



Workshop II: Traffic Estimation

Institute for Pure and Applied Mathematics, UCLA, October 12-16, 2015

Simulation-based Approaches for Traffic Estimation and Prediction in Networks: Models and Applications

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OUTLINE

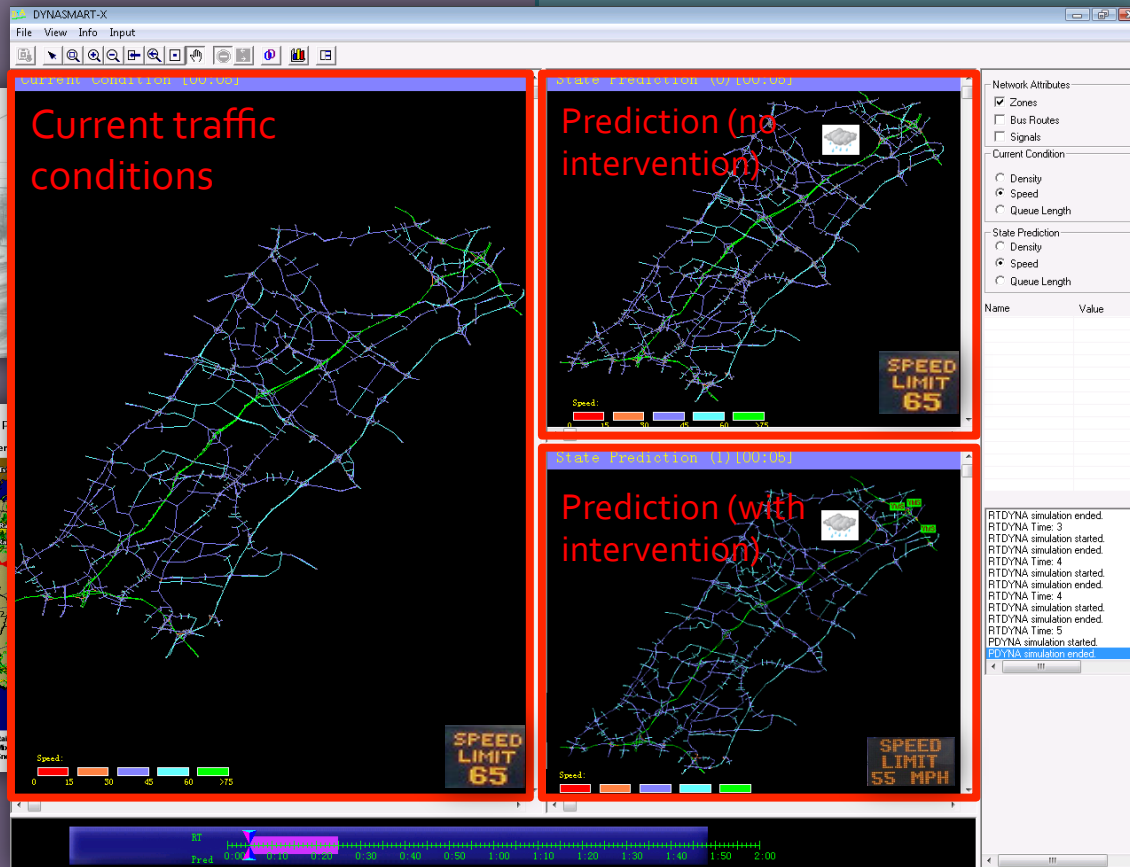
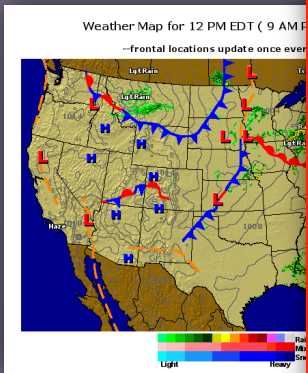
- Background and Motivation
- Methodological:
 - Framework and structure of simulation-based TrEPS
 - O-D estimation and prediction framework
- Integration with predictive control
 - Problem formulation
 - Iterated solution method
- On-line Applications:
 - Application I : Dynamic anticipatory pricing
 - Application II: Weather-sensitive Signal Control and Application to Salt Lake City Riverdale Corridor
- Concluding Comments

Motivation and Background

- **Focus:** Estimation of traffic state in large networks, in real-time, and short-term prediction of future states to support system management and control.
- Why do we need to estimate current traffic state if we have observations?
 - Limited sensor coverage, probe data only partial (and lagged)
 - As basis for and initial conditions for prediction
- Why model-based estimation and prediction?
 - Pure data-driven approaches not robust when system deviates from historical patterns
 - What-if analyses require correct physics and behavior
- Why use simulation models in estimation and prediction?
 - Complex interactions in networks preclude simple analytical models
 - Need to capture traffic and other controls, information strategies, user behavior explicitly
 - Combine structural model representation with statistical/AI models (hybrid)

Traffic Estimation and Prediction System (TrEPS)

ESTIMATION

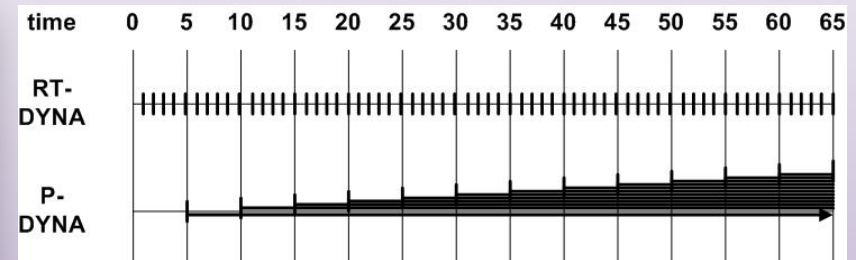
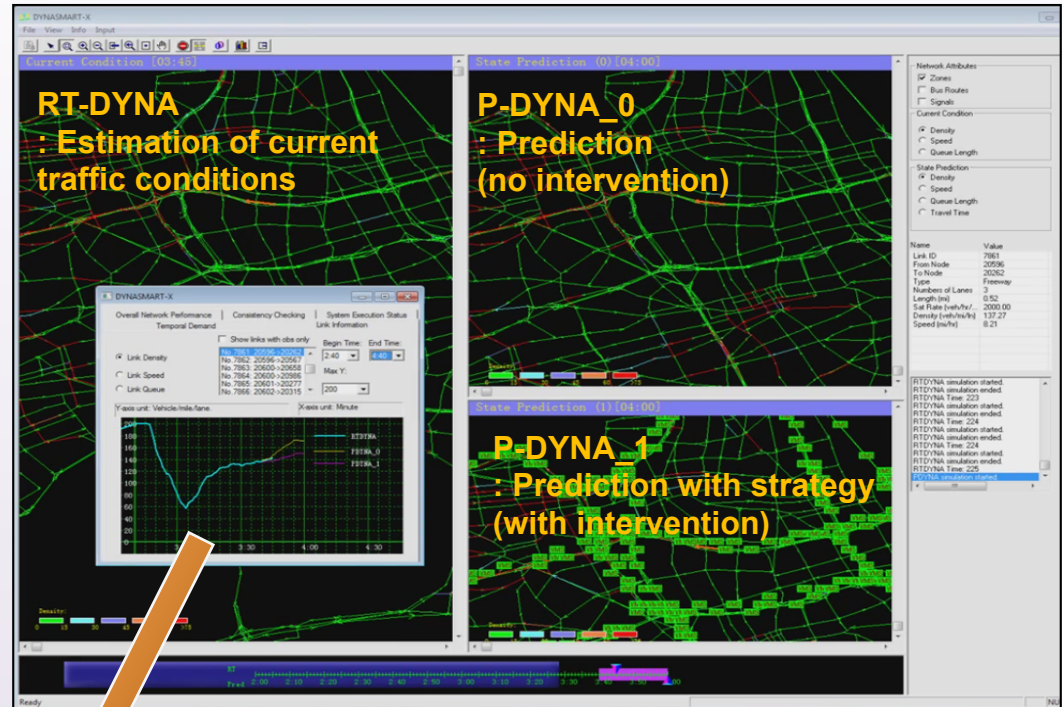


PREDICTION



Real-time TrEPS: *DYNASmart-X*

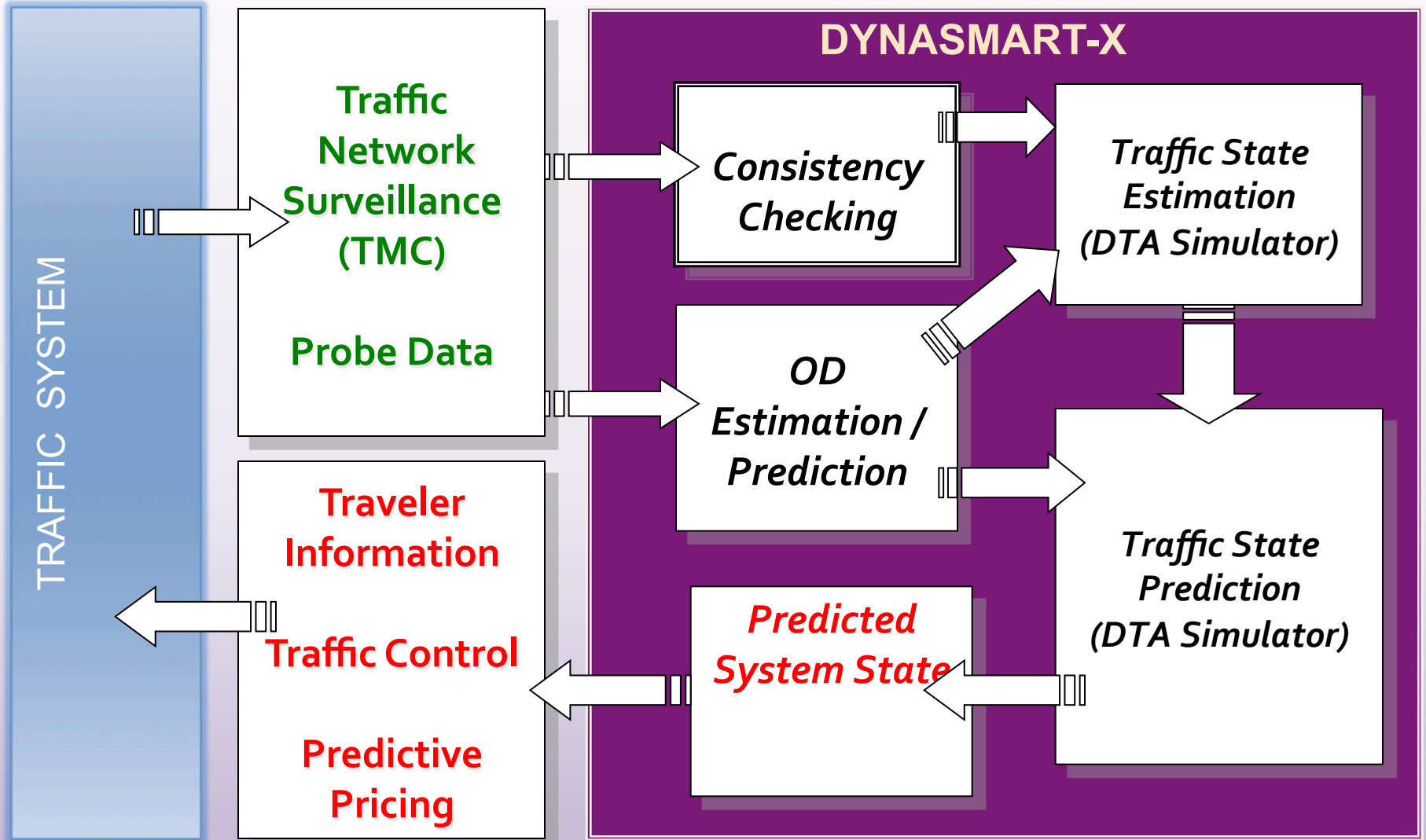
- Rolling horizon (RH) approach
- Enables parallel execution of alternative intervention scenarios.
- Displays various comparative statistics through the GUI.
- Supports decision making in on-line traffic management by showing the effectiveness of an intervention in real-time.



Rolling Horizon (RH)

- RT-DYNA: Update state estimates every 30 sec.
- P-DYNA: Project 1-hr future state every 5 min.

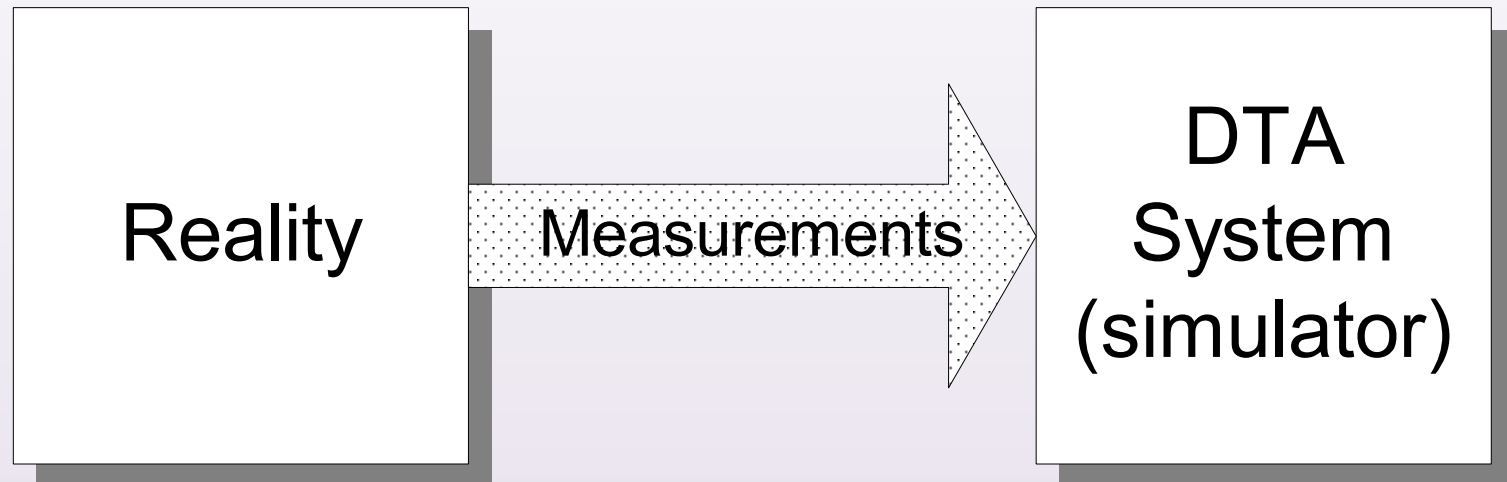
Real-Time Dynamic Traffic Assignment System Architecture



DYNASMART-X

- Two major outputs in real-time:
 - **Estimates** of current network traffic conditions;
 - **Predictions** of network flow patterns and travel times over the near and medium terms in response to various contemplated traffic control measures and information dissemination strategies.

Consistency Between Measurements and Estimated Model Values

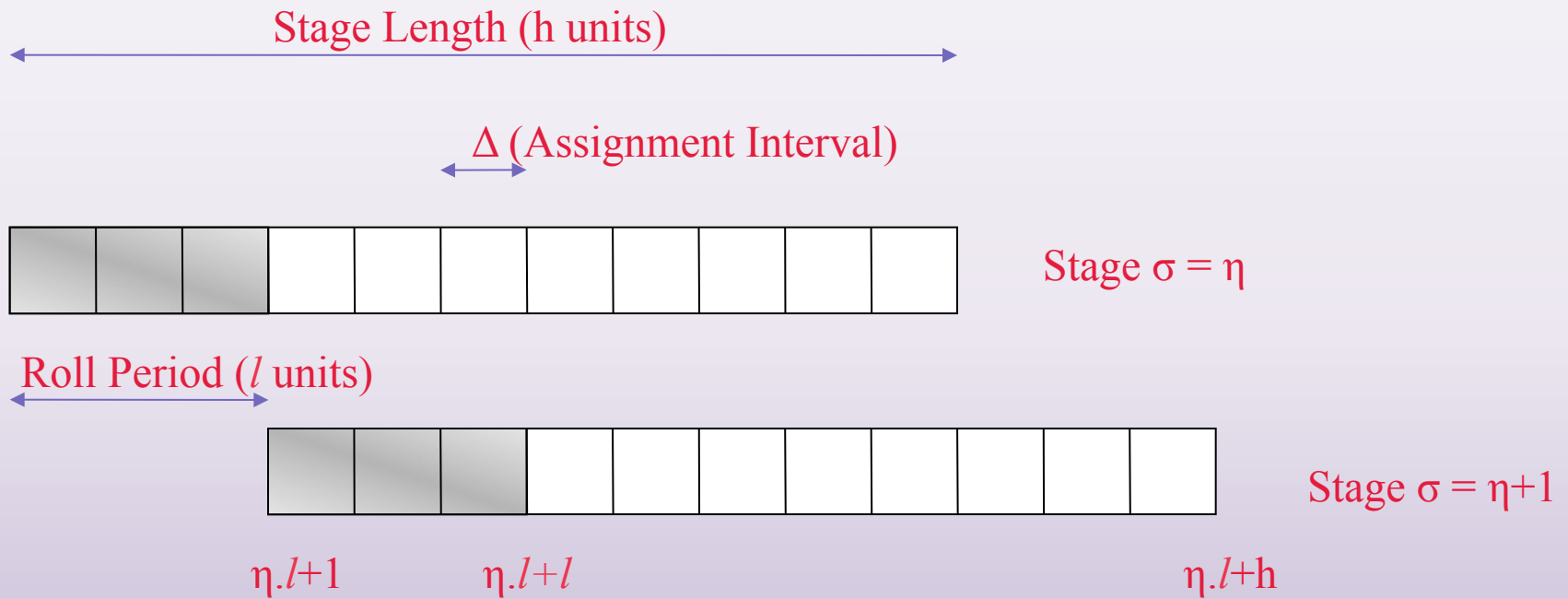


Sources of Error

- Time-dependent OD demands
- Incidents and other disruptions
- Path selection and other assumptions concerning user behavior
- Traffic modeling and propagation
- Online measurement errors

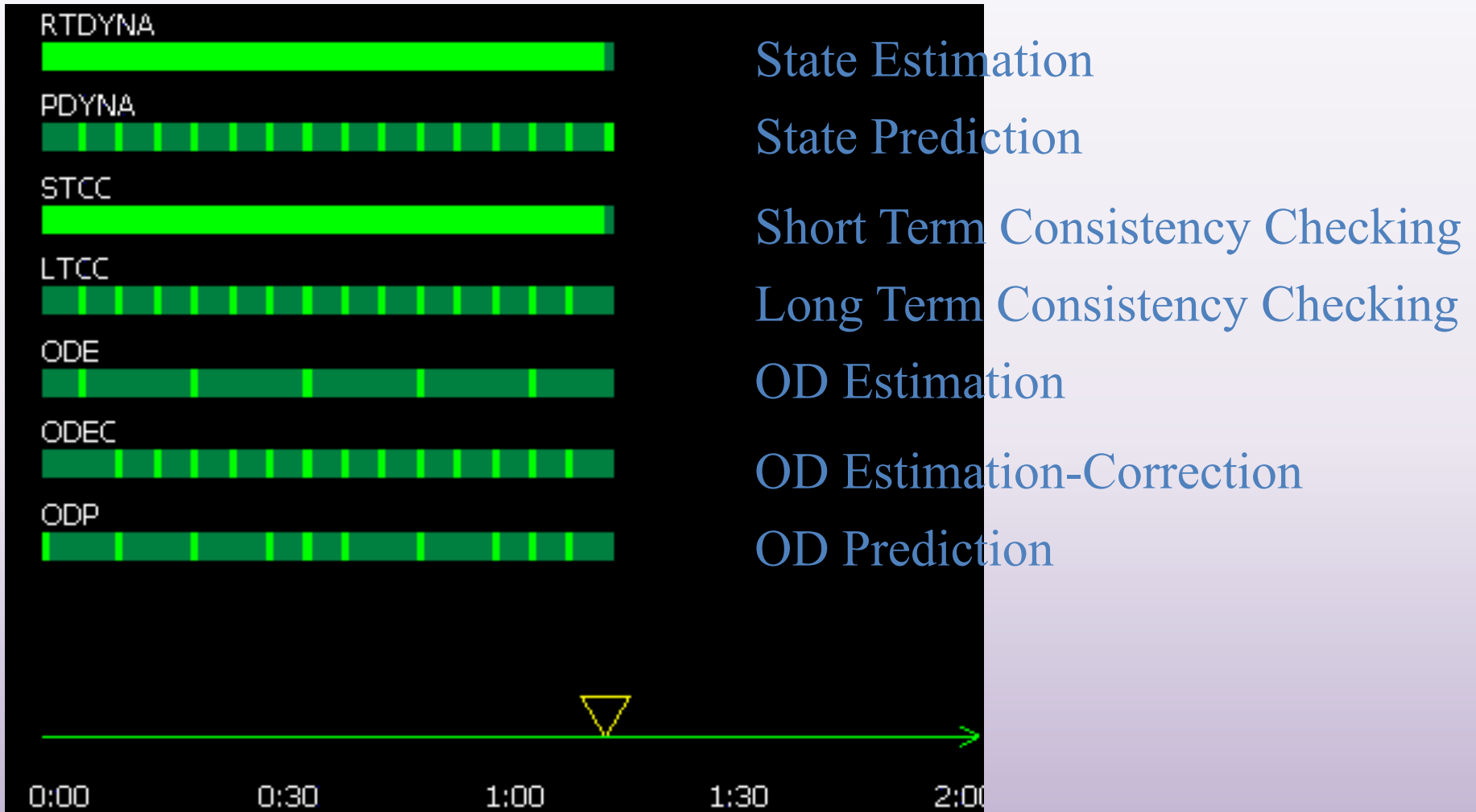
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Rolling Horizon Approach



Rolling Horizon Approach (cont'd)

- Distributed Multi-Horizon Asynchronous Framework



Why OD Demand?

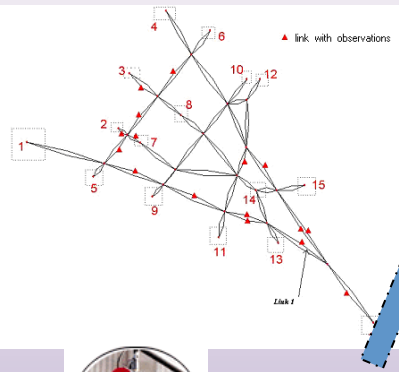
- OD Demand: Trip desires from origin i to destination j
- Essential input for traffic assignment systems to support transportation **network planning and operational decisions**
e.g. traveler information, route guidance, traffic control, road pricing, network evacuation

0-5 min	
1	2
3	4
5	6

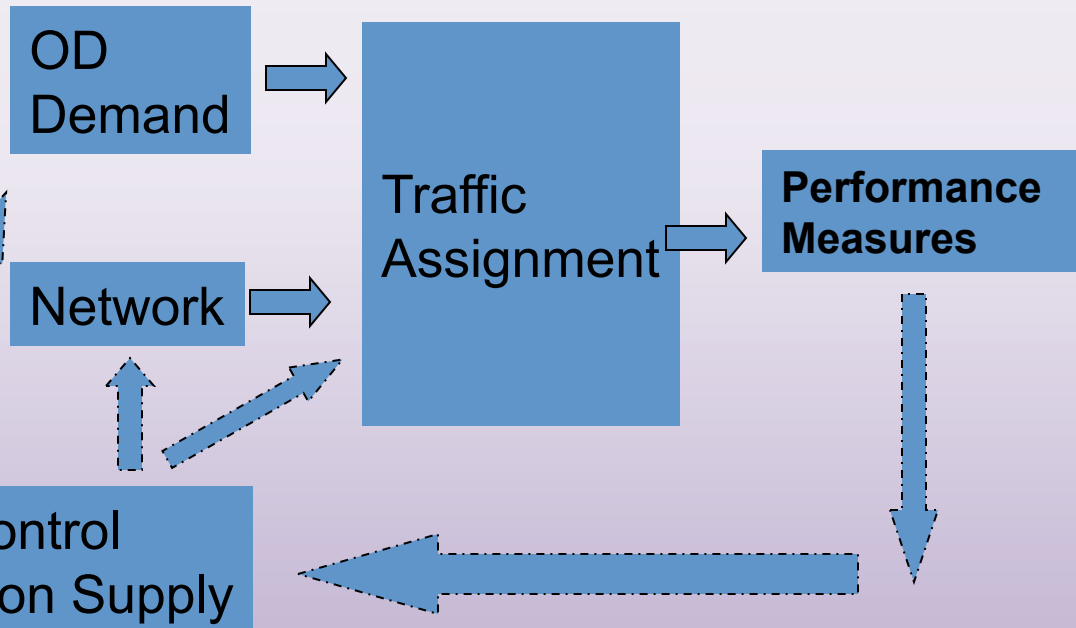
5-10 min	
1	2
3	4
5	6

10-15 min	
1	2
3	4
5	6

15-20 min	
1	2
3	4
5	6



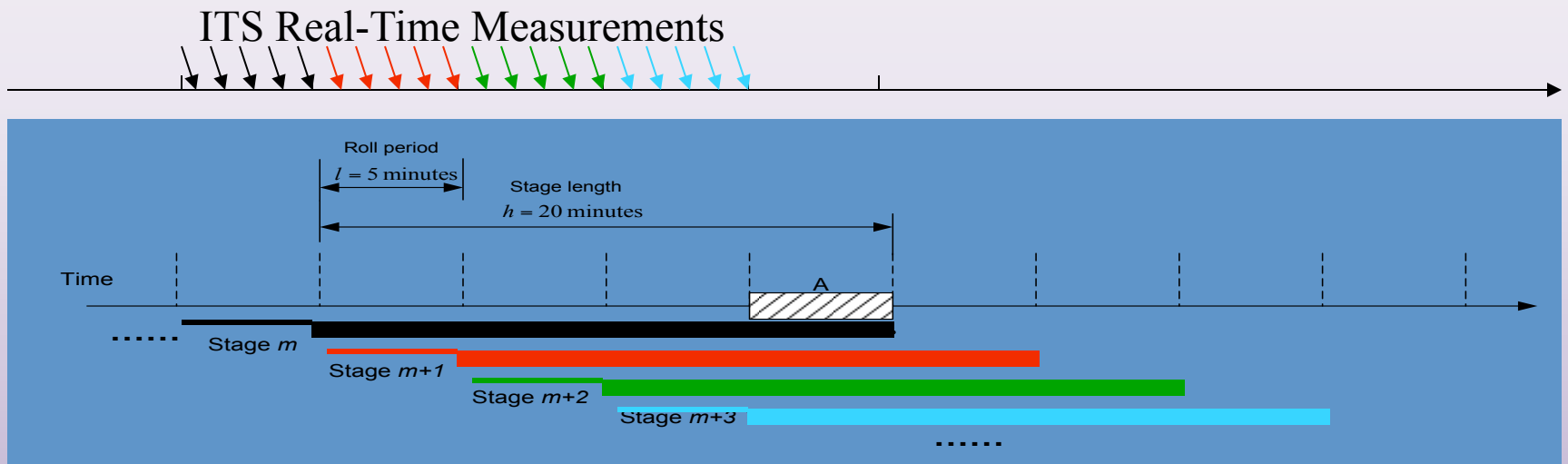
Traffic Control
Information Supply



Problem Statement:

