

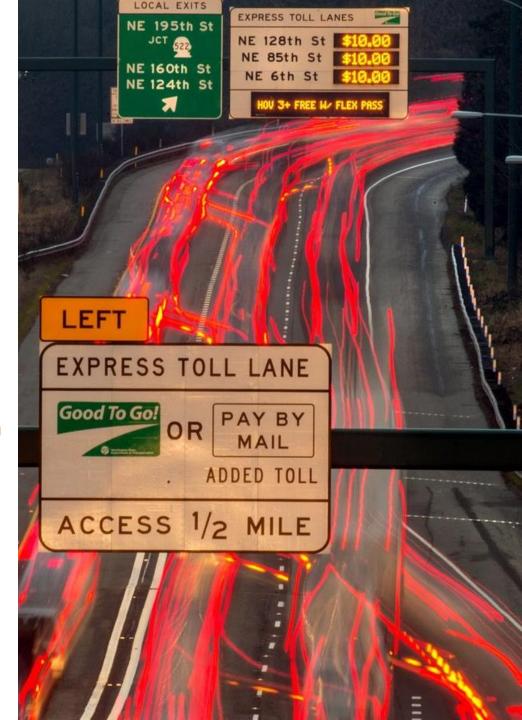
North Carolina Model Users Group November 1, 2018

Incorporating Big Data in Model Development



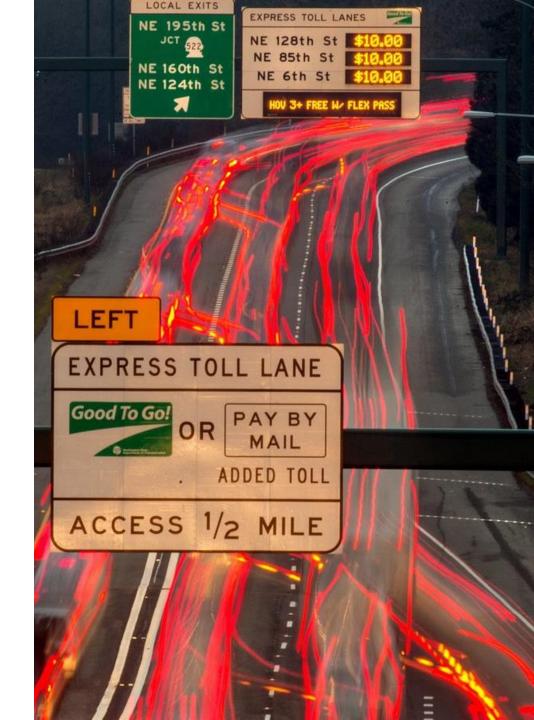
#### Overview

- Key Topics
  - Big Data Usage
  - Calibration Applications
- Four Projects
  - Greenville Model
  - 2. Mid-Currituck Bridge
  - 3. Lake Pontchartrain Causeway
  - 4. Central Texas Turnpike System
- Data Types
  - 1. Speed Data
  - 2. Trip Pattern Data



#### **Key Topics**

- 1. Big Data Usage:
  - Prior Data had Limitations
  - Data & Tools are improving
  - Data Evaluation is Critical
- 2. Model Calibration Objectives:
  - Trips by Vehicle Type
  - Speeds
  - Trip Patterns



#### Big Data Evolving and Improving

- Passive O-D Data Samples have expanded in recent years
  - Samples now much greater than obtained from household surveys
- Increased use of GPS-enabled vehicles and Smart Phones
  - Replaces less accurate approximation of cell phones via triangulation
  - Enables physical tracing of vehicles within network



#### Location-Based Services Data

Location Based Services data is provided from smartphone apps that track the locations of phones and other devices to provide specific services, such as weather forecasts, shopping options and restaurant reviews as well as other services. There are data available from hundreds of these apps and number of apps continues to expand.

#### O-D Sample Size Limitations with Various Methods

- Typical HH Survey Data < 1%
- Prior Versions of Streetlight <2%</li>



#### Larger Sample Size Yield Better Understanding of Travel Patterns

- As an example, Streetlight Data is currently at 23% sample
- Representative disaggregate samples



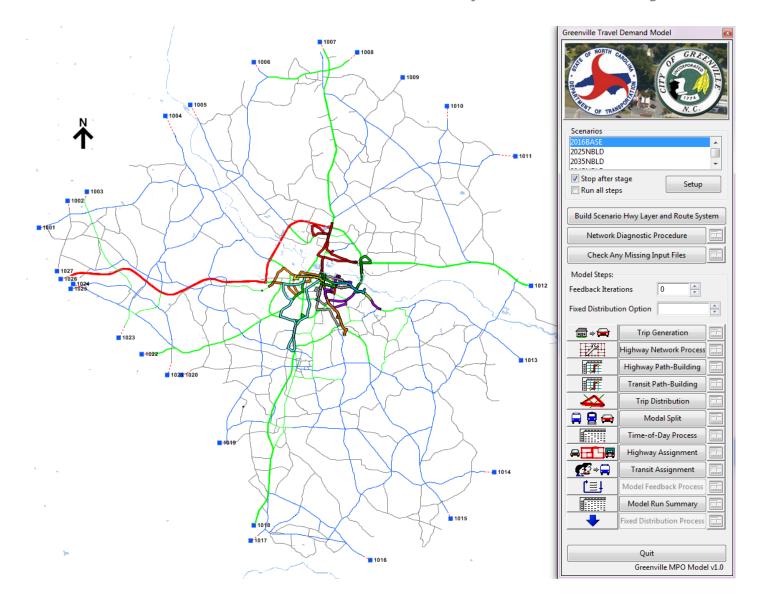
#### **Passive Data Limitations**

- Spatial Precision
  - LBS data:
    - 25 meter spatial precision
    - Pings are sent as devices are moving
  - Cellular data:
    - 100-300 meter spatial precision
    - Pings are sent less frequently
- Person Trip Characteristics
  - Traveler Information
    - inferred from home zone
  - Purpose Characteristics
    - inferred from frequency and duration
    - Aggregation into generic purposes (HBW, HBO, NHB)
- Truck Samples are still relatively small

#### **Passive Data Limitations**

- Device Activation
  - LBS data relies on users proactively opting in at apps that track location. Battery power consumption may restrict some usage.
  - Cellular data does not require proactive opting in
- Research has Identified Observed Biases
  - LBS data may be under-estimating short district trips.
- Passive Data should be Evaluated
  - O-D Patterns
  - Speeds

