

# Data-driven Estimation of Origin-Destination Demand and User Cost Functions for the Optimization of Transportation Networks<sup>\*</sup>

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## Abstract:

In earlier work (Zhang et al., 2016) we used actual traffic data from the Eastern Massachusetts transportation network in the form of spatial average speeds and road segment flow capacities in order to estimate Origin-Destination (OD) flow demand matrices for the network. Based on a Traffic Assignment Problem (TAP) formulation (termed “forward problem”), in this paper we use a scheme similar to our earlier work to estimate initial OD demand matrices and then propose a new inverse problem formulation in order to estimate user cost functions. This new formulation allows us to efficiently overcome numerical difficulties that limited our prior work to relatively small subnetworks and, assuming the cost functions are available, to adjust the values of the OD demands accordingly so that the flow observations are as close as possible to the solutions of the forward problem. Finally, using the same actual traffic data from the Eastern Massachusetts transportation network, we quantify the Price of Anarchy (PoA) for a much larger network than that in Zhang et al. (2016).

*Keywords:* optimization, transportation network, origin-destination demand estimation, travel latency cost function, traffic assignment, inverse variational inequality, price of anarchy

## 1. INTRODUCTION

Using actual traffic data from a transportation network, we measure its performance by using the total travel time all drivers experience across different Origin-Destination (OD) pairs. Our objective is to compare two different policies: a user-centric policy vs. a system-centric one and quantify the difference between the two through the Price of Anarchy (PoA) metric.

More specifically, for a user-optimal policy we face a system with non-cooperative agents (drivers) in which each individual driver follows her personally optimal policy without caring about the system performance. Such “selfish behavior” results in a Nash (Wardrop) equilibrium, a point where no agent can benefit by altering its actions assuming that the actions of all the other agents remain fixed (see Youn et al. (2008)). The equilibrium flows in traffic networks, known as the “Wardrop equilibrium,” (see Patriksson (2015)) is the solution to the Traffic Assignment Problem (TAP) that will be described in the next

section. It is known that the Nash equilibrium is usually suboptimal from the system point of view.

On the other hand, under a system-optimal policy we enjoy a system in which all agents (drivers) cooperate in order to achieve a social optimum, which is the best policy for the society as a whole (see Youn et al. (2008)). To assess the scope of improvement in a transportation system, we define the Price of Anarchy (PoA) as a measure to quantify the system inefficiency under a user-optimal policy vs. a system-optimal policy. The latter can be implemented, for example, by taking advantage of the emergence of Connected Automated Vehicles (CAVs) through which socially optimal routing decisions can be executed.

In Zhang et al. (2016) we have studied a similar problem using actual traffic data from the Eastern Massachusetts (EMA) road network. In particular we have investigated the system performance of a relatively small interstate highway subnetwork of EMA.

The goal of this paper is to quantify the PoA for a general single-class transportation network model. We take similar steps as in Zhang et al. (2016) which include inferring equilibrium flows from the speed/capacity datasets, estimating OD demand matrices, estimating per-road *travel latency cost functions* (we will also simply say *cost functions* in the

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following), and calculating social optimum flows in order to quantify the PoA. In contrast to Zhang et al. (2016), here we are able to analyze a much larger subnetwork of the EMA road network in the sense that it includes a much larger number of nodes and links.

To achieve this goal, we first propose an alternative formulation for the travel latency cost function estimation problem, which enables us to overcome numerical difficulties when the network gets larger. We then modify existing schemes to perform OD demand estimation (this has been widely-studied; see, e.g., Abrahamsson (1998), Bera and Rao (2011), and the references therein) for large-scale road networks, regardless of whether they exhibit congestion or not. In particular, we leverage a bi-level optimization problem formulation allowing us to estimate OD demand matrices for a given larger network based on the OD demands of its representative (landmark) subnetworks. Utilizing the estimated cost functions and OD demand matrices, we then quantify the PoA.

The rest of the paper is organized as follows: In Sec. 2 we introduce models and methods that we use. In Sec. 3 we describe the datasets and explain the data processing procedures. Numerical results are shown in Sec. 4.

**Notation:** All vectors are column vectors. For economy of space, we write  $\mathbf{x} = (x_1, \dots, x_{\dim(\mathbf{x})})$  to denote the column vector  $\mathbf{x}$ , where  $\dim(\mathbf{x})$  is the dimension of  $\mathbf{x}$ .  $\mathbf{M} \geq \mathbf{0}$  (resp.,  $\mathbf{x} \geq \mathbf{0}$ ) denotes that all entries of a matrix  $\mathbf{M}$  (resp., vector  $\mathbf{x}$ ) are nonnegative. We use “prime” to denote the transpose of a matrix or vector. Unless otherwise specified,  $\|\cdot\|$  denotes the  $\ell_2$  norm.  $|\mathcal{D}|$  denotes the cardinality of a set  $\mathcal{D}$ .  $A \stackrel{\text{def}}{=} B$  indicates  $A$  is defined using  $B$ .

