

Optimization of Traffic Count Locations for Estimation of Travel Demands with **Covariance** between Origin-Destination Flows

-- published in Transportation Research Part C

FU Hao 付豪

Supervisor: Ir Prof. William H.K. Lam

Department of Civil and Environmental Engineering

The Hong Kong Polytechnic University

Fu, H., Lam, W.H.K., Shao, H., Xu, X.P., Lo, H.P., Chen, B.Y., Sze, N.N., Sumalee, A., 2019. Optimization of traffic count locations for estimation of travel demands with covariance between origin-destination flows. Transportation Research Part C: Emerging Technologies 108, 49–73.



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Outline

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● Model Formulation

● Solution Algorithm

● Numerical Examples

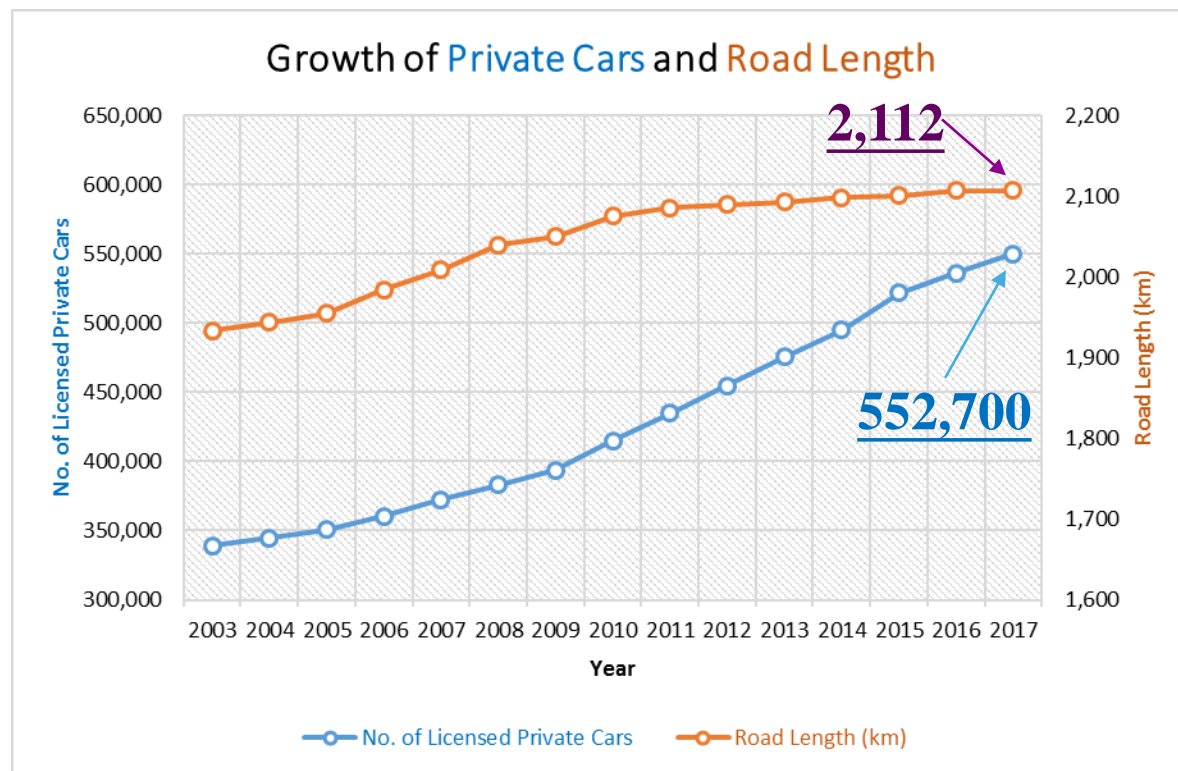
● Conclusions and Further Studies

Introduction – Hong Kong Statistics

- ❖ Population: 7.48 million
- ❖ Total area: 1,111 km²
(24% land developed)
- ❖ Population density:
 - 6,732 persons/km² (Total land average)
 - **28,050 persons/km²** (Developed land average) **Taipei: 9,950; Tokyo: 6,220; Bangkok: 5,300; Calgary: 1,833**
 - 55,000 persons/km² (Highest district)
- ❖ **Road length = 2,123 km**
- ❖ **No. of licensed vehicles = 784,400**
(as at December 2018)
- ❖ **565,200 private cars out of 784,400 licensed vehicles** in Hong Kong as at December 2018



Traffic Congestion in Hong Kong



No. of private cars: increased **> 60%** over the past 15 years

Road length: increased **< 10%** over the past 15 years

As a result, traffic density is increasing and average private car occupancy for private cars is also increasing.

Introduction – Vehicle Classification and Occupancy

**Hong Kong
External Cordon**
(Boundary between
the Northern Part
and Southern Part of
Hong Kong Island)



Time		Class of vehicle									
		Motor Cycle	Private Car	Taxi	Private LB	PLB	Goods veh.		Non-Fr. Bus	Fr. Bus	
							Light	Med./Heavy		SD	DD
0700-0800	Pro	5.1	42.8	20.1	2.5	1.1	15.4	4.5	3.2	0.0	5.3
	Ocp	1.0	1.3	2.2	6.5	14.6	1.5	1.3	17.7	0.0	62.4
0800-0900	Pro	4.5	56.0	12.6	0.7	0.8	13.0	3.6	3.2	0.1	5.6
	Ocp	1.0	1.3	2.1	5.7	12.4	1.6	1.5	30.6	44.0	70.4
0900-1000	Pro	3.0	44.9	16.1	0.3	0.6	24.2	4.3	1.8	0.0	4.9
	Ocp	1.1	1.3	2.3	4.1	13.6	1.7	1.5	14.7	0.0	39.3
1000-1100	Pro	2.9	45.5	17.0	0.6	0.4	23.4	4.5	1.8	0.1	3.8
	Ocp	1.0	1.4	2.2	1.6	12.0	1.5	1.4	13.4	3.5	32.9
1100-1200	Pro	2.1	44.5	18.0	0.4	0.3	24.6	3.9	2.5	0.1	3.7
	Ocp	1.1	1.4	2.3	1.7	15.2	1.5	1.3	17.8	1.0	34.9
1200-1300	Pro	2.1	45.9	16.2	1.1	0.5	24.9	3.9	2.1	0.1	3.3
	Ocp	1.1	1.4	2.3	4.6	9.4	1.4	1.3	17.7	1.0	35.5
1300-1400	Pro	2.3	43.5	17.6	0.9	0.4	22.3	6.7	2.7	0.0	3.6
	Ocp	1.1	1.4	2.3	5.2	10.3	1.5	1.4	15.9	0.0	38.3
1400-1500	Pro	2.8	44.8	17.9	0.8	0.3	23.7	4.4	1.9	0.0	3.4
	Ocp	1.1	1.5	2.4	2.1	13.0	1.5	1.3	14.6	0.0	38.6
1500-1600	Pro	2.4	49.1	15.5	1.5	0.3	21.3	4.5	2.0	0.0	3.3
	Ocp	1.1	1.5	2.3	6.3	14.7	1.5	1.3	16.3	0.0	39.8
1600-1700	Pro	3.0	45.1	16.1	1.6	0.5	23.4	3.5	2.8	0.1	4.1
	Ocp	1.1	1.5	2.3	3.6	12.1	1.5	1.2	9.7	1.0	41.0
1700-1800	Pro	4.9	56.3	12.3	0.6	0.6	15.9	1.5	3.3	0.1	4.5
	Ocp	1.1	1.4	2.3	2.5	13.5	1.6	1.4	19.3	24.0	53.4
1800-1900	Pro	5.9	61.7	12.1	0.3	0.9	9.8	1.2	3.4	0.1	4.7
	Ocp	1.1	1.3	2.4	2.1	15.7	1.4	1.3	28.1	1.0	72.3
1900-2000	Pro	3.4	62.6	16.3	0.1	1.0	6.6	1.4	3.3	0.1	5.3
	Ocp	1.1	1.3	2.3	1.2	14.6	1.4	1.4	16.2	22.0	53.6
2000-2100	Pro	2.7	57.8	23.4	0.1	1.3	6.1	1.3	1.8	0.0	5.6
	Ocp	1.1	1.4	2.4	1.0	11.5	1.4	1.4	13.0	0.0	43.0
2100-2200	Pro	2.7	52.2	31.8	0.1	1.4	4.5	1.3	1.1	0.0	4.9
	Ocp	1.1	1.4	2.2	2.5	9.5	1.4	1.3	13.0	0.0	44.6
2200-2300	Pro	2.8	52.9	32.6	0.1	1.4	3.9	0.8	0.9	0.0	4.6
	Ocp	1.1	1.4	2.3	2.2	12.2	1.5	1.4	12.9	0.0	46.9
16 hours	Pro	3.4	50.4	17.8	0.7	0.7	16.9	3.3	2.4	0.1	4.4
	Ocp	1.1	1.4	2.3	4.5	12.8	1.5	1.4	18.4	11.3	48.8