Dynamic OD Demand Estimation and Prediction

- Given:
 - Traffic network
 - Historical demand matrix $d_{(i,j,\tau)}$ obtained from off-line estimation
 - Link observations $c_{(l,t)}$
- **Estimate** time-dependent OD trip demand patterns for the current stage
- **Predict** OD demand volumes over the near and medium terms



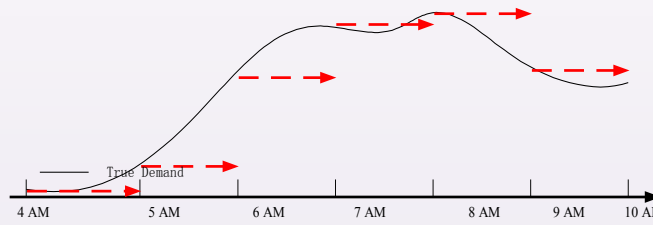
Some Existing Dynamic Origin-Destination Demand Predictors

Regular Conditions

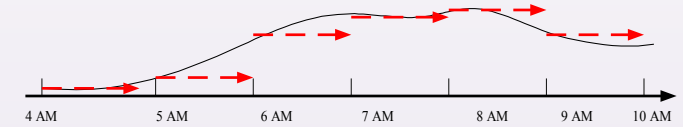
Structural Changes (e.g. snowstorm, rain storm)

Random walk

Cremer and Keller (1981, 1987)
Chang and Wu (1994)

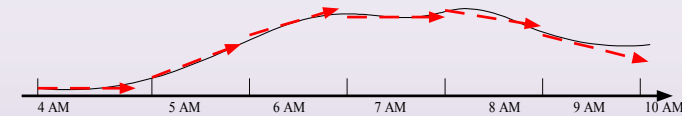
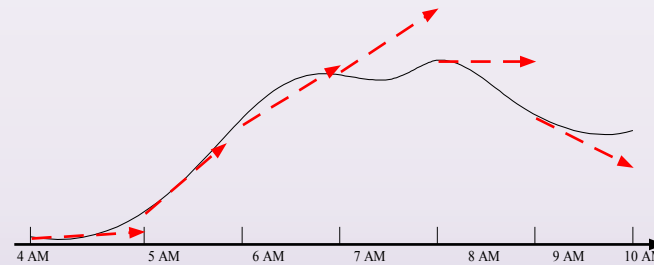


— True Demand
- - - Prediction



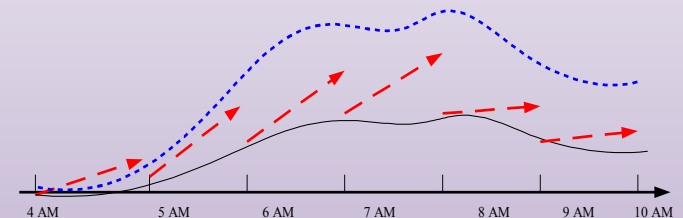
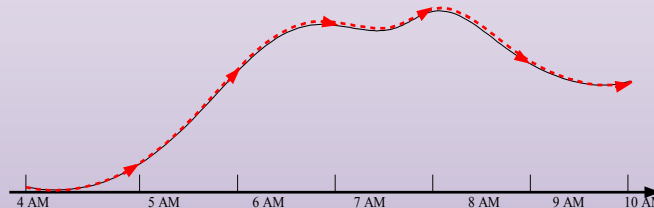
Polynomial trend

Kang and Mahmassani (1999)



Historical average + auto-regressive (AR)

Okutani and Stephanedes (1984)
Ashok and Ben-Akiva (1993, 2000)



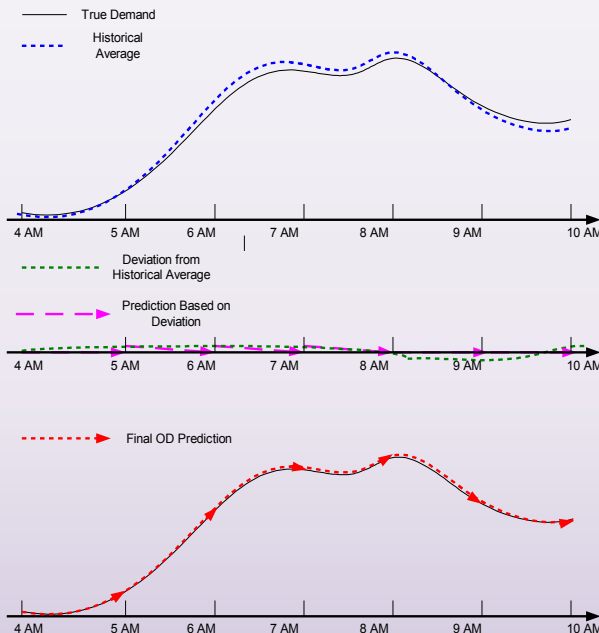
Real-Time Demand Prediction using Structural Model

(Zhou and Mahmassani, 2007)

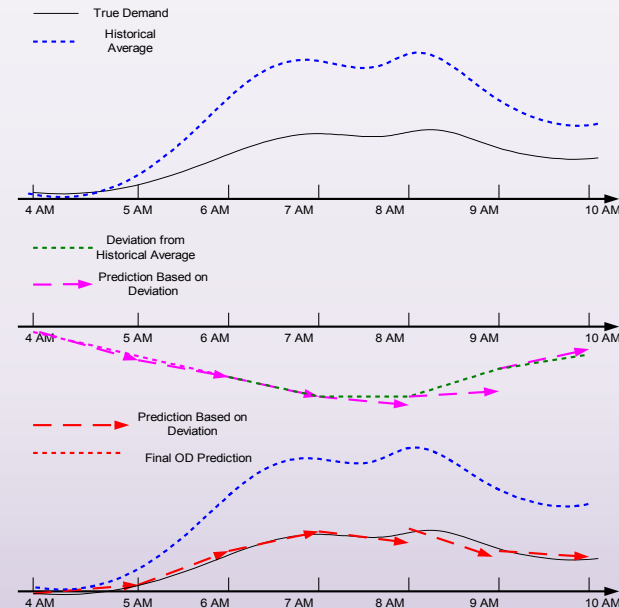
True demand = regular pattern + structural deviation + random fluctuation

$$d_{(i,j,\tau)} = \tilde{d}_{(i,j,\tau)}^r + \mu_{(i,j,\tau)} + \varepsilon_{(i,j,\tau)}$$

Regular Conditions



Structural Changes



Advantages of systematic integration

- ❑ Reduce the **order of the polynomial trend model** and
- ❑ Decrease the demand **prediction variability** and **computational complexity**

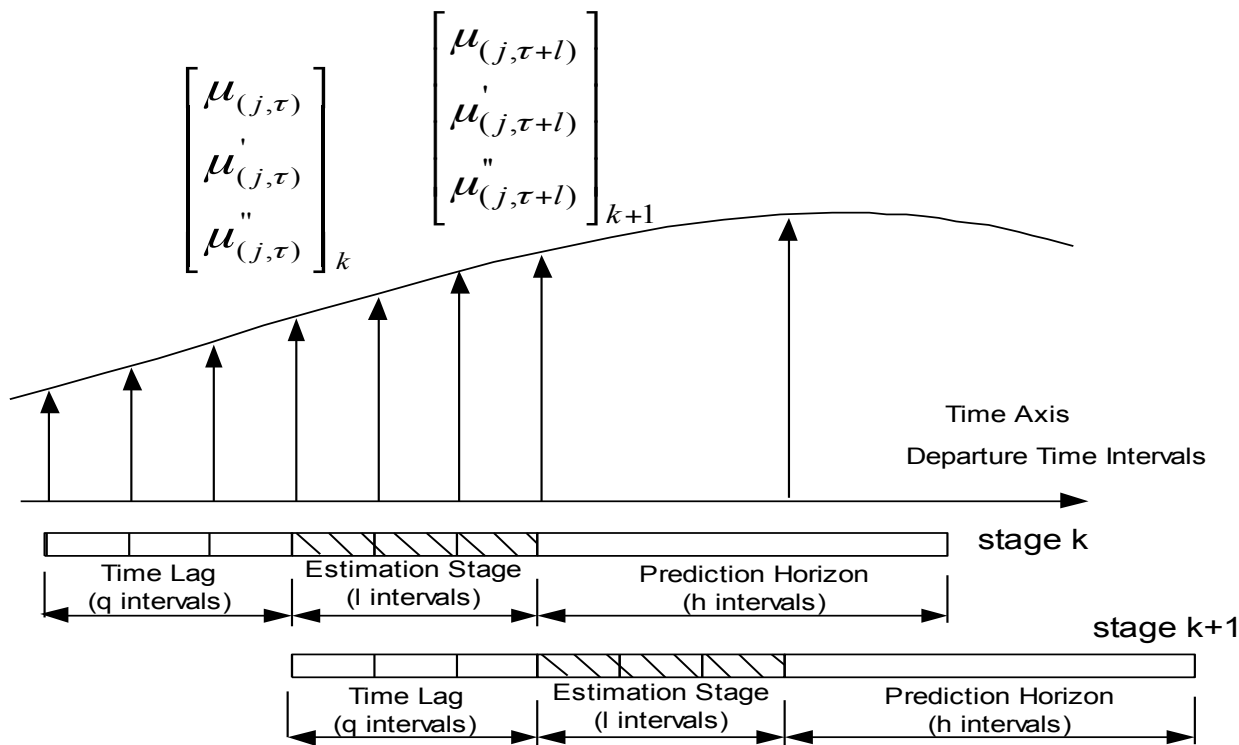
Kalman Filtering Formulation:

Transition Equation for Polynomial Trend Model

Assumption: Deviation at time $\tau + \zeta$ can be adequately represented *locally* by an m^{th} -order polynomial function near time τ for a small value of ζ ,

$$\mu_{(j,\tau+\zeta)} = b_0 + b_1\zeta + b_2\zeta^2 + \dots + b_p\zeta^p + \dots + b_m\zeta^m$$

$$b_p = 0 \quad \text{for } p > m.$$



Kalman Filtering Formulation: Measurement Equation

Sensor reading = Mapping matrix \times unknown demand + Sensor noise with covariance

$$c_{(l,t)} = \sum_{i,j} \sum_{\xi=-q}^{s-1} \left(p_{(l,t),(i,j,\tau+\xi)} \times d_{(i,j,\tau+\xi)} \right) + e_{(l,t)}$$

$c_{(l,t)}$ = link observations on link l at time t

$d_{(i,j,\tau+\xi)}$ = Traffic demand from OD pair (i, j) at time $\tau+\xi$

$p_{(l,t),(i,j,\tau+\xi)}$ = Link proportions (*assignment matrix*)
fraction of vehicular demand flow from **OD pair (i, j)** at time $\tau+\xi$ contributing to the observation on **link l at time t**

$e_{(l,t)}$ = combined error terms in the estimation of link observation due to inconsistencies in assumptions about traffic assignment, traffic control and flow propagation, as well as measurement noise.

Kalman Filtering Formulation and Algorithm

■ Formulation

Transition Equation

$$Z_{k+1} = A_k Z_k + w_k$$

$$\mu_{(j,\tau+\xi)} = b_0 + b_1 \xi + b_2 \xi^2 + \dots + b_m \xi^m$$

Measurement Equation

$$Y_k = H_k Z_k + v_k$$

$$y_{(l,t)} = c_{(l,t)} - \sum_{i,j} \sum_{\xi=-q}^{s-1} (LP_{(l,t),(i,j,\tau+\xi)} \times \tilde{d}_{(i,j,\tau+\xi)}^r)$$

□ Algorithm

▫ Estimation Step

- Calculate **weighting matrix**

$$K_k = P_{k,k-1} H_k^T (H_k P_{k,k-1} H_k^T + V_k)^{-1}$$

- Update *a posteriori* **mean** and **covariance** estimates

$$\hat{Z}_{k,k} = \hat{Z}_{k,k-1} + K_k (Y_k - H_k \hat{Z}_{k,k-1}) \quad P_{k,k} = (I - K_k H_k) P_{k,k-1}$$

▫ Prediction Step

- Propagate **mean** and **covariance** estimates

$$\hat{Z}_{k,k-1} = A_k \hat{Z}_{k-1,k-1} \quad P_{k,k-1} = A_k P_{k-1,k-1} A_k' + W_k$$

Adaptive Day-To-Day Updating of Regular Demand Pattern Information

- Realizations
 - Initial estimate for the regular demand pattern could be unreliable due to limited sample size
 - Normal daily pattern could evolve smoothly due to day-to-day demand dynamics
- Goals
 - Optimally update the *a priori* estimate of the regular pattern using new real-time estimation results and traffic observations
 - Adaptively recognize and capture the systematic day-to-day evolution
 - Maintain robustness under disruptions due to special events.

Kalman Filter for Day-to-Day Learning Framework

(Zhou and Mahmassani, 2007)

Transition Equation:
$$D_{d+1}^r = D_d^r + \xi_d$$

Measurement Equation:
$$\hat{D}_d = D_d^r + \eta_d$$

where

d = index for day

D_d^r = state variable vector of regular OD demand pattern on day d

ξ_d = day-to-day evolution deviation on day d

\hat{D}_d = vector of the real-time demand estimate on day d

η_d = measurement error matrix on day d

Optimal Updating Formulation

- Computation of *a priori* estimate: The *a posteriori* estimate $\hat{D}_{d-1,d-1}^r$ on previous day $d-1$ is used as the *a priori* estimate for current day d .

$$\begin{aligned}\hat{D}_{d,d-1}^r &= \hat{D}_{d-1,d-1}^r \\ \Sigma_{d,d-1} &= \Sigma_{d-1,d-1} + Q_d\end{aligned}$$

- Real-time OD estimation and prediction to obtain \hat{D}_d
- Update of gain matrix, *a posteriori* mean and covariance

$$K_d = \Sigma_{d,d-1} (\Sigma_{d,d-1} + R_d)^{-1}$$

$$\hat{D}_{d,d}^r = \hat{D}_{d,d-1}^r + K_d (\hat{D}_d - \hat{D}_{d,d-1}^r) = \hat{D}_{d,d-1}^r + K_d (\hat{D}_d - \tilde{D}_{d,d-1}^r)$$

$$\Sigma_{d,d} = (I - K_d) \Sigma_{d,d-1}$$

Heuristic vs. Optimal Updating Methods

- Simple Moving-average formula (Ashok,1996)

$$\hat{D}_{d,d}^r = \hat{D}_{d,d-1}^r + \alpha(\hat{D}_d - \hat{D}_{d,d-1}^r) \quad \text{where constant } \alpha \in (0,1)$$

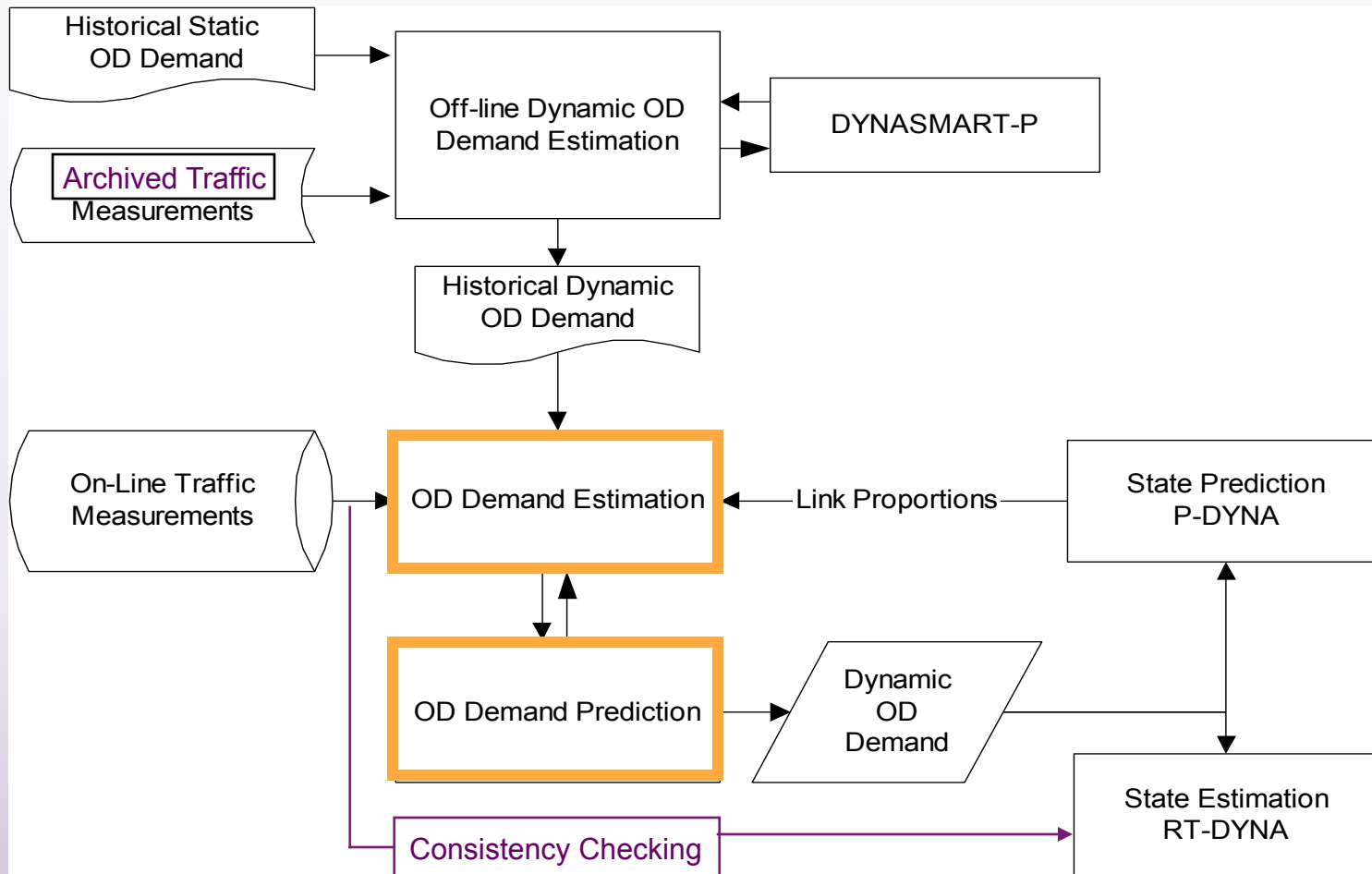
- Optimal Updating formula

$$\hat{D}_{d,d}^r = \hat{D}_{d,d-1}^r + K_d(\hat{D}_d - \hat{D}_{d,d-1}^r) = \hat{D}_{d,d-1}^r + K_d(\hat{D}_d - \tilde{D}_{d,d-1}^r)$$

where
$$K_d = \Sigma_{d,d-1} (\Sigma_{d,d-1} + R_d)^{-1}$$

- Take into account **covariance/uncertainty** of real-time estimates
- Can be viewed as a moving average method with **adaptive weights**, depending on the respective reliability of the *a priori* and real-time information sources
- **Reduce uncertainty** of *a priori* estimate for the regular demand pattern, after incorporating additional information from the new real-time estimation result

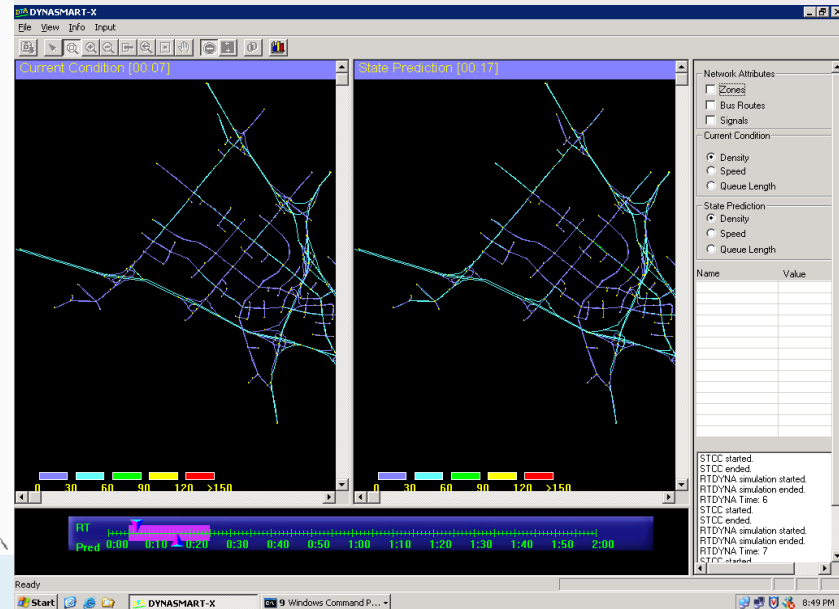
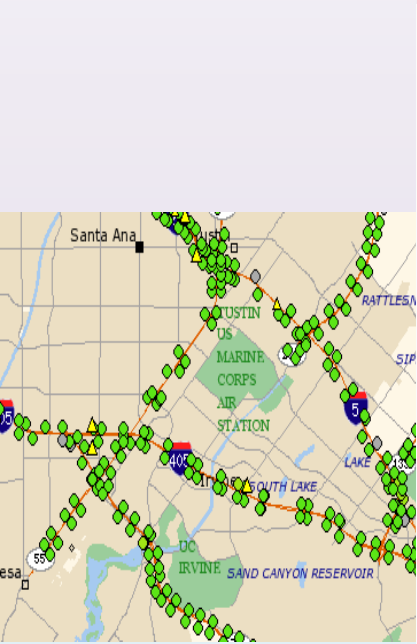
Data flow for OD Estimation and Prediction



Application to Irvine Network

Irvine network overview:

- 326 nodes and 626 links.
- 70 actuated-controlled urban intersections.
- 61 traffic demand zones
- Morning peak period (4:00 AM – 10:00 AM)
- 30-second observation intervals on 19 freeway links
- 5-minute observation interval on 28 arterial links



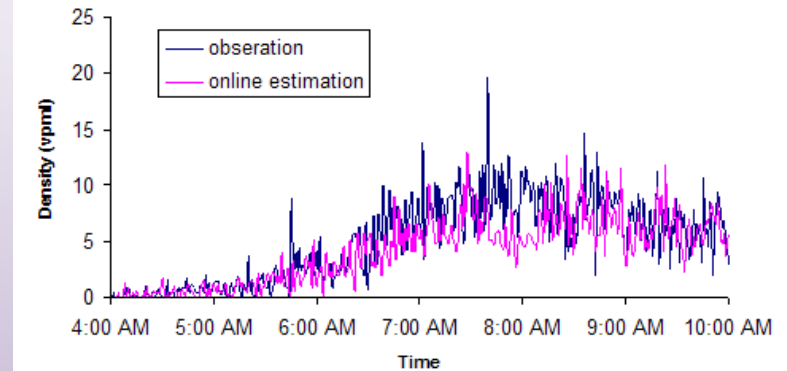
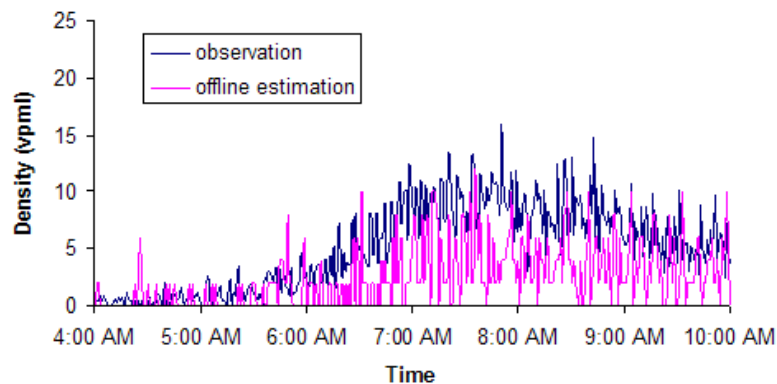
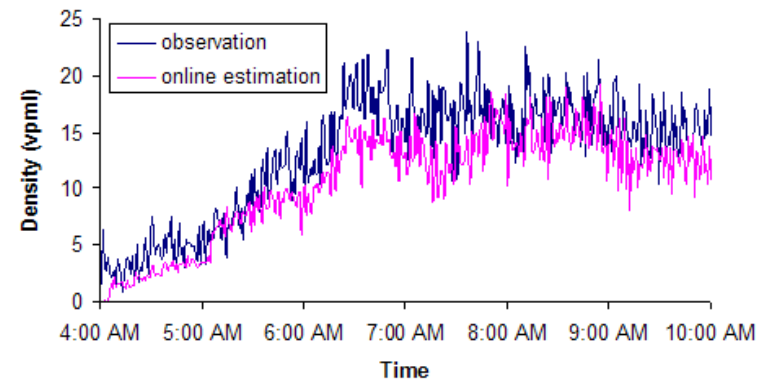
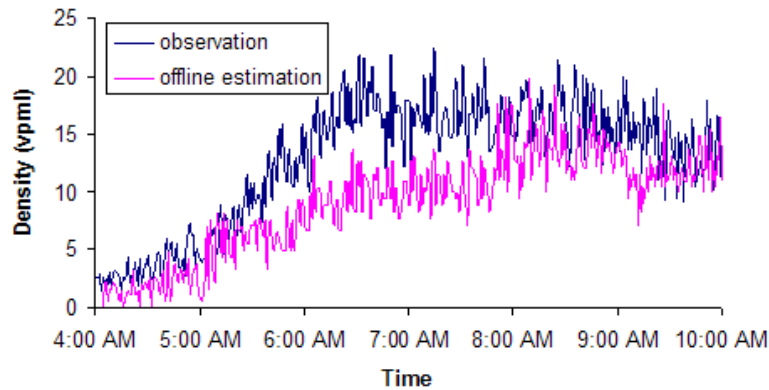
Online Estimation vs. Offline Estimation

