

# Statistical Early Warning Signs of Instability in Synchrophasor Data



IEEE GMS/PES  
Synchrophasor Meeting  
October 12, 2016



Goodarz Ghanavati,  
Taras Lakoba,  
Paul Hines\*

\*To whom all blame is due

Funding gratefully acknowledged:  
NSF Awards ECCS-1254549, DGE-1144388,  
DOE Award DE-OE0000447

NY city, Nov. 9, 1965  
© Bob Gomel, Life

US Northeast and Canada  
August 14, 2003  
50 million people





California, Arizona, Mexico  
September 8, 2011  
5 million people



Northern India

July 30, 2012: 350 million people

July 31, 2012: 700 million people

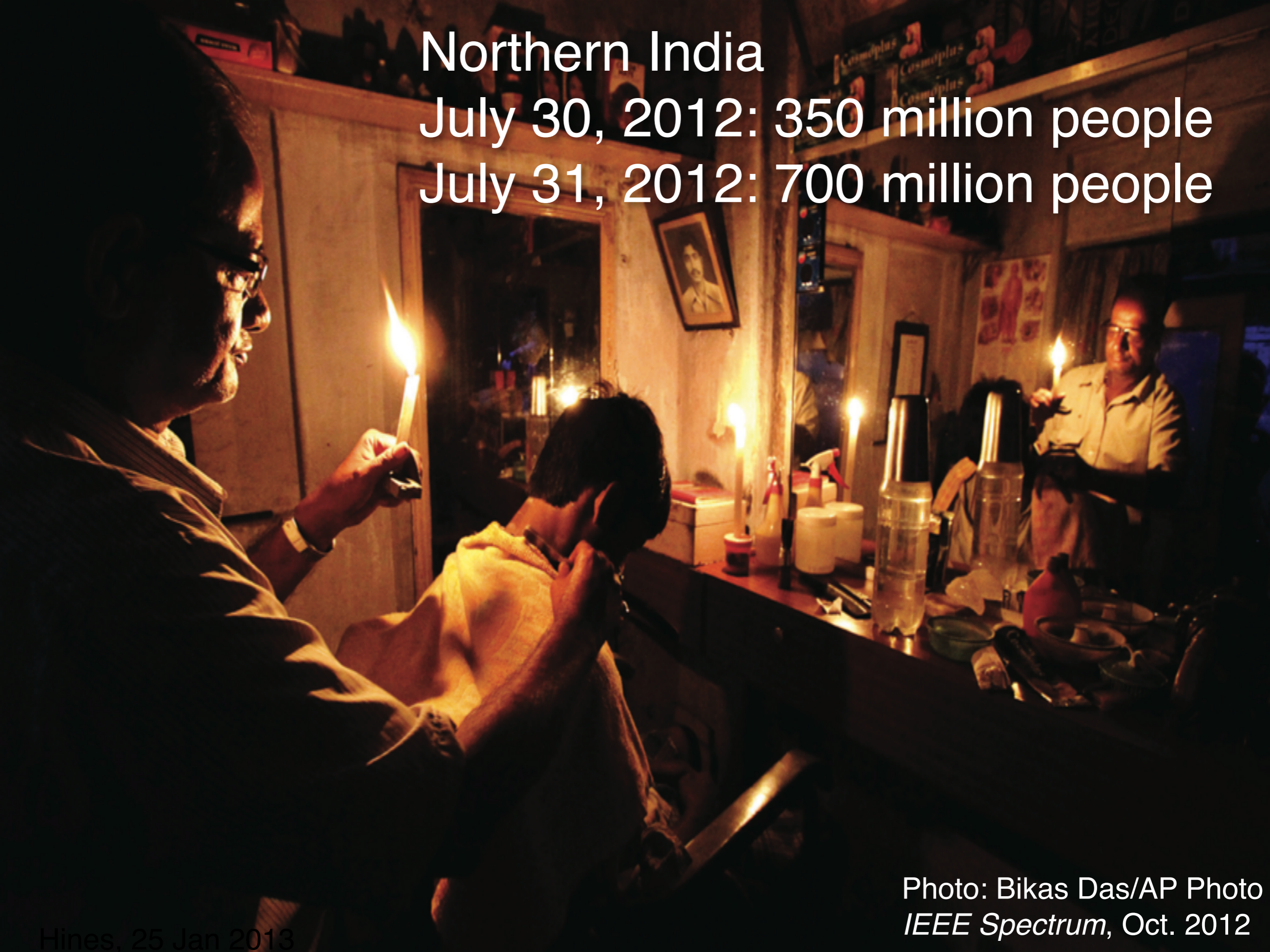


Photo: Bikas Das/AP Photo  
*IEEE Spectrum*, Oct. 2012

Bangladesh. 1 November 2014



**Officials said it would take at least 12 hours to repair the system and restore power to the capital Dhaka [AP]**

Washington DC, April 7, 2015



# Situational Awareness

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U.S.-Canada Power System Outage Task Force

**Final Report on the  
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**Causes and  
Recommendations**



Canada

April 2004



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Causes and Recommendations

## Inadequate Situational Awareness

The 2003 Blackout Report stated, “A principal cause of the August 14 blackout was a lack of situational awareness, which was in turn the result of inadequate reliability tools and backup capabilities.”<sup>109</sup> Similarly, the instant inquiry determined that inadequate real-time situational awareness contributed to the cascading outages. In



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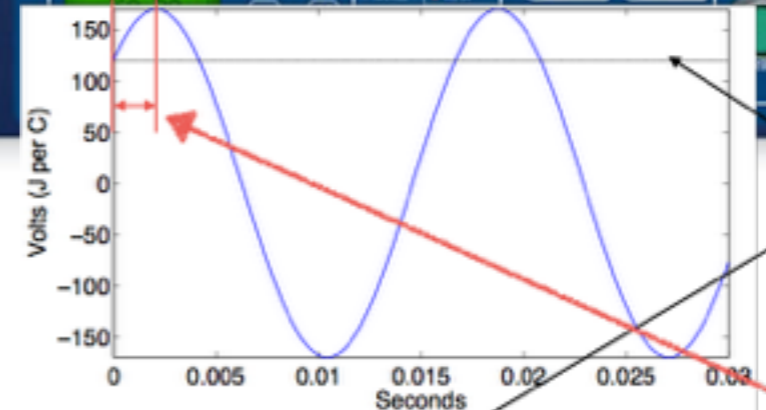
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Causes and Recommendations



Voltage magnitude

Voltage phase angle

$$v(t) = 120\sqrt{2} \cos(2\pi 60t - \pi/4)$$

## Inadequate Situational Awareness

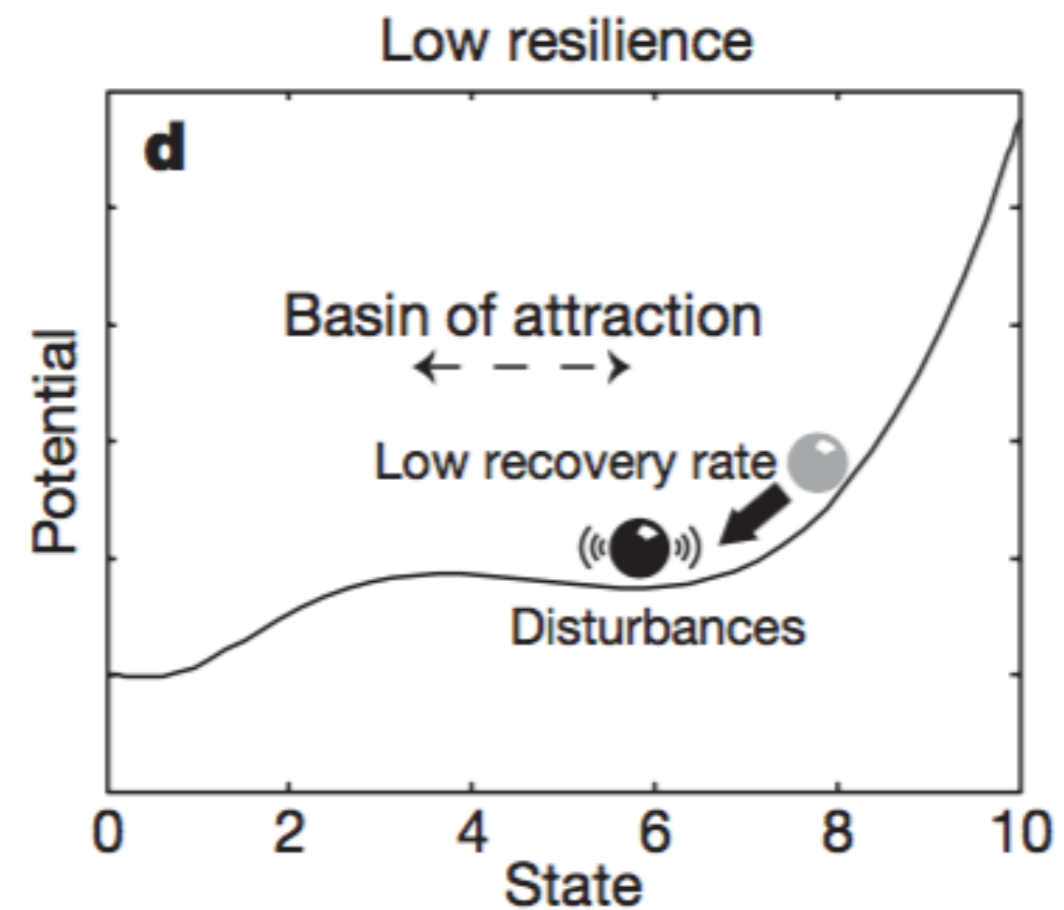
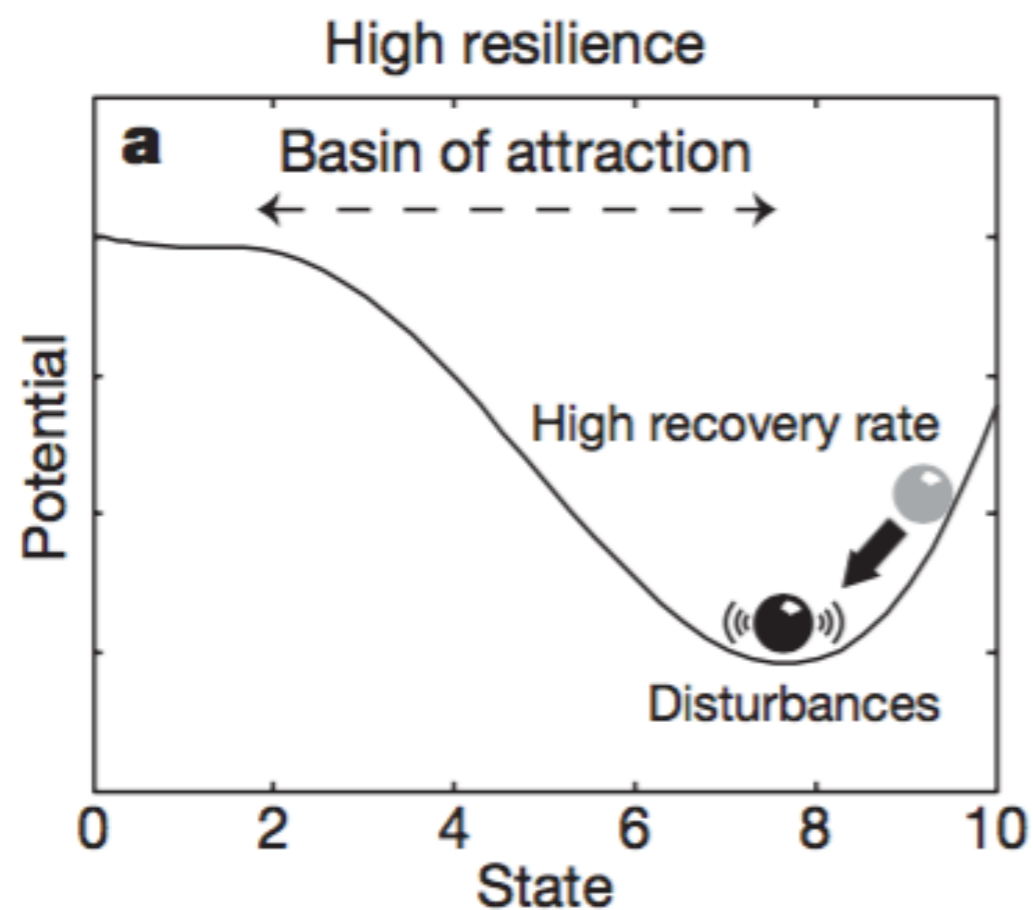
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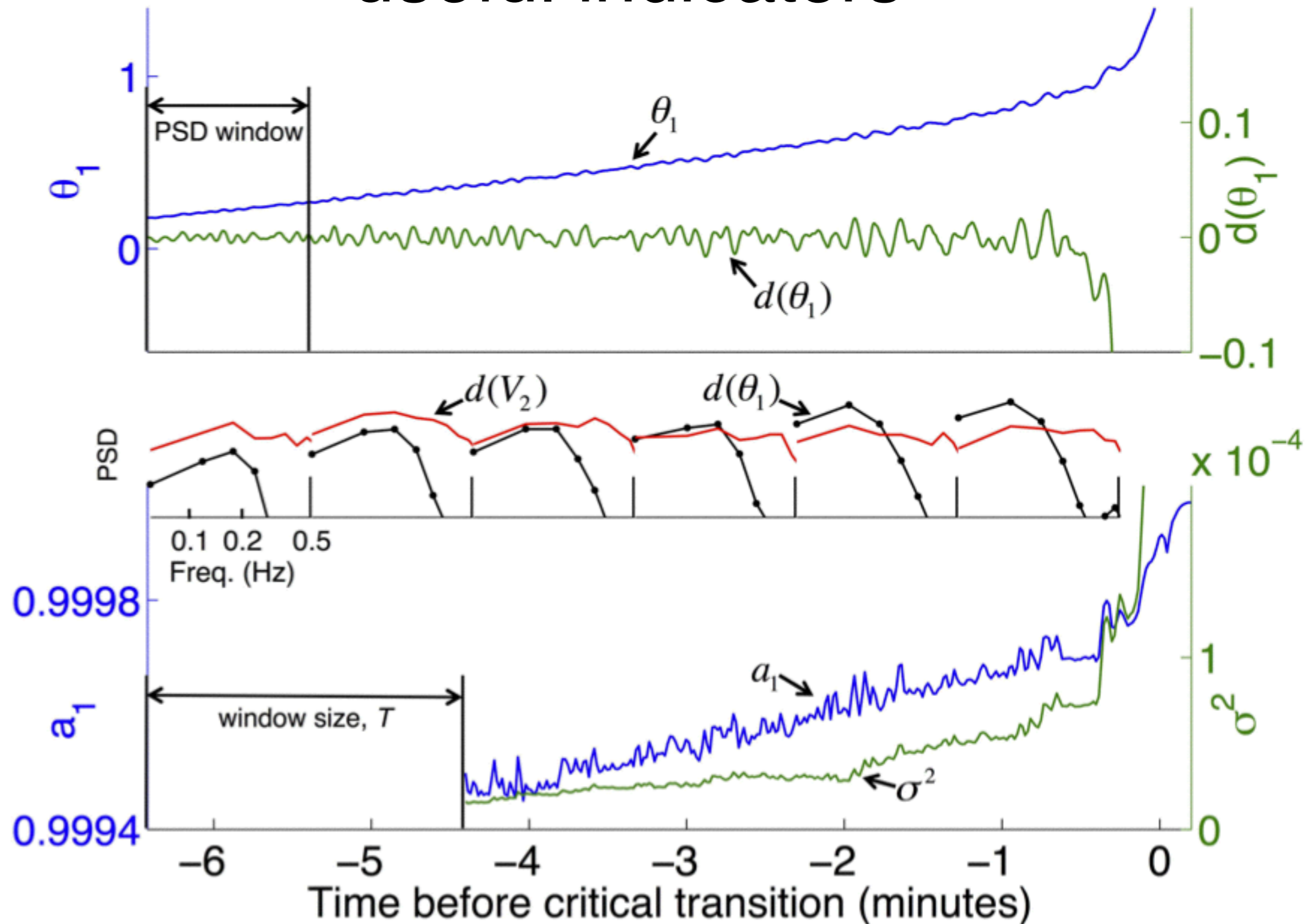
## REVIEWS