Legend

Pro. Proportion of vehicles in % (Sum may not add up to 100% due to figure rounding)

Ocp. Average occupancy of vehicles

AM Peak Hour

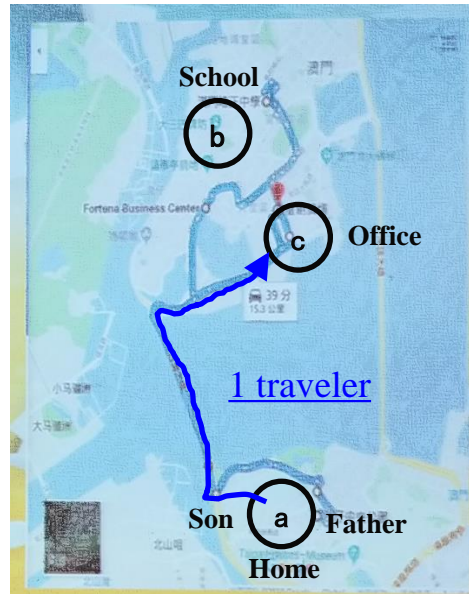
Average private car occupancy for private cars is 1.4;

Evidence of ride sharing

Introduction – Illustration Example

OD: (a-c)

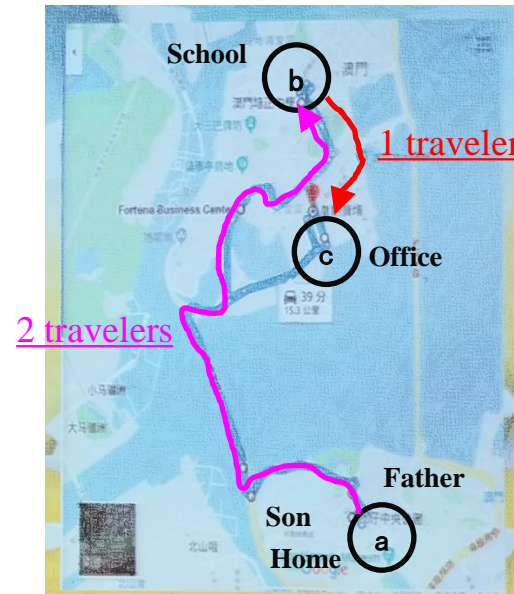
The father drives to office directly, and the son goes to school by bus.



(a) No Ridesharing mode

OD: (a-b)
(b-c)

The father and son travel from home to school together, and then the father travels from school to office alone.



(b) Ridesharing mode

In the case of “No Ridesharing mode”, we assume that all OD demands follow an independent normal distribution:

$$OD(a-c) \sim N(200, 30^2)$$

$$OD(a-b) \sim N(150, 36^2)$$

$$OD(b-c) \sim N(100, 25^2)$$

Total OD demands: **450**

Effect of Ridesharing on the OD demand covariance and average vehicle occupancy

Proportion of travelers using ridesharing	Covariance ($a-b$, $b-c$)	Average vehicle occupancy
0.0%	0.0	1.00
17.8%	28.5	1.19
50.0%	225.0	1.80
100.0%	900.0	2.25

Average vehicle occupancy: average number of people in a vehicle, including the driver

Introduction – Traffic Flow Variations

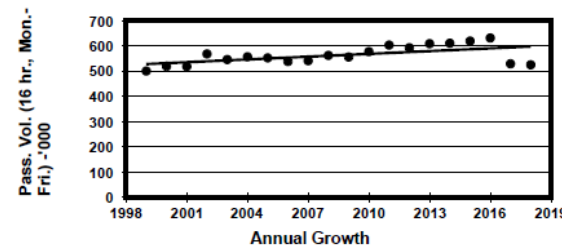
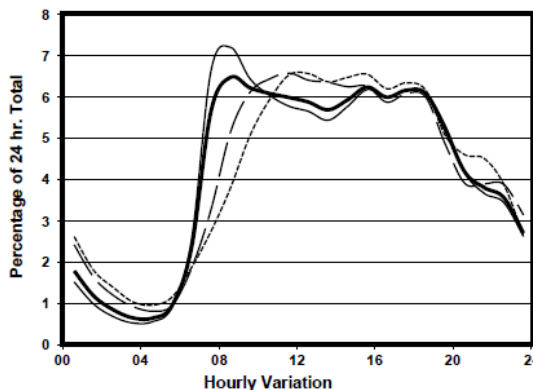
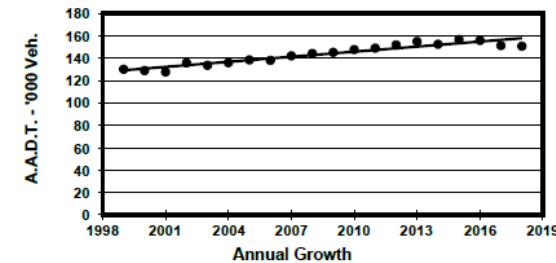
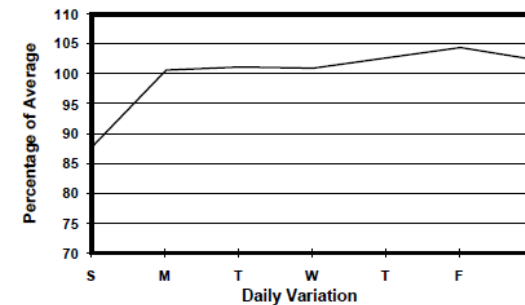
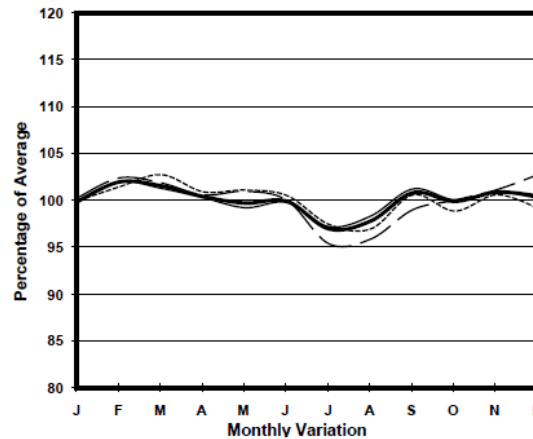
111 core
stations* in
ATC 2018