## Greenville Model Development Project

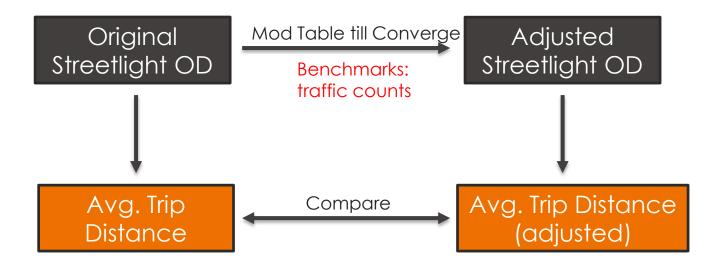


#### Greenville Model - Passive Data Evaluation

- Origin-Destination Patterns
  - If O-D is Under-Representing Short Distance trips, Capture that Difference via ODME Techniques
  - Effectively creates Band of Variation by Impedance Interval
- Speed Data
  - Verify HERE data with Independent Source (Google)

## Methodology

 Use Origin-Destination Matrix Estimation (ODME) to Identify Differences by Impedance Intervals

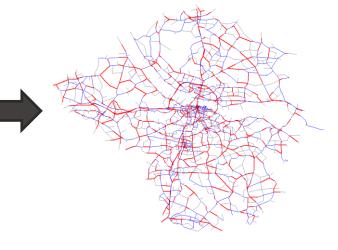


## Traffic Count Coverage – Pitt County

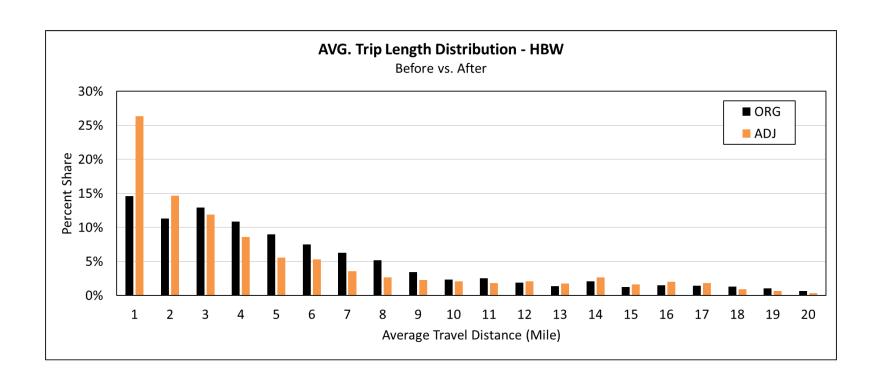
#### **TOTAL COUNTS**

FACILITY TVDF	AREA TYPE		
FACILITY TYPE	Urban	Rural	TOTAL
Freeway		30	30
Principal Arterial	213	72	285
Minor Arterial	563	112	675
Major Collector	294	446	740
Minor Collector		152	152
Local Road	188	530	718
Low-speed Ramp	1	3	4
High-speed Ramp	4	18	22
TOTAL	1,263	1,363	2,626

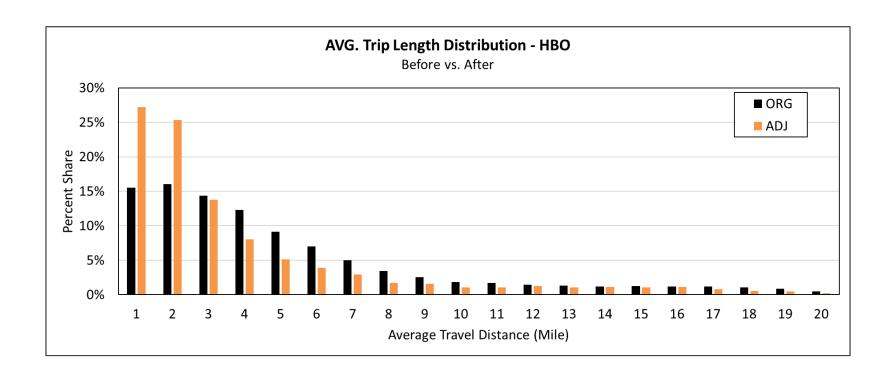
32.3% data coverage



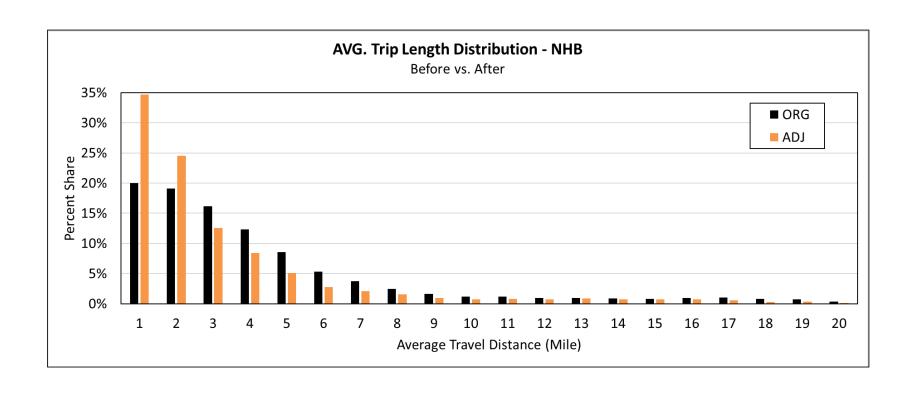
### Average Trip Length Distribution - HBW



### Average Trip Length Distribution - HBO



### Average Trip Length Distribution - NHB



## Adjusted Average Trip Length

PURPOSE	Avg. Distance		Avg	j. Travel T	ime	
FURFUSE	ORG	ADJ	%DIFF	ORG	ADJ	%DIFF
HBW	5.8	5.5	-5%	11.6	11.2	-4%
НВО	5.2	4.4	-16%	10.6	9.6	-10%
NHB	4.3	3.7	-15%	9.1	8.5	<b>-7</b> %

#### Greenville Model - Distribution Calibration

#### Person Trips

- Calibrate Individual Purposes using NHTS Data
  - HBW
  - HBSH
  - HBO
  - NHBW
  - NHBO
- For HBO and NHB, Aggregate to Streetlight Purposes
- E-I Purposes use Streetlight Aggregate Trip Purposes

