

AI-based Dynamic Arterial Signal Management – A Case Study

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VASITE

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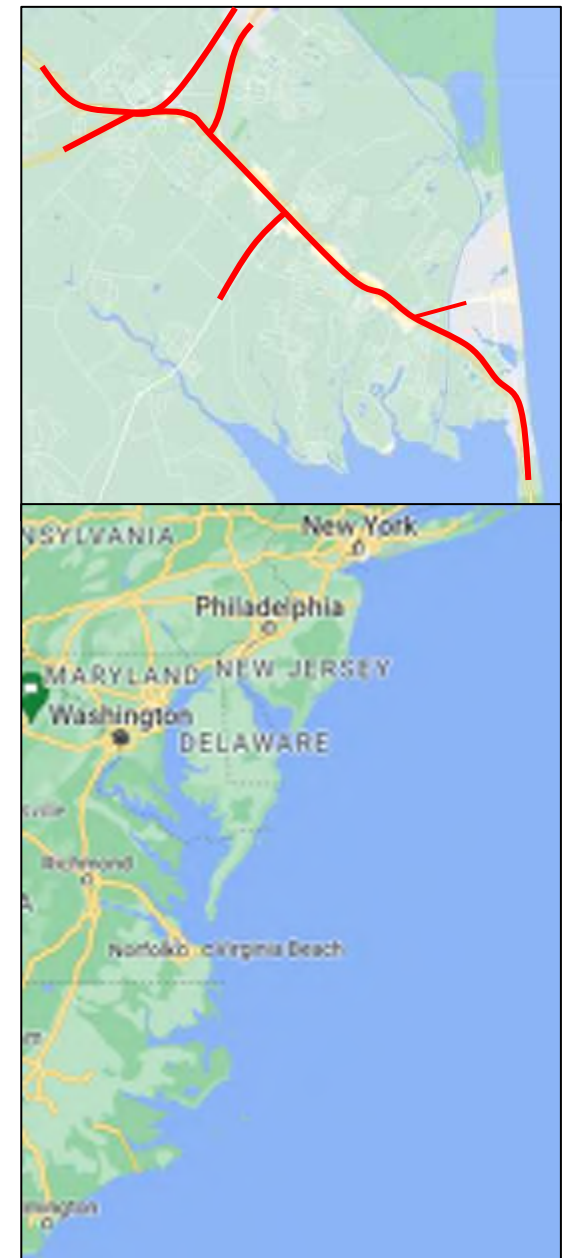
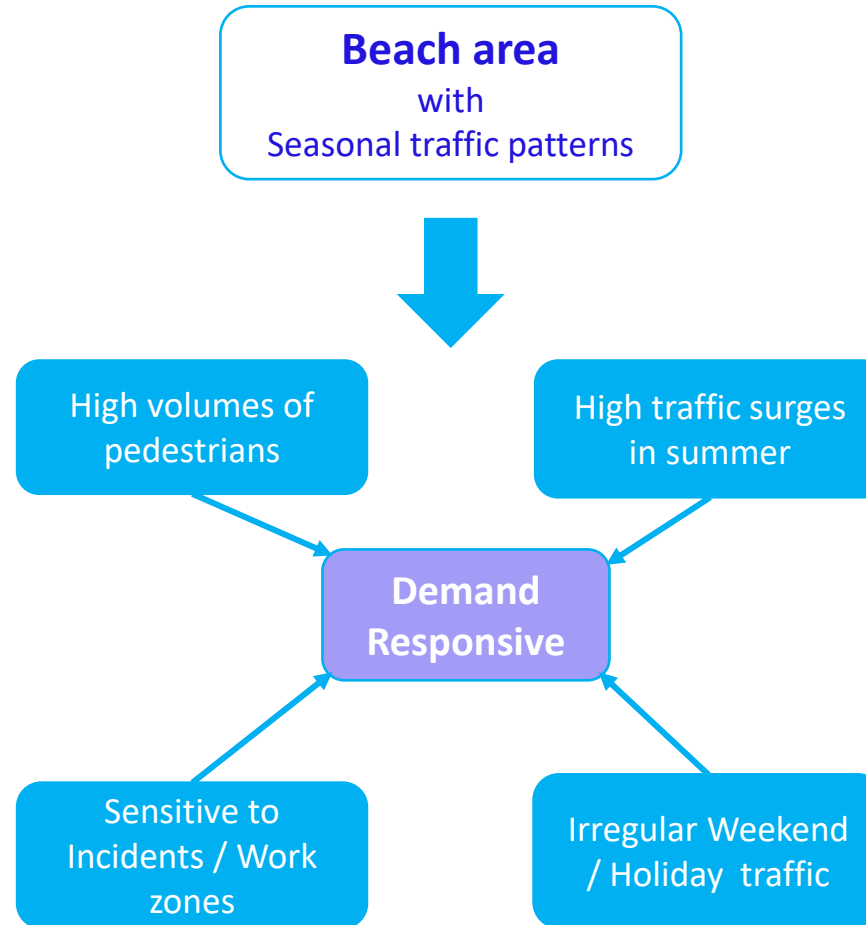
- 1. Introduction**
- 2. Methodology**
- 3. Traffic Volume & Occupancy Prediction**
- 4. Signal Controller & API Development**
- 5. Analysis Results**
- 6. Conclusion**

Introduction



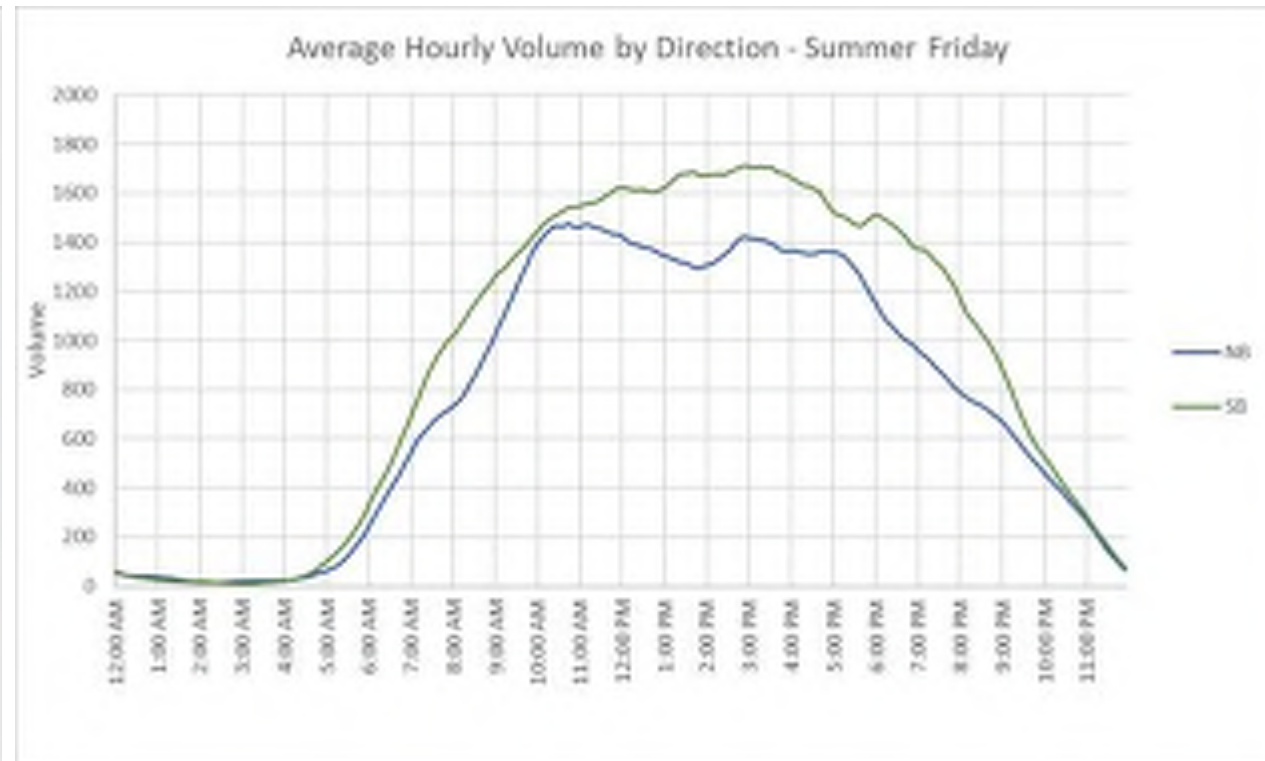
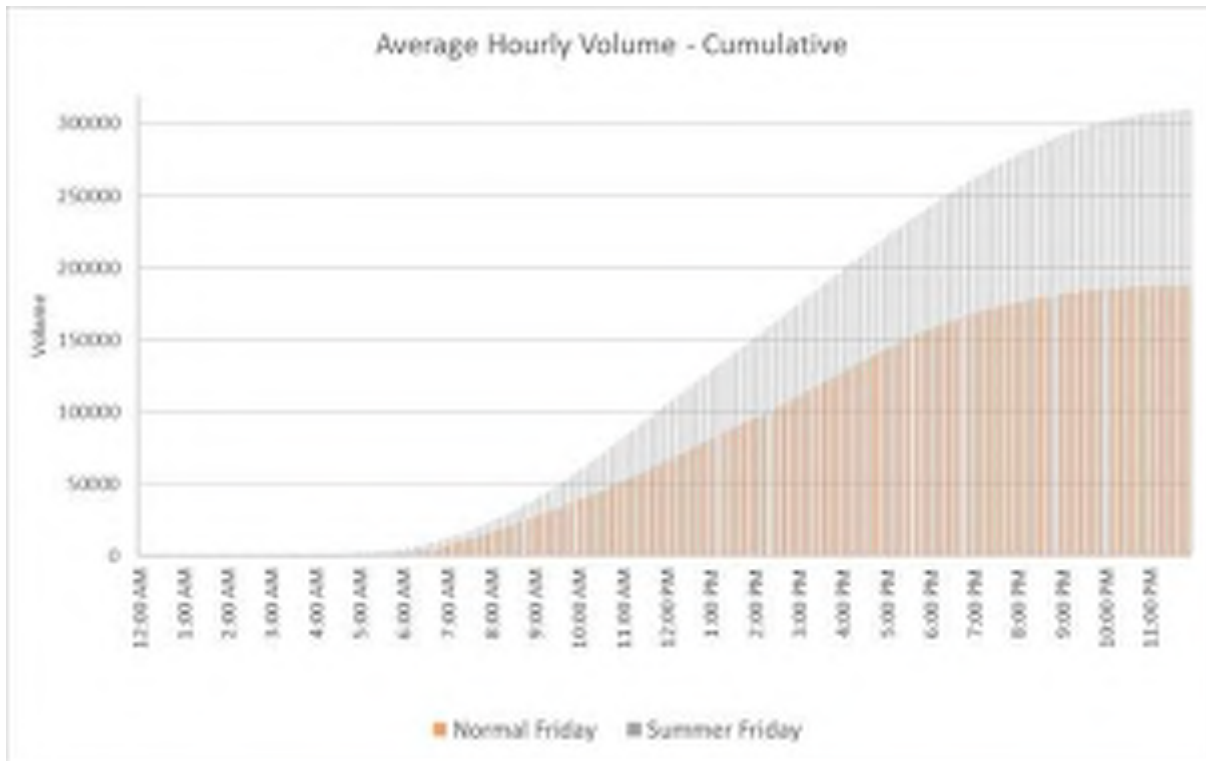
Study Scope

- Improve traffic operations on a beachbound arterial corridor
- Existing system is already actuated-coordinated with dynamic pattern changes based on real-time traffic conditions
- Traffic surges very fast during summer, reactive system cannot keep up
- Need for a proactive/ predictive system to manage pattern changes in real-time



Study Scope

- High volume on weekends than weekdays
- Overall high volume daily on Friday (summertime)
- High southbound volume to beach area

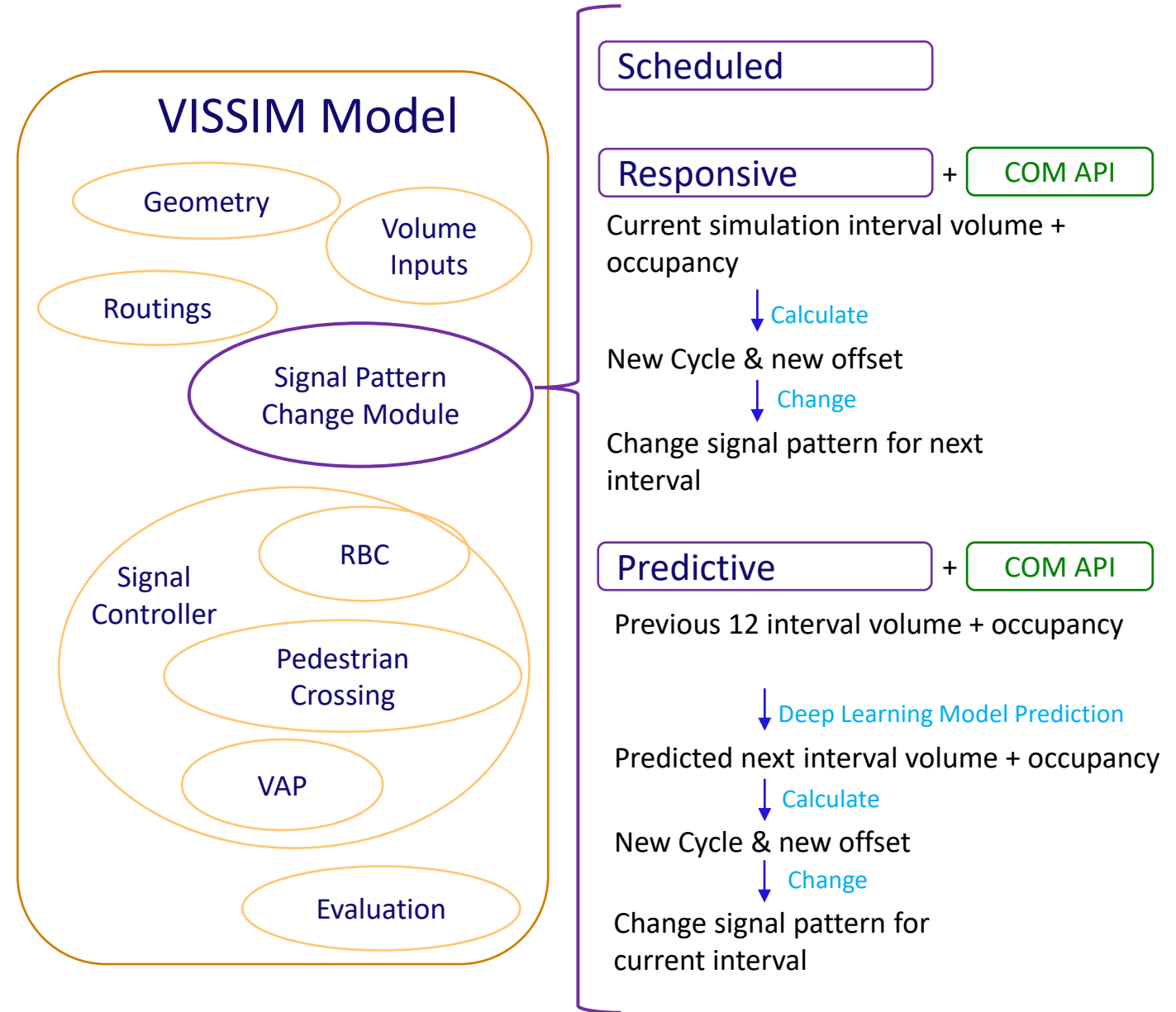


Methodology



Methodology

- Test alternative pattern change systems
 - Scheduled – Baseline
 - Responsive (Dynamic) – Current
 - Predictive - Planned
- Use Machine Learning (Deep Learning) algorithms for volume & occupancy prediction
 - Use predicted volume & occupancy to trigger responsive signal group signal cycle and offset change
- Model and evaluate system in microsimulation model
 - Collect data every 5-min simulation time interval.
- Compare with field data



