On Simulation and Optimization of Freeway Network Operations

B. Wiwatanapataphee, Yong Hong Wu, C Gu
Curtin University of Technology

Progress from last PSG meeting

1 Optimization of Traffic Flow under non-recurrent events using reinforcement learning-based VSL and RM

2. Control of ramp metering Using Deep Koopman model

1. Optimization of Traffic Flow under non-recurrent events using reinforcement learning-based VSL and RM controls

B. Wiwatanapataphee, Yong Hong Wu

Outline

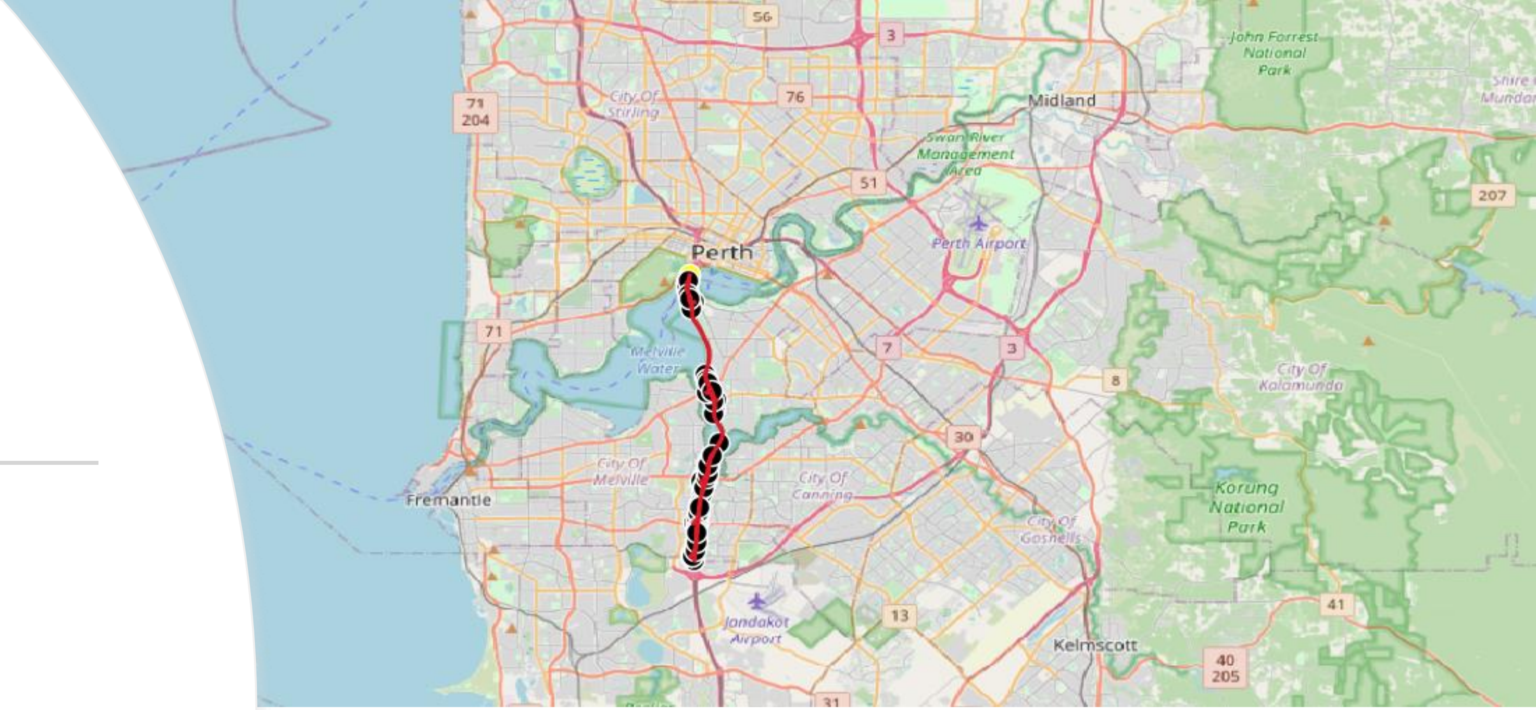
(1) Road Network model

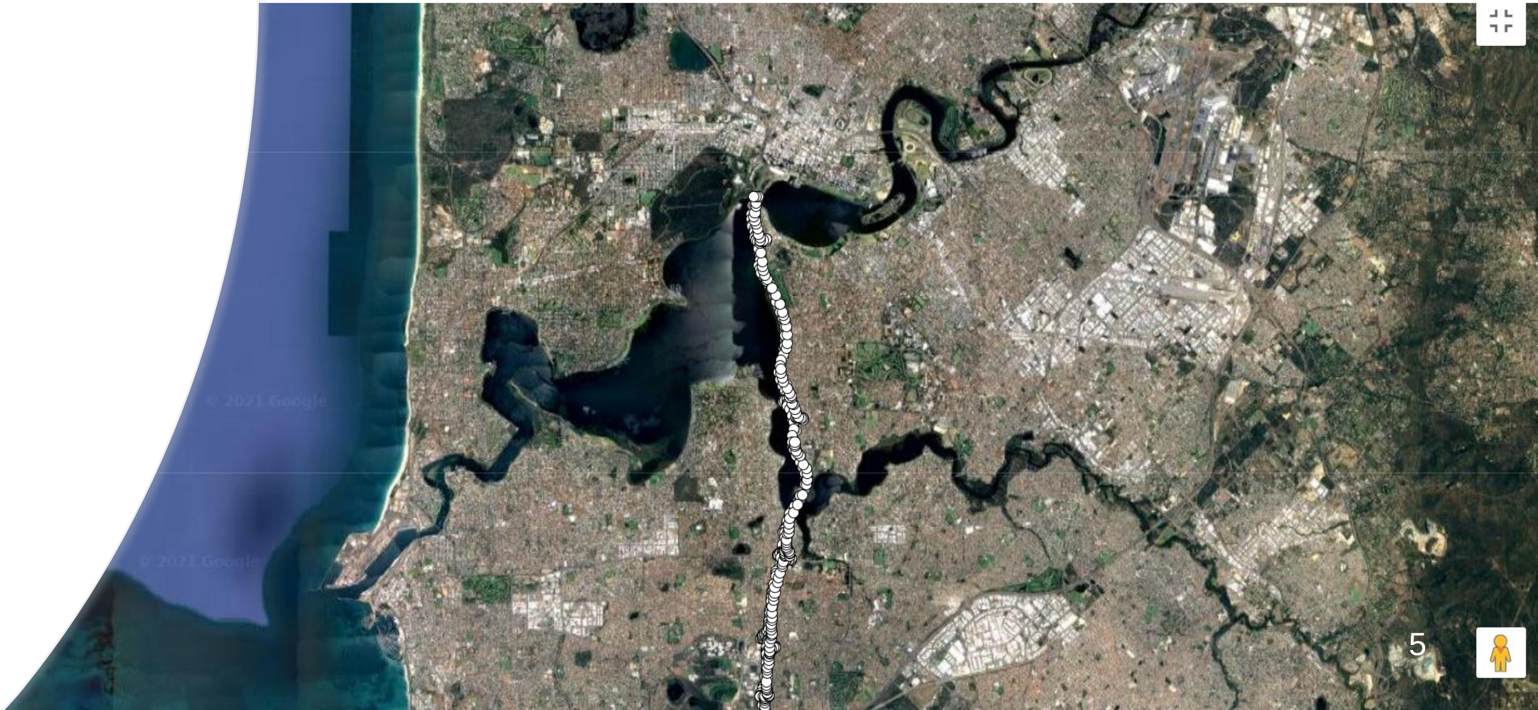
(2) Optimisation model for RM and VSL parameters

(3) Computational experiments

(1) Road Network Model

Kwinana Fwy Network from Farrington RD. to Narrows Bridge

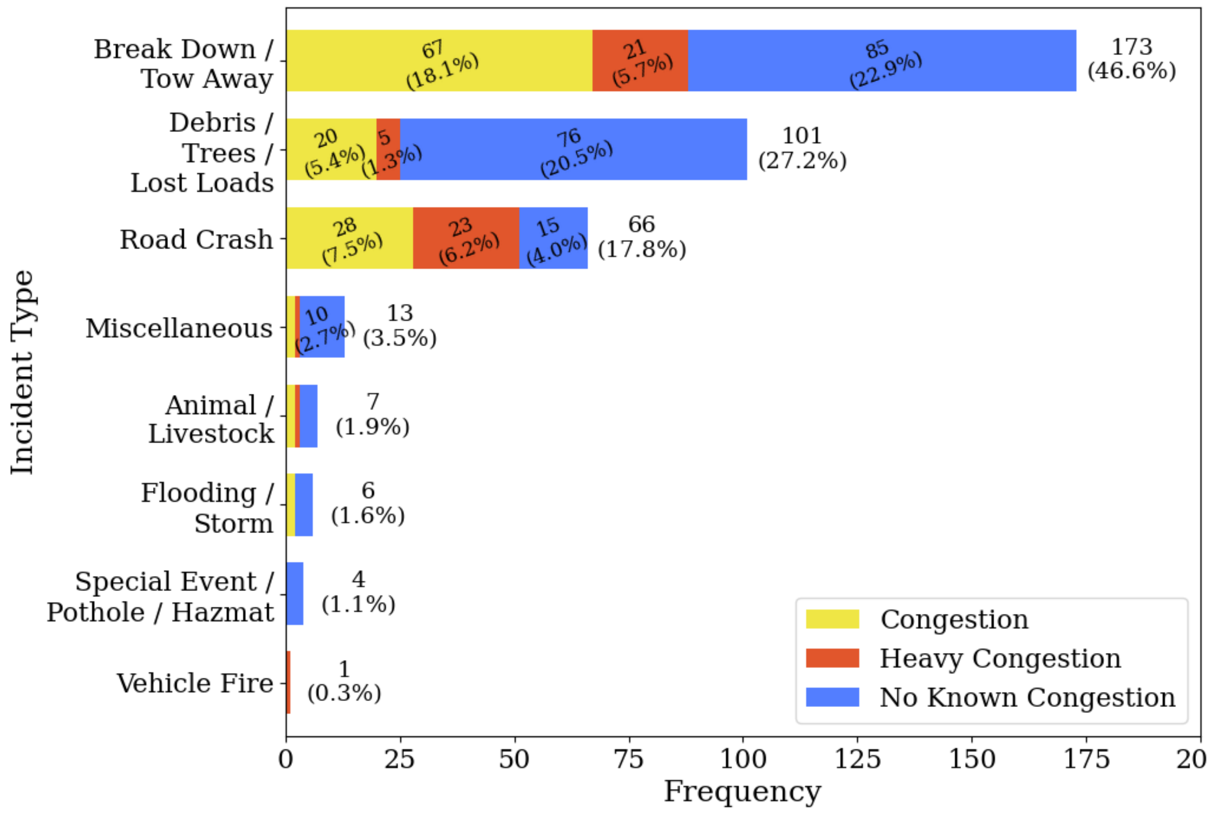


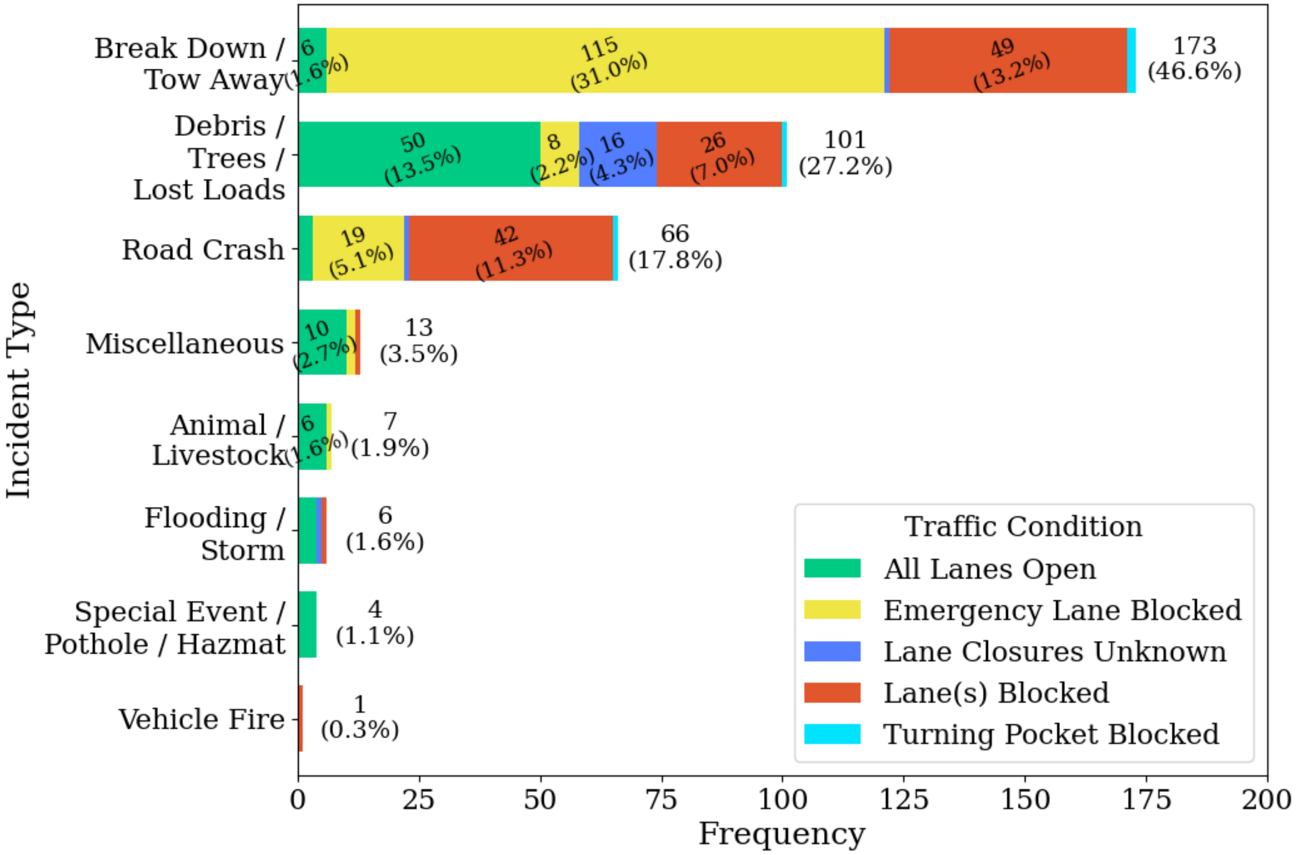


Network information

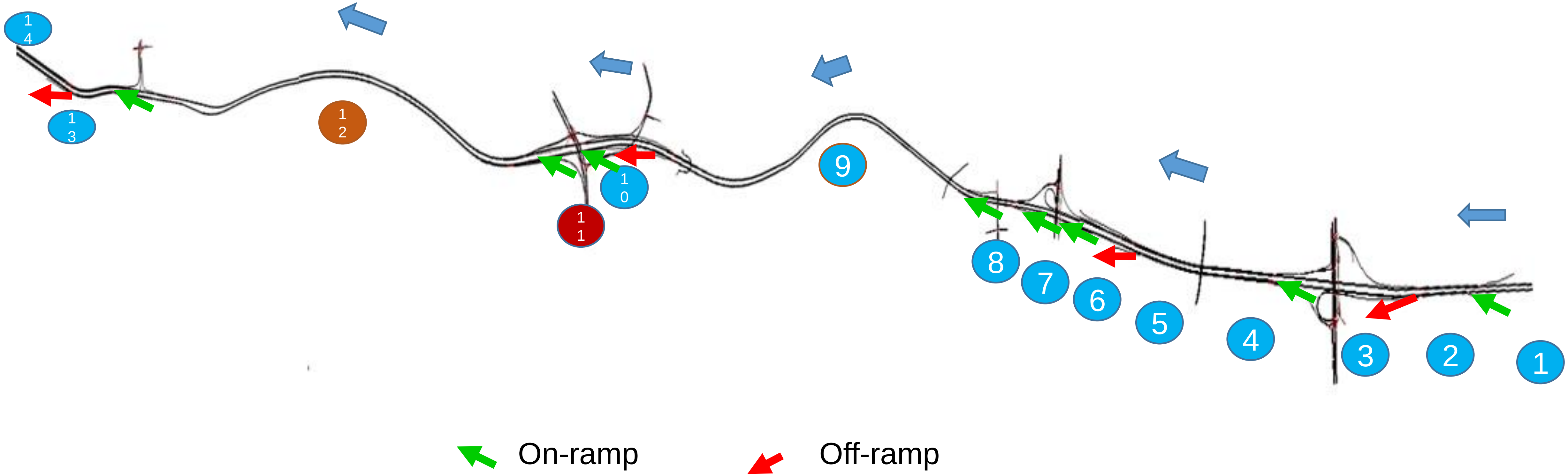
Edge	From	To	Length	lanes	RM/VSL	VDS	Remarks
1	J1	H622	540.62	3		0091, 0200	
2	H622	J2	150.74	4	RM	0090	Farrinton RD.
3	J2	H618	226.09	4		0190	
4	H618	J4	215.70	4			
5	J4	J5	398.23	3			
6	J5	H617	389.89	3		0089	
7	H617	J7	268.88	5	RM		South St.
8	J7	J8	146.65	4		0180, 0700	
9	J8	H559	590.53	4			
10	H559	H558	587.50	3		0170, 0702	Leach Hwy SB
11	H558	J11	230.21	4	RM		
12	J11	H554	211.05	3		0160	
13	H554	J13	123.91	4	RM		Leach Hwy NB
14	J13	H553	189.17	3		0088,0150	
15	H553	J15	227.38	4	RM		Cranford AV.
16	J15	J16	48.68	3			
17	J16	J17	685.48	3			
18	J17	J18	1435.18	3	VSL	0087, 0140, 0086	
19	J18	H551	293.21	3			
20	H551	H547	545.83	3	VSL	0130	
21	H547	J21	127.12	4			Canning SB Man.
22	J21	J22	128.3	3		0085	
23	J22	J23	273.33	3			
24	J23	J24	37.84	4			
25	J24	H549	130.44	3		0084	
26	H549	J26	134.99	4	VSL	0120	Canning NB
27	J26	J27	79.65	4	VSL		
28	J27	J28	3170.18	3	VSL	0003, 0083,0100,0082	
29	J28	J29	148.32	3	VSL		
30	J29	H500	370.6	4	VSL	0081	
31	H500	J31	119.89	4	VSL		Mill Pts
32	J31	H503	259.97	4	VSL		
33	H503	J33	239.04	5		0080	
34	J33	J34	363.95	5			

Road incidents on the Kwinana Freeway Northbound 1 January 2018 – 25 October 2018

