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Ideal Operating System for Networked and Automated Electric Vehicles in a Wireless Charging Environment at Signified Crossings

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ABSTRACT

Electric freight vehicles provide numerous advantages in connected and automated environments, making them a preferred means of transportation. Nonetheless, the growing demand for transportation is not being fulfilled by connected and automated electric freight vehicles (CAEFVs), which have a restricted working range. This study employs wireless charging technologies to create a complex driving environment featuring metropolitan highways and dynamic wireless charging outlets. To develop a wireless charging strategy for urban transportation systems, a number of variable-scale variables, such as automobiles, roads, and the environment, are studied hierarchically. An efficient driving model for CAEFVs in wireless charging situations at signalized crossings is provided, combining scenario boundaries with vehicle dynamic constraints. The model's objectives are passage efficiency, energy consumption, and passenger comfort. This approach is separated into a time priority strategy (TPS), balance priority strategy (BPS), and charging priority strategy (CPS) in order to account for the various charging requirements of cars.

Keywords: ***electric freight vehicle; wireless charging technology; optimal driving model; signalised intersection; market penetration rate; passing strategy.***

1. INTRODUCTION

Rapid urbanization has brought about many benefits for people, but it has also resulted in major energy and environmental crises, gridlock in metropolitan surface transportation systems, and other problems [1,2]. It is a difficult undertaking for nations and the automobile industry to reduce pollutant emissions and increase the energy economy of freight vehicles [3,4].

As a result, many nations have expressed political support for and interest in the electrification of freight vehicles as a potential means of boosting energy efficiency, reducing carbon emissions, and attaining sustainable development [5-8].However, two significant limitations influencing the adoption of electric freight vehicles (EFVs) are their limited operating range and lengthy charging times.Numerous studies on energy storage technologies and charging advances, such as battery storage upgrades [4,5], energy management optimization [5], high-power rapid charging , and driving strategies , have been carried out in an effort to address these problems. To sustainably meet the charging requirements of devices, a significant amount of charging infrastructure, including charging stations, battery swap stations, and wireless charging devices, has been constructed

The results showed that the proposed approach can help to reduce the downtime and cost of garbage truck charging while also lowering the environmental effect of traditional collection procedures.Meintz et al. demonstrated the feasibility of using wireless power transfer technology to charge shuttle buses in enclosed environments. The study discovered that wireless power-transfer technology has significant advantages for improving the sustainability and efficiency of transportation services. Yang et al. proposed an efficient charging algorithm for wireless sensor networks that employs unmanned aerial vehicles for wireless power delivery. The suggested approach seeks to improve the charging efficiency of wireless sensor nodes while lowering the energy consumption of unmanned aerial vehicles. As a result, the sensible application of wireless charging technology, as well as connected and automated technologies, in conjunction with a wireless charging lane (WCL) , can significantly expand the driving range of connected and automated EFVs from a sustainable vehicle operation standpoint. Furthermore, unlike Charging while walking, as opposed to staticparking, can reduce driving anxiety, shorten parking and charging wait times, and improve the adoption of CAEFVs.

Signalized crossroads are critical nodes of the urban surface transportation system, managing traffic flow, influencing the efficiency of safe passages, and reducing urban congestion. With the continuous improvement of intelligent driving systems consisting of vehicle-to-vehicle and vehicle-to-infrastructure technologies by installing devices such as the advanced driver assistance system, advanced emergency braking system, light detection and ranging, and global positioning system, vehicles can acquire more accurate and connected real-time data related to the driver-vehicle environment, enabling alerting, assistance, and intelligent decision-making.

