 Key Laboratory of Intelligent Air-Ground Cooperative Control for Universities in Chongqing, College of Automation, Chongqing University of Posts and Telecommunications, Chongqing, China

Abstract
This paper investigates the potential impacts of dynamic wireless power transfer (DWPT) systems on the urban road network with a particular focus on charging and energy consumption implications. The paper is motivated by the recent advancement of connected and autonomous vehicle (CAV) technology and innovations on smart transportation infrastructure. An eco-driving model aiming at energy consumption reduction is developed and a DWPT system layout suitable for charging eco-driving CAVs at a signalised intersection is proposed. The idea is demonstrated in a simulated environment with different market penetration rate (MPR) of CAVs travelling through a signalized intersection equipped with the proposed DWPT system. The results suggest that as MPR of CAV increases, the energy savings for both CAVs and human-driven vehicles (HVs) will increase significantly. At full MPR of CAVs, the reduction of average energy consumption of all types of vehicles can reach up to 62%. The average energy transferred and stored per battery electric vehicle can increase by up to 5% and 10%, respectively. These promising results indicate that a well-designed DWPT system layout together with the eco-driving behaviour of CAVs can have a positive impact on the urban transportation system in terms of resulting energy consumption and emissions.

1 INTRODUCTION

Road transportation is a key contributor to climate change and accounts for 48% of petroleum consumption and 23% of Green House Gas (GHG) emissions in China in 2019 [1]. The electrification of road transportation provides a viable solution for reducing the oil dependency and environmental impacts given that electricity can be produced from renewable energy sources such as solar energy, hydropower, and wind energy. The transfer from internal combustion engine vehicles (ICEs) to electric vehicles (EVs) is a significant step forward towards the decarbonisation of the transportation sector. Many studies have investigated the design and performance of EVs, which demonstrated their advantages in energy consumption and emission reduction [2, 3].

Meanwhile, the upcoming connected and autonomous vehicle technology has brought us a promising prospect to revolutionize our transportation systems [4, 5]. The ability of enhanced communication capabilities, such as vehicles to vehicles (V2V) and vehicle to infrastructure (V2I), will lead to more intelligent driving behaviours adapting to the surrounding traffic environment. The more precise control of the vehicles and their behaviours will enable more energy-efficient driving and opportunities to significantly improve the overall system performance. However, one of the critical challenges of successfully implementing electric-powered CAVs is to overcome the
battery limitation issue. The cruise distance of EVs is largely constrained by their battery capacity [6]. The scarce EVs charging infrastructure can result in extended driving time and extra energy loss to find a suitable charging facility. Moreover, the considerably longer charging time comparing with refilling the fuel will make EV a less attractive option for most consumers.

Dynamic Wireless Power Transfer (DWPT) technology, which can charge battery electric vehicles (BEVs) on the move, is one of the solutions to the battery limitation issue [6]. However, most studies on real-world applications of the DWPT system are in the domain of highway driving and electric buses [7–10]. Few studies have discussed the possibility of utilizing the DWPT system charging conventional electric vehicles at urban intersections [6, 11]. There is a lack of research on the optimal design of the DWPT system for eco-driving electric vehicles at urban intersections and the influence of driving behaviours on charging efficiency.

In this paper, we have investigated the potential implementation of the DWPT system for the urban road network. Different designs of the existing DWPT systems are reviewed, and the design layout for powering eco-driving vehicles at urban intersections is proposed.

The rest of the paper is organized as follows: Section 2 presents the literature review of eco-driving models for CAVs and the DWPT system; Section 3 introduces the problem settings of this paper. Section 4 describes the methodology used, including the eco-driving model, energy consumption, and wireless charging computational methods. Section 5 illustrates the simulation approach and vehicle models adopted in this paper. Section 6 highlights the results of the study. Finally, Section 7 gives conclusions and provides future directions of research.

## 2 LITERATURE REVIEW

### 2.1 Eco-driving models for CAVs

The idea of eco-driving was initially put forward in response to the energy crisis in the 1970s [12]. Various definitions can be found in the literature [13]. In this paper, the focus is on the driving behaviour of vehicles that aims towards energy savings and emissions reduction.

The earlier eco-driving models are mainly based on optimal control theory and seek to obtain the exact solutions with a single objective of energy or emissions reduction [14–16]. More recent research utilizes meta-heuristics, such as genetic algorithms (GA) [17] and particle swarm optimization (PSO) [18], to improve computational tractability and real-time implementation. With the emergence of connected and autonomous vehicle technology, the study of eco-driving models for CAVs became popular as eco-driving algorithms can be embedded in the system of CAVs to achieve accurate implementation. The optimisation algorithm has been expanded from solely addressing environmental concerns to incorporate multiple objectives such as improving mobility and ride comfort [17–19]. Table 1 has summarized the state-of-the-art literature on the research of eco-driving models mainly for CAVs.

One of the most important information required in developing efficient eco-driving model is traffic signal timings. For example, in 2011, Asadi and Vahidi [14] developed an optimal control algorithm for computing the optimal vehicle trajectory based on upcoming traffic signal information for reducing vehicle idling time and energy consumption at a signalized intersection. This research demonstrated that avoiding stoppings at the signal stop line will lead to the reduction of vehicle energy consumption. Another crucial information that can optimise eco-driving model is the data of surrounding vehicles. In 2013, Alsabaan et al. [15] developed an eco-driving model that made use of both traffic signal information and surrounding vehicles’ information which lead to a better result of fuel consumption and emission reduction.

