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Strategic Control of Intersections for Efficient Traffic Routing without Tolls

Yusuf Saltan * **Arda Kosay** * **Chung-Wei Lin** ** **Muhammed O. Sayin** *

* *Dept. Electrical & Electronics Eng., Bilkent University, Ankara 06800 Türkiye (e-mail: yusuf.saltan@bilkent.edu.tr, arda.kosay@ug.bilkent.edu.tr, sayin@ee.bilkent.edu.tr).*
** *Dept. Computer Science & Information Eng., National Taiwan University, Taipei 10617, Taiwan (e-mail: cwlin@csie.ntu.edu.tw)*

Abstract: Urban traffic congestion challenges sustainable transportation, causing economic losses (e.g., wasted fuel) and environmental damage. Two main factors contribute to this congestion: self-interested driver routing decisions, often misaligned with optimal traffic flow (as quantified by the Price of Anarchy), and intersections acting as bottlenecks with their limited resources. Prior research has addressed these issues separately, although an intersection's (in)efficiency can also influence driver routing behavior. We propose strategic control of intersections based on priority-based scheduling as a non-monetary solution incentivizing socially optimal routing and ultimately reducing congestion. We quantify the performance in traffic simulations and evaluate its effectiveness in the well-studied Pigou's example.

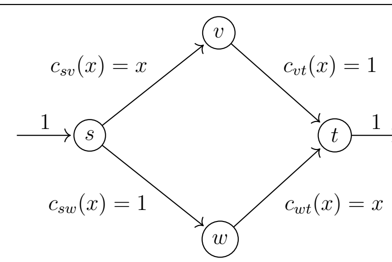
Keywords: Intelligent transportation systems, game theory, integrated traffic management

1. INTRODUCTION

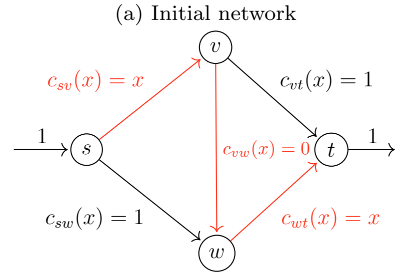
Urban traffic congestion significantly impacts sustainable transportation, leading to substantial economic losses due to wasted fuel, increased travel times, and environmental damage from heightened emissions (Schrank et al., 2019; Litman, 2017). Two primary factors contribute to this congestion: the self-interested routing decisions of drivers and the limited resources of intersections. Drivers often prioritize personal preferences over socially optimal traffic flow, leading to inefficiency quantified by the Price of Anarchy (Roughgarden, 2007). On the other hand, intersections frequently act as bottlenecks, exacerbating congestion (Papageorgiou et al., 2003). Each of these issues has been studied extensively yet separately. The interaction between intersection efficiency and driver behavior has not been thoroughly examined. Efficient/inefficient intersections can influence driver routing decisions and affect traffic flow across the network. This raises an important research question

whether we can address the inefficient routing problem effectively via strategic intersection management.

Motivating Example. *Braess' Paradox* is a well-known example on the intriguing adaptation of traffic flow to changing resources (Braess et al., 2005). Consider a unit traffic flow over a network with two routes, as illustrated in Fig. 1. Let $c_{ab}(x)$ denote the travel cost for the edge from the terminal a to the terminal b depending on the fraction x of the flow passing through that edge. In the initial network, the traffic flow is at *user equilibrium* (where no driver has an incentive to change their routing decisions) if the drivers evenly split across the routes $s \to v \to t$ and $s \to w \to t$. They have the travel cost of 1.5. However, in the augmented network, the traffic flow is at equilibrium if all flow goes through the path $s \to v \to w \to t$. They have the travel cost of 2 larger than 1.5 although the augmented network has more resources with that extra link. Therefore, adding (or removing) resources might have negative (or a positive) impacts on traffic networks due to the strategic adaptation of the traffic flow.



(a) Initial network



(b) Augmented network

Fig. 1. Before (a) and after (b) adding the zero-cost edge.

