7 SUPPLEMENTARY MATERIAL

7.1 Kalman Filter

This section is a reminder of the Kalman filter algorithm. The Kalman filter is an inference algorithm that allows a recursive estimate of the state in a linear dynamical system from a sequence of observations of that system. In our case, these observations are provided by the crowdsourced sensors.

The state of the hidden variables at a given time t is denoted by $x_t \in \mathbb{R}^d$ and $y_t \in \mathbb{R}^I$ are the observations of the system. The dynamic of the system is given by:

$$x_{t+1} = A_t x_t + w_t \tag{37}$$
$$y_t = C_t x_t + v_t \tag{38}$$
$$x_1 \sim \mathcal{N}(\bar{x}_1, \Sigma_1) \tag{39}$$
$$w_t \sim \mathcal{N}(\bar{w}_t, \Sigma_{w,t}) \tag{40}$$
$$v_t \sim \mathcal{N}(0, \Sigma_{v,t}) \ , \tag{41}$$

where w_t and v_t are Gaussian noise, independent from each other and from any other variable. $\mathcal{N}(0, \Sigma)$ denotes a multivariate Gaussian distribution of mean 0 and of variance Σ.

The goal of the Kalman filter is to obtain a distribution $P(x_t|y_{1:t})$, that is, a distribution over the system state at time t given the sequence of observations collected from times 1 to t. We will denote by $\hat{x}_{t|t} = E_{x|y_{1:t}}$ the mean of this distribution and by $\hat{\Sigma}_{t|t} = E_{x|y_{1:t}}(x_t - \hat{x}_{t|t})(x_t - \hat{x}_{t|t})^T$ its covariance matrix. Likewise, $P(x_t|y_{1:t-1}) = \mathcal{N}(\hat{x}_{t|t-1}, \hat{\Sigma}_{t|t-1})$.

The Kalman filter is initialized by

$$x_{1|0} = \bar{x}_1 \tag{42}$$
$$\Sigma_{1|0} = \Sigma_1 \ . \tag{43}$$

The recursive estimation corresponds to

$$S_t = C_t \hat{\Sigma}_{t|t-1} C_t^T + \Sigma_{v,t} \tag{44}$$
$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + \hat{\Sigma}_{t|t-1} C_t^T S_t^{-1} \left(y_t - C_t \hat{x}_{t|t-1}\right) \tag{45}$$
$$\hat{\Sigma}_{t|t} = \hat{\Sigma}_{t|t-1} - \hat{\Sigma}_{t|t-1} C_t^T S_t^{-1} C_t \hat{\Sigma}_{t|t-1} \tag{46}$$
$$\hat{x}_{t+1|t} = A_t \hat{x}_{t|t} + \bar{w}_t \tag{47}$$
$$\hat{\Sigma}_{t+1|t} = A_t \hat{\Sigma}_{t|t} A_t^T + \Sigma_{w,t} \ . \tag{48}$$

The equations for $\hat{\Sigma}_{t|t}$ and $\hat{\Sigma}_{t|t-1}$ do not depend on the value of observations y_t. Furthermore, the mean square estimation error is given by these matrices: $E_{x_t|y_{1:t}}||x_t - \hat{x}_{t|t}||_{l_2}^2 = \mathrm{tr}(\hat{\Sigma}_{t|t})$, see Appendix 7.2.

In our case, we do not have access to all observations at time t, but to a subset $u_t \in \{1, ..., I\}$. This has only a mild effect on the Kalman filter algorithm: C_t, the full observation matrix, and $\Sigma_{v,t}$, the full observation covariance noise matrix, are respectively replaced by C_{t,u_t}, composed of the rows r_i of C_t such that $i \in u_t$, and by Σ_{v,t,u_t}, containing the elements $\sigma_{i,j}^2$ of $\Sigma_{v,t}$ such that $i, j \in u_t$.

7.2 Mean square estimation error

In this section we show that the mean square estimation error is given by the trace of the state estimation covariance matrix: $E_{x_t|y_{1:t}}||x_t - \hat{x}_{t|t}||_{l_2}^2 = \mathrm{tr}(\hat{\Sigma}_{t|t})$.

$$E_{x_t|y_{1:t}}||x_t - \hat{x}_{t|t}||_{l_2}^2 \tag{49}$$
$$= E_{x_t|y_{1:t}}\left[(x_t - \hat{x}_{t|t})^T (x_t - \hat{x}_{t|t})\right] \tag{50}$$
$$= E_{x_t|y_{1:t}}\left[\mathrm{tr}\left\{(x_t - \hat{x}_{t|t})^T (x_t - \hat{x}_{t|t})\right\}\right] \tag{51}$$
$$= E_{x_t|y_{1:t}}\left[\mathrm{tr}\left\{(x_t - \hat{x}_{t|t})(x_t - \hat{x}_{t|t})^T\right\}\right] \tag{52}$$
$$= \mathrm{tr}\left\{E_{x_t|y_{1:t}}\left[(x_t - \hat{x}_{t|t})(x_t - \hat{x}_{t|t})^T\right]\right\} \tag{53}$$
$$= \mathrm{tr}\,\hat{\Sigma}_{t|t} \ , \tag{54}$$

where we used the fact that the trace of a scalar is equal to that scalar and that $\mathrm{tr}\, EF = \mathrm{tr}\, FE$ for $E \in \mathbb{R}^{m,n}$ and $F \in \mathbb{R}^{n,m}$.

