A bibliometric analysis and review on reinforcement learning for transportation applications

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ABSTRACT

Transportation is the backbone of the economy and urban development. Improving the efficiency, sustainability, resilience, and intelligence of transportation systems is critical and also challenging. The constantly changing traffic conditions, the uncertain influence of external factors (e.g. weather, accidents), and the interactions among multiple travel modes and multi-type flows result in the dynamic and stochastic natures of transportation systems. The planning, operation, and control of transportation systems require flexible and adaptable strategies in order to deal with uncertainty, non-linearity, variability, and high complexity. In this context, Reinforcement Learning (RL) that enables autonomous decision-makers to interact with the complex environment, learn from the experiences, and select optimal actions has been rapidly emerging as one of the most useful approaches for smart transportation applications. This paper conducts a bibliometric analysis to identify the development of RL-based methods for transportation applications, representative journals/conferences, and leading topics in recent 10 years. Then, this paper presents a comprehensive literature review on applications of RL in transportation based on specific topics. The potential future research directions of RL applications and developments are also discussed.

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1. Introduction

The travel demand is increasing along with the growth of social and economic activities, which results in great challenges in terms of crowding, congestion, emission, energy, and safety. Meanwhile, a massive amount of multi-source data has been continuously and/or automatically collected. In this context, artificial intelligence (AI) methods that can take advantage of the growing data availability have been proposed to address challenges faced by transportation systems and travellers and thus improve system safety, sustainability, resilience, and efficiency.

Reinforcement Learning (RL) is an essential branch of AI-based methods, which is an experience-driven autonomous learning strategy for decision-making that aims to obtain the maximum accumulative reward. The concepts and terminologies in relation to reinforcement learning are first proposed in 1954 (Minsky 1954), where the trial and error interaction with the environment is emphasized as the core mechanism of RL to learn optimal behaviours/decisions (Kaelbling, Littman, and Moore 1996).

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Bellman (1957) proposes the dynamic programming method to solve the discrete Markov Decision Process (MDP) for the optimal control problem, where the proposed method is similar to the trial and error mechanism, and thus MDP becomes the most common mathematical framework to define RL tasks. Later on, Q-learning is proposed (Watkins 1989) to find the optimal strategy under limited information/knowledge (e.g. without the knowledge of the state transition function), which further expands the application of RL. Since the development of Q-learning, applications with RL have grown rapidly. For instance, RL algorithms have been applied to Atari games proposed by DeepMind (Mnih et al. 2015). The design of AlphaGo (Silver et al. 2016), a deep RL-based Go program, defeats advanced human players, which demonstrates the huge potential of deep reinforcement learning.

In the past several years, many top conference papers and journal papers have reported diverse theoretical progress of RL, which have motivated wide applications of RL in different fields. For instance, RL-based methods are able to control complex machinery (Levine et al. 2016) and self-driving (Wang et al. 2019). Also, it has been applied in recommendation systems for commodity recommendation (Chen et al. 2018) and advertising placement (Lou et al. 2020). The utilization of RL in the natural language processing (NLP) domain has also been explored extensively, such as dialogue system (Mo et al. 2018) and context sequence modelling (Chen et al. 2021). In addition, RL can be used to improve communication network resource allocation efficiency (Mao et al. 2016), where the energy usage for data centres can be reduced.¹ The wide applications of Reinforcement Learning in different domains demonstrate the advantages of RL, which are further explained below. First, RL does not necessarily require substantial prior experiences or historical data to train the agent (Ye, Zhang, and Sun 2019). Second, model-free RL algorithms allow agents to learn the environment information for optimization without dependence on prior expert knowledge. Third, RL is able to handle long-term problems by acknowledging long-term returns rather than only considering an immediate return for short-term benefits (Pan et al. 2019). Also, multi-agent RL algorithms that can handle large-scale systems where multiple agents either cooperate or compete with each other have been proposed. Multi-agent RL shows strong scalability by distributing tasks appropriately for a large number of agents (Desjardins and Chaib-Draa 2011).

In line with the advantages of RL, many studies have developed and/or applied RL strategies in the transportation sector. The experimental results evaluated on real-world datasets or synthetic datasets demonstrate the effectiveness of Reinforcement Learning in learning and managing transportation systems, improving accuracy and efficiency, and reducing resource consumption. There are several existing reviews on RL studies in the transportation domain. In particular, Mannion, Duggan, and Howley (2016), Yau et al. (2017) and Noaeen et al. (2022) focus on traffic signal control with RL; Aradi (2022), Kiran et al. (2022) and Zhu and Zhao (2021) focus on deep RL models for autonomous driving; and Qin, Zhu, and Ye (2022) focus on RL algorithms for ride-sharing. Three additional review studies (Abdulhai and Kattan 2003; Haydari and Yilmaz 2022; Farazi et al. 2021) have covered more transportation applications with Reinforcement Learning. Abdulhai and Kattan (2003) is published in 2003, which does not cover the substantial development of RL methods in recent years. Farazi et al. (2021) mainly focus on deep RL methods for applications in transportation (e.g. autonomous driving and traffic signal control). However, non-deep RL models have not been examined. Haydari and Yilmaz (2022) have discussed both deep RL and non-deep RL methods and covers a wide range of RL applications in transportation (including traffic signal control, energy management for the electric vehicle, road control, and autonomous driving). However, the importance of fairness in developing RL methods for transportation applications is not emphasized. Moreover, none has provided a bibliometric analysis of RL methods for transportation applications. Differently, this study takes advantage of the bibliometric analysis to provide a systematic review on applications of both deep RL and non-deep RL methods in transportation and provide more comprehensive coverage of applications than related existing reviews (e.g. including RL applications in taxi and bus systems that have not been covered by Haydari and Yilmaz 2022). Besides, this paper further points out several aspects that require substantial efforts in terms of developing RL methods for real-world transportation applications, i.e. scalability, practicality, transferability, and fairness.
Specifically, this study provides a summary on applications of RL to address relevant transportation issues and takes advantage of the bibliometric analysis approach to uncover connections among the journals/conferences and use keywords to identify the influential journals/conferences and areas of concern. Several future directions of RL studies in transportation are also discussed. The major transportation topics that involve RL methods discussed in this study include traffic control, taxi and ride-sourcing/sharing, assistant and autonomous driving, routing, public transportation and bike-sharing system, and electric vehicles, which are identified based on an analysis of keywords summarized in Section 3. The detailed classification of topics is shown in Figure 1. In particular, this review has collected over 600 related papers mostly published in the last 13 years in major journals in the transportation domain (e.g. Transportation Research Part B, Part C, IEEE Transactions on Intelligent Transportation Systems, IET Intelligent Transport Systems) and major related conferences in the computer science domain (e.g. AAAI, KDD, WWW, CIKM), which will be further discussed in Section 3. To summarize, this paper provides a reference point to researchers for interdisciplinary Reinforcement Learning research in transportation and computer science.

The rest of this paper is structured as follows. Section 2 introduces basic formulations of Reinforcement Learning and Section 3 conducts the bibliometric study. The review of the six topic categories for transportation applications with RL are presented in Section 4–9, respectively. Future directions of RL in transportation and the conclusion of this paper are discussed in Section 10.

2. Preliminary

Markov Decision Process (MDP) is often used to provide the basic mathematical formulation for Reinforcement Learning, which is presented first in this section. Then, algorithms for Reinforcement Learning (including value-based algorithms, policy-based algorithms, and actor-critic-based algorithms) and data usage in transportation applications are discussed.

2.1. Markov decision process

MDP is a mathematical model for stochastic control processes that can simulate agents, stochastic policy, and rewards, which provides a mathematical framework for RL (Sutton and Barto 2018). RL aims to maximize the reward where the MDP framework is able to produce the delayed reward by adopting the reward function and discount factor. In MDP, the Markov property is a fundamental concept, which is defined as the next state being only related to the current state and is independent of previous states (Markov 1954). The Markov property (state independence) often helps simplify the optimization task of RL.

In detail, MDP consists of five elements, i.e. \((S, A, P, R, \gamma)\), where \(S\) represents the set of states, \(A\) denotes the set of actions, \(P\) is the probabilistic transition function, \(R\) is the reward function, and \(\gamma \in [0, 1]\) denotes the discount factor. At time step \(t\), under a state \(s_t \in S\), the agent performs an action \(a_t \in A\) and then receives an immediate reward \(r_t(s_t, a_t) \in R\) from the environment. The environment
state will change to \( s_{t+1} \in S \) based on the transition probability \( P(s_{t+1} | s_t, a_t) \). The goal of the agent is to find an optimal policy \( \pi^* \) for maximizing the cumulative reward with a discount factor where \( G = \sum_{t=1}^{T} \gamma^t r_t, \pi^* = \arg\max_{\pi} \mathbb{E}[G | \pi] \), and \( \mathbb{E} \) represents the expectation operator. Specifically, the state, action, and reward are all problem-specific. For instance, for traffic signal control problems, the state may include traffic flow and speed information, the action is the signal timing, and the reward is often defined to minimize traffic delay. The transition dynamics matrix maps the pair of the state and action into the distribution of states in the next time step, which consists of the probability between any two states. The specific values of transition matrices often do not need to be calculated after the development of Q-learning. The discount factor is often adopted to put more weight on more recent returns. The policy is the solution to MDP, which maps from the state to the action and indicates the action to be taken under the specific state.

Depending on the number of agents that are considered, RL can be divided into single-agent and multi-agent algorithms. When there are multiple agents, three relations among agents are often considered, i.e. the fully competitive, the semi-competitive and semi-cooperative, and the fully cooperative. Compared to single-agent RL, multi-agent RL faces more challenges. For example, the joint actions of all agents will affect the state, which increases the instability of the environment and leads to the difficulty of optimization. Also, in a multi-agent system, we may have to deal with agents with only local observation/information. In addition, the increase of agents will require more computation resources to handle the large or high-dimensional state and action spaces. This paper involves both single-agent and multi-agent RL methods for transportation applications.

### 2.2. Reinforcement learning algorithms

This subsection will introduce several major Reinforcement Learning algorithms, i.e. value-based algorithms, policy-based algorithms, and actor-critic-based algorithms, which are different in terms of how they optimize the decisions.

Different states/outcomes (in future time steps) may occur even under the same actions (at the current time step). Therefore, expected cumulative rewards are often considered. In particular, the state-value function \( V^\pi(s) \) calculates the expected cumulative reward under state \( s \) and policy \( \pi \). The state-action function \( Q^\pi(s, a) \) calculates the expected cumulative reward of taking action \( a \) under state \( s \). The state-value function and the state-action function can be formulated as follows:

\[
V^\pi(s) = \mathbb{E}[G | s] \quad (1)
\]

\[
Q^\pi(s, a) = \mathbb{E}[G | s, a] \quad (2)
\]

\[
V^\pi(s) = \sum_a \pi(a | s) Q^\pi(s, a) \quad (3)
\]

\[
Q^\pi(s, a) = \sum_{s'} P(s' | s, a) (r(s, a) + \gamma V^\pi(s')) \quad (4)
\]

Then, the optimal policy is obtained by letting \( \pi(s) = \arg\max_a Q(s, a) \) and the state-value function is \( V^\pi(s) = \max_a Q^\pi(s, a) \). Bellman Expectation Equation (Bellman 1952) can be used to solve the value function:

\[
V^\pi(s) = \sum_a \pi(a | s) \sum_{s', r} p(s', r | s, a) [r + \gamma V^\pi(s')] \quad (5)
\]

With the above value functions, one then aims to produce the optimal policy that maximizes the long-term reward, where dynamic programming is often used to solve the problem, based on value iteration, policy iteration, or their combination. For the value iteration approach (value-based RL), after the initialization for the state-value function, there are two major steps (to be repeated), i.e. (i) calculating the state-action value for each pair of the action and state and (ii) updating the value function.
by choosing the maximum state-action value as the current state value. The above two steps will be repeated until the state-value function convergence. For the policy iteration approach (policy-based RL), after selecting an initial policy, there are two main steps (to be repeated), i.e. (i) policy evaluation by the state-value function and (ii) calculating the best action under the current state for policy improvement. The policy evaluation and policy improvement are repeated continuously until the policy no longer changes. Actor-Critic-based RL combines value-based and policy-based approaches. The above three strategies based on value iteration, policy iteration, or their combination are introduced below.

2.2.1. Value-based reinforcement learning
In value-based RL, the value function \( V_\pi (s) \) is updated following the Bellman Optimal Equation (Bellman 1952) and Equation (5) can be rewritten as:

\[
V_{k+1}^\pi(s) = \max_a \mathbb{E}[r_{t+1} + \gamma V_k^\pi(S_{t+1})]|(S_t = s, A_t = a)]
\]

Two classic approaches have been used to estimate \( V_\pi (s) \), i.e. Monte-Carlo-based approach (MC) and Temporal-Difference-based approach (TD). In MC, based on current state \( s(t) \), the agent starts to interact with the environment until reaching a termination condition. Then, the cumulative reward \( G_t \) can be calculated. The value-based RL tries to drive \( V_t^\pi (s) \) close to \( G_t \), which updates the value-function as follows:

\[
V_t^\pi (s) \leftarrow V_t^\pi (s) + \alpha (G_t - V_t^\pi (s))
\]

where \( \alpha \) is the learning rate. Since the reward obtained by MC is estimated at the end of the episode in concern, there can be large variances in the cumulative reward. On the contrary, TD only simulates one step in the episode in concern and updates the value-function as follows:

\[
V_t^\pi (s) \leftarrow V_t^\pi (s) + \alpha (r_t + \gamma V_t^\pi (s + 1) - V_t^\pi (s))
\]

which yields smaller variances but can be less accurate due to a lack of a systematic consideration of the whole episode.

Typical TD-based strategies are Q-learning (Watkins and Dayan 1992) and State-Action-Reward-State-Action (Sarsa) algorithm (Sutton 1996), which replace \( V^\pi (s) \) with \( Q^\pi (s, a) \) following Equation (8). The update policy of Q-learning can be expressed as:

\[
Q^\pi (s_t, a_t) \leftarrow Q^\pi (s_t, a_t) + \alpha (r_t + \gamma \max_{a_{t+1}} Q^\pi (s_{t+1}, a_{t+1}) - Q^\pi (s_t, a_t))
\]

And the update policy of Sarsa can be expressed as:

\[
Q^\pi (s_t, a_t) \leftarrow Q^\pi (s_t, a_t) + \alpha (r_t + \gamma Q^\pi (s_{t+1}, a_{t+1}) - Q^\pi (s_t, a_t))
\]

Both Q-learning and Sarsa involve (i) a behaviour policy to interact with the environment and sample potential actions from the learning data with randomness and (ii) a target policy to improve the performance with the help of sampling data and thus obtain the optimal policy. The ‘off-policy method’ updates the target policy based on the data generated from the behaviour policy, while the ‘on-policy method’ updates the target policy based on the data generated by itself (Sutton and Barto 1998). Sarsa is an on-policy method (i.e. the target policy is the same as the behaviour policy), while Q-learning is an off-policy method (i.e. the target policy is to suppose the selecting action with the largest reward to update the value function).

Q-learning might not be able to accommodate a large number of states and actions in some applications. Therefore, different deep models have been embedded in Q-learning to approximate the value function to deal with such issues. Mnih et al. (2015) propose Deep Q-Network (DQN) for optimal policy finding. Given a Q-function \( Q \) and a target Q-function \( \hat{Q} \) initialized as \( \hat{Q} = Q \), an experience replay buffer is utilized to store the transition \( (s_t, a_t, r_t, s_{t+1}) \) in each time step where \( a_t \) is obtained by
When enough sample data is obtained from trials with the environment, a mini-batch of samples is randomly selected to produce the target $y$ (a target point that provides the direction to move in order to improve the solution) as follows:

$$y = r_t + \gamma \max_a \hat{Q}(s_{t+1}, a)$$ (11)

Then, parameters of $Q$ are updated by driving $Q(s_t, a_t)$ towards $y$ with the gradient descent method. The target network $\hat{Q}$ will be reset by $\hat{Q} = Q$ after a number of $C$ steps, where the value of $C$ is a hyper-parameter to decide the iteration step for updating the parameters of the target network. It is noteworthy that for the combination of deep learning and RL two issues remain. The samples (in the aforementioned to produce $y$ in Equation (11)) to be generated when combining deep learning with RL are independent, while the states often have correlations. Moreover, the distribution of targets is static in deep learning, but the states are continuously varying in RL. Thus, the experience replay buffer designed in DQN is used to accommodate the non-static distribution problem and correlations of states. Furthermore, the instability problem caused by the usage of non-linear neural networks to represent value functions can be solved by properly designing the target network. Moreover, the $\epsilon - \text{greedy}$ strategy is often used to increase randomness when generating actions to balance exploration and exploitation.

Further DQN-based methods such as Double-DQN (Van Hasselt, Guez, and Silver 2016) and Dueling-DQN (Wang et al. 2016) are developed for more robust and faster policy learning. In detail, to reduce the overestimations caused by the single estimator of Q-learning (i.e. the estimated value is larger than the true value) (Thrun and Schwartz 1993), Double Q-learning implements the choice and the evaluation of actions with a double-estimator where two Q-functions are defined, i.e. $Q^A(s, a)$ and $Q^B(s, a)$ (Van Hasselt 2010). Specifically, each Q-function is updated with the value obtained from the other Q-function in the next state, which can be expressed as follows:

$$Q^A(s_t, a_t) \leftarrow Q^A(s_t, a_t) + \alpha (r_t + \gamma \max_{a_{t+1}} Q^B(s_{t+1}, a_{t+1}, \text{argmax}_a Q^A(s_{t+1}, a_t)) - Q^A(s_t, a_t))$$

$$Q^B(s_t, a_t) \leftarrow Q^B(s_t, a_t) + \alpha (r_t + \gamma \max_{a_{t+1}} Q^A(s_{t+1}, a_{t+1}, \text{argmax}_a Q^B(s_{t+1}, a_t)) - Q^B(s_t, a_t))$$ (12)

Van Hasselt, Guez, and Silver (2016) further embed deep learning into Double Q-learning and propose Double-DQN. The evaluation of the current policy is estimated by the target network $\hat{Q}$ instead of the second network in Double Q-learning. And the derivation of the target $y$ in Double-DQN is obtained as follows:

$$y = r_t + \gamma \hat{Q}(s_{t+1}, \text{argmax}_a Q(s_{t+1}, a))$$ (13)

Similar to the target network in DQN, the target network in Double-DQN keeps fixed and updates after a predetermined number of steps by $\hat{Q} = Q$.

Dueling-DQN replaces the output state-action value function of DQN by the combination of the state-value function and the advantage function, i.e. $Q^T(s_t, a_t) = V^T(s_t) + A^T(s_t, a_t)$, where $A^T(s_t, a_t)$ is the advantage function for the strategy evaluation. The design of the advantage function helps identify whether rewards are mainly an outcome of the state or induced by different actions. The suitability of specific actions can be evaluated.