Recent studies intend to make use of queue information to further optimise eco-driving models. In 2016, Yang et al. [16] considered queue effects at the signalised intersection and proposed an Eco-CACC algorithm that computes the fuel-optimum trajectory by ensuring that the vehicle arrives at the stop line just as the queue dissipated. The Lighthill–Whitham–Richard (LWR) kinematic wave model was used to describe the

### Table 1: Research on eco-driving models for CAVs

| Location     | Author                        | Aim                                    | Approach                                                                 |
|--------------|-------------------------------|----------------------------------------|--------------------------------------------------------------------------|
| Isolated     | Asadi and Vahidi (2011) [14]  | Minimize energy consumption            | Divide the optimal control problem into a two-level sub-optimal problem   |
| Signalised   | Alsabaan et al. (2013) [15]   | Minimize energy consumption            | Heuristic methods to calculate near-optimum                                |
|              | Yang et al. (2016) [16]       | Minimize energy consumption            | LWR (Lighthill-Whitham-Richard) kinematic wave model to predict queue      |
|              | Chen et al. (2014) [17]       | Minimize fuel consumption and travel time | GA (Genetic algorithm)                                                   |
|              | Chen et al. (2016) [20]       | Verify the effectiveness of Eco-driving model | Field Test                                                               |
| Signalised   | Li et al. (2018) [18]         | Minimize delay and energy consumption  | Hybrid GA and PSO (Particle Swarm Optimization)                           |
| Corridor     | Jiang et al. (2017) [19]      | Optimize energy consumption, delay and ride comfort | Iterative PMP (Pontryagin Minimum Principle)                             |
|              | Wang et al. (2019) [21]       | Improve fuel efficiency                | Microscopic Traffic Simulation                                           |
traffic dynamics and predict the queue. However, in a heterogeneous traffic environment, with the presence of eco-driving CAV which acts differently from HVs, the fundamental diagram based method is inappropriate to estimate queue length. Hence, more recent studies [22, 23] have realized the real-time queue estimation using connected vehicle trajectories. However, even though the queue estimation was not accurate, the Eco-CACC algorithm proposed by Yang et al. was still managed to reduce the fuel consumption and achieved a 40% reduction at full CAV MPR in the simulation [16].

Most research on eco-driving models are targeted at the isolated signalized intersection [15–17, 20]. In recent years, some studies expand the research to signalized corridors [18, 19, 21]. In 2019, Wang et al. [21] described a cooperative eco-driving system for mixed traffic (a combination of HVs and CAVs) at a signalized corridor to improve fuel efficiency. In this study, a role transition protocol for CAVs to switch between a proceeding and following vehicle was proposed and a microscopic simulation tool was used to conduct mixed traffic stream simulation.

Apart from merely considering energy or emission reduction as optimisation objectives, many studies also considered mobility (e.g. delay), ride comfort, and safety into the optimization targets. In 2014, Chen et al. [17] proposed a driving behaviour optimization model that minimizes a linear combination of fuel consumption and travel time. A genetic algorithm (GA) was performed to solve the proposed optimization problem. In 2018, Li et al. [18] adopted an eco-driving model with a bi-objective formulation to minimise the delay and energy consumption for partly connected vehicles at the signalized corridor. Hybrid GA and PSO (Particle Swarm Optimization) were applied to solve the problem. Later, in 2017, Jiang et al. [19] put forward an eco-speed profiling method for CAVs under mixed CAVs and HVs environment considering energy consumption, vehicle delay, and ride comfort. The iterative PMP (Pontryagin Minimum Principle) approach was adopted, and microscopic traffic simulation was conducted to validate the proposed model.

### 2.2 Wireless power transfer technology for EVs

The wireless power transfer (WPT) technology dates back to more than two centuries ago [24]. There are mainly three operating principles of WPT technology, which are electromagnetic radiation, electric coupling, and magnetic coupling [25]. Compared with the other two, magnetic coupling is less harmful to humans and a more favourable technology for EVs [24].

Charging methods of EVs can be generally categorized as stationary charging and dynamic charging. EVs should be parked during stationary charging, and the driving range is constrained by the battery capacity [24]. On the other hand, dynamic charging is more attractive as it can continuously charge EVs while driving, which enables a smaller size/weight of batteries and a longer driving range [24]. In this paper, we mainly focus on the dynamic charging system.

| Location          | Subject               | Author                      |
|-------------------|-----------------------|-----------------------------|
| Highways          | Electric buses & trucks| Jang et al. (2015) [7]       |
|                   |                       | Jeong et al. (2015) [8]     |
|                   |                       | Kurs et al. (2007) [9]      |
|                   |                       | Wu and Masquelier (2015) [10]|
| Signalised        | Electric car          | Garcia-Vázquez et al. (2016) [33]|
| intersections     |                       | Mohrehkesh and Nadeem (2011) [6]|
|                   |                       | Tan et al. (2016) [11]      |
|                   |                       | Liu et al. (2019) [34]      |

The DWPT system can typically use two types of electrical track. One is the single-long-coil track, and the other is the segmented-coil track [26]. The layout of a single-long-coil track can be rather inefficient because the track is relatively long compared to the receiver coil, so the pickup coil only accounts for a small proportion of the entire track [27]. On the other hand, the structure of the segmented-coil track can be advantageous as every transmitting coil is separated and using its own compensated configuration, only coils that detected vehicles are activated, and the other coils are remained inactive, which leads to higher energy transfer efficiency [27].