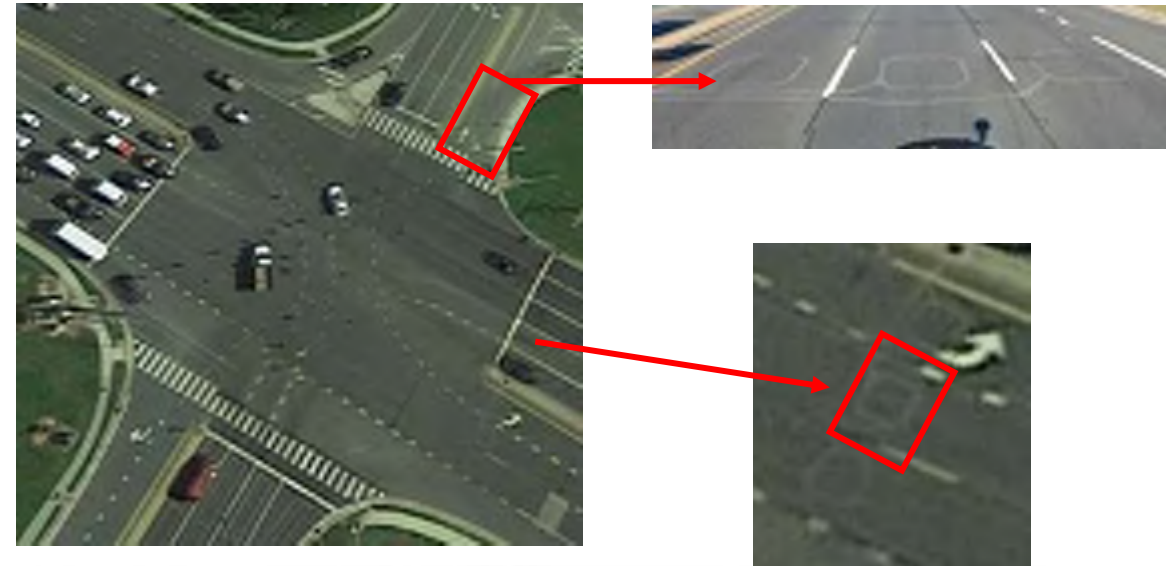
Signal Control Operations

- Signal patterns
 - Pre-coded and stored signal patterns
 - Common basic settings
 - Signal patterns vary by cycle length, phase split and offset
- Scheduled signal operation
 - Signal pattern changes based on time of day and day of week
 - Timetable based on historical traffic data
 - Serves recurring peak and off-peak traffic flows
 - Regions with typical and steady traffic patterns
- Dynamic/Responsive signal operation
 - Signal pattern change based on real-time traffic conditions
 - Serves non-recurring and fluctuating traffic pattern
 - Dynamic change rules and criteria
 - Respond to measured current conditions
- Respond to predicted future conditions

Proposed TOD Plan			
Hour	Min	Plan	Cycle
Everyday			
0	5	1/1/1	90 BAL
6	30	1/2/1	120 BAL
Weekdays (Days 2 - 6)			
7	30	2/1/1	150 SB
9	0	2/2/1	150 BAL
15	0	2/3/1	150 NB
20	0	1/2/1	120 BAL
Sunday (Day 1)			
9	30	2/2/1	150 BAL
13	30	3/3/1	165 NB
18	0	2/3/1	150 NB
22	30	1/2/1	120 BAL
Saturday (Day 7)			
7	30	2/2/1	150 BAL
11	0	3/1/1	165 SB
18	0	2/2/1	150 BAL
22	30	1/2/1	120 BAL

Siemens/Yunex Tactics - Dynamic Signal Operations

- Signal patterns change by responding to the traffic conditions measured by detector occupancy rate (o) and volumes (v)
- **(V+O)%** per direction per interval
 - Calculation based on per lane volumes and occupancy rate
 - Occupancy rate: percentage of time a vehicle is sensed over the detector
- **v** value per interval
 - Measure directional traffic flows
 - Identify congestion direction
 - Determine splits and offsets
- Trigger intersections
 - Seven intersections along the corridor
 - Detectors on downstream lanes



$$(V + O)\% = \frac{1}{n} \times \left(\sum_{d_i \in D} \frac{5\text{-min volume}_{d_i}}{150} \times 100 + \sum_{d_i \in D} 5\text{-min occupancy}_{d_i} \right) \%$$

where, d_i = per lane system detector i

$$D = \{d_1, d_2, d_3, \dots, d_n\}$$

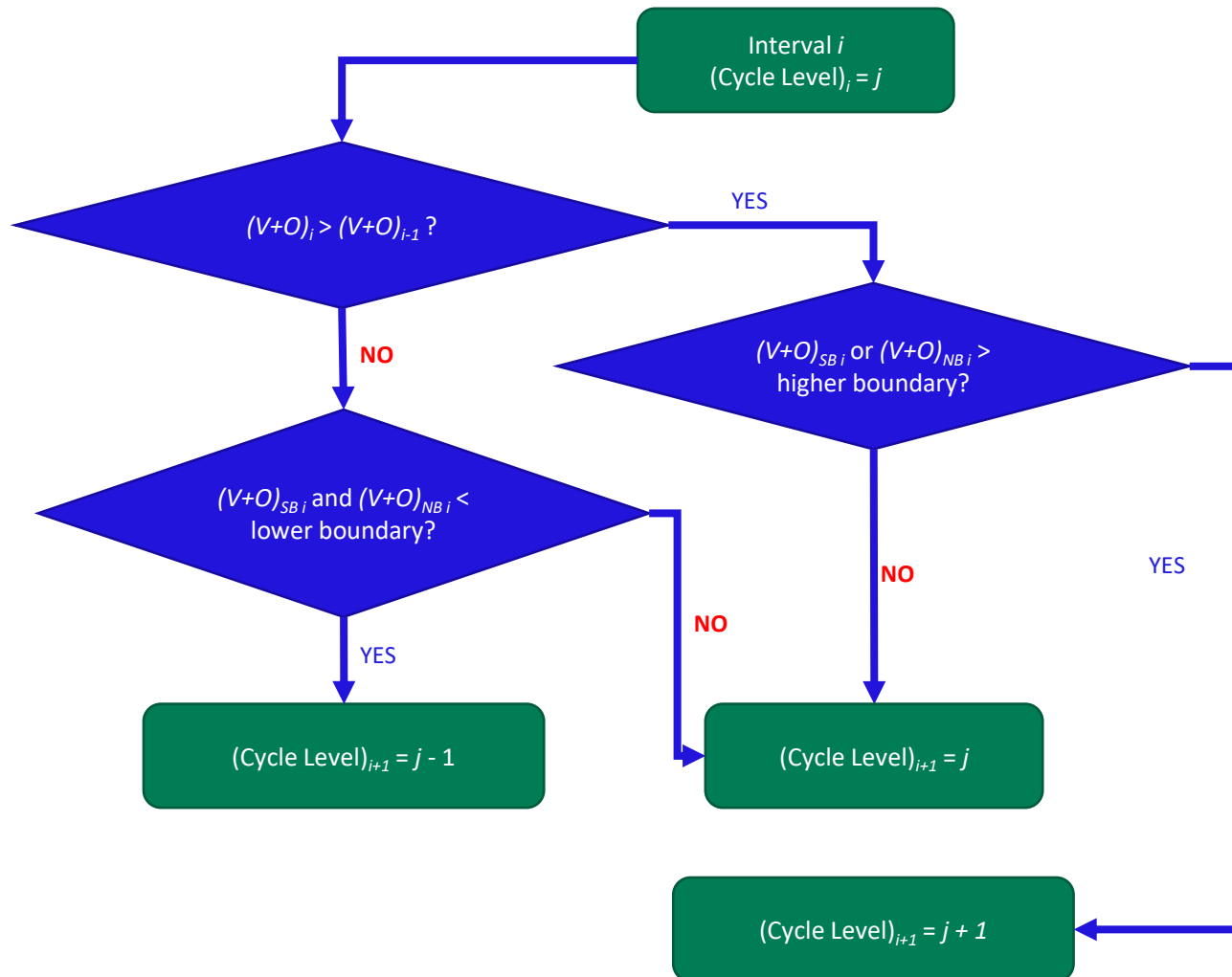
$$v\% = \frac{\frac{1}{m} \times \sum_{d_i \in DS} (SB \text{ volume})_{d_i}}{\left(\frac{1}{m} \times \sum_{d_i \in DS} (SB \text{ volume})_{d_i} + \frac{1}{n} \times \sum_{d_j \in DN} (NB \text{ volume})_{d_j} \right)}$$

where, d_i = per lane system detector i

$$DS = \{d_1, d_2, d_3, \dots, d_m\}$$

$$DN = \{d_1, d_2, d_3, \dots, d_n\}$$

Cycle Length and Split/Offset



Cycle Length – $(V+O)\%$

- To change to longer cycle length
 - $V+O$ is increasing
 - Either directional $V+O$ greater than entry line
- To change to shorter cycle length
 - $V+O$ is decreasing
 - Both directional $V+O$ less than exit line

Offset – v value

- Three levels of directionality
 - Default level = 1: balanced volumes at both directions
 - Level = 0: favor Northbound traffic
 - Level = 2: favor Southbound traffic

Example of Dynamic Signal Operation

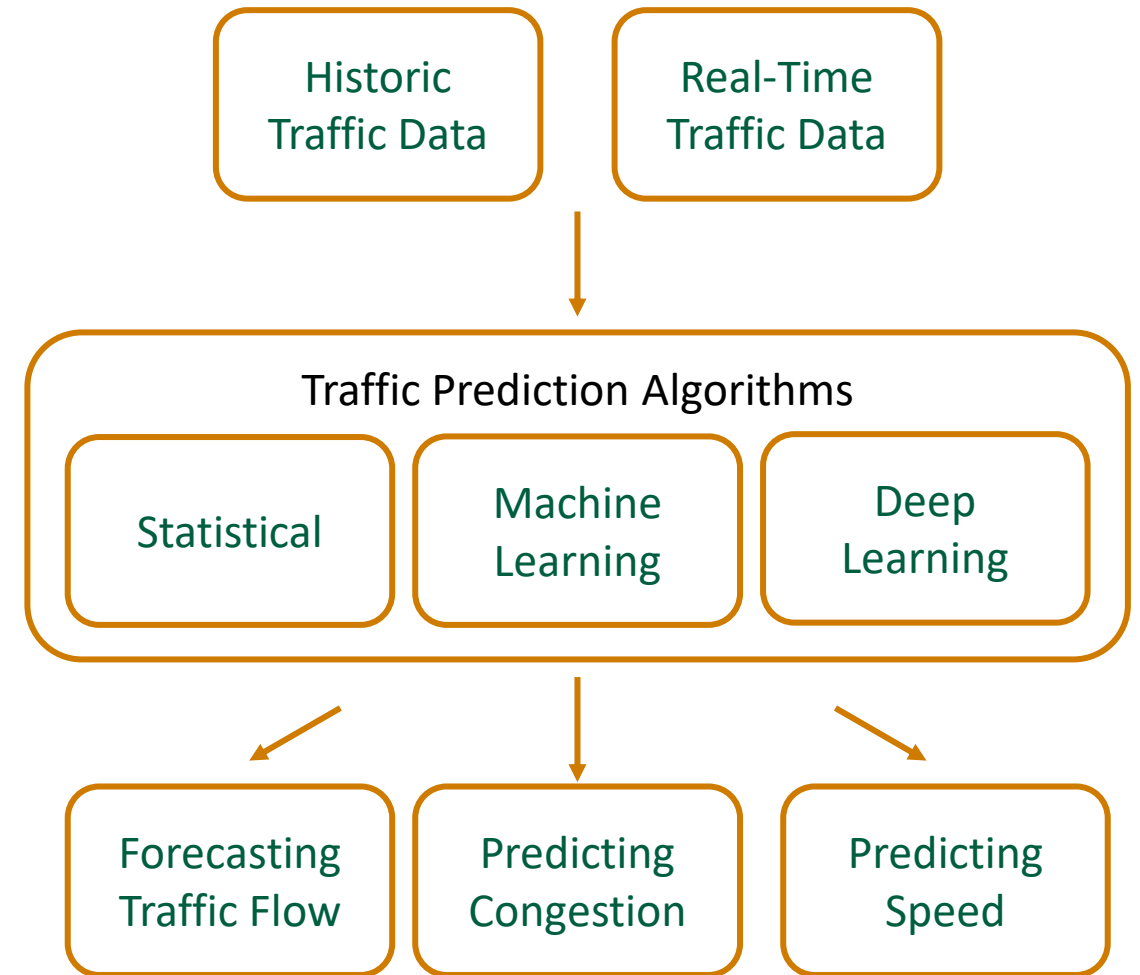


Traffic Volume & Occupancy Prediction



Traffic Data Prediction

- Traffic prediction
 - Forecasting the volume and density of traffic flow
- Traffic prediction algorithms
 - Statistical
 - Fast and cheaper but less accurate
 - Auto-Regressive Integrated Moving Average (ARIMA) model
 - Machine learning
 - Large masses of heterogeneous data
 - Random forest; k-nearest neighbors (KNN)
 - Deep Learning
 - Highly effective
 - Convolutional neural networks (CNNs); Recurrent neural networks (RNNs) – time series data



Deep Learning Model

- Neural network models

- RNN (Recurrent Neural Networks)

- Time-sequence data and prediction
 - With “memory” which remembers all information about what has been calculated.
 - Output of RNN depend on the prior elements within the sequence.