Given the success of DQN for decision-making, numerous variants of DQN have been proposed. For instance, Prioritized Replay DQN (Tom et al. 2016) is designed such that important transitions are selected more frequently and thus can help improve efficiency. Multi-step Learning (Yinlong et al. 2019) is proposed such that return in multiple steps is used instead of the reward in one step in order to reduce the bias and accelerate training. Noisy Network (Fortunato et al. 2017) approach replaces the $\epsilon - \text{greedy}$ strategy by adding noises on parameters to enhance the exploration ability. Moreover, Rainbow (Hessel et al. 2018) is proposed to combine Dueling DQN, Prioritized Replay, Multi-step Learning, Distributional RL, and Noisy Net to further improve the performance.
2.2.2. Policy-based reinforcement learning

Policy-based Reinforcement Learning algorithms model and estimate the policy function directly and optimize the policy function to maximize the reward. Specifically, REINFORCE (Williams 1992) optimizes policy $\pi_\theta$ with the parameter vector $\theta$ by maximizing the expected return $r_t$ where the gradient is approximated by the stochastic gradient descent technique for parameter updating. Based on REINFORCE, Sutton et al. (2000) introduce the Policy Gradient method to optimize policy $\pi_\theta (s, a)$ by maximizing the average reward $\rho(\pi) = \sum_s d^{\pi}(s) \sum_a \pi(s, a) r(s, a)$ as follows:

$$\frac{\partial \rho}{\partial \theta} = \sum_s d^{\pi}(s) \sum_a \frac{\partial \pi(s, a)}{\partial \theta} Q^{\pi}(s, a)$$  \hspace{1cm} (14)$$

where $d^{\pi}(s) = \lim_{t \to \infty} P(s_t = s|s_0, \pi)$ represents the stationary distribution of states under $\pi$ and $Q^{\pi}(s, a) = \sum_{t=1}^{\infty} E[r_t - \rho(\pi)|s_0 = s, a_0 = a, \pi]$. In MDP starting from a stationary state, $d^{\pi}(s)$ can also be defined as the discounted weighting of states under policy $\pi$ starting at state $s_0$ and $Q^{\pi}(s, a) = E[\sum_{k=1}^{\infty} \gamma^{k-1} r_{t+k}|s_t = s, a_t = a, \pi]$. Then, $Q^{\pi}$ is approximated by an estimator $f_w$ and thus the Policy Gradient with Function Approximation can be written as:

$$\frac{\partial \rho}{\partial \theta} = \sum_s d^{\pi}(s) \sum_a \frac{\partial \pi(s, a)}{\partial \theta} f_w(s, a)$$  \hspace{1cm} (15)$$

where $\frac{\partial f_w(s, a)}{\partial \theta} = \frac{\partial \pi(s, a)}{\partial \theta} \frac{1}{\pi(s, a)}$. Thus, the gradient can be expressed in a suitable form to find the locally optimal policy.

Further policy-based algorithms are also designed. For instance, Trust Region Policy Optimization (TRPO) (Schulman et al. 2015) is proposed, which tends to give monotonic improvement over iterations by constraining the Kullback–Leibler divergence between the old and updated policies so that the change of the entire parameter space will not be too large to avoid the collapse of state values caused by wrong decisions. Similarly, Proximal Policy Optimization (PPO) (Schulman et al. 2017) is a widely adopted algorithm to ensure the difference between the old and updated policies is also not too large by limiting the ratio between old and updated strategies under a hyper-parameter value.

2.2.3. Actor-Critic-based reinforcement learning

Actor-Critic-based (AC-based) RL (Sutton et al. 2000) takes advantage of both value-based function and policy-based function. The actor network interacts with the environment and generates actions. The critic network uses the value function to evaluate the performance of the actor and guide the actor’s actions in the next time step.

Some widely-used algorithms in AC-based RL are Deterministic Policy Gradient (DPG) (Silver et al. 2014), Deep Deterministic Policy Gradient (DDPG) (Lillicrap et al. 2016), Advantage Actor-Critic (A2C) (Mnih et al. 2016), and Asynchronous Advantage Actor-Critic (A3C) (Babaeizadeh et al. 2017). DPG and DDPG are off-policy methods that can be trained even in high-dimensional action space, and DDPG adopts deep learning into DPG. A2C and A3C are on-policy algorithms where A2C adopts a synchronous control method, and A3C adopts an asynchronous control method for actor network updating. A3C is often adopted in transportation problems for policy-making, which is further discussed below as an example to illustrate the mechanism of asynchronous methods. A3C takes advantage of the Actor-Critic framework and introduces the asynchronous method to improve performance and efficiency. Multiple threads are utilized in A3C to collect data in parallel, i.e. each thread is an independent agent to explore an independent environment. Also, each agent can use different strategies to sample data where sampling data independently is able to obtain unrelated samples and increase sampling speed.
2.3. Data

Synthetic and real-world data have been used in studies for transportation applications with RL. On the one hand, it is easier and more feasible to obtain synthetic data. A large number of scenarios/samples with different characteristics can be constructed to evaluate proposed methods. However, some uncertainties, disruptions, and accidents occurring in practice are hard to be measured or simulated, which leaves a certain and unknown gap with actual environments. On the other hand, the real-world data can reflect the actual situations more accurately, which means that the proposed method can be put into practice for the scenario corresponding to the collected data. It is harder to obtain complete and diverse real-world data due to several reasons, e.g. the confidentiality of various sources and the lack of information. Also, a real-world dataset may only represent the characteristics of a specific target, which has limited scenarios/samples to evaluate the generality of proposed models.

Although the applications and corresponding data are diverse, the type of data can be divided into three categories, i.e. road network relevant data, traffic flow relevant data, and vehicle operation relevant data. Specifically, road networks are regarded as directed graphs with nodes and edges (i.e. nodes denote intersections while edges represent roads). Some other road related characteristics (e.g. speed limit, the number of lanes/tracks, and distributions of bus/railway stations) are also concluded to construct the stationary environment of RL. The traffic flow relevant data (e.g. traffic speed and demand) and vehicle operation relevant data (e.g. fuel/electricity consumption, vehicle speed/acceleration, and lane changing) are used as the time-varying input of RL models to constitute the dynamic environment of RL. The agents learn and analyse the information of both stationary and dynamic environments for decision-making based on different RL-based optimization strategies.

3. Bibliometric analysis

This section provides a bibliometric analysis of studies for RL-based transportation applications. The distribution of published papers in journals/conferences and the characteristics of research fields or topics are explored. The VOSviewer software\(^2\) is used to measure the quantities and connections in relation to publications and keywords.

The selected journals and conferences covering January 2010 to December 2022 are summarized in Table 1 according to the number of published related papers. The list of journals and conferences is based on the following. The selected transportation-related journals are ranked as Q1, Q2, and Q3 by Scimago Journal & Country Rank in 2022.\(^3\) The selected conferences in the field of artificial intelligence and data mining are with the highest CORE ranking (CORE A+) in recent years.\(^4\) International Conference on Intelligent Transportation Systems (ITSC) is also included due to its high relevance and wide audience. It can be seen that ITSC covers a substantial number of RL-based transportation applications studies (i.e. about 27.24%), which indicates that Reinforcement Learning has attracted substantial attention for achieving intelligent traffic control and management. Other journals with considerable relevant publications are T-VT, T-ITS, and TR-C with 173 (28.22%), 100 (16.31%), and 49 (7.99%) papers, respectively, which indicates the fusion and interaction of traditional transportation applications and popular machine learning strategies over the recent decade. Several transportation journals involve a relatively small number of papers regarding applications of RL (e.g. TR-A, TR-D, and Transportmetrica A), indicating that there are significant research potentials here for developing advanced RL in diverse aspects of transportation.

In addition, the numbers of published papers in the aforementioned journals and conferences from January 2010 to December 2022 are shown in Figure 2. Before 2017, only a few studies per year focused on Reinforcement Learning to solve transportation problems, with only 40 articles published in total in the selected journals and conferences. And the number of published related papers from 2011 to 2016 is between three and seven (around five), which is regarded as a random fluctuation. In the following six years (i.e. 2017–2022), the number of related papers has grown substantially, which indicates the increasing importance and popularity of RL to deal with transportation problems.
Table 1. Numbers of related publications in major journals/conferences (as of December 31, 2022).

| Attribute | Name | Number of Related Papers |
|-----------|------|--------------------------|
| Journal   | IEEE Transactions on Vehicular Technology (T-VT) | 173 |
| Conference | IEEE International Conference on Intelligent Transportation Systems (ITSC) | 167 |
| Journal   | IEEE Transactions on Intelligent Transportation Systems (T-ITS) | 100 |
| Journal   | Transportation Research Part C: Emerging Technologies (TR-C) | 49 |
| Journal   | IET Intelligent Transport Systems | 19 |
| Journal   | IEEE Transactions on Transportation Electrification | 16 |
| Conference | Association for the Advancement of Artificial Intelligence (AAAI) | 15 |
| Conference | Special Interest Group on Knowledge Discovery and Data Mining (SIGKDD) | 13 |
| Journal   | Transportation Research Record: Journal of the Transportation Research Board | 12 |
| Journal   | Transportation Research Part E: Logistics and Transportation Review (TR-E) | 10 |
| Conference | International Joint Conference on Artificial Intelligence (IJCAI) | 8 |
| Conference | Conference on Information and Knowledge Management (CIKM) | 8 |
| Journal   | Transportation Research Part B: Methodological (TR-B) | 5 |
| Conference | World Wide Web Conference (WWW) | 4 |
| Conference | International Conference on Data Mining (ICDM) | 3 |
| Journal   | Transportation | 1 |
| Journal   | Transportation Science | 1 |
| Journal   | Transportation Research Part F: Traffic Psychology and Behaviour (TR-F) | 1 |
| Journal   | Journal of Transportation Engineering Part A: Systems | 1 |
| Journal   | Research in Transportation Economics | 1 |
| Journal   | Journal of Air Transport Management | 1 |
| Journal   | Travel Behaviour and Society | 1 |
| Journal   | Transport Reviews | 0 |
| Journal   | Transportation Research Part A: Policy and Practice (TR-A) | 0 |
| Journal   | Transportation Research Part D: Transport and Environment (TR-D) | 0 |
| Journal   | Journal of Transport Geography | 0 |
| Journal   | Transportmetrica A: Transport Science | 0 |
| Journal   | Transport Policy | 0 |
| Journal   | International Journal of Sustainable Transportation | 0 |
| Journal   | Maritime Policy & Management | 0 |
| Journal   | Journal of Transportation Engineering, Part B: Pavements | 0 |

![Figure 2](image-url)  
**Figure 2.** Number of published related papers per year (Jan. 2010–Dec. 2022).

Furthermore, in order to identify the major transportation application areas/topics in relation to Reinforcement Learning, Figure 3 shows the bibliographic coupling network of keywords where the minimum number of occurrences of a keyword is five. The size of the circle represents the number of occurrences of the keyword. And the keywords represented by the same colour mean the high co-appearance of these words in one paper. Excluding the words with similar meanings, the keywords with high frequency can be described as two aspects, i.e. learning algorithms and intelligent transportation applications. The learning strategies mainly cover deep learning or Neural Network and...
Reinforcement Learning. The major topics related to RL methods include the following nine categories: autonomous driving/vehicles, adaptive cruise control, fleet operations, ride-sharing, traffic signal control, highway/street/air traffic control, electric vehicle, taxicabs, and scheduling. Motivated by these keywords with high frequency, we identify six groups as shown in Figure 1, which will be reviewed in the following sections, respectively.

4. Traffic control: road and air

Traffic control is a critical issue in traffic flow management. This section summarizes RL-based controlling strategies proposed for both roadway traffic and air traffic in order to reduce traffic congestion and delays. Due to a large number of studies for traffic signal control and to facilitate reading, we summarize studies on roadway traffic signal control (TSC) in Table 2 and summarize studies on other aspects (i.e. speed limit, price management, perimeter control, and air traffic control) in Table 3.

4.1. Roadway traffic control

On roadway traffic control, we review the following five major issues: traffic signal control; speed limit control; pricing management; perimeter control; and ramp metering.

4.1.1. Traffic signal control

The congestion and delays caused by traffic bottlenecks motivate the development of methods for traffic signal control (TSC) (Yau et al. 2017). Conventional pre-timed control systems set constant time...
| Framework | Q-learning | Reference |
|-----------|------------|-----------|
|           |            | Prashanth and Bhatnagar (2010), Ozan et al. (2015), El-Tantawy, Abdulhai, and Abdelgawad (2013, 2014), Mannion, Duggan, and Howley (2015), Reyad and Sayed (2022), Wiering (2000), Balaji, German, and Srinivasan (2010), Arel et al. (2010) and Abdooos, Mozyani, and Bazzan (2011) |
| DQN       |            | Mousavi, Schukat, and Howley (2017), Wei et al. (2018), Zhang et al. (2020), Xu et al. (2019), Van der Pol and Oliehoek (2016), Darmoul et al. (2017), Devailly, Larocque, and Charlin (2021), Wang, Cao, and Hussain (2021), Wei et al. (2018), Wei et al. (2019), Wei et al. (2019), Chen et al. (2020), Zang et al. (2020), Zhang et al. (2021), Yu et al. (2020) and Xu et al. (2021) |
| A2C       |            | Chu et al. (2019) and Wang, Cao, and Hussain (2021) |
| DDPG      |            | Li et al. (2021) and Ni and Cassidy (2019) |
| Actor-Critic | Neural fitted Q-iteration | Nishi et al. (2018) |
| Ape-X DQN |            | Zheng et al. (2019) |
| Agent     | single-agent | Prashanth and Bhatnagar (2010), Ozan et al. (2015), Reyad and Sayed (2022), El-Tantawy, Abdulhai, and Abdelgawad (2014), Mousavi, Schukat, and Howley (2017), Xu et al. (2019), Wei et al. (2018), Zhang et al. (2021) and Ni and Cassidy (2019) |
|           | multi-agent | Nishi et al. (2018), Wiering (2000), Abdulhai, Pringle, and Karakoulas (2003), Abdooos, Mozyani, and Bazzan (2011), Chu et al. (2019), Balaji, German, and Srinivasan (2010), El-Tantawy, Abdulhai, and Abdelgawad (2013), Arel et al. (2010), Van der Pol and Oliehoek (2016), Yu et al. (2020), Wang, Cao, and Hussain (2021), Zheng et al. (2019), Chen et al. (2020), Xu et al. (2021) Devailly, Larocque, and Charlin (2021), Mannion, Duggan, and Howley (2015), Zang et al. (2020), Zhang et al. (2020), Wei et al. (2019), Wei et al. (2019), Li et al. (2021), Darmoul et al. (2017) and Aslani, Mesgari, and Wiering (2017) |
| Scenario/Data | synthetic network/data | Prashanth and Bhatnagar (2010), Abdooos, Mozyani, and Bazzan (2011), Ozan et al. (2015), El-Tantawy, Abdulhai, and Abdelgawad (2014), Mousavi, Schukat, and Howley (2017), Nishi et al. (2018), Wiering (2000), Abdulhai, Pringle, and Karakoulas (2003), Arel et al. (2010), Van der Pol and Oliehoek (2016), Darmoul et al. (2017), Reyad and Sayed (2022), Mannion, Duggan, and Howley (2015), Aslani, Mesgari, and Wiering (2017) and Ni and Cassidy (2019) |
|           | real-world network/data | Wei et al. (2018) (Jinan), Zheng et al. (2019) (Jinan, Hangzhou), Zhang et al. (2020) (Hangzhou, Atlanta), Chu et al. (2019) (Monaco), Wang, Cao, and Hussain (2021) (Monaco, Harbin), El-Tantawy, Abdulhai, and Abdelgawad (2013) (Toronto), Li et al. (2021) (Maryland), Zang et al. (2020) (Jinan, Hangzhou, Atlanta, Los Angeles), Chen et al. (2020), Devailly, Larocque, and Charlin (2021) (New York), Balaji, German, and Srinivasan (2010) (Singapore), Xu et al. (2019) (Hangzhou), Wei et al. (2019) (Jinan, New York), Zang et al. (2020b), Wei et al. (2019), Yu et al. (2020) (Hangzhou, Jinan, New York), Xu et al. (2021) (Hangzhou, Jinan, Shenzhen, New York) |
| Simulator | GLD simulator (Wiering et al. 2004) | Prashanth and Bhatnagar (2010) |
|           | Paramics | El-Tantawy, Abdulhai, and Abdelgawad (2013, 2014) and Balaji, German, and Srinivasan (2010) |
|           | SUMO (Lopez et al. 2018) | Mousavi, Schukat, and Howley (2017), Wei et al. (2018), Nishi et al. (2018), Chu et al. (2019), Mannion, Duggan, and Howley (2015), Van der Pol and Oliehoek (2016), Wang, Cao, and Hussain (2021), Li et al. (2021), Devailly, Larocque, and Charlin (2021), Zhang et al. (2021), Yu et al. (2020) and Xu et al. (2019) |
|           | CityFlow (Zhang et al. “CityFlow: A Multi-Agent Reinforcement Learning,” 2019) | Zhang et al. (2020), Wei et al. (2019), Wei et al. (2019), Zheng et al. (2019), Chen et al. (2020), Zang et al. (2020), Yu et al. (2020) and Xu et al. (2021) |
|           | AIMSUN1 | Aslani, Mesgari, and Wiering (2017) and Ni and Cassidy (2019) |
|           | VISSIM2 | Darmoul et al. (2017) and Reyad and Sayed (2022) |
|           | personal simulator | Ozan et al. (2015), Wiering (2000), Abdooos, Mozyani, and Bazzan (2011), Abdulhai, Pringle, and Karakoulas (2003) and Arel et al. (2010) |

1 http://www.AIMSUN.com.
2 http://vision-traffic.ptvgroup.com/en-uk/home
### Table 3. Summary of RL applications in speed limit control, price management, perimeter control, and air traffic control.

| Reference | Application       | Framework                  | Agent                                | Scenario/Data                                      | Simulator               |
|-----------|-------------------|----------------------------|--------------------------------------|---------------------------------------------------|--------------------------|
| Zhu and Ukkusuri (2014) | Speed limit control | TD-based RL               | Single-agent, the controller          | Sioux Falls network                               | Personal simulator       |
| Li et al. (2017)       | Speed limit control | Q-learning                | Single-agent, the controller, the controller | Interstate freeway in Oakland                      | Personal simulator       |
| Wu et al. (2020)       | Speed limit control | DDPG                      | Single-agent, the controller, the controller | Northbound freeway of I405 in California           | SUMO                     |
| Pandey and Boyles (2018) | Price management  | Sparse Cooperative Q-learning | Multi-agent, a toll                  | Express lanes in Dallas and Austin                 | Personal simulator       |
| Pandey, Wang, and Boyles (2020) | Price management  | A2C, PPO                   | Multi-agent, a toll                  | Personal simulator                                 |
| Zhou and Gayah (2021)  | Perimeter control  | DQN, DDPG                 | Single-agent, the controller          | Synthetic network                                 | Personal simulator       |
| Chen et al. (2022)     | Perimeter control  | Policy iteration          | Single-agent, the controller          | Synthetic network                                 | SUMO                     |
| Yang, Zheng, and Menendez (2017) | Perimeter control  | DQN                       | Single-agent, the controller          | In the City of Toronto                             | Personal simulator       |
| Rezaee, Abdulhai, and Abdelgawad (2012) | Ramp metering   | Q-learning                | Single-agent, the controller          | Synthetic network                                 | Personal simulator       |
| Fares and Gomaa (2014)  | Ramp metering     | Q-learning                | Single-agent, the controller          | San Francisco Bay Bridge                          | BeATs                   |
| Belletti et al. (2017)  | Ramp metering     | DDPG                      | Multi-agent, the controller for a region | Tampa International Airport                        | FACET                    |
| Tumer and Agogino (2007) | Air traffic management | Q-learning                | Multi-agent, a location               | Synthetic network                                 | Personal simulator       |
| Balakrishna, Ganesan, and Sherry (2010)  | Flight delay      | Q-learning                | Single-agent, the controller          | Tampa International Airport                        | FACET b                  |

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a [https://connected-corridors.berkeley.edu/berkeley-advanced-traffic-simulator](https://connected-corridors.berkeley.edu/berkeley-advanced-traffic-simulator).

b [https://www.nasa.gov/centers/ames/research/lifeonearth/lifeonearth-facet.html](https://www.nasa.gov/centers/ames/research/lifeonearth/lifeonearth-facet.html).

signals, while RL-based approaches have been used to dynamically and adaptively optimize traffic signal timing. We first illustrate a four-approach intersection as depicted in Figure 4(a) (left-hand driving is assumed) and a typical signal plan with eight phases as shown in Figure 4(b). Many studies are formulated based on such four-approach intersections with eight phases (Arel et al. 2010).

