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A Decision Support System for Evaluating the Impacts of Routing Applications on Urban Mobility

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***Abstract*—The rise of congestion across the United States and the increasing adoption of mobile routing services have enabled drivers with the ability to find the fastest routes available in urban road networks. Arterial roads and side streets originally designed for local traffic are impacted by the influx of selfishly routed drivers, garnering much recent media attention and civic debate. Classic flow-based game theoretic models provide the framework for simulating the behavior of routed and non-routed drivers on a road network. We developed an interactive policy decision support system called the Routing Impact Detection, Evaluation, and Response Decision Support System (RIDER DSS) as a tool for policymakers and practitioners to hone in on areas most impacted by routing apps and assess potential policy actions to mitigate the effects of cut-through traffic on a local and regional scale. In a case study of Baxter Street in the Los Angeles Basin we demonstrate how the RIDER DSS can relate the percentage of app users in a network to the distribution of traffic flow on side streets.**

I. Introduction

A. Motivation and Context

Congestion is on the rise in urban areas across the United States. Each year, American auto commuters spend 42 hours in peak hour traffic, amounting to a yearly cost of $960 per person [1]. As suburbanization remains the dominant trend in the growth of urban areas, the demand for road travel is rapidly outstripping the capacity of the nation's regional and local transportation infrastructure [2]. Total *vehicle miles traveled* (VMT) in the U.S. rose 8% from 2012 to 2017, with a 4.2% increase in VMT per capita over the same period [3].

In addition, the growth of the smartphone industry has equipped individuals with unprecedented access to information via mobile internet services, including real-time traffic information and routing guidance. Seventy-seven percent of American adults own smartphones today (up from 35% in 2011) and, as of December 2016, Google Maps and Apple Maps were among the top 15 most popular mobile apps in the U.S., with 102 million and 53.9 million unique monthly users, respectively [4],[5]. The rapidly growing real-time traffic information industry includes competitors such as Apple, Google, HERE, INRIX, TomTom, and Waze, all of which strive to offer highly responsive and reliable routing services through routing applications on smartphones and/or aftermarket devices in connected vehicles, guiding drivers along the fastest routes available on public roads. The use of routing apps by *ridesourcing* drivers working for companies such as Lyft and Uber is also contributing to the dramatic increase of app-guided traffic in urban areas. In San Francisco, for example, there are over 45,000 registered ridesourcing drivers mostly using the same routing app (Waze/Google) [6].

While app-based routing is perceived as beneficial by individuals whose travel times are seemingly minimized, the resulting allocation of selfishly routed traffic is being blamed for a significant increase in congestion on local, low-capacity road networks [7]. During peak hours, traffic is routed from highways onto local roads ranging from arterials to residential streets, often greatly exceeding the design capacity of those facilities. Communities impacted by the influx of cut-through traffic suffer from numerous negative externalities, including excessive noise, air pollution, wear and tear to roads and sewage lines- not to mention degraded neighborhood safety and quality of life [8],[9]. In response, residents have employed tactics of installing counterfeited road blockage signs, falsifying hazard reports to crowdsourced routing apps such as Waze, and even equipping elderly pedestrians with routing app-enabled smartphones to influence estimated average travel speeds. All in all, citizens can do little more than voice their concerns to local government and the media.

City officials and policymakers have been slow to respond, however. In Los Angeles, the most congested city in the U.S., a yearlong study completed in December 2017 revealed flows of more than 900 cars an hour on streets scarcely 20 feet wide, built for 2,000 cars a day [1],[8]. Eighty-six percent of that traffic was found to be cut-through traffic, yet city officials' attempts to convince companies like Waze to stop diverting traffic from highways to local streets have been unfruitful. Many cities are considering traffic calming techniques such as speed humps, *road diets* (road capacity reduction), *semi-diverters* (barricades to two-way traffic), small traffic circles, or redesigning the road networks altogether. However, these measures are expensive and could result in degraded road capacity for locals. In an effort to put a stop to the influx of rerouted commute traffic, the borough of Leonia, New Jersey installed ”Do Not Enter” signs in January 2018 effective during commute hours on 60 residential streets, with a $200 fine for violators [10]. Soon after the signs went into effect, a lawsuit was filed against the city, citing that the road closures caused traffic to be rerouted into neighboring communities.