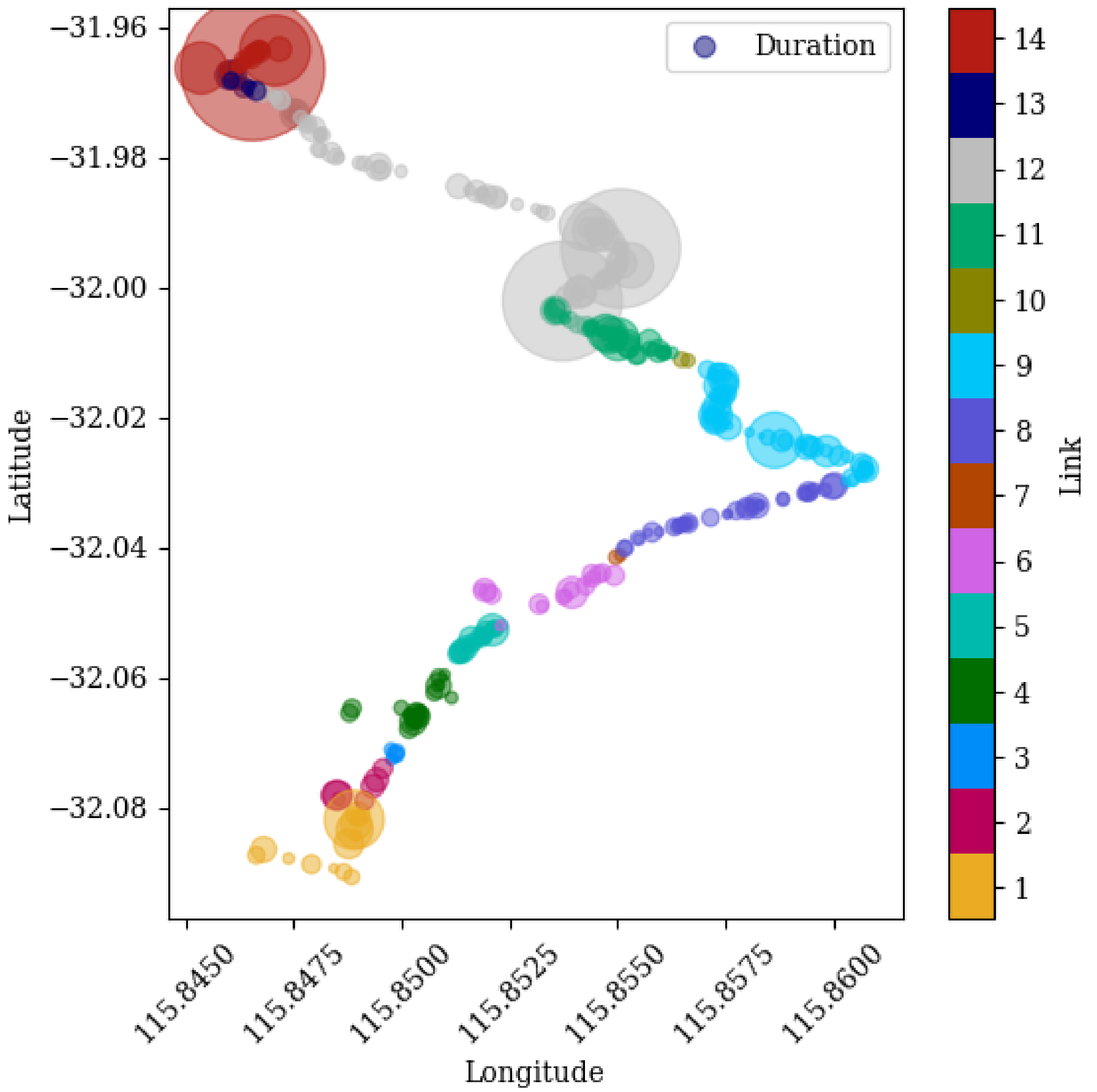




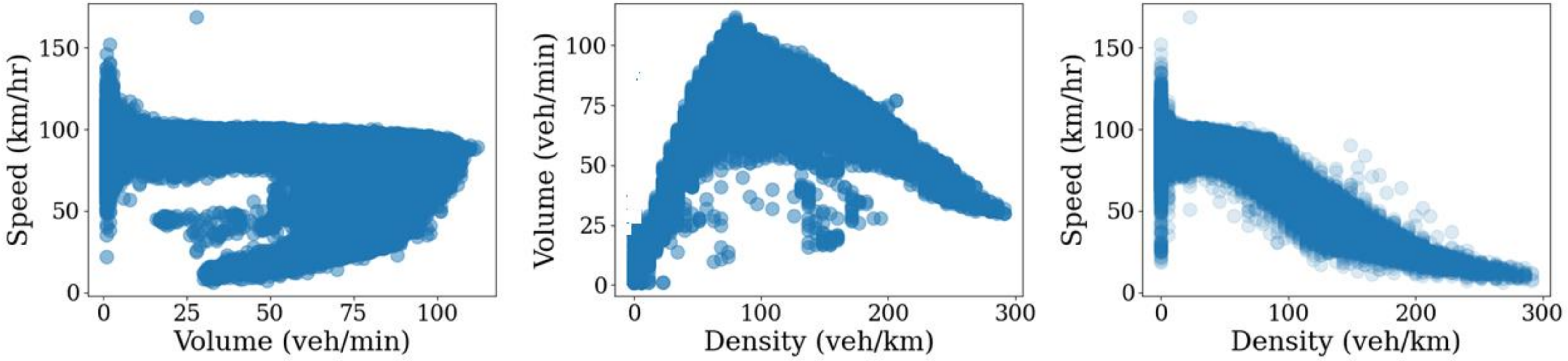
14 Links of the Kwinana Freeway Northbound



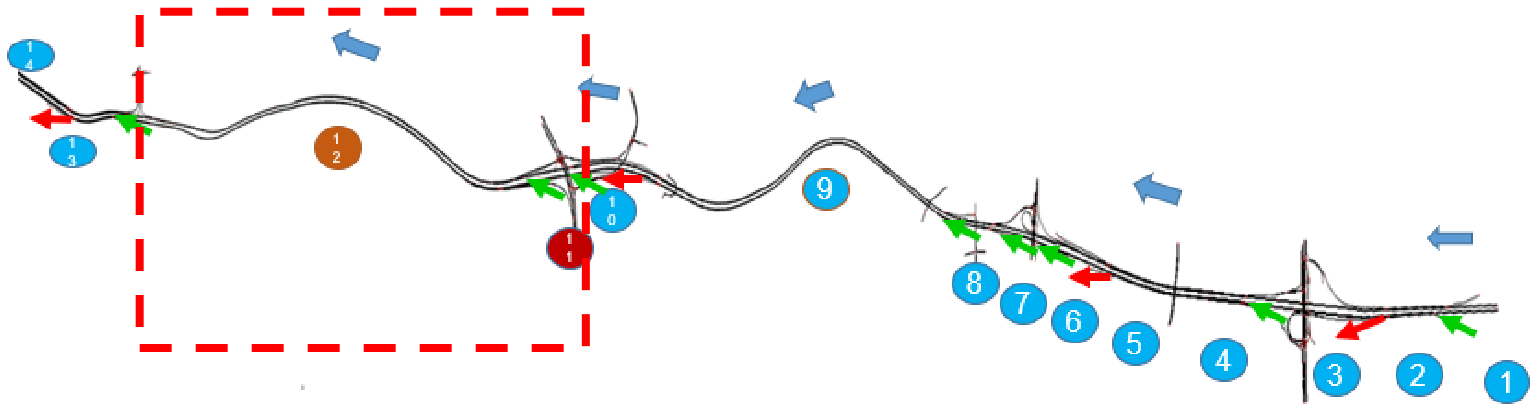
Duration of road incidents occurring on the Kwinana Freeway northbound from NPI link 1 to 14



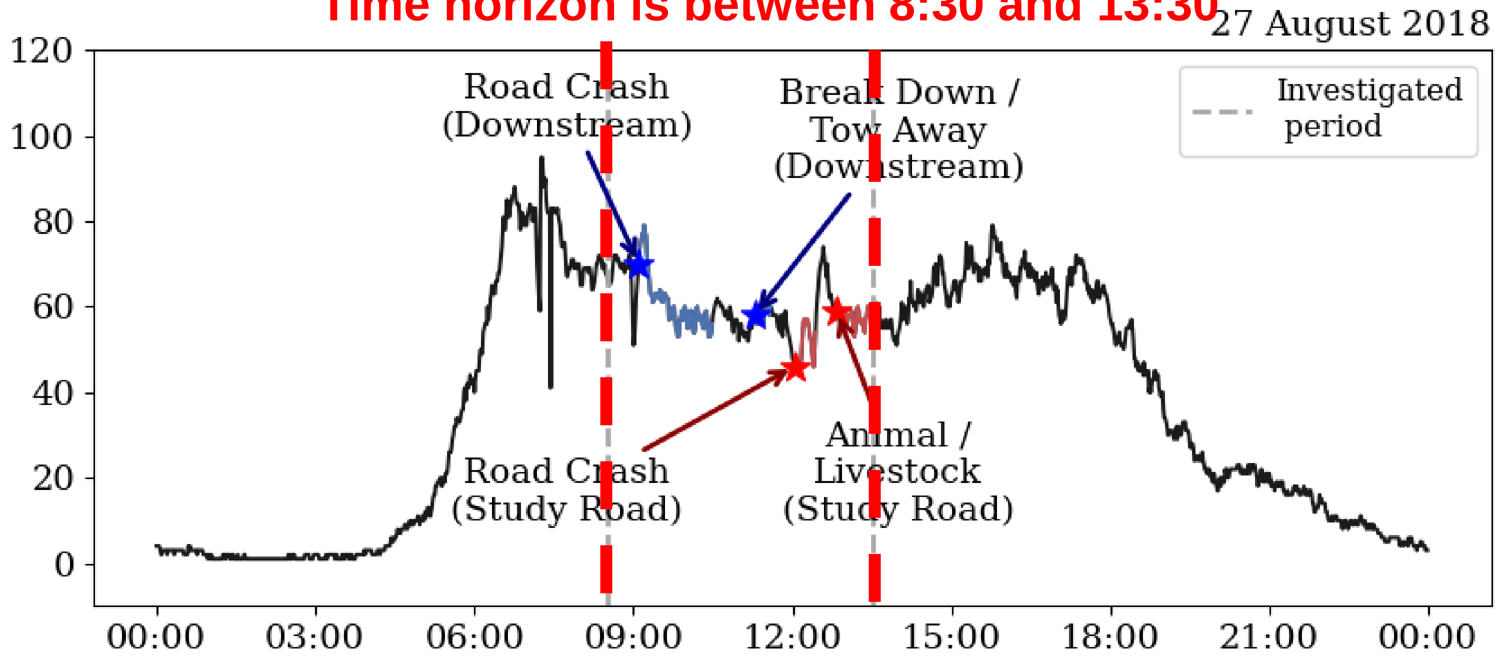
Fundamental diagrams



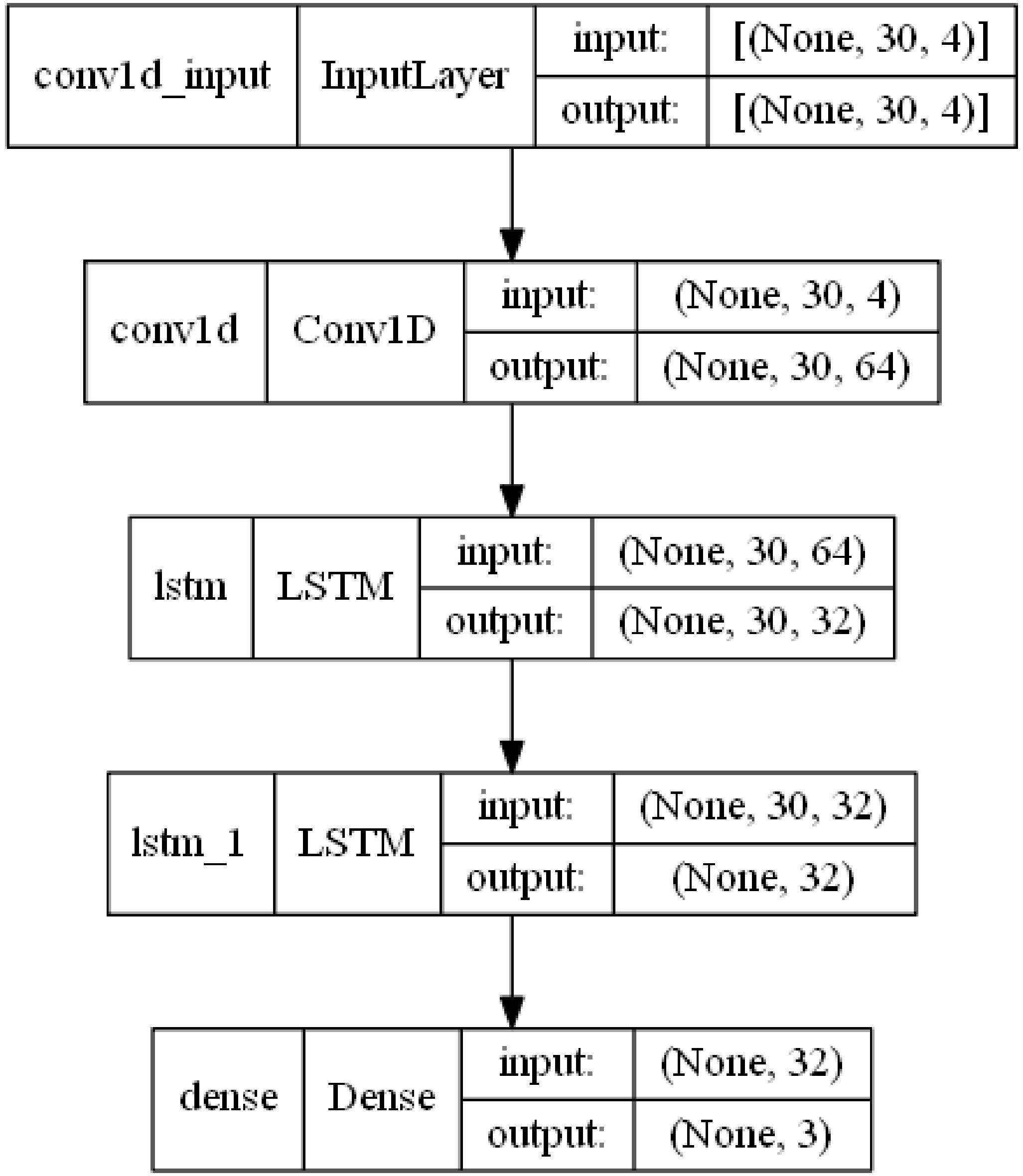
Observed traffic flow under road incidents

