A real-time simulation-based decision support system for traffic management: the San Diego I-15 ICM model

IPAM Workshop IV: Decision Support for Traffic
Matthew Juckes
November
Presentation Overview

• Program Background
• System Overview
• Network Prediction System (NPS)
• Response Plans & Corridor Scoring
• Maintenance & Real Time Targets
• Related Projects
7-Year Federally-sponsored program supporting development of improved mobility, safety, and other transportation objectives for people and goods through integrated management of transportation networks and cross-network connections in major transportation corridors in metropolitan areas.
FHWA ICM Program

- **Phase 1:** Conducted research into the current state of corridor management
- **Phase 2:** Develops analytic tools and methods that enable the implementation and evaluation of ICM strategies.
- **Phase 3:** Corridor Site Development, Analysis and Demonstration - San Diego and Dallas
- **Phase 4:** ICM Outreach and Knowledge and Technology Transfer
Project Partners/Stakeholders

- SANDAG
- Kimley-Horn and Associates, Inc.
- National ICM Evaluator
- The City of San Diego
- National AMS Contractor
- MTS
- Caltrans
- Delcan
- TSS Transport Simulation Systems
- NCTD
- Department of Transportation
- United States of America
- PATH
- Escondido City of Choice
- National ICM Evaluator
  Battelle
  The Business of Innovation
- National AMS Contractor
  Cambridge Systematics
Five primary ICM goals:

1. The corridor’s multi-modal and smart-growth approach shall improve accessibility to travel options and attain an enhanced level of mobility for corridor travelers.

2. The corridor’s safety record shall be enhanced through an integrated multimodal approach.

3. The corridor’s travelers shall have the informational tools to make smart travel choices within the corridor.

4. The corridor’s institutional partners shall employ an integrated approach through a corridor-wide perspective to resolve problems.

5. The corridor’s networks shall be managed holistically under both normal operating and incident/event conditions in a collaborative and coordinated way.
ICMS Innovation

Paradigm shift to more pro-active traffic management method, making use of prediction tools, on-line micro simulation and improved decision support
21 mile North-South Stretch of I-15 between SR-78 and SR-163

I-15 is a 6-10 lane freeway with a 4 lane managed HOV/SOV toll road in the center

Multiple parallel arterials including: Black Mountain Road, Pomerado Rd and Center City Parkway

Encompasses three cities: Escondido, Poway, San Diego

A microsimulation network coded in Aimsun software

60 minute prediction engine coded in Aimsun Online
Model Description

- I-15 ICM Model generated from the SANDAG Regional Macro Model
Data Inputs and Outputs

- **ICMS**
- **REMS**
- **CPS**
- **RTMS**
- **ATMS**
- **ATTS**
- **RAMS**
- **Data Hub DSS**
- **Ramps**
- **Freeway**
- **Signals**
- **Travel Time**
- **Weather**
- **Tolling**
- **Events**
- **Transit**
System Evolution

Response Plan Evaluation

1. Inventory + Prediction
2. Business Rules Engine
3. Event Response Suite
4. Multi Layer Analysis
5. Corridor MOE
6. Recommended Response Plan

{0.00, -13.28, 11.14, 1.19, 7.81, 2.2}
Aimsun Online Architecture

Historical data
- Traffic patterns
- Travel demand

Live data feeds
- Sensor data
- Equipment status
- Traffic events

Aimsun Online
- Demand matching and adjustment
- Sensor server and status updater
- Analytics and multi-level simulation
- Incident detection
- Response plan generation
- Response plan evaluation

Outputs
- Network-wide traffic prediction
- Traffic management plans

Quality manager
Network Prediction System

- Historical Data Sets
- Real Time Detector data

  - Speed, Flow and Occupancy Analytical Predictions (every 5 minutes)
  - Microsimulation Predictions (every 5 minutes)
  - Microsimulation Evaluations (on request)

- Demand Matrix Adjustments (every 15 minutes)

  - Quality Manager
  - DataHub
The Network Prediction System (NPS), summarizing, consists in an analytical model for each detector such that:

$$Y_{D}^{k,t} = f(X^t),$$

where

- $Y_{D}^{k,t}$ represents the $k$ predicted variable for detector $D$ at time $t$.
- $f$, represents the analytical model.
- $X^t$, represents the real detector measures available at time $t$. 
“Given a time point $t$ and a detector $D$, a prediction of the flow (or other provided measure) of that detector at time $t+h$ is wanted, using all the information available at the moment $t$”. Mathematically expressed:

$$Y = f(X)$$

where

- $Y$ is the objective variable (flow, occupancy or speed at time $t+h$),
- $X$ is the matrix containing all the necessary input information at time $t$,
- $f$ is the model representing the relationship between $X$ and $Y$.

