同行专家业内评价意见书编号：20250861032

附件1

浙江工程师学院（浙江大学工程师学院）
同行专家业内评价意见书

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申报工程师职称专业类别（领域）：交通运输

浙江工程师学院（浙江大学工程师学院）制

2025年05月21日

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一、个人申报

（一）基本情况【围绕《浙江工程师学院（浙江大学工程师学院）工程类专业学位研究生工程师职称评审参考指标》，结合该专业类别(领域)工程师职称评审相关标准，举例说明】

1.对本专业基础理论知识和专业技术知识掌握情况(不少于200字)

本人在浙江大学工程师学院智慧交通项目制就读期间，修读了“智慧交通仿真实践”、“智能交通系统与实践应用”等相关专业课程，系统掌握了交通管理、交通规划、交通信息、交通控制等方向的基础理论知识，熟悉自动驾驶、人工智能与大数据融合、车路云一体化发展等智慧交通发展趋势与前沿技术。本人能够熟练运用SUMO、VISSIM构建城市道路网络，模拟交通流运行情况并做出分析。本人在硕士阶段重点研究城市道路交通信号控制问题，能够利用优化理论构建基于模型的交通信号控制算法（如绿波带算法），能够利用深度强化学习理论构建强自适应的智能信控算法。作为拓展，本人学习并掌握了网络聚类、图结构数据补全等方法与技术，并能将其应用于解决交通流控制问题当中。

2.工程实践的经历(不少于200字)

本人在2023年杭州亚运会期间，作为算法实习生，参与了浙江云通数达科技有限公司的亚运数智交通保畅专班，从事基于SCATS系统的智慧信号灯项目的配时计算优化设计和道路测试工作。具体内容为：参与信号配时算法优化，撰写在不同饱和度情况下调整绿信比或周期的规则；参与路测实时信控方案下发，记录及分析路测数据；基于从高德智慧交通平台导出的路段分钟级车速拥堵指数数据对路测结果进行分析。以上工作对于整个专班的技术应用创新和成果转化做出了贡献，最终专班也取得了26条亚运数字专用车道，255条数智绿波，49182班次赛事车辆100%准点等成绩，并且在全天90%以上的时间都允许社会车辆通行，带来了极为可观的经济和社会效益。

3.在实际工作中综合运用所学知识解决复杂工程问题的案例（不少于1000字）

一、问题背景与难点分析

当前，在基于SCATS系统的交通信号配时算法优化实践中，经典绿波带宽优化模型（如MAXBAND、MULTIBAND等）被广泛采用，且已被证明能够在一定程度上提升道路交通控制效率。然而，这类模型存在明显的缺陷，包括但不限于：（1）其优化目标——带宽，是一个抽象概念，与延误、停车次数等直观交通评价指标之间没有直接关联；（2）对于存在较多路口或较长路段的道路，各路口信号协调难度高，可能出现无解的问题。另外，实际工作中常用的模型求解算法（如分支定界法）过于传统，存在计算复杂度高、收敛速度慢、难以处理非线性或非凸问题等不足，也亟待优化。

在亚运数智交通保畅专班的智慧信号灯项目中，我们旨在直接优化目标道路的延误、停车次数等直观交通评价指标，并进一步提升优化效果，以满足不同场景或任务的需求。技术难点在于如何准确地将不同优化目标与其它交通变量之间的关系构建出来，构成模型的约束条件，并做到快速、准确的求解，得到最优的信号配时时段方案。

二、技术路线与解决过程

为了构建多优化目标的干道信号协调控制方法，我们的技术路线是结合延误/停车次数优化模型与启发式算法，首先在交通仿真环境中进行性能验证，然后应用于实际道路的控制。具体的解决过程如下：

（1）与企业团队确定问题需求以及具体研究目标，查阅相关文献，充分调研并总结了文献中延误、停车次数等不同优化目标与路段长度、路段车流量、路段车流转向比、信号灯周期及绿信比等参数之间的约束条件构建思路和方法。

