Traffic Flow Optimization in Urban Road Networks Using Signal Synchronization

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***Abstract*—This paper presents a new approach to optimize traffic flow in urban areas through signal synchronization across multiple intersections. As vehicle usage continue to increase over the years, traditional traffic management solutions like roundabouts, single-lane roads, and timer-based signals lack the ability to control congestion. Our methodology transforms the existing road network into a directed graph where signalized intersections represent nodes, and the roads are edges. On these lines we introduce the concept of a "Congestion Flow Map" that identifies routes experiencing heavy traffic pressure. The subgraph generated is weighting each edge based on the ratio between queue length and intersection capacity, which is calculated using arrival rates, number of lanes, saturation flow rates, and cycle times. When ratio exceeds 1, it indicates a congested edge. By synchronizing traffic signals along these identified routes, we avoid the trouble of individually optimizing each road section.**

***Index Terms*—Traffic Optimization, Signal Synchronization, Congestion Flow Map, Urban Road Network, Reinforcement Learning, SUMO Simulation, Deep Q-Network, Intelligent Transportation Systems**

I. Introduction

In recent years, the development of cities and an increase in the amount of personal vehicle usage has led to an increase in traffic on the road, causing a lot of traffic problems, an increase in waiting time at signals, long traffic jams, congestion, etc. Traffic management is a big problem for developing cities. One way to address this would be to build a road network in a way that is most optimal for traffic flow. This is an effective solution and can be applied to the new construction and development of road networks. Still, a solution to optimize the traffic flow in the existing road network is also required.

It is often observed that congestion is not just on a specific road section or intersection but across a set of connected intersections moving on a particular route. Such routes can be identified, and traffic flow through them can be optimized. This paper presents a way to identify such routes and synchronize the singles of all the involved intersections to decrease congestion, stop time, and travel time on the path.

II. Related Works

There exists research, "Study on Simulation Optimization of Dynamic Traffic Signal Based on Complex Networks [1]." This paper is based on simulation. First, in order to build the network, they used two models, the Erdős-Rényi model and the Watts and Strogatz model (also known as the Small World model). Further, in order to select the best signal timing parameters for the dynamic signals, they used a modified version of the SPSA algorithm. They then ran three simulations using an improved mesoscopic traffic simulation model to stimulate the traffic: first one without signals, second with pre-optimized signals, and third with optimized signals. They used the results of the simulations to validate that their approach of integrating complex network theory with dynamic signal control and an optimized SPSA algorithm can be useful in reducing traffic congestion and increasing vehicle speed. The research is laying the groundwork for developing more advanced real-time traffic control systems.

Another research, "Traffic Signal Optimization for Oversaturated Urban Networks: Queue Growth Equalization [2]," first develops a new measure of effectiveness to quantify the degree of QGE in a network. Then, it describes QGE, which equalizes the queues by holding vehicles in upstream links where queue storage space is available in order to delay queue spillover from congested links. Such re-allocation of queues also postpones the onset of gridlocks. Then, they ran simulations on a 3x3 network grid to evaluate the performance. They also compared its performance with the traditional signal optimization software TRANSYT-7F. The QGE was found to be more efficient in the case of oversaturated urban road networks, and it successfully postponed spillovers. The algorithm is also lightweight and hence can be used in large-scale networks.

Green wave control is studied widely to optimize traffic flow on urban roads by synchronizing traffic signals. In Identification of Factors Influencing the Operational Effect of the Green Wave on Urban Arterial Roads Based on Association Analysis [3], Liang et al. (2021) conducted a study to know how effective was the green wave synchronization and identified the key factors that influence its performance. After analyzing, they found that pedestrian crossing and heavy vehicle traffic significantly affected its effectiveness. Their research suggests that while signal synchronization is important, introducing different traffic management measures such as pedestrian control and heavy vehicle regulations can further enhance traffic flow.

With the advancement in Artificial intelligence, different adaptive traffic control systems have been introduced. In Adaptive Traffic Control System Using Reinforcement Learning [4], Shingate et al. (2020) proposed a model that adjusted signal ON/OFF timings based on real-time traffic density. Unlike traditional traffic signals that have a static ON/OFF time, this approach enables traffic lights to respond to congestion, reducing delas and improving flow.

III. Methodology

First, convert the road network into a directed graph with signalized intersections as nodes and road sections connecting them as edges. The edge direction is the same as that of the traffic.