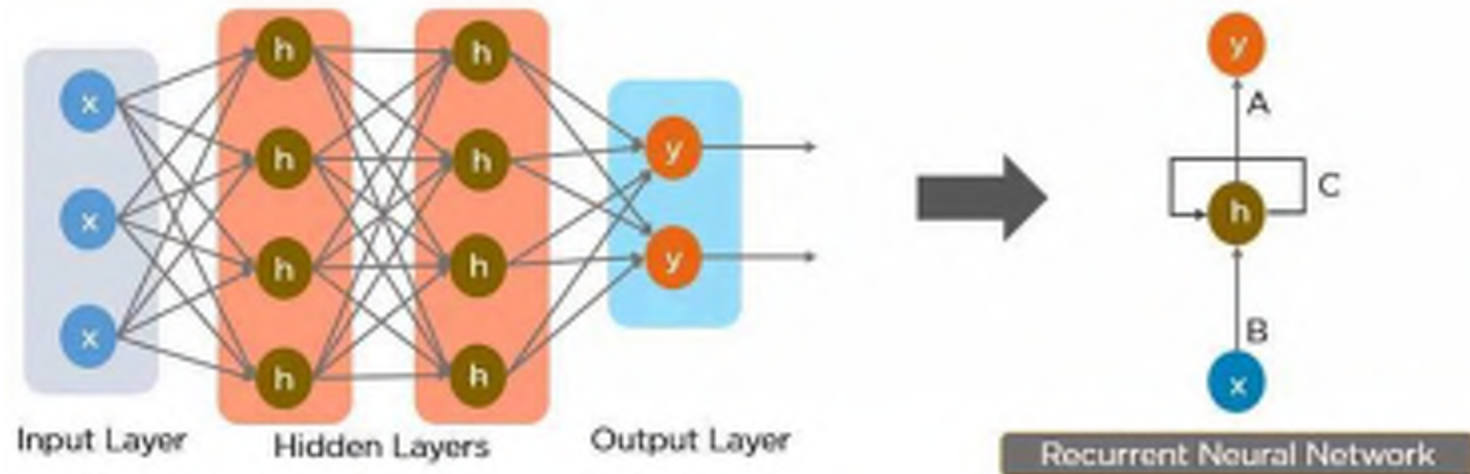
- Types:

- 1 – 1; 1 – many; many – 1; many - many

- Vanishing gradient issue

- LSTM

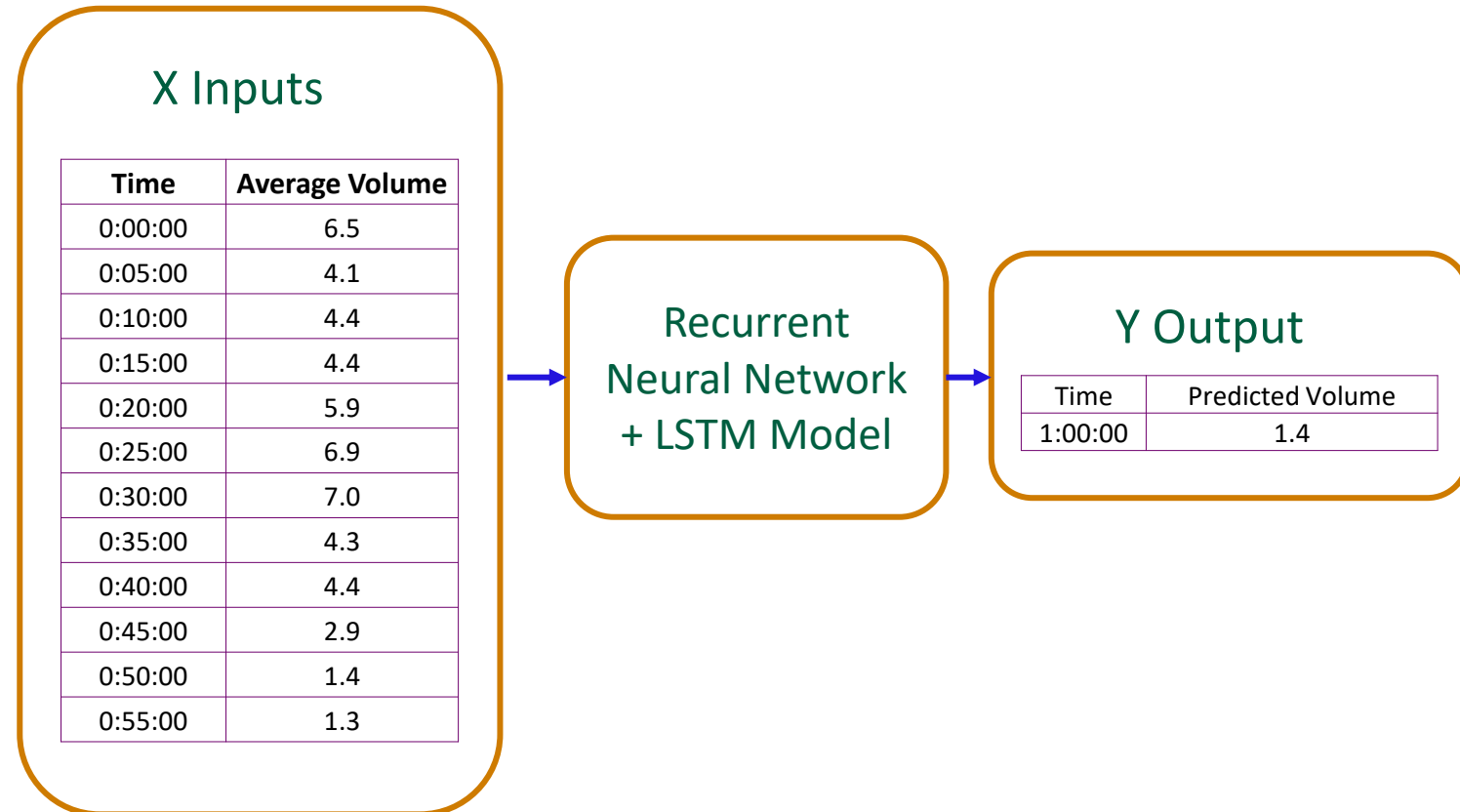
- Long Short-Term Memory Networks
 - Address vanishing gradient issue



From: <https://www.simplilearn.com/tutorials/deep-learning-tutorial/rnn>

Deep Learning Model – Data Selection

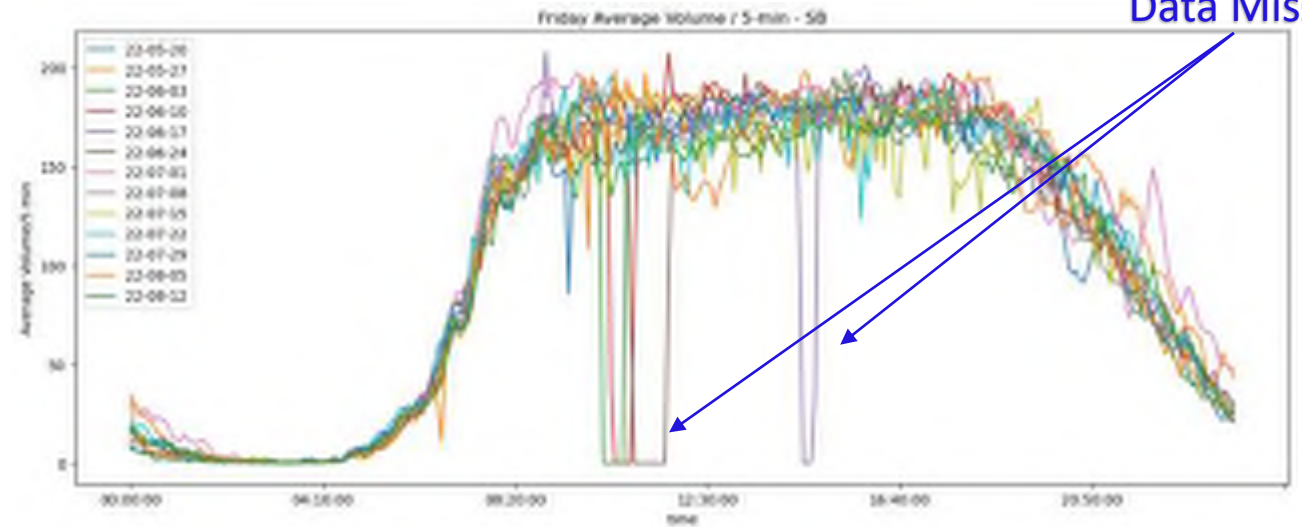
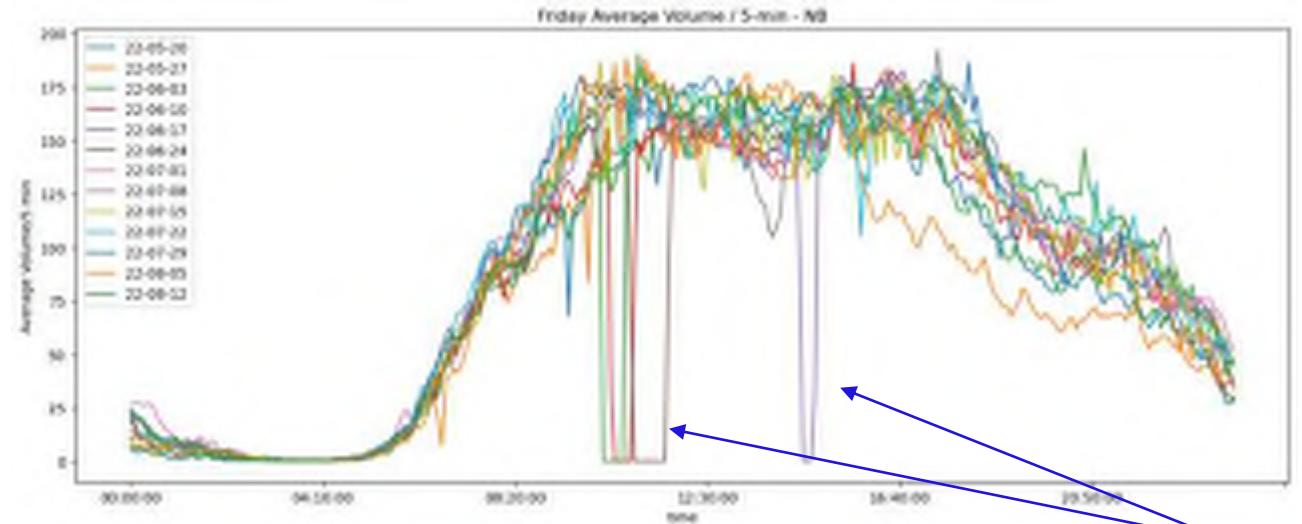
- Traffic Volume & Occupancy
 - Select key intersections in study area
 - Southbound and Northbound volume, southbound and northbound occupancy
 - Average volume & occupancy for all selected intersection by directions
- Summer weekends
- Data
 - Train dataset: Fridays from May to September 2022, except 7/15/2022 (13 days)
 - Test dataset: 7/15/2022
 - 24 hours by 5-min data point



Deep Learning Model – Data Clean Up & Processing

1. Data clean up & processing

- 1) **Select** Friday data
 - 2) **Clean up and process** missing & error data
 - 3) **Split** training set and testing set
 - 4) **Calculate** average data by selected intersections and directions for training set
- Cycle pattern change
 - SB: 7 intersections
 - NB: 5 intersections
 - Offset pattern change
 - SB: 5 intersections
 - NB: 5 intersections



Data Missing

Deep Learning Model – Model Training & Testing

2. Deep Learning Model Training

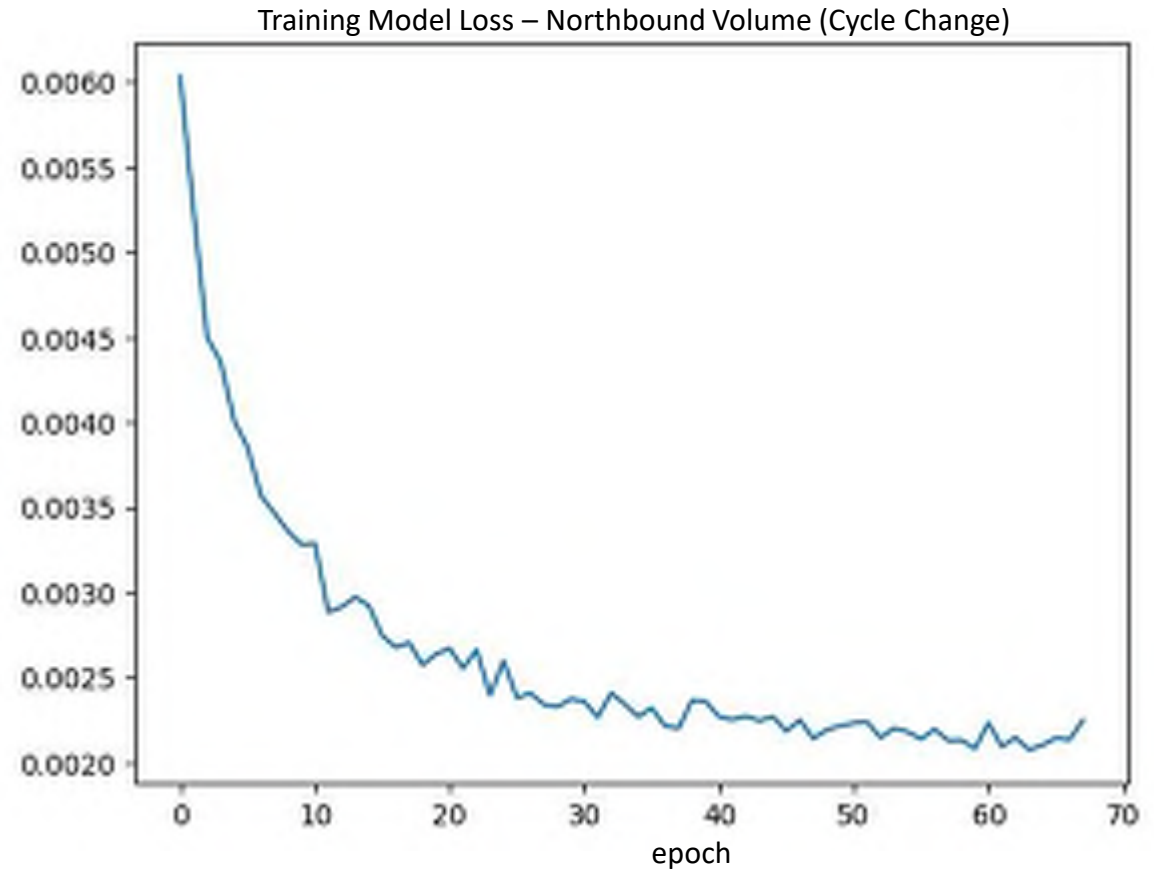
- 4 LSTM layers with output layer
- “ADAM” optimizer
- Loss function: mean squared error
- TensorFlow – keras / scikit-learn - MinMaxScaler
- 6 deep learning models
 - Cycle change – volume : SB + NB
 - Cycle change – occupancy : SB + NB
 - Offset change – volume: SB + NB

3. Deep Learning Model Testing

- Use trained model to test 7/15/2022 data
- Run and test multiple attributes with multiple epochs

