Estimation of urban traffic state with probe vehicles

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Context

- In order to improve road traffic conditions, we think an accurate information on traffic state is needed
- High resolution data will be available for road traffic applications : speed, location, acceleration rate, eventually origin and destination of equipped vehicles

Problem statement

- Urban road traffic with vehicles that communicate their location at periodic intervals (probe vehicles)

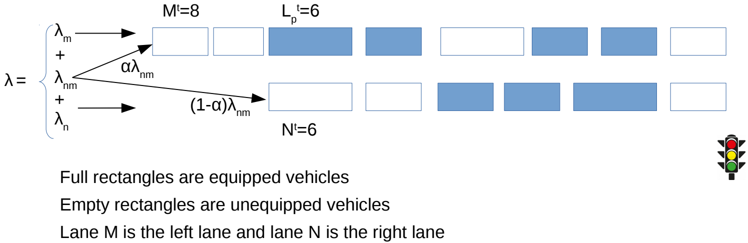

Figure – Queues in two incoming lanes. Vehicles that can choose both lanes are assigned on lane M with probability α and lane N with probability $(1-\alpha)$.

Turn ratios and incoming flow composition

We assume that the turn ratios are known. Indeed, it is possible to measure them by following where the communicating vehicles are going from/to. On a 2-lanes link, we assume that the main flow λ is composed of three flows :

1. the flow with arrival rate λ_n which is necessarily assigned to lane N (vehicles turning right).
2. the flow with arrival rate λ_m which is necessarily assigned to lane M (vehicles turning left).
3. the flow with arrival rate λ_{nm} which can be assigned to both lanes N or M (vehicles go straight).

We define :

$$\mu_N(t) = r_N(t)(\lambda_n + (1-\alpha)\lambda_{nm}) \quad (1)$$

$$\mu_M(t) = r_M(t)(\lambda_m + \alpha\lambda_{nm}) \quad (2)$$

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Definition of the queue

The total number of incoming probe vehicles $x_p(t)$ in a given link to the junction is known. We consider vehicles i moving at speed $v_i(t)$ and at a distance $\rho_i(t)$ (depending on time t) from the traffic light.

Definition 1

For a given threshold car-speed v^* and a given threshold car-distance ρ^* to the junction, the vehicles queue $Q = Q(t, v^*, \rho^*)$ is defined by $Q = \{i, v_i < v^* \text{ and } \rho_i < \rho^*\}$.

Primary parameters : location of last probe l_p

Q_p the subset of Q that includes only the probe vehicles, $Q_p \subset Q$.

$$max_{i \in Q_p}(\rho_i) = \rho_0 + l_p L_V + (l_p - 1) G_V \qquad (3)$$

such that :

$$l_p = \lceil (max_{i \in Q_p}(\rho_i) - \rho_0 + G_V)/(L_V + G_V) \rceil \qquad (4)$$

where :
L_V the average vehicle length
G_V the minimum gap between vehicles
ρ_0 the offset distance from the front vehicle of the queue to the RSU (Road Side Unit)

Primary parameters : penetration ratio of probe vehicles

c_p the total number of probe vehicles in all the lanes and all the queues at time t.

- p, $0 \leq p \leq 1$, the penetration ratio of probe vehicles.

We propose :

$$\hat{p} = \frac{c_p}{n+m} \tag{5}$$

which leads to :

$$\hat{p} = c_\kappa / l_p \tag{6}$$

where :
$c_\kappa = c_p/(1+\kappa)$ and
$\kappa = \min(n,m)/\max(n,m) = \min(\mu_n,\mu_m)/\max(\mu_n,\mu_m)$ and
$max(n,m) = max(\mu_n,\mu_m) = l_p$

Primary parameters : penetration ratio of probe vehicles

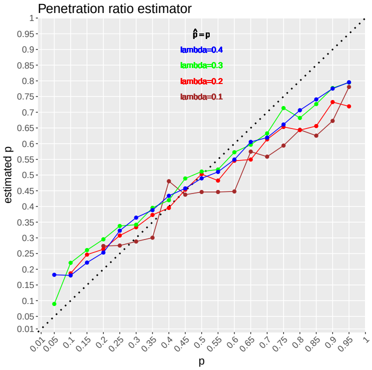

Figure – Estimated penetration ratio depending on penetration ratio for various demand scenarios. Simulated time = 1 hour.