The matrix $X$ is built with the explicative variables of the model, that is those variables considered as necessary to explain the behavior of $Y$, including:

- Previous values of the selected detector $D$ at time points $t$, $t-1$, $t-2$ ...
- Previous values of the upstream and downstream of $D$ at time points $t$, $t-1$, $t-2$ ...
- Or even other quantities such as occupancies or speeds. The rows of $X$ determine the observed day.

The model $f$ has to be trained with historical data and has to be estimated by means of statistical techniques. The set of upstream and downstream have also to be specified.
NPS – Problem Description
NPS – Technical Issues

- Linearity
- Multicollinearity
- Variable selection/Dimensionality Reduction
- Missing Data
**NPS - Methodology**

- **LASSO** (least absolute shrinkage and selection operator) is an alternative regularized version of least squares which uses the constraint that \( \| \cdot \|_1 \), the \( L_1 \)-norm of the parameter vector, is no greater than a given value.

- Regularization methods are used for model selection, in particular to prevent overfitting by penalizing models with extreme parameter values. One of the most common variants in machine learning is \( L_1 \)-norm (being the other the squared \( L_2 \)-norm) regularization, which can be added to learning algorithms that minimize a loss function \( E(X, Y) \) by instead minimizing

\[
E(X, Y) + \alpha \|w\|,
\]

where
- \( w \) is the model's parameter vector,
- \( \| \cdot \| \) is the \( L_1 \)-norm,
- \( \alpha \) is a free hyperparameter that needs to be tuned empirically (in ours case using the described k-fold cross-validation).
$L_1$-norm regularization is often preferred because it produces sparse models and thus performs feature selection within the learning algorithm (increasing the penalty cause more and more of the parameters to be driven to zero and this deselects the features from the regression, thus Lasso automatically selects more relevant features and discards the others).

But since the $L_1$-norm is not differentiable, it may require changes to learning algorithms, in particular gradient-based learners. For that reason the optimization problem may be solved using quadratic programming or more general convex optimization methods, as well as by specific algorithms such as the least angle regression algorithm.
When training a model, the deviations of the predictions from the data set used for training (such as the $R^2$ coefficient in linear regression) can be calculated. However, these errors are not representative of the error within the model when another set of new data is used. Thus, another way to measure the error is needed.

In order to select the model with higher accuracy, a **k-fold cross-validation** scheme is used. This is the most standard way to ensure that the errors estimated in the training stage will be consistent with future predictions. In the k-fold cross-validation, the set of historical days is split into k groups. For each group the procedure is:

1. Remove the group of days (called the test sample) from the historical data. The remaining set is called the training sample.
2. Train the model with the training sample.
3. Evaluate predictions with the test sample
4. Then the mean of the errors achieved by these k test samples is calculated.

In our problem, $k = 10$. 
Two performance evaluation measurements have been used.

- Mean absolute percentage error (MAPE) is defined:

\[
MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{\bar{y}_t} \right|
\]

where

- \( y_t \) is the actual value,
- \( \hat{y}_t \) is the forecast value.

- Quality measurement criteria:
  - If flow > 750 veh/h: check if relative error (MAPE) is below 15% to satisfy the quality criteria
  - Else: check if absolute difference between actual and forecast is below 150 veh/h.
NPS – Tests with Training Data

( aggregated results )