With

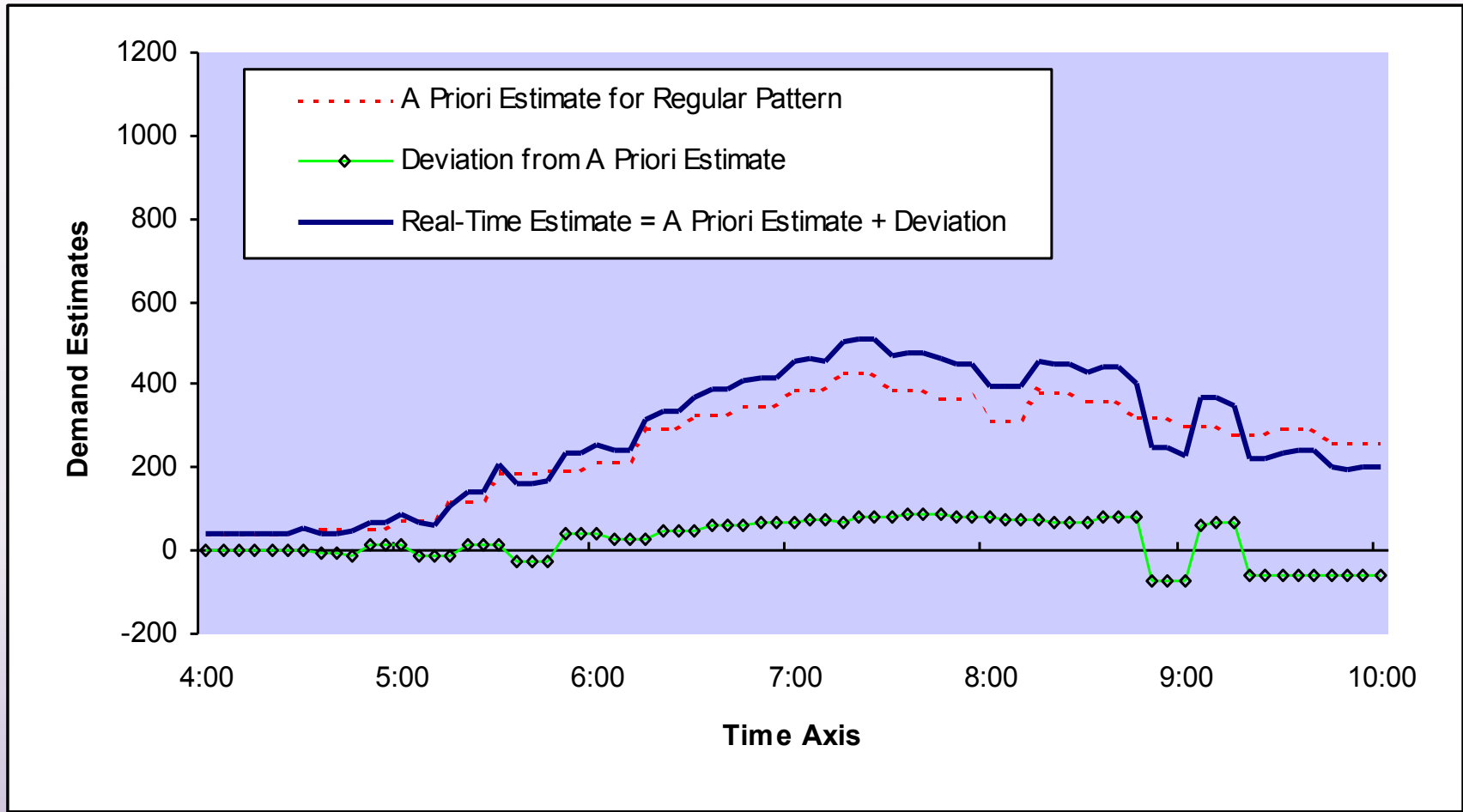
Without

real-time consistent checking and OD estimation/prediction

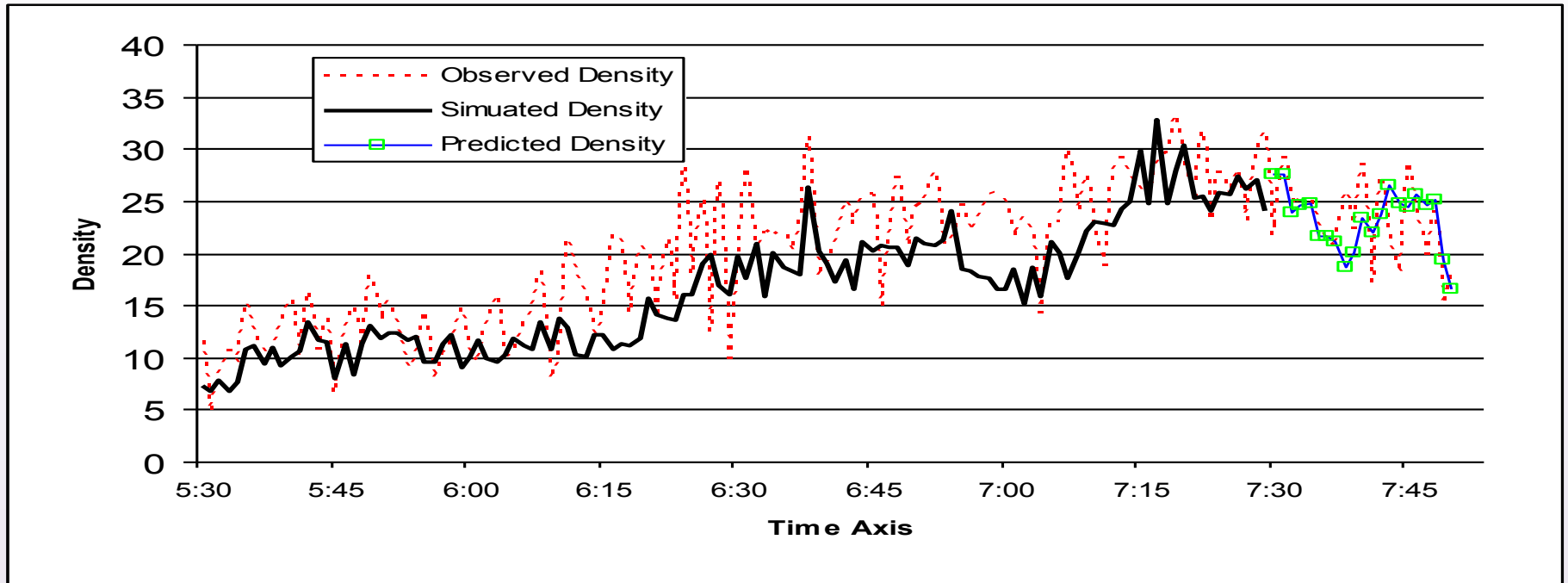
Exam



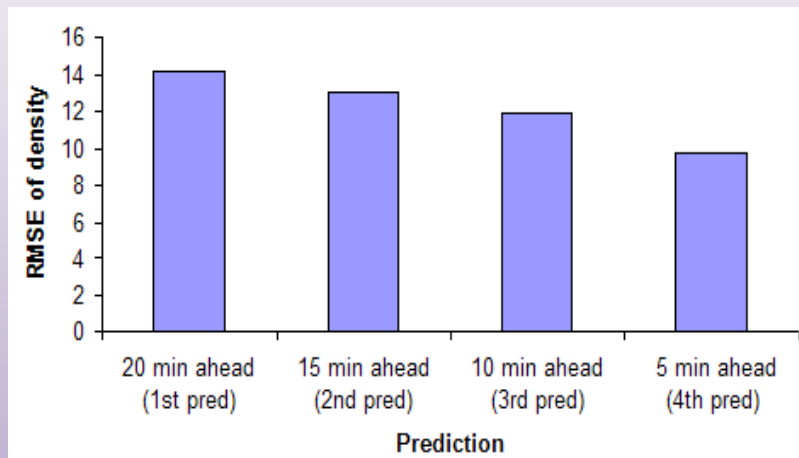
Polynomial Trend Model



Estimation and Prediction vs. Observation



Prediction Accuracy



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Real-Time Traffic Management Problem

Problem definition

- Given
 - traffic network
 - historical demand matrix
 - **real-time measurements**
 - **users behavioral assumption (homogeneous vs. heterogeneous)**
- **Find** *dynamic control policies*

Applications

- Adaptive signal control (e.g. OPAC, Gartner, 1982)
- State-dependent pricing (e.g. I-15 in San Diego)
- Real-time traffic info (e.g. INRIX)

Formulation

- Objective: min/max $\theta(\omega)$
- Feasibility constraint:
 - Control variable $\omega \in \Omega(\omega)$
 - Flow variable $r \in P(\omega)$
- ~~User equilibrium constraint~~
 - ~~$c(r)^T \cdot (q-r) \geq 0, \forall q \in P(\omega)$~~
- System dynamics:
 - Network loading $s^t = L(r^{t-1})$
 - User decisions $r^t = \Theta(\omega^t, \hat{s}^t, s^t)$

[Traffic assignment]

Formulation (cont'd)

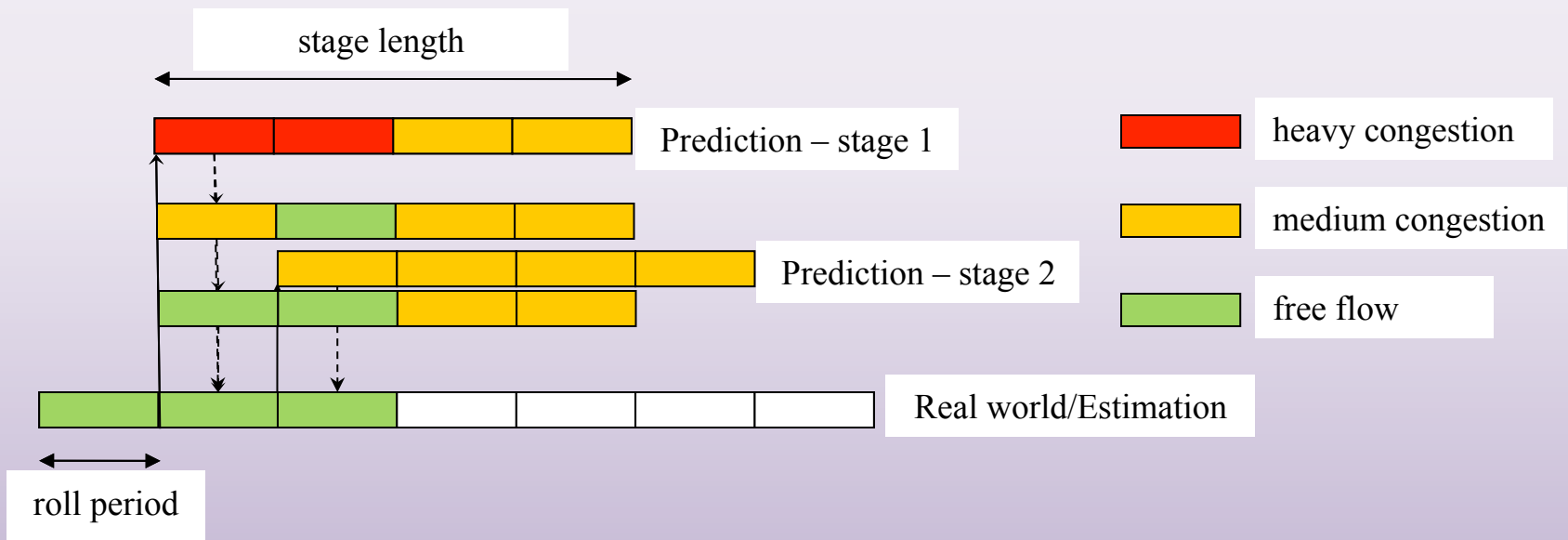
- Notation
 - ω^t : control policy to be determined for time interval t
 - \hat{s}^t : vehicles generated in time interval t
 - s^t : vehicles generated in previous time interval and still in the network at time t
 - r^t : path flow assignment at time t
- Control policy ω^t
 - determines traffic assignment at time t
 - **affects future traffic states** that contribute to the objective function
- Network loading equation
 - depicts current states of existing vehicles in the network
 - depends on flow assignment in previous time interval: $s^t = L(r^{t-1})$
- User decisions [Traffic assignment]
 - Given current control policy ω^t , all vehicles in the network \hat{s}^t and s^t , and behavioral assumption of route choice, path flow assignment at time t :
 $r^t = \Theta(\omega^t, \hat{s}^t, s^t)$

Solution Approach: Anticipatory Traffic Management

- **Anticipatory traffic management**
 - An approximate solution approach to real-time traffic management problems
 - Predict future traffic conditions based on up-to-date information
 - Generate control policy considering its impact on future traffic conditions
- **Rolling horizon framework**
 - to generate and implement solutions to the dynamic program
- **A real-time traffic estimation and prediction system to**
 - interface with surveillance systems and integrate real-time measurements
 - estimate and predict traffic conditions
- **Solution algorithms**
 - One-shot algorithm to generate control policy based on look-ahead traffic forecast vs.
 - Iterative algorithm to maintain consistency between predicted and experienced conditions: more effective control, heavier computational burden

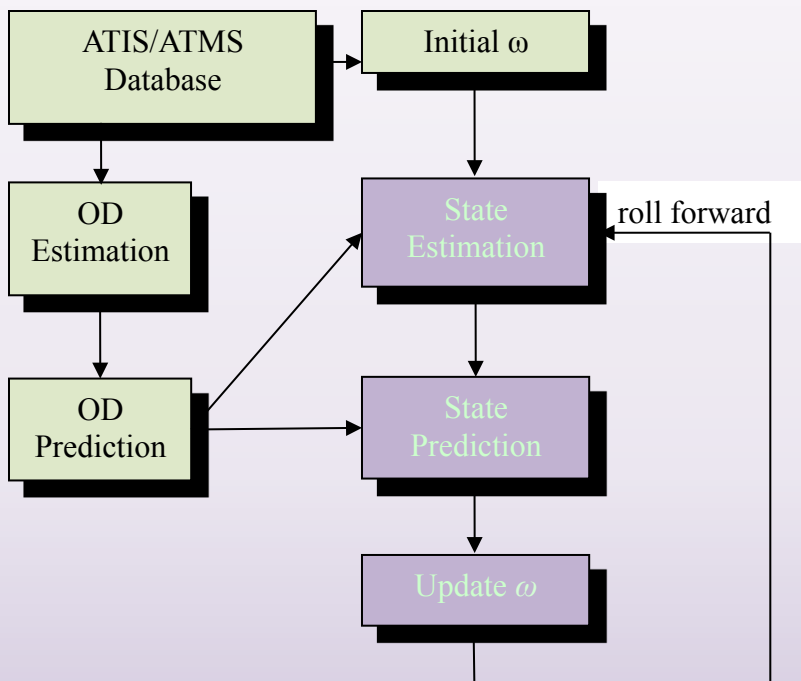
Closed-loop Rolling Horizon Framework

- RH approach is a practical method for generating and implementing solutions to dynamic programming problems.
- Closed-loop structure allows the control policies obtained in traffic prediction model to be implemented in real world and transferred to state estimation model.

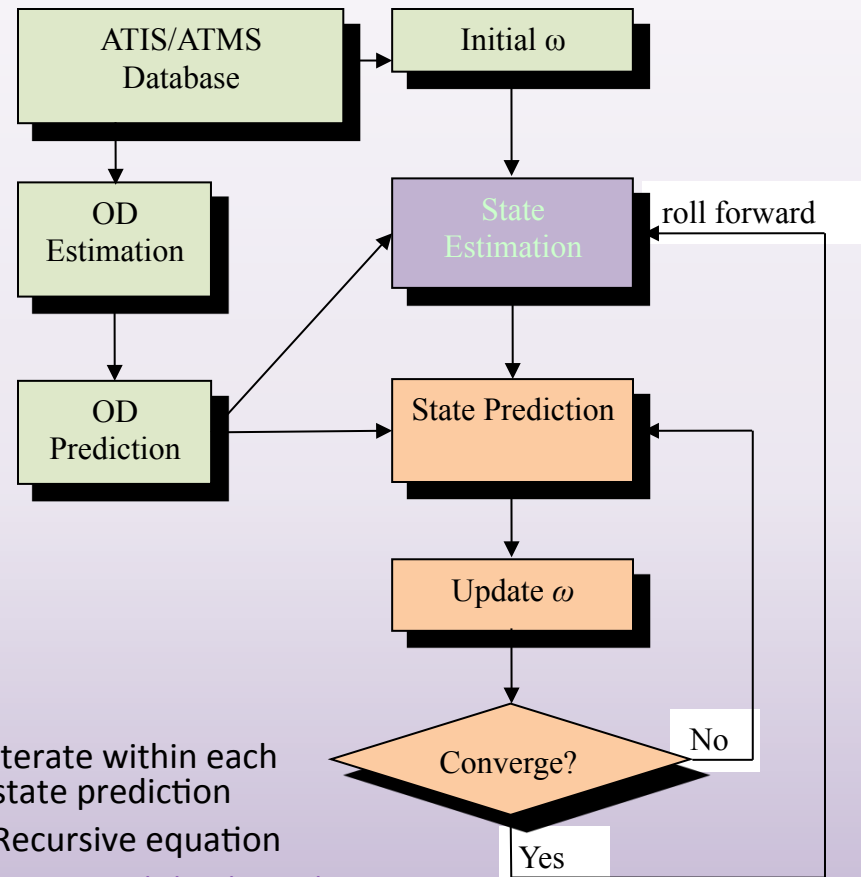


Solution Algorithms Embedded in TrEPS

One-shot algorithm



Iterative algorithm

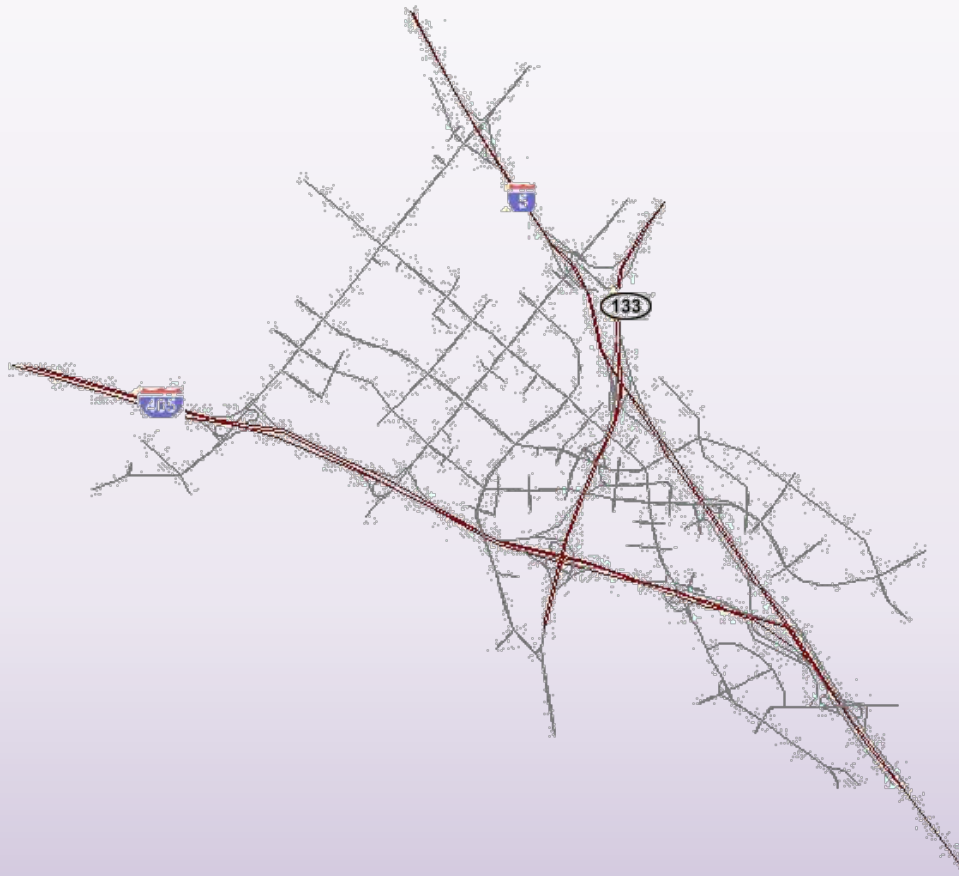


- > Iterate within each state prediction
- > Recursive equation

$$c_k = c_{k-1} + \alpha_{k-1} \cdot (T(c_{k-1}) - c_{k-1})$$

k = iteration number

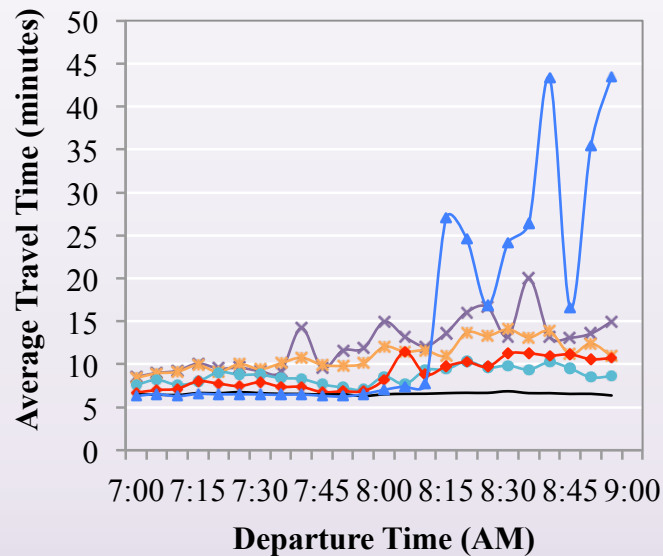
The Test Bed Network : Irvine



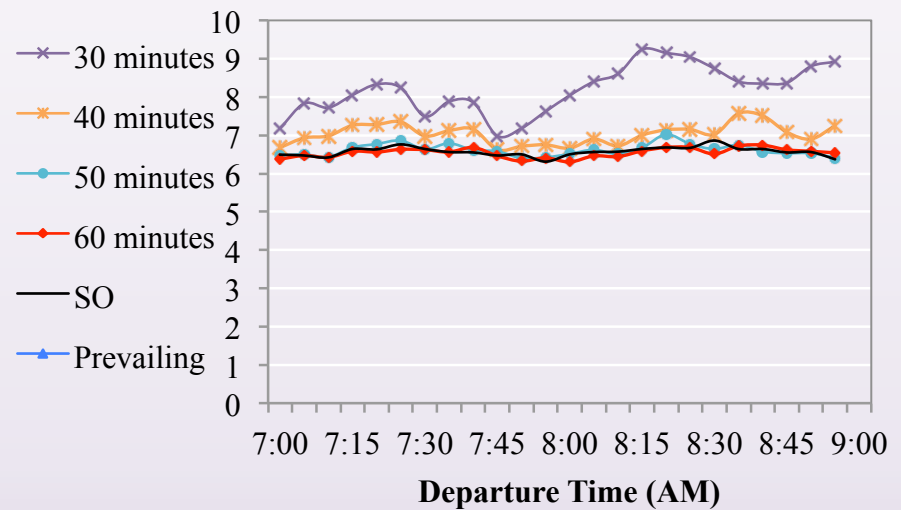
- **Network**
 - Freeways I-405, I-5, state highway 133
 - 326 nodes
 - 626 links
 - 61 TAZs
 - 57 road detectors
- **Demand**
 - Two hours morning peak
 - 15min warm-up period + 45 min clearance time
- **Parameters**
 - Roll period: 5 minutes
 - Prediction horizon varying from 30 to 60 minutes

Sensitivity to Prediction Horizon

look-ahead algorithm

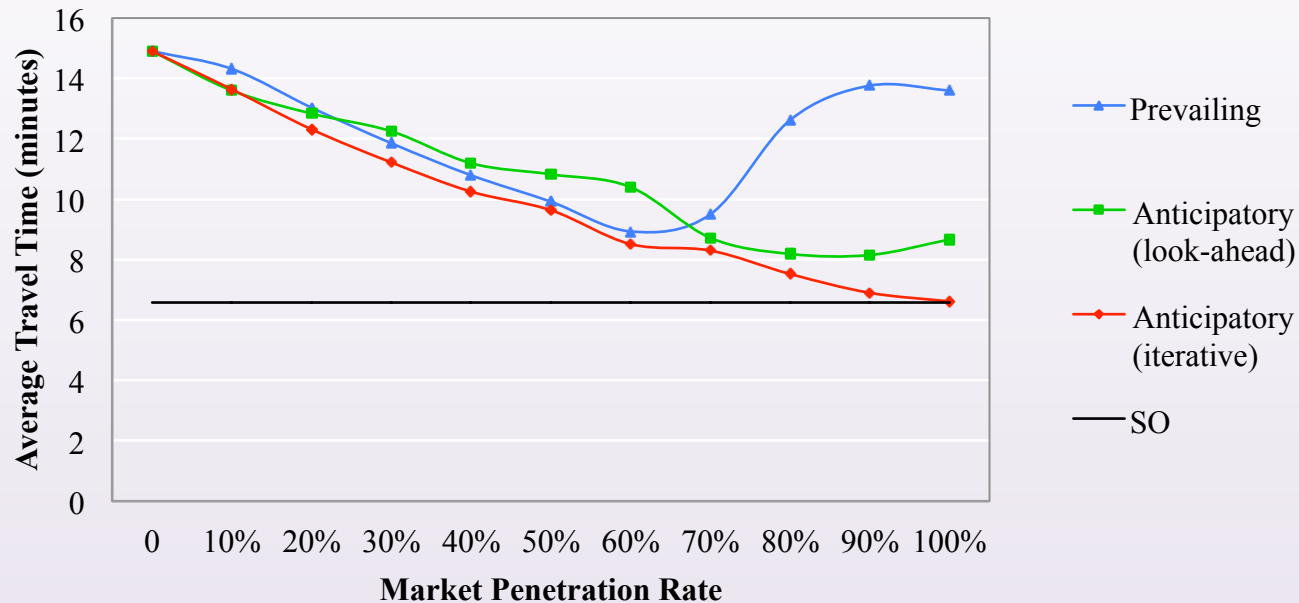


recursive averaging algorithm



- **Anticipatory** information works better than **prevailing** information
- Longer prediction horizon provides better performance

Sensitivity to Market Penetration Rate



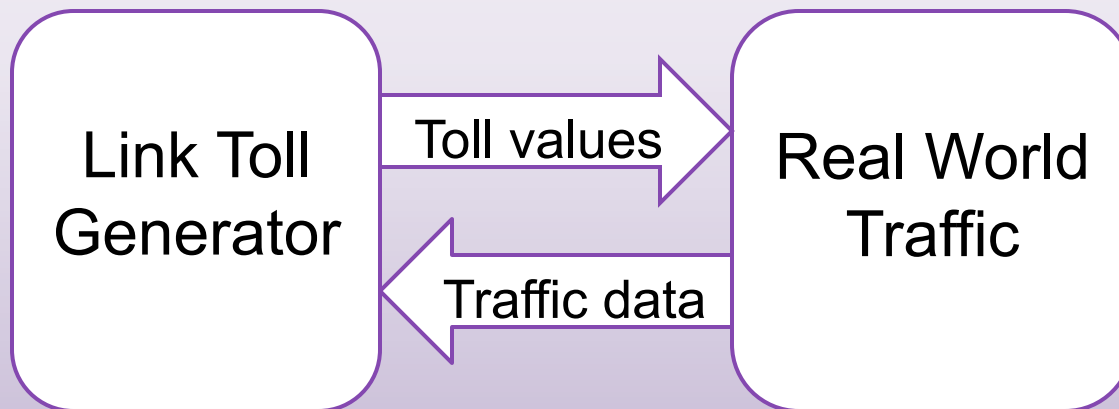
- Provision of **anticipatory travel time information** improves the overall network performance
- Solves the overreaction problem caused by providing **prevailing (instantaneous) information**

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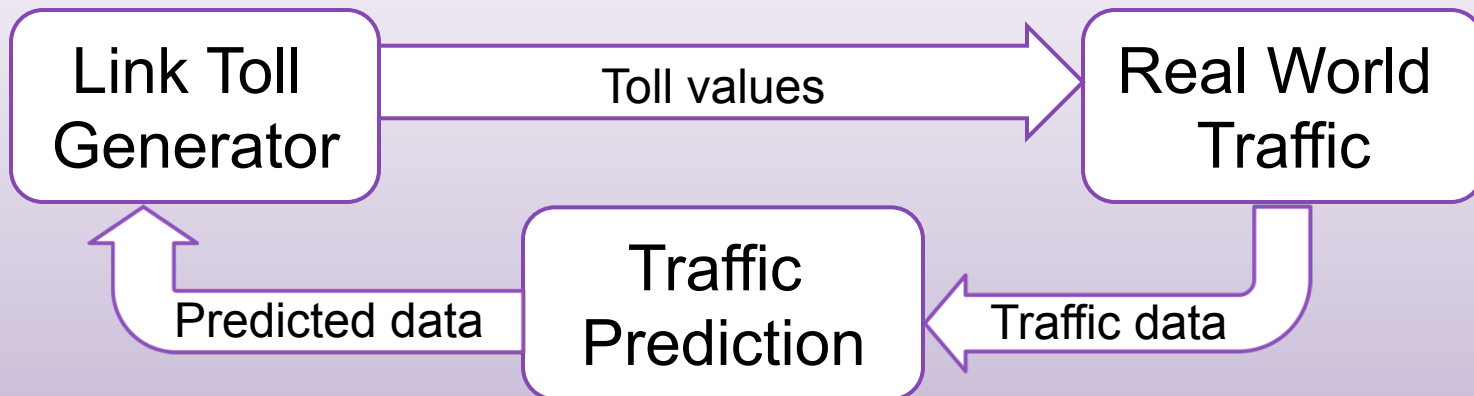
Reactive Pricing Strategy

- How does reactive pricing work?
 - obtain the **prevailing** traffic measures/conditions
 - adjust **current link tolls** accordingly
 - communicate to drivers via local VMS at the entry point
 - could also disseminate via radio, in-vehicle equipment, mobile, internet etc.