Many researchers have studied the feasibility of powering EVs using the DWPT system in the past [28–32] and proved that it could save more money and produce less emission than fossil fuel. Furthermore, many standards have been set for the safe and efficient application of wireless charging systems, such as ISO 19363, IEC 61980, and SAE J2954 [28]. Therefore, there is great potential in the real-world application of the DWPT system.

The real-world applications of the DWPT system for charging EVs are shown in Table 2. Most of the studies are in the domain of highway driving and electric buses [7–10]. Only few studies have discussed the application of the DWPT system for the passenger vehicle at the urban environment. Mohrehkesh and Nadeem [6] and Tan et al. [11] studied the potential for wireless power transfer (WPT) system charging EVs at the approaching arm of the signalized intersection when EVs stop and wait at the signal stop line. Figure 1 shows the layout of the WPT system proposed in [11]. They adopted a layout of a rectangular single-long-coil track. When the traffic light is red, EVs can be charged wirelessly when they are in an effective wireless charging area.

As vehicles usually spend time waiting for the signal at urban intersections, the idea of charging vehicles while they are queuing at the stop line proposed in [11] is plausible. However, vehicles consume more energy on stop-and-start behaviour than smooth driving [14, 18, 35]. Moreover, the layout of a single-long-coil track has more energy loss than the layout of a segmented-coil track [25]. Hence, more energy-efficient matching between vehicle behaviour and the WPT system at urban signalized intersections should be investigated.
Liu et al. [34] verified that the behaviour of vehicles could affect the charging amount transferred by the DWPT system. In this paper, an idea of charging eco-driving vehicles that drive smoothly passing the intersection above a segmented-coil track DWPT system at the approaching arm of the intersection is proposed, shown in Figure 2. Microscopic traffic simulation is used to verify the design of the proposed design of the DWPT system for charging eco-driving vehicles. Different levels of penetration of CAVs are conducted for the sensitivity analysis.

The paper contributed to the state-of-the-art development of DWPT systems in the following aspects: (i) It investigated the impacts of vehicle driving behaviours on the charging efficiency of DWPT system, in particular with the view of emerging connected and autonomous vehicles; (ii) The different layout of DWPT systems on the urban road network is carefully reviewed, and simulations and experiments verify the effectiveness of the proposed system layout; (iii) As the transition to 100% MPR of CAVs is a gradual process, it is expected that the co-existence of CAVs and HVs are the most likely scenario in the near future. The paper evaluated the effects of the different MPRs of CAVs on the traffic network regarding energy consumption and traffic performance.

3 | NOTATION AND PROBLEM SETTINGS

3.1 | Notation

The notation of variables and parameters used in our models are summarized in Table 3.

3.2 | Problem settings

A typical urban intersection with four arms of fixed-time signal control is adopted in this paper (see in Figure 3).

There are eight traffic streams with each approach that can go straight, turn left or right. The length of the wireless charging zone covers the distance of the V2I communication range. Figure 3 shows an example of a potential layout of the DWPT system at the western arm.

The microscopic traffic simulator is used in this study to model a mixed traffic stream of human-driven combustive vehicles, human-driven battery electric vehicles, and battery electric CAVs, passing through the above described signalized intersection. It is worth noting that BEVs contain two types of vehicles, human-driven BEVs and CAVs. The simulation design framework is illustrated in Figure 4. For each simulation step, vehicles in the network are classified by their vehicle type and controlled differently. The control variable is the vehicle’s desired speed at the next time step $u_i(t + \Delta t)$, which may not be the actual speed, but CAV will accelerate or decelerate towards this desired speed. Vehicle trajectory is collected in an evaluation period $T$ to calculate energy consumption and energy transferred. The potential effects of eco-driving behaviour on the energy consumed/transferred of vehicles can be quantified by the following criteria;

1. The average energy consumption per vehicle per km: $E_a$ (MPR = 0) and $E_a$ (MPR = 100) can be compared to investigate the difference between conventional vehicle behaviour and eco-driving behaviour regarding the amount of energy consumed.
2. The average energy transferred per BEV: $E_b$ (MPR = 0) and $E_b$ (MPR = 100) can be compared to investigate the difference between conventional vehicle behaviour and...
eco-driving behaviour regarding the amount of energy transferred by the DWPT system.

