# Reinforcement Learning and ABM for Traffic Signal Control: A Literature Review

## 1. Introduction:

Traffic congestion is one of the most common and vexing issues in modern cities. It not only results in significant time wastage but also increases carbon emissions, thereby negatively impacting the environment, which conflicts with UN Sustainable Development Goals ([Goal 11] (https://www.un.org/sustainabledevelopment/cities/)). According to a previous inquiry ‘Transport and the Economy’, the rising cost of congestion would cost the UK economy an extra £22 billion per annum by 2025(‘GOVERNMENT CAN DO MORE TO TACKLE CONGESTION ON UK ROADS, SAY MPS’, 2011).

Control of traffic signals in the existing traffic network can effectively reduce traffic congestion and even reduce fuel consumption and financial expenditures, which claimed by Sunkari in his journal article. The project (Sunkari, 2004) on San Jose Boulevard in Jacksonville, FL, reduced average arterial delay by 35%, result in estimated annual fuel savings of 65,000 gallons and overall annual cost savings of $2.5 million (2001). Another project (Sunkari, 2004) in Burlington, Canada, re-managed the signal pattern in 62 intersections, observed 7% savings in travel time, 6% savings in fuel consumption. And this project demonstrated an annual savings of $1.06 million for delays and fuel consumption alone (2001).

To find out more about the traffic signal pattern with more efficient, this article will try to use mulit-agent-based model and reinforcement learning methods to help release the traffic pressure.

## 2. Basics of Reinforcement Learning and ABM:

(Discuss the key concepts in reinforcement learning and ABM.)

Agent-Based Modeling (ABM) is a computational modeling paradigm that simulates the actions and interactions of individual entities, known as agents, within a system to assess their effects on the system as a whole. In the context of traffic simulation, an agent could represent a vehicle, pedestrian, or traffic signal, each with its own attributes, objectives, and decision-making rules. The power of ABM lies in its ability to model complex systems from the ground up, capturing emergent phenomena that result from the interactions of individual agents.

Reinforcement Learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment. The agent performs actions, receives feedback in the form of rewards or punishments, and adjusts its decisions to maximize the cumulative reward over time. The learning process is guided by the concepts of exploration (trying out new actions) and exploitation (repeating actions that led to high rewards in the past).

In the realm of traffic simulation, RL can be employed to optimize traffic signal timings, route choices, and other operational decisions. For instance, an RL algorithm could learn the optimal traffic signal timings that minimize overall travel time or congestion, based on the feedback received from the simulated traffic conditions. By combining ABM's realistic modeling of traffic flows with RL's ability to learn from interactions, we can potentially develop highly efficient and adaptive traffic management systems.

The following sections will discuss in detail the application of these two paradigms in traffic simulation, focusing on notable studies and their findings.

## 3. Application in Traffic Signal Control:

(Provide a detailed account of the research or applications of reinforcement learning and ABM in traffic signal control.)

There have been many related studies to optimize the traffic signal patterns and there are many ways to optimize the signal pattern to achieve the 11th UN Sustainable Development Goal. Many researchers have made their contribution in this area. Most research mainly has three parts in their methodology. The first part is simulating the urban traffic system by using some methods, the second part is using different methods to investigate the best proper pattern of the traffic signal and the third part of is how to evaluate these methods and how extend it can integrate to the current traffic system.

For the first part, In the context of traffic simulation, ABM (Agent-based model) enables us to model the intricate interactions between different road users - motorists, pedestrians, cyclists, public transportation vehicles, etc., as well as the interaction of these users with traffic control measures such as traffic lights. The application of ABM in traffic simulations brings the promise of capturing the heterogeneity, interactions, and adaptive behaviors of individual agents, thereby offering more realistic traffic flow patterns and congestion scenarios. This method has been proved that is an efficient way to simulate urban transportation in many researches (Dia, 2002; Cools, Gershenson and D’Hooghe, 2008; Shen, Wang and Zhu, 2011; Treiber and Kesting, 2013; Kühnel, Thunig and Nagel, 2018; Thunig, Kühnel and Nagel, 2019; Viridi *et al.*, 2019; Zhang *et al.*, 2019). Thus, ABM is an elegant way to simulate the urban transportation network and it will have a considerable result.

For the second part, traditional traffic signal control methods often adopt fixed-time intervals, which tend to be ineffective in the face of complex and ever-changing urban traffic flows. With the recent advancements in artificial intelligence and machine learning technologies, new tools have emerged to tackle traffic congestion, among which Reinforcement Learning (RL) shows immense potential capabilities (Khamis and Gomaa, 2012, 2014; Sutton and Barto, 2018; Wei *et al.*, 2018; Maadi *et al.*, 2022). Reinforcement Learning is a method of machine learning that enables an agent to learn how to take actions in an environment to maximize some notion of cumulative reward and we can consider the scenario where the traffic network is combined with traffic signals as a game in which agents change the traffic signal pattern to obtain the optimal traffic flow. By employing RL algorithms, we can empower traffic signal control systems to self-learn how to make optimal decisions under various traffic situations, with the goal of minimizing traffic congestion and enhance road traffic efficiency to the greatest extent.