## 2. MODELS AND METHODS

### 2.1 Model for a single-class transportation network

We begin by reviewing the model of Zhang et al. (2016). Denote a road network by  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$ , where  $(\mathcal{V}, \mathcal{A})$  forms a directed graph with  $\mathcal{V}$  being the set of nodes and  $\mathcal{A}$  the set of links, and  $\mathcal{W} = \{\mathbf{w}_i : \mathbf{w}_i = (w_{si}, w_{ti}), i = 1, \dots, |\mathcal{W}|\}$  indicates the set of all OD pairs. Assume the graph  $(\mathcal{V}, \mathcal{A})$  is strongly connected and let  $\mathbf{N} \in \{0, 1, -1\}^{|\mathcal{V}| \times |\mathcal{A}|}$  be its node-link incidence matrix. Denote by  $\mathbf{e}_a$  the vector with an entry being 1 corresponding to link  $a$  and all the other entries being 0. For any OD pair  $\mathbf{w} = (w_s, w_t)$ , denote by  $d^{\mathbf{w}} \geq 0$  the amount of the flow demand from  $w_s$  to  $w_t$ . Let  $\mathbf{d}^{\mathbf{w}} \in \mathbb{R}^{|\mathcal{V}|}$  be the vector which is all zeros, except for a  $-d^{\mathbf{w}}$  (resp.,  $d^{\mathbf{w}}$ ) in the coordinate mapping to node  $w_s$  (resp.,  $w_t$ ).

Denote by  $\mathcal{R}_i$  the set of simple routes (a route without cycles is called “simple route”) between OD pair  $i$ . For each  $a \in \mathcal{A}$ ,  $i \in \{1, \dots, |\mathcal{W}|\}$ ,  $r \in \mathcal{R}_i$ , define the link-route incidence by

$$\delta_{ra}^i = \begin{cases} 1, & \text{if route } r \in \mathcal{R}_i \text{ uses link } a, \\ 0, & \text{otherwise.} \end{cases}$$

Let  $x_a$  denote the flow on link  $a \in \mathcal{A}$  and  $\mathbf{x} \stackrel{\text{def}}{=} (x_a; a \in \mathcal{A})$  the flow vector. Denote by  $t_a(\mathbf{x}) : \mathbb{R}_+^{|\mathcal{A}|} \rightarrow \mathbb{R}_+$  the travel latency cost (i.e., travel time) function for link  $a \in \mathcal{A}$ . If for all  $a \in \mathcal{A}$ ,  $t_a(\mathbf{x})$  only depends on  $x_a$ , we say the

cost function  $\mathbf{t}(\mathbf{x}) = (t_a(x_a); a \in \mathcal{A})$  is *separable* (see Patriksson (2015)). Throughout the paper, we assume that the cost functions are separable and take the following form (see Bertsimas et al. (2015) & Branston (1976)):

$$t_a(x_a) = t_a^0 f\left(\frac{x_a}{m_a}\right), \quad (1)$$

where  $t_a^0$  is the *free-flow travel time* of  $a \in \mathcal{A}$ ,  $f(0) = 1$ ,  $f(\cdot)$  is strictly increasing and continuously differentiable on  $\mathbb{R}_+$ , and  $m_a$  is the *flow capacity* of  $a \in \mathcal{A}$ .

Define the set of feasible flow vectors  $\mathcal{F}$  as (see Bertsimas et al. (2015))

$$\left\{ \mathbf{x} : \exists \mathbf{x}^{\mathbf{w}} \in \mathbb{R}_+^{|\mathcal{A}|} \text{ s.t. } \mathbf{x} = \sum_{\mathbf{w} \in \mathcal{W}} \mathbf{x}^{\mathbf{w}}, \mathbf{N}\mathbf{x}^{\mathbf{w}} = \mathbf{d}^{\mathbf{w}}, \forall \mathbf{w} \in \mathcal{W} \right\},$$

where  $\mathbf{x}^{\mathbf{w}}$  indicates the flow vector attributed to OD pair  $\mathbf{w}$ . In order to formulate appropriate optimization and inverse optimization problems arising in transportation networks, we state the definition of *Wardrop equilibrium*:

**Definition 1**

(Patriksson (2015)). A feasible flow  $\mathbf{x}^* \in \mathcal{F}$  is a *Wardrop equilibrium* if for every OD pair  $\mathbf{w} \in \mathcal{W}$ , and any route connecting  $(w_s, w_t)$  with positive flow in  $\mathbf{x}^*$ , the cost of traveling along that route is no greater than the cost of traveling along any other route that connects  $(w_s, w_t)$ . Here, the cost of traveling along a route is the sum of the costs of each of its constituent links.

