Traffic Prediction for Dynamic Traffic Engineering Considering Traffic Variation

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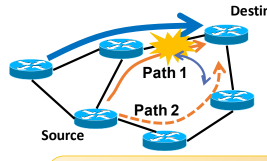
Traffic Engineering

- Increasing the time variation of traffic in a backbone network
  - Deployment of streaming, cloud services, etc.
- Traffic Engineering(TE)[1,3]
  - Periodical measurement of traffic and optimization of routes

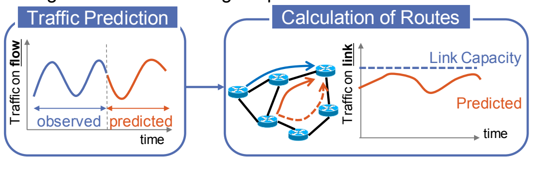


[1] N. Wang, K. H. Ho, G. Pavlou, and M. Howarth, "An overview of routing optimization for Internet traffic engineering," IEEE Communications Survey & Tutorials, vol. 10, no. 1, pp. 36–56, first quarter 2008.
[3] H. Wang, H. Xie, L. Qiu, Y. R. Yang, Y. Zhang, and A. Greenberg, "COPE: traffic engineering in dynamic networks," in Proceedings of SIGCOMM, vol. 36, no. 4. pp. 99–110, Aug. 2006.

Problems of existing TE
・Time lag of response to traffic change
・Frequent route change caused by quick response
⟶ Network instability

Applying Traffic Prediction to TE

- Overview
  - Predicting the future traffic variation based on the observed traffic
  - Calculating a routes considering the predicted traffic variation



- Advantages
  - Calculating routes in advance of a traffic change
  - Stable routes change by considering the traffic in a prediction target period

The prediction errors affects the TE performance

Objective

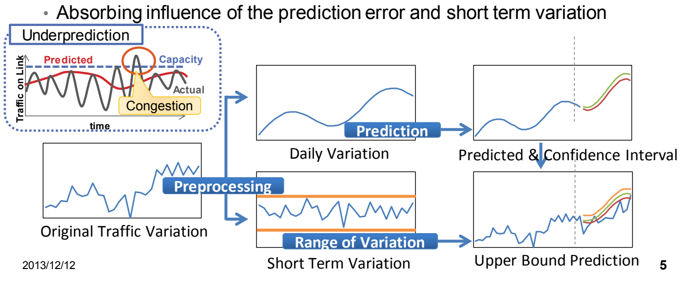
- It's unclear how the prediction errors affect the TE performance
  - Traffic prediction hasn't been evaluated for being applied to TE
  - Major metric of prediction performance is only prediction error
- Short-term traffic variation is hard to predict
  - It often behaves as noise
  - Only one step ahead prediction is often applied[8]

We investigate the traffic prediction method in the view of being applied to TE, focusing on how to consider the prediction errors and short-term variation

[8] B. Krithikaivasan, T. Zenf, K. Deka, and D. Medhi, "ARCH-based traffic forecasting and dynamic bandwidth provisioning for periodically measured nonstationary traffic," IEEE/ACM Trans. On Networking, vol. 15, no. 3, pp. 683–696, Jun. 2007.

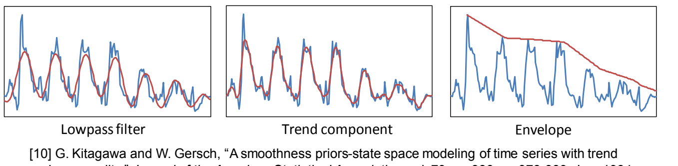
Overview of Our Prediction Method

- Extracting daily variation to improve the prediction accuracy
  - Extracting the predictable pattern, removing the noisy variation
- Predicting the upper bound of traffic to avoid underprediction
  - The unexpected traffic arrival causes the congestion
  - Absorbing influence of the prediction error and short term variation



Prediction Preprocessing

- Lowpass filter
  - Extracts the daily variation by Fourier analysis
- Trend component
  - Extracts the increasing/decreasing tendency according to the model[10]
- Envelope
  - Extracts the upper bound of traffic by tracing the peak values



[10] G. Kitagawa and W. Gersch, "A smoothness priors-state space modeling of time series with trend and seasonality," *Journal of the American Statistical Association*, vol. 79, no.386, pp.378-389, Jun. 1984

Prediction Model

preprocessed data → Model fitting → Model → Prediction → Predicted value & Confidence interval

- ARIMA model: the value depends on previous values and errors

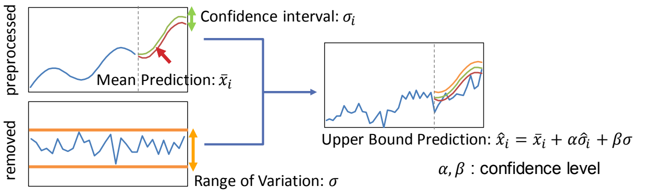
$$\begin{cases} y_k = \Delta^d x_k \\ y_k = \sum_{i=1}^{p} a_i x_{n-i} + \sum_{i=0}^{q} b_i \epsilon_{n-i} + c \end{cases}$$

x_k : observed value
$\epsilon_k \overset{i.i.d.}{\sim} N(0, \sigma^2)$: modeling error
a_i, b_i, A_j, B_j: coefficients
p, q, P, Q: the number of coefficients
s: period length of variation
$\Delta x_k = x_k - x_{k-1}, \Delta^d x_k = \Delta(\Delta^{d-1} x_k)$
$\Delta_s x_k = x_k - x_{k-s}$