Contributions. We propose to *strategically* control the (in)efficiency of intersections specific to the vehicles based on their routing decisions to incentivize them to follow the socially efficient ones. We use *user equilibrium*, also

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known as Wardrop or Nash equilibrium, as a solution concept modeling how self-interested drivers would make their routing decisions (Wardrop, 1952). We focus on *autonomous intersection management (AIM)* for further efficient use of the limited intersection resources by scheduling the intersection usage at the vehicle-level, e.g., see the survey (Zhong et al., 2020). For AIMs, we present strategic priority-based scheduling that can (de)prioritize the drivers' intersection usage depending on the alignment between their routing decisions and socially optimal routing.

However, priority-based scheduling has a direct impact on the total travel cost and, therefore, the socially optimal routing, different from the (external) monetary incentives such as tolls. This challenge necessitates new approaches in the design of the priorities, i.e., incentives. As a first step toward this goal, we focus on *Pigou's example* (Pigou, 1920) to obtain explicit results, as in (Das et al., 2017). Despite its simplicity, as illustrated later in Fig. 3, the Pigou's example is the worst network topology for efficient routing (Roughgarden, 2007). We quantify the effectiveness of the strategic control of intersections for efficient routing in the Pigou's network (e.g., see Propositions 1 and 2) and validate the performance via traffic simulations. This approach paves the way to enhance transportation sustainability while democratizing its usage across our society via non-monetary solutions beyond tolls.

Related Works. There have been several attempts for achieving socially efficient routing for self-interested drivers. For example, Roughgarden (2007) showed that we can achieve efficient routing with small increase in the capacity for high-order nonlinear latency functions, common in the Internet routing. However, such latency functions are less relevant for transportation networks.

Auction-based schemes, tolling, and marginal cost pricing can be effective in incentivizing the self-interested drivers to follow socially efficient routes (Fleischer et al., 2004; Cole et al., 2003). These methods rely on exchanging time (i.e., travel cost) and money to influence behavior. However, such exchanges can cause inequalities among drivers, by disproportionately burdening less wealthy individuals (Gemici et al., 2018). Tokens can serve as an artificial money specific to the traffic usage (Sayin et al., 2018; Censi et al., 2019). However, when the tokens do not have any value outside the traffic, they may not create incentives like the actual money.

Alternatively, we can induce drivers to follow socially efficient routing by controlling the information available to them, as in the Bayesian persuasion framework (Kamenica and Gentzkow, 2011). Existing results often focus on simplified traffic networks similar to Pigou's example, e.g., see (Das et al., 2017), due to the computational complexity of large-scale solutions. Furthermore, competition among navigation applications may lead to full information disclosure, potentially resulting in suboptimal outcomes (Tavafoghi et al., 2019).

On the other hand, intersections can often worsen the congestion due to their limited resources. Classical traffic signal control methods, e.g., see the survey (Wei et al., 2019), typically rely on fixed or adaptive timing plans to manage traffic flow. However, these methods often struggle to adapt to real-time traffic conditions and varying demands. There is a critical need for dynamic intersection management strategies.

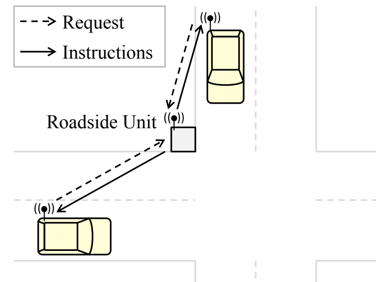


Fig. 2. Autonomous Intersection Management.

Advancements in information and communication technologies (such as dedicated short-range or 5G cellular communications) present opportunities to improve the efficiency beyond these classical approaches via vehicle-to-vehicle and vehicle-to-infrastructure communications (Kenney, 2011; Weber et al., 2019). For example, in AIMs, roadside units can *autonomously* schedule the intersection usage based on the requests coming from the drivers, as illustrated in Fig. 2 (Dresner and Stone, 2008). Generally, simple-to-implement and effective heuristic solutions are developed to address the computational complexity of optimal scheduling. For example, Lin et al. (2019) have presented a graph-based solution to ensure deadlock-free intersection usage in AIMs.

