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CONNECTED CITIES WITH SMART TRANSPORTATION
A USDOT University Transportation Center

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Integrative Vehicle Infrastructure Traffic System (iVITS) Control in Connected Cities

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Camille Kamga
City College of New York
ORC-ID 0000-0002-9223-700X

Sandeep Mudigonda
University Transportation Research Center
0000-0003-1734-673X

Rodrigue Tchamna
University Transportation Research Center
0000-0001-8205-988X

Bahman Moghimi
City College of New York
0000-0003-4129-1388

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Acknowledgements

Executive Summary

With the rapid rise in smartphones and GPS-enabled devices, vehicles are becoming increasingly connected. Some newly manufactured vehicles are equipped with devices that provide information about vehicle characteristics such as speed and acceleration, and aftermarket devices also share vehicle data. This information in addition to that provided by road infrastructure, such as traffic signal status, weather and road conditions can be shared between connected vehicles (CVs) to enhance mobility, safety, and environmental impact.

The information exchange between one or more vehicles and between vehicles and infrastructure is enabled through applications whose efficacy can be evaluated in simulation environments, representing real traffic scenarios.

One of the key efforts in the CV domain is the ongoing, U.S. Department of Transportation sponsored New York City Connected Vehicle Pilot (NYC CVP). As a part of this pilot, 2000 vehicles operated by NYC government are equipped with DSRC aftermarket devices on vehicles being operated. Infrastructure to vehicle communication is enabled by installing devices on 250 signals and the highway of Franklin D Roosevelt (FDR) Drive.

To evaluate these device applications on user mobility and safety, this project developed a calibrated model of FDR. Calibration was performed using procedure elaborated in the Federal Highway Authority’s Traffic Analysis Toolkit using several different datasets such as traffic counts, travel time and traffic incidents from different sources.

As the NYC CVP starts delivering data, the calibrated simulation model will be utilized to test different scenarios such as varying demand, traffic incidents, and levels of market adoption of CV technology,. will be evaluated for different applications of the pilot.

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Section 1: Introduction

Connected vehicle (CV) technology is becoming more commonplace with each passing year. Information such as location, speed, brake status of neighboring vehicles, traffic signal phasing and timing, congestion, traffic incidents, inclement weather, special events can be shared with drivers and provide benefit in terms of better safety, more efficient mobility,, harmonized traffic flow and lower vehicular emissions. This is especially significant in urban arterials by providing CVs information on traffic signal timings resulting in smoother acceleration and deceleration and reducing spot speeding.

CV technology can be realized through different means of communication such as cellular, WiFi, and Direct Short-Range Communication (DSRC). The U.S. Department of Transportation (USDOT) has been exploring the benefits of DSRC for CV. To understand the benefits and challenges of CV technology, the USDOT has invested in three pilots for DSRC deployment (1). The New York City Connected Vehicle (NYC CV) pilot is one such pilot. The NYC CV pilot involves installation of DSRC equipment on 2,000 vehicles, at 250 intersections and along a highway – the Franklin D Roosevelt (FDR) Drive (2). The impact of CV technology in the pilot will be evaluated as the demonstration begins and CV message and other corresponding traffic data are analyzed. However, the data analysis does not consider several scenarios, account for increase in market penetration of technology and robust predictions. Hence, a simulation testbed for the CV technology will be ideal to test scenarios and estimate future impact of CV technology.

In this project, the research team developed a simulation-based approach for the evaluation of CV applications and traffic control algorithms that will utilize CV technologies. The proposed project will tie into the objectives of the NYC CV pilot deployment program.

In this report, the methodology and model preparation, data assembled and analyzed and calibration plan for the FDR model are described.

Section 2: CV Modeling Methodology

Connected vehicle modeling involves simulation of several layers such as mobility layer, physical layer, medium access control (MAC) layer and application layer (3). Among these layers, the physical, MAC and application layers for the communication modeling for which there are several tools such as NS3 (4), NCTUns (5), iTETRIS (6), and OMNet++(7). For modeling the mobility layer there are several traffic simulation packages both commercial (VISSIM (8), PARAMICS (9), AIMSUN(10)) and open source (SUMO (11), MATSIM(12)). It is important to choose the optimal tools for CV modeling to balance modeling accuracy as well as ease of modeling various scenarios.

In addition to using the right modeling tool, CV technology modeling also needs extensive data for calibration of the mobility layer and modeling communications. To calibrate the mobility layer, several sources of data such as traffic volumes, turn counts, speeds, vehicle composition, travel time, traffic signal timings and pedestrian crossings data are used. Data such as the location of roadside equipment (RSE), location of traffic signals, CV message and transmission rates and standards are required. The data used in this study, data processing and checks are described in the subsequent sections.

Subsection 1.1: Vehicular Modeling Tool Section

Each of the vehicular traffic simulation tools listed above provide a detailed framework to model different types of vehicle and roadway geometries, in addition to accurate traffic flow modeling. Commercial traffic simulation software can technically be connected to communication modeling software, albeit with a need to wrap the vehicular traffic output to match the input needs of communication modeling tools.

In this study, due to the advantages mentioned in the earlier section, Simulation of Urban Mobility (SUMO) was chosen as the modeling tool. SUMO can model each vehicle and pedestrian in a study area, and infrastructure such as traffic signals and CV roadside units. Furthermore, additional modules in SUMO help model network communications.

SUMO provides the readymade ability to combine the mobility layer with abstraction of communication modeling through a package called Veins. Veins connects OMNet++ to vehicular traces in SUMO. Furthermore, the open source nature of the software helps in reusing and extending the modeling framework in this study by other researchers in future.

SUMO provides the flexibility to build road network model with the ability to accept Open Street Map (OSM) files. The geometry information such as number of lanes, shape of links, speed limit, etc. embedded in OSM are imported into SUMO.

Section 3: Modeling Process Outline

To accurately capture the movement of vehicles in microscopic simulation, the modeling building process can broadly be categorized into four steps:

1. Data collection
2. Model development & refinement
3. Metrics from Data & Model Outputs
4. Calibration

The sub-steps involved in building the FDR model are included in Figure 1. To obtain an accepted level of accuracy of outputs, steps 2 through 4 are performed iteratively. Detailed description of each of the steps is presented in each of the below sections in this report.

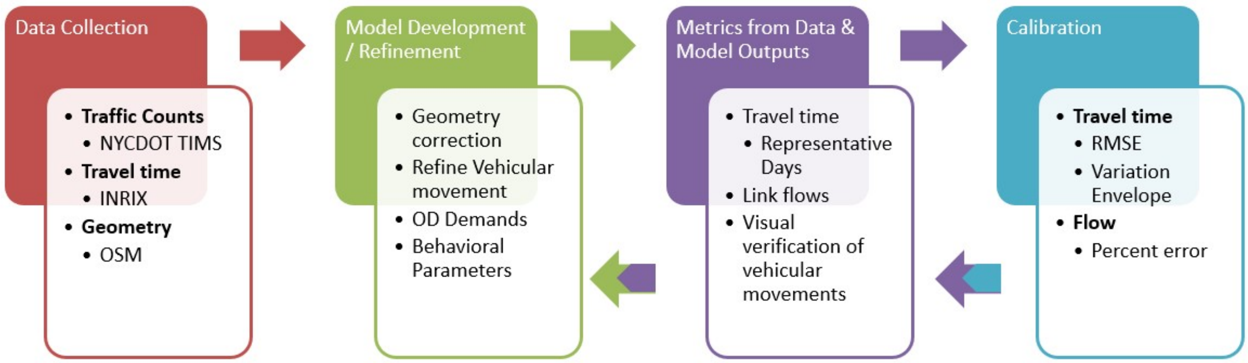
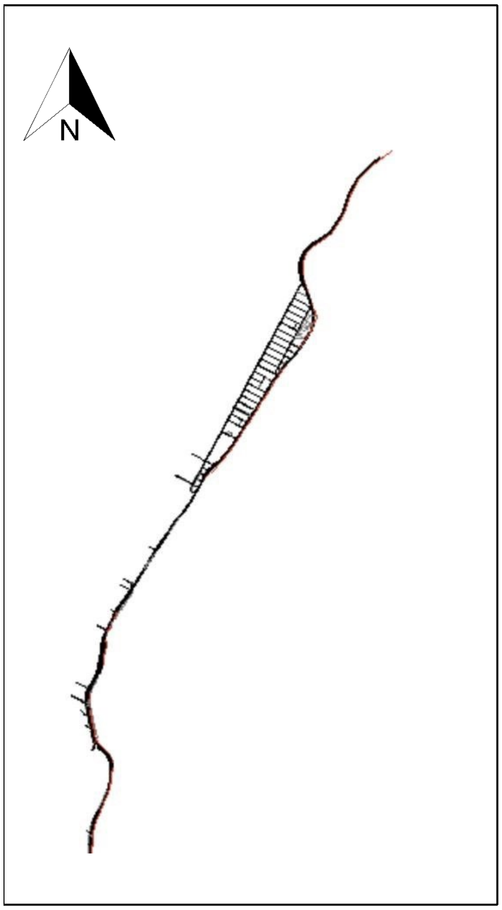


Figure 1 Simulation Model Building Workflow

Section 4: Data Collection

The three aspects of data collection for the development of microscopic simulation models of FDR Drive in SUMO are discussed in this section.

