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# Sharing is Caring: Socially-Compliant Autonomous Intersection Negotiation

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*Abstract*—Current methods for autonomous management use strict first-come, first-serve (FCFS) ordering to manage incoming autonomous vehicles at an intersection. In this work, we present a coordination policy that swaps agent ordering to increase the system-wide performance while ensuring that the swaps are socially compliant. By considering an agent’s Social Value Orientation (SVO), a social psychology metric for their willingness to help another vehicle, the central coordinator can reduce system delays while ensuring each individual vehicle increases their own utility. The FCFS-SVO algorithm is both computationally tractable and accounts for a variety of real-world agent types, such as human drivers and a variety of social orientations. Simulation results show that average vehicle delays decrease with swapping by enabling cooperation between agents. In addition, we show that the proportion of human drivers, as well as, the distribution of prosocial and egoistic vehicles in the system can have a prominent effect on the performance of the system.

## I. INTRODUCTION

A major challenge in autonomous driving is interacting with human drivers. For roads with both human and autonomous vehicles, it is important to design socially-compliant autonomous policies. As autonomous vehicles proliferate, we can take advantage of greater communication and cooperation among vehicles. Inter-vehicle coordination can reduce congestion and wait times at intersections. Smarter intersections can improve optimization and scheduling of vehicles.

This paper considers smart intersection coordination for both human and autonomous vehicles. We start from a standard First-Come, First-Served (FCFS) policy that assigns intersection reservations to vehicles, then locally optimize based on the social preferences of the vehicles. As vehicles queue in the intersection, we perform reservation swapping to improve system performance, but only if it is seen as a benefit to both vehicles. Each vehicle has different social preferences, which manifests as varying tolerances to accept delays at the intersection to help others. We leverage communication with vehicles to determine their intent, but do not require communication for scheduling.

At intersections, human drivers engage in socially-compliant behavior, where drivers coordinate their actions for safe and efficient joint maneuvers. We classify these

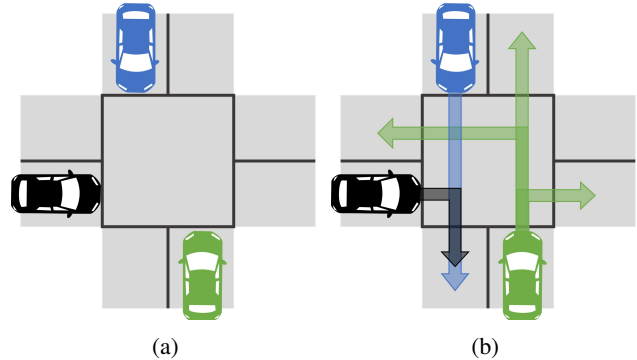


Fig. 1: (a) We coordinate cars to safely pass through intersection by assigning reservations for intersection use. (b) Cars may signal their intended direction and reserve a single path (blue and black cars), or may have an unknown intention (green car), and reserve all possible paths.

interactions as social dilemmas, where the group interests do not necessarily align with the private interests. For example, at intersections, the group interests are to reduce congestion, while the individual interests are to reduce personal delays. We define **socially-compliant driving** as behavior during this sequence of social dilemmas that complies with the social expectations of the group. Our goal is to design autonomous system policies that conform to the socially-compliant driving expected by the human drivers, which is fundamentally important for the safety of all passengers.

In this work, we design a central coordinator to assign reservations and manage traffic through the intersection. The central coordinator first assigns reservations using FCFS, then swaps reservations between cars based on their social preferences. If cars are able to communicate their intent, the coordinator reserves that path through the intersection. If the car cannot communicate its intent, then the coordinator reserves all possible paths through the intersection, as shown in Figure 1. We model each vehicle’s social preferences through the Social Value Orientation (SVO), a common metric from social psychology that measures how individuals weigh personal rewards against rewards to others. While the SVO concept encompasses a broad range of social interactions, we focus on a range of egoistic to prosocial preferences. Here, the SVO intuitively correlates to how an individual will tolerate an additional time delay to reduce the wait time of another vehicle. An egoistic vehicle will not tolerate any swapping that increases its wait time, while a prosocial car will be more inclined to take a minor increase

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in wait time if it improves the overall system efficiency. For autonomous vehicles [1], we design the SVO preference of the vehicle to best interact with the human drivers. Our results show that both individual wait times and system-wide average wait times decrease as the percentage of prosocial cars increase in the system.

The main contribution of this work is incorporating the SVO behavior-based utility functions as both a heuristic for improved system-performance and as an encoding of user-level acceptability in deviating from the naive approach of FCFS. In addition, a tractable and flexible utility swapping framework which accounts for varied agent personalities and vehicle capabilities.