Prioritizing traffic flow at intersections can significantly enhance urban traffic networks, particularly benefiting emergency services, public transportation, and high-occupancy vehicles, thus reducing congestion and environmental impact (Litman, 2009). For example, Zhang et al. (2015) have presented priority scheduling mechanism for AIMs with an event-triggered control procedure. Other solutions include allowing higher-priority drivers to overtake using global or local priority lists, with priority as an inherent property of each driver (Harks et al., 2018; Hoefer et al., 2011).

Notably, Scheffler et al. (2022) have introduced an edge-priority model for competitive packet routing games. They have provided an efficient algorithm for computing equilibria in symmetric games and prove the NP-hardness of finding Nash equilibria in asymmetric games without the uniqueness guarantee. The model can lead to potential inefficiencies where players may repeatedly visit nodes to gain higher priority. The model also does not consider different priority levels within the same edges whereas our strategic priority-based scheduling scheme assign priorities at the vehicle level. Furthermore, the model includes a simplified cost model for the routes with constant transit times, meaning the travel cost does not depend on the congestion, whereas we consider polynomial latency functions that are more relevant for transportation networks.

Organization. The remainder of this paper is organized as follows. We introduce the strategic priority-based scheduling and analyze its effectiveness for Pigou's example both analytically and numerically in Section 2. We conclude the paper in Section 3 with some remarks.

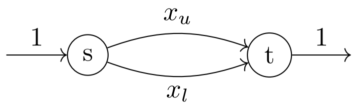


Fig. 3. Pigou's example.

2. STRATEGIC PRIORITY-BASED SCHEDULING

In this section, we present and analyze the *strategic priority-based scheduling (SPBS)*. To this end, we first focus on the *First-Come-First-Serve (FCFS)* scheme as a benchmark to show the effectiveness of our approach. In the FCFS, vehicles pass through intersections in the order they arrive. This simple heuristic can improve the efficiency of the intersection usage for AIM significantly compared to the classical or adaptive traffic lights (Dresner and Stone, 2008).

However, in the FCFS, each vehicle has the same priority level. We can, alternatively, prioritize certain special vehicles such as the ones in emergency services and public transportation while scheduling their intersection usage for the effective use of the traffic network (Litman, 2009). Correspondingly, we propose to use the intersection usage priorities to incentivize drivers to follow the socially optimal routing for the effective use of the traffic network in terms of the social travel cost.

Consider an AIM, as depicted in Fig. 2. In the SPBS scheme, vehicles communicate with the roadside unit upon entering a predefined communication zone by requesting the intersection usage. Each vehicle has a dynamic *score* based on their predefined priority level and the waiting time since the request. For example, there can be three priority levels: low, medium, and high. The roadside unit sorts the requests received based on their scores and schedule the intersection usage based on that order.

However, the priority-based scheduling can lead to inconsistency in the queue order and the physical locations of vehicles in a lane. For instance, a high-priority vehicle might be behind lower-priority ones on the same lane. This can cause an issue if the high-priority vehicle moves to the top of the queue when it is not in front of the lane. We resolve this inconsistency by temporarily elevating the scores of all vehicles in front of the high-priority vehicle to infinity such that those vehicles move to the top of the queue, as in (Zhang et al., 2015).

A key challenge for SPBSs is to determine the priorities of the vehicles to incentivize socially optimal routing. This challenge gets elevated for complex network topologies. As a first step toward this goal, here, we focus on the Pigou's example due to its inefficiency in terms of the PoA metric (as discussed in Section 2.1) and simplicity to show the effectiveness of the scheme explicitly.

2.1 Case Study: Pigou's Example

Fig. 3 provides an illustration of the Pigou's example. There are two terminals: source s and destination t. We have a non-atomic unit flow from s to t going through two edges called *upper* and *lower* routes. The upper and lower edges, resp., have the *edge cost functions* given by

$$c_u(x_u) := 1 \quad \text{and} \quad c_l(x_l) := x_l^n \tag{1}$$

for some $n \in \mathbb{N}$, where $x_u \in [0, 1]$ and $x_l \in [0, 1]$ denote the flow passing through the associated edges. Note that $x_u + x_l = 1$. Based on (1), the flow $\mathrm{x} = (x_u, x_l)$ leads to the *total edge cost* of

$$C(\mathrm{x}) := 1 - x_l + x_l^{n+1}. \tag{2}$$

Recall that a traffic flow is at user equilibrium if no driver can unilaterally reduce their travel cost by changing routes. In the following, we provide a formal description of the user equilibrium.

