This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication. Citation information: DOI10.1109/UPEC57427.2023.10294498, 2023 58th International Universities Power Engineering Conference (UPEC)

A Critical Evaluation of Eco-driving Strategies for Connected Autonomous Electric Vehicles at Signalized Intersections

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Abstract*—Signalized intersections are significant spots of energy consumption because of frequent stop-and-go behavior. Eco-driving aims to reduce energy usage by optimizing driving behavior. Researchers have reviewed optimization-based method while lack of them reviewed the learning-based approaches. This work critically reviewed two different types of approach. In addition, one well-known rule-based car-following model and two state-of-the-art optimization-based and learning-based methods are selected to test in a signalized intersections environment with the metrics of energy consumption, travelling time and algorithm execution time. The experiment results show that the travelling time of three algorithms are similar, while the energy consumption of the learning-based method and optimization-based method are 30.72% and 51.82% less than that of the rule-based method respectively. However, due to algorithm execution time, the optimization-based method is not suitable to be used in real-time.

***Keywords*—connected autonomous electric vehicles, eco-driving strategy, signalized intersections**

I. Introduction and Literature Review

Transportation is one of the largest contributors to the greenhouse gas (GHG), it contributes up to 25% of the co_2 total emission in global[1], due to the extension of road networks, the growth in the number of cars on the roads, and the rise in the total yearly vehicle miles travelled (VMT), it is anticipated that the overall energy requirements of surface transportation will continue to rise in the near future [2]. Specifically, in urban areas,e.g., singlaized intersections areas, throughout the United States, travel delays caused drivers to waste more than 3 billion gallons of fuel and kept travellers in their vehicles for nearly 7 billion extra hours – 42 hours per rush-hour commuter. The nationwide total price: $160 billion, or $960 per commuting passenger [3]. Although this data is about vehicles powered by fuel, Electric vehicles (EVs) will consume extra energy at the proximity of signalized intersections as well because of frequent stop-and-go.

EVs is considered as a potential solution for that, while range anxiety is the trickiest problem for EVs. Normally, by improving battery capacity [4] or improving the powertrain efficiency, e.g., motor, inverter and converter [5-7], range of EVs could be extended. In addition, energy consumption could be formulated as an equation of acceleration and speed . Thus, good driving behaviour, e.g., eco-driving could reduce the energy consumption as well. Eco-driving strategies compute acceleration for each time step to improve energy efficiency, especially in proximity to signalized intersections.

Connected vehicles (CVs) are able to increase traffic mobility and energy efficiency through vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) connection due to the fast development of vehicle communication technology and signal phase and timing (SPaT) message's standardization [8]. In addition, autonomous vehicles (AVs) equipped with sensor technology (e.g., camera, Lidar, radar, etc.) and artificial intelligent (AI) technology are able to detect their surroundings and take the appropriate actions via complete or partial automation [9]. Recently, using both vehicle-to-everything (V2X) communication and autonomous driving technologies, connected autonomous electric vehicles (CAEVs) have enabled the development of eco-driving applications [10-18].

Eco-driving control strategy could be classified into optimization-based [10-13] and learning-based [14-18]. Although optimization-based approaches are capable of generating optimal result, the computational burden of them is large, meanwhile, it is hard to consider all traffic situations into constraints, thus, most of them are simulated in ideal environment. With the immense generalisation potential of deep learning (DL) [19] and reinforcement learning (RL) [20], which do not depend on particular models or rules, it is now feasible, as a result of the development of learning-based approaches, to overcome the aforementioned limits.

A few academics have previously evaluated the relevant literature on eco-driving. Alam $et\ al.$ discussed the policy and technological concerns regarding eco-driving [21]. Taiebat $et\ al.$ emphasised the energy implications of eco-driving in a connected and automated road environment [22]. Mintsis $et\ al.$ rigorously and explicitly examined dynamic eco-driving in the vicinity of signalized junctions [23]. However, the experiment results of approaches reviewed above were conducted in different traffic simulators, traffic environments, vehicle parameters, and energy consumption models, which is hard to evaluate the approaches fairly and critically. Further, none of the above researches reviewed the learning-based methods.