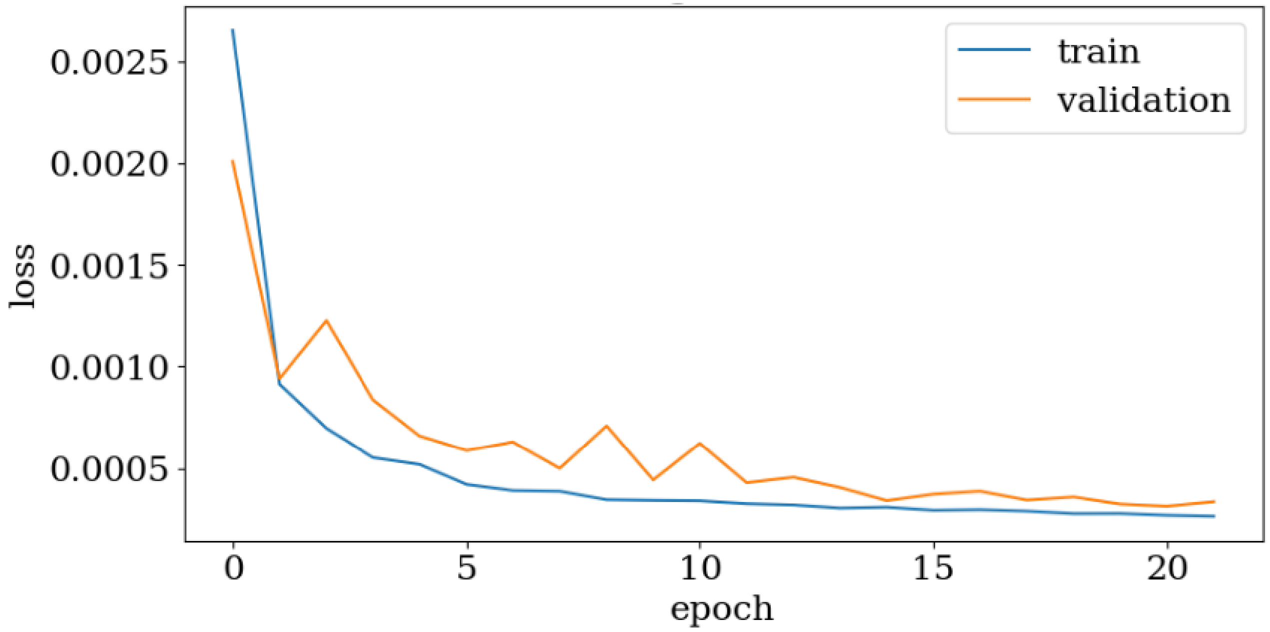


Time horizon is between 8:30 and 13:30

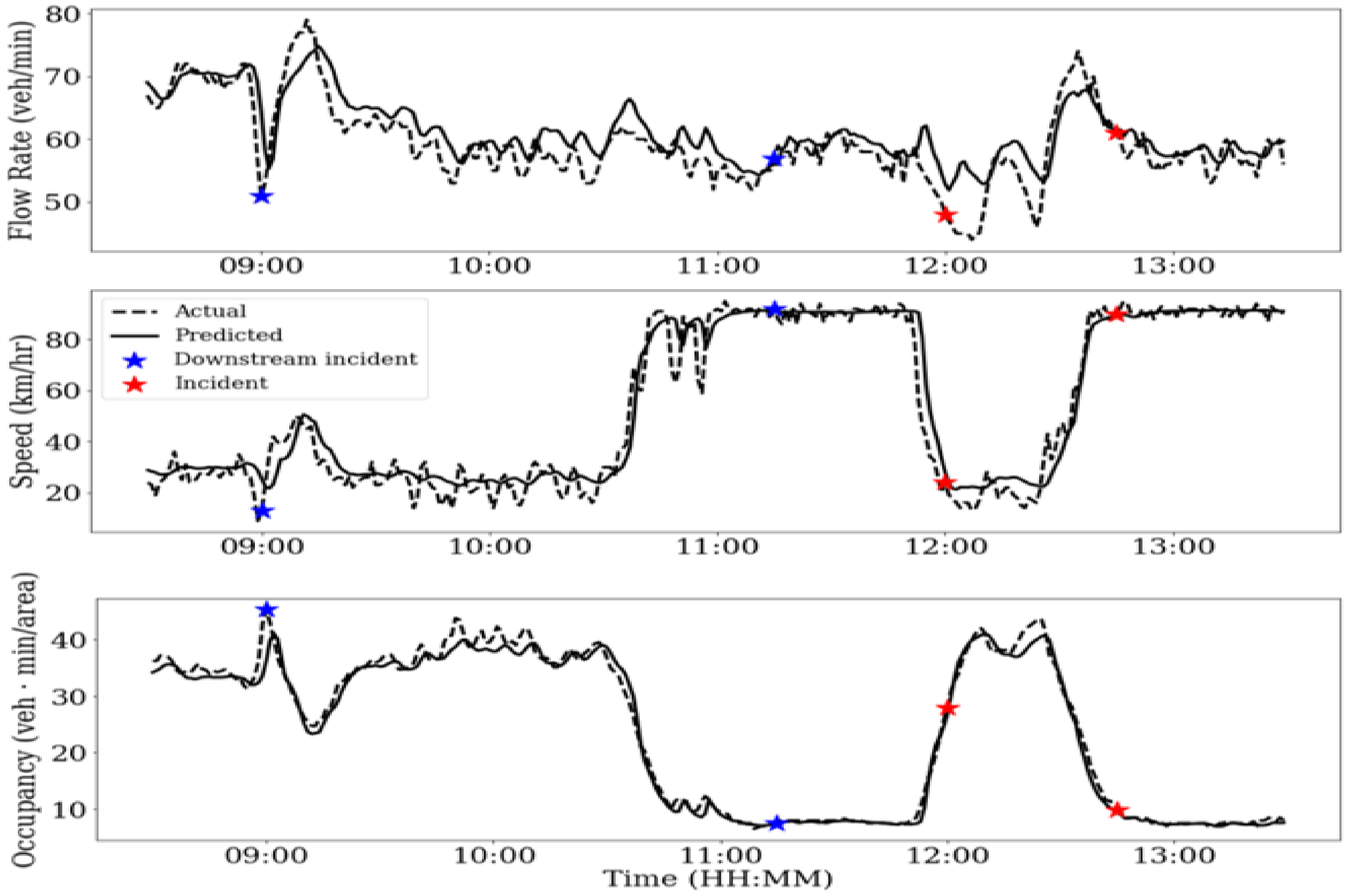


Traffic prediction under non-recurrent events using 1-D CNN LSTM model

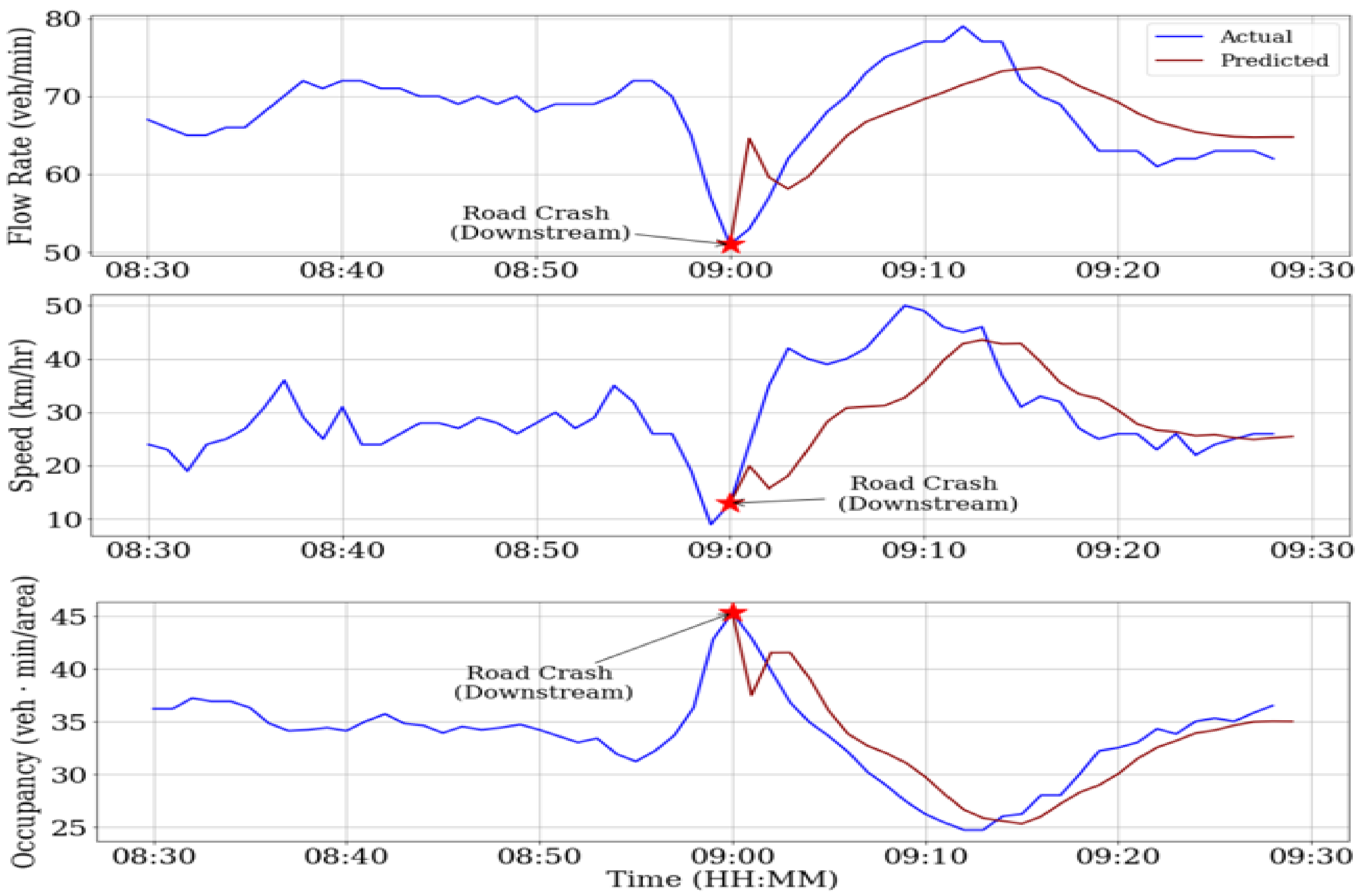




Long-term predictions



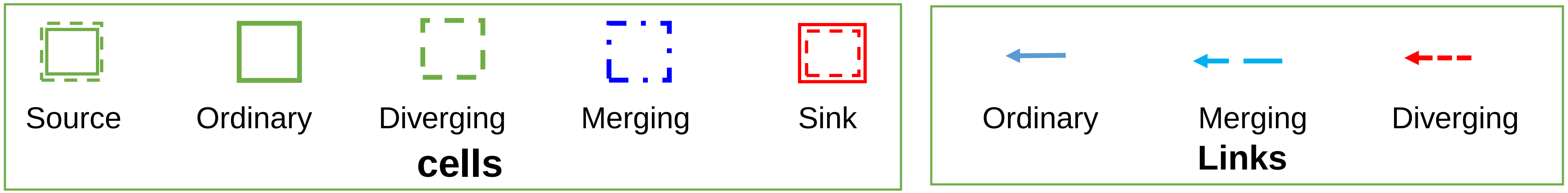
Short-term predictions



(2) Optimisation model for RM and VSL parameters

Kwinana Freeway Northbound Network

Legend



The optimisation model:

$$\min \sum_{t=\tau}^{t_{end}} T\left(\sum_{i=1}^{rs} L_i k_i\,(t)\right) + \lambda_{rm} \sum_{t=\tau+1}^{t_{end}-1} \sum_{i=1}^{rs_{rm}} (\alpha_i(t) - \alpha_i(t-1))^2 + \lambda_{vsl} \sum_{t=\tau+1}^{t_{end}-1} \sum_{i=1}^{rs_{vsl}} (\beta_i(t) - \beta_i(t-1))^2$$

- $\frac{n_i \partial k_i}{\partial t} + \frac{\partial}{\partial x} \Delta q_i(t) = 0, \qquad 0 \le k_i(t) \le k_{jam,i}$

$$\Delta q_i(t) = q_i^{in}(t-1) - q_i^{out}(t-1) + r_i(t-1) - s_i(t-1)$$

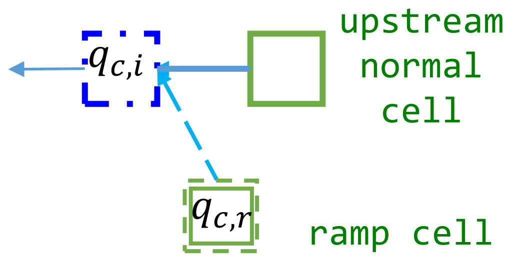
$$r_i(\mathrm{t}) = \min \left[\begin{matrix} n_{i,r} q_{c,r};\ \beta_{i,r} v_{f,r} k_{i,r}(t-1); \\ \max\left\{\ r_i^{\alpha}(t);\ queue_{i,r}(t)\right\} \end{matrix} \right]$$

- $queue_{i,r}(t) = arr_{i,r}(t-1) - \frac{1}{T}\left(\widehat{m}_{i,r} - m_{i,r}(t-1)\right);$
- $m_{i,r}(t) = m_{i,r}(t-1) + T(arr_{i,r}(t-1) - r_i(\mathrm{t})) \le \widehat{m}_{i,r}$
- $r_i^{\alpha}(\mathrm{t}) = r_i^{\alpha}(\mathrm{t}-1) + \boldsymbol{\alpha_i(t)} \frac{L_i}{T}(n_i k_{c,i} - k_i(t-1)) > 0$

Metering parameter

- Capacity constraints

$$\sum_{t=\tau}^{t_{end}} T\left\{\sum_{i=1}^{rs} (\Delta q_i(t) - q_{c,i})\right\} \le 0$$