The studies for traffic signal control started with the exploration for one intersection with single-agent RL methods, which provides the fundamental methods for TSC in environments with multiple intersections. Specifically, for one intersection, an intuitive designing scheme is to regard the intersection as an agent for signal control policy optimization and the agent’s decision is subject to the setting of phases. To deal with the single-agent (one intersection) scenario, Q-learning (Prashanth and Bhatnagar 2010; Ozan et al. 2015; El-Tantawy, Abdulhai, and Abdelgawad 2014; Reyad and Sayed 2022) and DQN (Mousavi, Schukat, and Howley 2017; Wei et al. 2018; Zhang et al. 2021) have been the most commonly used framework to learn the action-value function in order to reduce the total/average delay of vehicles. The deep model, DQN, for traffic light optimization is able to accommodate more complex and non-linear environmental information of an intersection. Different types of states might be adopted. For example, the congestion level (low, medium, or high) indicated by the queue lengths and elapsed times of each signalled lane (Prashanth and Bhatnagar 2010) are designed to reduce the dimensionality of the state. Exact values regarding traffic conditions (e.g. link flows and the free-flow travel time) (El-Tantawy, Abdulhai, and Abdelgawad 2014; Ozan et al. 2015), a vector of row pixel values (Mousavi, Schukat, and Howley 2017), and the image representation of vehicles’ positions (Wei et al. 2018) are collected to provide more completed environments.

The control strategies for one intersection can hardly relieve the traffic congestion in large metropolises with complex and dense networks, which motivates traffic control studies to simultaneously...
Figure 4. Traffic signal-related schematic diagrams. (a) A typical four-approach intersection and (b) Phase competition matrix.

consider multiple intersections. As multiple intersections (especially neighbouring intersections) may interact with each other, the optimal policy strategies should be considered at the target-area level to further improve traffic efficiency. Different reward functions have been used for TSC problems, i.e. the overall waiting time (Wiering 2000; Nishi et al. 2018), overall delay (Abdulhai, Pringle, and Karakoulas 2003; Balaji, German, and Srinivasan 2010) of all vehicles in multiple intersections, and the pressure (Varaiya 2013) of all intersections (Wei et al. 2019). Though these studies achieve satisfactory performance, the relations or impacts among various intersections have not been explored explicitly.

A series of studies focus on the coordination or competition among multiple agents/intersections to find area-wide or system-wide TSC strategies. Similar states and reward functions as aforementioned studies have been used based on various RL algorithms. Specifically, El-Tantawy, Abdulhai, and Abdelgawad (2013) adopt the principle of Multi-agent Modular Q-learning (Ono and Fukumoto 1996) to explicitly analyse the correlations of the target agent and one of its neighbour intersections to learn the joint policy. Arel et al. (2010) design two types of agents for collaboration, a central agent extracting the information from itself and neighbouring intersections to learn a value function and assist an outbound agent to schedule its own signals where Q-learning is used as the optimizing strategy. Furthermore, based on the Advantage Actor-Critic (A2C) framework, Chu et al. (2019) constructs the state of the agent as the composition of its observation and neighbour policies to achieve agents’ coordination. The performance of the discussed coordination-based methods is superior to the isolated intersection models in terms of average intersection delay, queue length, link stop time, and link travel time.

In the aforementioned approaches, the agent of an intersection communicates with its adjacent locations but does not coordinate with further away intersections. A number of RL-based strategies are proposed to address more general system-wide or area-wide signal control issues. For instance, Van der Pol and Oliehoek (2016) combine multiple local Q-functions linearly as a global Q-function and utilizes the max-plus coordination algorithm (Kok and Vlassis 2005) to optimize the joint action for multiple intersections in an area. Similarly, Mannion, Duggan, and Howley (2015) define Master and Slave agents where the Master agent uses a shared experience pool to deal with experiences from Master Agents for coordination. Yu et al. (2020) design an active cross-agent communication mechanism to generate coordinated actions and uses the predicted traffic of the whole road network to mitigate the unnecessary impact of other agents’ actions. Moreover, in Wang, Cao, and Hussain (2021), the Mobile Edge Computing server with a fixed number of Road Side Units collects and deals with the local states
from target intersections. The processed information is sent back to each individual agent to decide the phase of the traffic light. Li et al. (2021) propose a shared knowledge container to store the information obtained from the whole environment by embedding the observation vectors through Gated Recurrent Unit (GRU). Each agent then chooses relevant features from the container to make its own decision based on the Deep Deterministic Policy Gradient (DDPG) algorithm.

The aforementioned studies test their approaches on small-scale environments for illustration (e.g. one intersection or dozens of intersections) while leaving scalability issues and large-scale applications for further research. In practice, megalopolis usually involves thousands of traffic light intersections, which has to be controlled simultaneously. In this context, some studies (Wei et al. 2019; Zheng et al. 2019; Chen et al. 2020; Xu et al. 2021) focus on handling large-scale TSC problems based on various RL frameworks. In detail, Wei et al. (2019) design a graph attentional network named PressLight for agents’ coordination by calculating and normalizing the importance score (i.e. the value to evaluate the importance of the information from the source intersection when determining the policy for the target intersection) for all intersections in pairs. The influence affected by relevant intersections is modelled by the combination of the representation obtained by the target agent and its corresponding importance score. However, determining the importance score in pair still occupies a large number of computation resources. To reduce the exploration space, Zheng et al. (2019) propose the FRAP (i.e. Flipping and Rotation and considers All Phase configurations) model to calculate the phase score. The score of the target phase is obtained by the element-wise multiplication of the phase pair demand representation and the phase competition mask. The representation is obtained by the number of vehicles and the current signal phase, and the mask is derived from the phase competition matrix shown in Figure 4(b). The phase with the highest score is chosen to be the action. The in-variance to symmetries (e.g. flipping and rotation) in traffic signal control is achieved by pair-wise phase completion modelling to reduce the exploration space under complex scenarios. The method is combined with both value-based and policy-based RL algorithms for optimization. Furthermore, Chen et al. (2020) combine PressLight (Wei et al. 2019) for reward function designing and FRAP (Zheng et al. 2019) for a faster training process with parameter sharing among the agents. The model is evaluated on a simulated environment with thousands of intersections to show its effectiveness. More recently, Xu et al. (2021) illustrate that minimizing the queue length, waiting time, or delay is not equivalent to minimizing average travel time, which motivates the design of different agents with different optimizing sub-targets (e.g. queue length). A high-level policy is then proposed to align all sub-policies and avoid directly minimizing average travel time.

The optimization for large-scale environments needs numerous computational resources and time, which limits such strategies to be put into practice. Therefore, given that insufficient relevant data or computing resources in the target area, Xu et al. (2019), Zang et al. (2020), Zhang et al. (2020) and Devalilly, Larocque, and Charlin (2021) propose to transfer and adapt experiences learned from existing scenarios to new scenarios, which can reduce the reliance on sufficient data and decrease training consumption. As for the transfer strategies, Xu et al. (2019) selects the similar source and target intersections by calculating similarity values, Zang et al. (2020) and Zhang et al. (2020) adopt Meta-Reinforcement Learning (Finn and Levine 2018), while Devalilly, Larocque, and Charlin (2021) apply zero-short transfer learning (Higgins et al. 2017) into the TSC framework. As for the framework of Reinforcement Learning, Zang et al. (2020) develop a model based on FRAP (Zheng et al. 2019) and Xu et al. (2019), Zhang et al. (2020) and Devailly, Larocque, and Charlin (2021) utilize DQN directly.

The aforementioned studies focus on regular traffic situations, while Darmoul et al. (2017) and Aslani, Mesgari, and Wiering (2017) focus on finding optimal solutions for traffic disruptions that are also practical and useful. In detail, Darmoul et al. (2017) investigate the impact of accidents on traffic light control by mitigating the concepts of primary and secondary immune responses (i.e. the disturbance on the road is regarded as an antigen and the associated control decision is denoted as an antibody). The multi-agent DQN method has been used for policy optimization. More specifically, the studied traffic network in Aslani, Mesgari, and Wiering (2017) consider impatient pedestrians with illegal crossing behaviour, vehicles parking beside the streets, and incidents (e.g. vehicle breakdown).
The Actor-Critic framework is adopted to determine the duration of each phase (red/green light), which shows the capability of reducing average travel time when traffic disruptions have occurred. Furthermore, cordon control to determine the traffic signal metering rates is also an efficient way for vehicle inflows restriction. To find the optimal distribution for the metered vertices of roads, Ni and Cassidy (2019) adopt the Graph Convolution Network (GCN) to formulate the directed graph representation of the environment (i.e. the street network’s geometry) and traffic (i.e. traffic conditions and directions of movements) of an intersection. The optimal actions are obtained via the DDPG method to maximize the metered flow passing through the cordon.

The promising performance of RL on traffic signal control problems motivates applications of RL in other transportation problems and also provides application examples.

### 4.1.2. Speed limit control

For flow maximization, speed limit control (adjusting the speed limit) is often used to drive the freeway recurrent traffic bottleneck density to be close to the desired density and thus avoid capacity drops (Liu, Yin, and Yang 2015). The mechanism of conventional feedback-based strategies requires significant time (Li et al. 2017), which stimulates adopting RL-based methods to deal with highly dynamic traffic situations in a timely manner.

The speed limit controller is often designed as the agent with various RL frameworks, where the research has evolved from discrete state formulations to continuous state formulations in order to accommodate complex and varying environments. Specifically, Zhu and Ukkusuri (2014) define four congestion levels (i.e. free flow state, slight congestion state, moderate congestion state, and heavy congestion state) as the input state based on the flow density and optimizes the policy by the temporal difference (TD) algorithm. However, four discrete congestion levels might not be sufficient to fully depict the complicated and varying environment that would affect decision-making. Thus, Li et al. (2017) use the density at the downstream of the merge area, the density at the upstream mainline section, and the density on the ramp by specific variables instead of congestion levels to minimize the travel time. The posted speed limits set as integer multiples of five mph for freeway bottlenecks are determined by the Q-learning strategy. Similar state representations are utilized in Wu et al. (2020) for variable speed limits control based on the optimization by the DDPG algorithm with single-agent. The proposed method is able to reduce congestion, accidents, and emissions by defining the reward function as the combination of total travel time, average velocity reported by detectors, the number of emergency braking vehicles, and related gas emissions. Though the research for speed limit control with RL does not receive much attention, the success of existing studies provides a solid foundation for future optimization.

### 4.1.3. Pricing

Dynamic pricing for managed lanes can be used to offer a premium service and alleviate congestion (Devarasetty et al. 2014). Pandey and Boyles (2018) and Pandey, Wang, and Boyles (2020) examine pricing management via Reinforcement Learning to find optimal policies that maximize the revenue of the managed lanes. In these strategies, the vector containing the number of vehicles detected by the loop detectors is used as the state while the toll is set as the agent at the entrance of each managed line to decide the real-time price. A sparse cooperative Q-learning algorithm (Kok and Vlassis 2006) is adopted in Pandey and Boyles (2018) while A2C and PPO are used in Pandey, Wang, and Boyles (2020) to optimize the pricing policy.

### 4.1.4. Perimeter control

Perimeter control is regarded as an efficient way for regional traffic control to optimize the network level traffic performance (Yang, Zheng, and Menendez 2017). The appealing performance obtained by RL-based optimizing strategies for traffic signal control illustrates their ability to handle complex and varying road environments. Similar environments analysing in perimeter control and traffic signal control provide a novel direction for perimeter control, i.e. RL-based methods. Specifically, in Yoon
et al. (2020), the agent determines green time ratios as discrete values with the optimization by DQN. However, this method is only able to handle discrete actions, which is less practical. To avoid relying on the full knowledge of the road network and design continuous action, Zhou and Gayah (2021) propose an RL-based scheme for an urban network composed of two homogeneous sub-regions to improve the network throughput (i.e. the number of trips completed). Discrete-RL (D-RL) model optimized by DQN and Continuous-RL (C-RL) model optimized by DDPG are designed for discrete actions and continuous actions, respectively. Acknowledging the information of accumulations and estimated traffic demands as the state, the agent of D-RL decides the range while the agent of C-RL controls the allowable decrease/increase value of perimeter controllers (i.e. the parameter defined by the allowable portions of transfer flows) by maximizing actual portions of transfer flows. In addition, Chen et al. (2022) propose a deep-based integral policy iteration approach to minimize the total time spent for multi-region perimeter control in a continuous manner.

4.1.5. Ramp metering
Ramp metering takes advantage of traffic signals at freeway on-ramps to control the rate of vehicles entering the freeway. To decide on passing and prohibiting phases on the freeway, the information of the numbers of vehicles in the mainstream and entering the freeway and the status of the ramp traffic signal are denoted as the state in existing studies with either single-agent or multi-agent methods. Rezaee, Abdulhai, and Abdelgawad (2012) and Fares and Gomaa (2014) utilize Q-learning-based methods to minimize the total travel time of the whole network and the freeway density, respectively. The proposed models have been tested on a case study (e.g. the City of Toronto) and a synthetic network, which illustrates the effectiveness of RL-based methods in dealing with the ramp metering problem. However, the aforementioned two single-agent-based methods have limited scalability for controlling numerous intersections simultaneously. This motivates Belletti et al. (2017) to design a multi-agent DDPG framework for ramp metering. The highway vehicle density is modelled by the Partial Differential Equation to decide the incoming flow by maximizing the total observed outflow with the policy gradient algorithm. The interaction among agents is achieved by the introduction of Mutual Weight Regularization (Caruana 1997).

4.2. Air traffic control
Congestion in air traffic creates substantial flight delays and limits efficiency and productivity. As reported in Balakrishna, Ganesan, and Sherry (2010), one of the major factors leading to flight delays is the taxi-out delay (i.e. the time between gate push back and time of takeoff). In order to mitigate congestion in the airport, a novel way to predict the delay based on RL is proposed, which has a relatively low demand on training data for optimization when compared to classical supervised learning strategies. The agent learns the information from the environment of the aircraft and airport (e.g. the number of aircraft in the queue at the runway and the number of departure aircraft co-taxiing) to estimate the taxi-out time by minimizing the absolute value of the error between the actual taxi-out time and predicted taxi-out time. In addition, Tumer and Agogino (2007) apply multi-agent Reinforcement Learning in air traffic flow management to minimize the sum of total delay penalty and total congestion penalty for all aircraft in the system. The ground locations throughout the airspace are split into multiple individual ‘fixes’ (i.e. individual locations) where each ‘fix’ is regarded as an agent. The task of the agent is to decide the distance between the approaching aircraft and itself, which can control the rate of aircraft going through a ‘fix’. The proposed method is tested on a simulation tool, FACET, developed by NASA to show its ability for congestion reduction. The effectiveness of numerous RL strategies for air traffic control still has to be tested and evaluated in future research under complex and practical scenarios.

5. Taxi and ride-sourcing/sharing
Cooperative mobility-on-demand (MOD) systems (e.g. Uber, Lyft, and Didi Chuxing) have been spreading widely (He and Shin 2019) and provide multiple online taxi services such as express car,
Table 4. Summary of RL applications in taxi and ride-sourcing/sharing service systems.

| Reference | Application | Framework | Agent | Data | Simulator |
|-----------|-------------|-----------|-------|------|-----------|
| Lin et al. (2018) | Vehicle re-positioning | Contextual DQN and Actor-Critic | Multi-agent, an available vehicle | Real data from Didi Chuxing in Chengdu | Contextual simulator (Lin et al. 2018) |
| Shou and Di (2020) | Vehicle re-positioning | Mean Field Actor-Critic algorithm | Multi-agent, an available vehicle | Synthetic data, real data from NYC TLC | Personal simulator |
| Nguyen, Kumar, and Lau (2017) | Vehicle re-positioning | Actor-Critic algorithm | Multi-agent, an available vehicle | Synthetic data, real taxi data from Singapore TLC | Personal simulator |
| Mao, Liu, and Shen (2020) | Vehicle re-positioning | Deep Actor-Critic algorithm | Multi-agent, an available vehicle | Real data from NYC TLC | Personal simulator |
| Oda and Joe-Wong (2018) | Order dispatching | Double-DQN | Single-agent, dispatch centre | Real data from Didi Chuxing | Personal simulator |
| Zhou et al. (2019) | Order dispatching | DQN | Multi-agent, a driver | Real data from Didi Chuxing of three cities | Simulator provided by Didi Chuxing |
| Xu et al. (2018) | Order dispatching | TD-based RL | Multi-agent, a driver | Synthetic data, real data from Didi Chuxing | Personal simulator |
| Li et al. (2019) | Order dispatching | Actor-Critic, Mean Field RL | Multi-agent, a driver | Real data from Uber, Yellow Taxi and Didi Chuxing | Personal simulator |
| He and Shin (2019) | Order dispatching | Double-DQN | Single-agent, coordination centre | Real data from Uber, Yellow Taxi and Didi Chuxing | Personal simulator |
| Wang et al. (2018) | Order dispatching | Double-DQN | Multi-agent, a driver | ExpressCar data from Didi Chuxing | Personal simulator |
| Tang et al. (2019) | Order dispatching | TD-based RL | multi-agent, a driver | Real data from Didi Chuxing | Personal simulator |
| Jin et al. (2019) | Order dispatching and vehicle re-positioning | Hierarchical RL, DDPG | multi-agent, a region cell | Real data from Didi Chuxing | Personal simulator |
| Holler et al. (2019) | Order dispatching and vehicle re-positioning | DQN, PPO | Multi-agent, a driver | Synthetic data, real GAIA dataset from Didi Chuxing | Personal simulator |
| Chen et al. (2019) | Order dispatching and pricing | TD-based RL | Single-agent, coordination centre | Real data from Didi Chuxing | Personal simulator |
| Manchella, Umrawal, and Aggarwal (2021) | Order dispatching and goods delivery | Double-DQN | Multi-agent, a vehicle | Real data from New York City Taxicab | Personal simulator |
| James, Yu, and Gu (2019) | Vehicle routing | Deep Policy Gradient algorithm | Single-agent, dispatch centre | Real data from Cologne | Personal simulator |
| Zhang et al. (2020) | Vehicle routing | Deep Policy Gradient algorithm | Multi-agent, a Vehicle | synthetic data | Personal simulator |
| Silva et al. (2019) | Vehicle routing | Q-learning | Multi-agent, a vehicle | Synthetic data | Personal simulator |
| Al-Abbasi, Ghosh, and Aggarwal (2019) | Order dispatching and vehicle routing | Double-DQN | Multi-agent, a vehicle | Real data of taxi from NYC TLC | Personal simulator |

*https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page.*

ride-sharing, ride-sourcing, and traditional taxi. The real-time large-scale order information provides the opportunity to analyse demand patterns for further forecasting and management. To reduce resource utilization, decrease the waiting time, and increase profit, Reinforcement Learning has been investigated for vehicle re-positioning, order dispatching, and vehicle routing in the taxi and ride-sourcing/sharing service systems, where a summary of related papers is provided in Table 4.
5.1. Vehicle re-positioning

The imbalance between supply and demand leads to long waiting times for passengers and time/energy loss for drivers. Re-positioning available vehicles/drivers to potential locations (e.g., locations with massive demand) is necessary to improve system efficiency and better match supply and demand. Methods requiring accurate information on a wide range of parameters or variables (e.g., customer demand and travel time) are often time-consuming (Mao, Liu, and Shen 2020). Therefore, RL-based methods without the need for prior knowledge are broadly utilized for vehicle re-positioning in traditional taxi and ride-sourcing/sharing systems.