3. Energy stored per vehicle: $E_s$, which is defined as the result of average energy transferred to the vehicle battery by DWPT system $E_b$ subtracts average energy consumed by the battery whilst travelling the same distance $E_a \times L/km$. This is used to evaluate the total impact of eco-driving behaviour of CAVs on energy consumption and energy transferred by DWPT system at an urban signalized intersection.
TABLE 3 Notation of variables and parameters

| Eco-driving model notation | V2I module |
|---------------------------|------------|
| $i$                       | Vehicle index |
| $k_i$                     | Lane number of vehicle $i$ |
| $\Psi$                    | Set of the intersection approaching lane |
| $p_i$                     | Position of the signal stop line, m |
| $L$                       | V2I communication range, m |
| $D$                       | V2V communication range, m |
| $v_{max}$                 | The maximum speed limit of the road, m/s |
| $v_{min}$                 | The minimum speed limit for energy-efficiency consideration, m/s |
| $t_{start}$               | The time when the next green stage starts, s |
| $t_{end}$                 | The time when the next green stage ends, s |
| $p_i(t)$                  | Position of CAV $i$ at time $t$, m |
| $p_{f}(t)$                | Position of CAV $f$ at time $t$, which is the front CAV of CAV $i$, m |
| $n_i$                     | The minimum speed which enables CAV $i$ to pass the stop line before the green stage ends at time $t$, m/s |
| $n_i$                     | The maximum speed which enables CAV $i$ to pass the stop line after the green stage starts at time $t$, m/s |
| $v(t)$                    | The desired speed of CAV $i$ at time $t$, m/s |
| $v(t + \Delta t)$        | The desired speed for CAV $i$ at the next time step, m/s |
| $v(t + \Delta t)$        | The desired speed of CAV $i$ at the next time step, which is the front CAV of CAV $i$, m/s |

Energy consumption model notation

| $c_d$                     | Drag coefficient |
| $\rho$                    | Pressure coefficient |
| $l$                       | The height of the slope, m |
| $R$                       | The wheel radius of the vehicle, m |
| $A$                       | The frontal area of the vehicle, m$^2$ |
| $W$                       | Vehicle weight, N |
| $m$                       | Vehicle mass, kg |
| $v$                       | Vehicle velocity, m/s |
| $a$                       | Vehicle acceleration, m/s$^2$ |
| $F_t$                     | Tractive force, N |
| $t_1$                     | The entry time of the vehicle to the network, h |
| $t_2$                     | The departure time of the vehicle from the network, h |
| $S_i$                     | The total driving distance of vehicle $i$, m |
| $\delta$                  | Total energy transmission efficiency |
| $P$                       | Propulsive power, W |
| $E_{c}$                   | The average energy consumption per vehicle per km of all types of vehicles, Wh |
| $E_{a}$                   | The average energy transferred per vehicle of all types of BEVs, Wh |

Wireless charging model notation

| $j$                       | Coil index |
| $\Delta t$                | The period that the vehicle receives power from the coil $j$, s |
| $P_c$                     | Changing power of the DWPT system, W |
| $E_{average}$             | The average energy transferred per vehicle of all types of BEVs, Wh |
| $E_{stored}$              | The average energy stored per vehicle of all types of BEVs, Wh |

4 | METHODOLOGY

4.1 | Eco-driving model for CAVs

It is plausible to assume that the future CAVs will have the eco-driving function embedded in its system. In this study, a version of the eco-driving model is developed, which takes advantage of V2I and V2V technologies to minimize vehicle number of stops at the signal stop line and avoid abrupt speed changes in car-following behavior. As conventional vehicles driven by humans, precise control of speed and acceleration is difficult to attain. On the other hand, CAVs are controlled by algorithms and can achieve high-level precision control. The eco-driving model is only applied to CAVs in this paper. A rule of role transition between “CAV” and “CAV follower” is also designed to distinguish the different status of a CAV in the network to achieve more precise control. Therefore, our eco-driving model is only applied to CAVs and is composed of two modules, V2I module, and V2V module. The V2V module takes effect over the entire intersection whilst the V2I module only works within the V2I range at the approaching arms.

4.1.1 | Rule of role transition between “CAV” and “CAV follower”

In order to realize the V2V functionality in the simulation, two CAV types are defined according to different scenarios. Three possible scenarios are considered: (1) CAV is a leader in a stream of traffic; (2) CAV follows a HV; (3) CAV follows a CAV. In the first two scenarios, the vehicle behavior is governed by CAV itself and doesn’t require communication from the front vehicle. We define this type of vehicle as “CAV”. In the last scenario, CAV is acting as a follower, and its behavior depends on the front CAV. Therefore, its vehicle type is set as “CAV follower”. The vehicle type of the same CAV can be “CAV” or “CAV follower” depending on its position in the network. The purpose of distinguishing “CAV” and “CAV follower” is to simulate the more realistic performance of CAVs’ car-following behavior, which is essential for the V2V module designed in this paper.