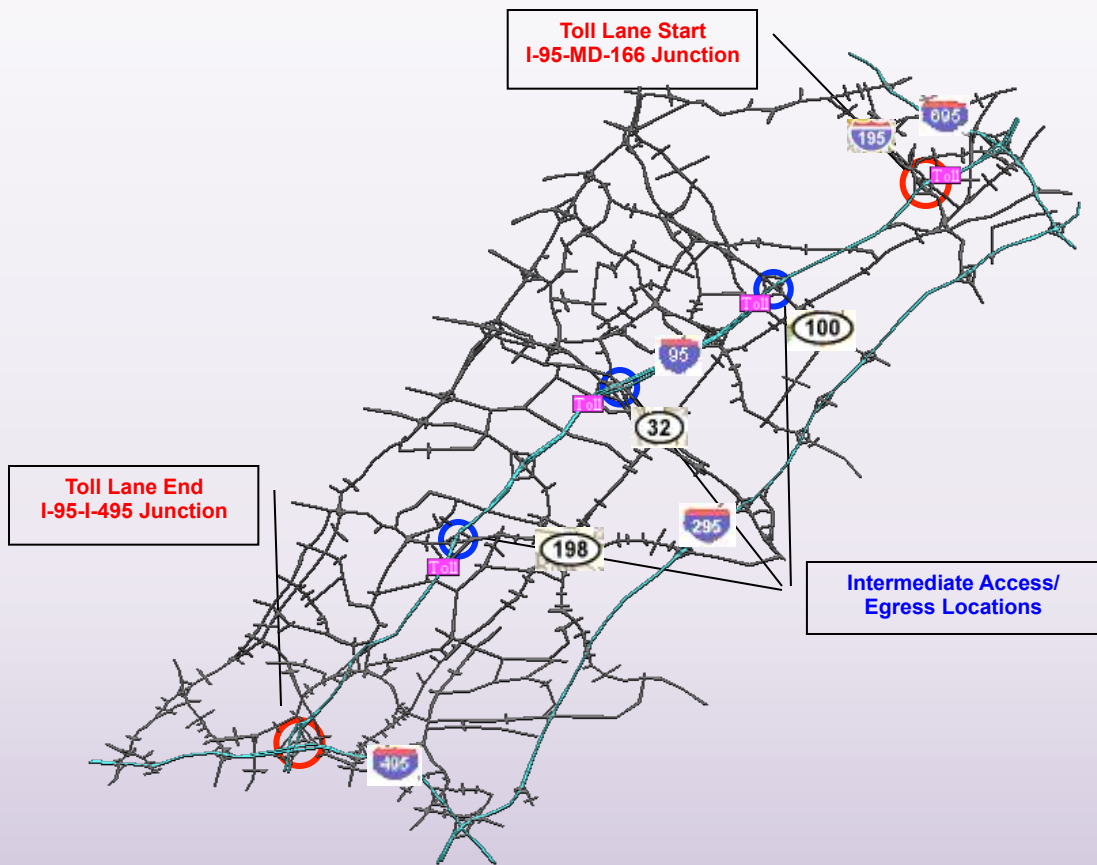


Anticipatory Pricing

INTRODUCE PREDICTION IN THE CONTROL LOOP



The Test Bed Network: CHART



- I-95 corridor between Washington, DC and Baltimore, MD, US
- 2 toll lanes
- 2241 nodes
- 3459 links
- 111 TAZ zones
- 2 hours morning peak demand

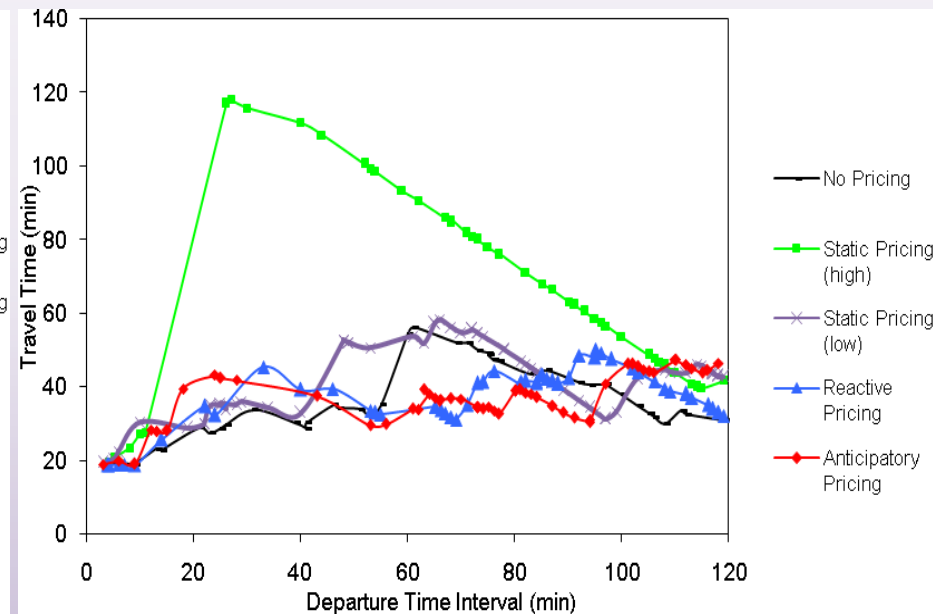
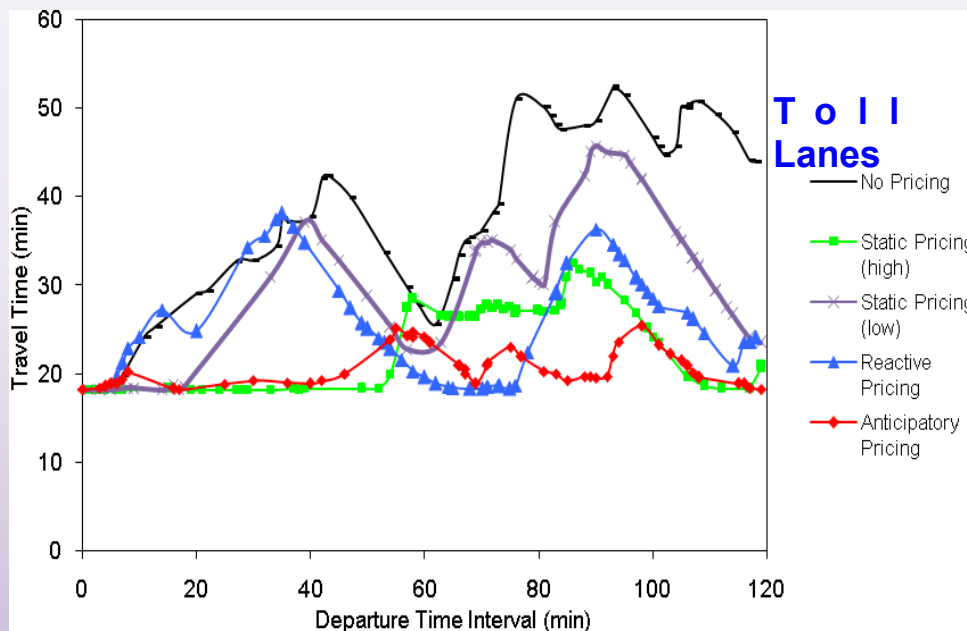
Pricing Strategies Compared

- No pricing (base case)
- Static pricing
 - Predetermine the time-varying link tolls based on the historical information
- Reactive pricing
 - Set time-varying link tolls based on prevailing traffic conditions
- Anticipatory pricing
 - Set time-dependent link tolls based on predicted traffic conditions

OBJECTIVE: AVOID BREAKDOWN— optimize throughput, reliability, under economically efficient allocation

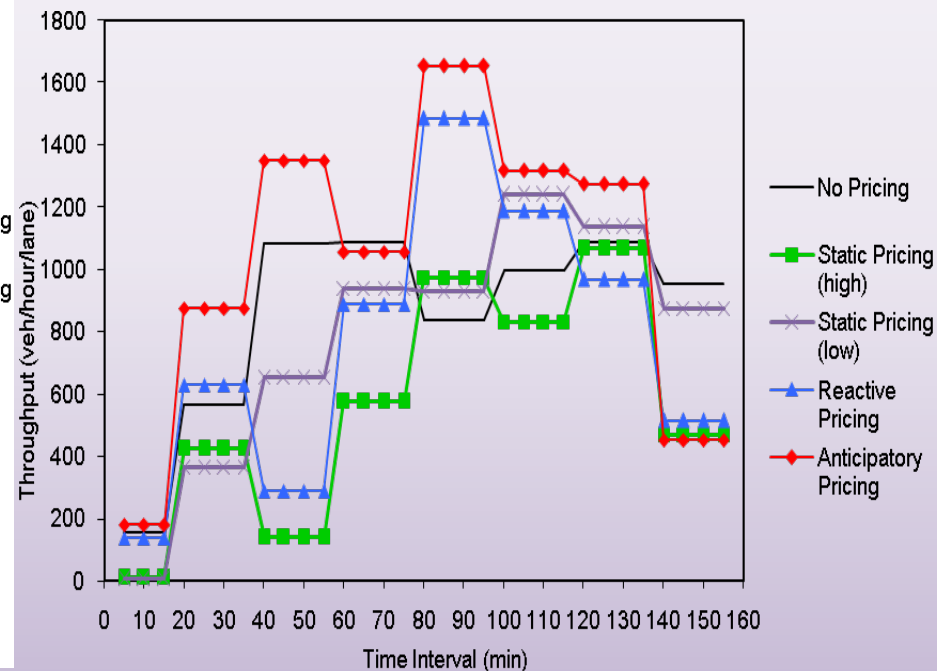
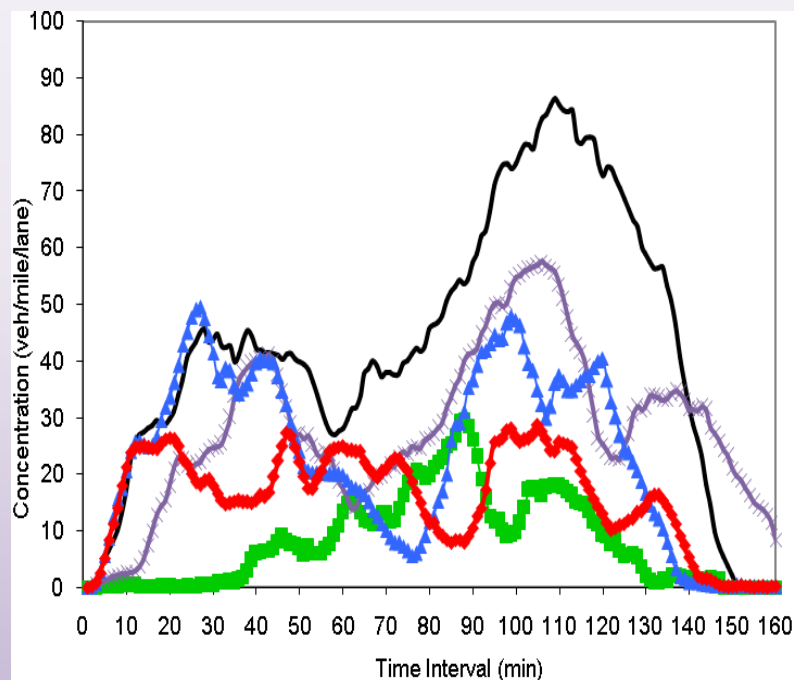
Illustrative Results – Travel Time

- Warm-up period: increase in travel time at the beginning
- With the anticipatory pricing strategy, the travel times become steady after 1 hour (free flow condition)
- Static pricing strategy provides free flow condition on the toll lanes, but reduces the LOS on the alternative freeway lanes

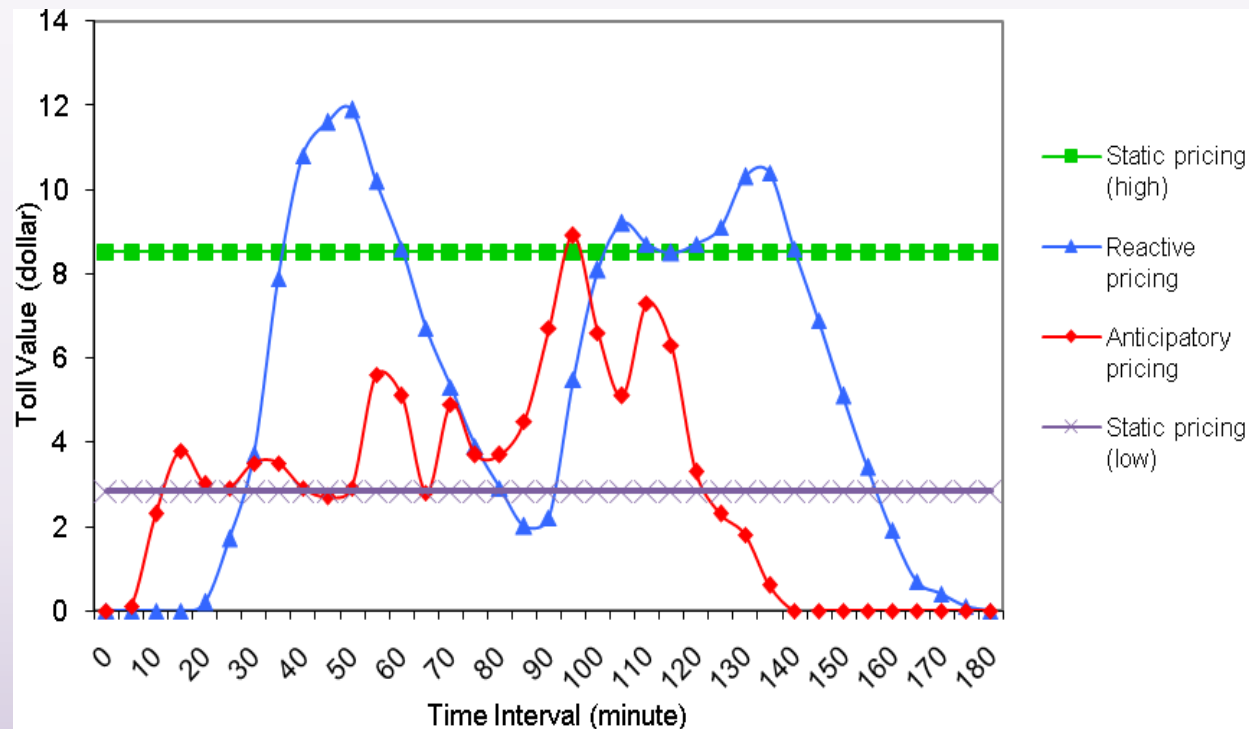


Illustrative Results – Traffic Measures

- Concentrations averaged over links along the congested portion of toll road, weighted by the link length
- Throughputs measured at downstream of where traffic breaks down in base case (no pricing)
- Anticipatory pricing strategy can provide higher throughput while maintaining lower concentration (steady traffic flow)

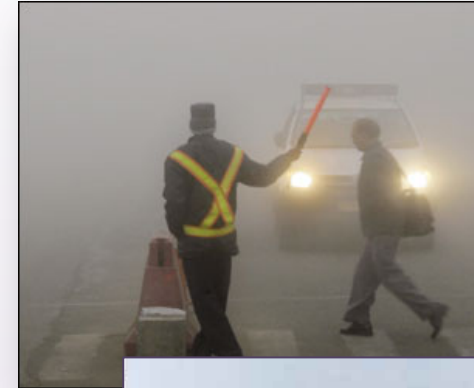


Illustrative Results – Toll Variation

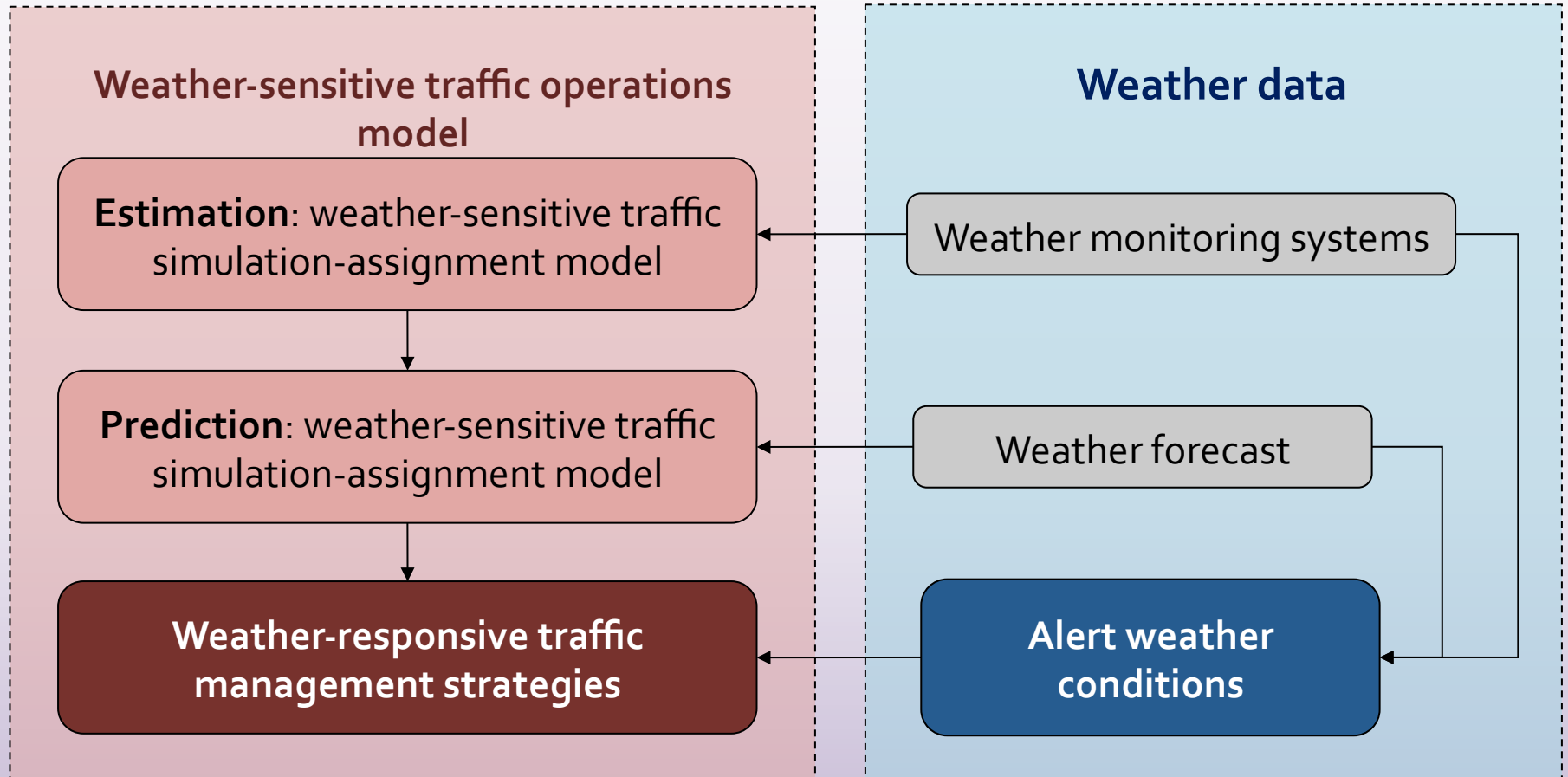


Introduction

- Weather Impact on Traffic Safety
 - Low visibility
 - Slick pavement
 - Reduce road capacity
 - Other hazardous conditions on roadways
- Weather Responsive Traffic Management (WRTM)
 - Forecasting weather in real-time for operational purposes
 - Sensing of traffic conditions

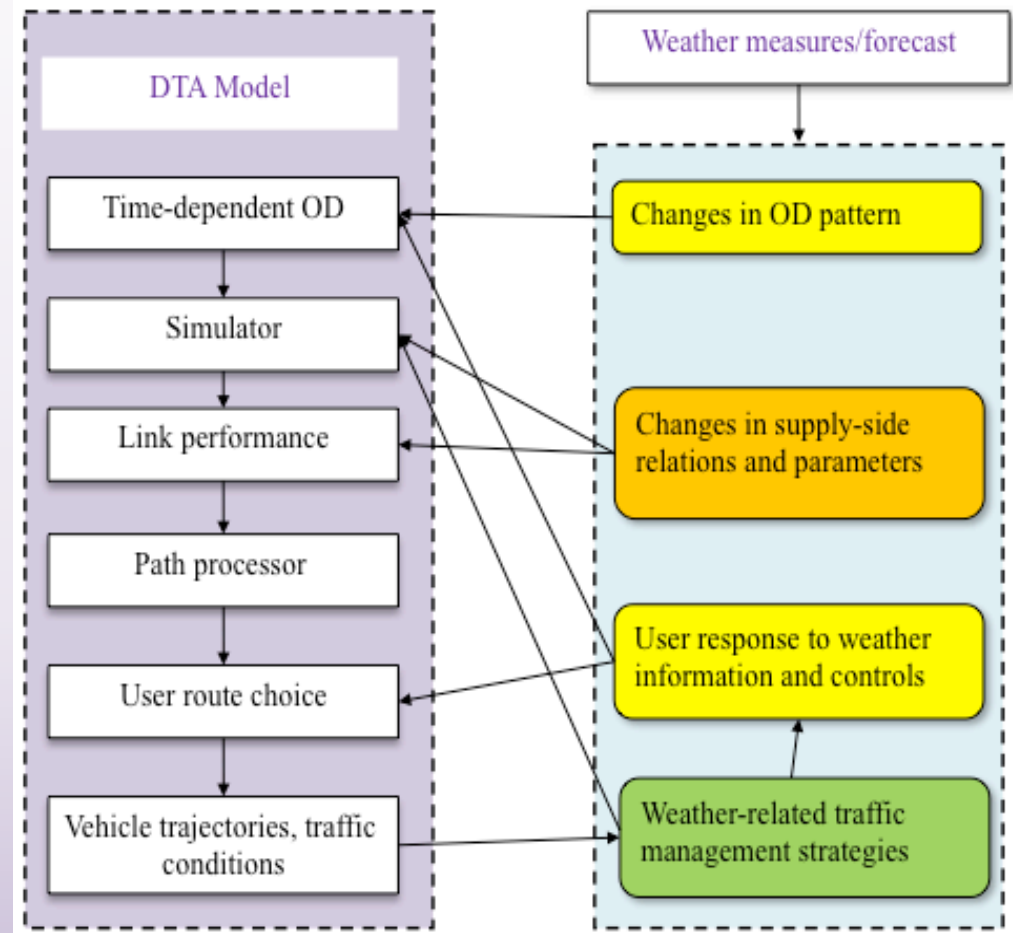


Weather-sensitive Traffic Estimation and Prediction System (TrEPS)



Incorporating Weather in TrEPS

- Capture weather effects in a DTA model
- Weather-sensitive TrEPS
 - Assess the **impacts of adverse weather** on transportation networks.
 - Evaluate the **effectiveness of weather-responsive traffic management (WRTM) strategies** in alleviating traffic congestion due to adverse weather conditions.



