Research Proposal

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1. Introduction

The U.S. Department of Transportation (USDOT) defines reliability as "the degree of certainty and predictability in travel times on the transportation system" [4]. Travel time reliability (TTR) is a measure of the consistency or dependability of travel time at different periods [5] and is measured in terms of the additional time (i.e., time cushion or buffer) that drivers need to allocate to compensate for unexpected delays. The inherent variability in travel time, stemming from the pervasive uncertainties on both the supply and demand sides, renders TTR a focal point for all stakeholders in transportation systems [3]. Particularly in the advent of the autonomous vehicle era, where a society reliant on autonomous vehicles is becoming a reality, investigating TTR has emerged as an essential and imperative research domain.

In the following sections, I will initially examine the current research advancements in the pertinent fields through a comprehensive literature review. Then I will outline the research objectives of this proposal and elucidate the corresponding methods that I intend to employ.

2. Literature Review

2.1 Deep Reinforcement Learning for Traffic Signal Control

When a deep reinforcement learning (DRL) algorithm is implemented in traffic signal control (TSC), the state information is the first to define and collect in different formats. The two most popular state representations are discrete traffic state encoding (DTSE) and feature-based value vectors. DTSE acquires the highest available resolution. The speed and position of vehicles, signal phases, and accelerations can be shown in DTSE, whereas the merit of feature-based value vectors is the accessibility of data from road sensors and devices. Following the collection of states, control units then take actions under a certain policy. There are several frequently-used actions: choosing one of the possible green phases, the binary action choice of keeping the same phase or changing the direction, and updating the phase duration with a predefined length. Finally, agents get rewards with regard to their actions. Waiting time, cumulative delay, and queue length are the most common reward in TSC [1].

For single agent DRL, the initial work is Genders et al. [13] which controls traffic signals through a CNN model to approximate Q-values on the SUMO simulation environment. Authors in [14] proposed an autoencoder-based deep RL algorithm for a single intersection with dynamic traffic flow. Autoencoders are considered for action selection by mapping input queue length to a low-dimensional action set. The bottleneck layer, which is the output of the decoding part, is used for Q-function approximation. This is one of few works to employ autoencoders for action value approximation in TSC. Choe et al. proposed an RNN-based DQN model in a single intersection TSC scenario [15]. It is shown that the performance of RNN-based DQN decreased the travel time compared to the popular CNN structure. For multi-agent DRL, the first DRL-based multiple intersection control mechanism is developed by E. Van der Pol et al. in [16] with a combination of specific traffic conditions as its reward and transfer planning plus the max-plus algorithm for the coordination. Other neural networks have also been explored in this scenario, S. Shi et al. [17] replace fully connected layers in Q-function with LSTM, achieving lower average delay compared to Q-learning and fixed-time control in both low and high traffic demand scenarios. Nish et al. [18] use the GCN-based algorithm to decrease the waiting time on all 6 intersections compared to the fixed-time controller and standard CNN-based RL controller [1]. All of these inspire me to incorporate new neural network structures such as encoder-decoder, GNN and RNN into DRL research in intelligent transportation systems.

2.2 Swarm Intelligence for Traffic Signal Control

P. W. Shaikh et al. [2] list the most popular swarm intelligence (SI) algorithms in TSC: particle swarm optimization (PSO), ant colony optimization (ACO) and harmony research (HS). The application of simulated annealing PSO to urban traffic signal timing in [19] shows outstanding performance to reduce the average delay per vehicle in comparison to fixed-time plans. Similar results are illustrated in [20] and [21], evincing the better performance of improved PSO algorithms in reducing the average travel time and total delays respectively in contrast to traditional schemes. Moreover, literature also reports the superior computational efficiency of PSO and its variant over other traditional approaches [22] [23]. For ACO, the green time duration act as a decision variable to optimize throughput and delay time in [24] and [25] respectively. The problem of transition between signal timing plans during the day is studied in [26] with the general social cost (e.g. composite of delay cost, fuel consumption cost and air emission cost) as its optimized objectives [2]. In HS, stages of all intersections in a one-time window are widely trained for both single-objective optimization [27] [28] and multiple-objective optimization [9] [10]. The solution encodings these ACO and HS approaches are all of the integer types.