To achieve the dual objectives of optimal charging and passing benefits, a combination of signalized intersections located upstream and downstream of wireless charging facilities allows vehicles to pass through intersections at reduced speeds while replenishing power, increasing traffic efficiency and mileage. As a result, several energy-consumption models for electric cars (EVs) and EFVs, wireless charging, and eco-driving control have been investigated to meet the needs of vehicles operating in complicated situations. Improved current energy-consumption models for EVs and EFVs by integrating the energy-consumption functions of individual EVs for different phases into an aggregate energy-consumption model by simplifying the driving action of EVs at signalized crossings. Li et al. employed the minimum principle theory to create novel EV car-following models with zero and non-zero initial states based on the optimal energy-consumption model. Numerical trials demonstrated the model's usefulness in terms of vehicle location, velocity, and acceleration distributions.Fiori et al. [2] investigated the efficiency of regenerative braking energy and the impact of auxiliary systems on vehicle energy consumption. They created an electric vehicle energy model that used different deceleration levels to calculate instantaneous regenerative braking energy and estimate electric vehicle energy consumption using vehicle speed, acceleration, and roadway grade as input variables. On this basis, Fiori and Marzano [3] proposed and validated a microscopic backward highly resolved power-based EFV energy consumption model (EFV-ECM) that uses vehicle speed, actual weight, roadway grade, and vehicle characteristics updated every second as input features combined with actual EFV driving data. Later, Fiori et al. [4] extended and validated the EFV-ECM by identifying model.

The most significant inputs influenced the variability of simulated energy use, resulting in typical or extreme model scenarios. The results showed that the EFV-ECM accurately reproduced the inherent uncertainty of energy-consumption measurements during real-world EFV driving. As a result, this study uses the EFV-ECM as an energy consumption model to calculate instantaneous power usage. He et al. [3] investigated the movement of

EVs in a WCL using a car-following model and lane-change rules, as well as the driving behavior of each EV in a two-lane system with a WCL and the influence of the WCL on EV mobility. He et al. [5] provided a new method for evaluating various energy-consumption models and calibrations to investigate the influence of WCL on EV travel time and energy consumption in a two-lane system. Li et al. assessed the longitudinal safety of EVs equipped with a partial WCL on freeways using time-exposed and time-integrated time-to-collision as safety evaluation indicators.To improve eco-driving control, Zhao et al employed a model-predictive control technique to govern the trajectory of automated cars and suggested a real-time cooperative eco-driving control model for hybrid automated vehicles and human-driven vehicles approaching signalized crossings. Xin et al. [1] created an eco-driving model with a slowing strategy that took into account signal phase, timing, and vehicle state at signalized junctions. This model could direct vehicles through an intersection without stopping by analyzing the red and green light conditions at the signalized intersection and slowing them down ahead of time. Liao et al. [2] took into account the internal features of a powertrain and incorporated a battery temperature impact into a powertrain-based longitudinal dynamic model of EVs, employing a holistic approach to build optimal driving strategies. By this technique to regulate the trajectory of automated vehicles by merging eco-driving and traditional cooperative adaptive cruise-control technologies, Ma et al. [3] suggested an ecological cooperative adaptive cruise-control model that allows for energy optimization and multi-vehicle speed trajectory planning.

Sun et al. [4] employed motion wave and car-following models to create an eco-driving algorithm based on linked and automated technologies. The algorithm used accurately estimated the moment each vehicle entered a signalised intersection based on signal timing and vehicle speed. It then created an advisory speed limit approach for each automated vehicle to allow speed-controlled vehicles to enter the intersection at the scheduled time, so achieving the goal of reducing traffic fluctuations and improving traffic congestion. However, the eco-driving model outlined here did not take wireless charging scenarios into account. Table 1 summarizes the aforementioned eco-driving-related works in the literature; the last row denotes the contribution made by this study.

2.SCENARIO DESCRIPTION AND SCHEMATIC

CAEFVs in the upstream area of signalized intersections can receive important state information in advance, including their positions, traffic signal phase status, and surrounding vehicle information, thanks to intelligent urban transportation systems, vehicle-to-vehicle, and vehicle-to-infrastructure technologies. Furthermore, the wireless charging scenario at signalized intersections (WCSSI) is made up of several scenario pieces, including automobiles, static environments, and dynamic environments. To hierarchically analyze a mix of automobiles, roads, and environmental components in a coupled scenario, a modified hierarchical model was employed for a scenario representation based on Menzel et al's research. [5]. In this model, scenarios are divided into basic components, and only the interactions between all five layers represent a complete scene. The five-layer model is used to construct the scene depicted in Figure 1a with the three lower layers describing its static parts. The fourth layer focuses on moving objects, while the fifth layer describes the environmental conditions and vehicle-to-everything communication.