This study focuses on addressing above research gaps, the key contributions of this research include: 1) critically evaluate the literature about optimization-based, and learning-based eco-driving control strategies. 2) a case study conducted in Simulator of Urban Mobility (SUMO) to fairly and critically evaluate one baseline rule-based car-following model and two state-of-the-art optimization-based and learning-based models with the metrics of energy consumption, travelling time and algorithm execution time. The following content of this section will review optimization-based, and learning-based eco-driving control

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strategies critically. A brief introduction of two selected models and a baseline rule-based car-following model for this case study will be given in section II, while the experimental setup and the results of the case study will be given in section III. Finally, the conclusion will be given in section IV.

In order to reduce energy consumption, a good algorithm is expected to let the vehicle avoid stopping in front of the traffic light and accelerate/decelerate as small as possible. Both optimization-based and learning based method follow these two basic ideas.

A. Optimization-based eco-driving

Early dynamic eco-driving models estimated and recommended an energy-optimal speed trajectory by combining SPaT data with vehicle dynamic status and location data. Mandava $et\ al.$ [10] proposed Arterial Velocity Planning Algorithms, which minimizes the absolute value of acceleration/ deceleration with the constraints of passing the intersection in green phase and never stopping in front of the traffic light. Barth $et\ al.$ [11] proposed Dynamic eco-driving algorithm which optimizes a set of trigonometric accelerations instead of constant acceleration, which makes the speed trajectory smoother. However, the aforementioned models only optimized the acceleration while the energy consumption is related to both acceleration and speed . Meanwhile, they only consider the upstream of traffic intersection. Furthermore, they are assumed that the traffic is free, which is unrealistic.

In order for speed guidance to be applied in real complicated traffic, the basic architecture of following models was appropriately modified to account for queue discharge information and traffic signal downstream. Chen $et\ al.$ [12] proposed a model for optimization of eco-driving at signalized intersections, which minimizes the energy consumption by solving optimal accelerations for upstream and downstream, meanwhile, it puts the queue discharge information into constraints. However, the shortcoming of this model is, it assumes that the cruising velocities in upstream and downstream are same, which would be suboptimal for minimizing the energy consumption. Li $et\ al.$ [13] proposed an eco-driving system for electric vehicles with signalling control under V2X environment, which minimizes the energy consumption by solving optimal accelerations and the time duration for acceleration so that solving the optimal speed as well. As a result, the algorithm developed by Li $et\ al.$ is selected as the optimization-based algorithm using in following case study.

B. Learning-based eco-driving

Different from optimization-based method, learning-based method is capable of reducing energy consumption on the premise of complex traffic condition except for queue, such as car-following, overtake and merge.

Shi $et\ al.$ [14] implemented eco-driving for a CV under free flow conditions using a standard Q-learning algorithm. Using the total CO2 emission as the incentive signal, they sought to maximise the driving behaviour of the equipped vehicle, e.g., the vehicle equipped with eco-driving algorithm, by generating a discrete acceleration rate at each time step. Being one of the value-based reinforcement learning algorithms, the Q-learning technique cannot manage a vehicle in continuous acceleration space, resulting in a local optimum and an uneven trajectory in the majority of instances. The framework created by Mousa $et\ al.$ [15] offers insight into the DRL-based eco-driving system, which incorporates deep Q network (DQN) to enhance the fuel efficiency of the controlled CV. Yet, a significant drawback comparable to that of Shi $et\ al.$ was observed in their research, namely the loss of effectiveness in continuous action space. As policy-based algorithms are capable of learning control policies with continuous action sets, subsequent researchers often employ policy-based DRL algorithms to overcome the continuous space barrier. Zhou $et\ al.$ [16] introduced a car-following model based on the deep deterministic policy gradient (DDPG) algorithm, which has been shown to increase travel efficiency, fuel consumption, and safety at an isolated signalized junction. About traffic oscillations, a similar analysis was devised for electric vehicles by Qu et al. [17]. Wegener $et\ al.$ [18] investigated the application of the twin-delayed deep deterministic policy gradient (TD3) method, which adheres to the identical core concept of DDPG but incorporates a number of tactics to address the Q function overestimate issue of DDPG.