Primary parameters : arrival rate of vehicles onto the link

In addition we propose to compute λ with formula (7) by simply accumulating probe vehicles on the entire radio range area of the RSU during red time, and using $\hat{x} = x_p/p$. We denote by R the maximum duration of the red time in the cycle in the case where $r_N = r_M$, $0 \leq r_N(t) \leq R$, $0 \leq r_M(t) \leq R$.

$$\hat{\lambda} = \frac{x_p(R) - x_p(0)}{pR} \tag{7}$$

Primary parameters : arrival rate of vehicles onto the link

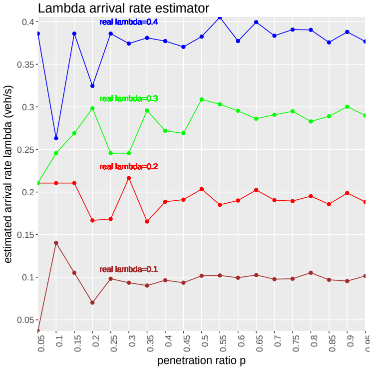

Figure – $(\lambda_n + \lambda_m + \lambda_{nm})$ in vehicles/second, depending on penetration ratio for various demand scenarios. Simulated time = 20 min.

Queue length estimation without data from probe vehicles

We define :

- λ_l the average (on one cycle) arrival rate for lane l in vehicles/second.
- A^t is a random variable representing the assignment of a vehicle entering the edge at time t. $A^t = 1$ if the vehicle is assigned on lane M and $A^t = 0$ if it is assigned on lane N.
- $r_N(t)$ the time since the beginning of the red phase for lane N (it is 0 if we are not in red phase at time t), $0 \leq r_N(t) \leq R$.
- $r_M(t)$ the time since the beginning of the red phase for lane M (it is 0 if we are not in red phase at time t), $0 \leq r_M(t) \leq R$.

Queue length estimation without data from probe vehicles

With the notions of splitting and combining Poisson process

Proposition 1

$$P(N^t = n, M^t = m) = \frac{\mu_N(t)^n e^{-\mu_N(t)}}{n!} \frac{\mu_M(t)^m e^{-\mu_M(t)}}{m!} \tag{8}$$

where

- $\mu_N(t) = r_N(t)(\lambda_n + (1-\alpha)\lambda_{nm})$
- $\mu_M(t) = r_M(t)(\lambda_m + \alpha\lambda_{nm})$

Queue length estimation with data from probe vehicles

We recall here N_p^t and M_p^t are the number of probe vehicles respectively on the lane N and on the lane M, at time t.

Proposition 2

- *If* $lp \leq \max(n, m), c_p \leq n + m,$ *then*

$$P(N^t = n, M^t = m | L_p^t = l_p, N_p^t + M_p^t = c_p) = \frac{\binom{l_p - 1 + \min(l_p, n, m)}{c_p - 1}(1-p)^{n+m} P(N^t = n, M^t = m)}{\sum\limits_{\substack{j,k \geq 0 \\ \text{subject to} \\ \max(j,k) \geq l_p \\ j+k \geq c_p}} \binom{l_p - 1 + \min(l_p, j, k)}{c_p - 1}(1-p)^{j+k} P(N^t = j, M^t = k)}$$

- *Otherwise,* $P(N^t = n, M^t = m | L_p^t = l_p, N_p^t + M_p^t = c_p) = 0$

Traffic light control and optimal assignment of vehicles onto the lanes : definitions

Let us now define $f(\alpha, \bar{r})$ as follows :

$$f(\alpha, \bar{r}) = |\mathbb{E}_{(\alpha, r_N)}(N^t) - \mathbb{E}_{(\alpha, r_M)}(M^t)| / \mathbb{E}_{(\alpha, r_N)}(N^t)$$

$$= \frac{|\bar{r}(\lambda_n + (1-\alpha)\lambda_{nm})) - (\lambda_m + \alpha\lambda_{nm})|}{\bar{r}(\lambda_n + (1-\alpha)\lambda_{nm})}.$$

We search for

- $\alpha^*(\bar{r}) := \arg\min_\alpha f(\alpha, \bar{r})$
- $r^*(\alpha) := \arg\min_{\bar{r}} f(\alpha, \bar{r})$

where $\bar{r} := r_N / r_M$

Proposition 3

$\forall \bar{r} \geq 0,$

$$\alpha^*(\bar{r}) = \max\left(0, \min\left(1, \frac{\bar{r}\lambda_n + \bar{r}\lambda_{nm} - \lambda_m}{\lambda_{nm}(\bar{r}+1)}\right)\right).$$

Moreover, if $\bar{r} \in I := [\frac{\lambda_m}{\lambda_n+\lambda_{nm}}, \frac{\lambda_m+\lambda_{nm}}{\lambda_n}]$, *then*

$$\alpha^*(\bar{r}) = \frac{\bar{r}\lambda_n + \bar{r}\lambda_{nm} - \lambda_m}{\lambda_{nm}(\bar{r}+1)}, \text{ and } f(\alpha^*(\bar{r}), \bar{r}) = 0.$$