In the ride-hailing system, considering the influence from all vehicles and customers, existing studies (Nguyen, Kumar, and Lau 2017; Lin et al. 2018; Shou and Di 2020; Mao, Liu, and Shen 2020) take each available vehicle (or driver) as an agent for vehicle re-position, and develop various multi-agent RL models with different reward functions. For instance, gross merchandise volume (GMV, i.e. the number of all orders served) and order response rate are set as the reward function by Lin et al. (2018) with contextual DQN and Actor-Critic frameworks. The contextual DQN model is designed for the allocation instructing to filter out invalid directions and avoid conflicting directions for agents. The contextual Actor-Critic framework is designed for explicit coordination among agents to enhance policy-making by acknowledging spatial distributions of available vehicles and orders. The influence of waiting time on passenger loss is overlooked in Lin et al. (2018), while Mao, Liu, and Shen (2020) further consider impatient passengers that may leave the market. The cancellation cost caused by user-specific tolerance of waiting time is regarded as one of the components of the reward function. The proposed model shows its superiority in reducing the cancellation rate and total waiting time of impatient passengers for the taxi system by the Actor-Critic framework.

As for the traditional taxi system, global information, such as the distribution of all taxis, is hard to be obtained in a short time for optimization. Thus, Shou and Di (2020) develop a taxi re-positioning method that only uses local observations from each driver/vehicle through multi-agent Mean Field Actor-Critic algorithm (Yang et al. 2018). The aim of each agent (i.e. an available vehicle/driver) is to maximize their own monetary return. To accommodate the selfishness of each agent, Bayesian optimization is adopted to design the reward function, which helps achieve a better equilibrium for the overall system.

The computational complexity of the vanilla Actor-Critic-based method is relatively high for large-scale multi-agent vehicle re-positioning, which can take a very long time for convergence and is neglected in Lin et al. (2018) and Shou and Di (2020). Thus, in favour of reducing the computational complexity and speeding up the optimization process, Nguyen, Kumar, and Lau (2017) decompose the approximation of the action-value function over agents and derives a modified loss function to train the critic for each agent based on its own reward. The proposed strategy is tested on datasets with a large agent population size to decide whether drivers should stay in the current zone or move to another zone to look for passengers for total profit maximization.

5.2. Order dispatching

On the premise of ensuring available vehicles in various areas by vehicle re-positioning, the dispatching strategies to meet the large volume of orders in real-time are emphasized in a large number of studies. Traditional rule-based solutions for order dispatching require sophisticated hand-crafted parameter design but are only effective on simplified problem settings (Li et al. 2019), which motivates the utilization of Reinforcement Learning.

Oda and Joe-Wong (2018) examine the framework of DQN with the dispatch centre as the agent to minimize the passenger waiting time and idle cruising time and reduce the number of requests that are not responded to. However, all idle vehicles need to sequentially decide their destinations which will increase computation time and decrease the dispatching efficiency. Thus, the following studies to
be discussed consider the agent as the driver/vehicle to construct a multi-agent-based RL framework for order dispatching.

Multi-agent RL strategies for order dispatching are also examined with either cooperative or independent agents. Zhou et al. (2019) illustrate that explicit cooperation among various drivers is helpless for order dispatching since each driver serves different orders with different starting times, duration, and destination grids. Thus, each driver/vehicle is regarded as an agent working independently in this proposed method to explore the environmental information on the current locations, including the number of idle vehicles, valid orders, and destinations. To maximize the accumulated driver income (ADI) and order response rate (ORR), Double-DQN is extended with Kullback–Leibler (KL) divergence optimization to select optimal orders for drivers. More studies (Xu et al. 2018; Li et al. 2019; He and Shin 2019) held a different opinion with Zhou et al. (2019), which demonstrate the necessity of coordination among drivers for order dispatching. In detail, Li et al. (2019) clarify that active agents sharing orders in the same/nearby areas might select the same order according to their own policy, which may cause conflicts. Thus, different methods have been proposed to solve such an issue based on the RL framework. Specifically, Mean Field Reinforcement Learning (Yang et al. 2018) is adopted to evaluate the average response among agents for agents interactions where the average response is derived from the number of drivers arriving at the same neighbourhood and available orders. He and Shin (2019) propose a capsule-based Double-DQN for coordination policy learning where the capsule means a structured group of neurons (Sabour, Frosst, and Hinton 2017). The capsule construction helps the agent to analyse spatial (e.g. geographical distributions of demands and supplies) and temporal (e.g. weather conditions over time) relations and further learn the final policy. In addition, Xu et al. (2018) formulate the action-value function as a bipartite graph matching problem (i.e. the edge between one driver and one order is set as the action-value function). The Kuhn-Munkres (KM) algorithm (Munkres 1957) is employed for optimization to ensure that each order is assigned to at most one driver and avoid conflicts.

The mass deployment of MOD systems shows great success and high profits in megalopolis, which motivates the popularization of MOD systems in tier-three cities, which lack data for optimization and management. Therefore, on the ride order dispatching problem, Wang et al. (2018) and Tang et al. (2019) propose transfer learning methods to enable knowledge transfer from source cities with sufficient historical data to target cities with limited historical data. Since travel patterns of different cities often share common spatial and temporal characteristics, reusing previously trained DQN models learned from source cities to determine the optimal policies for target cities can be flexible and useful. Three transfer learning methods are tested in these two studies, i.e. fine-tune (Hinton and Salakhutdinov 2006), progressive network (Rusu et al. 2016), and correlated-feature progressive transfer (Wang et al. 2018).

The aforementioned studies dealing with order dispatching, vehicle re-positioning, and pricing independently may ignore the high correlations between them Jin et al. (2019). Thus, Holler et al. (2019) and Jin et al. (2019) explore these two tasks (order dispatching and vehicle re-positioning) simultaneously with different RL frameworks and agents, where actions of agents include vehicle re-positioning without an order and orders serving. Chen et al. (2019) study the pricing strategy and order dispatching jointly since the user decides whether to submit the order request after knowing the estimated price of the input trip (i.e. origin and destination) given by the MOD system. In detail, Holler et al. (2019) aim to maximize the revenue of each driver independently from driver-perspective and maximize the combined revenue across all drivers from system-perspective by using different reward specifications and optimization algorithms (i.e. DQN and PPO). The optimization results show that the driver-perspective system is more competitive than the system-perspective approach. It is noteworthy that most multi-agent-based RL methods designed for MOD systems management regard each driver/vehicle as an agent, which results in high computational costs due to a large number of agents. Based on the framework of Hierarchical RL, Jin et al. (2019) choose the region as an agent where large districts are manager agents while small grids are worker agents to model the ride-hailing system. The goal of the manager agent is to maximize ADI and ORR based on observations and peer messages
The worker agents generate actions (i.e. pick up orders or re-position) following the objective developed by its manager and own observations. The action value of order dispatching depends on environmental states (e.g. locations of drivers and passengers) and pricing strategies. Thus, the total expected reward of the pricing strategy is composed of expected driver income before order completion and actual driver income, which means the optimal pricing strategy also relies on order dispatching.

More recently, Manchella, Umrawal, and Aggarwal (2021) present a novel and valuable direction for joint goods delivery and ride-sharing service with deep RL methods. Using the status of available vehicles and pick-up requests, the proposed model adopts Double-DQN to find optimal dispatching policies for passengers pooling and goods delivery. The ride-sharing data collected from New York City taxi-cab and customer check-in traffic data from Google Maps give the opportunity for this work to verify that jointly serving passengers and goods can be cost-efficient and environmentally friendly.

5.3. Vehicle routing

In ride-sharing systems, multiple orders and various passengers with similar itineraries can be handled simultaneously, which means that the policies for vehicle routing after order dispatching should be addressed and studied. The methods with computational complexity issues are hard to be applied in time-sensitive vehicle routing applications. RL has already shown strong capabilities in vehicle routing/navigation. Also, the training process of RL-based strategies can be conducted offline so that the route generation process can be handled handy and fast (James, Yu, and Gu 2019) in large transportation networks. Therefore, RL becomes an essential tool for vehicle routing in ride-sharing service systems.

RL strategies for vehicle routing in MOD systems include both single-agent algorithms (James, Yu, and Gu 2019) and multi-agent algorithms (Al-Abbasi, Ghosh, and Aggarwal 2019; Silva et al. 2019; Zhang et al. 2020). Specifically, the dispatch centre is regarded as the agent in James, Yu, and Gu (2019) based on the formulation of green logistic systems (James and Lam 2017). The Asynchronous Advantage Actor-Critic (A3C) method is adopted to train the route construction policy to serve more orders while minimizing the driving distances of all vehicles. To further explicitly study the cooperation or competition among vehicles or customers, Zhang et al. (2020) regard each vehicle as an agent and design a multi-agent attention RL-based model. The model consists of an encoder-decoder structure where the encoder module analyses the relations among customers while the decoder module decides the choice of the next visited customer via reinforcing gradient estimator optimization. The optimization of vehicle routing independently neglects the correlations between order dispatching and vehicle routing, which motivates Al-Abbasi, Ghosh, and Aggarwal (2019) to focus on providing policies for two tasks simultaneously via Double-DQN. Each vehicle works as an agent to decide whether to serve existing or new users after observing and analysing the predicted future demand and the time cost before vehicles become available. If a new user is chosen or the vehicle is empty, the agent determines the zone to arrive. This study shows the superiority of ride-sharing in reducing traffic congestion through experiments on the real-world dataset from New York City. Silva et al. (2019) determine a set of routes to make each customer can be served by one vehicle based on a single depot with Q-learning. In order to minimize the number of vehicles and reduce travel distances, the action is set to decide the locations and order of passengers to be served by acknowledging the information of all vehicles and customers.

6. Assistant and autonomous driving

Ensuring safety is the most critical objective in transportation systems for both human-piloted driving and autonomous driving. Driver-assistance systems (DASs) and autonomous vehicles (AVs) are expected to enhance driving safety and also improve traffic efficiency (Pan et al. 2021). In this section,
Table 5. Summary of RL applications in assistant and autonomous driving.

| Reference                         | Application                                         | Framework       | Agent                                 | Scenario/Data              | Simulator                        |
|-----------------------------------|-----------------------------------------------------|-----------------|---------------------------------------|-----------------------------|----------------------------------|
| Desjardins and Chaib-Draa (2011)  | Adaptive cruise control                             | DDPG            | Single-agent, a vehicle               | Synthetic network           | Personal simulator               |
| Li et al. (2017)                  | Adaptive cruise control                             | Q-learning      | Single-agent, a vehicle               | Synthetic network           | Personal simulator               |
| Li and Görges (2019)              | Adaptive cruise control                             | Deep Actor-Critic | Single-agent, a vehicle              | Synthetic network           | Personal simulator               |
| Gao et al. (2019)                 | Adaptive cruise control for buses                   | Policy Iteration | Single-agent, the centre             | Lincoln Tunnel Corridor     | Paramics                         |
| Nascimento et al. (2021)          | Drivers’ comfort modelling                          | Double-DQN      | Single-agent, a vehicle               | Synthetic network           | GTA V simulator a                |
| Zhu, Wang, and Wang (2018)        | Acceleration control                                | DDPG            | Single-agent, a vehicle               | Synthetic network           | Personal simulator               |
| Zhou, Yu, and Qu (2019b)          | Acceleration control                                | DDPG            | Single-agent, the centre             | Synthetic network           | Personal simulator               |
| Zhu et al. (2020)                 | Velocity control for electric vehicle               | DDPG            | Two agents, following and lead vehicle | NGSIM dataset b             | Next Generation Simulation 2     |
| Wegener et al. (2021)             | Acceleration control - lane keeping                 | Twin-delayed DDPG | Single-agent, a vehicle              | NGSIM dataset              | Intelligent Driver Model Simulator from OpenAI Gym |
| Liu et al. (2021)                 | Acceleration control - lane changing                | DDPG            | Single-agent, a vehicle               | Real and synthetic scenarios | OpenAI Gym                      |
| Cao et al. (2020)                 | Acceleration control and lane changing for highway | Monte Carlo Tree Search | Single-agent, a vehicle              | Synthetic network           | Personal simulator               |
| Ye, Zhang, and Sun (2019)         | Acceleration control and lane changing              | DDPG            | Single-agent, a vehicle               | synthetic network           | VISSIM                           |
| Guo et al. (2021)                 | Acceleration control and lane changing              | DDPG            | Single-agent, a vehicle               | Synthetic network           | SUMO                             |
| Sathyan, Ma, and Cohen (2021)     | Acceleration control and lane changing              | DQN             | Multi-agent, a vehicle                | Synthetic network           | SUMO                             |
| Pan et al. (2021)                 | Ramp metering, lane changing, speed limit control   | Cross-Entropy-Method | Single-agent, a vehicle              | Synthetic network           | Personal simulator               |
| Wachi (2019)                      | Failure scenario finding                            | DDPG            | Multi-agent, a vehicle                | Synthetic network           | Microsoft AirSim, (Shah et al. 2018) |

a https://github.com/aitorzip/DeepGTAV.
b https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm.

a widely studied DAS technology, adaptive cruise control (ACC), with the strategies of Reinforcement Learning, is introduced first. Then, two types of training methods for decision-making modelling based on RL (i.e. car-following modelling to decide the velocity/acceleration and lane-changing modelling for steering control) are presented. A list of studies using RL for assistant/autonomous driving is provided in Table 5.

6.1. Adaptive cruise control

The technologies of driver-assistance systems have been embedded into vehicles to improve the driving experience and reduce traffic accidents. Adaptive cruise control (ACC), as an essential function of the system, has the ability to adjust the speed and acceleration of the current vehicle and further maintain a safe distance from the vehicle in front of it. To reduce reliance on prior knowledge of disturbance measurements (Li et al. 2017), Reinforcement Learning becomes a valuable tool for ACC.

Adaptive cruise control with RL has been examined for both private vehicles and buses. As for the private vehicle, the speed and acceleration of the current vehicle and the distance from the front
vehicle are collected as the state for adaptive cruise control policy optimization (Desjardins and Chaib-Draa 2011; Li et al. 2017; Li and Görges 2019) with various reward functions and RL frameworks. Specifically, Desjardins and Chaib-Draa (2011) take advantage of DDPG to determine the action (e.g. braking, accelerating). Li et al. (2017) utilize Q-learning to select the specific values of permissive accelerations, which can be more feasible in practice. Li and Görges (2019) investigate driving safety and fuel consumption simultaneously by optimizing the velocity and the online gear shift jointly. The utilized deep Actor-Critic framework consists of two actor networks and a critic network. Two actor networks are used to generate the traction force for velocity tracking and provide the gear position for fuel economy, respectively. And the critic network evaluates the control performance for these two purposes.

The investigation of the bus adaptive cruise control with RL has received less attention. Gao et al. (2019) propose a cooperative ACC algorithm with a central controller for a fleet of autonomous buses on the exclusive bus lane (XBL). The policy iteration RL method is employed to approximate the value of the control gain introduced in the linear optimal control theory (Lewis, Vrabie, and Syrmos 2012). The experimental results show that the proposed method is able to increase the traffic throughput and save the travel time of buses.

More recently, Nascimento et al. (2021) report that safe driving can be affected by the driver’s comfort and feel, which can be adaptable for all types of vehicles. To investigate the interplay between the perceived sounds of a vehicle and the driver’s attention/enjoyment, a psychoacoustic (PA) metric (Pedersen and Zacharov 2008) is used as the reward function to measure the driver’s feeling where lower PA values mean more comfort. The agent analyses environmental sounds (e.g. pedestrians and traffic) and noises (e.g. sounds of bells and beeps) to decide the states of the window (no change, open, close), radio (no change, on, off), and speed (no change, accelerate, decelerate) with the optimization via Double-DQN. The proposed method has the ability to change the state of the vehicle to maintain the driver’s concentration for driving safety.

6.2. Velocity and acceleration control

Velocity/acceleration control of the autonomous vehicle has the promise of improving traffic safety and increasing road capacity (Zhu et al. 2020), which has been studied in numerous studies with Reinforcement Learning.

Zhu, Wang, and Wang (2018) introduce an autonomous driving model based on DDPG to reproduce behaviours and trajectories of drivers. To determine the acceleration of the vehicle, the agent sets the reward function as minimizing the disparity of spacing and velocity between the simulated and observed data. Note that solely imitating human driving behaviours for autonomous vehicles may not reduce traffic accidents or increase road capacity due to the hardly optimal operation of human drivers (Zhu et al. 2020). Thus, the following studies (Zhou, Yu, and Qu 2019b; Zhu et al. 2020; Wegener et al. 2021) directly optimize autonomous driving from interactions with the simulated environment (i.e. surrounding vehicles information, own driving information, and road networks) by adopting various deep RL strategies under different scenarios. As for the framework of RL, DDPG is adopted in Zhou, Yu, and Qu (2019b) and Zhu et al. (2020) while Twin-delayed Deep Deterministic Policy Gradient (TD3) (Fujimoto, Hoof, and Meger 2018) is used by Wegener et al. (2021). As for the application scenarios, Zhou, Yu, and Qu (2019b) and Wegener et al. (2021) focus on obtaining appropriate driving acceleration under different levels of traffic and lengths of the signal cycle at intersections. Zhu et al. (2020) examine velocity control of autonomous driving under different road incidents/events, which improves safety, efficiency, and comfortableness, as shown by their experimental results.

6.3. Steering control and lane changing

Keeping the vehicle within the lane and driving stably are essential for the safety of autonomous driving (Liu et al. 2021). Liu et al. (2021) collect the distances from the vehicle to the road lane borders from
the GPS information as the state to decide the vehicle’s steering angle via the framework of DDPG. To accommodate the real-world scenario with information noise, a noise compensation approach is used. The independent optimization of steering control or lane changing can be less practical since the change in position often results in the change in velocity or acceleration. Thus, many studies determine longitudinal and lateral positions simultaneously to achieve safer and more efficient autonomous driving.

Initial works only depend on one optimizing strategy for two tasks (Ye, Zhang, and Sun 2019; Cao et al. 2020; Sathyan, Ma, and Cohen 2021). In detail, in order to increase the success rate of exiting from highways in heavy dynamic traffic, Cao et al. (2020) and Sathyan, Ma, and Cohen (2021) optimize longitudinal acceleration and the policy of lane changing by Monte Carlo Tree Search (Browne et al. 2012) and DQN, respectively, where the distance to the exit ramp and the surrounding vehicles’ positions and speeds are regarded as the state. Ye, Zhang, and Sun (2019) propose a more general strategy to decide the longitudinal and lateral position of the vehicle jointly under different driving environments based on DDPG with the driving information of surrounding vehicles. The reward form is calculated by its distance from the preceding vehicle, its speed, and the speed difference to the preceding vehicle. The collision, uncomfortableness, and inefficient driving performances are also penalized in the reward. Guo et al. (2021) find the optimal policies for the continuous longitudinal acceleration/deceleration and discrete lane changing via DDPG and DQN, respectively. The two optimizing strategies are able to interact with each other and reduce the error probability, which is more robust in unusual driving conditions (e.g. abrupt deceleration of the front vehicle).

Furthermore, an integrated model is proposed to deal with more comprehensive tasks, i.e. ramp metering, variable speed limit, and lane changing control for both connected autonomous vehicles and regular human-piloted vehicles to minimize the total travel cost in Pan et al. (2021). The proposed model is optimized by the gradient-free Cross-Entropy-Method-based algorithm (Szita and Lörincz 2006).

In addition, a novel way to deal with the safety of autonomous driving is introduced (Wachi 2019), i.e. identifying failure scenarios of the vehicle. The environment consists of two types of vehicles, the player and multiple non-player characters (NPCs). And the aim is to train NPCs to make the player cause an accident or arrive at the destination late. When the player fails, NPCs get the adversarial reward based on their own contributions to the failure. Multi-agent DDPG algorithm (Lowe et al. 2017) is employed to train the agents to find the optimum driving directions and velocity. Their strategy provides a novel and effective direction to avoid catastrophic accidents for autonomous driving.