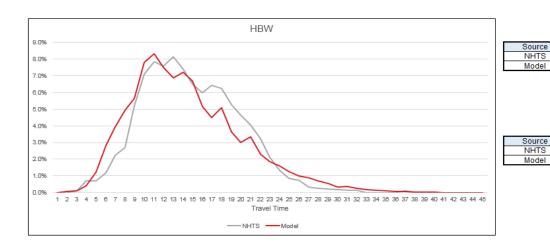
#### Truck Trips

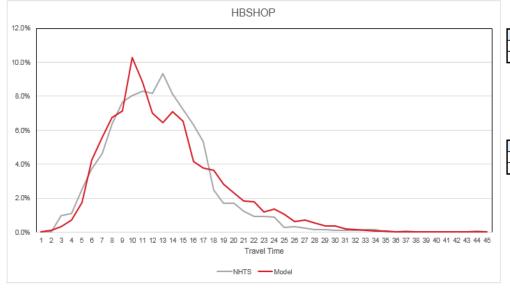
- Use Streetlight Patterns by Truck Type
- Separate Internal and E-I Distributions

#### E-E Trips

Use Streetlight Patterns by Vehicle Type

## Calibration using 2017 NHTS (HBW & HBSH)





Source	Time
NHTS	12.07
Model	12.65

Time

14.33 13.92

Intra Zonal

2.1%

1.3%

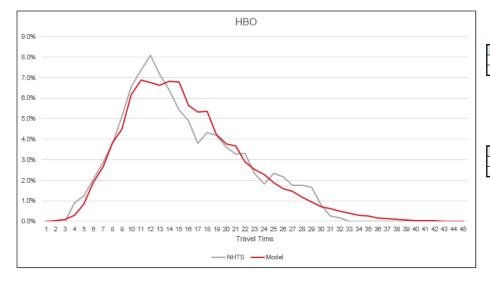
NHTS

Model

Model

Source	Intra Zonal
NHTS	3.2%
Model	2.1%

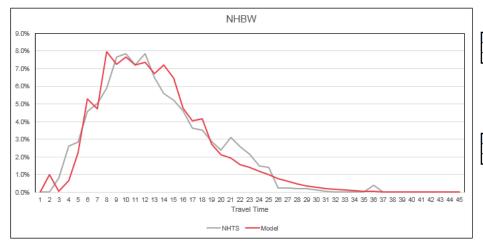
# Calibration using 2017 NHTS (HBO)



Source	Time
NHTS	14.89
Model	15.37

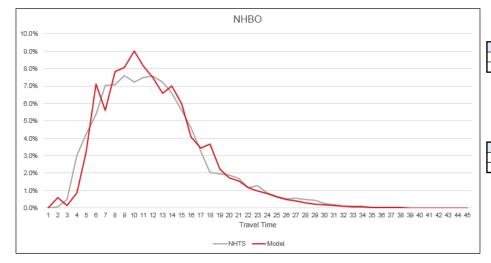
Source	Intra Zonal
NHTS	0.5%
Model	1.2%

## Calibration using 2017 NHTS (NHBW & NHBO)



Source	Time
NHTS	12.58
Model	12.61

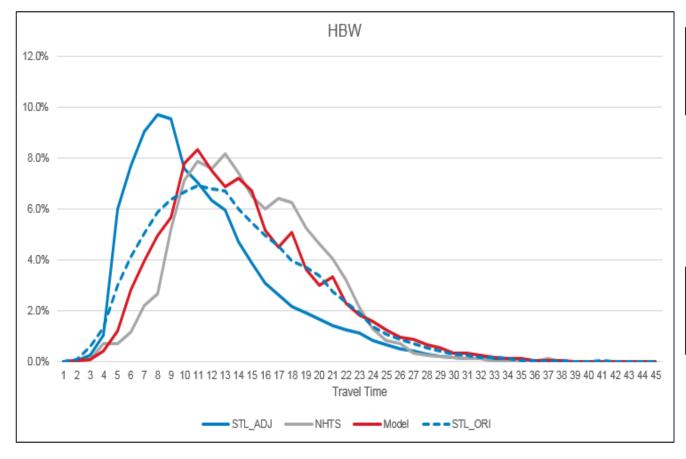
Source	Intra Zonal
NHTS	6.6%
Model	4.6%



Source	Time
NHTS	11.59
Model	11.75

Source	Intra Zonal
NHTS	5.8%
Model	6.6%

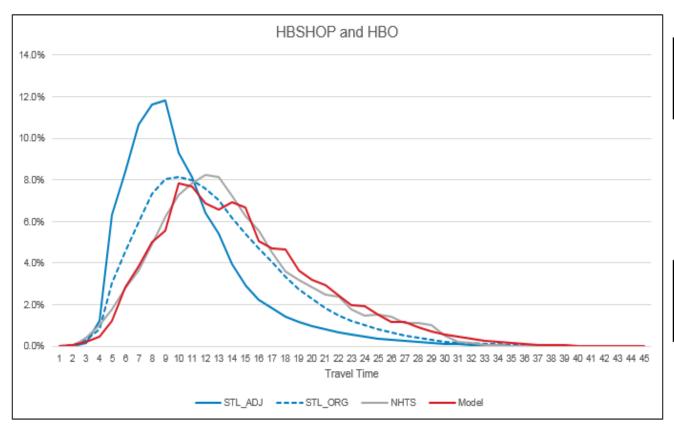
#### **HBW** Distribution Validation



Source	Time
STL_ADJ	10.79
STL_ORG	13.11
NHTS	14.33
Modeled	13.92

Source	Intra Zonal
STL_ADJ	1.4%
STL_ORG	3.2%
NHTS	2.1%
Modeled	1.3%

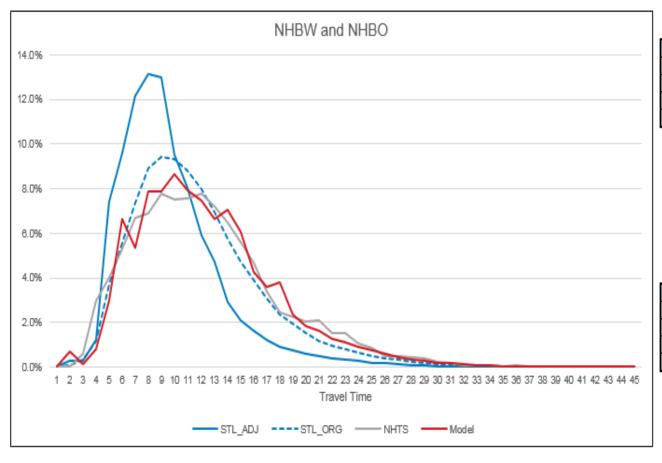
## Aggregate HBO Distribution Validation