### A. Related Work

Safe control of multiple autonomous vehicles has been explored in a number of centralized and decentralized approaches. If the intent of all vehicles is known, the global solution is known to be NP-hard and quickly becomes intractable with large numbers of vehicles. Thus, many approaches look to find locally-optimal solutions, using control policies that guarantee safe passage [2], [3], [4], [5], [6], game theoretic approaches [7], learning-based control methods [8], [9], and decentralized algorithms [10], [11]. In this paper, we use a central coordinator to manage human and autonomous vehicles using intersection reservations. We start from a common FCFS policy that introduces pairwise socially-complaint swapping. Other centralized approaches include market-based auction systems, as well as system-wide optimization.

System-wide optimization approaches focus on optimizing all vehicles simultaneously to achieve the system optimum. In [12], the authors formulate an integer-program using specific regions of the intersection known as conflict-points to reduce the decision variables. Heuristics can be used to achieve improved performance [13], but rely on pre-determined trajectories to obtain conflict-points, which may not be possible in the case of unknown dynamics or multi-lane systems. Finally, [14] showed that in systems with a mixture of compliant and selfish vehicles, the system-wide equilibrium (that of all compliant vehicles) and the user equilibrium (that achieved of selfish agents) may be very different from one another. Thus, in considering only the system-wide delays and not the agent-specific utility, current optimization methods are at odds with the agent-centered optimization that occurs by each vehicle in the system.

Market-based approaches coordinate vehicles by allowing each vehicle to enter an auction for time in the intersection given some budget. The Intersection Time-Slot Auction (ITSA) [15] allows agents to bid in the auction based on their own budget and wait-time. Agents in the same lane can cooperate by pooling resources to bid on the intersection. However, auctions are limited in that they rely on an actual budget constraint for each vehicle and cooperation is limited to within a given lane. In [16], three budgets are proposed, however, they represent extreme scenarios such as infinite budget, zero budget, or a "fair" budget based

on distance traveled. In general, market-based systems pose the fundamental issue that the coordinator may bias towards "wealthier" agents.

Reservation-based systems often rely on a First-Come, First-Serve (FCFS) policy that provide a tractable method for allocating agents safely within an intersection. In [17], the authors introduce a tile-based reservation (TBR) policy which discretizes the intersection into tiles so the intersection coordinator can reserve portions of the intersection for vehicles as they arrive. While these methods perform best in systems with only connected vehicles, [18], [19] accounted for the uncertainty in human intentions by reserving all trajectories in the intersection. Alternatively, [20] propose a priority-preserving control law that ensures even human drivers only enter the intersection according to their FCFS ordering. A common result in these approaches is that human drivers lead to large inefficiencies in the system, compared to the autonomous vehicles which can share the intersection. A major drawback of current reservation-based systems is that they rely on a simple FCFS policy for ordering the vehicles. While FCFS provides a tractable solution to an otherwise NP-Hard scheduling problem, [21] highlights major limitations in the system's ability to effectively coordinate vehicles. In [22], the authors analyze the intersection problem as a polling problem. By using a fixed polling policy which cycles through the lanes, they are able to provide analytic guarantees on safety and wait time. However, polling policies require that entire intersections are reserved for every vehicle and still rely on fixed ordering policies such as FCFS or  $k$ -limited.

The remainder of the paper is organized as follows: Section II provides an SVO primer. In Section III, we present our problem definition and formulation. Section IV introduces our socially-compliant reservation swapping algorithm. Analysis of simulation results is presented in Section V, and we present our conclusions in Section VI.

## II. SOCIAL VALUE ORIENTATION

In a social dilemma game, the reward for an individual agent is often at odds with the reward of the other agents. Similarly, in our setting the wait time of one agent is at odds with the wait time of another agent. A key insight of this paper is that an agent's utility function is not only a function of their own wait time but also, depending on the agent's personality, the wait times of other agents in the system. We use the Social Value Orientation (SVO), a common metric from social psychology [24], to quantify human personalities. The SVO indicates how an individual weights personal rewards against rewards to others, allowing them to be classified as prosocial, individualistic, competitive, and altruistic among others. The corresponding mapping in Fig. 2 relates the reward to self against the reward to other in a social dilemma game.

