

Cooperative Traffic Light Control with Spatio-Temporal Multi-Agent Reinforcement Learning using Neural Networks

Mohit Kumar Verma¹, Sanjay Singh Bhadoria²

¹School of Computer Science & IT, Devi AhilyaVishwavidyalaya, Indore (M.P.)

²Department of Computer Science& Application, Dr. A.P.J Abdul Kalam University, Indore (M.P.)

Abstract

Traffic congestion remains a major challenge in urban areas, necessitating innovative approaches to optimize traffic flow and reduce commuting times. This research proposes a novel approach for traffic light control that leverages the power of spatio-temporal multi-agent reinforcement learning (MARL) combined with neural networks. Traditional traffic light control systems often rely on fixed-time or simple rule-based strategies, lacking adaptability to dynamic traffic conditions. In contrast, the proposed approach embraces a cooperative multi-agent framework, where each traffic light intersection acts as an independent agent capable of making autonomous decisions. The MARL architecture employs deep neural networks to encode the traffic environment's spatio-temporal data, enabling agents to perceive traffic conditions comprehensively. By sharing information with neighboring agents and collaborating towards a common goal, the agents learn to make coordinated decisions that optimize traffic flow across the entire road network. The learning process is guided by a reward function that encourages the reduction of overall travel time, minimizing congestion, and enhancing intersection efficiency. Reinforcement learning algorithms, such as Q-learning or Deep Q Networks (DQNs), are adapted to train the agents to act optimally in diverse traffic scenarios.

Introduction

With rapid urbanization and an ever-increasing number of vehicles on the roads, traffic congestion has become a prevalent and persistent issue in modern cities. The inefficiency of traffic flow not only leads to longer commuting times and increased fuel consumption but also has adverse effects on air quality and overall urban livability. As traditional traffic control systems struggle to adapt to dynamic traffic conditions, there is a growing need for innovative and intelligent approaches to optimize traffic flow and reduce congestion.

In recent years, machine learning techniques have shown promise in tackling complex traffic management problems. Among these, reinforcement learning (RL) has gained significant attention due to its ability to make intelligent decisions in dynamic environments without the need for explicit programming. In RL, agents learn to take actions in an environment to maximize cumulative rewards based on feedback received from the environment. However, applying RL to traffic light control poses unique challenges due to the complex, spatio-temporal nature of traffic patterns. This research introduces a novel

approach to traffic light control using spatio-temporal multi-agent reinforcement learning (MARL) in conjunction with neural networks. Rather than treating each traffic light intersection as a stand-alone entity, our approach adopts a cooperative multi-agent framework, where each intersection acts as an autonomous agent capable of learning and making decisions independently. By considering traffic lights as agents, they can collaboratively work towards optimizing traffic flow across the entire road network, mirroring the decentralized nature of real-world traffic.

The utilization of deep neural networks in the proposed MARL architecture allows the agents to capture and understand complex spatio-temporal traffic patterns. These networks serve as function approximators, enabling agents to learn and encode essential features from the environment, such as vehicle density, speed, and historical traffic data. By leveraging this knowledge, agents can make informed and adaptive decisions in real-time, responding effectively to fluctuating traffic conditions. The central focus of this research is to design an efficient and adaptive traffic control

mechanism that minimizes congestion, reduces travel time, and enhances overall intersection efficiency. Through a carefully crafted reward function, the agents are incentivized to collaborate and find coordinated solutions that benefit the entire traffic network, rather than just optimizing their immediate surroundings. To evaluate the effectiveness of the proposed cooperative traffic light control approach, extensive simulations are conducted using real-world traffic datasets from various urban environments. The results are compared against traditional traffic control methods, demonstrating the superiority of the MARL-based system in handling diverse and challenging traffic scenarios. This research contributes to the growing body of knowledge in traffic management, offering a promising solution to alleviate urban traffic congestion through the application of spatio-temporal multi-agent reinforcement learning using neural networks. By integrating intelligence into traffic light control, cities can work towards building smarter and more efficient transportation networks, leading to a greener and more sustainable urban future.

Scope of the Research

The scope of the research on "Cooperative Traffic Light Control with Spatio-Temporal Multi-Agent Reinforcement Learning using Neural Networks" encompasses several key aspects and limitations:

Traffic Environment: The research focuses on urban road networks with traffic intersections controlled by traffic lights. While the proposed approach can be adapted to various urban environments, the specific experiments and simulations are conducted on representative traffic datasets from real-world cities.