7.3 Expectation-Maximisation

Here, we derive the E and M step of the EM algorithm (equation 8):

$$s_{i,t,k} = E_{\tilde{x}_t^k|\Theta_k y_{1:T}}\left[(y_{i,t} - C_{i,t}\tilde{x}_t^k)^2\right] \tag{55}$$
$$= (y_{i,t} - C_{i,t}\hat{x}_{t,u_{1:t}}^k)^2 + C_{i,t}\hat{\Sigma}_{t,u_{1:t}}^k C_{i,t}^T \tag{56}$$
$$\Theta_{k+1}(i) = \frac{1}{\sum_{t'=1}^T \mathbb{1}(i \in u_{t'})} \sum_{t=1}^T \mathbb{1}(i \in u_t) s_{i,t,k} \ . \tag{57}$$

Θ is estimated based on the observations $y_{1:t}$ and an estimate of the state of the hidden variables $x_{1:t}$. The complete likelihood is

$$P(y_{1:t}, \tilde{x}_{1:t}^k) = P(\tilde{x}_1^k) \prod_{t'=2}^t P(\tilde{x}_{t'}^k|\tilde{x}_{t'-1}^k) \tag{58}$$
$$\prod_{t'=1}^t \prod_{i \in u_t} P(y_{i,t'}|\tilde{x}_{t'}^k) \ . \tag{59}$$

In EM, the quantity to be maximized is not the likelihood but its expectation with respect to the distribution $P(\tilde{x}_{1:t}^k|y_{1:t})$ (based on the values of $\hat{\sigma}_i^2$ at the previous iteration). Let $\tilde{v}_{i,t}^k \sim \mathcal{N}(0, \Theta_k(i))$ for all $i \in \{1, \ldots, I\}$, $t \in \{1, \ldots, T\}$ and k. We define $\tilde{x}_t^k$ such that $\tilde{x}_t^k$ is identically distributed for all k and $y_{i,t} = C_{i,t}\tilde{x}_t^k + \tilde{v}_{i,t}^k$, for all $i \in \{1, \ldots, I\}$, $t \in \{1, \ldots, T\}$ and k.

$$Q_k(\Theta) = \frac{1}{T} E_{\tilde{x}^k_{1:T}|\Theta_k y_{1:T}} L(\tilde{x}^k_{1:T}, y_{1:T}, \Theta) \quad (60)$$

$$= \frac{1}{T} \int_{\mathbb{R}^{Td}} \log p(\tilde{x}^k_{1:T}, y_{1:T}|\Theta) p(\tilde{x}^k_{1:T}|\Theta_k y_{1:T}) \mathrm{d}\tilde{x}^k_{1:T}$$

$$= \int d\tilde{x}^k_{1:t} p(\tilde{x}^k_{1:t}|y_{1:t}) \Big[(D+K)t \log(2\pi) + \log|\Sigma_1| + \sum_{t=2}^{T} \log|\Sigma_{w,t}| + \sum_{t=1}^{T}\sum_{i\in u_t} \log \sigma_i^2 + (\tilde{x}^k_1 - \bar{x}_1)^T \Sigma_1^{-1} (\tilde{x}^k_1 - \bar{x}_1) + \sum_{t=2}^{T} (\tilde{x}^k_t - A_{t-1}\tilde{x}^k_{t-1})^T \Sigma^{-1}_{w,t-1} (\tilde{x}^k_t - A_{t-1}\tilde{x}^k_{t-1}) + \sum_{t=1}^{T}\sum_{i\in u_t} (y_{i,t} - C_{i,t}\tilde{x}^k_t)^T \frac{1}{\sigma_i^2} (y_{i,t} - C_{i,t}\tilde{x}^k_t) \Big] \ . \quad (61)$$

In what follows, we use the notation

$$N_i = |t \in \{1, ..., T\} : i \in u_t| = \sum_{t=1}^{T} \mathbb{1}(i \in u_t) \ . \quad (62)$$

Next, $Q(\Theta)$ is derived with respect to σ_i^2:

$$\frac{\partial}{\partial \sigma_i^2} Q = \int d\tilde{x}^k_{1:t} p(\tilde{x}^k_{1:t}|y_{1:t}) \Big[N_i \sigma_i^{-2} - \sum_{t=1}^{T} \mathbb{1}(i \in u_t) \sigma_i^{-2} (y_{i,t} - C_{i,t}\tilde{x}^k_t)(y_{i,t} - C_{i,t}\tilde{x}^k_t)^T \sigma_i^{-2} \Big] \ . \quad (63)$$

By taking this derivative equal zero, we obtain

$$\sigma_i^2 = \frac{1}{N_i} \int d\tilde{x}^k_{1:t} p(\tilde{x}^k_{1:t}|y_{1:t}) \sum_{t=1}^{T} \mathbb{1}(i \in u_t)(y_{i,t} - C_{i,t}\tilde{x}^k_t)(y_{i,t} - C_{i,t}\tilde{x}^k_t)^T \quad (64)$$

$$= \frac{1}{N_i} \sum_{t=1}^{T} \mathbb{1}(i \in u_t) \Big[y_{i,t} y_{i,t}^T - C_{i,t}\hat{x}^k_{t,u_{1:T}} y_{i,t}^T - C_{i,t}^T \hat{x}^{kT}_{t,u_{1:T}} y_{i,t} + C_{i,t} \left(\int \tilde{x}^k_t \tilde{x}^{kT}_t p(\tilde{x}^k_t|y_{1:t}) d\tilde{x}^k_t \right) C_{i,t}^T \Big] \quad (65)$$

$$= \frac{1}{N_i} \sum_{t=1}^{T} \mathbb{1}(i \in u_t) \Big[y_{i,t} y_{i,t}^T - C_{i,t}\hat{x}^k_{t,u_{1:T}} y_{i,t}^T - C_{i,t}^T \hat{x}^{kT}_{t,u_{1:T}} y_{i,t} + C_{i,t} \left(\hat{\Sigma}^k_{t,u_{1:T}} + \hat{x}^k_{t,u_{1:T}} \hat{x}^{kT}_{t,u_{1:T}} \right) C_{i,t}^T \Big] \ . \quad (66)$$