4.1.2 | V2I module

The V2I module utilizes the vehicle to traffic signal communication to minimize vehicle number of stops at the signal stop line. It is assumed that the V2I communication range is 150 m, which is within effective Dedicated Short Range Communication (DSRC) distance 300 meters used in the vehicle to traffic signal communication [36, 37]. When a CAV is within the V2I communication range, the signal timings information can be obtained via V2I communication. At each time step, CAV receives the signal timing information and calculates whether it can pass the stop line with the original planned speed or not. Hence, there are four possible scenarios: (1) Current signal state
is green, and it is able to pass: Trajectory 1 shown in Figure 5(a); (2) current signal state is green, but it is unable to pass using current speed: Trajectory 2 shown in Figure 5(a), it should decelerate and drive at a slower speed so that it could arrive at the stop line after the signal light turns green from red; (3) current signal state is red, and it is unable to pass using current speed: Trajectory 3 shown in Figure 5(b), it will calculate the next green time and adjust its speed to reach the stop line after the signal turns green from red; (4) current signal state is red but is able to pass when the vehicle approaches the intersection: Trajectory 4 shown in Figure 5(b). According to these possible scenarios, the algorithm of the V2I module is developed in Python programming language. Its logic is illustrated in Figure 6. The constraints and computations for the parameters used in Figure 6 are listed below:

1. The desired speed of CAV at time \( t \) and next time step \( t + \Delta t \)

\[
u_t (t) \in [v_{\min}, v_{\max}] \quad (1)
\]

where \( v_{\min} \) is assumed to be 5 km/h and \( v_{\max} \) is assumed to be 30 km/h. Please note that \( u_t (t) \) and \( u_t (t + \Delta t) \) may not be the actual speed at their corresponding time but CAV will accelerate/decelerate/maintain towards this target speed.

2. The minimum speed which enables vehicle \( i \) passes the stop line before the green stage ends \( u_{i, end} \)

\[
u_i (t) \in [v_{\min}, v_{\max}] \quad (2)
\]

where \( u_{i, end} \) is the minimum speed which enables CAV \( i \) passes the stop line before the green stage ends at time \( t \), m/s.

3. The maximum speed which enables vehicle \( i \) passes the stop line after the next green stage starts \( u_{i, start} \)

\[
u_i (t) \in [v_{\min}, v_{\max}] \quad (3)
\]

where \( u_{i, start} \) is the maximum speed which enables CAV \( i \) passes the stop line after the next green stage starts at time \( t \), m/s.

4.1.3 V2V module

The V2V module utilizes vehicle-to-vehicle communications to reduce vehicle energy consumption by avoiding abrupt speed change of CAV follower resulting from the leader CAV's speed change. The V2V communication range is assumed to be 50 m, according to Xu et al. [38]. They studied V2V safety message distance and found that when vehicle distance headway was 10 m on a four-lane jammed highway road, the V2V communication range was about 50 m. In this paper, the same V2V communication range is adopted. The logic of the V2V module algorithm is illustrated in Figure 7. When two consecutive CAVs are within the V2V communication range, the leader CAV will inform its desired speed to its following CAV. The vehicle type of the following CAV is switched from “CAV” to “CAV follower”. The gap between two consecutive CAVs will be reduced.

4.2 Energy consumption model

According to Newton's second law of motion, forces on moving vehicles are tractive force (provided by the propulsive power of vehicle engine) and driving resistance (provided by the environment). The vehicles' tractive force \( FT \) overcome driving resistance and move the vehicle [39], as given in Equation (4).

\[
u_t (t) \in [v_{\min}, v_{\max}] \quad (4)
\]

Please note that the weight of the vehicle is the vehicle's net weight plus the weight of passengers and luggage in the vehicle. It is assumed that the average weight of passengers and luggage is 200 kg. It is also assumed that the ground-level air temperature is around 20 °C, thus the air density \( \rho \) is 1.2041 kg/m³.
The logic for the V2I module of CAV eco-driving algorithm

Input: $k_i, \mathcal{P}, p_s, L, v_{\text{max}}, v_{\text{min}}, p_i(t), u_i(t), u_{i,\text{end}}(t), u_{i,\text{start}}(t)$

Output: $u_i(t + \Delta t)$

for $k_i \in \mathcal{P}$:

if $p_i(t) < (p_s - L)$ or $p_i(t) > p_s$:

$u_i(t + \Delta t) = v_{\text{max}}$

else:

if $u_{i,\text{end}}(t) < u_{i,\text{start}}(t)$

if $u_i(t) < u_{i,\text{end}}(t)$

$u_i(t + \Delta t) = \min(u_{i,\text{start}}, u_i(t))$

else:

$u_i(t + \Delta t) = u_i(t)$

else:

$u_i(t + \Delta t) = \min(u_{i,\text{start}}, u_i(t))$

$u_i(t + \Delta t) = \max(u_i(t + \Delta t), v_{\text{min}})$

\# CAV $i$ desired speed cannot be lower than $v_{\text{min}}$

\# CAV $i$ is on approaching lane

\# CAV $i$ is not in V2I range

\# CAV $i$ is in V2I range

\# the current signal state is green

\# cannot pass in the current green stage

\# can pass in the current green stage

\# the current signal state is red

FIGURE 6 The logic for the V2I module

The logic for the V2V module of CAV eco-driving algorithm

Input: $p_i(t), p_f(t), u_f(t + \Delta t)$

Output: $u_i(t + \Delta t)$

for $p_f(t) - p_i(t) < D$:

Set the vehicle type of CAV $i$ as CAV follower

$u_i(t + \Delta t) = u_f(t + \Delta t)$

\# CAV $i$ and CAV $f$ is in V2V range

FIGURE 7 The logic for the V2V module

When a vehicle is travelling through the signalised intersection, there are four possible states, which are:

1. Maintaining the desired speed
2. Accelerating
3. Decelerating
4. Standstill

As for the first two vehicle states, the propulsive power $P$ can be obtained via Equation (5).