Source	Time
STL_ADJ	9.81
STL_ORG	12.25
NHTS	13.73
Modeled	14.27

Source	Intra Zonal
STL_ADJ	0.7%
STL_ORG	2.3%
NHTS	1.6%
Modeled	1.5%

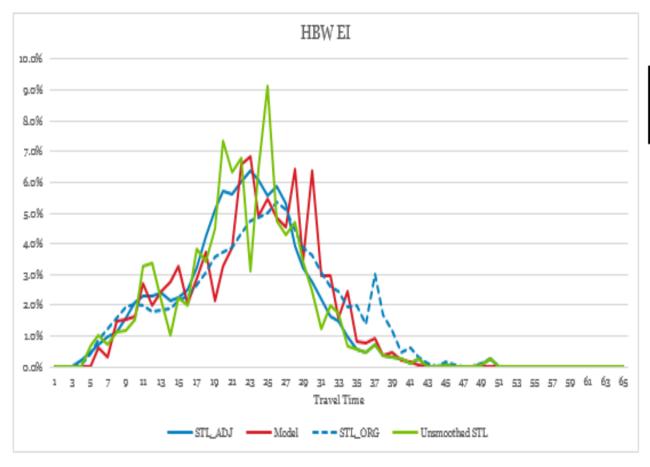
## Aggregate NHB Distribution Validation



Source	Time
STL_ADJ	8.97
STL_ORG	11.14
NHTS	11.83
Modeled	11.97

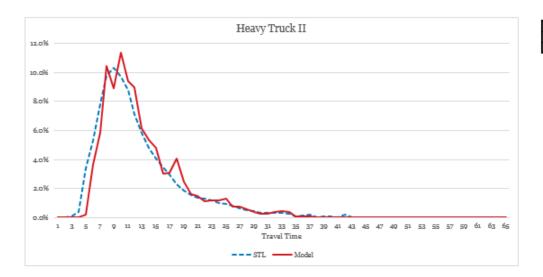
Source	Intra Zonal
STL_ADJ	0.9%
STL_ORG	3.1%
NHTS	6.0%
Modeled	6.1%

## Example E-I Auto Distribution - HBW

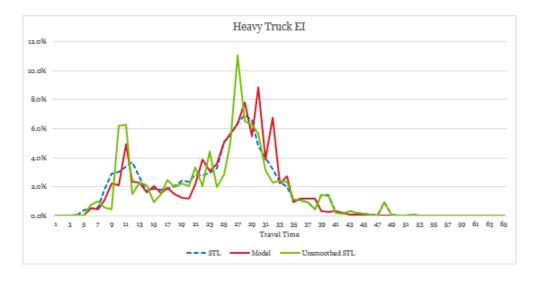


Source	Time
STL-ADJ	21.43
STL_ORG	23.38
Model	22.52

## Example Truck Distribution - Heavy

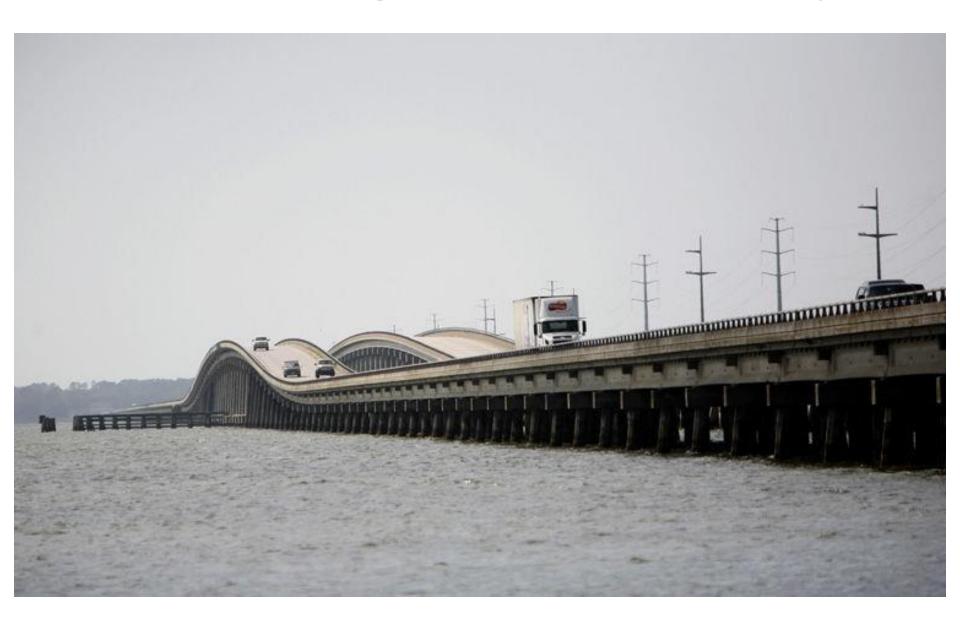


Source	Time
STL	11.91
Modeled	12.59



Source	Time
STL	23.34
Modeled	23.96

## Mid-Currituck Bridge Traffic & Revenue Study



## Mid-Currituck Bridge Traffic & Revenue Study

#### Outer Banks, North Carolina

- Traffic variation highly seasonal
- One entry point at Wright Memorial Bridge
- 2+ hours of delay



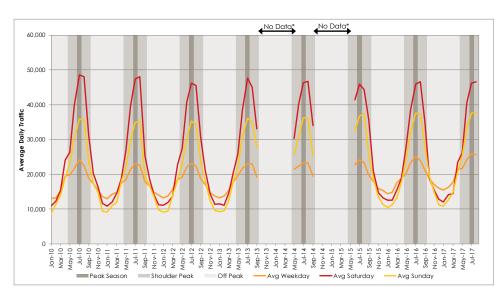




## Mid-Currituck Bridge Travel Times

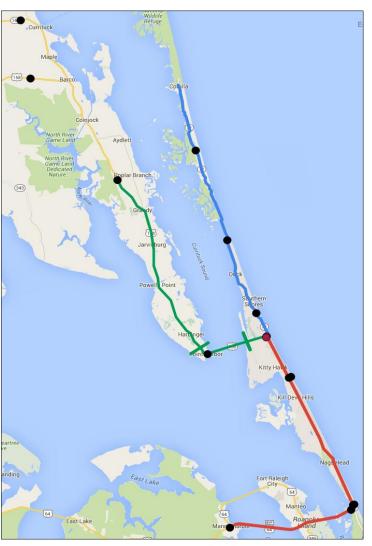
#### Three Distinct Seasons:

Off-Peak	Winter	32 weeks
Shoulder Peak	Spring, Fall	12 weeks
Peak	Summer	8 weeks



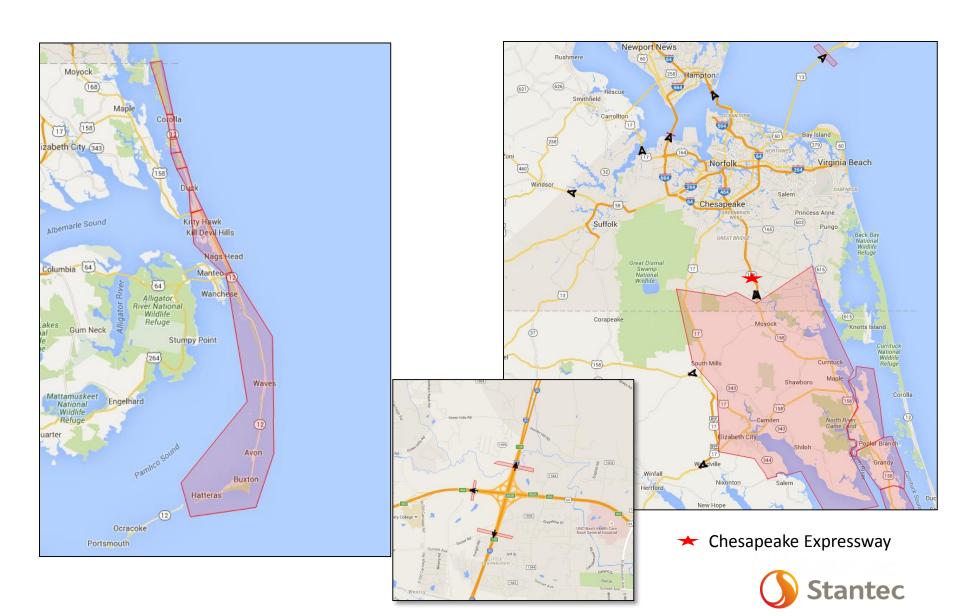
#### Speed Data Collection:

HERE data & independent travel time runs





## StreetLight Origin-Destination Data



## Early Version of Data

- Data Source
  - INRIX 1% Sample
- User-Defined Zones and Selected Links
  - For selected links, some issues with capturing traffic
- Obtained Data by Season
  - Wednesday
  - Saturday
  - Sunday



## **Expansion Process**

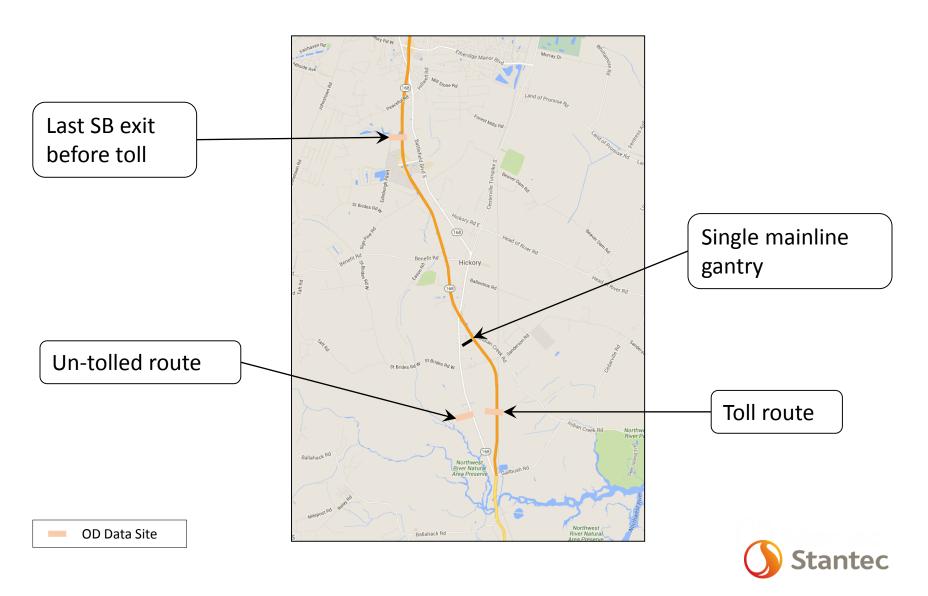
DE	STINATION →	01/02	03/04	O5	06	07	08	D1	D100	
ORIGIN ↓		Corolla & North	Between Corolla & Duck	Duck	Southern Shores	Kitty Hawk, Nags Head	South of Baum Bridge	Wright Bridge	Roanoke Island & West	TOTAL
				AM PE	AK					
	NC north of Albemarle Sound	8%	8%	6%	5%	54%	3%	1%	3%	88%
3, 4, 33	Norfolk, Chesapeake, VA Beach*	0%	0%	0%	1%	6%	1%		1%	10%
	Long Distance Trips north of VA	0%			0%	1%	0%		0%	2%
	Total	8%	<b>9</b> %	6%	6%	61%	4%	1%	5%	100%
				MIDD	AY					
,,,	NC north of Albemarle Sound	3%	4%	4%	10%	57%	3%	1%	2%	84%
3, 4, 33	Norfolk, Chesapeake, VA Beach*	1%	0%	0%	0%	9%	1%	0%	1%	13%
	Long Distance Trips north of VA				0%	3%	0%	0%		3%
	Total	4%	4%	4%	10%	68%	4%	1%	3%	100%
				PM PE	AK			ı		
	NC north of Albemarle Sound	5%	4%	2%	2%	60%	1%	3%	5%	82%
3, 4, 33	Norfolk, Chesapeake, VA Beach*	1%				9%	2%	1%	2%	16%
	Long Distance Trips north of VA					2%				2%
	Total	5%	4%	2%	2%	72%	3%	4%	7%	100%