（2）结合图解法、数解法等，推导出可切换多优化目标的干道信号协调控制模型，并使用P

ython语言完成了代码实现。
（3）对优化算法，即启发式算法进行充分调研，选择并构建了改进遗传算法，用于模型求解。改进遗传算法通过自适应机制、混合策略、并行化等技术，显著提升了传统遗传算法的效率、精度和鲁棒性，尤其在处理现实中的复杂优化问题时表现突出。为了提升算法适用性，对应用于求解干道信号协调控制模型的改进遗传算法进行了参数设计。
（4）根据云通数达团队提供的真实道路案例（包括道路结构数据与车流量数据），在SUMO交通仿真环境中对不同优化目标下的模型性能进行验证，同时与MAXBAND、MULTIBAND等经典模型进行比较，最后总结并分析实验结果。
（5）考虑到现实路网中部分路口或路段的传感设备缺失或故障，将多优化目标的干道信号协调控制模型应用于现实道路的控制之前，还需完成交通感知数据扫盲补缺工作，具体内容包括：利用浮动车数据进行卡口位置纠偏；ETC设备数据收集；杭州市区主要路口灯态数据收集；亚运专用道路段车速数据异常排查。
（6）排除各种干扰因素后，参与路测实时信控方案下发，记录并分析路测数据。
三、实施成效
将所构建的多优化目标的干道信号协调控制模型在杭州市区多条干道部署，取得了26条亚运数字专用车道，255条数智绿波，49182班次赛事车辆100%准点等成绩，并且在全天90%以上的时间都允许社会车辆通行，实现了对社会面交通的最小干预，最大限度“还路与民”，实现了赛事交通与城市交通车畅人欢，实现了交通安全“五个确保”，带来了极为可观的经济和社会效益。

（二）取得的业绩（代表作）【限填3项，须提交证明原件（包括发表的论文、出版的著作、专利证书、获奖证书、科技项目立项文件或合同、企业证明等）供核实，并提供复印件一份】					
1. 公开成果代表作【论文发表、专利成果、软件著作权、标准规范与行业工法制定、著作编写、科技成果获奖、学位论文等】					
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Network Clustering-based Multi-agent Reinforcement Learning for Large-scale Traffic Signal Control	会议论文	2023年12月27日	2023 International Annual Conference on Complex Systems and Intelligent Science (CSIS-IAC)	1/3	EI会议收录
一种面向高峰时段拥堵的大规模自适应交通信号控制方法	发明专利申请	2024年05月27日	申请号：CN 202410659837.0	2/5	实审中
一种可实时补全缺失观测的强适应性路网级交通信号控制方法	发明专利申请	2024年05月27日	申请号：CN 202410659835.1	2/5	实审中

2. 其他代表作【主持或参与的课题研究项目、科技成果应用转化推广、企业技术难题解决方案、自主研发设计的产品或样机、技术报告、设计图纸、软课题研究报告、可行性研究报告、规划设计方案、施工或调试报告、工程实验、技术培训教材、推动行业发展中发挥的作用及取得的经济社会效益等】

（三）在校期间课程、专业实践训练及学位论文相关情况	
课程成绩情况	按课程学分核算的平均成绩： 83 分
专业实践训练时间及考核情况(具有三年及以上工作经历的不作要求)	累计时间： 1.1 年（要求1年及以上） 考核成绩： 86 分
本人承诺	
个人声明：本人上述所填资料均为真实有效，如有虚假，愿承担一切责任，特此声明！ 申报人签名：陶治成	

2226017/-

二、日常表现考核评价及申报材料审核公示结果

日常表现考核评价	非定向生由德育导师考核评价、定向生由所在工作单位考核评价： ☑优秀　　□良好　　□合格　　□不合格 德育导师/定向生所在工作单位分管领导签字（公章）：　　年　月　日
申报材料审核公示	根据评审条件，工程师学院已对申报人员进行材料审核（学位课程成绩、专业实践训练时间及考核、学位论文、代表作等情况），并将符合要求的申报材料在学院网站公示不少于5个工作日，具体公示结果如下： □通过　　□不通过（具体原因：　　　　　　） 工程师学院教学管理办公室审核签字（公章）：　　年　月　日

浙 江 大 学 研 究 生 院

攻读硕士学位研究生成绩表

学号：22260197	姓名：陶治成	性别：男	学院：工程师学院	专业：交通运输	学制：2.5年
毕业时最低应获：24.0学分		已获得：27.0学分		入学年月：2022-09	毕业年月：
学位证书号：			毕业证书号：		授予学位：