2.1. Energy Consumption and Wireless Charging Model for CAEFVs

Because the vehicle speed and acceleration data can be easily obtained from the intelligent transportation system, this study uses a physical model proposed by Fiori et al. [3],

which is a backward-structured EFV–ECM, to calculate the energy consumption of EVs. It utilises the instantaneous speed, acceleration, and road gradient as the input parameters and the the input parameters and the instantaneous power or energy consumption as the output and calculates the instantaneous energy consumption and power state of the vehicle by inputting the speed and acceleration data obtained every second.

3.NUMERICAL STUDIES

The effectiveness of the optimal driving model based on customised requirements was evaluated to assess the impacts of various key factors on the traffic benefits of CAEFVs in the WCSSI. The ability of vehicles to pass the

CA in mixed traffic with different market penetration rates (MPRs) was examined to verify the adaptability of the proposed model. The main simulation parameters, including the basic vehicle parameters [3].

3.1. Single-Vehicle Simulation with a Communication Delay

To verify the effectiveness of the proposed model, a particle swarm optimisation algorithm [4] and regularisation method [1] were employed to compare the optimal driving model considering a communication delay with an unguided model (IDM) using the same initial state parameters. Based on the simulation parameters listed in Table 3, comparison experiments were conducted for the same initial state, including an initial speed of 20 m/s and charging area of 200 m.

The minimum speed of the vehicle without a control strategy is 0 m/s, and the vehicle remains stationary at the stop line of the signalised intersection. For the CAEFVs controlled by the optimal driving control model, no STOP–GO behaviour is observed in the CPS, BPS, and TPS, and the vehicles pass through the signalised intersection without stopping in different modes. After introducing a communication delay, the speed curves of the three modes become different. The time required for the CAEFVs driving in the CPS mode to cross the entire signalised intersection is approximately 70 s, and the largest difference between their lowest speeds is 0.24 m/s. However, the times required for the CAEFVs driving in the BPS and TPS modes to cross the entire signalised intersection are equal to 48 and 40 s, and the corresponding minimum speed differences are 0.33 and 0.18 m/s, respectively. Figure 2b illustrates the vehicle passing process through a signalised intersection. In the scenario without a control strategy, the vehicle is affected by the red light and remains idle before the stop line at the signalised intersection. The CAEFVs that consider a communication delay can receive road and signal-light status information in advance, enabling effective decision-making optimisation control and avoiding the idling of vehicles at the signalised intersections.

The numerical simulation results obtained for the four scenarios are listed in Table 4. The time required for CAEFVs to cross the signalised intersection in the TPS mode is the lowest one. The power consumption of the vehicles operating in this mode is also relatively low, the energy recovered by the regenerative braking system without a control strategy is relatively high, and the charging efficiency of EVs driving in the CPS mode is the highest. Compared with the vehicles without a control strategy, the vehicle driving in the CPS mode saves 0.2014 kWh of electricity; the vehicle operating in the BPS mode saves slightly more than 0.0896 kWh of electricity, and the vehicle driving in the TPS mode saves slightly more than 0.0457 kWh of electricity. However, it takes longer times for the vehicles driving in the CPS mode to pass through the signalised intersection. In contrast, the vehicles driving in the TPS mode save less electricity than those operated using the other two strategies, which significantly reduces the passing time and increases the passing efficiency.

3.2. Effects of Different Key Factors on Single-Vehicle Simulation

To analyse the effects of the initial vehicle speed, WCL length, and charging efficiency on the model performance and differences between the three passing strategies, nine scenarios are considered in this study to determine the SOC. According to Table 5, scenarios A, B, and C are constructed for different initial speeds with a fixed WCA and charging efficiency. Scenarios D, E, and F and G, H, and I are constructed for different charging area lengths and charging efficiencies, respectively.