4. Deep Learning Model Save

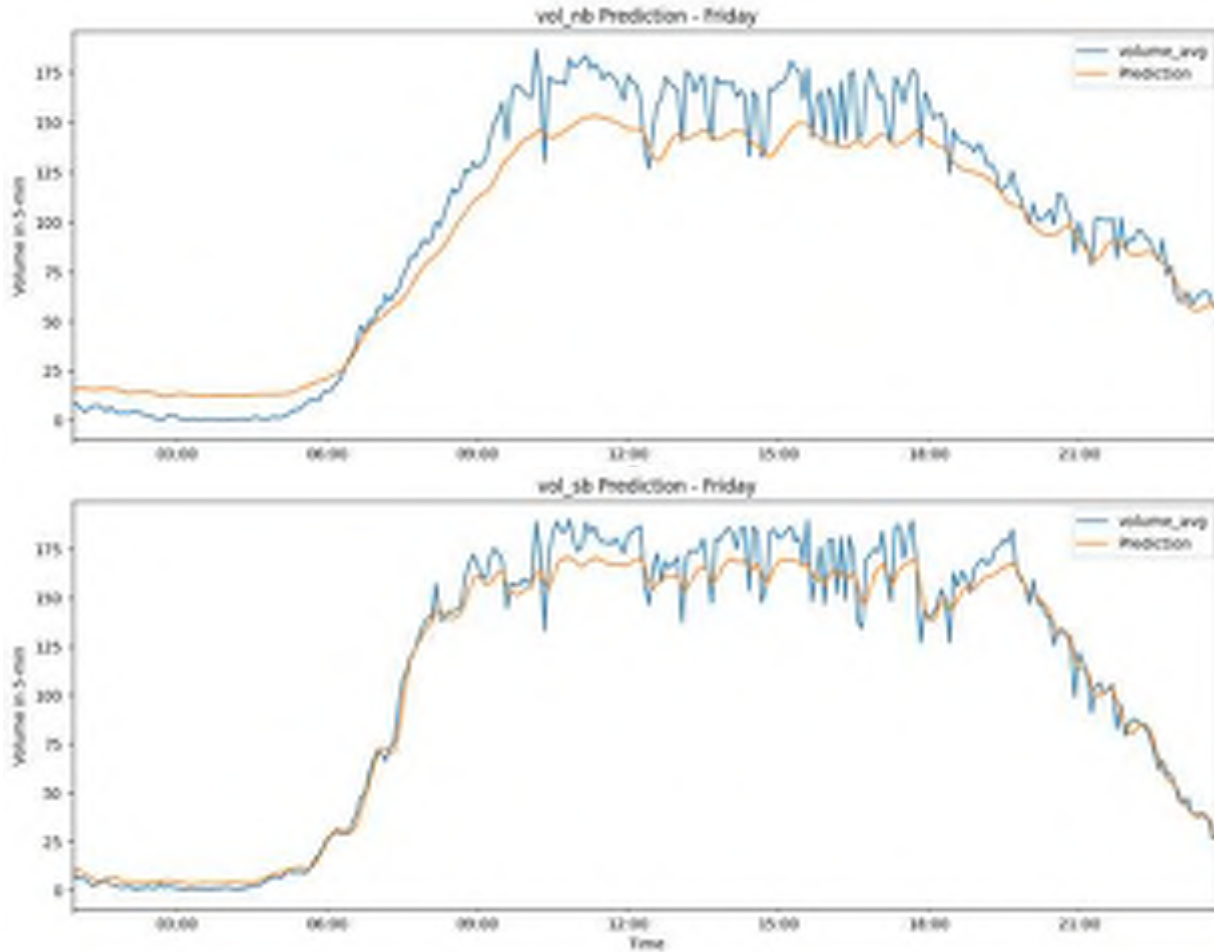
- Pickle format



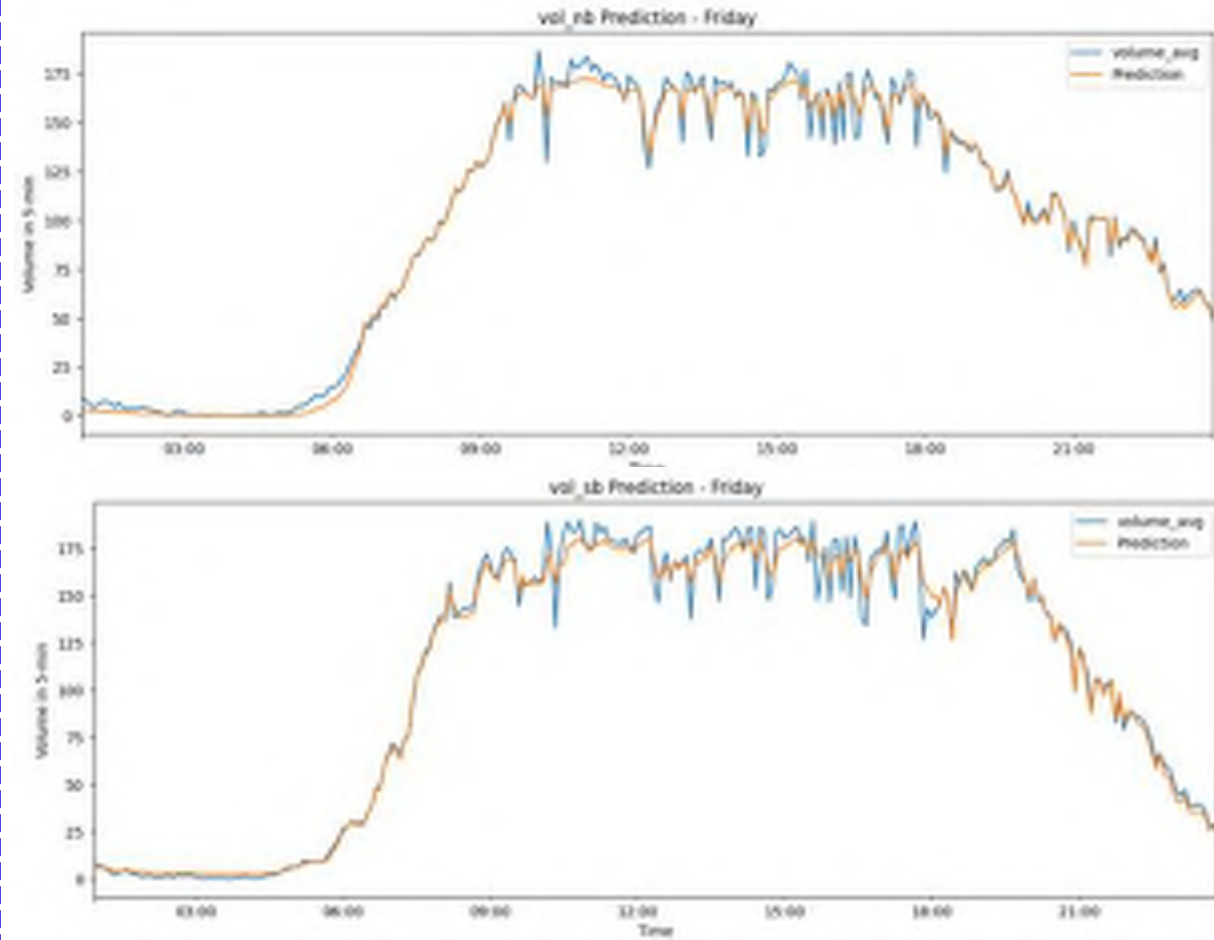
Deep Learning Model – Prediction

- Traffic Volume & Occupancy

Before



After

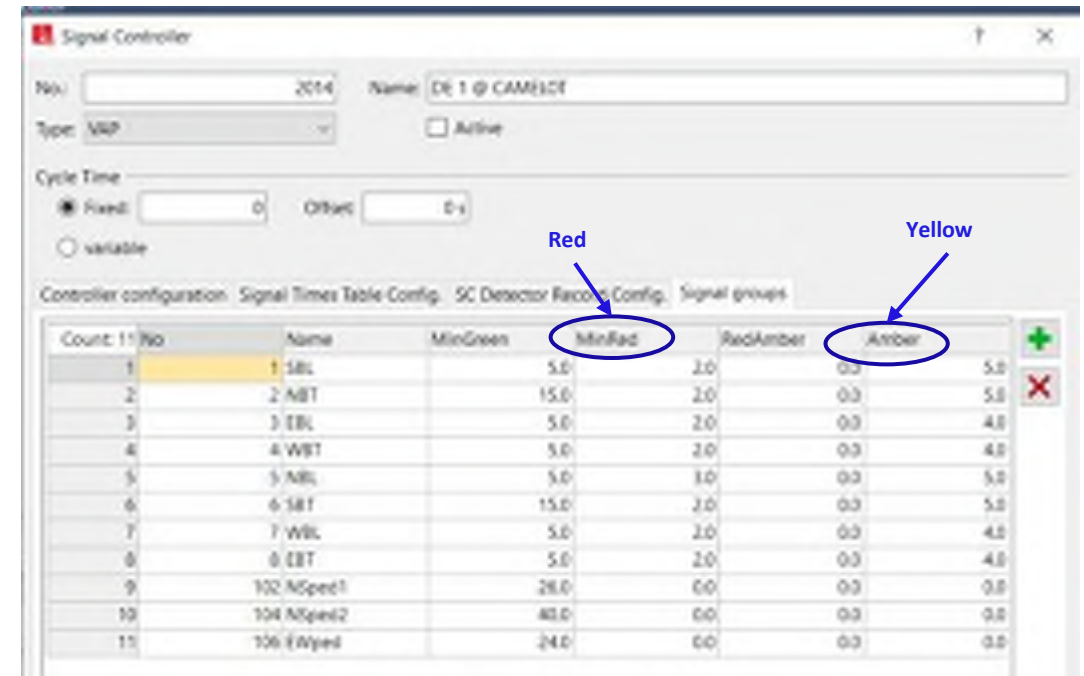
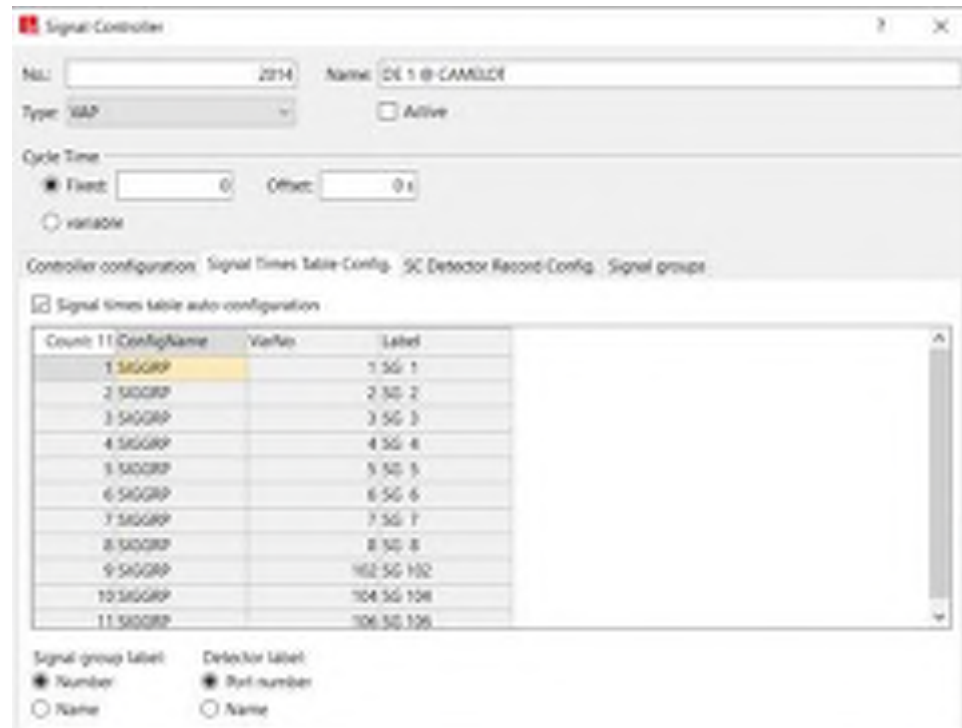


Signal Controller and API Development



VAP Controller

- VAP Controller: traffic dependent programming
 - Simulate programmable vehicle-actuated signal controls
 - Interpret control logic commands and generate signal control commands
 - Stage- or group-based



- In VISSIM
 - Pre-coded basic signal group settings for all patterns
 - Signal patterns saved in text files
 - *.pua: signal data file
 - *.vap: program logic

Files of VAP Controller

- PUA file:
 - SIGNAL_GROUPS: phase groups
 - STAGES: signal operational statuses
 - STARTING_STAGE: first operational status
- VAP file
 - Signal group concept
 - Define signal patterns and recall modes
 - All patterns have the same phases sequence

```
ARRAY
  MAXGREEN[9,8] = [[25,84,0,5,25,84,0,5],[25,114,0,5,25,114,0,5],[25,144,0,5,25,144,0,5],
                  [25,144,0,5,25,144,0,5],[25,144,0,5,25,144,0,5],[25,144,0,5,25,144,0,5],
                  [25,159,0,5,25,159,0,5],[25,159,0,5,25,159,0,5],[25,159,0,5,25,159,0,5]],
  /* maxgreen is basically the max green time of each phase in each pattern */
  MINGAP10[8] = [30,50,0,40,30,50,0,40], /* min gaps are entered in tenths of secs */
  MAXRECALL[8] = [0,0,0,0,0,0,0,0],
  MINRECALL[8] = [0,1,0,0,0,1,0,0], /* MAXRECALL and MINRECALL cannot be true at the same time */
  PEDPHASE[8] = [0,1,0,1,0,1,0,0], /* indicate if the phase has pedestrian phase */
  PEDRECALL[8] = [0,0,0,0,0,0,0,0], /* indicate if the ped phase has ped-recall */
  OFFSET[9] = [02,60,26,5,137,0,26,5,137], /* This number is the (REC offset - first_phase_split_time) */
  VEHDETECTOR[8] = [1,0,0,1,1,0,0,1], /* if the movement has detectors. */
  CYCLE[9] = [90,120,150,150,150,150,165,165,165], /* cycle length of patterns */
  YellowRed[8] = [6,6,0,6,6,6,0,6], /* yellow time + red time of each phase */
  Conflicts[8,4] = [[2,4,8,8],[1,4,8,8],[0,0,0,0],[1,2,5,6],[4,6,8,8],[4,5,8,8],[0,0,0,0],[1,2,5,6]],
  /* define the conflict phases/movements of current phase/movement */
```

Phase split

```
$SIGNAL_GROUPS
$
SBL 1
NBT 2
EBL 3
WBT 4
NBL 5
SBT 6
WBL 7
EBT 8
NSped1 102
EWped 104
NSped2 106

$STAGES
$
stage_1 SBL NBL
red NBT EBL WBT SBT WBL EBT NSped1 EWped NSped2
stage_2 NBT NBL
red SBL EBL WBT SBT WBL EBT NSped1 EWped NSped2
stage_3 NBT SBT
red SBL EBL WBT NBL WBL EBT NSped1 EWped NSped2
stage_4 EBL WBL
red SBL NBT WBT NBL SBT EBT NSped1 EWped NSped2
stage_5 WBT WBL
red SBL NBT EBL NBL SBT EBT NSped1 EWped NSped2
stage_6 WBT EBT
red SBL NBT EBL NBL SBT WBL NSped1 EWped NSped2

$STARTING_STAGE
$
stage_1

$END
```