Applied to traffic counts to produce 'observed' data used in model



#### Observed Toll Diversion Data

Capturing Diversion Shares for Long Distance Travelers



## Streetlight Data (Early Version)

4	Α	В	С	D	E	F	G	Н	I	J	K	L	М	N	0	Р
				Origin			Destinati				Origin	Destinati				
			Origin	Zone		Destinati	on Zone			O-D	Zone	on Zone				
		Origin	Zone Is	Direction	Destinati	on Zone	Direction			Traffic	Traffic	Traffic	Avg Trip			% By
	Vehicle	Zone	Pass-	(degrees	on Zone	Is Pass-	(degrees			(StL	(StL	(StL	Duration	Dest	% By	Destinati
1	Туре	Name	Through	)	Name	Through	)	Day Type	Day Part	Index)	Index)	Index)	(sec)	code	Origin	on
2	Personal	01	no	N/A	01	no	N/A	0: Average Day (M-Su)	0: All Day (12am-12am)	132	175	263	673	01	75%	50%
3	Personal	01	no	N/A	01	no	N/A	0: Average Day (M-Su)	1: Early AM (12am-6am)	1	1	1	931	01	100%	100%
4	Personal	01	no	N/A	01	no	N/A	0: Average Day (M-Su)	2: Peak AM (6am-10am)	12	21	20	600	01	57%	60%
5	Personal	01	no	N/A	01	no	N/A	0: Average Day (M-Su)	3: Mid-Day (10am-3pm)	69	86	127	736	01	80%	54%
6	Personal	01	no	N/A	01	no	N/A	0: Average Day (M-Su)	4: Peak PM (3pm-7pm)	40	53	79	610	01	75%	51%
7	Personal	01	no	N/A	01	no	N/A	0: Average Day (M-Su)	5: Late PM (7pm-12am)	11	14	35	544	01	79%	31%
8	Personal	01	no	N/A	01	no	N/A	1: Average Weekday (M-Th)	0: All Day (12am-12am)	129	176	236	633	01	73%	55%
9	Personal	01	no	N/A	01	no	N/A	1: Average Weekday (M-Th)	1: Early AM (12am-6am)	2	2	2	931	01	100%	100%
10	Personal	01	no	N/A	01	no	N/A	1: Average Weekday (M-Th)	2: Peak AM (6am-10am)	9	15	17	661	01	60%	53%
11	Darconal	Ω1	no	N/A	Ω1	no	NI/A	1. Average Weekday (M-Th)	3. Mid-Day (10am-3nm)	69	92	11/	622	Ω1	75%	61%

#### Issues & Limitations

- Early version
  - Required tedious & intricate analysis
  - Vehicle type but no inferred trip purpose
- Cannot obtain origins of very long trips
- '5 meters in 5 minutes' rule used to define trips
- Sample size created issues with expansion



#### Lessons Learned

- Trip definition rules (5 meters in 5 minutes) can greatly affect data for longer trips encountering severe congestion, where delays may appear as separate trips
- Zone boundaries precise to avoid double counting
- Compare season progression first
  - Had to make many adjustments during post-processing



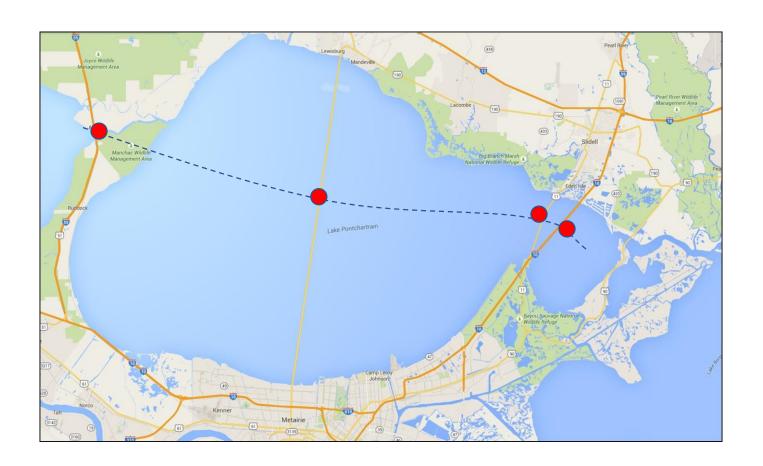
# Lake Pontchartrain Causeway Traffic & Revenue Study





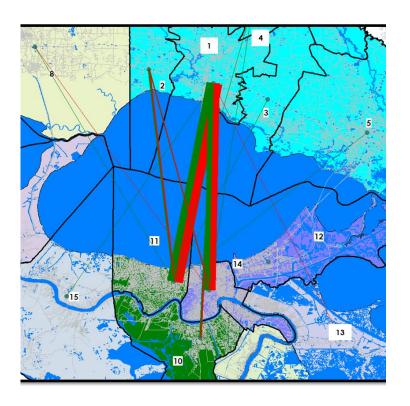
## AirSage Data

- Origin-Destination Data for Crossing Links
  - Causeway & Competing Roadways (I-55, I-10, and US 90)
  - One Month of Data (April 2015)

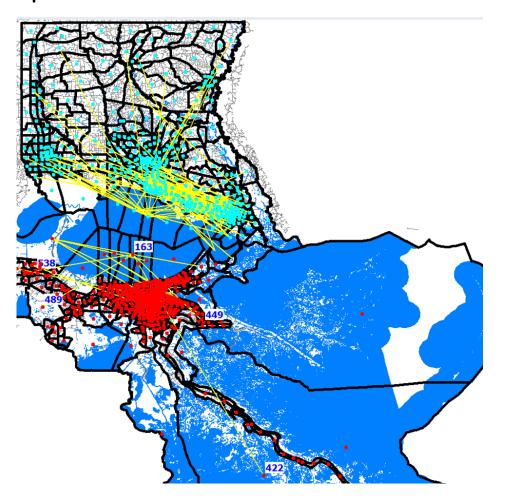


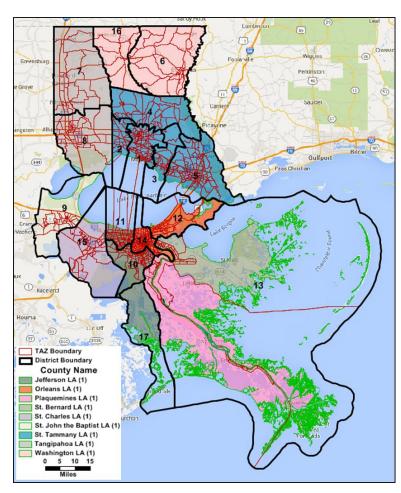
### Data Characteristics

- Data Source
  - Cell Phone Signaling Data
- Type of Day
  - Average Weekday
  - Average Weekend Day
- Time Periods
  - AM Peak Period (6AM 10 AM)
  - PM Peak Period (3PM 7PM)
  - Daily
- Inferred Trip Purposes
  - HBW
  - HBO
  - NHB
- Data expanded with Traffic Counts