学习时间	课程名称	备注	学分	成绩	课程性质	学习时间	课程名称	备注	学分	成绩	课程性质
2022-2023学年秋季学期	研究生英语		2.0	免修	公共学位课	2022-2023学年冬季学期	智慧交通仿真实践		1.0	90	专业选修课
2022-2023学年秋季学期	工程技术创新前沿		1.5	72	专业学位课	2022-2023学年冬季学期	新时代中国特色社会主义理论与实践		2.0	90	公共学位课
2022-2023学年秋季学期	数值计算方法		2.0	93	专业选修课	2022-2023学年冬季学期	产业技术发展前沿		1.5	87	专业学位课
2022-2023学年秋季学期	研究生英语能力提升		1.0	免修	跨专业课	2022-2023学年春季学期	数学建模		2.0	60	专业选修课
2022-2023学年秋季学期	研究生英语基础技能		1.0	免修	公共学位课	2022-2023学年春季学期	自然辩证法概论		1.0	85	公共学位课
2022-2023学年秋冬学期	工程伦理		2.0	89	公共学位课	2022-2023学年夏季学期	研究生论文写作指导		1.0	95	专业学位课
2022-2023学年秋冬学期	信息安全前沿技术与研究方法论		2.0	82	跨专业课	2022-2023学年夏季学期	智能交通系统与实践应用		2.0	91	专业学位课
2022-2023学年秋冬学期	高阶工程认知实践		3.0	77	专业学位课		硕士生读书报告		2.0	通过	

说明：1. 研究生课程按三种方法计分：百分制，两级制（通过、不通过），五级制（优、良、中、及格、不及格）。

2. 备注中“*”表示重修课程。

学院成绩校核章：

成绩校核人：张梦依

打印日期：2025-06-03

浙江大学研究生院（60）成绩校核章

Network Clustering-Based Multi-Agent Reinforcement Learning for Large-Scale Traffic Signal Control

Publisher: IEEE

Zhicheng Tao ; Chao Li ; Qinmin Yang All Authors

Abstract:
Reinforcement learning (RL) has proven successful in the field of traffic signal control (TSC) within urban traffic networks. Moreover, multi-agent RL (MARL) achieves large-scale TSC by distributing the global control to each local RL agent. However, as the scale of joint TSC continues to expand, MARL faces greater convergence challenges. In this paper, a method combining network clustering and MARL is proposed to address this issue. We apply the Normalized Cut (Ncut) algorithm to effectively partition a large-scale traffic network, and then adopt MADQN to complete TSC tasks for each subnetwork. Meanwhile, a novel reward function based on impedance has been adopted. The results demonstrate that our method has high control performance and could effectively alleviate congestion in large-scale network under peak-hour traffic conditions.

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SECTION I. Introduction

Due to population growth and urbanization, the demand for transportation in major cities worldwide has steadily increased. The substantial volume of daily traffic exerts immense pressure on existing urban transportation infrastructure [1], resulting in persistent traffic congestion [2]. Traffic signal control (TSC) methods are cost-effective, easy to implement and adjust, so they are widely applied to solve traffic congestion problems in major cities around the world. Classic TSC technologies include mature commercial software such as SCOOT [3] and SCATS [4], as well as some optimization algorithms like genetic algorithm [5] and fuzzy logic [6]. Recently, POI embedding [2] and swarm intelligent algorithms [7] have also shown some success in alleviating traffic congestion.

Reinforcement Learning (RL) is a machine learning approach that facilitates sequential decision-making. Over the past few years, RL has found extensive application in the realm of TSC. In this context, RL models TSC as a Markov Decision Process (MDP), wherein the agent gathers experience by engaging with the traffic environment and acquires the ability to make action decisions based on the prevailing states, thereby striving to achieve the desired control objective. RL algorithms generally include value-based (such as Q-Learning [8]), policy-based (such as REINFORCE [9]), and Actor- Critic (such as A2C [10]) architectures. Methods based on Q-Learning have been widely applied. [11] have adopted tabular Q-Learning in RL-TSC. Recently, deep neural net-works (DNNs) have been commonly used for

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Network Clustering-based Multi-agent Reinforcement Learning for Large-scale Traffic Signal Control

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***Index Terms*—Traffic signal control, Multi-agent reinforcement learning, Network clustering, Deep Q-network**

I. INTRODUCTION

Due to population growth and urbanization, the demand for transportation in major cities worldwide has steadily increased. The substantial volume of daily traffic exerts immense pressure on existing urban transportation infrastructure [1], resulting in persistent traffic congestion [2]. Traffic signal control (TSC) methods are cost-effective, easy to implement and adjust, so they are widely applied to solve traffic congestion problems in major cities around the world. Classic TSC technologies include mature commercial software such as SCOOT [3] and SCATS [4], as well as some optimization algorithms like genetic algorithm [5] and fuzzy logic [6]. Recently, POI embedding [2] and swarm intelligent algorithms [7] have also shown some success in alleviating traffic congestion.