Regional policies such as *high-occupancy vehicle lanes* (HOV), *high-occupancy toll lanes* (HOT), spatial and/or temporal road use pricing, cordon tolling, and digital impact fees have potential for reducing both cut-through traffic and hypercongestion by incentivizing high-occupancy mode use and reduced travel demand during peak travel times [11]. Pricing policies are politically sensitive, requiring careful analyses and compelling messaging to garner public support. Public officials, policymakers, and transportation planners would benefit from a standardized method for visualizing and quantifying the externalities of routing apps in congested urban networks.

B. Background

Selfish routing is a phenomenon of *noncooperative networks* in which *users* of a network choose to travel from their origin to destination along a path that minimizes their individual *latency*, or cost function [12]. Such noncooperative behavior is exhibited by drivers on a road network and can be studied using a game-theoretic approach in which the resulting traffic flows represent a *Nash equilibrium* [13]. A Nash equilibrium, also referred to as a *user equilibrium* or *Wardrop equilibrium* in traffic theory, is achieved when unilateral deviation by any user from its path would result in no improvement to that user's latency [14]. Nash equilibria are well studied in economic theory and have been shown to be socially suboptimal [12].

In traffic modeling, a user's latency is typically a function of the travel time of each arc along a path in the network. In reality, users have varying degrees of access to information about network travel times, thus constraining their behavior with *boundedly rational* decision-making, which may result in suboptimal choices due to the lack and/or price of information [15],[16],[17]. Thai et al., present a *static heterogeneous traffic assignment* problem with two classes of users: *routed users* that follow travel time minimizing directions from a routing app, and *non-routed users* that make routing decisions based on a *multiplicative cognitive cost model* that accounts for the relative convenience of choosing high capacity road segments for a driver with limited information [7]. Thai et al. demonstrate the rationality of the multiplicative cognitive cost model for routing under conditions of low traffic demand as well as its suboptimality during peak hours, thereby exhibiting the attractiveness of app-based routing. Application of their model in a static traffic assignment for the Los Angeles road network with varying percentages of routed users reveals that the selfish routing enabled by apps causes a 300% increase in VMT on low-capacity roads. Cabannes et al. propose the *restricted path choice* model, a refinement of the cognitive cost model in which non-routed users' routing options are restricted to a subset of all possible paths between their origin and destination in the network [18].

C. Contributions and Outline

We present a traffic routing model-based decision support system (DSS) that leverages the realism achieved by flow-based game theoretic traffic assignment models to provide practitioners and policymakers with the ability to assess the impacts of selfish routing on local and regional networks. The Routing Impact Detection, Evaluation, and Response (RIDER) DSS is a realistic, computationally efficient modeling and simulation resource that contributes to the improvement of the state of the art in travel modeling and transportation planning by enabling policy makers to assess and respond to the externalities produced by selfish routing in urban networks. The RIDER DSS is equipped with multiple routing models to allow for the evaluation of mltiple paradigms of routed and non-routed travel behavior as well as policy scenarios in which access to particular roads is restricted and/or subject to tolls, such as digital impact fees.

In section II, we detail the architecture of the RIDER DSS. Section III demonstrates a use case of the RIDER DSS in the Los Angeles basin. In section IV we discuss further applications of the RIDER DSS as well as several planned improvements for future iterations of the software.

II. The RIDER DSS

The RIDER DSS is an interactive visualization and scenario analysis dashboard that leverages static heterogeneous traffic assignment models with routed and unrouted users to assess the impacts of routing apps in dense urban networks and evaluate feasible policy scenarios. In this section we detail the architecture of the RIDER DSS, the main components of which are displayed in Figure 1. As in many modern model-based DSS frameworks, the RIDER DSS includes four main components: a model base, a solver, a database, and a user interface [19],[20]. We begin by presenting the formulations of the models included in the model base, then define the algorithmic base, or solver of the DSS. Next, we describe the database architecture and finally discuss the performance metrics and visualization modules in the user interface.