Definition 1. (User Equilibrium). Consider a traffic network with multiple routes. Let R denote the set of routes. Let also $c_i(x_i)$ denote the cost of the flow x_i passing through route $i \in R$. We say that a flow $\mathrm{x} = \{x_i\}_{i\in R}$ is at user equilibrium provided that

$$c_i(x_i) \leq c_j(x_j) \quad \forall j \in R. \tag{3}$$

In Fig. 4a, we provide illustrations of edge and node costs for upper and lower routes. The left-most plot in Fig. 4a uses color-coded lines to show how the edge cost for upper and lower routes change depending on the flow x_l for the quadratic cost of the lower edge, i.e., $n = 2$. The (highlighted) intersection of the edge costs for upper and lower routes would have corresponded to equilibrium if there were only edge costs.

The travel cost of the drivers also includes the *node costs* induced by the waiting times at intersections. For the FCFS scheme, the flows coming from the upper and lower routes have the node costs, resp., given by

$$d_u(x_u) := w \quad \text{and} \quad d_l(x_l) := w \tag{4}$$

for some $w > 0$ for all flow x. The drivers have approximately the same *average* waiting time at intersections irrespective of their routes due to the symmetric nature of the FCFS, as illustrated in the middle of Fig. 4a. Then, the *total node cost* is given by

$$D_{\mathrm{FCFS}}(\mathrm{x}) := w \quad \forall \mathrm{x}. \tag{5}$$

Based on the edge cost (2) and node cost (5), we define the *total travel cost* for the upper and lower routes by

$$T_{\mathrm{FCFS}}(\mathrm{x}) := C(\mathrm{x}) + D_{\mathrm{FCFS}}(\mathrm{x}). \tag{6}$$

The right-most plot in Fig. 4a uses color-coded lines to show how the travel cost for upper and lower routes change depending on the flow x_l for $n = 2$. Note that the right-most plot is the shifted version of the left-most plot by the average intersection waiting time w. The highlighted intersection of the travel costs for the upper and lower routes correspond to the *unique* equilibrium where all flow goes through the lower route, i.e., $\mathrm{x}^e = (0, 1)$. Furthermore, the color-coded shaded area represents the total travel cost $T_{\mathrm{FCFS}}(\mathrm{x}^e) = w + 1$.