# Early-warning signals for critical transitions

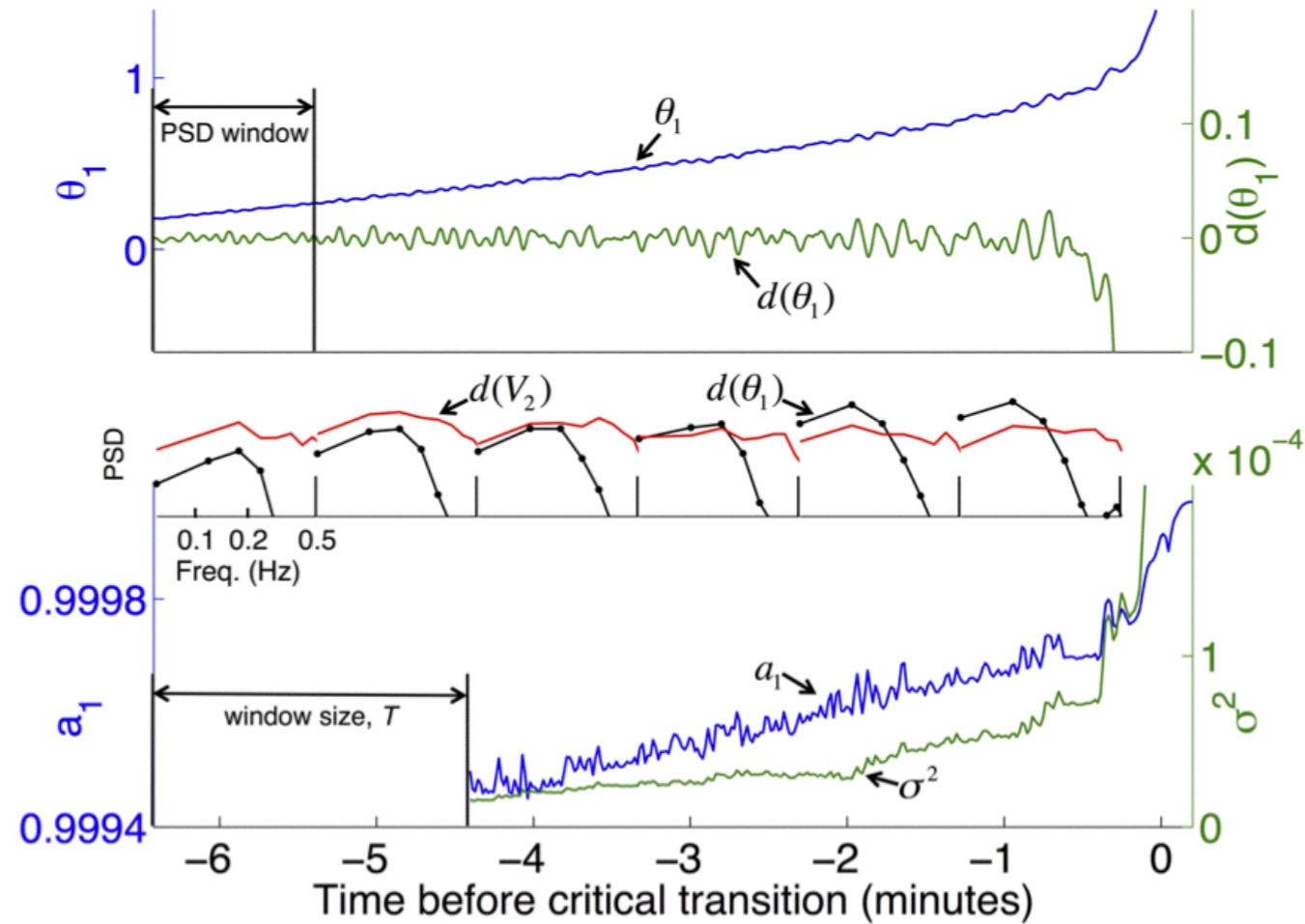
Marten Scheffer<sup>1</sup>, Jordi Bascompte<sup>2</sup>, William A. Brock<sup>3</sup>, Victor Brovkin<sup>5</sup>, Stephen R. Carpenter<sup>4</sup>, Vasilis Dakos<sup>1</sup>, Hermann Held<sup>6</sup>, Egbert H. van Nes<sup>1</sup>, Max Rietkerk<sup>7</sup> & George Sugihara<sup>8</sup>



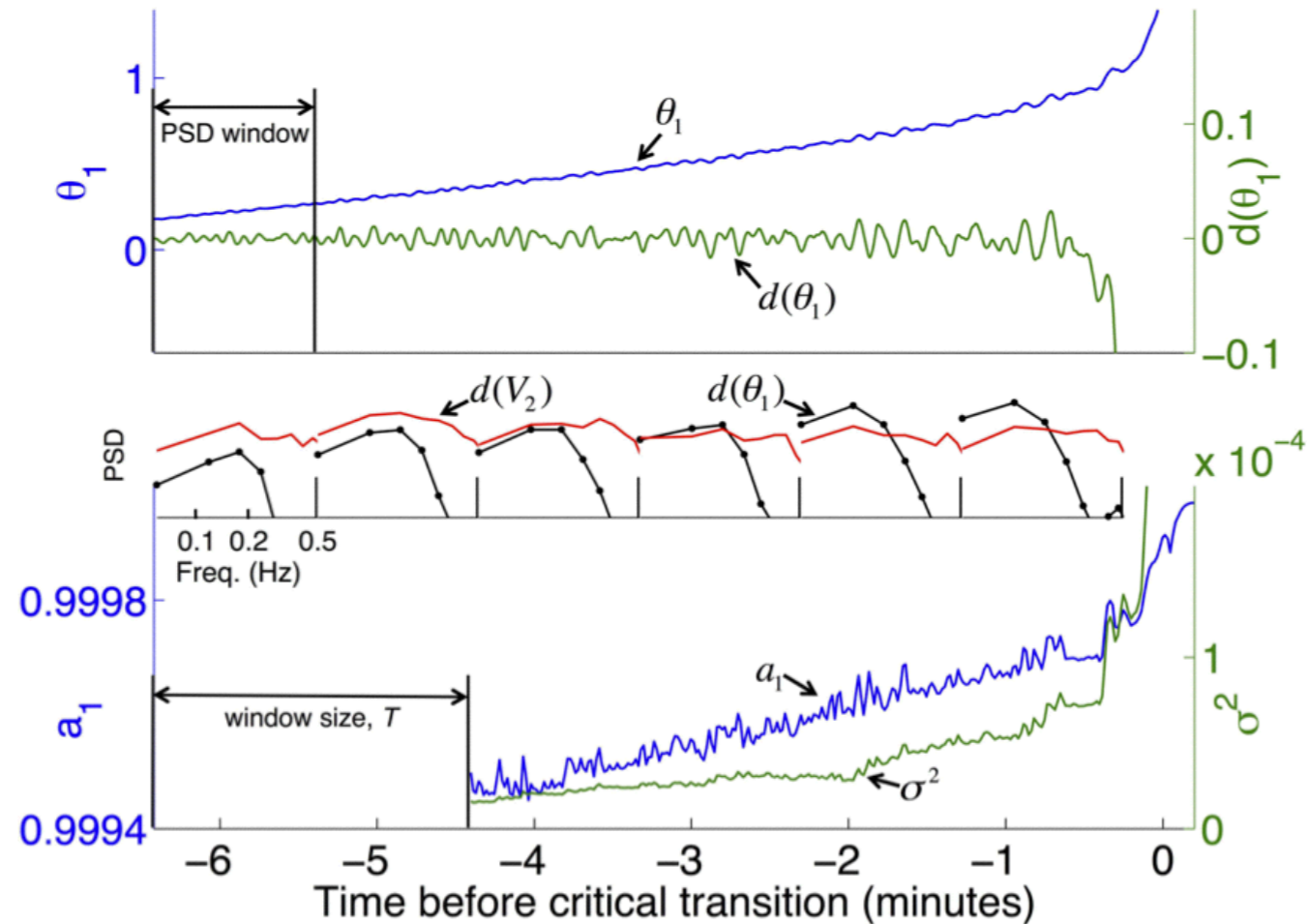
# Sure enough...statistics can be useful indicators



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*Cotilla-Sanchez, Hines, Danforth, IEEE Trans Smart Grid, 2012.*

See also:

DeMarco and Berge, IEEE Trans on Ckt & Sys, 1987.

Dhople, Chen, DeVille, Domínguez-García, IEEE Trans on Ckt Sys, 2013

Podolsky and Turitsyn, arXiv:1307.4318, Jul. 2013.

Susuki and Mezic, IEEE Trans. Power Syst., 2012 (and others)



# How can we find the useful\* statistical early warning signs?

\**Useful*: A sign that shows up early enough that we might actually be able to do something about it, even if there is measurement noise

# First let's define our SDEs

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$$\dot{\underline{x}} = f(\underline{x}, \underline{y})$$

Differential equations.  
(swing eqs., governors,  
exciters, etc.)

$$0 = g(\underline{x}, \underline{y}, \underline{u})$$

Algebraic equations

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Ind. Gaussian r.v.s, 1% std. dev.

Encodes corr. time of load fluctuations

# Choose an operating point, and linearize around that point

$$\Delta \underline{y} = \begin{bmatrix} -g_y^{-1} g_x & -g_y^{-1} g_u \end{bmatrix} \begin{bmatrix} \Delta \underline{x} \\ \Delta \underline{u} \end{bmatrix}$$
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Jacobian matrix:  $df/dx$

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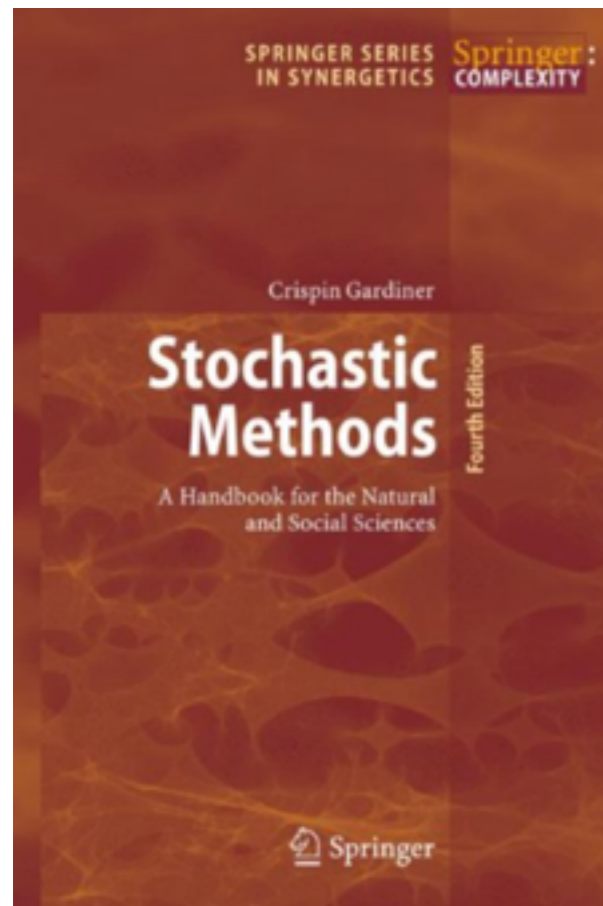
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I'd like to tell you that we came up with new, elegant mathematics to solve. In reality...

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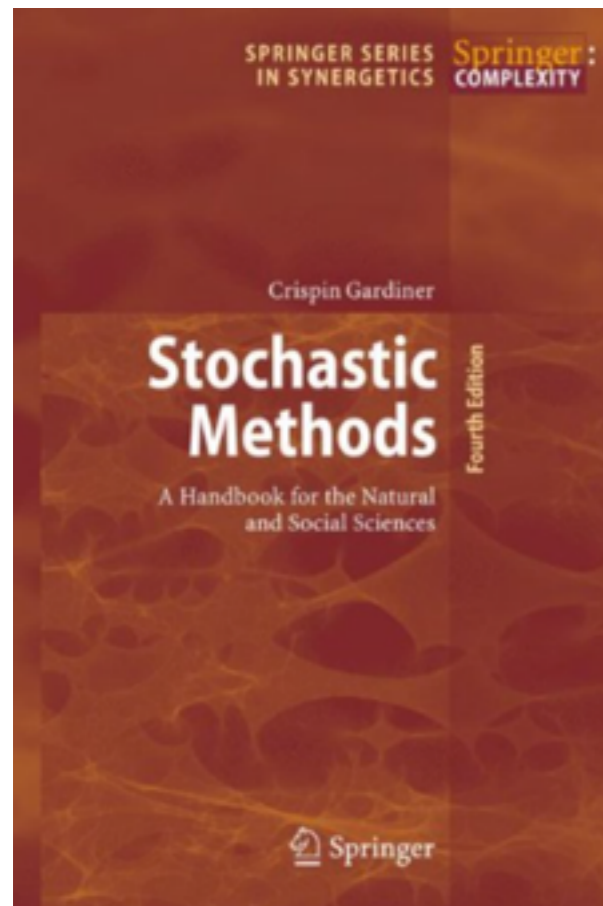
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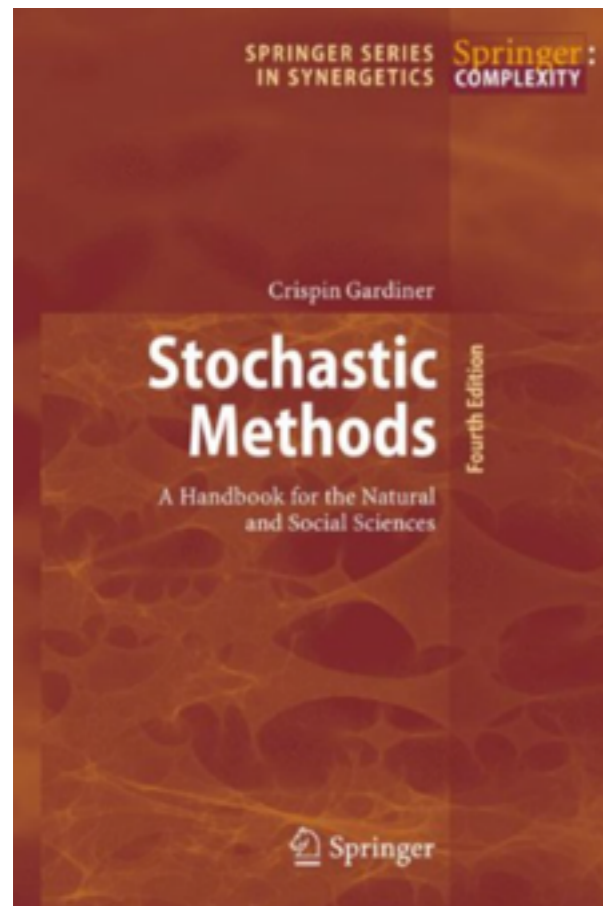
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$$A\sigma_{\underline{z}} + \sigma_{\underline{z}}A^T = -BB^T$$
$$\mathbf{E} [\underline{z}(t) \underline{z}^T(s)] = \exp[-A|t-s|] \sigma_{\underline{z}}$$