II. Methodology

This section will give a brief review of the baseline rule-based car-following model and 2 state-of-the-art optimization-based and learning-based model, e.g., Li's model and Wegener's model.

A. Rule-based car-following model

IDM (Intelligent Driver Model) developed in [24] is a rule-based car-following model that controls the vehicle dynamics. In details, given the leading-vehicle dynamics, the acceleration of vehicle could be formulated as follow:

$$a_a = a^{(a)}\left[1-\left(\frac{v_a}{v_0^{(a)}}\right)^{\delta}-\left(\frac{s^*(v_a,\Delta v_a)}{s_a}\right)^2\right] \quad (1)$$

with $s^*(v_a,\Delta v_a) = s_0^{(a)} + T^a v_a + \frac{v_a \Delta v_a}{2\sqrt{a^{(a)}b^{(a)}}}$

Where $a^{(a)}$ and $v_0^{(a)}$ represent the maximum possible acceleration and speed ; The desired minimum gap and distance are represented by $s^*(v_a,\Delta v_a)$ and $s_0^{(a)}$; The actual gap and speed variation are s_a and Δv_a, respectively; Time headway is denoted by T^a, and the required deceleration rate is given by $b^{(a)}$.

B. Li's model

The optimization-based approach developed in [14] is selected in this case study. The road between two traffic intersections could be seen as a stage. Step-wise energy consumption in a stage could be formulated as an equation of speed v_t and acceleration a_t, e.g., $P(v_t,a_t)$. The total energy consumption in this stage could be formulated as:

$$E = \int_{t_0}^{t_f} P(v_t,a_t)dt \quad (2)$$

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Where t_0 and t_f are the time that the vehicle enters and finishes the travel of a stage, respectively. The goal of this approach is to minimize the above equation with a series of physical constraints. However, solve such a continuous function will be a complex and high-computational task.

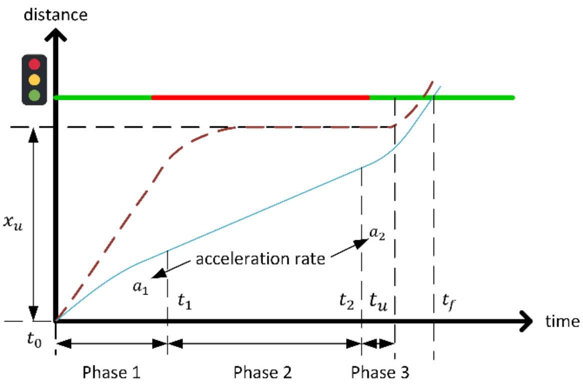

Fig. 1. The approximation model for eco-driving in Li's model.

As shown in Figure 1, intuitively, eco-driving strategy in the proximity of traffic intersection could be approximated as 3 phases: 1) accelerating or decelerating at a constant rate a_1 from t_0 to t_1, 2) cruising among t_1 and t_2, 3) from t_2 to t_u, again accelerating or decelerating at a constant rate a_2.

Each time the controlled vehicle enters a road, an IDM will be simulated to run in this road and get (x_u, t_u) first. Where x_u is the position where the IDM stopped in front of the intersection, while t_u is the time when IDM started from the queue. As a result, the optimization function could be approximated as follow:

$$\min_{a_1,a_2,t_1,t_2} \tilde{E} = \int_{t_0}^{t_1} P(v_1(a_1,t),a_1)dt + \int_{t_1}^{t_2} P(v_c,0)dt + \int_{t_2}^{t_u} P(v_2(a_2,t),a_2)dt \quad (3)$$

$$s.t.\ v_0 + a_1(t_1 - t_0) = v_c$$

$$x_u = p_0 + v_0(t_1 - t_0) + \frac{1}{2}a_1(t_1 - t_0)^2 + v_c(t_2 - t_1) + v_c(t_u - t_2) + \frac{1}{2}a_2(t_u - t_2)^2$$

