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Dynamic Network Analysis & Real-time Traffic Management for Philadelphia Metropolitan Area

FINAL REPORT

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16. Abstract

This project developed a general regional network model to estimate/predict time-varying traffic evolution on all highways and major arterials in the Philadelphia Metropolitan Region. A real-time Dynamic Traffic Assignment (DTA) algorithm was developed to real-time update the underlying flow propagation by reading real-time incident reports and real-time speed measurements. In addition to predicting next-hour network flow, we intend to intervene the network flow by optimizing the routing messages fed to dynamic message signs (DMS). Real-time DTA is essentially solved with, in part, optimal traffic routing only at limited DMS locations. The proposed model is implemented as an internet web application, a website built to visualize the control strategies and animate the predicted flow evolutions. All the user interactions with the real-time traffic management model are based on the browser. A case study was conducted for assessing the dynamic traffic impact of road closures on I-95 in the Philadelphia Region and generating optimal detouring messages.

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Executive Summary

This project developed a general regional network model to estimate/predict time-varying traffic evolution on all highways and major arterials in Philadelphia Metropolitan Region. A case study was conducted for assessing the dynamic traffic impact of road closures on freeways and/or major arterials in the Philadelphia Region; and propose real-time traffic detour plans as a way of using travel demand management (TDM) strategies to mitigate overall impact caused by closures.

The first phase involved the collection of data for the project and summarizing the data with a major focus on establishing a dynamic network model for the Philadelphia Metropolitan Region. This dynamic transportation network model that provides estimated day-to-day origin-destination demand among all Traffic Analysis Zones (TAZs) is developed. We examined and carefully calibrated the route choices for all the travelers with different origins and destinations using observed traffic counts and speed data. The calibrated model is capable of estimating network-wide traffic impacts caused by any incident based upon a generic regional network consisting of freeway and major arterials.

We also developed real-time Dynamic Traffic Assignment (DTA) algorithms that take real-time incident reports and real-time speed measurements simultaneously to update the underlying flow propagation. In addition to predicting next-hour network flow, we intervene the network flow by optimizing the messages fed to dynamic message signs (DMS). Real-time DTA is essentially solved with, in part, optimal traffic routing only at limited DMS locations. The real-time prediction and message optimum are solved with algorithms that are computationally efficient for large-scale network.

The proposed model is implemented as an internet web application, a website built to visualize the control strategies and animate the flow evolutions. All the user interactions with the real-time traffic management model are based on browsers.

Abbreviations

API: Application Programming Interface

BUE: Boston User Equilibrium

CTM: Cell Transmission Model

DODE: Dynamic Origin-Destination Estimation

DTA: Dynamic Traffic Assignment

DMS: Dynamic Message Signs

DVRPC: Delaware Valley Regional Planning Commission

LPFE: Logit Path Flow Estimator

O-D: Origin-Destination

PUE: Predictive User Equilibrium

RMSE: Root Mean Square Error

TAZ: Traffic Analysis Zones

TDM: Travel Demand Management

TMC: Traffic Message Channel

UE: User Equilibrium

VHT: Vehicle Hours Traveled

VMT: Vehicle Miles Traveled

1 Introduction

Non-recurrent traffic congestion caused by roadway construction work, planned events, and unplanned traffic incidents can create massive traffic tie-ups and can have equally large economic and environmental regional impacts. More roadway rehabilitation/reconstruction work has been conducted over the recent years on heavily travelled urban corridors which are already "capacity-hungry". With the availability of various traffic data to identify congestion (real-time and historically archived), how to minimize incident-induced disruption to commuting traffic and its impact to the environment presents a big challenge to public agencies. While planned and unplanned incidents require careful evaluation of alternative construction plans and corresponding traffic management plans, guidelines to develop efficient traffic demand management strategies are often lacking. Consequently, there is a real need to study planned and unplanned traffic incidents to learn valuable lessons to prepare public agencies to deal more effectively with large routine highway maintenance, reconstruction, big sports events, catastrophic vehicle crash and emergency situations.

The Philadelphia Metropolitan Region is traffic data rich compared to other metropolitan areas in the U.S. Various data sets in the Philadelphia region, including traditional traffic sensors (loops, cameras, etc.) and cutting-edge sensors (Bluetooth, GPS probe, parking, etc.), are available and have been archived for a decade. The rich data sets allow us to learn travelers' behavior more accurately and develop an in-depth understanding of non-recurrent traffic in large-scale networks, which is usually influenced by abnormal disruptions (such as incidents, events, weather, etc.).

Therefore we want to develop a general regional network model to estimate/predict time-varying traffic evolution on all highways and major arterials in Philadelphia Metropolitan Region. We accomplish this by conducting a case study for I-95 closures, assessing the dynamic traffic impact of the closures on both freeways and major arterials in the Philadelphia Region; and propose real-time traffic detour plans as a way of using travel demand management (TDM) strategies to mitigate overall impact caused by closures.

The purposes of the project are:

- Develop a generic regional network model to estimate/predict time-varying traffic evolution on all highways and major arterials in Philadelphia Metropolitan Region. The model estimates origin-destination demands within the region and captures travel behavior of those travelers (in particular their time-varying route choices).
- Conduct a case study for Center City bridge closures: assess the dynamic traffic impact of Center City Bridge closures on both freeways and major

arterials in the Philadelphia Region; propose real-time traffic detour plans as a way of travel demand management (TDM) to mitigate overall impact caused by closures. The traffic detour plans include optimized traffic signal timing on major intersections and on-site detour strategies through Dynamic Message Signs (DMS).
- Conduct a second case study for hypothetical I-95 closures: assess traffic impact of I-95 closures in Downtown Philadelphia and prepare traffic detour plans.

The remainder of this report is organized as follows.

- Section 2 briefly reviews the cutting-edge off-line and on-line dynamic traffic network models.
- Section 3 summarizes and describes the road network files and date we obtained.
- Section 4 describes the procedures of constructing the network and pre-processing the traffic data.
- Section 5 presents the model details of the off-line dynamic traffic assignment model on Philadelphia Metropolitan Region.
- Section 6 presents the model details of the on-line dynamic traffic assignment model on Philadelphia Metropolitan Region.

2. Model review

As an emerging technology in transportation area, Dynamic Traffic Assignment (DTA) plays a vital role for real-time traffic management and planning. DTA consists of various kinds of sub-models such as dynamic routing, traffic flow evolution theory, travel behavior model and economic models (Peeta & Ziliaskopoulos 2001). There are two main components in the DTA families, off-line DTA and on-line DTA. Off-line DTA collects the data before learning the travelers' behavior and simulating traffic. While the on-line DTA model collects the real time data as the simulation goes. It uses the real-time data to correct the estimation of demand and behavior on the fly, and there is usually more challenging. The off-line DTA model is usually used for traffic planning/operation, whereas the on-line DTA model is used for real-time traffic prediction and management.

In this section, we build both off-line DTA model and real-time DTA for the Philadelphia Metropolitan Region and analyze the traffic impact of road closures. To familiarize readers the development of DTA models, we present a brief literature review on some important issues on simulation-based DTA models and discuss several cutting-edge on-line and off-line DTA models.

2.1 Route choice model

Route choice model is a crucial part to real-time traffic simulation. Under static network setting, the route choice of travelers is usually determined by a user-equilibrium (UE) flow pattern (Sheffi 1985). In dynamic context, there are generally two types of UE in the literature. One is the so-called Boston User Equilibrium (BUE) (Friesz et al. 1993), which is an adaption of the static Wardroppian UE. It assumes a traveler chooses the shortest route only based on the prevailing traffic condition at the time of his choice decision (Kuwahara & Akamatsu 2001). The other UE type is the so-called Predictive User Equilibrium (PUE). Under this behavioral assumption, travelers choose the shortest route based on “anticipated" travel times, or travel times that they actually experienced from previous days. The result is a UE in which the actual travel times/costs for travelers from any O-D pair are minimal and identical (Friesz et al. 1993), regardless the routes they take. In reality, traveler's route choice behavior is likely to be more complicated and unpredicted than BUE and PUE. For example, travelers may not consider all the possible routes but have several pre-trip routes in mind prior to their departure, which are selected from their day-to-day traveling experiences. Moreover, these pre-selected routes may not be user-optimal ones. In view of this, a hybrid traffic assignment model was purposed to model both equilibrium and disequilibrium traffic conditions (Qian & Zhang 2013). We adopt the hybrid model in this project with the diversion ratio indicating how reactive travelers are in choosing routes.

2.2 Flow evolution model

The flow evolution models describe the dynamic relationship between vehicle density, speed and volume for one road segment. Three models are most adopted by various mesoscopic traffic simulation tools: Point Queue (PQ) (Jin 2015), Spatial Queue (SQ) (Balmer et al. 2004; Breuer 2001) and Cell Transmission Model (CTM) (Daganzo 1995; Daganzo 1999). Though mathematically and practically simple, PQ and SQ are considered to underestimate the network congestion during the simulation (Zhang et al. 2013). CTM as a finite element approximation to the partial differential equation of fluid evolution is proved to best simulate the flow propagation on road segments. A vital issue exists for all dynamic flow evolution models, which is the unrealistic "gridlock" caused by improper routing behavior and misbehave of flow evolution models (Mahmassani et al. 2013).

In this project, we adopt CTM to simulate the flow propagation on links, and the unrealistic gridlock condition is eliminated by calibrating behavior model parameters and network dynamic features.

2.3 Off-line DTA

Off-line DTA models have been thoroughly studied in recent years. According to the simulation resolution, there are three types: macroscopic, microscopic and mesoscopic DTA models. Mesoscopic model is considered to have great potentials for large-scale network simulation with satisfactory precisions. Two pioneers of mesoscopic off-line DTA are DNASMART (Jayakrishnan et al. 1994) and DYNAMIT (Ben-akiva et al. 1998). Both softwares utilize density-speed relationship function to calculate the position of vehicle and simulation the flow propagation, so they do not need to keep track of all vehicles. This simplification significantly reduces the computational complexity.

For all off-line DTA models, an important issue is the trade-off between the simulation accuracy and running time. If a high accuracy is needed, then the running time will be almost implausible for large scale networks. Therefore, we need to tune the best simulation resolution as a compromise between computational efficiency and accuracy.

2.4 On-line DTA

While emerging Advanced Traveler Information Systems/Advanced Traffic Management Systems (ATIS/ATMS) technologies (Mahmassani 1998; Ben-Akiva et al. 1991), which search for routing policies for travelers to achieve real-time network-wise optimum, require the DTA models take on-line data feeds and update management strategies in real time. DTA models that can take real-time data feeds is known as on-line DTA or real-time DTA. Researches of real-time DTA arise accordingly from different disciplines. After two decades' development, real-time DTA models formulate various control mechanisms which take different kinds of data feeds (travel time, traffic flow), adopt various controls (ramp metering, signal timing, VMS, routing) and achieve different objectives (user equilibrium, system optimal).

The idea of real-time DTA originates from the field of optimal control, which assumes the observations of network are complete and travel demands and supplies are pre-determined. Studies (Papageorgiou 1990) build a node based DTA model and control the splitting rate to achieve system optimal or user equilibrium, linearization regulation of the original non-linear DTA model is also developed to handle the large scale network. They also develop METANET as a traffic routing and control framework. Similar real-time DTA problem is also settled by adjusting point diversion using linearization (Kachroo & Özbay 1998). Instead of open-loop framework, (Kachroo & Özbay 2005) further formulate a H_∞ closed-loop feed-back control mechanism on splitting rate. Many other studies also attempt to dynamically control traffic by ramp metering (Zhang et al. 2001), signal timing (Mirchandani & Head 2001; Yang & Yagar 1995), routing guidance (Jahn et al. 2005) and dynamic message sign (DMS) (Shi et al. 2009; Mammar et al. 1996). Among them (Papageorgiou 1995) provides an integrated framework to control traffic flows using all above methods.

In real world, only partial network conditions can be observed and travel demands and supplies are usually unknown. Current/future traffic conditions are estimated/predicted and then reactive/predictive control are applied (Doan & Ziliaskopoulos n.d.). There are literature (Van Arem et al. 1993; Wang & Papageorgiou 2005) focusing on calibrating the supply parameters such as road capacity. Techniques such as ARMA (Hashemi & Abdelghany 2015), Kalman Filter (Wang & Papageorgiou 2005; Antoniou 2004) are also adopted in various models to predict future traffic conditions. Recently an approach called ``rolling horizon" is adopted to tackle network-wise general real-time traffic problem based on simulation software such as DYNASMART (Peeta & Mahmassani 1995; Samaranayake et al. 2015), DynaMIT (Ben-Akiva & Bierlaire 2001), DynusT (Chiu & Mirchandani 2008). The methods estimate current traffic conditions and predict future conditions in each time interval (Zhou & Mahmassani 2007; Mahmassani 2001; Antoniou 2004), then the control policies are determined by the estimated/predicted traffic condition (Li et al. 2015; Du et al. 2014).

Some of real-time DTA models are also implemented in commercial software such as PTV Optima[1] and Aimsun[2]. Both softwares are able to provide real time

[1] http://vision-traffic.ptvgroup.com/en-uk/products/ptv-optima/

[2] https://www.aimsun.com/

information and provide forecasts on traffic conditions of entire networks. Aimsun has already built an Integrated Corridor Management (ICM) system within the I-15 corridor in San Diego County. The whole ICM system is fully automatic and equipped with various combinations of strategies such traveler information platform, traffic management and transit management.

In this project, we develop a framework that takes the real time vehicle speed data feed as inputs and update the real-time O-D demand, as well as routing behavior. The predicted travel time along with routing guidance recommendation will be disseminated to the travelers by Variable Message Signs (VMS) and radio broadcasts. The model will be specially tailored for applications to the Philadelphia Metropolitan Region.

3. Data summary

Figure 1 DVRPC Regional Map (retrieved from DVRPC website)

Data from nine counties in the Delaware Valley Regional Planning Commission (DVRPC) region were collected for this project. Figure 1[3] shows the geographical boundaries of the DVRPC region. Data obtained includes network topological data, historical O-D, traffic counts and traffic speeds. Since they were collected from different sources, we briefly discuss the format and contents for each data.

3.1 Network topological data

The nine-county network was obtained from DVRPC in the format of PTV Visum. The file contains 3,399 traffic analysis zones (TAZ), 90,083 junctions and 255,992 road segments. The network includes Bucks, Chester, Delaware, Montgomery and Philadelphia counties in Pennsylvania; and Burlington, Camden, Gloucester and Mercer counties in New Jersey. Figure 2 is a screenshot of the obtained network, and the colors represent different road levels. The road segments have attributes such as street names, street levels (highway, major arterials, minor streets, alleys, etc.), number of lanes, and speed limit.

Together with the network file, the regional travel planning model (TIM2.1) from DVRPC was also contained in the same data file. The static traffic assignment model may help build our dynamic analytic model.

[3] http://www.dvrpc.org/img/homepage/DVRPC_Regional_Map.png, retrieved on 28th Oct 2015.

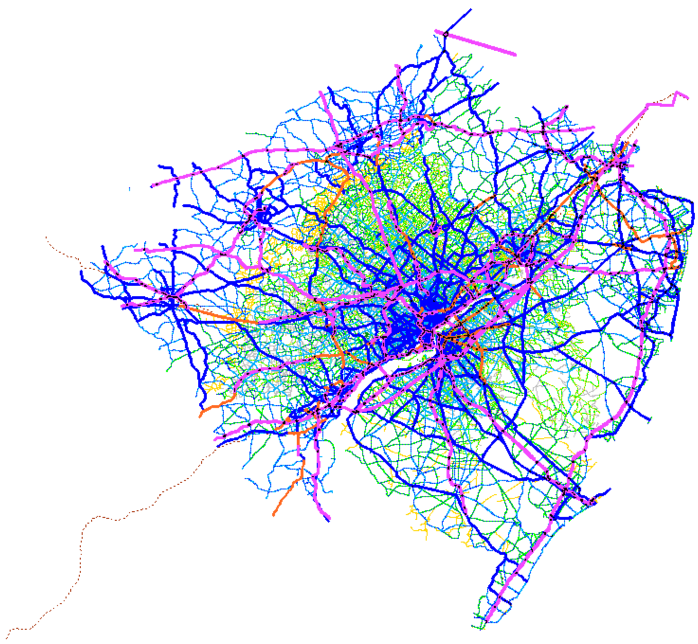

Figure 2 Screenshot of DVRPC network

3.2 History O-D

The historical O-D demand data was also obtained from DVRPC in the format of VISUM. The O-D matrix is represented by a 3399×3399 matrix and in float precision. DVRPC also provided a main O-D pairs profile, which contains 10,000 main O-Ds. O-D connectors are also contained in the TIM2.1 model, the total number of O-D connectors is 11,553,201.

3.3 Traffic counts

DVRPC provided us with 15-minute interval traffic volume counts data from 3rd Jan 2013 to 15th Oct 2015. The data file has 568,524 rows; each row indicates the count of a 15-minute period on a certain day collected by a loop detector on various roadway segments. There are in all 3,565 different detectors, each detector has the information of its geographic location (latitude and longitude), and road name. However, the dates when those measurements were collected vary throughout the year.

3.4 Traffic speed

Travel speed data provided by INRIX were obtained from the Regional Integrated Transportation Information System (RITIS). The data set includes 13,104 Traffic Management Channels (TMCs) for the nine counties of DVRPC. The data includes speed, travel time, historic average speed and reference speed (namely 85% quantile of all observed probe vehicle speeds, used as the free-flow speed). All data are averaged into 15 minute intervals to meet the needs of our dynamic analytic model.

Due to the limitation that each exported file can have at most 5000 TMCs, we divided the region into three parts as show in Figure 3. Table 1 illustrates how we divided the region. The three areas have roughly the same number of TMCs. Table 1 is a sample data of the travel speed, consisting of tmc code (reference id for each TMC), measurement stamp time, speed, average speed and reference speed in miles per hour, travel time in miniutes, confidence score and cvalue The column ‘tmc_code’ can be matched with the road segments in the DVRPC TIM2.1 model. The column ‘measurement_tstamp’ indicates the measurement time of the speed.

Table 1 Partition of TMCs

Region	Counties	Number of TMCs
Green region	Chester, Delaware and Montgomery	4,373
Yellow region	Philadelphia and Bucks	4,011
Purple region	Burlington, Camden, Gloucester and Mercer	4,720

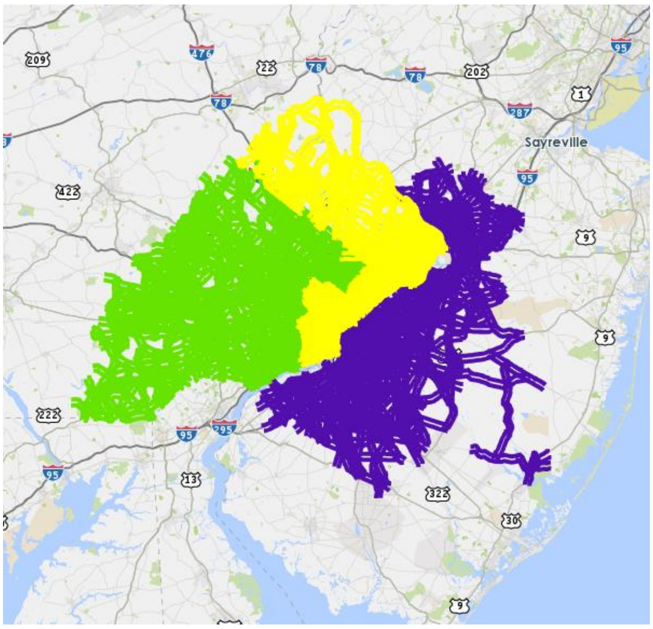

Figure 3 Partitions of TMCs in the modeling region

Table 2 Sample data of travel speed

tmc_code	measurement_tstamp	speed	average_speed	reference_speed	travel_time_minutes	confidence_score	cvalue
103+13758	1/1/2013 5:00	34	34	34	2.12	20	0
103N11940	1/1/2013 5:00	34	34	36	0.01	20	0
103P04934	1/1/2013 5:15	34	34	35	0.08	20	0
103-12881	1/1/2013 5:15	39	39	39	2.15	20	0

3.5 Dynamic message sign (DMS)

All the information about dynamic message signs on Philadelphia Metropolitan Region is provided by DVRPC. A brief description of the location of DMS and the coordinates are given in the file. The file also specifies the suggest detour link the DMSs.

4. Data preparation

Network description files and traffic data sets for the nine counties of Delaware Valley Regional Planning Commission (DVRPC) region were collected for this project. The network description files are trimmed, consolidated and further coded into our state-of-art traffic simulation tools, and the traffic data sets are processed, smoothed and matched to each road segments.

4.1 Network description

The network for Philadelphia Metropolitan Area is from the Delaware Valley Regional Planning Commission (DVRPC) in the format of PTV Visum. The file contains 3,399 traffic analysis zones (TAZ), 90,083 junctions and 255,992 road segments. The network includes Bucks, Chester, Delaware, Montgomery and Philadelphia counties in Pennsylvania; and Burlington, Camden, Gloucester and Mercer counties in New Jersey. Figure 4 is a screenshot of the obtained network, and the colors represent different road levels. The road segments have attributes such as street names, street levels (highway, major arterials, minor streets, alleys, etc.), number of lanes, and speed limits.

A network consolidation was conducted to trim the original network. The following steps were carried out to conduct the consolidation before the simulation:

- We consolidated the network according to the road levels. The entire network was divided into 3 parts, for those areas far away from Philadelphia County, we retain the highways; for those areas neighbored with Philadelphia County, we retain the highways and major arterials; and we retain all the roads inside the Philadelphia County.
- The network was then trimmed such that no “isolated" nodes and links exist. “Isolated" nodes are those who have only one forward link and one backward link, and the head node of the forward link is exactly the tail node of the backward link. Further, “isolated" links are the forward links and backward links of “isolated" nodes. The absence of such nodes and links does not affect the dynamic network analysis, but allows for a more precise estimation of network performance indicators.
- We consolidated neighboring links with small lengths and the same speed limit. This process substantially reduced the network scale. More importantly, this was desirable to achieve more accuracy for the mesoscopic traffic flow models.

Figures 4 and 5 present a comparison between the original network and the consolidated one, as can be seen, all the highways and major arterials are retained after the consolidation. Meanwhile we ensure the running time of the dynamic traffic analysis within a short time interval (e.g., 5 minutes) for real-time deployment in real-time DTA model.