Model Impacts of Adverse Weather



Weather Scenario Specification

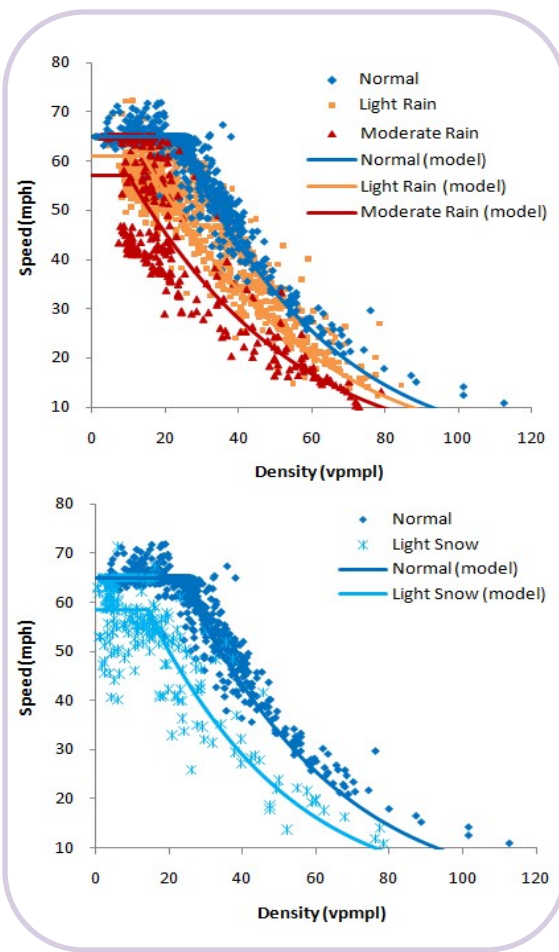
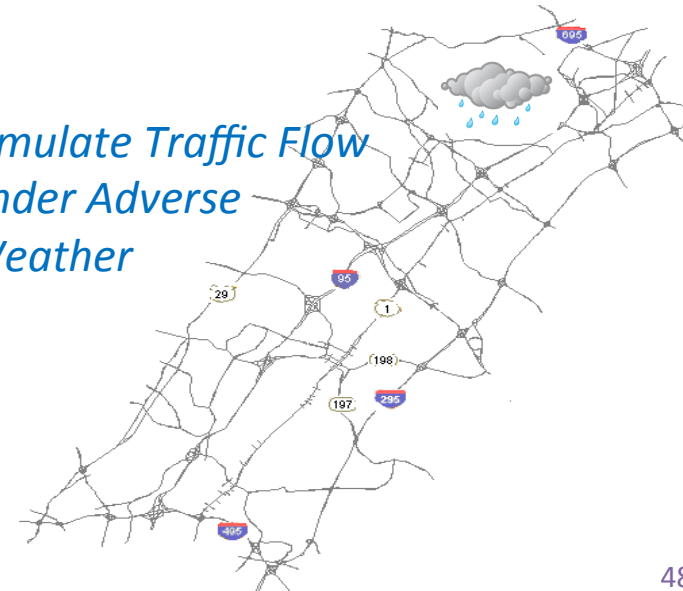
- Rain intensity (r)
- Snow intensity (s)
- Visibility (v)

TrEPS
DYNASMART

Supply-side Parameter Calibration Weather Adjustment Factor (WAF)

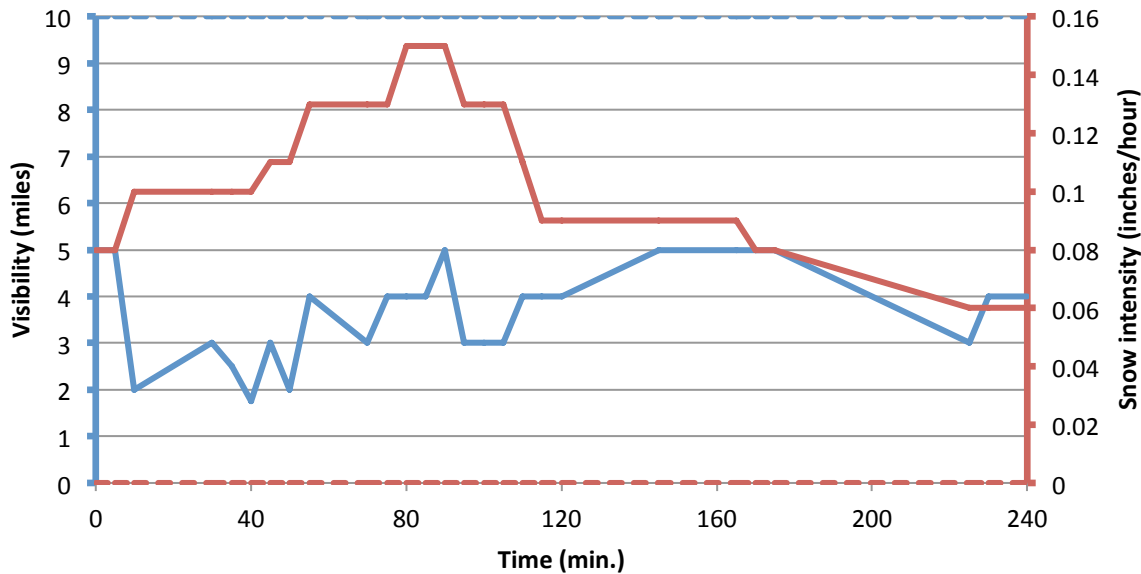
- Free-flow speed,
- Saturation flow rate,
- Section capacity,
- etc.

*Simulate Traffic Flow
under Adverse
Weather*



Weather Scenario (Heavy Snow)

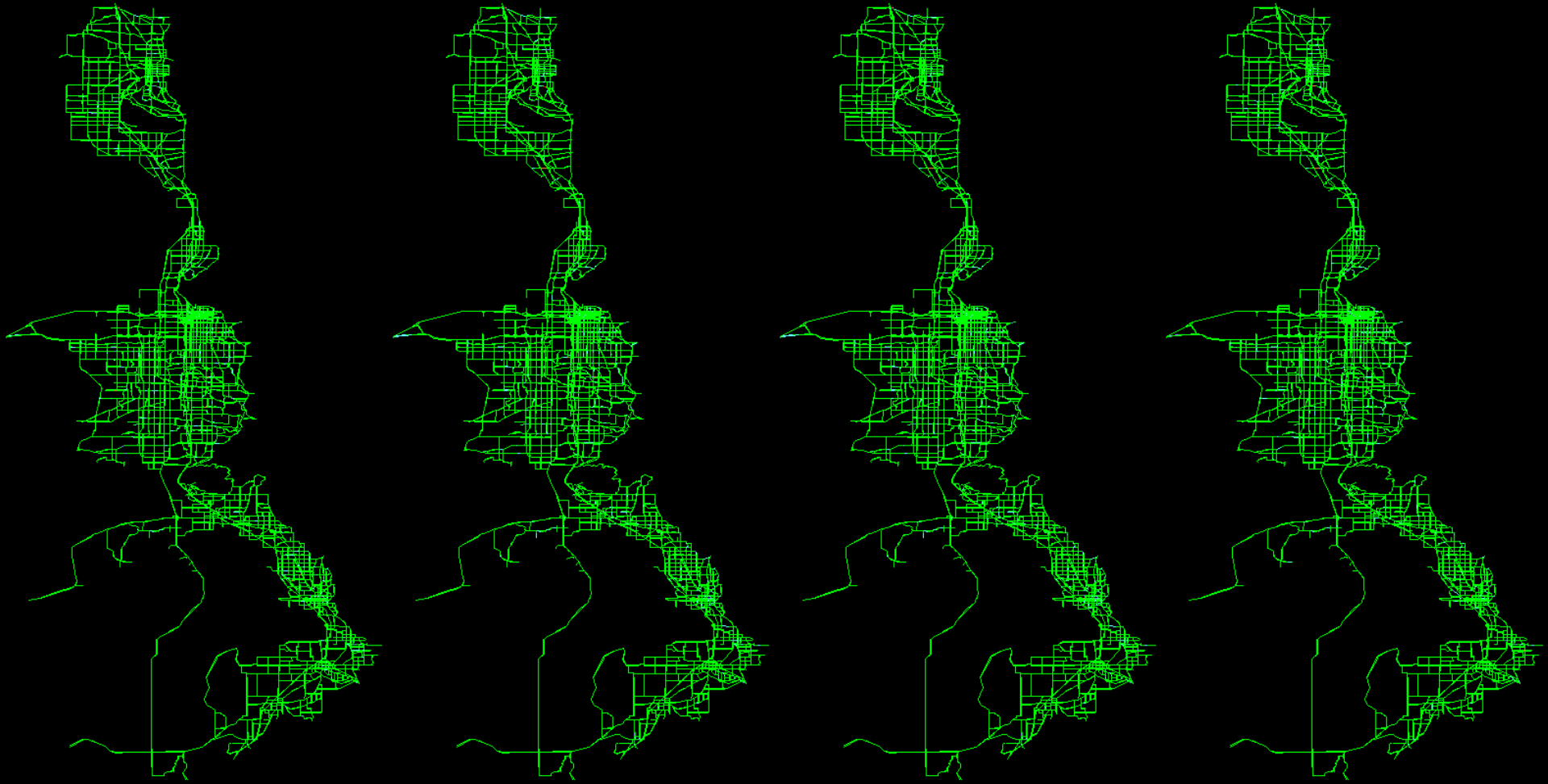
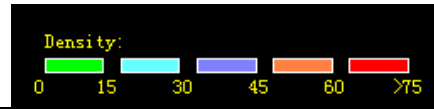
Visibility and Snow Intensity vs. Time



— Visibility (Snowy Day) - - - Visibility (Clear Day)
— Snow Intensity (Snowy Day) - - - Snow Intensity (Clear Day)

- Snow intensity ranges:
 - Light snow: < 0.05 inches/hour
 - Medium snow: 0.05 – 0.1 inches/hour
 - Heavy snow: > 0.1 inches/hour
- Visibility ranges:
 - Max. 10 miles
 - Min. 0 miles

6:00 am



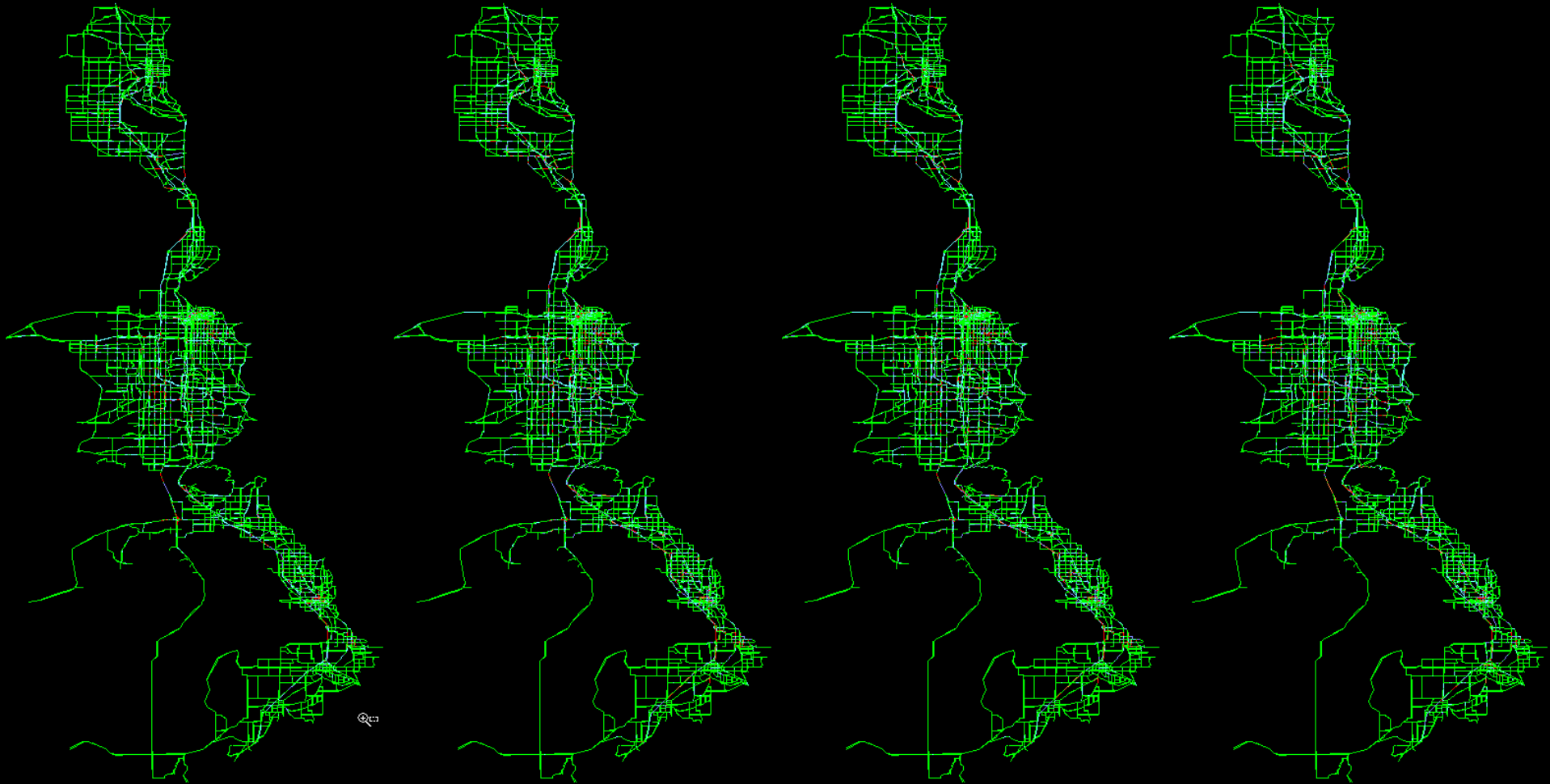
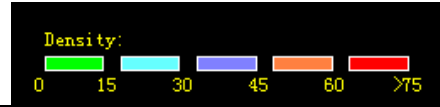
01-00.Regular

01-01.NoWRTM

01-02.VSL7

01-03.VMS2

6:30 am



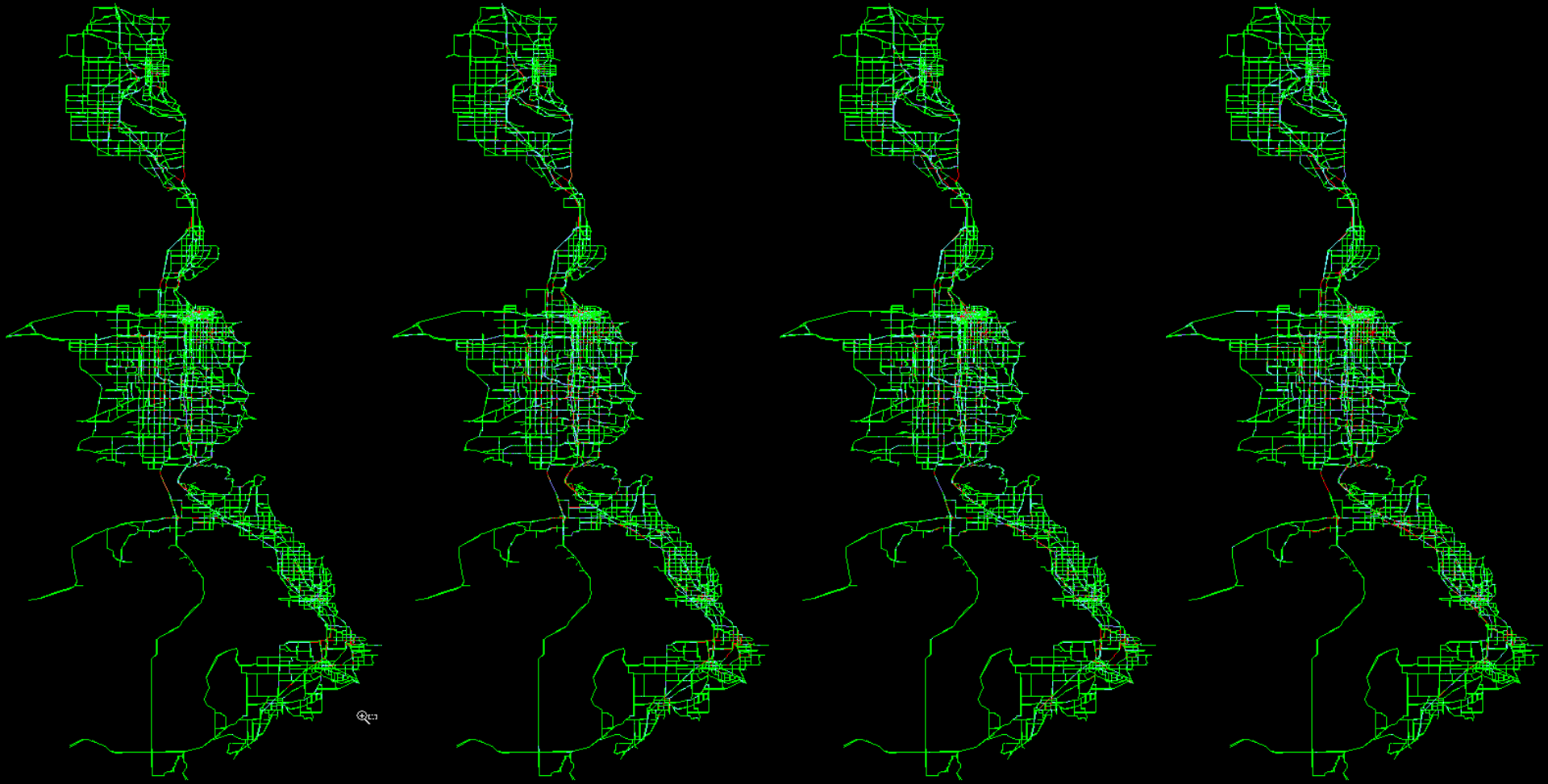
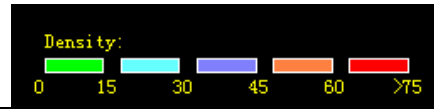
07-00.Regular

07-01.NoWRTM

07-02.VSL7

07-03.VMS2

7:00 am



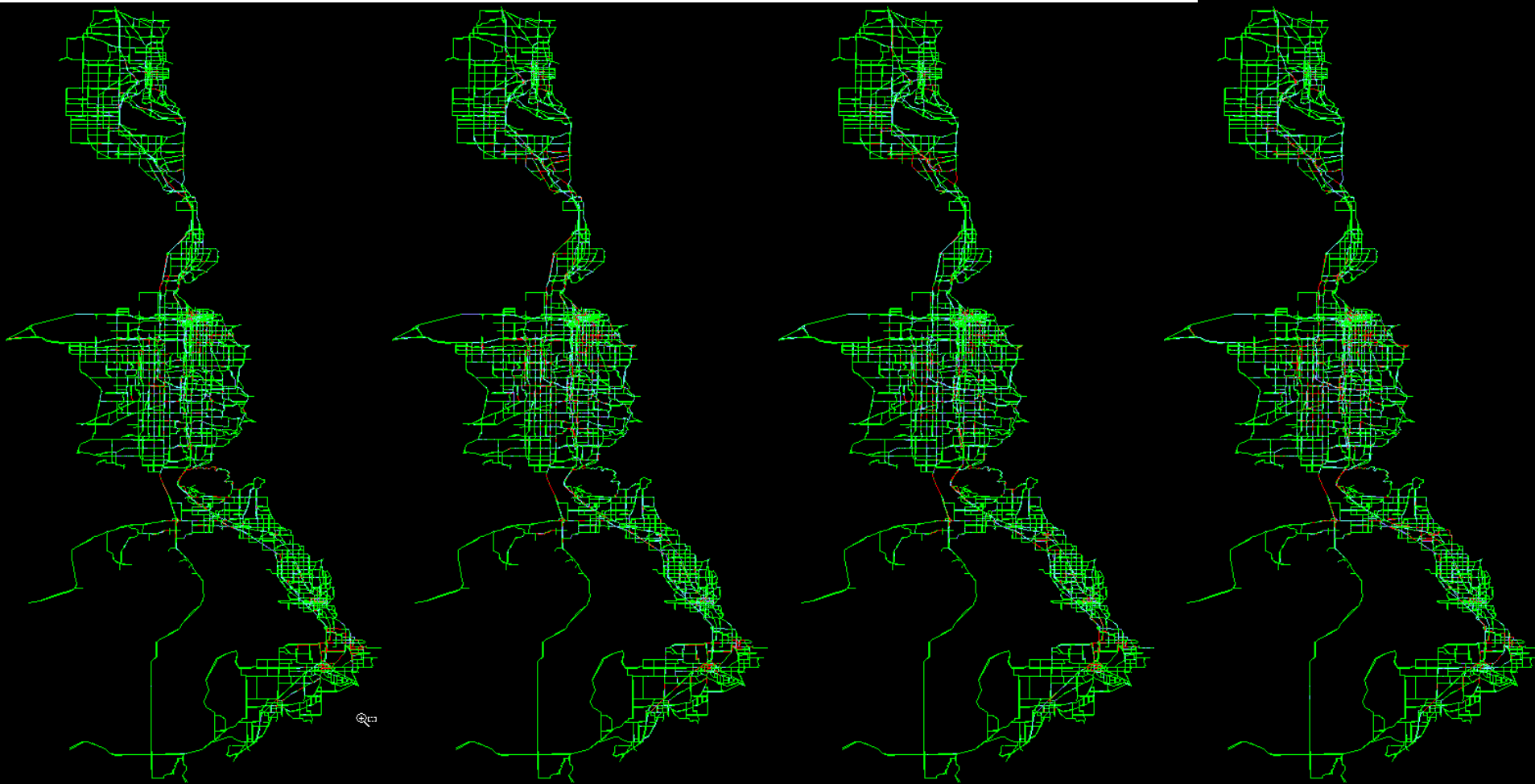
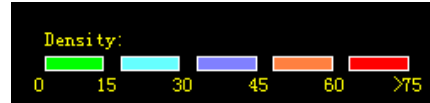
13-00.Regular

13-01.NoWRTM

13-02.VSL7

13-03.VMS2

7:30 am



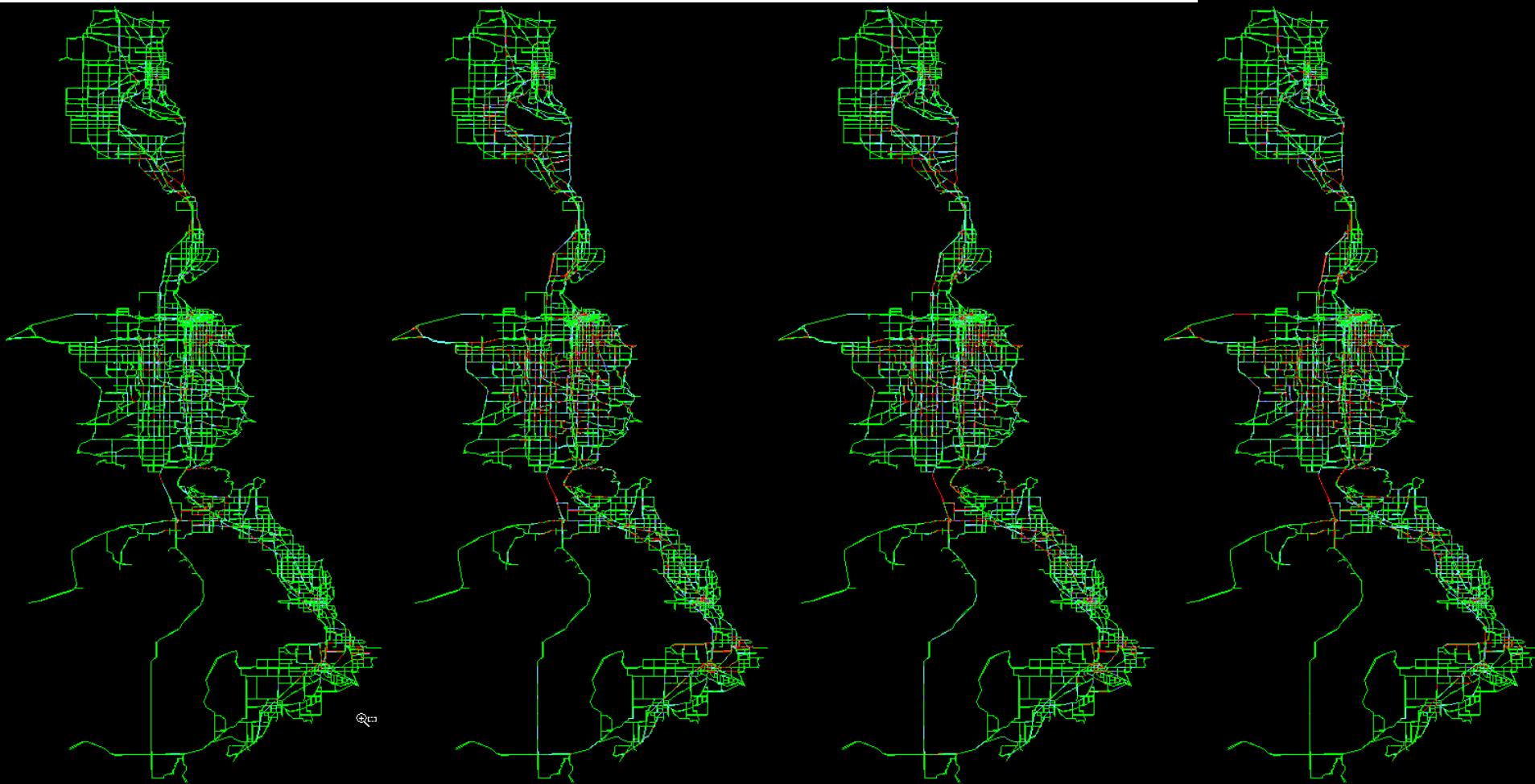
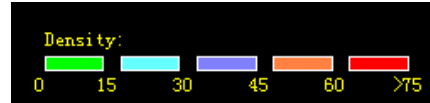
19-00.Regular

19-01.NoWRTM

19-02.VSL7

19-03.VMS2

8:00 am



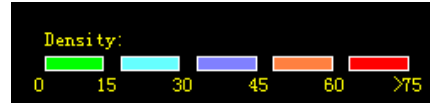
25-00.Regular

25-01.NoWRTM

25-02.VSL7

25-03.VMS2

8:30 am



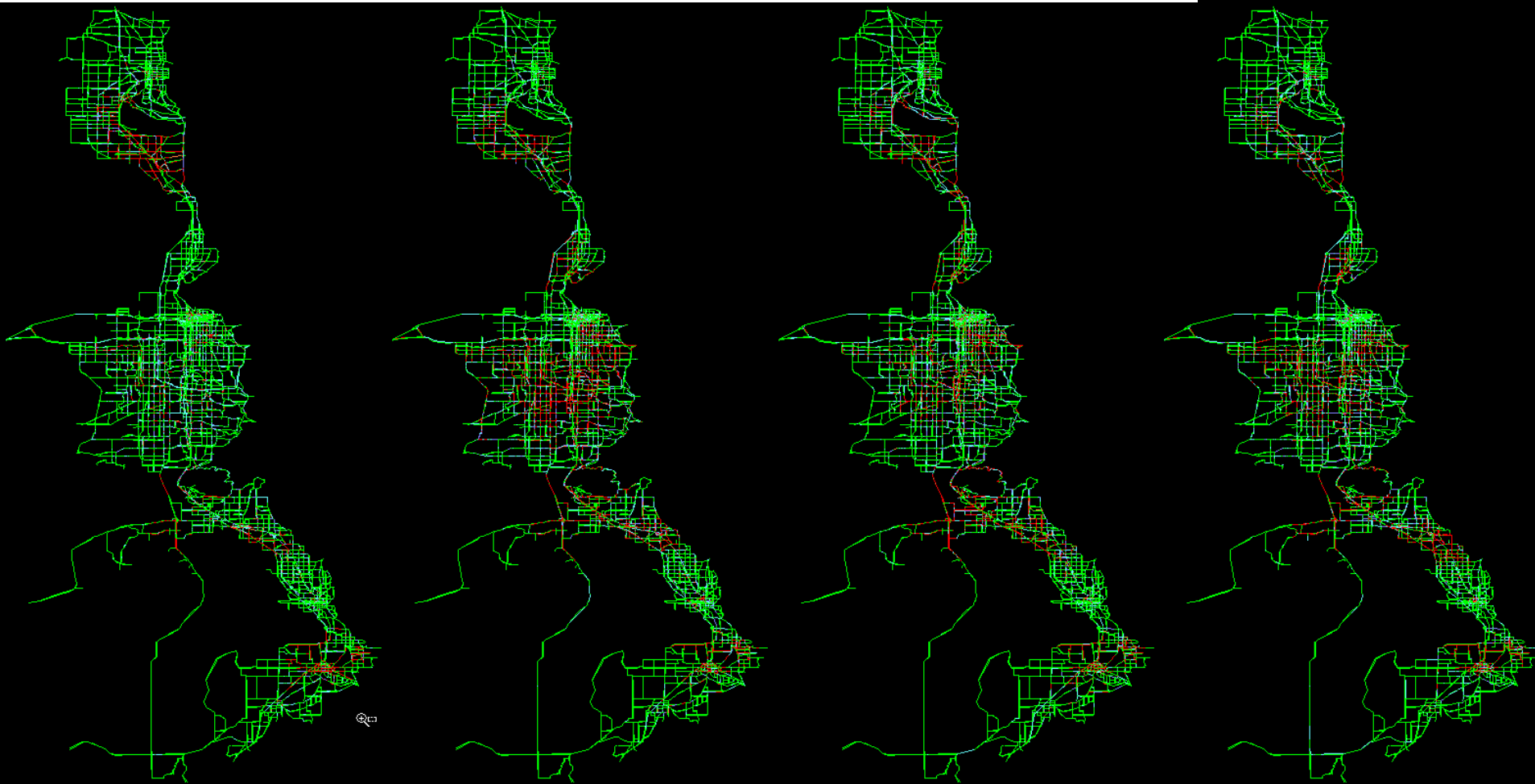
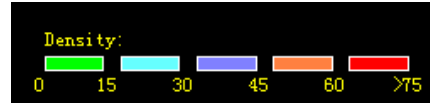
31-00.Regular