7.4 Central Dublin Traffic Model

This traffic model is based on measurements collected from 2013-01-01 to 2013-05-14[4] by 512 vehicle count sensors located in central Dublin. 470 sensors remain after removing the trivial ones. We model the evolution of the sensor measurements from 5am to 12am. We then use this model to evaluate our algorithm, assuming that we do not observe the sensors anymore. The purpose of this model is only to demonstrate our algorithm on a realistic model. In practice, this algorithm would be applied mostly for locations where no sensors is continuously available.

We construct an auto-regressive model where each hidden variable corresponds to a SCATS sensor saturation value, after removing trivial sensors. Measurements are reported for every minute. However, each sensor generates a measurement approximately every 2 minutes, and the measurement period varies greatly across sensors. Therefore, we aggregate every 4 successive measurements by averaging, ignoring missing values. We construct our model using the resulting learning set, that we denote by $x_{j,t,d}$, $j \in \{1, ..., 470\}$ is a sensor, $t \in \{1, ..., 106\}$ a 4-minute interval and $d \in \{1, ..., 133\}$ is a day.

A different matrix A_t is learned for every time step. Each matrix A_t is learned using samples collected for $t' \in \{t - \delta_t, ..., t + \delta_t\}$, weighted by a Gaussian kernel:

$$exp(-(t - t')^2/\delta_t) \ . \quad (67)$$

For each matrix A_t, each row $r_{j,t}$ is learned by an elastic net (Zou and Hastie, 2005; Friedman *et al.*, 2010):

$$r_{j,t} = \arg\min_r \sum_d \sum_{t' \in [t-\delta_t, t+\delta_t]} e^{\frac{-(t-t')^2}{\delta_t}} (r x_{t'-1,d} - x_{j,t',d})^2 + \zeta f_\eta(r) \quad (68)$$

$$f_\eta(r) = (1-\eta)\frac{1}{2}||r||^2_{l_2} + \eta ||r||_{l_1} \ . \quad (69)$$

Ten-fold cross-validation was used to select ζ, and $\eta = 0.9$. Σ_1 and each $\Sigma_{w,t}$ are diagonal covariance matrices estimated by the graphical lasso (Friedman *et al.*, 2008).

7.5 Estimation error on the parameters

This section provides additional results for the analysis of the estimation error on Θ as a function of time for the articial model. Figure 6(a) provides the sum of the quadratic estimation error for all parameters, $||\Theta - \Theta_t||^2_{l_2}$, while Figure 6(b) contains the same

[4] http://dublinked.ie/datastore/datasets/dataset-305.php

error restricted to the sensors queried, $||\{\sigma_i^2\}_{i\in u_t} - \{\sigma_{i,t}^2\}_{i\in u_t}||_{l_2}^2$.

For *oracle*, the estimation error over the variance of the K sensors queried (u_t) decreases rapidly close to 0: the online estimation converges. However, the estimation error of all I parameters does not converge to 0: some sensors are never queried.

The estimation error on Θ initially deteriorates for *EMo*, *VB* and *random*. *EMo* and *VB* quickly focusses on the promising sensors while *random* keeps using them all. As a result, the estimation error for the noise of the suboptimal sensors (and thus Θ) remains high for *EMo* and *VB*, but the error for queried sensors decreases faster than for *random*.

7.6 Estimation results on traffic in Dublin

This section contains additional experiments on real traffic measurements from Dublin, Ireland. These results extend Section 4.3. Note that the estimation of the sensor noise is reinitialized for every day.

Figure 7 contains experiments performed on the days of a full week, except friday, which is very similar to Thursday and is omitted to fit the plots associated to the six other days on the same page. Figure 8 contains experiments performed on five successive Tuesdays.

On 2013-01-22 (Figure 8(b)), at least 4 SCATS sensors (and therefore 20 selectable sensors) were reporting constant, aberrant values for several hours. The accuracy of these 20 sensors (with respect to the true traffic state) was therefore negatively affected, and the corresponding elements of Θ did not reflect their true variances. Because *oracle* uses Θ to make its decisions, it selects suboptimal sensors during this anomaly, and *EMo* and *VB* produces more accurate estimates than *oracle*, since these two algorithms can adapt. Another shorter malfunctioning happened on 2013-01-08, with similar results.