Green duration $\quad g_i(t) = \frac{r_i(t)}{r_s(t)} C_i$

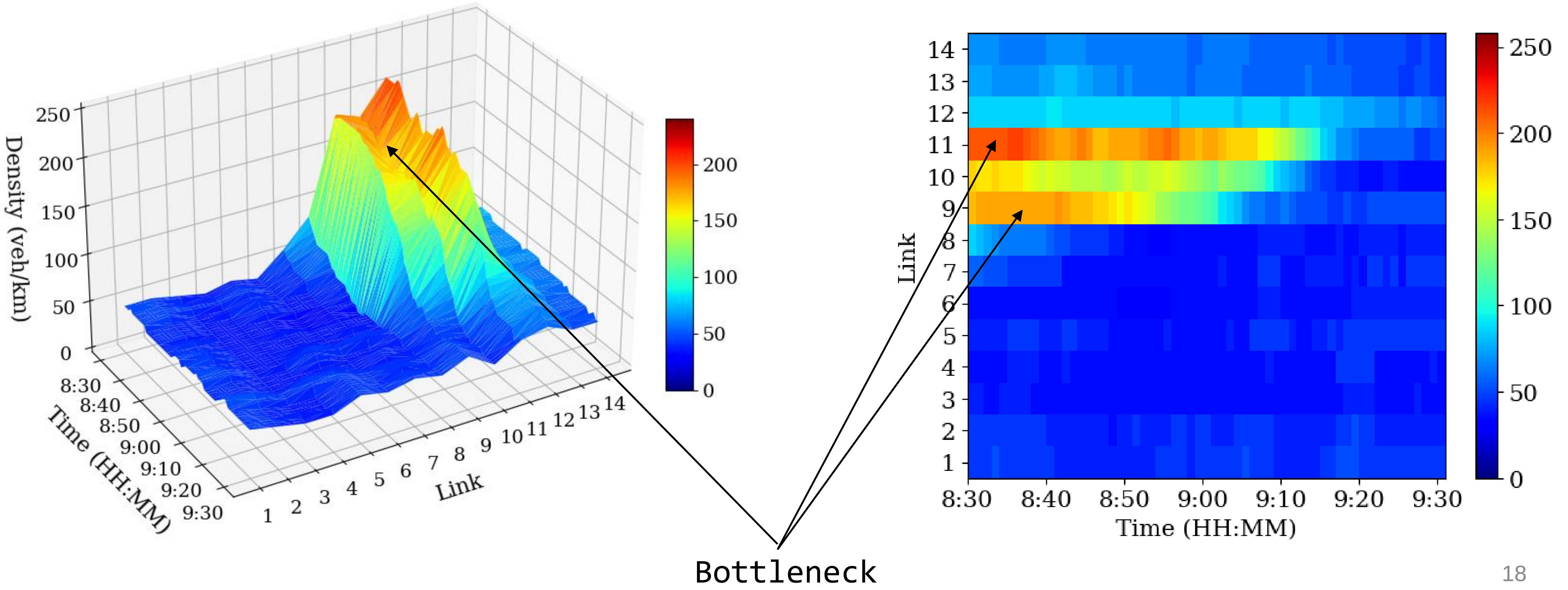
$$T = t_{record}/3600$$

(3) Computational Experiments

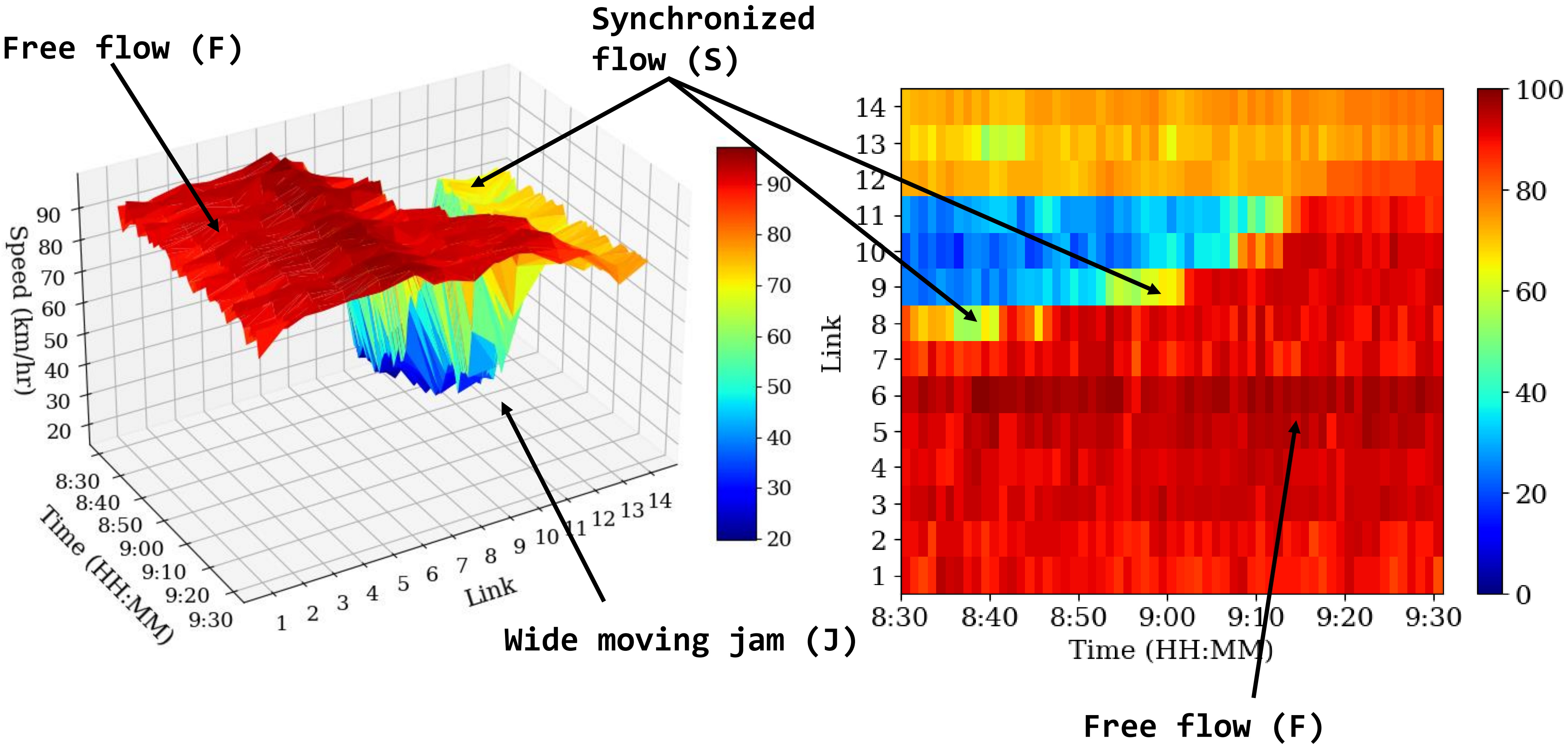
Case I: With no incidents

Link.csv, node.csv

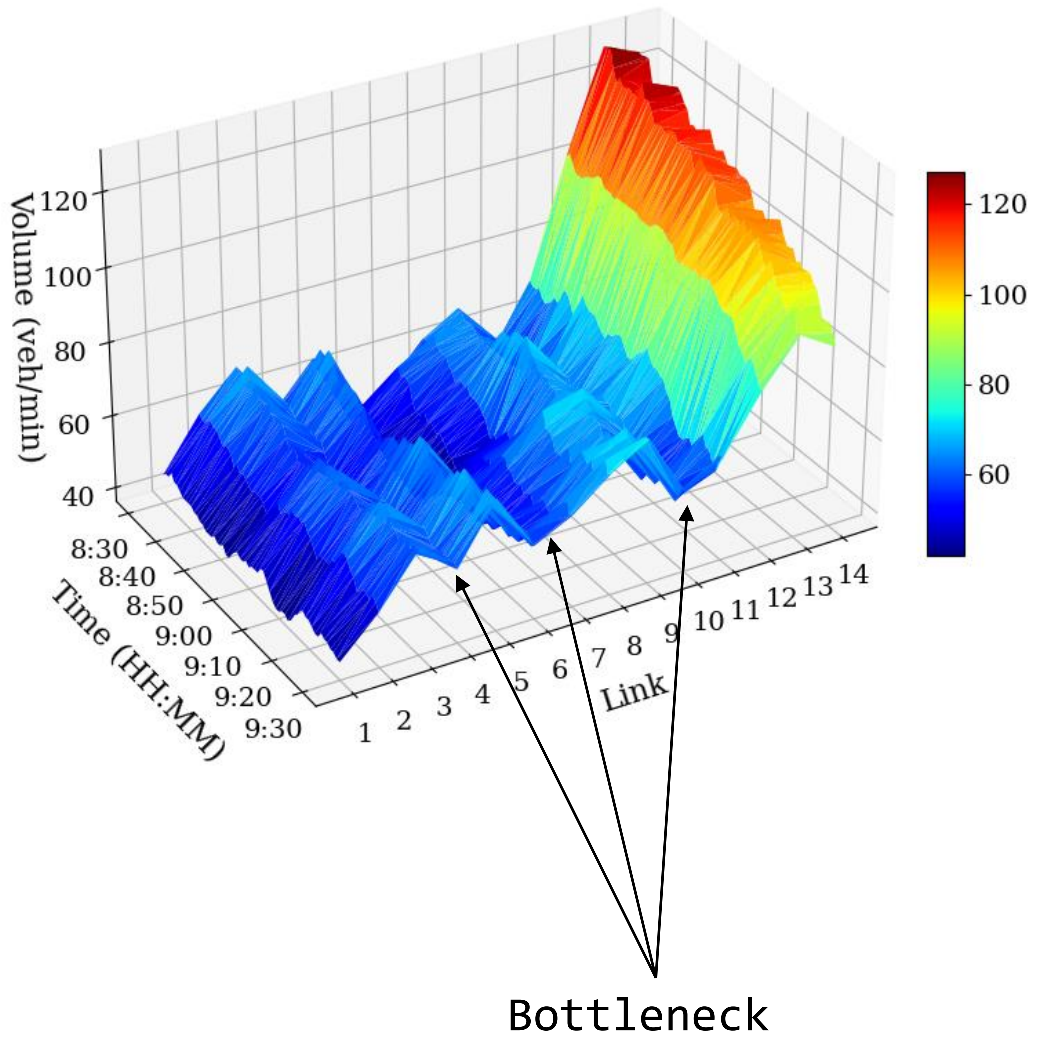
3 September 2018

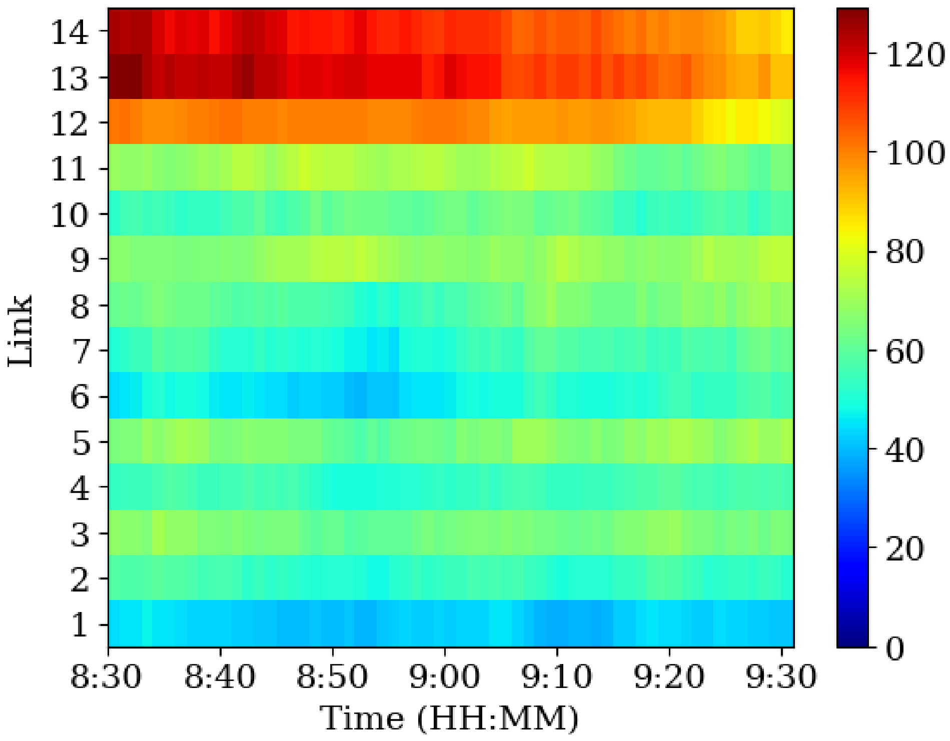


Case I: Traffic speed (km / hr)

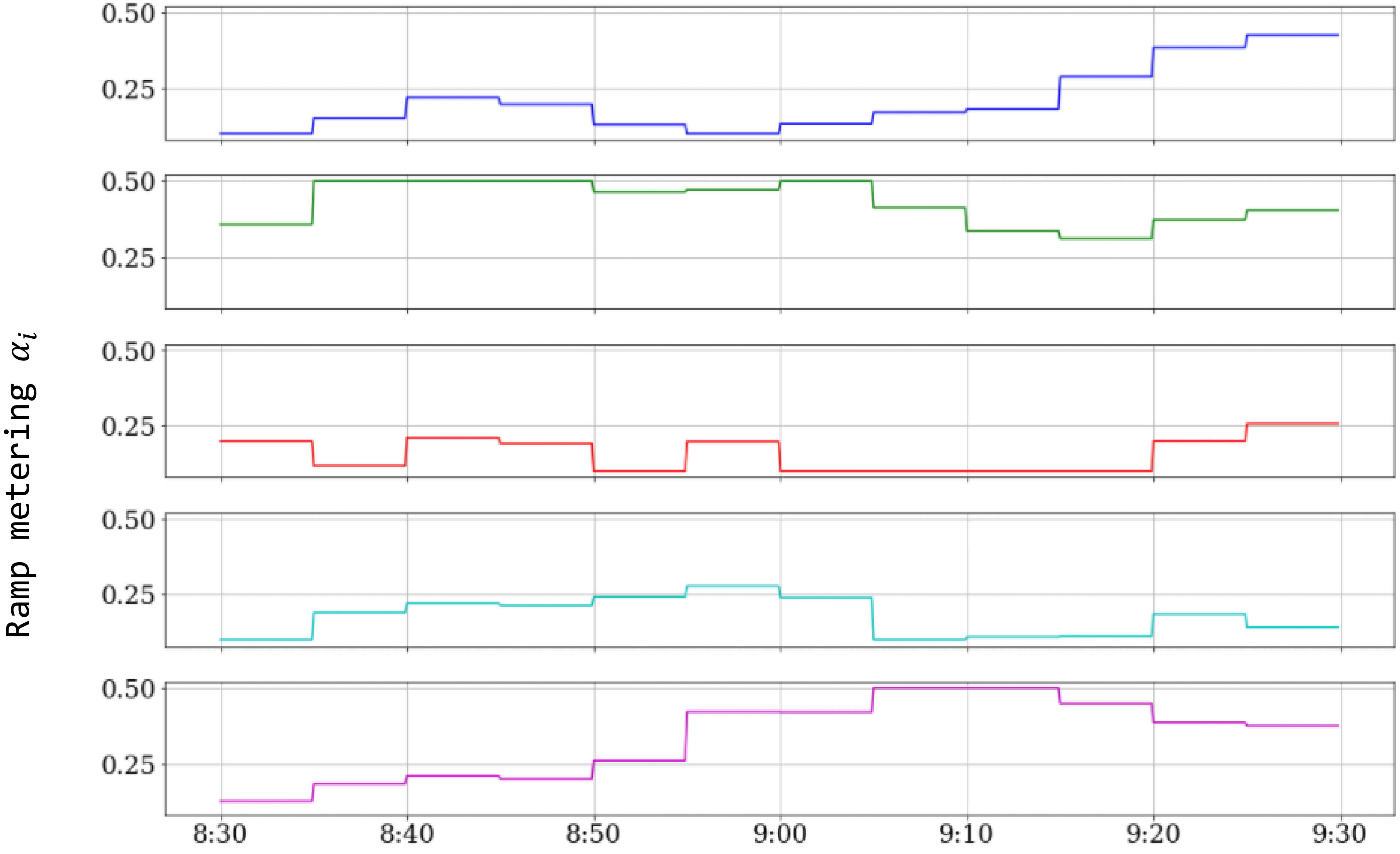


Case I: Traffic flow rate (veh/min)

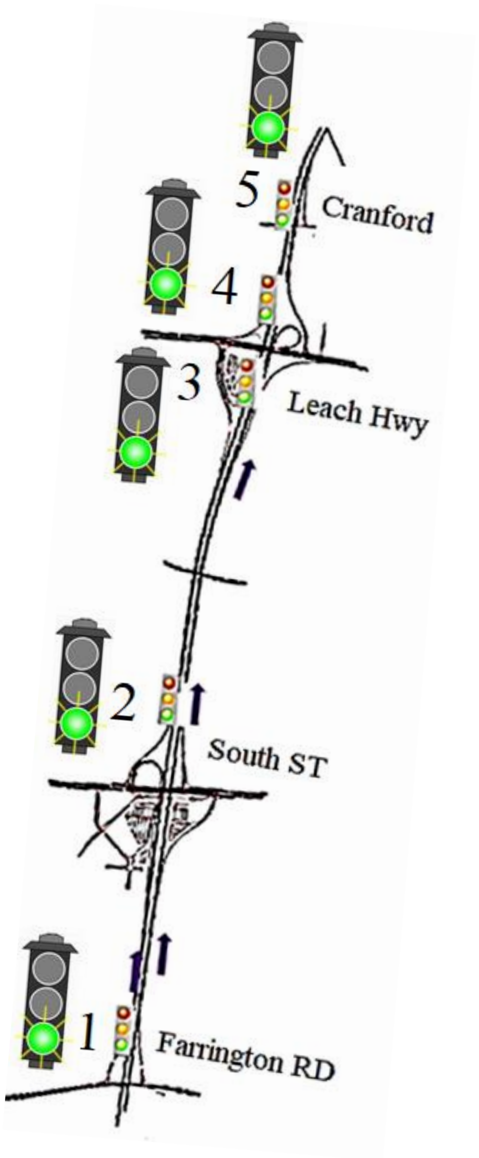




Case I: RM

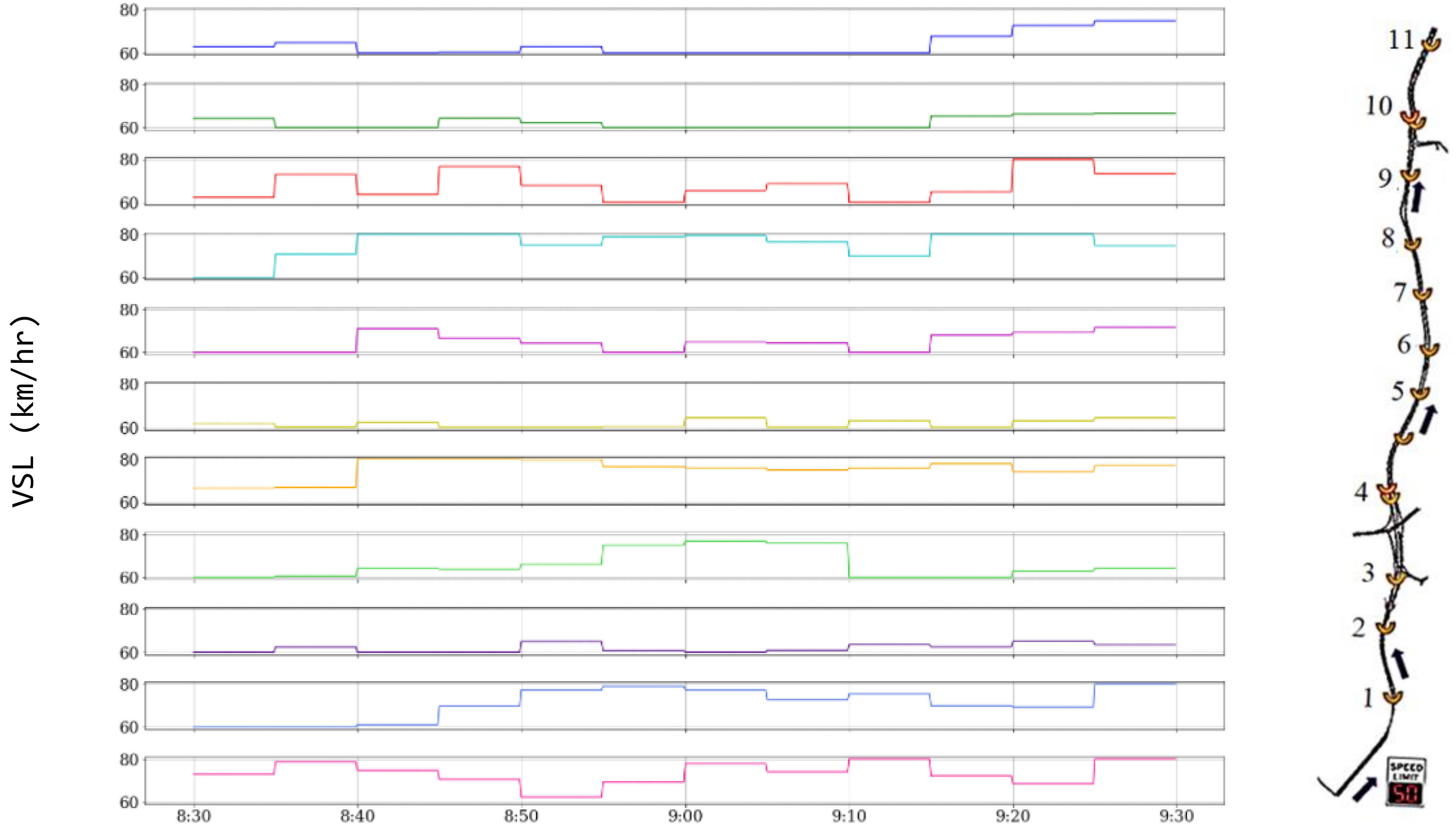


Ramp metering α_i
0.50
0.25
8:30
8:40
8:50
9:00
9:10
9:20
9:30



5
Cranford
4
3
Leach Hwy
2
South ST
1
Farrington RD

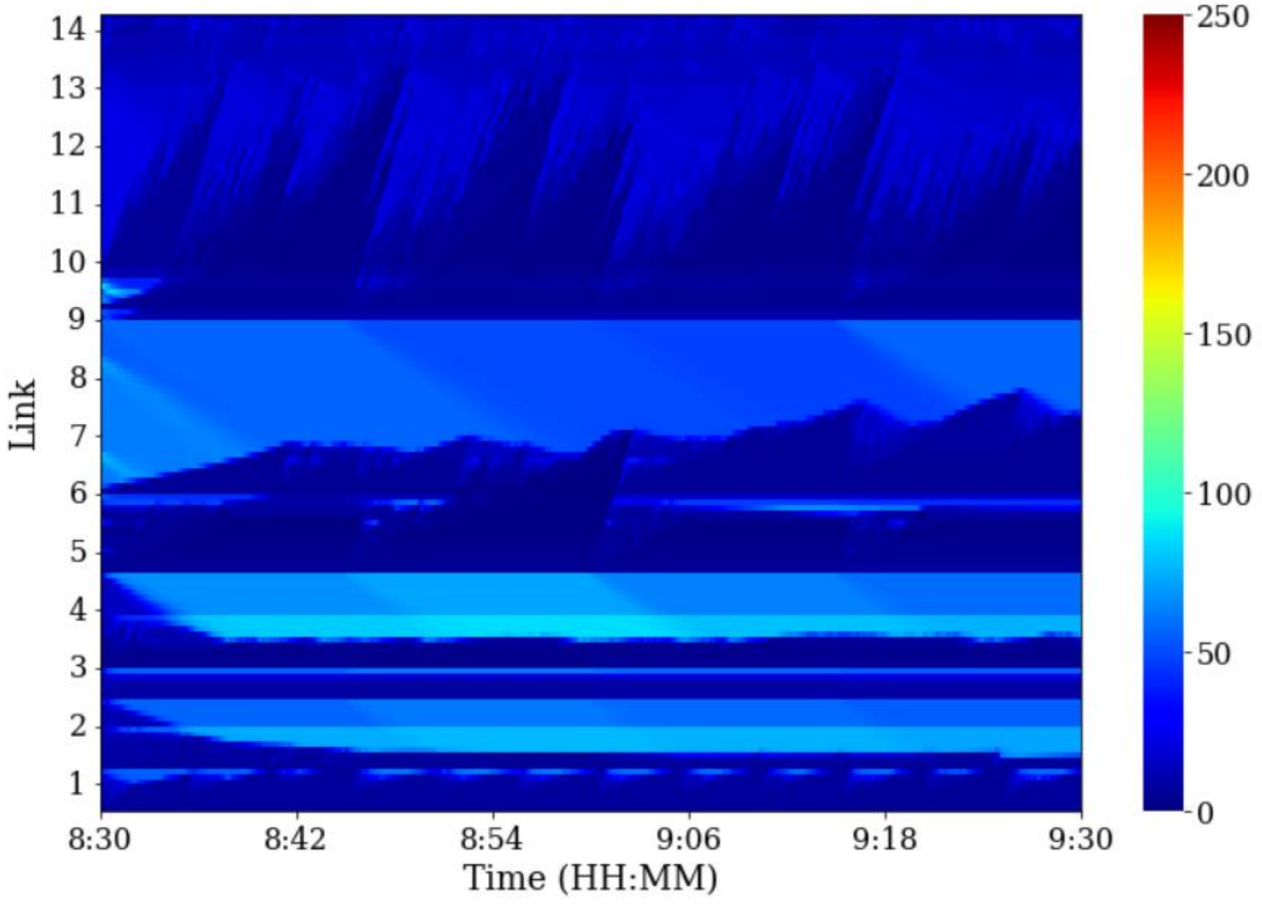
Case I: VSL



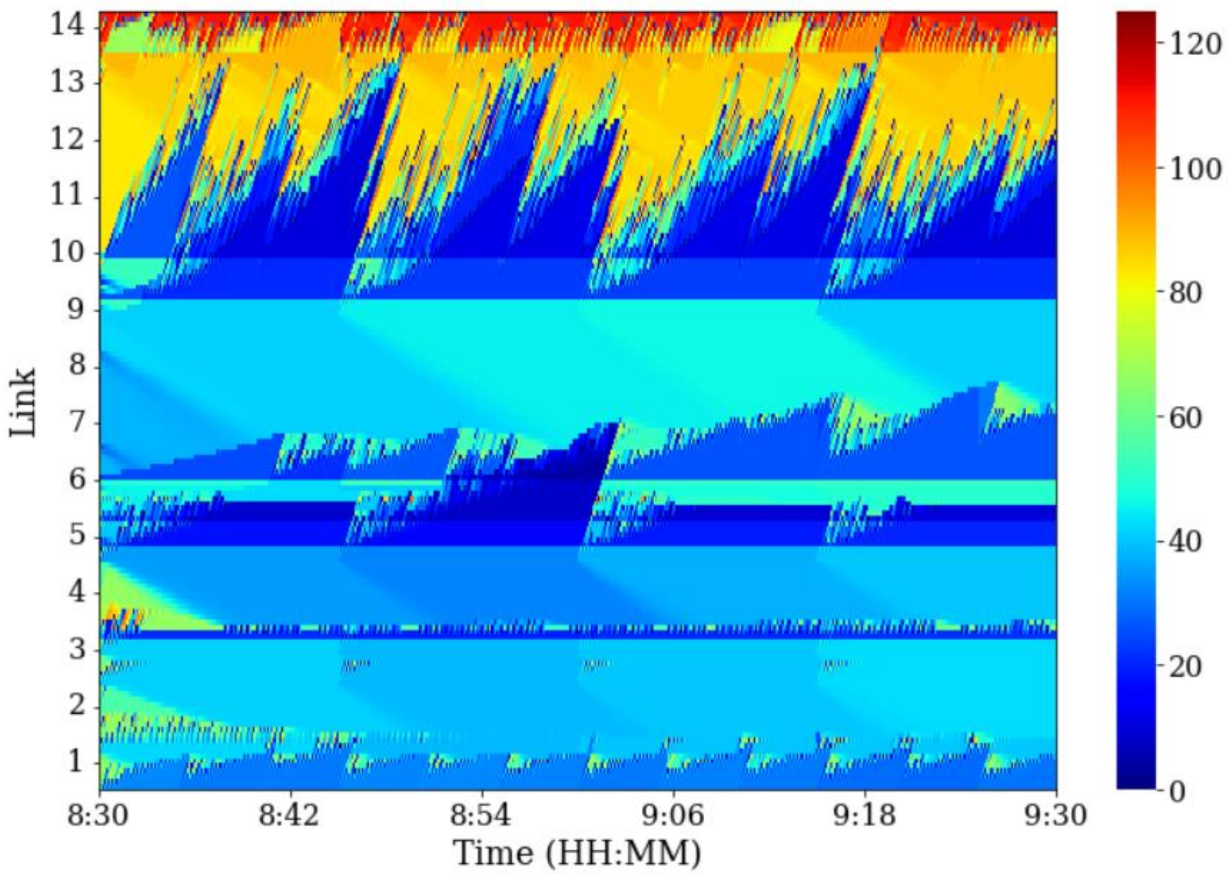
VSL (km/hr)
80
60
8:30
8:40
8:50
9:00
9:10
9:20
9:30
11
10
9
8
7
6
5
4
3
2
1
SPEED LIMIT