$$0 \le v_c + a_2(t_u - t_2) \le v_{max}$$

$$t_0 \le t_1 \le t_2$$

$$t_1 \le t_2 \le t_u$$

$$a_{min} \le a_1 \le a_{max}$$

$$a_{min} \le a_2 \le a_{max}$$

Where v_c is the cruising speed while p_0 is the start point of a stage. There are only 4 variables need to be optimized in the approximated function. However, the realistic traffic environment is dynamic, overtake and merge will happen anytime. Thus, just following the optimized acceleration probably causes safety issue. As a result, an IDM is embedded into this algorithm as a safety monitor, so the final acceleration is the smaller one between optimized acceleration and the acceleration determined by IDM.

C. *Wegener's model*

The reinforcement-learning-based approach developed in [18] is selected in this case study. The framework of algorithm is shown in Figure 2, as agent inputs, the present state of the equipped vehicle, sensor data, and the state of the next traffic light are considered, the completed state variables are shown in Table I. With the help of sensors, the RL agent could measure the state of leading-vehicle including the speed v_{lead}, the acceleration a_{lead} of leading vehicle and the distance from the leading vehicle d_{lead}. At the same time, with the help of V2I technique, the phase of next traffic light b_{TL}, the distance from traffic light d_{TL}, and the beginning time and end time of next green phase $t_{TL,greenBegin}$, $t_{TL,greenEnd}$ could be obtained for RL agent. Meanwhile, the maximum and minimum speed to go through the intersection $v_{TL,max}$ and $v_{TL,min}$ are included to facilitate training, which are determined by traffic light information and will be introduced later.

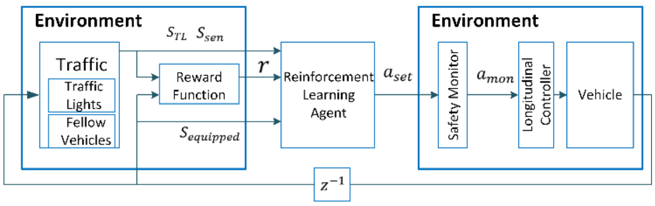

Fig. 2. The framework of RL-based eco-driving in Wegener's model.

TABLE I

RL AGENT STATE DESCRIPTION

	Equipped-Vehicle $s_{equipped}$	Sensor s_{sen}	Traffic-light s_{TL}
Input states	$v_{equipped}$ $a_{equipped}$	v_{lead} a_{lead} d_{lead}	b_{TL} d_{TL} $t_{TL,greenBegin}$ $t_{TL,greenEnd}$ $v_{TL,max}$ $v_{TL,min}$

To make sure the equipped vehicle will not stop in front of the intersection, accelerate/decelerate as smooth as possible and drive safely, following reward function is designed to let RL agent output an appropriate acceleration/deceleration to realize above objectives.

$$r = r_{TL} - r_{v_{opt}} - r_a - r_{mon} \quad (4)$$

Where r_{TL} will be +1 if the vehicle passes the traffic light during a green phase.

In addition, velocities are punished to encourage maintaining steady velocities: The speed term of the reward function $r_{v_{opt}}$ is zero if the equipped vehicle's speed is between v_{tar} and $v_{TL,max}$, and it drops linearly with a factor f_v if the speed falls below v_{tar} or exceeds $v_{TL,max}$.

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$$r_{v_{opt}} = f_v \cdot \left(\max\left(v - v_{TL,max}\right) + \max(v_{tar} - v, 0)\right) \quad (5)$$

with $v_{tar} = \max(f_{tar} \cdot v_{TL,max}, 1.1 \cdot v_{TL,min})$

Where v_{tar} is generated from GLOSA algorithm to provide a reference for the energy-savings of the RL agent. Utilizing the distance to the traffic light and the beginning and end of the next green phase (d_{TL} and $t_{TL,greenBegin}$ and $t_{TL,greenEnd}$), the maximum and minimum constant velocities ($v_{TL,max}$and $v_{TL,min}$) necessary for the vehicle to reach the traffic light during this green phase are computed. If a green phase cannot be reached within the legal speed limit, the next green phase is selected as the target phase. To account for delays caused by other cars between the ego-vehicle and the traffic light, the target speed v_{tar} is computed by subtracting a factor f_{tar} from the maximum speed $v_{TL,max}$, but not below 1.1 times the minimum speed $V_{TL,min}$.