### 2.2 The forward problem

As in Zhang et al. (2016), here we refer to the Traffic Assignment Problem (TAP) as the *forward problem*, whose goal is to find the Wardrop equilibrium for a given single-class transportation network with a given OD demand matrix. It is a well-known fact that, for network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$ , the TAP can be formulated as the following optimization problem (see Dafermos and Sparrow (1969)):

$$(\text{TAP}) \quad \min_{\mathbf{x} \in \mathcal{F}} \sum_{a \in \mathcal{A}} \int_0^{x_a} t_a(s) ds. \quad (2)$$

As an alternative, we also formulate the TAP as a Variational Inequality (VI) problem:

**Definition 2**

(Bertsimas et al. (2015)). The VI problem, denoted as VI( $\mathbf{t}, \mathcal{F}$ ), is to find an  $\mathbf{x}^* \in \mathcal{F}$  s.t.

$$\mathbf{t}(\mathbf{x}^*)'(\mathbf{x} - \mathbf{x}^*) \geq 0, \quad \forall \mathbf{x} \in \mathcal{F}. \quad (3)$$

We introduce an assumption:

**Assumption A**

$\mathbf{t}(\cdot)$  is strongly monotone (see Patriksson (2015)) and continuously differentiable on  $\mathbb{R}_+^{|\mathcal{A}|}$ .  $\mathcal{F}$  is nonempty and contains an interior point (Slater’s condition).

**Theorem 1.** (Patriksson (2015)). *Assump. A* implies that there exists a Wardrop equilibrium of the network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$ , which is the unique solution to VI( $\mathbf{t}, \mathcal{F}$ ).

### 2.3 The inverse problem

To solve the forward problem, we need to know the travel latency cost function and the OD demand matrix. Assuming that we know the OD demand matrix and

have observed the Wardrop equilibrium flows, we seek to formulate the inverse problem (the inverse VI problem, in particular), so as to estimate the travel latency cost function.

For a given  $\epsilon > 0$ , we define an  $\epsilon$ -approximate solution to  $\text{VI}(\mathbf{t}, \mathcal{F})$  by changing the right-hand side of (3) to  $-\epsilon$ :

*Definition 3*

(Bertsimas et al. (2015)). Given  $\epsilon > 0$ ,  $\hat{\mathbf{x}} \in \mathcal{F}$  is called an  $\epsilon$ -approximate solution to  $\text{VI}(\mathbf{t}, \mathcal{F})$  if  $\mathbf{t}(\hat{\mathbf{x}})'(\mathbf{x} - \hat{\mathbf{x}}) \geq -\epsilon$ ,  $\forall \mathbf{x} \in \mathcal{F}$ .

Given observation  $\hat{\mathbf{x}} \in \mathcal{F}$ , the inverse VI problem amounts to finding a function  $\mathbf{t}$  such that  $\hat{\mathbf{x}}$  is an  $\epsilon$ -approximate solution to  $\text{VI}(\mathbf{t}, \mathcal{F})$ . We can formulate the inverse VI problem as (see Bertsimas et al. (2015))

$$\begin{aligned} \min_{\mathbf{t}; \epsilon > 0} \quad & \epsilon \\ \text{s.t.} \quad & \mathbf{t}(\hat{\mathbf{x}})'(\mathbf{x} - \hat{\mathbf{x}}) \geq -\epsilon, \quad \forall \mathbf{x} \in \mathcal{F}. \end{aligned} \quad (4)$$

To make (4) solvable, we apply an estimation approach which expresses the cost function in a Reproducing Kernel Hilbert Space (RKHS) (see Bertsimas et al. (2015)). To be specific, we pick the polynomial kernel, i.e.,  $\phi(x, y) \stackrel{\text{def}}{=} (c + xy)^n$  for some choice of  $c > 0$  and  $n \in \mathbb{N}$ . Assume we are given network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$  with equilibrium flow data  $\{\mathbf{x} = (x_a; a \in \mathcal{A})\}$ . By (Bertsimas et al., 2015, Thm. 2), we can reformulate (4) as a Quadratic Program (QP) denoted by  $\text{invVI-1}$ ; see (Zhang et al., 2016, (6)), which leads to an estimator for  $f(\cdot)$ , the cornerstone of  $\mathbf{t}(\cdot)$ ; see (Zhang et al., 2016, (7)).

However, directly solving  $\text{invVI-1}$  would typically encounter numerical difficulties, due to the low rank of the involved kernel matrix (especially in networks with many links). Thus, in our implementation, we will consider another formulation, by directly using the polynomial base functions of the same RKHS. In particular, by (Evgeniou et al., 2000, (3.2), (3.3), and (3.6)), writing  $\phi(x, y) = (c + xy)^n = \sum_{i=0}^n \binom{n}{i} c^{n-i} x^i y^i$ , we reformulate  $\text{invVI-1}$  as