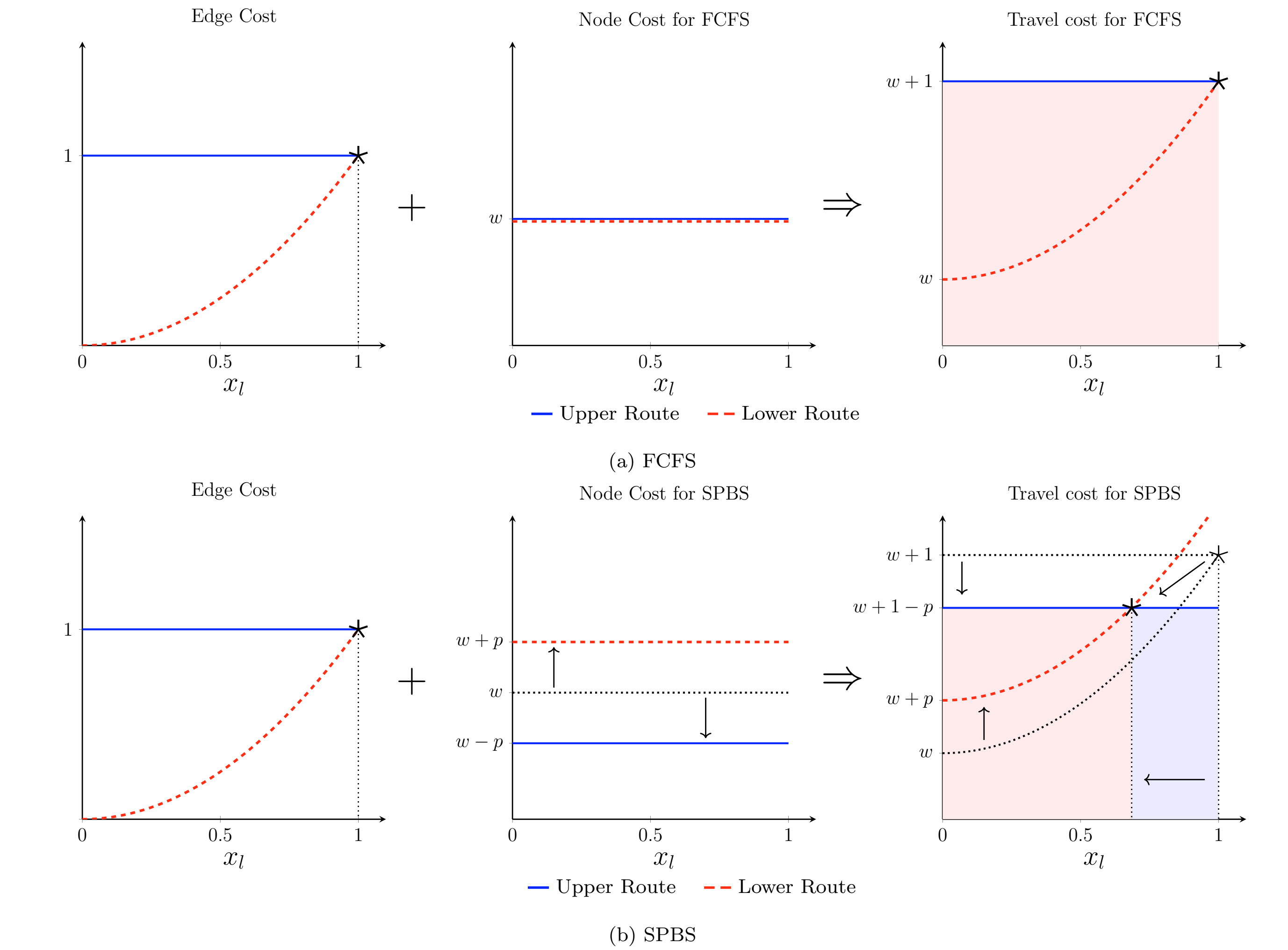
For the FCFS, the *socially optimal routing* minimizing the total travel cost (6) is attained for $\mathrm{x}^* = (1 - x_l^*, x_l^*)$, where

$$x_l^* = \left(\frac{1}{n+1}\right)^{1/n}. \tag{7}$$

The total travel cost for the socially optimal routing is given by

$$T_{\mathrm{FCFS}}(\mathrm{x}^*) = 1 - x_l^* + (x_l^*)^{n+1} + w \geq w. \tag{8}$$

To quantify the efficiency of a traffic network, we use the Price-of-Anarchy (PoA) metric defined by



(a) FCFS

(b) SPBS

Fig. 4. A comparison of the FCFS and SPBS schemes on edge cost (left-most plot), node cost (middle plot), and travel cost (right-most plot) for upper and lower routes. The arrows illustrate how the costs change from FCFS to SPBS. Here, $x_l \in [0, 1]$ denotes the flow through the lower route. The travel cost under the SPBS policy decreases (and increases) for the upper (and lower) route. Such prioritization incentivizes some drivers to choose the upper route at equilibrium (highlighted with the star symbol). Red and blue shaded areas, resp., represent the total travel costs for the lower and upper routes at equilibrium.

$$\text{PoA} := \frac{\text{Cost under Worst Equilibrium}}{\text{Cost under Socially Optimal Routing}}. \tag{9}$$

For the FCFS scheme, we have

$$\text{PoA}_{\text{FCFS}} = \frac{1+w}{1+w-n\cdot\left(\frac{1}{n+1}\right)^{\frac{n+1}{n}}} \le \frac{1+w}{w} \tag{10}$$

for x_l^* as described in (7). For example, if the lower edge has a linear cost, i.e., $n = 1$, then the optimal flow evenly splits across the lower and upper routes, and $x_l^* = 1/2$. Correspondingly, the PoA is given by $(w + 1)/(w + 3/4)$, which reduces to 4/3 if there were no node cost, i.e., $w = 0$.