Table 2 summarizes the experiments performed on the 105 days of our data set. Two quantities summarizing the performance of the algorithms are provided:

- for each method, the average (over 10 simulations) of the sum (over 100 time steps) of the quadratic estimation error:

$$||x_t - \hat{x}_{t|\Theta_{0:t-1}y_{1:t}}||_{l_2}^2 \ ; \tag{70}$$

- for each method except oracle, the number of time steps when the quadratic estimation error of the method considered is smaller than the quadratic estimation error of the oracle:

$$||x_t - \hat{x}^{oracle}_{t|\Theta_{0:t-1}y_{1:t}}||_{l_2}^2 > ||x_t - \hat{x}^{method}_{t|\Theta_{0:t-1}y_{1:t}}||_{l_2}^2 \ . \tag{71}$$

EMo typically outperform *VB*. This can be explained by the initially good estimate of the sensor noise, equal to the average true sensor noise. If the initial conditions are worse, *VB* can be expected to performed better, as seen in the experimental section of the paper.

For most days, *oracle* is the best method. However, sometimes, malfunctionning sensors cause *oracle* to take bad decisions, and the other methods can achieve a performance closer to or better than *oracle*. This is in particular the case on 2013-01-08 and 2013-01-22, which we have already discussed, but also on 2013-05-15.

Other perturbations of the variance of the sensors can also have a positive impact on the relative performance of our methods with respect to *oracle*. The most striking example is 2013-03-17. On that particular day, the average quadratic estimation error of *EMo* is smaller than the error of *oracle*. This day is also when *EMo* and *VB* achieves a lower estimation error than *oracle* during the largest number of time steps. We conjecture this is due to St. Patrick's Day Parade, which we assume caused a big alteration to the traffic patterns in the city and in particular shifted traffic from the main streets to smaller ones. Such a change would modify the variance of the sensors in both small and big streets, and allow the methods estimating the sensor variance (*EMo* and *VB*) to outperform the methods using set values. To support our hypothesis, we note that the quadratic estimation error for that particular day is higher than most other days. A similar situation happened on 2013-01-01 (New Year) and probably 2013-01-31, although we found no particular event on this latter day.

Figure 9 details the evolution of the quadratic estimation error over time for these 4 atypical days.

References

Friedman, J., Hastie, T., and Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, **9**(3), 432–441.

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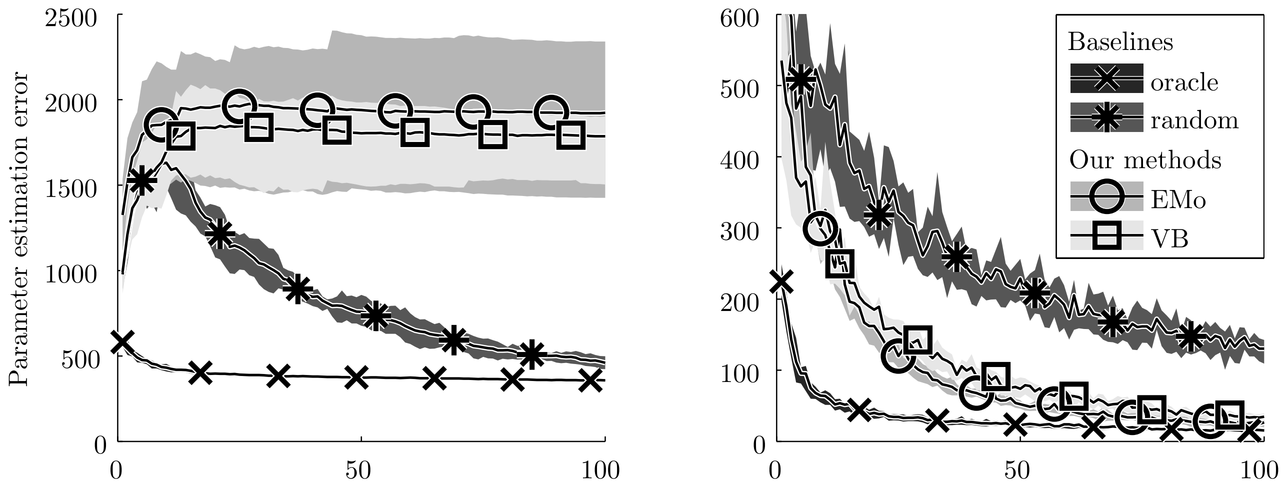
Zou, H. and Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, **67**(2), 301–320.



(a) All parameters (Θ)

(b) Parameters of queried sensors only ($\{\sigma_i^2\}_{i \in u_t}$)

Figure 6: Evolution of the estimation error on Θ for the artificial problem.