Meanwhile, an absolute acceleration penalty $a^2_{equppied}$ of the vehicle multiplied by a factor f_a implicitly tries to reduce energy consumption while maximising driving comfort.

$$r_a = f_a \cdot a^2_{equppied} \quad (6)$$

Furthermore, this method incorporates an IDM as a safety monitor, thus the final acceleration $a_{set}$is the smaller one of the accelerations computed by RL agent and the IDM-determined acceleration. However, the interventions of IDM-based safe monitor are punished to prevent extreme interference with its capability. The squared difference between the intended acceleration a_{set} and the safe acceleration a_{mon} is punished by a factor f_{mon} to prevent interventions and allow the agent to develop a safe and consistent acceleration profile.

$$r_{mon} = f_{mon} \cdot (a_{set} - a_{mon})^2 \quad (7)$$

III. CASE STUDY

A case study is given to compare the above 3 algorithms with the metrics of energy consumption, travelling time and execution time.

A. Experiment Setup

The traffic environment of this case study is conducted in Simulator of Urban Mobility (SUMO), while all the algorithms are implemented via python, which interacts with SUMO through Traci API. The traffic environment is shown in Figure 3, which is a 600 meters road with 2 traffic lights and speed limit of 15m/s. The first traffic light is located in 300 meters, while the second one is located in 600 meters. The total phase cycle of traffic lights is 43s (30s for green/3s for yellow/10s for red), and the initial phase time of the first traffic light is 10s left in green phase, while that for the second one is 5s left in green phase.

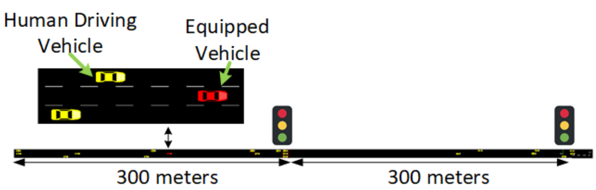

Fig. 3. The traffic environment built in SUMO.

There are Human Driving Vehicles and Equipped Vehicle in the road. There are 3 lanes in the test road environment, for Equipped Vehicle, it is forced to drive in the middle lane, while for Human Driving Vehicles, they are allowed to change lane. The car-following model of Human Driving Vehicles is IDM, meanwhile, the lane changing model of them is LC2013 [25]. In addition, the traffic flow in this experiment is 1300 vehicles/hour.

TABLE II . MMPEVEM PARAMETERS

Parameter	Value
Mass of the vehicle	1000kg
Wheel radius	0.3588m
Internal components' moment of inertia	$0.01\text{kg} \cdot \text{m}^2$
Rolling resistance coefficient	0.01
Air drag coefficient	0.6
Cross-sectional area of the front of the vehicle	5.0m^2
Combined ratio of the single reduction gear and the differential	10
Combined ratio of the single reduction gear and the differential	0.96
Maximum generative torque of the electric motor	310 Nm
Maximum generative power of the electric motor	107kW
Maximum recuperation torque of the electric motor	95.5Nm
Maximum recuperation power of the electric motor	42.8kW
Internal battery resistance	0.1142Ohm
Nominal battery voltage	396V
Constant power consumption of auxiliary devices	0.1kW

TABLE III

IDM CAR-FOLLOWING MODEL PARAMETERS

Parameter	Description	Value
$v_0^{(a)}$	Maximum speed	15m/s
$a^{(a)}$	Maximum acceleration	3m/s^2
$b^{(a)}$	Maximum deceleration	-3m/s^2
$s_0^{(a)}$	Minimum distance	2.5m
T^a	Time headway	1s
δ	Acceleration exponent	4

The selection of the emission model has a significant impact on the accuracy and reality of the experiment. This case study utilises Mechatronics in Mobile Propulsion of RWTH Aachen University's Electric Vehicle Emission Model (MMPEVEM) [26], which takes into account each component of the powertrain in order to calculate the power consumption properly at each simulation step. This consists of the transmission (i.e., a single reduction gear and a differential) with constant efficiency, a constant power consumer representing auxiliary devices such as air conditioning, and the battery. The parameters for MMPEVEM, e.g., vehicle parameters are shown in Table II.