Case I: Density and Flow rate

Density (veh/km)



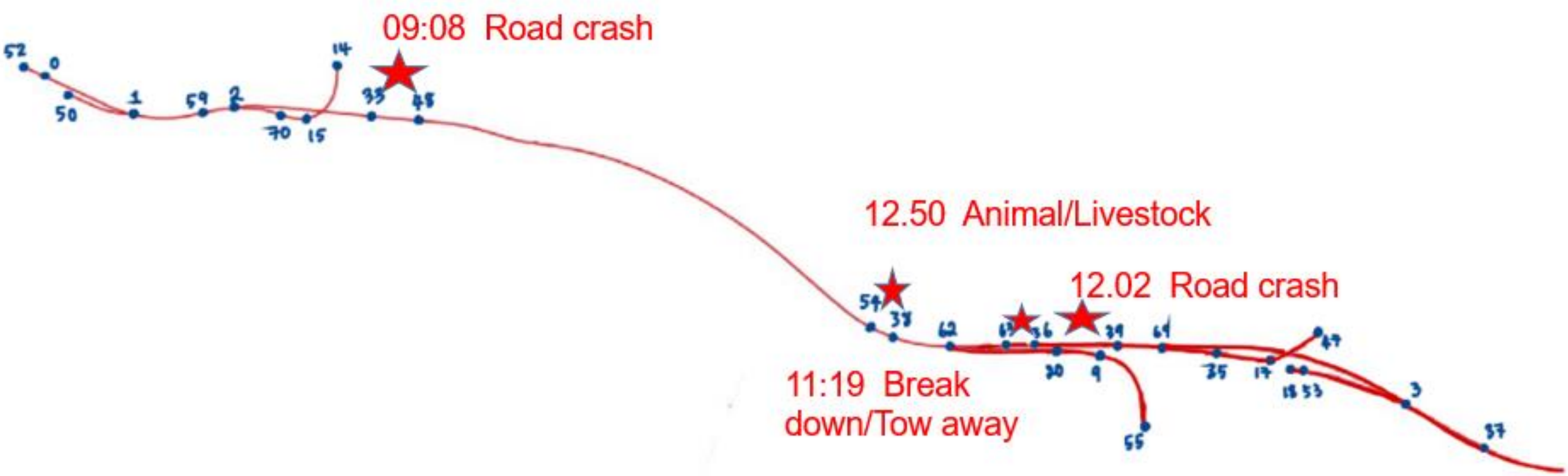
Flow rate (veh/min)



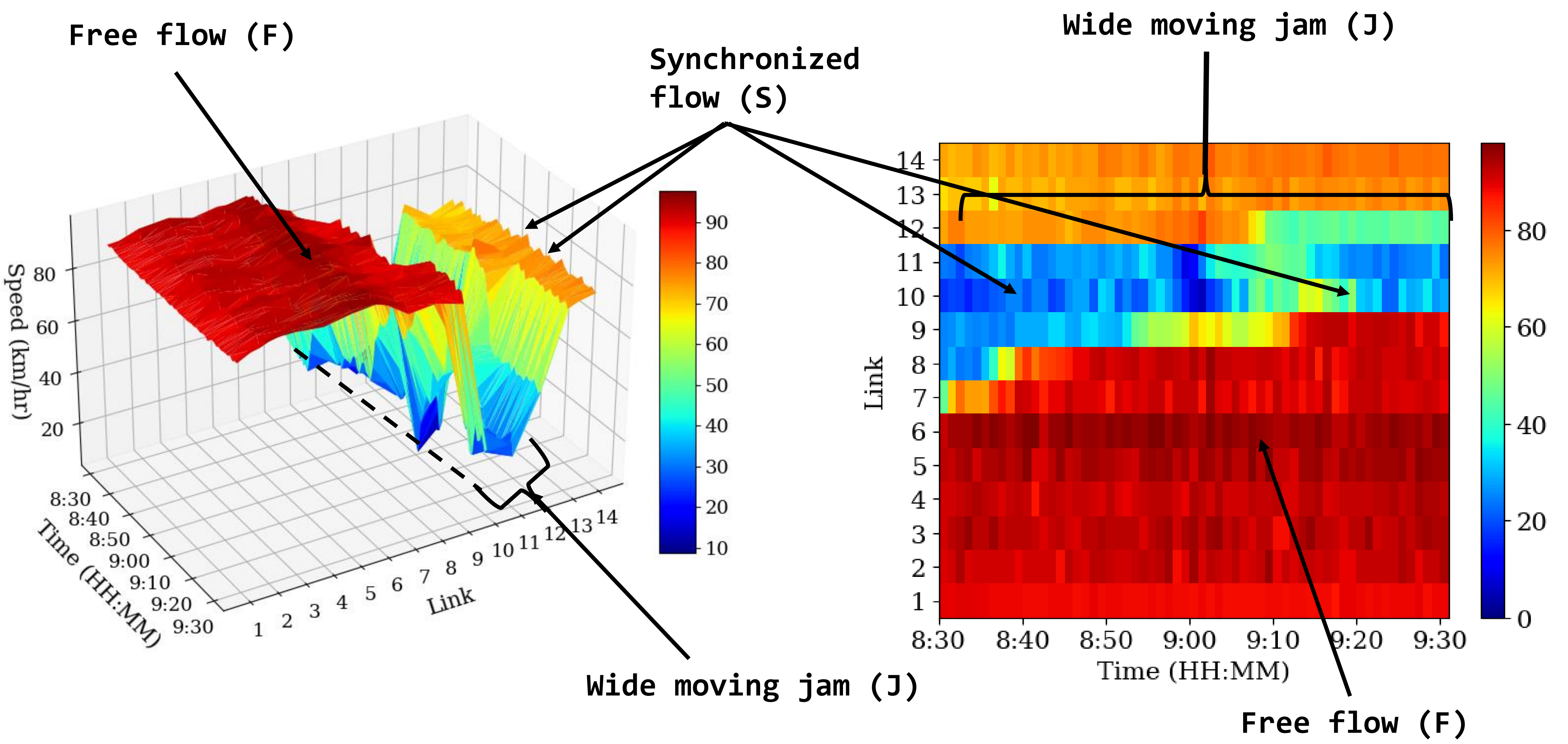
Case II: With road incidents

Link.csv, node.csv

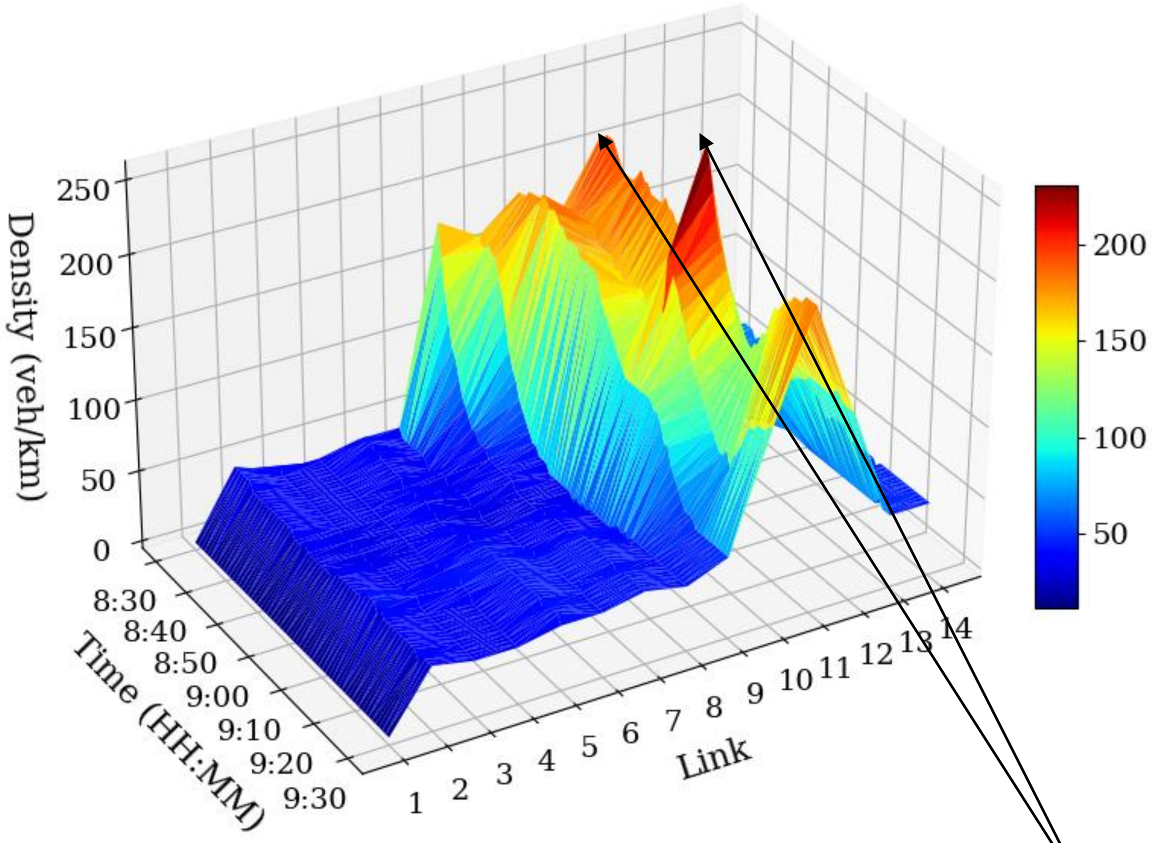
27 August 2018

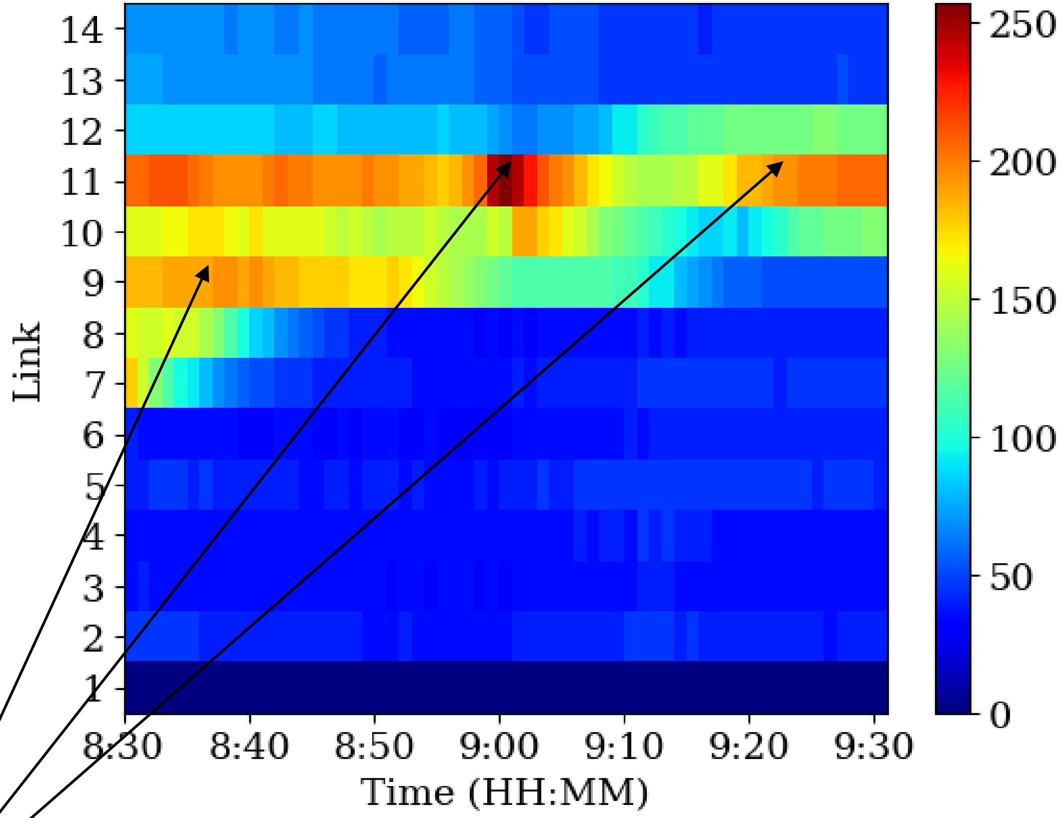


Case II: Traffic speed (km / hr)



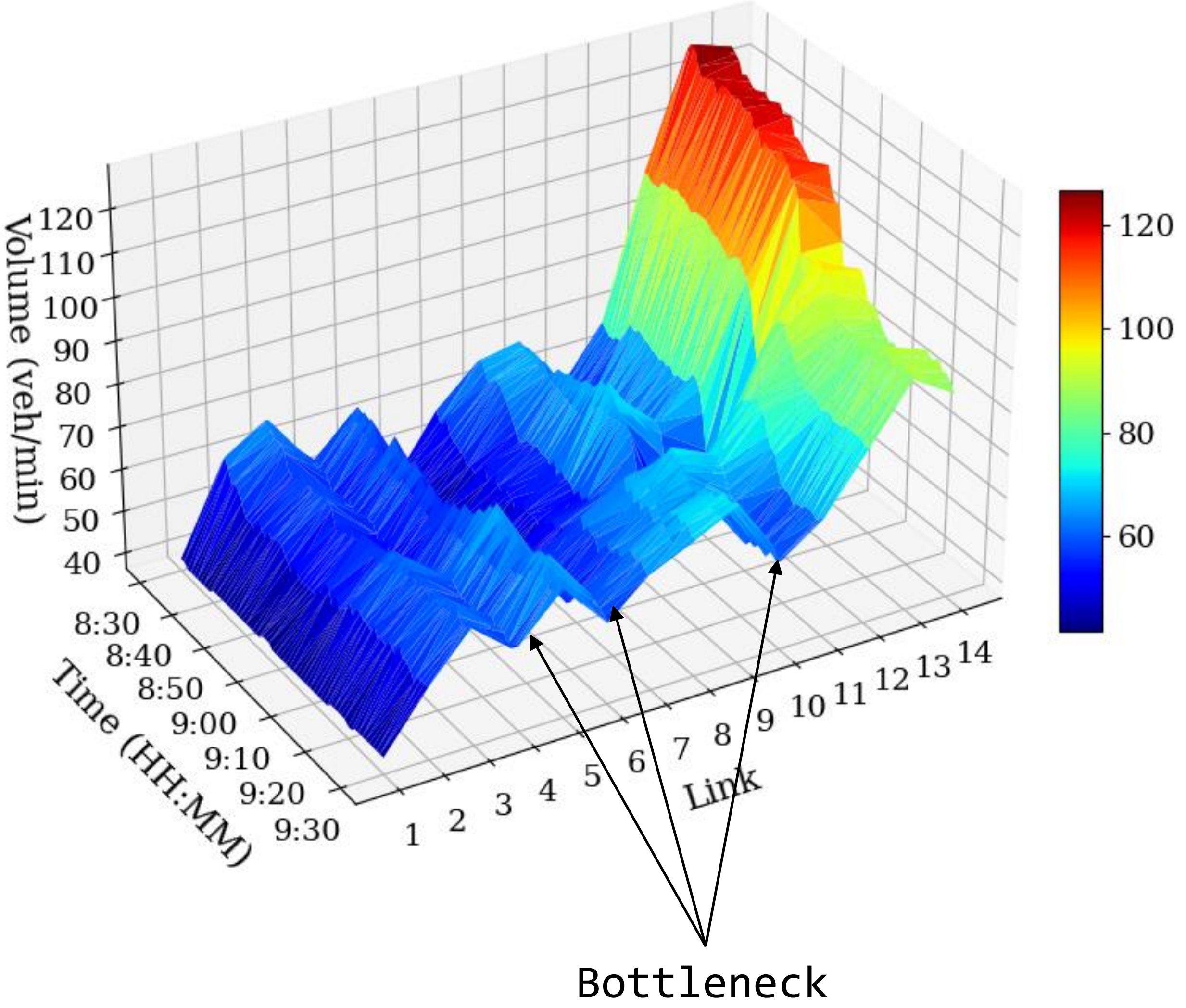
Case II: Traffic density (veh / km)