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Recent studies have primarily focused on TSC problems at the road network level rather than individual intersections. To achieve large-scale RL-TSC, multi-agent RL (MARL) methods are a popular choice [14]–[16]. According to different patterns of cooperation and competition between agents, we can classify MARL methods into various paradigms. Decentralized and centralized paradigms are the two most classic ones. However, the former suffers from the issue of environmental instability, while the latter encounters challenges related to the explosion of joint state and action spaces. Corresponding solutions have been proposed, such as CTDE [17]. However, as the network size further expands, MARL faces inevitable convergence challenges, leading to a significant decline in algorithm performance. For large-scale RL-TSC, the mainstream approach is to improve RL algorithms, e.g. [18]–[20], but few have started from the segmentation of traffic networks. In fact, most authors have not explained the standards and methods used for partitioning traffic network cases. Assuming there is a significant disparity in congestion levels among road segments within a traffic network, it becomes evident that the difficulty of TSC in non-congested areas is much lower than that in congested areas. In such cases, the MARL approach may prioritize non-congested areas, as they offer better opportunities for improving global rewards. However, this prioritization comes at the cost of exacerbating congestion in already congested areas, leading to imbalanced optimization.

《Ei Compendex》收录证明

经检索“Engineering Village”，下述论文被《Ei Compendex》收录。（检索时间：2024 年 7 月 25 日）。

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Author affiliation:(1) College of Control Science and Engineering, Zhejiang University, Hangzhou, China; (2) Center for Data Science, Zhejiang University, Hangzhou, China
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Controlled terms:Deep learning - Fertilizers - Learning systems - Multi agent systems - Traffic congestion - Traffic signals
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注：

1. 以上检索结果来自 CALIS 查收查引系统。

2. 以上检索结果均得到委托人及被检索作者的确认。

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检索人（签章）：王柳敏
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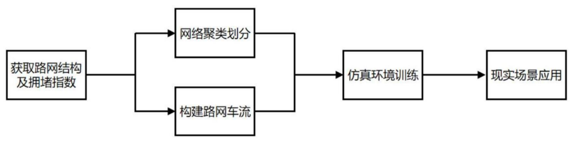
(54)发明名称

一种面向高峰时段拥堵的大规模自适应交通信号控制方法

(57)摘要

本发明公开一种面向高峰时段拥堵的大规模自适应交通信号控制方法,包括以下步骤:构建路网结构作为后续训练及测试场景;获取该路网在待研究时段的路段级拥堵指数数据并构建高峰车流量文件,作为仿真阶段的车流量数据;进行交通网络聚类;对每个子路网进行多智能体强化学习训练;将训练好的MADQN控制器投入对应子路网执行信号控制任务,实时输出当前状态下最优的信号相位选择。本发明方法能够适应各种道路结构复杂、车流密集时变的路网场景,高效、自适应地完成交通信号控制任务,在平均车速、平均车辆行驶时间、平均路口停车次数等各项交通评价指标上都表现出显著优势,具有应用潜力和价值,扩展性强。



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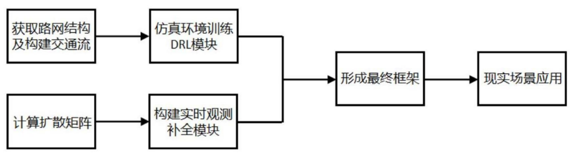
(54)发明名称

一种可实时补全缺失观测的强适应性路网级交通信号控制方法

(57)摘要

本发明公开一种可实时补全缺失观测的强适应性路网级交通信号控制方法,包括以下步骤:选取待进行交通信号控制的现实道路网络,作为后续训练及测试场景;构建交通场景,作为仿真阶段的训练环境;利用MAT编码器-解码器架构设计DRL信号控制器,在SUMO交通模拟器中进行DRL信号控制器训练,得到MAT控制器;基于特征传播构FP建实时观测补全模块;结合训练好的MAT控制器和构建的实时观测补全模块FP,形成FP-MAT联合框架,将其投入对应路网执行信号控制任务。本方法能够自动识别全局状态中的缺失观测并进行实时、准确的补全,保证信号控制器正常工作,具有环境适应性和高效性。



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