A. The Model Base and Solver

The DSS employs the static heterogeneous traffic assignment model presented by Thai et al. [7]. The current implementation of the DSS includes routed and non-routed users, although variations of these two user classes could be incorporated. For the remainder of this article, we refer to routed users as app users and unrouted users as non-app users. App users are routed using the shortest path model and non-app users are routed using either the cognitive cost model or the restricted path choice model [18].

1) Mathematical formulation and notation: A road network is modeled as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where $\mathcal{V}$ is the set of all vertices $v \in \mathcal{V}$ connected by the set of all directed arcs $\mathcal{A}$. Each origin-destination (OD) pair $w = \{s, t\} \in \mathcal{W}$ such that $\mathcal{W} \in \mathcal{V} \times \mathcal{V}$ corresponds to a quantity of user demand per unit time $d_w = d_w^{nr} + d_w^r$ where $d_w^{nr} \in \mathbb{R}_+^{\mathcal{W}}$ is the demand of non-app users and $d_w^r \in \mathbb{R}_+^{\mathcal{W}}$ is the demand of app users. Users choose the minimum cost route $p \in \mathcal{P}_w$ with respect to their latency function $\ell_p(\cdot)$, where $\mathcal{P}_w$ is the set of all paths from s to t.

The state of the network is defined by a vector of total route flows $f = [f_p]_{p \in \mathcal{P}} \in \mathbb{R}^{\mathcal{P}}$ where $\mathcal{P} = \cup_{w \in \mathcal{W}} \mathcal{P}_w$ is the set of all paths in the network. The total route flow f is the sum of the route flows of app users, $f^r = [f_p^r]_{p \in \mathcal{P}}$, and of non-app users, $f^{nr} = [f_p^{nr}]_{p \in \mathcal{P}}$ such that $f = f^r + f^{nr} = [f_p^r + f_p^{nr}]_{p \in \mathcal{P}}$. A flow vector is feasible if for all $w \in \mathcal{W}$, $\sum_{p \in \mathcal{P}_w} f_p = d_w$, $f_p \geq 0, \forall p \in \mathcal{P}_w$. In matrix form, f^r and f^{nr} are feasible if they are in the sets $\mathcal{X}^r$ and $\mathcal{X}^{nr}$, respectively, given by:

$$\mathcal{X}^r := \{f^r \in \mathbb{R}^{\mathcal{P}} : f^r \succeq 0, \Lambda f^r = d^r\} \tag{1}$$

$$\mathcal{X}^{nr} := \{f^{nr} \in \mathbb{R}^{\mathcal{P}} : f^{nr} \succeq 0, \Lambda f^{nr} = d^{nr}\} \tag{2}$$