The trajectory, speed, and SOC values of CAEFVs obtained for different scenarios. Figure 3a indicates that for the CPS, the time required for CAEFVs to arrive at the intersection is approximately 65 s and that the total time required to cross the control section is approximately 70 s, while for the TPS, the vehicles arrive at the intersection in 35 s and pass through the CA in 42 s or less. For the BPS, the vehicles arrive at the intersection through the CA in 50, 53, and 56 s, which indicates that the CAEFVs driving in the TPS mode can cross the intersection faster than the vehicles using the other strategies and thus reduce the total travel time. Figure 3b, c show that the trajectory curves obtained for the BPS are more dispersed than those constructed for the TPS and that the time at which the vehicles arrive at the intersection is uncertain. The temporal trajectory curves obtained for the TPS are more concentrated, and the vehicles arrive at the intersection stop line when the traffic light changes from red to green. Meanwhile, the CPS ensures that a vehicle passes through the intersection and CA before the traffic light turns red. For BPS, the increase in the charging efficiency effectively extends the charging time of CAEFVs. Similarly, the vehicles following the TPS require less time to cross the CA.

Indicate that the speed of the vehicle driving in the TPS mode is generally higher than those of the vehicles driving in the other two modes and that its speed fluctuations are small. Overall, the average speed in the CPS mode is lower than those in the other two modes, especially the minimum speed. The minimum speed in the CPS mode is approximately equal to the minimum speed of the vehicle, while the minimum speeds achieved in the BPS and TPS modes amount to 4–9 and 10–15 m/s, respectively. For the CPS, a vehicle requires more charging power, which necessitates travelling at a lower speed in the charging zone. For the TPS, the charging weighting coefficient is not a major factor; therefore, driving at a lower speed is not required when passing through the wireless charging zone.The maximum capacity of the battery is assumed to be 60 kWh with an initial SOC of 0.5. When a vehicle drives in the WCA or decelerates, its remaining power increases significantly. When the vehicle accelerates, the remaining power decreases considerably.For the BPS, the remaining powers of the vehicles at the terminal moment in scenarios A, B, and C are equal to 0.5017, 0.5014, and 0.5010 kWh, respectively. Therefore, it can be concluded that the higher the initial speed of the vehicle, the greater the power consumption in the CA. Simultaneously, the remaining power at the terminal time decreases with an increase in the initial speed. The WCL length and charging efficiency exert a stronger impact on the SOC, and the charging distance and charging efficiency have a significant effect on the power replenishment of CAEFVs.

The numerical results obtained for the different scenarios are listed in Table 6. Here, t_f is the terminal moment, T_{cha} is the charging time, E_{cha} is the charge replenished by the vehicle in the CA, E_{con} is the pure energy consumption, E_{rec} is the charge recovered by the regenerative braking system, and SOC is the remaining battery capacity.

3.3. Multi-Vehicle Simulations in Different Modes

3.3.1. Simulation Using a Fleet of CAEFVs

To adapt the optimal driving mode to a fleet of CAEFVs at the intersection, scenario A in Table 5 is selected as the base scenario, where eight CAEFVs sequentially enter the upstream start of the intersection at an initial speed of 20 m/s and CA length of 200 m the delay time is equal to 0.15 s. Depicts the spatiotemporal trajectory and speed distribution curves of the fleet driving in different modes (the dashed lines indicate the coordinate points for entering and exiting the WCA). Figure 4a shows that for the TPS, the first vehicle in the fleet arrives at the intersection in 35 s and that the entire queue passes through the CA in approximately 47 s. According to Fthe vehicle queues with the BPS and CPS pass through the signalised intersection within the green-light cycle. Generally, in a CAEFV queue, the leading vehicle operating characteristics are part of the optimised or better trajectory, and the other vehicles are more likely to travel along suboptimal trajectories and use the wireless charging road with low latency. However, the fleet of CAEFVs using the CPS crosses the intersection after a longer time.The speed fluctuations of the fleet of CAEFVs following the CPS are significantly larger than those depicted in the perturbations created by this situation are more likely to cause traffic congestions.