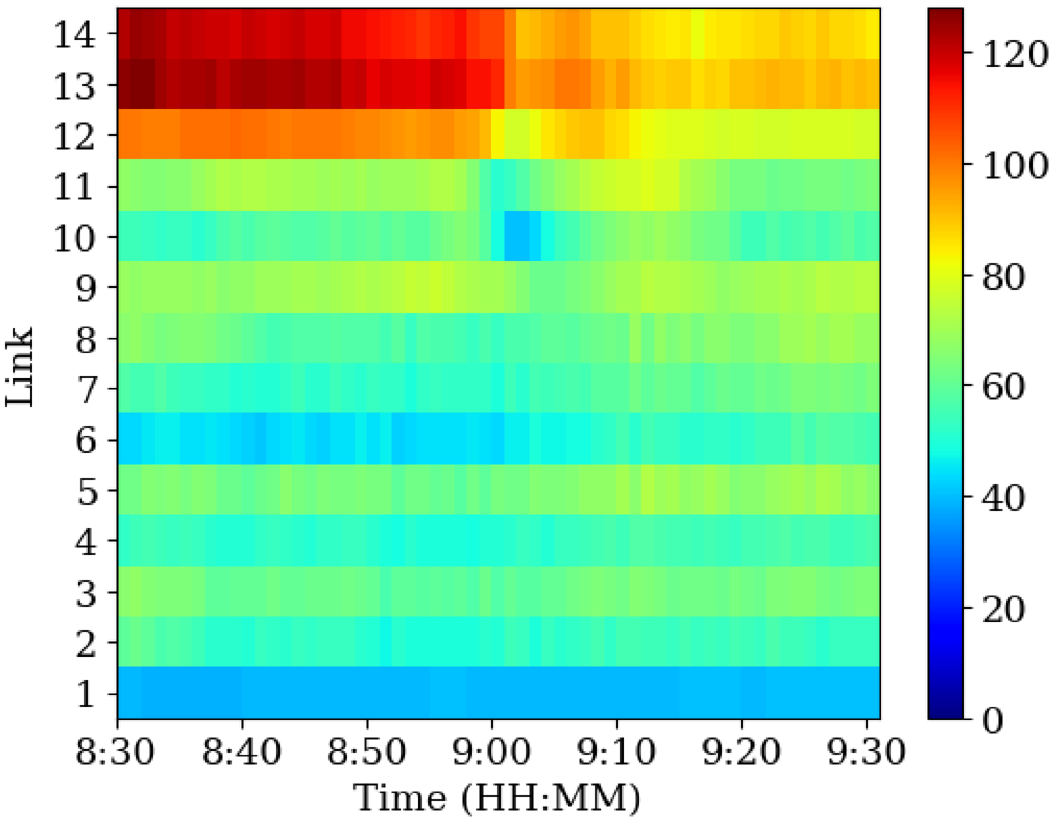




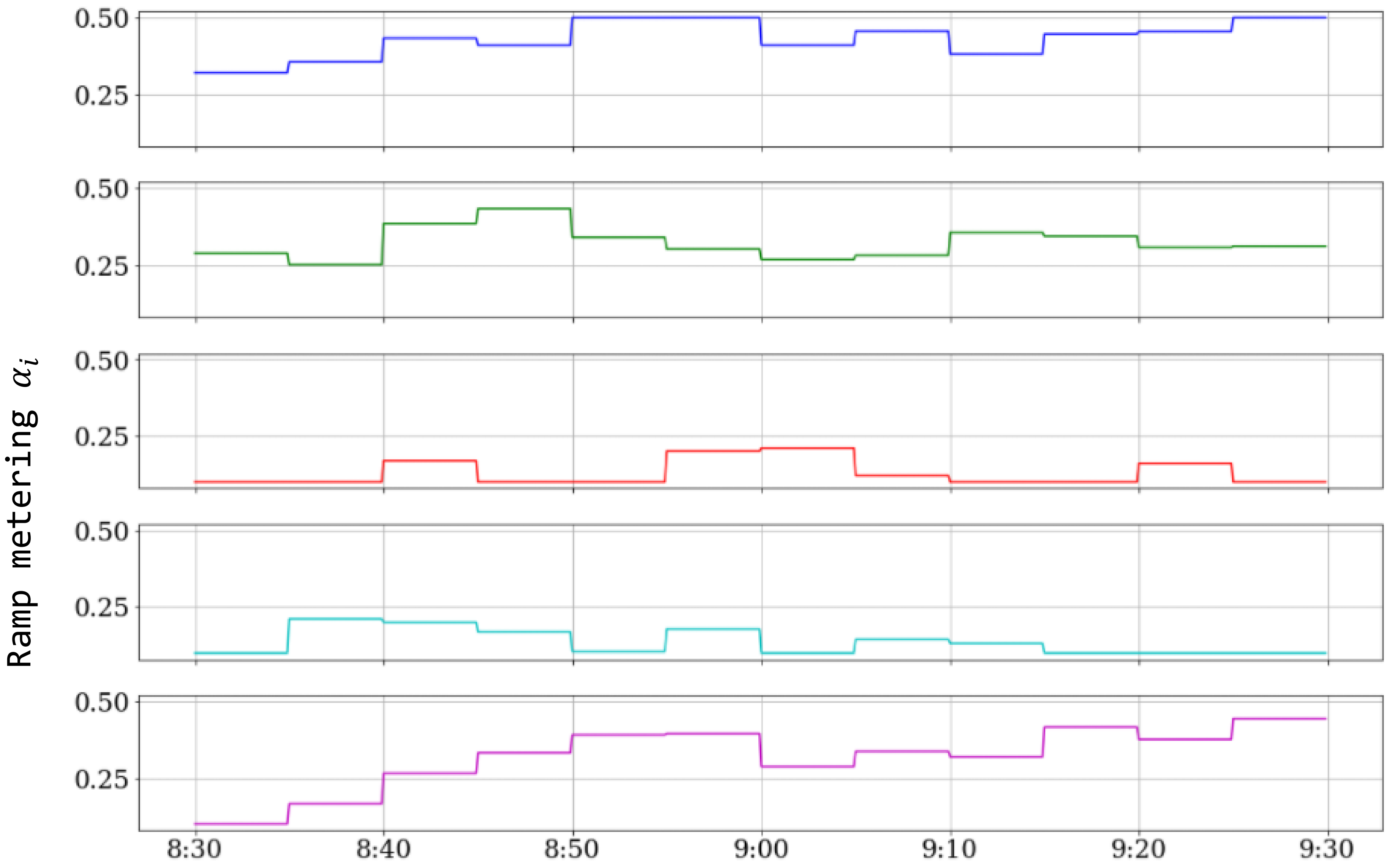
Bottleneck

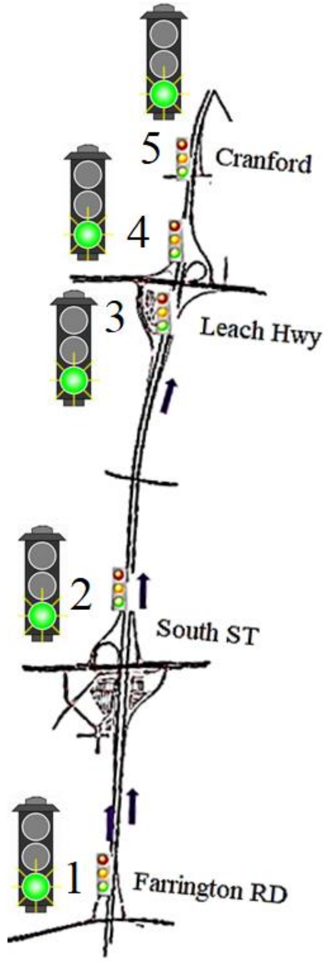
Case II: Traffic flow rate (veh/min)



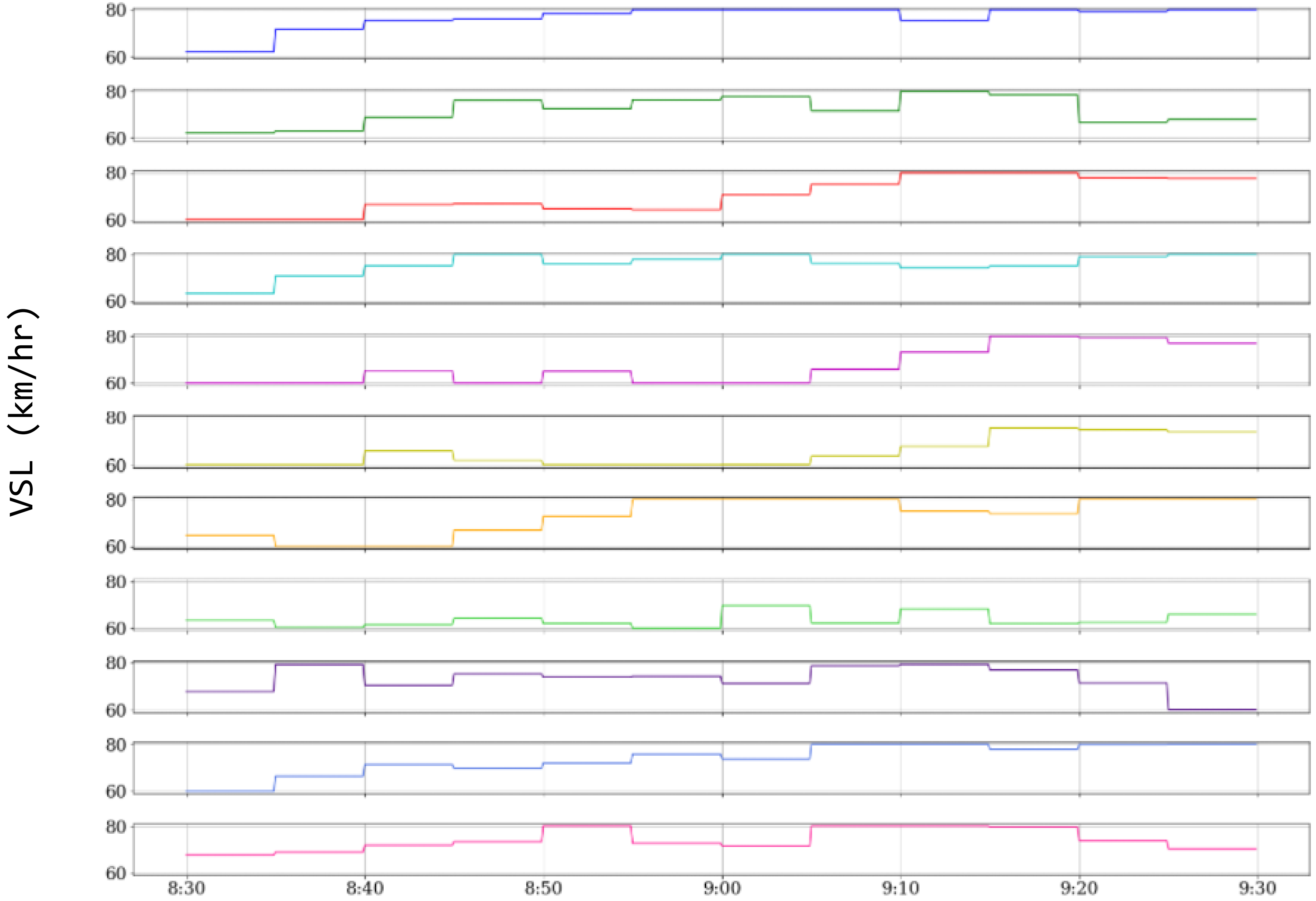


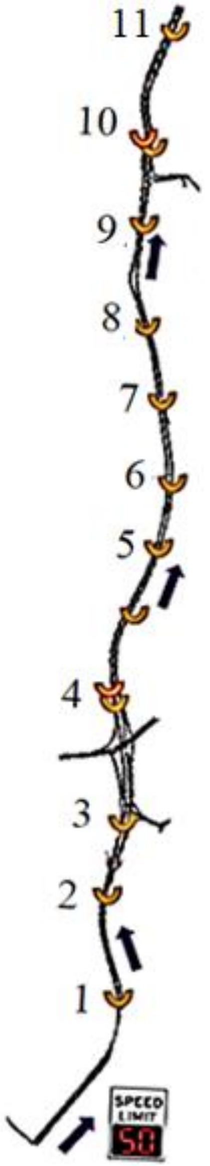
Case II: RM


Ramp metering α_i
0.50
0.25
8:30
8:40
8:50
9:00
9:10
9:20
9:30


5
Cranford
4
3
Leach Hwy
2
South ST
1
Farrington RD

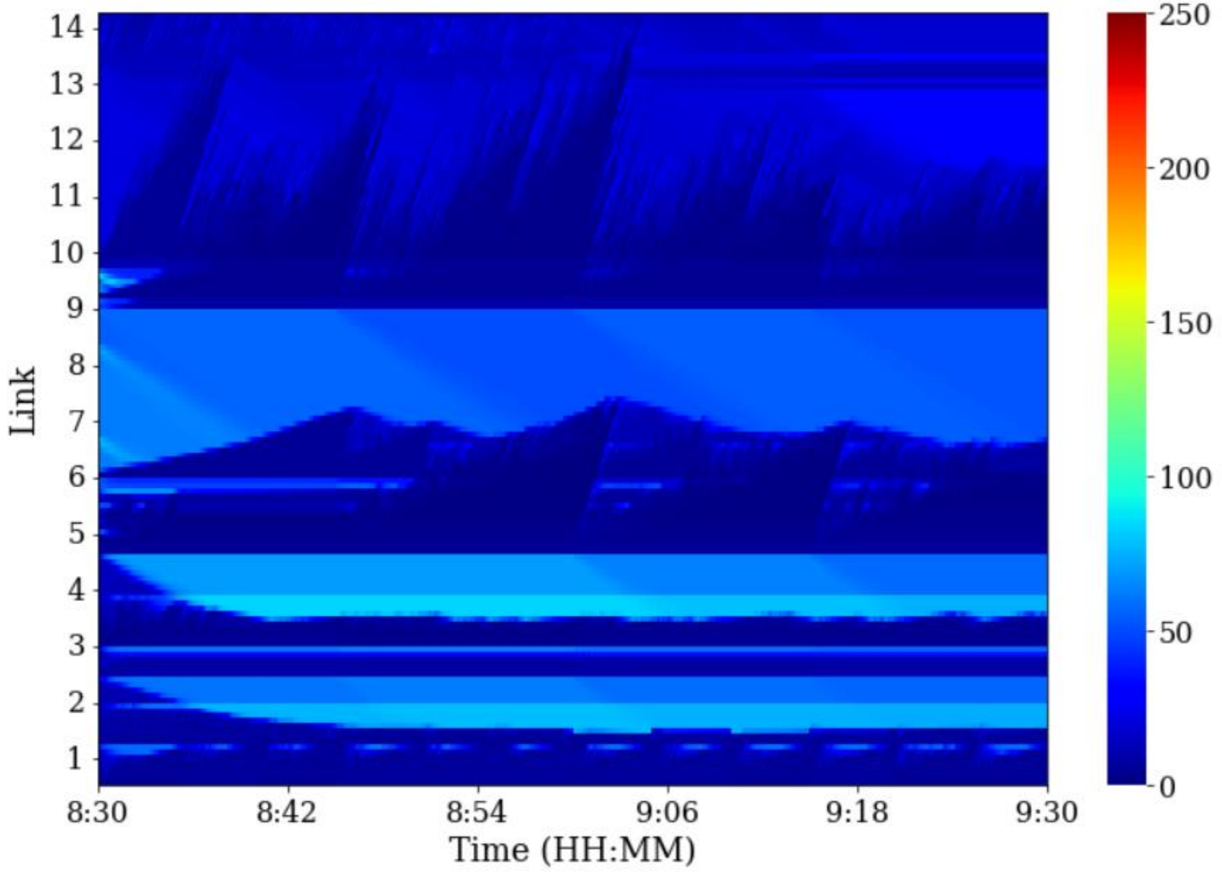
Case II: VSL


VSL (km/hr)
80
60
8:30
8:40
8:50
9:00
9:10
9:20
9:30

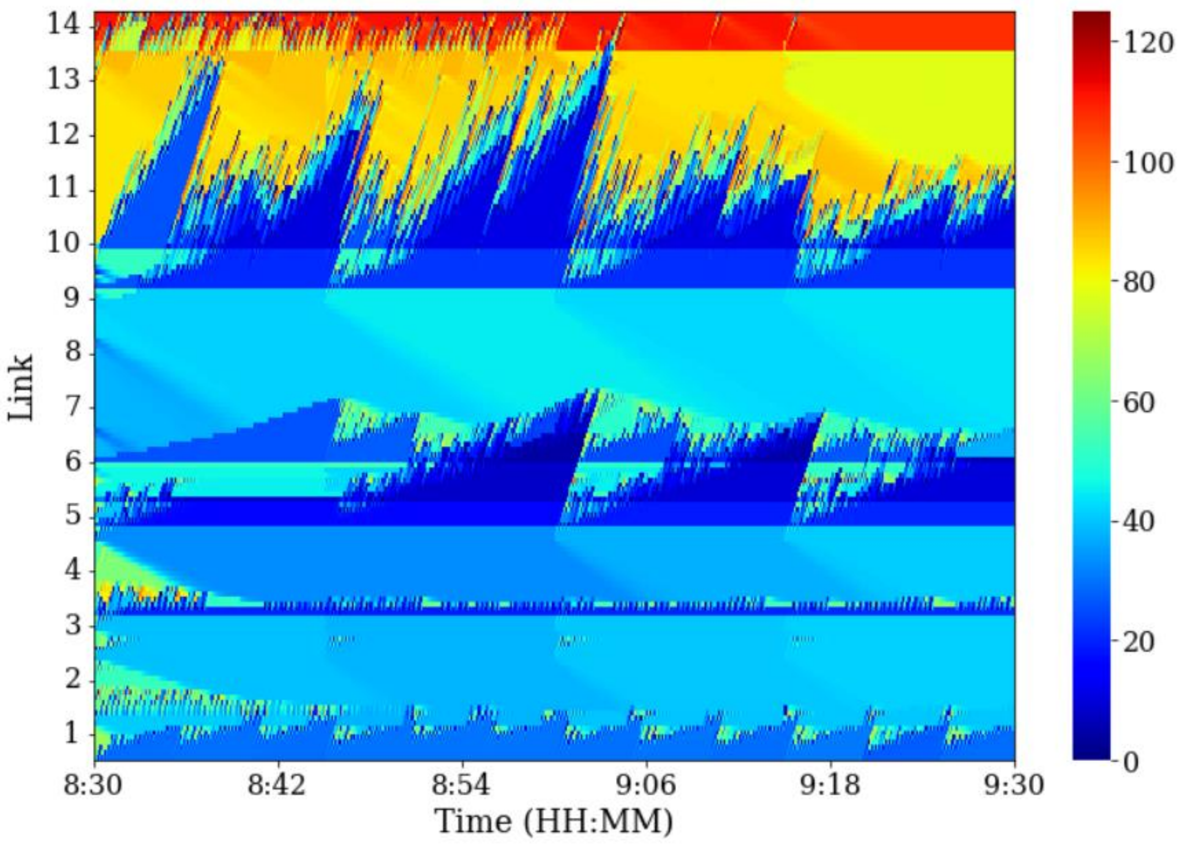

11
10
9
8
7
6
5
4
3
2
1
SPEED LIMIT
50

Case II: Density and Flow rate

Density (veh/km)



Flow rate (veh/min)



2. Control of ramp metering Using Deep Koopman model

PhD Student: C. Gu; Supervisors: YH Wu & B Wiwatanapataphee

Model design

Dynamic system:

$$
\begin{aligned}
x_{t+1} &= f(x_t, u_t), \\
x_t &= [o_{t,l_1}, \ldots, o_{t,l_L}, o_{t,m_M}, q_{t,j_1}, \ldots, q_{t,j_J}]^\top, \\
u_t &= [a_{t,n_1}, \ldots, a_{t,n_N}, d_{t,n_1}, \ldots, d_{t,n_N}, d_{t,m_1}]^\top, \quad (1)
\end{aligned}
$$

Optimization model:

$$
\begin{aligned}
\max_{u_t, t=0,\ldots,T-1} \mathrm{T} &= \sum_{t=0}^{T} v_t^\top x_t - \lambda \sum_{t=0}^{T-2} ||u_{t+1} - u_t||^2, \quad (2) \\
\text{s.t.} & \\
x_{t+1} &= f(x_t, u_t), t = 0, \ldots, T-1, \quad (3) \\
x_{min} \leq\ & x_t \leq x_{max}, t = 0, \ldots, T, \quad (4) \\
u_{min} \leq\ & u_t \leq u_{max}, t = 0, \ldots, T-1, \quad (5)
\end{aligned}
$$