- SARIMA model: adding periodic dependency to ARIMA

$$\begin{cases} y_k = \Delta^d \Delta_s^D x_k \\ y_k = \sum_{i=1}^{p} a_i x_{n-i} + \sum_{i=0}^{q} b_i \epsilon_{n-i} + \sum_{j=1}^{P} A_j \sum_{i=1}^{p} a_i x_{n-sj-i} + \sum_{j=1}^{Q} B_j \sum_{i=0}^{q} b_i \epsilon_{n-sj-i} + c \end{cases}$$

Upper bound prediction

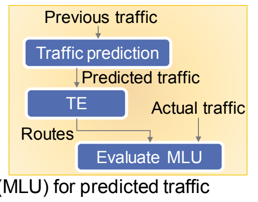


- Confidence interval of prediction error for daily variation
  - Standard deviation of prediction error
  - $\sigma_i = \sqrt{V[x_i | x_{t-h+1}, x_2, \cdots, x_t]}$
- Range of short term variation
  - Standard deviation of removed traffic variation
  - $\sigma = \sqrt{V[x_i - x_i']}$

x_i': preprocessed data
$V[\cdot]$: variance
$V[x|y]$: conditional variance
h: number of previous data

Evaluation Environment

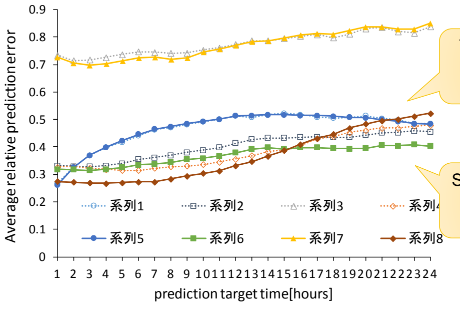
- Data
  - Actual traffic traces in the backbone network of Internet2[15]
  - 72 flows, each of which traverses PoP(Point-of-Presence) routers
  - 4 weeks data(Nov. 28 – Dec. 25, 2011)
- Prediction
  - Training data : previous 2 weeks
  - Prediction granularity : 1 hour
  - 24 times prediction changing the start time
- Routing
  - Minimizing the peak maximum link utilization(MLU) for predicted traffic
- Metric
  - Actual MLU with calculated route and actual traffic



[15] "Internet2 data," available from http://internet2.edu/observatory/archive/data-collections.html

Prediction Error

- Average relative prediction error = $\frac{average(|predicted - actual|)}{average(actual)}$

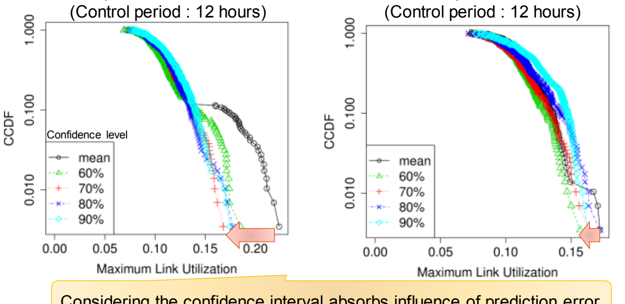


Trend component and lowpass filter achieve low prediction error

SARIMA model predicts more accurately than ARIMA model

Effect of Considering Confidence Interval

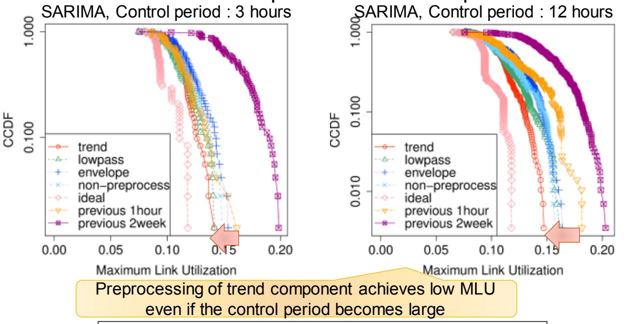
- CCDF of MLU for various confidence level



Considering the confidence interval absorbs influence of prediction error

Comparison of Various Prediction Methods

- CCDF of MLU for various prediction and non-prediction methods



Preprocessing of trend component achieves low MLU even if the control period becomes large

"ideal": the case that future traffic is completely known
"previous α": observation based TE using previous α data

Conclusion & Future work

- Considering the confidence interval absorbs prediction errors
- Using traffic prediction improves the TE performance
- SARIMA with the trend component is suitable to TE

Future Work

・How to set the optimum confidence levels
・TE method to use traffic prediction