## 4. Discussion on Selected Literature:

(Discuss the selected literature in detail, focusing on the methodology, problems addressed, and results obtained.)

In this section, we'll delve deeper into the exploration of selected key studies and their findings, focusing on the application of ABM and RL in traffic simulations.

Agent-based Modelling (ABM) has progressively evolved to become a key approach in simulating traffic scenarios, with a range of studies applying the method to various traffic-related issues. For instance, Dia's (Dia, 2002) research demonstrates an innovative use of ABM in modelling driver route choice behavior under the influence of real-time traffic information. The study showcases the effectiveness of ABM in representing adaptive and individualized driver decision-making processes, a central characteristic of real-world traffic scenarios. However, the complexity and individuality of driver behavior, as indicated in Dia's study, signal that more research is needed in refining ABM parameters and improving its realism.

(Viridi *et al.*, 2019) applied ABM to simulate traffic flow in a single-lane setup with multiple traffic lights and input-output nodes. Their findings reveal ABM's potential in simulating real-world traffic conditions and phenomena. Yet, the study predominantly focused on single-lane simulations, implying a research gap in exploring ABM's application in more complex multi-lane scenarios.

(Zhang *et al.*, 2019) integrated ABM with data-driven methods to present a distributed adaptive cooperative control for urban traffic signal timing. The data-driven approach showcased in their study introduces a promising avenue to enhance ABM's capability by integrating real-time traffic data. This hints at a potential research gap in further merging ABM with real-time data incorporation techniques for more accurate and adaptive traffic simulations.

(Thunig, Kühnel and Nagel, 2019) also utilized ABM to implement an adaptive traffic signal control in real-world scenarios. They successfully showcased that adaptive signal control reduced delays and stabilized queue lengths more than fixed-time signals. However, the study noted that in situations of overload, adaptive signal control behaves similar to fixed-time control. This finding poses a question regarding ABM's efficacy in extremely dense traffic situations, suggesting an area for further exploration.

Taken together, these studies illustrate the promising capabilities of ABM in traffic simulations but also highlight areas requiring further research. Specifically, the need to improve the realism of agent behavior, explore multi-lane traffic scenarios, integrate real-time data more effectively, and enhance the model's performance under extreme traffic conditions, are all areas warranting attention. Such discussions further emphasize the need for ongoing research in applying and enhancing ABM for traffic simulations.

Moving to the RL combined with ABM side, the integration of reinforcement learning (RL) and agent-based modelling (ABM) in traffic light control is a burgeoning field of research with noteworthy contributions. Some existing literature also reveals areas of potential exploration.

(Wei *et al.*, 2018) proposed an advanced deep RL model for traffic light control, offering an important perspective on real-time adaptive control systems. The research highlights the untapped potential in applying RL to real-world traffic data, but the lack of interpretability of the learned policies indicates a possible research gap. Understanding the decisions made by RL agents in traffic light control scenarios would foster a better comprehension of their strengths and limitations, thereby supporting their improvement.

(Maadi *et al.*, 2022) developed a RL-based adaptive traffic signal control, combining a speed guidance system with a RL traffic signal control. This approach offers a unique perspective on the intersection of Connected and Automated Vehicles (CAVs) with RL, showing its efficacy in reducing traffic congestion. However, this study signals a need for further research on the integration of RL with emerging traffic environments, particularly in the presence of CAVs.

In a similar vein, (Wang, Cao and Hussain, 2021) proposed a Cooperative Group-Based Multi-Agent RL traffic signal control (CGB-MATSC) framework. The study illustrates the application of RL in managing complex road networks, yet it also reveals challenges in coordinating agents within such environments. The research gap in addressing these coordination demands could offer a promising avenue for future exploration.

Furthermore, (Khamis and Gomaa, 2012, 2014) applied multi-objective RL to traffic light control within a multi-agent framework. The research offers an insightful perspective on minimizing trip time and enhancing environmental impacts, showcasing the potential benefits of RL in addressing multiple objectives in traffic light control. Despite these advancements, the studies indicate the need for more in-depth exploration into multi-objective RL for traffic signal control, particularly with respect to adaptability in changing road dynamics and varying traffic demand.

In conclusion, existing literature demonstrates the potential of RL and ABM for adaptive traffic light control while indicating areas for further exploration, including the interpretation of RL policies, integration with CAVs, agent coordination in complex networks, and adaptability in multi-objective scenarios. Further research in these areas would contribute to the development of more efficient and effective traffic management systems.

## 5. Conclusion and Future Works:

(Conclude the review and discuss potential future directions in the application of reinforcement learning to traffic signal control.)

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