$u_i(t) \in [v_{\text{min}}, v_{\text{max}}]$  \hspace{1cm} (5)

According to [2, 3], the total energy transmission efficiency for CAVs and human-driven BEVs can be assumed to be 87%;
the total energy transmission efficiency for human-driven combustive vehicles is around 30% [40].

As for the decelerating state, it is assumed that vehicles do not consume or regenerate energy when braking. As for the standstill state, vehicles consume energy when the engine is idling [13]. It is assumed that the propulsive power \( P \) is constant when the vehicle is standstill waiting for the green signal.

After calculating the vehicle propulsive power \( P \) at every time step, the vehicle energy consumption \( E \) during the journey time can be calculated as:

\[
u_i(t) \in [v_{min}, v_{max}]
\]

The average energy consumption per vehicle per km of all types of vehicles \( E_a \) can be calculated by:

\[
u_i(t) \in [v_{min}, v_{max}]
\]

where \( n \) is the total number of vehicles in one simulation run, \( d_i \) is the total driving distance of vehicle \( i \), m.

Similarly, the average energy consumption per vehicle per km of all types of BEVs \( E_b \) can be calculated by:

\[
u_i(t) \in [v_{min}, v_{max}]
\]

where \( n_{BEV} \) is the number of BEVs in one simulation run, which includes human-driven BEVs and all CAVs.

The energy used in auxiliaries is not considered in the energy model of this paper.

### 4.3 Wireless charging model

A DWPT system which is made up of consecutive rectangular power transfer coils is adopted. Each coil has a length of 8 m, and there is a gap of 5 m between every two coils. In this paper, the impact of eco-driving behaviours on the energy transferred by the DWPT system is emphasized. In our eco-driving model, both V2I and V2V modules function at 150 m distance upstream of the stop line on the approaching arm. Therefore, a layout of 12 segmented coils, which covers 151 m \((11 \times (8 + 5) + 8 = 151)\) distance upstream the stop line on four approaching arms is adopted. As a vehicle travelling above the DWPT system, the secondary coil installed beneath the vehicle body can receive the power of up to 40 kW (It takes 1 h for fully charging a 40 kWh battery vehicle) from the primary coil beneath the road when using Nissan leaf vehicle type [33]. Please note that in the real-world situation, the charging power is not constant (e.g. due to different driving conditions, the shape, or lateral misalignment of the primary and secondary coil). It is assumed that the average charging power that vehicle received is 40 kW. The total energy transferred \( E_c \) can be computed by adding up the time \( \Delta t_j \) of vehicles on each coil \( j \) and multiplied by the charging power \( P_c \), shown in Equation (9).

\[
u_i(t) \in [v_{min}, v_{max}]
\]

To ensure the variation of the BEVs charging amount is merely due to the difference of driving behaviours, not by the state of charge, we assume that the battery of all BEVs can accommodate the energy transferred by the DWPT system when BEVs passing through the approaching arm of the signalized intersection.

## 5 IMPLEMENTATION

### 5.1 Simulation approach

PTV-VISSIM is a widely used microscopic traffic simulation software and is capable of modelling the individual behaviour of CAVs in mixed traffic stream [19, 21, 34]. In this study, VISSIM is adopted to verify our proposed DWPT system and assess its impacts on energy and traffic performance. Traffic networks are coded up in the simulator, and the driving behaviours of HVs are controlled internally by the car-following model (i.e. Wiedemann 74 car following model), lane changing parameters etc. While the behaviours of CAVs are controlled externally by the algorithm (e.g. eco-driving model) via the Common Object Model (COM) Interface. Various languages such as C#, Java and Python can be used to write up the algorithm [41].

In this study, the eco-driving model is written in python and implemented via COM Interface. Before each simulation step starts, VISSIM passes on the vehicle and signal information to the COM Interface and executes event-based eco-driving algorithm scripts. The optimal eco-driving speed (vehicle desired speed at the next time step \( u_i(t + \Delta t) \)) is calculated for each CAV involved in the V2I and V2V communication. Then, \( u_i(t + \Delta t) \) is returned to the simulator and changes the behaviour of CAV accordingly before the next simulation time step. At the end of the simulation, a vehicle record file that contains vehicle trajectory information is generated for the calculation of energy consumption, the energy transferred, and other traffic KPIs. In this study, 11 scenarios with 10% CAV MPR increment from 0% to 100% are simulated. The evaluation time period \( T \) is 1 h from 1800 to 5400 s in each run. The first 1800 s period is used for the simulation to warm up. Each scenario is run at least ten times with different random seeds to obtain a statistically significant result.

### 5.2 Parameter settings

In the simulation, the selected vehicle model for CAVs and human-driven BEVs is Nissan leaf 30 kWh business edition, which is compatible with wireless charging vehicle type. The default conventional vehicle fleet composition in VISSIM is adopted for human-driven combustive vehicles. For simplification, the BMW 540i 2017 vehicle model is used to calculate the energy consumption of human-driven combustive vehicles. The parameters of these two vehicle types and vehicle driving parameters can be found in [34].
5.3 | Assumptions

The following assumptions are made for the simulation study:

1. The simulated intersection is at the ground level hence the slope resistance can be neglected;
2. The traffic volume is 400 veh/h for each arm and the cycle length is 90 s;
3. HVs are made up of 50% human-driven BEVs and 50% human-driven combustive vehicles. Our eco-driving algorithm is not implemented on HVs and they obey Wiedemann 74 car-following model;
4. The maximum acceleration and deceleration values for CAVs are solely for the eco-driving mode and may be overruled under the emergency braking conditions [19];
5. The route choice proportion of left turn, go straight, and right turn are set to be 27%, 55%, 18% according to saturation flow proportion of left turn, go straight and right turn stated in [42].