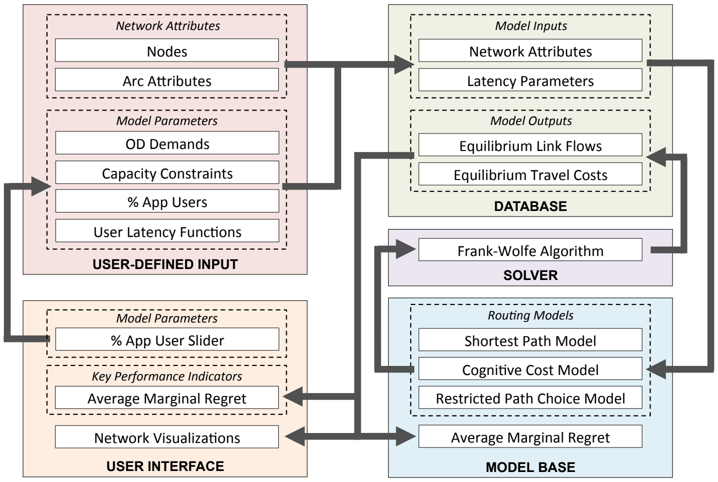

Fig. 1. Flowchart of the RIDER DSS

where Λ is the OD-path incidence matrix. The latency $\ell_p(\cdot)$ of each path $p \in \mathcal{P}$ is given by $\ell_p(f) = \sum_{a\in p} c_a(x_a)$ where $c_a(x_a)$ is the travel cost of arc a. We assume the travel cost of arc a depends only on the sum of the flows of vehicles on the arc $x_a = \sum_{p\in\mathcal{P}} I(a \in p) f_p$, where $I(B)$ is the indicator function of the Boolean B. The total arc flow is $x = x^r + x^{nr} = [x_a^r + x_a^{nr}]_{a\in\mathcal{A}}$ where the arc flow vectors of the app users and non-app users are denoted by $x^r = [x_a^r]_{a\in\mathcal{A}}$ and $x^{nr} = [x_a^{nr}]_{a\in\mathcal{A}}$, respectively. Arc flow vectors x^r and x^{nr} are feasible if they belong to the following sets respectively:

$$\mathcal{K}^r := \{x^r \in \mathbb{R}^{\mathcal{A}} : \exists\ f^r \in \mathcal{X}^r, x^r = \Delta f^r\} \tag{3}$$

$$\mathcal{K}^{nr} := \{x^{nr} \in \mathbb{R}^{\mathcal{A}} : \exists\ f^{nr} \in \mathcal{X}^{nr}, x^{nr} = \Delta f^{nr}\} \tag{4}$$

2) Nash equilibrium: Both app users and non-app users are routed to minimize their associated latency functions. The resulting equilibrium flows describe a Nash equilibrium in which no individual user can achieve a faster travel time by switching paths. The equilibrium flows are thus the feasible flows f^r and f^{nr} such that $\forall w \in \mathcal{W}$

$$\forall p \in \mathcal{P}_w, f_p^r > 0 \implies \ell_p^r(f) = \min_{q\in\mathcal{P}_w} \ell_q^r(f) \tag{5}$$

$$\forall p \in \mathcal{P}_w^{nr}, f_p^{nr} > 0 \implies \ell_p^{nr}(f) = \min_{q\in\mathcal{P}_w^{nr}} \ell_q^{nr}(f) \tag{6}$$

where the latency function of app users, ℓ_p^r, is defined by the shortest path model while that of the non-app users, ℓ_p^{nr} is defined by either the cognitive cost model or the restricted path choice model, all three of which are described below. Users can specify which of the two latter models to apply to the non-app users. Since routing apps consider all public road segments, the path choice set for app users is simply the set of all paths from s to t, $\mathcal{P}_w$. The path choice set for non-app users is dependent on the routing model used, thus we specify $\mathcal{P}_w^{nr}$ in the subsections for each of the models. All three models depend on a measure of travel time on arc a, $t_a(x_a)$, which is a function of the arc flow, free-flow travel time, and scaling parameter accounting for the effects of congestion on arc a.

3) Shortest path model: App users' latency function is given by

$$\ell_p^r(f) = \sum_{a\in p} t_a(x_a), \quad \forall p \in \mathcal{P} \tag{7}$$

4) Multiplicative cognitive cost model: The arc set is partitioned into a low-capacity arc set $\mathcal{A}^{lo} := \{a \in \mathcal{A} : c_a < c_{lo}\}$ and a high-capacity arc set $\mathcal{A}^{hi} := \{a \in \mathcal{A} : c_a \geq c_{lo}\}$ based on the capacity c_a of each arc and an arbitrary capacity threshold c_{lo}, which can be defined in the dashboard. Thus the arc cost function for non-app users is

$$c_a^{nr}(x_a) = \begin{cases} \mathcal{C} \cdot t_a(x_a) & if\ a \in \mathcal{A}^{lo} \\ t_a(x_a) & if\ a \in \mathcal{A}^{hi} \end{cases} \tag{8}$$

and the route latency function is

$$\ell_p^{nr}(f) = \sum_{a\in p^{hi}} t_a(x_a) + \mathcal{C} \sum_{a\in p^{lo}} t_a(x_a) \tag{9}$$

where $\mathcal{C} > 1$ is a constant representing a non-app user's preference for high-capacity road segments over low-capacity road segments when choosing a route and p^{hi} and p^{lo} are the high- and low-capacity road segments in path p, respectively. In this model, the path choice set of non-app users is not restricted, thus $\mathcal{P}_w^{nr} := \mathcal{P}_w$.