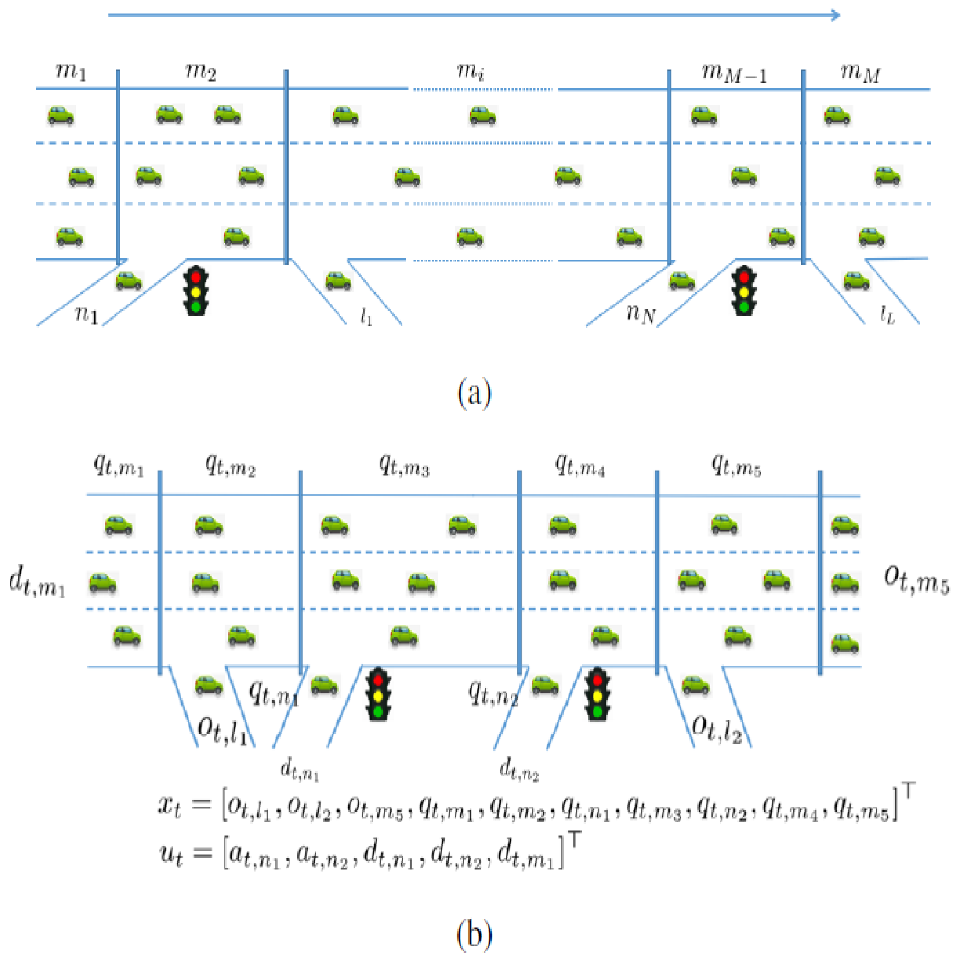


Fig. 1: Schematic diagram of ramp metering for a freeway (a) and an example of describing the state x_t and control u_t with ramp metering (b)

Deep Koopman model

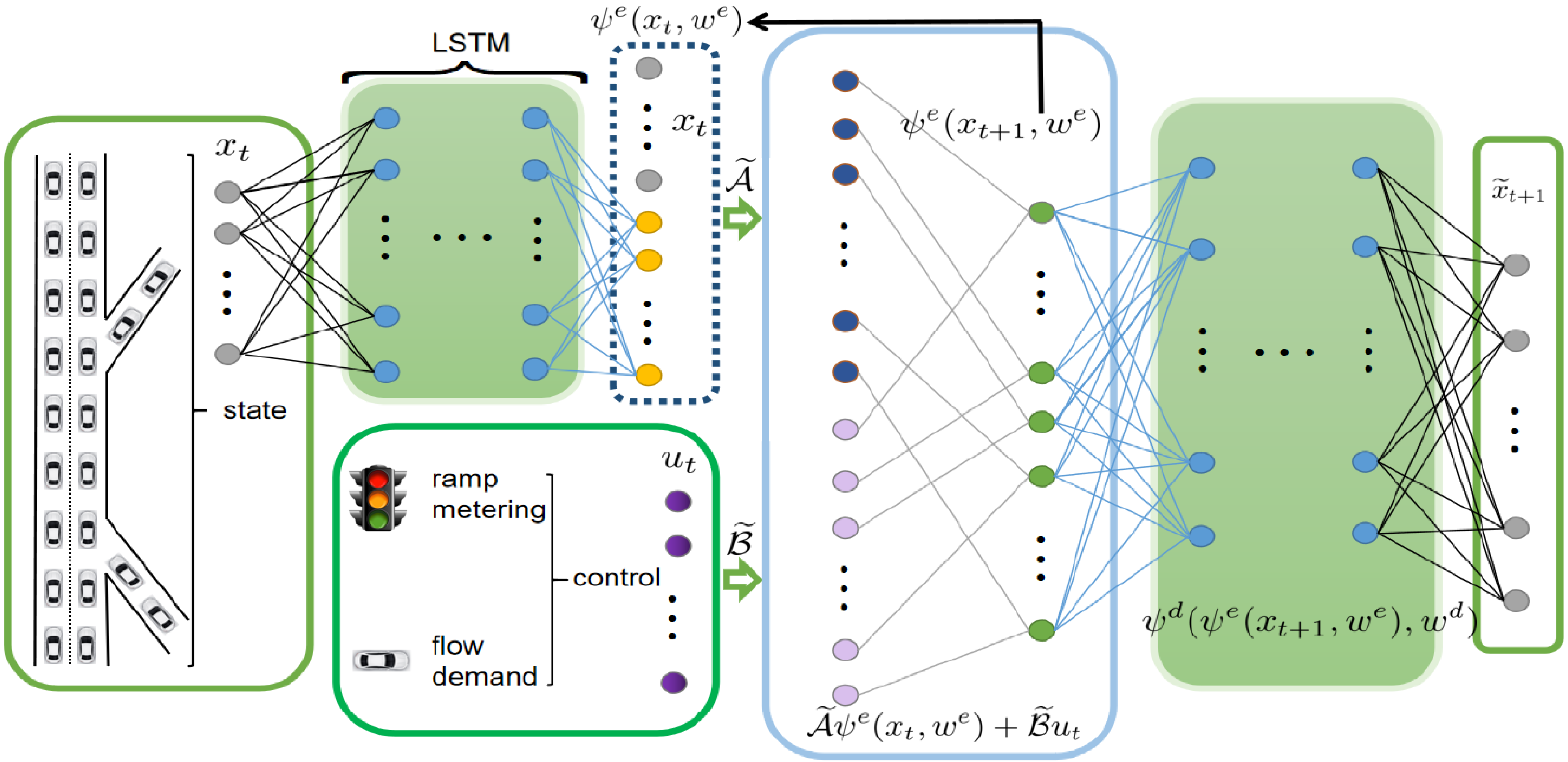


Fig. 2: The diagram of the proposed DKM. The original state x_t is lifted with the encoder, i.e.,$\psi^e(x_t, w^e)$. Then $\psi^e(x_t, w^e), u_t$ forms the lifted state for constructing the linear evolution in the vector-valued observables. The freeway traffic flow dynamics can be recovered via a decoder $\psi^d(\psi^e(x_{t+1}, w^e), w^d)$ from the vector-valued observables

$$x_{t+1} = f(x_t, u_t).$$

$$\begin{aligned} \psi^e(x_{t+1}) &= \widetilde{\mathcal{A}}\psi^e(x_t, w^e) + \widetilde{\mathcal{B}}u_t \\ \widetilde{x}_t &= \psi^d(\psi^e(x_t, w^e), w^d). \end{aligned}$$

Algorithm 2 The Deep Koopman Method (DKM)

Initialization: w^e, w^d, $\widetilde{\mathcal{A}}$, $\widetilde{\mathcal{B}}$, M. $Epoch = 0$, $Epoch_{max}$, $\alpha_i, i = 1, \ldots, 5$, batch size b_s, a small constant $\epsilon > 0$;
Train: trained w^e, w^d, $\widetilde{\mathcal{A}}$ and $\widetilde{\mathcal{B}}$;
while $Epoch > Epoch_{max}$ or $|L| \leq \epsilon$ **do**
    Reset the training episodes;
    while $Epoch$ is not Terminated **do**
        Sample a batch data sequences of state x and control u;
        Compute the vector-valued observables $\psi^e(x, w^e)$ with (18) and reconstruction states $\widetilde{x} = \psi^d(\psi^e(x, w^e), w^d)$ with (20);
        Calculate the multi-step vector-valued observables $\mathrm{A}^l\Phi(x_0, w^e, u_0)$ with (22) and predicted states $\widetilde{x}_l = \psi^d(\mathrm{A}^l\Phi(x_0, w^e, u_0), w^d)$, where $l = 1, 2, \ldots, M$;
        Compute the loss function L with (26);
        Update w^e, w^d, $\widetilde{\mathcal{A}}$ and $\widetilde{\mathcal{B}}$ via solving problem (26);
    end while
    $Epoch = Epoch + 1$
end while

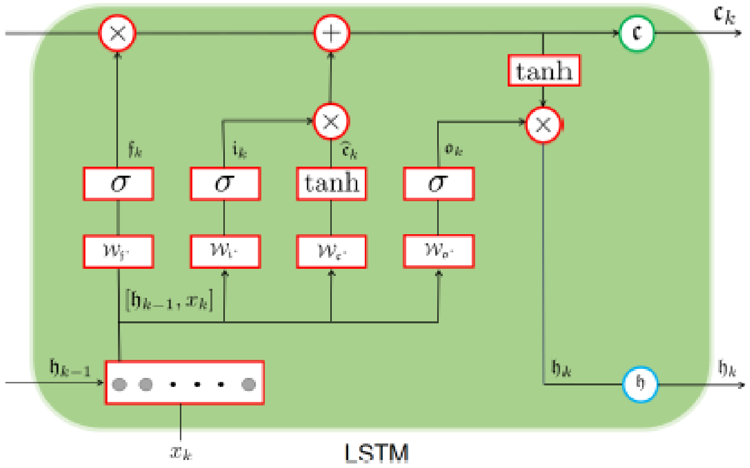


Fig. 3: The diagram of the LSTM

Algorithm 1 : Compute the output sequence of an LSTM network

Input: Sequence $x_1, x_2, \ldots, x_K$,
Output: Sequence $\mathfrak{h}_1, \mathfrak{h}_2, \ldots, \mathfrak{h}_K$,
Set $\mathfrak{h}_0 = 0$
Set $\mathfrak{c}_0 = 0$
for $k \leftarrow k$ to K do **do**
    $\mathfrak{f}_k = \sigma(\mathcal{W}_\mathfrak{f}[\mathfrak{h}_{k-1}, x_k] + \mathfrak{b}_\mathfrak{f})$
    $\mathfrak{i}_k = \sigma(\mathcal{W}_\mathfrak{i}[\mathfrak{h}_{k-1}, x_k] + \mathfrak{b}_\mathfrak{i})$
    $\widehat{\mathfrak{c}}_k = \tanh(\mathcal{W}_\mathfrak{c}[\mathfrak{h}_{k-1}, x_k] + \mathfrak{b}_\mathfrak{c})$
    $\mathfrak{c}_k = \mathfrak{f}_k \otimes \mathfrak{c}_{k-1} + \mathfrak{i}_k \otimes \widehat{\mathfrak{c}}_k$
    $\mathfrak{o}_k = \sigma(\mathcal{W}_\mathfrak{o}[\mathfrak{h}_{k-1}, x_k] + \mathfrak{b}_\mathfrak{o})$
    $\mathfrak{h}_k = \mathfrak{o}_k \otimes \tanh(\mathfrak{c}_{k-1})$
end for

Algorithm 3 : MPC-Deep-Koopman to compute the control sequence of Problem T

1: **for** $t = 0, 1, \ldots, T$ **do**
2: Let $z_0 = \psi^e(x_t, w^e)$;
3: Minimize Problem T to obtain an optimal solution U^*;
4: Let $u_t = U^*(1 : m)$;
5: Update $\widetilde{x}_{t+1}$ with system (28).
6: Obtain practical x_{t+1} with SUMO by implementing the control u_t.
7: **end for**

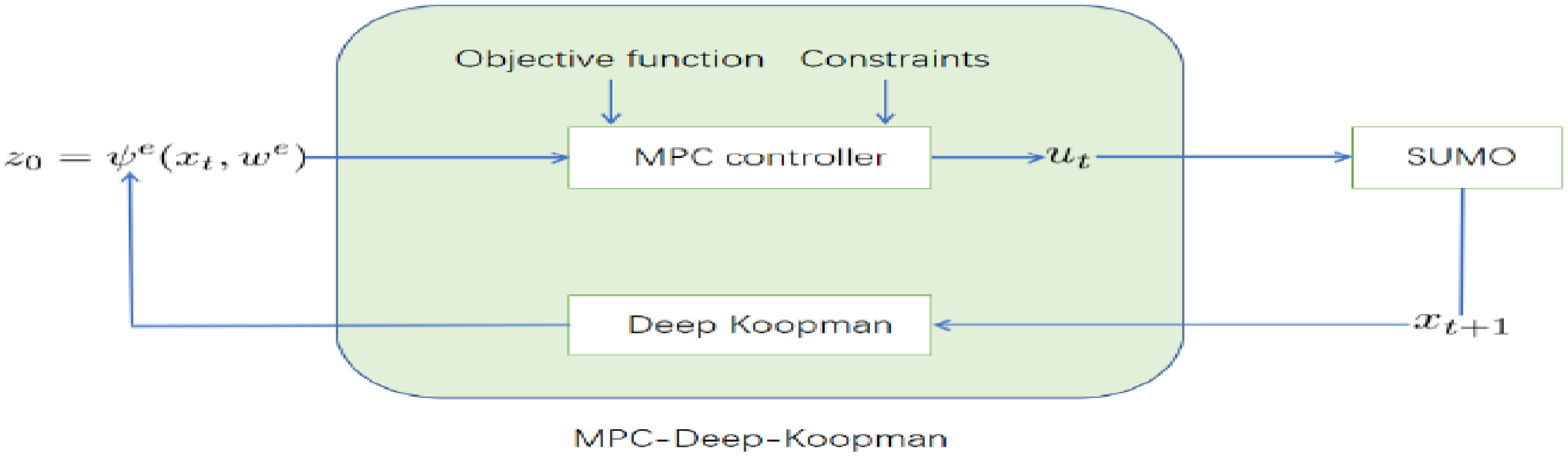
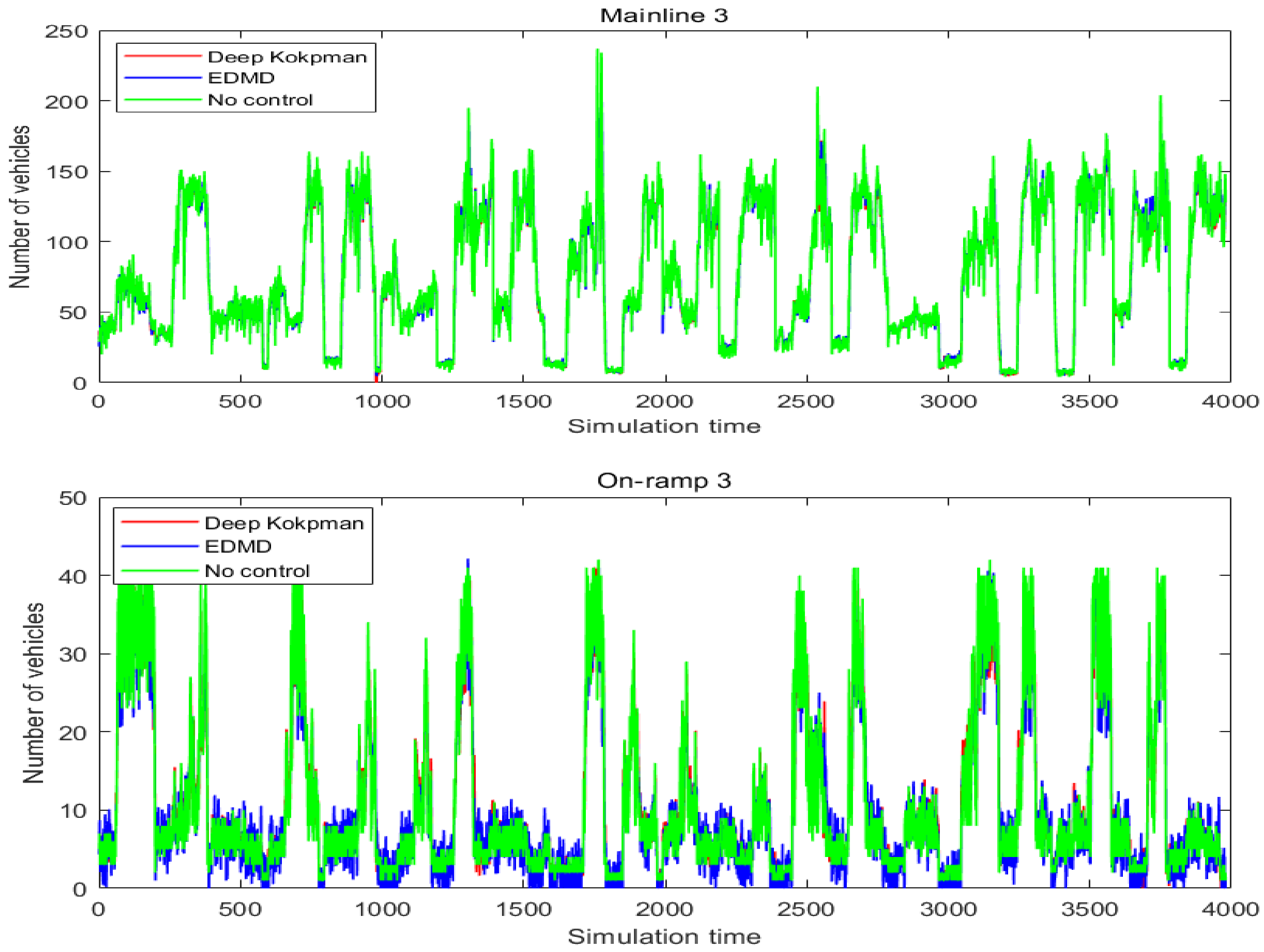
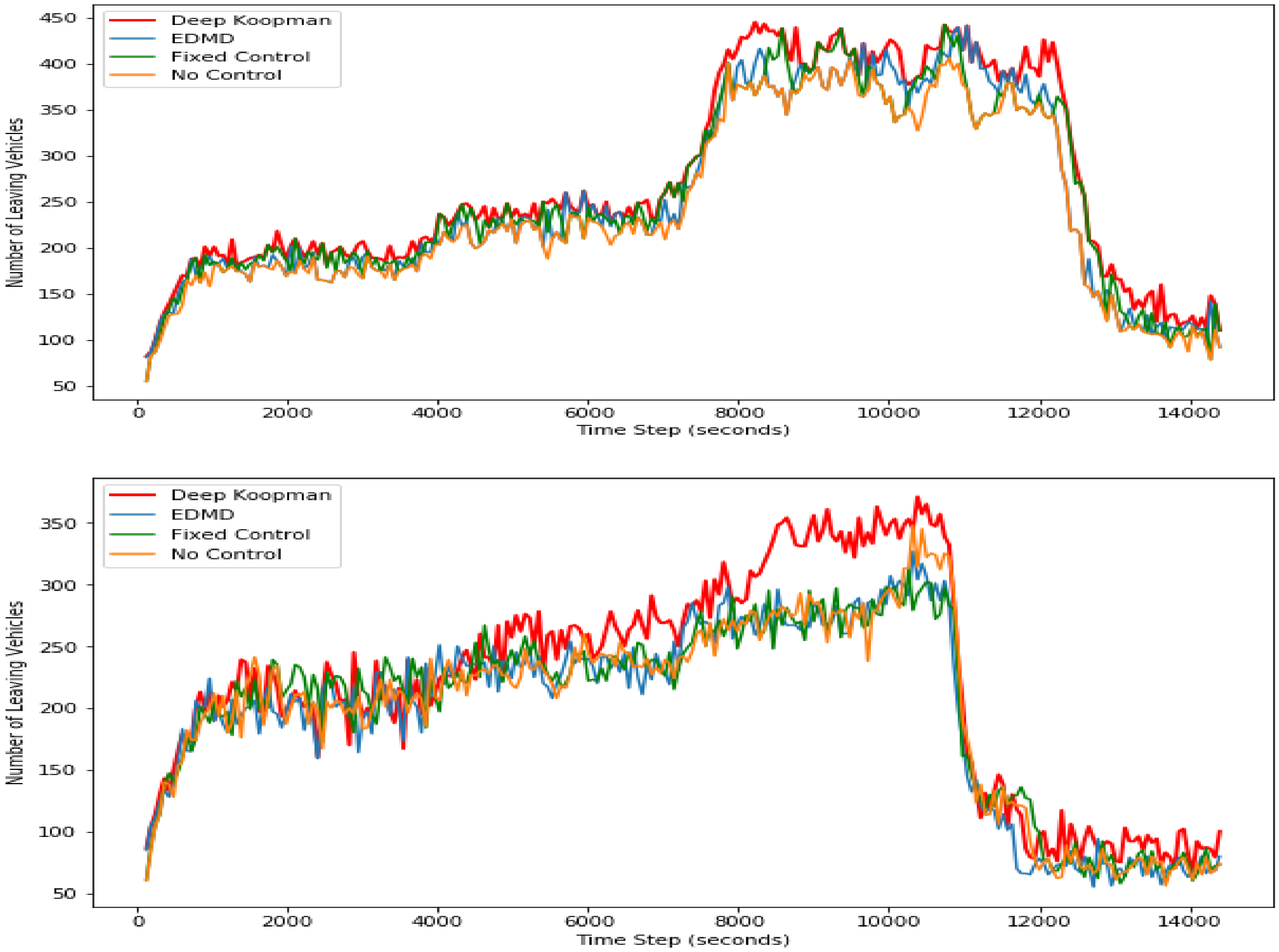