6 | RESULT AND ANALYSIS

In this section, the numerical results of energy consumption, network performance, the energy transferred, and energy stored calculated by the vehicle trajectory record from the simulation are demonstrated and discussed.

6.1 | Energy consumption

Figure 8 illustrates the average energy consumption per vehicle per kilometre of all vehicles, that is, HVs and CAVs, respectively.

As shown in Figure 8(a), the average energy consumption of all vehicles consistently decreases with the increase of MPR of CAVs. This result is in line with previous literature [34, 43]. To be more specific, the average energy consumption of all types of vehicles reduces from 628.47 Wh km$^{-1}$ in 0% CAVs case to 237.67 Wh km$^{-1}$ in 100% CAVs case that accounts for 62% energy savings. Figure 8(b) illustrates that the average energy consumption of HVs decreases from 628.47 Wh km$^{-1}$ to 546.76 Wh km$^{-1}$ which accounts for 13% of energy savings. The energy reduction is attributed to the eco-driving style of CAVs, which gradually replace HVs. As for CAVs, Figure 8(c) demonstrates that the average energy consumption of CAVs only decreases slightly, from 251.78 Wh km$^{-1}$ in 10% CAVs case to 250.02 Wh km$^{-1}$ in 30% CAVs case, when CAVs starts to mix into the traffic. The average energy consumption of CAVs decreases faster when the MPR of CAVs increases above 30%. However, it can be seen that the average energy consumption of CAVs decreases less rapidly than HVs with the increase of MPR of CAVs. This is due to the fact that CAVs behaviours are more homogenous and consistent, less affected by the surrounding traffic compared to HVs.

Figure 9 illustrates the average energy consumption per vehicle per kilometre of all BEVs, human-driven BEVs, and CAVs.

As human-driven BEVs and CAVs are using the same vehicle model to calculate energy consumption, the difference in the result is owing to the driving behaviour. It can be concluded that eco-driving CAVs consume less energy than human-driven BEVs per km. It can also be noticed that the energy consumption difference between human-driven BEVs and CAVs
is decreasing, from 62 Wh km\(^{-1}\) in 10% CAVs case to 41 Wh km\(^{-1}\) in 90% CAVs case. This is because of the increasing possibility of eco-driving CAVs occupying both lanes; thus, human-driven BEVs behind must follow their eco-driving behaviour.

### 6.2 Network performance

The network performance indicators of average delay of vehicles (defined as the time loss when using actual speed compared to vehicle desired speed), the average number of stops, average queuing time of vehicles, the average speed of all vehicles, number of vehicles arrived at the destination during evaluation time \(N_{1800-5400}\) and number of vehicles in the network at the last simulation second \(N_{5400}\) are shown in Tables 4 and 5.

It can be computed from the tables that eco-driving behaviour brings a 37% decrease in the average vehicle queuing time. Even though the average speed decreased 6%, the traffic throughput during 1800–5400 s remains the same level. These indicate that the energy consumption saving brought by the eco-driving behaviour is not at the compromise of network performance.

We can find that CAVs experience less delay than HVs. The average delay decreased with CAVs gradually replace HVs. This is due to the average delay of vehicles in PTV VISSIM is defined as the time loss when using actual speed compared to vehicle desired speed. The desired speed of HVs is the free-flow speed, while the desired speed of CAVs is controlled by the eco-driving algorithm. When CAV approaching the red signal, its desired speed calculated by the algorithm is slower than the free-flow speed. This explains why CAVs have less delay than HVs. It can also be noticed that if we only look at the delay of HVs or CAVs, they all increased with the increase of CAV MPR, which means a large amount of eco-driving CAVs will increase the delay of both HVs and CAVs themselves. This is owing to the lower desired acceleration and deceleration rate of eco-driving CAVs than the HVs. With the increased amount of CAVs, the chance of CAVs occupying both lanes will increase. Hence, the possibility of HVs overtake CAVs will decrease and HVs are forced to follow the behaviour of leading CAVs with slower acceleration and deceleration. Thereby, the delay of HVs will also increase.

### 6.3 Energy transferred

The average energy transferred by the DWPT system per vehicle of all BEVs, human-driven BEVs and CAVs are shown in Figure 10. It can be seen that the average energy transferred of CAVs is always higher than that of human-driven BEVs, which means eco-driving behaviour can receive more energy from the designed DWPT system layout than conventional driving behaviour. It proves that our designed DWPT system layout is suitable for charging eco-driving vehicles. The average energy
transferred of all BEVs fluctuates from 10% to 60% CAV MPR cases and soars from 60% to 100% CAV MPR cases. It can be calculated that eco-driving behaviour brings a 5% increase in energy transferred at full CAV case. As for human-driven BEVs, even though the average energy transferred fluctuates after the increase of MPR of CAVs, the lowest amount is found at full human-driven BEVs case and the highest amount is found at 90% CAVs case. It is interesting that the average energy transferred to CAVs drops from 10% to 30% MPR, which may attribute to the heterogeneous traffic flow result from the lower level of MPR. It creates disturbances to the system. However, it soars when CAVs dominates the traffic (MPR > 60%). The highest amount is found at the full CAVs case.