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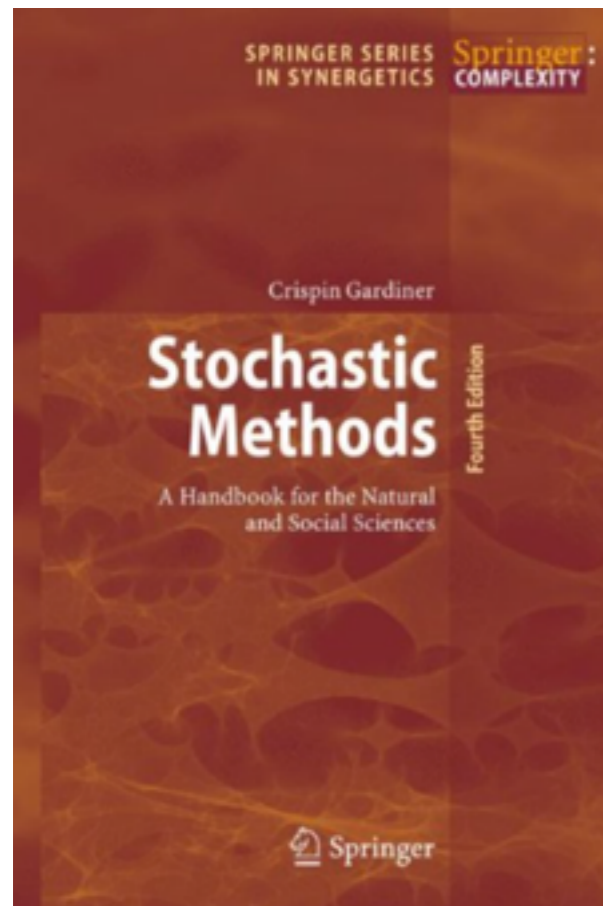
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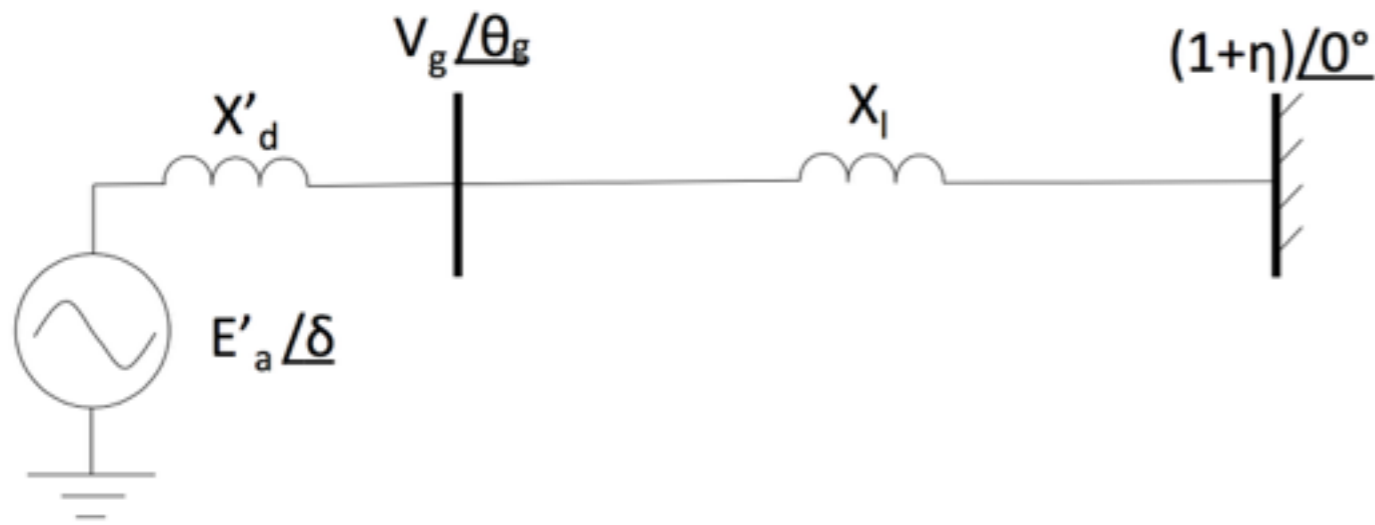


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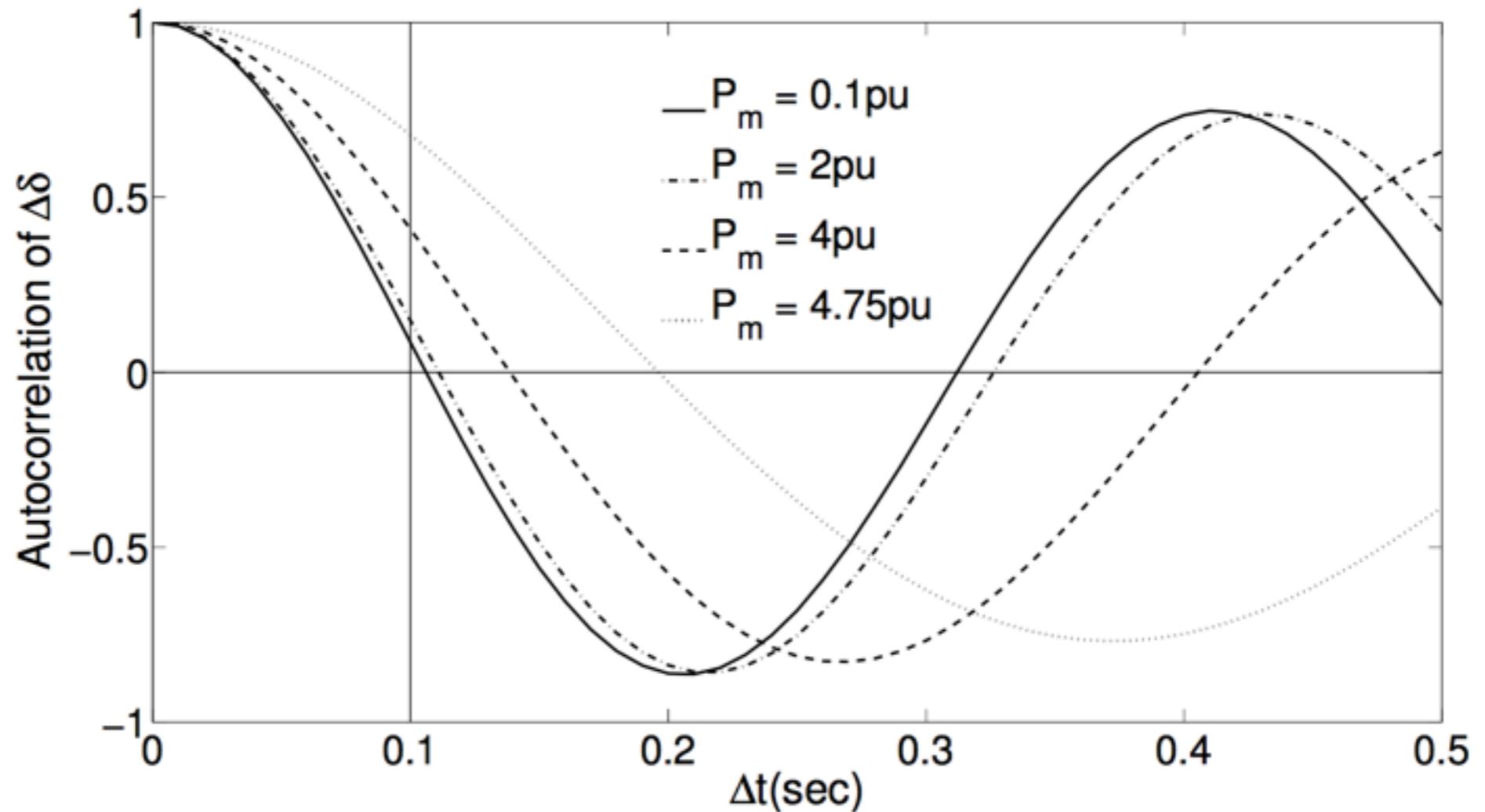
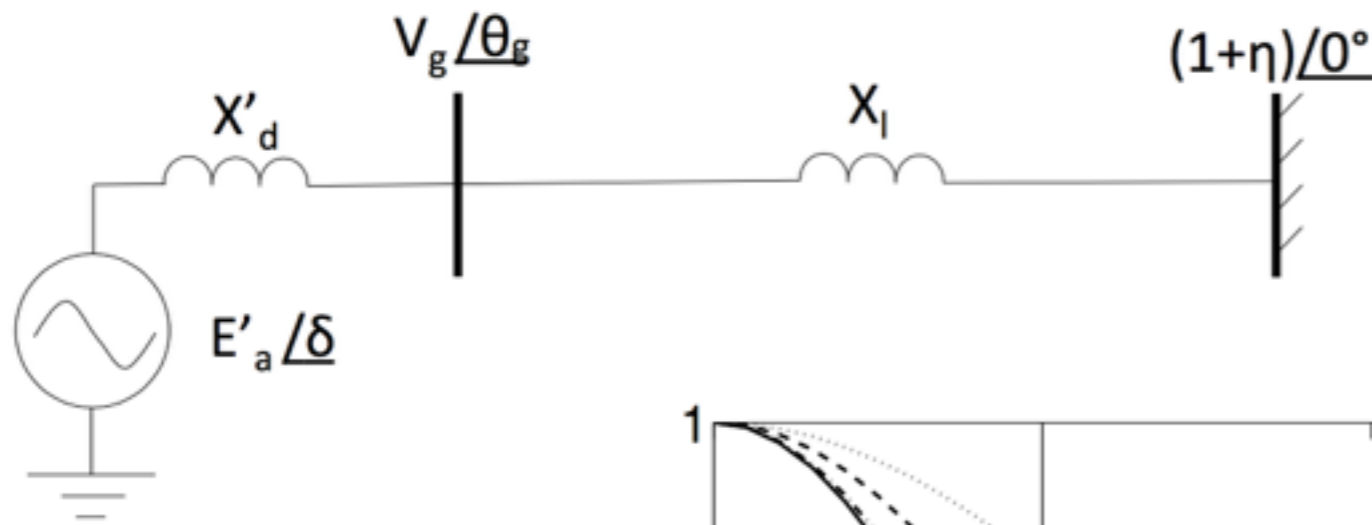
And then reverse the Kron reduction to compute the variance and autocorrelation of voltage and current magnitudes.

and choose a time delay for  
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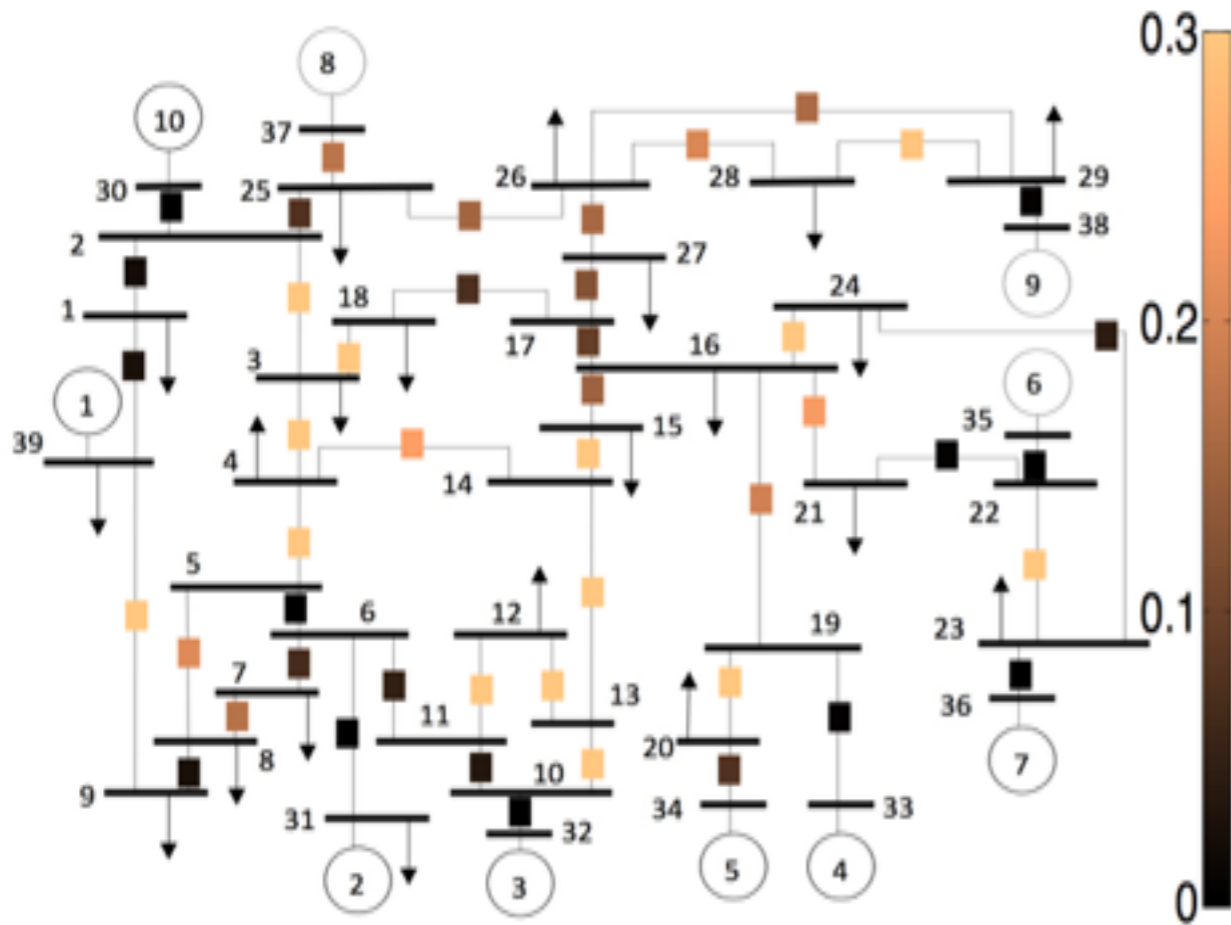


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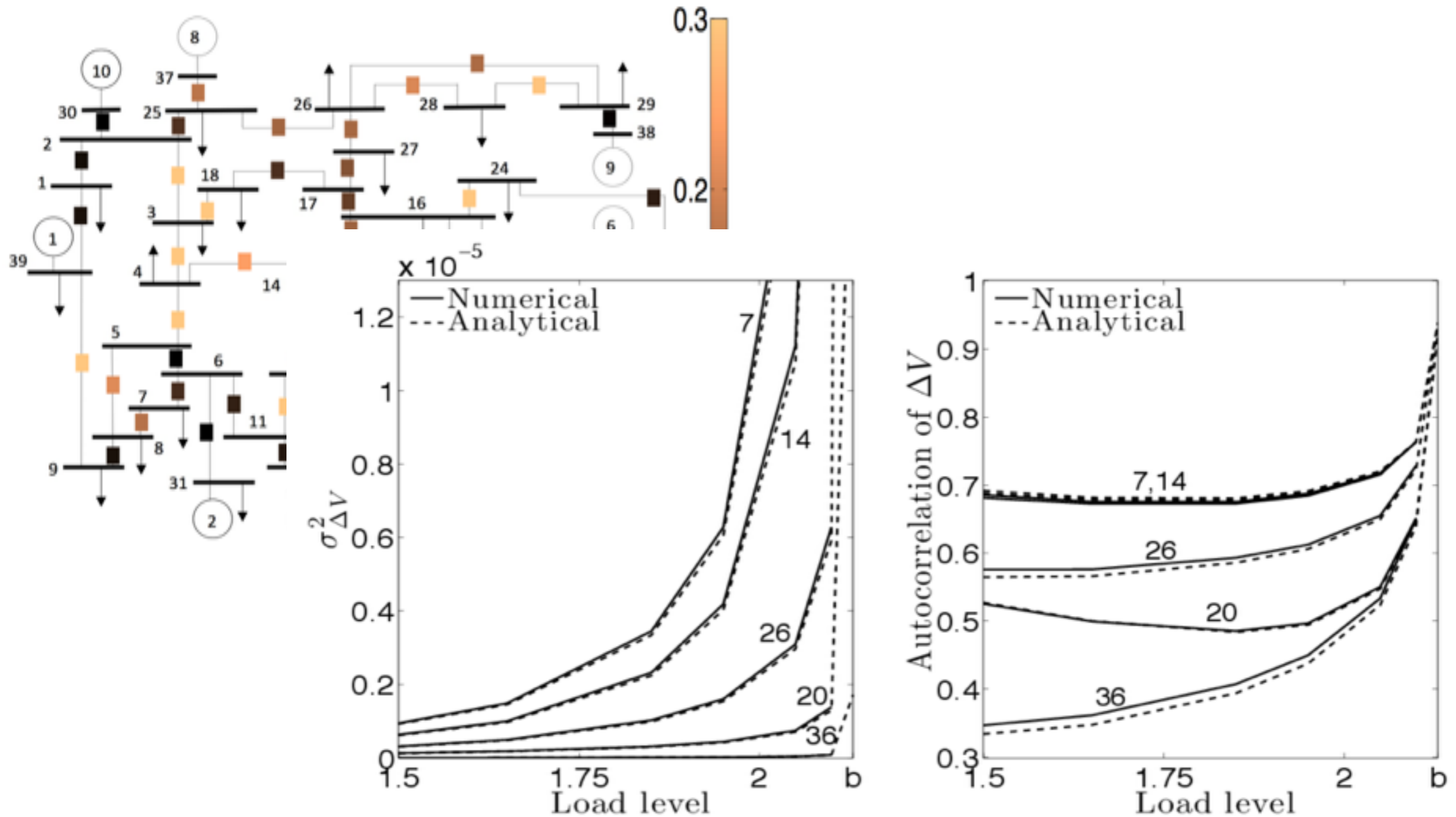
Check to make sure that the analytical and numerical line up