Subsection 4.1: Model Geometry



The network that is modeled as a part of this project includes a 4-mile section of FDR from 28th - 96th streets in both the northbound (NB) & southbound (SB) directions and few adjacent streets. This section includes 9 exits.

The network geometry for the stretch of FDR was imported from OSM to create the basic skeleton of the network. The skeleton network was further refined by checking for consistencies such as speed limit, turning movements, and lane configuration.

Subsection 4.2: Data Availability

To prepare a calibrated simulation model of an uninterrupted highway, the following data need to be collected:

- Counts at different locations: used to generate the origin-destination demand
- Travel time along different links / sections: used to calibrate the simulation model
- Incident data: used to identify representative days for modeling

The data assembled from different sources, extent of availability and important notes can be seen in Table 1.

Source	Data	Start	End	Description
TIMS	Automatic Traffic Recorder (ATR)	Multiple days during 2012 – 2018. Available for: • 4/9 SB sections • 4/6 NB sections		Mid-section traffic counts of every 15 minutes, without vehicle classification. Availability different for different links, typically 10 days in total, including weekdays and weekends.
TIMS	Turning movement counts (TMC)	1-2 days for 4 Intersections on York Ave & 1st Ave to estimate ramp volumes to/from FDR		Turning movement counts every 15 minutes, without vehicles classification. 1-2 weekday available
NYCDOT	Counts	1-2 days during 2014 – 2015. 30 records for 14 locations		Midsection counts every 60 minutes, with vehicle classification. Data availability may be different for different intersections, 1 to 2 days in

				total, including weekdays and weekends.
INRIX	Travel time	10/1/2014	11/30/2014	Segment travel time averaged to every 5 minutes. NB and SB direction.
Videos	NYCDOT Cameras	4/29/2019	5/9/2019	Video recordings at three locations on FDR. 6-10 AM 4-5 weekdays, typically, for NB & SB.
Geometry	Open Street Maps (OSM)	-	-	OSM import module in SUMO

Table 1 Summary of Data Accessed for FDR Calibration

Subsection 4.3: Data Processing

The data shown in Table 1 was processed and analyzed for consistency. The results of these consistency checks are presented in this section

The ATR counts available for different sections of the FDR and number of days of data (over 2012-2017) are shown in Table 2.

Cross Street	NB/SB	NB data sets	SB data sets	Days
110	SB			
96	NB/SB			
90	NB/SB	1		9
79	SB			

72	SB		1	9
63	SB			
62	NB/SB	7		100*
48	NB	1		9
42	SB		8	109 #
38	SB			
36	SB			
34	NB/SB	7		75
30	SB		2	30
28-26	SB		1	9
23	NB/SB		3	21

Table 2: ATR Count for different sections of FDR

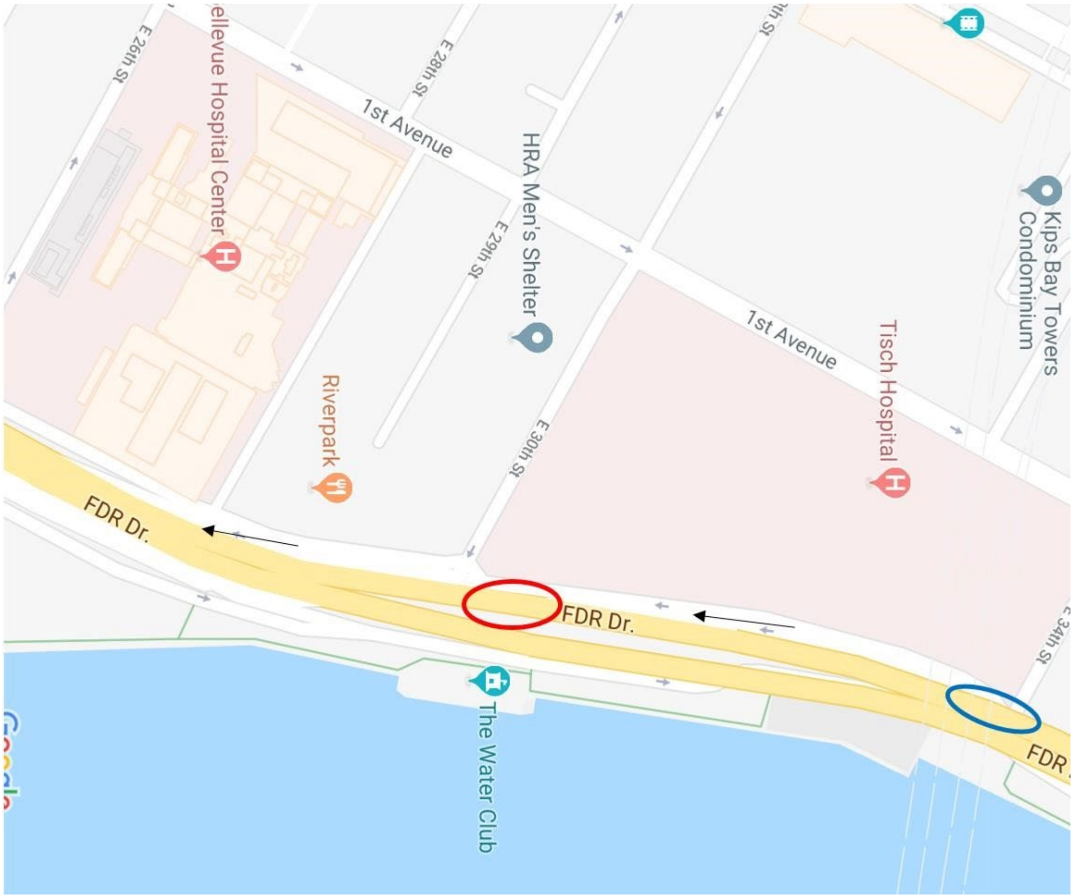
**18+18+14+16+16 days each year 2012-2017 from 60th to 61st and 9 from 57th to Sutton Square and 9 from 56th to 57th*

#18+18+14+16+16 each year 2012-2017 from 61st to 60sth and 9 from Sutton Square to 57th and 9 from 56th to 57th and 9 from 48th to 42nd

As can be seen from Table 2, there are some sections which do not have any data available. Although, there are some sections with several hours of data, there is no single day or year for which data is available for all sections.

One method to check consistency of ATR counts is by comparing flow between two entry/exit ramps. Even among sections with data available, there is only one pair of adjacent sections (downstream and upstream on a ramp) for which data is available for the same period. This location is shown in Figure 1. Counts are available before and after an entry ramp at 30th St. Flow downstream of the entry ramp must always be higher than flow in the upstream location. However, Figure 1 shows several time periods where the upstream flow is higher than downstream flow. This pattern was also seen among several other days, which has resulted in not using ATR count data for calibration.