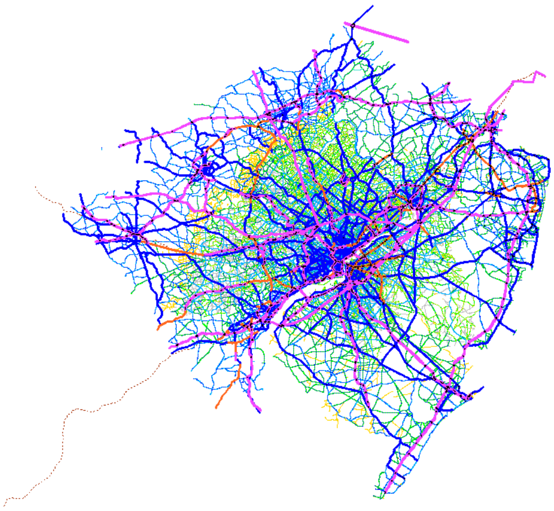

Figure 4 Before consolidation

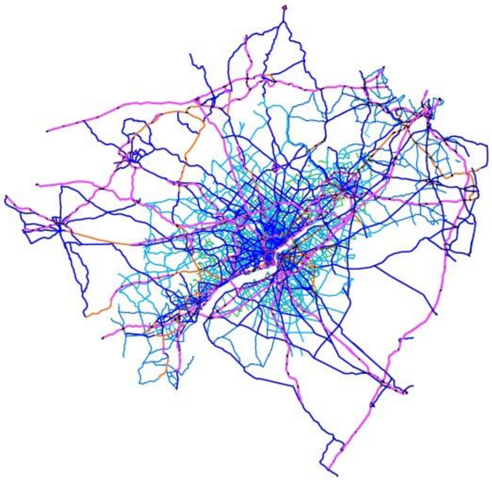

Figure 5 After consolidation

4.2 O-D connectors

The OD connectors are constructed based on the main zone information given in the DVRPC network, 214 traffic analysis zones (TAZs) are built in our analysis network. An origin dummy node and a destination dummy node were attached to each centroid. Therefore, the entire network contained 214 origin/destination nodes with 473,796 O-D pairs. For each traffic zone, a select set of connector nodes from the original networks within the zone was constructed. A connector node is a real network node that is neither on the freeway (or equivalently, the speed limits of both its forward links and backward links are more than 55 miles per hour) nor on the freeway ramp, so that all traffic is assigned to surface streets in the large-scale network. Connector nodes were constructed in a different way from the regular method, because trips are most likely to start and end on local streets. In addition, we made three or four connections between real network nodes (in the selection set) and those dummy nodes, rather than those centroids directly. This method ensures through traffic will never unrealistically use connectors to reduce travel time.

Figure 6 represents the final network for dynamic analysis coded in our simulate tool, black links are actual road segments and green and blue links are origin connectors and destination connectors, respectively.

Figure 6 Network visualization in simulation software

4.3 Flow counts

The flow counts raw data are provided from two sources. The first data set is from PennDOT, which contains the geo-location of sensors and the 1 hour traffic counts in a csv file; the second data set is from DVRPC, both geo-information and counts are also encoded in a csv file. Since the sensor location is either geo-referenced by the street centerlines GIS system or global coordinate system (GCS), to match the counts to the network, an algorithm considering relative distance, angle and length was developed.

We also smoothed the traffic flow counts into 15 minutes resolution by using linear interpolation. The missing data are either imputed or discarded based on a case by case review. Finally, both data were merged and reformatted for dynamic origin destination estimation (DODE).

4.4 Traffic speed

Traffic speed data were also obtained from INRIX. The traffic speed data is provided at the geographic level of Traffic Message Channel (TMC), one of the geo-reference protocols. To match the traffic speed data with the links in DVPRC network, an algorithm considering relative distance and direction was developed to search for the best match of traffic speed. Finally, the speed data were smoothed and reformatted for DODE, which is detailed in the next section.

Figure 7 represents the road segments with different kinds of traffic data. Green links are those with speed measurements, purple links are those with counts measurements.

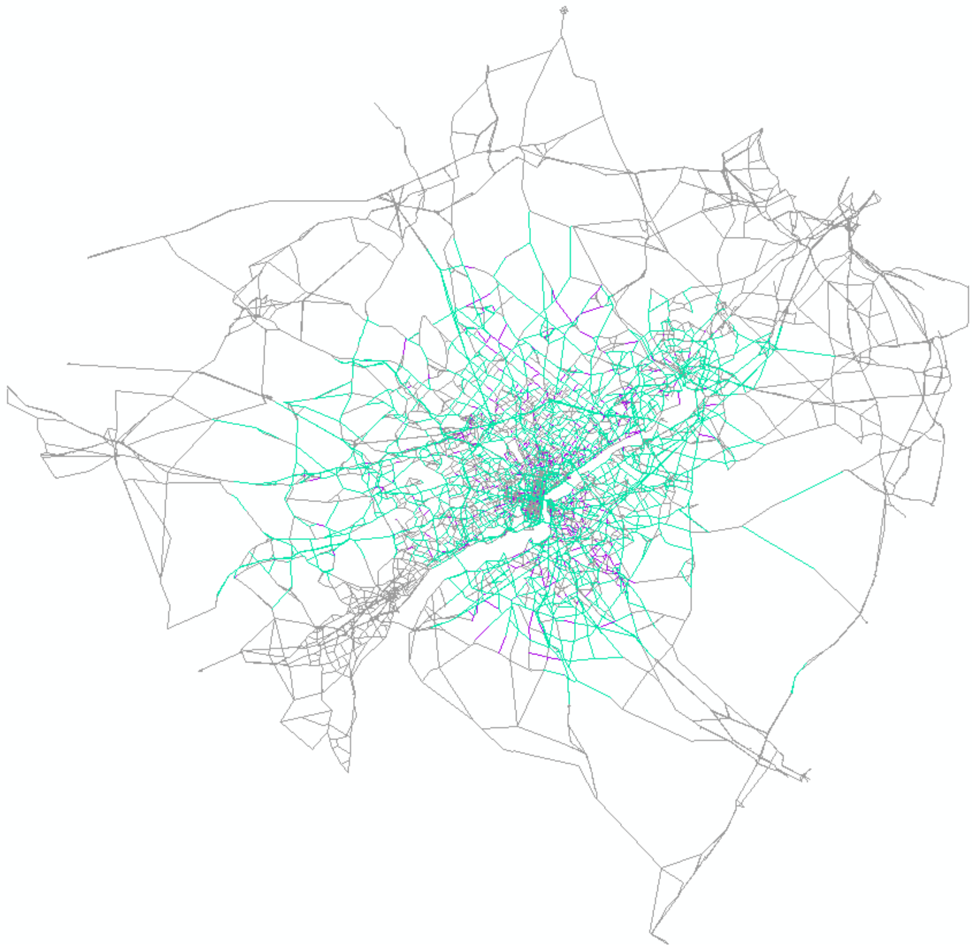

Figure 7 Speed and counts data measurements in the regional network

4.5 Dynamic origin-destination estimation (DODE)

Reliable dynamic origin-destination data are critical to the dynamic network analysis. However, “true" O-D data cannot be obtained directly in most cases. Therefore, we estimate time-dependent O-D demands from link flows (traffic counts collected by vehicle detectors) and traffic speed using a Dynamic Origin-Destination Estimator (DODE). The objective of the DODE problem is to obtain a time-dependent O-D table (expressed in the form of time-dependent path flows) that, once loaded onto the network, will reproduce observed link traffic counts and other observations as closely as possible.

4.5.1 Methodology

We adopt Logit Path Flow Estimator (LPFE) to derive path flows (hence an estimation of O-D demands). LPFE borrows the ideas of stochastic traffic assignment models which recognize that travelers are unlikely to get perfect information about network conditions. Therefore it is considered to be able to model individuals' route choice behaviors more realistically.

In this project, the complete observations of traffic flows and speeds are obtained (under healthy conditions) from 1992 road segments. We estimated time-dependent O-D demands in 15 minute interval based on flow count data. We verified the accuracy of the estimated O-D demands by comparing the estimated link flow (based on estimated O-D demands) to the observed link ow (input).

The O-D demands for both AM peak and PM peak are estimated separately by using data inputs from different time of day. The total number of travel demand in PM is significantly higher than in AM, therefore we can conjecture that the network will get more congested during the PM peak.

4.5.2 Morning peak

As shown in Figure 8, the estimated link flows generally approximate the measured link flows, the average Root Mean Square Error (RMSE) for each interval is around 30. Several link flows are estimated to be zero since we didn't enumerate paths due to the exponential path size in such a large scale network. Our model is capable of capturing the majority of the measured link flow information, so the dynamic O-D can be used to reproduce the recurrent traffic conditions in Philadelphia Metropolitan Region.

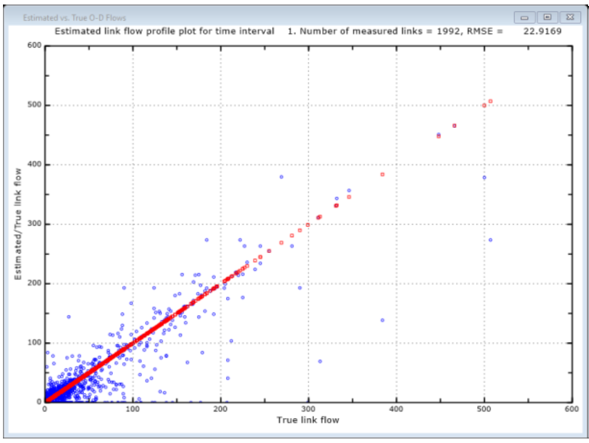

Figure 8a Interval 5:00 AM to 5:15 AM

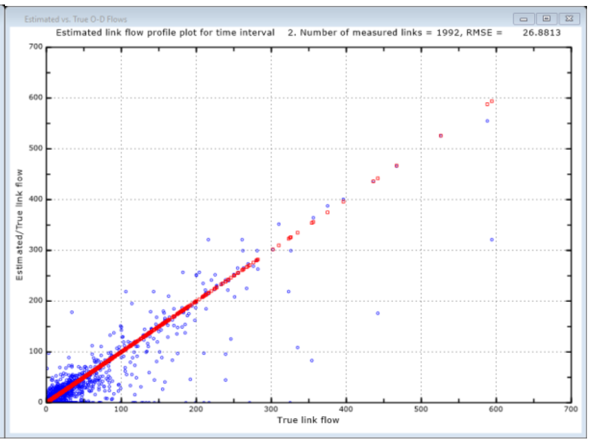

Figure 8b Interval 5:15 AM to 5:30 AM

Figure 8 Estimated vs. measured link flows in LPFE for AM peak

4.5.3 Afternoon peak

Follow the same procedures, we estimate the dynamic O-D for afternoon peak. The amount of traffic flows and O-D demands are larger than those of in morning peak, which indicates the traffic conditions during afternoon peak is more severe than morning peak. Figure 9 picks two time intervals to present the errors between estimated flows and measured flows. The RMSE is larger than the morning peak since the absolute values of traffic counts are larger.

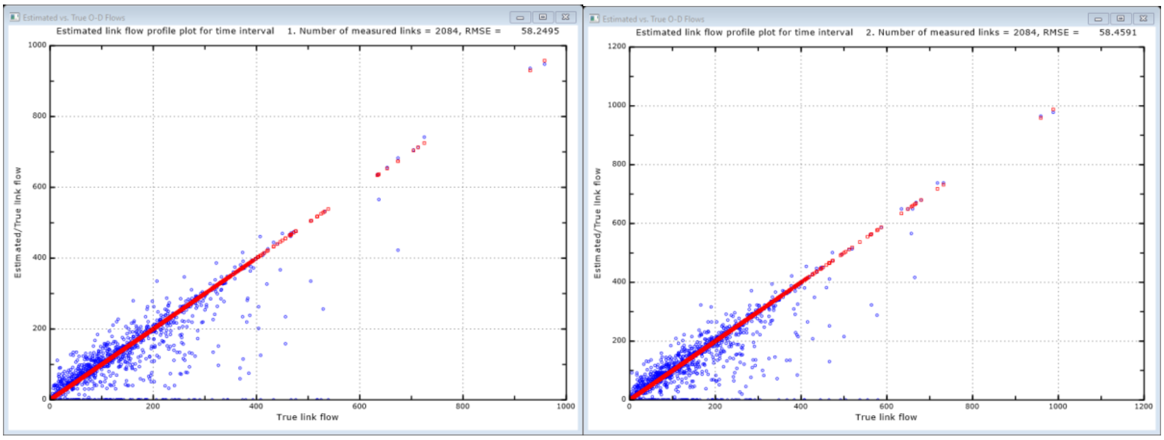

Figure 9a Interval 3:00 PM to 3:15 PM **Figure 9b Interval 3:15 PM to 3:30 PM**

Figure 9 Estimated vs. measured link flows in LPFE for PM peak

Further adjustments on dynamic O-D for both AM peak and PM peak are conducted during the model calibration. Several O-D demands are adjusted manually to better reproduce the measured traffic conditions.

5. Off-line DTA for Philadelphia Metropolitan Region

The regional network, together with construction/road closure plans of I-95 corridor, is coded into the dynamic network model. Baseline travel demand is estimated in the first place using the integrated traffic data (counts, INRIX data) on typical weekdays without the presence of large incidents. Under the actual I-95 corridor construction/road closure plans, the change of traffic conditions can be estimated by simulating traffic in the calibrated dynamic network.

Two time windows are analyzed for the Philadelphia Metropolitan Region: the AM peak and PM peak. AM peak represents the time horizon from 5AM to 10AM in the morning, and PM peak represents 3PM to 8PM in the afternoon.

The overall traffic impact for each scenario without deploying any real-time traffic management strategies can be measured by time-of-day traffic evolution in the region, as well as performance metrics, such as total traffic delay, average travel time, emissions, energy use, vehicle-miles travelled, etc.

Detailed information for each road segment is also available after applying the model. The most impacted highways and arterials under each scenario are identified, along with possible explanations and suggestions. Travel times between selected origin-designation pairs in each scenario are also compared to gain for insights and prediction power.

5.1 Methodology

A mesoscopic network simulation framework is used to evaluate the network under different settings. Before the simulation can be done, we need to calibrate the model with the observed data. We tune the properties of road segments such that the simulation results are consistent with the obtained speed/counts data in those measured locations.

Additionally, it is possible that the simulation terminates unsuccessfully because sometimes the network loading produces “grid-lock", a notorious condition defined as the inability of vehicles to move. This is a common issue in mesoscopic network simulation and will lead the simulation to fail.

By trial-and-error, we calibrated the parameters of link properties and routing behavior such that the simulations can succeed without a gridlock and meanwhile produce traffic conditions as close as possible to the observed data.

In the remaining part of this section, the simulation results on the calibrated network will be presented. After the calibration work, we see that the simulation model yields good results.

5.2 Morning peak

Figure 10 shows the simulated counts and speed versus observed counts for major roads throughout the entire network. Ideally, the scatter should be around the line of x=y. We got R^2 = 0.54 for counts and R^2=0.88 for speed. This means that globally, the simulation model has a good performance.

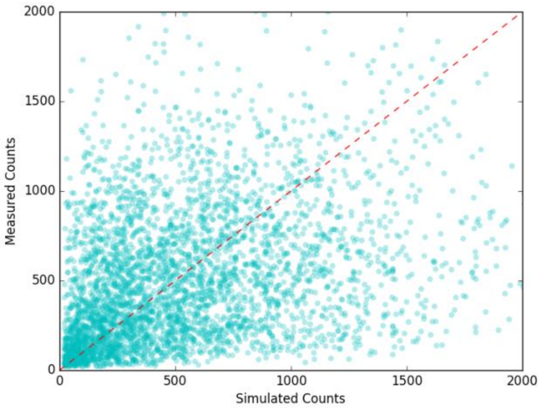

Figure 10a Simulated counts vs. observed counts

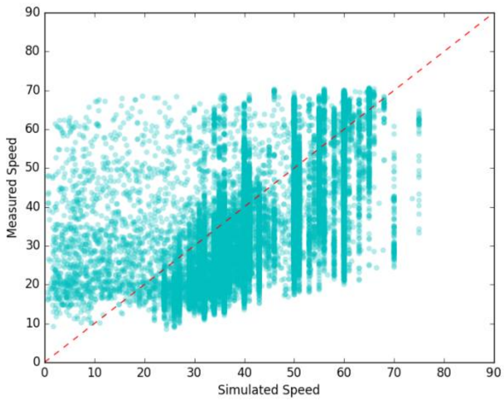

Figure 10b Simulated speed vs. observed speed

Figure 10 Simulated traffic characteristics vs. observed traffic characteristics for morning

We also compare the simulation results to the actual traffic speed measurements on a typical weekday in various locations of the region. Generally the calibrated model has a good ability to reproduce the evolution of the traffic in the real world. For example, Figure 11 shows the measured speed from Google Map and the simulated speeds in a local area in the morning. The simulated spatial distribution of speed is consistent with the actual distribution.

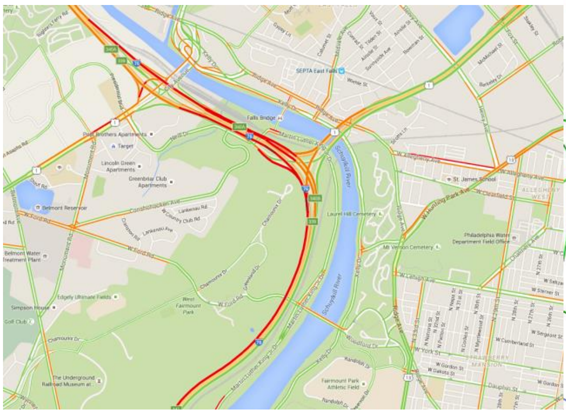

Figure 11a Actual speed (source: Google Maps)

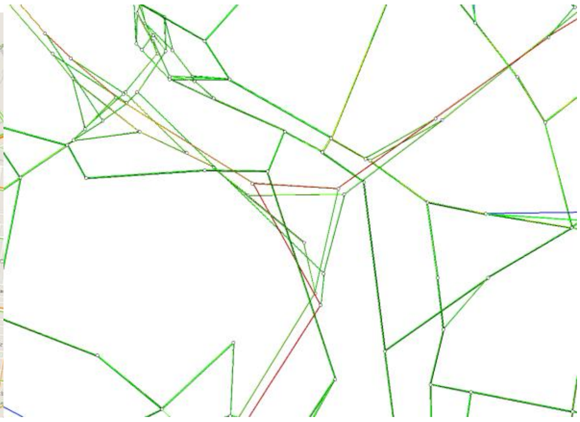

Figure 11b Simulated speed

Figure 11 Local speed distributions at 7 am around I-76

5.3 Afternoon peak

Similar to the morning peak model, we tune the network properties for the afternoon peak for the simulation generally reproducing the actual observation. Figure 12 shows the simulated counts and speed versus observed counts for major roads throughout the entire network. We got R2 = 0.54 for counts and R2=0.85 for speed. In figure 13, the spatial speed distribution for area near I-76 is extracted from Google Map and simulated results.

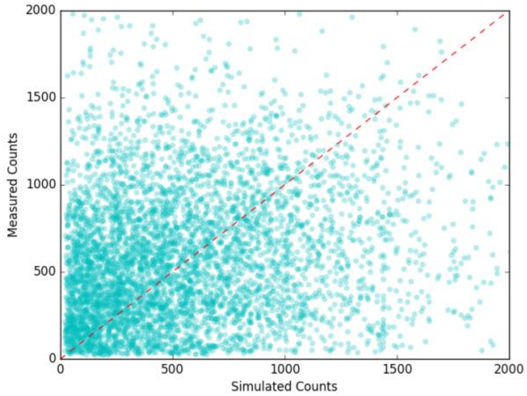

Figure 12a Simulated counts vs. observed counts

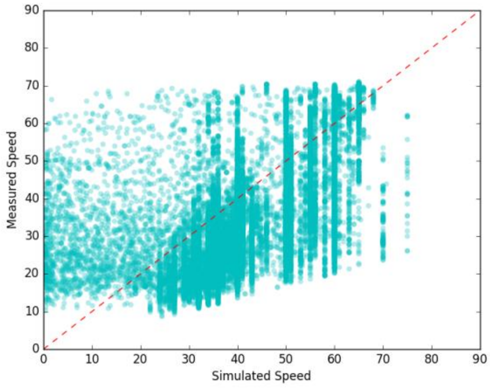

Figure 12b Simulated speed vs. observed speed

Figure 12 Simulated traffic characteristics vs. observed traffic characteristics for afternoon

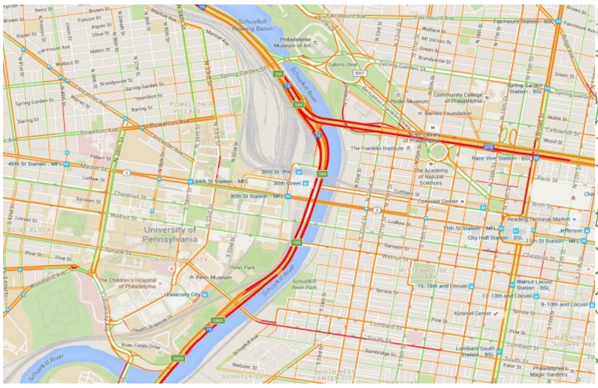

Figure 13a Actual speed (source: Google Maps)

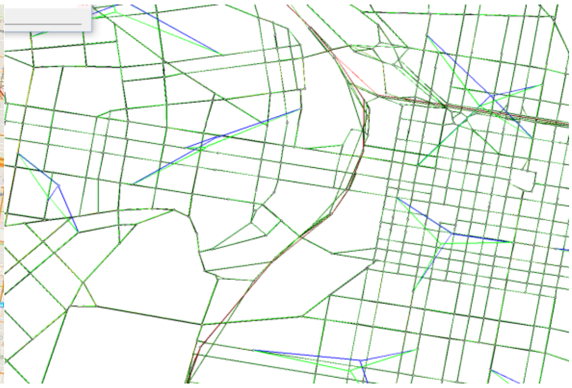

Figure 13b Simulated speed

Figure 13 Local speed distributions at 6 pm around I-76

5.4 Scenarios settings

In this section, we will summarize the scenarios which we had studied. As discussed with PennDOT, three scenarios are identified.

- Both directions of I-95 closed in the focused limits;
- Northbound of I-95 closed at the focused limits;
- Southbound of I-95 closed at the focused limits.

The scenarios will be studied in two time periods on a typical day:

- Morning peak hours: from 5 am to 10 am;
- Afternoon peak hours: from 3 pm to 8 pm.

Hence together with the two baseline cases, there are in all eight scenarios to analyze. The settings of the eight scenarios are summarized in table 3.

Table 3 Scenario settings

Scenario index	Scenario name	Road closure	Time of day
1	Morning baseline	Null	5am-10am
2	Morning SB closure	Southbound closed	5am-10am
3	Morning NB closure	Northbound closed	5am-10am
4	Morning both closure	Both directions closed	5am-10am
5	Afternoon baseline	Null	3pm -8pm
6	Afternoon SB closure	Southbound closed	3pm -8pm
7	Afternoon NB closure	Northbound closed	3pm -8pm
8	Afternoon both closure	Both directions closed	3pm -8pm

The settings of the scenarios are encoded into the simulation model. Figure 14 shows the location of the closed segment in map and in simulation model respectively. In the simulation model, a road closure is modeled as setting the corresponding road segment's capacity and free flow speed to 0 so that no vehicles were able to enter this road.

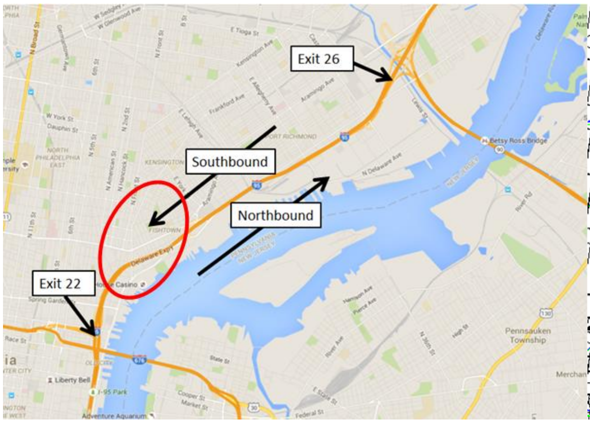

Figure 14a Road closure in Map


Figure 14b Road closure in simulation model

Figure 14 Road closure in map and in model

5.5 Morning peak network performance

Four scenarios were conducted to estimate the existing network performance and predict the performance after the I-95 corridor closure during the morning peak. We compare the baseline scenario with the other three closure scenarios to evaluate the traffic impact of corridor closures.