The power consumption values and travel times of the vehicles travelling in different modes. For the CPS, the vehicle consumes, recovers, and charges approximately 0.137, 0.054, and 0.241 kW/h, respectively, and its travel time and charging time are equal to approximately 63 and 39.5 s, respectively. These values are larger than those obtained for the BPS (0.02 kW/h, 0.008 kW/h, 0.199 kW/h, 19.1 s, and 18.8 s, respectively). The vehicle driving in the TPS mode crosses the signal crossing with less power consumption; however, in this case, it also receives the lowest amount of recovered energy and charging power. This means that CAEFVs driving in different modes can reasonably use the WCA and that the vehicles must consume more power at larger driving speed variations. The regenerative braking recovery energy does not significantly fluctuate with speed; however, it gradually increases with decreasing speed. Furthermore, the travel time in the TPS mode is shorter than that in the CPS mode by approximately 23 s, which is advantageous in terms of traffic efficiency.

3.3.2. Mixed-Traffic Simulations Using Different MPRs

In the mixed-traffic simulations, the adaptability and robustness of the proposed model were analysed in different modes by varying the MPRs of CAEFVs to determine their traffic benefits. Based on scenario E in Table 5, the dynamic initial speeds of the IDM and CAEFVs were set to 16–22 and 18–20 m/s, respectively, with an initial time distance of 30–60 m. The vehicle trajectories determined for the TPS, BPS, CPS, and IDM (control) are represented by the dark blue, red, light blue, and black lines, respectively.

Overall, as the MPR value increases, the number of vehicles stopping and waiting at the intersection stop line gradually decreases, and more vehicles travel through the signalised intersection along the optimised or suboptimal trajectories. However, a low penetration rate increases the fluctuations of vehicle trajectories, and even the IDM-controlled vehicles may not be able to cross the CA within the required timeframe. As shown in Figure 6c,d, when the preceding vehicle is a CAEFV, it can effectively shape the trajectory of the following vehicle. However, when the preceding vehicle is an IDM-controlled vehicle, it cannot effectively guide the following vehicle driving in the CPS mode. Therefore, increasing the market share of CAEFVs may significantly improve the passing efficiency of vehicles in the CA.

The average travel times and power consumption values obtained in different modes at MPRs varying from 0 and 100%. According to Figure 7a, the power consumption, regenerative braking recovery energy, charging power, and average travel time determined for the mixed traffic with the TPS at an MPR of 0% are equal to 1.388 kW,0.56 kW, 0.943 kW, and 39.7 s, respectively. When the MPR value is increased from 20% to 100%, the regenerative braking recovery energy decreases by approximately 4.6–37.2%, and the average travel time saving amounts to 2.1 s. This indicates that as the MPR increases, the TPS has an advantage in terms of the traffic efficiency. When the MPR reaches 100%, the rise in the power consumption as compared with the values obtained at other MPRs is approximately 3.3–37.1%. For the BPS and CPS modes described in Figure 5b,c, the power consumption increases with increasing MPR from 1.388 kW by approximately 11.7–39.4% and 6.8–37.3%, respectively. Meanwhile, the charging power increases from 0.943 kW to 2.073 and 2.276 kW, respectively, while the regenerative braking recovery energy also exhibits a slow upward trend, which indicates that the vehicle has a significant charging advantage when driving through signalised intersections in the CPS mode. For the BPS, the average vehicle travel time increases slightly. In contrast, the average travel time in the CPS mode increases significantly, which also indicates that the vehicle inevitably sacrifices travel time to gain more power while driving. Thus, each mode succeeds in achieving its own objectives.