7. Routing

RL-based vehicle routing in taxi, ride-sourcing, and ride-sharing systems have been reviewed in Section 5. This section discusses RL-based routing in a more general context, where routing plays an important role in both human-driving and autonomous driving vehicles. It should be noted that the accuracy of Global Positioning System (GPS) localization is critical in vehicle navigation/routing applications, which might be affected by environmental factors (e.g. weather and occlusion of buildings). Raw GPS observations (i.e. longitude and latitude coordinates) are corrected in Zhang and Masoud (2021) by the algorithm of A3C, where the state is the observation history trajectory consisting of the last reported position and the most recent predicted positions within a certain period. Many previous studies on routing problems are based on parametric models with strong behaviour assumptions (Mao and Shen 2018). Tail-based research (Lim et al. 2013) for routing often suffers from the issue of low accuracy and high computational cost. Instead, given its capability for optimal policy discovery without expert knowledge and its scalability for adapting the proposed methods to large-scale real-world networks, RL-based models have been used to find the shortest path and minimize total travel time. This section mainly introduces routing problems from two aspects, i.e. the stochastic shortest path problem and real-time routing. The introduced RL-based works for routing are summarized in Table 6.
| Reference                      | Application                                      | Framework   | Agent                      | Scenario/Data                  | Simulator            |
|--------------------------------|--------------------------------------------------|-------------|----------------------------|--------------------------------|----------------------|
| Cao et al. (2017)              | Path recommendation                               | DQN         | Single-agent, the driver   | Networks of Munich, Singapore, Beijing | Personal simulator   |
| Ramos, Bazzan, and da Silva (2018) | Routing for travel time minimization               | Q-learning | Multi-agent, the driver    | Synthetic data                | Personal simulator   |
| Boutilier et al. (2018)        | Shortest path routing                              | DQN         | Single-agent, the driver   | Network in San Francisco Bay Area | Personal simulator   |
| Chandak et al. (2020)          | Shortest path routing                              | Policy Gradient algorithm | Single-agent, the driver   | Network in San Francisco Bay Area | Personal simulator   |
| Mao and Shen (2018)            | Routing for travel time minimization               | Neural fitted Q-iteration, Q-learning | Single-agent, the driver   | Sioux Falls network           | Personal simulator   |
| Zhang and Masoud (2021)        | GPS correctness                                   | A3C         | Single-agent, the controller | GPS trip recorder in Southeast Michigan synthetic data | Personal simulator   |
| An et al. (2020)               | Routing for travel time minimization               | DQN         | Single-agent, the controller | Personal simulator            | Personal simulator   |
| Zhang et al. (2019)            | Parking                                           | DDPG        | Single-agent, the controller | Synthetic data                | Personal simulator   |
| Wang et al. (2021)             | Parking                                           | Monte-Carlo | Single-agent, the controller | Synthetic data                | Personal simulator   |

The stochastic shortest path (SSP) problem with RL is first studied by Cao et al. (2017) by adopting Q-learning as the framework and designing a deep-based approximator to represent the value function for adaptation to large road networks. In practice, some travel paths are not always reachable due to road construction or other reasons, which motivates the exploration of the unavailability of actions by introducing stochastic action sets (SAS) (Boutilier et al. 2018). DQN is adopted as the framework to illustrate the effects on the shortest path sought problem with the consideration of the probability of the shortest path availability. The results indicate that the optimal policy with SAS has the ability to yield an expected travel time between the origin and destination within a target small range. Following studies (Boutilier et al. 2018; Chandak et al. 2020) further examine each node as the origin and learns the shortest path from each node. The proposed framework generalizes the Policy Gradient algorithm to estimate the optimal policy in a large-scale network.

RL methods for the SSP problem build the foundation for the real-time routing strategy, which needs to minimize the expected total travel time by accounting for real-time traffic conditions. Therefore, continuous variables describing real-time traffic congestion are used in many studies (Ramos, Bazzan, and da Silva 2018; Mao and Shen 2018; An et al. 2020) to look for the path that minimizes travel time or travel delay based on different developed RL strategies. The adaptation of Q-learning is combined with the regret-minimising method in Ramos, Bazzan, and da Silva (2018) to minimize travel time for routing. The Neural Fitted Q Iteration (FQI) (Ernst, Geurts, and Wehenkel 2005) is adopted by Mao and Shen (2018) to accommodate the large state space (i.e. the constantly changing instantaneous travel cost) and produce a more refined representation of the Q-function for further routing policy optimization. An et al. (2020) utilize DQN with the help of the Dijkstra algorithm and k-shortest path algorithm to determine the platoon size on the monitor link where the platoon strategy is used to avoid conflict points in platoons for routing assistance.

Moreover, routing for parking issues has been discussed in Zhang et al. (2019) and Wang et al. (2021). Specifically, Zhang et al. (2019) adopt DDPG for autonomous parking (i.e. determine the steering wheel angle) with the coordinates of the four corner points in the vehicle. Wang et al. (2021) propose a Monte-Carlo-based optimization model on parking spot selections, which becomes a crucial problem in mega-cities for automated multistory parking facilities. In order to reduce customers'
Table 7. Summary of RL applications in public transportation and bike-sharing system.

| Reference                        | Application                                | Framework           | Agent                                      | Data                                      | Simulator         |
|----------------------------------|--------------------------------------------|---------------------|--------------------------------------------|-------------------------------------------|-------------------|
| Alesianni and Gkiotsalitis (2018) | Bus Holding                               | Double-DQN          | Multi-agent, a bus                               | A main bus line in Singapore             | Personal simulator|
| Chen, Zhou, and Chen (2016)      | Bus holding                               | Q-learning          | Multi-agent, a bus                               | Synthetic data                          | Personal simulator|
| Menda et al. (2018)              | Bus holding                               | PS-TRPO deep PPO    | Multi-agent, a bus                               | Synthetic data                          | Personal simulator|
| Wang and Sun (2020)              | Bus holding                               | Q-learning          | Multi-agent, a bus                               | Synthetic data                          | Personal simulator|
| Yin, Chen, and Li (2014)         | Acceleration control for the subway       | Q-learning          | Single-agent, a subway                          | real data from Beijing Subway            | Personal simulator|
| Yang, Zhu, and Lin (2021)        | Voltage control for urban railway         | DQN                 | Single-agent, the centre                       | Real data from Beijing Subway            | Personal simulator|
| Šemrov et al. (2016)             | Train scheduling                          | Q-learning          | Single-agent, the centre                       | Railway network in Slovenia              | Personal simulator|
| Khadilkar (2018)                 | Train scheduling                          | Q-learning          | Single-agent, the centre                       | Railway lines from Indian                | Personal simulator|
| Ying, Chow, and Lin (2020)       | Subway scheduling                         | DDPG                | Single-agent, the centre                       | London Underground metro line in Shanghai| Personal simulator|
| Jiang et al. (2018)              | Inflow control for urban rail transit     | Q-learning          | Single-agent, the centre                       | The current metro network in Xi’an       | Personal simulator|
| Wei et al. (2020)                | Next metro line design                    | Deep Actor-Critic   | Single-agent, the centre                       | Citi Bike data from New York             | Personal simulator|
| Li, Zheng, and Yang (2018)       | Bike re-position for bike-sharing system  | DQN                 | Multi-agent, a trike                           | Mobike dataset from Shanghai             | Personal simulator|
| Pan et al. (2019)                | Price management for bike-sharing system  | DDPG, Hierarchical RL| Multi-agent, a user                             | Mobike’s original system                 | Personal simulator|

waiting time, the agent is in charge of choosing the parking level for each vehicle on the elevator by analysing the status of available parking spots and the current time.

8. Public transportation and bike-sharing system

The public transportation system (e.g., buses and trains) and bike-sharing system serve a large number of passengers and play a vital role (Li et al. 2021) in metropolitan areas for environmental protection. RL-based strategies have been examined for public transit and bike-sharing systems scheduling and management to improve efficiency and profitability, which are reviewed in this section. A summary of the papers to be discussed is provided in Table 7.

8.1. Bus holding

Bus holding, a strategy that delays buses at control points (Dai et al. 2019), has received substantial attention for many decades in order to reduce the probability of bus delay, decrease the waiting/travel time of passengers, and thus improve the efficiency of the bus system (Berrebi et al. 2018). A large number of strategies mainly consider local information with a pre-specified headway/schedule. However, the global coordination of the whole bus fleet and the long-term effect are often overlooked (Wang and Sun 2020), which can be potentially addressed by RL-based methods.

Owing to the mutual influence among buses, existing studies (Chen, Zhou, and Chen 2016; Alesianni and Gkiotsalitis 2018; Menda et al. 2018; Wang and Sun 2020) adopt different multi-agent RL frameworks by regarding each bus as an agent to analyse the input state (e.g., treating departure time, arrival time, and target headway time of the bus) and determine bus holding duration with different granularity. Specifically, 30 seconds is set as the minimum unit of holding time in Alesianni and Gkiotsalitis (2018) with the optimization by Double-DQN. Since the bus holding time less than 30 seconds is not practical
considering constraints from real-world driving conditions, the holding time is chosen as some multiple of the holding time unit (e.g. 30 seconds) in Chen, Zhou, and Chen (2016) optimizing by Q-learning and Menda et al. (2018) optimizing by PS-TRPO (Gupta, Egorov, and Kochenderfer 2017). Though these methods adopt multi-agent frameworks to deal with holding time for multiple buses simultaneously, less attention has been paid to agents’ cooperation. More recently, Wang and Sun (2020) propose a global joint action tracker embedding into the PPO framework to incorporate global coordination for dynamic bus holding control. The action tracker network is used to adopt the global information of buses and passengers to further track the policies of each agent (i.e. a bus). Thus, the state evaluation of each agent’s policy is based on the local environment and other agents’ decisions.

### 8.2. Urban rail transit system management

Adopting the mechanism of Reinforcement Learning, multiple research topics have been investigated for the operation of the urban rail transit system (e.g. train and subway), such as energy management, vehicle re-scheduling, passenger flow control, and network expansion which will be introduced in this subsection.

**Energy management:** A few studies aim to use RL method to minimize the energy consumption of subway operation where two optimizing types are proposed, i.e. managing one subway vehicle independently and managing the whole subway system. In detail, Yin, Chen, and Li (2014) define the current vehicle position, the speed, and the reserved trip time as the state and each subway vehicle as an agent to decide the variation of acceleration via Q-learning. In order to cooperate with other subways to acknowledge the time-variant traffic, Yang, Zhu, and Lin (2021) use the super-capacitor energy management system (SCESS) as the central agent for energy-saving and voltage stabilization of the whole subway system. The states of the subways nearing the SCESS and the rectifier current/voltage of the substation where the SCESS is installed are accounted for the state in the implementation of RL. And the agent decides on the combination of charging and discharging voltage threshold to increase the energy-saving rate and voltage stabilization rate in each time step.

**Scheduling:** Scheduling is one of the core issues for urban rail transit systems, e.g. in order to reduce the travel/waiting time and the operating cost (Zhao, Yang, and Wu 2021). Train scheduling for both the single-track railway (Šemrov et al. 2016) and multi-track railway (Khadiilkar 2018) are examined. The information in relation to the locations of trains, the infrastructure availability of block sections, and the time is considered in Šemrov et al. (2016) for single-track railway scheduling. Q-learning is used to decide the actions for each signalling element, i.e. setting it to red (stop) or green (go) colour, indicating which trains can move on to the next section, which helps reduce the total delay effectively. However, the study dealing with the single-track railway cannot be directly adapted to multi-track railway systems (e.g. the trains operating on multiple tracks can be merged into one track which may cause disruption). Train scheduling on multi-track is taken into consideration by the study of Khadiilkar (2018), where directions of trains’ motion are analysed for further decision-making with Q-learning. Different to train scheduling, urban subway scheduling has to take the number of passengers into account for decision-making (Ying, Chow, and Chin 2020). The optimizing framework based on DDPG shows very satisfactory performance in terms of reducing passenger waiting times and saving subway operating costs.

**Passenger flow control:** To decrease the waiting time of passengers and reduce accidents caused by crowds in railway stations, the control of passenger inflow for railway systems has been investigated on Jiang et al. (2018). The environmental state includes information of real-time passenger demand, the arrival/departure time, the available capacity of trains, and the platform capacity of stations. Q-learning is adopted to set the rate of inflow volume for each station. The experimental results show that inflow control with RL can reduce the number of passengers being stranded and relieve passenger congestion at certain stations.

**Network expansion:** The design or the expansion of a railway transit network is another primary concern in public rail/transit systems (Laporte, Mesa, and Perea 2010). Most existing strategies dealing with
network expansion are often based on conventional mathematical programming approaches, which are heavily dependent on expert guidance and behaviour assumptions (Wei et al. 2020). Instead of the usage of domain knowledge and behaviour assumptions, the Actor-Critic framework with single-agent is adopted by Wei et al. (2020) to select the locations of expanded stations in the city metro network. Specifically, the actor network is an Encoder-Decoder Neural Network coupling with an attention layer to parameterize the station selection policy for metro line expansion, while the critic network consists of three convolutional layers and two fully connected layers to estimate the expected cumulative reward of the next metro line.

8.3. Bike-sharing system

Bike-sharing systems, including dock and dock-less systems, are widely deployed in urban and rural areas to ease the first/last-mile problems and reduce the usage of private vehicles. Li, Zheng, and Yang (2018) and Pan et al. (2019) aim to balance the supply and demand of these two systems, respectively. In order to minimize the customer loss of the system with dock, Li, Zheng, and Yang (2018) propose a multi-agent DQN-based bike re-positioning method. Each trike (i.e. the tool for moving bikes) is regarded as the agent that chooses the location of the station and the number of picking up or unloading bikes after observing the system status (i.e. bike and dock availability at each station), its own status (i.e. the available location for bikes), and the status of other trikes. Pan et al. (2019) focus on pricing management to incentive users for the dock-less bike-sharing system. Building upon DDPG and Hierarchical RL, the proposed pricing algorithm suggests the user return the bike to neighbouring regions by offering a price incentive under a default budget.

9. Electric vehicle: energy management, charging, and ride service

To mitigate the crisis of resource scarcity and climate change, electrification has been the trend of the automotive industry to achieve the merits of high performance and long-term economy (Wu et al. 2020). Reinforcement Learning methods have been adopted for electric vehicle (EV) control and management in recent years, especially for ground electric vehicles. This section mainly introduces the RL applications on two major ground vehicles, hybrid-electric vehicles (HEVs) and pure-electric vehicles (PEVs). The mentioned works in this study are summarized in Table 8.

9.1. Hybrid-Electric vehicle

A hybrid-electric vehicle usually combines a conventional powertrain (e.g. gasoline) with an electric engine. Most existing studies dealing with energy management of HEVs follow pre-defined rules, which heavily rely on the accurate prediction of future traffic conditions and are not straightforward for applications under time-sensitive driving conditions (Qi et al. 2019). RL strategies have been effective tools to avoid the need for precise forecasts.

The studies start to regard the energy management centre as the agent for engine power control via Q-learning in Liu et al. (2015), Qi et al. (2016) and Liu et al. (2017) with different state settings. In detail, Liu et al. (2015) explore the knowledge of environmental features, the battery state-of-charge (SOC), and the rotational speed of the generator (i.e. engine speed) to determine fuel consumption. More related characteristics are analysed in Qi et al. (2016), i.e. the vehicle velocity, road grade, percentage of remaining time to destination, SOC, and available charging gain of the selected charging station. The internal combustion engine (ICE) power supply level (discrete form) obtained from the optimization is chosen to further control the proportions of electricity and fuel to use. The predicted future velocity profile and the information of SOC are utilized in Liu et al. (2017) as the state to select the throttle engine power and further determine the power distribution of the electrical energy source and conventional powertrain source. The velocity profile is obtained by two novel velocity predictors (i.e. Nearest Neighbor Velocity Predictor and Fuzzy Encoding Velocity Predictor).
A number of deep RL studies have shown their capability to handle non-linear and complicated relations among vehicles and the traffic environment for traffic control, which motivates the utilization of deep learning in energy management. Complex and powerful deep RL methods are proposed to control electricity and conventional powertrain energy split for HEVs with different reward functions and state settings (Qi et al. 2019; Wu et al. 2019; Lian et al. 2020). In detail, Qi et al. (2019) use DQN and Dueling-DQN to select an optimal fuel/electricity split's level (i.e. 24 power level outputs are set for the engine) with the information regarding the power demand at the wheel, the battery pack's state-of-charge, and the distance to the destination to reduce fuel consumption. This study optimizes the agents based on a single driving cycle that might not be able to deal with different driving cycles (DCs) or the entire driving profile of a vehicle (Wu et al. 2019). Therefore, Wu et al. (2019) adopt the framework of DDPG to model the energy split management for multiple driving cycles. Given the control variables (e.g. rational speed of engine/motor) as the current state of the environment, the actor network represented by the structured control net (SCN) (Srouji, Zhang, and Salakhutdinov 2018) produces an

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### Table 8. Summary of RL applications in electric vehicle.

| Reference            | Application                              | Framework               | Agent                              | Data                              | Simulator                  |
|----------------------|------------------------------------------|-------------------------|------------------------------------|-----------------------------------|----------------------------|
| Liu et al. (2015)    | Fuel and electricity sources control     | Q-learning              | Single-agent, a vehicle            | Synthetic data                   | MotoTune                  |
| Qi et al. (2016)     | Fuel and electricity sources control     | Q-learning              | Single-agent, a vehicle            | Inductive loops detector data archived in the California Freeway PEMS | Motor Vehicle Emission Simulator |
| Liu et al. (2017)    | Fuel and electricity sources control     | Q-learning              | Single-agent, a vehicle            | Synthetic data                   | Personal simulator        |
| Qi et al. (2019)     | Fuel and electricity sources control     | DQN Dueling-DQN         | Single-agent, a vehicle            | Inductive loops detector data archived in the California Freeway PEMS | Personal simulator        |
| Wu et al. (2019)     | Fuel and electricity sources control     | DDPG                    | Single-agent, a vehicle            | Synthetic data                   | Paramics                  |
| Lian et al. (2020)   | Fuel and electricity sources control     | DDPG                    | Single-agent, a vehicle            | Synthetic data                   | Personal simulator        |
| Wan et al. (2018)    | EV charging/discharging scheduling       | DQN                     | Single-agent, a vehicle            | Real scenario from the California ISO | Personal simulator     |
| Zhang et al. (2021)  | EV charging/discharging scheduling       | DQN                     | Single-agent, a vehicle            | Real data from EV charging stations data in Beijing | Personal simulator |
| Luo et al. (2020)    | EV re-positioning                        | PPO                     | multi-agent, a hexagonal grid      | Real EV sharing data in Shanghai | Personal simulator        |
| Shi et al. (2019)    | EV dispatching and charging management   | DQN                     | Multi-agent, a vehicle             | Synthetic data                   | Personal simulator        |
| Tang et al. (2020)   | EV taxi-customer assignments, vehicle dispatching and charging | Deep RL | Single-agent, a central controller | Real data from Tongzhou and Beijing | Personal simulator |
| Zhang, Wu, and Shi (2020) | EV route planning and energy management | Actor-Critic, Q-learning | Single-agent, the controller        | Synthetic data                   | ADVISOR                  |
| Lin, Ghaddar, and Nathwani (2022) | Vehicle routing for Electric Vehicles | REINFORCE               | single-agent, the controller        | Synthetic data                   | Personal simulator        |

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*A number of deep RL studies have shown their capability to handle non-linear and complicated relations among vehicles and the traffic environment for traffic control, which motivates the utilization of deep learning in energy management. Complex and powerful deep RL methods are proposed to control electricity and conventional powertrain energy split for HEVs with different reward functions and state settings (Qi et al. 2019; Wu et al. 2019; Lian et al. 2020). In detail, Qi et al. (2019) use DQN and Dueling-DQN to select an optimal fuel/electricity split's level (i.e. 24 power level outputs are set for the engine) with the information regarding the power demand at the wheel, the battery pack's state-of-charge, and the distance to the destination to reduce fuel consumption. This study optimizes the agents based on a single driving cycle that might not be able to deal with different driving cycles (DCs) or the entire driving profile of a vehicle (Wu et al. 2019). Therefore, Wu et al. (2019) adopt the framework of DDPG to model the energy split management for multiple driving cycles. Given the control variables (e.g. rational speed of engine/motor) as the current state of the environment, the actor network represented by the structured control net (SCN) (Srouji, Zhang, and Salakhutdinov 2018) produces an*

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1. ^a^ http://mcs.woodward.com/support/wiki/index.php?title=MotoTune.
2. ^b^ http://pems.dot.ca.gov.
3. ^c^ https://www.epa.gov/moves.
4. ^d^ http://bigladdersoftware.com/advisor/docs/advisor_doc.html.
action while the critic network consisting of several fully connected layers estimates the action-value function. Moreover, considering that human expertise can provide optimal training samples or preferences for the learning agent to guide exploration in the training process, Lian et al. (2020) propose a rule-interposing DDPG model to deal with the time-consuming problem caused by deep RL strategies. The added expert knowledge includes the optimal brake specific fuel consumption curve of the HEV engine and the battery characteristics, which helps set control variables of RL models. The aim of the controller is to optimize the engine power increment or decrement (e.g. remain unchanged, increase one kilowatt, decrease one kilowatt).