<table>
<thead>
<tr>
<th>Forecast horizon [min]</th>
<th>Minimum error [%]</th>
<th>Maximum error [%]</th>
<th>Mean error [%]</th>
<th>Standard deviation [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>2.43</td>
<td>23.75</td>
<td>7.87</td>
<td>4.49</td>
</tr>
<tr>
<td>30</td>
<td>2.8</td>
<td>24.7</td>
<td>8.43</td>
<td>4.49</td>
</tr>
<tr>
<td>45</td>
<td>3.06</td>
<td>24.67</td>
<td>8.72</td>
<td>4.51</td>
</tr>
<tr>
<td>60</td>
<td>3.23</td>
<td>25.78</td>
<td>8.99</td>
<td>4.56</td>
</tr>
<tr>
<td>75</td>
<td>3.37</td>
<td>26.47</td>
<td>9.24</td>
<td>4.61</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Forecast horizon [min]</th>
<th>Minimum Quality ratio [0, 1]</th>
<th>Maximum Quality ratio [0, 1]</th>
<th>Mean Quality ratio [0, 1]</th>
<th>Standard deviation [0, 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>0.93</td>
<td>1</td>
<td>1</td>
<td>0.01</td>
</tr>
<tr>
<td>30</td>
<td>0.89</td>
<td>1</td>
<td>1</td>
<td>0.01</td>
</tr>
<tr>
<td>45</td>
<td>0.85</td>
<td>1</td>
<td>0.99</td>
<td>0.01</td>
</tr>
<tr>
<td>60</td>
<td>0.83</td>
<td>1</td>
<td>0.99</td>
<td>0.01</td>
</tr>
<tr>
<td>75</td>
<td>0.81</td>
<td>1</td>
<td>0.99</td>
<td>0.02</td>
</tr>
</tbody>
</table>
NPS – Tests with Real Data

ID: 1100575 [Horizon: 15 – MAPE(%): 7.24 – R²: 0.96 – MeanDataReliability: 0.55]
NPS – Tests with Real Data

ID: 1108415 [Horizon: 15 – MAPE(%): 2.75 – R2: 0.98 – MeanDataReliability: 0.46]
Pattern and historical data for 24/7 model
24/7 Model

- 11 Day Patterns
  - Weekdays
  - Holidays
  - Rainy Days
  - Special events

- 15 – Minute data sets
- Runs every 5 minutes

Aimsun Online Dashboard
Corridor Performance Needs

- **Measures**
  - Intersection
  - Ramp Meter
  - Express Lanes
  - Sections
  - Transit
  - Routes

- **Targets (within 15%)**
  - 0-15 minutes 92%
  - 15-30 minutes 80%
  - 30-60 minutes 40%
Response Plan Generation
Response Plan Scoring

Recommended Plan A: 7.26

Do Nothing: 0.00

Plan B: 1.06

Approval Needed
What ICM Will Do
System Configuration
1. Bounding Box – size defined by response posture to identify minimum selection set

2. LOS Comparison – to identify additional links where response plan implementation has changed operations within the network
## Corridor Score

### LOS Comparison

<table>
<thead>
<tr>
<th>Link</th>
<th>Do Nothing</th>
<th>Response Plan A</th>
<th>Response Plan B</th>
<th>Response Plan C</th>
<th>Included in Evaluation?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>C</td>
<td>D</td>
<td>E</td>
<td>C</td>
<td>Yes</td>
</tr>
<tr>
<td>2</td>
<td>B</td>
<td>A</td>
<td>B</td>
<td>B</td>
<td>No*</td>
</tr>
<tr>
<td>3</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>D</td>
<td>Yes</td>
</tr>
<tr>
<td>4</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>No</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>No</td>
</tr>
<tr>
<td>6</td>
<td>D</td>
<td>E</td>
<td>D</td>
<td>C</td>
<td>Yes</td>
</tr>
<tr>
<td>7</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>B</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* This link is not included with LOS A and LOS B exclusion options turned on.
Corridor Score

Determined by comparing each Response Plan against ‘Do Nothing’

\[ \text{Corridor Score} = \frac{D_0 - D_z}{D_0} \times 100 \]

- \( D_0 \) = Person-delay under Do Nothing Case
- \( z \) corresponds to the response plan evaluation
  - \( D_1 \) = Person-delay under Response Plan A
  - \( D_2 \) = Person-delay under Response Plan B
  - \( D_3 \) = Person-delay under Response Plan C
Corridor Score

Person Delay per link = \((SV_{SOV} + HV_{HOV} + TV_{Truck} + BV_{Bus}) \times D_{Avg}\)

- \(D_{Avg}\) = Average Link Delay
- Configurable Static Occupancy Factors:
  » S – Single Occupancy Vehicle
  » H – High Occupancy Vehicle
  » T – Truck
  » B – Bus
- \(V_{SOV}\) = Link Volume of SOVs
- \(V_{HOV}\) = Link Volume of HOVs
- \(V_{Truck}\) = Link Volume of Trucks
- \(V_{Bus}\) = Link Volume of Buses
Corridor Score