The New York Best Practice Model (NYBPM) output also provides an estimate of volumes of major roadways in New York City. However, these volumes are aggregated for four hours of the AM peak period and are not available for all sections of the FDR due to the aggregation of links. In addition, the BPM data also suffers from flow inconsistencies at a few links.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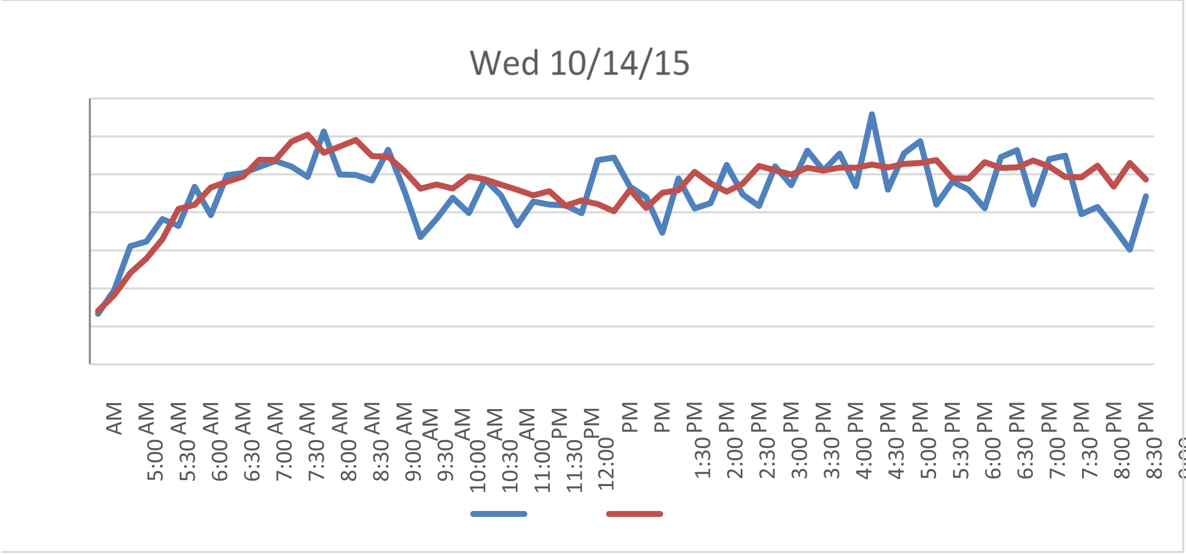
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Figure 2 Example Consistency check of ATR counts

The NYCDOT counts from NYC Open Data are used for generating the OD matrix. These counts do not show the inconsistency shown in Figure 1.

Travel time data for different links on the FDR in the NB and SB directions is available from January-June 2017. Since, travel time data is available for a much longer and continuous duration than volume data, travel time data is used to identify representative days. In addition, the traffic crash data available through NYC Open Data (13) is also used to assess outliers and identify clusters in the travel time data.

Section 5: Model Development and Refinement

Subsection 5.1: Geometry and Vehicular Movement Corrections

Microscopic simulation model geometry inputs include number of lanes, street curvature, speed limit, and traffic control at intersections. Though geometry is ingested through OSM, not all the imported data is accurate. Hence, each link was verified for speed limit and number of lanes and appropriate corrections were made.

Simulation in SUMO was then run using a dummy demand to check vehicular movement and traffic flow to ensure that movement of vehicles is reasonable at different parts of the model such as at highway ramps and intersections.

Subsection 5.2: OD Demand

Simulation was performed in SUMO for three hours from 6 AM to 9 AM. The first hour was considered as simulation warmup; thus, final SUMO simulation output is for two hours from 7 AM to 9 AM. The NYCDOT midsection counts were used to generate the base OD matrix for the time period. This base matrix is not calibrated but used as a starting point.

Table 3 below shows a sample of the OD matrix of the FDR in the southbound direction generated for every 15 minutes. Entry streets/ramps are: 92nd, 78th, 73rd, 61st, and 38th. Also, exit streets/ramps are: 73rd, 63rd, 53rd, 59th, 42nd, 33rd. In the calibration process, the entry of each OD pairs was changed at every 15 min time interval in order to reach the lowest possible error between the simulated and observed OD volume The travel time of some segments of the corridor were also checked to better improve the macroscopic calibration process.

Sources/Sinks	73rd	63rd	53rd	49th	33rd	S. End
N. End	250	27	147	0	122	651
92nd	318	0	0	0	0	0
78th	10	0	0	0	0	0
71st	0	0	0	0	0	0
61st	0	0	0	0	97	0
38th	0	0	0	0	97	0

Table 3: Base OD matrix for FDR Southbound for one period 7:00-7:15 AM

Subsection 5.3: Model Parameters

Microscopic simulation software models each individual vehicle's movement. Hence, there are several parameters that can be modified and tweaked to replicate observed output metrics. SUMO has many of such parameters that can modify user behavior for the network as a whole or at specific locations and geometries.

The global parameters in SUMO influence the car following and lane changing behavior of vehicles. Though there are several other parameters in SUMO based on the kind of car following model adopted, for this study the default, Krauß car following model (14) is used. Some of the parameters controlling the Krauß car following behavior are:

- minGap – minimum gap when speed = 0
- sigma – driver imperfection
- tau – desired time headway

Some of these parameters are tweaked in the calibration step to generate observed output. Additional information on model calibration parameters used is presented in the next section.

Section 6: Calibration Plan using Metrics from Observed Data & Model Output

Simulation models can generally be expressed as mathematical models that can generate an output given a particular input. The input consists of two main groups of data: physical data (e.g., volume counts, capacity, and physical features of roadway sections) and calibration parameters (i.e., adjustable components of driver behavior). Thus, a simulation system (S_s) can be described generally as: (15)

$$S_C: f(I_s, C_s) \rightarrow [simulation\ model] \rightarrow O_{sim} | \, I_s, C_s + \varepsilon: O_{obs}$$

$f(I_s, C_s)$ = functional specification of the internal models in a simulation system

I_s = physical input data observed in the field (origin-destination demand, geometric design, operational rules, etc.),

C_s = set of calibration parameters for a simulation system

(user- and traffic-related parameters), and

O_{sim} = simulation output data given the input data and calibrations,

ε = acceptable margin of error between simulation output and observed field data

O_{obs} = observed field data.

The process of calibration entails adjusting the calibration parameters (C_s) so that the error between the output from simulation and field conditions is minimized,

$$\min_{C_s} U(O_{obs}, O_{sim}(I_s, C_s))$$

where,

O_{obs}, O_{sim} - observed and simulated outputs at location i

C_s - parameter set for time period $t$and iteration k

U - error functions for outputs

Several studies have presented various methods of calibrating microsimulation models with several types and sizes of traffic networks.

Toledo et al. (16) modeled a part of the three-highway network of Stockholm. The authors used traffic count data obtained from loop detectors for five weekdays for calibration of the microsimulation model. Balakrishna et al. (17) used microsimulation to model a fairly large-scale highway network in New York state. Calibration was performed using 15-min count data from 33 detector stations. Lee and Ozbay (18) used microsimulation for stochastic calibration using 5-minute counts from 16 AM peak days. Mudigonda and Ozbay (19) introduced a method of capturing variability in traffic through simulation using several weeks of traffic count data from the New Jersey Turnpike. 30-mintes of NGSIM data was also used by Henclewood et al. (20) to model the Peachtree Street in Atlanta, Georgia in microsimulation to generate travel time distribution. Similarly, Punzo et al. (21) used NGSIM data from I-180 data to identify and calibrate significant parameters in VISSIM simulation. Ozbay et al (15) identify several aspects of calibrating microsimulation models and how Big Data can be used to capture stochasticity via microsimulation.

It is evident that many sources of data, as model inputs, calibration parameters and observed outputs, are required in traffic simulation modeling and calibration. Federal Highway Administration (FHWA)'s Traffic Analysis Toolbox (22) recommends a calibration procedure that was utilized in this study. This broadly includes the following phases:

1. Identify Representative Days
2. Metric Generation
3. Prepare Variation Envelopes (for each Travel Condition)
4. Calibrate Model Within Acceptability Criteria
5. Implementation of each of these phases for calibrating the FDR model is described below.