YEAR 2018
Location Hong Kong External Cordon (Boundary between the Northern Part and Southern Part of Hong Kong Island)
Stations on Cordon/Screenline 1004, 1021, 2201, 2202, 2206, 2401 and 2407



Video detector data Loop detector data

1. TRAFFIC FLOW VARIATION AND GROWTH



— All day — Mon.-Fri. - - - Sat. - - - - Sun.

Day to day

Year to year



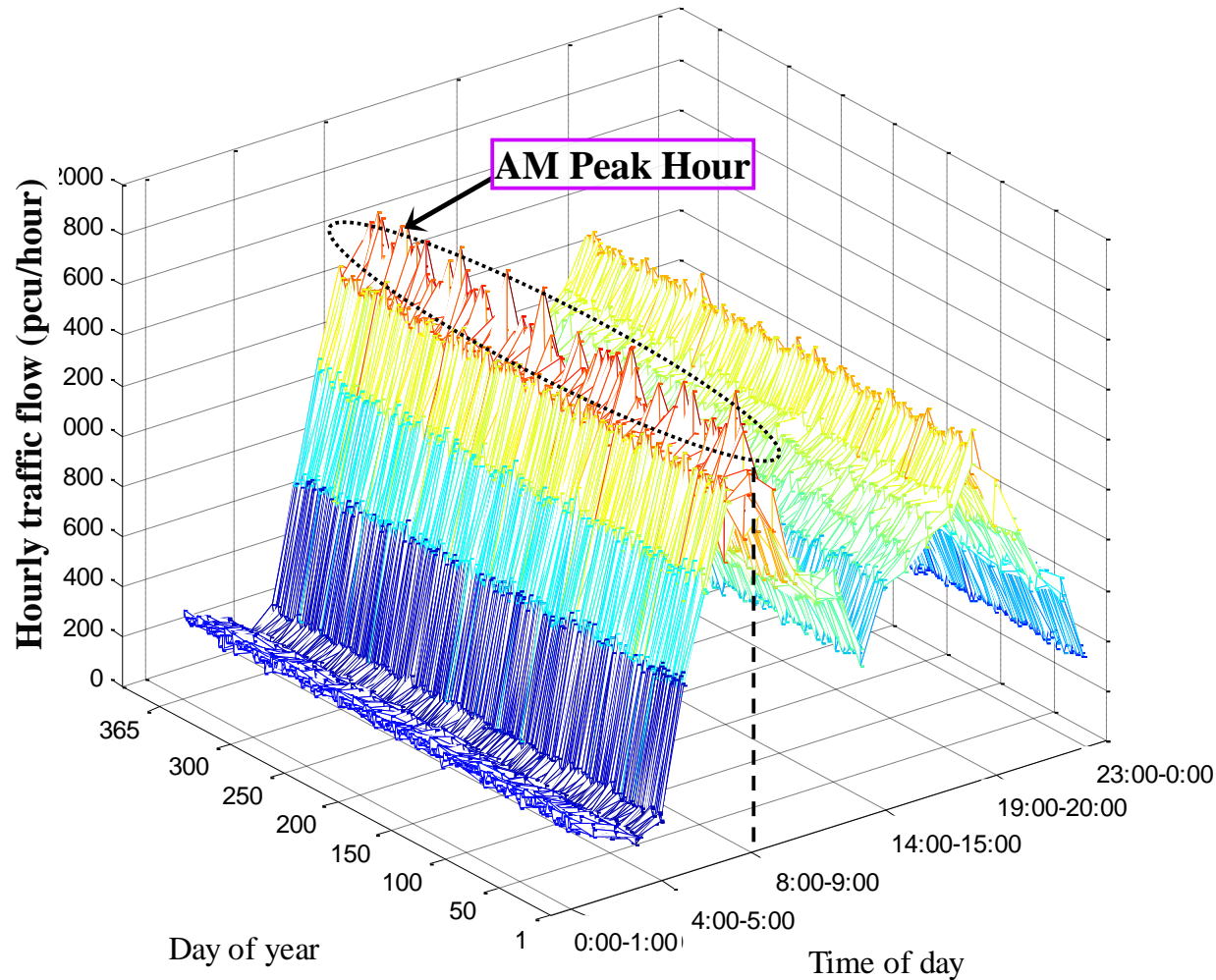
Month to month

Hour to hour

*Core station is a randomly selected count station providing hourly, daily, monthly factors to generalize the traffic characteristics for its own group of links

Introduction

– Hourly Origin-Destination Demands under Uncertainty



Introduction – Contributions

❖ Theoretical development:

- Propose a **new criterion** for measuring the estimation accuracy of OD demand covariance in stochastic road networks under uncertainty.
- Introduce a **new model formulation** for investigating how to optimize the traffic count locations for minimizing the weighted maximum deviation of estimated mean and covariance of OD demands from the observed values together with their mathematical properties.

❖ Methodology development:

- Adopt a weighted-sum objective by considering the effect of mean and covariance OD demand on the traffic count locations.
- Propose the solution algorithm for solving the **bi-criteria and/or bi-objective** optimization problems.
- Link choice proportions are regarded as stochastic variables and updated by an adapted traffic flow simulator in this study.

Model Formulation – Assumptions

- ❖ **A1.** It is assumed that all the observed link traffic counts are error free (Yang et al., 1991; Yang and Zhou, 1998) .
- ❖ **A2.** The **covariance** of traffic demand between each OD pair is **positive**. Note that the latent demand could not be observed on the basis of traffic counts in practice. As the OD demand is estimated by actual traffic counts in this study, the traffic counts should then be positive. As a result, the covariance between OD flows should also be **positive** always.
- ❖ **A3.** It is assumed that there is only one traffic sensor allocated at each selected count location.

Model Formulation

– Sample mean and sample covariance of observed link traffic flows

The sample mean of observed AM Peak hourly link flows vector (\mathbf{v}) over h days can be calculated as:

$$\mathbf{v} = (\cdots, v_a, \cdots)^T = \frac{1}{h} \sum_{l=1}^h \mathbf{v}^{(l)}$$

Sample size h , say 300 weekdays

The sample covariance matrix of observed AM Peak hourly link flows (Σ^v) over h days can be calculated as:

$$\Sigma^v = \left\{ \sigma_{a,b}^v \right\}_{\tilde{m} \times \tilde{m}} = \frac{1}{h-1} \sum_{l=1}^h \left\{ \left(\mathbf{v}^{(l)} - \mathbf{v} \right) \left(\mathbf{v}^{(l)} - \mathbf{v} \right)^T \right\}$$

where $\sigma_{a,b}^v$ is the sample covariance between observed traffic flows V_a and V_b (random variables), $a, b \in \tilde{\mathbf{A}}$.