While an individualistic, or more colloquially egoistic, agent only considers its own wait time, other agents prioritize both their own reward  $R_i$  and to some degree, the rewards of the other agents in the system,  $R_j$ . This tendency can

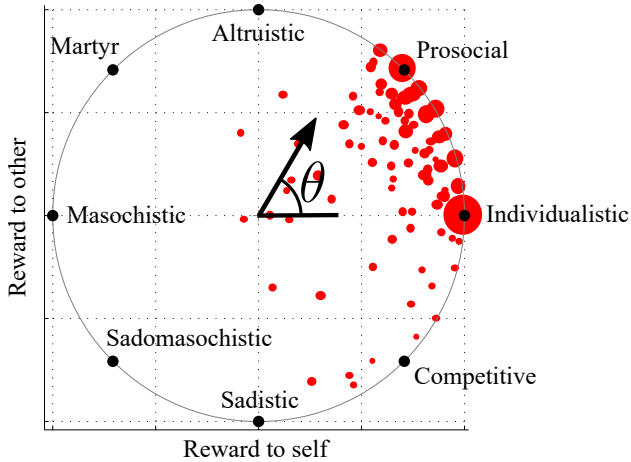


Fig. 2: The Social Value Orientation represented as an angular preference  $\theta$  that relates how individuals weight rewards in a social dilemma. Experimental data from [23] has been added to represent individual preferences. As shown, most people fall between individualistic (also known as egoistic) and prosocial.

be categorized by the Social Value Orientation (SVO) [25] where the utility for an ego-vehicle ( $i$ ) includes the other agent's reward

$$u_i = R_i \cos \theta_i + R_j \sin \theta_i. \quad (1)$$

Here  $\theta_i$  is the SVO angle of agent  $i$ , a representation of agent  $i$ 's amount of consideration for the other agents' rewards. Note from (1) that an agent  $i$ 's utility is a function of its own SVO and the rewards of everyone in the system. Figure 2 shows the correspondence of  $\theta_i$  to social orientations. While  $\theta_i$  can take any value, in a cooperative setting such as traffic assignment, realistic values of  $\theta_i$  will be in the range  $\theta_i \in [0, \pi/4]$ , where the extreme behaviors correspond to an *egoistic* ( $\theta_i = 0$ ) and *prosocial* ( $\theta_i = \pi/4$ ). In reality, we expect that most users will have at least a minimal level of interest for their own reward, and thus we limit the SVO of any given agent to  $0 \leq \theta_i \leq \pi/4$ . This reasonable argument is further supported by data from social-dilemma games in the literature [23], [26], [27].

In general, each agent considers the rewards of *all* agents in the system, however, that quickly becomes intractable for large systems. Instead, the coordinator will consider the utility of two vehicles ( $v_i, v_j$ ) in a pair-wise joint optimization only,

$$\max_{t_{w,i}, t_{w,j}} u_i + u_j \quad (2)$$

under the constraint that each agent's individual utility increases after the swap.

### III. PROBLEM FORMULATION

We consider a four-way intersection through which human-driven and autonomous vehicles traverse. The intersection is signalized, with a traffic light that indicates when vehicles may proceed. A control coordina-

tor negotiates reservations for each vehicle, based on their arrival lane and if known, desired path through the intersection. We denote the vehicles  $v_i$  for  $i = \{1, \dots, N\}$  total vehicles, with state  $x_i$  and intention  $a_i \in \{\text{LEFT}, \text{RIGHT}, \text{STRAIGHT}, \text{UNKNOWN}\}$ . The state  $x_i$  comprises its position, orientation, and maximum speed. We assume that the state  $x_i$  is known when the vehicles enter the system, either through direct communication from the vehicle or some form of tracking system. A simplified, single integrator dynamic model is used to model vehicle dynamics, though more complicated dynamics can be used, as in [17]. Intention  $a_i$  may be communicated by autonomous vehicles to the central coordinator, but we allow the intent to be unknown to model both human drivers unable to communicate intent, as well as autonomous vehicles that would like to keep their intention private. For the remainder of this paper, we assume the intention of autonomous vehicles is always known, and the intention of human-driven vehicles is always unknown. Each vehicle also has an SVO preference  $\theta_i$ . For human drivers, we assume this is a fixed quantity that can be observed by the system. For autonomous vehicles, we design the SVO preference and can leverage this as an additional optimization parameter. We simulate a wide range of SVO distributions, and show that choosing prosocial SVO preferences increase both individual and group performance.

#### A. Vehicle Arrival

Vehicles arrive into the system at  $t_{0,i}$ , at which point the central coordinator receives their reservation request for the intersection. The coordinator returns a start time  $t_{s,i}$ , representing when the vehicle is allowed to enter the intersection. We assume all vehicles are compliant to their assigned start times, which can be enforced by traffic signals. In congestion, vehicles may need to wait for some amount of time  $t_{w,i}$  before proceeding. The goal of the central coordinator is to assign reservations to each vehicle so they safely traverse the intersection while minimizing the average wait time of each vehicle. The coordinator then performs local pairwise swapping between vehicles in queue. The swapping compares the joint utility of the current assignments against the joint utility of the swapped assignments. When both utility functions improve, the coordinator swaps the vehicle assignments. Each agent's individual utility varies based on their individual social preferences. Overall, the goal of our coordination algorithm is to improve the system-wide performance by minimizing the average wait time, while maintaining that individual utilities are not increasing.