Subsection 6.1: Representative Day Identification

The identification of representative days was performed following steps:

Step 1: Identify Key Attributes: This step is used to describe the travel conditions experienced at the site. For this research, travel time is used as a metric. Travel time converted to average link speed is used to identify different conditions as travel time data that is available over several days during 7-10 AM.

Step 2: Process Data: The travel time data from October-November 2014-15 is used for travel time. Traffic crash data for the FDR is also obtained for the days for which travel time is available. The travel time data from holidays and incident days is removed from the analysis.

Step 3: Normalize Data: The travel time data has been processed to aggregate INRIX links into links that are similar in length. In addition, the analysis for clustering (Step 5) is performed using average speed rather than travel time so the measure of congestion is consistent across all links.

Step 4: Down Select Attributes: Since travel time is the only type of data available for a large span of time, travel time is the attribute chosen. In addition, travel time - in other words, average speed - can provide a good measure for congestion.

Step 5: Perform Clustering: K-Means clustering algorithm is being performed over average speed calculated using travel time observations from INRIX. An example illustration of clusters for one southbound link on the FDR is shown in Figure 3.

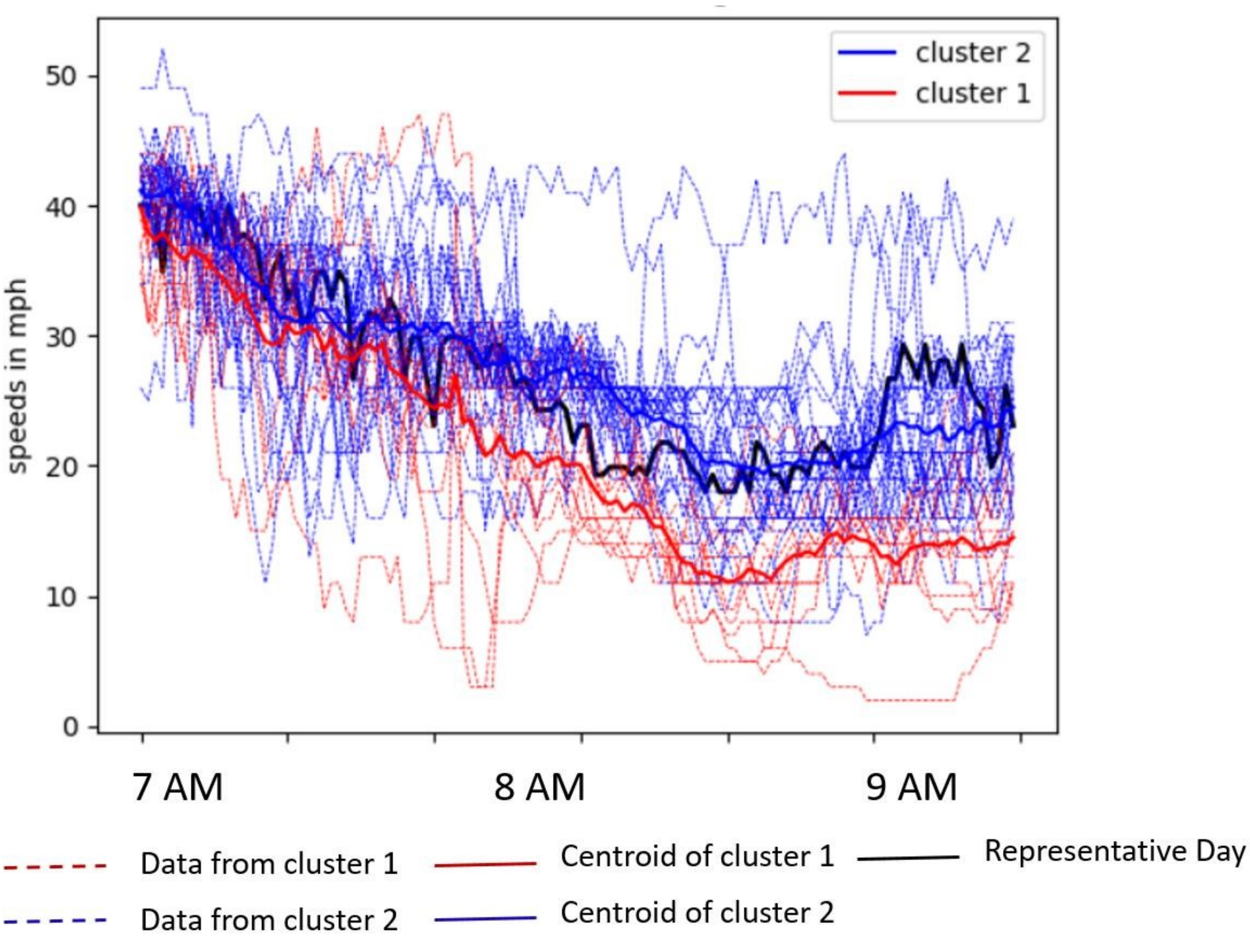


Figure 3: Illustration of Clustering of Link Average Speed, Centroids and Representative Day

The counts data used for OD matrix generation does not have corresponding travel time. For such a day, following the procedure mentioned in (22) the root mean squared error for each 15-minute time period between day with count availability and cluster centroids is performed to associate the 'representative day' with the corresponding average speed cluster.

Furthermore, the 'representative day' is checked to verify whether there are any incidents, as in this study the calibration is being performed for a 'normal' day without traffic incidents.

The travel time data we used spanned from October to November 2014, for each 15-minute time interval from 6 AM to 11:45 AM. From this dataset, only weekday data were selected for the analysis. Days where the travel time for at least four consecutive time-periods were outside the 2-sigma band were considered outliers days and removed from the data.

Subsection 6.2: Algorithm for Representative day Identification

For a given time period, let T_p be the travel time of a particular day. In order to find the representative day in a cluster, the following algorithm is executed:

1. Find the average travel time, $(T_p)_{av}$, of all the days in the cluster.
$$(T_p)_{av} = average(T_p)$$
2. Calculate (δ_p) , the difference between each individual day travel time, (T_p), and the average travel time $(T_p)_{av}$, and expressed as a percentage of the average travel time.
$$\delta_p = \frac{|T_p - (T_p)_{av}|}{(T_p)_{av}} \times 100$$
3. For a given day, calculate $(\delta_p)_{av}$, the average of δ_p for all the time periods.
4. The representative day of the cluster is the day for which $(\delta_p)_{av}$ is the minimum.

Using the above algorithm, we found that, when using 24 time-periods from 6:00 AM to 11:45AM, the representative day for 42nd-49st was October 16, 2014, the representative day for 63rd and61st street was October 8, 2014, and that of 79th street was October 17, 2014. When using only four time-periods from 7:15 AM to 8:00AM, the representative day for 42nd-49st was October 9, 2014, the representative day for 63rd and 61st street was October 17, 2014, and that of 79th street was November 4, 2014. The average travel time, $(T_p)_{av}$, of all the days for 42nd-49th street is shown in Table 4, while Table 5 shows δ_p, the difference between each day travel time T_p, and the average travel time $(T_p)_{av}$. These tables show selected days for the sake of presentation.