Since all equilibrium flow goes through the lower route, we propose to give high-level (or low-level) priority to the vehicles in the SPBS scheme if they choose the upper (or lower) route. We also consider that Pigou's example is a part of a larger network such that there also exists traffic flow coming to the terminal t since intersections generally involve more than two incoming edges, e.g., see Fig. 2. The external flow has the medium-level priority. Then, the edge costs are again as described in (1). On the other hand, the vehicles now can face different *average* waiting times at the intersection t depending on their priority levels. To this end, we make the following assumption about the node cost under the SPBS. We justify the assumption via numerical simulations later in Section 2.2 (e.g., see Fig. 5).

Assumption 1. For the SPBS, the node costs of the upper and lower routes, resp., are given by

$$d_u(x_u) := w - p \quad \text{and} \quad d_l(x_l) := w + p \tag{11}$$

for some $p \in [0, w]$. The changes in the flow x have tolerable impacts on the average waiting time of the external flow.

Based on Assumption 1, the total node cost for the SPBS is given by

$$D_{\text{SPBS}}(\text{x}) := (1 - x_l) \cdot (w - p) + x_l \cdot (w + p). \tag{12}$$

Correspondingly, the total travel cost is given by

$$T_{\text{SPBS}}(\text{x}) := C(\text{x}) + D_{\text{SPBS}}(\text{x}). \tag{13}$$

In Fig. 4b, we provide illustrations of edge and node costs for the SPBS, similar to Fig. 4a. The right-most plot in

Fig. 4b uses color-coded lines to show how the travel cost for upper and lower routes change depending on the flow x_l for $n = 2$. The highlighted intersection of the travel costs for the upper and lower routes correspond to the equilibrium under the SPBS scheme.

For large $p \in [0, w]$, we might have $w + 1 - p < w + p$. Then, the travel costs for the routes do not intersect in the graph and the travel cost for the upper route is strictly less than the cost for the lower one. In such cases, all flow goes through the upper route at equilibrium.

In the following, we characterize the equilibrium for the SPBS scheme.

Proposition 1. Under Assumption 1, for the SPBS, the *unique* equilibrium flow is $\mathrm{x}^e = (1 - x_l^e, x_l^e)$, where

$$x_l^e = \begin{cases} (1-2p)^{1/n} & \text{if } p \in [0, 1/2) \\ 0 & \text{if } p \geq 1/2 \end{cases} \tag{14}$$

and the equilibrium travel cost is given by

$$T_{\mathrm{SPBS}}(\mathrm{x}^e) = w + 1 - p. \tag{15}$$

Proof. The proof follows from solving

$$w + 1 - p = w + (x_l^e)^n + p \tag{16}$$

for $x_l^e \in [0, 1]$, as illustrated in the right-most plot of Fig. 4b, if a solution exists. A solution does not exists if $w + 1 - p < w + (x_l)^n + p$ for all $x_l \in [0, 1]$. Then, the lower route gets dominated by the upper route and all flow goes through the upper one. Furthermore, the color-coded shaded areas in that plot correspond to the equilibrium travel cost. □

Remark 1. The equilibrium travel cost for the SPBS is strictly less than the one for the FCFS when $p > 0$. Furthermore, different from the FCFS, non-zero flow goes through the upper route, i.e., $\mathrm{x}^e \neq (0, 1)$ for $p > 0$. This shows that the SPBS incentivizes drivers to follow socially efficient routes to a certain extent.

Remark 2. The parameters $w \geq 0$ and $p \in [0, w]$ depend on the underlying intersection topology and the external flow coming to the intersection. The parameter p also depends on the scores assigned based on the priority levels in the SPBS scheme. Therefore, in the SPBS, we can determine the equilibrium flow (14) by controlling p to a certain extent. For example, we can aim to keep $x_l^e \geq 1/2$ such that the majority of the flow coming from s to t have low-level priority so that the impact on the external flow's node cost is at a tolerable level.

