A novel Dynamic Pricing Route Reservations architecture

G.D. Katsifaraki, C. Menelaou, S. Timotheou and C.G. Panayiotou

***Abstract*— Route reservations have been proposed as an effective solution to mitigate traffic congestion while preserving the road network in free-flow traffic conditions, offering users some limited departure time and route choices. However, high user compliance is required. To provide users with the freedom to choose among any spatiotemporal route in the road network, in this work we propose a *dynamic pricing route reservations architecture*. At each time step, the central controller sets prices dynamically, using the network's reservations status and the users' demand characteristics. Rational users will ultimately choose the route that minimizes their disutility by considering routes' travel time, schedule delays, and reservation price. A series of microscopic simulations reveal that the proposed approach demonstrates a similar traffic performance as other optimal route reservation approaches. It however outperforms them in terms of social welfare, user satisfaction and flexibility, providing users with numerous spatiotemporal free-flow route choices, while minimizing aggregated disutility.**

I. Introduction

For the past several years now, traffic is a blunt reality in big cities, caused by urbanization and negatively affecting citizens' quality of life. In the U.S. alone, traffic congestion costs billions of dollars and billions of travel hours in lost time, further generating massive greenhouse gas emissions [1]. Considering its immense consequences, research to alleviate congestion is ongoing. To date, a number of different solutions have been proposed to combat congestion, like the many navigation applications aiming to redistribute demand away from hotspot areas in real-time. Such practices ultimately result in poor road network performance, however [2]. Recent state-of-the-art elaborates on more socially-oriented solutions, like the social optimum approaches that redistribute demand in time and space [3].

A traffic management route reservations architecture (RRA) of this kind has been recently proposed in [4]. In this setting, the controller proposes to the user a single, congestion-free path of the earliest arrival time, given the system reservations status. If the majority of the users comply (i.e., at least 70%), RRA achieves a (near) free-flow operation of the network. Users' personal choice however is restricted, as they cannot deviate from the controller's directions for the system to operate smoothly. Recent attempts tried to overcome this issue by applying static-priced techniques to RRA. In [5], a flexible RRA (FRRA) was proposed: a single path is again suggested by the controller, who uses a fixed piecewise linear pricing function to set tolls. The user may choose to depart with a minimum toll price within a specific time window, after (or before) which (s)he will have to pay a maximum price. The authors went a step further in [6] to propose alternative path and departure time choices using pricing along with different routing algorithms; however, choices of users are limited in this architecture as well.

A core revenue management mechanism that uses price as the primary control variable to manage demand is *dynamic pricing*, which arose with the birth of commerce itself, where sellers used price adjustments to sell their goods at the highest price possible, but also affordable to customers [7]. Dynamic pricing is extensively applied in industries such as airlines, hospitality, and electric utilities [8], being further integrated in Intelligent Transportation Systems to facilitate fare pricing, charging pricing for electric vehicles, parking management, as well as congestion control pricing [9] [10]. *Utility models* are commonly used in such systems to model user choice behavior. Utility by definition denotes a user's satisfaction of a phenomenon. The utility of travel however, is generally negative [11], usually referred to as *travel disutility*, and defined in Transport Economics as a user's perceived difficulty in making a trip [12]. Another important related concept is the *maximum Willingness to Pay (WtP)*, denoting the subjective inherent maximum value a user assigns to an offering in monetary terms [13]. WtP has been used in designing optimal pricing solutions for airline reservations (e.g., [14]), intelligent transportation (e.g., [15]) and more. We hereby define WtP in route reservations as *the maximum price a user of the road network is willing to pay to reserve a route from an origin to a destination at time t*. Note here that, without loss of generality, prices can be measured in utils instead of monetary units [16].

In this work, we propose a *demand-driven Dynamic Pricing* (DP) route reservations mechanism that preserves the network in free-flow traffic conditions, while giving users the desired freedom of choice. From the controller's side, the aim is to use dynamic pricing to affect the users' decision making in an implicit manner, so that the network can keep operating in free-flow. Spatiotemporal route options that vary both spatially, as well as temporally are available to users any time within a prespecified time horizon, and priced dynamically in view of demand and users' WtP. Users will ultimately choose a spatiotemporal route based on their distinct disutility.

