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Recasting and optimizing intersection automation as a connected-and-automated-vehicle (CAV) scheduling problem: A sequential branch-and-bound search approach in phase-time-traffic hypernetwork

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ABSTRACT

It is a common vision that connected and automated vehicles (CAVs) will increasingly appear on the road in the near future and share roads with traditional vehicles. Through sharing real-time locations and receiving guidance from infrastructure, a CAV's arrival and request for green light at intersections can be approximately predicted along their routes. When many CAVs from multiple approaches at intersections place such requests, a central challenge is how to develop an intersection automation policy (IAP) to capture complex traffic dynamics and schedule resources (green lights) to serve both CAV requests (interpreted as request for green lights on a particular signal phase at time t) and traditional vehicles. To represent heterogeneous vehicle movements and dynamic signal timing plans, we first formulate the IAP optimization as a special case of machine scheduling problem using a mixed integer linear programming formulation. Then we develop a novel phase-time-traffic (PTR) hypernetwork model to represent heterogeneous traffic propagation under traffic signal operations. Since the IAP optimization, by nature, is a special sequential decision process, we also develop sequential branch-and-bound search algorithms over time to IAP optimization considering both CAVs and traditional vehicles in the PTR hypernetwork. As the critical part of the branch-and-bound search, special dominance and bounding rules are also developed to reduce the search space and find the exact optimum efficiently. Multiple numerical experiments are conducted to examine the performance of the proposed IAP optimization approach.

1. Introduction

With the rapid development of wireless communication, sensing and computing techniques, it has become a common vision that connected and automated vehicles (CAV) will soon go beyond testbeds to appear on roads with traditional vehicles at large scale. In the meantime, it is also envisioned that we will live in an era with both CAVs and traditional vehicles for a long time before CAVs completely replace traditional vehicles. The traditional vehicles refer to the vehicles operated by human drivers. The human drivers plan their routes primarily based on their historical experiences and personal pref-

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erences with limited real-time road information. Therefore they mostly follow the originally planned routes. The human drivers also have perception-reaction (P-R) times to respond the intersection control measures. By contrast, the CAVs have short or even zero P-R times, can continuously share their locations and receive guidance from infrastructure. As a result, the CAVs can notify the downstream intersections when to arrive, offering more time for those intersections to schedule appropriate control strategies. The CAVs can change its route dynamically to avoid delays and congestions.

CAVs will undoubtedly bring new potential of improving the automation level at intersections. However, the co-existence of CAVs and traditional vehicles in the real world makes it challenging to describe the dynamic interaction between heterogeneous vehicle movements and signal operations. It is necessary to determine an optimal policy to schedule resources (green lights) to serve CAV requests at the minimal cost like the total delays in this paper to achieve optimal intersection automation for both CAVs and traditional vehicles. We refer to such a policy as intersection automation policy or IAP.

1.1. Intersection automation policy with 100% CAVs: a special resource scheduling problem

Within an ideal 100% CAV traffic environment, the traffic system will become completely controllable and share many similarities with manufacturing systems. If we view CAVs as jobs, an intersection would in essence be a group of competing machines to process arriving jobs and each machine can be open to allow CAVs (jobs) on an approach to cross (processed) or be closed. In comparison, classic machine scheduling problems typically consider parallel or sequence machines but without the tight coupling between machine transitions. On non-competing machines (concurrent movements), jobs can be processed simultaneously whereas on competing machines (conflict movements), jobs on one machine (waiting CAVs at one stop line) must be suspended (stopped) when the other machine is open.

1.2. Intersection automation as a special case of sequential decision process

Within the heterogeneous traffic environment, CAVs are viewed as a player with dual roles at intersections: (a) a part of traffic flow which interacts with traditional vehicles and (b) identities sending green requests to intersection(s). The CAV's first role (as vehicles) is explicitly separated from the second (as green request senders). Furthermore, we view the urban traffic dynamics as a *sequential decision process* or SDP. Let T denote the time horizon and traffic vehicle locations or states at time t are the direct result of traffic signal operations from time 0 to time t where $t \sim [0, T]$. On the other hand, traffic signal operations from t to the future also needs to consider both current and future traffic states according to their inherent traffic vehicular dynamics. As such, the target problem modeling and solution algorithms developed in this paper aim to fully capture the nature of the sequential decision process through coupling heterogeneous traffic and traffic signal operations.

Extended from the notations due to Karp and Held (1967), traffic propagation over time can be represented by a quintuple $\mathbb{N} = (A, R, r_0, r_T, \Gamma)$, where $\mathbb{N}$ is the subject traffic system; A is the set of time-dependent inputs such as traffic lights; R is the set of all feasible traffic states including vehicles' locations, traffic signal status and the set of served green requests; r_0 represents the initial state; r_T represents the final traffic state and Γ is the state transition function. In addition, it is also necessary to define ρ, an input data set for SDP including the link travel times, saturation flow rates, etc. and let P denote all possible input data sets ($\rho \in P$) as well as two conceptual functions:

1. State transition function $H = h(R, A, P)$: for a given data set $\rho \in P$, $a \in A$, the quantity of $h(r, a, \rho)$ gives the cost of transition from the initial state r to an updated traffic state $r' = \Gamma(r, a)$ due to the control measure a, where Γ is the traffic state transition function. H is critical in traffic signal modeling and optimization because it is necessary to evaluate the traffic state evolution as well as incurring costs under a feasible traffic operation during the optimization. As examples, in addition to signal phasing transition rules, traffic state transition function h is most commonly defined based on cumulative vehicle counting curves in which traffic signal operations change the departure curve (the "D curve") and control delays (Daganzo, 1997). H is also defined as changes to the arterial "green band" under traffic signal timings at intersections in a mixed-integer linear programming (MILP) form in the literature due to Little et al. (1981) and Gartner et al. (1991); defined as the changes to queue length and delay changes at intersections under a traffic signal operation by Mirchandani and Head (2001) and Tiaprasert et al. (2015); defined as traffic dynamics changes under given traffic signal operations in the cell transmission model (CTM) developed by Daganzo (1994) in the literature due to Lin and Wang (2004) and Lo (1999); as the propagation of vehicles stored on links by Aboudalas et al. (2009); as the propagation of traffic shockwaves by Wu and Liu (2011); as the total vehicle waiting time by Wang et al. (2017); as the queue length changes estimated from vehicle trajectories by Zheng and Liu (2017) and as changes to a vehicle routing plan in the literature due to Li et al. (2015).
2. Cost function $K = k(P, R)$, for a given data $\rho \in P$, the quantity of $k(\rho, r)$ gives the cost of traffic state $r \in R$.

Based on the concept of SDP, the intersection automation policy optimization can be defined as follows: construct an algorithm which schedules the traffic signal operations during the time horizon T, given the (prior known) data set ρ so as to make $\mathbb{N}$ reach a feasible final state q_T at the minimum cost. In particular, within the heterogeneous traffic environment, a traffic state r contains two groups of objects: CAV requests for green and traffic dynamics comprised of all vehicles. A CAV request can be represented in a form like "*Requesting green light on a particular signal phase at time t*" while all vehicle locations on roads are governed by traffic dynamics defined in R and Γ.