5.5.1 Overall performance

The simulation profile for the baseline scenario is shown in Figure 15, where blue, green and red lines represent the changes in the number of en-route vehicles, moving vehicles and queued vehicles, respectively, during the simulation horizon. This profile provides general information regarding time-of-day network traffic conditions.

As can be seen, the congestion in the network increases from 6:30 AM and peaks at 8:00 AM, and levels off all the way till 9:00 AM. The total number of trips loaded on the network achieves its peak around 7:50 AM, and drops a bit afterwards. The simulation stops releasing vehicles after 10:00 AM, and the entire simulation terminates at about 13:00 PM, which indicates that there are quite a few long distance vehicles through Philadelphia.

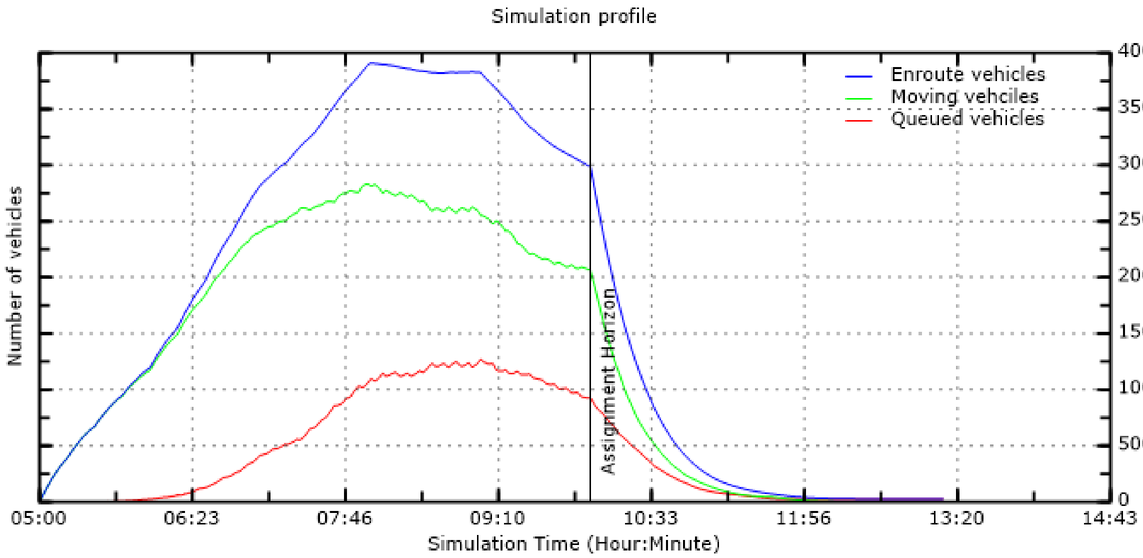

Figure 15 Simulation profile for morning peak baseline

The simulation results on the network performance in four scenarios during the morning peak (5:00am -10:00 am) are shown in Table 4.

Table 4 Total network performance for four scenarios from 5:00am to 10:00am

Item	Tot. Number of Trips	Tot. Travel Time	Avg. Travel Time	Tot. Delay	Avg. Delay	Avg. Travel Distance	VMT
Unit	Vehicle	Hour	Minute	Hour	Minute	Mile	Mile
Baseline	1,382,625	739,132.02	32.08	196,584.1	8.53	20.33	28,108,302
Northbound Closure	1,382,625	754,097.3	32.72	209,221.49	9.08	20.37	28,162,087
Change by percentage	0.00%	2.02%	2.00%	6.43%	6.45%	0.20%	0.19%
Southbound Closure	1,382,625	793,725.54	34.44	247,197.73	10.73	20.39	28,197,359.6
Change by percentage	0.00%	7.39%	7.36%	25.75%	25.79%	0.30%	0.32%

Both Closure	1,382,625	806,418.82	35	258,457.33	11.22	20.48	28,206,580
Change by percentage	0.00%	9.10%	9.10%	31.47%	31.54%	0.74%	0.35%

Generally, the network becomes more congested after the corridor closure. The total number of trips remains the same, because we assume the traffic demands are mainly composed of commuters who do not cancel trips in the morning peak. The Vehicle-Mile-Traveled (VMT) and average travel distance will increase since travelers may detour to a slightly longer route.

The average travel time and total travel time (namely Vehicle-Hour-Traveled, VHT) will increase as well in each closure scenario. The main reason is that the vehicles used to use I-95 will detour to other highways or corridors, which make those roads become more congested. As a result, the overall performance of the network is more congested. Increasing more vehicles on those roads will lead to a worse road performance, which leads to a longer travel time. In the morning peak, since the number of vehicles on I-95 southbound is larger than that of northbound, the southbound closure is more congested than the northbound closure scenario. The scenario of both southbound and northbound closures is the most congested case.

5.5.2 Emissions

The simulation results on the emissions for the four scenarios during morning peak are shown in Table 5. The changes in emissions of CO2, HC, CO and NOX before and after the corridor generally follow a similar pattern to that of VMT. While the emissions are also relevant to the average speed and acceleration of vehicles, the exact values may vary in different scenarios. In general, the I-95 corridor closure will lead to an increase of emission and fuel consumption.

Table 5 Total network performance for four scenarios from 5:00am to 10:00am

Item	Fuel	CO2	HC	CO	NOX
Unit	Gallon	Ton	Ton	Ton	Ton
Baseline	914603.32	8117.1	20.58	34.5	31.19
Northbound Closure	916943.67	8137.88	20.8	34.51	31.27
Change by percentage	0.26%	0.26%	1.07%	0.03%	0.26%
Southbound Closure	918947.74	8155.66	21.02	34.60	31.39
Change by percentage	0.48%	0.48%	2.14%	0.29%	0.64%
Both Closure	918745.1	8153.86	21.01	34.65	31.41
Change by percentage	0.45%	0.45%	2.09%	0.43%	0.71%

5.5.3 Delay on selected road segments

To evaluate the impact of the closure on specific road segments, 20 road segments near the closure corridor were chosen. Most of them are interstate highways. The layout of these roads is shown as in Figure 16. Both directions of each road segments will be evaluated. These roads are numbered from 1 to 20.

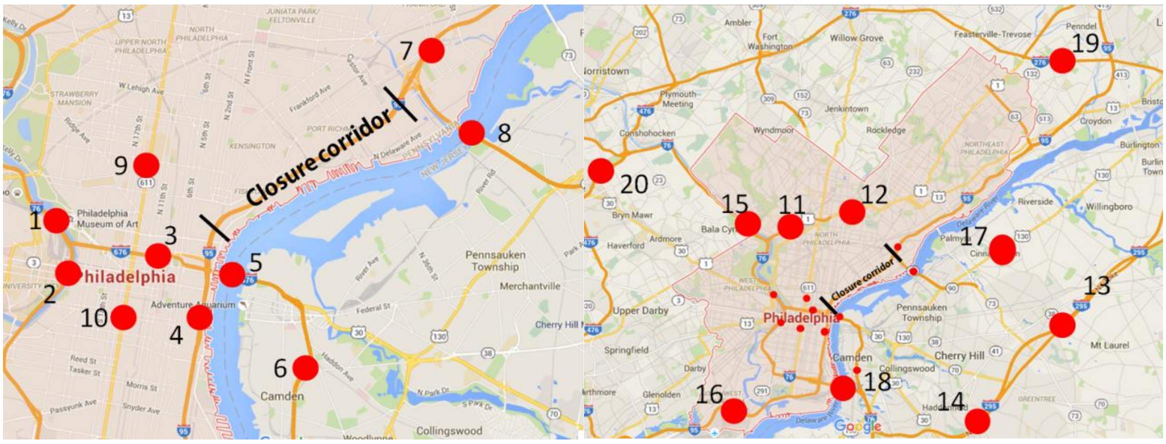

Figure 16a Chosen roads near the closure corridor **Figure 16b Chosen roads farther from the corridor**

Figure 16 Chosen roads for analyzing travel time change

Table 6 summarizes the percentage change of travel time of each scenario compared to the baseline scenarios. This percentage change is, in fact, an indicator of the change in delay. The first column shows the number of each road segments, corresponding to those numbers in Figure 16. The second column lists the names of these roads. The third column shows the direction of that road segment. From the fourth column on is the travel time in the baseline case in minutes and the percentage change in average travel time of each scenario compared to the baseline scenario. The average travel time was taken over all travelers who used this road segment in our 5-hour analysis period.

Note that the zero change in the table means the road segments are not congested throughout the whole analysis period. In other words, the traffic demand for these road segments is relatively small. The signs of the percentage changes imply how travelers' routes are changed after the closure. For example, for the northwest bound of I-90, the travel time increased when southbound of the corridor is closed, while in the other two closure scenarios, the travel time decreases. If the northbound of the corridor was closed, travelers who want to go the northeast and are used to use I-95 switch to use I-676, which leads a drop in travel time on I-95 and an increase on I-676.

Table 6 Travel time change of selected road segments for four scenarios from 5:00am to 10:00am

Number	Road	Direction	Average travel time	Percentage change of average travel time		
			Baseline/min	Southbound	Northbound	Both
1	I76	NW	1.89	28.63%	-68.76%	-68.41%
		SE	1	0.00%	0.00%	0.00%
2	I76	NE	0.61	69.42%	23.60%	7.41%
		SW	0.17	0.00%	0.00%	0.00%
3	I676	NW	0.94	73.98%	-53.56%	-53.56%
		SE	0.53	-4.73%	-10.15%	47.05%
4	I95	N	0.53	18.96%	0.00%	0.00%
		S	0.5	41.16%	-10.92%	-10.92%
5	I676	W	8.92	58.46%	135.89%	120.12%
		E	1.51	54.48%	-0.90%	41.14%
6	I676	S	0.81	-23.88%	-49.93%	-62.10%
		N	1.68	-87.35%	-87.35%	-87.35%
7	I95	NE	1.82	0.00%	0.00%	0.00%
		SW	5.59	-7.61%	66.98%	56.59%
8	I90	NW	9.61	-22.71%	38.38%	18.19%
		SE	1.88	0.00%	2.41%	0.00%
9	PA611	SW	0.19	0.00%	26.69%	12.54%
		NE	0.19	0.00%	0.00%	0.00%
10	PA611	NE	0.46	-41.76%	-44.21%	-44.42%
		SW	0.2	0.00%	0.00%	0.00%
11	US1	SW	3.92	-1.60%	-10.66%	-3.81%
		NE	1.20	-9.15%	0.67%	59.39%
12	US13	NE	0.49	121.52%	0.00%	13.69%
		SW	4.30	13.60%	8.19%	16.88%
13	I295	SW	1.55	-8.20%	-12.01%	-10.40%
		NE	1.53	13.06%	7.35%	23.51%
14	I295	SW	1.00	-0.41%	0.00%	0.00%
		NE	0.96	0.00%	0.00%	0.00%
15	I76	SE	0.99	0.00%	0.00%	0.00%
		NW	2.15	5.46%	-14.67%	2.07%
16	I95	SW	1.30	0.00%	0.00%	0.00%
		NE	0.03	0.00%	0.00%	0.00%
17	US130	SW	1.28	3.42%	117.22%	53.92%
		NE	0.94	0.00%	6.74%	0.00%
18	I76	NW	3.47	6.28%	1.89%	2.32%
		SE	2.40	24.17%	35.23%	82.92%
19	I276	NW	0.45	0.00%	0.00%	0.00%
		SE	0.32	0.00%	0.00%	0.00%
20	I476	SE	2.10	0.00%	-0.04%	-0.26%

		NW	2.09	0.00%	4.85%	0.00%

We see that I-76 Southbound (Road segment No. 1 and No. 2) was not impacted by the closure. Northbound of road segment No. 9 (part of PA611) and southbound of road No.10 (part of PA611) were not affected much either.

The road segment that is impacted most is the westbound of I-676 (road segment No.5). Due to the I-95 closure, travelers who drive to downtown from the north and are used to use I-95 now need to detour through I-676. Those travelers may also switch to I-76 (Road segment No.18) for detours, which increased its travel time as well.

5.5.4 Change in travel time between ODs

Besides the network performance indicators and time-varying traffic flow characteristics for any location, the simulations also yield the travel time between any two TAZs under the eight scenarios. We select several representative O-D pairs to compare the travel time for the four scenarios, the representative O-Ds are shown in Figure 17.

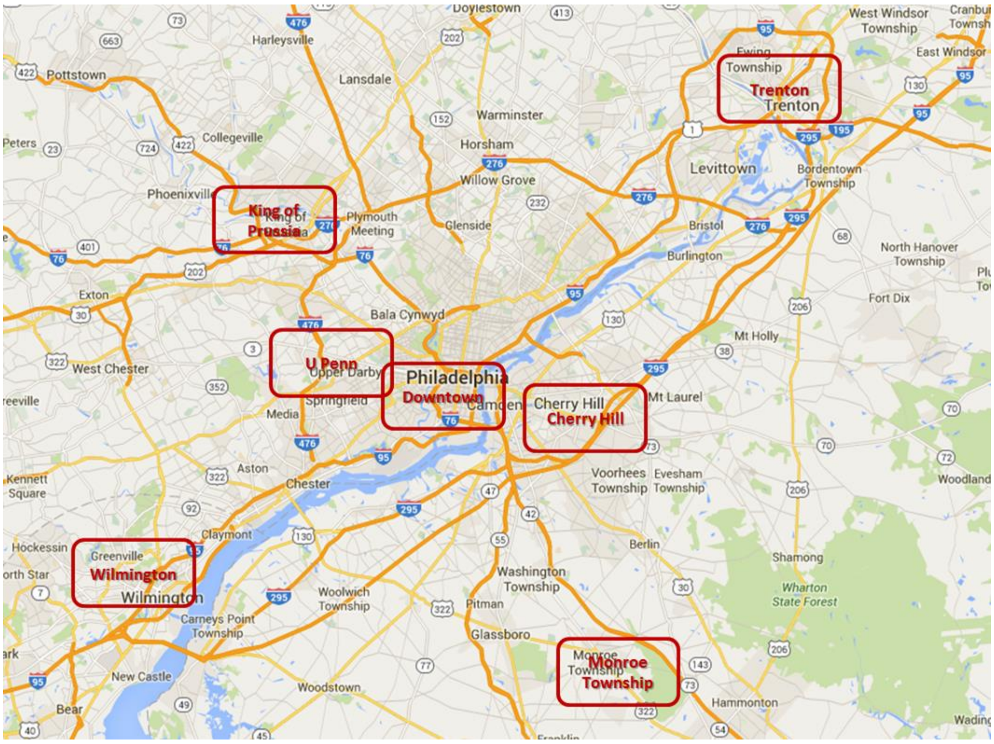

Figure 17 Selected OD pairs in Philadelphia Metropolitan Region

We compute the travel time for all the combinations of representative O-Ds for four scenarios, the complete results can be found in Appendix A. Here we select several representative results in Table 7.

The travel time from Trenton to the University of Pennsylvania will increase after the I-95 closure, especially after the closure of both directions of the I-95. The main reason is that the fastest route for this O-D pair is I-95, the travel time for any alternative routes are much higher than the I-95 route, so the travel time after the closure will significantly increase. For the travel time from Wilmington to Philadelphia downtown, since the original route does not contain the I-95 corridor, the travel time will not change as much after the closure.

The result on the travel time from the University of Pennsylvania to Wilmington is quite interesting. During 7:00am to 8:00am, the travel time is getting slightly worse since the closure will make the network more congested in general, so the route between this O-D pair is also affected. However, during 8:00am to 9:00am, since the north part of I-95 is closed, there are fewer vehicles in the south part of I-95 (both directions). The fastest route contains the south part of I-95, and thus it will be smoother to drive on the south part of I-95, resulting in a less travel time.

Table 7 Travel time change of selected ODs for four scenarios from 5:00am to 10:00am (minutes)

Origin	Destination	Time Interval	Base line	I-95 south closure	I-95 north closure	I-95 both closure
Trenton	University of Pennsylvania	7:00 - 8:00	44.9	44.9	49.4	53.1
Trenton	University of Pennsylvania	8:00 - 9:00	45.6	47.3	53.3	53.9
Wilmington	Philadelphia Downtown	7:00 - 8:00	31.9	31.9	31.9	31.9
Wilmington	Philadelphia Downtown	8:00 - 9:00	31.9	32.9	31.9	31.9
University of Pennsylvania	Wilmington	7:00 - 8:00	34.2	34.2	32.2	33.1
University of Pennsylvania	Wilmington	8:00 - 9:00	34.5	34.5	32.2	32.2

5.6 Afternoon peak network performance

5.6.1 Overall performance

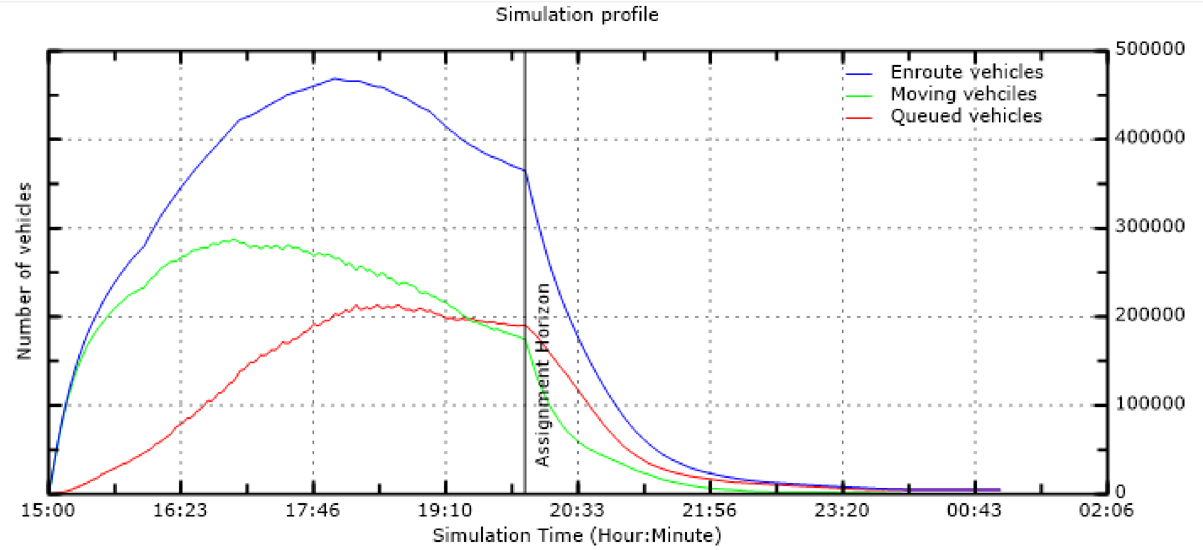

Figure 18 Simulation profile for morning peak baseline

The simulation profile for the afternoon peak baseline scenario is shown in Figure 18. As can be seen, the congestion in the network increases from 14:00 PM and peaks at 17:45 PM, and levels off all the way till 19:00 PM. The total number of trips loaded on the network achieves its peak around 17:50 PM, and drops a bit afterwards. The simulation stops releasing vehicles after 20:00 PM, and the entire simulation terminates at about 1:00 AM, which indicates that there are quite a few long distance vehicles through Philadelphia and several links are discharging vehicles in an unrealistic speed. This is a common issue caused by CTM when the network is over saturated, but this issue will only affect a small portion of vehicles so the general behavior of the simulation can still reproduce the current traffic.

The simulation results on the network performance in four scenarios during the morning peak (15:00pm -20:00pm) are shown in Table 8.

Table 8 Total network performance for four scenarios from 15:00pm to 20:00pm

Item	Tot. Number of Travels	Tot. Travel Time	Avg. Travel Time	Tot. Delay	Avg. Delay	Avg. Travel Distance	VMT
Unit	Vehicles	Hour	Minute	Hour	Minute	Mile	Mile
Baseline	1,638,222	1,041,517.92	38.15	421,667.31	15.44	19.61	32,132,274
Northbound Closure	1,638,222	1,0717,56.91	39.25	447,446.24	16.39	19.68	32,238,986
Change by percentage	0.00%	2.90%	2.88%	6.11%	6.15%	0.36%	0.33%
Southbound Closure	1,638,222	1,123,642.84	41.15	499,238.01	18.28	19.68	32,233,924
Change by percentage	0.00%	7.89%	7.86%	18.40%	18.39 %	0.36%	0.32%
Both Closure	1,638,222	1,140,006.33	41.75	513,806.06	18.82	19.68	32,247,227
Change by percentage	0.00%	9.46%	9.44%	21.85%	21.89 %	0.36%	0.36%

As can be seen, the network becomes more congested after the corridor closure. The changes in average travel distance and VMT are similar to that in the morning peak. The percentage change in the delay for the I-95 southbound closure scenario is higher than that of the I-95 northbound closure scenario. This is possibly due to the oversaturation on the I-95 northbound in the baseline scenario. When the I-95 northbound is closed, flow switches to other alternative routes, which results in the same congestion level and travel time. I-95 southbound is not as bad as the northbound during the PM peak. If the I-95 southbound is closed, the system performance can reduce more prominently than closing the already oversaturated northbound.

5.6.2 Emissions

The simulation results on the emissions for the four scenarios during morning peak are shown in Table 9. The changes in emissions of CO2, HC, CO and

NOX before and after the corridor generally follow a similar pattern to that of in AM peak.

Table 9 Total network performance for four scenarios from 15:00pm to 20:00pm

Item	Fuel	CO2	HC	CO	NOX
Unit	Gallon	Ton	Ton	Ton	Ton
Baseline	1047483.49	9296.42	23.82	39.55	35.8
Northbound Closure	1051571.08	9332.69	24.14	39.63	35.96
Change by percentage	0.39%	0.39%	1.34%	0.20%	0.45%
Southbound Closure	1052208.63	9338.35	24.33	39.63	36.01
Change by percentage	0.45%	0.45%	2.14%	0.20%	0.59%
Both Closure	1053393.72	9348.87	24.54	39.7	36.11
Change by percentage	0.56%	0.56%	3.02%	0.38%	0.87%

5.6.3 Delay on road segments

The same 20 road segments were examined as we did for the morning peak. The percentage change in travel time is shown in table 10.

For most road segments, the signs of percentage change are the same as in the morning. An apparent difference is that, the traffic congestions of northbound closure appear much more severe in the afternoon than in the morning. Note that for southbound of PA611 (Road segment No.9) and northbound (road segment No.10), the travel time increases dramatically under the northbound closure, especially for PA611 southbound. It implies that users may switch to PA611 from I-95.