- Person delay is totaled for all of the Evaluation Area links, for each Response Plan and the Do Nothing case. Resulting in four corridor delay values for each 15 minute time period.

\[ D_{15} = 0-15 \text{ minute} \]
\[ D_{30} = 15-30 \text{ minute} \]
\[ D_{45} = 30-45 \text{ minute} \]
\[ D_{60} = 45-60 \text{ minute} \]
The Corridor Person Delay value utilized for comparison of response plans is determined by factoring each of the 15 minute evaluation period by configurable weighting factors:

$$D_y = (W_{15} \times D_{15}) + (W_{30} \times D_{30}) + (W_{45} \times D_{45}) + (W_{60} \times D_{60})$$

- $W_{15}$ = 0-15 minute weighting factor
- $W_{30}$ = 15-30 minute weighting factor
- $W_{45}$ = 30-45 minute weighting factor
- $W_{60}$ = 45-60 minute weighting factor
- $W_{15} + W_{30} + W_{45} + W_{60} = 1$

- $y$ corresponds to the Response Plan Evaluation
  - 0 = Do Nothing
  - 1 = Response Plan A
  - 2 = Response Plan B
  - Etc.
New Methodology Being Explored

• Travel Time Index & Travel Time Reliability
  – Percentage of trips below Travel Time threshold
  – Freeway Threshold example - 1.33 * Free Flow Travel Time;
  – Arterial Threshold example 2.50 * Free Flow Travel Time;
Offline Model Calibration

USDOT Traffic Analysis Toolbox Guidelines

1. Establish Calibration MOEs and Targets
2. Calibrate Capacity
3. Calibrate Traffic Volumes and Route Choice
4. Calibrate System Performance
5. Are All Calibration Targets met?
   - Yes: Model is Calibrated
   - No: Process for Each Calibration Step
     a. Field MOEs
     b. Model MOEs
     c. Acceptable Match?
       - No: Adjust Model Parameters
       - Yes: Advance to next Calibration Step

TSS TRANSPORT SIMULATION SYSTEMS
Reasons for Model Updates

• Change in travel patterns and demands;
• New Infrastructure;
• New ITS systems;
• New Public Transit;
• New Developments;
Real Time Validation Data

• Speed
• Count (with 15%; R^2; Slope)
  – 15 minute periods
  – Targets:
    • 80% counts within 15%
    • R^2 & slope between 0.92 & 1.08
Speed Contours

Real Data               VS               Predicted Data
Related Projects

• SANDAG DTA-ABM Integration
• USDOT ATDM-DMA Testbed
• Post Deployment AMS Evaluation
• MIT Optimization Project
• Future ICM Corridors (13 USDOT Grants)
Why DTA-ABM Integration

• ABM Temporal Integration
  – Choice models
• Congestion Duration
• Dynamic Tolling
• Travel Time Reliability
• Refined Speeds for Air Quality Analysis
• Launching Point for New ICM Corridors
What DTA Brings to RTP

- Operational Analysis
  - ITS/System management applications
  - Signal timing
  - Transit improvements/projects
  - Connected Vehicles
USDOT AMS ATDM-DMA

• ATDM Strategies
  – Network Prediction Sensitivity
  – Dynamic routing
  – Dynamic Pricing
  – Dynamic Lane Use Control
  – Dynamic Managed Use Lanes
• DMA Strategies
  – INFLO
    • Queue Warning (Q-Warn)
    • Dynamic Speed Harmonization (SPD-HARM)
    • Cooperative Adaptive Cruise Control (CACC)
  – MMITSS
    • Intelligent Traffic Signal System (ISIG)
    • Transit Signal Priority (TSP)
Questions

Matthew Juckes
Transportation Simulation Systems, Inc., Senior Project Manager
20 West 22nd Street, Suite 612
New York, NY 10010
+1-917-515-3830, matthew.juckes@aimsun.com

Alex Torday
Transportation Simulation Systems, Pty Ltd, Managing Director
+61 (0)2-9299-8598, alex.torday@aimsun.com

Alex Estrella
Senior Transportation Planner – Department of Operations SANDAG
alex.estrella@sandag.org