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TABLE IV

EXPERIMENT RESULT FOR 3 MODELS

	IDM	RL	PSO
Energy consumption (kWh/100km)	9.96	6.90	4.80
Travelling time(s)	67.0	68.0	67.0
Algorithm execution time (s)	≈ 0	≈ 0	8
Average acceleration (m/ s^2)	1.00	0.67	0.26
Average speed(m/s)	9.07	8.91	9.13

B. *Algorithms Implementation*

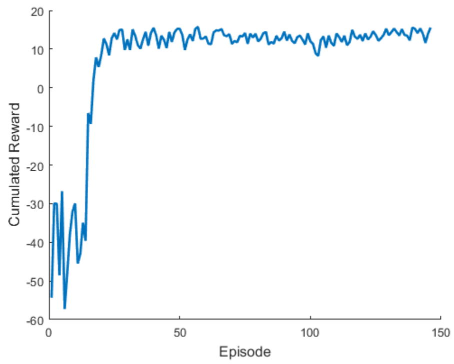


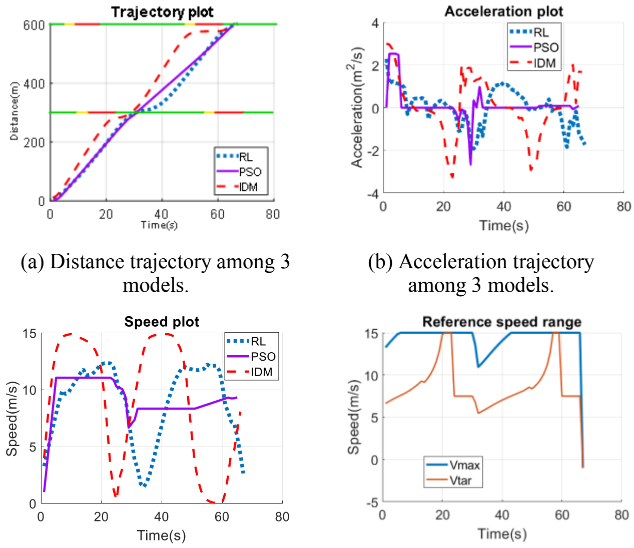
Fig. 4. The training process of RL agent.

For the equipped vehicles controlled by IDM and using IDM as safety monitor, they share same vehicle dynamics parameters, which are shown in Table III. Meanwhile, PSO is selected to solve the optimization-based approach, the population size of PSO is 5 while the maximum generalization is 30. For learning-based approach, the RL agent is built by Pytorch, the network topologies, training parameters and reward function parameters are same as [18]. The neural network is optimized using ADAM optimizer, and the resulting training process can be observed in Figure 4.

C. *Result & Dicussion*

The energy consumption, travelling time, and execution time are shown in Table IV. In order to evaluate the reason of the above results, the distance trajectory, speed trajectory and acceleration trajectory are demonstrated in Figure 5(a) to Figure 5(b) as well.

Table IV shows that the travelling time of vehicles control by RL, PSO, IDM are nearly same, while energy consumption of them are 6.90, 4.80, 9.96 kWh/100km respectively. In special, RL one consumes 30.72% less energy than IDM one, while PSO one consumes 51.82% less energy than IDM one. In terms of average acceleration, the value of them are 0.67, 0.26, 1.00 respectively. Specifically, the average acceleration of RL one is 33% less than IDM one, and that of PSO one is 74% less than the IDM one. Obviously, it could be seen that energy consumption is significantly proportional to average acceleration. From the Figure 5(a), it could be seen that the vehicle controlled by IDM will stop in front of two traffic lights, and the accelerations will be fuluctuated in these two periods, which could be observed from Figure 5(b). However, the vehicles controlled by RL agent and PSO will not stop in front of the traffic, thus their average accelerations are relatively low. This is because the vehicles controlled by RL agent and PSO are driven in relatively low velocities given the traffic light information, which could be observed from Figure 5(c).