Table 10 Travel time change of selected road segments for four scenarios from 15:00pm to 20:00pm

Number	Road	Direction	Average travel time	Percentage change of average travel time		
			Baseline/min	Southbound	Northbound	Both
1	I76	NW	1.89	-6.89%	11.84%	13.20%
		SE	1	0.00%	46.52%	0.00%
2	I76	NE	0.61	-7.59%	61.22%	51.91%
		SW	0.17	-55.04%	64.73%	-48.59%
3	I676	NW	0.94	4.51%	30.04%	-47.43%
		SE	0.53	13.68%	159.11%	82.48%
4	I95	N	0.53	10.72%	16.00%	31.01%
		S	0.5	-14.23%	-10.31%	-12.54%
5	I676	W	8.92	6.10%	41.43%	15.19%
		E	1.51	28.19%	22.72%	99.24%
6	I676	S	0.81	31.04%	159.61%	90.93%
		N	1.68	0.00%	0.00%	8.09%
7	I95	NE	1.82	0.00%	0.00%	0.00%

		SW	5.59	82.10%	5.13%	84.97%
8	I90	NW	9.61	63.27%	15.87%	53.81%
		SE	1.88	1.84%	0.00%	0.00%
9	PA611	SW	0.19	22.06%	196.61%	66.27%
		NE	0.19	0.00%	0.00%	50.04%
10	PA611	NE	0.46	-17.68%	103.56%	1.64%
		SW	0.2	0.00%	5.69%	28.49%
11	US1	SW	16.90	-1.60%	-21.91%	-16.62%
		NE	2.09	-9.15%	128.26%	246.52%
12	US13	NE	0.49	121.52%	93.39%	158.16%
		SW	13.80	13.60%	-31.73%	-2.45%
13	I295	SW	3.46	-8.20%	10.57%	-2.55%
		NE	3.16	13.06%	-2.49%	-42.55%
14	I295	SW	1.00	-0.41%	5.66%	7.30%
		NE	0.96	0.00%	0.00%	0.00%
15	I76	SE	0.99	0.00%	197.27%	225.33%
		NW	4.00	5.46%	-5.88%	-3.76%
16	I95	SW	1.30	0.00%	0.00%	0.00%
		NE	1.50	0.00%	0.00%	0.00%
17	US130	SW	1.29	3.42%	-1.35%	16.63%
		NE	0.94	0.00%	0.00%	0.00%
18	I76	NW	7.37	6.28%	17.54%	19.41%
		SE	3.72	24.17%	34.14%	98.66%
19	I276	NW	0.45	0.00%	0.00%	0.00%
		SE	0.32	0.00%	0.00%	0.00%
20	I476	SE	2.10	0.00%	0.00%	0.00%
		NW	2.09	0.00%	0.00%	0.00%

It also indicates that the percentage change in travel time on I-95 is significantly different between the two segments. The segment far south from the closure area have a lower travel time than the baseline due to less through traffic on I-95, while the travel time for the segment north of the closure area increases substantially.

Northbound of Route 1 (road segment no.11) and Route 13 (road segment no.12) have sharp increases in travel time, different from the morning case. This indicates that in the afternoon, more travelers travel from the southwest of Philadelphia downtown to the northeast of Philadelphia downtown. Those travelers switch from I-95 to I-76 or Route 1.

5.6.4 Change of travel time between O-Ds

We also computed the travel time for all the combinations of representative O-Ds in Figure 12 for four scenarios during the PM peak, the complete results can be found in Appendix B.

The general findings for the travel time change is that: if the chosen route before I-95 closure contains I-95, then the travel time for that O-D pair will significantly increase after the closure unless there exist alternative detour routes that are comparable to I-95. For those O-D pairs that do not contain I-95 but are along the detour routes of I-95, then their travel time is slightly influenced by the closure. For those travelers along the O-D pairs located on the south of I-95, the closure may even benefit them due to the reduced volume on I-95 south of downtown.

5.7 Conclusions

In off-line DTA modeling of this project, we conducted a dynamic network analysis for Philadelphia Metropolitan Area and studied the traffic impact of the I-95 corridor closure for both morning and afternoon peaks.

We utilize the network description files provided by DVPRC, archived traffic flow data by PennDOT and DVPRC, and traffic speed data from INRIX to validate the off-line dynamic traffic assignment model. We use the calibrated model to predict and evaluate the traffic impact of I-95 corridor closures. System performance, traffic delay on critical road segments and travel time between selected O-Ds are compared and analyzed, which help better understand the network conditions with and without I-95 closures.

In this part, we only calibrated the baseline scenario and predict the traffic conditions for different I-95 closure scenarios for both AM and PM peaks, but no management and operational strategies are made to reduce the traffic congestion caused by the I-95 closure. In next section, we will design a methodology to simulate the traffic on the real time basis. An on-site detour strategy through Dynamic Message Signs (DMS) will be proposed to suggest efficient detour routes, optimal traffic diversion ratios and text displays for DMS.

6. Real-time DTA for Philadelphia Metropolitan Region

In this section we develop a regional dynamic network model that simulates millions of trips in the Philadelphia metropolitan region and captures those travelers' travel behavior on real-time basis. It can be applied directly to predict traffic impact of planned and unplanned incidents, and provide real-time decision making for traffic operations.

The model takes incident reports and traffic speeds as real-time data feeds, and O-D demands as the historical data feeds. The management strategy is adjusted in the real time to achieve overall best performance for the entire network. The model contains a closed-loop feedback learning mechanism, the estimation/prediction accuracy will improve as the model runs.

In the case study, the model is developed to control all the dynamic message signs (DMS) on I-95 corridor. On-site detour strategies through DMS will be proposed to suggest efficient detour routes, optimal traffic diversion ratios and texts for DMS. The real-time optimal compliance rates for each detour route can be updated as time progresses by analyzing real-time traffic data (INRIX and/or counts) and provided to PennDOT Transportation Management Center on the real-time basis.

The model is implemented as an internet web application, a website built to visualize the control strategies and animate the flow evolutions. All the user interactions with the real-time traffic management model are based on browser.

6.1 Network settings

In this section we discuss the preparations especially for building the real-time traffic management framework.

6.1.1 Dynamic network loading

Dynamic network loading (DNL) model is an essential component in real-time DTA model. DNL models take time-dependent O-D demand and travelers' behavior parameters as input and simulate the network conditions with a high spatial-temporal resolution. The traffic flow, travel time of every links and trajectory of every vehicle can be recorded during the simulation. We denote the simulation process as:

$$S_{t+1} = \mathrm{DNL}(q, p, S_t)$$

Where S_t is the traffic state of the whole network on time t, q is the O-D demand vector and p is the route choice probability of each route. After the DNL for one interval, we have the network condition on time $t + 1$, denoted as S_{t+1}.

Two major components in DNL models are link flow evolution models and node flow evolution models. The link flow evolution models describe the dynamic relationship between vehicle density, speed and volume for one road segment. Cell transmission model (CTM), as a finite element approximation to the partial differential equation of fluid evolution, is proved to best simulate the flow propagation on road segments. This project adopts CTM to simulate the flow propagation on links. Node flow evolution models depict the traffic flow propagation (merge and diverge) on junctions. A simple node model (Jin & Zhang 2003) that satisfies the “fairness” condition is adopted. The adopted node model is proved to have high-throughput and is computationally efficient. The DNL model is implemented under C++. The dependency management is due to CMake.

6.1.2 Real-time traffic speed measurements

Traffic speed data were obtained from INRIX[4]. The traffic speed data is provided at the geographic level of Traffic Message Channel (TMC), one of the geo-reference protocols. To match the TMC units with links in the road network, an algorithm considering relative distance and direction was developed to search for the best match for each TMC.

Traffic speed data cover most of the corridors and major roads in Philadelphia Metropolitan Region. The data set includes 13,104 TMCs for the nine counties of DVRPC. The data includes speed, travel time, historic average speed and reference speed (namely 85% quantile of all observed probe vehicle speeds, used as the free-flow speed).

INRIX provides an API to let users request the real-time traffic speed data feeds nation-wide. We implemented a crawler to continuously retrieves, processes, summarizes the real-time traffic speed and reports the results to the traffic management server.

6.1.3 Path set generation

The paths for each O-D pair are pre-determined before the real-time traffic management. To generate paths for one O-D pair, we execute the shortest path algorithm from origin to destination under different traffic conditions: light, heavy and congested. The path set contains paths for all different pairs of O-D. For DVPRC network, totally 189,065 paths are generated for 473,796 O-D pairs.

6.2 DMS based real-time network flow model

In this section we present the proposed real-time traffic management model. We first overview its structure and define each component in the model, then we formulate and interpret each component separately. The solution algorithm to each proposed component is also provided.

[4] INRIX, http://www.inrix.com

6.2.1 Overview

Figure 19 is the overview of the real-time traffic management model, the model is based on a closed-loop feedback-learning mechanism. In each interval, the management model takes real time speed, historical O-D and capacity drop report as input, and then estimates the current traffic condition of the whole network, optimizes the future network condition by adjusting the route choice probability. According to the optimized future route choice probability, DMS messages are generated to suggest travelers selecting the system optimal route. Since only some of the travelers will follow the instruction on DMS, we define the compliance rate to be the portion of travelers following the instruction. The compliance rate is assumed different for difference DMS. The compliance rate is updated by the estimated current traffic conditions and last interval's instruction. Finally the traffic prediction for next one hour is simulated by using current route choice probability, optimized route choice probability and updated compliance rate. After the whole iteration form the server, the prediction results and DMS messages are stored in the database, then the browser will retrieve the results from database and visualize it on the internet.

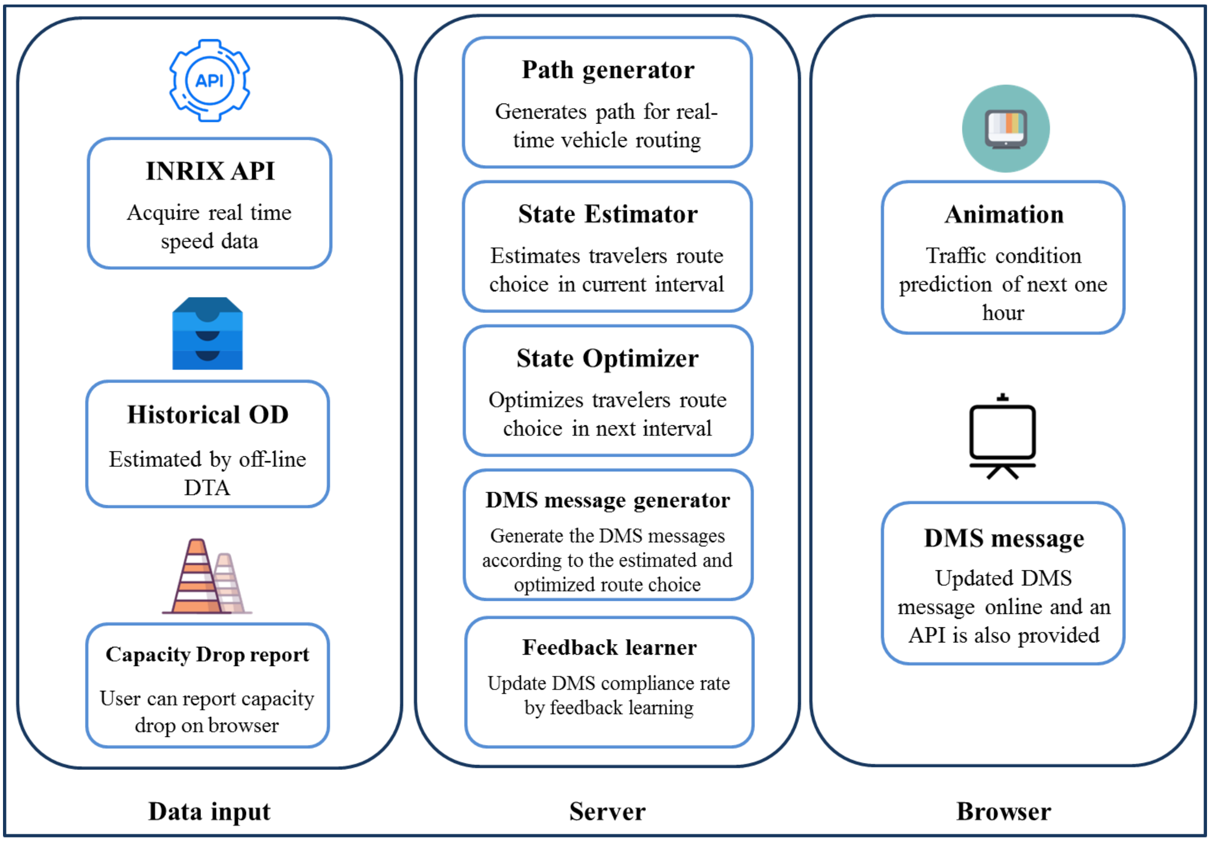

Figure 19 Overview of real-time traffic management framework

To further explain each component of real-time traffic management framework, we suppose current time is 8:15, and then the model will:

- Acquire data: acquire the real-time traffic speed and incident reports in [8:00, 8:15]
- Estimate Previous: estimate the route choice probability in [8:00, 8:15]
- Compliance rate update: update the DMS compliance rate calculated in [7:45, 8:00]
- Optimize Next interval: optimize the route choice probability in [8:15, 8:30]
- Generate DMS Message: based on the optimized and estimated route choice, generate DMS message for [8:15, 8:30]
- Predict Future: Predict traffic state in next one hour using updated compliance rate
- Next interval: Wait until current time is 8:30, go back to acquire data
  In the following sections, we discuss each component in detail, we assume the current interval is $t + 1$.

6.2.2 Traffic state estimation for the current stage

In the current traffic state estimation component, we want to find the current travelers' route choice probability that makes DNL model better reproduce the observed traffic speed. So the formulation is to minimize the errors between observed traffic speed t_a^o and simulated traffic speed t_a. t_a is obtained from the simulated network condition S_{t+1}, the function $T_a(\cdot)$ is the travel time retrieval function to get travel time on link a from simulated network conditions. The overall formulation for estimating current traffic state is as follows.

$$
\begin{aligned}
\min_{p} \quad & \sum_{a \in A^o} \|t_a - t_a^o\|_2^2 \\
\text{s.t.} \quad & \textstyle\sum_{k \in K_{rs}} p_{rs}^k = 1 \\
& p \geq 0 \\
& S_{t+1} = \text{DNL}(q, p, S_t) \\
& t_a = T_a(S_{t+1}), \forall a
\end{aligned}
$$

The first constraint in the formulation requires the sum of route choice probability for one O-D pair is 1, r represents the origin, s represents destination and k represents path. The second constraint requires all route choice probabilities are non-negative. The third constraint indicates that the current traffic condition S_{t+1} is simulated from traffic state of last interval with demand q and route choice probability. Different route choice probability will result in different link travel time t_a. The whole formulation searches for the best p which approximates the observed link travel time t_a^o best.

After solving the above formulation, the solved route choice probabilities represent travelers' behavior in current interval. By running the DNL model with route choice probability p and O-D demand q, current traffic conditions on every link can be retrieved.

Since DNL(q, p, S_t) is a simulation process, which can't be analytically decomposed, above formulation is a hard non-linear optimization problem. Analytically calculating the derivative of the objective function is impossible, the numerical derivative can still be calculated (Qian et al. 2012). Qian proposed the method to numerically calculate the derivative of path flow, by chain rule the derivative of route choice probability can also be obtained. The chain rule is formulated as follows:

$$\frac{\partial t_a}{\partial p_{rs}^k} = \frac{\partial t_a}{\partial f_{rs}^k}\frac{\partial f_{rs}^k}{\partial p_{rs}^k} = \frac{\partial t_a}{\partial f_{rs}^k}\frac{\partial q_{rs}p_{rs}^k}{\partial p_{rs}^k} = q_{rs}\frac{\partial t_a}{\partial f_{rs}^k}$$

6.2.3 Traffic state optimization for future stages

In the sub-problem of optimizing future traffic state, we search for the best route choice probability for all O-D pairs such that the total travel time in the whole network is minimum. The optimization is formulated as follows:

$$\begin{array}{rrcl} \min\limits_{p} & \sum\limits_{a\in A} x_a t_a & & \\ \text{s.t.} & \sum_{k\in K_{rs}} p_{rs}^k & = & 1 \\ & p & \geq & 0 \\ & S_{t+2} & = & \text{DNL}(q,p,S_{t+1}) \\ & t_a & = & T_a(S_{t+2}), \forall a \\ & x_a & = & X_a(S_{t+2}), \forall a \end{array}$$

The first two constraints are the same as those in the former formulation, the third constraint indicates we use the estimated current state S_{t+1} as input and simulate the future interval S_{t+2}. T_a and X_a are link travel time and link flow retrieval function, respectively. The formulation above searches for the best route choice probability p such that the total network travel time on interval t+2 is minimized.

After solving the above formulation, the solved route choice probability represents the best route choice probability for the next interval. However, since we cannot directly control travelers' route choice, we can only use DMS messages to suggest the best route for travelers. If the compliance rate is high, the network approaches more to the system optimal.

Similar with former formulation, the numerical derivative of the objective function can be calculated from the simulation (Qian et al. 2012). Though objective function is different, the solution algorithm is almost the same.

6.2.4 Feedback learning of compliance rate

The feedback learning of compliance rate is based on the estimated route choice calculated in interval t, detour instruction generated in interval t and estimated route choice calculated in interval t+1. Both route choice probability represent the estimated current traffic state, but the former is the results for interval t and latter is the results for interval t+1. We denote the former as $\mathrm{p_t}$ and latter as $\mathrm{p_{t+1}}$.

So the new compliance rate can be calculated by comparing $\mathrm{p_t}$, $\mathrm{p_{t+1}}$ and detour link $\mathrm{a_{detour}}$. Define $\mathrm{I}(\cdot)$ is an indicator function, the compliance rate for DMS d, $\mathrm{c_d}$ can be calculated as:

$$c_d = 1 - \frac{\sum_{rs}\sum_k I(a_{\text{detour}} \text{ not in path } f_{rs}^k) q_{rs} p_{rs}^{k(t+1)}}{\sum_{rs}\sum_k I(a_{\text{detour}} \text{ not in path } f_{rs}^k) q_{rs} p_{rs}^{kt}}$$

A method of successive averaging (MSA) mechanism can be adopted to update the compliance rate in each interval.

According to the definition of compliance rate, it represents the portion of travelers that follow the DMS instruction. If all travelers follow the instruction, then $\mathrm{p_{rs}^k} = 0$ if $\mathrm{a_{detour}}$ is not in path $\mathrm{f_{rs}^k}$. The feedback learning sub-problem can be done after the current state estimation sub-problem, it is independent with the future traffic state optimization sub-problem.

6.2.5 DMS message generation

The generation of DMS message is based on the estimated route choice probability $\mathrm{p^{est}}$ and optimized route choice probability$\mathrm{p^{opt}}$. For link a, if the optimized link flow is smaller than the estimated route flow, then it means some travelers shouldn't take link a, therefore a detour is suggested.

Our model is based on such criterion to decide whether travelers are supposed to take the detour on certain links. After calculated the detour link (or decide not to detour), the message generation rule is as follows:

- If the congestion is ahead and the travelers on the highways are supposed to take the detour, the message will be “CONGESTION AHEAD, XX MINUTES TO NEXT EXIT, TAKE NEXT EXIT”, paired with a disclaimer message for traffic engineers, “if taking exits is suggested, it should be paired with DMS on the arterials guiding drivers”.

- If the congestion is ahead but the travelers on the highways should still take the highway, the message will be “CONGESTION AHEAD, XX MINUTES TO NEXT EXIT”.
- If there is no congestion ahead, the message will be “DRIVE WITH CARE”.

The above rule is only for demonstration purpose, a detailed generation rule can be easily extended from current framework. Note the DMS message generation process is independent with feedback learning of compliance rate process, and solving these two sub-problems can be in any order or not necessarily sequential.

Note if we display “CONGESTION AHEAD, XX MINUTES TO NEXT EXIT”, we’re not suggesting a detour to travelers. We just provide the information to let them choose whether to take next exit or not. However, “CONGESTION AHEAD, TAKE NEXT EXIT” message is suggesting travelers taking next exit.

This tool that generates optimal DMS can be fed to ATMS for displaying and coordinating DMS. However, it also requires ATMS to set up proper messages for DMS on those alternative detour routes. Alternative routes at certain locations (or freeway exits) can be predetermined. When congestion is detected and detour from freeway is suggested due to incidents, the ATMS can automate the DMS texts on those predetermined alternative routes to guide travelers. This tool will work best under the coordination with ATMS, which should be further investigated.

6.2.6 Traffic states prediction for future stages

We predict the traffic conditions for the next hour, the prediction is based on the DMS message, current traffic conditions and compliance rate. Since we have already decided the DMS messages and also updated the compliance rate, predicted route choice probability p^{pre} can be calculated from current route choice probability p^{est}. Then by running the DNL model using the predicted route choice probability p^{pre}, traffic evolution for next one hour can be calculated.

6.3 Browser-based implementation

In this section we present a browser-based implementation of the proposed real-time traffic management model. On the back-end, a server keeps updating the real-time traffic conditions and predicting the future traffic conditions, and on the front-end users can visualize the DMS messages and the animation of predicted network flow evolution through a web browser.

The web application can be visited using the following link:

http://bruno.heinz.cmu.edu/traffic/congestion_online/

username: penndot2 password: penndot2

The web application is designed to achieve high efficiency and stability. On the back-end, Gunicorn(19.6.0), Django(3.4.0), PostgreSQL(9.5) are used to build up the server; on the front-end, Leaflet(0.7.7), Bootstrap(3.3.1) and Leaflet TimeDimension(1.0.3) are used to visualize and animate the prediction results. The work-flow of the system is described in Figure 20.

Figure 20 Structure of implemented web application

The user first requests the estimation results from our web application through the browser. Our web application sends predicted traffic data back to the browser. Since the simulation results contain massive data points, a cache technique is employed to speed up the animation.

We split the map into rectangles of regions so the browser could load the data according to user's view resolution, which makes the loading faster and caches easier. Figure 21 is an example to show how we split the map. The animation data are also sent by stream, so users can watch the animation even when the future prediction data are not completely loaded. The network is also hierarchically divided into different zoom levels, such as corridors, major roads and minor roads. Roads from different zoom level will be displayed on the map when users zooming in/out.