Time	2014-10-02	2014-10-07	2014-10-15	**2014-10-16**	2014-11-13	2014-11-18	2014-11-25	**Average**
6:00	41.24	43.71	47.1	**28.94**	27.28	35.21	37.58	**37.15**
6:15	40.06	47.11	46.75	**44.52**	41.83	40.83	37.63	**40.96**
6:30	50.28	42.84	45.31	**46.78**	41.15	43.31	52.71	**43.59**
6:45	44.6	44.15	40.46	**33.23**	28.06	54.25	44.85	**43.92**
7:00	50.6	47.62	46.63	**50.17**	47.51	45.92	47.06	**45.14**
7:15	53.32	52.28	31.13	**50.24**	54.44	53.54	32.63	**45.23**
7:30	54.59	54.03	75.83	**48.54**	49.66	45.99	76.06	**53.71**
7:45	56.62	49.17	51.2	**49.26**	54.53	50.88	50.83	**49.31**
8:00	64.67	54.73	47.8	**54.45**	54.18	49.99	58.11	**51.77**
8:15	37.67	57.76	83.55	**53.62**	71.77	93.78	89.65	**60.79**
8:30	49.7	54.29	49.51	**49.93**	51.9	77.23	84.48	**58.85**

8:45	53.54	47.63	47.48	**52.54**	51.81	53.13	68.14	**53.83**
9:00	54.73	51.81	67.49	**54.01**	55.51	50.07	52.83	**51.63**
9:15	55.89	52.35	50.31	**64.01**	64.6	51.85	54.35	**51.83**
9:30	58.33	49.3	46.59	**51.32**	53.1	52.71	49.72	**50.20**
9:45	37.34	44.5	60.68	**54.69**	52.75	59.56	41.74	**49.89**
10:00	39.34	38.72	52.56	**57.57**	48.4	51.14	48.98	**47.44**
10:15	37.63	35.62	41.8	**57.56**	65.59	60.5	46.27	**50.77**
10:30	38.92	28.37	39.57	**47.55**	42.07	186.07	93.53	**54.93**
10:45	46.57	40	46.76	**51.33**	41.37	97.95	42.39	**49.52**
11:00	38.92	45.3	28.52	**39.54**	41.14	63.38	42.58	**43.47**
11:15	43.53	40.23	48.64	**49.17**	45.92	185.98	41.74	**52.94**
11:30	41.66	38.24	42.97	**47.71**	49.29	75.89	52.71	**45.88**
11:45	48.72	42.75	51.73	**44.82**	40.59	42.41	47.21	**48.61**

Table 4: Average travel time, (Tp)av , of all the weekdays, for 42nd-49 street

Time	2014-10-02	2014-10-07	2014-10-15	2014-10-16	2014-11-13	2014-11-18	2014-11-25
6:00	11.00	17.64	26.77	**22.11**	26.58	5.23	1.14
6:15	2.19	15.03	14.15	**8.70**	2.14	0.31	8.12
6:30	15.34	1.72	3.94	**7.31**	5.60	0.65	20.92
6:45	1.56	0.53	7.87	**24.33**	36.10	23.53	2.13
7:00	12.10	5.50	3.31	**11.15**	5.26	1.73	4.26
7:15	17.90	15.60	31.17	**11.08**	20.37	18.38	27.85
7:30	1.63	0.59	41.18	**9.63**	7.55	14.38	41.60
7:45	14.83	0.28	3.84	**0.10**	10.59	3.19	3.09
8:00	24.93	5.73	7.66	**5.18**	4.66	3.43	12.25
8:15	38.04	4.99	37.43	**11.80**	18.06	54.26	47.47
8:30	15.55	7.75	15.87	**15.15**	11.81	31.24	43.56

8:45	0.53	11.51	11.79	**2.39**	3.75	1.29	26.59
9:00	6.00	0.35	30.72	**4.61**	7.51	3.02	2.32
9:15	7.84	1.01	2.93	**23.51**	24.65	0.05	4.87
9:30	16.19	1.80	7.19	**2.23**	5.77	5.00	0.96
9:45	25.15	10.80	21.63	**9.62**	5.74	19.39	16.33
10:00	17.07	18.38	10.80	**21.36**	2.03	7.80	3.25
10:15	25.89	29.85	17.67	**13.37**	29.18	19.16	8.87
10:30	29.15	48.35	27.97	**13.44**	23.41	238.73	70.27
10:45	5.95	19.22	5.57	**3.66**	16.45	97.82	14.39
11:00	10.47	4.21	34.39	**9.04**	5.36	45.80	2.05
11:15	17.78	24.01	8.13	**7.13**	13.27	251.28	21.16
11:30	9.20	16.65	6.34	**3.99**	7.44	65.41	14.89
11:45	0.23	12.05	6.42	**7.79**	16.50	12.75	2.88
Average	13.60 %	11.40 %	16.03 %	**10.36 %**	12.91 %	38.49 %	16.72 %

Table 5: Difference between each day travel time and average travel time, for 42nd-49th street

As can be seen in Table 5, the mean percentage error, also called average of percentage errors is minimum on 42nd-49 street on October 16, 2014. Therefore, this day is the representative day for this street.

The algorithm to identify representative days is applied to other highway sections as well.

Subsection 6.3: Metric Generation & Selection

The performance measures used for calibration must include travel time and speed along important paths in the network. In this study, link travel times are aggregated to build the travel time over important paths along the FDR as a performance metric. The average speed estimation using link travel time will not be impacted significantly by the aggregation process as the link lengths on FDR are between 0.11.5 miles.

Using the data available for performance measures, variation bands are generated for the representative day identified using the algorithm mentioned earlier. The objective of simulation calibration is to contain the simulation output for the performance measures within the variation bands generated from observed data and thus be statistically significant to that of observed data.

Variation band generation using sigma band is calculated using the following: (22)

The outer band describes 95% of the observed variation based on a single standard deviation:

~2 Sigma Band Maximum Value: $\hat{I}_{\sim 2}(t) = c_r(t) + Z_{95\%}(\sigma(t))$

~2 Sigma Band Minimum Value: $\check{I}_{\sim 2}(t) = c_r(t) - Z_{95\%}(\sigma(t))$

$c_r(t)$: the observed travel times from the representative day

$\sigma(t)$: the standard deviation in travel time for each time interval

The inner band describes 2/3 of the observed variation based on a single standard deviation:

1 Sigma Band Maximum Value: $\hat{I}_1(t) = c_r(t) + \sigma(t)$

1 Sigma Band Minimum Value: $\check{I}_1(t) = c_r(t) - \sigma(t)$

Subsection 6.4: Calibration with Selected Criteria

The calibration process involves adjusting model parameters and the OD matrix to fit simulation output within the variation band with observed data.

As a first step the preliminary OD calibration was performed to generate an initial calibrated OD matrix. This process entails using the traffic count data as a reference to general origin-destination demand on the simulation network.

Sources / Sinks	73rd	63rd	53rd	49th	33rd	S. End
N. End	250	27	0	201	261	651
92nd	150	150	0	0	0	0
78th	114	75	200	150	210	
71st	0	0	100	50	150	0
61st	0	0	0	32	97	65
38th	0	0	0	32	97	194

Table 6: Initial Calibrated OD matrix

SUMO provides several parameters that allow the control of user behavior during simulation. During this phase of calibration, the origin destination demands, and simulation parameters are adjusted iteratively to reduce the error between the simulation output and variation band of travel time from observed data.

Simulation was performed for three hours from 6 AM to 9 AM. The first hour was considered for simulation warmup; thus, the SUMO simulation output is for two hours from 7 AM to 9 AM. The table below shows the OD matrix of the FDR in the southbound direction. Entry streets/ramps are: 92nd, 78th, 73rd, 61st, and 38th. Also, exist streets/ramps are: 73rd, 63rd, 53rd, 49th, and 33rd. In the calibration process, the entry of each OD pair was changed at 15-minute intervals to reach the lowest possible error between the simulated and observed OD volume.

To further improve the model calibration, the travel time of some segments of the corridor was also checked to better improve the simulation output through behavioral parameters. The global parameters in SUMO influence the car following and lane changing behavior of vehicles. Though there are several other parameters in SUMO based on the kind of car following model adopted, for this study the default, the Krauß car following model (14) is used. Some of the parameters controlling the Krauß car following behavior are,

minGap – minimum gap when speed = 0

sigma – driver imperfection

tau – desired time headway

For this study, SUMO's default lane changing model (24) is used. However, several parameters such as those meant for strategic lane changing, cooperative lane changing, impatience are adjusted in the calibration step to generate observed output.

By default, the simulated merging behavior on highway merge ramps did not reflect normally observed behavior on FDR drive. Thus, behavior parameters for gap acceptance and speed were also adjusted in calibration step.

In order to capture the stochastic nature of traffic, the simulation in SUMO can use random seeds for each simulation run. This models the variable nature of various aspects of traffic flow from human behavior, traffic conditions, and varying demand.. Thus, the simulation is run for multiple seeds.

The following criteria, prescribed by the FHWA guidelines for microsimulation modeling is used as a part of the calibration process after each iteration of simulation: (22)

Criteria I: 95% of simulation output lies in the 2-sigma variation band

Criteria II: For two critical time periods – defined as the top two most congested, non-adjacent time periods, the simulation output must fall in the 1-sigma variation band.