$$\begin{aligned} (\text{invVI-2}) \quad & \min_{\beta, \mathbf{y}, \epsilon} \quad \epsilon + \gamma \sum_{i=0}^n \frac{\beta_i^2}{\binom{n}{i} c^{n-i}} \\ \text{s.t.} \quad & \mathbf{e}_a' \mathbf{N}' \mathbf{y}^{\mathbf{w}} \leq t_a^0 \sum_{i=0}^n \beta_i \left( \frac{x_a}{m_a} \right)^i, \quad \forall \mathbf{w} \in \mathcal{W}, a \in \mathcal{A}, \\ & \sum_{a \in \mathcal{A}} t_a^0 x_a \sum_{i=0}^n \beta_i \left( \frac{x_a}{m_a} \right)^i - \sum_{\mathbf{w} \in \mathcal{W}} (\mathbf{d}^{\mathbf{w}})' \mathbf{y}^{\mathbf{w}} \leq \epsilon, \\ & \sum_{i=0}^n \beta_i \left( \frac{x_a}{m_a} \right)^i \leq \sum_{i=0}^n \beta_i \left( \frac{x_{\tilde{a}}}{m_{\tilde{a}}} \right)^i, \\ & \quad \forall a, \tilde{a} \in \mathcal{A} \text{ s.t. } \frac{x_a}{m_a} \leq \frac{x_{\tilde{a}}}{m_{\tilde{a}}}, \\ & \epsilon > 0, \quad \beta_0 = 1, \end{aligned} \quad (5)$$

where  $\beta, \mathbf{y} = (\mathbf{y}^{\mathbf{w}}; \mathbf{w} \in \mathcal{W})$ , and  $\epsilon$  are decision variables ( $\mathbf{y}^{\mathbf{w}}$  is the “price” of  $\mathbf{d}^{\mathbf{w}}$ , in particular),  $\gamma$  is a regularization parameter. The first constraint is for dual feasibility. The second constraint is for the primal-dual gap suboptimality. The third constraint forces the function  $f(\cdot)$  to be non-decreasing. The last constraint  $\beta_0 = 1$  is for normalization purposes. Note that  $(\text{invVI-2})$  can be directly extended to the case where  $K (> 1)$  different flow observations (and the corresponding OD demand matrices) are

available. Assuming an optimal  $\beta^* = (\beta_i^*; i = 0, 1, \dots, n)$  is obtained by solving (5), then we have the following estimator for  $f(\cdot)$ :

$$\hat{f}(x) = \sum_{i=0}^n \beta_i^* x^i = 1 + \sum_{i=1}^n \beta_i^* x^i. \quad (6)$$

## 2.4 OD demand estimation

Given network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$ , to estimate an initial OD demand matrix, we borrow the Generalized Least Squares (GLS) method proposed in Hazelton (2000), which assumes that the transportation network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$  is uncongested (in other words, for each OD pair the route choice probabilities are independent of traffic flow), and that the OD trips (traffic counts) are Poisson distributed. Note that such assumptions are a bit strong and we will relax them when finalizing our OD demand estimator by performing an adjustment procedure.

Let  $\{\mathbf{x}^{(k)}; k = 1, \dots, K\}$  denote  $K$  observations of the flow vector and  $\bar{\mathbf{x}}$  the average. Denote by  $\mathbf{S} = (1/(K-1)) \sum_{k=1}^K (\mathbf{x}^{(k)} - \bar{\mathbf{x}})(\mathbf{x}^{(k)} - \bar{\mathbf{x}})'$  the sample covariance matrix. Let  $\mathbf{P} = [p_{ir}]$  be the route choice probability matrix, where  $p_{ir}$  is the probability that a traveler between OD pair  $i$  uses route  $r$ . Vectorize the OD demand matrix as  $\mathbf{g}$  and let  $\boldsymbol{\xi} = \mathbf{P}'\mathbf{g}$ . Then, the GLS method proceeds as follows: (i) Find feasible routes for each OD pair, thus obtaining the link-route incidence matrix  $\mathbf{A}$ . (ii) Solve sequentially the following two problems:

$$(\text{P1}) \quad \min_{\boldsymbol{\xi} \geq 0} \quad \frac{K}{2} \boldsymbol{\xi}' \mathbf{Q} \boldsymbol{\xi} - \mathbf{b}' \boldsymbol{\xi}, \quad (7)$$

where  $\mathbf{Q} = \mathbf{A}'\mathbf{S}^{-1}\mathbf{A}$  and  $\mathbf{b} = \sum_{k=1}^K \mathbf{A}'\mathbf{S}^{-1}\mathbf{x}^{(k)}$ , and

$$\begin{aligned} (\text{P2}) \quad & \min_{\mathbf{P} \geq 0, \mathbf{g} \geq 0} \quad h(\mathbf{P}, \mathbf{g}) \\ \text{s.t.} \quad & p_{ir} = 0 \quad \forall (i, r) \in \{(i, r) : r \notin \mathcal{R}_i\}, \\ & \mathbf{P}'\mathbf{g} = \boldsymbol{\xi}^*, \\ & \mathbf{P}\mathbf{1} = \mathbf{1}, \end{aligned} \quad (8)$$

where  $h(\mathbf{P}, \mathbf{g})$  can be taken as any smooth scalar-valued function,  $\boldsymbol{\xi}^*$  is the optimal solution to (P1), and  $\mathbf{1}$  denotes the vector with all 1's as its entries. Note that (P1) (resp., (P2)) is a typical *Quadratic Program (QP)* (resp., *Quadratically Constrained Program (QCP)*). Letting  $(\mathbf{P}^*, \mathbf{g}^*)$  be an optimal solution to (P2), then  $\mathbf{g}^*$  is our initial estimate of the demand vector.