Model Formulation

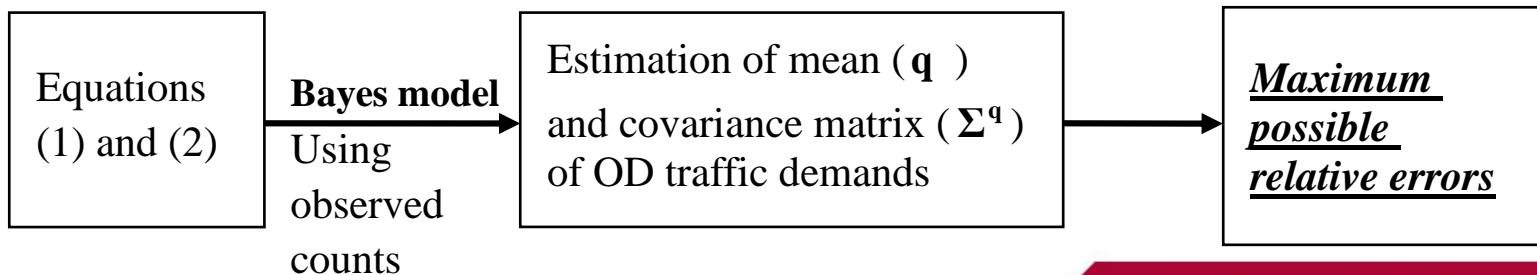
– Relationship between observed traffic counts and estimated **mean** and **covariance** of OD demand

The mean of observed link flow (v_a) can be obtained by following Equation (1) that:

$$v_a = E \left[\sum_{w \in W} p_{a,w} Q_w \right] = \sum_{w \in W} p_{a,w} q_w \quad \forall a \in \tilde{\mathbf{A}} \quad \text{matrix form} \rightarrow \mathbf{v} = \tilde{\mathbf{P}} \mathbf{q} \quad (1)$$

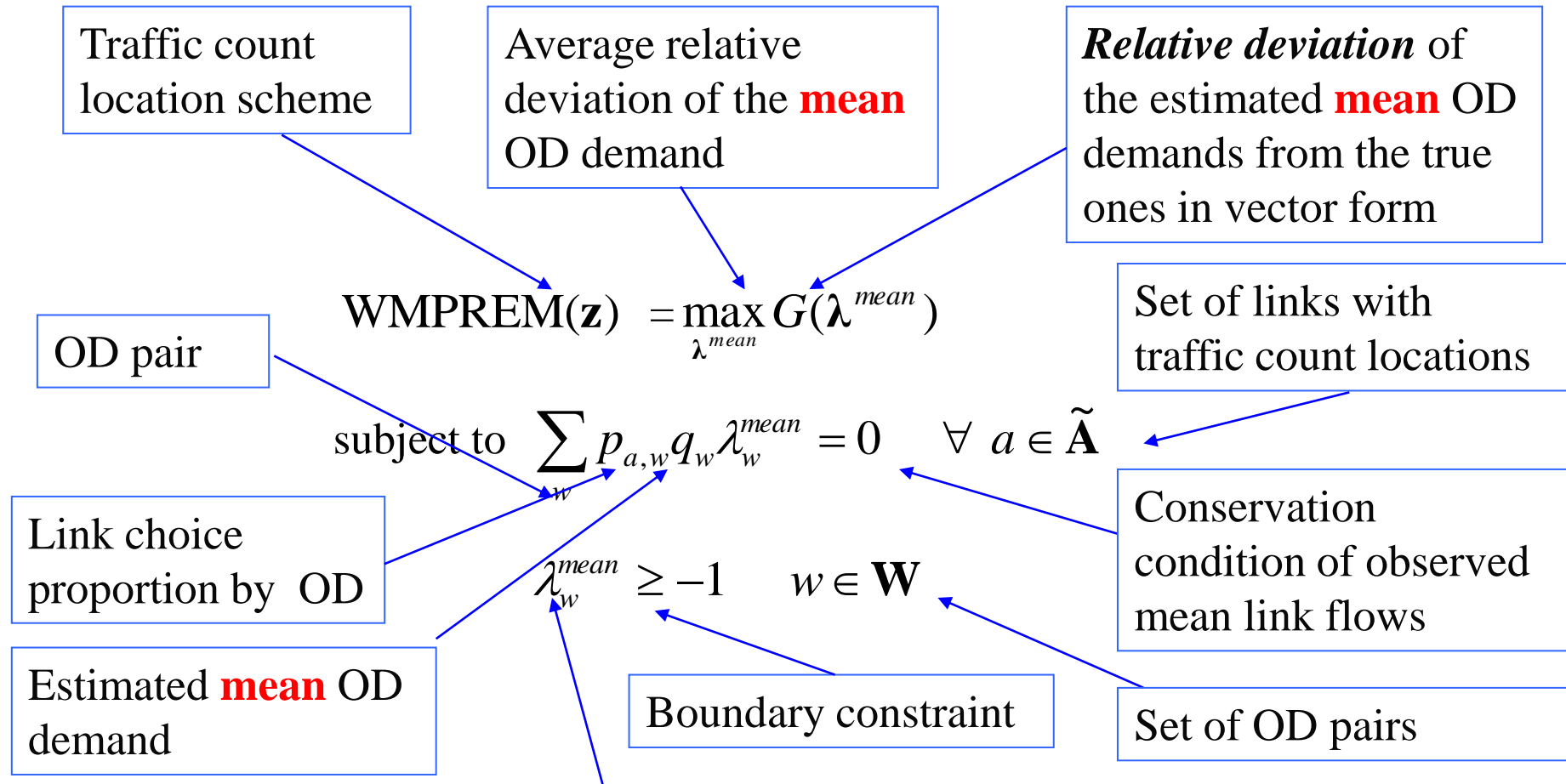
The covariance between stochastic link flow V_a and V_b can be deduced as:

$$\sigma_{a,b}^v = \text{cov}[V_a, V_b] = \sum_{w \in W} \sum_{w' \in W} p_{a,w} p_{b,w'} \sigma_{w,w'}^q \quad \forall a, b \in \tilde{\mathbf{A}} \quad \text{matrix form} \rightarrow \Sigma^v = \tilde{\mathbf{P}} \Sigma^q \tilde{\mathbf{P}}^T \quad (2)$$



Model Formulation – WMPREM (Yang et al. 1991)

Weighted *Maximum possible relative error* for the **mean** OD demand (WMPREM)