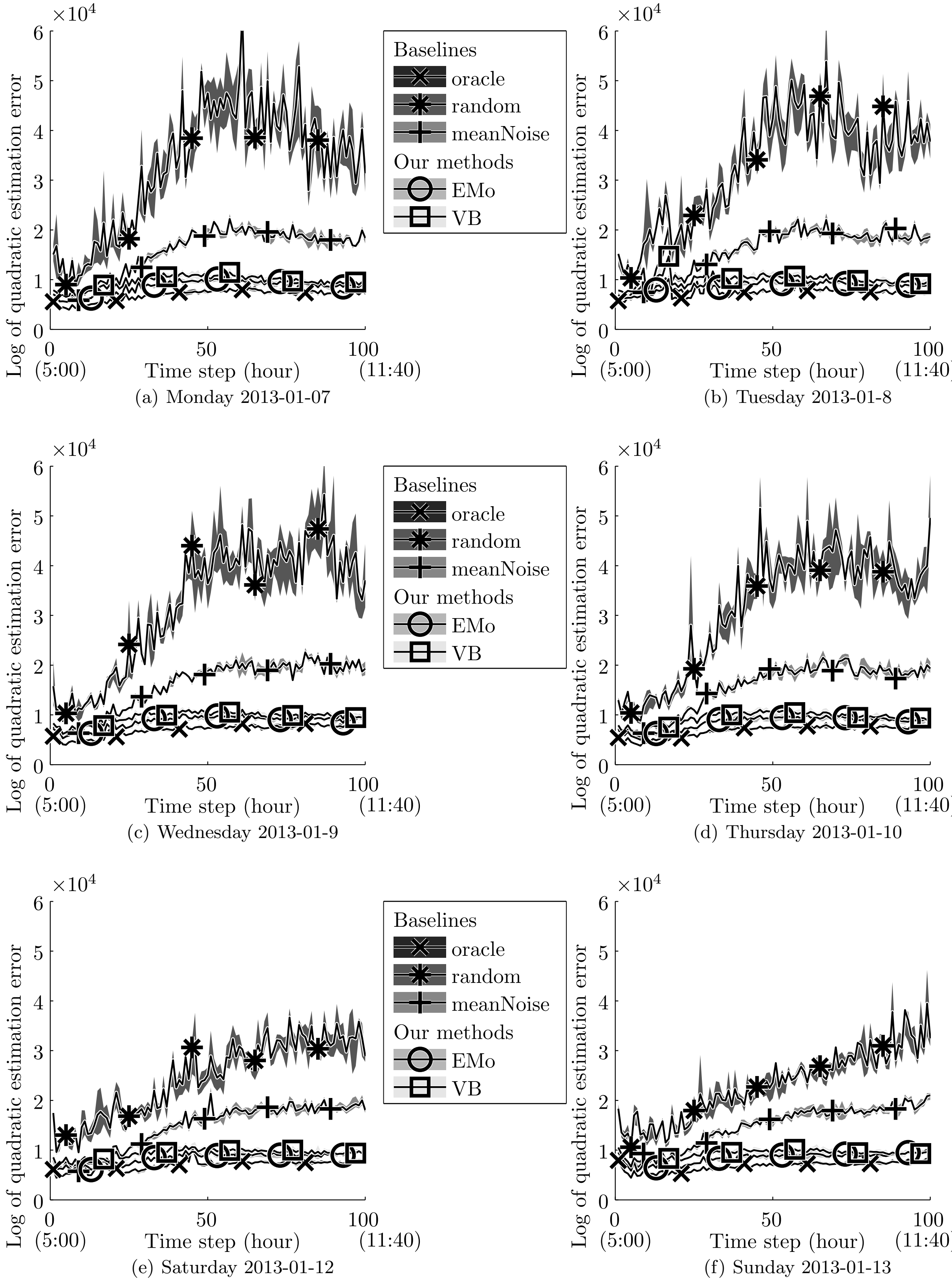
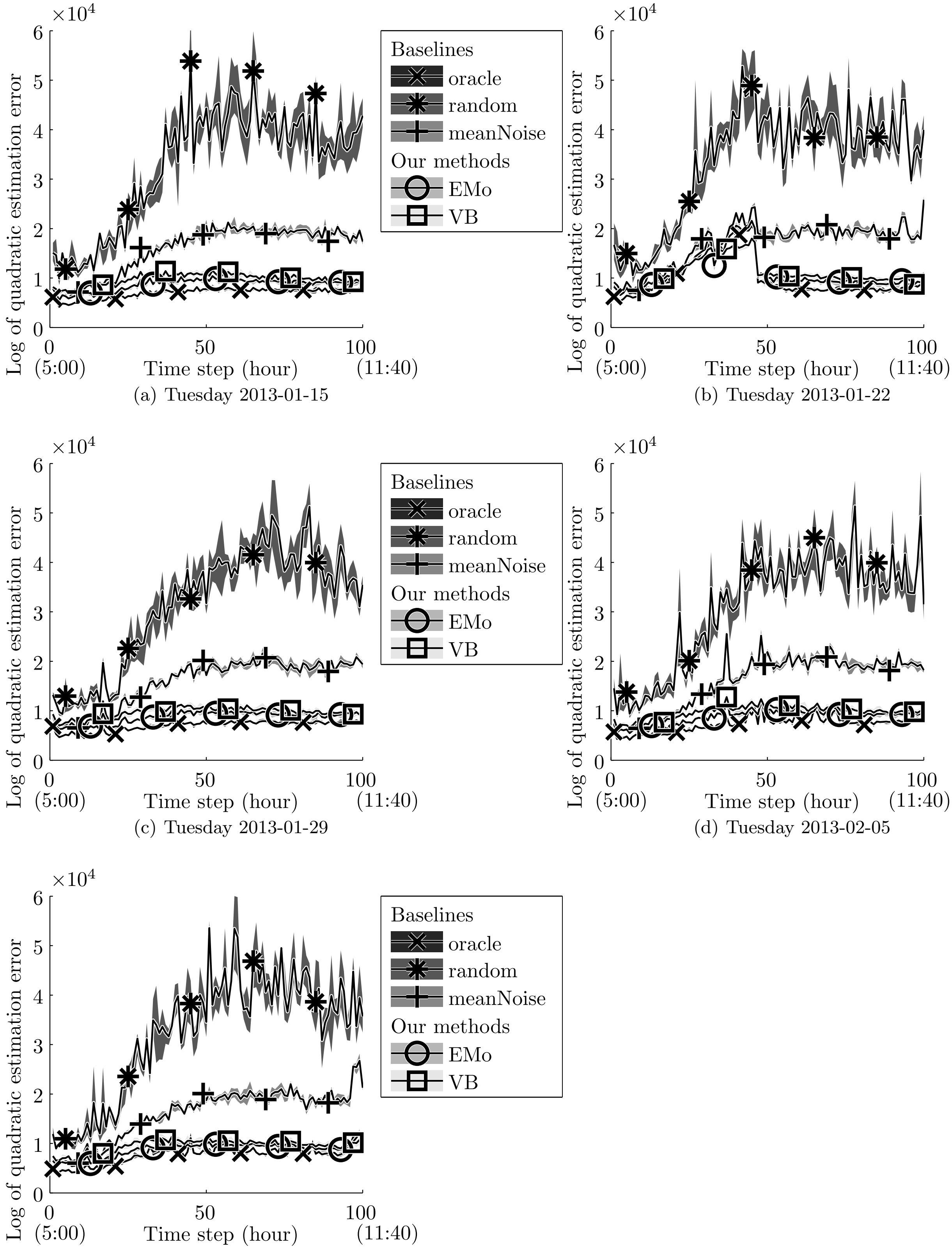