5) Restricted path choice model: The second option for non-app user routing is the restricted path choice model, which reduces the available path choice set for a particular class of users. For the implementation of this model in the RIDER DSS, we consider that the non-app users have limited information about the real-time traffic conditions on the network, and thus are restricted to the path that minimizes the total travel time under free flow conditions. The latency function is thus the same as the shortest path model

$$\ell_p^{nr}(f) = \sum_{a\in p} t_a(x_a), \quad \forall p \in \mathcal{P}_w^{nr} \tag{10}$$

where the path choice set is restricted to $\mathcal{P}_w^{nr} := \{\operatorname*{argmin}_{q\in\mathcal{P}_w} \sum_{a\in p} t_a(0),\ \forall p \in \mathcal{P}_w\}$.

6) Frank-Wolfe: We use the theory of variational inequality [21] to solve for the equilibrium flows described in (1) and (2) with the Frank-Wolfe algorithm (FW) [22]. The equilibrium f can be described as a feasible solution $(f^r, f^{nr}) \in \mathcal{K}^r \times \mathcal{K}^{nr}$ of the following variational inequality problem

$$\ell^r(f)^T g^r + \ell^{nr}(f)^T g^{nr} \geq \ell^r(f)^T f^r + \ell^{nr}(f)^T f^{nr}, \forall (g^r, g^{nr}) \in \mathcal{K}^r \times \mathcal{K}^{nr} \quad (11)$$

The network equilibrium is computed for every integer percentage of app users $\alpha \in \{0, .01, .02, ..., .99\}$ such that

$$d_w = (1-\alpha)d_w^{nr} + \alpha d_w^r \ \forall w \in \mathcal{W} \quad (12)$$

7) Average Marginal Regret: The equilibrium flows resulting from the heterogeneous traffic assignment model differ by some amount from the user equilibrium that would result from universal access to real time information. In these proceedings, Cabannes et al. present the *average marginal regret*, a metric for quantifying the difference between the actual costs of the equilibrium flow in a heterogeneous traffic assignment and the costs of the theoretical Wardrop equilibrium [23]. The *average marginal regret* for the network, $\mathcal{R}(f)$, is the weighted arithmetic mean of the *instantaneous marginal regret* $\mathcal{R}(f,p) = \ell_p(f) - \dot{\ell}_p(f)$ over every path $p \in \mathcal{P}_w$ for all $w \in \mathcal{W}$ such that $\dot{\ell}_p(f) = \underset{p \in \mathcal{P}_w}{\text{argmin}} \ \ell_p(f)$ is the minimum latency for path $p \in \mathcal{P}_w$. It follows that the *average marginal regret* is given by:

$$\mathcal{R}(f) = \frac{1}{\|d\|_1} \sum_{p \in \mathcal{P}} f_p \cdot \mathcal{R}(f,p) \quad (13)$$

where $\|d\|_1 = \sum_{w \in \mathcal{W}} d_w$.

B. User Defined Input

1) Network attributes: To instantiate the RIDER DSS for a particular road network, the user must provide the network configuration, including the set of nodes in the network with the corresponding latitude and longitude pairs, the arc set, and arc characteristics such as the free flow travel time and the scaling parameter for each arc.

2) Model parameters: The user must upload the total travel demand d_w for each O-D pair w in units of vehicles per time. The user can toggle between the two available non-app user route choice models. For the cognitive cost model, the user can specify the capacity threshold for low versus high-capacity road segments, c_{lo}, and the cognitive cost constant, $\mathcal{C}$.

C. Database

The DSS database stores the user-defined input and results from the model base in a NodeJS static server with ExpressJS middleware in REST API convention. The data required for the visualization modules in the user interface is rendered in a geoJSON format.

D. User Interface

The user interface of the RIDER DSS is a modular dashboard with three types of expandable modules that can be toggled on or off: network visualization, model parameters, and key performance indicators (KPIs). The dashboard runs in a web browser using a ReactJS framework. This front-end framework was chosen because of a strong user community that provides technical support and a certain reliability that the technology will continue to be accessible in the foreseeable future.