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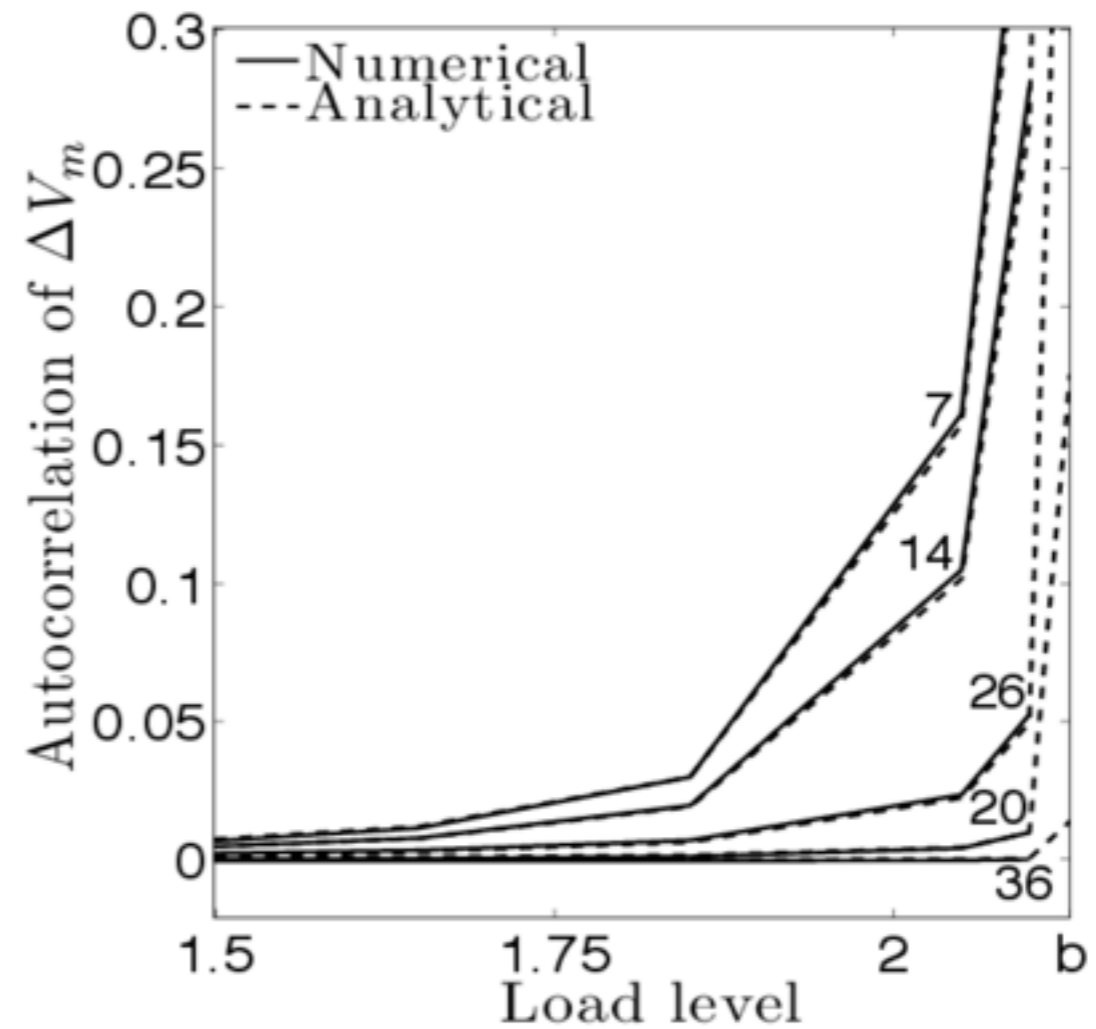
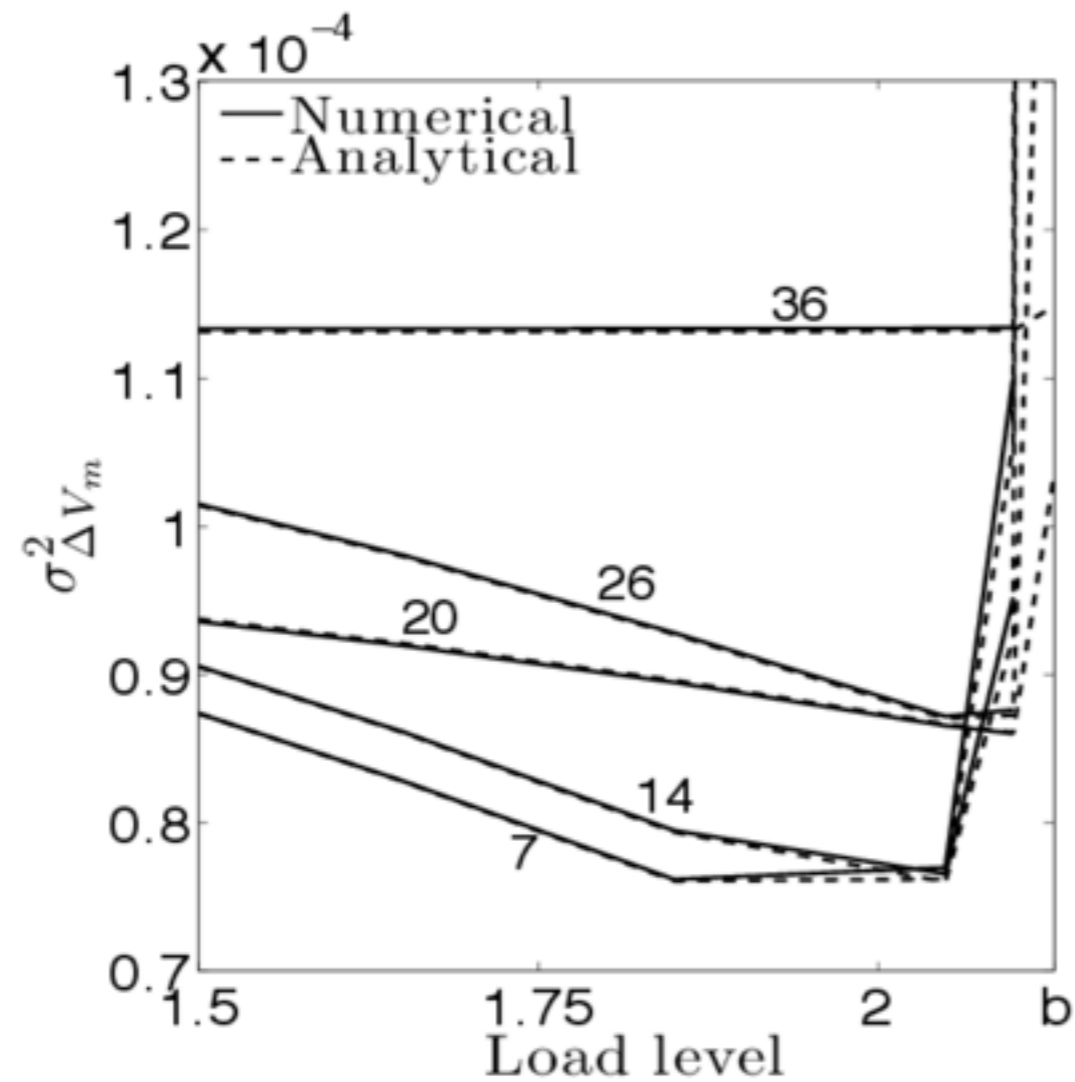




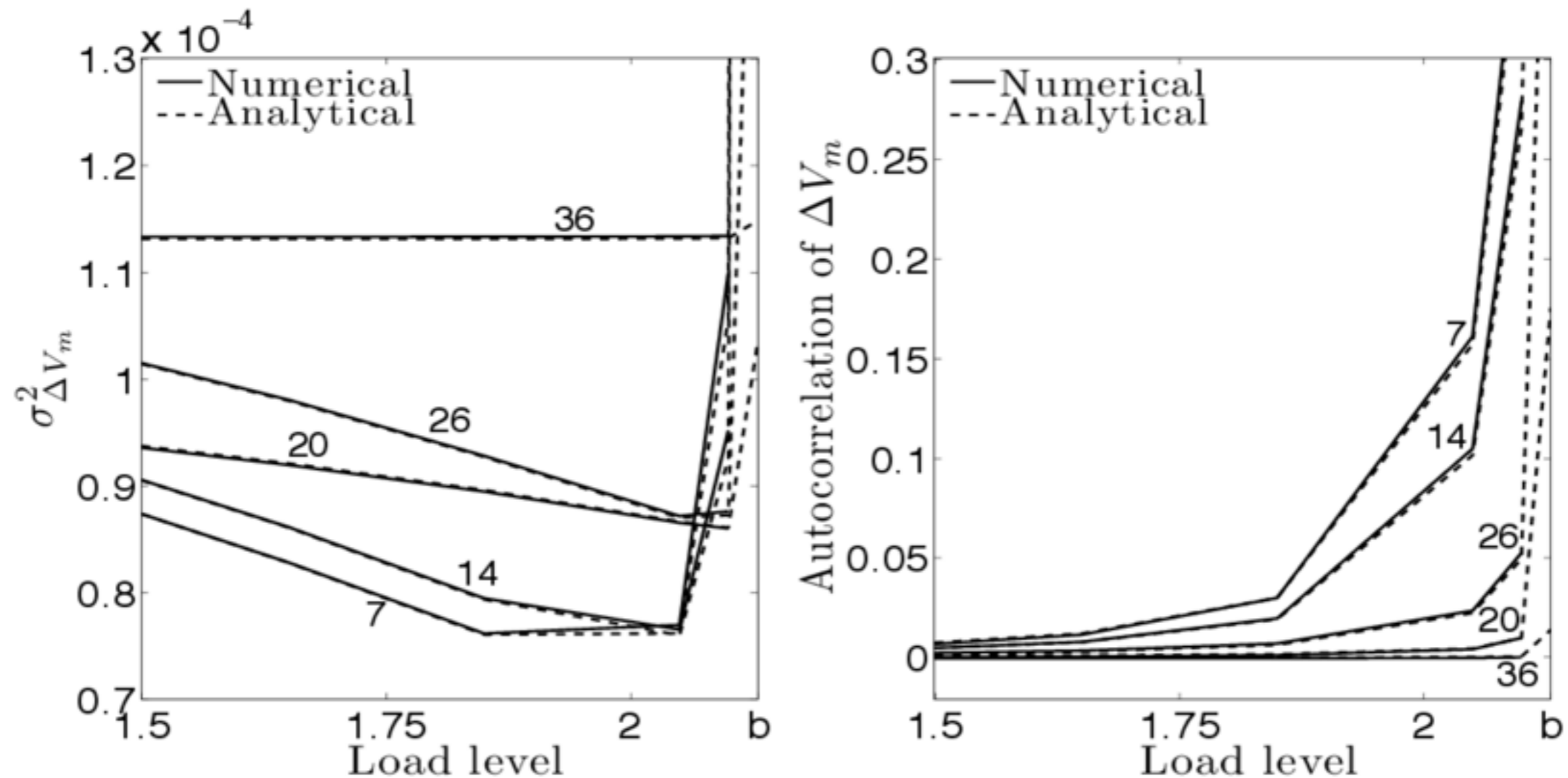
# Check to make sure that the analytical and numerical line up



# And add measurement noise



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Which we can subsequently filter to largely regain our original signal, with the interesting side-effect that some of the variance now appears as autocorrelation.