Figure 7: Estimation error using traffic data recorded in Dublin, Ireland, on various days of the week.



(a) Tuesday 2013-01-15

(b) Tuesday 2013-01-22

(c) Tuesday 2013-01-29

(d) Tuesday 2013-02-05

(e) Tuesday 2013-02-12

Figure 8: Estimation error using traffic data recorded in Dublin, Ireland, on various Tuesdays.

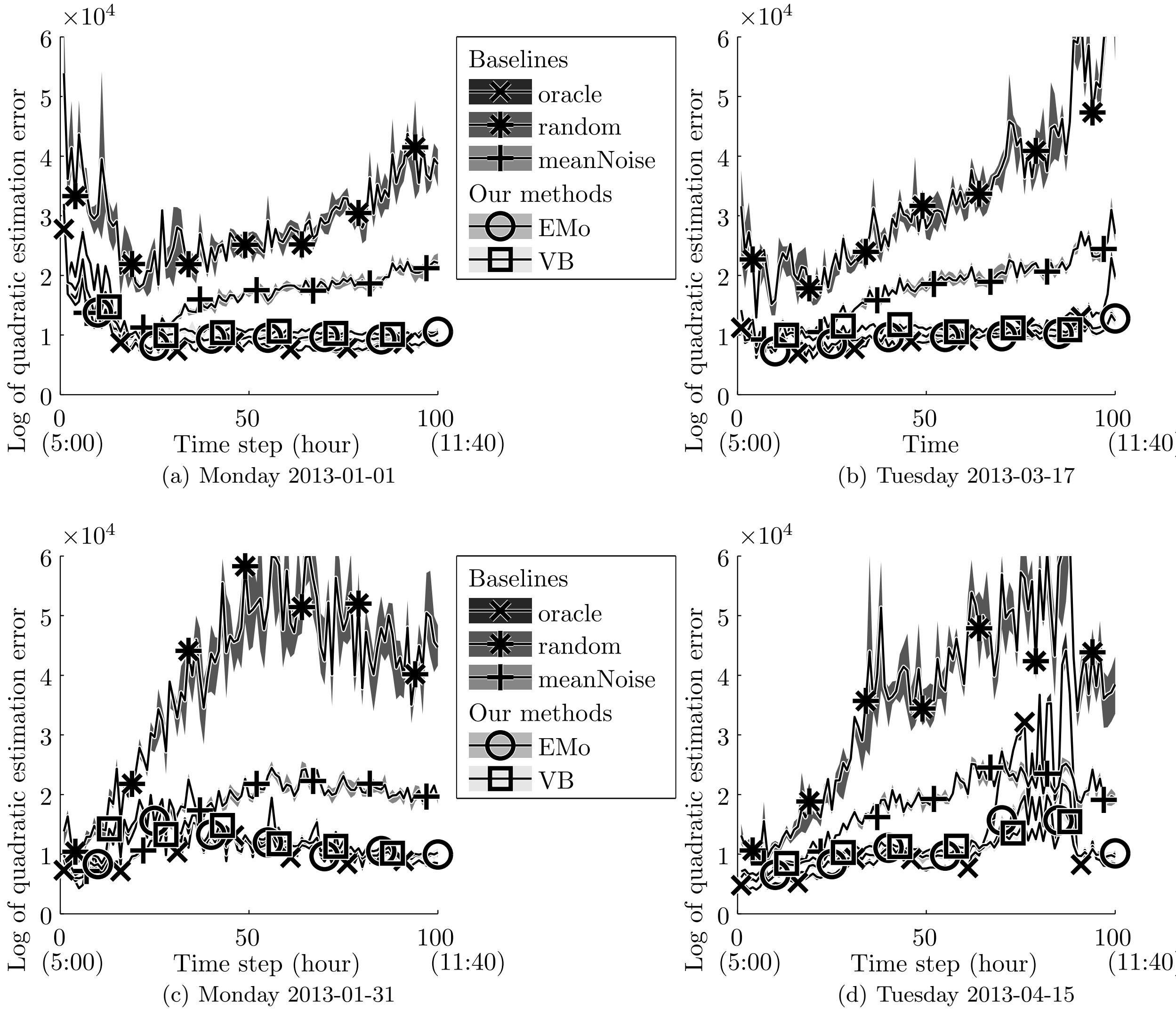


Figure 9: Estimation error using traffic data recorded in Dublin, Ireland, for atypical days in Table 2.