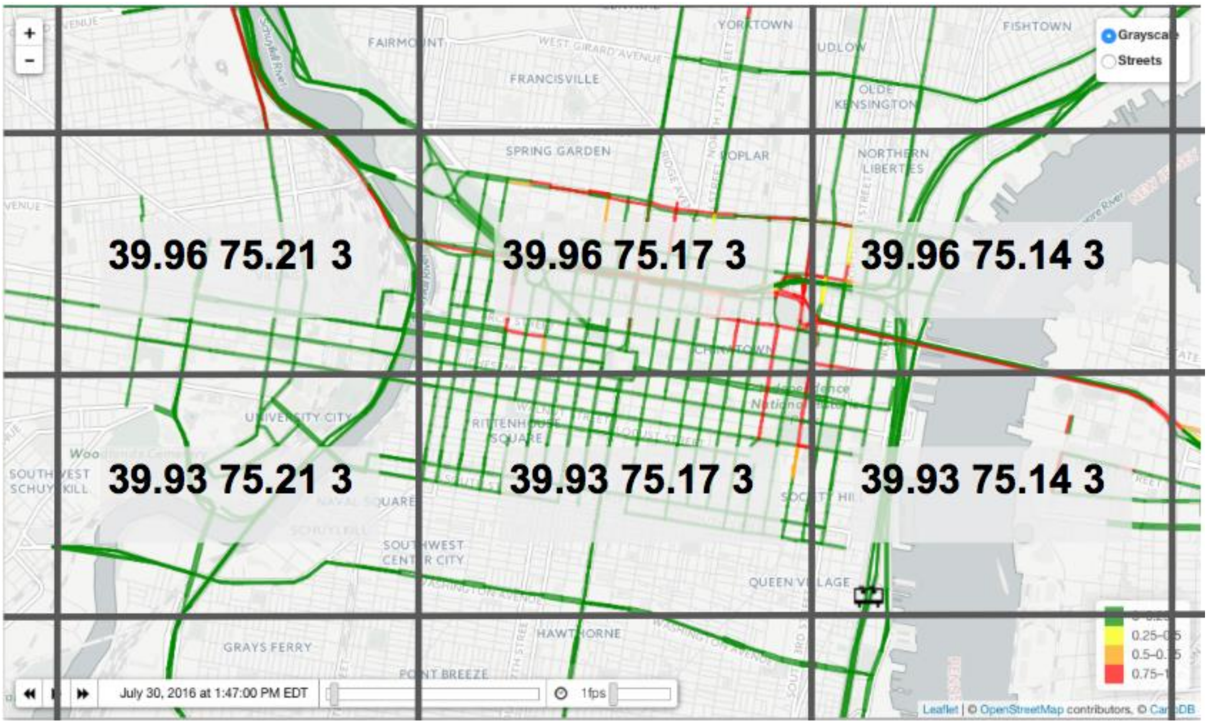

Figure 21 Example of map splitting

For the top-left rectangle, (39.96, 75.21) is the coordinate to locate the rectangle and 3 is the zoom level

Users can view the animation and change the speed of the animation by adjusting fps, as shown in Figure 22. They can also change the threshold of the coloring by moving the knots on the slider, and press "Change Threshold" button. "Default" button is used to revert to the default coloring scheme.

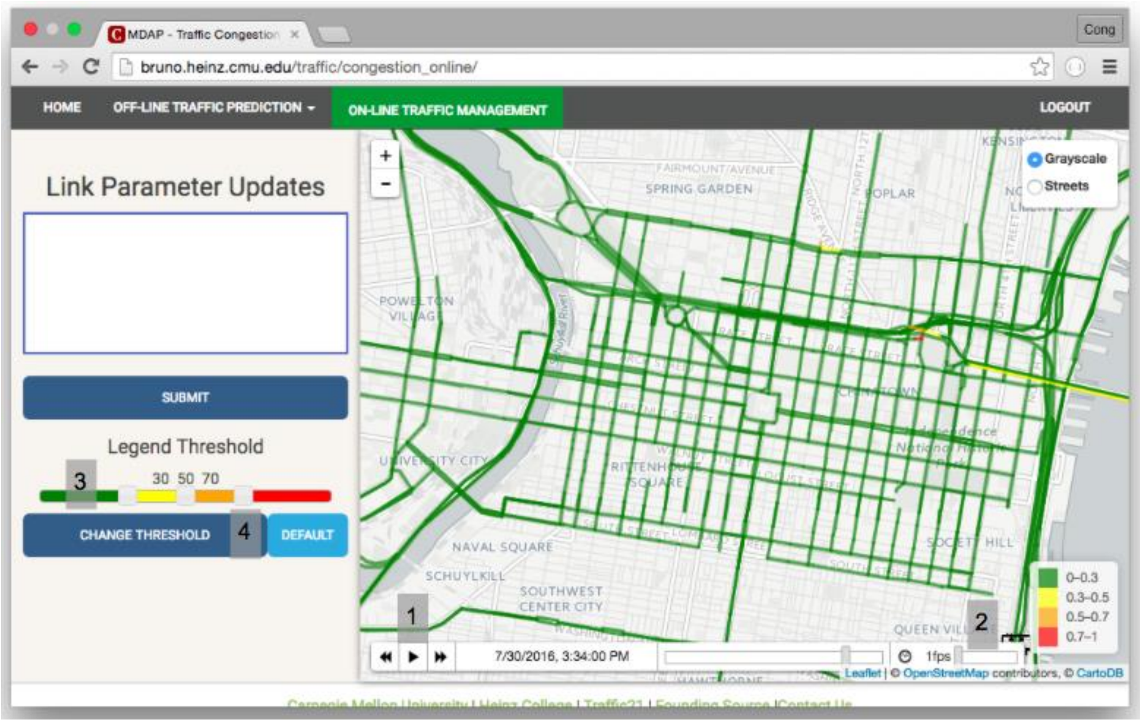

Figure 22 View the animation

Users can report capacity drop for any link on the web browser by clicking the link on the map. A popup will appear with the information about this link, as shown in Figure 23. A slider representing capacity drop lies on the bottom of the popup. When users report the capacity drop, updates will be shown in the text box on the left-side panel. When finish reporting, users can press submit button and the reported capacity drops will be taken into account for the next round of iteration.

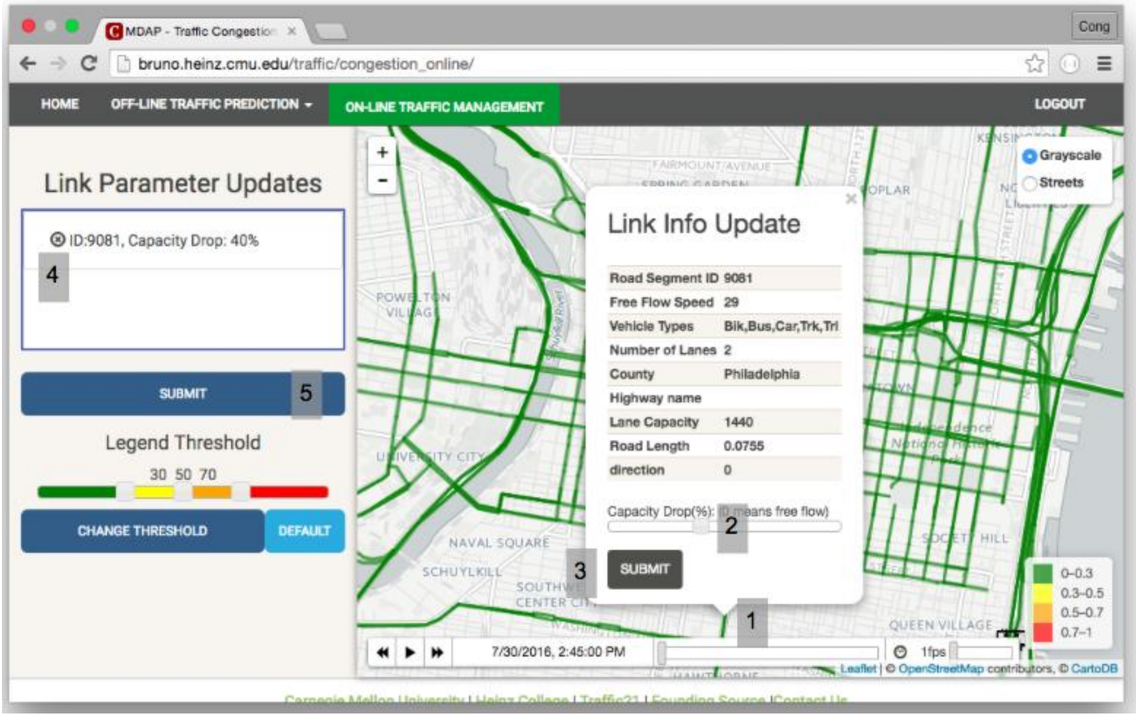

Figure 23 Report capacity drop

Users can also view the information and suggested display of the DMS by simply clicking the DMS icon on the map. A popup containing the DMS information will appear, as presented in Figure 24.

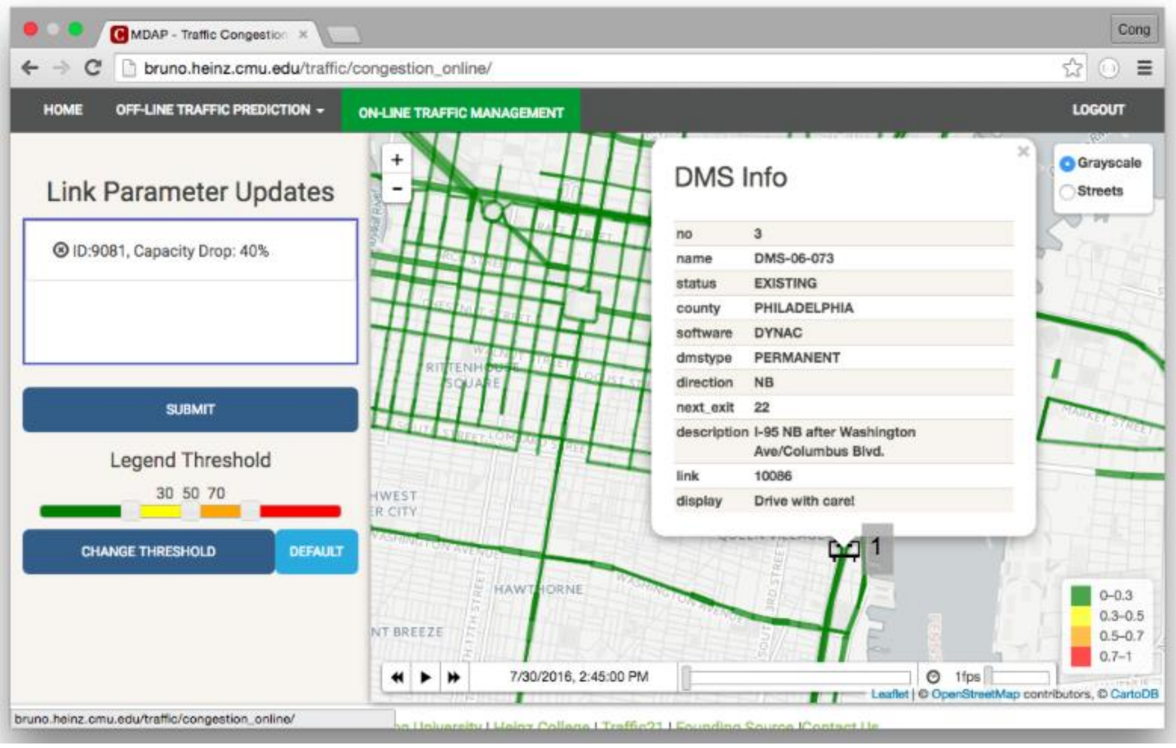

Figure 24 View DMS information

In the updated version of the web application, users can also choose to view the road density or road speed, as shown in Figure 25. The overall estimation error for real-time speed is represented by R-square between simulated traffic speed and observed traffic speed. It's presented below the "CHANGE THRESHOLD" button. The estimation accuracy will be discussed on the evaluation section.

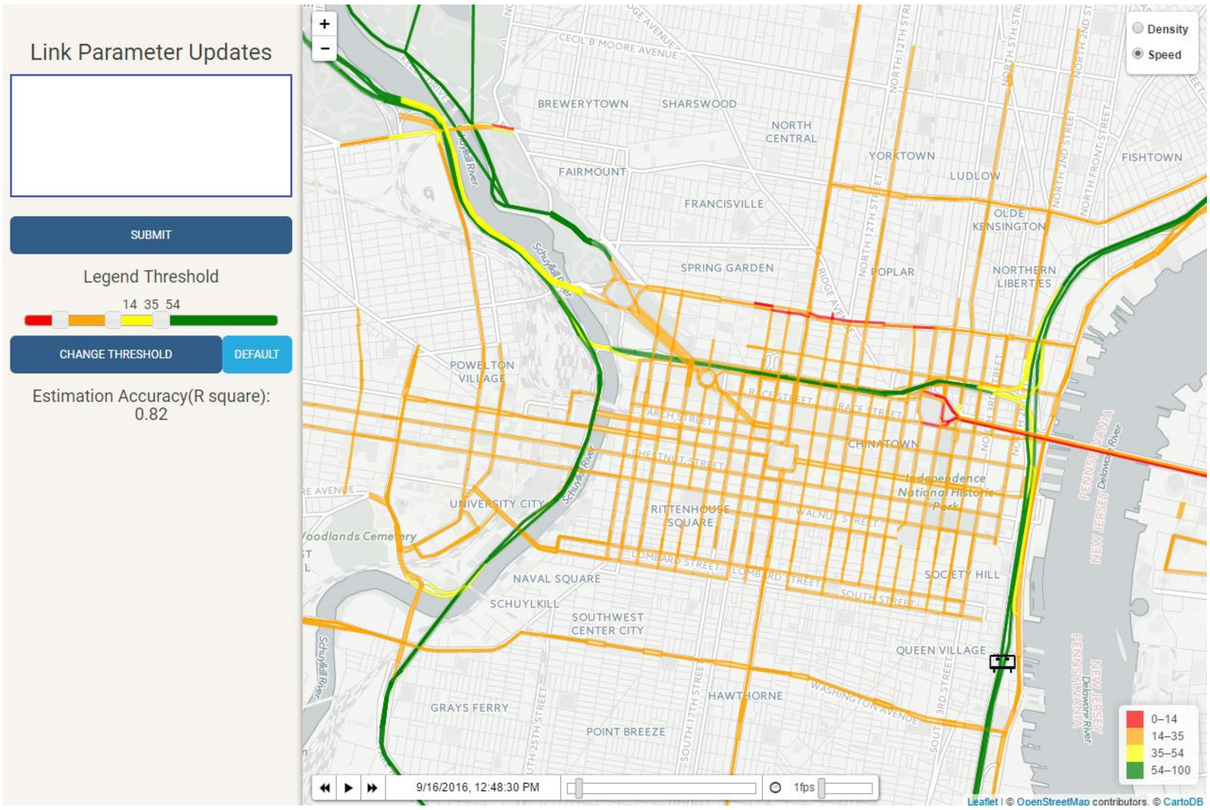

Figure 25 Simulated speed and estimation accuracy

We also provide an API for users to retrieve the generated DMS message data. The data is formatted in JSON, and the website of API is:

http://bruno.heinz.cmu.edu/traffic/get_real_time_VMS/

6.4 Evaluation

In this section, we use field data to test the proposed real-time network flow model and demonstrate its effectiveness. The traffic speed data on Wednesday July 13 2016, from 7:00 AM to 8:00 AM, are acquired from the INRIX website. The speed data are provided to the traffic management center on a real-time basis. Since the time interval is set as 15 minutes, there are in total 4 updates of the messages on the DMS in one hour. And all the DMS on I-95 corridor are optimized. The location of those DMS are shown in Figure 26.

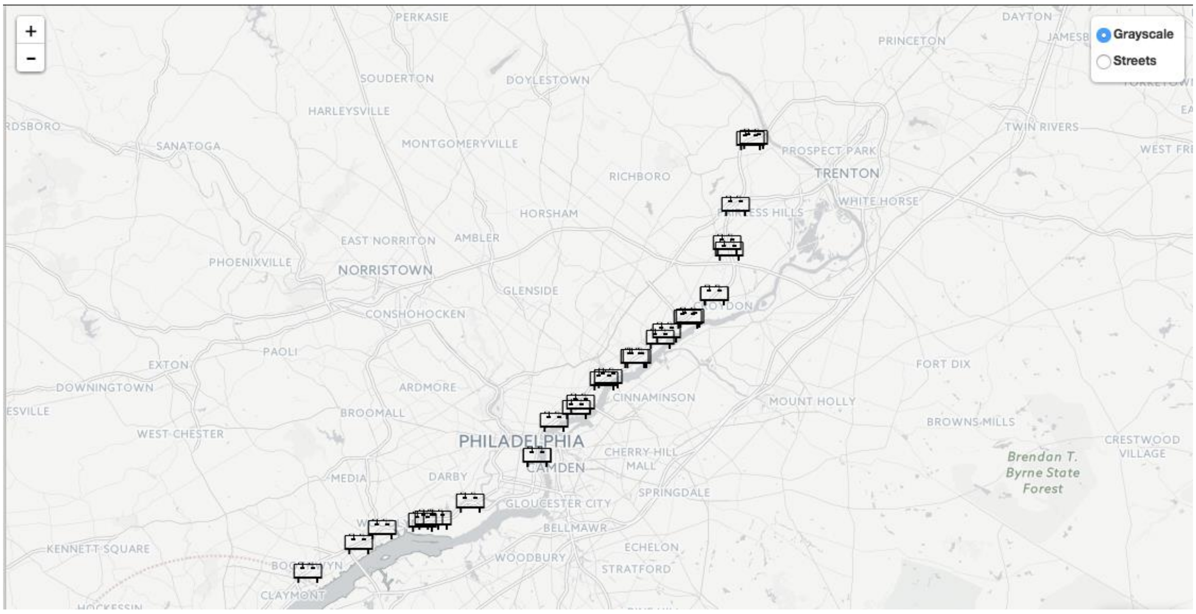

Figure 26 Dynamic message signs along the I-95 corridor in Philadelphia

In each iteration, the sever conducts the whole process described in section 3. Due to the limited time constraint (one iteration must be finished within one time interval 15 minutes), the estimation and optimization processes perform 5 gradient descents and terminate. The estimation and prediction take approximately 3 minutes separately and prediction takes around 2 minutes. So the whole process takes around 8 minutes on a 8-cores, Intel(R) Xeon(R) CPU L5420@2.50GHz based, 16GB RAM server.

6.4.1 Estimation/Prediction accuracy

First we evaluate the accuracy of the traffic speed estimation and prediction of the proposed model. The model performed 4 iterations, in each iteration we use estimated route choice probability and predicted route choice probability to simulate the traffic conditions for next one hour. For example, at 7:15 we estimate the traffic conditions in [7:00, 7:15] and simulate traffic from 7:00 to

8:00, then compare the results with the observed traffic speeds. Similarly, at 7:15 we predict the traffic conditions on [7:15, 7:30] and simulate traffic from 7:15 to 8:15 and compare the results with observed traffic speeds on every link.

The estimation accuracy is presented in Figure 27, x-axis represents estimated traffic speed on each link and y-axis represents observed traffic speed data retrieved from INRIX API. Errors between estimated speed and observed speed are measured by r^2, its formulation is as follows:

$$r^2 = 1 - \sum_{a \in A^o} \frac{\left\| t\hat{t}_a - tt_a \right\|_2^2}{\left\| tt_a \right\|_2^2}$$

where tt_a is the observed traffic speed on link a and $\widehat{tt_a}$ is the estimated traffic speed on link a, $A^o$is the set of all observed links (more than 3,000 links matched from 13,104 TMC units).

As can be seen, the first iteration achieves the maximum r^2 during the simulation, which is 0.80. r^2 decreases as the iterations progress, because that the DNL model overestimates the congestion level on the networks. Unrealistically low throughput of node models is the major cause of this problem. However, most of the estimated traffic speeds match the observed speeds, and r^2s are acceptable for all four iterations.

One way to mitigate the congestion overestimation problem in practice is to clear vehicles on networks regularly, this engineering practice is also used in the implementation of our web application.

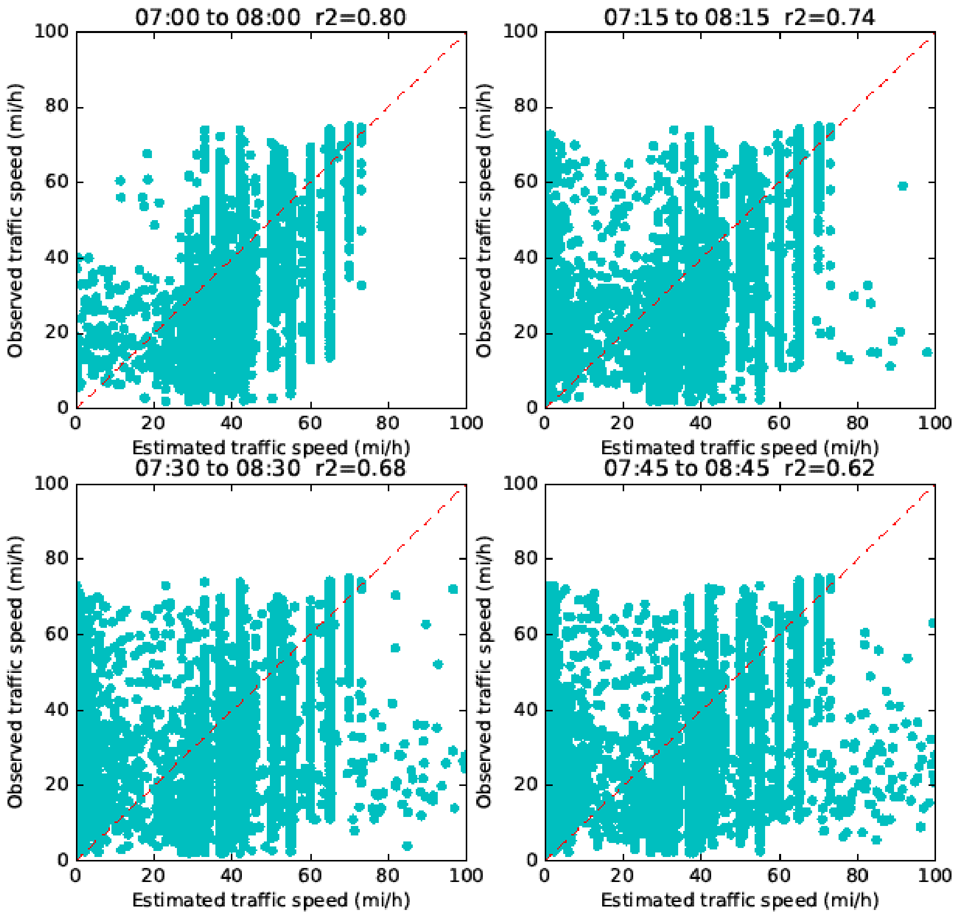

Figure 27 Estimated vs. observed traffic speeds in 4 iterations

The prediction accuracy is presented in Figure 28. X-axis, y-axis and error measurement are the same with Figure 10. r^2 for prediction is smaller than that of estimation, this is because we test on the historical data, the DMS messages do not really control the traffic flows, while the prediction takes account of the DMS messages, therefore the r^2 for prediction is smaller.