31-01.NoWRTM

31-02.VSL7

31-03.VMS2

9:00 am



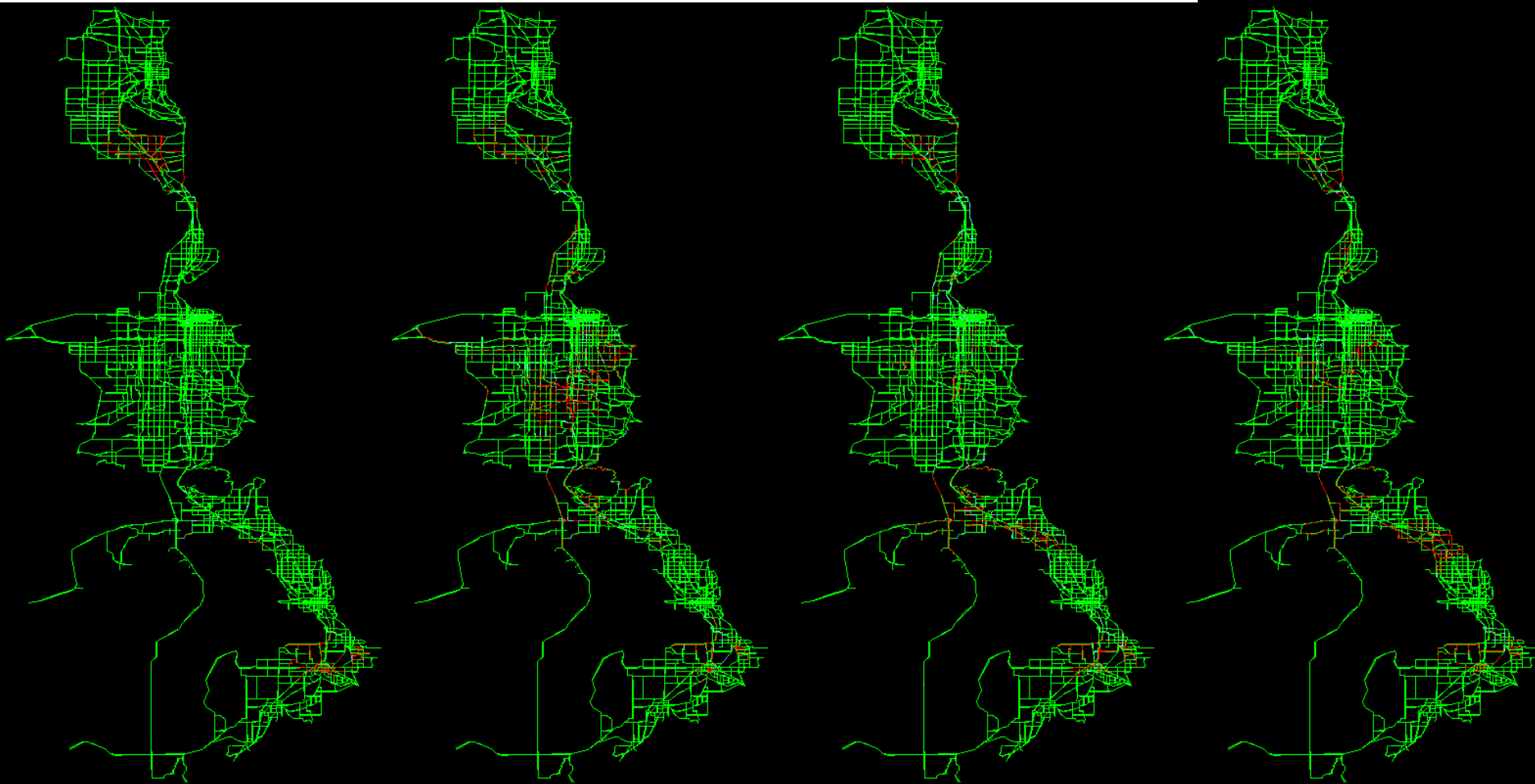
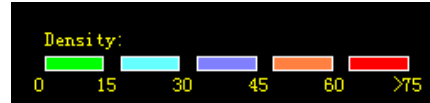
37-00.Regular

37-01.NoWRTM

37-02.VSL7

37-03.VMS2

9:30 am



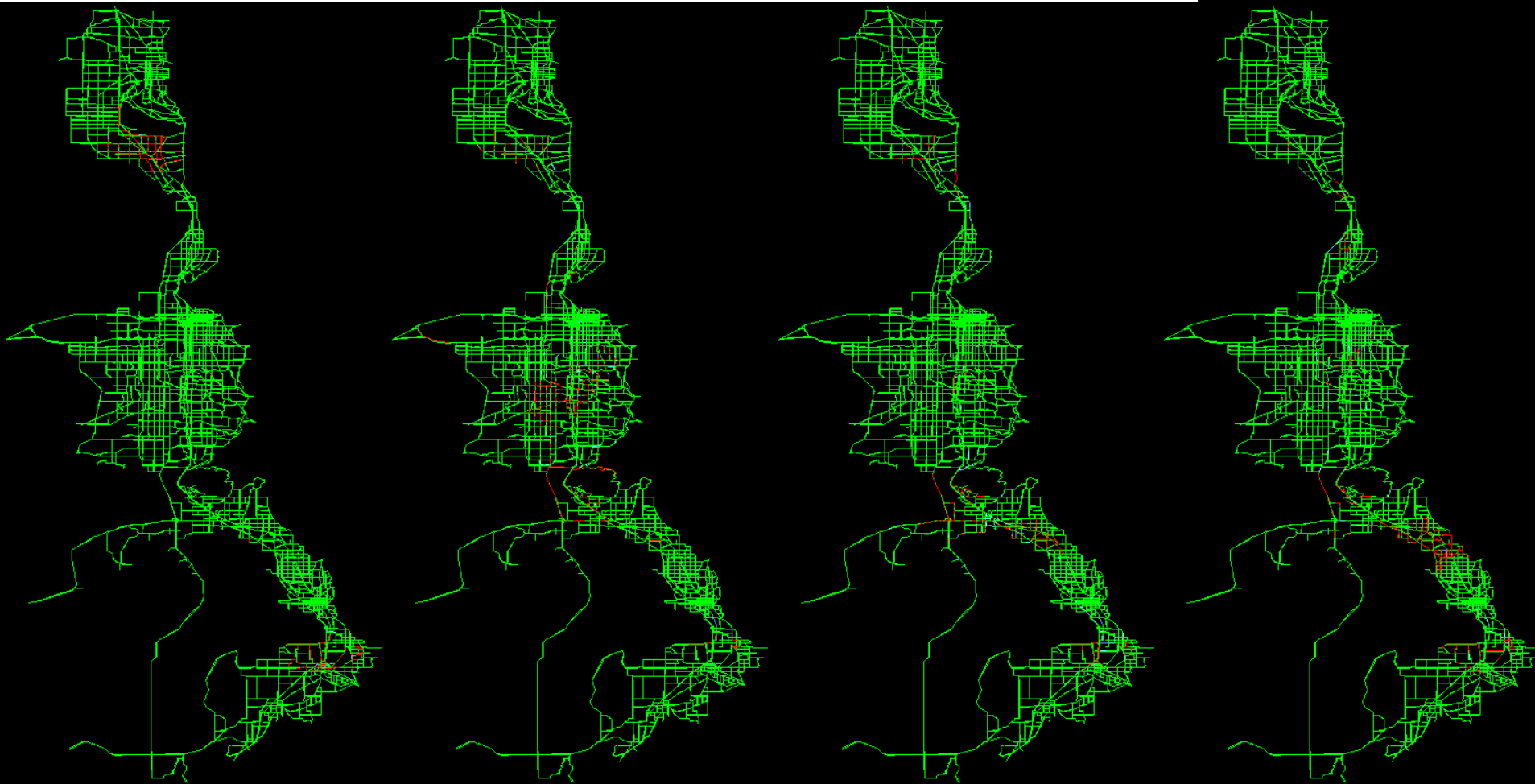
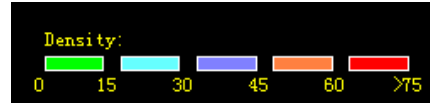
43-00.Regular

43-01.NoWRTM

43-02.VSL7

43-03.VMS2

10:00 am



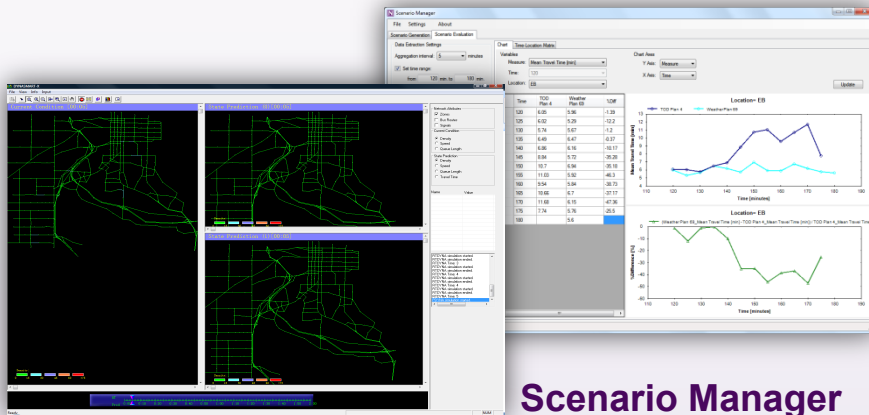
49-00.Regular

49-01.NoWRTM

49-02.VSL7

49-03.VMS2

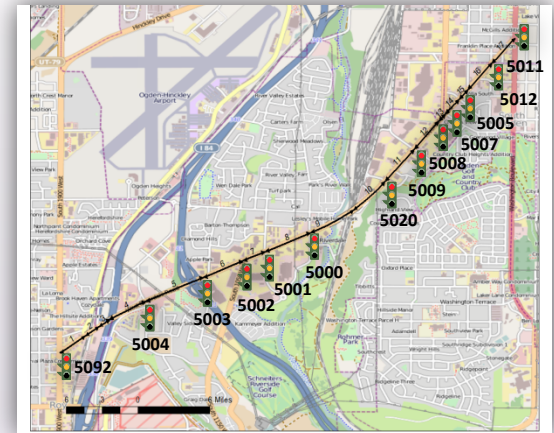
Real-time Decision Support Systems for Weather-Responsive Signal Timing (Utah DOT, USA)



DYNASMART-X
: real-time traffic simulator

Scenario Manager
: scenario generation & management tool

Real-time traffic and weather information



Riverdale Rd, UT, USA
: 13 signalized intersections
(3.5 miles = 5.6 km)

Information for Decision Making

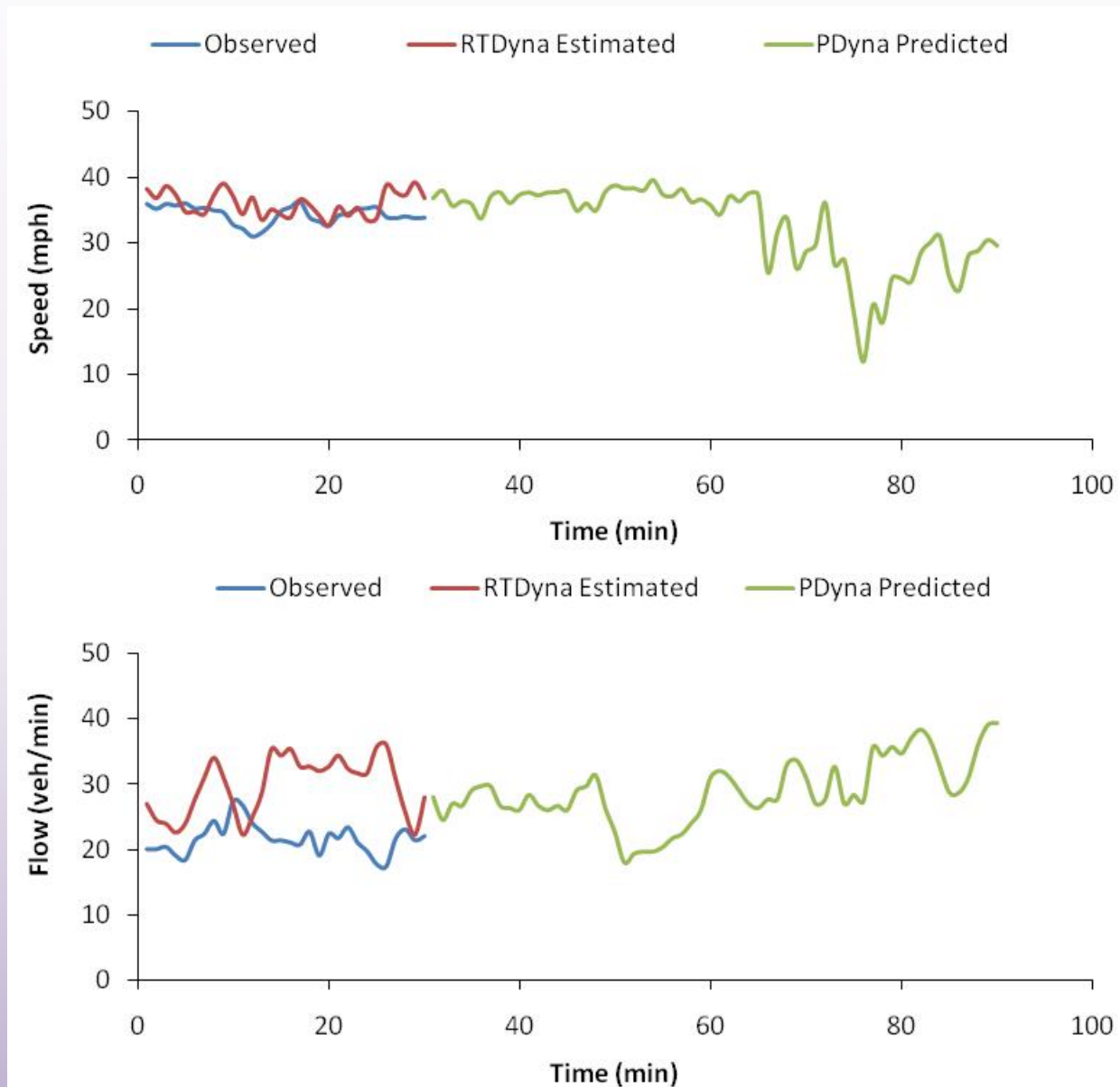
- Anticipated traffic conditions
- Suggested signal timing plans
- Performance evaluation results



Traffic Signal Operators

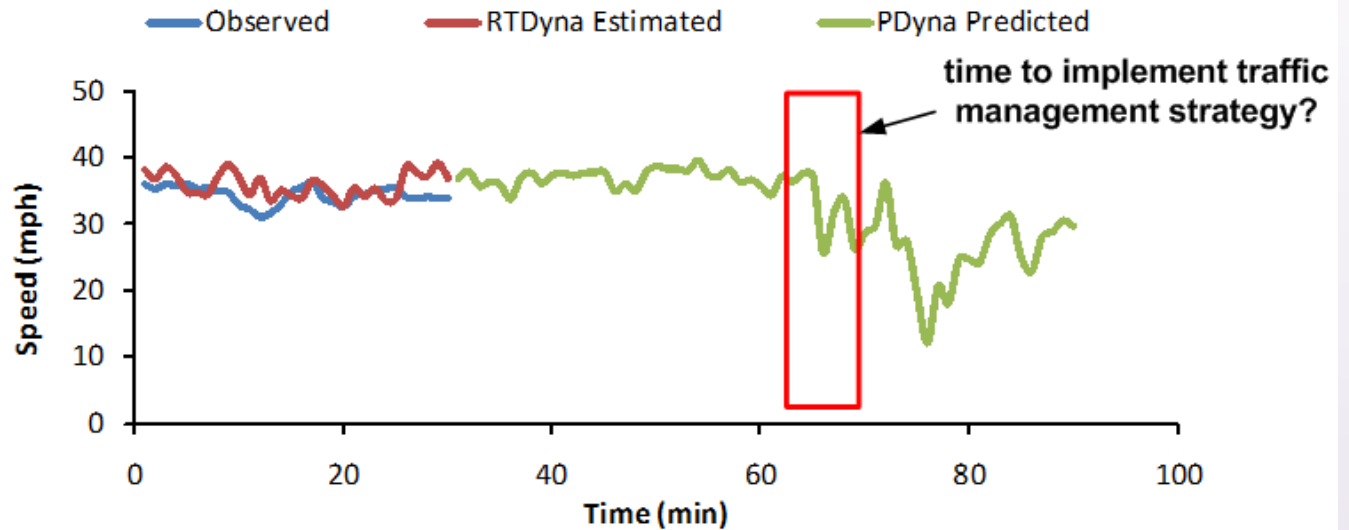
Deploy alternative signal timing plans (adjust offsets)

Selected Arterial Link on Riverdale Rd

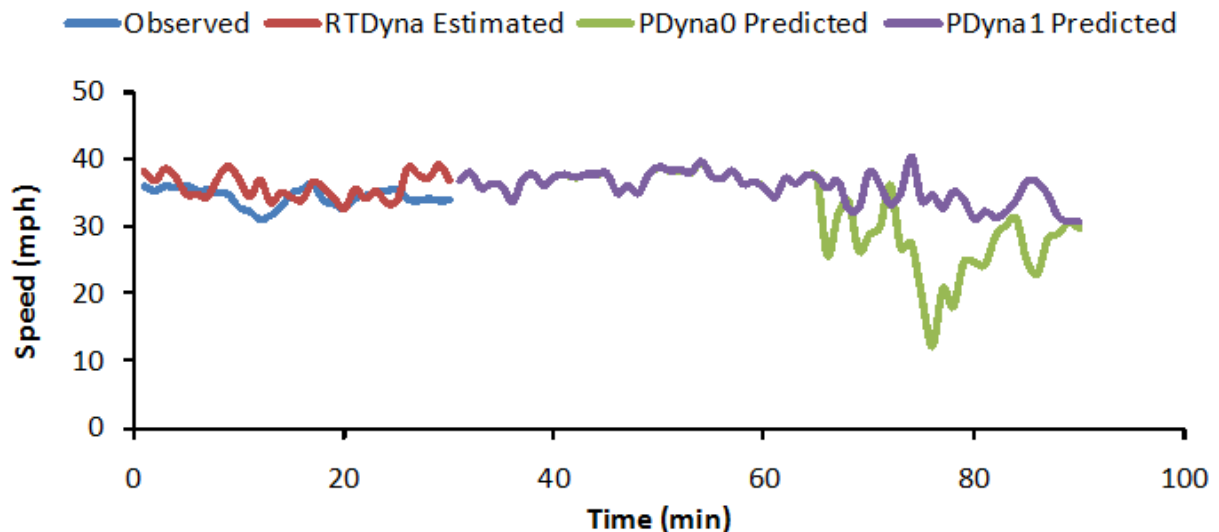


Real-time Traffic Management

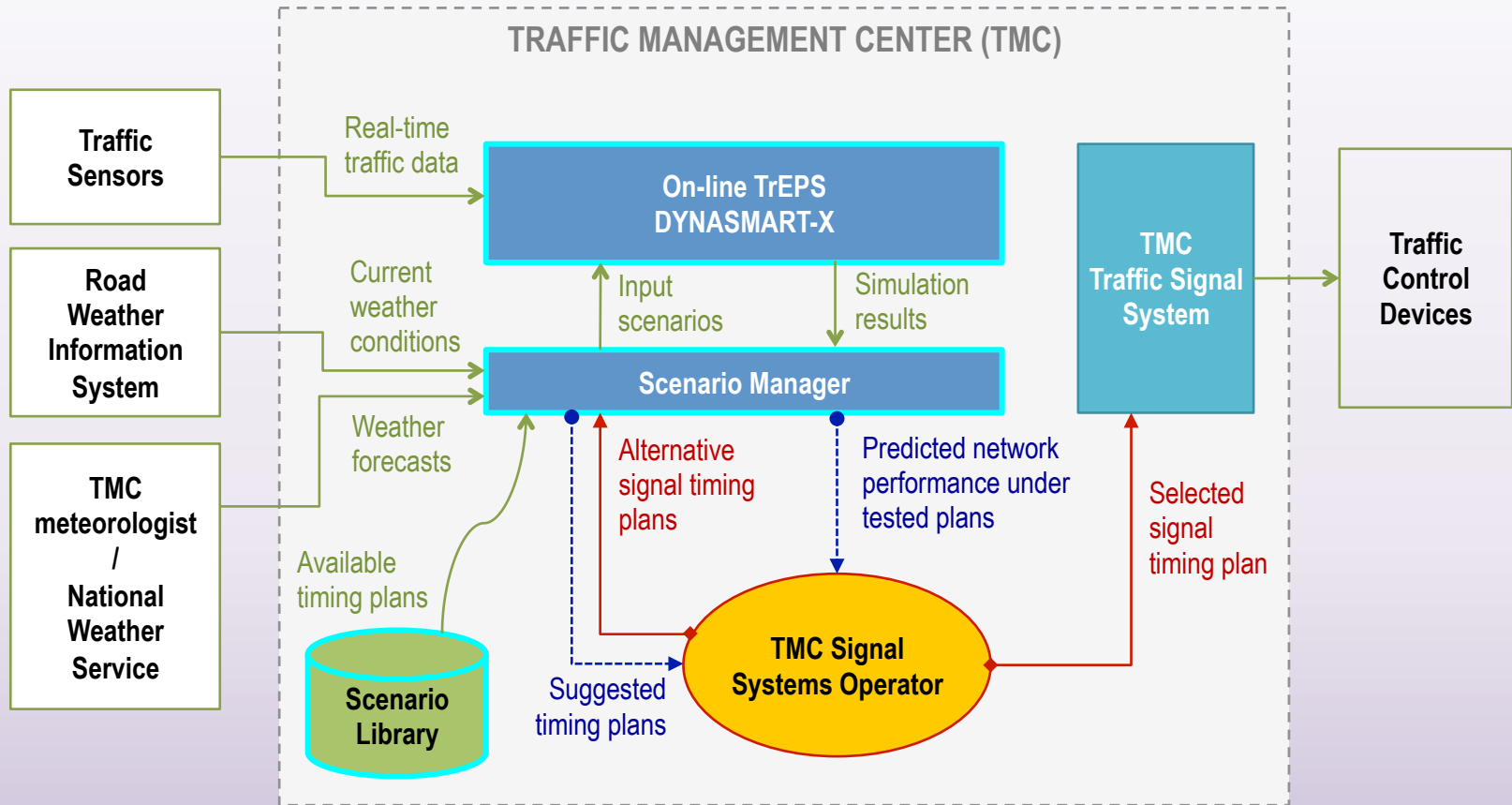
before implement management strategy



after implement management strategy

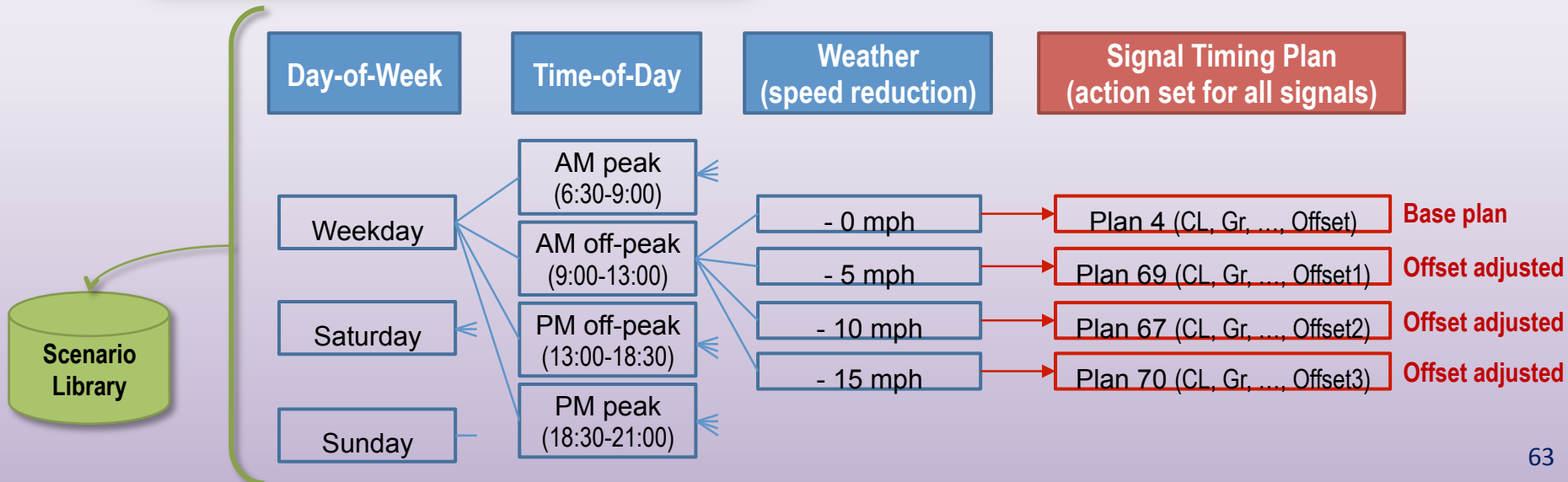
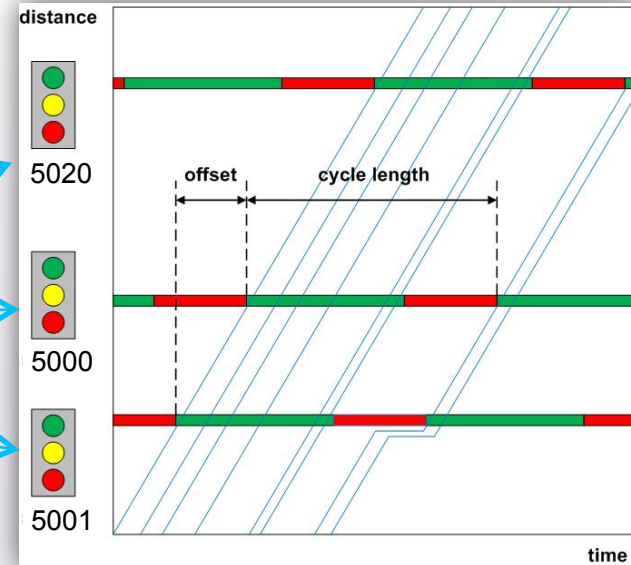
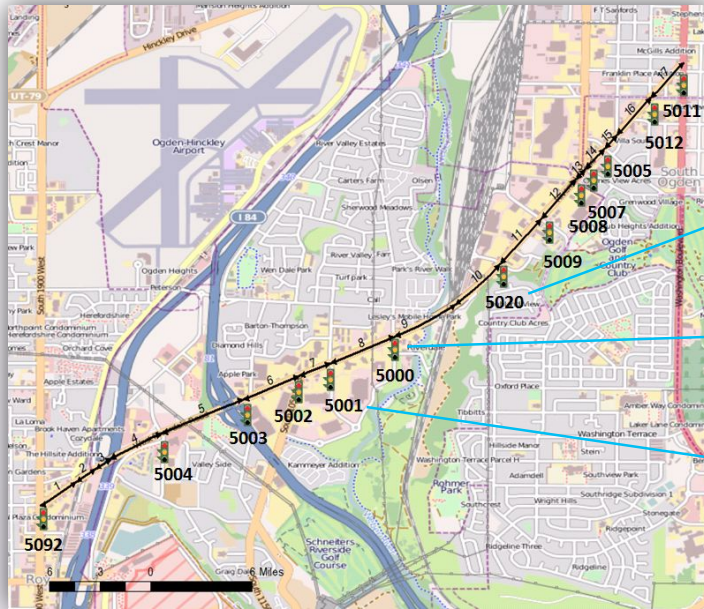