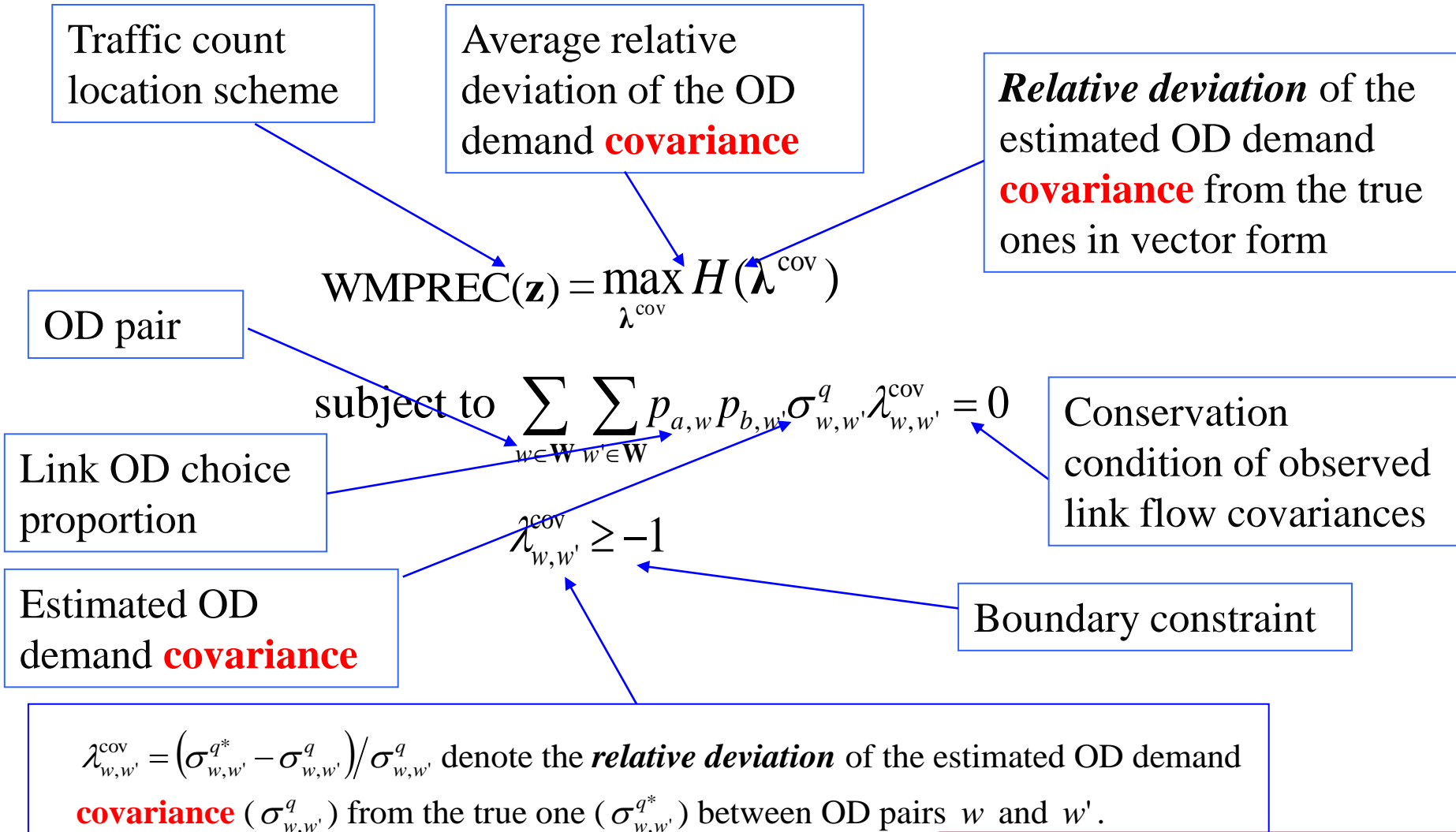


$\lambda_w^{\text{mean}} = (q_w^* - q_w) / q_w$ denote the *relative deviation* of the estimated **mean** OD demand (q_w) from the true one (q_w^*) for OD pair $w \in \mathbf{W}$, q_w^* is the true **mean** (or actual average) OD demand for OD pair $w \in \mathbf{W}$

$$G(\lambda^{\text{mean}}) = \sqrt{\sum_w \rho_w (\lambda_w^{\text{mean}})^2 / n} \text{ where } \rho_w = q_w / \sum_w q_w,$$

Model Formulation – WMPREC (This Study)

Weighted Maximum possible relative error for the **covariance** OD demand (**WMPREC**)



$$H(\lambda^{\text{cov}}) = \sqrt{\sum_w \sum_{w'} \rho_{w,w'} (\lambda^{\text{cov}})^2 / n^2} \text{ where } \rho_{w,w'} = \sigma_{w,w'} / \sum_w \sum_{w'} \sigma_{w,w'}$$

Model Formulation – Properties of WMPREC

Property 1: If \tilde{P} is a matrix with full column rank, i.e., $rank(\tilde{P}) = \text{the number of column of } \tilde{P}$, Σ^q must be **uniquely** identified when the number of sensors is greater than or equal to the number of OD pairs

Property 2: The WMPREM ($G(\lambda^{mean})$) and WMPREC ($H(\lambda^{cov})$) are both finite if and only if the OD Covering Rule is satisfied.

OD Covering Rule: the traffic count locations should be allocated on the network so that the traffic flows (or vehicles/hour) between **any OD pair** can be observed.

Model Formulation – Optimal traffic count location model (bi-objective model)

Traffic count location scheme

$$\min \begin{cases} O_1 = \text{WMPREM}(\mathbf{z}) \\ O_2 = \text{WMPREC}(\mathbf{z}) \end{cases} \quad \text{Objective Function}$$

s.t.

$$\sum_{a=1}^m \delta_{w,a} z_a \geq 1 \quad \forall w \in \mathbf{W} \quad \text{OD covering rule}$$

Constraints

Denote $\tilde{\mathbf{P}}$ as the sub-matrix of OD-link choice proportion matrix \mathbf{P} with the element $p_{a,w}$, $a \in \tilde{\mathbf{A}}$
 $\text{rank}(\tilde{\mathbf{P}}) = \tilde{m}$ link independence rule