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This is a novel traffic management dynamic pricing architecture that contributes to the literature by: i) effectively controlling and balancing traffic in space and time, ii) accommodating users to choose road trips tailored to their needs, thus achieving higher user satisfaction, and iii) minimizing total aggregated user disutility and increasing social welfare.

The remainder of this paper is organized as follows: Section 2 illustrates the dynamic pricing route reservations architecture. Section 3 formulates the problem, discussing further user's disutility in context. In Section 4, we describe the dynamic pricing mechanism used by the controller to affect users' routing decisions. In Section 5, the minimum disutility routing problem is presented and a solution is discussed in Section 6. In the final sections we present simulations, discuss results and conclude this work.

II. Dynamic Pricing Route Reservations architecture

The DP Route Reservations architecture has a centralized structure, with a central controller implementing traffic management activities, so that the network's utilization is maximized while its operation is maintained at free-flow conditions. The controller is specifically responsible for:

i) monitoring the utilization of the road-segments and coordinating the route reservations process.
ii) spreading the reservations load in space and time so that congestion is avoided.
iii) setting demand-based dynamic prices for all road-network's segments, so that users reserve a route without compromizing the network's free-flow operation.

A user initially makes a route reservations request to the central controller, sending the desired origin-destination pair, the time (s)he wants to depart, as well the desired arrival time. The controller replies with dynamic prices for all segments of the road-network, using the road segments' reservations status, as well as the user's demand characteristics. Essentially, when a segment has reached a reservations' threshold value predefined by the controller, its price is set over the highest value that the user is willing to pay to traverse it. This way, dynamic pricing aims to affect the user's choice implicitly by deterring him/her from traversing high traffic paths, so that the network will keep operating in free-flow mode. On the basis of the provided dynamic prices and route characteristics, the user will eventually choose a spatiotemporal route that minimizes user's disutility. The controller will then reserve the route for the user on a first-come-first-served basis, and update the reservation state of all the road segments included in the chosen route, at the exact time slots the user is expected to traverse them in free-flow. In this way, accurate traffic state estimates and future demands of road segments are maintained.

III. Problem Formulation

Let a homogeneous region of an urban road-network be modeled as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where vertices $\mathcal{V}$ represent road-junctions and edges $\mathcal{E}$ represent road-segments. Road-segments $(i,j) \in \mathcal{E}$ have λ_{ij} number of

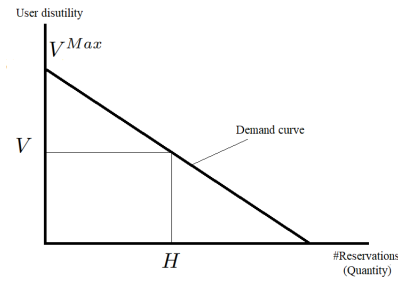


Fig. 1: Users' demand curve as a function of their disutility and number of reservations they make.

lanes and l_{ij} length, and the time horizon is divided into discrete time-slots $k \in \mathcal{K} = \{1, \ldots, K\}$. Regional traffic dynamics follow the Macroscopic Fundamental Diagram (MFD), with $v(k)$, $q(k)$ and $\rho(k)$ representing speed, flow and density at time-step k, respectively. Also, $\rho_{ij}(k)$, ρ_{ij}^C and ρ_{ij}^J represent the density of the (i,j) segment, its critical and jam density respectively. At time-step k, when $\rho_{ij}(k) \le \rho_{ij}^C \; \forall (i,j) \in \mathcal{E}$, vehicles travel with free-flow speed v^F. Otherwise, their speed is given by $v(k) = q(k)/\rho(k)$. Furthermore, a vehicle traverses (i,j) at k in $\tau_{ij}(k)$ slots:

$$\tau_{ij}(k) = \lfloor l_{ij}/v(k)/T \rceil, \tag{1}$$

where T is the sampling interval and $\lfloor y \rceil$ denotes the nearest integer to y.