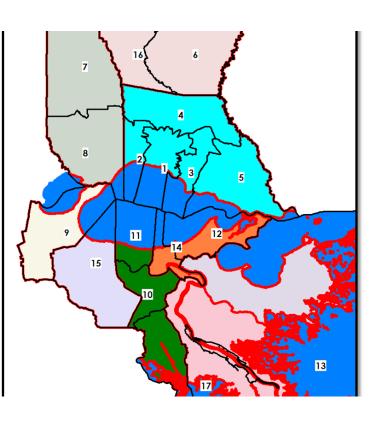


# Data assessment revealed some unreasonable trip patterns





# Data Usage – Verification of Market & Share



### Markets using Causeway

OD Flov	v Between	Districts	Pct Trips
11	and	1	37.6%
14	and	1	26.5%
11	and	2	6.0%
10	and	1	4.7%
14	and	2	3.6%
11	and	4	2.3%
15	and	1	2.3%
11	and	3	2.1%
11	and	8	1.9%
11	and	5	1.8%
	Total		88.7%

### Causeway Share of Key Markets

BRIDGE CROSSING DISTRIBUTION				
BRIDGE	% DIST			
I-55	0.7%			
Causeway	97.6%			
US 11 / I-10	1.7%			
Total	100.0%			

# Central Texas Turnpike System 2018 Traffic & Revenue Study



### **HERE Speed Data**

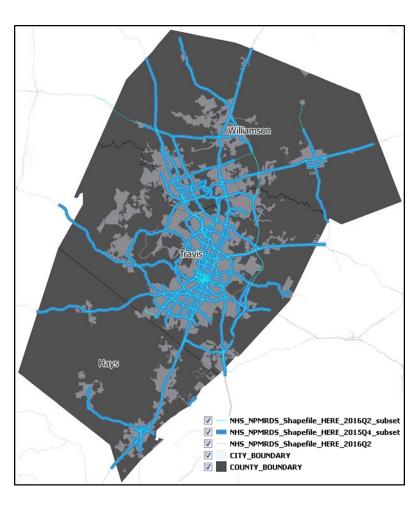
Provided as shape file, collection station information and travel time data

### Features

- Collects data every 5 mins ,288 collection points per day
- Data points include major highways and some local roads

### Lessons Learned

- Provided shapefile does not align well with network, lots of manual work needed
- Some link data appeared illogical and hard to locate
- Temporary congestion or traffic signals could impact the overall average speed values



# SigAlert Speed Data

### Features

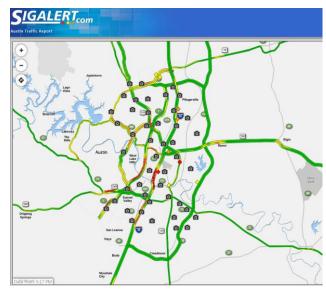
- Real-time traffic map
- 24/7 speed/accident/construction coverage
- Average lag time 3-5 minutes

### Data Limitations for Modeling

- Data coverage on main highways only
- Sparse data collection points

### Lessons Learned

- Good open-source reference for general verification
- Data are often too general for subtle speed variations study



35 (Pan Am Expy) North North					
Loc	Location				
0	Holly St	11			
0	Riverside Dr	11			
0	S I- 35 Svc Rd	25			
Olt	orf St	65			
0	Ramp from US-290/TX-71	66			
0	Teri Rd	66			
0	US-290 West / TX-71 Johnson City Bastrop	66			
0	S I-35 Service NB	66			
Wr	68				
S I-	-35 Service NB	68			
0	I-35 Frontage Rd	68			
0	S I-35 Service NB	68			
Sla	ughter Ln	69			

# O-D Patterns (Bluetooth Data)

- Bluetooth instruments along major roadways
- Less points in a larger area
- Features
  - 24/7 data collection
  - Traces long-distance travel

### Limitations

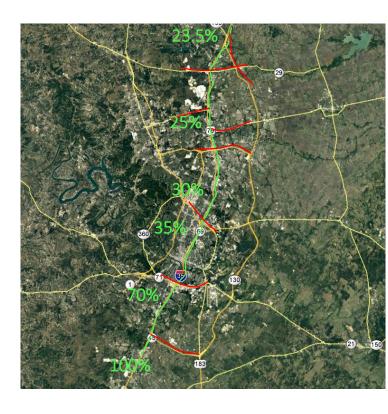
- Vehicle classification not available
- Could miss some data points, trip may be split/merged
- Inadvertent data capture processing



# Bluetooth Data Usage

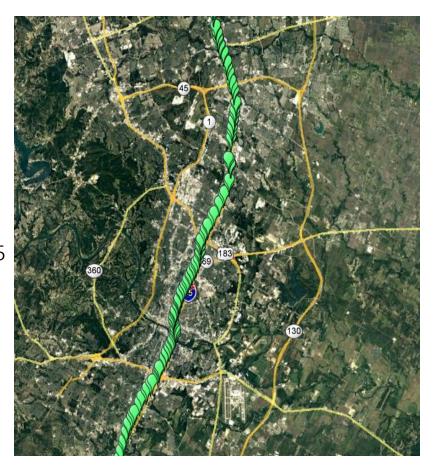
- Percentage of long-distance trips at each collection point by route
- Gives pattern of long-distance O-D between collection points

NB TRAFFIC (From IH-35 Buda)							
IH-35							
Destination Location	Obs.	Estimated					
Destination Location	%Total	Trips	% Total				
IH-35_SlaughterLn	86.8%	71,677	95.0%				
IH-35_StassneyLn	73.3%	52,786	70.0%				
IH-35_Riverside	55.3%	33,922	45.0%				
IH-35_5thSt	53.1%	32,632	43.3%				
IH-35_AirportBlvd	47.9%	26,286	34.8%				
IH-35_US-183/US-290	43.5%	24,754	32.8%				
IH-35_Braker	39.7%	22,937	30.4%				
IH-35_Parmer	38.8%	22,606	30.0%				
IH-35_SH-45Toll	36.7%	20,856	27.6%				
IH-35_US-79	35.4%	18,844	25.0%				
IH-35_FM-1431-RoundRock	32.3%	18,657	24.7%				
IH-35_SH-29-Georgetown	30.4%	18,557	24.6%				
IH-35_Georgetown	23.5%	17,634	23.4%				