#### B. FCFS Tile-Based Reservation

Vehicles automatically request a reservation when they enter the system, and may additionally communicate their intent at that time. The preliminary assignment of reservations is determined by an FCFS tile-based reservation (TBR) system. First proposed in [17], a TBR system accepts reservation requests  $r_i$  from each agent as they enter the control region. Each agent's request includes the the arrival time into the system and its predicted time to arrive at the

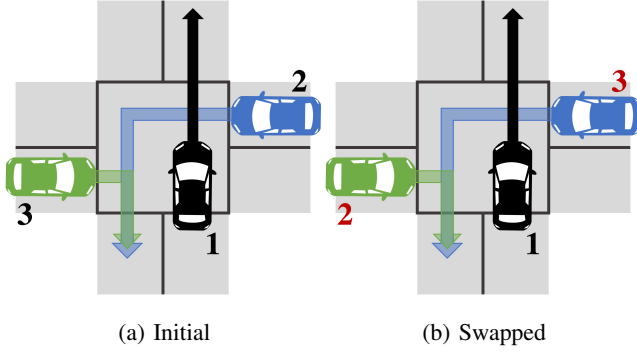


Fig. 3: Example of assignment swapping. Initially, Car 2 (blue) is making a left turn before Car 3 (green). However, since Car 2 is blocked by Car 1 (black), the assignments swap so Car 3 can move simultaneously with Car 1.

intersection. The system arrival time  $t_{0,i}$  is used to maintain a FCFS queue  $Q$  of requests such that an agent arriving first to the intersection is also first to enter the intersection, or  $t_{s,i} < t_{s,j}$  if  $t_{0,i} < t_{0,j}$ . Once a request is received, the central coordinator internally simulates the trajectory of the vehicle (using the vehicle’s communicated state and dynamics) and reserves the tiles within the intersection to ensure collision free reservations. The reservation start time  $t_{s,i}$  is returned to each agent, and a predicted vehicle wait time can be calculated based on start time and vehicle dynamics.

#### IV. SVO-BASED RESERVATION SWAPS

In this section, we describe our main contribution, the FCFS-SVO policy which includes a two-agent priority swap to allow each agent to delay their own priority in the queue to allow for joint optimization of utilities based on the agents’ SVOs. Our FCFS-SVO policy builds from the preliminary FCFS assignments presented in the previous section. We also describe some implementation details that allow for increased cooperation between the agents towards system-level improvement.

##### A. Pairwise SVO Swapping

A main limitation of TBR methods is that the reservations are required to follow the FCFS queue ordering. Our approach, FCFS-SVO, allows the coordinator to consider pairwise swapping of two sequential agents within the queue. More specifically, if agent  $v_i$  is located at position  $n$  within the queue and agent  $v_j$  is located at position  $n+1$  (immediately afterwards), then the coordinator may consider swapping positions and reserving  $v_j$  first. Implicit in this procedure is that agent  $v_i$  is willing to forgo its earlier position in the queue. Since agents can readily observe (and are aware) of the FCFS ordering of agents, a socially “fair” swap must ensure that both agents benefit from such a swap. The realization that each agent has their own Social Value Orientation allows the coordinator to swap the agents. Theoretically, the coordinator could consider every possible re-ordering of agents within the queue, however, to maintain

a tractable solution (similar to that of FCFS), we limit swap to single, sequential swaps through the queue.

First, the coordinator reserves the intersection with FCFS, assigning agent  $v_i$  its reservation  $r_i^n$  before assigning  $v_j$  its reservation  $r_j^{n+1}$ . From the initial assignments, the coordinator computes the utility in (1) of each agent based on their SVO and wait times,

$$\begin{aligned} u_i &= -t_{w,i} \cos \theta_i - t_{w,j} \sin \theta_i, \\ u_j &= -t_{w,j} \cos \theta_j - t_{w,i} \sin \theta_j. \end{aligned}$$