(a) Distance trajectory among 3 models.

(b) Acceleration trajectory among 3 models.

(c) Speed trajectory among 3 models.

(d) Reference speed range for RL agent.

Fig. 5. The case study results for (a) distance trajectory, (b) acceleration trajectory and (c) speed trajectory among 3 models, respectively. (d) is the reference speed range for RL agent.

When comparing the results of RL agent and PSO, the energy consumption of RL agent is higher than that of PSO and the average acceleration of RL agent is higher than that of PSO. On the one hand, for the PSO one, there is a cruising period in each stage, where the acceleration is zero. On the other hand, for the RL agent one, although it will follow the reference speed to avoid stopping in front of the traffic lights and will accelerate/decelerate as small as possible, it will still implement some unnecessary accelerations. For instance, it could be seen that from Figure 5(c), an unnecessary acceleration will be implemented during 15 to 20s, which will result in another unnecessary deceleration during 20 to 25s to avoid stopping in front of the traffic light. One reason for that might be the reference speed range is not suitable in this case, it could be observed from Figure 5(d), the lower limit of the speed range is very high, which is not suitable and make the vehicle implemented unnecessary acceleration.

Although the performance of energy-efficiency of PSO one is the best, it will take 8s to compute optimal solution in each time (i7-11700@2.5GHz with 16G RAM), which could not be used in reality, while the algorithm execution time of RL agent and IDM is nearly zero.

IV. Conclusion

This study evaluated the optimization-based and learning-based approaches in eco-driving. In addition, IDM, two state-of-the-art optimization-based and learning-based approaches, are chosen to be evaluated in a signalized junctions environment constructed by SUMO, using the metrics of energy consumption, travel time, and algorithm execution time. The results of the experiment indicate that the travel time of the vehicles controlled by the three algorithms is comparable, whereas the energy consumption of the vehicles controlled by learning-based methods and optimization-based methods is 30.72% and 51.82% less than that of the vehicle controlled by the rule-based method. The primary reason is that the acceleration values calculated by optimization-based methods is lower. In terms of algorithm execution time, the optimization-based technique requires 8s to complete a single calculation, which is unrealistic for real-world application, but the execution time of the rule-based and learning-based methods could be disregarded.

In order to take both advantage of learning-based method and optimization-based method, it is required to transform the objective function of optimization-based methods into reward function of learning-based methods. Using the results of optimization-based method to train the neural network in learning-based method might be potential solutions.

References

[1] Y. Huang, E. C. Y. Ng, J. L. Zhou, N. C. Surawski, E. F. C. Chan, and G. Hong, "Eco-driving technology for sustainable road transport: A review," Renew. Sustain. Energy Rev., vol. 93, pp. 596–609, 2018.

[2] *Explaining the evolution of passenger vehicle miles travelled in the United States*. .

[3] D. Schrank, B. Eisele, T. Lomax, and J. Bak, "2015 Urban Mobility Scorecard," 2015.

[4] C. Huang, Z. Wang, Z. Zhao, L. Wang, C. S. Lai, and D. Wang, "Robustness evaluation of extended and unscented Kalman filter for battery state of charge estimation," IEEE Access, vol. 6, pp. 27617–27628, 2018.

[5] A. Eldho Aliasand and F. T. Josh, "Selection of Motor foran Electric Vehicle: A Review," *Mater. Today*, vol. 24, pp. 1804–1815, 2020.

[6] A. Poorfakhraei, M. Narimani, and A. Emadi, "A review of multilevel inverter topologies in electric vehicles: Current status and future

[7] M. S. H. Lipu *et al.*, "Review of electric vehicle converter configurations, control schemes and optimizations: Challenges and suggestions," *Electronics (Basel)*, vol. 10, no. 4, p. 477, 2021.

[8] A. Vahidi and A. Sciarretta, "Energy saving potentials of connected and automated vehicles," *Transp. Res. Part C Emerg. Technol.*, vol. 95, pp. 822–843, 2018.