Table 2: Comparison of the performance of the different methods using different days as the true trajectory of the process being monitored.

	Area under the curve ($\times 10^5$)					Number of time steps where the estimation error is better than oracle (max:10000)			
date	*oracle*	*random*	*meanNoise*	*EMo*	*VB*	*random*	*meanNoise*	*EMo*	*VB*
2013-1-1	**10.0**	29.3	16.6	10.2	11.5	0	142	**223**	139
2013-1-2	**06.8**	27.5	15.0	08.4	09.3	0	0	0	**1**
2013-1-3	**06.8**	29.3	15.3	08.5	09.4	0	0	**4**	0
2013-1-4	**06.8**	28.5	15.3	08.5	09.4	0	0	**1**	0
2013-1-5	**06.6**	24.4	14.5	08.2	09.1	0	0	0	0
2013-1-6	**06.8**	23.4	14.6	08.3	09.3	0	1	**27**	16
2013-1-7	**06.9**	32.8	15.6	08.6	09.6	0	0	**1**	0
2013-1-8	**08.1**	32.7	15.7	08.8	10.0	4	123	**171**	109
2013-1-9	**06.9**	32.2	15.9	08.6	09.6	0	0	**2**	0
2013-1-10	**06.8**	31.4	15.5	08.5	09.5	0	0	0	0
2013-1-11	**06.9**	31.1	15.7	08.6	09.6	0	0	**5**	1
2013-1-12	**07.0**	24.7	14.7	08.3	09.3	0	7	**65**	13
2013-1-13	**06.8**	23.2	14.7	08.4	09.3	0	0	0	0
2013-1-14	**08.3**	32.2	16.4	09.8	10.3	0	1	**36**	33
2013-1-15	**07.0**	32.9	15.9	08.6	09.6	0	0	**4**	1
2013-1-16	**06.8**	31.8	15.6	08.6	09.4	0	0	**4**	0
2013-1-17	**07.0**	33.8	16.1	08.7	09.6	0	0	**1**	0
2013-1-18	**07.7**	38.5	17.3	09.2	10.3	0	5	**44**	4
2013-1-19	**06.6**	25.7	14.7	08.3	09.1	0	0	**1**	0
2013-1-20	**06.7**	23.3	14.5	08.4	09.3	0	0	0	0
2013-1-21	**07.4**	32.4	16.3	09.0	09.8	0	0	**9**	5
2013-1-22	**09.9**	33.8	17.0	10.9	11.1	0	57	159	**226**
2013-1-23	**07.7**	33.7	16.4	09.3	09.9	0	0	**15**	12
2013-1-24	**07.2**	33.9	16.1	08.7	09.8	0	1	**5**	2
2013-1-25	**07.4**	33.4	16.6	09.0	09.8	0	0	35	**39**
2013-1-26	**07.1**	23.7	14.9	08.5	09.4	0	20	**28**	23
2013-1-27	**06.8**	22.7	14.6	08.5	09.4	0	0	0	0
2013-1-28	**07.0**	31.6	15.7	08.6	09.5	0	0	**2**	0
2013-1-29	**06.9**	31.3	15.8	08.7	09.6	0	0	**1**	0
2013-1-30	**07.2**	33.7	16.0	08.6	09.7	0	0	**66**	53
2013-1-31	**11.1**	39.2	17.2	11.4	12.2	1	208	**354**	200
2013-2-1	**07.0**	32.0	15.9	08.7	09.7	0	0	**5**	0
2013-2-2	**06.5**	23.8	14.3	08.1	09.1	0	0	**1**	0
2013-2-3	**06.8**	23.7	14.5	08.5	09.3	0	0	0	0
2013-2-4	**06.9**	30.4	15.6	08.5	09.5	0	0	0	0
2013-2-5	**07.3**	31.1	16.1	08.8	09.8	0	0	**42**	23
2013-2-6	**07.0**	31.4	15.9	08.6	09.6	0	1	**5**	1
2013-2-7	**06.9**	31.3	15.8	08.7	09.6	0	0	**2**	0
2013-2-8	**07.7**	31.7	16.2	09.0	09.8	2	10	**42**	31
2013-2-10	**07.4**	23.9	14.7	08.7	09.5	0	4	**93**	74
2013-2-11	**07.6**	32.1	16.0	08.9	09.9	0	0	**74**	35
2013-2-12	**07.7**	32.2	16.0	08.8	09.6	0	0	**97**	62
2013-2-13	**07.2**	31.9	15.8	08.6	09.6	0	0	**23**	3
2013-2-14	**07.2**	31.2	15.8	08.7	09.6	0	0	**21**	2
2013-2-15	**07.3**	30.6	15.7	08.7	09.6	0	0	**22**	12
2013-2-16	**07.0**	24.1	14.5	08.4	09.3	6	34	**35**	31
2013-2-17	**06.7**	22.8	14.3	08.3	09.1	0	0	0	0