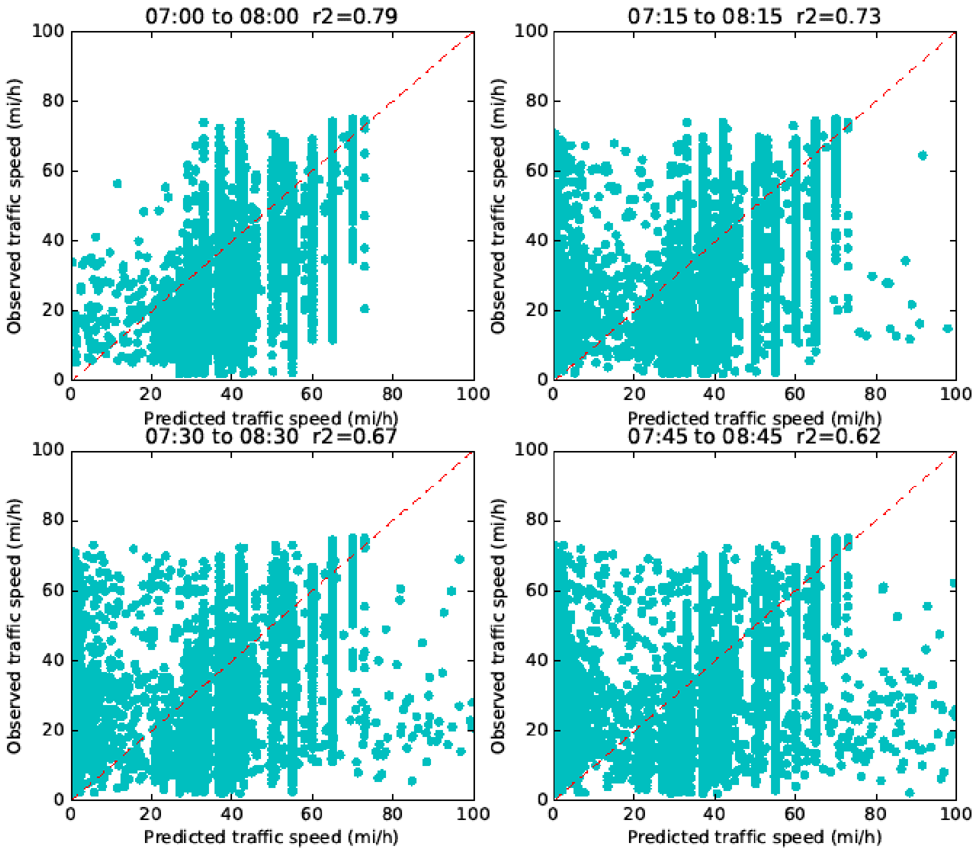

Figure 28 Predicted vs. observed traffic speeds in 4 iterations

6.4.2 Control effectiveness

To measure the impacts of DMS messages on the overall network performance, we inspect the total travel time on every link, the total travel time on link a is denoted as:

$$\mathrm{Tot}_a = x_a t_a$$

where Tot_a is the total travel time on link a, x_a is the traffic flow on link a and t_a is the travel time on link a. The box plots for total travel time of all links on 4 iterations are shown in Figure 29 separately. As can be seen, the boxes for different traffic conditions are on similar level, which indicates that the control of DMS on I-95 has small influence on the overall network performance. This is because the network we use is large so the controls on single corridor do not have significant impacts on the overall network. However, the intervened traffic still yields a lower total travel time. If we have more controls over the network flow, the effectiveness of the control would be anticipated to increase.

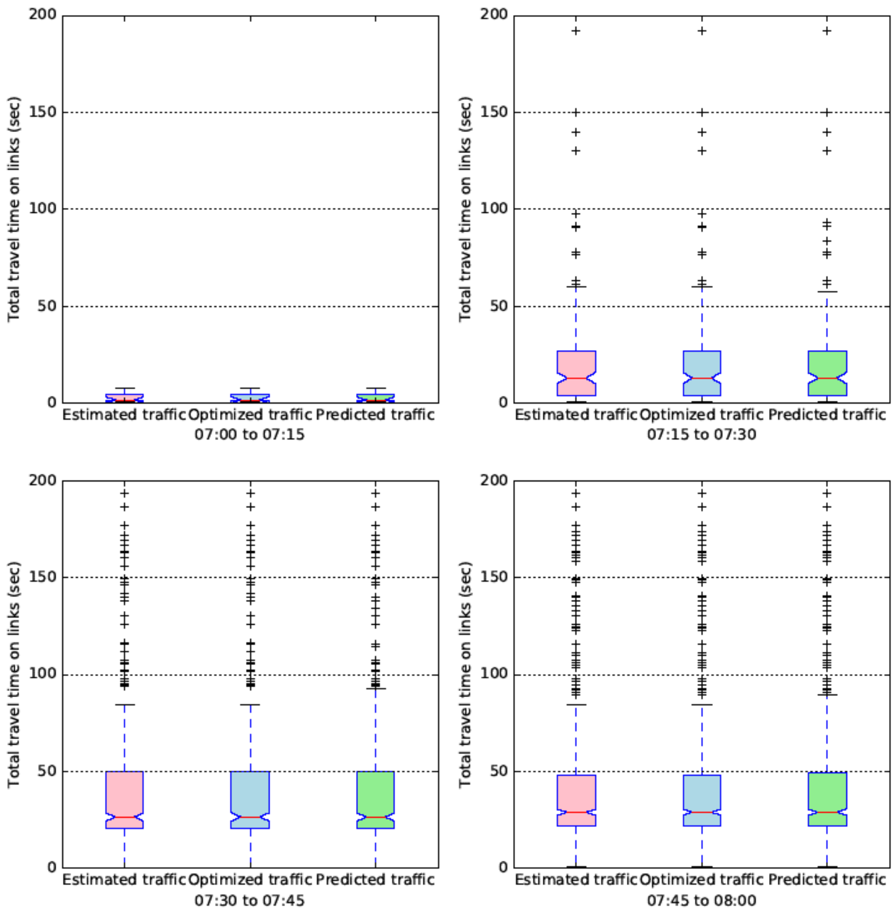

Figure 29 Box plot for total travel time of all links in 4 iterations

Another observation is that the first iteration has little congestion since the network is empty before loading, while the remaining iterations maintain a stable congestion level. This indicates that the DNL model needs to be warmed up before actual use. However as we discuss above, in practice we have to clear the vehicles regularly to prevent "gridlocks". Studies on how to balance the warming ups and network clearance are a real need for practical use of the on-line simulation models.

6.4.3 Real-time message generation

During the iterations, the instructions on DMS are also generated, though not applied to actually control the traffic. Table 1 presents the generated messages on 10 DMS randomly selected from all DMS on I-95 corridor. As can be seen, the messages of the DMS vary from interval to interval and location to location according to estimated traffic conditions.

Some DMS such as DMS-06-082 are located away from Philadelphia Downtown area so there is no congestion ahead of this DMS, the message is

Table 11 Generated messages on selected DMSs in 4 iterations

DMC name	COUNTY	Next Exit	Descriptiv	7:00-7:15	7:15-7:30	7:30-7:45	7:45-8:00
DMS-06-082	BUCKS	51	NB across from the Rest Area	DC	DC	DC	DC
DMS-06-005	PHILADELPHIA	25	NB AFTER GIRARD OFF-RAMP	DC	DC	DC	CA
DMS-06-073	PHILADELPHIA	22	NB after Washington Ave/Columbus Blvd.	TD	TD	DC	CA
DMS-06-177	PHILADELPHIA	17	NB APPROACHING BROAD ST/PA 611	TD	TD	DC	TD
DMS-06-008	PHILADELPHIA	32	NB AT ASHBURNER ST.	DC	DC	DC	DC
DMS-06-062	DELAWARE	NA	NB at the Rest Area	DC	DC	DC	DC
DMS-06-006	PHILADELPHIA	32	NB BEFORE COTTMAN AVE. EXIT 30	DC	CA	CA	CA
DMS-06-010	PHILADELPHIA	35	NB BEFORE GRANT AVENUE	TD	DC	TD	TD
DMS-06-003	PHILADELPHIA	37	NB BEFORE STREET RD.	DC	DC	DC	DC
DMS-06-002	DELAWARE	12	NB NORTH OF AIRPORT EXIT 10	DC	DC	DC	DC

DC: Drive with Care
CA: Congestion Ahead
TD: Take next detour link

always "Drive with care". Some DMSs such as DMS-06-177 are located on the highways entering down town area, where the congestion is usually severe; therefore the messages are generally CA and TD.

6.5 Conclusion

In this section we develop a real-time regional dynamic network model that simulates millions of trips for large-scale networks. The network model utilizes the real-time speed measurements to update travel behavior and network flow prediction, forming a closed-loop feedback learning and control. The model can be applied directly to predict traffic impact of planned and unplanned incidents, and provide real-time decision making for traffic operations. In particular, this model takes real-time traffic speed feeds, incident reports and historical O-D demand as input and optimizes the messages sent to DMS to achieve the best network performance. A browser-based web application implementing the proposed real-time network model is also presented. Users can visualize the DMS messages and the animation of predicted network flow evolution through a web browser.

Experiments are conducted on DMS along I-95 corridor in the Philadelphia Region. The experiments indicate the proposed framework is able to reduce the overall congestion by real-time updating DMS messages. However, the traffic routing on merely I-95 corridor exits has very limited influence on the overall network performance. Allowing more traffic control across the network, such as signal timing, ramp metering and arterial traffic routing, would achieve a better network performance. Our future research will be focusing on further improving the prediction accuracy and field tests for PennDOT traffic management centers.

7. Discussions

In this section we present how our models can be tied with ATMS model and what are the limitations of the propose model.

7.1 Extension with ATMS

In the proposed method, we pre-determine the detour route before the real-time control. Our method evaluates the congestion level of detour route and optimal route on the real-time basis and provides suggestions to travelers through DMS. With ATMS, the detour route at certain locations can be determined on a real-time basis. For example, when congestion is detected due to incidents on certain road, the ATMS can automate our model not to select that road, and generate texts to divert people on those alternative routes (e.g., Exit X, take street A).

Also, since the control is based on DMS message, only aggregated control can be applied on I-95 corridor. Travelers to different destination receive the same control message, control on individuals is impossible. But if our model is tied with ATMS, the model can be tailored to provide different suggestion for travelers with different destinations.

Besides, ATMS can also be an input to our proposed model. For example, weather information, accident information and major events have significant impact to the prediction accuracy. If ATMS can provide such information to our real-time control model, the control policy is expected to be more precise.

7.2 Limitation of the proposed model

One major limitation of the proposed model is due to the restricted performance of the estimation/optimization algorithms through entire road networks. Although state-of-art algorithm is employed in this project, the convergence of the estimation/optimization algorithm is still not guaranteed. The main reason for the limited performance on network results from the convoluted relationship between network variables.

Another limitation is due to the computational complexity of the traffic simulation process. To achieve an accurate simulation result, more computational time is usually required for the model. Since our model runs on a real-time basis, the computational time is strictly constrained. In the future extension, multi-thread/process algorithm can be developed to enhance the simulation accuracy.

8. Summary

This project developed a general regional network model to estimate/predict time-varying traffic evolution on all highways and major arterials in Philadelphia Metropolitan Region. A case study was conducted for Center City bridge closures: assess the dynamic traffic impact of Center City bridge closures on both freeways and major arterials in the Philadelphia Region; propose real-time traffic detour plans as a way of using travel demand management (TDM) strategies to mitigate overall impact caused by closures.

We first collect data we need for the project and summarize the data. Then we focus on establishing a dynamic network model for the Philadelphia Metropolitan Region. A dynamic transportation network model that provides estimated day-to-day origin-destination demand among all Traffic Analysis Zones (TAZs) is developed. We examine and carefully calibrate the route choices for all the travelers with different origins and destinations using observed traffic counts and speed data. The calibrated model is capable of estimating network-wide traffic impact caused by any incident based upon a generic regional network consisting of freeway and major arterials.

We also developed a real-time DTA algorithm that take real-time incident reports and real-time speed measurements simultaneously to update the underlying flow propagation. In addition to predicting next-hour network flow, we intend to intervene the network flow by optimizing the messages fed to dynamic message signs (DMS). Real-time DTA is essentially solved with, in part, optimal traffic routing only at limited DMS locations. The real-time prediction and message optimum are solved with algorithms that are computationally efficient for large-scale network.

This project contributes to the methodology foundation of a real-time traffic control system in three aspects. First, we develop real-time DTA algorithms that take real-time incident reports and real-time speed measurements simultaneously to update the underlying flow propagation. Second, in addition to predicting next-hour network flow, we intend to intervene the network flow by optimizing the messages fed to dynamic message signs (DMS). Real-time DTA is essentially solved with, in part, optimal traffic routing only at limited DMS locations. Third, the real-time prediction and message optimum are solved with algorithms that are computationally efficient for large-scale network.

The proposed model is implemented as an internet web application, a website built to visualize the control strategies and animate the flow evolutions. All the user interactions with the real-time traffic management model are based on browser.

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Appendix A. Travel time change in different scenarios for AM peak (minutes)

Origin	Destination	Time Interval	Baseline	I-95 south closure	I-95 north closure	I-95 both closure
Trenton	Monroe Township	5:00 - 6:00	36.1	36.1	36.1	36.1
Trenton	Monroe Township	6:00 - 7:00	36.1	36.1	36.1	36.1
Trenton	Monroe Township	7:00 - 8:00	36.1	36.1	36.1	36.1
Trenton	Monroe Township	8:00 - 9:00	36.1	36.5	36.1	36.1
Trenton	Monroe Township	9:00 - 10:00	36.1	36.1	36.1	36.1
Trenton	University of Pennsylvania	5:00 - 6:00	45.3	45.3	61.8	62.1
Trenton	University of Pennsylvania	6:00 - 7:00	45.3	45.3	53.9	61.8
Trenton	University of Pennsylvania	7:00 - 8:00	44.9	44.9	49.4	53.1
Trenton	University of Pennsylvania	8:00 - 9:00	45.6	47.3	53.3	53.9
Trenton	University of Pennsylvania	9:00 - 10:00	50.4	51.7	54.3	49.2
Trenton	Wilmington	5:00 - 6:00	74.1	74.1	92.4	92.8
Trenton	Wilmington	6:00 - 7:00	73.2	73.2	71.2	92.4
Trenton	Wilmington	7:00 - 8:00	72.1	72.1	72.1	71.2
Trenton	Wilmington	8:00 - 9:00	72.7	72.1	72.1	71.2
Trenton	Wilmington	9:00 - 10:00	72.1	72.7	72.1	71.2
Trenton	Cherry Hill	5:00 - 6:00	32.0	32.0	32.0	32.0
Trenton	Cherry Hill	6:00 - 7:00	32.0	32.0	32.0	32.0
Trenton	Cherry Hill	7:00 - 8:00	32.0	32.0	32.0	32.0
Trenton	Cherry Hill	8:00 - 9:00	32.0	32.0	32.0	32.0
Trenton	Cherry Hill	9:00 - 10:00	32.0	32.0	32.0	32.0
Trenton	King of Prussia	5:00 - 6:00	57.7	57.7	57.7	57.7
Trenton	King of Prussia	6:00 - 7:00	57.7	57.7	57.7	57.7
Trenton	King of Prussia	7:00 - 8:00	57.8	57.8	57.7	57.7
Trenton	King of Prussia	8:00 - 9:00	62.3	62.8	62.8	57.7
Trenton	King of Prussia	9:00 - 10:00	62.8	57.7	57.8	57.2
Trenton	Philadelphia Downtown	5:00 - 6:00	42.3	42.3	56.8	62.4
Trenton	Philadelphia Downtown	6:00 - 7:00	42.3	42.3	51.3	56.8
Trenton	Philadelphia Downtown	7:00 - 8:00	42.3	42.3	46.8	48.9
Trenton	Philadelphia Downtown	8:00 - 9:00	42.3	43.1	51.5	51.3
Trenton	Philadelphia Downtown	9:00 - 10:00	48.5	49.7	52.4	46.8
Monroe Township	Trenton	5:00 - 6:00	36.0	36.0	36.0	36.0
Monroe Township	Trenton	6:00 - 7:00	36.0	36.0	36.0	36.0
Monroe Township	Trenton	7:00 - 8:00	36.0	36.0	36.0	36.0
Monroe Township	Trenton	8:00 - 9:00	40.1	36.0	36.0	36.0
Monroe Township	Trenton	9:00 - 10:00	36.0	36.0	36.0	36.0
Monroe Township	University of Pennsylvania	5:00 - 6:00	21.5	21.5	21.5	21.5

Monroe Township	University of Pennsylvania	6:00 - 7:00	21.5	21.5	21.5	21.5
Monroe Township	University of Pennsylvania	7:00 - 8:00	21.5	21.5	21.8	21.5
Monroe Township	University of Pennsylvania	8:00 - 9:00	24.1	24.3	24.1	21.5
Monroe Township	University of Pennsylvania	9:00 - 10:00	24.1	25.3	24.3	21.5
Monroe Township	Wilmington	5:00 - 6:00	40.8	40.8	40.8	40.8
Monroe Township	Wilmington	6:00 - 7:00	40.4	40.4	40.4	40.8
Monroe Township	Wilmington	7:00 - 8:00	40.6	40.6	40.6	40.4
Monroe Township	Wilmington	8:00 - 9:00	40.6	40.6	40.6	40.4
Monroe Township	Wilmington	9:00 - 10:00	40.6	40.6	40.6	40.4
Monroe Township	Cherry Hill	5:00 - 6:00	10.5	10.5	10.5	10.5
Monroe Township	Cherry Hill	6:00 - 7:00	10.5	10.5	10.5	10.5
Monroe Township	Cherry Hill	7:00 - 8:00	10.5	10.5	10.5	10.5
Monroe Township	Cherry Hill	8:00 - 9:00	10.5	10.5	10.5	10.5
Monroe Township	Cherry Hill	9:00 - 10:00	10.5	10.5	10.5	10.5
Monroe Township	King of Prussia	5:00 - 6:00	49.4	49.4	49.4	49.4
Monroe Township	King of Prussia	6:00 - 7:00	46.3	46.3	47.6	49.4
Monroe Township	King of Prussia	7:00 - 8:00	46.7	48.9	48.4	47.6
Monroe Township	King of Prussia	8:00 - 9:00	49.8	49.2	49.2	47.6
Monroe Township	King of Prussia	9:00 - 10:00	50.2	51.0	49.2	46.1
Monroe Township	Philadelphia Downtown	5:00 - 6:00	22.7	22.7	22.7	22.7
Monroe Township	Philadelphia Downtown	6:00 - 7:00	21.4	21.4	21.4	22.7
Monroe Township	Philadelphia Downtown	7:00 - 8:00	22.3	23.9	22.8	21.4
Monroe Township	Philadelphia Downtown	8:00 - 9:00	24.0	23.5	24.2	21.4
Monroe Township	Philadelphia Downtown	9:00 - 10:00	24.0	24.7	24.2	21.4
University of Pennsylvania	Trenton	5:00 - 6:00	38.1	42.1	38.1	42.1
University of Pennsylvania	Trenton	6:00 - 7:00	38.1	42.1	38.1	42.1
University of Pennsylvania	Trenton	7:00 - 8:00	39.6	43.7	38.1	42.1
University of Pennsylvania	Trenton	8:00 - 9:00	41.6	44.1	38.1	42.5
University of Pennsylvania	Trenton	9:00 - 10:00	41.6	43.1	38.1	41.6
University of Pennsylvania	Monroe Township	5:00 - 6:00	17.5	17.5	17.5	17.5
University of Pennsylvania	Monroe Township	6:00 - 7:00	17.5	17.5	17.5	17.5
University of Pennsylvania	Monroe Township	7:00 - 8:00	17.5	17.5	17.5	17.5
University of Pennsylvania	Monroe Township	8:00 - 9:00	17.5	17.5	17.5	17.5
University of Pennsylvania	Monroe Township	9:00 - 10:00	17.5	17.5	17.5	17.5
University of Pennsylvania	Wilmington	5:00 - 6:00	33.1	33.1	33.1	33.1
University of Pennsylvania	Wilmington	6:00 - 7:00	32.2	32.2	32.2	33.1
University of Pennsylvania	Wilmington	7:00 - 8:00	34.2	34.2	32.2	33.1
University of Pennsylvania	Wilmington	8:00 - 9:00	34.5	34.5	32.2	32.2

University of Pennsylvania	Wilmington	9:00 - 10:00	32.2	32.2	33.1	32.2
University of Pennsylvania	Cherry Hill	5:00 - 6:00	15.0	15.0	15.0	15.0
University of Pennsylvania	Cherry Hill	6:00 - 7:00	15.0	15.0	15.0	15.0
University of Pennsylvania	Cherry Hill	7:00 - 8:00	15.0	15.0	15.0	15.0
University of Pennsylvania	Cherry Hill	8:00 - 9:00	15.0	15.2	15.2	15.0
University of Pennsylvania	Cherry Hill	9:00 - 10:00	15.0	15.2	15.2	15.0
University of Pennsylvania	King of Prussia	5:00 - 6:00	28.8	28.8	28.8	28.8
University of Pennsylvania	King of Prussia	6:00 - 7:00	25.9	25.9	25.9	28.8
University of Pennsylvania	King of Prussia	7:00 - 8:00	25.3	25.6	26.0	28.8
University of Pennsylvania	King of Prussia	8:00 - 9:00	25.3	25.3	25.3	26.0
University of Pennsylvania	King of Prussia	9:00 - 10:00	25.9	25.9	25.9	25.3
University of Pennsylvania	Philadelphia Downtown	5:00 - 6:00	3.8	3.8	3.8	3.8
University of Pennsylvania	Philadelphia Downtown	6:00 - 7:00	3.8	3.8	3.8	3.8
University of Pennsylvania	Philadelphia Downtown	7:00 - 8:00	3.8	3.8	3.8	3.8
University of Pennsylvania	Philadelphia Downtown	8:00 - 9:00	3.8	3.8	3.8	3.8
University of Pennsylvania	Philadelphia Downtown	9:00 - 10:00	3.8	3.8	3.8	3.8
Wilmington	Trenton	5:00 - 6:00	65.9	70.5	65.9	70.5
Wilmington	Trenton	6:00 - 7:00	65.9	70.5	65.9	70.5
Wilmington	Trenton	7:00 - 8:00	67.1	69.3	65.6	70.5
Wilmington	Trenton	8:00 - 9:00	69.3	69.3	65.7	70.9
Wilmington	Trenton	9:00 - 10:00	65.9	69.3	65.6	69.3
Wilmington	Monroe Township	5:00 - 6:00	38.1	38.1	38.1	38.1
Wilmington	Monroe Township	6:00 - 7:00	39.8	39.8	39.8	38.1
Wilmington	Monroe Township	7:00 - 8:00	38.1	38.1	38.1	38.3
Wilmington	Monroe Township	8:00 - 9:00	39.8	38.1	38.1	39.8
Wilmington	Monroe Township	9:00 - 10:00	39.8	40.1	38.1	38.1
Wilmington	University of Pennsylvania	5:00 - 6:00	31.2	31.2	31.2	31.2
Wilmington	University of Pennsylvania	6:00 - 7:00	31.2	31.2	31.2	31.2
Wilmington	University of Pennsylvania	7:00 - 8:00	31.2	31.2	31.2	31.2
Wilmington	University of Pennsylvania	8:00 - 9:00	31.2	31.2	31.2	31.2
Wilmington	University of Pennsylvania	9:00 - 10:00	31.2	31.2	31.2	31.2
Wilmington	Cherry Hill	5:00 - 6:00	40.9	40.9	40.9	40.9
Wilmington	Cherry Hill	6:00 - 7:00	40.9	40.9	40.9	40.9
Wilmington	Cherry Hill	7:00 - 8:00	40.9	40.9	40.9	40.9
Wilmington	Cherry Hill	8:00 - 9:00	43.3	44.0	40.9	40.9
Wilmington	Cherry Hill	9:00 - 10:00	40.9	40.9	43.0	40.9
Wilmington	King of Prussia	5:00 - 6:00	42.0	42.0	42.0	42.0
Wilmington	King of Prussia	6:00 - 7:00	39.2	39.2	39.2	42.0
Wilmington	King of Prussia	7:00 - 8:00	39.2	39.2	39.2	42.0