Criteria III: One other criteria to check the simulation prescribed in the FHWA toolbox (22) is the Bounded Dynamic Absolute Error (BDAE). The BDAE criterion tests if the average absolute error between simulation and representative day data is less than the error between representative day data with all other days.

The following describes the procedure to estimate the BDAE:

~2 Sigma Band Maximum Value: $\hat{I}_{\sim 2}(t) = c_r(t) + Z_{95\%}(\sigma(t))$

~2 Sigma Band Minimum Value: $\check{I}_{\sim 2}(t) = c_r(t) - Z_{95\%}(\sigma(t))$

$c_r(t)$: the observed travel times from the representative day

$\sigma(t)$: the standard deviation in travel time for each time interval

The inner band describes 2/3 of the observed variation based on a single standard deviation:

1 Sigma Band Maximum Value: $\hat{I}_1(t) = c_r(t) + \sigma(t)$

1 Sigma Band Minimum Value: $\check{I}_1(t) = c_r(t) - \sigma(t)$

The following describes the procedure to estimate the BDAE:

$c_r(t)$ be the observed value of representative day during time interval t

$c_i(t)$ be the observed value of non-representative day within the cluster during time interval t

$\widetilde{c_r}(t)$ be the simulated performance measure during time interval t

N_T the number of time intervals

$N_{cluster}$ the number of days in the cluster representing this travel condition

The BDAE Threshold is given as:

$$BDAE_{Threshold} = \frac{\sum_{i \neq r} \sum_t \frac{|c_r(t) - c_i(t)|}{N_T}}{N_{cluster} - 1}$$

$$\sum_t \frac{|c_r(t) - \tilde{c}_i(t)|}{N_T} \leq BDAE_{Threshold}$$

The model parameters and OD table are adjusted in order to improve the simulation output.

Section 7: Metrics Comparison during Calibration

Simulation output of travel time and traffic flow at links along the southbound direction of the FDR from the initial iterations of simulation are presented in Figure 4 (a) and (b) respectively. Initial OD matrix is shown in Table 6.

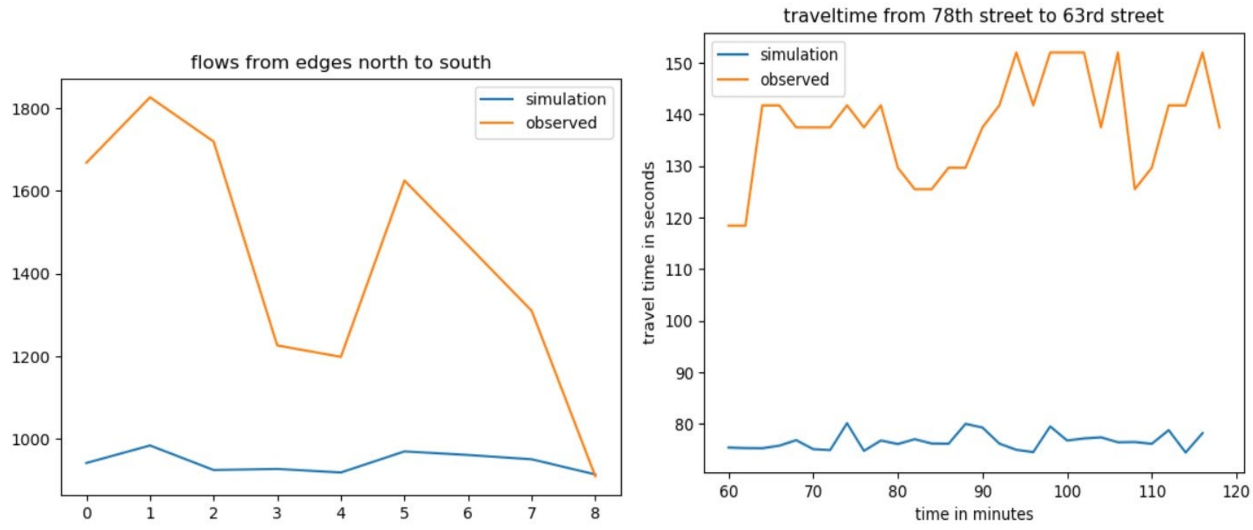
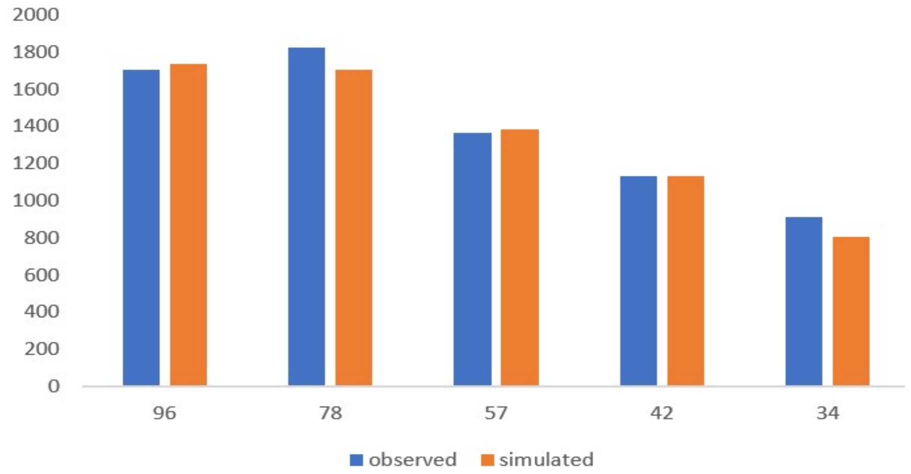


Figure 4 Comparison of Simulation & Observed Metrics before calibration

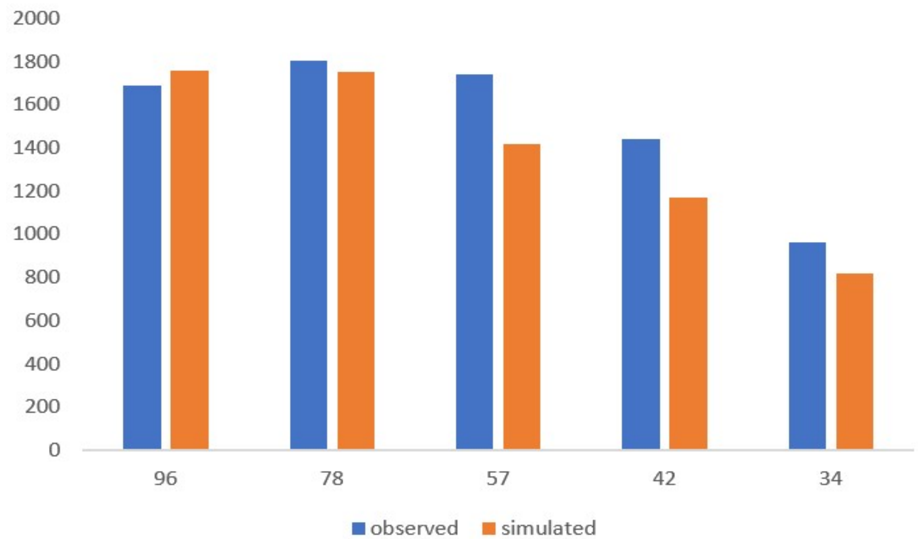
The calibration was performed through adjusting input demand of each OD pair from the OD demand matrix above. OD error is reduced and the travel time on some segments of the FDR are also checked to capture the underlying characteristic of the network. Three segments of FDR were chosen for calibration. The segments are: *1)* 92nd street to 73rd street; *2)* 70th street to 60th street; and *3)* 49th street to 42nd street.

During the calibration process, the error was reduced both in terms of traffic counts on different links along the section of FDR being modeled and travel time along sections identified earlier. The errors in traffic counts are calculated from the difference between SUMO simulation flow and the observed flow during 7 AM to 9 AM. As result, the OD error was reduced to 7.6% in the southbound direction.

Figure 5 shows both the observed and simulated traffic flow throughout two-hour simulation run.