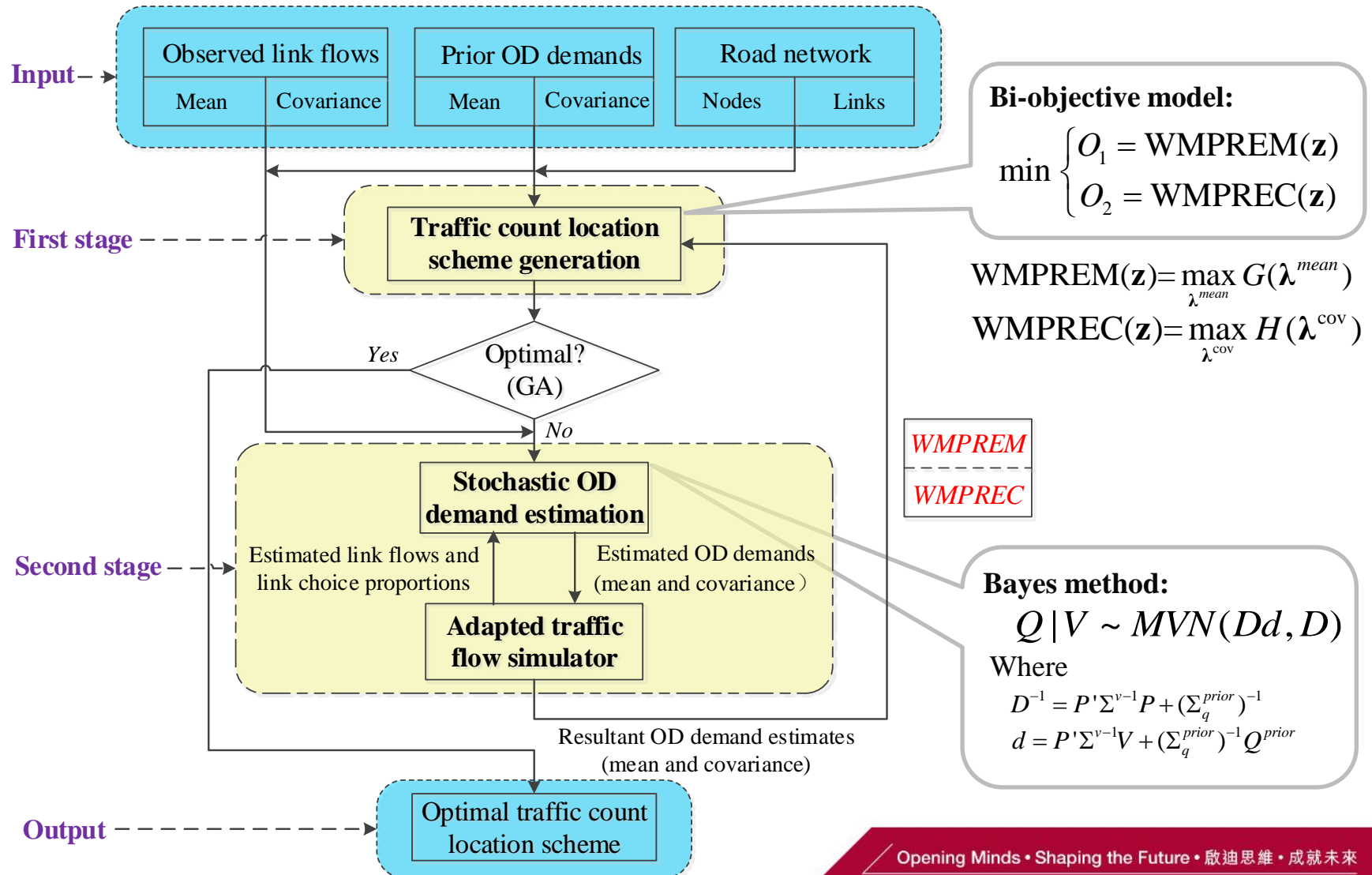
Denote \tilde{m} as number of observed links

$\Pr(V_a > \bar{v}) \geq p^0 \quad \forall a \in \tilde{\mathbf{A}}$ maximal probability of flow intercepting rule
 V_a is the estimated link flow, \bar{v} is a given threshold, p^0 is a given probability. e.g. $p^0 = 70\%$.

$$\sum_{a \in \mathbf{A}} c_a z_a \leq B \quad \text{budget constraint}$$

where c_a is the cost for installing and maintaining one sensor on link a and B is the budget.

Problem Statement and Model Formulation



Solution Algorithm

- ❖ Since the integer linear programming problem is NP-hard, the proposed model is intractable and so heuristic solution algorithm is used in this study.
- ❖ For example,
 - Firefly Algorithm (FA) (used in this study)
 - Genetic Algorithm (GA)
 - Branch and bound method
 - Backtracking method
 - Tabu search algorithm
 - etc.

Solution Algorithm – Fitness Function

Firefly Algorithm (FA)

- Weighted-sum approach

$$\min_{\mathbf{z}} \text{WMPRE}(\mathbf{z}) = \alpha \cdot \text{WMPREC}(\mathbf{z}) + (1 - \alpha) \cdot \text{WMPREM}(\mathbf{z})$$

where $0 \leq \alpha \leq 1$ is the weight of the WMPREC and $(1 - \alpha)$ is the weight of WMPREM

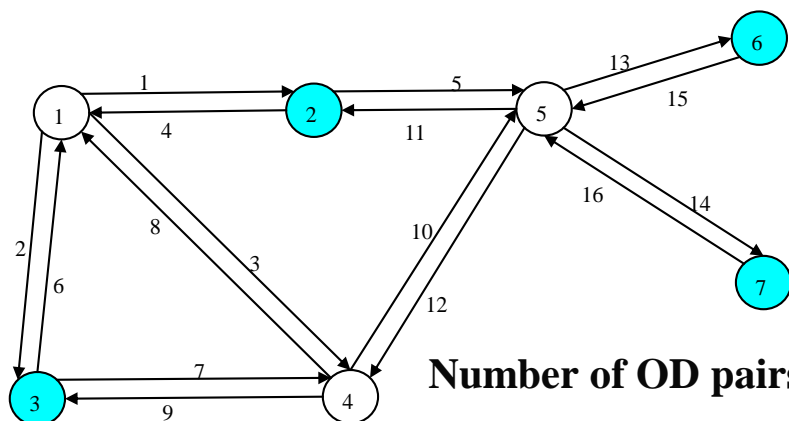
- Bi-objective approach

$$\min \begin{cases} O_1 = \text{WMPREM}(\mathbf{z}) \\ O_2 = \text{WMPREC}(\mathbf{z}) \end{cases}$$

As for our bi-objective problem, the solution is **non-dominated (Pareto optimal)**. In each iteration, the non-dominated solutions but **not a unique optimal solution** will be determined. The population in the next iteration will be generated based on the non-dominated solutions.

In the following numerical examples, only the results of the weighted-sum approach will be presented to illustrate the key findings.

Example 1 – Small Road Network



Number of OD pairs: 12

Number of links: 16

Table 1 The network parameters

OD number	Origin-Destination	Routes	Prior mean OD demands
1	2-3	4-2; 4-3-9	168
2	2-6	4-3-10-13; 5-13	240
3	2-7	4-3-10-14; 5-14	96
4	3-2	6-1; 7-8-1; 7-10-11	208
5	3-6	6-1-5-13; 6-3-10-13; 7-10-13	224
6	3-7	6-1-5-14; 6-3-10-14; 7-10-14	240
7	6-2	15-11; 15-12-8-1	144
8	6-3	15-12-9; 15-12-8-2	168
9	6-7	15-14	184
10	7-2	16-11; 16-12-8-1	120
11	7-3	16-12-8-2; 16-12-9	136
12	7-6	16-13	208

Table 2 Initial Link choice proportions by OD pairs

OD pair Link	1	2	3	4	5	6	7	8	9	10	11	12	Link flow
1				0.9	0.2	0.3	0.4			0.4			485.6
2	0.8							0.4			0.5		350
3	0.2	0.2	0.2	0.1	0.4	0.3							358.1
4	1	0.2	0.2										284
5		0.8	0.8		0.2	0.3							477
6				0.9	0.6	0.6							565.9
7				0.1	0.4	0.4							274.1
8				0.1			0.4	0.4		0.4	0.5		343.9
9	0.2						0.6				0.5		240
10		0.2	0.2	0.1	0.8	0.7							560.1
11				0.1			0.6			0.6			235.4
12						0.4	1			0.4	1		511.8
13		1			1							1	840
14			1			1			1				650
15							1	1	1				620
16										1	1	1	580

