# Reinforcement Learning and ABM for Traffic Signal Control

## 1. Introduction:

### 1.1 Background and Motivation

With the development of modern cities, more and more cars are driving in the traffic system, which not only results in significant time and economy wastage but also increases carbon emissions. As the UK Transportation Committee Chair Louise Ellman reported in 2011 said,” Congestion costs the economy billions of pounds each year”. Based on a previous inquiry, 'Transport and the Economy' shows that, by 2025, the cost of congestion will rise to an extra £22 billion per annum[[link](https://committees.parliament.uk/committee/153/transport-committee/news/177672/etm-report/)](‘GOVERNMENT CAN DO MORE TO TACKLE CONGESTION ON UK ROADS, SAY MPS’, 2011). Thus, reducing traffic congestion is necessary and it is helpful for us to follow the UN Sustainable Development Goals.

One of the effect ways to reduce traffic congestion is the control of traffic signals in the existing traffic network. As Sunkari mentioned 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 in 2001. And 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 annual savings of $1.06 million for delays and fuel consumption alone in 2001.

Therefore, it is of great significance to explore the optimization of traffic signal patterns in order to reduce economic and energy costs and make it possible to reach the UN Sustainable Development Goals faster. However, how to better optimize traffic light patterns has become a hot topic.

### 1.2 Research Question and Objectives

With the development of artificial intelligence, reinforcement learning shows its potential in decision and strategy making (Sutton and Barto, 2018). For traffic signal control, reinforcement learning enables signal control systems to dynamically adjust signal patterns based on real-time traffic conditions to achieve the goal of reducing congestion and optimizing traffic efficiency (Wei *et al.*, 2018; Wei, Chen, *et al.*, 2019; Wei, Xu, *et al.*, 2019; Zheng *et al.*, 2019; Chen *et al.*, 2020; Jamil, Ganguly and Nower, 2020). Furthermore, as a traditional simulation model, agent-based model has made a great contribution to traffic simulation (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, the optimization of traffic signal patterns by combining agent-based model and reinforcement learning is a worthwhile research topic.

In order to contribute to the research in this field, the main aim of this paper is to try to come up with a traffic signal pattern which can reduce traffic congestion based on the traffic flow data of London. Hence, the corresponding basic research questions are put forward as follows:

What is the best strategy of the traffic signal when the intersection faced with different kinds of traffic flow?

Guided by this main question, there are several objectives for this paper which we list according to the analytical steps in this research. These are as follows:

1. Review the relevant literature and empirical studies on the use of reinforcement learning and agent-based model methods to optimize the traffic signal pattern.

2. Establish an agent-based model to simulate the scene of the intersection in the traffic network.

3. Define the reinforcement learning algorithm and train the model to get the optimal pattern of the traffic signal.

4. Quantitatively measure the result compared with the pre-defined traffic signal pattern.

5. Expand the method to the London traffic network and evaluate the result.

### 1.3 Research Scope

This study will focus on finding optimal traffic signal patterns using RL (reinforcement learning) and ABM (agent-based models). The research will focus on intersections to study the optimal control strategies for signals under different traffic flow patterns. The study does not include the control of other traffic control devices, such as road signs and crosswalks. Also, the study does not consider the influence of some microscopic traffic factors, such as pedestrians.

The geographic data and statistical data on London's transportation network used in this study are obtained from the London Department of Statistics. The time period is xxxx

### 1.4 Report Structure

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## 2. Literature review

There have been many related studies to optimize the traffic signal patterns and there are many ways to optimize the signal. 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 most 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. Depending on the different aspects, I discuss some of relative literatures with the following sections.

### 2.1 The analysis of the traffic system

In contemplating urban traffic network congestion, various methods can be employed to evaluate the traffic system. The majority of current research simplifies the network into a topology composed of nodes and edges for the analysis and assessment of road networks. Notably, contributions from Zhao Tian and his team shed light on this aspect(Tian *et al.*, 2016). They took the road traffic network of Beijing as an example to illustrate the impact of different topological structures on traffic efficiency. In their study, they proposed three different network models: the road length-weighted network model, the road traffic capacity-weighted network model, and the road traffic efficiency-weighted network model. Through data analysis of these models, they explicated the influence of distinct road characteristics, traffic capacity, and traffic efficiency on traffic flow. Their research attempted to fill the gaps in previous studies, which had overlooked factors such as road characteristics, traffic capacity, and traffic efficiency, all of which could affect the traffic performance of road sections. Their study ultimately proved that the weighted network model could effectively describe the performance characteristics of roads under different topological structures and traffic loads.

In the meantime, Mengyao Zhang and her team attempted to use complex network theory for traffic network system analysis(Zhang *et al.*, 2022). They applied methods such as centrality measurement for local and global network analysis. However, they focused on network robustness, thus details of their research were not extensively discussed. Nonetheless, their study confirmed that simplifying real-world networks into topological networks is an effective approach for traffic network analysis.

In addition, some insightful work has been conducted by Allister Loder(Loder *et al.*, 2019). As heavy congestion in current urban traffic networks leads to exacerbating congestion issues, Allister Loder endeavored to evaluate the system by analyzing the capacity of the urban traffic network, discovering the relationship between congestion and capacity, and ultimately resolving congestion issues. Compared to traditional research, Allister Loder paid more attention to the presence of congestion points in urban networks. He employed a regression-based method to accurately calculate the total congestion points and combined urban traffic critical point analysis with modern high-tech methods such as analyzing OpenStreetMap data, using observational weight calculation, data fitting goodness analysis, which led to pioneering results. Despite the limited universality of the research results and relatively small sample size, the proposed method is feasible and offers significant guidance for future urban traffic network construction and planning. Allister Loder's work focuses more on the microscopic aspects of the network system and holds more practical significance compared to simplified topological models.

In terms of traffic flow description, Mathew, T. V. emphasized the traffic stream model in his book "Transportation Engineering I"(Tom, 2006). The Greenshield’s macroscopic stream model, in particular, can quantify traffic flow directly into a mathematical model, enabling us to evaluate road performance more intuitively through numerical calculation, such as the average waiting time for vehicles, average speed, throughput, and so on. In addition, based on this model, some research has proposed congestion solutions dominated by the "green wave"(Zheng *et al.*, 2020; Bloder and Jäger, 2021). The core idea is to create a continuous green light environment in a short time, allowing unidirectional traffic to pass at extremely high speeds, ultimately making the road network operate efficiently.

Overall, the fluidity of a traffic system can be evaluated from various angles. This study will use quantitative methods to analyze the smoothness of the road network, evaluating the network's operational efficiency based on factors such as average vehicle speed, average vehicle waiting time, and others.

### 2.2 The application of ABM in traffic system simulation

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.

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.

### 2.3 The application of RL in investigation of the traffic signal

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).

(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.

### 2.4 Conclusion

In summary, the existing literature shows that suitable adaptation of traffic light patterns can help alleviate traffic stress and the potential of RL and ABM for adaptive traffic light control, while pointing out areas that need further exploration, including the interpretation of RL strategies, agent coordination in complex networks, and adaptation in multi-objective scenarios, with applications to microscopic scenarios still lacking. Further research in these areas will contribute to the development of more efficient and effective traffic management systems. Therefore, this study attempts to fill this gap in microscopic traffic intersections.

## 3. Methodology

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## 4. Results and Discussion

## 5. Conclusion

## Reference

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