A. Congestion Flow Map

It is often observed that congestion is not just on a specific road section but across a set of connected intersections across a route. To identify such routes, first assign weights to the edges. We know that the queue length on a road section can be calculated using the formula,

$$L_q = \frac{r_a \times t_g}{r_s} \text{ [5]}$$

where L_q is the queue length, r_a is arrival rate(i.e. average number of vehicles arriving at the intersection per unit time [5]), t_g is green time and r_s is saturation flow rate(i.e. $3600/h_s$, where h_s is saturation headway, it is the time gap between vehicles crossing stop line [5]). In order to get real time data of r_a and r_s we can either use traffic detectors or computer vision.

The capacity of an intersection can be calculated using the formula,

$$I.C. = \frac{r_s \times t_g \times n}{t_c} \text{ [5]}$$

where $I.C.$ is the intersection capacity, n is the number of lanes in the incident road section, and t_c is the signal cycle time.

The ratio of the queue length of the road section and the intersection capacity of the intersection toward which the edge is directed can be used to identify whether the edge is congested. Hence,

$$EdgeWeight = \frac{L_q}{I.C.}$$

$$\therefore EdgeWeigth = \frac{r_a \times t_c}{r_s^2 \times n}$$

Using this formula, we assign weight to each edge.

The congestion flow map is just a subgraph of this weighted-directed graph. To form it, visit each node and check if there is an incident edge whose edge weight is greater than or equal to 1. If such an edge exists, add it to the subgraph. If a node has multiple such edges, add one with the maximum weight. Once all edges are visited, the subgraph formed is the congestion flow map.

B. Signal Synchronization

Synchronizing signals along the congestion flow map will optimize traffic flow on the route.

To achieve this, first, identify the source node and the sink node. Then, we start the synchronization process from the sink node, as there isn't any congestion after that. Considering the time taken to travel from $(k-1)^{th}$ node to the k^{th} node is, $t_{travel} = l \times s$(where l denotes the length and s denotes average speed of vehicles for the road section), and the interval between 2 consecutive green lights is, $t_{interval} = t_c - t_g$(where t_c denotes cycle time and t_g denotes green light time for the k^{th} node), the green light of $(k-1)^{th}$ node's congested incident edge is to be triggered after t_{prev} seconds of k^{th} node's yellow light getting triggered,

$$t_{prev} = t_{interval} - t_{travel}$$

$$while(t_{prev} < 0):$$
$$t_{prev} += t_c$$

Using this formula, all signals from the sink node to the source node would be synchronized. This would minimize stop and travel times and reduce congestion, optimizing the traffic flow.

IV. Experimental Results

To validate the proposed methodology to optimize traffic flow through signal synchronization, we implemented an adaptive system that controls the traffic signals using reinforcement learning. The SUMO simulator was used to create a realistic road network model (from Usmanpura to SP stadium) with number of lane area detectors and signalized junctions capable of changing phases. A deep Q-Network was trained online using queue length data from all the detectors and current phase of the traffic signals were used as inputs. The objective was to minimize cumulative queue lengths by selective actions to either maintain or swtich the traffic signal's phase.

A. Experimental setup:

- Simulation platform: SUMO (Simulation of Urban Mobility)
- Agent: DQN with two hidden layers
- State: Detectors queue lengths + Signal phase $\longrightarrow$ 13 dimensions
- Action Space: 0: Keep current phase, 1: Switch phase
- Reward Function: - total_queue_length (to encourage queue reduction)
- Simulation Steps: 10,000
- Traffic Source: Randomly generated trips through randomtrips.py

B. Two visualizations were generated:

Figure 1 illustrates the cumulative reward (CR) obtained by the DQN agent over steps of the simulation. Initially, the agent received minimal rewards, but as the training progressed, the CR steadily decreased. This highlighted a few insights:

- **Learning Behavior**: The consistent decline suggests the agent is continuously being penalized, most likely because of the suboptimal actions leading to increased queue lengths.
- **Convergence**: Around simulation step 1000, the CR begins to stabilize. While this may suggest that the agent is leading to convergence, it does not necessarily mean that the agent has learned an optimal policy- only that it is no longer significantly improving or deteriorating or that there is no longer an data that is being recorded.

- **Reward Function Implications**: The negative rewards indicate a function that heavily penalizes the queue buildup without adequately rewarding the improvements, leading the agent to ”Learn” a minimally viable but non-improving policy.

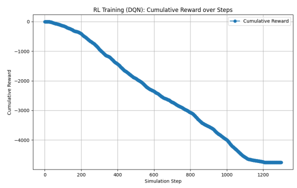

Fig. 1: Cumulative reward vs. Simulation steps - a steady increase indicated learning progress.