We further define c_{ij} as a threshold on the number of vehicles desired in a road-segment (i,j):

$$c_{ij} = w\,(l_{ij}\lambda_{ij})/C, \tag{2}$$

where w is a parameter ratio and C is the average car length. At each time slot k, the controller keeps the number of vehicle reservations $r_{ij}(k) \; \forall (i,j) \in \mathcal{E}$, and further sets each road segment's price dynamically, for a given future time horizon $\mathcal{M} = [k+1, \cdots, k+M]$.

We assume that a user sends at time $k \in \mathcal{K}$ a route reservation request (OD, t^d, t^a) to the controller, where OD is the origin-destination pair, and t^d and t^a are the user's desired departure and arrival time respectively, with $t^d, t^a \in \mathcal{M}$. We further assume that users in the system are perfectly rational having a specific demand for route reservations[1], modeled typically as a linear decreasing function (e.g., [17]) of the form: $H(V) = a' - b'V$, where $H()$ is the users' demand expressed as the number (quantity) of route reservations they make, V is their disutility, and a' ,b' are the intercept and demand elasticity respectively. Figure 1 depicts that the quantity of total route reservations H made by the users decreases as their disutility V increases, until it reaches the *maximum disutility* accepted V^{Max}, after which the users are unwilling to reserve and exit the system (i.e., they may choose other means of transport like public transportation, walking, etc., or not travel at all).

The aim of the controller is to serve the user, while keeping the network running in free-flow and distributing incoming

[1]Different utility types of users will have different demand curves, as in [17]. For simplicity, in this work we consider all users of the same utility type and demand.

demand in a balanced way. Therefore, prices set should be a function of i) the network reservations' status at each $k \in \mathcal{K}$ for traffic balancing, and ii) some price $\bar{d}$ that will set the user's disutility over the maximum accepted V^{Max}, for deterring the user from choosing routes containing segments that have reached reservations' threshold.

Then, let the *Availability Ratio* $\alpha_{ij}(k)$ be the available threshold ratio of a road segment (i, j) at slot k:

$$\alpha_{ij}(k) = (c_{ij} - r_{ij}(k))/c_{ij} \tag{3}$$

For each time-step $k \in \mathcal{K}$ and road segment $(i, j) \in \mathcal{E}$, dynamic prices $d_{ij}(k)$ may be determined as

$$d_{ij}(k) = f(V^{Max}, \alpha_{ij}(k)),\ \forall (i, j) \in \mathcal{E},\ \forall k \in \mathcal{K}. \tag{4}$$

On the basis of these dynamic prices, the user will select the spatiotemporal path that minimizes the user's disutility. The minimum disutility routing problem is discussed in Section V.

A *spatiotemporal path* is defined here as a tuple $P_h = (t^c, p_h)$, where $t^c \in \mathcal{K}$ is the chosen starting time of the routing process, and p_h is the h-th spatial path from O to D. Path p_h is specifically defined as $p_h = (0^h, 1^h),\ (1^h, 2^h),\ (2^h, 3^h), \cdots, (L^h{-}1, L^h)$, where $j^h \in \mathcal{V}$ is the j-th visited node in path p_h, with $0^h = O$ and $L^h = D$. A spatiotemporal path's toll price is then defined as $d_h(t^c)$.

A. User's disutility in the context of route reservations

We now define user disutility within the route reservations context, adopting an adapted version of the random utility model found in [18]. We specifically assume that drivers spend their day participating in activities, travelling in between to reach the destination of the next activity. Rational users will seek to minimize their travel disutility, associated with the activity before they depart, the actual trip, as well as the activity they perform at arrival. Below we adjusted the disutility framework of [18] to consider the more general case where user disutilities are associated with the activities and respective scheduling preferences at both departure and arrival as in [19], as interferences with both activities are considered in practice by users when evaluating a potential spatiotemporal route.