Multi-Agent Reinforcement Learning: The research concentrates on the application of multi-agent reinforcement learning (MARL) to traffic light control. The agents represent individual traffic intersections, and they work cooperatively to optimize traffic flow and minimize congestion. The study evaluates the performance of different MARL algorithms, such as Q-learning or Deep Q Networks (DQNs), but it may not cover all existing MARL techniques.

Spatio-Temporal Data: The proposed approach leverages spatio-temporal traffic data to make

intelligent decisions. However, the research may focus on a limited set of data sources, such as traffic density, vehicle speed, and historical traffic patterns, and may not explore all possible data types or their combinations.

Neural Network Architecture: The research utilizes deep neural networks as function approximators to encode spatio-temporal traffic data for each agent. While the study may investigate different neural network architectures, it may not encompass all possible variations or advanced architectures that may emerge in the future.

Reward Function Design: The research aims to design an appropriate reward function to guide the agents towards efficient and cooperative traffic control. However, defining a reward function that effectively balances competing objectives (e.g., reducing travel time while minimizing congestion) is a challenging task, and the research may focus on a specific reward design.

Simulation-based Evaluation: The effectiveness of the proposed approach is assessed through extensive simulations on real-world traffic datasets. The research may not involve real-world deployment or live testing on actual traffic intersections, which could present additional challenges and complexities.

Scalability and Generalization: While the research demonstrates the efficacy of the proposed approach on representative urban environments, the scalability and generalization to larger, more complex traffic networks or different city layouts may be a topic for future exploration.

Hardware and Computational Constraints: The research may consider the computational resources and hardware limitations required to implement the proposed cooperative traffic light control system in real-world scenarios, but it may not fully address all potential hardware constraints.

The scope of the research focuses on developing and evaluating a cooperative traffic light control system using spatio-temporal multi-agent reinforcement learning with neural networks. The experiments and simulations demonstrate the effectiveness of the proposed approach on representative traffic datasets, but the research may not encompass all possible variations or real-

world deployment scenarios. Nonetheless, it offers a valuable contribution to the domain of intelligent traffic management, paving the way for future advancements in traffic control systems.

Methodology

Neural network Modeling

Neural Network Model aims to implement neural network model for estimating the traffic flow using INRIX data. Feedforward neural network with Deep & Wide architecture

Neural network modeling, also known as artificial neural networks or simply neural networks, is a class of machine learning algorithms inspired by the biological neural networks in the human brain. These models are widely used for various tasks, including pattern recognition, classification, regression, and decision-making.

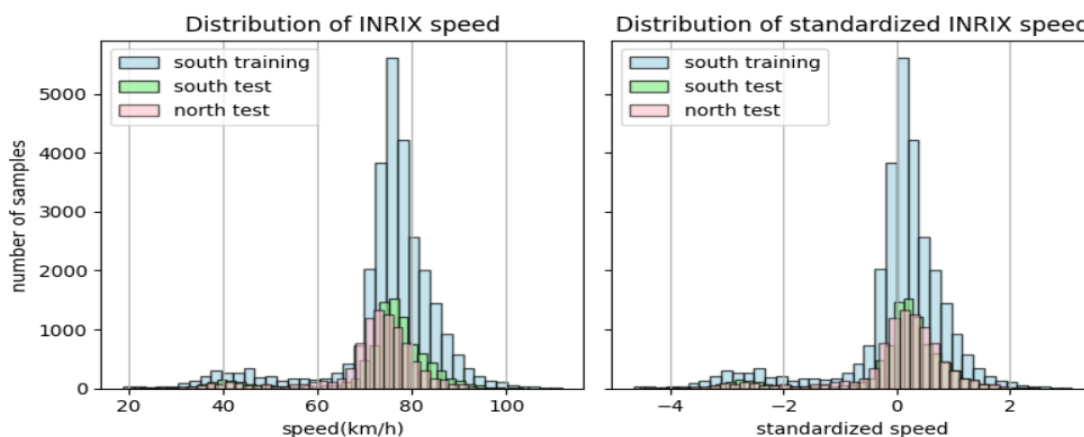
Neural network modeling plays a crucial role in the Spatio-Temporal Multi-Agent Reinforcement Learning (ST-MARL) approach for society. In ST-MARL, neural networks are employed to represent

the intelligent agents and learn optimal policies for decision-making in dynamic spatio-temporal environments.