VISSIM COM Application

- Developed in Python 3.9 script
- Identify signal controller and change its pattern number
- Use VISSIM event-based script
- Text files of inputs:
 - List of intersections and responsive zone
 - List of trigger intersections for collecting measurements
 - List of pre-coded signal patterns
 - $(V+O)\%$ threshold for selecting cycle length
 - v value threshold and changing matrix for selecting directionality
- Output: VISSIM MOEs

1	zone	V+O	threshold	lower_threshold	high_threshold	exit_cycle	entry_cycle
2	S020	1	3	8	90	120	
3	S020	2	10	18	120	150	
4	S020	3	30	40	150	165	

zone	cycle	direction	pattern_id	vap_prg_no
S020	90	BAL 111	1	
S020	120	BAL 121	2	
S020	150	SB 211	3	
S020	150	BAL 221	4	
S020	150	NB 231	5	
S020	150	NB SLOW 232	6	
S020	165	SB 311	7	
S020	165	NB 331	8	
S020	165	BAL 321	9	

zone	int_id
S020	2005
S020	2007
S020	2010
S020	2014
S020	2016
S020	2017
S020	2026

```
def main():
    time = Vissim.Simulation.AttValue('SimSec')
    # 1. get v+o information from the data collection measurement
    if (time > EVAL_TIME_STEP) and (time % EVAL_TIME_STEP == 1):
        for zone in TARGET_ZONE:
            result = get_vo_vol_info(zone)

            # 2. check v+o calculation results with thresholds and
            # check if there are any changes
            proposed_vap_prg, new_cycle, new_offset_level
            = cycle_offset_check(result, zone)

            # 3. get the v+o thresholds and
            # get the zone-20 target pattern number
            try:
                if current_prg_no[zone] != proposed_vap_prg:
                    switch_vap_prg_zone(zone, proposed_vap_prg)
                    cur_offset_level[zone] = new_offset_level
                    cur_cycles[zone] = new_cycle
            except:
                print("Change VAP program error.")

            vo_vol_track(result, zone, time, proposed_vap_prg)

    return
```

Analysis Results



Simulation Assumption

- Simulation period: 9:00 AM – 9:00 PM
- One hour seeding time
- Scenarios
 - **Scheduled:** signal pattern change follows preset timetable.
 - **Responsive:** signal pattern change corresponds to $(V+O)\%$ and $v\%$ value of current interval in simulation run.
 - **Predictive:** signal pattern change corresponds to $(V+O)\%$ and $v\%$ value of deep learning model predicted values based on simulation output.
- Vehicle volume input: 15-min interval
- Trigger measurements
 - Captured using Data Collection Measurements (DCM)
 - Volume and occupancy rate: 5-min interval
- Output MOEs
 - Arterial throughputs: 15-min interval, aggregated by one hour
 - Corridor travel time: 1-hour interval
 - Intersection operation: 1-hour interval

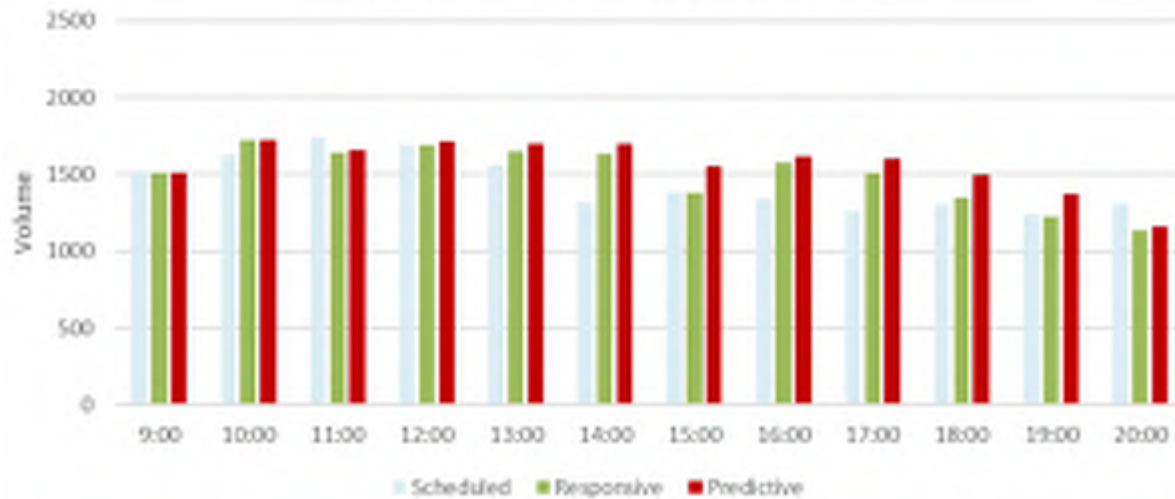
VISSIM Network



Simulation Results - *Friday*

- Comparable corridor throughputs
- Dynamic pattern switch improved
 - Intersection operation
 - Corridor travel time

Average Hourly Volumes - Northbound

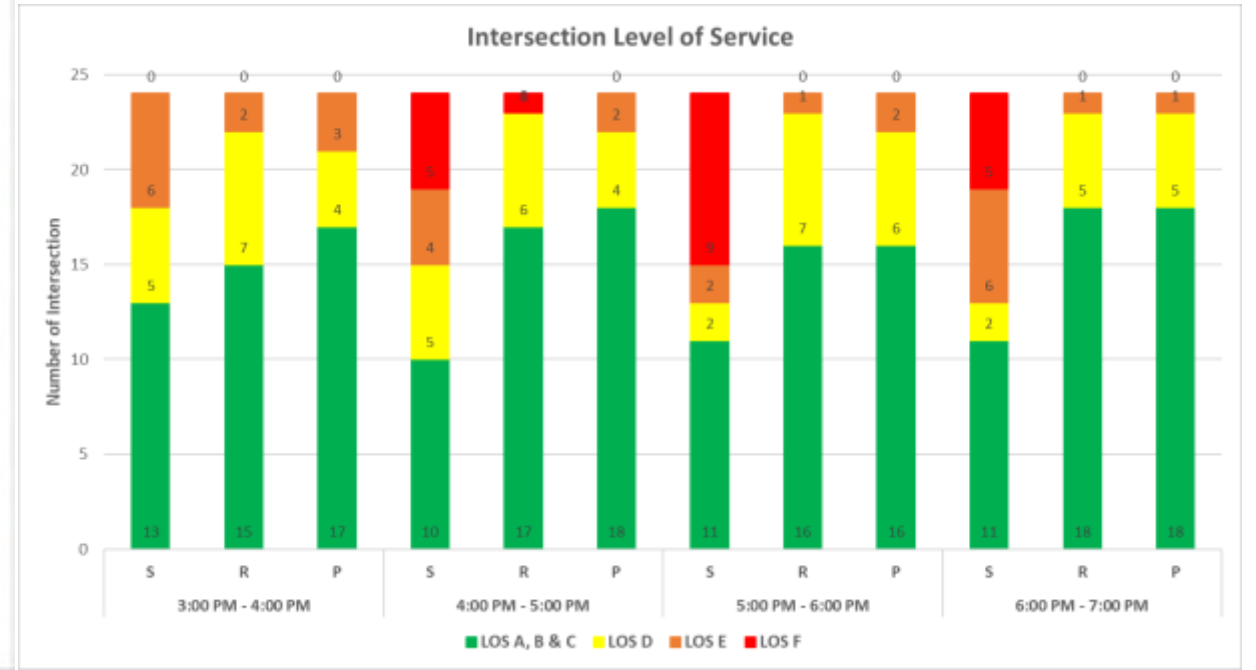
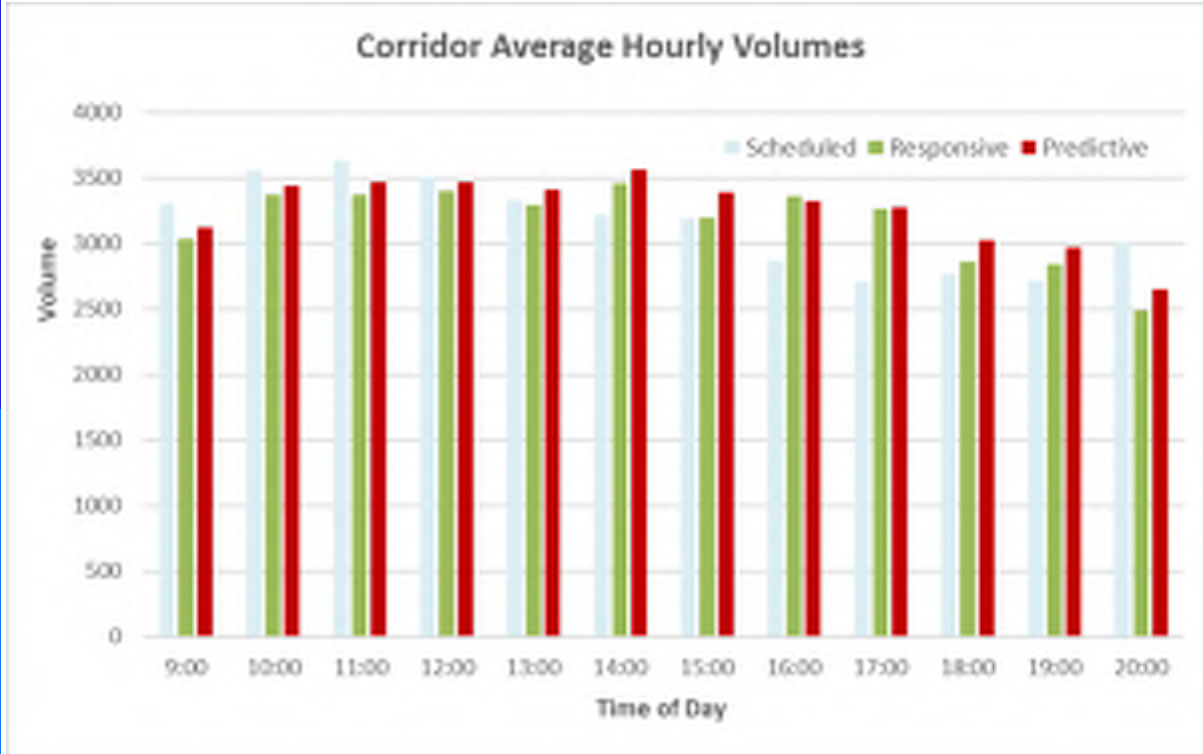
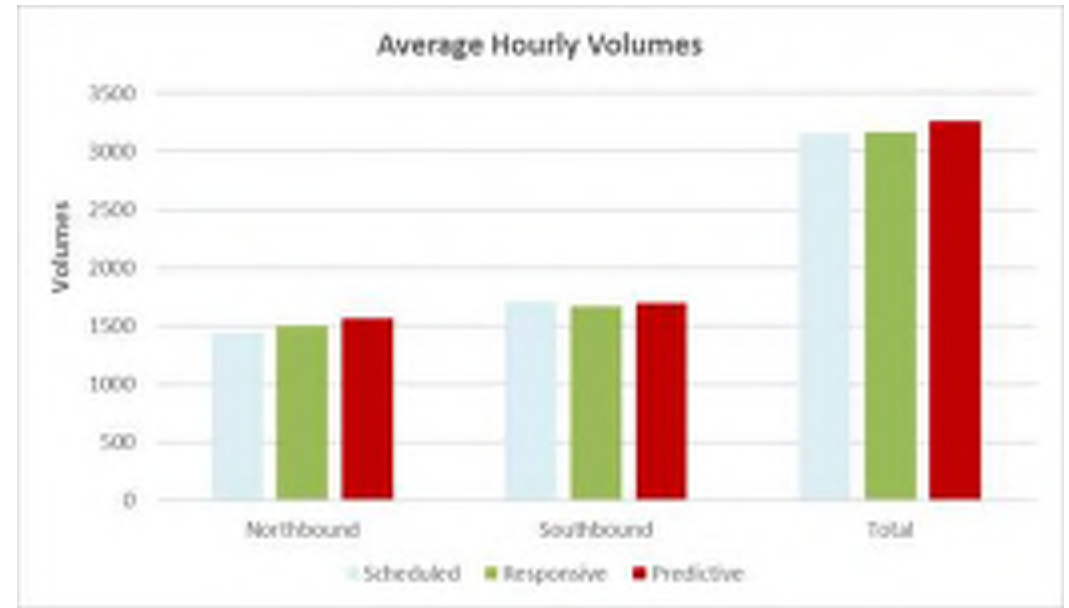