In the following, we characterize the socially optimal flow for the SPBS scheme.

Proposition 2. Under Assumption 1, for the SPBS, the socially optimal flow is $\mathrm{x}^* = (1 - x_l^*, x_l^*)$, where

$$x_l^* = \begin{cases} \left(\dfrac{1-2p}{n+1}\right)^{1/n} & \text{if } p \in [0, 1/2) \\ 0 & \text{if } p \geq 1/2 \end{cases} \tag{17}$$

and the PoA is given by

$$\mathrm{PoA}_{\mathrm{SPBS}} = \frac{1 + w - p}{1 + w - p - n \cdot \left(\frac{1-2p}{n+1}\right)^{\frac{n+1}{n}}}. \tag{18}$$

Proof. We can obtain (17) by solving

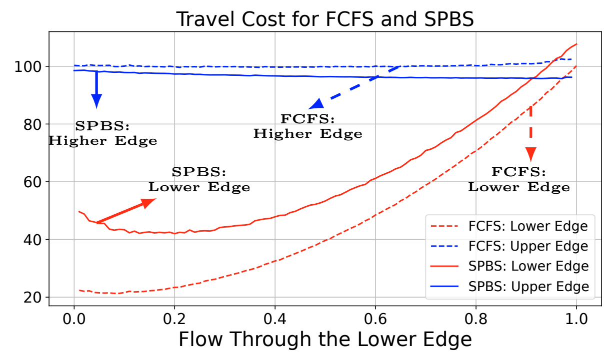


Fig. 5. Simulation results for Pigou's example under the FCFS and SPBS schemes for the travel (node+edge) cost of upper and lower routes.

$$\min_{x_l \in [0,1]} \{1 + w - p - (1 - 2p)x_l + (x_l)^{n+1}\} \tag{19}$$

due to (2), (12) and (13), and obtain (18) based on (9) and (15). □

2.2 Numerical Simulations

We conduct numerical simulations using Eclipse SUMO (**S**imulation of **U**rban **MO**bility), a traffic simulation package designed for large road networks (Lopez et al., 2018). The setup includes three 300-meter incoming edges (one of which correspond to the external flow) and one outgoing edge. The unit flow rate is set to 0.15 vehicles per second while the external flow is half as much. Vehicle departure times follow a Poisson process with a rate parameter 4.5. In the SPBS scheme, we choose the priority scores according to

$$f_i(t, s) := t \times s_i^2 \tag{20}$$

where t is the time since the i-th vehicle's request at 100 meters from the intersection, and $s_i \in \{1, 1.5, 2\}$ represents low, medium, and high priority levels, respectively. We create a global queue using these scores in a descending order and let vehicles pass based on the global queue order and calculated node costs based on queue time.

We perform 100 independent trials for each 0.01 step from 0.0 to 1.0. Each trial runs for 3600 seconds with a step size of 1, using the same type of vehicles to observe the effect of priority-based scheduling more explicitly. To simulate the travel cost, we add edge and node costs as in Fig. 4b, while scaling the edge costs by 80. We plot the average travel costs for upper and lower routes for both FCFS and SPBS scheme in Fig. 5. We highlight the resemblance between Fig. 5 and the right-most plot in Fig. 4b. The resemblance justifies the node cost mode for the SPBS in Assumption 1, especially when the flow through the lower edge is larger than $x_l \geq 0.5$, as discussed in Remark 2.

3. CONCLUSION

In this paper, we proposed strategic control of intersections via priority-based scheduling to induce desired driver behavior for efficient traffic routing. Our analytical model (supported with numerical simulations) demonstrated the effectiveness of the strategic priority-based scheduling for the Pigou's example by incentivizing certain percentage of the flow to go through the dominated route while reducing the overall travel cost.

Future research directions include design and analysis of the strategic priority-based scheduling for arbitrary network topologies, and develop data-driven solutions such as reinforcement learning (as in (Huang et al., 2023)) to learn optimal dynamic prioritization for arbitrary and multi-intersection networks.

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