1) Network visualization: The Leaflet library is used to create the network visualization module, which display attributes of the traffic assignment on an interactive map of the network. The user can choose which attributes or combinations of attributes to display in each visualization module, including but not limited to: arc flows, distributions of app user and non-app user arc flows, arc capacities, and arc travel times. The visualization module allows users to display attributes of all equilibrium flows on the network, as well as those of specified OD pairs.

2) Model parameters: Model parameters such as latency functions, arc capacity thresholds, and the percentage of app users can be updated using a model parameter module on the dashboard. The app user percentage slider, for example, allows the user to adjust the percentage of app users present in the entire network using an integer sliding scale from 0 to 99% app users. All other modules update in real time to reflect the app user percentage selected by the slider.

3) Key performance indicators: The KPI module provides measurements of the average marginal regret and total travel time of the static traffic assignment.

III. Case Study: The Los Angeles Basin

We demonstrate a case study using the RIDER DSS with the network of the Los Angeles basin. In early 2018 residents of Echo Park, Los Angeles County began reporting excessive through traffic on Baxter St.-one of the steepest streets in America (see Figure 2). Drivers unfamiliar with the 32% grade of Baxter St. are in danger of collisions with difficult to see oncoming traffic and brake failures- many vehicles even spun out onto neighbors' gardens [9]. The rerouting typically occurred during peak hours, when Southbound vehicles on Alessandro St. was routed onto N. Alvarado St. to avoid the build up of traffic caused by the merging of both the Glendale Freeway and Alessandro St. onto Glendale Blvd. The app users were directed to turn left onto Baxter St. from Alessandro St. to bypass the bottleneck by traveling down either N. Alvarado St. or Lake Shore Blvd. instead of Glendale Blvd. In May 2018, Echo Park converted the two blocks of Baxter St. on either side of N.Alvarado St. into disjoint one-way roadways to prohibit through traffic from driving uphill on Baxter St. For this case study, we use the DSS to explore the phenomenon that caused the build up of rerouted traffic on Baxter St., demonstrating the ability of the RIDER DSS to identify areas likely to be impacted by increasing routing app adoption.

A. Data Sources

The demand matrix of the Los Angeles Basin includes 96,077 OD pairs derived from the Census Transportation Planning Products database and the 2006-2010 5-Year American Community Survey Data [24]. The road network parameters are sourced from *Open Street Maps* (OSM), including 14,617 vertices and 28,376 arcs. Road capacities are defined by the OSM category of each road (motorway, primary, secondary, tertiary).

Fig. 2. The RIDER DSS Dashboard displaying the demand distribution across the LA Basin network, and the demand distribution on Baxter St. and N. Alvarado St. with 0, 50, and 99% app users (best viewed in color).

B. Computation

The case study was implemented on a computer with 16 GB of RAM, with an intel i5-6600k processor. The computation time for each app user percentage value α was 49 minutes, resulting in a total computation time of 3.5 days to populate the dashboard with a particular network specification. For the pusposes of the case study, the dashboard is loaded with the results of a single network specification.

C. Visualization

Figure 2 displays the RIDER DSS dashboard with three modules: the app user percentage slider, the average marginal regret KPI, and the overall network demand distribution map. The demand distribution map shows the distribution of arc flows as a proportion of the maximum arc flow on each road segment. We zoom in on Baxter St. and N. Alvarado St. to examine how the arc flow distribution changes with respect to increasing app user percentages on the network. In the top right window of Figure 2, there are no app users on the network, and the distribution of flow on both Baxter and N. Alvarado is relatively small. With 50% app users, there is an increase in flow on N. Alvarado St. as well as on Baxter St. on both sides of N. Alvarado St. Additionally, there is a slight decrease in flow on the Glendale Freeway and an increase on Alessandro St., as drivers are routed onto the shortcut. Lastly, with 99% app users, the flow on the part of Baxter St. between Alessandro and N. Alvarado St.s (the portion on which many accidents were occurring) increases to maximum.