We further issue the following assumptions for the user of route reservations:

- All users have a particular disutility function associated with predefined activities at the departure and destination. The disutilities for these activities are independent of the trip's travel time.
- The user disutility depends on the required travel time to traverse the chosen path.
- The activity at departure has a desired end time, equal to the desired t^d of the user.
- The activity at arrival has a desired starting time, equal to the desired t^a of the user.
- A user has a certain disutility due to early/late departures/arrivals.
- A user has a certain disutility due to toll prices.

In our framework, the user evaluates a set of $P_{h'} = (t^c, p_h)$ spatiotemporal paths, consisting of the starting routing time t^c and the spatial path p_h, which is traversed in t_h time units. Let $V_h(t^c, t^d, t^a)$ denote the disutility of the spatiotemporal path (t^c, p_h), defined as the sum of the trip and activity utilities as follows:

$$V_h(t^c, t^d, t^a) = V_h^T(t^c) + V_h^d(t^c, t^d) + V_h^a(t^c, t^a), \tag{5}$$

where $V_h^T(t^c)$, $V_h^d(t^c, t^d)$ and $V_h^a(t^c, t^a)$ denote the trip, departure activity and arrival activity disutilities of the user, respectively.

The trip disutility $V_h^T(t^c)$ is the sum of the disutilities of the trip made D_h, the trip's travel time t_h, and the travel cost associated with the path's toll price $d_h(t^c)$ such that

$$V_h^T(t^c) = D_h + \xi t_h + \zeta d_h(t^c), \tag{6}$$

where ξ and ζ are constant parameters denoting user's weights of travel time and trip cost, respectively.

The disutility of the user with respect to the activity at departure is defined as

$$V_h^d(t^c, t^d) = W + \beta Z + \gamma V_h^H(t^c, t^d), \tag{7}$$

where W and Z denote the time-of-the-day and the duration of the activity, respectively, and β and γ are constant parameters. $V_h^H(t^c, t^d)$ represents the disutility of the deviation of t^c from the end time of the activity at departure, defined as

$$V_h^H(t^c, t^d) = \gamma_1 SDE(t^c, t^d) + \gamma_2 SDL(t^c, t^d), \tag{8}$$

where parameters γ_1 and γ_2 are weights and $SDE(t^c, t^d)$ and $SDL(t^c, t^d)$ are the early and late schedule delays defined as

$$SDE(t^c, t^d) = \max(0, (t^d - t^c)) \tag{9}$$

$$SDL(t^c, t^d) = \max(0, (t^c - t^d)). \tag{10}$$

In a similar manner, the user's disutility with respect to the activity at arrival is defined as

$$V_h^a(t^c, t^a) = F + \delta G + \epsilon V_h^Y(t^c, t^a), \tag{11}$$

where F and G denote the time-of-the-day and the duration of the activity, respectively and δ and ϵ are constant parameters. $V_h^Y(t^c, t^a)$ is defined as

$$V_h^Y(t^c, t^a) = \epsilon_1 SDE(t^c, t_h, t^a) + \epsilon_2 SDL(t^c, t_h, t^a), \tag{12}$$

where ϵ_1 and ϵ_2 are weights and $SDE(t^c, t_h, t^a)$ and $SDL(t^c, t_h, t^a)$ are defined as

$$SDE(t^c, t_h, t^a) = \max(0, (t^a - (t^c + t_h))) \tag{13}$$

$$SDL(t^c, t_h, t^a) = \max(0, ((t^c + t_h) - t^a)). \tag{14}$$

IV. Dynamic pricing mechanism

With respect to the dynamic pricing mechanism of the proposed architecture, at each time k, and $\forall (i, j)$ road-segment, the controller should define future dynamic prices within a given reservation horizon $\mathcal{M} = [k{+}1, \cdots, k{+}M]$, i.e., a pricing decision vector $[\, d_{ij}(k+1), \ldots, d_{ij}(k+M)\,]$. Essentially, at each time-step k, the controller returns an