Different from the aforementioned studies focusing on energy management and splitting independently, Lin, Ghaddar, and Nathwani (2022) adopt the Actor-Critic framework and Q-learning for route planning with power management of plug-in HEVs to minimize energy consumption. The inner loop is in charge of managing power by controlling the desired output torque from the engine, the gear shift command, and the direction by analysing the state (i.e. vehicle status and geographic information). Meanwhile, the outer loop decides the changes in road slope and vehicle speed, which can affect energy utilization. The overall reward is designed to minimize fuel consumption and battery recuperation instead of only considering the shortest distance between the origin and the destination.

9.2. Pure-Electric vehicle

The usage of pure-electric vehicles is rapidly growing, while the driving range and insufficient charging stations of EVs are two adverse factors on the widespread adoption of pure-electric vehicles (He et al. 2018). In order to solve such issues, recently, DQN-based frameworks are designed for EV charging/discharging scheduling subject to different objectives (Wan et al. 2018; Zhang et al. 2021). Wan et al. (2018) aim to improve user benefit by designing a representation network to extract discriminative features from the battery state-of-charge (SOC) and the future price trends predicted by Long Short-Term Memory (LSTM). The Q-network is utilized to approximate the optimal action-value function and then make the decision for the amount of energy that the EV battery will be charged or discharged. Zhang et al. (2021) aim to minimize the total charging time of EVs and reduce the distance between the origin and charging stations. The EVs charging schedule system analyses the features from the available charging piles and the EVs electricity consumption (predicted by distance travelled with linear regression) to obtain Q-value for selecting a charging station for the vehicle.

Pure-electric vehicles have also been introduced to provide ride-sourcing services with the fast improvement of battery technologies and the rapid growth of recharging facilities (Kim, Ko, and Park 2015; Ke et al. 2019). As presented in Section 5, a number of RL-based methods have been put into use for dispatching and routing gasoline vehicles, which can also be adapted for ride-sourcing management of EVs. Different from conventional gasoline vehicles, EV re-position, dispatching, and routing often more explicitly take into account the recharging or electricity consumption issues of EVs.

Specifically, unbalanced/skewed distributions of EV fleets motivate Luo et al. (2020) to propose a multi-agent RL model for EV re-positioning in order to improve demand rate and net revenue. The designed actor-critic-based PPO model consists of two connected policy networks, one used for choosing the grid and another adopting the output from the first network for further selecting the station in the chosen grid with the agent (i.e. each hexagon grid of the urban area in concern). The proposed model can deal with the non-stationarity in action spaces caused by the station extension or closure by the regularization of the reward function.

Vehicle dispatching considering an electric vehicle fleet has also been studied (Shi et al. 2019; Tang et al. 2020; Lin, Ghaddar, and Nathwani 2022) with different RL frameworks and optimizing aims. Shi et al. (2019) design a DQN-based algorithm to dispatch the electric vehicle for ride-hailing services in terms of reducing EV operational costs and customer waiting time. The proposed framework consists of two components: the decentralized learning process to approximate the state-value
function with the knowledge of vehicles and dispatching tasks; the centralized decision-making process to formulate and maximize the state-value function for EV fleets by a linear assignment problem and further to find the optimal dispatching policy. Tang et al. (2020) design a two-step framework, advisor-student RL, to dispatch vehicles and arrange charging activities. In the advisor network, the control centre assigns the status of vehicles (i.e. to be charged or to accept the order) to minimize the system cost (i.e. customer waiting cost, customer abandon penalty, vehicle travel cost, and vehicle charging cost) through the optimization by DQN. The student network decides the vehicle-customer pair and vehicle-charging-station pair via assignment problem optimization. Lin, Ghaddar, and Nathwani (2022) focus on reducing total distances of electric vehicles by solving routing problems (i.e. choosing the geographical coordinate of the next location) with the REINFORCE algorithm (Williams 1992).

10. Future directions and conclusion

In the past decade, we have seen a growing number of studies that develop/adapt Reinforcement Learning methods for applications in the transportation sector. However, the development and utilization of advanced RL strategies for a more efficient and sustainable transportation system are still at an early stage. This section will discuss several aspects that deserve substantial further efforts in terms of developing RL methods for real-world transportation applications, i.e. scalability, practicality, transferability, and fairness.

Scalability:

- Existing RL-based studies for transportation applications are often capable of dealing with a single subject and/or one aspect of the system (e.g. speed limit control for a target part of the freeway (Zhu and Ukkusuri 2014)). The demand for computing resources and computing time can be extremely high when adapting these methods to multiple-object large-scale environments, especially where there are complex interactions among objects or sub-systems within the system (e.g. a city often is served with thousands of intersections). Developing competent models with a cooperative and/or competitive multi-agent RL-based framework to deal with multi-object large-scale transportation systems is crucial. For instance, handling a single train in urban rail transit system management will be more feasible given the current development of RL methods, while optimizing the whole system with a large number of objects (or agents) will be much more challenging. Developing a scalable model with the ability to adopt and analyse large-scale spatial-temporal features and jointly optimize the actions of multi-object requires substantial novel efforts and innovations. For example, hierarchical RL can be a promising concept for handling such large-scale problems with a centralized manager for overall control and optimization and multiple decentralized workers for implementations at the local level.

Practicality:

- The design of the environment and reward function is critical for RL-based methods. Many methods are evaluated based on simulations with simulated observations and rewards. Only several works take advantage of real-world platforms for evaluation (e.g. Zhou et al. 2019 use the platform provided by Didi Chuxing for optimizing order dispatching). A certain (and unknown) gap between simulation and reality may exist. It is essential to train and evaluate the proposed methods based on real-world environments for policy optimization. For instance, order dispatching for MOD systems might be tested on real-world platforms such as Uber and Didi Chuxing so that the actual values of order response rate, driver income, and waiting/travel time can be obtained. Also, the utilization of a digital twin framework to mimic the real transportation system as a virtual system can be helpful in obtaining more realistic feedback. This often requires coordinated and cooperative efforts from academia, industry, and government.
• Existing studies are able to accommodate soft constraints effectively by introducing the penalty to reward functions. For instance, Tang et al. (2020) introduce a customer abandon penalty to reduce the possibility of order cancellation. The hard/rigid constraints of the environment are sometimes not straightforward to be incorporated, which should be investigated in future studies. This might require proper designs of environments and actions with limitations. For instance, the number of moving bikes in the bike-sharing system cannot exceed the capacity of the trike (the tool for moving bikes), which can be achieved by designing the range of the action vector.

• The evaluation of RL methods is sometimes based on ideal simulated environments (e.g. bus holding without considering the sluggish of passengers (Alesiani and Gkiotsalitis 2018)). In practice, uncertainties, disruptions, and accidents often occur for road traffic, rail traffic, and air traffic. External factors which may influence the transportation system and network traffic should be analysed or predicted (e.g. accurate weather forecasting can effectively help aircraft scheduling) and then incorporated for more capable RL tools.

• Some information such as travel demand, traffic flow, vehicle speed, trip distance, and trip time might be simulated or estimated for further decision-making with RL methods. For example, Citi Bike demand data from New York is collected in Li, Zheng, and Yang (2018) for bike re-positioning. However, precise information in terms of some specific characteristics in the environment may not be readily available or hard to be obtained. For instance, some existing research for energy management of electric vehicles may require precise information regarding the drivers’ behaviours, which might not be available at the time of decision-making. Therefore, some estimations or expectations might have to be assumed or further methods without such information request have to be developed (Qi et al. 2019; Wu et al. 2019).

• Some existing methods use discrete formulations for environmental features (e.g. the level of traffic congestion) and actions (e.g. slow down or speed up in adaptive cruise control (Desjardins and Chaib-Draa 2011)), which achieve satisfactory performance based on private and public simulators. This is likely not universal and might not be sufficient in many real-world occasions. Inappropriate extensions of such methods to other applications might not be feasible or might result in low-quality solutions. It is necessary to develop methods that are able to deal with the continuity and granularity of actions in transportation and optimize the choice of continuity and granularity since different scenarios require continuous or discrete actions with different (optimal) granularity. For example, the acceleration and steering control for autonomous driving requires extremely precise decisions since a slight adjustment in steering may cause a large change in the direction of a vehicle in the case of high-speed driving. On the contrary, it might be less meaningful to have a holding time for buses of ten seconds (while ten seconds might be too long for autonomous driving applications).

• The isolated design of different types of actions may also limit the practicality of RL in solving more complex transportation problems with substantial endogeneity or correlations among actions. Studies dealing with only one or two specific aspects of autonomous driving (e.g. lane changing, motion control, and collision avoidance) are still not ready for practical applications. More comprehensive consideration of multi-type actions simultaneously can be critical and essential in solving more complicated transportation problems in future research (e.g. to ensure safe, reliable, and efficient autonomous driving, the velocity, acceleration, angle change, route, and passengers’ preference might have to be examined in an integrated manner).

Transferability:

• Studies targeting on existing road networks and public transit routes/stations have shown great success in numerous aspects, such as train scheduling (Khadilkar 2018) and routing (Mao and Shen 2018). Due to urban expansion, new transportation facilities have to be designed and arranged in existing or new regions, which receives less attention in the literature. The construction of new facilities requires sufficient expert knowledge due to the scarcity of historical data for
policy optimization in RL. The utilization of transfer learning (Pan and Yang 2009) and Meta-based RL (Finn and Levine 2018) (i.e. the combination of Meta-Learning and Reinforcement Learning) are potentially effective tools for addressing new tasks or applications that lack sufficient training data. These strategies are able to transfer/adapt the trained RL-based model parameters/policies learned from the regions that already have related facilities to the new model for new regions.

Fairness:

- Existing studies aiming at improving the efficiency, profit, and safety of transportation systems by utilizing RL methods have made promising progress. However, the fairness issue of transportation systems has not been considered much and is indeed often ignored in the development of RL methods. Different targets or entities (e.g. intersections or vehicles) may have to be fairly treated in the formulation of RL. To better address fairness issues in transportation, exploring the combination of survey data (stated preference) and other multi-source data is necessary. How to incorporate such a combination of data into RL method development is a direction that is worth further examination. Therefore, combinational weighted rewarding optimization problems with multiple objectives might have to be considered and addressed in transportation applications to achieve both efficiency and fairness. Effective combinational weighted rewards are not straightforward to be designed (e.g. the safety, efficiency, and comfort in autonomous driving are hard to be evaluated simultaneously), which might have to be solved by introducing other new algorithms or methodologies. For instance, Inverse Reinforcement Learning may be an effective solution to learn the reward function based on the agent’s decisions and then find the optimal policy (e.g. Lanzaro, Sayed, and Alsaleh 2022 take advantage of Inverse RL to recover the reward function of motorcyclists based on their actual trajectories for traffic conflicts modelling).

Reinforcement Learning and smart transportation are research topics that attracted substantial interest in recent years, where we see a large number of novel developments on strategies, techniques, and applications of RL to support smart transportation. It is also noted that applications of Reinforcement Learning in some sub-domains of transportation are limited, e.g. air traffic control and the aviation sector. For these application sub-domains, examining relevant and useful features is necessary.

In summary, this paper first uses bibliometric analysis to identify the development of RL methods for transportation applications in recent years and then provide a review of the most relevant works covering a wide range of topics. This review provides readers with an understanding of RL-based method developments and applications in smart transportation and can serve as a reference point for researchers interested in interdisciplinary Reinforcement Learning research in transportation and computer science.

Notes

1. https://www.deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40
2. https://www.vosviewer.com/
3. https://www.scimagojr.com/journalrank.php
4. http://cic.tju.edu.cn/faculty/zhileiliu/doc/COREComputerScienceConferenceRankings.html

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References
Abdoos, M., N. Mozayani, and A. L. Bazzan. 2011. “Traffic Light Control in Non-Stationary Environments Based on Multi Agent Q-Learning.” In 14th International IEEE Conference on Intelligent Transportation Systems. Washington, DC, USA.
Abdulhai, B., and L. Kattan. 2003. “Reinforcement Learning: Introduction to Theory and Potential for Transport Applications.” Canadian Journal of Civil Engineering 30 (6): 981–991. doi:10.1139/03-014.
Abdulhai, B., R. Pringle, and G. J. Karakoulas. 2003. “Reinforcement Learning for True Adaptive Traffic Signal Control.” Journal of Transportation Engineering 129 (3): 278–285. doi:10.1061/(ASCE)0733-947X(2003)129:3(278).
Al-Abbasi, A. O., A. Ghosh, and V. Aggarwal. 2019. “Deeppool: Distributed Model-free Algorithm for Ride-sharing Using Deep Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 20 (12): 4714–4727. doi:10.1109/TITS.6979.
Alesiani, F., and K. Gkiotsalitis. 2018. “Reinforcement Learning-Based Bus Holding for High-Frequency Services.” In 2018 21st International Conference on Intelligent Transportation Systems, 3162–3168. IEEE.
An, Y., M. Li, X. Lin, F. He, and H. Yang. 2020. “Space-time Routing in Dedicated Automated Vehicle Zones.” Transportation Research Part C: Emerging Technologies 120: Article ID 102777. doi:10.1016/j.trc.2020.102777.
Aradi, S. 2022. “Survey of Deep Reinforcement Learning for Motion Planning of Autonomous Vehicles.” IEEE Transactions on Intelligent Transportation Systems 23 (2): 740–759. doi:10.1109/TITS.2020.3024655.
Arel, I., C. Liu, T. Urbanik, and A. G. Kohls. 2010. “Reinforcement Learning-based Multi-agent System for Network Traffic Signal Control.” IET Intelligent Transport Systems 4 (2): 128–135. doi:10.1049/iet-its.2009.0070.
Aslani, M., M. S. Mesgari, and M. Wiering. 2017. “Adaptive Traffic Signal Control with Actor-critic Methods in a Real-world Traffic Network with Different Traffic Disruption Events.” Transportation Research Part C: Emerging Technologies 85: 732–752. doi:10.1016/j.trc.2017.09.020.
Babaeizadeh, M., I. Frosio, S. Tyree, J. Clemons, and J. Kautz. 2017. “Reinforcement Learning Through Asynchronous Advantage Actor-Critic on a GPU.” In 5th International Conference on Learning Representations. Toulon, France.
Balaji, P., X. German, and D. Srinivasan. 2010. “Urban Traffic Signal Control Using Reinforcement Learning Agents.” IET Intelligent Transport Systems 4 (3): 177–188. doi:10.1049/iet-its.2009.0096.
Balakrishna, P., R. Ganesan, and L. Sherry. 2010. “Accuracy of Reinforcement Learning Algorithms for Predicting Aircraft Taxi-out Times: A Case-study of Tampa Bay Departures.” Transportation Research Part C: Emerging Technologies 18 (6): 950–962. doi:10.1016/j.trc.2010.03.003.
Belletti, F., D. Haziza, G. Gomes, and A. M. Bayen. 2017. “Expert Level Control of Ramp Metering Based on Multi-task Deep Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 19 (4): 1198–1207. doi:10.1109/TITS.2017.2725912.
Bellman, R. 1952. “On the Theory of Dynamic Programming.” Proceedings of the National Academy of Sciences of the United States of America 38 (8): 716. doi:10.1073/pnas.38.8.716.
Bellman, R. 1957. “A Markovian Decision Process.” Journal of Mathematics and Mechanics 6 (4): 679–684. doi:10.1512/iiumj.1957.6.56038.
Berrebi, S. J., E. Hans, N. Chiabaut, J. A. Laval, L. Leclercq, and K. E. Watkins. 2018. “Comparing Bus Holding Methods with and Without Real-time Predictions.” Transportation Research Part C: Emerging Technologies 87: 197–211. doi:10.1016/j.trc.2017.07.012.
Boutilier, C., A. Cohen, A. Hassidim, Y. Mansour, O. Meshi, M. Mladenov, and D. Schuurmans. 2018. “Planning and Learning With Stochastic Action Sets.” In Proceedings of the 27th International Joint Conference on Artificial Intelligence. Stockholm, Sweden.
Browne, C. B., E. Powley, D. Whitehouse, S. M. Lucas, P. I. Cowling, P. Rohlfshagen, S. Tavener, et al. 2012. “A Survey of Monte Carlo Tree Search Methods.” IEEE Transactions on Computational Intelligence and AI in Games 4 (1): 1–43. doi:10.1109/TCIAIG.2012.2186810.
Cao, Z., H. Guo, J. Zhang, F. Oliehoek, and U. Fastenrath. 2017. “Maximizing the Probability of Arriving on Time: A Practical Q-Learning Method.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 31, 4481–4487. San Francisco, California, USA.
Cao, Z., D. Yang, S. Xu, H. Peng, B. Li, S. Feng, and D. Zhao. 2020. “Highway Exiting Planner for Automated Vehicles Using Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 22 (2): 990–1000. doi:10.1109/TITS.6979.
Caruana, R. 1997. “Multitask Learning.” Machine Learning 28 (1): 41–75. doi:10.1023/A:1007379606734.
Chandak, Y., G. Theocharous, B. Metevier, and P. Thomas. 2020. “Reinforcement Learning When All Actions are not Always Available.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, 3381–3388. New York, NY, USA.
Chen, C., Y. Huang, W. Lam, T. Pan, S. Hsu, A. Sumalee, and R. Zhong. 2022. "Data Efficient Reinforcement Learning and Adaptive Optimal Perimeter Control of Network Traffic Dynamics." Transportation Research Part C: Emerging Technologies 142: Article ID 103759. doi:10.1016/j.trc.2022.103759.

Chen, H., Y. Jiao, Z. Qin, X. Tang, H. Li, B. An, H. Zhu, and J. Ye. 2019. "Integrating Contextual Bandit With TD Learning for Joint Pricing and Dispatch of Ride-Hailing Platforms." In IEEE International Conference on Data Mining, 61–70. IEEE.

Chen, L., K. Lu, A. Rajeswaran, K. Lee, A. Grover, M. Laskin, P. Abbeel, A. Srivinas, and I. Mordatch. 2021. "Decision Transformer: Reinforcement Learning Via Sequence Modeling." Advances in Neural Information Processing Systems 34: 15084–15097. doi:10.21236/asm.3971444.

Chen, C., H. Wei, N. Xu, G. Zheng, M. Yang, Y. Xiong, K. Xu, and Z. Li. 2020. "Toward a Thousand Lights: Decentralized Deep Reinforcement Learning for Large-Scale Traffic Signal Control." In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, 3414–3421. New York, NY, USA.