Real-time Decision Support Systems for Weather-Responsive Signal Timing (Utah DOT, USA)

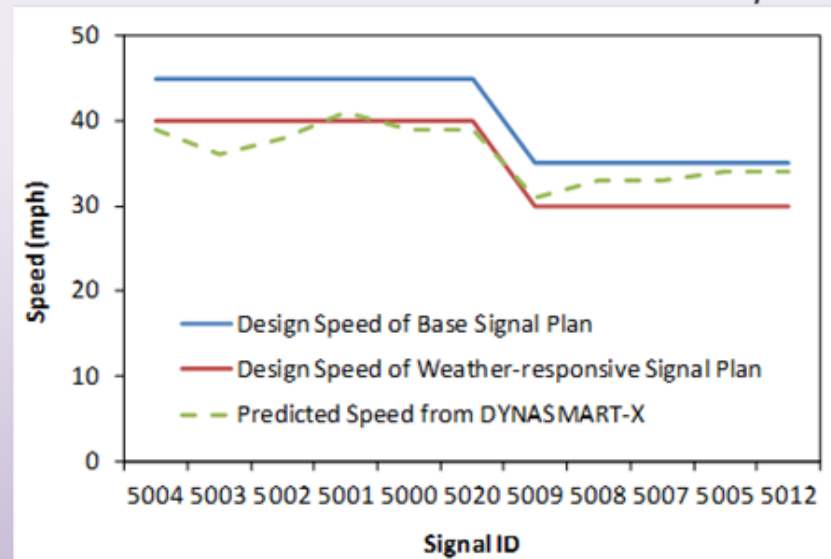
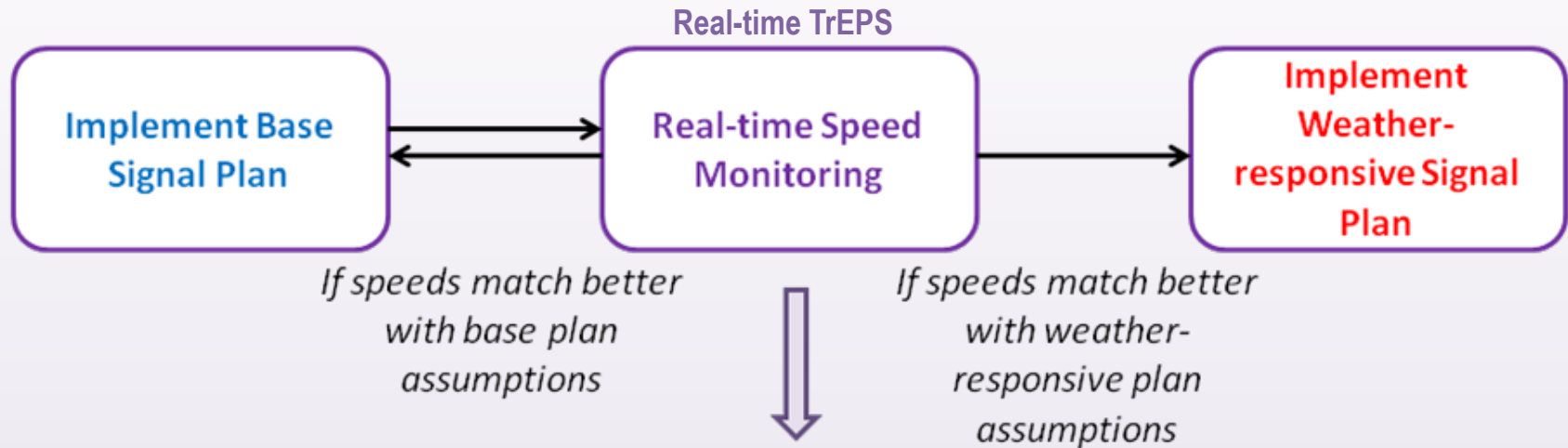


← : Data ←◆ : Decision Maker's Action ←● : Information to Support Decision-making

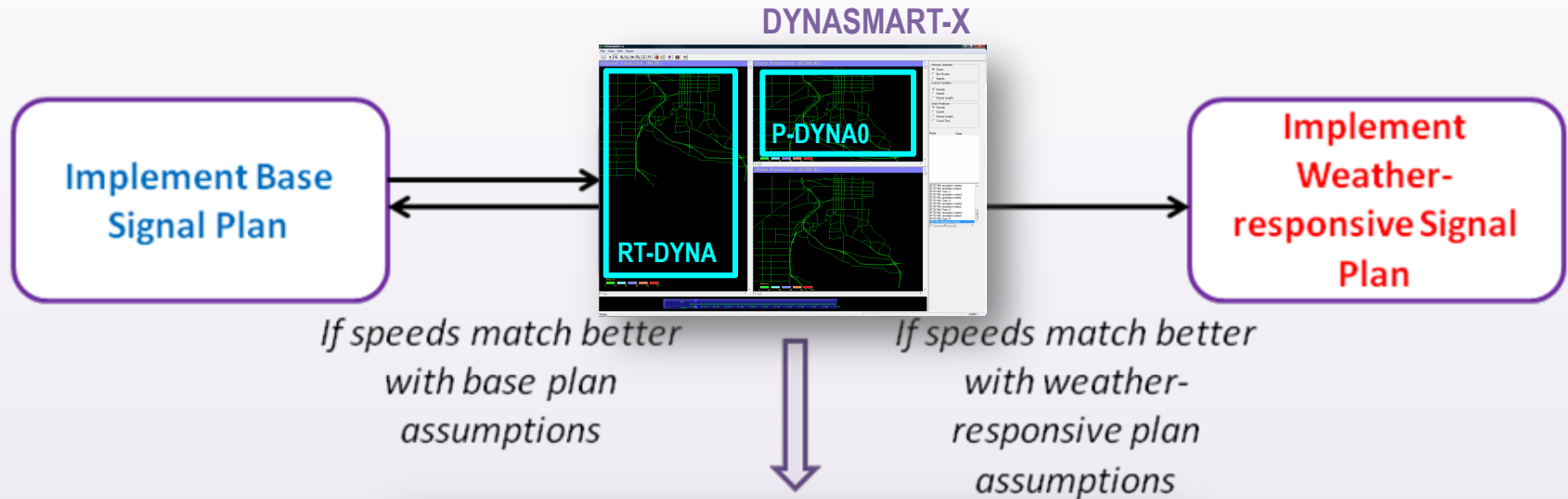
Weather-Responsive Signal Timing Plans



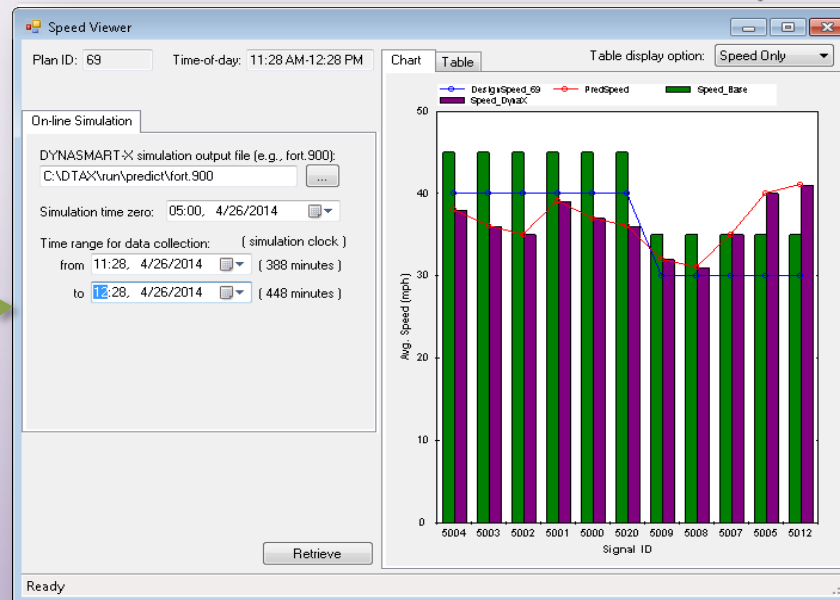
Online Implementation



Online Implementation



SCENARIO MANAGER



Scenario Generation

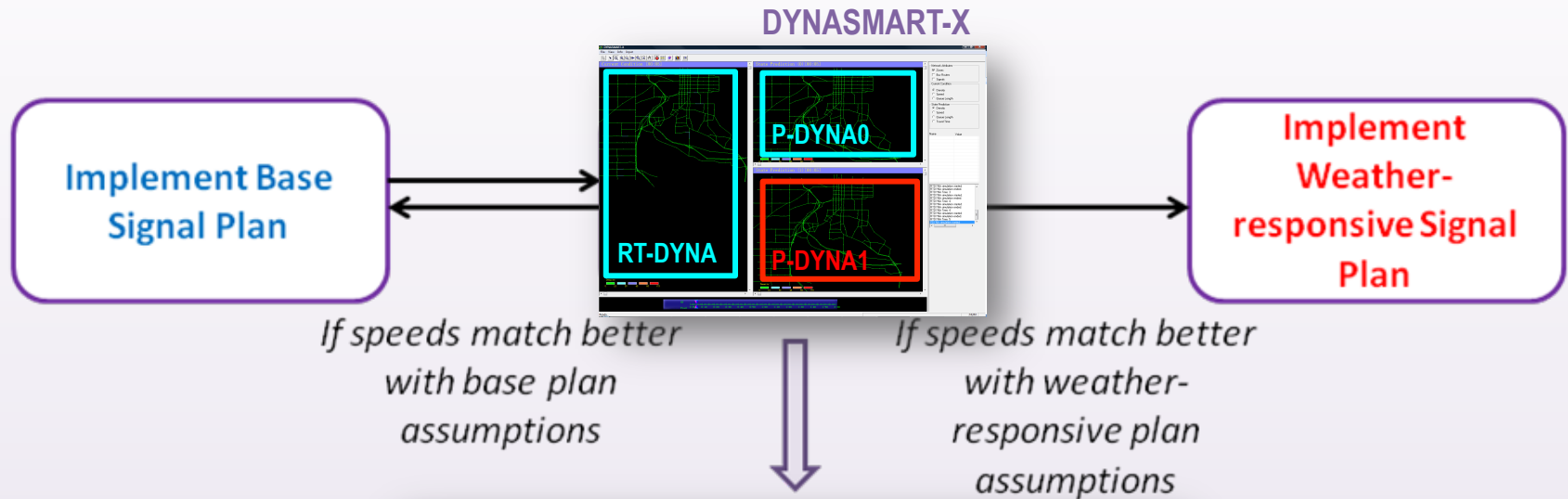
Find the best-matching timing plan that minimizes the diff. between the assumed and predicted speeds:

$$\min_{k \in K} \sum_{i \in I} (U_i^k - V_i)^2$$

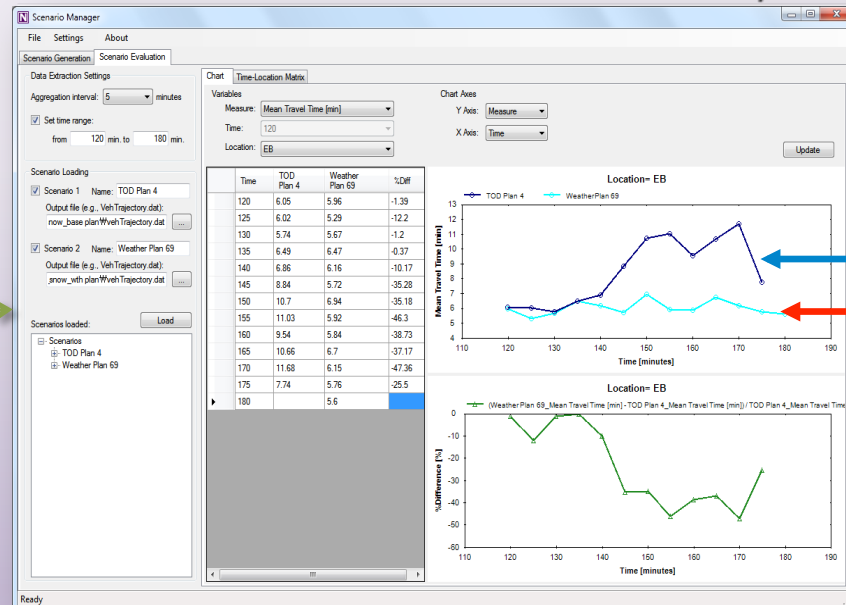
- k : signal timing plan
- i : intersection (traffic signal)
- U_i^k : design speed at i under k
- V_i : predicted speed at i



Online Implementation



SCENARIO MANAGER



Scenario Evaluation

Predict the performance of the alternative plan before deployment

Current Plan (Base Plan): P-DYNA0

Alternative Plan (Weather Plan): P-DYNA1

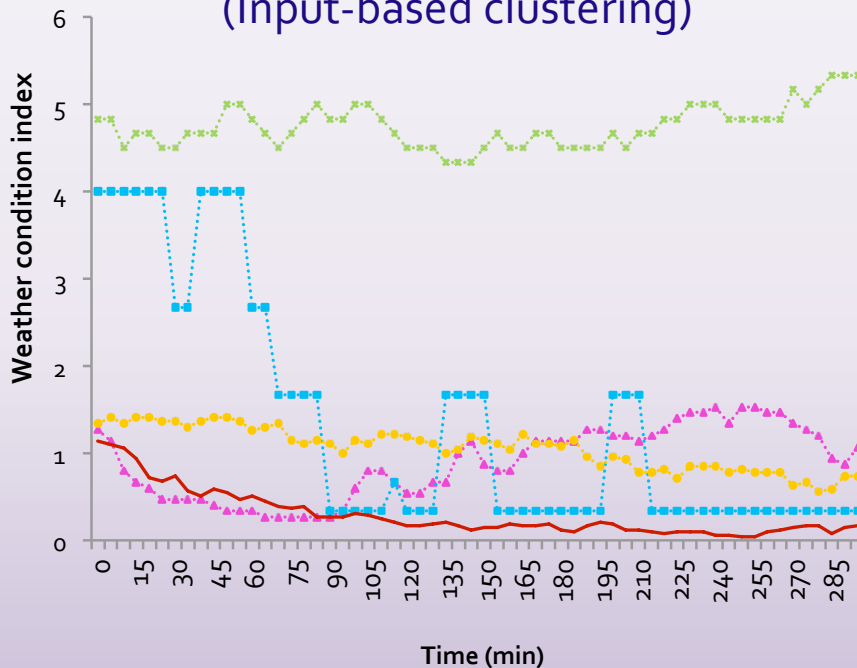


Data Mining on Historical Patterns

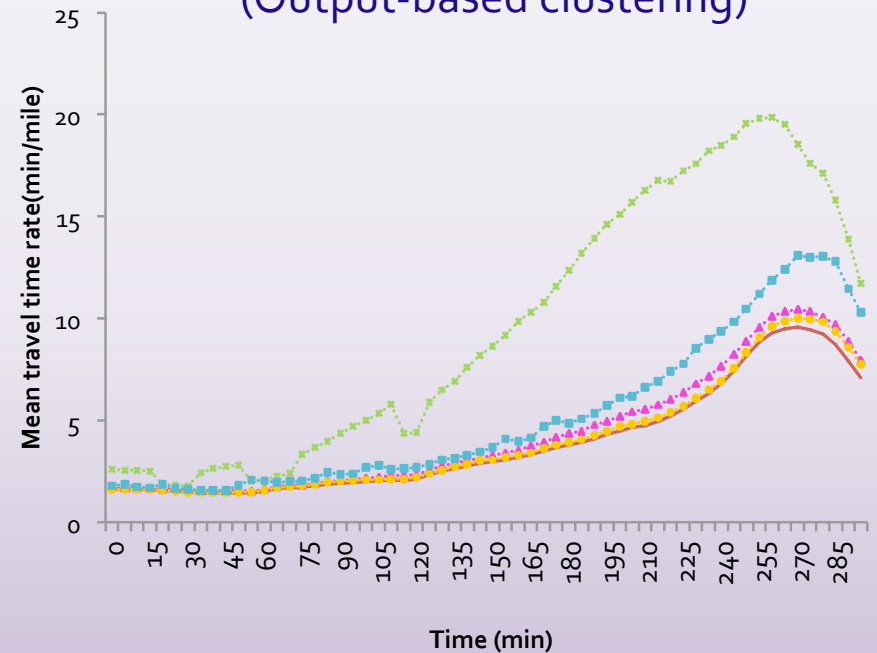
Cluster historical weather patterns to identify and define distinct weather categories

Weather clusters map well onto network traffic patterns; Organize and prepare different plans for each weather category

Clustering Weather Scenarios (Input-based clustering)



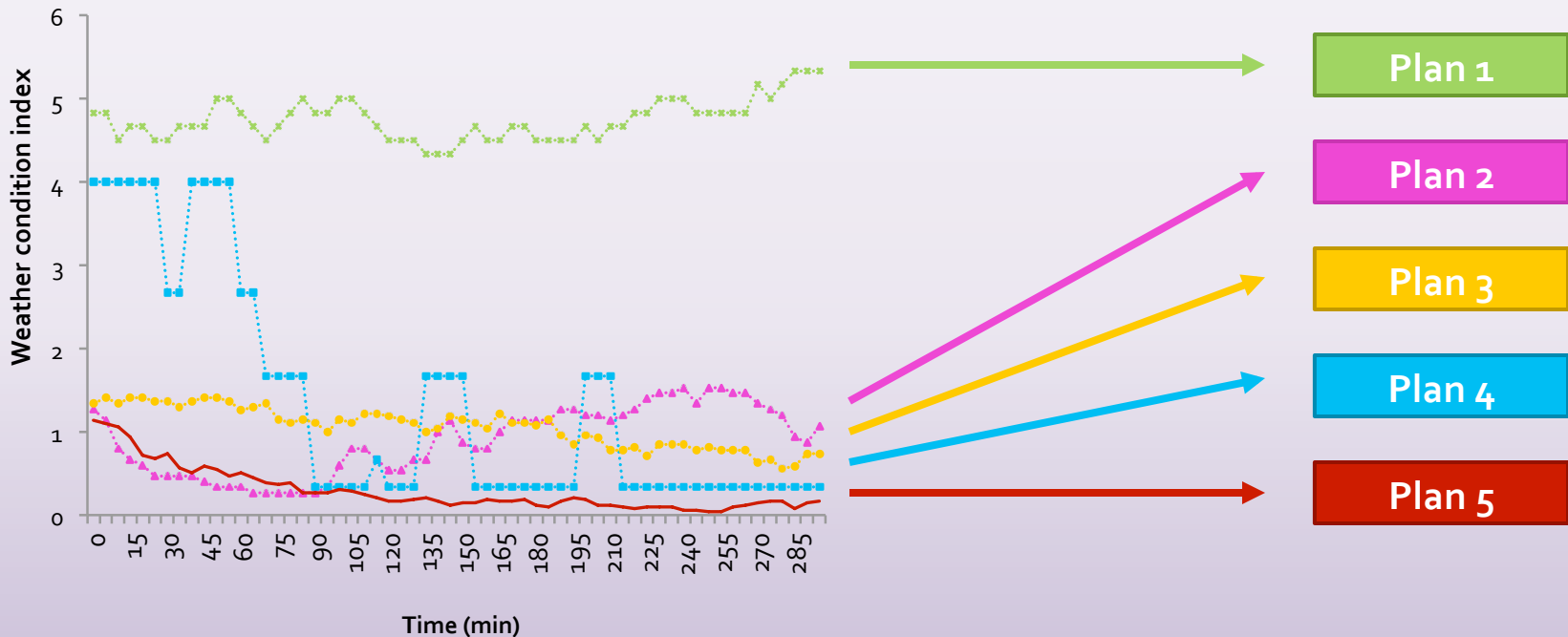
Clustering Network Mean Travel Times (Output-based clustering)



Data Mining on Historical Patterns

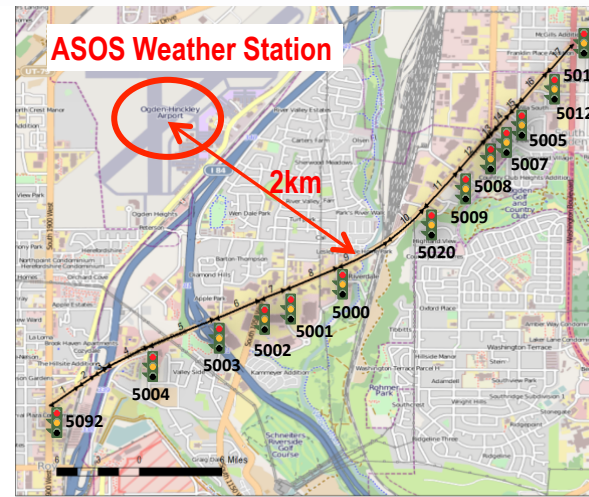
Cluster historical weather patterns to identify and define distinct weather categories

Identify the best plans for a given weather category based on prior deployment experiences and performance history



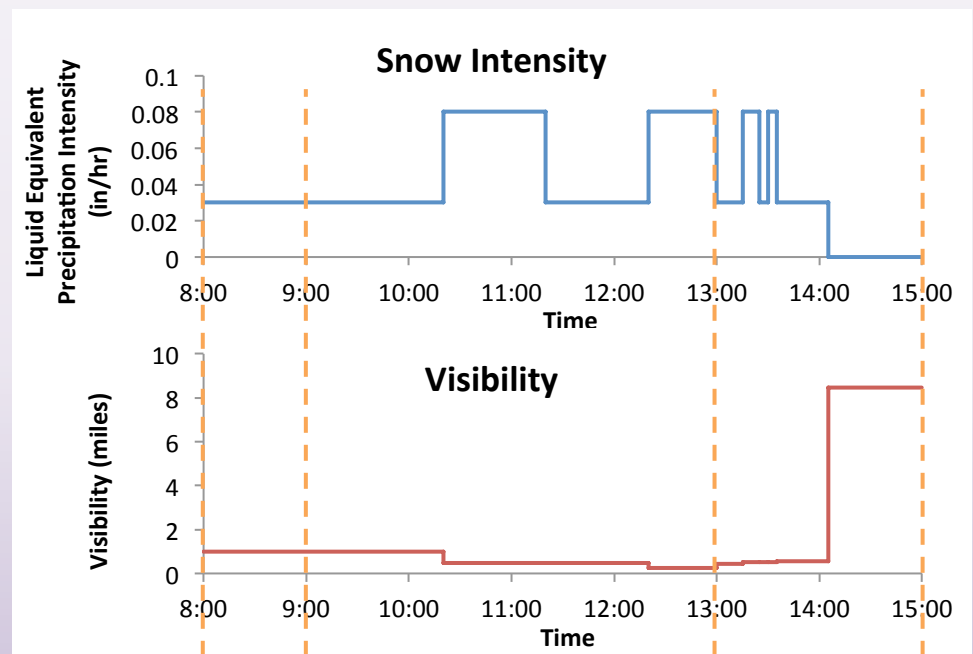
Case Study

- To demonstrate potential benefits of the proposed system during snow events



**Riverdale Rd,
UT, USA**
: 13 signalized
intersections

- Snow scenario:
 - Historical weather data from 8:00 to 15:00 on January 8, 2014
 - Automated Surface Observing System (ASOS) station at Ogden-Hinckley Airport
- Normal Time-of-Day (TOD) Signal Timing Plan (Base plan)
 - Plan 1 → Plan 4 → Plan 13