Wilmington	King of Prussia	8:00 - 9:00	39.2	39.2	39.2	39.2
Wilmington	King of Prussia	9:00 - 10:00	39.2	39.2	39.2	39.2
Wilmington	Philadelphia Downtown	5:00 - 6:00	31.9	31.9	31.9	31.9
Wilmington	Philadelphia Downtown	6:00 - 7:00	31.9	31.9	31.9	31.9
Wilmington	Philadelphia Downtown	7:00 - 8:00	31.9	31.9	31.9	31.9
Wilmington	Philadelphia Downtown	8:00 - 9:00	31.9	32.9	31.9	31.9
Wilmington	Philadelphia Downtown	9:00 - 10:00	31.9	32.9	31.9	31.9
Cherry Hill	Trenton	5:00 - 6:00	31.9	31.9	31.9	31.9
Cherry Hill	Trenton	6:00 - 7:00	31.9	31.9	31.9	31.9
Cherry Hill	Trenton	7:00 - 8:00	32.0	31.9	31.9	31.9
Cherry Hill	Trenton	8:00 - 9:00	36.2	32.0	32.0	31.9
Cherry Hill	Trenton	9:00 - 10:00	32.0	31.9	32.0	31.9
Cherry Hill	Monroe Township	5:00 - 6:00	10.6	10.6	10.6	10.6
Cherry Hill	Monroe Township	6:00 - 7:00	10.6	10.6	10.6	10.6
Cherry Hill	Monroe Township	7:00 - 8:00	11.4	10.6	10.6	10.6
Cherry Hill	Monroe Township	8:00 - 9:00	11.4	11.4	11.4	10.6
Cherry Hill	Monroe Township	9:00 - 10:00	11.4	10.6	10.6	10.6
Cherry Hill	University of Pennsylvania	5:00 - 6:00	21.7	21.7	21.7	21.7
Cherry Hill	University of Pennsylvania	6:00 - 7:00	21.7	21.7	21.7	21.7
Cherry Hill	University of Pennsylvania	7:00 - 8:00	20.4	21.8	19.8	21.7
Cherry Hill	University of Pennsylvania	8:00 - 9:00	22.0	23.9	20.4	21.7
Cherry Hill	University of Pennsylvania	9:00 - 10:00	26.4	20.6	20.4	19.8
Cherry Hill	Wilmington	5:00 - 6:00	51.1	51.1	51.1	51.1
Cherry Hill	Wilmington	6:00 - 7:00	50.2	50.2	50.2	51.1
Cherry Hill	Wilmington	7:00 - 8:00	47.4	46.9	46.7	51.1
Cherry Hill	Wilmington	8:00 - 9:00	48.7	49.0	48.5	50.2
Cherry Hill	Wilmington	9:00 - 10:00	47.3	48.3	48.4	45.8
Cherry Hill	King of Prussia	5:00 - 6:00	45.4	45.4	45.4	45.4
Cherry Hill	King of Prussia	6:00 - 7:00	43.4	44.0	45.4	45.4
Cherry Hill	King of Prussia	7:00 - 8:00	42.8	44.3	42.9	45.4
Cherry Hill	King of Prussia	8:00 - 9:00	44.5	46.4	42.8	45.4
Cherry Hill	King of Prussia	9:00 - 10:00	44.6	43.6	42.8	41.9
Cherry Hill	Philadelphia Downtown	5:00 - 6:00	18.7	18.7	18.7	18.7
Cherry Hill	Philadelphia Downtown	6:00 - 7:00	18.7	18.7	18.7	18.7
Cherry Hill	Philadelphia Downtown	7:00 - 8:00	17.7	19.3	17.2	18.7
Cherry Hill	Philadelphia Downtown	8:00 - 9:00	18.7	20.6	17.7	18.7
Cherry Hill	Philadelphia Downtown	9:00 - 10:00	18.8	17.4	17.7	17.2
King of Prussia	Trenton	5:00 - 6:00	45.9	45.9	45.9	45.9
King of Prussia	Trenton	6:00 - 7:00	45.9	45.9	45.9	45.9
King of Prussia	Trenton	7:00 - 8:00	45.4	45.4	45.4	45.9

King of Prussia	Trenton	8:00 - 9:00	45.4	45.4	45.4	45.9
King of Prussia	Trenton	9:00 - 10:00	45.4	45.4	45.4	45.4
King of Prussia	Monroe Township	5:00 - 6:00	41.1	41.1	41.1	41.1
King of Prussia	Monroe Township	6:00 - 7:00	41.1	41.1	41.1	41.1
King of Prussia	Monroe Township	7:00 - 8:00	41.1	39.5	40.0	41.1
King of Prussia	Monroe Township	8:00 - 9:00	39.5	39.5	40.0	41.1
King of Prussia	Monroe Township	9:00 - 10:00	40.0	40.0	40.0	39.5
King of Prussia	University of Pennsylvania	5:00 - 6:00	24.9	24.9	24.9	24.9
King of Prussia	University of Pennsylvania	6:00 - 7:00	24.9	24.9	24.9	24.9
King of Prussia	University of Pennsylvania	7:00 - 8:00	24.9	25.7	24.9	24.9
King of Prussia	University of Pennsylvania	8:00 - 9:00	24.5	24.5	24.9	24.9
King of Prussia	University of Pennsylvania	9:00 - 10:00	24.9	24.9	24.9	24.5
King of Prussia	Wilmington	5:00 - 6:00	41.0	41.0	41.0	41.0
King of Prussia	Wilmington	6:00 - 7:00	40.5	40.5	40.5	41.0
King of Prussia	Wilmington	7:00 - 8:00	40.5	40.5	40.5	40.5
King of Prussia	Wilmington	8:00 - 9:00	41.0	40.5	43.3	40.5
King of Prussia	Wilmington	9:00 - 10:00	40.5	41.0	40.5	40.5
King of Prussia	Cherry Hill	5:00 - 6:00	35.7	35.7	35.7	35.7
King of Prussia	Cherry Hill	6:00 - 7:00	35.7	35.7	35.7	35.7
King of Prussia	Cherry Hill	7:00 - 8:00	35.7	35.2	35.7	35.7
King of Prussia	Cherry Hill	8:00 - 9:00	35.2	35.4	35.9	35.7
King of Prussia	Cherry Hill	9:00 - 10:00	35.7	35.9	35.9	35.2
King of Prussia	Philadelphia Downtown	5:00 - 6:00	25.2	25.2	25.2	25.2
King of Prussia	Philadelphia Downtown	6:00 - 7:00	25.2	25.2	25.2	25.2
King of Prussia	Philadelphia Downtown	7:00 - 8:00	25.2	24.8	25.2	25.2
King of Prussia	Philadelphia Downtown	8:00 - 9:00	25.3	24.8	25.2	25.2
King of Prussia	Philadelphia Downtown	9:00 - 10:00	25.2	25.2	25.2	24.8
Philadelphia downtown	Trenton	5:00 - 6:00	35.6	40.0	35.6	40.0
Philadelphia downtown	Trenton	6:00 - 7:00	35.6	41.3	35.6	40.0
Philadelphia downtown	Trenton	7:00 - 8:00	37.1	41.3	35.6	40.0
Philadelphia downtown	Trenton	8:00 - 9:00	36.5	41.5	35.6	41.5
Philadelphia downtown	Trenton	9:00 - 10:00	35.6	41.1	35.6	40.0
Philadelphia downtown	Monroe Township	5:00 - 6:00	17.1	17.1	17.1	17.1
Philadelphia downtown	Monroe Township	6:00 - 7:00	17.1	17.1	17.1	17.1
Philadelphia downtown	Monroe Township	7:00 - 8:00	17.1	17.1	17.1	17.1
Philadelphia downtown	Monroe Township	8:00 - 9:00	17.1	17.1	17.1	17.1
Philadelphia downtown	Monroe Township	9:00 - 10:00	17.1	17.1	17.1	17.1
Philadelphia downtown	University of Pennsylvania	5:00 - 6:00	4.3	4.3	4.3	4.3
Philadelphia	University of	6:00 - 7:00	4.3	4.3	4.3	4.3

downtown	Pennsylvania					
Philadelphia downtown	University of Pennsylvania	7:00 - 8:00	4.3	4.3	4.3	4.3
Philadelphia downtown	University of Pennsylvania	8:00 - 9:00	4.4	4.3	4.3	4.3
Philadelphia downtown	University of Pennsylvania	9:00 - 10:00	4.3	4.3	4.3	4.3
Philadelphia downtown	Wilmington	5:00 - 6:00	34.3	34.3	34.3	34.3
Philadelphia downtown	Wilmington	6:00 - 7:00	33.4	33.4	33.4	34.3
Philadelphia downtown	Wilmington	7:00 - 8:00	35.4	35.4	33.4	34.3
Philadelphia downtown	Wilmington	8:00 - 9:00	35.7	35.7	33.4	33.4
Philadelphia downtown	Wilmington	9:00 - 10:00	33.4	33.4	34.3	33.4
Philadelphia downtown	Cherry Hill	5:00 - 6:00	11.7	11.7	11.7	11.7
Philadelphia downtown	Cherry Hill	6:00 - 7:00	11.7	11.7	11.7	11.7
Philadelphia downtown	Cherry Hill	7:00 - 8:00	11.7	11.7	11.7	11.7
Philadelphia downtown	Cherry Hill	8:00 - 9:00	11.7	11.9	11.9	11.7
Philadelphia downtown	Cherry Hill	9:00 - 10:00	11.7	12.3	11.9	11.7
Philadelphia downtown	King of Prussia	5:00 - 6:00	30.0	30.0	30.0	30.0
Philadelphia downtown	King of Prussia	6:00 - 7:00	27.7	28.5	30.1	30.0
Philadelphia downtown	King of Prussia	7:00 - 8:00	28.0	28.0	28.6	30.0
Philadelphia downtown	King of Prussia	8:00 - 9:00	28.0	28.0	28.0	29.8
Philadelphia downtown	King of Prussia	9:00 - 10:00	28.0	28.5	28.0	27.6

Appendix B. Travel time change in different scenarios for PM peak (minutes)

Origin	Destination	Time Interval	Baseline	I-95 south closure	I-95 north closure	I-95 both closure
Trenton	Monroe Township	15:00-16:00	36.7	36.7	36.7	36.7
Trenton	Monroe Township	16:00-17:00	37.1	37.1	36.7	37.1
Trenton	Monroe Township	17:00-18:00	36.7	36.7	37.1	37.1
Trenton	Monroe Township	18:00-19:00	37.1	36.7	36.7	36.7
Trenton	Monroe Township	19:00-20:00	36.7	36.7	36.7	36.7
Trenton	University of Pennsylvania	15:00-16:00	54.1	54.1	58.6	58.6
Trenton	University of Pennsylvania	16:00-17:00	53.7	53.7	65.0	55.3
Trenton	University of Pennsylvania	17:00-18:00	53.3	64.8	54.9	64.1
Trenton	University of Pennsylvania	18:00-19:00	60.0	60.6	51.5	55.9
Trenton	University of Pennsylvania	19:00-20:00	63.4	60.3	58.8	51.4
Trenton	Wilmington	15:00-16:00	80.4	80.4	73.2	73.2
Trenton	Wilmington	16:00-17:00	80.4	80.4	72.7	73.6
Trenton	Wilmington	17:00-18:00	77.5	77.5	72.8	72.8
Trenton	Wilmington	18:00-19:00	77.5	77.5	75.2	77.5
Trenton	Wilmington	19:00-20:00	77.5	77.5	75.2	72.7
Trenton	Cherry Hill	15:00-16:00	31.0	31.0	31.0	31.0
Trenton	Cherry Hill	16:00-17:00	31.0	31.0	31.0	31.0
Trenton	Cherry Hill	17:00-18:00	31.0	31.0	31.0	31.0
Trenton	Cherry Hill	18:00-19:00	31.0	31.0	31.0	31.0
Trenton	Cherry Hill	19:00-20:00	31.0	31.0	31.0	31.0
Trenton	King of Prussia	15:00-16:00	51.8	51.8	51.8	51.8
Trenton	King of Prussia	16:00-17:00	51.8	51.6	51.8	51.6
Trenton	King of Prussia	17:00-18:00	51.8	51.8	51.6	51.8
Trenton	King of Prussia	18:00-19:00	51.8	51.8	49.5	51.8
Trenton	King of Prussia	19:00-20:00	51.8	51.8	49.5	49.3
Trenton	Philadelphia Downtown	15:00-16:00	50.4	50.4	52.8	52.8
Trenton	Philadelphia Downtown	16:00-17:00	50.4	50.4	54.6	52.8
Trenton	Philadelphia Downtown	17:00-18:00	50.9	63.0	53.0	64.5
Trenton	Philadelphia Downtown	18:00-19:00	58.5	59.2	49.9	54.9
Trenton	Philadelphia Downtown	19:00-20:00	58.0	50.9	57.2	49.8
Monroe Township	Trenton	15:00-16:00	36.2	36.2	36.2	36.2
Monroe Township	Trenton	16:00-17:00	36.2	36.2	36.2	36.2
Monroe Township	Trenton	17:00-	36.2	36.2	36.2	36.2

		18:00				
Monroe Township	Trenton	18:00-19:00	36.2	36.2	36.2	36.2
Monroe Township	Trenton	19:00-20:00	36.2	36.2	36.2	36.2
Monroe Township	University of Pennsylvania	15:00-16:00	31.9	31.9	31.9	31.9
Monroe Township	University of Pennsylvania	16:00-17:00	31.9	31.3	32.5	31.3
Monroe Township	University of Pennsylvania	17:00-18:00	31.3	30.8	29.1	29.2
Monroe Township	University of Pennsylvania	18:00-19:00	29.2	28.9	29.6	29.9
Monroe Township	University of Pennsylvania	19:00-20:00	29.1	28.9	30.0	27.3
Monroe Township	Wilmington	15:00-16:00	41.9	41.9	41.9	41.9
Monroe Township	Wilmington	16:00-17:00	41.9	41.9	42.5	41.9
Monroe Township	Wilmington	17:00-18:00	40.6	40.6	40.6	40.6
Monroe Township	Wilmington	18:00-19:00	40.6	40.6	40.6	40.6
Monroe Township	Wilmington	19:00-20:00	41.9	40.6	40.6	40.6
Monroe Township	Cherry Hill	15:00-16:00	10.5	10.5	10.5	10.5
Monroe Township	Cherry Hill	16:00-17:00	10.5	10.5	11.0	10.5
Monroe Township	Cherry Hill	17:00-18:00	10.5	10.5	10.5	10.5
Monroe Township	Cherry Hill	18:00-19:00	10.5	10.5	11.0	11.0
Monroe Township	Cherry Hill	19:00-20:00	10.5	10.5	10.5	10.5
Monroe Township	King of Prussia	15:00-16:00	53.7	63.7	64.1	64.1
Monroe Township	King of Prussia	16:00-17:00	59.4	59.1	53.6	54.5
Monroe Township	King of Prussia	17:00-18:00	50.4	54.2	52.1	50.7
Monroe Township	King of Prussia	18:00-19:00	51.0	52.0	50.9	50.4
Monroe Township	King of Prussia	19:00-20:00	50.6	50.1	51.5	48.4
Monroe Township	Philadelphia Downtown	15:00-16:00	27.0	28.2	27.0	27.0
Monroe Township	Philadelphia Downtown	16:00-17:00	27.0	27.0	27.6	27.0
Monroe Township	Philadelphia Downtown	17:00-18:00	24.2	27.0	25.6	26.8
Monroe Township	Philadelphia Downtown	18:00-19:00	25.7	25.1	25.6	27.7
Monroe Township	Philadelphia Downtown	19:00-20:00	25.8	25.1	26.7	24.1
University of Pennsylvania	Trenton	15:00-16:00	37.6	63.7	37.6	63.7
University of Pennsylvania	Trenton	16:00-17:00	37.6	54.8	37.6	53.6
University of Pennsylvania	Trenton	17:00-18:00	37.8	55.9	38.2	51.1
University of Pennsylvania	Trenton	18:00-19:00	37.8	56.1	37.8	51.7
University of Pennsylvania	Trenton	19:00-20:00	37.6	54.1	37.6	47.7
University of Pennsylvania	Monroe Township	15:00-16:00	27.0	27.0	27.0	27.0
University of Pennsylvania	Monroe Township	16:00-17:00	27.0	27.0	27.7	27.0
University of Pennsylvania	Monroe Township	17:00-18:00	26.2	26.3	26.2	27.0
University of	Monroe Township	18:00-	25.5	26.8	26.2	26.1

Pennsylvania		19:00				
University of Pennsylvania	Monroe Township	19:00-20:00	25.3	25.3	26.1	25.3
University of Pennsylvania	Wilmington	15:00-16:00	36.1	36.1	36.1	36.1
University of Pennsylvania	Wilmington	16:00-17:00	36.1	36.1	36.1	36.1
University of Pennsylvania	Wilmington	17:00-18:00	34.3	35.4	35.4	36.1
University of Pennsylvania	Wilmington	18:00-19:00	34.4	34.3	35.4	35.3
University of Pennsylvania	Wilmington	19:00-20:00	34.0	34.2	35.3	34.0
University of Pennsylvania	Cherry Hill	15:00-16:00	23.6	23.6	23.6	23.6
University of Pennsylvania	Cherry Hill	16:00-17:00	23.6	23.6	23.6	23.6
University of Pennsylvania	Cherry Hill	17:00-18:00	23.8	24.1	24.2	23.8
University of Pennsylvania	Cherry Hill	18:00-19:00	23.8	24.1	23.1	23.4
University of Pennsylvania	Cherry Hill	19:00-20:00	23.6	23.7	22.7	22.2
University of Pennsylvania	King of Prussia	15:00-16:00	27.5	27.5	27.5	27.5
University of Pennsylvania	King of Prussia	16:00-17:00	27.5	27.8	27.8	27.5
University of Pennsylvania	King of Prussia	17:00-18:00	27.5	27.8	27.9	25.1
University of Pennsylvania	King of Prussia	18:00-19:00	25.1	25.1	27.7	28.0
University of Pennsylvania	King of Prussia	19:00-20:00	25.1	25.3	25.1	25.1
University of Pennsylvania	Philadelphia Downtown	15:00-16:00	3.8	3.8	3.8	3.8
University of Pennsylvania	Philadelphia Downtown	16:00-17:00	3.8	3.8	3.8	3.8
University of Pennsylvania	Philadelphia Downtown	17:00-18:00	4.1	4.1	4.1	4.1
University of Pennsylvania	Philadelphia Downtown	18:00-19:00	4.1	3.8	4.1	4.1
University of Pennsylvania	Philadelphia Downtown	19:00-20:00	3.8	3.8	3.8	3.8
Wilmington	Trenton	15:00-16:00	72.0	107.3	72.0	115.9
Wilmington	Trenton	16:00-17:00	72.0	86.7	72.0	86.7
Wilmington	Trenton	17:00-18:00	89.9	89.9	89.9	86.7
Wilmington	Trenton	18:00-19:00	86.7	86.7	70.3	72.2
Wilmington	Trenton	19:00-20:00	86.7	86.7	72.2	72.2
Wilmington	Monroe Township	15:00-16:00	40.6	40.6	40.6	40.6
Wilmington	Monroe Township	16:00-17:00	40.6	40.8	40.6	40.6
Wilmington	Monroe Township	17:00-18:00	42.1	42.0	40.6	40.6
Wilmington	Monroe Township	18:00-19:00	40.6	40.7	40.6	40.6
Wilmington	Monroe Township	19:00-20:00	40.6	40.6	40.6	40.6
Wilmington	University of Pennsylvania	15:00-16:00	46.6	46.6	46.6	46.6
Wilmington	University of Pennsylvania	16:00-17:00	46.6	45.9	46.6	45.9
Wilmington	University of Pennsylvania	17:00-18:00	35.6	35.6	34.2	34.2
Wilmington	University of Pennsylvania	18:00-19:00	34.2	34.2	34.1	34.2
Wilmington	University of	19:00-	34.2	34.2	34.2	34.1

	Pennsylvania	20:00				
Wilmington	Cherry Hill	15:00-16:00	55.6	55.6	55.6	55.6
Wilmington	Cherry Hill	16:00-17:00	53.3	48.9	48.8	48.8
Wilmington	Cherry Hill	17:00-18:00	48.0	49.5	46.5	48.8
Wilmington	Cherry Hill	18:00-19:00	46.5	46.5	47.0	47.0
Wilmington	Cherry Hill	19:00-20:00	46.5	48.8	46.5	46.2
Wilmington	King of Prussia	15:00-16:00	39.4	39.4	39.4	39.4
Wilmington	King of Prussia	16:00-17:00	39.4	39.4	39.4	39.4
Wilmington	King of Prussia	17:00-18:00	42.6	42.6	42.6	39.4
Wilmington	King of Prussia	18:00-19:00	41.2	39.4	41.2	39.4
Wilmington	King of Prussia	19:00-20:00	39.4	39.4	39.4	39.4
Wilmington	Philadelphia Downtown	15:00-16:00	49.7	49.7	49.7	49.7
Wilmington	Philadelphia Downtown	16:00-17:00	43.0	43.0	49.7	43.0
Wilmington	Philadelphia Downtown	17:00-18:00	40.3	42.0	38.8	40.6
Wilmington	Philadelphia Downtown	18:00-19:00	38.2	37.8	38.8	37.9
Wilmington	Philadelphia Downtown	19:00-20:00	37.8	39.0	37.8	37.4
Cherry Hill	Trenton	15:00-16:00	32.0	32.0	32.0	32.0
Cherry Hill	Trenton	16:00-17:00	32.0	32.0	32.0	32.0
Cherry Hill	Trenton	17:00-18:00	32.0	32.0	32.0	32.0
Cherry Hill	Trenton	18:00-19:00	32.0	32.0	32.0	32.0
Cherry Hill	Trenton	19:00-20:00	32.0	35.7	32.0	32.0
Cherry Hill	Monroe Township	15:00-16:00	11.3	11.3	11.3	11.3
Cherry Hill	Monroe Township	16:00-17:00	11.4	11.4	11.4	11.4
Cherry Hill	Monroe Township	17:00-18:00	11.4	11.9	11.9	11.9
Cherry Hill	Monroe Township	18:00-19:00	11.9	11.4	11.4	11.4
Cherry Hill	Monroe Township	19:00-20:00	11.4	11.3	11.3	11.3
Cherry Hill	University of Pennsylvania	15:00-16:00	30.9	30.9	30.9	30.9
Cherry Hill	University of Pennsylvania	16:00-17:00	27.3	26.4	31.0	31.0
Cherry Hill	University of Pennsylvania	17:00-18:00	29.9	29.5	29.7	27.1
Cherry Hill	University of Pennsylvania	18:00-19:00	29.0	29.1	27.4	28.1
Cherry Hill	University of Pennsylvania	19:00-20:00	29.3	26.3	26.5	24.9
Cherry Hill	Wilmington	15:00-16:00	59.4	59.4	59.4	59.4
Cherry Hill	Wilmington	16:00-17:00	50.6	48.0	47.9	47.9
Cherry Hill	Wilmington	17:00-18:00	47.9	48.4	48.8	48.1
Cherry Hill	Wilmington	18:00-19:00	47.9	48.5	47.7	47.7
Cherry Hill	Wilmington	19:00-20:00	47.9	47.6	47.5	47.5
Cherry Hill	King of Prussia	15:00-	52.7	53.5	57.9	57.9