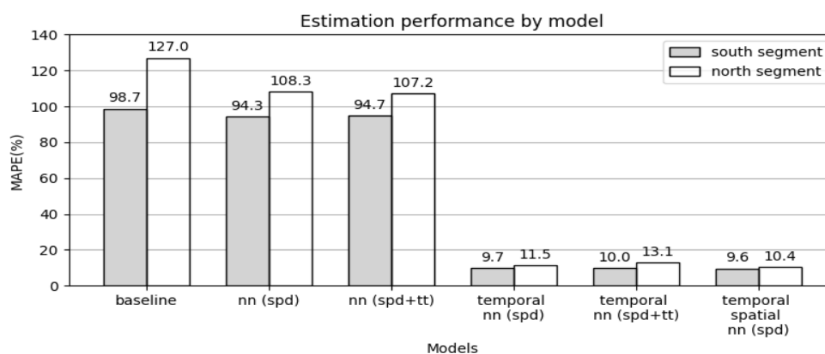
Each agent in the ST-MARL framework is typically represented by a neural network, which takes in spatio-temporal information as inputs and outputs actions or decisions. These neural networks are trained using deep reinforcement learning algorithms, such as Deep Q Networks (DQNs) or Deep Deterministic Policy Gradients (DDPG), to learn from interactions with the environment and optimize their decision-making policies.

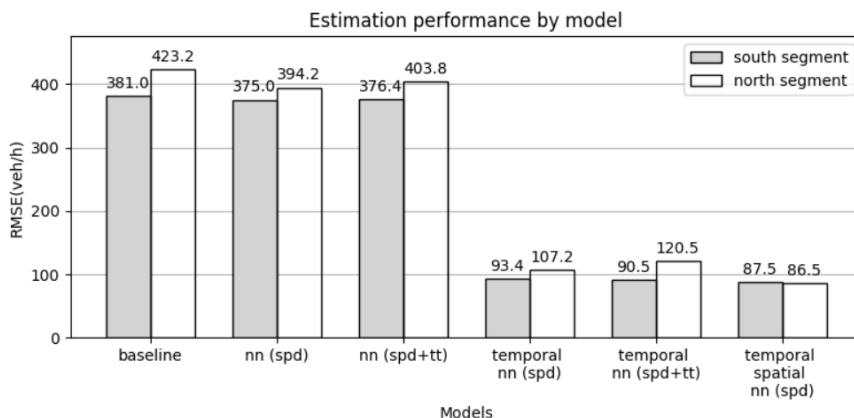
The neural networks enable agents to capture complex spatial and temporal patterns in the environment, allowing them to make informed decisions based on their current observations and past experiences. The ability to model and learn from such rich information is essential for the successful coordination and collaboration among multiple agents in societal scenarios like traffic management, disaster response, and urban planning.