The conversion of the affected segments of Baxter St. into one-way roadways has impeded drivers from taking the dangerous shortcut. However, other shortcuts are available on neighboring streets which has prompted the city to make three additional changes to disrupt the flow of traffic on neighboring streets. The RIDER DSS in its full capacity would enable city's such as Echo Park to take a more holistic approach to forecasting and verifying the impacts of routing applications at the local as well regional scale, and in taking action to reducing those impacts and maintaining the quality of mobility and safety on local streets.

IV. Future Work and Applications

Future work on the RIDER DSS includes the implementation of additional model parameter and KPI modules in concert with high performance computing (HPC) to enable the user to tune various network and routing parameters directly through the user interface and immediately view the impacts of the resulting distribution of traffic.

A. Parallel Franke-Wolfe

The computational cost of calculating Nash equilibria with the sequential FW is too high to be used in a practical setting. As seen in the case study, determining the equilibrium flows for one integer percentage of app users $\alpha \in \{0, .01, .02, ..., .99\}$ on the LA Basin network takes 49 minutes, and a total time of 3.5 days to compute the equilibria for all 100 percentage values. This is not useful for real-time traffic operation nor for a responsive policy scenario analysis tool. Hence, we designed and implemented a parallel version of the FW that can run on high performance computing resources to speed up computation time.

A performance analysis found that the all-pairs shortest-path computation step in the sequential FW accounts for more than 95% of the computation time. Hence, as shown in figure 3, the parallel FW parallelizes the shortest-path calculation in accordance with the number of computing cores available. Each compute core can run several processes concurrently. The set of OD pairs in the demand matrix is then divided equally among all the processes running on the compute cores that solve for the network equilibrium in parallel. Cabannes et al. found that, on average, this parallel FW implementation reduced the equilibrium computation time by a factor of 50 using 10 compute cores running 160 processes simultaneously on the Cori supercomputer at the Lawrence Berkeley National Lab (LBNL) [25],[18]. The computation time for one percentage of app users was reduced from 22 minutes to 44 seconds.

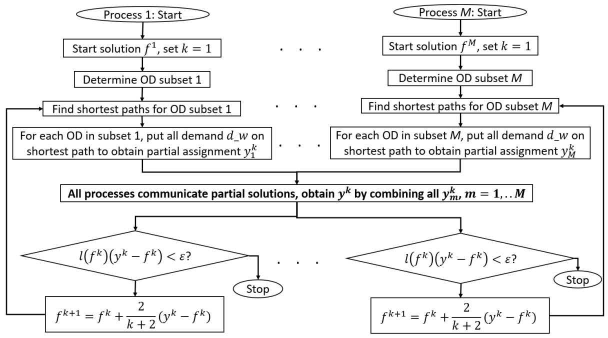

Fig. 3. Parallel Frank-Wolfe: Parallelized over origin-destination pairs

In our future work, we will extend the RIDER DSS software to work with the parallel FW. The significant speed up in computation time will enable the DSS to be used for responsive policy scenario analyses and, eventually, real-time traffic operation settings.

In addition, we plan to extend the functionality of the user interface to allow users to alter the network parameters by interacting with the model parameter and visualization modules. For example, the capacity of an arc could be increased or decreased to simulate the occurrence of a traffic incident, the installation of a speed bump or additional traffic stop, or a change in speed limit. A user could adjust the latency functions for different classes of users or for particular arcs in the network to model the effects of road pricing policies and include heterogeneous values of time, if desired.

V. Conclusion

Classic flow-based game theoretic models simulate the routing behavior of mixed traffic consisting of routed and non-routed users in a congested road network. The RIDER DSS implements these models in a static traffic assignment, allowing policymakers and practitioners to assess the impacts of routing applications on urban mobility at a local and even regional scale. Users can inspect particular corridors or pain points, and are able to adjust the network parameters to reflect the current network demands to visualize the allocation of traffic under different scenarios of routing app adoption in the area. In the future, the DSS will enable users to alter the network to reflect policy actions and evaluate the network effects of various alternatives.

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