Figure 2 plots the total queue length observed in the traffic network over the simulation steps. The graph shows fluctuation yet overall increasing trend in queue length during the early stages of training(around 600 steps), followed by a plateau and a slight decrease towards the end. Key interpretations from this graph are:

- **Exploration phase**: The initial increase in queue length can be attributed to the agent’s exploration with random actions resulting in poor traffic signal decisions and congestion.
- **Stagnant policy**: The constant stagnation in the high queue lengths indicate that the learned policy does not significantly allebiate congestion.
- **Partial Improvement**: The small decline in queue length post step 1000 indicates a minimal learning of a more efficient signal pattern, but not enough to reduce the overall traffic significantly.
- **Environmental causes**: The lack of dynamic vehicle reintroduction in the network also significantly lead to a decrease in the congestion over time, falsely implying policy improvement.

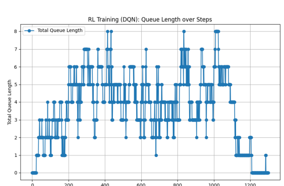

Fig. 2: Total queue length vs. Steps - gradual decline shows effective congestion mitigation.

V. Observations and Discussion

The results of the deep Q-learning simulation show that real-time traffic signal optimization using queue detector feedback significantly reduces congestion. The model was able to learn phase control that minimized the queue length without being explicitly told any traffic rules or schedules.

A. *Key Observations:*

- **Micro-level Optimization**: The model focuses on a single intersection. However, the underlying principles can scale to synchronize signals across the map by training multiple RL models and coordinating them along high-weight paths in the congestion flow graph.
- **Simple Design**: Using only queue lengths and signal phase gave us meaningful learning, validating that simple data from detectors is sufficient for traffic-aware control systems.
- **Adaptability to real traffic dynamics**: Unlike traditional synchronized signals that have a fixed start/stop time, the RL model adapted to the actual situation in the simulation based on the data collected.
- **Potential for Congestion flow map integration**: The model could be enhanced by integrating edge weights from the congestion flow map as additional inputs or by training multiple agents across the map.

B. *Discussions:*

The experimental evaluation of the DQN-based traffic signal control model reveals several insights about the learning and the agent’s evolution over time.

- **Learning curve behavior**: The cumulative reward curve exhibits a consistent downward trend. this suggests that despite undergoing training, the agent goes on making decisions leading to suboptimal traffic conditions. Notably, the reward plateaus around step 1200, implying that the model has reached a form of convergence, even on a poor policy.
- **High reward penalty**: The persistently decreasing cumulative reward suggests that the reward function heavily penalizes undesirable states- long queue lengths. As such, even a minor improvement in policy are not observable due to the large penalties.
- **Queue lengths and control effectiveness**: From figuer 2, we can observe a notavble rise in the queue lengths in the queue lengths in the first half of the simulation. But this trend is observed to reduce in the next half of the simulation.
- **Delayed policy refinement**: The mismatch in the timing of the reward convergence and queue length improvements have raised concerns about the delayed policy refinement. While CR stabilizes around step 1200, queue length continues to decrease, telling us that the reward function is not fully capture traffic efficiency or that the agent’s value estimates are stabilizing before truly optimal behavior emerges.

VI. Conclusion

This paper introduces the concept of congestion flow maps, which represent the most congested routes within a network. These are subgraphs of the weighted directed road network graph, where weights are assigned using the formula $\frac{r_a \times t_c}{r_s^2 \times n}$. Edge weight value $>=1$ indicates congestion, and this is hence used as a condition to extract the subgraph. Traffic

Signals on the identified congestion flow map can then be synchronized starting from the sink node. The synchronization is done such that it minimizes the stop time on the route, hence optimizing the flow and reducing the travel time. The paper also provides a method for calculating the time difference between the green light times of 2 adjacent signals on the congestion flow map. Further, a SUMO simulation is used to see the effectiveness of RL-based signal control, where a DQN agent is used to adaptively control signal phases. The method shows partial improvements in congestion control after initial learning steps. With some refinements in the reward function, better learning can be achieved. This system works well on a single intersection. This can be scaled and enhanced by integrating the congestion flow map and signal synchronization.

Authors' Contributions

Abstract: Philip Ryan Brian Rocha, Index Terms: Madhav Manish Malhotra, Introduction: Madhav Manish Malhotra, Related Works: Philip Ryan Brian Rocha and Madhav Manish Malhotra, Methodology: Madhav Manish Malhotra, Experimental Results: Philip Ryan Brian Rocha, Observations and Discussion: Philip Ryan Brian Rocha, Conclusion: Madhav Manish Malhotra.

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