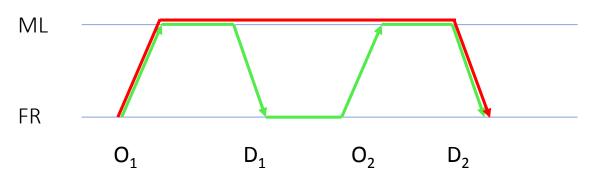


# Skycomp Data

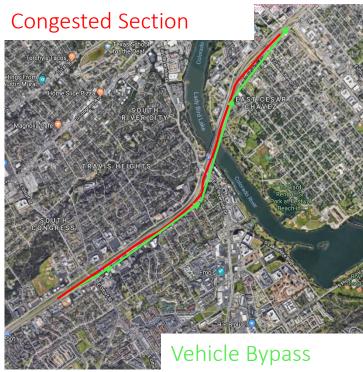
- INRIX GPS data
- Features
  - Tracks vehicle trajectory
  - Corridor entrance-exit pattern between I-35
    & frontage roads
  - Traces bypass behavior
  - Extract true O-D for trips
- Lessons Learned/Data Limitation
  - Sample size very small
    - Some movements have minimal observations a month
  - Early samples biased towards trucks
    - More than 70% of samples are truck



## Skycomp Data - True O-D vs. Observed O-D

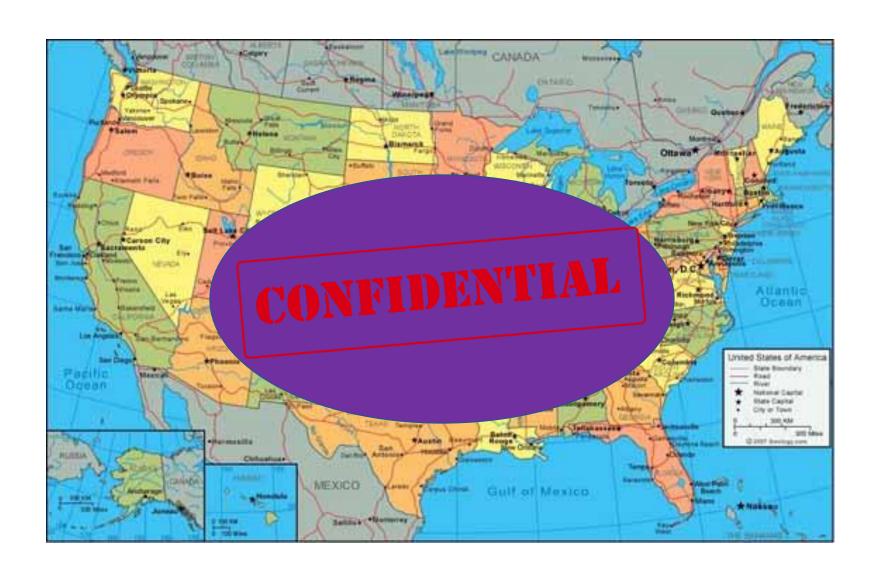


- 'True O-D' is the actual O-D of a trip.
  Provides the first entrance and the last exit a vehicle take during one trip
- In this case, 2 O-Ds  $(O_1 \rightarrow D_1, O_2 \rightarrow D_2)$ observed, but true O-D is  $O_1 \rightarrow D_2$
- 1 or more bypass movements can be made for each trip. Tracing complete trajectory generates true O-D



"Bypass" Behavior: Vehicles take frontage road for a short distance and then go back to mainline to avoid congested sections of highway

# Off the Record....



### Summarize Transaction and Trip Databases

### Data:

200,000+ daily and 52+million annual records of transactions on the express lane facility. The input data was provided in individual daily excel files by direction. Each record has fields for time stamp, type of transaction, plaza location identifier, confidence of detection and corresponding toll.

#### Process:

Chaining transactions into trips to determine entry exit patterns, and full trip tolls.

Screening for low detection confidence, incomplete trip records, duplicate trips etc.

#### **Product:**

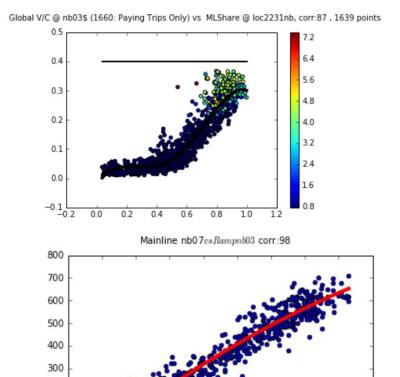
Generate weekly, monthly, yearly summaries of tolls and trips by Origin and Destination, and use this information to predict toll rates and expected utilization by time of day.

#### Software:

VBA in Excel and python pandas to clean up the input data files and re-format fields PostgreSQL to create an aggregate database for all transactions

### **Develop Predictive Analytics**

- Used python scripts to aggregate transaction and traffic into thousands of 15-minute periods over a several-month period.
- Identified trends between overall congestion indicators (global v/c) and the percent of traffic using the tolled express lanes (mainline market share)
- Apply this curve to determine future demand and toll rates in 15-minute increments based on projected traffic volumes from the travel demand model.
- The process also included an application of the actual toll algorithm simulator to forecast future tolls based on speed and flow rate metrics



200

100

### Toll Algorithm Simulator

#### Data:

- Volume, Occupancy, and Speed data in 20 second increments for at least 2 weeks (~15.25 Million data points)
- All the above data from both Express Lanes and General Purpose Lanes
- Loop Assignment paths as well as a set of fuzzy parameters that control the toll calculation per O-D

### **Process:**

Dynamic Toll is calculated based on fuzzy logic algorithm, a mathematical technique for handling data with many-valued logic solutions.

### **Product:**

Toll Rates in 20 second intervals for each O-D pattern on the proposed facility

### Software:

R-statistical programing language used to develop routine

Final routine implemented in CUBE