Chen, S.-Y., Y. Yu, Q. Da, J. Tan, H.-K. Huang, and H.-H. Tang. 2018. "Stabilizing Reinforcement Learning in Dynamic Environment With Application to Online Recommendation." In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 1187–1196. London, UK.

Chen, W., K. Zhou, and C. Chen. 2016. "Real-Time Bus Holding Control on a Transit Corridor Based On Multi-Agent Reinforcement Learning." In IEEE 19th International Conference on Intelligent Transportation Systems, 100–106. IEEE.

Chu, T., J. Wang, L. Codecà, and Z. Li. 2019. "Multi-agent Deep Reinforcement Learning for Large-scale Traffic Signal Control." IEEE Transactions on Intelligent Transportation Systems 21 (3): 1086–1095. doi:10.1109/TITS.6979.

Dai, Z., X. C. Liu, Z. Chen, R. Guo, and X. Ma. 2019. "A Predictive Headway-Based Bus-Holding Strategy With Dynamic Control Point Selection: A Cooperative Game Theory Approach." Transportation Research Part B: Methodological 125: 29–51. doi:10.1016/j.trb.2019.05.001.

Darmoul, S., S. Elkosantini, A. Louati, and L. B. Said. 2017. "Multi-agent Immune Networks to Control Interrupted Flow at Signalized Intersections." Transportation Research Part C: Emerging Technologies 82: 290–313. doi:10.1016/j.trc.2017.07.003.

Desjardins, C., and B. Chaib-Draa. 2011. "Cooperative Adaptive Cruise Control: A Reinforcement Learning Approach." IEEE Transactions on Intelligent Transportation Systems 12 (4): 1248–1260. doi:10.1109/TITS.2011.2157145.

Devailliy, F.-X., D. Larocque, and L. Charlin. 2021. "Ig-rl: Inductive Graph Reinforcement Learning for Massive-Scale Traffic Control." In IEEE 19th International Conference on Intelligent Transportation Systems, 61–66. IEEE.

El-Tantawy, S., B. Abdulhai, and H. Abdelgawad. 2013. "Multiagent Reinforcement Learning for Integrated Network of Adaptive Traffic Signal Controllers (marlin-atsc): Methodology and Large-scale Application on Downtown Toronto." IEEE Transactions on Intelligent Transportation Systems 14 (3): 1140–1150. doi:10.1109/TITS.2013.2255286.

El-Tantawy, S., B. Abdulhai, and H. Abdelgawad. 2014. "Design of Reinforcement Learning Parameters for Seamless Application of Adaptive Traffic Signal Control." Journal of Intelligent Transportation Systems 18 (3): 227–245. doi:10.1080/15472450.2013.810991.

Ernst, D., P. Geurts, and L. Wehenkel. 2005. "Tree-based Batch Mode Reinforcement Learning." Journal of Machine Learning Research 6: 503–556. doi:10.5555/1046920.1088690.

Farazi, N. P., B. Zou, T. Ahamed, and L. Barua. 2021. "Deep Reinforcement Learning in Transportation Research: A Review." Transportation Research Interdisciplinary Perspectives 11: Article ID 100425. doi:10.1016/j.trip.2021.100425.

Fares, A., and W. Gomaa. 2014. "Freeway Ramp-Metering Control Based on Reinforcement Learning." In 11th IEEE International Conference on Control & Automation, 1226–1231. IEEE.

Finn, C., and S. Levine. 2018. "Meta-Learning and Universality: Deep Representations and Gradient Descent can Approximate any Learning Algorithm." In International Conference on Learning Representations. Vancouver, BC, Canada.

Fortunato, M., M. G. Azar, B. Piot, J. Menick, I. Osband, A. Graves, V. Mnih, et al. 2017. "Noisy Networks for Exploration." CoRR, abs/1706.10295.

Fujimoto, S., H. Hoof, and D. Meger. 2018. "Addressing Function Approximation Error in Actor-Critic Methods." In International Conference on Machine Learning, 1587–1596. PMLR.

Gao, W., J. Gao, K. Ozbay, and Z.-P. Jiang. 2019. "Reinforcement-learning-based Cooperative Adaptive Cruise Control of Buses in the Lincoln Tunnel Corridor with Time-varying Topology." IEEE Transactions on Intelligent Transportation Systems 20 (10): 3796–3805. doi:10.1109/TITS.6979.

Guo, Q., O. Angah, Z. Liu, and X. J. Ban. 2021. "Hybrid Deep Reinforcement Learning Based Eco-Driving for Low-Level Connected and Automated Vehicles Along Signalized Corridors." Transportation Research Part C: Emerging Technologies 124: Article ID 102980. doi:10.1016/j.trc.2021.102980.

Gupta, J. K., M. Egorov, and M. Kochenderfer. 2017. "Cooperative Multi-Agent Control Using Deep Reinforcement Learning." In International Conference on Autonomous Agents and Multiagent Systems, 66–83. Springer.

Haydari, A., and Y. Yilmaz. 2022. "Deep Reinforcement Learning for Intelligent Transportation Systems: A Survey." IEEE Transactions on Intelligent Transportation Systems 23 (1): 11–32. doi:10.1109/TITS.2020.3008612.

He, S., and K. G. Shin. 2019. "Spatio-Temporal Capsule-Based Reinforcement Learning for Mobility-on-Demand Network Coordination." In The World Wide Web Conference, 2806–2813. San Francisco, USA.
He, J., H. Yang, T.-Q. Tang, and H.-J. Huang. 2018. “An Optimal Charging Station Location Model with the Consideration of Electric Vehicle’s Driving Range.” Transportation Research Part C: Emerging Technologies 88: 641–654. doi:10.1016/j.trc.2017.11.026.

Hessel, M., J. Modayil, H. van Hasselt, T. Schaul, G. Ostrovski, W. Dabney, D. Horgan. 2018. “Rainbow: Combining Improvements in Deep Reinforcement Learning.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 32. New Orleans, LA, USA.

Higgins, I., A. Pal, A. Rusu, L. Matthey, C. Burgess, A. Pritzel, M. Botvinick, C. Blundell, and A. Lerchner. 2017. “Darla: Improving Zero-Shot Transfer in Reinforcement Learning.” In International Conference on Machine Learning, 1480–1490. PMLR.

Hinton, G. E., and R. R. Salakhutdinov. 2006. “Reducing the Dimensionality of Data with Neural Networks.” Science (New York, N.Y.) 313 (5786): 504–507. doi:10.1126/science.1127647.

Holler, J., R. Vuorio, Z. Qin, X. Tang, Y. Jiao, T. Jin, S. Singh, C. Wang, and J. Ye. 2019. “Deep Reinforcement Learning for Multi-Drvier Vehicle Dispatching and Repositioning Problem.” In IEEE International Conference on Data Mining, 1090–1095. IEEE.

James, J., and A. Y. Lam. 2017. “Autonomous Vehicle Logistic System: Joint Routing and Charging Strategy.” IEEE Transactions on Intelligent Transportation Systems 19 (7): 2175–2187. doi:10.1109/itts.2017.2766682.

James, J., W. Yu, and J. Gu. 2019. “Online Vehicle Routing with Neural Combinatorial Optimization and Deep Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 20 (10): 3806–3817. doi:10.1109/TITS.6979.

Jiang, Z., W. Fan, W. Liu, B. Zhu, and J. Gu. 2018. “Reinforcement Learning Approach for Coordinated Passenger Inflow Control of Urban Rail Transit in Peak Periods.” Transportation Research Part C: Emerging Technologies 88: 1–16. doi:10.1016/j.trc.2018.01.008.

Jin, J., M. Zhou, W. Zhang, M. Li, Z. Guo, Z. Qin, and Y. Jiao. 2019. “Coride: Joint Order Dispatching and Fleet Management for Multi-Scale Ride-Hailing Platforms.” In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1983–1992. Beijing, China.

Kaelbling, L. P., M. L. Littman, and A. W. Moore. 1996. “Reinforcement Learning: A Survey.” Journal of Artificial Intelligence Research 4: 237–285. doi:10.1613/jair.301.

Ke, J., X. Cen, H. Yang, X. Chen, and J. Ye. 2019. “Modelling Drivers’ Working and Recharging Schedules in a Ride-Sourcing Market with Electric Vehicles and Gasoline Vehicles.” Transportation Research Part E: Logistics and Transportation Review 125: 160–180. doi:10.1016/j.ijre.2019.03.010.

Khadilkar, H. 2018. “A Scalable Reinforcement Learning Algorithm for Scheduling Railway Lines.” IEEE Transactions on Intelligent Transportation Systems 20 (2): 727–736. doi:10.1109/TITS.2018.2829165.

Kim, D., J. Ko, and Y. Park. 2015. “Factors Affecting Electric Vehicle Sharing Program Participants’ Attitudes About Car Ownership and Program Participation.” Transportation Research Part D: Transport and Environment 36: 96–106. doi:10.1016/j.trrd.2015.02.009.

Kiran, B. R., I. Sobh, V. Talpaert, P. Mannion, A. A. A. Sallab, S. Yogamani, and P. Pérez. 2022. “Deep Reinforcement Learning for Autonomous Driving: A Survey.” IEEE Transactions on Intelligent Transportation Systems 23 (6): 4909–4926. doi:10.1109/TITS.2021.3054625.

Kok, J. R., and N. Vlassis. 2005. “Using the Max-Plus Algorithm for Multiagent Decision Making in Coordination Graphs.” In Robot Soccer World Cup, 1–12. Springer.

Kok, J. R., and N. Vlassis. 2006. “Collaborative Multiagent Reinforcement Learning by Payoff Propagation.” Journal of Machine Learning Research 7 (65): 1789–1828. doi:10.5555/1248547.1248612.

Lanzaro, G., T. Sayed, and R. Alsaleh. 2022. “Can Motorcyclist Behavior in Traffic Conflicts Be Modeled? A Deep Reinforcement Learning Framework for Motorcycle-pedestrian Interactions.” Transportmetrica B: Transport Dynamics 10 (1): 396–420. doi:10.1080/21680566.2021.2004954.

Laporte, G., J. A. Mesa, and F. Perea. 2010. “A Game Theoretic Framework for the Robust Railway Transit Network Design Problem.” Transportation Research Part B: Methodological 44 (4): 447–459. doi:10.1016/j.trb.2009.08.004.

Levine, S., C. Finn, T. Darrell, and P. Abbeel. 2016. “End-to-end Training of Deep Visuomotor Policies.” The Journal of Machine Learning Research 17 (1): 1334–1373. doi:10.5555/2946645.2946684.

Lewis, F. L., D. Vrabie, and V. L. Syrmos. 2012. Optimal Control. New Jersey and Canada: John Wiley & Sons.

Li, C., L. Bai, W. Liu, L. Yao, and S. T. Waller. 2021. “Urban Mobility Analytics: A Deep Spatial–temporal Product Neural Network for Traveler Attributes Inference.” Transportation Research Part C: Emerging Technologies 124: Article ID 102921. doi:10.1016/j.trc.2020.102921.

Li, Z., T. Chu, I. V. Kolmanovsky, and X. Yin. 2017. “Training Drift Counteraction Optimal Control Policies Using Reinforcement Learning: An Adaptive Cruise Control Example.” IEEE Transactions on Intelligent Transportation Systems 19 (9): 2903–2912. doi:10.1109/TITS.2017.2767083.

Li, G., and D. Görges. 2019. “Ecological Adaptive Cruise Control for Vehicles with Step-gear Transmission Based on Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 21 (11): 4895–4905. doi:10.1109/TITS.6979.

Li, Z., P. Liu, C. Xu, H. Duan, and W. Wang. 2017. “Reinforcement Learning-based Variable Speed Limit Control Strategy to Reduce Traffic Congestion At Freeway Recurrent Bottlenecks.” IEEE Transactions on Intelligent Transportation Systems 18 (11): 3204–3217. doi:10.1109/TITS.2017.2687620.
Li, M., Z. Qin, Y. Jiao, Y. Yang, J. Wang, C. Wang, G. Wu, and J. Ye. 2019. “Efficient Ridesharing Order Dispatching With Mean Field Multi-Agent Reinforcement Learning.” In The World Wide Web Conference, 983–994. San Francisco, USA.

Li, Z., H. Yu, G. Zhang, S. Dong, and C.-Z. Xu. 2021. “Network-Wide Traffic Signal Control Optimization Using a Multi-agent Deep Reinforcement Learning.” Transportation Research Part C: Emerging Technologies 125: Article ID 103059. doi:10.1016/j.trc.2021.103059.

Li, Y., Y. Zheng, and Q. Yang. 2018. “Dynamic Bike Reposition: A Spatio-Temporal Reinforcement Learning Approach.” In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 1724–1733. London, UK.

Lian, R., J. Peng, Y. Wu, H. Tan, and H. Zhang. 2020. “Rule-interposing Deep Reinforcement Learning Based Energy Management Strategy for Power-split Hybrid Electric Vehicle.” Energy 197: Article ID 117297. doi:10.1016/j.energy.2020.117297.

Lillicrap, T. P., J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra. 2016. “Continuous Control With Deep Reinforcement Learning.” In 4th International Conference on Learning Representations. San Juan, Puerto Rico.

Lim, S., C. Sommer, E. Nikolova, and D. Rus. 2013. “Practical Route Planning Under Delay Uncertainty: Stochastic Shortest Path Queries.” In Robotics: Science and Systems, Vol. 8, 249–256. MIT Press.

Lin, B., B. Ghaddar, and J. Nathwani. 2022. “Deep Reinforcement Learning for the Electric Vehicle Routing Problem with Time Windows.” IEEE Transactions on Intelligent Transportation Systems 23 (8): 11528–11538. doi:10.1109/TITS.2021.3128406.

Lin, K., R. Zhao, Z. Xu, and J. Zhou. 2018. “Efficient Large-Scale Fleet Management Via Multi-Agent Deep Reinforcement Learning.” In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 1774–1783. London, UK.

Liu, T., X. Hu, S. E. Li, and D. Cao. 2017. “Reinforcement Learning Optimized Look-ahead Energy Management of a Parallel Hybrid Electric Vehicle.” IEEE/ASME Transactions on Mechatronics 22 (4): 1497–1507. doi:10.1109/TMECH.2017.2707338.

Liu, W., Y. Yin, and H. Yang. 2015. “Effectiveness of Variable Speed Limits Considering Commuters’ Long-term Response.” Transportation Research Part B: Methodological 81: 498–519. doi:10.1016/j.trb.2014.12.001.

Liu, M., F. Zhao, J. Niu, and Y. Liu. 2021. “Reinforcement driving: Exploring Trajectories and Navigation for Autonomous Vehicles.” IEEE Transactions on Intelligent Transportation Systems 22 (2): 808–820. doi:10.1109/TITS.6979.

Liu, T., Y. Zou, D. Liu, and F. Sun. 2015. “Reinforcement Learning–based Energy Management Strategy for a Hybrid Electric Tracked Vehicle.” Energies 8 (7): 7243–7260. doi:10.3390/en8077243.

Lopez, P. A., M. Behrisch, L. Bieker-Walz, J. Erdmann, Y. -P. Flötteröd, T. Hilbrich, L. Lücken, et al. 2018. “Microscopic Traffic Simulation Using Sumo.” In 21st International Conference on Intelligent Transportation Systems, 2575–2582. IEEE.

Lou, K., Y. Yang, E. Wang, Z. Liu, T. Baker, and A. K. Bashir. 2020. “Reinforcement Learning Based Advertising Strategy Using Crowdsensing Vehicular Data.” IEEE Transactions on Intelligent Transportation Systems 22 (7): 4635–4647. doi:10.1109/TITS.2020.2991029.

Lowe, R., Y. WU, A. Tamar, J. Harb, O. Pieter Abbeel, and I. Mordatch. 2017. “Multi-agent Actor-critic for Mixed Cooperative-competitive Environments.” Advances in Neural Information Processing Systems30: 6379–6390. doi:10.5555/3295222.3295385.

Luo, M., W. Zhang, T. Song, K. Li, H. Zhu, B. Du, and H. Wen. 2020. “Rebalancing Expanding EV Sharing Systems With Deep Reinforcement Learning.” In Proceedings of the 29th International Joint Conference on Artificial Intelligence, 1338–1344. Yokohama, Japan.

Manchella, K., A. K. Umrawal, and V. Aggarwal. 2021. “Flexpool: A Distributed Model-free Deep Reinforcement Learning Algorithm for Joint Passengers and Goods Transportation.” IEEE Transactions on Intelligent Transportation Systems 22 (4): 2035–2047. doi:10.1109/TITS.2020.3048361.

Mannion, P., J. Duggan, and E. Howley. 2015. “Parallel Reinforcement Learning for Traffic Signal Control.” Procedia Computer Science 52: 956–961. doi:10.1016/j.procs.2015.05.172.

Mannion, P., J. Duggan, and E. Howley. 2016. Autonomic Road Transport Support Systems, 47–66. Switzerland: Birkhäuser Cham. doi:10.1007/978-3-319-25808-9.

Mao, H., M. Alizadeh, I. Menache, and S. Kundula. 2016. “Resource Management With Deep Reinforcement Learning.” In Proceedings of the 15th ACM Workshop on Hot Topics in Networks, 50–56. Red Hook, NY, USA.

Mao, C., Y. Liu, and Z.-J. M. Shen. 2020. “Dispatch of Autonomous Vehicles for Taxi Services: A Deep Reinforcement Learning Approach.” Transportation Research Part C: Emerging Technologies 115: Article ID 102626. doi:10.1016/j.trc.2020.102626.

Markov, A. A. 1954. Theory of Algorithms. Moscow Leningrad, Russia: Springer.

Mende, K., Y.-C. Chen, J. Grana, J. W. Bonf, B. D. Tracey, M. J. Kochenderfer, and D. Wolpert. 2018. “Deep Reinforcement Learning for Event-driven Multi-agent Decision Processes.” IEEE Transactions on Intelligent Transportation Systems 20 (4): 1259–1268. doi:10.1109/TITS.6979.

Minsky, M. L. 1954. Theory of Neural-Analog Reinforcement Systems and Its Application to the Brain-model Problem. New Jersey, USA: Princeton University.

Mnih, V., A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu. 2016. “Asynchronous Methods for Deep Reinforcement Learning.” In International Conference on Machine Learning, 1928–1937. PMLR.
Mnih, V., K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, and A. Graves, et al. 2015. “Human-level Control Through Deep Reinforcement Learning.” Nature 518 (7540): 529–533. doi:10.1038/nature14236.

Mo, K., Y. Zhang, S. Li, J. Li, and Q. Yang. 2018. “Personalizing a Dialogue System With Transfer Reinforcement Learning.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 32. New Orleans, LA, USA.

Mousavi, S. S., M. Schukat, and E. Howley. 2017. “Traffic Light Control Using Deep Policy-gradient and Value-function-based Reinforcement Learning.” IEEE Intelligent Transportation Systems 11 (7): 417–423. doi:10.1049/iet-trs.2017.0117.

Munkres, J. 1957. “Algorithms for the Assignment and Transportation Problems.” Journal of the Society for Industrial and Applied Mathematics 5 (1): 32–38. doi:10.1137/0105003.

Nascimento, E. R., R. Bajcsy, M. Gregor, I. Huang, I. Villegas, and G. Kurillo. 2021. “On the Development of An Acoustic-driven Method to Improve Driver’s Comfort Based on Deep Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 22 (5): 2923–2932. doi:10.1109/TITS.2020.2977983.

Nguyen, D. T., A. Kumar, and H. C. Lau. 2017. “Policy Gradient With Value Function Approximation for Collective Multi-agent Planning.” In Proceedings of the 31st International Conference on Neural Information Processing Systems, 4320–4330. Long Beach, CA, USA.