*Remark 1*

We note here that the GLS method would encounter numerical difficulties when the network size is large, because there would be too many decision variables in (P2). Note also that the GLS method is valid under an “uncongestion” assumption and, to take the congestion, here the link flows, into account, we in turn consider a bi-level optimization problem in the following.

Assume now the function  $f(\cdot)$  in (1) is available. For any given feasible  $\mathbf{g} (\geq 0)$ , let  $\mathbf{x}(\mathbf{g})$  be the optimal solution to the TAP (2). In the following, assume  $\tilde{\mathbf{x}} = (\tilde{x}_a; a \in \mathcal{A})$  to be the observed flow vector. Assuming we are given an initial demand vector  $\mathbf{g}^0$ , we consider the following bi-level optimization problem (BiLev) (see Spiess (1990) & Lundgren and Peterson (2008)):

$$(\text{BiLev}) \quad \min_{\mathbf{g} \geq \mathbf{0}} F(\mathbf{g}) \stackrel{\text{def}}{=} \sum_{a \in \mathcal{A}} (x_a(\mathbf{g}) - \tilde{x}_a)^2. \quad (9)$$

Note that  $F(\mathbf{g})$  has a lower bound 0 which guarantees the convergence of the algorithm (see Alg. 1) that we are going to apply. To solve the (BiLev) numerically, thus adjusting the demand vector iteratively, we leverage a gradient-based algorithm (Alg. 1). In particular, suppose that the route probabilities are locally constant. For OD pair  $i$ , considering only the shortest route  $r_i(\mathbf{g})$ , we have (see Spiess (1990))

$$\frac{\partial x_a(\mathbf{g})}{\partial g_i} = \delta_{r_i(\mathbf{g})a} = \begin{cases} 1, & \text{if } a \in r_i(\mathbf{g}), \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

Thus, by (10) we obtain the Jacobian matrix

$$\left[ \frac{\partial x_a(\mathbf{g})}{\partial g_i}; a \in \mathcal{A}, i \in \{1, \dots, |\mathcal{W}|\} \right]. \quad (11)$$

*Remark 2*

There are three reasons why we consider only the shortest routes for the purpose of calculating the Jacobian: (i) GPS navigation is widely-used by vehicle drivers so that they tend to always select the shortest routes between their OD pairs. (ii) There are many efficient algorithms for finding the shortest route for each OD pair. (iii) If considering more than one route for an OD pair, then the route flows cannot be uniquely determined by solving the TAP (2), thus leading to unstable route-choice probabilities, which would undermine the accuracy of the approximation to the Jacobian matrix in (11).

Let us now compute the gradient of  $F(\mathbf{g})$ . We have

$$\begin{aligned} \nabla F(\mathbf{g}) &= \left( \frac{\partial F(\mathbf{g})}{\partial g_i}; i = 1, \dots, |\mathcal{W}| \right) \\ &= \left( \sum_{a \in \mathcal{A}} 2(x_a(\mathbf{g}) - \tilde{x}_a) \frac{\partial x_a(\mathbf{g})}{\partial g_i}; i = 1, \dots, |\mathcal{W}| \right). \end{aligned} \quad (12)$$

We summarize the procedures for adjusting the OD demand matrices as Alg. 1, whose convergence can be guaranteed by construction and the well-known monotone convergence theorem.

*Remark 3*

Alg. 1 is a variant of the algorithms proposed in Spiess (1990) & Lundgren and Peterson (2008). We use a different method to calculate the *step-sizes* (resp., *Jacobian matrix*) than that in Spiess (1990) (resp., Lundgren and Peterson (2008)).

## 2.5 Price of anarchy

As discussed in Sec. 1, our goal is to measure inefficiency in the traffic network performance due to the non-cooperative behavior of drivers. Thus, we compare the network performance under a user-centric policy vs. a system-centric policy. As a metric for this comparison we define the PoA as the ratio between the total latency cost over all drivers in different OD pairs, obtained under Wardrop flows (user-centric policy) and that obtained under socially optimal flows (system-centric policy).

Given network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$ , as in Zhang et al. (2016), we define its *total latency* as  $L(\mathbf{x}) = \sum_{a \in \mathcal{A}} x_a t_a(x_a)$ .