Here, we define the reward for each agent as the inverse of their wait time,  $R_i = -t_{w,i}$  and  $R_j = -t_{w,j}$ . The coordinator then computes the reservations  $\hat{r}_i^{n+1}$  and  $\hat{r}_j^n$  as if the queue order was swapped, and then determines the corresponding utilities,

$$\begin{aligned} \hat{u}_i &= -\hat{t}_{w,i} \cos \theta_i - \hat{t}_{w,j} \sin \theta_i, \\ \hat{u}_j &= -\hat{t}_{w,j} \cos \theta_j - \hat{t}_{w,i} \sin \theta_j, \end{aligned}$$

where  $\hat{u}_i, \hat{u}_j$  are the utilities of agents  $i$  and  $j$  when the order of reservations are swapped, and  $\hat{t}_{w,i}, \hat{t}_{w,j}$  are the respective wait time in the swapped configurations. If both agents’ SVO-utilities are higher after the swap

$$\begin{aligned} \hat{u}_i &> u_i \\ \hat{u}_j &> u_j, \end{aligned} \quad (3)$$

then the order is swapped. Equation (3) becomes the decision equation to determine the ordering of agents  $v_i$  and  $v_j$ . The reservation is returned to the agent and the process continues for the remaining positions in the queue. Algorithm 1 presents our swapping algorithm.

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#### Algorithm 1 FCFS-SVO: Two-Agent Swap