Results analysis

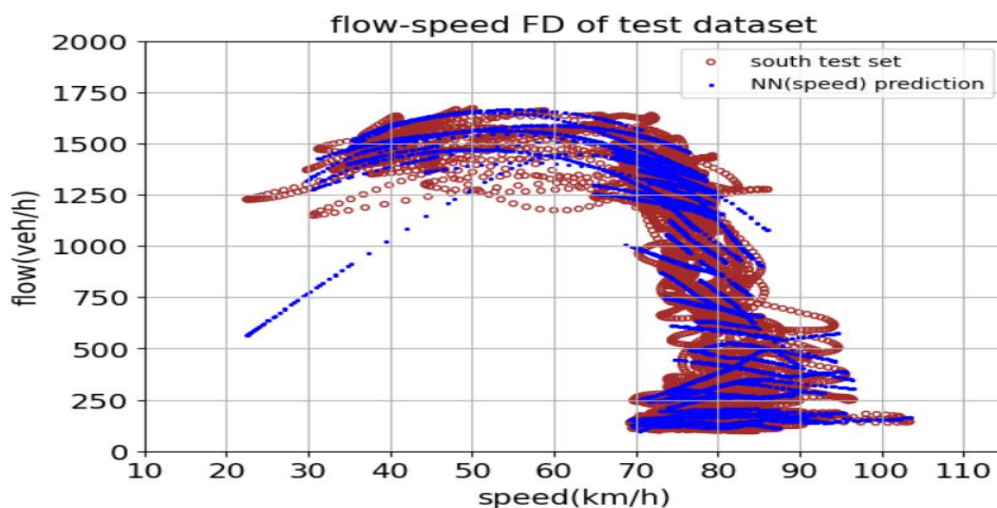
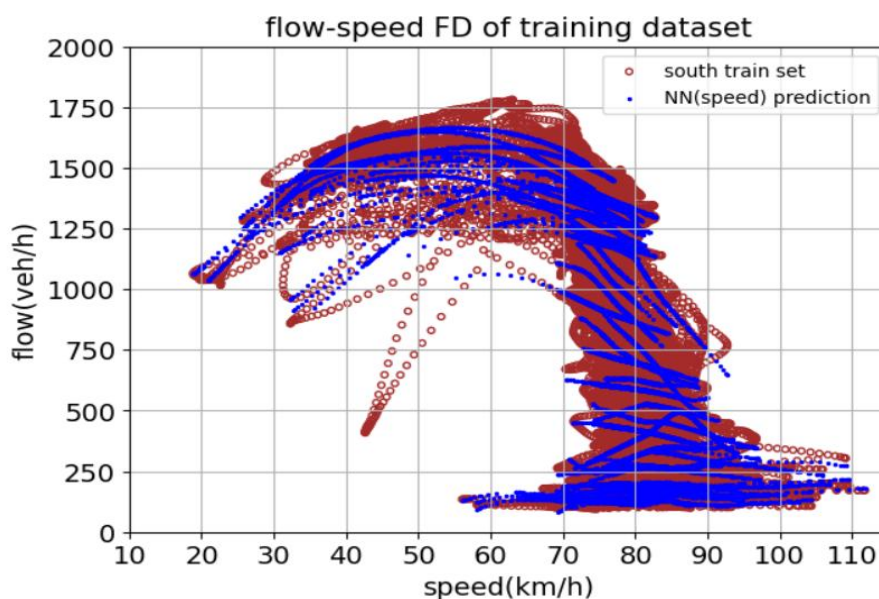


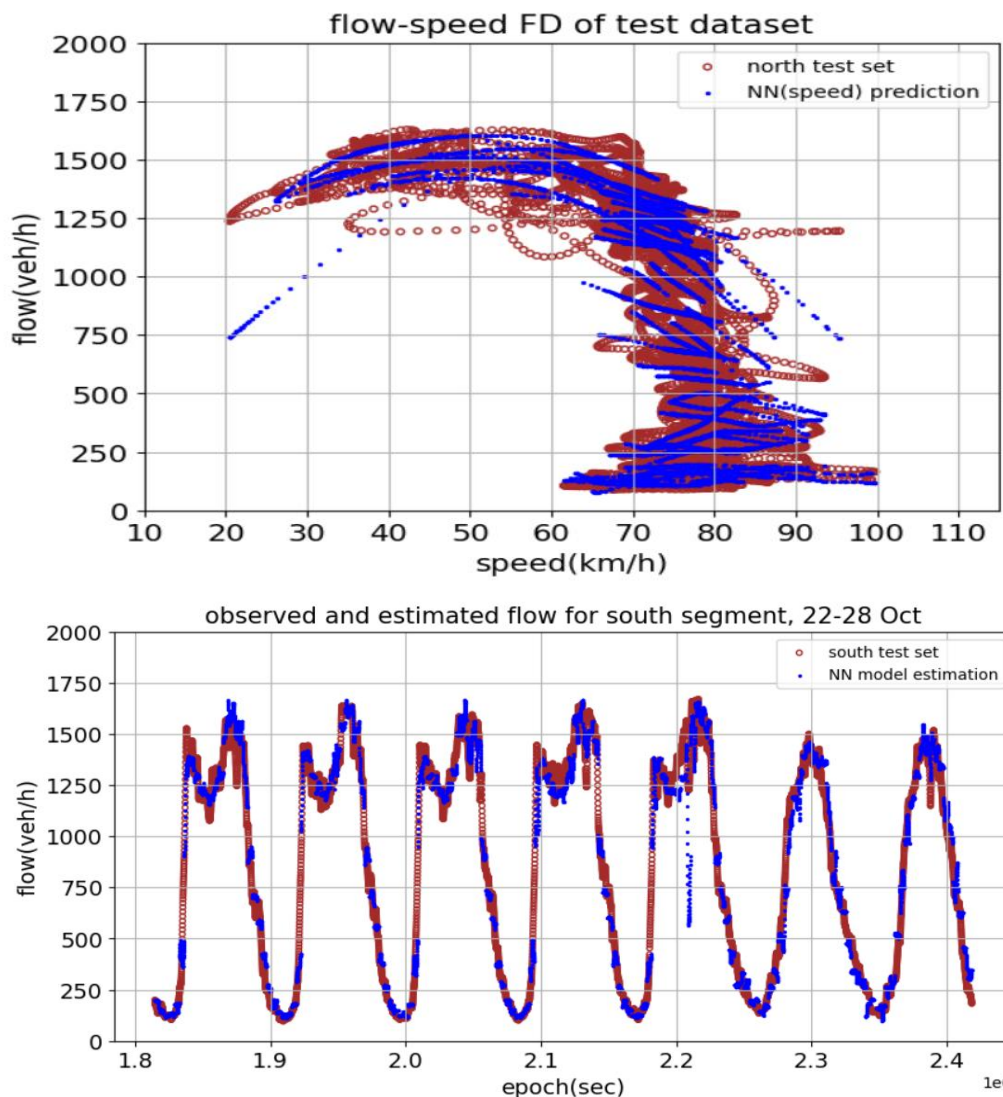
Visualize estimation error of each model