[9] D. J. Fagnant and K. Kockelman, "Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations," *Transp. Res. Part A Policy Pract.*, vol. 77, pp. 167–181, 2015.

[10] S. Mandava, K. Boriboonsomsin, and M. Barth, "Arterial velocity planning based on traffic signal information under light traffic conditions," in *2009 12th International IEEE Conference on Intelligent Transportation Systems*, 2009.

[11] H. Xia, K. Boriboonsomsin, and M. Barth, "Dynamic Eco-driving for signalized arterial corridors and its indirect network-wide energy/emissions benefits," *J. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 31–41, 2013.

[12] Z. Chen, Y. Zhang, J. Lv, and Y. Zou, "Model for optimization of ecodriving at signalized intersections," *Transp. Res. Rec.*, vol. 2427, no. 1, pp. 54–62, 2014.

[13] M. Li, X. Wu, X. He, G. Yu, and Y. Wang, "An eco-driving system for electric vehicles with signal control under V2X environment," *Transp. Res. Part C Emerg. Technol.*, vol. 93, pp. 335–350, 2018.

[14] J. Shi, F. Qiao, Q. Li, L. Yu, and Y. Hu, "Application and evaluation of the reinforcement learning approach to Eco-driving at intersections under infrastructure-to-vehicle communications," *Transp. Res. Rec.*, vol. 2672, no. 25, pp. 89–98, 2018.

[15] S. R. Mousa, S. Ishak, R. M. Mousa, J. Codjoe, and M. Elhenawy, "Deep reinforcement learning agent with varying actions strategy for solving the Eco-approach and departure problem at signalized intersections," *Transp. Res. Rec.*, vol. 2674, no. 8, pp. 119–131, 2020.

[16] M. Zhou, Y. Yu, and X. Qu, "Development of an efficient driving strategy for connected and automated vehicles at signalized intersections: A reinforcement learning approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 1, pp. 433–443, 2020.

[17] X. Qu, Y. Yu, M. Zhou, C.-T. Lin, and X. Wang, "Jointly dampening traffic oscillations and improving energy consumption with electric, connected and automated vehicles: A reinforcement learning based approach," *Appl. Energy*, vol. 257, no. 114030, p. 114030, 2020.

[18] M. Wegener, L. Koch, M. Eisenbarth, and J. Andert, "Automated eco-driving in urban scenarios using deep reinforcement learning," *Transp. Res. Part C Emerg. Technol.*, vol. 126, no. 102967, p. 102967, 2021.

[19] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[20] R. S. Sutton and A. G. Barto, "Reinforcement Learning: An Introduction," *IEEE Trans. Neural Netw.*, vol. 9, no. 5, pp. 1054–1054, 1998.

[21] M. S. Alam and A. McNabola, "A critical review and assessment of Eco-Driving policy & technology: Benefits & limitations," *Transp. Policy (Oxf.)*, vol. 35, pp. 42–49, 2014.

[22] M. Taiebat, A. L. Brown, H. R. Safford, S. Qu, and M. Xu, "A review on energy, environmental, and sustainability implications of connected and automated vehicles," *Environ. Sci. Technol.*, vol. 52, no. 20, pp. 11449–11465, 2018.

[23] E. Mintsis, E. I. Vlahogianni, E. Mitsakis, and S. Ozkul, "Evaluation of a cooperative speed advice service implemented along an urban arterial corridor," in *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, 2017.

[24] M. Treiber, A. Hennecke, and D. Helbing, "Congested traffic states in empirical observations and microscopic simulations," Phys. Rev. E Stat. Phys. Plasmas Fluids Relat. Interdiscip. Topics, vol. 62, no. 2 Pt A, pp. 1805–1824, 2000.

[25] J. Erdmann, "SUMO's Lane-changing model," in *Modeling Mobility with Open Data*, Cham: Springer International Publishing, 2015, pp. 105–123.

[26] L. Koch *et al.*, "Accurate physics-based modeling of electric vehicle energy consumption in the SUMO traffic microsimulator," in *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, 2021.