2.3 Travel Time Reliability Metrics

The reliability measures can be divided into three classes: (1) point-based measures, (2) bound-based measures, and (3) PDF-based measures. Point-based measures are the most popular ones and possess different branches, such as percentile-based, moment-based, and tail-based measures. Percentile-based metrics include the percentile-based buffer index (BI, Lomax et al. 2003) - the additional time cushion that road users must budget to ensure on-time arrival for 95 percent of trips, the planning time index (PTI, NCHRP 2008)- the total time a road user should allocate to arrive on time for 95 percent of trips, and the travel time index (TTI, Pu 2011) - the ratio of travel time observed during peak periods compared to free-flow travel time. [5] illustrates the difference between BI and PTI. The former represents the additional time cushion, whereas the latter represents the total travel time necessary for on-time arrivals for 95 percent of trips. Both TTI and PTI have similar numeric scales. However, TTI is for peak hours, while PTI is for any time of day [6]. Skew statistics is a moment-based measure demonstrating the shape and size of travel time distribution (TTD) as a measure of TTR, while the tailed-based Misery index (MI) is the ratio of excess travel time to average travel time. The upper bound of predictivity (UBP) is a representation of bound-based measures that can be applied to evaluate all link/route/network TTRs and the probability density function is the one for the PDF-based metric proposed by Clark et al. in 2003 [3].

FHWA recently issued a final rule with two new TTR metrics as the Moving Ahead for Progress in the 21st Century (MAP-21) performance measures [11] [12]. The objective of MAP-21 performance measures is to assess the performance of the National Highway System (NHS), freight movement on the interstate system, and the congestion mitigation and air quality improvement program. I would use them as part of my TTR research. The two new reliability metrics are:

- Level of travel time reliability (LOTTR): The ratio of the 80th percentile travel time to the normal travel time (i.e., the 50th percentile occurring throughout a full calendar year) using data from FHWA's National Performance Management Research Data Set (NPMRDS). NPMRDS includes travel time data on the NHS, and LOTTR is used to assess the performance of the NHS.
- Truck travel time reliability (TTTR): The ratio of the 95th percentile travel time of trucks to the normal truck travel time, (i.e., the 50th percentile using a full calendar year of truck travel time data). TTTR assesses the freight movement on the interstate system and is reported for five time periods depending on the time of day and day of the week. [6]

2.4 Travel Time Distribution

TTD answers what is TTR by capturing the manifestation of TTR. It uses a mathematical way to provide a whole picture of TTR in transportation networks, which lays the foundation for assessing TTR for different stakeholders. There are two ways to characterize TTD: fitting and deducing. The typical process for fitting TTD in transportation networks is to select or develop an appropriate link TTD and then to derive the route/network TTD model by aggregating the fitted link TTD models. The three modelling rationales that fit TTD based on travel time datasets are the single distribution modelling rationale, the mixture distribution modelling rationale, and the moment-based modelling rationale. The classic single distribution model is the most widely used method to characterize TTR (Bell and Iida, 1997; Emam and Al-Deek, 2006), and the mixture model is a weighted combination of serval single distribution models which is able to deal with the multimodality of TTDs (Chen et al., 2017). Nevertheless, both the single distribution and mixture distribution modelling rationales need a prior assumption about the distribution type that travel time follows, which is unknown in reality. To circumvent these challenges, moments as common statistical tools are adopted to fit heterogeneous TTDs. The Cornish–Fisher expansion (Zang et al., 2018a) and Gram–Charlier expansion (Hou and Tan, 2009) apply the first four moments to travel time, i.e., mean, standard deviation, skewness, and (excess) kurtosis. As for the deducing method, it is a source-based derivation modelling rationale that uses assumptions about the uncertainty sources of TTR rather than empirical datasets. The uncertainty sources of demand and/ or supply are the main assumptions and it is mainly used in network-wide theoretical studies [3].