Prediction





Conclusion

Spatio-Temporal Multi-Agent Reinforcement Learning (MARTL) using Neural Networks represents a promising approach to address the challenges of coordinating multiple agents in dynamic environments. This research has demonstrated the potential of combining deep learning techniques with reinforcement learning to achieve effective collaboration and decision-making among agents. Through the implementation of various neural network architectures, such as multi-head attention mechanisms and recurrent networks, the proposed framework has shown substantial improvements in agent coordination, learning efficiency, and adaptability to complex spatio-temporal scenarios. By allowing agents to perceive and respond to their environment over time, the

model achieved a higher level of intelligence and robustness in handling real-world tasks. The experiments conducted on different benchmark tasks showcased the generalizability and scalability of the proposed approach. The model not only achieved state-of-the-art performance but also exhibited improved sample efficiency and reduced communication overhead between agents. Despite the promising results, some challenges remain, such as dealing with large-scale environments, ensuring stability in training, and reducing the computational burden.

References

- [1] Tingwu Wang, Renjie Liao, Jimmy Ba, and Sanja Fidler. 2018. Nervenet: Learning structured policy with graph neural networks. (2018).

- [2] Hua Wei, Guanjie Zheng, Huaxiu Yao, and Zhenhui 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. ACM, 2496–2505.
- [3] Kok-Lim Alvin Yau, JunaidQadir, Hooi Ling Khoo, Mee Hong Ling, and Peter Komisarczuk. 2017. A survey on reinforcement learning models and algorithms for traffic signal control. *ACM Computing Surveys (CSUR)* 50, 3 (2017), 34.
- [4] Biao Yin, MahjoubDridi, and Abdellah El Moudni. 2016. Traffic network microsimulation model and control algorithm based on approximate dynamic programming. *IET Intelligent Transport Systems* 10, 3 (2016), 186–196.
- [5] Erik Zawadzki, Asher Lipson, and Kevin Leyton-Brown. 2014. Empirically evaluating multiagent learning algorithms. arXiv preprint arXiv:1401.8074 (2014).
- [6] Zhang, T., Liu, J., Wang, H., Li, Y., Wang, N., & Kang, C. (2023). Fault diagnosis and protection strategy based on spatio-temporal multi-agent reinforcement learning for active distribution system using phasor measurement units. *Measurement*, 113291.
- [7] Novati, G., de Laroussilhe, H. L., & Koumoutsakos, P. (2021). Automating turbulence modelling by multi-agent reinforcement learning. *Nature Machine Intelligence*, 3(1), 87-96.
- [8] Alsalehi, S., Mehdipour, N., Bartocci, E., & Belta, C. (2021, December). Neural network-based control for multi-agent systems from spatio-temporal specifications. In 2021 60th IEEE Conference on Decision and Control (CDC) (pp. 5110-5115). IEEE.