4. CONCLUSIONS

To increase the driving range and market share of CAEFVs as well as to solve the problem of their power and time wastage at signal intersections owing to the frequent speed fluctuations, an optimal driving model of CAEFVs at signal intersections with different passing strategies is proposed. Based on the WCSSI, a joint multi-objective optimisation model that considers the passing efficiency, vehicle energy consumption, driving comfort, and charging efficiency was developed. Based on the actual needs of CAEFVs, the passing modes were divided into the CPS, BPS, and TPS with various weighting coefficients. The obtained results revealed that a single vehicle could pass faster through a signalised intersection in the TPS mode, while more charging power could be obtained with the CPS. The effectiveness of the proposed model was verified by estimating the power consumption in different passing modes using the initial speed, WCL length, and charging efficiency as the key parameters. It was found that the CPS significantly increased the charging power at the expense of a small amount of passing time, while the BPS increased both the passing efficiency and charging power, and the model exhibited high robustness in different initial states. Moreover, the WCL length and charging efficiency produced a significant impact on the SOC and power replenishment of CAEFVs.

For the fleet of CAEFVs, the adaptability of the optimal driving model was verified by evaluating and analysing the trajectories, speeds, and SOCs of the vehicles under the influence of different policies. The obtained results indicated that the model utilising a proper passing strategy could identify the optimal vehicle driving path through multiobjective speed planning. Moreover, speed-guidance recommendations for fleets that could help pass through signalised intersections without stopping were provided to satisfy the differentiated demand while taking the WCL into account. For the mixed traffic, the TPS significantly outperformed the unguided model in terms of the power consumption and average travel time. The BPS and CPS outperformed the unguided model in terms of the charging benefits, while the CPS negatively influenced the average travel time. It is noteworthy that a lower MPR generates trajectory fluctuations strongly affecting the vehicle efficiency and that traffic benefits are closely related to the type of the leading vehicle. However, owing to the complexity of the existing traffic systems, it is necessary to extend the list of the key factors affecting the model validity and calibrate the model parameters more accurately. In addition, the influence of background vehicles on lane changes must be considered to satisfy the real-world requirements established by the current developments in autonomous driving and other technologies. Future research should focus on (1) studying the game effects between conflicting control strategies in mixed traffic where the three strategies coexist with human driving and (2) improving and optimising the proposed control method.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] Quak, H.; Nesterova, N.; van Rooijen, T.; Dong, Y. Zero emission city logistics: Current practices in freight electromobility and feasibility in the near future. Transp. Res. Procedia 2016, 14, 1506–1515. [CrossRef]

[2] Muñoz-Villamizar, A.; Quintero-Araújo, C.L.; Montoya-Torres, J.R.; Faulin, J. Short-and mid-term evaluation of the use of electric vehicles in urban freight transport collaborative networks: A case study. Int. J. Logist. Res. Appl. 2019, 22, 229–252. [CrossRef]

[3] Nowakowska-Grunt, J.; Strzelzcyk, M. Problem of air pollution and road freight in European Union. Transp. Res Procedia 2016, 16, 418–424. [CrossRef]

[4] Kin, B.; Verlinde, S.; Macharis, C. Sustainable urban freight transport in megacities in emerging markets. Sustain. Cities Soc. 2017, 32, 31–41. [CrossRef]

[5] Taefi, T.T.; Kreutzfeldt, J.; Held, T.; Fink, A. Supporting the adoption of electric vehicles in urban road freight transport–A multi-criteria analysis of policy measures in Germany. Transp. Res. Part A Policy Pract. 2016, 91, 61–79. [CrossRef]

[6] Rizet, C.; Cruz, C.; Vromant, M. The constraints of vehicle range and congestion for the use of electric vehicles for urban freight in France. Transp. Res. Procedia 2016, 12, 500–507. [CrossRef]

[7] Imre, S¸.; Celebi, D.; Koca, F. Understanding barriers and enablers of electric vehicles in urban freight transport: Addressing˙ stakeholder needs in Turkey. Sustain. Cities Soc. 2021, 68, 102794. [CrossRef]