Base TOD plan

Plan 1

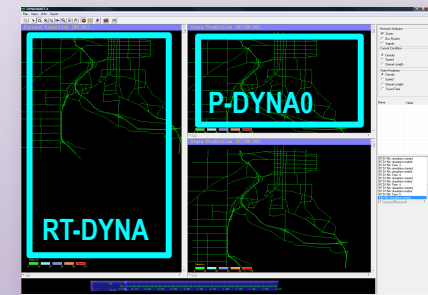
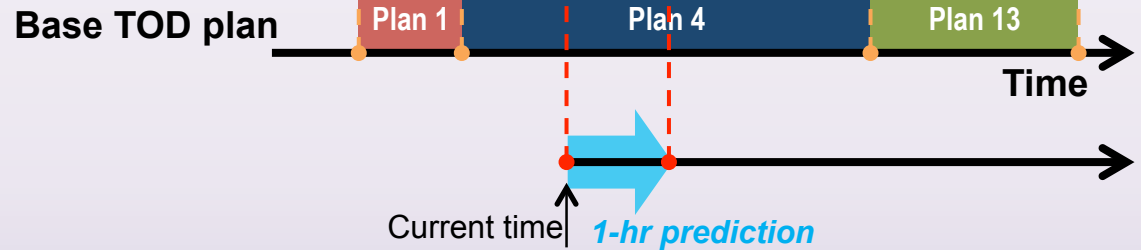
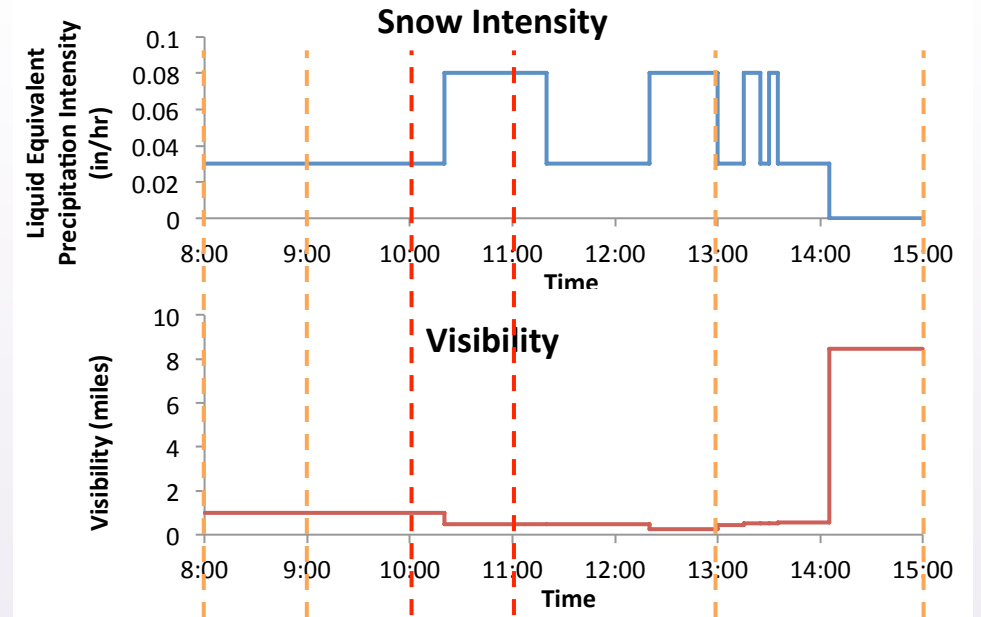
Plan 4

Plan 13

Time →

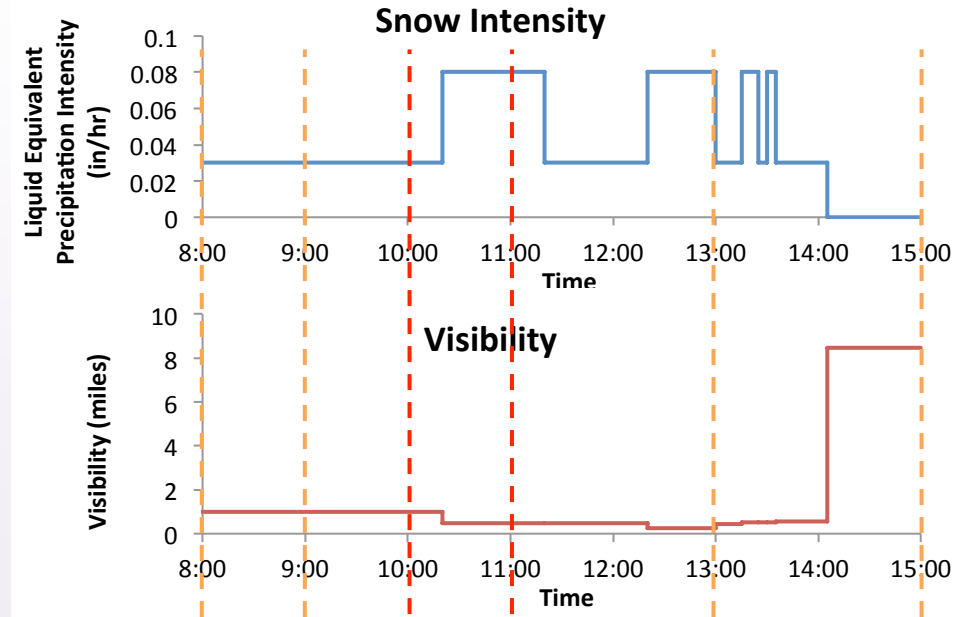
Case Study

- At 10:00, obtain the predicted corridor speeds for the next 1 hour from TrEPS.

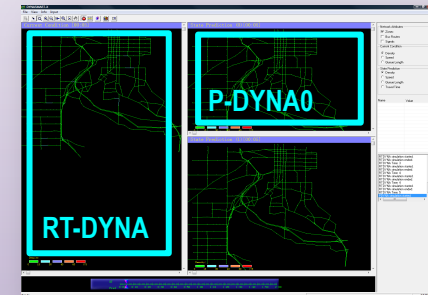
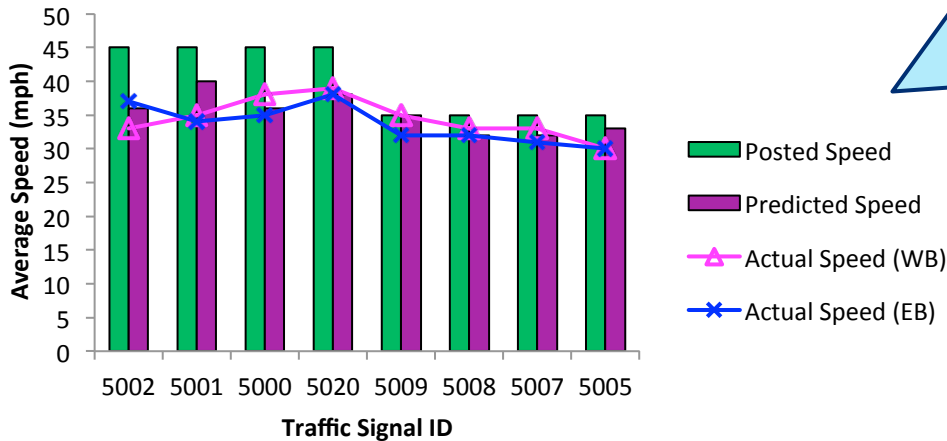
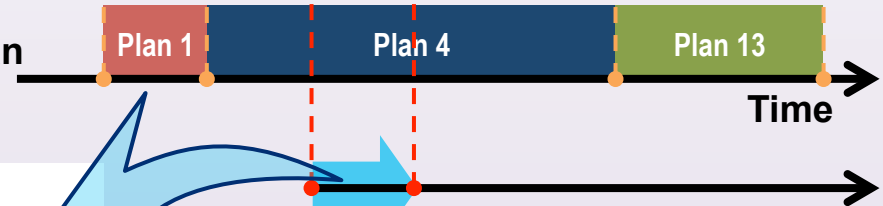


Case Study

- At 10:00, obtain the predicted corridor speeds for the next 1 hour from TrEPS.
- The overall speed drop due to snow is 5 mph.

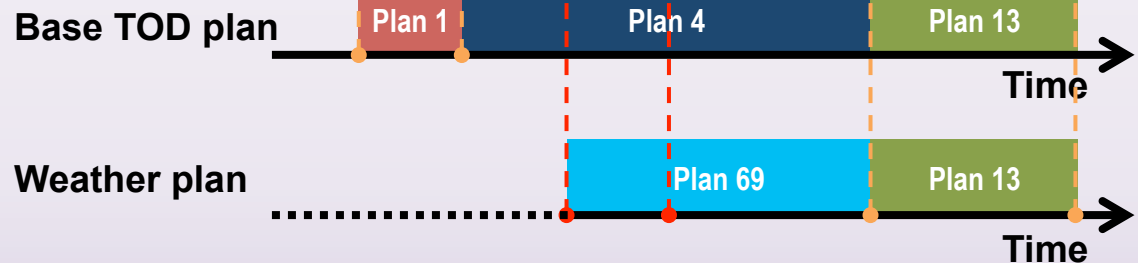
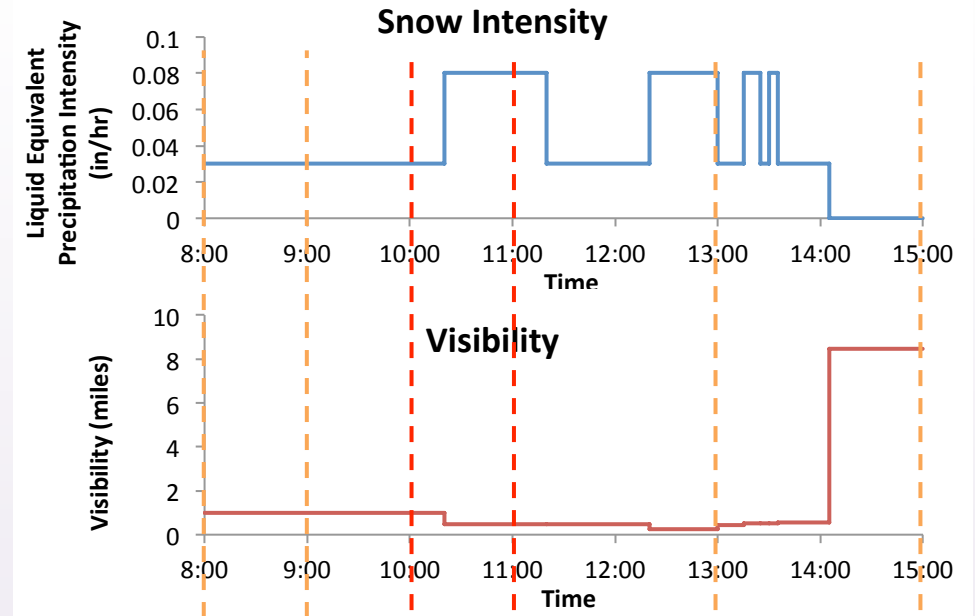


Base TOD plan



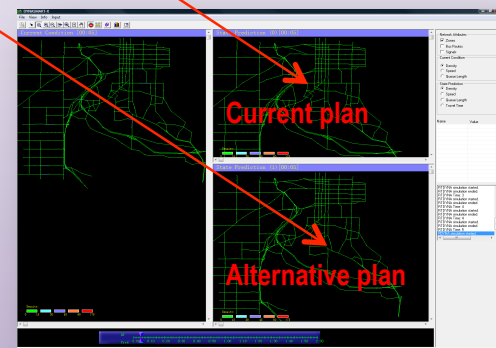
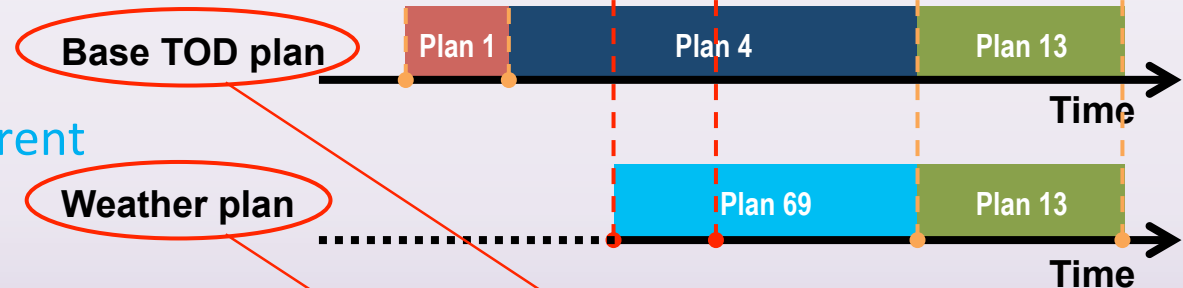
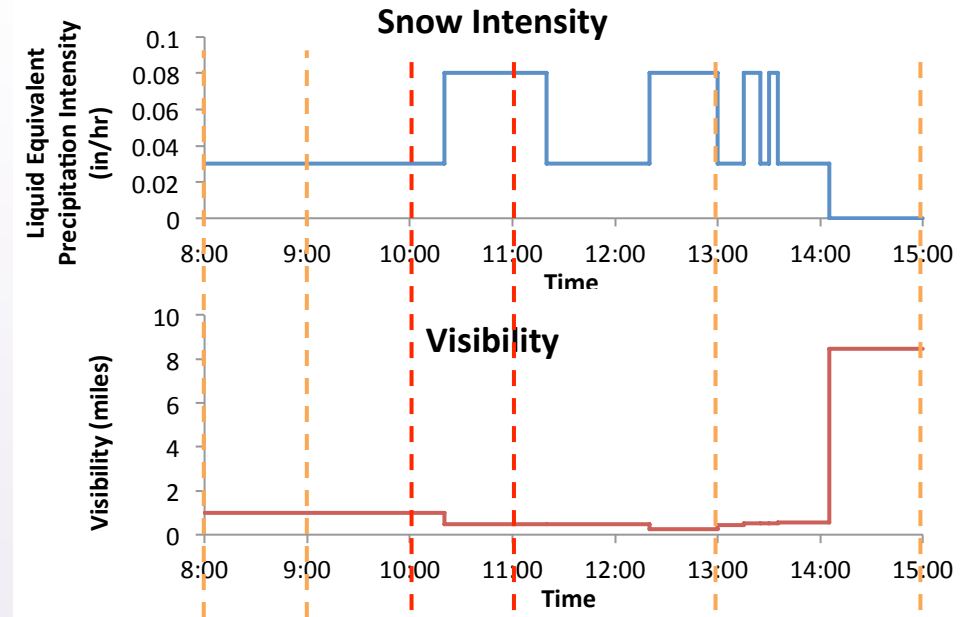
Case Study

- At 10:00, obtain the predicted corridor speeds for the next 1 hour from TrEPS.
- The overall speed drop due to snow is 5 mph.
- The best-matching weather plan is Plan 69.

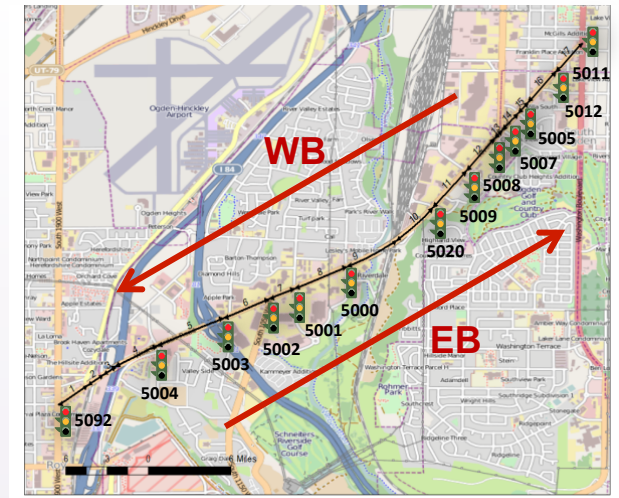


Case Study

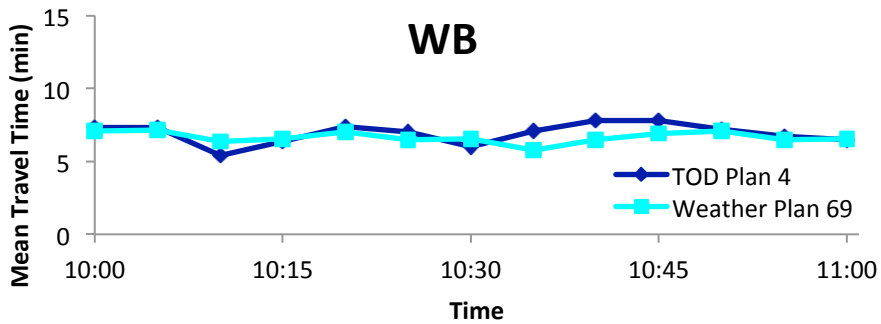
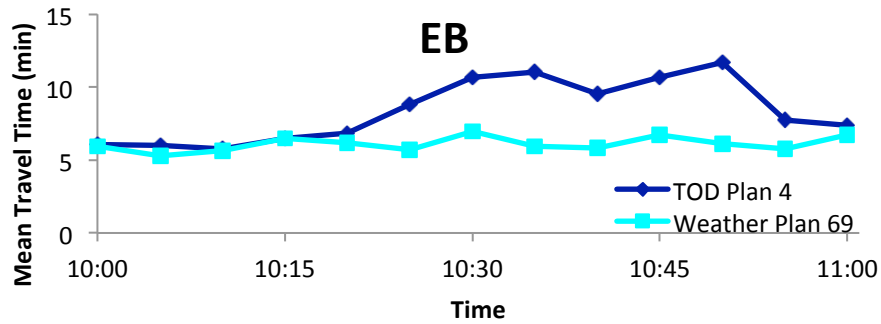
- At 10:00, obtain the predicted corridor speeds for the next 1 hour from TrEPS.
- The overall speed drop due to snow is 5 mph.
- The best-matching weather plan is Plan 69.
- Compare performance measures under the current and alternative plans.



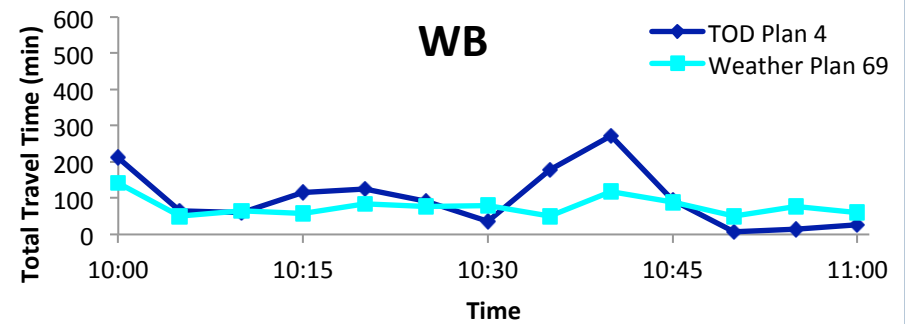
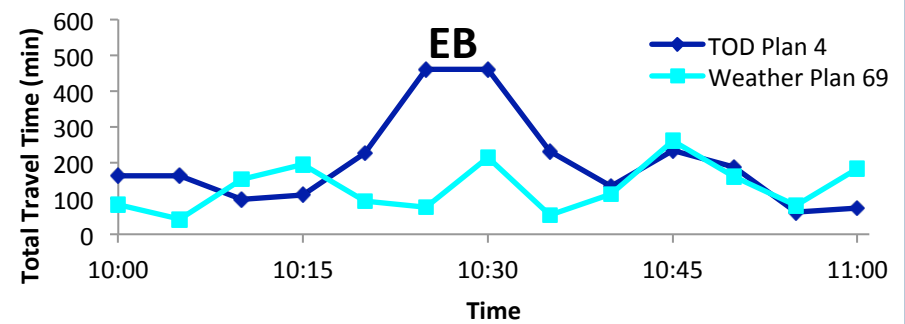
Performance Measures



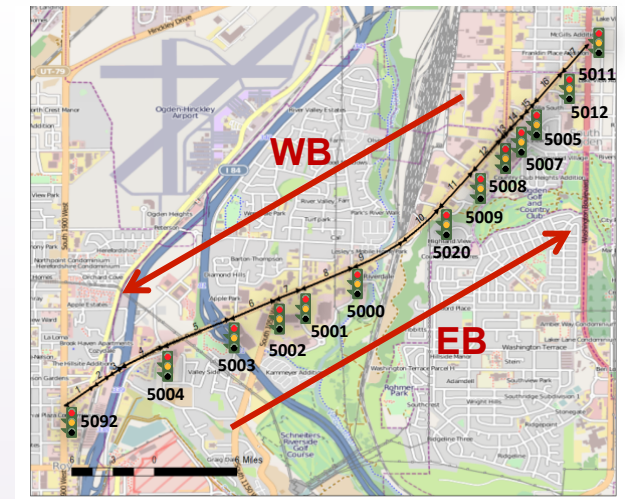
Mean Travel Time



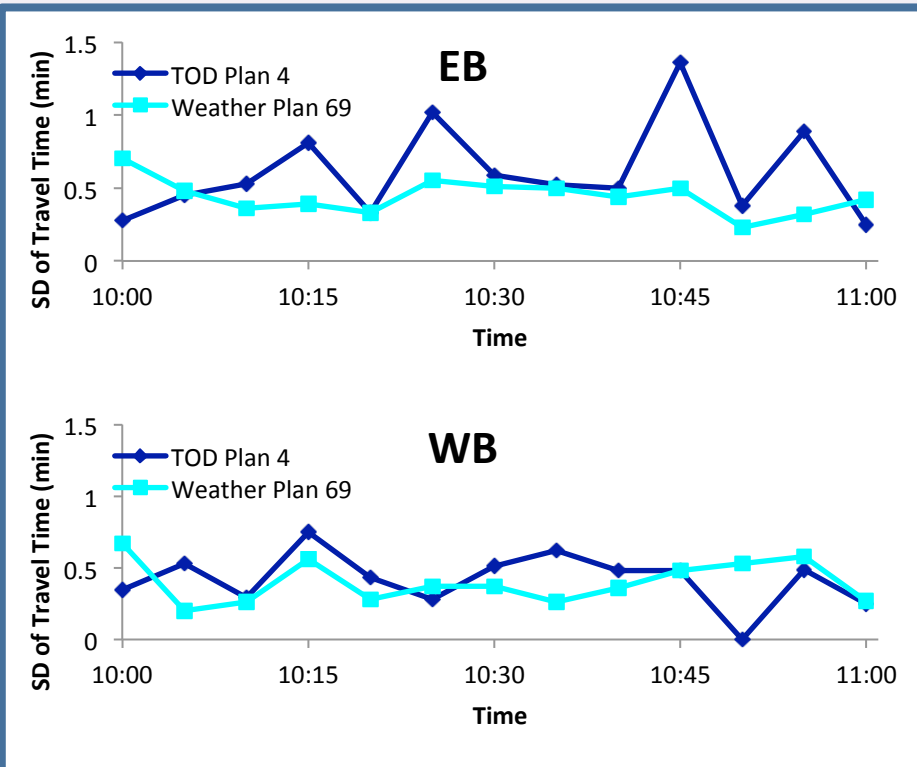
Total Travel Time



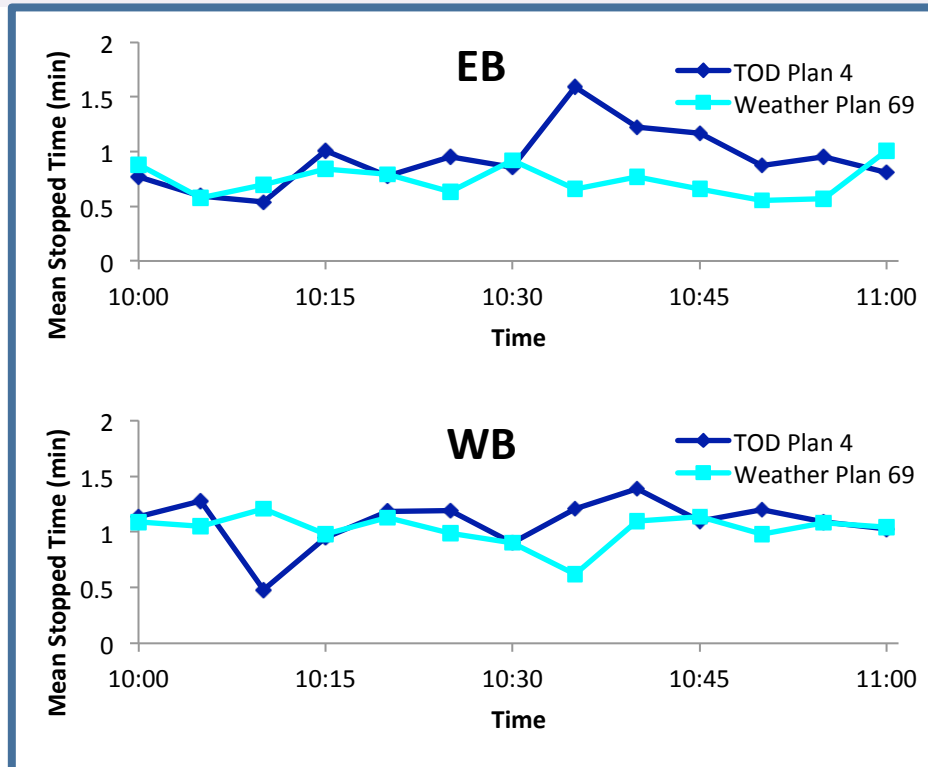
Performance Measures




Standard Deviation of Travel Times



Mean Stopped Time



Approach to TrEPS-WRTM Integration

	PRE-EVENT	EVENT	POST-EVENT
SCENARIO MANAGER	<ul style="list-style-type: none"> Construct a weather scenario based on weather forecast, historical data or past event scenarios. Given the weather scenario, prepare a set of possible scenario combinations by mix-and-matching demand patterns and different signal timing plans (<i>one could also test effects of other factors such as incidents or snow-plowing</i>). 	<ul style="list-style-type: none"> Retrieve the most relevant signal timing plans to the prevailing and anticipated weather and traffic conditions; and prepare scenario input files for DYNASMART-X. 	<ul style="list-style-type: none"> Maintain and update a scenario library, where signal timing scenarios (either actually deployed or only tested within TrEPS) are stored in connection with their performances under the realized/observed weather and demand conditions.
INFORMATION	 Input Scenarios	 Input Scenarios	 Output Performance
TrEPS	<ul style="list-style-type: none"> Run DYNASMART-P to predict performances of various signal timing plans under anticipated weather. Develop “if-then” plans for weather-responsive signal timing to improve preparedness and facilitate during-event traffic signal operations. 	<ul style="list-style-type: none"> Run DYNASMART-X to monitor estimated and predicted traffic states under different signal timing plans; and determine when, where and which strategy to deploy at any point in time. 	<ul style="list-style-type: none"> Using the observed weather and demand scenarios, run DYNASMART-P to conduct a post-analysis for identifying other strategies that might have performed better.

Conclusions I

- Key benefits of the TrEPS-based decision support system include:
 - (a) the ability to detect speed drops in progression speed in advance through real-time TrEPS simulation;
 - (b) the ability to quickly identify the best-matching signal timing plan in response to anticipated traffic conditions; and
 - (c) the ability to test and evaluate the performance of alternative timing plans in real-time before making the deployment decision.

Conclusions II

- PREDICTION essential in real-time traffic management
- Considerable opportunities: new sources of personal information, emerging technologies
- Growing role for DTA models in evaluating (off-line) and improving (on-line) reliability of networks, as DECISION SUPPORT SYSTEMS and Real-time Predictive Traffic Management Systems
- Critical role for scenario manager capability in agency adoption
- KEY CHALLENGE: THE HUMAN FACTOR – User behavior – will remain moving target, because users will adapt hence need for a daptive schemes



Thank you

Q/A