Average Hourly Volumes - Southbound

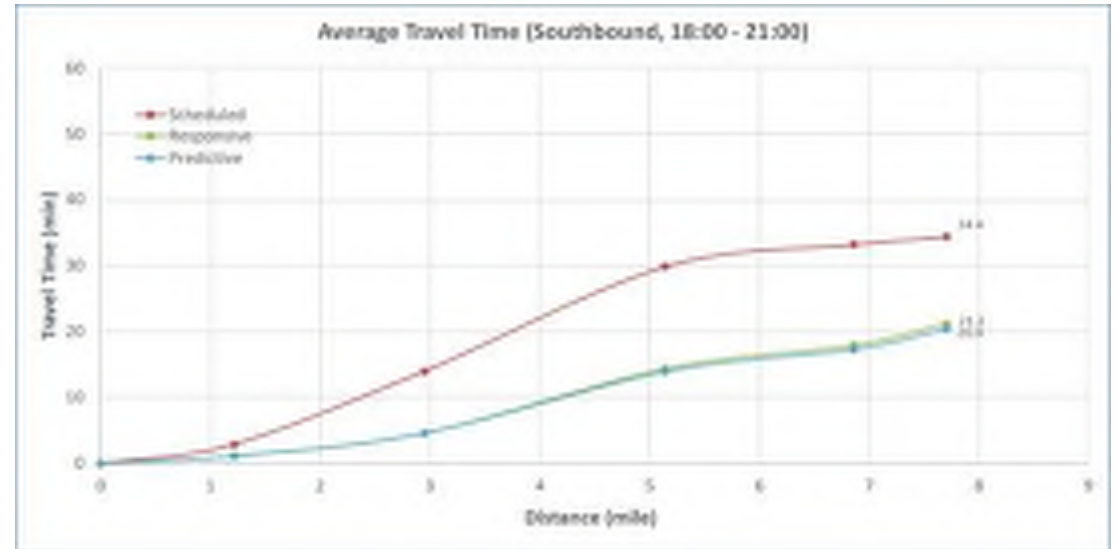
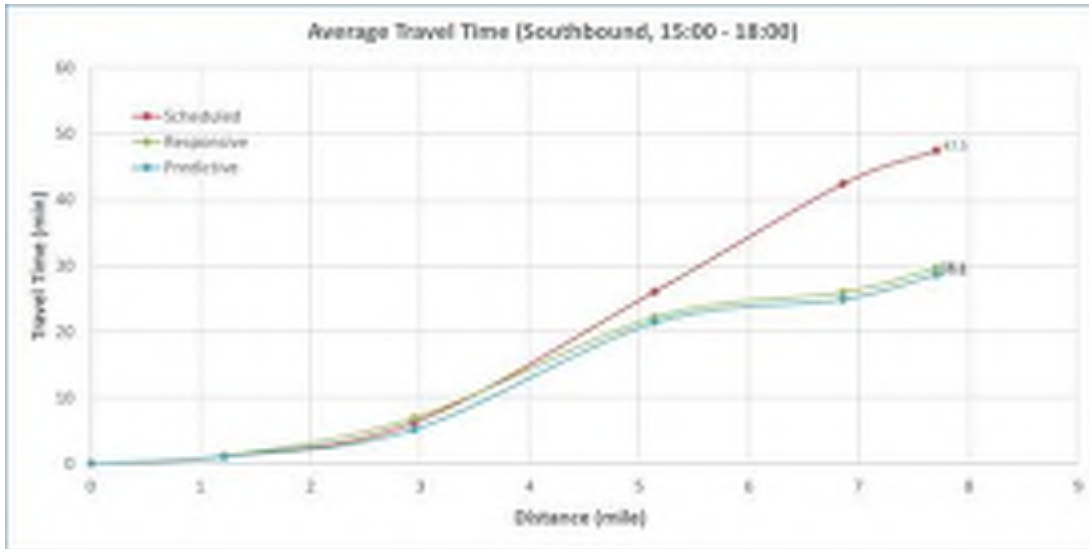
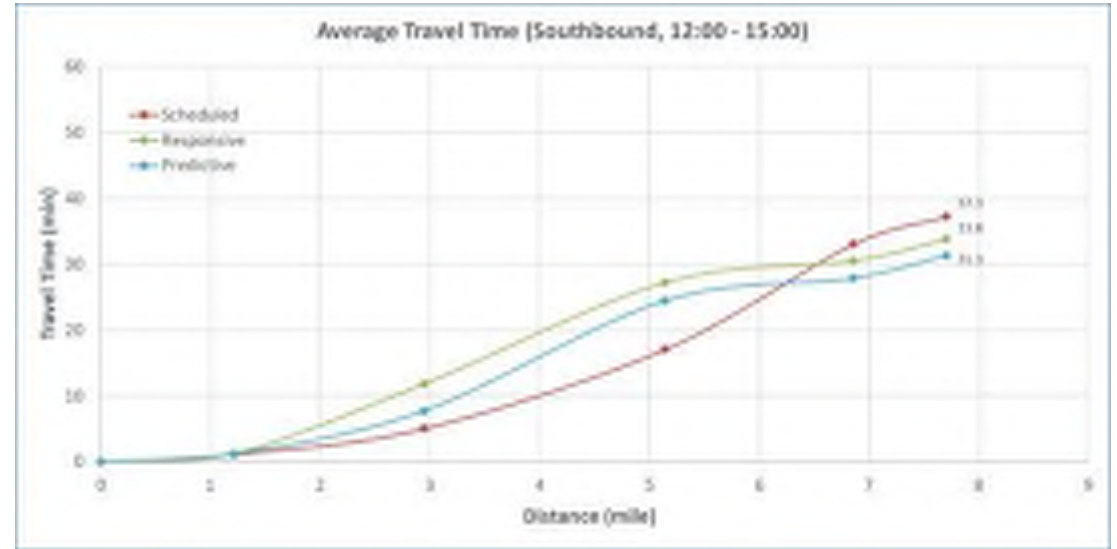
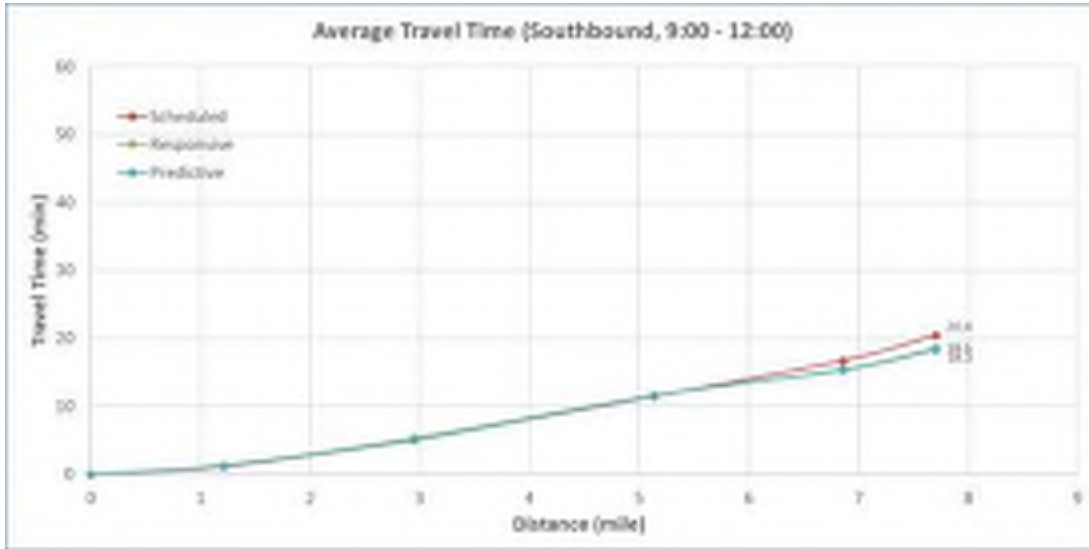


Simulation Results - *Friday*

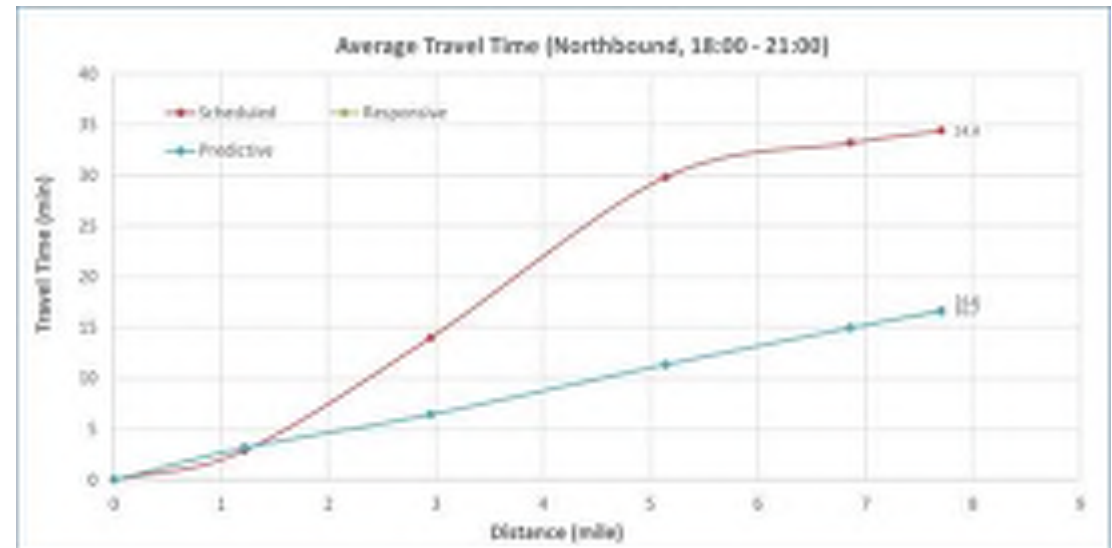
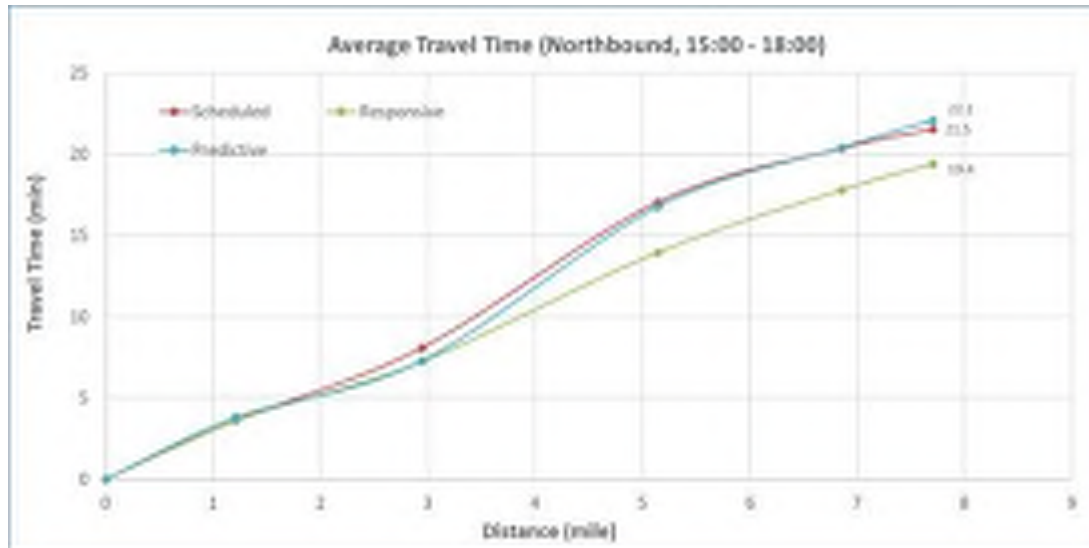
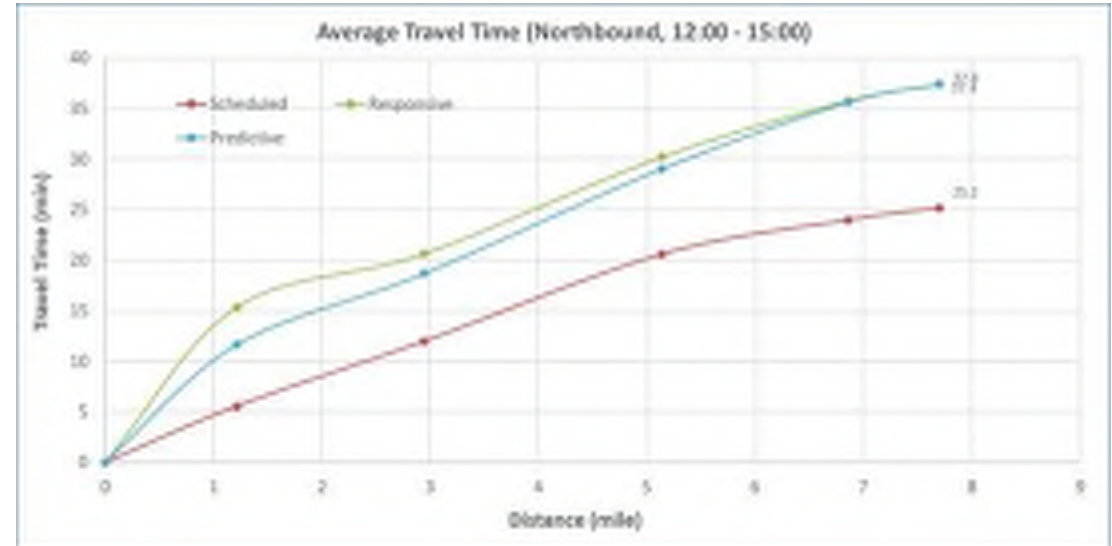
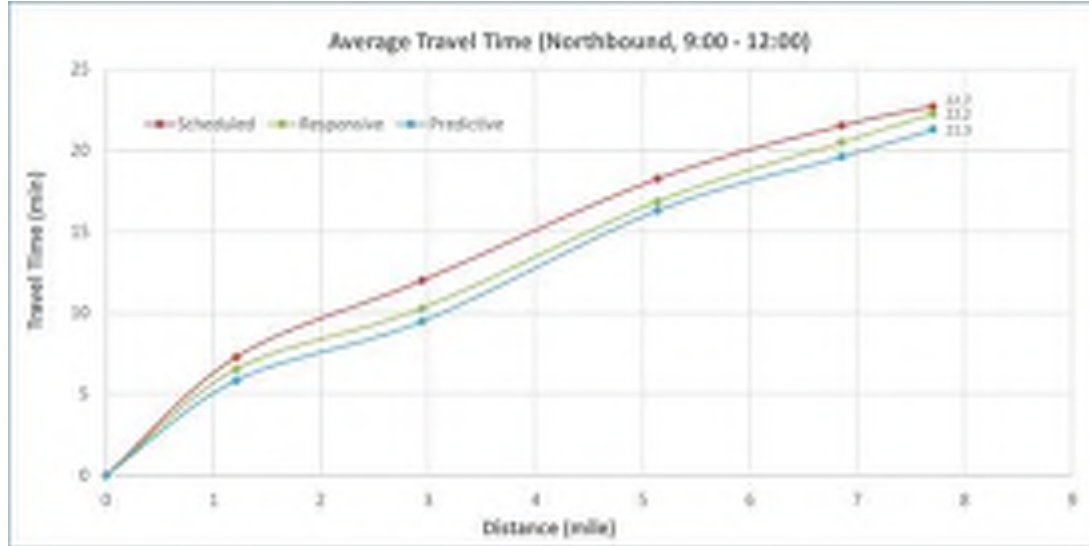
- Comparable corridor throughputs
- Dynamic pattern switch improved