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```

1:  $i = Q[0]$ 
2: for  $n = 1 \dots |Q| - 1$  do
3:   ASSIGN  $j = Q[n]$ 
4:    $u_i, u_j, t_i, t_j = \text{ATTEMPTRESERVATION}(v_i, v_j)$ 
5:    $\hat{u}_j, \hat{u}_i, \hat{t}_j, \hat{t}_i = \text{ATTEMPTRESERVATION}(v_j, v_i)$ 
6:   if  $\hat{u}_i > u_i$  and  $\hat{u}_j > u_j$  then
7:     RESERVE( $j, \hat{t}_j$ )
8:   else
9:     RESERVE( $i, t_i$ )
10:     $i \leftarrow j$ 
11:  end if
12: end for

```

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From Algorithm 1, we see that swapping occurs in a pairwise fashion, iterating through the queue of agents, with a runtime of  $O(|Q|)$ . To better illustrate the behavior of our swapping algorithm, Proposition 1 shows the swapping behavior if a vehicle is egoistic, and Proposition 2 details how swapping may lead to an increase in wait time for non-egoistic vehicles.

**Proposition 1.** *An egoistic vehicle  $v_i$  will only swap reservations if their wait time decreases,  $\hat{t}_{w,i} < t_{w,i}$ .*



*Proof.* For  $\theta_i = 0$ , the utility function  $u_i$  reduces to

$$u_i = R_i = -t_{w,i}.$$

By design, a swap only occurs if the utility function of both agents increases. For  $\hat{u}_i > u_i$  to be true, we see that  $\hat{t}_{w,i} < t_{w,i}$ , thus showing that vehicle  $v_i$  will only swap its reservation if their wait time decreases.  $\square$

While egoistic agents are not incentivized to swap, increasingly prosocial agents will swap positions even if it incurs some time delay penalty. This is due to their social utility function also encoding the reward (or in this case, delay) of the other agents. As a result, an increase in prosocial agents leads to a reduction in overall system wait time at the potential expense of their own wait time.

**Proposition 2.** *A non-egoistic vehicle  $v_i$  ( $\theta_i > 0$ ) may incur an increase in wait time  $\Delta t_i$  due to a reservation swap.*

*Proof.* Consider the case where the next agent in the queue  $v_j$  is egoistic ( $\theta_j = 0$ ) and a potential swap would lead to delay  $\Delta t_i$  to  $v_i$  and a reduction in wait time  $\Delta t_j$  for  $v_j$ . A swap will occur if  $\hat{u}_i > u_i$  and  $\hat{u}_j > u_j$ . In this scenario, the initial FCFS utility and swapped utilities for each vehicle are

$$\begin{aligned} u_i &= -t_{w,i} \cos \theta_i - t_{w,j} \sin \theta_i \\ u_j &= -t_{w,j} \\ \hat{u}_i &= -(t_{w,i} + \Delta t_i) \cos \theta_i - (t_{w,j} - \Delta t_j) \sin \theta_i \\ \hat{u}_j &= -(t_{w,j} - \Delta t_j) \end{aligned}$$

The utilities for the swapped configurations  $\hat{u}_i, \hat{u}_j$  can be rewritten in terms of the FCFS utilities  $u_i, u_j$  to arrive at a more convenient form

$$\begin{aligned} \hat{u}_i &= u_i - \Delta t_i \cos \theta_i + \Delta t_j \sin \theta_i \\ \hat{u}_j &= u_j + \Delta t_j \end{aligned}$$

For any  $\Delta t_j > 0$ , the utility of  $v_j$  increases from the swap since the egoistic vehicle benefits purely from its own decrease in wait time. Thus, the only remaining condition for a swap in this case is for  $\Delta t_j \sin \theta_i > \Delta t_i \cos \theta_i$ . Equivalently, a swap will occur if the social benefit to  $v_i$ , from reducing the wait time to  $v_j$ , is greater than social cost of delaying itself by  $\Delta t_i$ . This occurs, for example, if agent  $i$  is prosocial ( $\theta_i = \pi/4$ ) thus simplifying the swap condition to  $\Delta t_j > \Delta t_i$ , i.e., if the decrease in delay to  $v_j$  is greater than the increase in delay to  $v_i$ . In this case, both utilities increase, leading to swap in priorities, even though  $v_i$  incurs a delay  $\Delta t_i > 0$ .  $\square$

### B. Batched Reservations

In [17], the coordinator constantly processes requests and returns reservations. In FCFS-SVO, the coordinator processes requests in batches. This encourages collaboration by allowing for multiple swaps. If too few agents are in the queue, then swaps would not be possible, and only one agent is considered at a time. To ensure that agents are not waiting at the intersection line for additional agents to enter the queue, the coordinator triggers a batch of reservations if an agent is waiting at the entrance without a reservation.

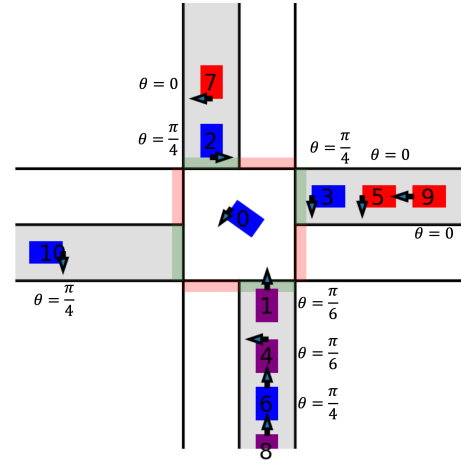


Fig. 4: Snapshot of traffic simulation with agents approaching intersection. All agents request the intersection as they enter the control region (grey). Autonomous vehicles send their intended direction while human vehicles do not communicate directions. Social Value Orientations are shown for each agent, along with their initial FCFS queue ordering.