Please note that there is no specific mechanism of how eco-driving model is related to the performance of the DWPT system. The energy transferred to vehicles is depending on the time that vehicles stay on the coil, but the behaviour of vehicles is independent from the layout of the DWPT system in our simulation. The results showed that CAVs with our eco-driving mode benefits from the adopted coil layout. If the coil layout changes or the vehicle behaviour changes, the result may be quite different.

6.4 Energy stored

The average energy stored per BEV can be calculated by average energy transferred by the DWPT system subtracting average energy consumed in the same distance (151 m), shown in Equation (10).

\[ u_i(t) \in [v_{min}, v_{max}] \quad (10) \]

Figure 11 shows the result of average energy stored of all BEVs, human-driven BEVs and CAVs. The average energy stored of CAVs decreases from 10% to 30% MPR cases, fluctuates from 30% to 60% MPR cases and then increases steadily to 100% MPR case after CAVs dominate the traffic. The energy stored of human-driven BEVs raises from 305.83 Wh in full human-driven BEVs case to 321.05 Wh at 90% CAVs case, which accounts for 5% increase. This increase potentially benefits from the influence of high CAV MPR that leads to the human-driven BEVs following behind to have similar eco-driving behaviour as CAVs. In total, the average energy stored of all BEVs consistently increases with the penetration of CAVs, from 305.83 Wh in full human-driven BEVs case to 335.56 Wh in full CAVs case that accounts for 10% energy stored increasing, which indicates that the idea of charging eco-driving vehicles on the move by the DWPT system layout designed at the approaching arm of the signalized intersection is better than fully stopping and charging at the signal stop line.

It can be assumed that there is a city network equipped with the mentioned DWPT system at intersections. Based on the result of this study, at full CAVs case, the energy consumption is 237.67 Wh km\(^{-1}\) and the energy transferred is 371.45 Wh at every intersection, which means if CAVs can encounter an intersection at every 1.5 km driving distance, they can provide non-stop driving service (note that the energy used in auxiliaries are not considered). Compared to stationary charging, which requires standstill charging that will reduce service time, dynamic wireless charging that enables non-stop driving service and particularly attractive to on-demand ride-hailing companies. It can help them to maximise their vehicle utilization. It will also enable companies to own a smaller CAV fleet to meet the same demand, thus reducing their cost. With the technology advancement, the cost of the DWPT system will be further reduced, and more robust standards for the application of the DWPT systems. Therefore, our proposed idea provides an attractive framework and evidence for the future implementation of such system.

7 CONCLUSIONS AND REMARKS

This paper proposed an idea of charging connected and autonomous vehicles (CAVs) which drive smoothly passing the
signalized intersection above a dynamic wireless power transfer (DWPT) system at the approaching arms of an urban intersection. 11 scenarios with different MPRs of eco-driving CAVs passing through a DWPT system-equipped signalized intersection are tested under the simulation environment. The results calculated from the simulation output suggest that the average energy transferred for eco-driving CAVs is always higher than that of human-driven BEVs. At full CAV MPR, the reduction of average energy consumption of all types of vehicles can reach up to 62% due to CAV eco-driving behaviour. The average energy transferred and stored per BEV can increase by up to 5% and 10%, respectively. These promising results indicate that a well-designed DWPT system layout together with the eco-driving behaviour of CAVs can have a positive impact on the urban transportation system in terms of resulting energy consumption and emissions. The findings from this study will be able to provide insights on the impacts of CAVs’ behaviours on the DWPT system and help the future design of such system.

In real-world practice, there is potential chaos that human-driven BEVs may tend to drive slower when they are on the coils and drive faster when they are on the gaps if they know the changing status of the vehicle from the panel, which may lead to larger energy transfer amount of human-driven BEVs compared to the simulation result.

In future work, multi-objective eco-driving models considering other traffic KPIs such as delay and ride comfort can be tested, queue effect and vehicle platooning can be also considered to improve the model, more efficient layouts of DWPT systems will be explored and can be expanded to multiple signalized intersections.

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NOMENCLATURE

BEV  Battery Electric Vehicle  
CAV  Connected and Autonomous Vehicle  
DWPT  Dynamic Wireless Power Transfer  
Eco-CACC  Eco-Cooperative Adaptive Cruise Control  
EV  Electric (Engine) Vehicle  
GA  Genetic Algorithm  
GHG  Greenhouse Gas  
HV  Human-driven Vehicle  
ICE  Internal Combustion Engine vehicle  
KAIST  Korea Advanced Institute of Science and Technology  
MPR  Market Penetration Rate  
PMP  Pontryagin Minimum Principle  
PSO  Particle Swarm Optimization  
TRL  Transport Research Laboratory  
V2I  Vehicle to Infrastructure  
V2V  Vehicle to Vehicle  
WPT  Wireless Power Transfer

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