(a)



(b)

Figure 5: Comparison of Observed and Simulated Counts

Figure 6 below shows the travel time of all three segments in both the simulation and pre-calibration observed data. The error between these two datasets from 92nd to 73rd Street is reduced from about 43.5% to 15%. The travel time error from 70th to 60th Street is 23%, and the error from 49th to 42nd Street is 30%. However, this error should be seen in the travel time data band.

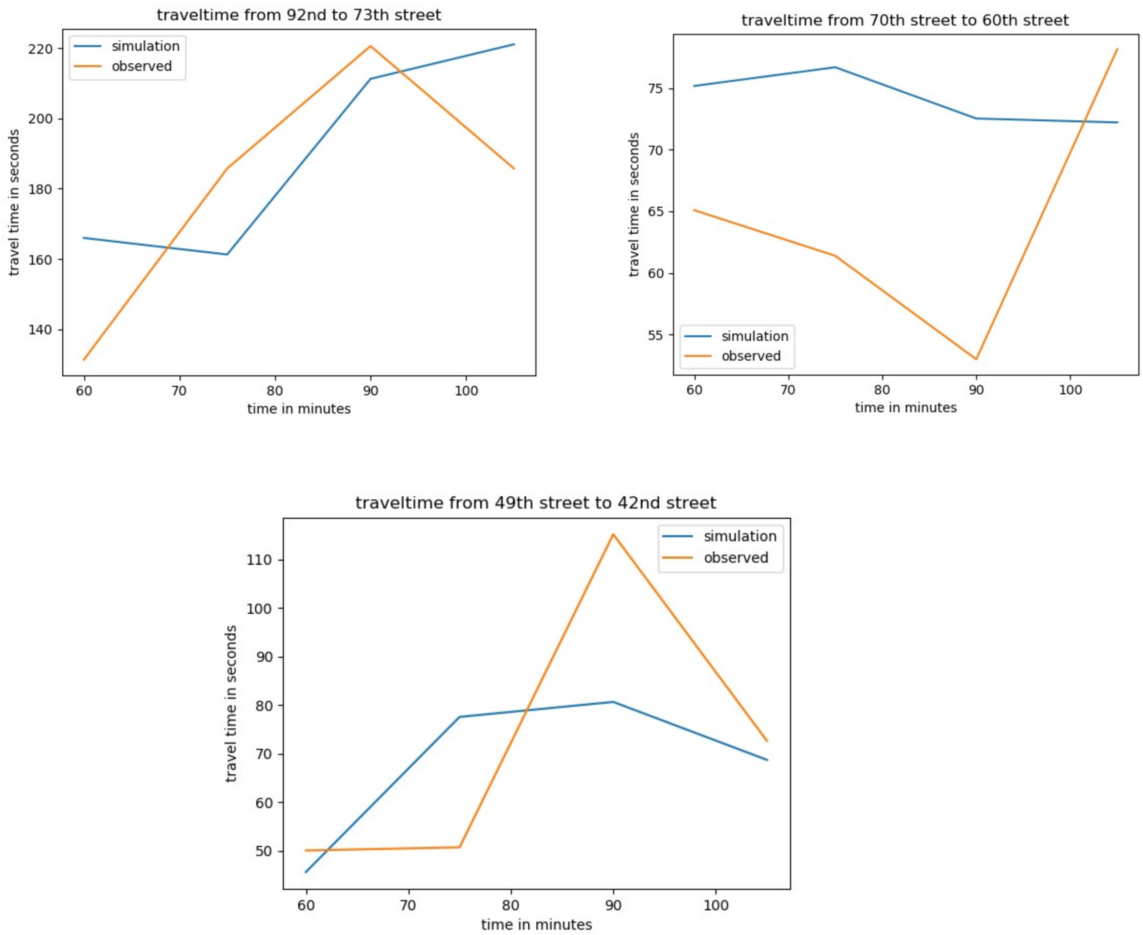


Figure 6: Pre-calibration travel times on three different sections

The metric used for calibrating the error in travel time is the root mean squared error, calculated as follows:

$$RMSE_{TT} = \sqrt[2]{\sum_{i=0}^{n} \frac{\left(TT_{Sim,i} - TT_{Obs,i}\right)^2}{n}}$$

For the purpose of calibration, the sum of $RMSE_{TT}$ for the three sections available is used as the objective function and shown as:

$$\min_{cs} \sum RMSE_{TT}\,(I_s, C_s)$$

O_{obs}, O_{sim} - observed and simulated outputs at location i

C_s - parameter set for iteration k

The convergence of $RMSE_{TT}$ over several iterations of the calibration process is shown in Figure 7.

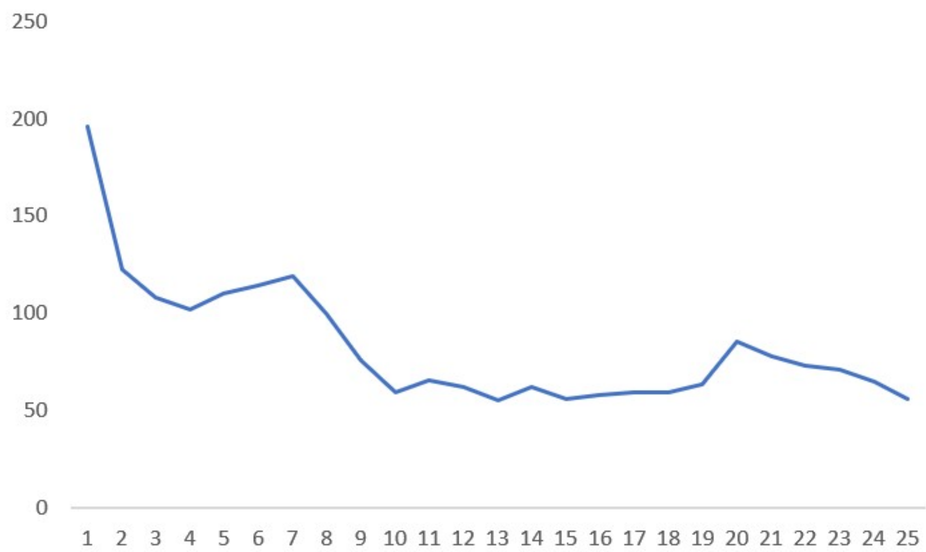


Figure 7: Convergence of calibration process over consecutive iterations

The next criteria for calibration are verifying if simulation output lies within the variation bands of the 2sigma of observed data. This criterion ensures that most simulated results fall close to the representative day, and that during the most congested time periods the simulated results are close to the observed data.

Subsection 7.1: Travel Time Variation Band

Figure 8 shows the 1-sigma and 2-sigma travel time variation bands, along with the average day, the representative day, and the simulation, for 42nd-49 streets. Figure 9 and Figure 10 show the same plot for 96 – 78street and for 71st-63st sections respectively. Simulation was carried out for eight seeds, the average of which is shown in Figure 8. For 96nd-79st street section, two of the travel time values are outside the 1-sigma variation band but within the 2-sigma band. For the two other sections, the average travel times are all within the 1-sigma variation band boundary, and hence, are also close to the average and the representative day, which validate the calibrated model.