In addition, after a batch of swapping is performed, the last vehicle in the queue is returned without a reservation. In the next batch, it will enter at the front of the queue. This allows additional swapping for the agent with vehicles that make requests later.

### C. Benefits of SVO

Without SVO, central coordinators are restricted to FCFS policies to remain tractable as more agents enter the intersection. In addition, FCFS maintains a level of fairness across the intersection, in that agents that arrive at the intersection first enter the intersection first. If, for example, an arbitrary optimization over vehicles was allowed, individual agents would not necessarily benefit, and more importantly, would incur socially-unacceptable delays as later vehicles would enter the intersection before them. By incorporating the SVO utility in determining the order of the vehicles, we ensure that any re-optimization over FCFS remains socially-compliant by each agent in the intersection. Even in scenarios with mostly egoistic vehicles, FCFS-SVO swapping can allow for reduced wait times because some re-orderings will cost a higher-priority vehicle no delays. In real-world systems, humans have shown to act in a more prosocial manner not only caring about their own delays but also about delays of others, as shown in Fig. 2, and thus we expect that a SVO-based reservation system can provide additional gains over FCFS. Finally, by including both an agent's arrival priority and the impact on later vehicles in SVO utility, we attempt to bridge the gap between FCFS policies, which only account for arrival priority, and auction policies, which consider the cost of a reservation on an agent in determining the final ordering.

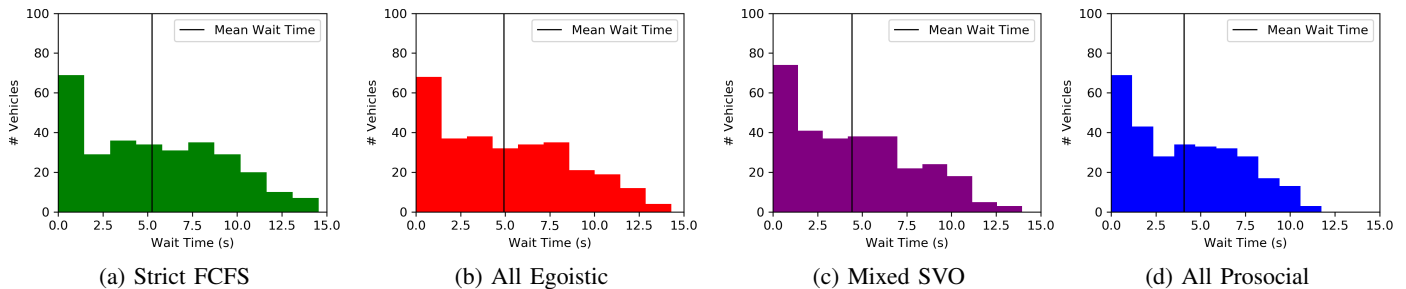


Fig. 5: Vehicle wait times for different SVO distributions. When all agents are egoistic, marginal improvement occurs over FCFS. Wait time reduction occurs as agents become increasingly prosocial, with the minimal wait time occurring when all agents are prosocial.

## V. RESULTS

We implement the FCFS reservation and SVO swapping policies in a traffic simulator to validate the efficacy of the FCFS-SVO framework. Figure 4 shows our simulated four-way intersection. In addition, we evaluate the impact of varying vehicle SVOs and the proportion of human drivers in the system under the impact of our method on different agents.

### A. Intersection Simulations

Each simulation consists of an episode of 12 vehicles arriving into the system according to a Poisson process. Simulated vehicles are randomly assigned a turning direction with probability  $p_{left} = 0.3$ ,  $p_{right} = 0.3$ ,  $p_{straight} = 0.4$  and randomly assigned one of four incoming lanes to enter the system. Agents are assigned to be a human driver with probability  $p_{human}$ . Human drivers do not communicate their intended direction to the coordinator, and thus effectively reserve all three possible directions. In addition, an SVO preference  $\theta_i$  is assigned to each agent and their utility is computed according to (1). In prosocial and egoistic simulations, all agents are assigned  $\theta_i = \pi/4$  and  $\theta_i = 0$ , respectively. In mixed simulations, agents are randomly chosen to have SVOs where  $\theta_i \in \{0, \pi/6, \pi/4\}$  with equal probability.

Each of the 25 simulations are re-run with different types of coordinators. The baseline, Strict FCFS, requires agents only enter the intersection according to the order in which they arrive at the intersection. We then add our socially-compliant swapping, denoted FCFS-SVO. We vary both the percent of human drivers and different SVO distributions.

### B. Effect of SVO on Vehicle Wait Time

The performance of FCFS-SVO is directly impacted by the distribution of SVO personalities within the system. Figure 5 compares the wait time distributions when we vary the SVO distributions in the group, compared to a strict FCFS baseline. In Fig. 5, simulations with all ego vehicles lead to less improvement compared to all prosocial or even a mix of SVO personalities. The mean wait times corresponding to Fig. 5 are recorded in Table I. The wait time in the system is calculated as the time from when the vehicle enters the system to when the vehicle passes through the intersection.

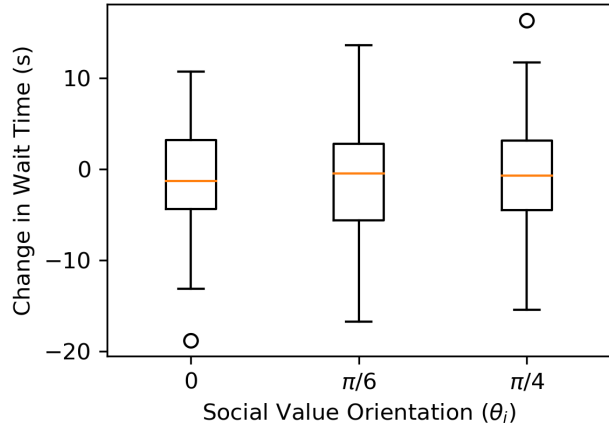