## Algorithm 1 Adjusting OD demand matrices

**Input:** the road network  $(\mathcal{V}, \mathcal{A}, \mathcal{W})$ ; the function  $f(\cdot)$  in (1); the observed flow vector  $\tilde{\mathbf{x}} = (\tilde{x}_a; a \in \mathcal{A})$ ; the initial demand vector  $\mathbf{g}^0 = (g_i^0; i = 1, \dots, |\mathcal{W}|)$ ; two positive integer parameters  $\rho, T$ ; two real parameters  $\varepsilon_1 \geq 0, \varepsilon_2 > 0$ .

1: **Step 0:** Initialization. Take the demand vector  $\mathbf{g}^0$  as the input, solve the TAP (2) using the Method of Successive Averages (see Noriega and Florian (2007)) to obtain  $\mathbf{x}^0$ . Set  $l = 0$ . If  $F(\mathbf{g}^0) = 0$ , stop; otherwise, go onto Step 1.

2: **Step 1:** Computation of a descent direction. Calculate  $\mathbf{h}^l = -\nabla F(\mathbf{g}^l)$  by (12).

3: **Step 2:** Calculation of a search direction. For  $i = 1, \dots, |\mathcal{W}|$  set

$$\bar{h}_i^l = \begin{cases} h_i^l, & \text{if } (g_i^l > \varepsilon_1) \text{ or } (g_i^l \leq \varepsilon_1 \text{ and } h_i^l > 0), \\ 0, & \text{otherwise.} \end{cases}$$

4: **Step 3:** Armijo-type line search.

**3.1:** Calculate the maximum possible step-size  $\theta_{\max}^l = \min \left\{ -\frac{g_i^l}{\bar{h}_i^l}; \bar{h}_i^l < 0, i = 1, \dots, |\mathcal{W}| \right\}$ .

**3.2:** Determine  $\theta^l = \arg \min_{\theta \in \mathcal{S}} F(\mathbf{g}^l + \theta \bar{\mathbf{h}}^l)$ , where

$$\mathcal{S} \stackrel{\text{def}}{=} \left\{ \theta_{\max}^l, \theta_{\max}^l / \rho, \theta_{\max}^l / \rho^2, \dots, \theta_{\max}^l / \rho^T, 0 \right\}.$$

5: **Step 4:** Update and termination.

**4.1:** Set  $\mathbf{g}^{l+1} = \mathbf{g}^l + \theta^l \bar{\mathbf{h}}^l$ . Using  $\mathbf{g}^{l+1}$  as the input, solve the TAP (2) to obtain  $\mathbf{x}^{l+1}$ .

**4.2:** If  $\frac{F(\mathbf{g}^l) - F(\mathbf{g}^{l+1})}{F(\mathbf{g}^0)} < \varepsilon_2$ , stop the iteration; otherwise, go onto Step 4.3.

**4.3:** Set  $l = l + 1$  and return to Step 1.

Then, the socially optimum flow vector, denoted by  $\mathbf{x}^{\text{social}}$ , is the solution to the following Non-Linear Programming (NLP) problem (see Patriksson (2015) & Pourazarm et al. (2016)):

$$\min_{\mathbf{x} \in \mathcal{F}} \sum_{a \in \mathcal{A}} x_a t_a(x_a). \quad (13)$$

Note that here the objective function is different from the one we use in the TAP (see Sec. 2.2); for a detailed explanation, see Dafermos and Sparrow (1969). Recalling that we consider the total latency as the performance metric, we explicitly define the *Price of Anarchy* as

$$\text{PoA} \stackrel{\text{def}}{=} \frac{L(\mathbf{x}^{\text{user}})}{L(\mathbf{x}^{\text{social}})} = \frac{\sum_{a \in \mathcal{A}} x_a^{\text{user}} t_a(x_a^{\text{user}})}{\sum_{a \in \mathcal{A}} x_a^{\text{social}} t_a(x_a^{\text{social}})} \geq 1, \quad (14)$$

where  $x_a^{\text{user}}$  denotes the Wardrop's equilibrium flow on link  $a \in \mathcal{A}$  (estimated from the speed/capacity datasets), and  $x_a^{\text{social}}$  is the socially optimal flow on link  $a \in \mathcal{A}$  obtained by solving (13), which requires the cost functions  $t_a(\cdot)$  that are estimated by solving the inverse problem (see Sec. 2.3). It is seen that the larger the PoA, the worse the performance of the network; PoA quantifies the inefficiency that a society has to deal with due to non-cooperative behavior of its members.

## 3. DATASET DESCRIPTION AND PROCESSING

### 3.1 Description of the Eastern Massachusetts dataset

We deal with two datasets for the Eastern Massachusetts (EMA) road network: (i) The speed dataset, provided to us

by the Boston Region Metropolitan Planning Organization (MPO), includes the spatial average speeds for more than 13,000 road segments (with an average distance of 0.7 miles; see Fig. 1(a)) of EMA, covering the average speed for every minute of the year 2012. (ii) The flow capacity (# of vehicles per hour) dataset, also provided by the MPO, includes capacity data for more than 100,000 road segments (average distance of 0.13 miles) in EMA. For more detailed information, see Zhang et al. (2016).