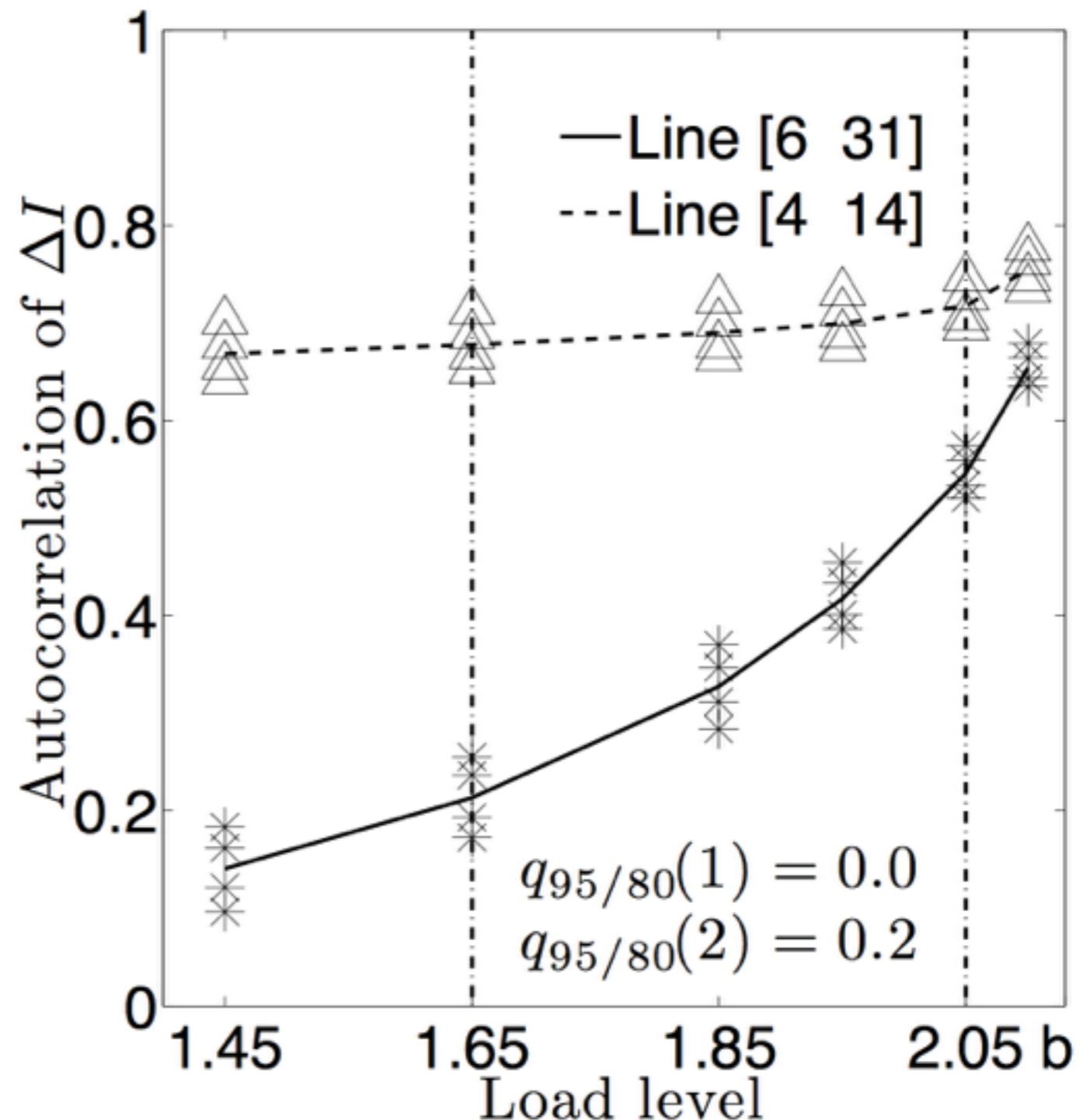
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How do we measure  
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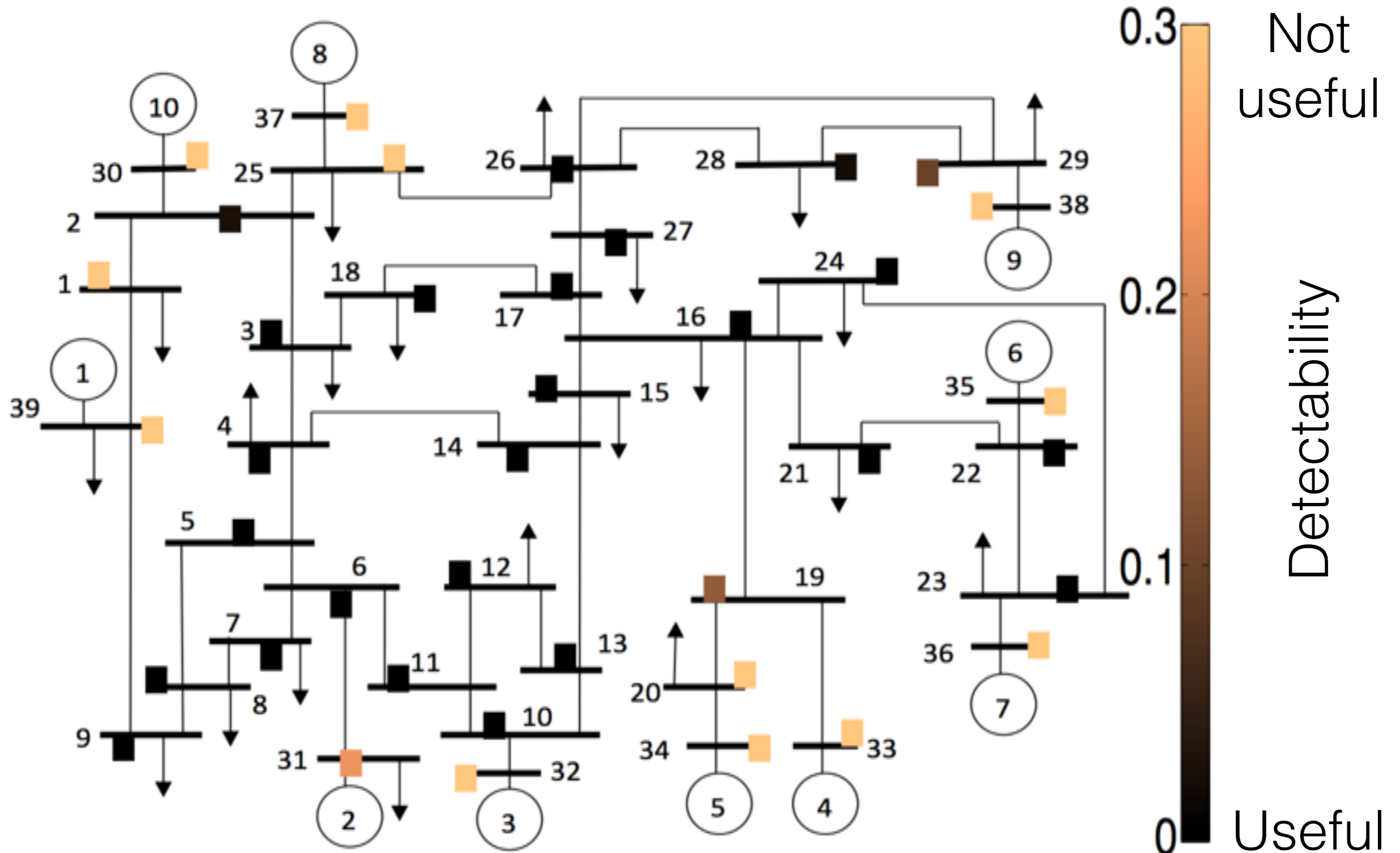
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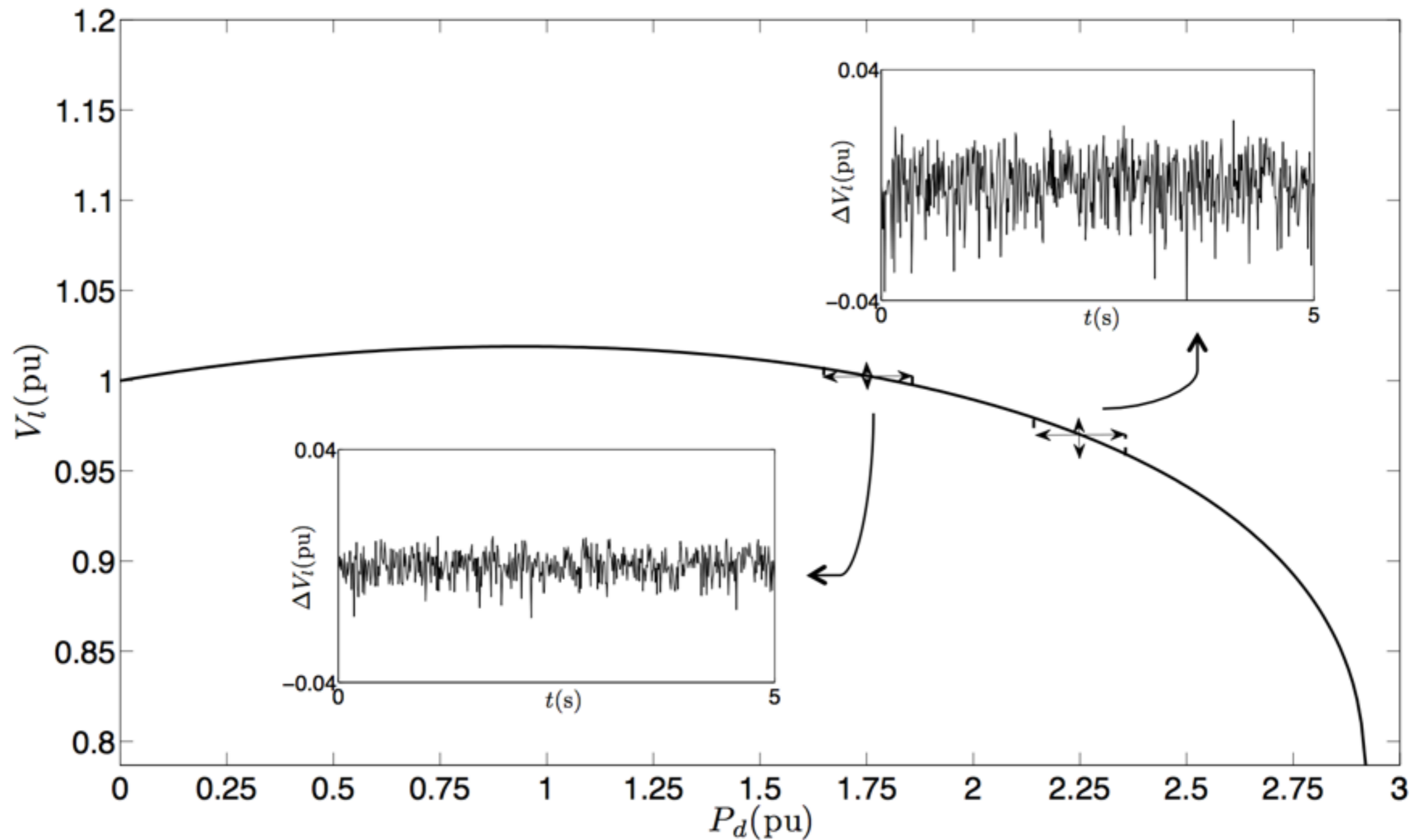
**Which statistics provide  
useful (detectable)  
early warning?**

# Variance of voltages

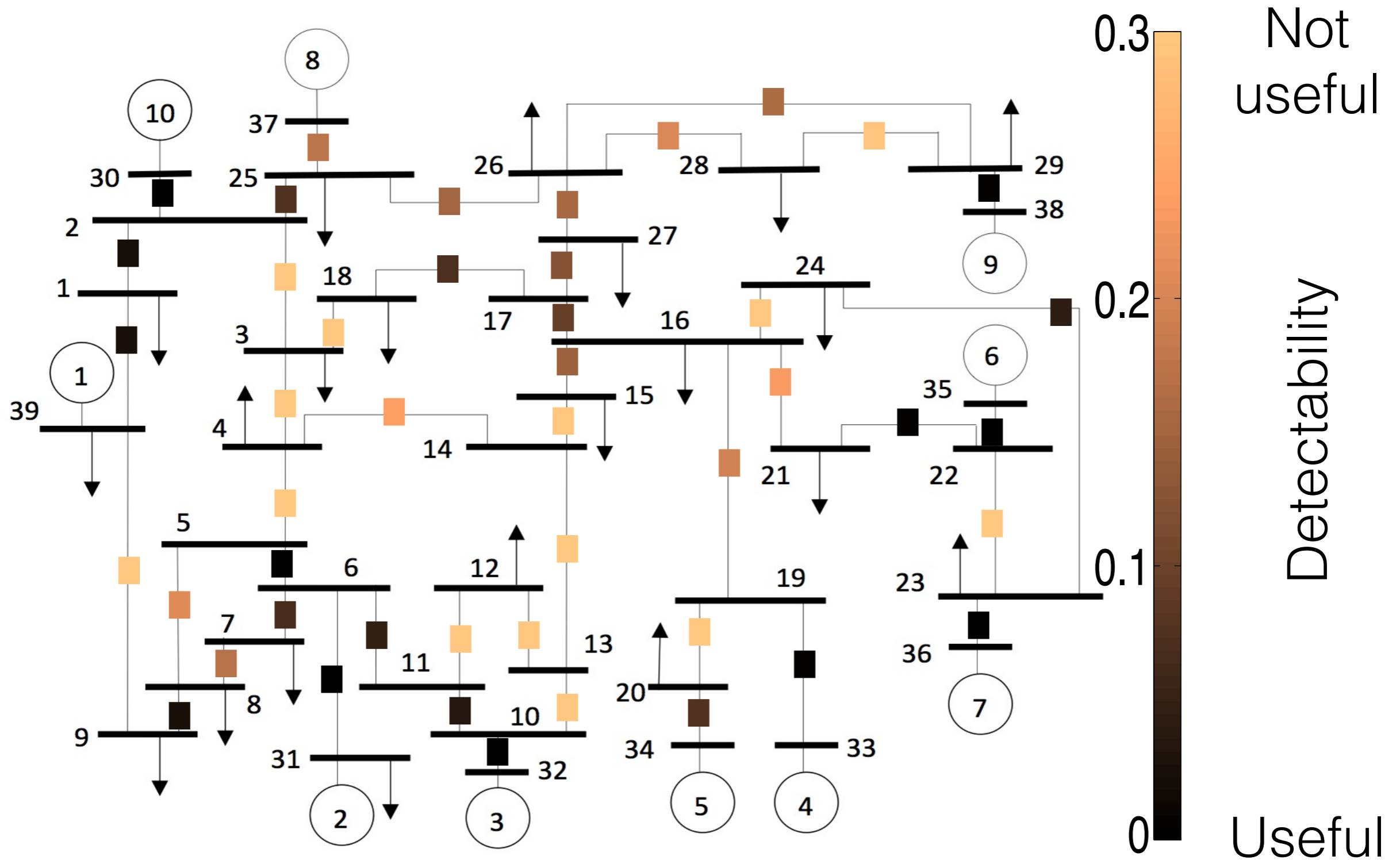




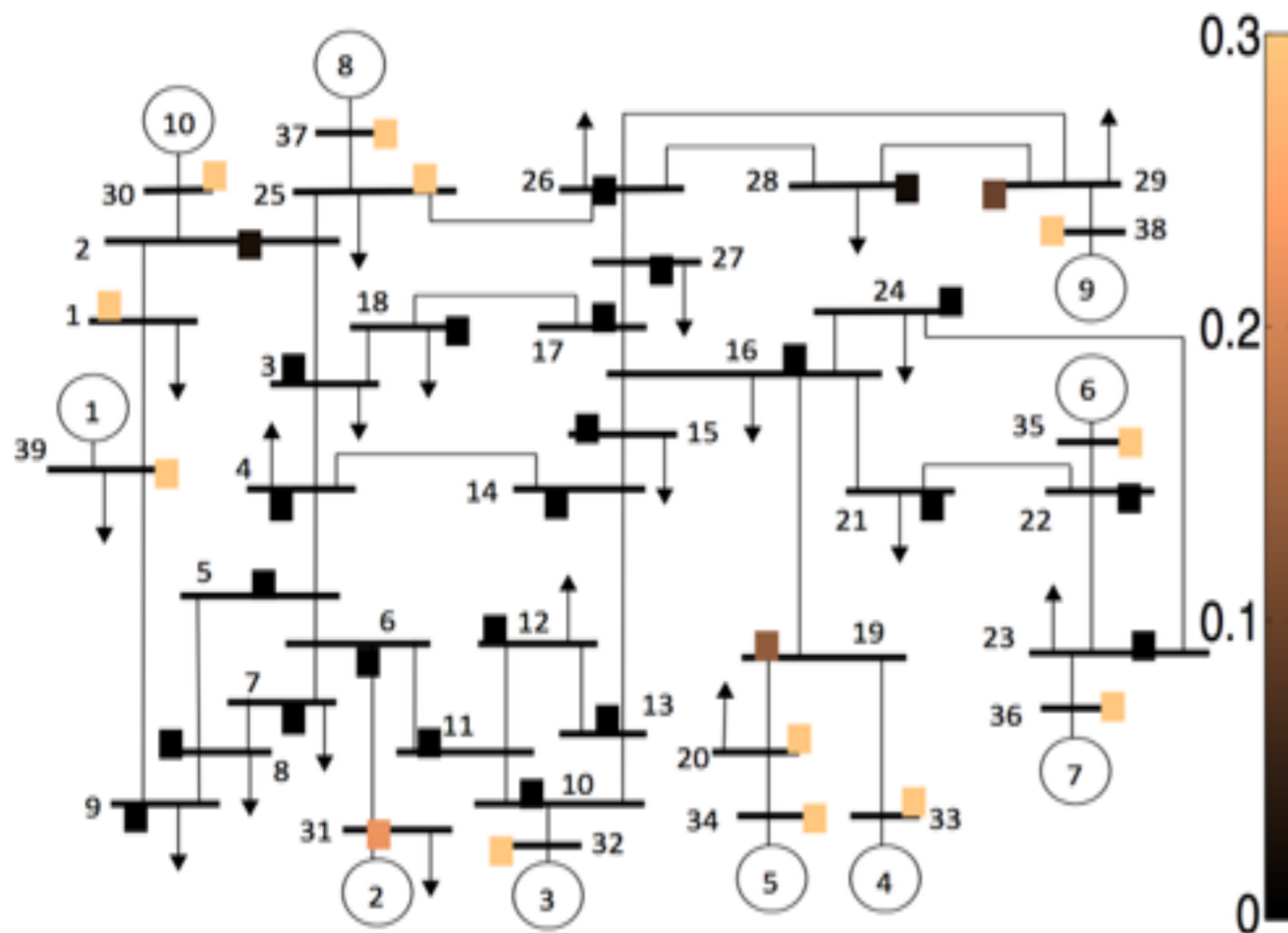
# Why is variance in voltage useful?