Given an optimal assignment : traffic light control margin

$$I := [\frac{\lambda_m}{\lambda_n+\lambda_{nm}}, \frac{\lambda_m+\lambda_{nm}}{\lambda_n}]$$

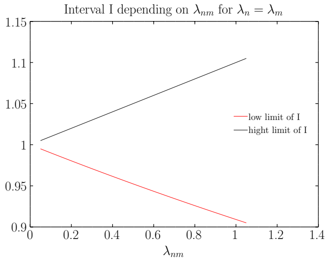

Figure – I depending on λ_{nm} for $\lambda_n = \lambda_m$

Proposition 4

$\forall \alpha \in [0,1], r^*(\alpha) = \frac{\lambda_m + \alpha\lambda_{nm}}{\lambda_n + (1-\alpha)\lambda_{nm}}$, *and* $f(\alpha, r^*(\alpha)) = 0$.

Optimal assignment of vehicles onto the lanes

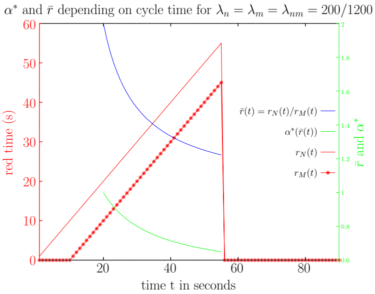

Figure – α^* and $\bar{r}$ depending on cycle time of 90s for $\lambda_n = \lambda_m = \lambda_{nm} = \frac{200}{1200} = 0.17$ vehicles/second.

Scenarios

We used VEINS [1] simulator wich bi-directionnaly couples the road traffic simulator SUMO [2] and the communication simulator OMNET++ [3]. We vary the arrival demand λ_n, λ_m and λ_{nm} and derive the optimal $\alpha^*(1)$ by Proposition 3. We obtain the values $\alpha^*(1) = [0, 0.25, 0.5, 0.75, 1.0]$.

Scenario	S1	S2	S3	S4	S5
α^*	0	0.25	0.5	0.75	1
λ_{nm}	50	100	50	100	50
λ_m	200	125	200	75	100
λ_n	100	75	200	125	200
Arrival rates	**Amount of vehicles for 1200 s**				

Table – Demand for different scenarios (simulated time=1200 s) and for $r_N = r_M$

Scenario results for lane N

Scenario	Average Queue	Max Queue	p=0.2 sd	p=0.5 sd	p=0.7 sd	p=0.9 sd
S1	2.14	8.80	1.52	1.40	1.24	1.08
S2	2.47	8.80	1.28	1.03	1.07	0.96
S3	3.42	13.80	1.53	1.59	1.61	1.50
S4	2.82	8.80	1.16	0.84	0.70	0.66
S5	3.38	10.80	1.44	0.91	0.77	0.75

Table – Results for queue on lane N (expectation estimator), sd=Standard Deviation of the error

Scenario results for lane M

Scenario	Average Queue	Max Queue	p=0.2 sd	p=0.5 sd	p=0.7 sd	p=0.9 sd
S1	3.60	14.80	1.94	1.11	1.07	0.98
S2	2.78	8.80	1.39	1.09	0.89	0.94
S3	3.94	15.80	2.09	1.74	1.56	1.53
S4	2.53	8.80	1.21	0.97	0.88	0.81
S5	2.48	9.80	1.27	0.90	0.86	0.83

Table – Results for queue on lane M (expectation estimator), sd=Standard Deviation of the error

Queue length estimation without data from probe vehicles

without data

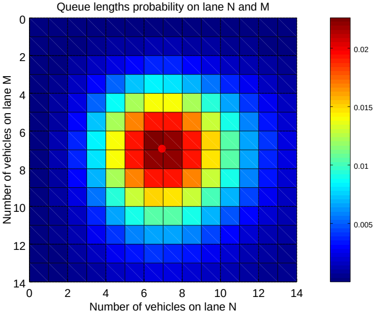

Figure – Probability law of proposition 1.
Scenario S3 with $r(t) = 37$, $p = 0.2$, $c_p = 3$, $l_p = 4$
Red disk is the expectation of the probability distribution.

with data

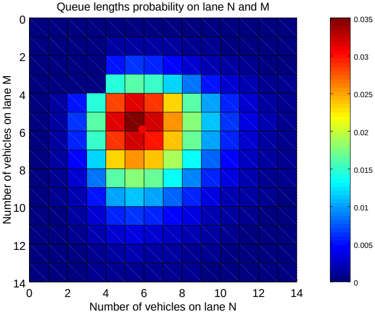

Figure – Probability law of proposition2
Scenario S3 with $r(t) = 37$, $p = 0.2$, $c_p = 3$, $l_p = 4$
Red disk is the expectation of the probability distribution.

