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Decentralized Optimization Vehicle Route Planning
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1. General Problem and Context

The rise of Connected and Autonomous Vehicles, CAVs, introduces new possibilities in vehicles and traffic management. This study considers the application of an adaptive routing framework for a fleet of autonomous vehicles, while considering the impact of each vehicle's selfishness on the network as a whole. There is already dynamic traffic routing services through applications like Google Maps, Waze, and Uber. However, their contribution to traffic flow is unknown because their suggested routes are not enforceable and are dependent on the number of users. As vehicle technology approaches fully autonomous vehicles and companies like Uber and Lyft consider replacing their drivers with CAVs, the understanding of optimized routing of CAVs is crucial for societal acceptance of this new technology.

The goal of this research was to explore the sensitivity of *system optimal* (SO) traffic assignment to dynamic vehicle routing using agent-based planning [1] [2]. SUMO (Simulation of Urban Mobility), is a widely accepted traffic simulator that was used along with TraCI (Traffic Control Interface), to dynamically route the cars, or agents, in the simulation. EPOS (Economic Planning and Optimization Selection), is a decentralized optimization framework that interfaced with the simulation environment to select optimal agent routes that was used with the preexisting adaptive routing framework TRAPP [3] [4].

2. Description of the Specific Human-Cyber Physical System (HCPS) Problem

Traffic control is a complex problem that is affected by human desires, physical constraints and computation limitations. It is necessary to take into account traffic laws, traffic patterns, and the number of times that routes can be re-evaluated on large networks. Therefore, for this project the HCPS problem is determining how the selfishness of a driver can affect route optimization and ultimately the traffic flow as a whole. The project was testing the hypothesis that if a driver is more altruistic then they may choose to take a route that does not provide the highest level of benefit to them in order to benefit the system. If there are more routes being chosen that do not directly benefit the drivers but rather optimize the whole system then there is potential for CAVs to improve traffic flow if their assigned routes are made to serve everyone.

In this setting, altruism is defined as the willingness of an agent to choose a route optimized for the global objective. It is represented by the β parameter in EPOS. The simulation was run on each city with β values varying from completely selfish to completely altruistic. At the start of each run, EPOS was evoked to select a route that reflects a particular altruism level of the agent.

3. The Challenges of Reaching a Functional System

Finding the right data proved challenging in developing a system that produced useful results. It was necessary to add more networks and cities to the simulation to produce a realistic traffic situation. To improve the traffic patterns we introduced a new feature that incorporated ZIP code data to assign vehicles to origins based on the population density [6]. It was challenging to find widespread Origin-Destination data for cities other than Manhattan because there is Yellow Cab taxi data that could have been usable for the OD matrix, but other cities did not have any similar information. Additionally, rideshare companies like Uber and Lyft could have provided information similar to the Manhattan data for the other cities, but this information is not widely available. The ZIP code population data proved to be consistent across all US cities and provided an improvement upon random route assignment.

There was a limit on how many cars could run simultaneously to receive results in reasonable time to complete the project. This limited the choice of cities to those where the number of cars on the road is not more than 10,000, which still took almost an entire day to run each. To determine the number of cars to run within each city, we used the percentage of residents who commuted by car and then represented a segment of the morning commute population. Many medium-to-large size American cities with little public transportation had to be ruled out because the number of people who commute by car was too large to simulate. Even cities with moderately extensive public transportation were not viable because a large number of their populations still commuted by car. This made it challenging to test a diverse set of cities because the simulation would simply take too long if enough agents were placed on the network to accurately represent many of the cities’ traffic patterns.

4. The Technical Problem and the Research Setting

We conducted our research at Technische Universität München under the supervision of Ilias Gerostathopoulos and Raphael Stern. The study focused on the trade-offs between optimizing for local costs of individual agents and the global costs of the network as a whole. In particular the study aimed to answer these questions using an agent-based model:

i. Can increasing the altruism of traffic agents lead to positive traffic effects related to reduced trip times?
ii. If yes, what is the level of altruism necessary for observing such positive effects?
iii. Which are the city attributes and characteristics that determine whether such positive effects are observed?

A simulation of traffic networks under peak morning traffic was used to answer these questions [5]. The simulation environment used a specific number of agents to represent the number of commuters in an average commute time in each network. To understand the impact of urban structure on the ability to optimize trip routing, the study considered four cities with diverse characteristics, Annapolis, Boulder, Duluth and the borough of Manhattan in New York City. The study found that load balancing can indeed be achieved by increasing the agents' altruism, and the positive effect on network performance depends on the characteristics of the cities and, in particular, on the density of the city network.

5. Future Research

Specifically for this project, the next step would be to explore further optimizations of EPOS and the framework that connects EPOS with SUMO and TRACI. This would enable the simulation to handle a greater number of agents for longer periods of time, improving the simulation results and widening the scope of possible networks. A more specific study of sparse vs. dense networks and the addition of a fairness objective would provide valuable information to better understand the positive effects of SO routing [5].

This research is important for the future incorporation of CAVs into our current road networks. It is necessary to understand the implications that decentralized route planning has on traffic before CAVs are fully introduced. More generally, this research can be continued by exploring system optimality in cities currently using real time route planners such as Google Maps.

References

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