Fig. 4: The diagram of MPC-Deep-Koopman to compute the control sequence

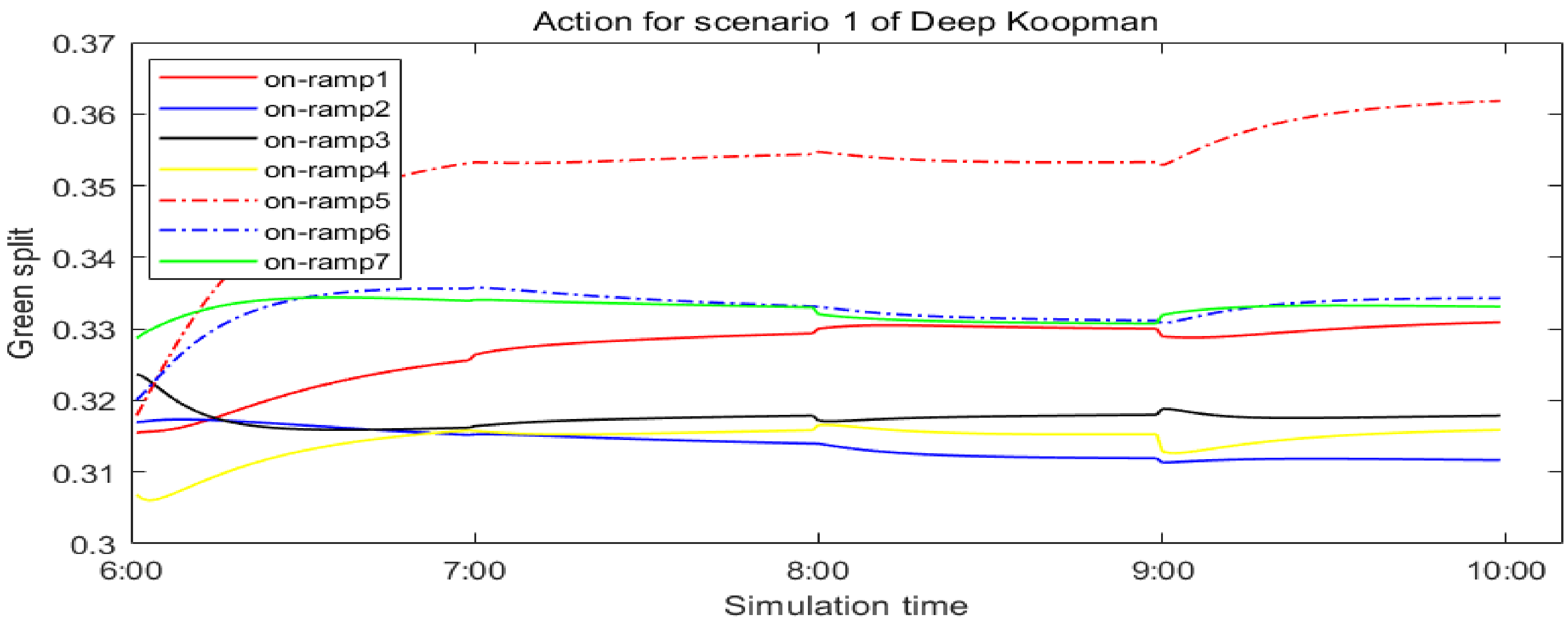
Result

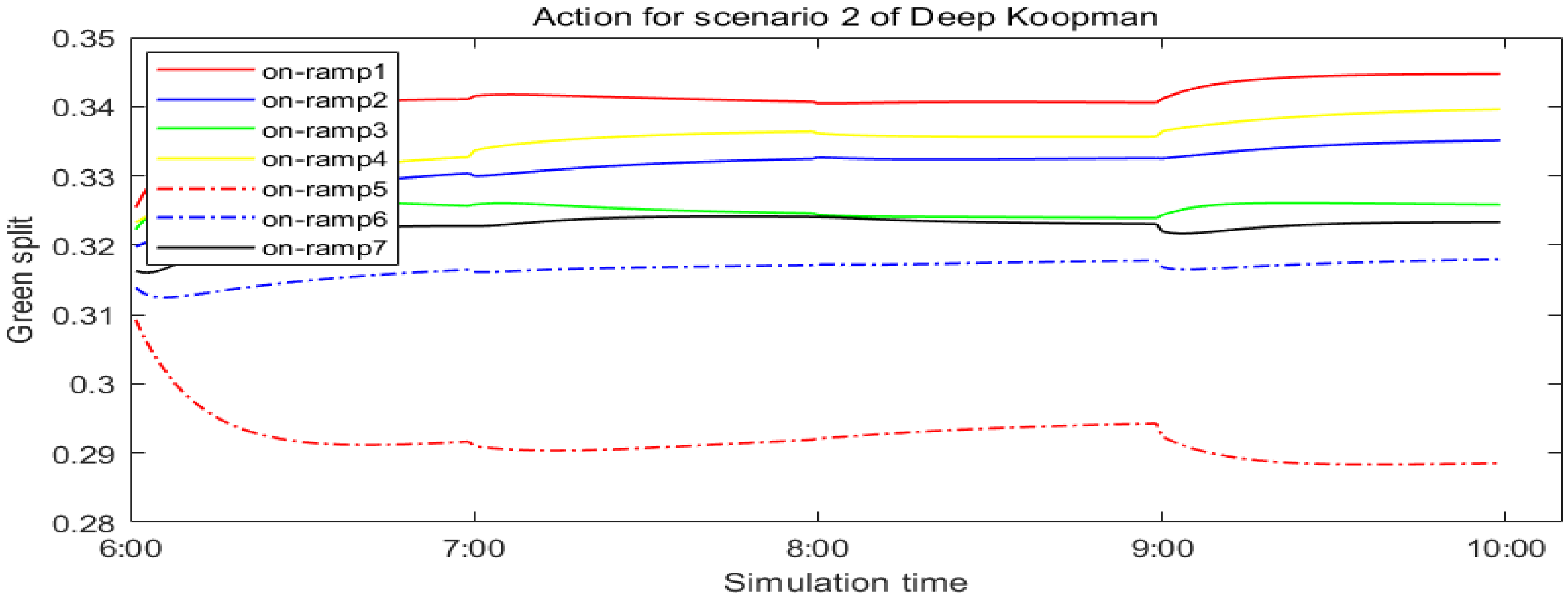


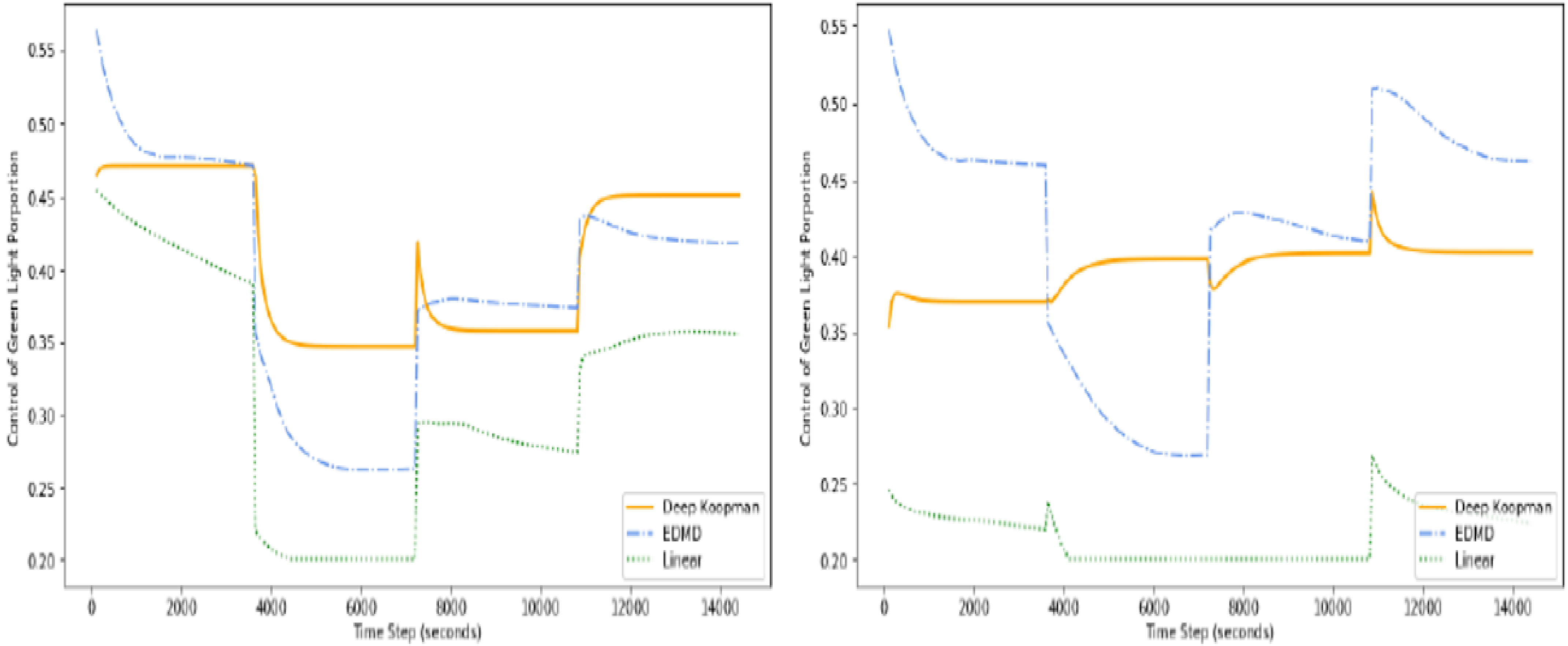
The Comparison of State Prediction between EDMD and the proposed Deep Koopman for Scenario 1



The Comparison of Number of Leaving Vehicles between baseline approaches and the proposed Deep Koopman Method


Action for scenario 1 of Deep Koopman
on-ramp1
on-ramp2
on-ramp3
on-ramp4
on-ramp5
on-ramp6
on-ramp7
Green split
0.37
0.36
0.35
0.34
0.33
0.32
0.31
0.3
6:00
7:00
8:00
9:00
10:00
Simulation time

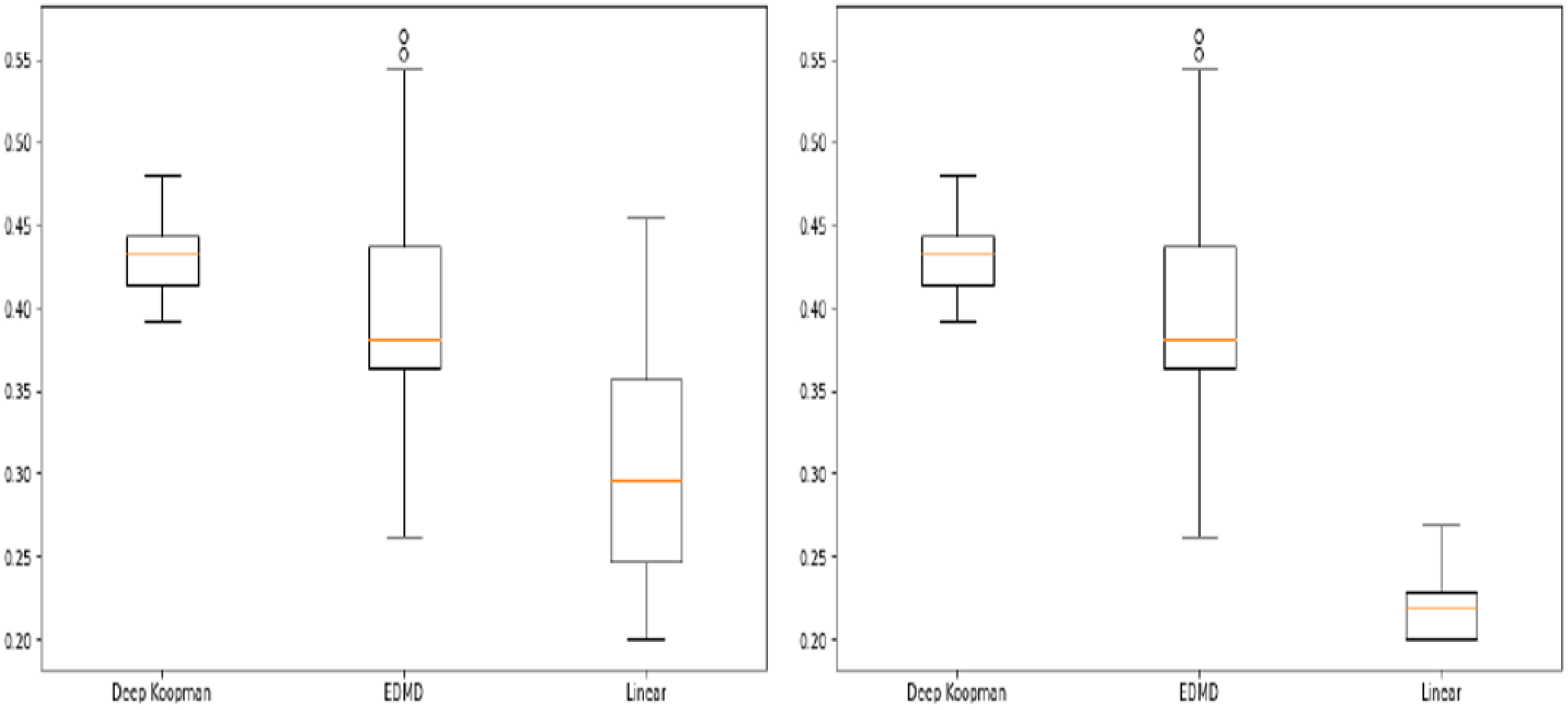

Action for scenario 2 of Deep Koopman
on-ramp1
on-ramp2
on-ramp3
on-ramp4
on-ramp5
on-ramp6
on-ramp7
Green split
0.35
0.34
0.33
0.32
0.31
0.3
0.29
0.28
6:00
7:00
8:00
9:00
10:00
Simulation time



(a) Scenario 1

(b) Scenario 3

The Comparison of Ramp Control for On-ramp No.1



(a) Scenario 1 (b) Scenario 3

The Comparison of Ramp Control Fluctuation for On Ramp No.1

Performance Comparison of Average Objectives (ATT: Average Travel Time, ToT: Total throughput, DoC: Deviation of Control)

Approach	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
	ATT	TTC	DCV	ATT	TTC	DCV	ATT	TTC	DCV	ATT	TTC	DCV
EDMD	1571.74	32613	0.20779	1514.45	30948	0.20336	1459.89	32674	0.2293	1370.05	32723	0.15006
Linear	1626.27	32290	0.28700	1554.33	32195	0.21649	1549.06	31057	0.32817	1433.83	31608	0.32998
Fixed Control	1810.53	29403	-	1774.38	28662	-	1763.53	30582	0	1640.8	31029	0
No Control	1893.01	27998	-	1829.19	27560	-	1792.48	28903	-	1696.09	29106	-
Deep Koopman	**1457.96**	**34333**	**0.09384**	**1433.62**	**33951**	**0.13973**	**1363.08**	**34267**	**0.15235**	**1295.33**	**34615**	**0.11362**

ACKNOWLEDGEMENTS

The project is funded by the Australian Research Council, Main Roads WA, and Roads and Maritime Services NSW.

Acknowledgement is made to the Australian Research Council, Main Roads WA, Roads and Maritime Services NSW, and the Australia's Sustainable Built Environment National Research Centre (SBEnrc) for their support.


THANK YOU
For Your Attention