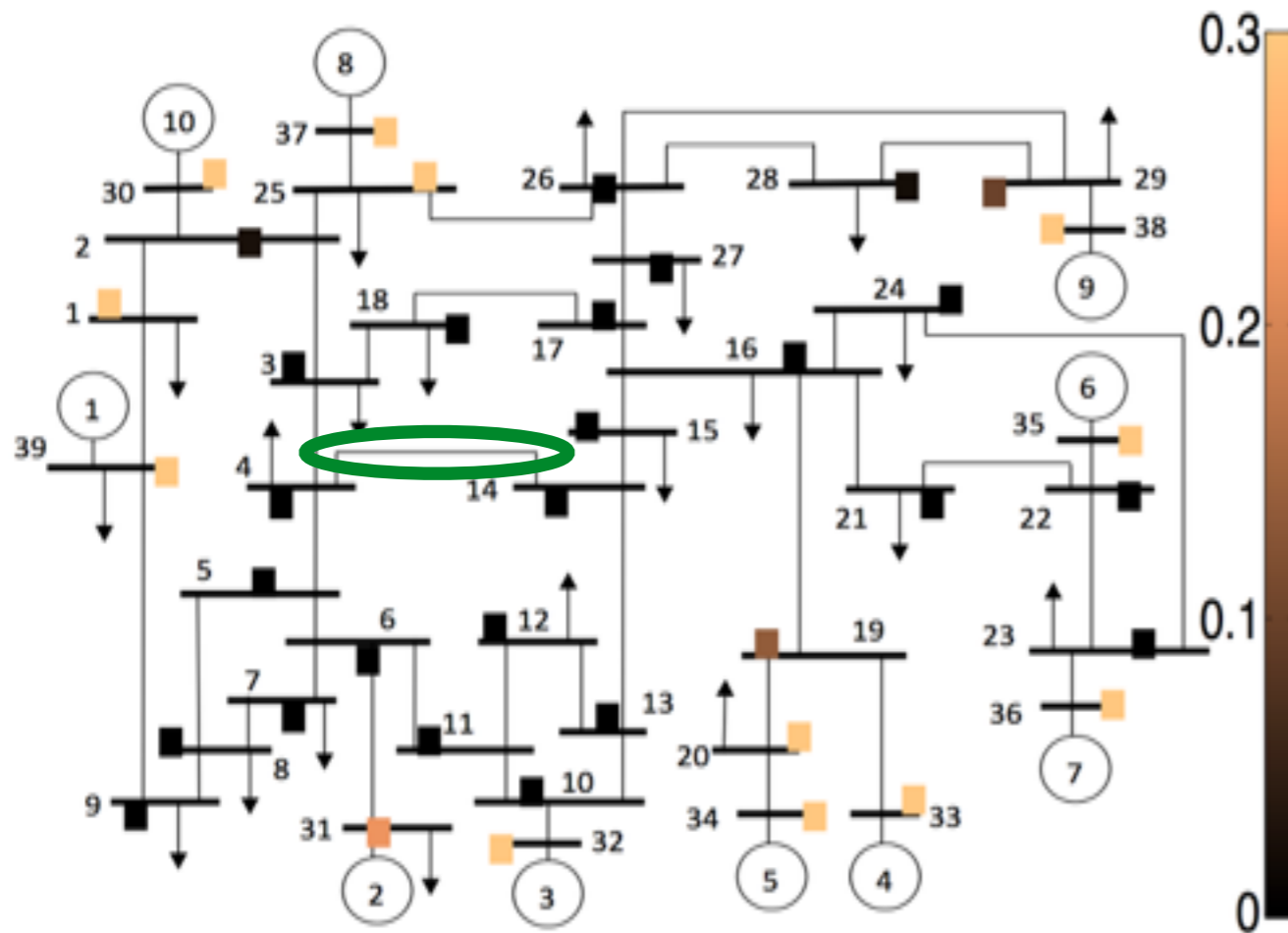
# Autocorrelation of currents



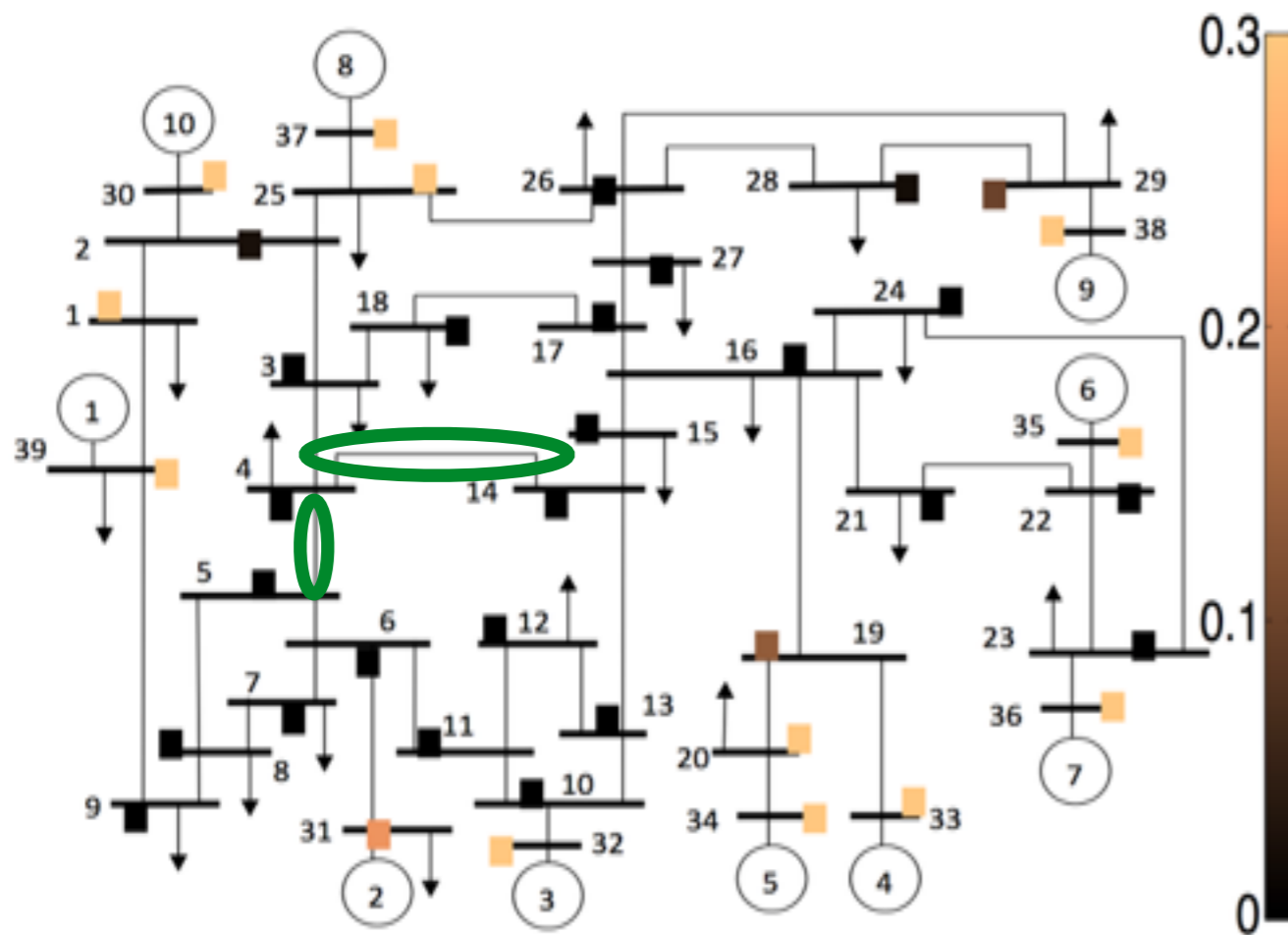
# Can we find the location/source of a problem given the statistics?