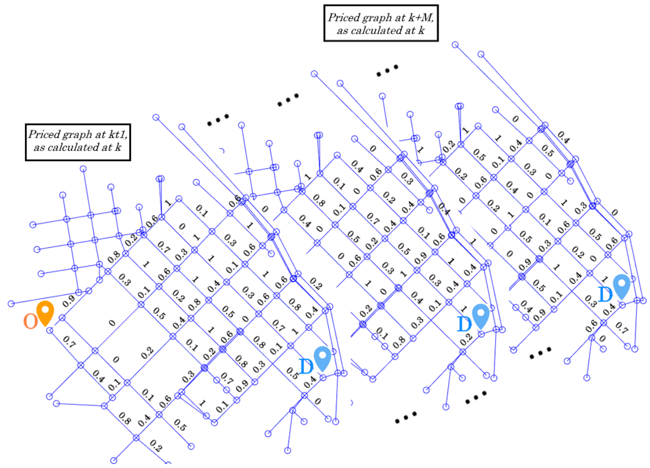


Fig. 2: M road-network's priced graphs calculated by the controller at k

$\mathcal{M}x\mathcal{E}$ vector of prices (Figure 2), where all road segments (i,j) are assigned with prices for $\mathcal{M} = [k+1, \cdots, k+M]$.

The controller decides on prices using a function of segment reservations, unless a road-segment reaches its reservation threshold. Then, the segment is priced much higher than what the user would be willing to pay to traverse it. Thus, being a rational user, (s)he will not choose any of the paths including this road segment. In this way, the controller is *implicitly* excluding the road segment that has reached its reservation threshold from the eligible user choices, though not explicitly forbidding the user from traversing it.

For the purposes of this paper we utilize a function of exponential form [2]:

$$d_{ij}(k) = \frac{WtP}{(e^{\theta} - 1)}(e^{\theta(1-a_{ij}(k))} - 1), \tag{15}$$

where $d_{ij}(k)$ is the price of the road segment (i,j), and θ a curve convexity parameter. We hereby assume knowledge of the users' WtP, which can be found using survey or experimental methods as in [20].

V. Minimum disutility routing problem

Given the user's reservation request (OD,t^d,t^a), the Minimum Disutility (MD) routing problem seeks to find a spatiotemporal path so that the user's disutility is minimized. A rational user is expected to choose this MD path.

Let $P_h = (t^c, p_h)$ denote any h-th spatiotemporal path consisting of the spatial path p_h from O to D and departure time t^c, so that the path disutility V_h of the user does not surpass the user's V^{Max},

$$V_h \leq V^{Max} \tag{16}$$

[2]We set the following requirements with respect to the pricing function of a segment (i,j) at time step k: i) to be monotonically increasing; ii) to be continuously differentiable; iii) when reservations $r_{ij}(k)$ are zero, the price of the segment should be zero as well; iv) when $r_{ij}(k)$ reaches the segment's threshold, the price of the segment should be set to a maximum price above which the user won't be willing to reserve, e.g., the user's WtP. The route reservations platform does not aim to generate income, thus functions that keep prices low when utilization is low can be of use, such as exponential functions.

The spatial p_h is defined as $(0^h, 1^h)$, $(1^h, 2^h)$, $(2^h, 3^h), \cdots (L^h_h - 1, L^h_h)$, where $j^h \in \mathcal{V}$ is the j-th visited node in the path, with $0^h = O$ and $L^h_h = D$. Let also $U_{h\,j}$ denote the *Disutility Contribution* of the partial path from O to $j^h \in \mathcal{V}$ to the overall disutility of the user for the h-th spatiotemporal path. Then the disutility contribution at each node of P_h, can be expressed as:

$$\begin{aligned} U_{h\,0^h} &= V^d_h(t^c, t^d) \\ U_{h\,1^h} &= U_{h\,0^h} + V^T_{h\,(0^h,1^h)}(t^c) \\ &\vdots \\ U_{h\,L^h_h} &= U_{h\,L^h_h-1} + V^T_{h\,(L^h_h-1,L^h_h)}(t^c_{L^h_h-1}) + V^a_h(t^c, t^a), \end{aligned} \tag{17}$$

