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On Simulation and Optimization of Freeway Network Operations

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Progress from last PSG meeting

- Optimization of freeway traffic flow via ramp metering
- Microscopic simulation with VSL and RM based on traffic date & ALINEA – HERO algorithms
- Further data analysis: traffic prediction by CNN-LSTM

1. Optimization of freeway traffic flow via ramp metering

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Road map:

Model Predictive Control (MPC)

Model with capacity drop for ramp metering:

$$
(DP)\min_{\mathbf{T}} Z = \sum_{t=1}^{N_p-1} \sum_{i=1}^{I} (\rho_{i,t} \Delta L_i \Delta T + q_{i,t} \Delta T) + \lambda_r \sum_{t=2}^{N_p-1} \sum_{i=1}^{I} (r_{i,t} - r_{i,t-1})^2
$$

s.t $\rho_{i,t+1} = \rho_{i,t} + \frac{\Delta T}{\Delta L_i} (f_{i-1,t} - f_{i,t} + r_{i,t} - s_{i,t})$.

$$
f_{i,t} = \min\{f_{i,t}^D, f_{i+1,t}^S - \theta r_{i+1,t}\}
$$

$$
f_{i,t}^D = \min\left\{v_{f,i}\rho_{i,t}, \left[Q_i + \alpha Q_i(\frac{\rho_{i,t} - \rho_{c,i}}{\rho_{c,r,i} - \rho_{max,i}})\right]\right\}
$$

Total Time Spent (TTS)
$$
f_{i+1,t}^S = \min\{Q_{i+1}, w_{i+1}(\rho_{max,i+1} - \rho_{i+1,t})\}
$$

$$
q_{i,t+1} = q_{i,t} + \Delta T(d_{i,t} - r_{i,t})
$$

$$
0 \le q_{i,t} \le q_{max,i}.
$$

$$
0 \le r_{i,t} \le r_{max,i}
$$
 the time-variations of the on-ramp flows

Fundamental diagram with capacity drop

Comparison of measured data (with no RM) with computed results With RM:

Computed On-ramp Queue Lengths

Comparison of demand and RM for each of the on-ramps

Results of Total time Spent:

Model with capacity drop for ramp metering and variable speed limit:

the time and space variations of VSL rates $b_{i,t}$

$$
\begin{aligned}\n\mathbf{S.t} \qquad & \rho_{i,t+1} = \rho_{i,t} + \frac{\Delta T}{\Delta L_i} (f_{i-1,t} - f_{i,t} + r_{i,t} - s_{i,t}) & \qquad v_{f,i}[b_{i,t}] = v_{f,i}b_{i,t} \\
& f_{i,t} = \min \{f_{i,t}^D, f_{i+1,t}^S - \theta r_{i+1,t}\} & \\
& f_{i,t}^D = \min \left\{ v_{f,i} \rho_{i,t}, \left[Q_i + \alpha Q_i \left(\frac{\rho_{i,t} - \rho_{cr,i}}{\rho_{cr,i} - \rho_{max,i}} \right) \right] \right\} & \qquad \rho_{cr,i}[b_{i,t}] = \frac{\rho_{\max,i} \rho_{cr,i}}{b_{i,t} \rho_{\max,i} + (1 - b_{i,t}) \rho_{cr,i}} \\
& f_{i+1,t}^S = \min \{ Q_{i+1}, w_{i+1} (\rho_{max,i+1} - \rho_{i+1,t}) \} \\
& q_{i,t+1} = q_{i,t} + \Delta T(d_{i,t} - r_{i,t}) & \qquad 0 \leq q_{i,t} \leq q_{max,i} \\
& 0 \leq r_{i,t} \leq r_{max,i}\n\end{aligned}
$$

model 1

 $\rho_{_{\scriptscriptstyle\ell}}$

2. Microscopic simulation with VSL and RM based on traffic date & ALINEA – HERO algorithm

The road Network System

RM & VSL control

Table 1.

The Farrington on-ramp

The South on-ramp

The Leach SB on-ramp

The Leach NB on-ramp

The Cranford Av. on-ramp

A non-linear constrained optimization problem

$$
\min \sum_{k=1}^{K} \sum_{j=1}^{D} \left(\hat{s}_j(k) - s_j(k) \right)^2 \quad \text{with} \quad \hat{s}_j(k) = \sum_{i=1}^{O} r_i(k) p_{ij}; \tag{1}
$$

subject to, for some i in all possible OD pairs,

$$
\left(r_i(k) = \max\{r_i^{LC}(k), \ r_i^m(k, m, \lambda)\}\left(1 - \text{rand}(0, 1)\frac{R}{C}\delta_{RM,k}\right) \le \lambda_i[k] + \frac{1}{\Delta t}m_i[k];\tag{2}
$$

$$
m_i(k) = m_i(k-1) + \Delta t(\lambda_i(k-1) - r_i(k-1)) \leq m_{max,i};
$$
\n(3)

$$
\sum_{j=1}^{D} p_{ij} = 1, \tag{4}
$$

where $r_i^m(k, m, \lambda)$ and $r_i^{LC}(k)$ are given by

$$
r_i^m(k, m, \lambda) = \frac{1}{T_c} \left(m_i(k) - m_{max,i} \right) + \lambda_i(k - 1); \tag{5}
$$

$$
r_i^{LC}(k) = r_i^{LC}(k-1) - K_p(\rho^d(k) - \rho^d(k-1)) + K_R(\rho_{cr} - \rho(k)).
$$
 (6)

On-ramp Demand, $\lambda_i[k]$

 O_o

 \mathbf{O}

 $O₂$

Off-ramp outgoing flow, $s_j(k)$

The proportion of trip from the ith original (origin) flowing to the jth destination (sink)

• Table 2.

Figure 20 29

3. Further data analysis: traffic prediction

by Convolutional Neural Network & Long-short Term Memory

Sequence modelling

• one-to-one:

one input, one output

- one-to many: one input, variable outputs
- many-to one: variable inputs, one output
- many-to-many:

Kwinana Freeway Network

Figure 22 $\frac{33}{3}$

Parameter Setting

- Split time = 5728
- Window size = 60 # Number of slices to create from the time series
- Batch size = 256
- Shuffle buffer size = 1000
- Forecast period = 30 # For splitting data in many-to-many sequence model

huber function

tf.keras.losses.huber(y_true, y_pred, delta=1.0)

Computes Huber loss value.

For each value x in error = y _true - y _pred:

 $loss = 0.5 * x^2$ if $|x| \le d$ loss = $0.5 * d^2 + d * (|x| - d)$ if $|x| > d$

where d is delta. See: https://en.wikipedia.org/wiki/Huber_loss

Arguments

- y_true: tensor of true targets.
- y_pred: tensor of predicted targets.
- delta: A float, the point where the Huber loss function changes from a quadratic to linear.

Returns

Tensor with one scalar loss entry per sample.

Training Loss function

Figure 25 38

Training Loss function

NPI-11 Speed

Figure 27 $\frac{40}{40}$

NPI-11 Flow rate

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THANK YOU

For Your Attention