Travel Time Comparison - Friday - Southbound

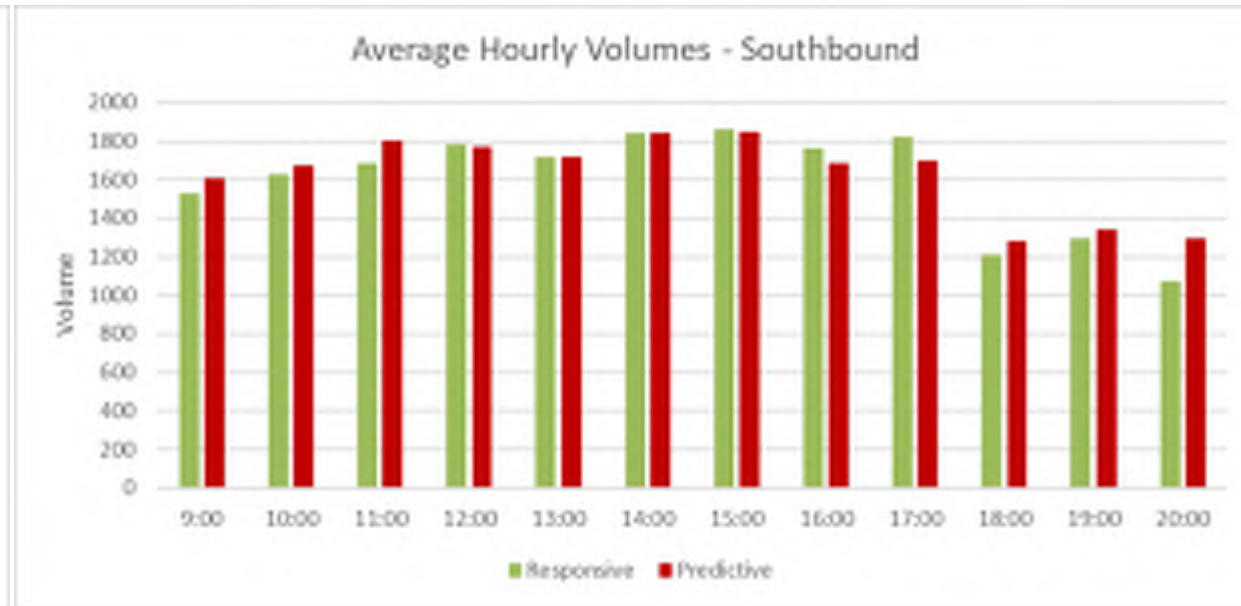
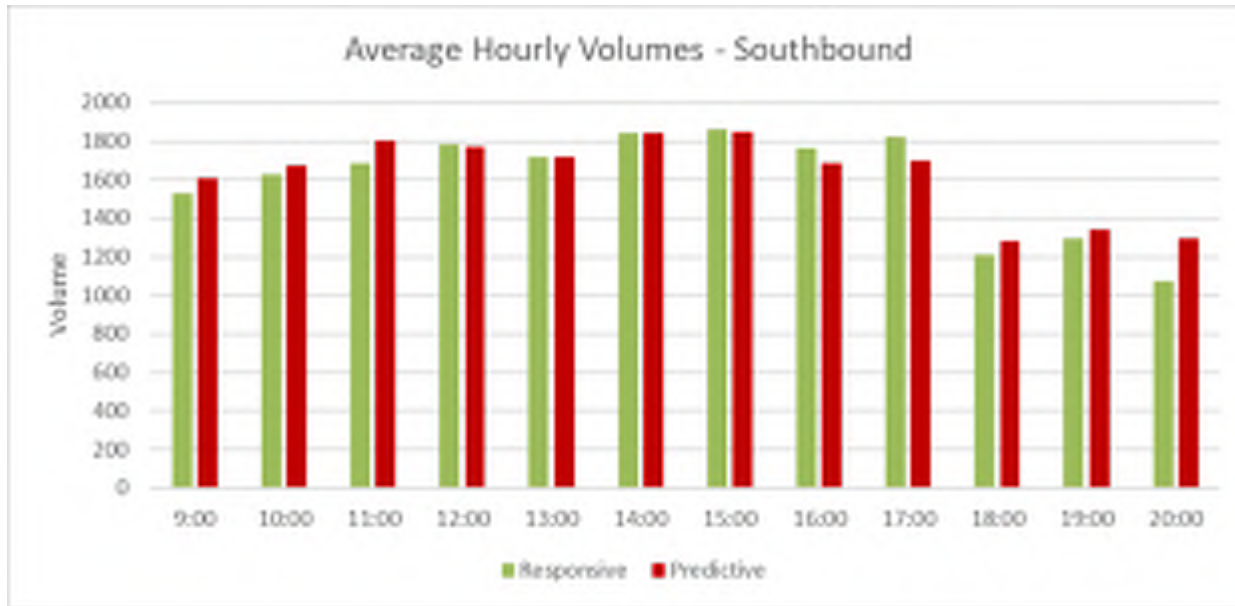
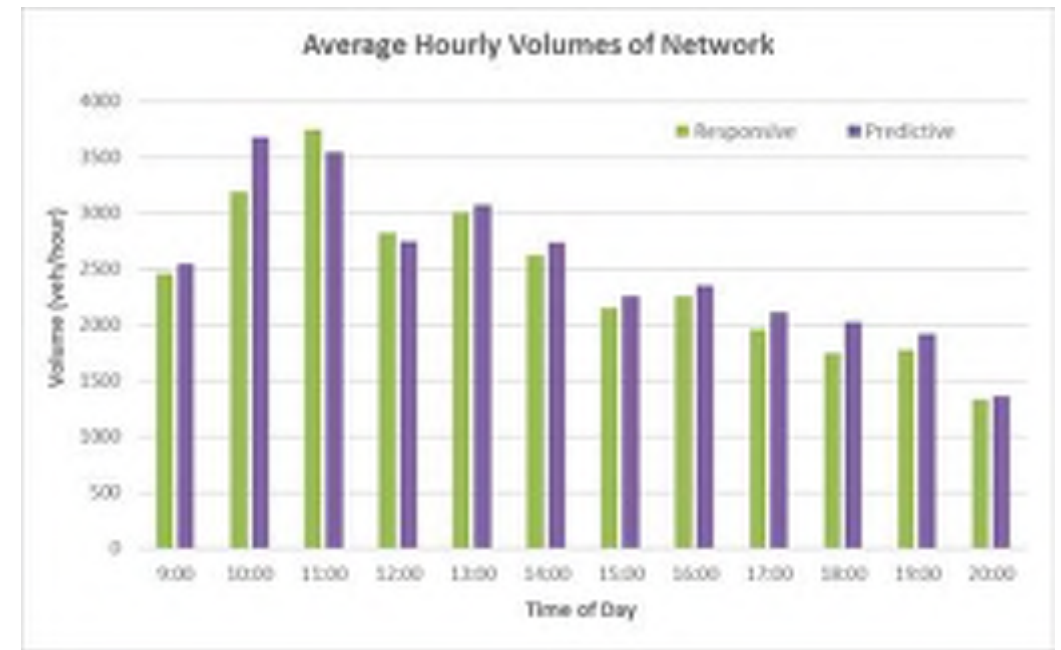


Travel Time Comparison - Friday - Northbound



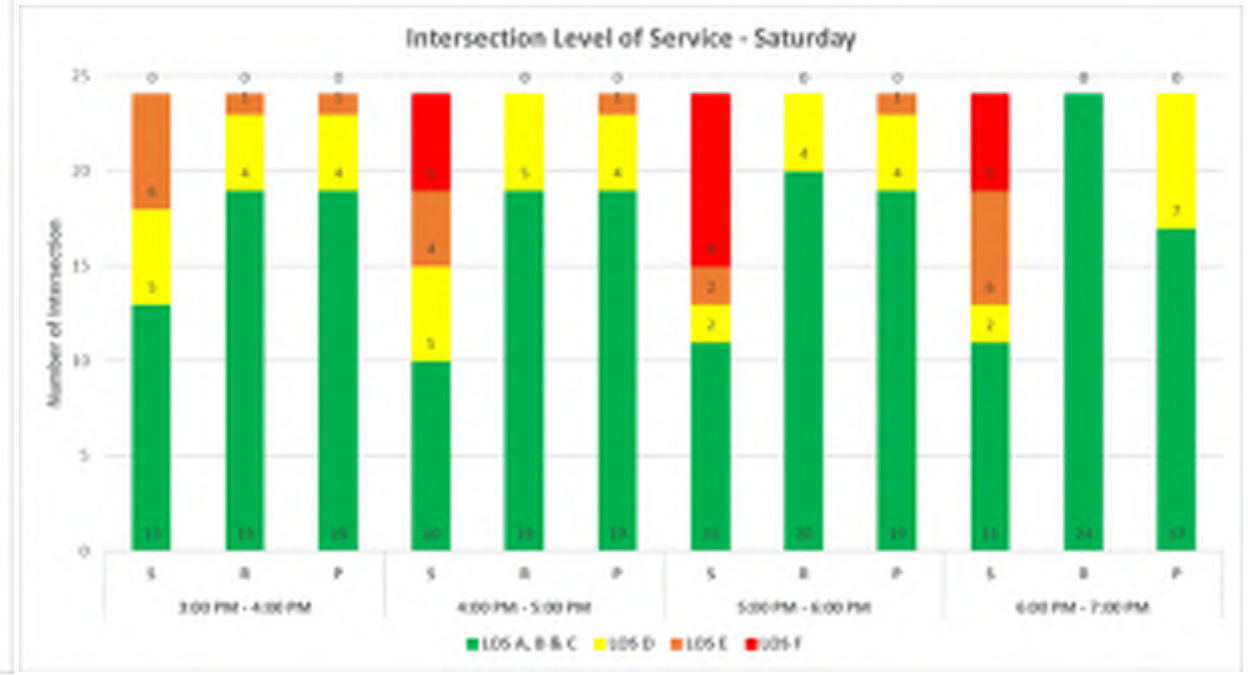
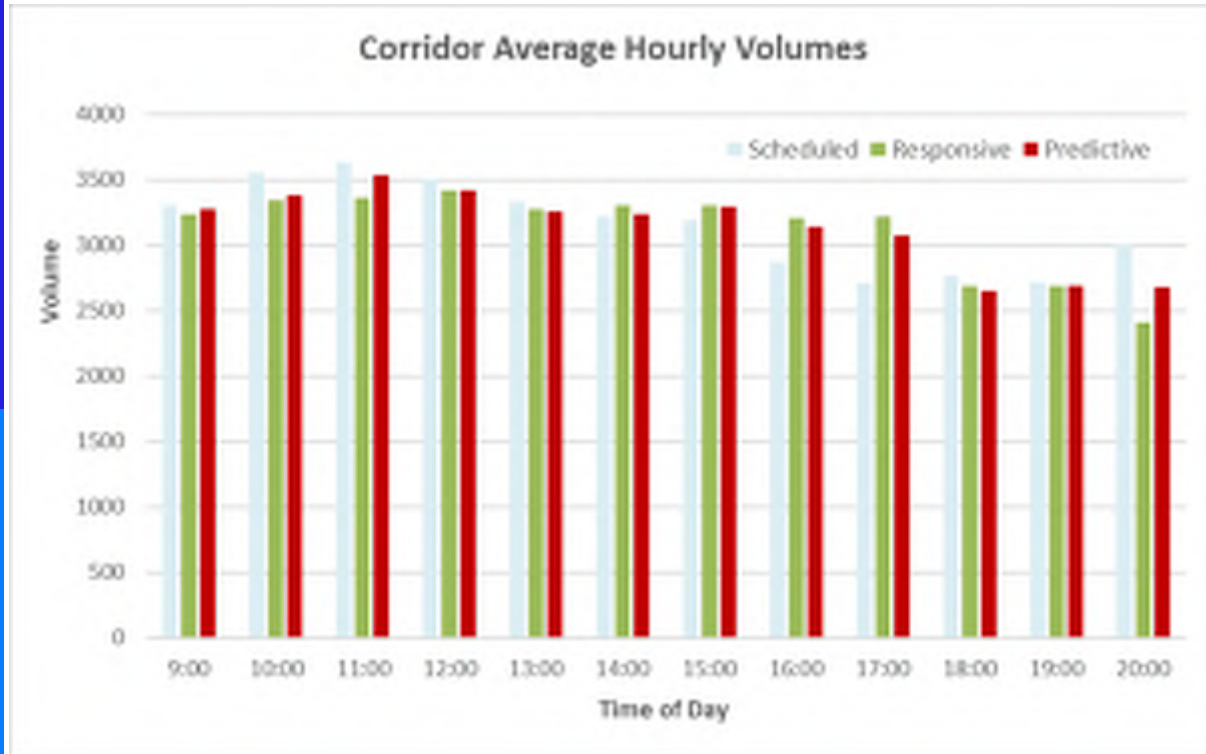
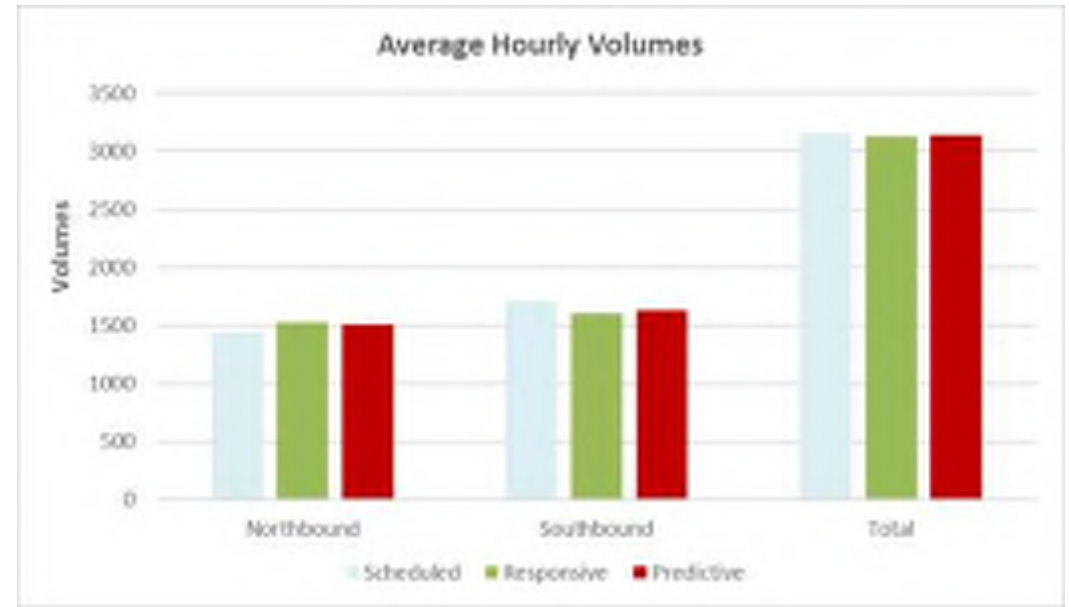
Simulation Results - *Saturday*

- Comparable corridor throughputs
- Dynamic pattern switch improved
 - Intersection operation
 - Corridor travel time