Table 3 The prior covariance matrix of OD demands

OD No.	1	2	3	4	5	6	7	8	9	10	11	12
1	1129.0											
2	1240.2	625.0										
3	366.6	450.1	368.6									
4	820.6	1996.1	354.9	1296.0								
5	831.5	996.1	333.1	648.2	900.0							
6	1526.3	1877.5	596.7	1461.7	1384.5	2304.0						
7	824.5	954.7	354.9	678.6	709.0	1089.7	829.4					
8	973.4	1151.3	429.8	841.6	960.2	1565.1	758.9	1129.0				
9	1049.1	1287.0	407.9	884.5	1282.3	1745.6	943.0	1077.9	1354.2			
10	490.6	514.0	123.2	325.3	471.1	756.6	274.6	447.7	544.4	576.0		
11	782.3	765.2	322.1	706.7	599.0	1205.9	570.2	769.1	780.8	279.2	739.8	
12	825.2	1047.5	295.6	819.0	726.2	1522.6	618.5	861.9	959.4	397.8	556.9	1730.6

Effects of OD demand covariance on the optimal traffic count locations

$$\min_z \text{WMPRE}(\mathbf{z}) = \alpha \cdot \text{WMPREC}(\mathbf{z}) + (1 - \alpha) \cdot \text{WMPREM}(\mathbf{z})$$

$\alpha=0$ (only mean)

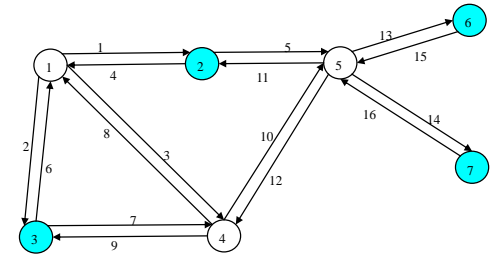
Number of traffic sensors	WMPRE	The optimal traffic count location scheme selected by WMPREM
5	3.84	3,10,13,15,16
7	2.59	3,4,7,10,13,14,16
8	1.71	1,4,7,10,12,13,14,15
11	0.17	2,3,4,7,8,9,10,11,12,13,15,16

$\alpha=0.5$ (both)

Number of traffic sensors	WMPRE	The optimal traffic count location scheme selected by WMPRE
5	2.99	3,5,10,15,16
7	1.79	1,2,4,5,7,13,16
8	1.36	1,3,6,9,11,12,13,14
11	0.15	1,2,3,4,5,7,9,11,12,13,15

$\alpha=1$ (only covariance)

Number of traffic sensors	WMPRE	The optimal traffic count location scheme selected by WMPREC
5	1.78	3,5,10,15,16
7	0.84	1,5,6,9,12,13,14
8	0.77	2,5,6,9,11,13,14,16
11	0.05	1,5,6,9,10,11,12,13,14,15,16



Findings

- links traversed by OD pairs 3-2 & 2-6 with **larger covariance** should be covered by traffic sensors if WMPREC is considered in the objective function.
- Considering the estimation accuracy of **covariance (WMPREC)** could reduce the number of sensors needed so as to have a similar overall estimation accuracy.

Effects of OD demand covariance on the optimal traffic count locations

$$\min_z \text{WMPRE}(\mathbf{z}) = \alpha \cdot \text{WMPREC}(\mathbf{z}) + (1 - \alpha) \cdot \text{WMPREM}(\mathbf{z})$$

$\alpha=0$ (only mean)

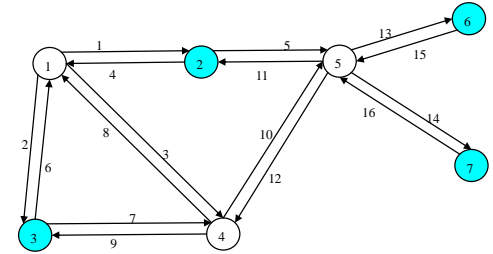
Number of traffic sensors	WMPREM	WMPREC	“Real” relative error of mean OD demands	“Real” relative error of covariance of OD demands
5	3.84	4.21	0.31	0.55
7	2.59	1.82	0.27	0.39
8	1.71	1.33	0.20	0.31
11	0.17	0.33	0.11	0.19

$\alpha=0.5$ (both)

Number of traffic sensors	WMPREM	WMPREC	“Real” relative error of mean OD demands	“Real” relative error of covariance of OD demands
5	3.92	2.05	0.35	0.29
7	2.65	0.92	0.31	0.21
8	1.80	0.91	0.24	0.17
11	0.21	0.08	0.12	0.09

$\alpha=1$ (only covariance)

Number of traffic sensors	WMPREM	WMPREC	“Real” relative error of mean OD demands	“Real” relative error of covariance of OD demands
5	4.03	1.78	0.40	0.11
7	2.75	0.84	0.39	0.07
8	1.86	0.77	0.25	0.06
11	0.23	0.05	0.15	0.02

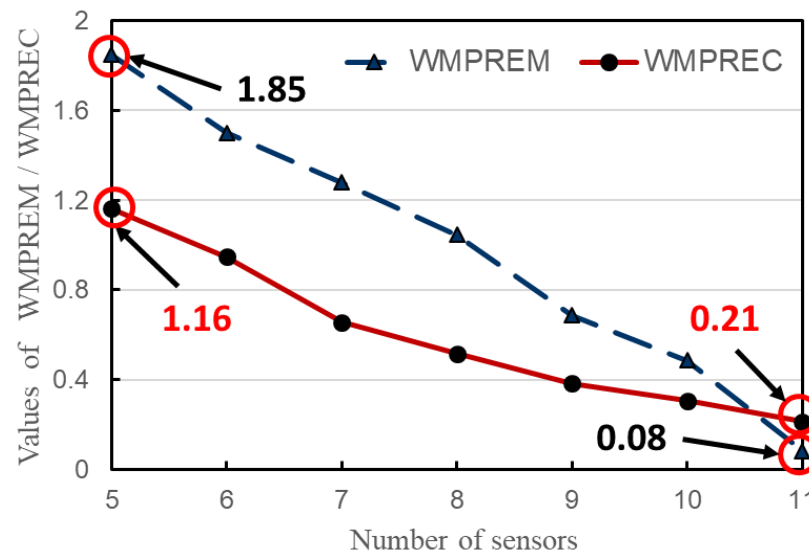


Finding:

Considering WMPREC can effectively reduce the estimation error of OD demand covariance

Effects of the number of traffic sensors on estimation reliability

$$\min_z \text{WMPRE}(\mathbf{z}) = \alpha \cdot \text{WMPREC}(\mathbf{z}) + (1 - \alpha) \cdot \text{WMPREM}(\mathbf{z}) \quad \alpha=0.5$$



Effects of number of sensors on WMPREM and WMPREC

Finding:

- It could be observed that when the number of traffic sensors increases, both the **optimal solutions** for WMPREM and WMPREC decrease;
- The reduction range of WMPREM is remarkably greater than that of WMPREC when the number of traffic sensors increases;