Fig. 6: Changes in wait time change compared to FCFS for different Social Value Orientation preferences.

This wait time includes any time the vehicle spends in its lane queue waiting for preceding vehicles. As we increase the percentage of prosocial agents in the system, the mean wait time decreases. Furthermore, we notice the overall variation in wait times is reduced, seemingly creating a more equitable distribution of delays across the system.

As noted in Proposition 1, egoistic agents will only swap positions if their time delay decreases, however, Proposition 2 shows that prosocial agents may swap even if it includes an increase in wait time. Figure 6 illustrates the distribution of changes in individual wait time categorized by their SVO preference. While egoistic agents benefit more, the distributions show that prosocial agents are not greatly disadvantaged by this system.

TABLE I: Mean Wait Times for Vehicles

Policy	$t_w$
FCFS	5.25 s
All Egoistic	4.94 s
Mixed SVO	4.43 s
All Prosocial	4.07 s

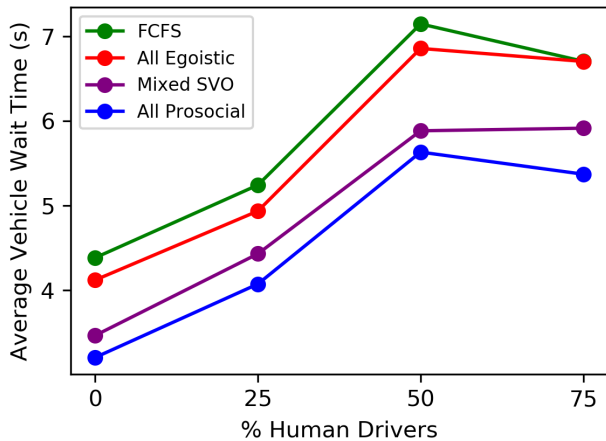


Fig. 7: Average vehicle wait time at the intersection for varying amount of human drivers in the system. All three types of SVO see improvement over the FCFS policy, with the largest decrease of delays occurring when all agents are prosocial.

### C. Effect of Human Drivers

In our simulations, we also varied the number of human drivers in the system. Figure 7 shows how the average wait time across vehicles is affected by the total number of humans. As the number of human drivers increases, the average wait time also increases, as human drivers do not communicate their intent and must reserve the entire intersection. We also note that for all cases, increasing the total number of prosocial vehicles reduces the average wait times across the system.

In Fig. 8, we look at the number of swaps that occur throughout the simulation. We notice that for all egoistic drivers, the fraction of vehicles that swap reservations is quite small, and the fraction of swaps increases as the fraction of prosocial vehicles increases. The fraction of swaps stays relatively consistent across the number of human drivers in the system, until there are more human drivers than autonomous vehicles.

Figure 9 shows the difference in wait times for human and autonomous vehicles using FCFS-SVO, with all SVO preferences set to prosocial. This scenario appears to benefit the autonomous vehicles more than the human vehicles, with a greater number of the autonomous vehicles reducing their time delay. Since human drivers reserve the full system, while autonomous vehicles only reserve their intended path, swapping tends to favor the autonomous vehicle, due to the fact that it requires a smaller time reservation of the intersection.

## VI. CONCLUSIONS

In this work, we present a centralized autonomous coordination algorithm that can plan for multiple levels of cooperation, from fully connected autonomous vehicles to human vehicles with limited communication, ensuring that

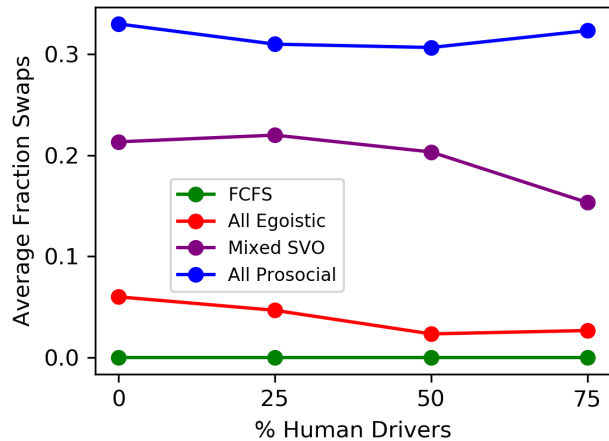


Fig. 8: Fraction of swaps executed by the central coordinator during FCFS-SVO. Since egoistic agents only swap when it incurs zero delays, very few swaps occur. In mixed SVO and prosocial settings, swaps occur 20%-40% reservations.

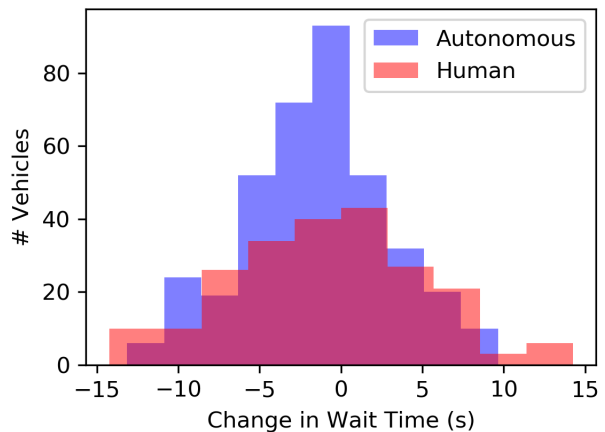


Fig. 9: Histogram of wait time change compared to FCFS in simulations where all agents are prosocial. Swapping leads to increased delays in human drivers, allowing for more efficient autonomous vehicles to enter the intersection first.

any optimization does not come at a cost to social utility of each agent. By leveraging SVO preferences among vehicles, we enable socially-compliant navigation through the intersection that adapts to the level of cooperation. Furthermore, we show that system performance improves with the percentage of prosocial cars in the system. For autonomous vehicles, this implies choosing to design prosocial vehicles can increase cooperation and efficiency on the road. While our system assumes a central coordinator for the purpose of reserving the intersection and negotiating swaps, future research directions include decentralized algorithms that can safely allow vehicles through an intersection. In such a system, the pair-wise swapping using SVOs proposed in this paper can easily be extended to a decentralized system, where vehicles negotiate directly with each other.



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