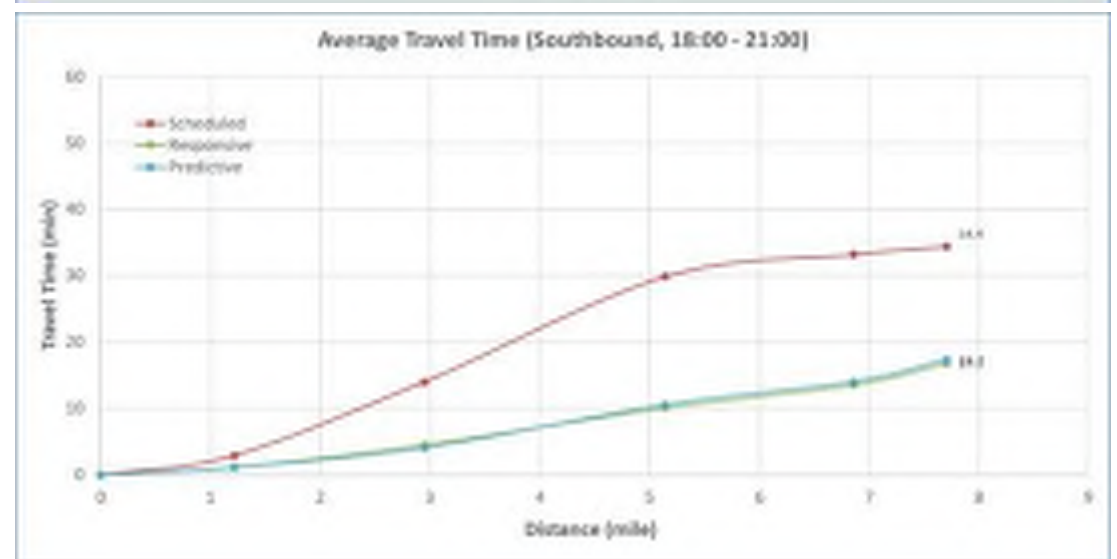
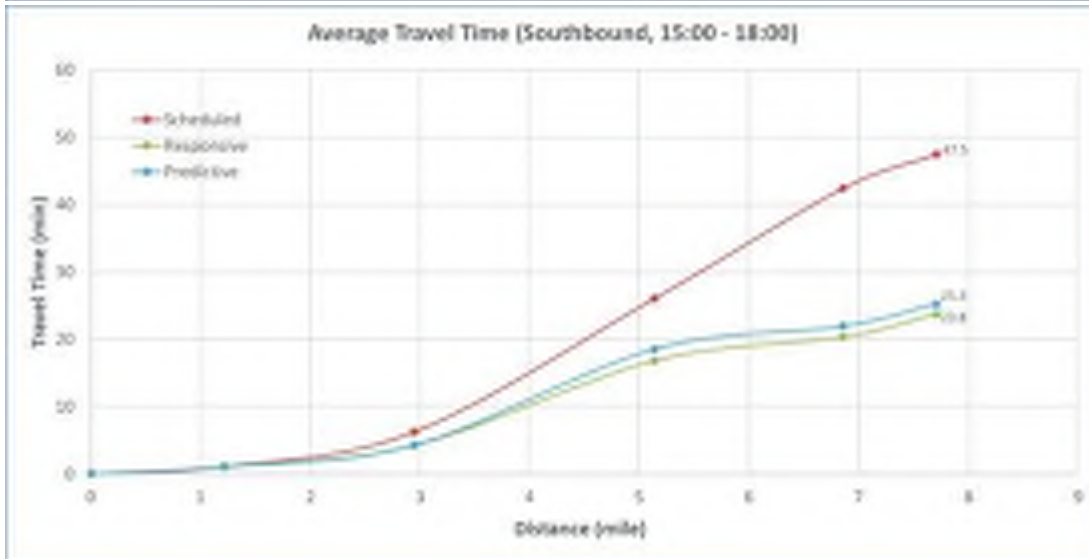
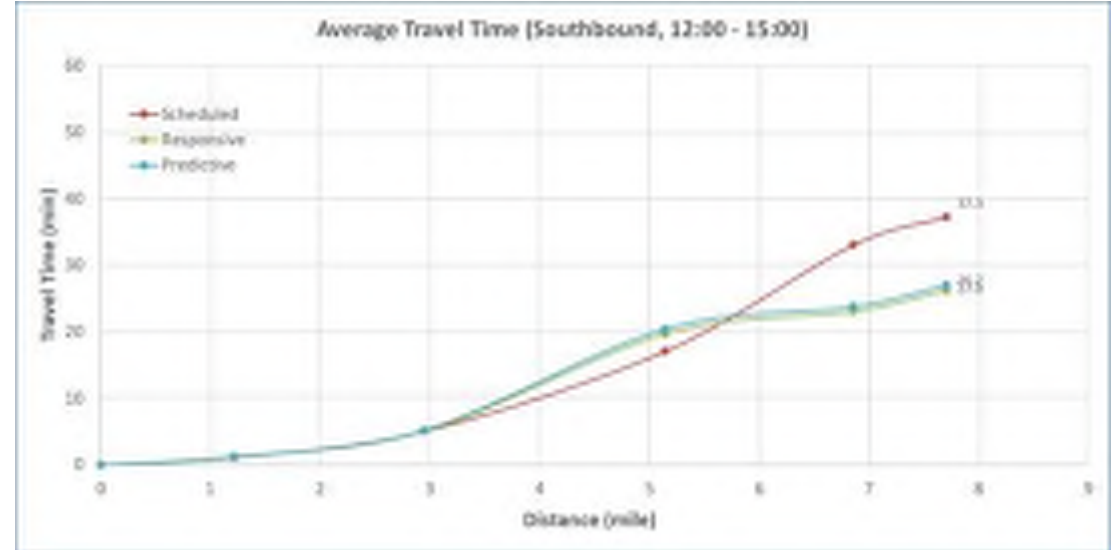
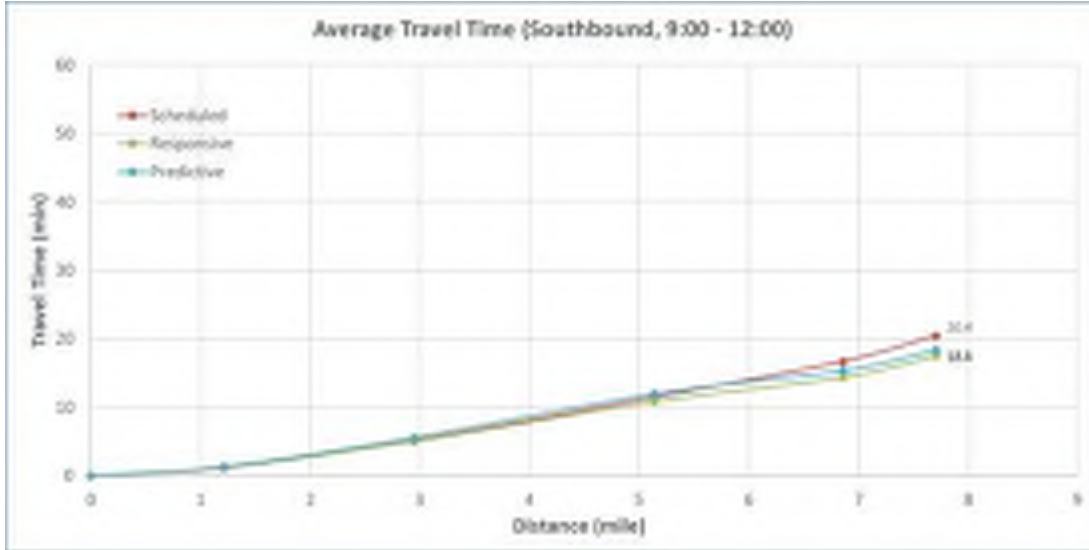


Simulation Results - *Saturday*

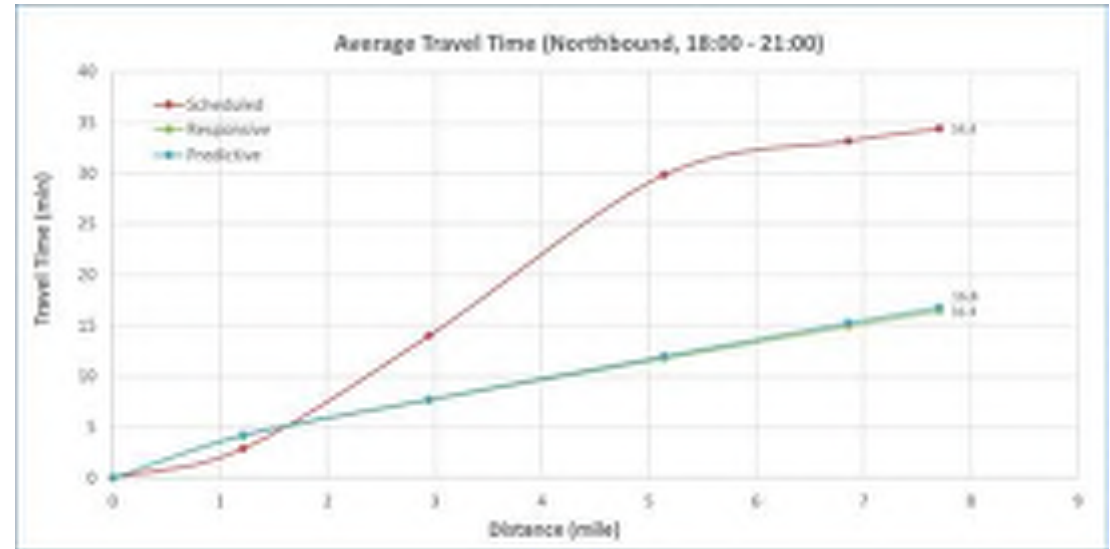
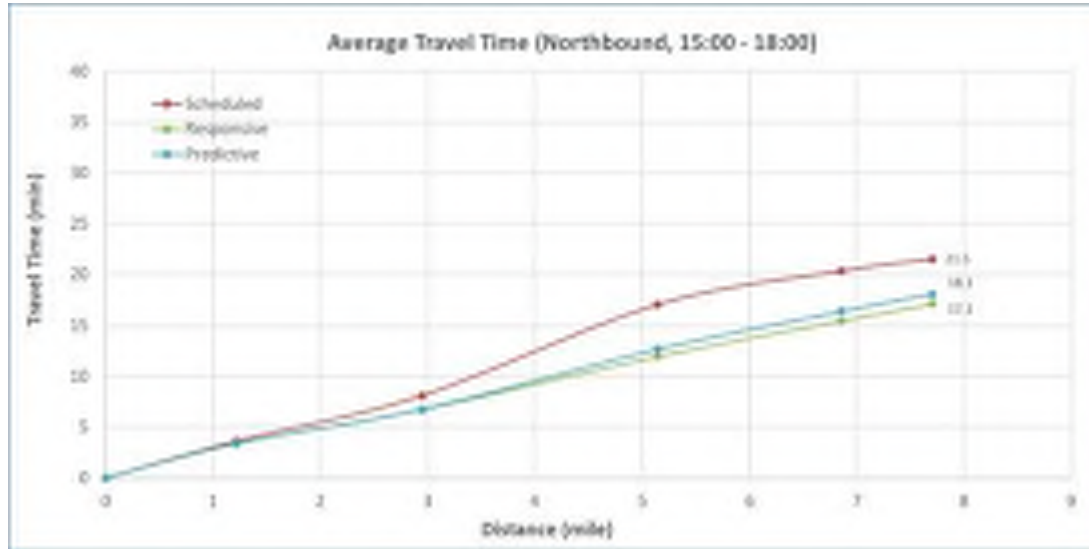
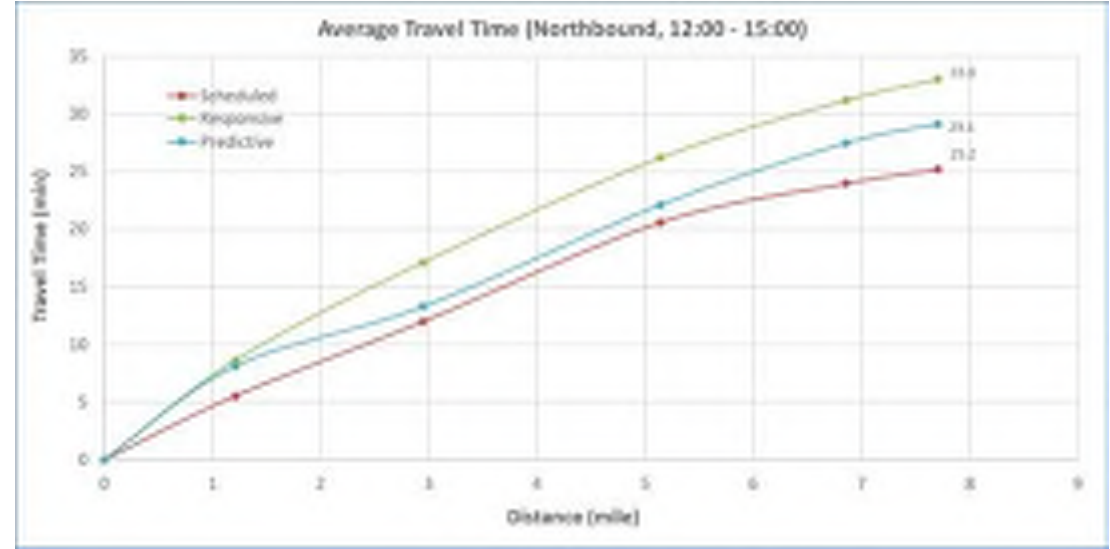
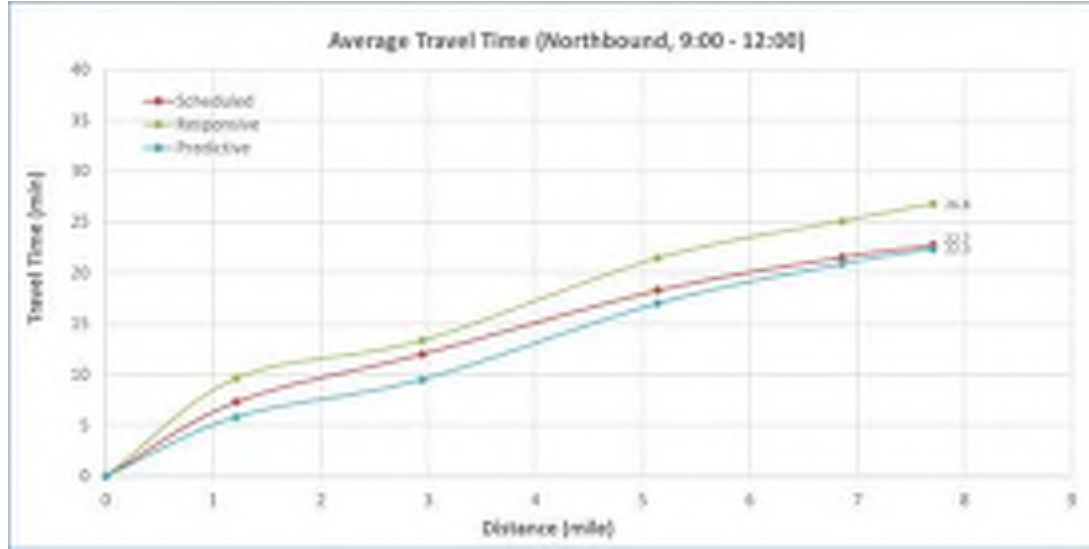
- Comparable corridor throughputs
- Dynamic pattern switch improved



Travel Time Comparison - Saturday - Southbound



Travel Time Comparison - Saturday - Northbound



Summary



Conclusions & Next Steps

- Prediction Algorithms have the potential to improve arterial signal operations
- Provides proactive response, especially when demand is surging and uneven
- More testing underway
 - Varying scenarios such as incidents, work zones, special events etc.
 - Different time variant inputs can be trained and tested.
 - Multiple hybrid machine learning algorithms can be trained and tested.
- Limitation
 - Analysis limited by field-measured demand, which is dependent on field signal operation.
 - Pilot deployments planned in the future, they will provide a better assessment of benefits

Questions?

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Challenging today.
Reinventing tomorrow.