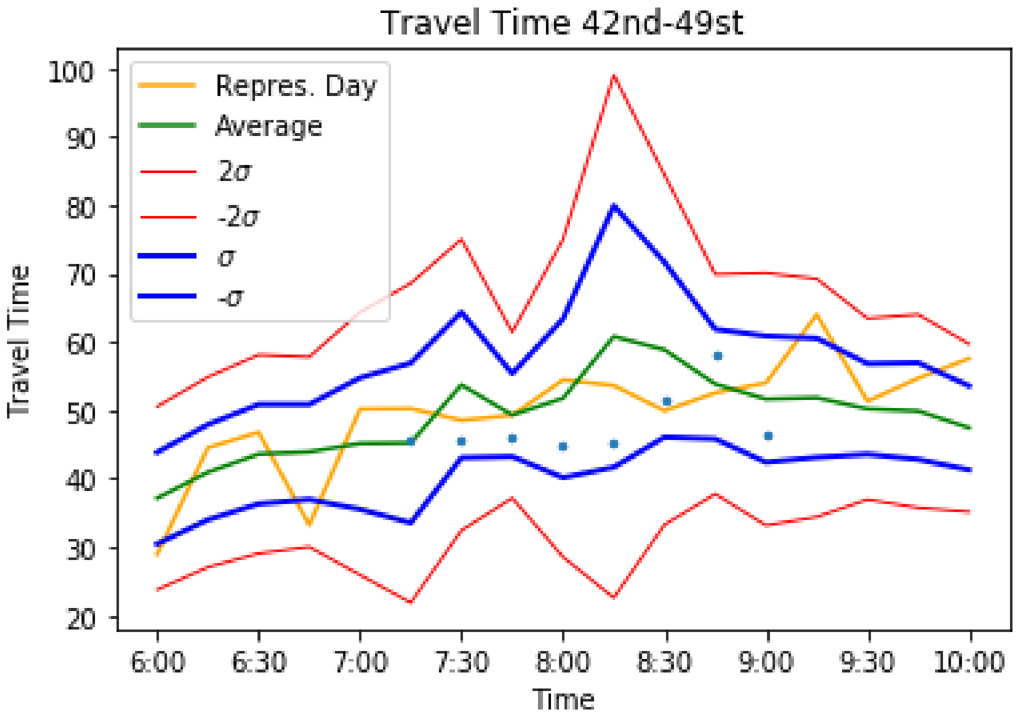


Figure 8: Travel time variation bands (1-sigma and 2-sigma) along with the average day, the representative day, and the simulation, between 42nd-49st exits.

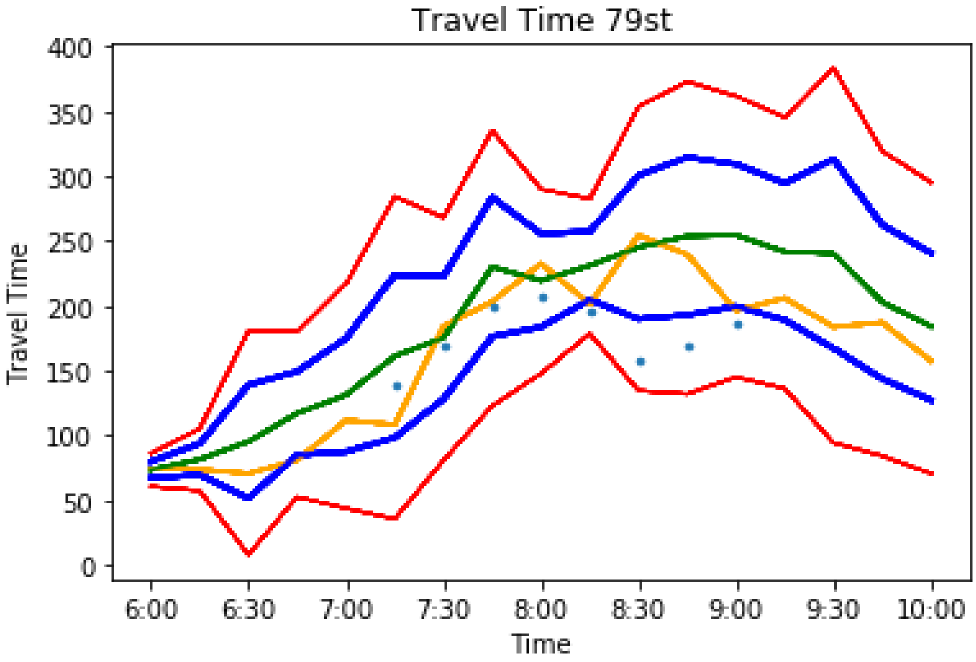


Figure 9: Travel time variation bands (1-sigma and 2-sigma) along with the average day, the representative day, and the simulation, between 96-78 St exits

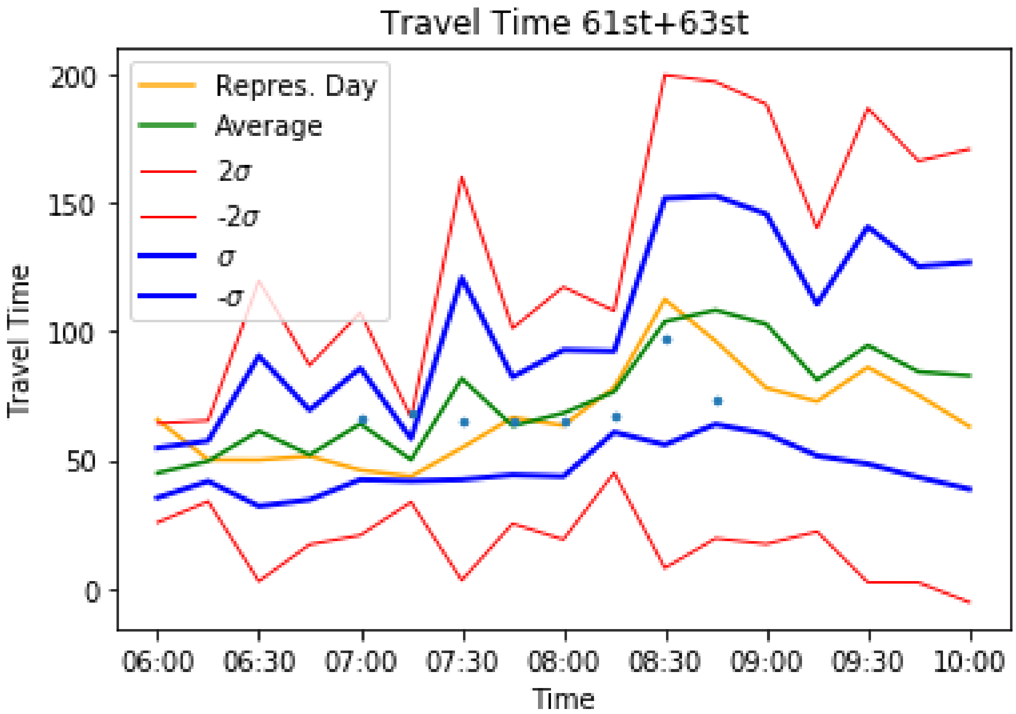


Figure 10: Travel time variation bands (1-sigma and 2-sigma) along with the average day, the representative day, and the simulation, for 71th-61st exits

The third criteria for calibration are verifying that the simulated BDAE is less than the threshold BDAE.

Street	BDAE Threshold	Simulated BDAE	Criteria met
42nd-49 street	13.39	9.33	Yes
63st-61st	28.41	11.52	Yes
79st	64.70	37.90	Yes

Table 7: Simulated and Threshold Bounded Dynamic Absolute Error

As shown in Table 7, the simulated BDAE is less than the Threshold BDAE for all the sections of the FDR. This means that, on average, simulated results are close to the observed representative day.

Section 8: Conclusions

Well calibrated simulation models are important for analyzing the impacts of technology on traffic mobility and safety. For CV applications evaluation, the simulation model has to represent mobility accurately for an effective estimation of application impact.

In this project, the research team developed a simulation-based approach for the evaluation of CV applications for the Franklin D Roosevelt highway in NYC. Given the ongoing CV pilot deployment in NYC, the proposed project will tie in to the objectives of the NYC CV pilot deployment program.

The model for FDR is created in SUMO microscopic simulation modeling framework. The calibration of the simulation model was performed in a systematic manner. Various data such as traffic counts from ATR devices and TMC from NYCDOT, travel time from automated vehicle location, crash data from NYC Open data were used. The methodology for calibration adopted in this study followed the criteria illustrated in the FHWA Traffic Analysis toolbox (22). The simulation output from the calibrated model fit the observed data based on the criteria mentioned.

As a part of ongoing work, the calibrated simulation model will be used to evaluate CV applications, which are a part of the ongoing NYC CV pilot.

The proposed simulation framework will provide a carefully validated test bed for future analyses of traffic control strategies as a part of connected cities initiative being undertaken across several cities. Among the major benefits of CV technology in urban areas are harmonized traffic flow, lower emissions and synchronized traffic signalization. The iVITS simulation modeling framework created will be utilized to evaluate the said benefits in a connected urban environment. The proposed study will incorporate several CV technology elements of the NYC CV pilot deployment in order to evaluate the CV applications in the most realistic settings.

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