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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

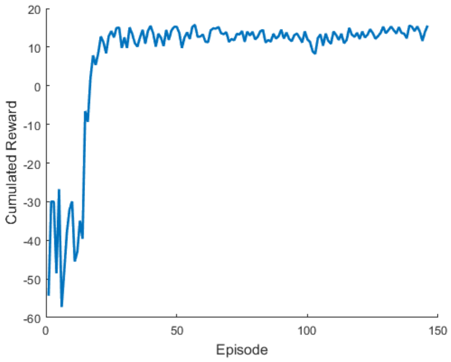


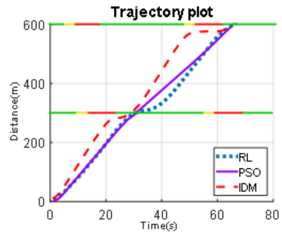
Fig. 4. The training process of RL agent.

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.

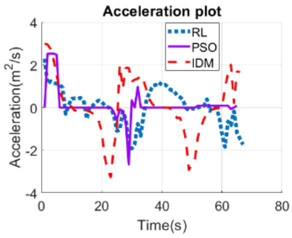
C. Result & Dicussion

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.

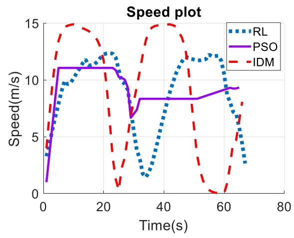
Table IV shows that the travelling time of vehicles control by RL, PSO, IDM are nearly same, while energy consumption of them are 6.90, 4.80, 9.96 kWh/100km respectively. In special, RL one consumes 30.72% less energy than IDM one, while PSO one consumes 51.82% less energy than IDM one. In terms of average 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).



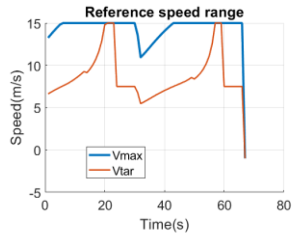
(a) Distance trajectory among 3 models.



(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.

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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.