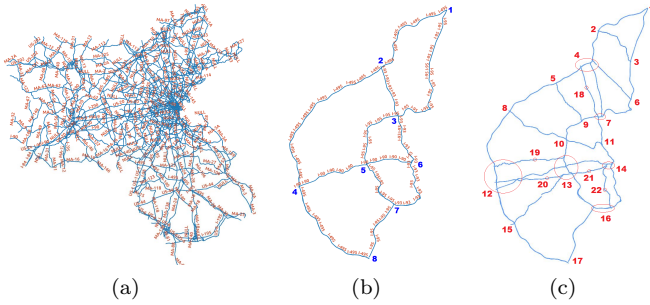


Fig. 1. (a) All available road segments in Eastern Massachusetts (from Zhang et al. (2016)); (b) An interstate highway sub-network of EMA (from Zhang et al. (2016); the blue numbers indicate node indices); (c) An extended highway sub-network of EMA (the red numbers indicate node indices).

### 3.2 Data preprocessing

Other than selecting an extended subnetwork (shown in Fig. 1(c) as opposed to the smaller subnetwork Fig. 1(b)) of the EMA road network (shown in Fig. 1(a)), we perform exactly the same preprocessing procedures as those in Zhang et al. (2016) on the datasets mentioned in Sec. 3.1. Thus, we end up with traffic flow data and road (link) parameters (*flow capacity* and *free-flow travel time*) for the two subnetworks (shown in Figs. 1(b) and 1(c) respectively; from now on, let us denote them by  $\mathcal{I}_1$  and  $\mathcal{I}_2$  respectively), where  $\mathcal{I}_1$  contains only the interstate highways and  $\mathcal{I}_2$  also contains the state highways in EMA. Note that  $\mathcal{I}_1$  (resp.,  $\mathcal{I}_2$ ) consists of 8 (resp., 22) nodes and 24 (resp., 74) links; their topologies can be found in Zhang (2016). Assuming that each node could be an origin and a destination, then there are  $8 \times (8 - 1) = 56$  (resp.,  $22 \times (22 - 1) = 462$ ) OD pairs in  $\mathcal{I}_1$  (resp.,  $\mathcal{I}_2$ ).

### 3.3 Data processing

First, operating on  $\mathcal{I}_1$ , we solve the QP (P1) and the QCP (P2) using data corresponding to five different time periods (AM, MD, PM, NT, and weekend) of four months (Jan., Apr., Jul., and Oct.) in 2012, thus obtaining 20 different OD demand matrices for these scenarios. As noted in Zhang et al. (2016), the GLS method assumes the traffic network to be uncongested, leading to the fact that the estimated OD demand matrices for non-peak periods (MD/NT/weekend) are relatively more accurate than those for peak periods (AM/PM). After obtaining estimates for cost functions (see the next paragraph) based on the estimates for the OD demand matrices of  $\mathcal{I}_1$ , we will conduct a demand adjustment procedure for  $\mathcal{I}_2$ .

Next, operating on  $\mathcal{I}_1$  using the flow data and the OD demand matrices obtained above, we estimate the cost functions for 20 different scenarios, via the estimator (6), by solving the QP (5) accordingly. As in Zhang et al. (2016), to make the estimates reliable, for each scenario, we perform a 3-fold cross-validation, thus determining appropriate values for parameters  $n$ ,  $c$ , and  $\gamma$ . Note that Zhang et al. (2016) applied a different estimator, which is numerically not as stable.

Then, we conduct a demand adjustment procedure, proceeding as follows. We first demonstrate the effectiveness of the demand-adjusting algorithm (Alg. 1) using the Sioux-Falls benchmark dataset (see Bar-Gera (2016)). Then, assuming the per-road cost functions are available (we take the cost functions derived from  $\mathcal{I}_1$ ), we apply Alg. 1 to  $\mathcal{I}_2$ , which contains  $\mathcal{I}_1$  as one of its representative subnetworks. Note that the main difference between  $\mathcal{I}_1$  and  $\mathcal{I}_2$  is the modeling emphasis ( $\mathcal{I}_1$  only takes account of the interstate highways, while  $\mathcal{I}_2$  also encompasses the state highways, thus containing more details of the real road network of EMA), and we can think of  $\mathcal{I}_1$  as a “landmark” subnetwork of  $\mathcal{I}_2$ . Based on the initially estimated demand matrices for  $\mathcal{I}_1$ , we will implement the following generic demand-adjusting scheme so as to derive the OD demand matrices for  $\mathcal{I}_2$ :

Given a network ( $\mathcal{I}_2$  in our case) with any size, we can select its “landmark” subnetworks ( $\mathcal{I}_1$  in our case) (based on the information of road types, pre-identified centroids, etc.) with acceptably smaller sizes, say, we end up with  $N$  ( $N = 1$  in our case) such subnetworks. Then, for each subnetwork, we estimate its demand matrix by solving sequentially the QP (P1) and the QCP (P2) (cf. Sec. 2.4). Setting the demand for any OD pair not belonging to this subnetwork to zero, we obtain a “rough” initial demand matrix for the entire network ( $\mathcal{I}_2$  in our case). Next, take the average of these initial demand matrices. Finally, we adjust the average demand matrix based on the flow observations of the entire network.