		16:00				
Cherry Hill	King of Prussia	16:00-17:00	50.0	50.0	51.7	53.6
Cherry Hill	King of Prussia	17:00-18:00	52.5	52.2	52.8	48.6
Cherry Hill	King of Prussia	18:00-19:00	50.9	52.2	48.7	48.6
Cherry Hill	King of Prussia	19:00-20:00	50.8	47.5	48.0	46.0
Cherry Hill	Philadelphia Downtown	15:00-16:00	27.2	27.2	27.2	27.2
Cherry Hill	Philadelphia Downtown	16:00-17:00	24.1	23.1	26.3	27.3
Cherry Hill	Philadelphia Downtown	17:00-18:00	26.3	25.2	26.3	24.7
Cherry Hill	Philadelphia Downtown	18:00-19:00	25.5	25.2	23.5	25.3
Cherry Hill	Philadelphia Downtown	19:00-20:00	26.0	22.5	23.2	21.7
King of Prussia	Trenton	15:00-16:00	62.5	62.5	62.5	62.5
King of Prussia	Trenton	16:00-17:00	62.5	62.5	62.5	62.5
King of Prussia	Trenton	17:00-18:00	62.5	62.5	62.5	62.5
King of Prussia	Trenton	18:00-19:00	62.5	62.5	55.2	62.5
King of Prussia	Trenton	19:00-20:00	62.4	62.4	55.1	55.1
King of Prussia	Monroe Township	15:00-16:00	58.2	58.2	58.2	58.2
King of Prussia	Monroe Township	16:00-17:00	58.2	58.2	58.2	58.2
King of Prussia	Monroe Township	17:00-18:00	58.2	61.0	61.0	60.7
King of Prussia	Monroe Township	18:00-19:00	57.4	50.8	57.4	54.4
King of Prussia	Monroe Township	19:00-20:00	57.4	50.7	60.9	50.0
King of Prussia	University of Pennsylvania	15:00-16:00	35.8	35.8	35.8	35.8
King of Prussia	University of Pennsylvania	16:00-17:00	35.8	35.8	35.8	35.8
King of Prussia	University of Pennsylvania	17:00-18:00	35.8	35.8	35.8	25.4
King of Prussia	University of Pennsylvania	18:00-19:00	35.8	26.0	35.8	26.0
King of Prussia	University of Pennsylvania	19:00-20:00	35.8	26.0	35.8	25.4
King of Prussia	Wilmington	15:00-16:00	40.0	40.8	40.8	40.8
King of Prussia	Wilmington	16:00-17:00	40.0	40.0	40.0	40.0
King of Prussia	Wilmington	17:00-18:00	40.0	40.0	40.0	40.0
King of Prussia	Wilmington	18:00-19:00	40.8	40.0	40.0	40.0
King of Prussia	Wilmington	19:00-20:00	40.4	40.4	40.4	40.0
King of Prussia	Cherry Hill	15:00-16:00	54.1	54.1	54.1	54.1
King of Prussia	Cherry Hill	16:00-17:00	54.1	54.1	54.1	54.1
King of Prussia	Cherry Hill	17:00-18:00	54.1	54.1	54.1	53.8
King of Prussia	Cherry Hill	18:00-19:00	54.1	49.0	53.5	47.3
King of Prussia	Cherry Hill	19:00-20:00	54.1	49.3	53.2	45.4
King of Prussia	Philadelphia Downtown	15:00-16:00	36.1	36.1	36.1	36.1
King of Prussia	Philadelphia	16:00-	36.6	36.1	36.1	36.1

	Downtown	17:00				
King of Prussia	Philadelphia Downtown	17:00-18:00	36.1	36.6	36.1	36.8
King of Prussia	Philadelphia Downtown	18:00-19:00	36.1	29.5	36.1	30.4
King of Prussia	Philadelphia Downtown	19:00-20:00	36.1	29.5	36.1	28.6
Philadelphia downtown	Trenton	15:00-16:00	34.3	58.6	34.3	58.6
Philadelphia downtown	Trenton	16:00-17:00	35.4	52.2	35.0	50.2
Philadelphia downtown	Trenton	17:00-18:00	34.3	53.7	35.0	49.3
Philadelphia downtown	Trenton	18:00-19:00	34.3	53.6	34.3	49.5
Philadelphia downtown	Trenton	19:00-20:00	34.3	51.1	34.3	45.0
Philadelphia downtown	Monroe Township	15:00-16:00	26.8	26.8	26.8	24.4
Philadelphia downtown	Monroe Township	16:00-17:00	26.8	25.2	26.8	25.2
Philadelphia downtown	Monroe Township	17:00-18:00	21.9	24.6	21.9	21.9
Philadelphia downtown	Monroe Township	18:00-19:00	22.1	22.1	21.9	22.1
Philadelphia downtown	Monroe Township	19:00-20:00	21.9	21.9	21.9	21.9
Philadelphia downtown	University of Pennsylvania	15:00-16:00	4.3	4.3	4.3	4.3
Philadelphia downtown	University of Pennsylvania	16:00-17:00	4.4	4.3	4.3	4.3
Philadelphia downtown	University of Pennsylvania	17:00-18:00	4.4	4.4	4.4	4.3
Philadelphia downtown	University of Pennsylvania	18:00-19:00	4.4	4.4	4.4	4.4
Philadelphia downtown	University of Pennsylvania	19:00-20:00	4.3	4.4	4.3	4.3
Philadelphia downtown	Wilmington	15:00-16:00	36.6	36.6	36.6	36.6
Philadelphia downtown	Wilmington	16:00-17:00	36.6	36.6	36.6	36.6
Philadelphia downtown	Wilmington	17:00-18:00	32.7	33.5	32.7	36.6
Philadelphia downtown	Wilmington	18:00-19:00	32.7	32.7	32.7	32.8
Philadelphia downtown	Wilmington	19:00-20:00	32.7	32.7	32.7	32.7
Philadelphia downtown	Cherry Hill	15:00-16:00	22.7	22.7	22.7	20.3
Philadelphia downtown	Cherry Hill	16:00-17:00	22.7	21.2	22.7	21.2
Philadelphia downtown	Cherry Hill	17:00-18:00	20.9	20.5	20.6	20.3
Philadelphia downtown	Cherry Hill	18:00-19:00	22.7	21.5	22.0	20.1
Philadelphia downtown	Cherry Hill	19:00-20:00	20.3	22.6	21.8	19.0
Philadelphia downtown	King of Prussia	15:00-16:00	27.4	28.3	27.4	33.7
Philadelphia downtown	King of Prussia	16:00-17:00	28.2	28.2	26.4	28.2
Philadelphia downtown	King of Prussia	17:00-18:00	28.3	28.3	28.7	27.0
Philadelphia downtown	King of Prussia	18:00-19:00	27.4	29.5	26.9	26.4
Philadelphia downtown	King of Prussia	19:00-20:00	27.1	27.6	27.1	26.4

Appendix C. User manual of the web application

In this section, we present users how to use the web application, report incidents and view DMS messages. As shown in Figure 30, the interface of our web application consists of three components: animation control bar, left control panel and map. Map component display the current traffic conditions on networks. The left control panel contains the estimation accuracy of current interval and information about link capacity updates. Left panel can also be used to change the color threshold of the map visualization. The animation control panel allows users to visualize the dynamic network flow evolution in next one hour.

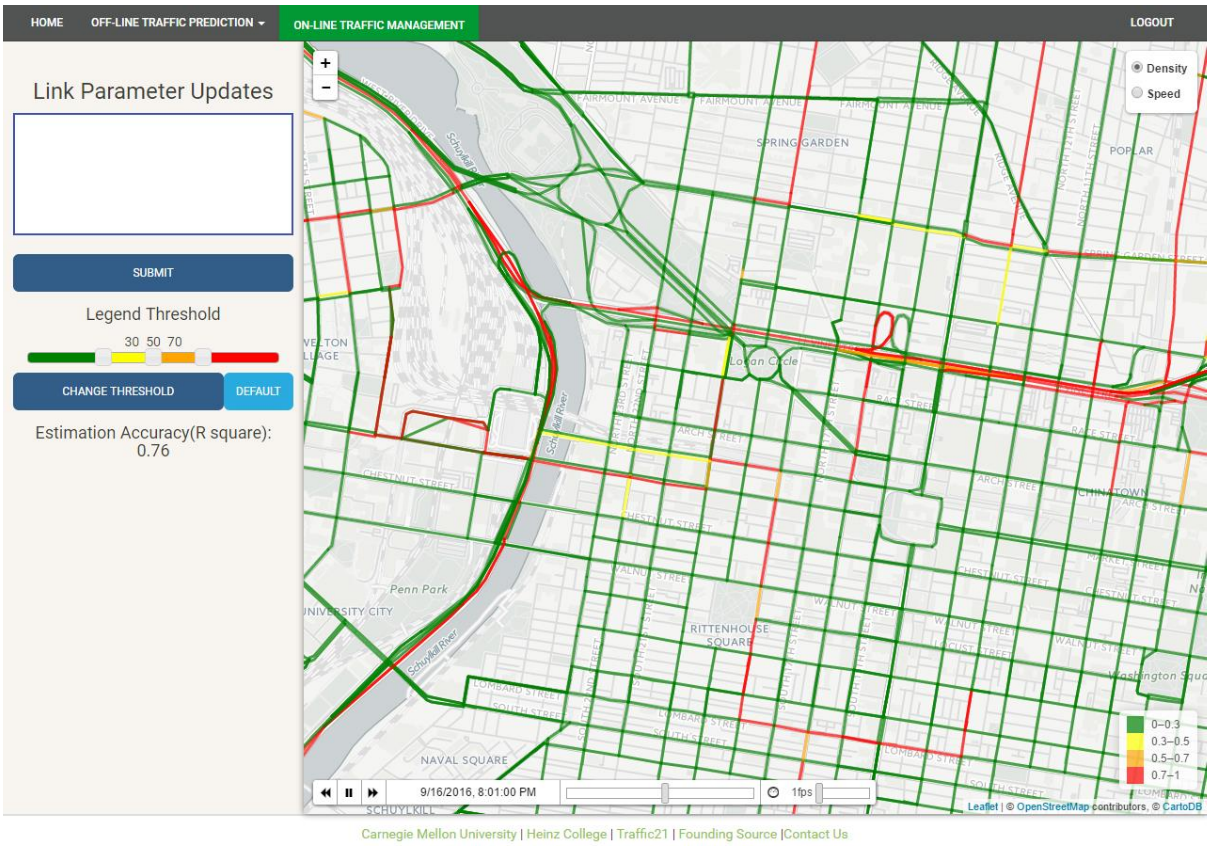

Figure 30 Overview of the web interface

C.1 Basic operation

Basic operations on the web interface include zoom in/out the map, adjust the legend threshold. Zoom in/out functions are used to help users to visualize the road networks in different detail level. By adjusting the legend threshold, users can customize the color of the map display.

C.2 Animation

The animation control bar located at the bottom of web interface is used to control the animation of traffic flow prediction. Users can view the animation and change the speed of the animation by adjusting fps. They can also pause the animation, jump forward/backward at any time during the animation. Users can also directly change the animation time by clicking at any position of the time bar.

C.3 Incident report

Users can view the road segment information by clicking that link on the map. A popup will appear with the information about this link, as shown in Figure 31. Some basic information about that link will be displayed on the popup, such as free flow speed, number of lanes and road length.

A slider representing capacity drop also lies on the bottom of the popup. When users report the capacity drop, updates will be shown in the text box on the left-side panel. When finish reporting, users can press submit button and the reported capacity drops will be taken into account for the next round of iteration.

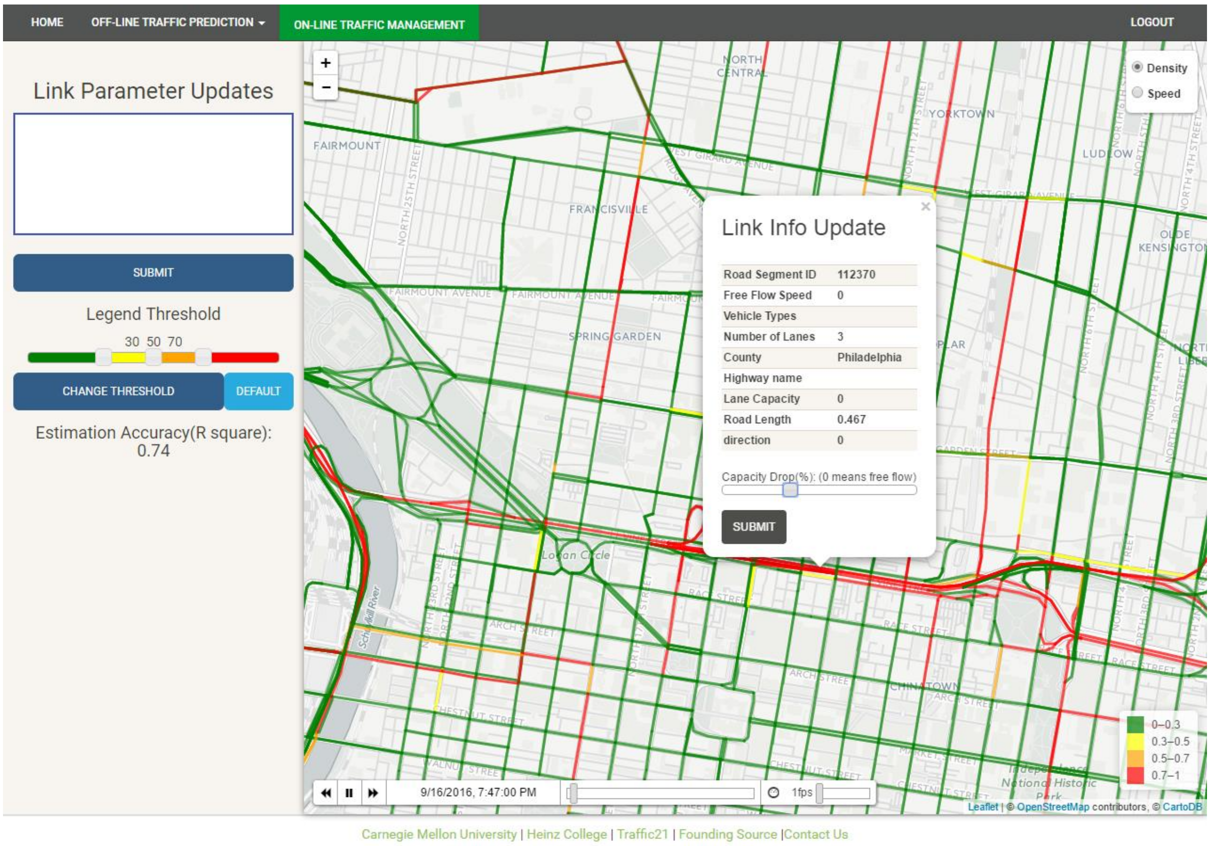

Figure 31 Link property and incident report

After users finish the link capacity drop report, the updated information will be displayed on the top of left panel, as shown in Figure 32.

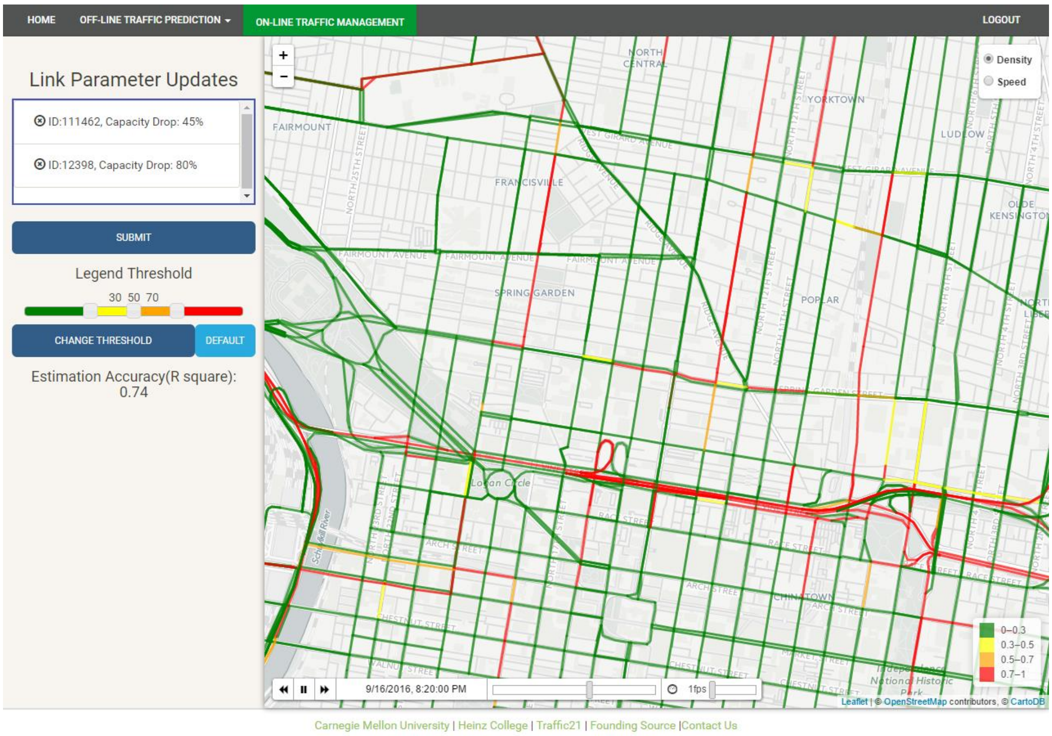

Figure 32 Example of link parameter updates

C.4 Density/Speed switch

Users can also switch to view the predicted traffic conditions based on road averaged speeds by clicking the “speed” icon on the top-right of the web interface. The color of the roads on map will be displayed based on its average speed, as shown in Figure 33. Also the legend threshold bar can be used to customize the speed/color mapping.

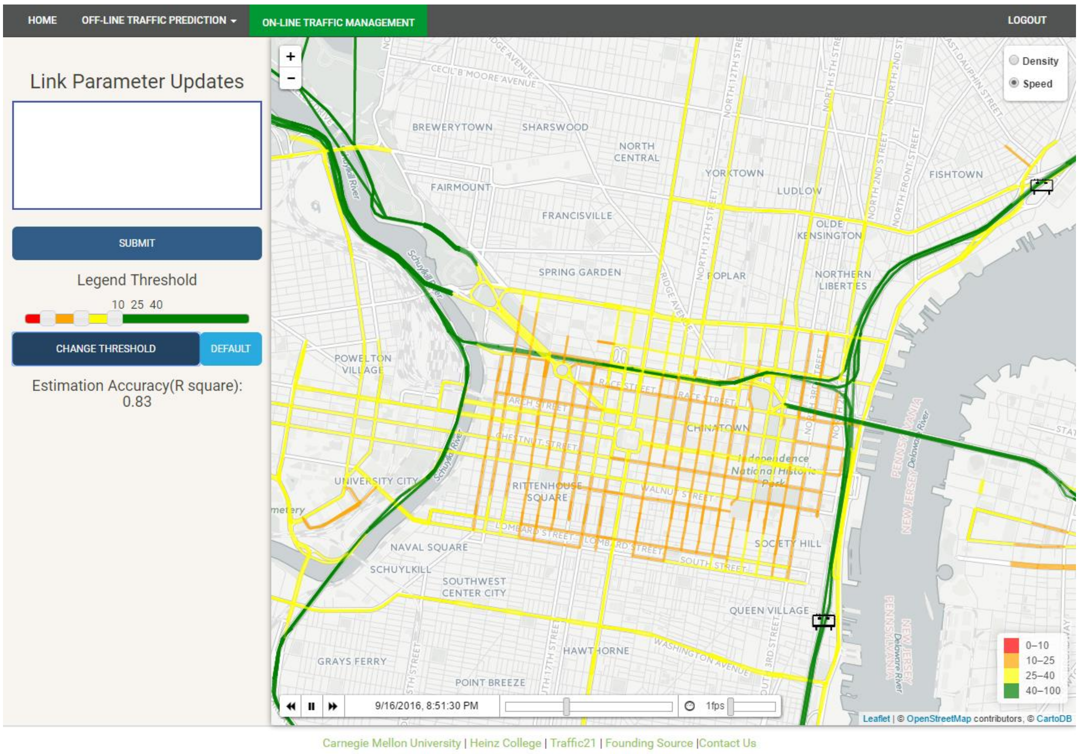

Figure 33 Road speed of predicted traffic

C.5 DMS message

DMS is displayed as a message board icon on the map. Users can also view the information by simply clicking the DMS icon on the map. A popup will appear contain the information of DMS including its name, direction and brief description. The suggested DMS messages are also displayed on the popup, as showed in Figure 34.

We also provide an API for users to retrieve the generated DMS message data. The data is formatted in JSON, and the website of API is:

http://bruno.heinz.cmu.edu/traffic/get_real_time_VMS/

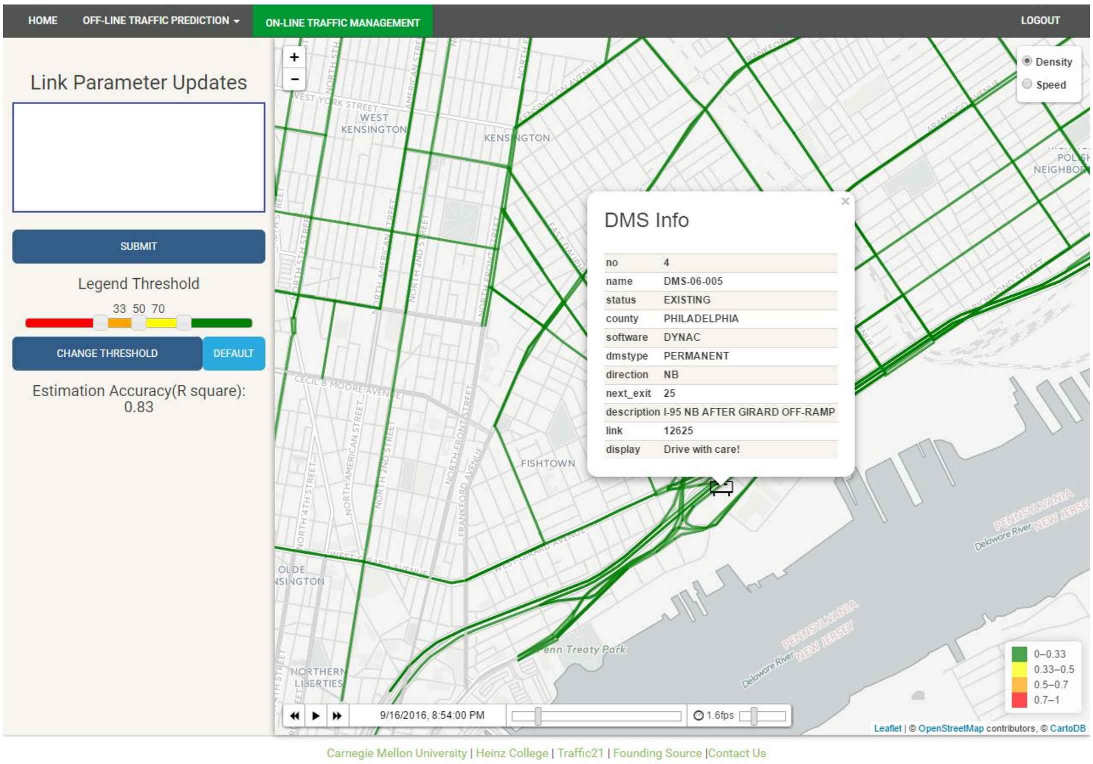

Figure 34 Example of DMS popup