where $V^d_h(t^c, t^d)$ and $V^a_h(t^c, t^a)$ have been defined in (7) and (11) respectively, and $t^c_{L^h_h-1}$ is the departure time from node $L^h_h - 1$. Essentially, at node 0^h the user initially experiences only the disutility associated with the activity at departure $V^d_h(t^c, t^d)$. As (s)he then travels to each following node, the trip disutility of the path travelled from the previous node is added up. At the final node, the disutility associated with the activity at arrival is added, resulting finally to $U_{h\,L^h_h}$, which is equal to the overall user's disutility V_h for the h-th path.

The MD problem is expressed as:

$$\begin{aligned} (t^{c*}, p^*) = \min_{t^c, p_h} V_h, \\ \text{s.t. Model Dynamics } (1), (5) - (17), \end{aligned} \tag{18}$$

where p^* and t^{c*}, are the spatial path and departure time respectively of the minimum user disutility path.

It is to be noted that users' actual utility functions and parameters can be obtained through experimental design and survey research, as in [20].

We solve this problem using an algorithmic variation on the principles of Dynamic Programming by constructing a time-expanded graph [21], which is described below.

VI. Solving the Minimum Disutility Routing Problem

We construct a Directed Acyclic Graph (DAG) denoted by $\mathcal{G}^{DP}(\mathcal{V}^{DP}, \mathcal{E}^{DP})$, in which:

i) the x-axis represents consecutive slots of the time horizon $\mathcal{K}'$. $\mathcal{K}'$ is defined as $[t^s, .., t^d, .., t^f]$, where $t^s \leq t^d$ and $t^f \geq t^d$ are the horizon bound values, calculated on the assumption that no user will choose a spatiotemporal path with disutility that surpasses the user's V^{max}. Therefore, by solving (16) for V^{max}, as well as the minimum reservation price (i.e., 0), minimum travel time value (i.e., shortest path time) and zero delays, the bound values t^s and t^f can be calculated.
ii) the y-axis represents a time instance of each node in the network, i.e., the node indices of $\mathcal{G}(\mathcal{V}, \mathcal{E})$.

In this setting, each node in DAG denotes the junction where a vehicle arrives at the specific time slot k, whereas each node's state value represents the disutility contribution U_j, considering there is a physical connection between the related node j and the origin. Initially, the algorithm

Algorithm 1 Minimum Disutility Solution for the m-th user

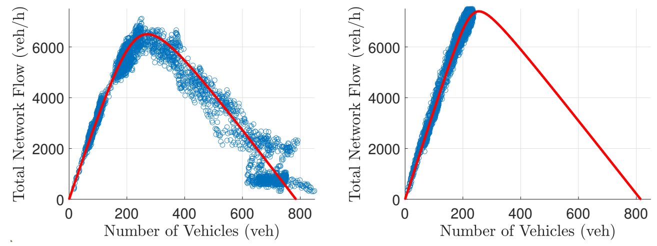
1: **Input:** (O_m, D_m, t_m^d), WtP_m, V_m^{Max}; $d_{ij}(k), \forall k \in \mathcal{K}', \forall (i,j) \in \mathcal{E}$
2: **Initialization:** Calculate t^s and t^f; initialize all states in $\mathcal{G}^{DP}(\mathcal{V}^{DP}, \mathcal{E}^{DP})$ as infinite
3: **Algorithm Execution:**
4: Initialize $U_j \, \forall k \in \mathcal{K}'$ for originating nodes
5: **for** $k \in [t^s, \dots, t^f]$ **do**
6:     **for** $(i,j) \in \mathcal{E}$ **do**
7:         **if** $U_j < U_i$ when adding the (i,j) trip disutility and $U_j < V_m^{Max}$ **then**
8:             Insert (i,j) and update U_j
9:         **if** U_j is destination node **then**
10:             update U_j with destination delay disutility as in (17)
11: **Output:** p^* and t^{c*} for the m-th user