As noted in Remark 1, the reason why we do not directly solve (P1) and (P2) for the larger network ( $\mathcal{I}_2$  in our case) is that there are too many decision variables in (P2) and this would lead to numerical difficulties.

Finally, we quantify the PoA of  $\mathcal{I}_2$  for the PM period of each and every day in April 2012.

## 4. NUMERICAL RESULTS

The results for the initial estimation of OD demand matrices and the estimation of cost functions are similar to those shown in Zhang et al. (2016), and we omit them here. We will focus on presenting the results for demand adjustment (derived for the Sioux-Falls benchmark network; note that we will not show the detailed demand adjustment results for  $\mathcal{I}_2$ , because we do not have the ground truth for a comparison), and the PoA (derived for  $\mathcal{I}_2$ ).

### 4.1 Results from OD demand adjustment

We conduct numerical experiments on the Sioux-Falls network, which contains 24 zones, 24 nodes, and 76 links. For each OD pair, the initial demand is taken by scaling

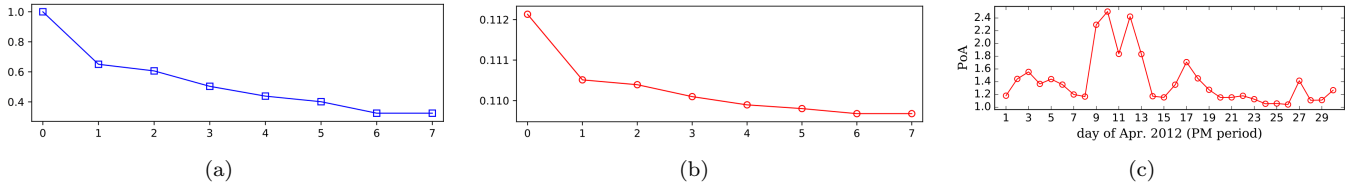


Fig. 2. (a) Objective function value of the (BiLev) vs. # of iterations (Sioux-Falls); (b) Demand difference w.r.t. ground truth vs. # of iterations (Sioux-Falls); (c) PoA of  $\mathcal{I}_2$  for PM period in Apr. 2012 based on avg. flow on each link.

the ground truth demand with a uniform distribution  $[0.8, 1.2]$ . The ground truth  $f(\cdot)$  is taken as  $f(x) = 1 + 0.15x^4$ ,  $\forall x \geq 0$ , and is assumed directly available. When implementing Alg. 1, we set  $\rho = 2$ ,  $T = 10$ ,  $\varepsilon_1 = 0$ , and  $\varepsilon_2 = 10^{-20}$ . Fig. 2(a) shows that, after 7 iterations, the objective function value of the (BiLev) (9) has been reduced by more than 65%. Fig. 2(b) shows that, the distance between the adjusted demand and the ground truth demand keeps decreasing with the number of iterations, and the distance changes very slightly, meaning the adjustment procedure does not alter the initial demand much. Note that in Fig. 2(a), the vertical axis corresponds to the normalized objective function value of the (BiLev), i.e.,  $F(\mathbf{g}^l)/F(\mathbf{g}^0)$  and, in Fig. 2(b), the vertical axis denotes the normalized distance between the adjusted demand vector and the ground truth, i.e.,  $\|\mathbf{g}^l - \tilde{\mathbf{g}}\|/\|\tilde{\mathbf{g}}\|$ , where  $\tilde{\mathbf{g}}$  is the ground-truth demand vector.

#### 4.2 Results for PoA estimation

After implementing the demand adjusting scheme, we obtain the demand matrices for  $\mathcal{I}_2$  on a daily-basis, as opposed to those for  $\mathcal{I}_1$  on a monthly-basis. Note that, even for the same period of a day and within the same month, slight demand variations among different days are possible; thus, our PoA results for  $\mathcal{I}_2$  would be more accurate than those for  $\mathcal{I}_1$  that have been shown in Zhang et al. (2016).

The PoA values shown in Fig. 2(c) have larger variations than those for  $\mathcal{I}_1$  in Zhang et al. (2016); some are now closer to 1 but some go beyond 2.2, meaning we have larger potential to improve the road network. However, when taking the average of the PoA values for all the 30 days, both  $\mathcal{I}_2$  and  $\mathcal{I}_1$  result in an average PoA approximately equal to 1.5, meaning we can gain an efficiency improvement of about 50%; thus, the results are consistent.

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