Continued on next page

date	*oracle*	*random*	*meanNoise*	*EMo*	*VB*	*random*	*meanNoise*	*EMo*	*VB*
2013-2-18	**07.0**	31.1	15.6	08.6	09.5	0	0	**34**	4
2013-2-19	**07.1**	31.9	15.8	08.7	09.8	1	**16**	12	10
2013-2-20	**07.0**	31.2	15.8	08.7	09.6	0	0	0	0
2013-2-21	**07.0**	32.4	15.9	08.6	09.5	0	0	**2**	1
2013-2-22	**07.1**	30.9	15.8	08.7	09.8	0	1	**4**	0
2013-2-23	**07.0**	25.1	14.7	08.4	09.5	0	0	**63**	0
2013-2-24	**06.6**	23.0	14.3	08.2	09.2	0	0	**1**	1
2013-2-25	**05.4**	25.0	12.5	06.9	07.6	0	0	0	0
2013-2-26	**06.8**	30.4	15.4	08.4	09.4	0	0	**1**	0
2013-2-27	**06.9**	31.9	15.7	08.7	09.5	0	0	**3**	1
2013-2-28	**07.8**	31.3	15.7	08.6	09.6	0	21	**175**	103
2013-3-1	**07.8**	33.0	16.4	09.0	09.9	0	0	**76**	40
2013-3-2	**06.7**	25.4	14.6	08.4	09.3	0	0	0	0
2013-3-3	**06.8**	23.4	14.4	08.5	09.3	0	10	**18**	7
2013-3-4	**07.8**	31.1	16.7	09.3	10.0	0	1	32	**90**
2013-3-5	**06.9**	31.0	15.7	08.5	09.4	0	0	**4**	0
2013-3-6	**06.9**	31.3	15.8	08.6	09.4	0	0	**17**	15
2013-3-7	**07.0**	33.1	16.0	08.6	09.6	0	0	**8**	0
2013-3-8	**07.5**	33.5	17.1	09.4	10.1	0	0	2	**41**
2013-3-9	**06.8**	25.3	14.8	08.5	09.4	0	0	**3**	1
2013-3-10	**07.9**	24.2	14.6	08.5	09.4	1	120	**168**	120
2013-3-11	**08.1**	33.3	16.8	09.0	10.0	0	2	**136**	104
2013-3-12	**07.2**	31.6	16.0	08.8	09.6	0	7	**42**	18
2013-3-13	**09.3**	36.0	17.1	09.6	10.2	0	5	**334**	299
2013-3-14	**07.6**	33.1	16.3	08.9	09.9	0	0	**74**	45
2013-3-15	**07.5**	31.1	16.2	08.8	09.8	0	0	**102**	43
2013-3-16	**07.6**	27.5	15.7	08.8	09.9	0	11	**100**	71
2013-3-17	10.1	33.2	17.4	**09.7**	10.9	0	40	**496**	308
2013-3-18	**08.1**	26.3	15.6	09.3	10.3	0	44	**118**	49
2013-3-19	**08.1**	32.4	16.3	08.8	09.8	0	0	**270**	151
2013-3-20	**06.9**	31.8	15.8	08.6	09.5	0	0	**17**	0
2013-3-21	**07.1**	32.2	16.1	08.7	09.6	0	0	**14**	3
2013-3-22	**07.7**	36.2	17.4	09.3	10.1	0	0	37	**43**
2013-3-23	**07.5**	25.4	15.5	09.1	09.8	0	0	**15**	2
2013-3-24	**06.7**	22.7	14.3	08.3	09.3	0	0	0	0
2013-3-25	**07.4**	30.7	16.4	09.1	09.8	0	0	1	**9**
2013-3-26	**07.0**	31.9	16.2	08.8	09.8	0	0	**7**	2
2013-3-27	**07.1**	31.9	16.3	08.8	09.7	0	0	**6**	1
2013-3-28	**07.1**	31.8	16.2	08.8	09.7	0	0	**4**	0
2013-3-29	**06.8**	25.7	15.0	08.4	09.4	0	0	**4**	1
2013-3-30	**06.6**	23.5	14.5	08.2	09.1	0	0	**7**	1
2013-4-1	**07.0**	23.9	14.9	08.6	09.3	0	0	**11**	3
2013-4-2	**07.0**	29.9	15.7	08.5	09.6	0	0	**5**	0
2013-4-3	**07.0**	31.2	15.9	08.5	09.6	0	0	**25**	13
2013-4-4	**07.0**	32.4	16.0	08.7	09.7	0	0	**3**	0
2013-4-5	**06.8**	31.2	15.7	08.5	09.5	0	0	0	0
2013-4-6	**08.4**	27.0	16.0	09.9	10.9	10	48	**93**	44
2013-4-7	**06.8**	23.5	14.7	08.5	09.3	0	0	0	**3**
2013-4-8	**07.1**	31.6	15.7	08.7	09.7	1	26	**45**	26
2013-4-9	**06.9**	32.0	15.9	08.6	09.4	0	0	**3**	0
2013-4-10	**07.9**	34.5	16.5	09.3	09.9	0	0	**62**	58
2013-4-11	**07.3**	36.2	16.6	08.9	09.9	0	0	**15**	8
2013-4-12	**07.5**	34.7	16.8	09.1	10.0	0	0	**16**	11

Continued on next page

date	*oracle*	*random*	*meanNoise*	*EMo*	*VB*	*random*	*meanNoise*	*EMo*	*VB*
2013-4-13	**06.9**	26.4	15.1	08.6	09.4	0	0	**1**	1
2013-4-14	**08.4**	25.5	14.8	08.5	09.4	0	95	**297**	223
2013-4-15	12.2	35.5	17.5	10.7	**10.7**	0	150	**289**	268
2013-4-16	**08.6**	34.3	17.2	10.0	10.4	0	0	76	**127**
2013-4-17	**07.0**	32.4	16.2	08.7	09.6	0	0	0	0