Ni, W., and M. J. Cassidy. 2019. “Cordon Control with Spatially-varying Metering Rates: A Reinforcement Learning Approach.” Transportation Research Part C: Emerging Technologies 98: 358–369. doi:10.1016/j.trc.2018.12.007.

Nishi, T., K. Otaki, K. Hayakawa, and T. Yoshimura. 2018. “Traffic Signal Control Based on Reinforcement Learning With Graph Convolutional Neural Nets.” In 21st International Conference on Intelligent Transportation Systems, 877–883. IEEE.

Noaeeen, M., A. Naik, L. Goodman, J. Crebo, T. Abrar, Z. S. H. Abad, A. L. Bazzan, and B. Far. 2022. “Reinforcement Learning in Urban Network Traffic Signal Control: A Systematic Literature Review.” Expert Systems with Applications 199. doi:10.1016/j.eswa.2022.116830.

Oda, T., and C. Joe-Wong. 2018. “Movi: A Model-Free Approach to Dynamic Fleet Management.” In IEEE INFOCOM Conference on Computer Communications, 2708–2716. IEEE.

Ono, N., and K. Fukumoto. 1996. “Multi-Agent Reinforcement Learning: A Modular Approach.” In 2nd International Conference on Multiagent Systems, 252–258. Boston, MA, USA.

Ozan, C., O. Baskan, S. Haldenbilen, and H. Ceylan. 2015. “A Modified Reinforcement Learning Algorithm for Solving Coordinated Signalized Networks.” Transportation Research Part C: Emerging Technologies 54: 40–55. doi:10.1016/j.trc.2015.03.010.

Pan, L., Q. Cai, Z. Fang, P. Tang, and L. Huang. 2019. “A Deep Reinforcement Learning Framework for Rebalancing Dockless Bike Sharing Systems.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33, 1393–1400. Honolulu, Hawaii, USA.

Pan, T., R. Guo, W. H. Lam, R. Zhong, W. Wang, and B. He. 2021. “Integrated Optimal Control Strategies for Freeway Traffic Mixed with Connected Automated Vehicles: A Model-based Reinforcement Learning Approach.” Transportation Research Part C: Emerging Technologies 123: Article ID 102987. doi:10.1016/j.trc.2021.102987.

Pan, S. J., and Q. Yang. 2009. “A Survey on Transfer Learning.” IEEE Transactions on Knowledge and Data Engineering 22 (10): 1345–1359. doi:10.1109/TKDE.2009.191.

Pandey, V., and S. D. Boyles. 2018. “Multiagent Reinforcement Learning Algorithm for Distributed Dynamic Pricing of Managed Lanes.” In 21st International Conference on Intelligent Transportation Systems, 2346–2351. IEEE.

Pandey, V., E. Wang, and S. D. Boyles. 2020. “Deep Reinforcement Learning Algorithm for Dynamic Pricing of Express Lanes with Multiple Access Locations.” Transportation Research Part C: Emerging Technologies 119: Article ID 102715. doi:10.1016/j.trc.2020.102715.

Pedersen, T. H., and N. Zacharov. 2008. “How Many Psycho-acoustic Attributes are Needed.” Journal of the Acoustical Society of America 123 (5): 3163–3163. doi:10.1121/1.2933214.

Prashanth, L., and S. Bhatnagar. 2010. “Reinforcement Learning with Function Approximation for Traffic Signal Control.” IEEE Transactions on Intelligent Transportation Systems 12 (2): 412–421. doi:10.1109/tits.2010.2091408.

Qi, X., Y. Luo, G. Wu, K. Boriboonsomsin, and M. Barth. 2019. “Deep Reinforcement Learning Enabled Self-learning Control for Energy Efficient Driving.” Transportation Research Part C: Emerging Technologies 99: 67–81. doi:10.1016/j.trc.2018.12.018.

Qi, X., G. Wu, K. Boriboonsomsin, M. J. Barth, and J. Gonder. 2016. “Data-driven Reinforcement Learning–based Real-time Energy Management System for Plug-in Hybrid Electric Vehicles.” Transportation Research Record 2572 (1): 1–8. doi:10.3141/2572-01.

Qin, Z. T., H. Zhu, and J. Ye. 2022. “Reinforcement Learning for Ridesharing: An Extended Survey.” Transportation Research Part C: Emerging Technologies 144: Article ID 103852. doi:10.1016/j.trc.2022.103852.

Ramos, G. d. O., A. L. Bazzan, and B. C. da Silva. 2018. “Analysing the Impact of Travel Information for Minimising the Regret of Route Choice.” Transportation Research Part C: Emerging Technologies88: 257–271. doi:10.1016/j.trc.2017.11.011.

Reyad, P., and T. Sayed. 2022. “Real-time Multi-objective Optimization of Safety and Mobility at Signalized Intersections.” Transportmetrica B: Transport Dynamics, 1–22. doi:10.1080/21680566.2022.2141911.

Rezaee, K., B. Abdulhai, and H. Abdelgawad. 2012. “Application of Reinforcement Learning With Continuous State Space to Ramp Metering in Real-World Conditions.” In The 15th International IEEE Conference on Intelligent Transportation Systems, 1590–1595. IEEE.
Wang, Z., H. Li, H. He, and D. Prokhorov. 2018. “Model-free Real-time Ev Charging Scheduling Based on Deep Reinforcement Learning.” *IEEE Transactions on Smart Grid* 10 (5): 5246–5257. doi:10.1109/TSG.5165411.

Wang, T., J. Cao, and A. Hussain. 2021. “Adaptive Traffic Signal Control for Large-scale Scenario with Cooperative Group-based Multi-agent Reinforcement Learning.” *Transportation Research Part C: Emerging Technologies* 125: Article ID 103046. doi:10.1016/j.trc.2021.103046.

Wang, X., Q. Huang, A. Celikyilmaz, J. Gao, D. Shen, Y.-F. Wang, W. Y. Wang, and L. Zhang. 2019. “Reinforced Cross-Modal Matching and Self-Supervised Imitation Learning for Vision-Language Navigation.” In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 6629–6638. Long Beach, CA, USA.

Wang, Y., M. Li, X. Lin, and F. He. 2021. “Online Strategies for Automated Multistory Parking Facilities.” *Transportation Research Part E: Logistics and Transportation Review* 145: Article ID 102135. doi:10.1016/j.tra.2020.102135.

Wang, Z., Z. Qin, X. Tang, J. Ye, and H. Zhu. 2018. “Deep Reinforcement Learning With Knowledge Transfer for Online Rides Order Dispatching.” In *2018 IEEE International Conference on Data Mining*, 617–626. IEEE.

Wang, Z., T. Schaul, M. Hessel, H. Hasselt, M. Lanctot, and N. Freitas. 2016. “Dueling Network Architectures for Deep Reinforcement Learning.” In *International Conference on Machine Learning*, 1995–2003. PMLR.

Wang, J., and L. Sun. 2020. “Dynamic Holding Control to Avoid Bus Bunching: A Multi-agent Deep Reinforcement Learning Framework.” *Transportation Research Part C: Emerging Technologies* 116: Article ID 102661. doi:10.1016/j.trc.2020.102661.

Wang, J., and L. Sun. 2020. “Hierarchically and Cooperatively Learning Traffic Signal Control.” In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2496–2505. London, UK.

Wiering, M. A. 2000. “Multi-Agent Reinforcement Learning for Traffic Light Control.” In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1913–1922. Beijing, China.

Wiering, M., N. Xu, H. Zhang, G. Zheng, X. Zang, C. Chen, W. Zhang, et al. 2019. “Colight: Learning Network-Level Cooperation for Traffic Signal Control.” In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1151–1158. San Francisco, CA, USA.

Wiering, M., J. Vreeken, J. Van Veenen, and A. Koopman. 2004. “Simulation and Optimization of Traffic in a City.” In *Proceedings of the 17th International Conference on Machine Learning*, 453–458. IEEE.

Williams, R. J. 1992. “Simple Statistical Gradient-following Algorithms for Connectionist Reinforcement Learning.” *Machine Learning* 8 (3-4): 229–292. doi:10.1007/BF00992698.

Wegener, M., L. Koch, M. Eisenbarth, and J. Andert. 2021. “Automated Eco-driving in Urban Scenarios Using Deep Reinforcement Learning.” *Transportation Research Part C: Emerging Technologies* 126: Article ID 102967. doi:10.1016/j.trc.2021.102967.

Wei, H., C. Chen, G. Zheng, K. Wu, V. Gayah, K. Xu, and Z. Li. 2019. “Presslight: Learning Max Pressure Control to Coordinate Traffic Signals in Arterial Network.” In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 1290–1298. Anchorage, AK, USA.

Wei, Y., M. Mao, J. Zou, and P. An. 2020. “City Metro Network Expansion With Reinforcement Learning.” In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2646–2656. Virtual Conference, USA.

Wei, H., N. Xu, H. Zhang, G. Zheng, X. Zang, C. Chen, W. Zhang, et al. 2019. “Colight: Learning Network-Level Cooperation for Traffic Signal Control.” In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1913–1922. Beijing, China.

Wei, H., G. Zheng, H. Yao, and Z. Li. 2018. “Intellilight: A Reinforcement Learning Approach for Intelligent Traffic Light Control.” In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2496–2505. London, UK.

Wiering, M. A. 2000. “Multi-Agent Reinforcement Learning for Traffic Light Control.” In *Proceedings of the 10th International Conference on Artificial Intelligence*, Vol. 35, 669–677. Virtual Event.

Wiering, M., J. Vreeken, J. Van Veenen, and A. Koopman. 2004. “Simulation and Optimization of Traffic in a City.” In *IEEE Intelligent Vehicles Symposium*, 453–458. IEEE.

Williams, R. J. 1992. “Simple Statistical Gradient-following Algorithms for Connectionist Reinforcement Learning.” *Machine Learning* 8 (3): 229–296. doi:10.1007/BF00992698.

Wu, Y., H. Tan, J. Peng, H. Zhang, and H. He. 2019. “Deep Reinforcement Learning of Energy Management with Continuous Control Strategy and Traffic Information for a Series-parallel Plug-in Hybrid Electric Bus.” *Applied Energy* 247: 454–466. doi:10.1016/j.apenergy.2019.04.021.

Wu, Y., H. Tan, L. Qin, and B. Ran. 2020. “Differential Variable Speed Limits Control for Freeway Recurrent Bottlenecks Via Deep Actor-critic Algorithm.” *Transportation Research Part C: Emerging Technologies* 117: Article ID 102649. doi:10.1016/j.trc.2020.102649.

Wu, J., Z. Wei, K. Liu, Z. Quan, and Y. Li. 2020. “Battery-Involved Energy Management for Hybrid Electric Bus Based on Expert-assistance Deep Deterministic Policy Gradient Algorithm.” *IEEE Transactions on Vehicular Technology* 69 (11): 12786–12796. doi:10.1109/TVT.25.

Xu, Z., Z. Li, Q. Guan, D. Zhang, Q. Li, J. Nan, C. Liu, W. Bian, and J. Ye. 2018. “Large-Scale Order Dispatch in On-Demand Ride-Hailing Platforms: A Learning and Planning Approach.” In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 905–913. Longdon, UK.

Xu, B., Y. Wang, Z. Wang, H. Jia, and Z. Lu. 2021. “Hierarchically and Cooperatively Learning Traffic Signal Control.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 35, 669–677. Virtual Event.

Xu, N., G. Zheng, K. Xu, Y. Zhu, and Z. Li. 2019. “Targeted Knowledge Transfer for Learning Traffic Signal Plans.” In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, 175–187. Springer.

Yang, Y., R. Luo, M. Li, M. Zhou, W. Zhang, and J. Wang. 2018. “Mean Field Multi-Agent Reinforcement Learning.” In *International Conference on Machine Learning*, 5571–5580. PMLR.

Yang, K., N. Zheng, and M. Menendez. 2017. “Multi-scale Perimeter Control Approach in a Connected-vehicle Environment.” *Transportation Research Procedia* 23: 101–120. doi:10.1016/j.trpro.2017.05.007.
Yang, Z., F. Zhu, and F. Lin. 2021. “Deep-reinforcement-learning-based Energy Management Strategy for Supercapacitor Energy Storage Systems in Urban Rail Transit.” IEEE Transactions on Intelligent Transportation Systems 22 (2): 1150–1160. doi:10.1109/TITS.6979.

Yau, K.-L. A., J. Qadir, H. L. Khoo, M. H. Ling, and P. Komisarczuk. 2017. “A Survey on Reinforcement Learning Models and Algorithms for Traffic Signal Control.” ACM Computing Surveys 50 (3): 1–38. doi:10.1145/3068287.

Ye, Y., X. Zhang, and J. Sun. 2019. “Automated Vehicle’s Behavior Decision Making Using Deep Reinforcement Learning and High-fidelity Simulation Environment.” Transportation Research Part C: Emerging Technologies 107: 155–170. doi:10.1016/j.trc.2019.08.011.

Yin, J., D. Chen, and L. Li. 2014. “Intelligent Train Operation Algorithms for Subway by Expert System and Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 15 (6): 2561–2571. doi:10.1109/TITS.2014.2320757.

Ying, C.-s., A. H. Chow, and K.-S. Chin. 2020. “An Actor-critic Deep Reinforcement Learning Approach for Metro Train Scheduling with Rolling Stock Circulation Under Stochastic Demand.” Transportation Research Part B: Methodological 140: 210–235. doi:10.1016/j.trb.2020.08.005.

Yinlong, Y., Y. Zhuliang, G. Zhenghui, Y. Yao, W. Wu, D. Xiaoyan, L. Jingcong, and L. Yuanqing. 2019. “A Novel Multi-step Q-learning Method to Improve Data Efficiency for Deep Reinforcement Learning.” Knowledge-Based Systems 175: 107–117. doi:10.1016/j.knosys.2019.03.018.

Yoon, J., S. Kim, Y.-J. Byon, and H. Yeo. 2020. “Design of Reinforcement Learning for Perimeter Control Using Network Transmission Model Based Macroscopic Traffic Simulation.” PloS One 15 (7): e0236655. doi:10.1371/journal.pone.0236655.

Yu, Z., Z. Liang, L. Wei, Z. Jin, J. Huang, D. Cai, X. He, and X.-S. Hua. 2020. “Macar: Urban Traffic Light Control Via Active Multi-Agent Communication and Action Rectification.” In Proceedings of the 29th International Joint Conference on Artificial Intelligence, 2491–2497. Yokohama, Japan.

Zang, X., H. Yao, G. Zheng, N. Xu, K. Xu, and Z. Li. 2020. “Metalight: Value-Based Meta-Reinforcement Learning for Traffic Signal Control.” In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34, 1153–1160. New York, NY, USA.

Zhang, H., S. Feng, C. Liu, Y. Ding, Y. Zhu, Z. Zhou, W. Zhang, et al. 2019. “Cityflow: A Multi-Agent Reinforcement Learning Environment for Large Scale City Traffic Scenario.” In The World Wide Web Conference, 3620–3624. San Francisco, USA.

Zhang, K., F. He, Z. Zhang, X. Lin, and M. Li. 2020. “Multi-Vehicle Routing Problems with Soft Time Windows: A Multi-agent Reinforcement Learning Approach.” Transportation Research Part C: Emerging Technologies 121: Article ID 102861. doi:10.1016/j.trc.2020.102861.

Zhang, R., A. Ishikawa, W. Wang, B. Striner, and O. K. Tonguz. 2021. “Using Reinforcement Learning With Partial Vehicle Detection for Intelligent Traffic Signal Control.” IEEE Transactions on Intelligent Transportation Systems 22 (1): 404–415. doi:10.1109/TITS.6979.

Zhang, C., Y. Liu, F. Wu, B. Tang, and W. Fan. 2021. “Effective Charging Planning Based on Deep Reinforcement Learning for Electric Vehicles.” IEEE Transactions on Intelligent Transportation Systems 22 (1): 542–554. doi:10.1109/TITS.6979.

Zhang, H., C. Liu, W. Zhang, G. Zheng, and Y. Yu. 2020. “Generalight: Improving Environment Generalization of Traffic Signal Control Via Meta Reinforcement Learning.” In Proceedings of the 29th ACM International Conference on Information & Knowledge Management, 1783–1792. Virtual Event, Ireland.

Zhang, E., and N. Masoud. 2021. “Increasing Gps Localization Accuracy with Reinforcement Learning.” IEEE Transactions on Intelligent Transportation Systems 22 (5): 2615–2626. doi:10.1109/TITS.2020.2972409.

Zhang, Q., K. Wu, and Y. Shi. 2020. “Route Planning and Power Management for Phevs with Reinforcement Learning.” IEEE Transactions on Vehicular Technology 69 (5): 4751–4762. doi:10.1109/TVT.25.

Zhang, P., L. Xiong, Z. Yu, P. Fang, S. Yan, J. Yao, and Y. Zhou. 2019. “Reinforcement Learning-based End-to-end Parking for Automatic Parking System.” Sensors 19 (18): 3996. doi:10.3390/s19183996.

Zhao, S., H. Yang, and Y. Wu. 2021. “An Integrated Approach of Train Scheduling and Rolling Stock Circulation with Skip-stopping Pattern for Urban Rail Transit Lines.” Transportation Research Part C: Emerging Technologies 128: Article ID 103170. doi:10.1016/j.trc.2021.103170.

Zheng, G., Y. Xiong, X. Zang, J. Feng, H. Wei, H. Zhang, Y. Li, K. Xu, and Z. Li. 2019. “Learning Phase Competition for Traffic Signal Control.” In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 1963–1972. Beijing, China.

Zhou, D., and V. V. Gayah. 2021. “Model Free Perimeter Metering Control for Urban Networks Using Deep Reinforcement Learning.” In 100th Annual Meeting of the Transportation Research Board. Virtual Event.

Zhou, D., and V. V. Gayah. 2021. “Model-Free Perimeter Metering Control for Two-region Urban Networks Using Deep Reinforcement Learning.” Transportation Research Part C: Emerging Technologies 124: Article ID 102949. doi:10.1016/j.trc.2020.102949.

Zhou, M., J. Jin, W. Zhang, Z. Qin, Y. Jiao, C. Wang, G. Wu, Y. Yu, and J. Ye. 2019. “Multi-Agent Reinforcement Learning for Order-Dispatching Via Order-Vehicle Distribution Matching.” In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 2645–2653. Beijing, China.

Zhou, M., Y. Yu, and X. Qu. 2019b. “Development of An Efficient Driving Strategy for Connected and Automated Vehicles At Signalized Intersections: a Reinforcement Learning Approach.” IEEE Transactions on Intelligent Transportation Systems 21 (1): 433–443. doi:10.1109/TITS.6979.
Zhu, F., and S. V. Ukkusuri. 2014. “Accounting for Dynamic Speed Limit Control in a Stochastic Traffic Environment: A Reinforcement Learning Approach.” Transportation Research Part C: Emerging Technologies 41: 30–47. doi:10.1016/j.trc.2014.01.014.

Zhu, M., Y. Wang, Z. Pu, J. Hu, X. Wang, and R. Ke. 2020. “Safe, Efficient, and Comfortable Velocity Control Based on Reinforcement Learning for Autonomous Driving.” Transportation Research Part C: Emerging Technologies 117: Article ID 102662. doi:10.1016/j.trc.2020.102662.

Zhu, M., X. Wang, and Y. Wang. 2018. “Human-like Autonomous Car-following Model with Deep Reinforcement Learning.” Transportation Research Part C: Emerging Technologies 97: 348–368. doi:10.1016/j.trc.2018.10.024.

Zhu, Z., and H. Zhao. 2021. “A Survey of Deep RL and IL for Autonomous Driving Policy Learning.” IEEE Transactions on Intelligent Transportation Systems 23 (9): 14043–14065. doi:10.1109/TITS.2021.3134702.