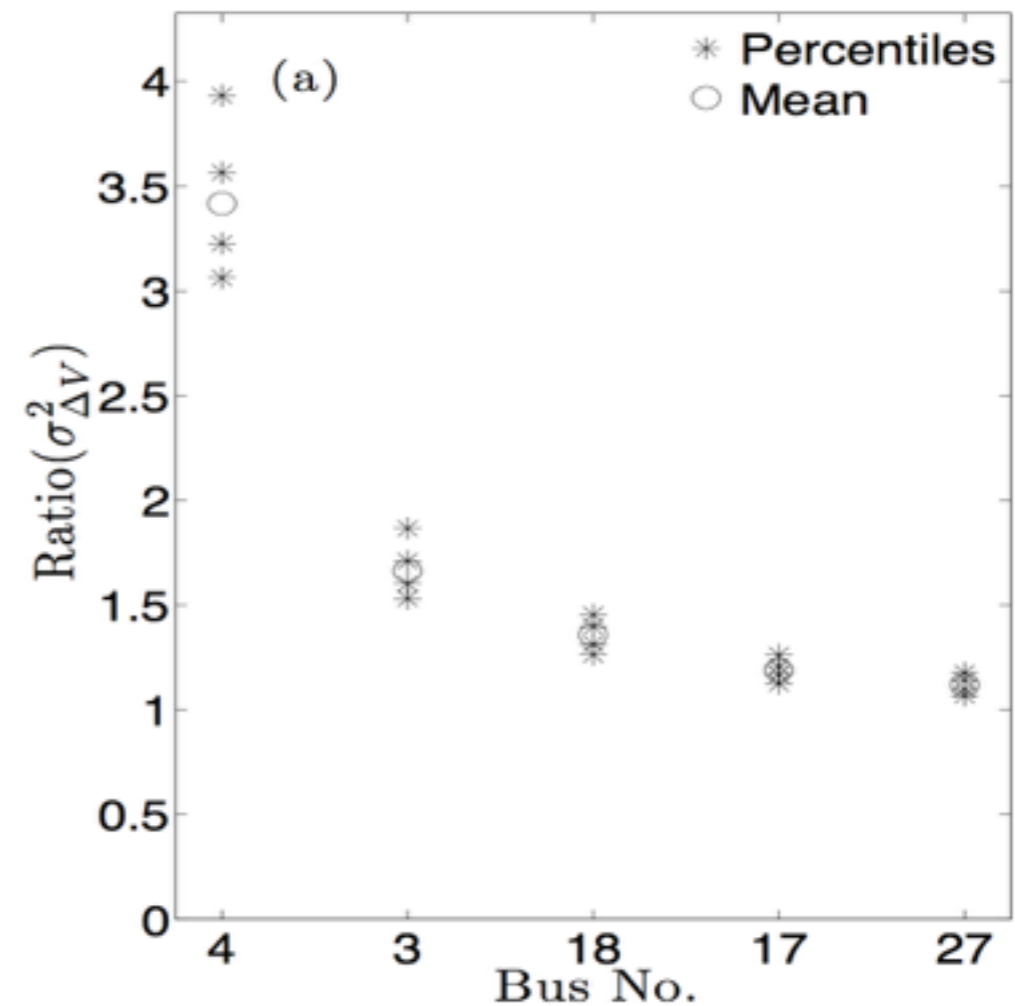
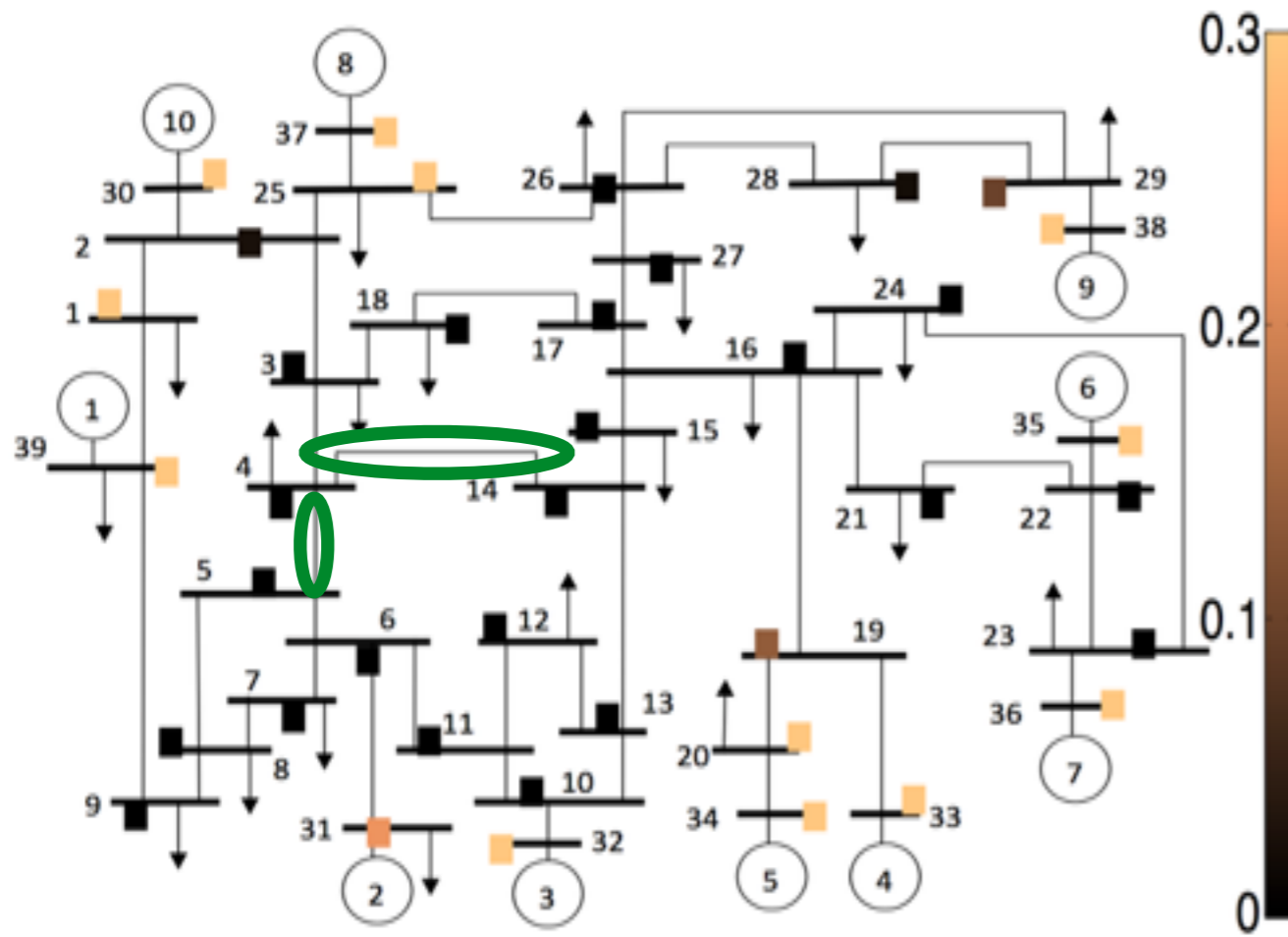
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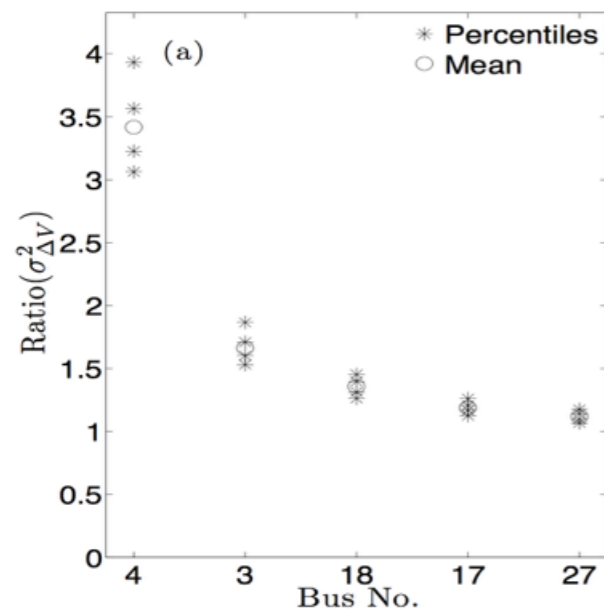
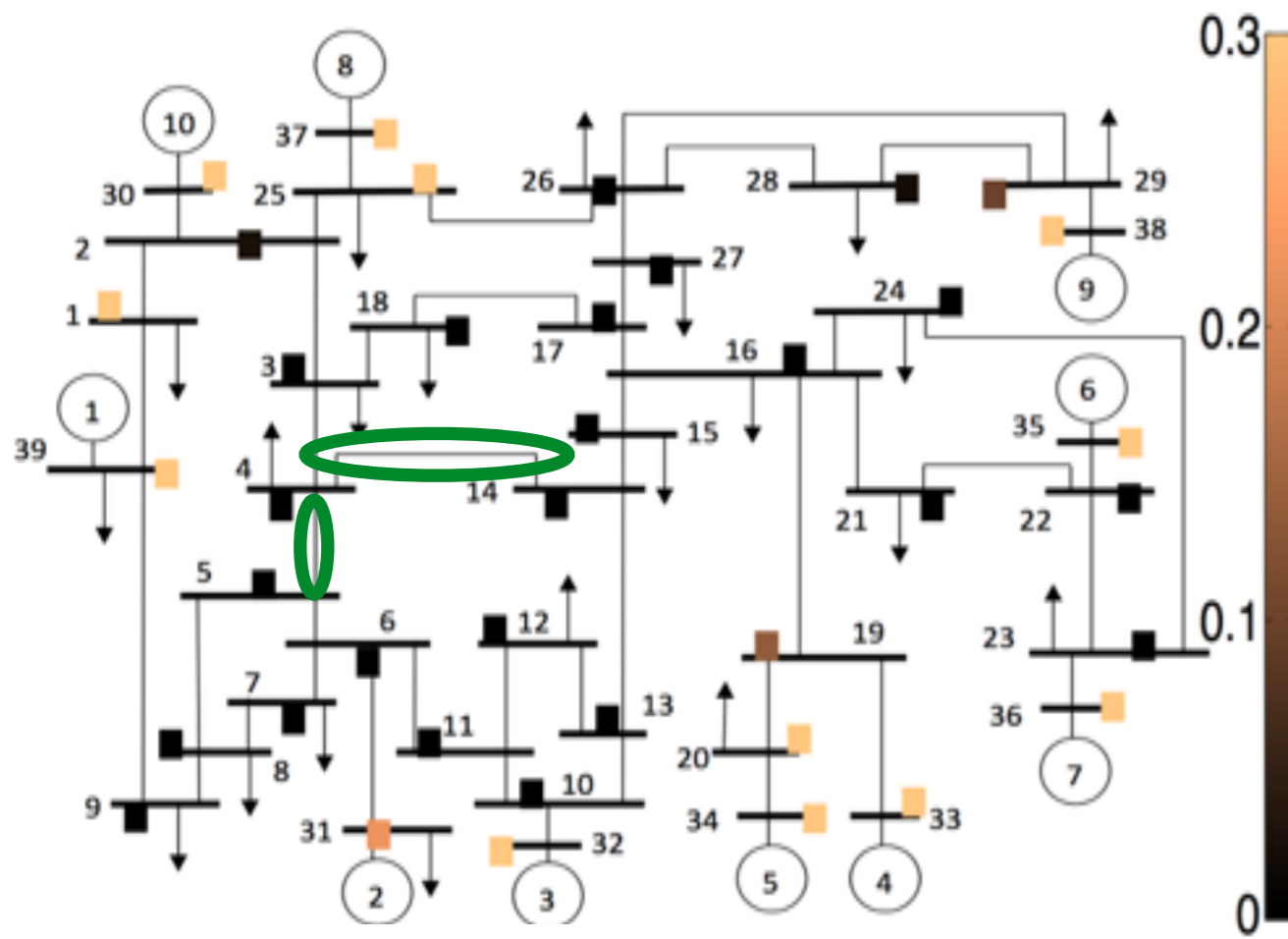
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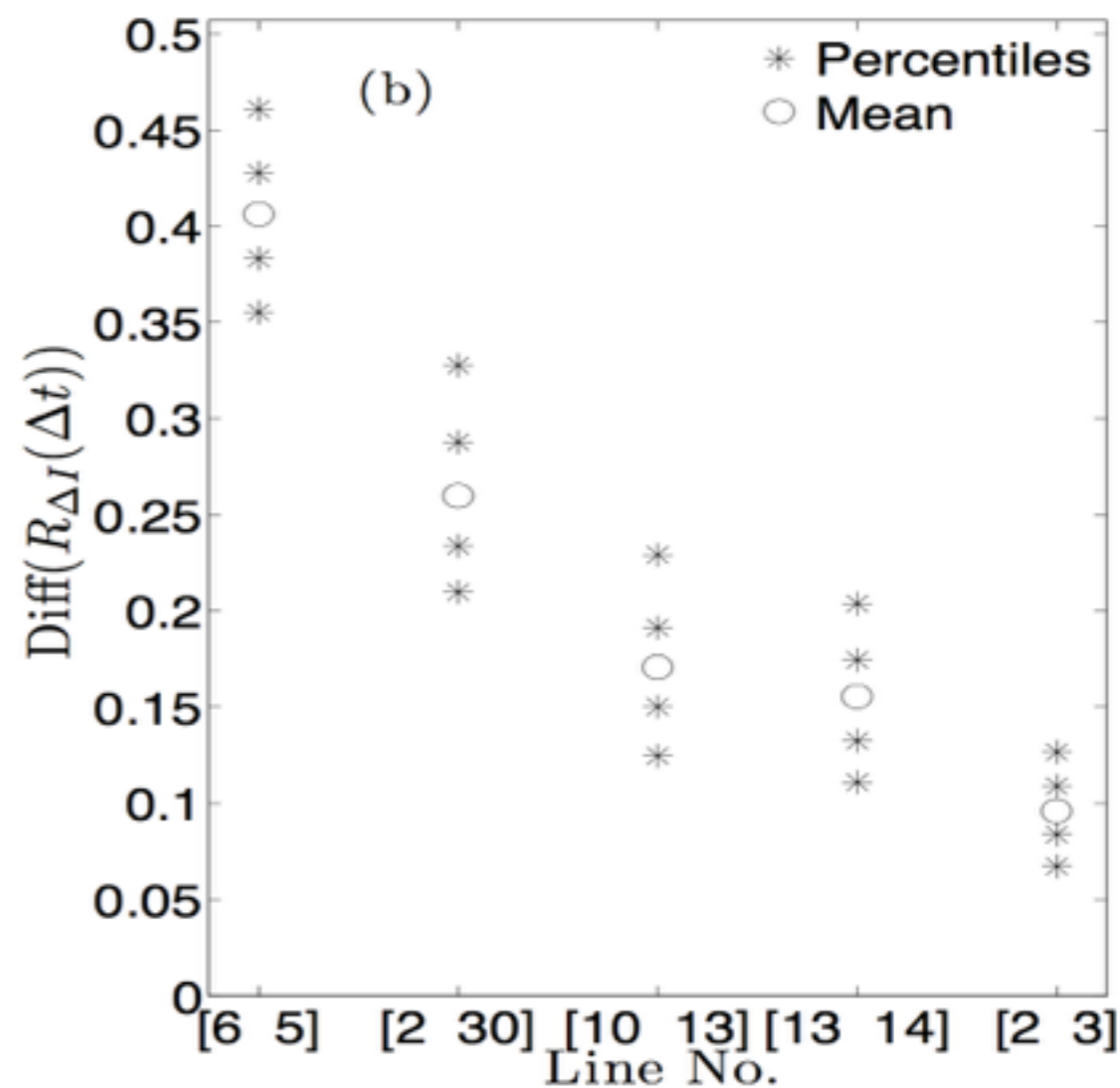
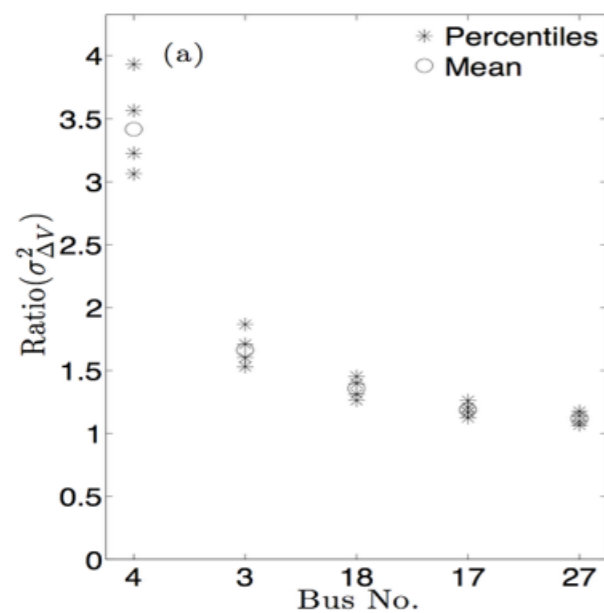
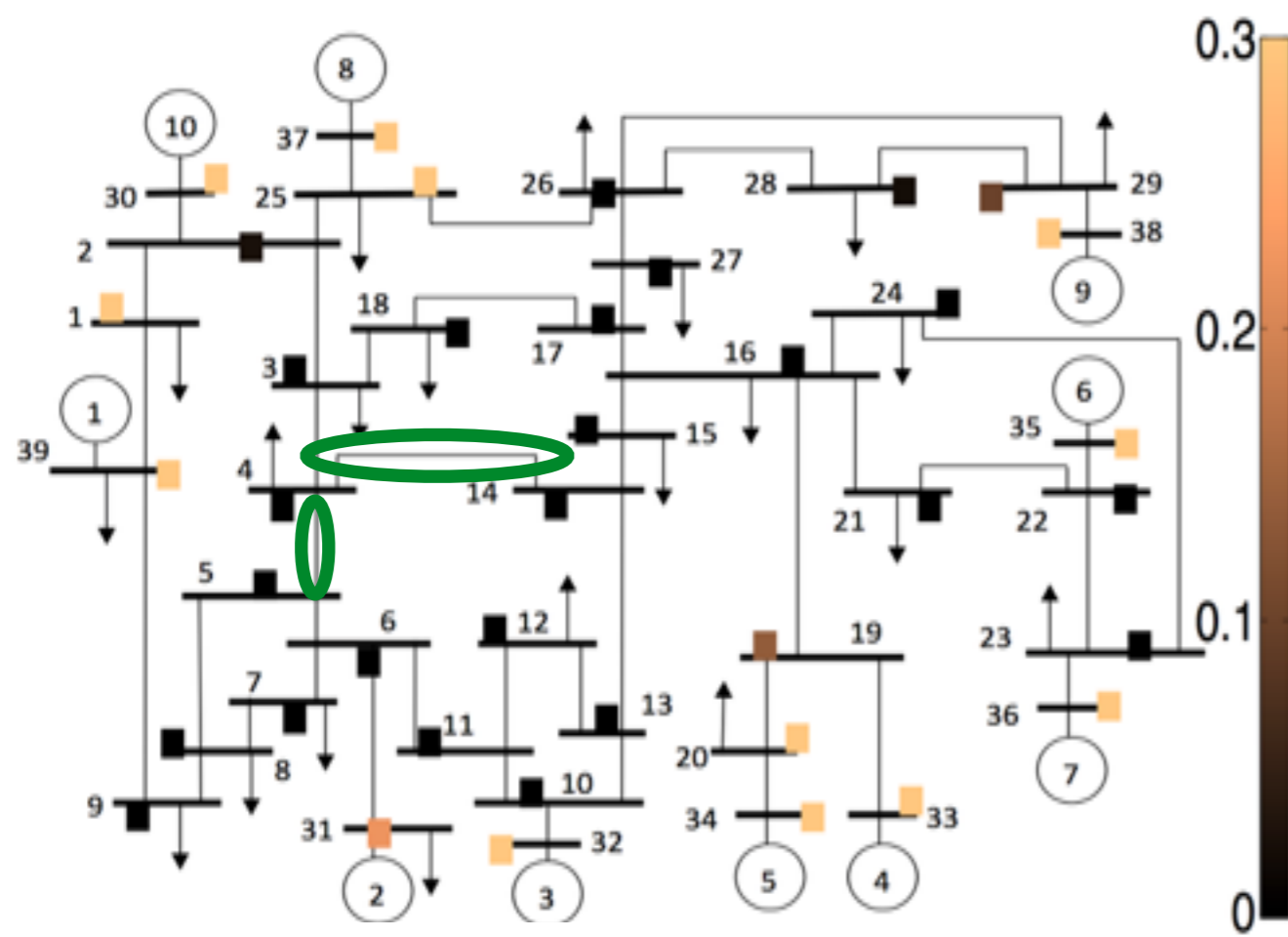
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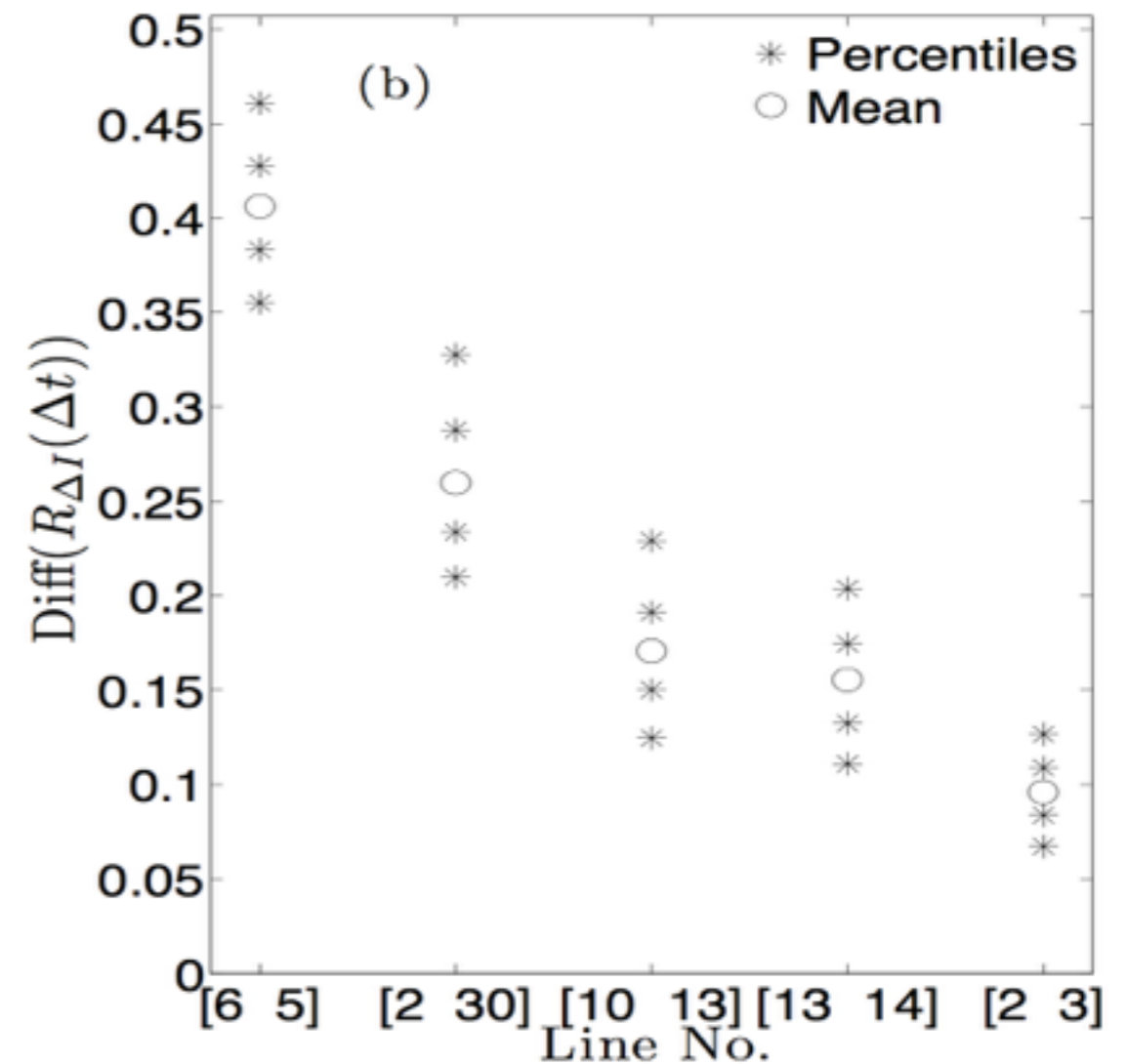
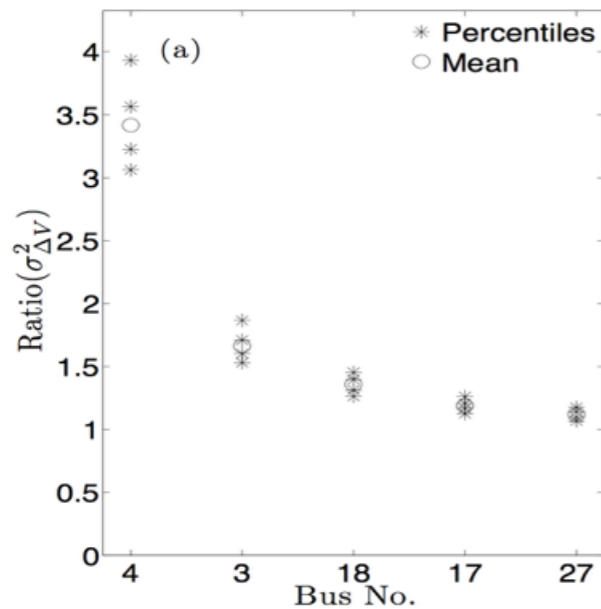
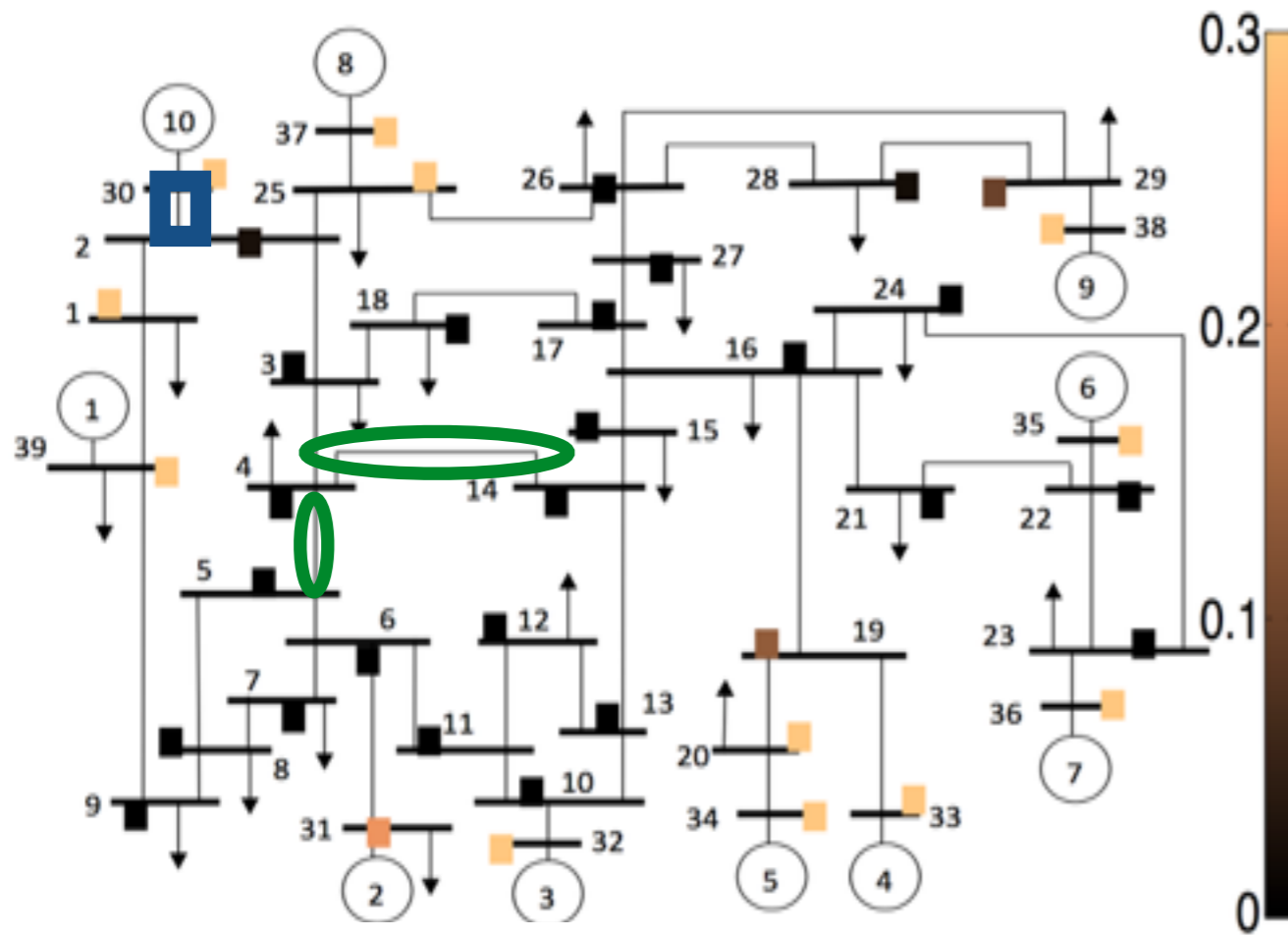