Effects of traffic congestion on the proposed model

– WMPREC is more sensitive to traffic congestion

$$\min_z \text{WMPRE}(\mathbf{z}) = \alpha \cdot \text{WMPREC}(\mathbf{z}) + (1 - \alpha) \cdot \text{WMPREM}(\mathbf{z}) \quad \alpha=0.5 \text{ (Both)}$$

Scenario A: Uncongested condition *Scenario B: Congested condition*
(**HALVE** Mean and covariance of OD demand) (**DOUBLE** Mean and covariance of OD demand)

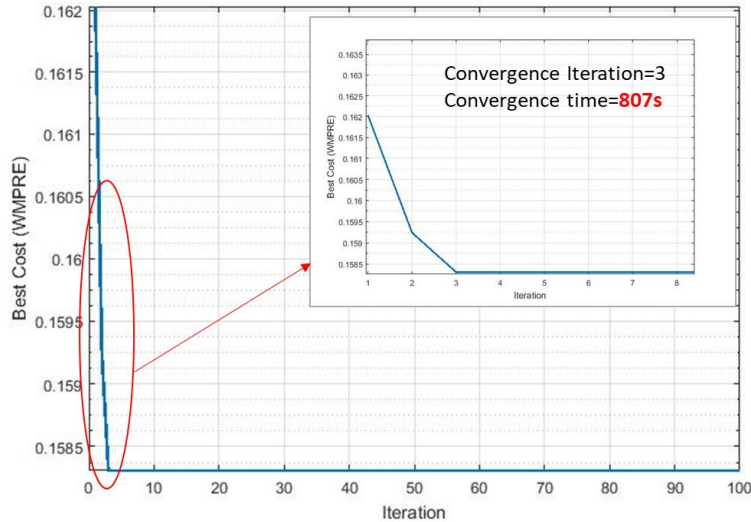
Relative increase for WMPREM and WMPREC under congested condition compared to that under uncongested condition

Number of traffic sensors	WMPREM		Relative increase (WMPRE _B - WMPRE _A) / WMPRE _A	WMPREC		Relative increase (WMPREC _B - WMPREC _A) / WMPREC _A
	Scenario A	Scenario B		Scenario A	Scenario B	
5	3.64	4.13	13.5%	4.01	6.88	71.5%
7	2.56	3.26	27.4%	2.72	2.97	9.1%
8	2.04	2.26	11.0%	1.99	1.77	-10.9%
11	0.95	0.97	1.9%	0.87	0.88	1.0%

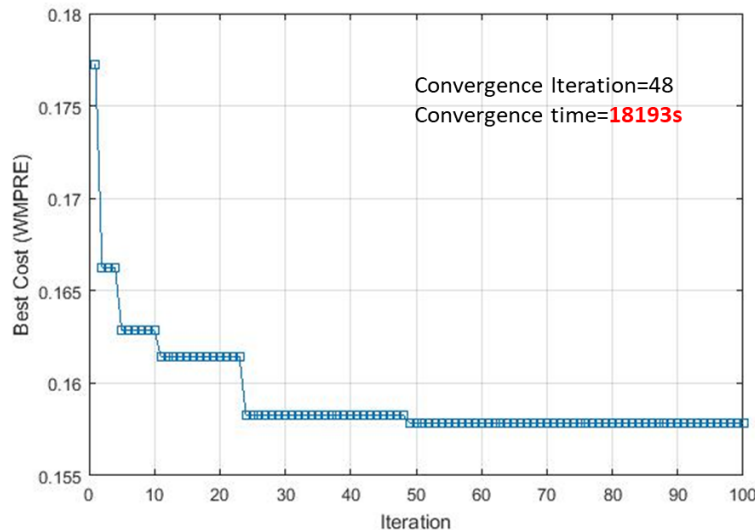
Finding:

WMPREC is **more sensitive** to the traffic congestion.

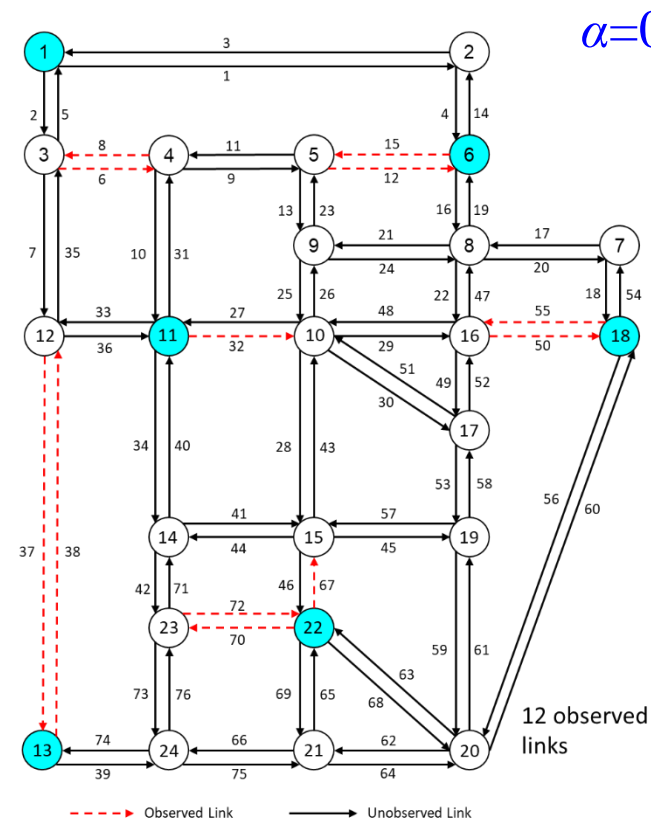
Example 2 – Convergence of solution algorithm



(a) Firefly algorithm



(b) Genetic algorithm



Optimal location schemes

Number of selected OD pairs: 30

Number of links: 76

Number of selected traffic count locations : 12

Conclusions

- ❖ An integer programming model is proposed for optimizing traffic account locations for simultaneous estimation of both **mean** and **covariance** of the OD demands using traffic counts.
- ❖ Weighted maximum possible relative error for the **covariance** (**WMPREC**) matrix of OD demand is proposed for measuring the quality of the estimated OD **covariance** matrix together with their properties.
- ❖ Links traversed by OD pairs with **larger covariance** should be covered by traffic sensors particularly when the covariance of OD demand is increasing in stochastic road networks with uncertainties.
- ❖ Considering the estimation accuracy of **covariance** (**WMPREC**) could reduce the number of sensors required so as to have a similar overall estimation accuracy.
- ❖ WMPREC is **more sensitive** to the traffic congestion.

Further Studies

- ❖ To facilitate the presentation of essential idea, only the simplest case with constant weighting parameter α is considered in this paper. How to determine **different weighting parameters** for various OD pairs may be investigated for further study.
- ❖ To develop efficient solution algorithm to solve the proposed model for **large-scale road networks** in practice.
- ❖ To extend the proposed model to consider **multi-user classes** with vehicular flow and vehicle occupancy data in multi-modal road network.
- ❖ To determine the optimal traffic count locations with considering the probability of **sensor failure**, as well as the counting errors of the traffic sensors.

ACKNOWLEDGEMENT

This presentation is supported by grant from the Research Grants Council of the Hong Kong Special Administrative Region (Project Nos. PolyU 152628/16E and R5029-18).



**THANK YOU
FOR YOUR
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