calculates the time horizon bounds (i.e., t^s and t^f) for the request (O_m, D_m, t_m^d) of the m-th user having WtP_m and V_m^{Max}, and further initializes all state values of the $\mathcal{G}^{DP}(\mathcal{V}^{DP}, \mathcal{E}^{DP})$ as infinite (line 3). At the main part of the algorithm, all possible states at the originating node O_m (denoting different potential departure times) are first initiated with the early or late departure disutility values, for each column (line 5). Next, the edge insertion process starts, where an edge is inserted based on two discrete conditions: 1) the newly inserted edge (i,j) of $\mathcal{G}^{DP}(\mathcal{V}^{DP}, \mathcal{E}^{DP})$ is reachable from the source node O_m, meaning that there is a path that connects the source node with (i,j). 2) The DAG value of the ending node, denoting the disutility contribution as in Eq. (17), is reduced (e.g., from ∞) when adding the edge, and it is also not higher than V_m^{Max}. Only in the case that both conditions are satisfied, an edge (i,j) is added on $\mathcal{G}^{DP}(\mathcal{V}^{DP}, \mathcal{E}^{DP})$, (lines 8-9). The process is repeated for t^s to t^f, and for all nodes. Finally, at the destination node, the disutility contribution is updated with the user's early or late arrival disutility (lines 11-12).

The algorithm's outputs are the optimal path p^* and departure time t^{c*} that minimize the m-th user's total disutility. This information is used to make the appropriate route reservations on each road segment at the expected traversal times, and also calculate the segments' prices. The algorithm converges in $O(|\mathcal{K}'N|)$ and results in an optimal solution.

VII. Simulation Results

The proposed DP Route Reservations are evaluated within the SUMO micro-simulator, considering a 1.8-km^2 non-signalized urban region of downtown San Francisco as in [22]. Within simulations vehicles dynamics following the Krauss car following model the following parameters: vehicle length 5 m, maximum speed 15 m/s, acceleration 2.5 m/s^2, deceleration 4.5 m/s^2, and minimum-gap-distance 2.5 m. Simulations were run for the i) RRA, ii) DP, and iii) the uncontrolled scenario (USP), where users depart at the desired starting time, following the shortest path. For DP, the disutility parameters of (5)-(14) equations were set as follows: the travel time weight $\xi = 0.1$, the toll price weight $\zeta = 1.0$, the activity at departure schedule delay weights for



(a) (b)

Fig. 3: MFD analysis for (a) USP, (b) DP cases

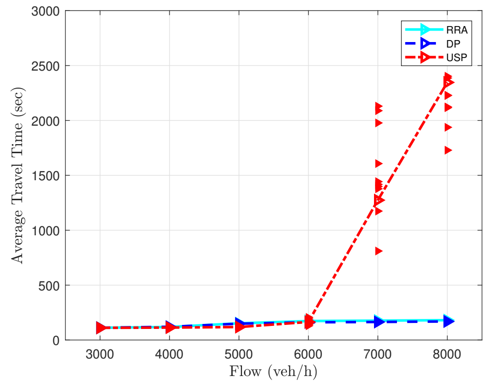
early and late departure $\gamma_1 = 0.8$ and $\gamma_2 = 0.4$ respectively, and the activity at arrival respective weights $\epsilon_1 = 0.4$ and $\epsilon_2 = 0.8$. D_h, W, Z, F and G constants were further set to zero for simplicity. WtP was set to 4000 utils. A minimum threshold for V^{max} was set to 4000 in (16), and the price convexity parameter θ to 15.0 in (15).