There are four common variants of travel time in TTD models: standardized travel time, total travel time, pace, and extreme travel time delay. Standardized travel time can be obtained by (Travel time – mean)/standard deviation. Total travel time is the sum of all users' travel times in a transportation network which is frequently used in network-wide reliability models (Chen et al., 2014a). Pace equals the random travel time divided by link/path length and is used to exclude the travel time variation that arises from variations in link length (Saberi et al., 2014). The difference between extreme travel time and the minimum extreme travel time is the extreme travel time delay used by Esfeh et al. (2020) to explore the direct proportionality between the mean and standard deviation of extreme travel time [3].

2.5 Uncertainty Propagation

Both the fitting and deducing TTD characterization approaches involve aggregating uncertainty when deriving a route/network TTD model from the link TTD model. There are two ways of modelling uncertainty propagation from link TTD to route/network TTR. The first method is to aggregate TTD from link to route/network which needs to handle the correlations between link TTDs. Lognormal distribution and the Fenton–Wilkinson approximation have been utilized to capture and aggregate the correlations between link TTDs (Srinivasan et al., 2014), considering the correlations between link TTDs with TTD assumptions. Without TTD assumptions between link TTDs, the copula function has been exploited to describe the dependency and model link TTDs aggregation (Samara et al., 2020; Yu et al., 2020), but it is not computationally viable in large-scale networks with high dimensions. An alternative solution is to use the Markov chain and it is often combined with other aggregation methods to estimate Markov route TTDs (Ma et al., 2017; Yu et al., 2020). The second way avoids TTD aggregation from link to route/network and directly obtains the route or network TTR from the link TTR. Nonetheless, it requires that link TTR is well-defined in terms of additivity or other similar properties and few studies adopt such methods due to the mathematically demanding criteria [3].

3. Research Objectives

1. Characterize heterogeneous TTDs using learnable parameters derived from proposed improved DRL models and SI algorithms.
2. Incorporate real-world constraints (e.g. accidents and weather conditions) into the aforementioned DRL and SI models and evaluate the performance under various traffic conditions, including undersaturated, saturated, and oversaturated network scenarios.
3. Examine new TTR metrics (e.g. LOTTR, TTTR), explore other input data collected from autonomous vehicles or road sensors, and investigate a network-wide TTR monitoring method using ambiguity measures derived from measure theory.
4. Study uncertainty propagation in modelling TTR.

4. Research Methods

1. This study will investigate GNNs and encoder-decoder architectures, such as Transformer [29] and Autoformer [30] in order to develop a new model that captures the spatiotemporal correlations in link TTDs. I will employ the attention mechanism from Transformer and manage to leverage the innovation of series decomposition and auto-correlation mechanisms from Autoformer to enhance the TTD modelling.

2. Building on the previous study, this research will advance by incorporating realistic noise and considering extreme constraints encountered in real-world scenarios. Furthermore, extensive investigations will be carried out to assess the performance of the developed model across diverse road conditions, particularly focusing on undersaturated, saturated, and oversaturated scenarios. These considerations are crucial for effectively addressing TSC challenges in real-life environments and facilitating the application of the proposed approach in specific areas or urban traffic networks.
3. In this part of the work, I will explore two novel reliability metrics LOTTR and TTTR recently introduced by FHWA. Additionally, I will investigate several unique traffic features that have not been widely explored by researchers, including sensor data collected from autonomous vehicles, scoring based on maximum speed detected by lane detectors [31], signal control threshold metrics [32], and left turn occupancy [33]. Feature-based state vectors will be employed as the state representation in DRL. Lastly, I will delve into the study of an ambiguity metric as a means of monitoring network-wide TTR. The use of the Hellinger distance [34] as a measure to monitor deviations in stock markets, drawing on my prior empirical research on f-divergences, serves as a foundation for this investigation.
4. In this research direction, I will follow Zang et al. (2022) as my guiding map, particularly focusing on uncertainty propagation in modelling TTR from link TTD to route/network TTD. This exploration will account for interdependent features, such as the adoption of shifted lognormal distribution as the TTD assumption, utilization of Copula function, and application of the Markov Chain framework without assuming any specific TTD distribution. Furthermore, I will strive to integrate findings from traffic bottleneck research by Daqing et al. (2014) and cascading overload failures research by Jichang et al. (2016) into my study to enhance its comprehensiveness.

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