Queue length estimation without data from probe vehicles

without data

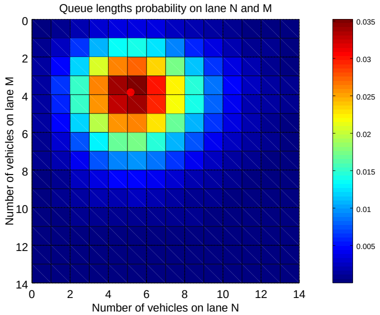

Figure – Probability law of proposition 1.
Scenario S5 with $r(t) = 31$, $p = 0.5$, $c_p = 8$, $l_p = 9$
Red dot is the expectation of the probability distribution.

Queue length estimation with data from probe vehicles

with data

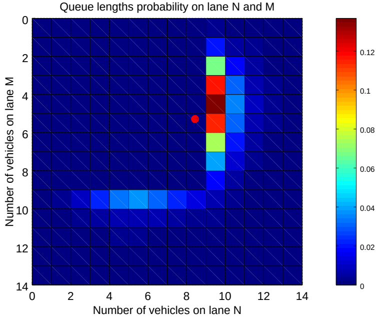

Figure – Probability law of proposition2
Scenario S5 with $r(t) = 31$, $p = 0.5$, $c_p = 8$, $l_p = 9$
Red dot is the expectation of the probability distribution.

Queue length estimation with data from probe vehicles

$(\lambda_n + \lambda_m + \lambda_{nm}) = 0.067$ vehicles/second. The phase where lane N is at red light while lane M is at green light has a duration of 8 seconds, $(r_N \neq r_M)$. We estimate queue lengths for $r_N > 0$ and $r_M > 0$.

$p = 0.2$

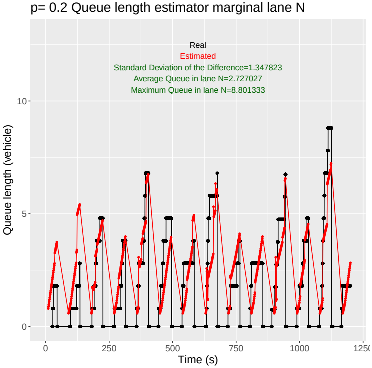

Figure – Queue lengths estimator for varying $p = 0.2$ and lane N, $r_N \neq r_M$

Queue length estimation with data from probe vehicles

$p = 0.9$

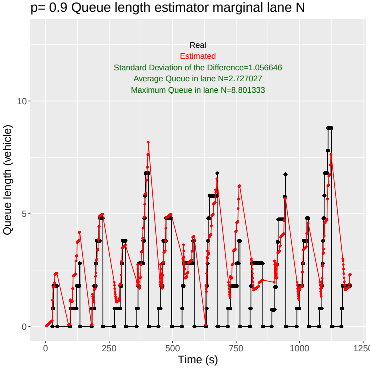

Figure – Queue lengths estimator for varying $p = 0.9$ and lane N, $r_N \neq r_M$

$p = 0.2$

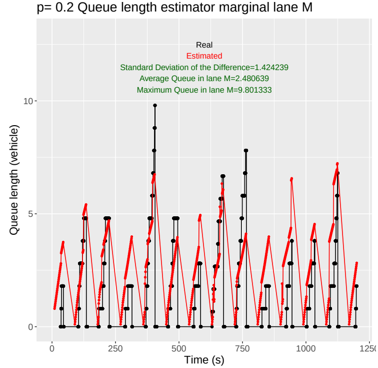

Figure – Queue lengths estimator for varying $p = 0.2$ and lane M, $r_N \neq r_M$

$p = 0.9$

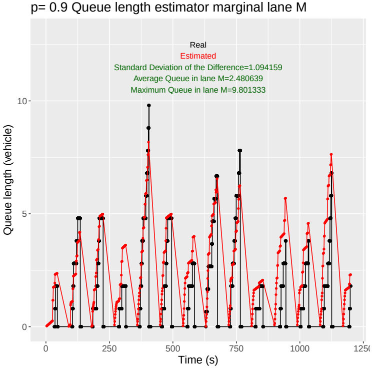

Figure – Queue lengths estimator for varying $p = 0.9$ and lane M, $r_N \neq r_M$

Conclusion

- We proposed a way to estimate some parameters of urban traffic state in the case of two-lanes incoming links.
- This method relies on the assumption that some vehicles will communicate their location with Wave (Wireless Access in Vehicular Environment).

Perspectives

- We plan to conduct more experimental simulations to assess the relevance of the method.
- Giving a bound of the standard deviation error should be done.
- Controlling the traffic light with the data we estimate here, could benefit to road traffic conditions.

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Thank you !