We initially conducted MFD Analysis for USP and DP, following [4]. To generate the MFD, a 6-hour scenario is used, with traffic flow in the first hour set at 2000 veh/h, gradually increasing by 2000 veh/h for the next 4 hours, while no vehicles enter in the last hours, allowing the system to evacuate the vehicles. Figures 3(a) and 3(b) demonstrate the resulting MFD when the USP and DP algorithm is employed. From the figure it is clear that if we do not employ any control action, then traffic congestion can not be avoided. On the other hand, in case the DP algorithm is used, even though the drivers are free to make their own decisions, no congestion emerges. Similar to the work in [22], the USP case is used to derive the following MFD parameters: critical density 30 veh/km/lane, a free-flow speed of 30.0 m/s.

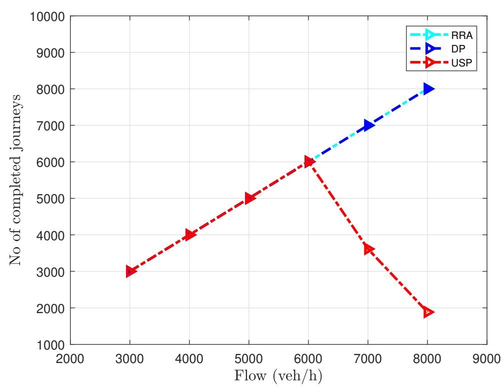
Ten Monte Carlo simulations were then run for each architecture over a 2-hour simulation horizon with demand varying from 3000 to 8000 veh/h. As demonstrated in Figures 4(a) and 4(b), the traffic performance in the DP case is similar to the RRA and therefore optimal [4], in terms of both average travel time and the number of vehicles that complete their journey. Nevertheless, while RRA instructs users on the route and departure time requiring their full compliance, DP provides limitless user route choice flexibility. Figure 5 further demonstrates that while in both DP and RRA cases the aggregated disutility of users is similar, and even lower in DP for higher flow rates, there is significant total aggregate of utils in DP (nil for RRA). If money is used, this aggregated revenue could be used e.g., for the maintenance and further development of the road network. Overall, the performance of the DP is similar to the optimal RRA platform, considering similar travel times and number of vehicles with completed journeys. Nevertheless, DP further exhibits lower aggregated disutility for higher flow rates, designating higher user satisfaction and overall social welfare.

VIII. Conclusions

In this work, we propose a dynamic pricing route reservations architecture, where the controller applies dynamic prices to sustain the network under free-flow conditions, while users are free to choose among any spatiotemporal



(a)



(b)

Fig. 4: (a) Average Travel Time, (b) Number of Vehicles with Completed Journeys for the RRA, DP, and USP cases

path in the network. Simulation results illustrate that the DP approach demonstrates similar traffic performance as the optimal RRA, where users are instructed on the specific route and departure time to follow. Most importantly, DP decreases users' disutility exhibiting higher overall social welfare. Future research should investigate users' responses to dynamic pricing within the route reservation context using experimental design methods, to extract appropriate choice models and utility functions. Furthermore, the robustness of the DP platform when users are bounded rational and inaccuracies are present due to e.g., speed and travel time deviations should be further investigated.

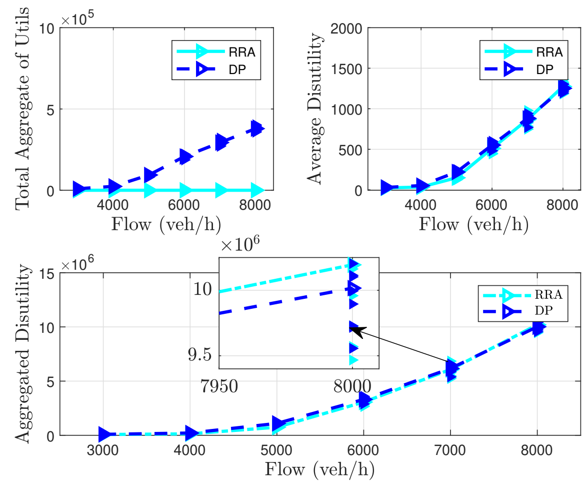


Fig. 5: Total Aggregate of Utils, Average Disutility, and Aggregated Disutility for the RRA, and DP cases

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