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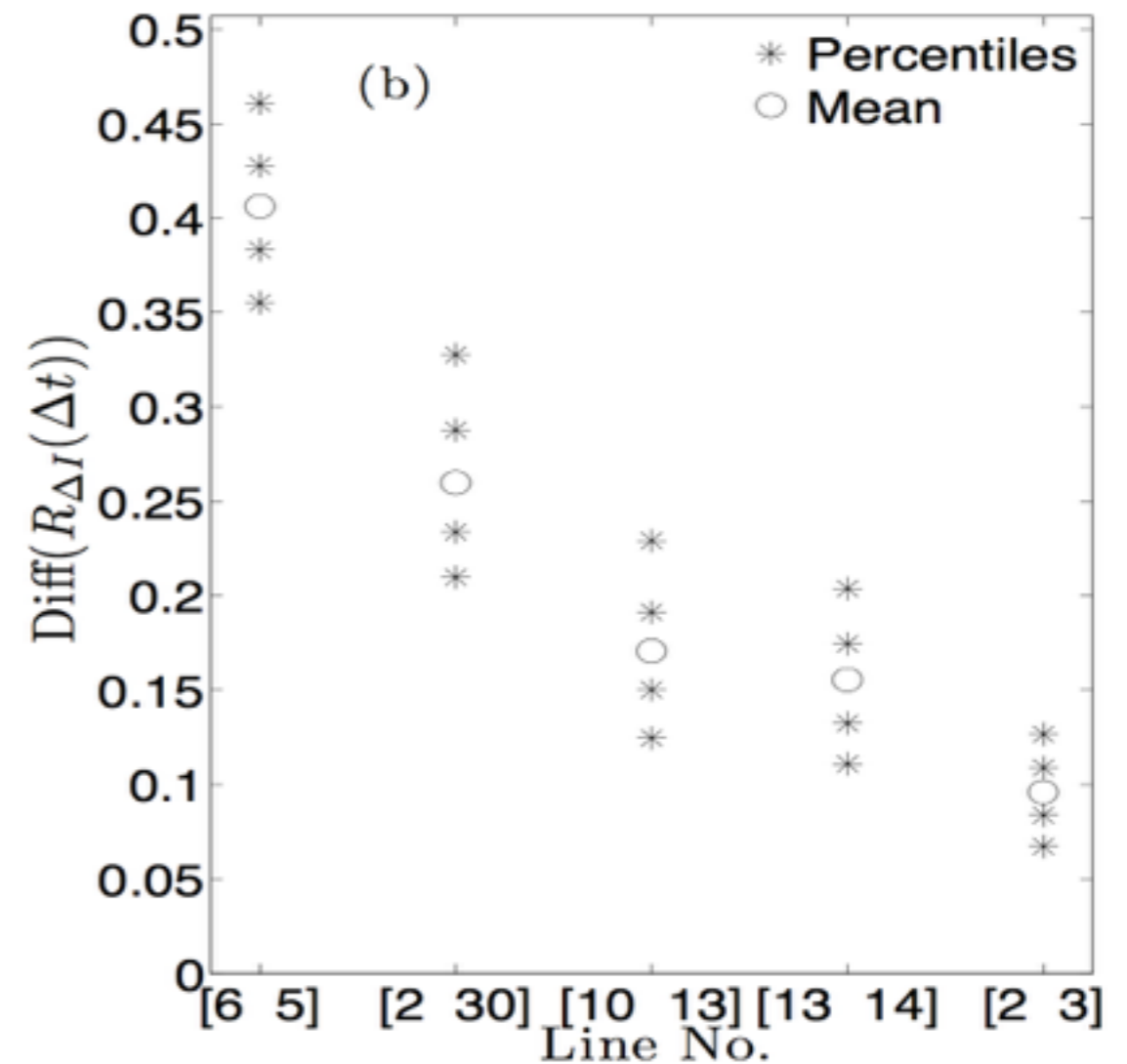
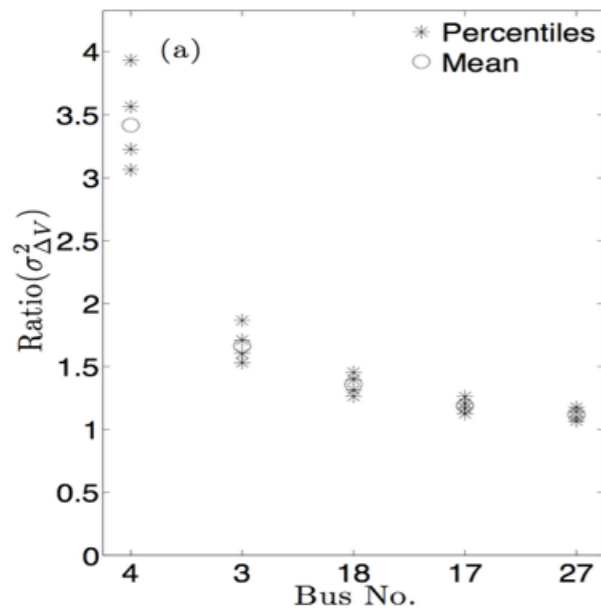
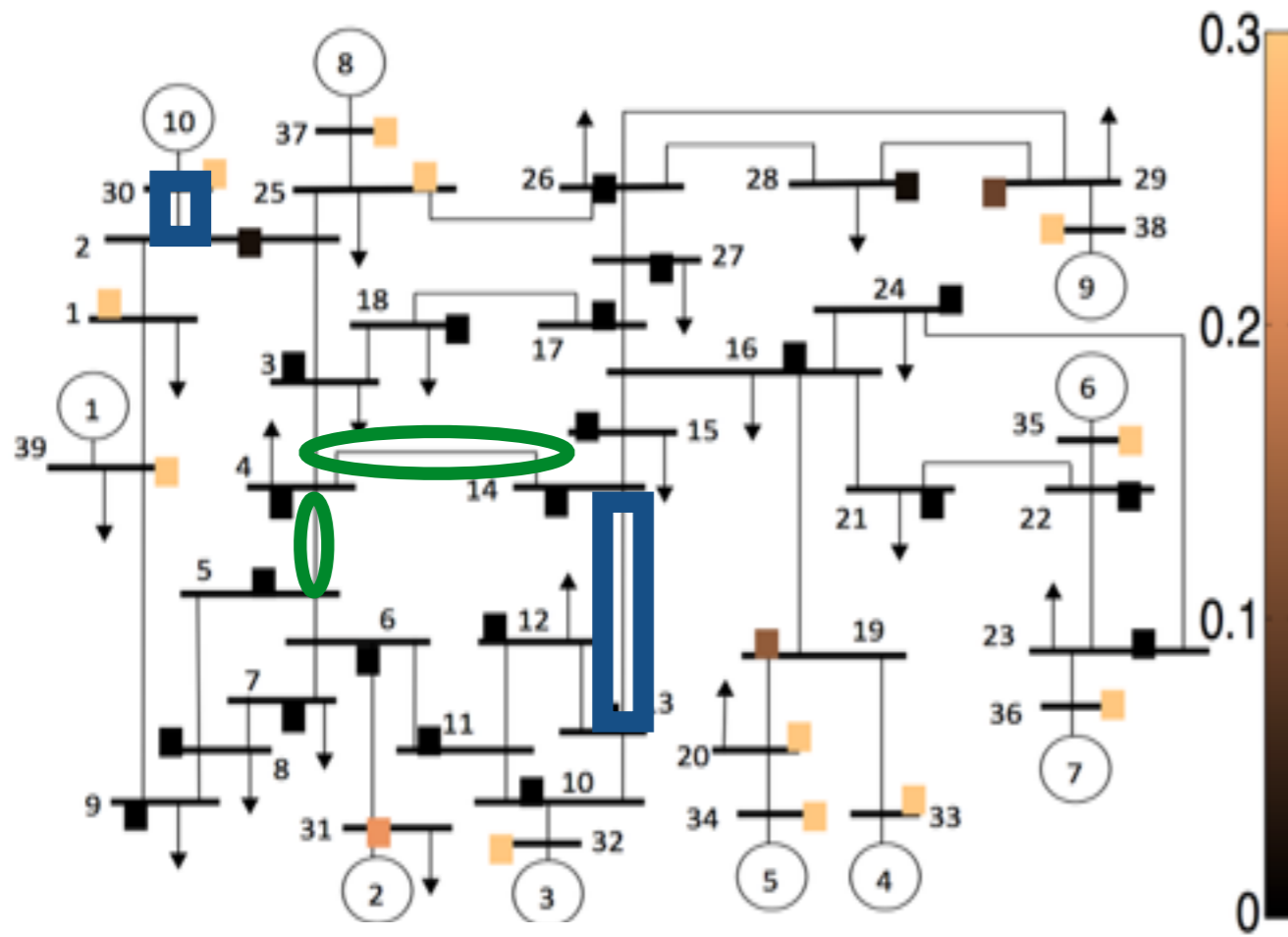




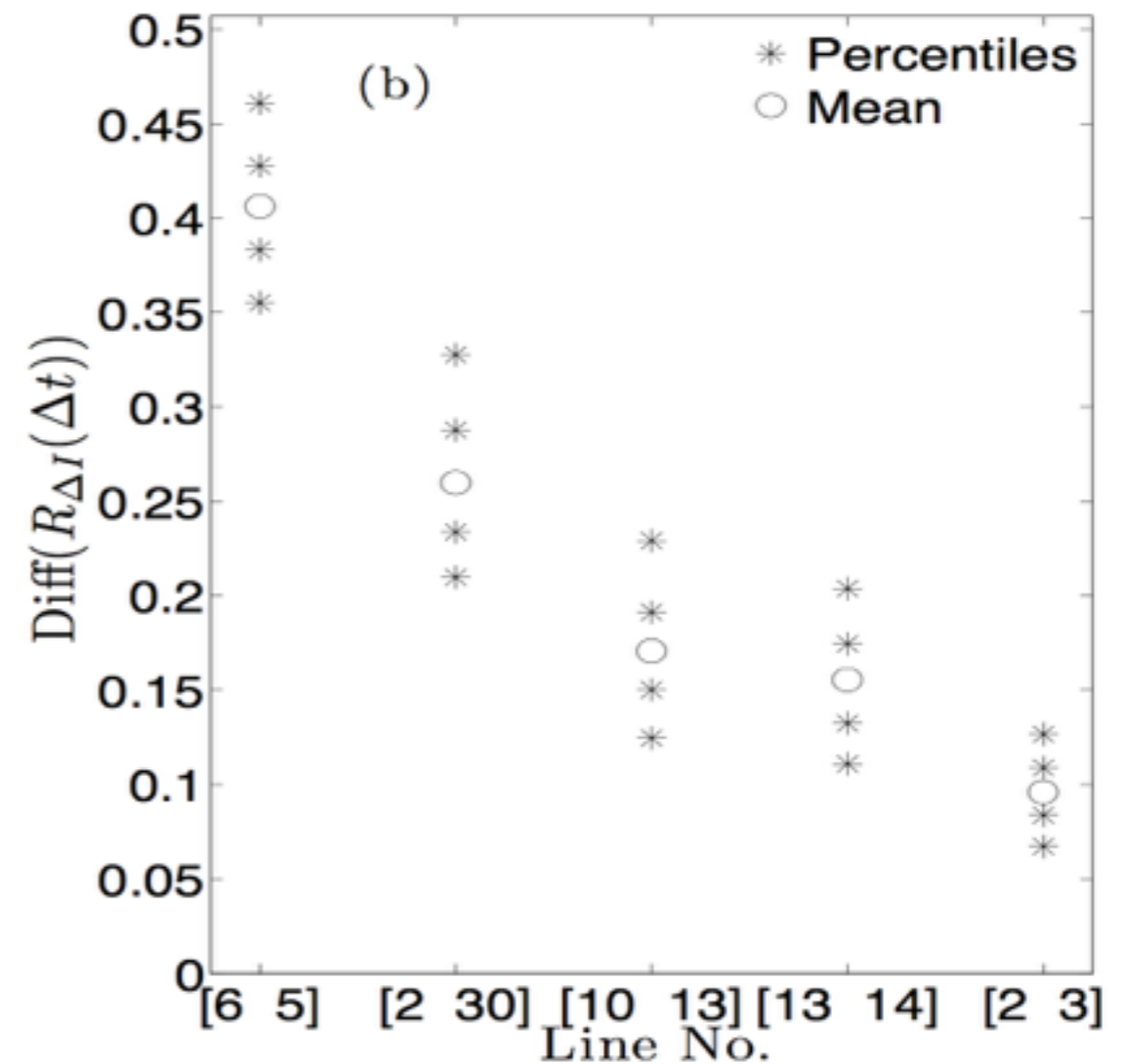
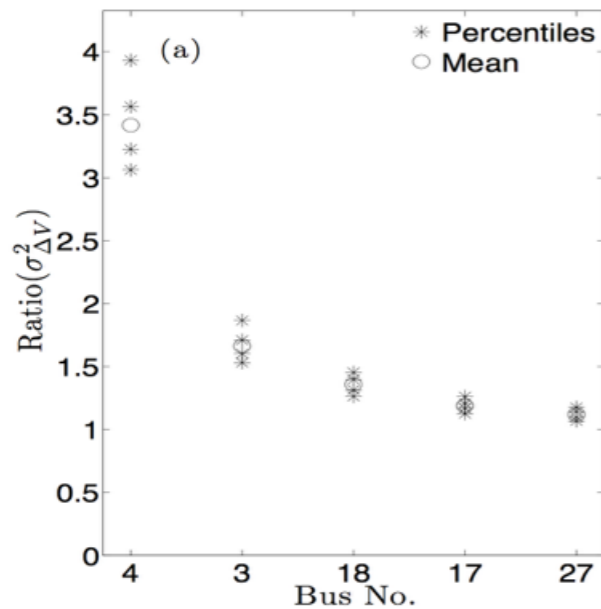
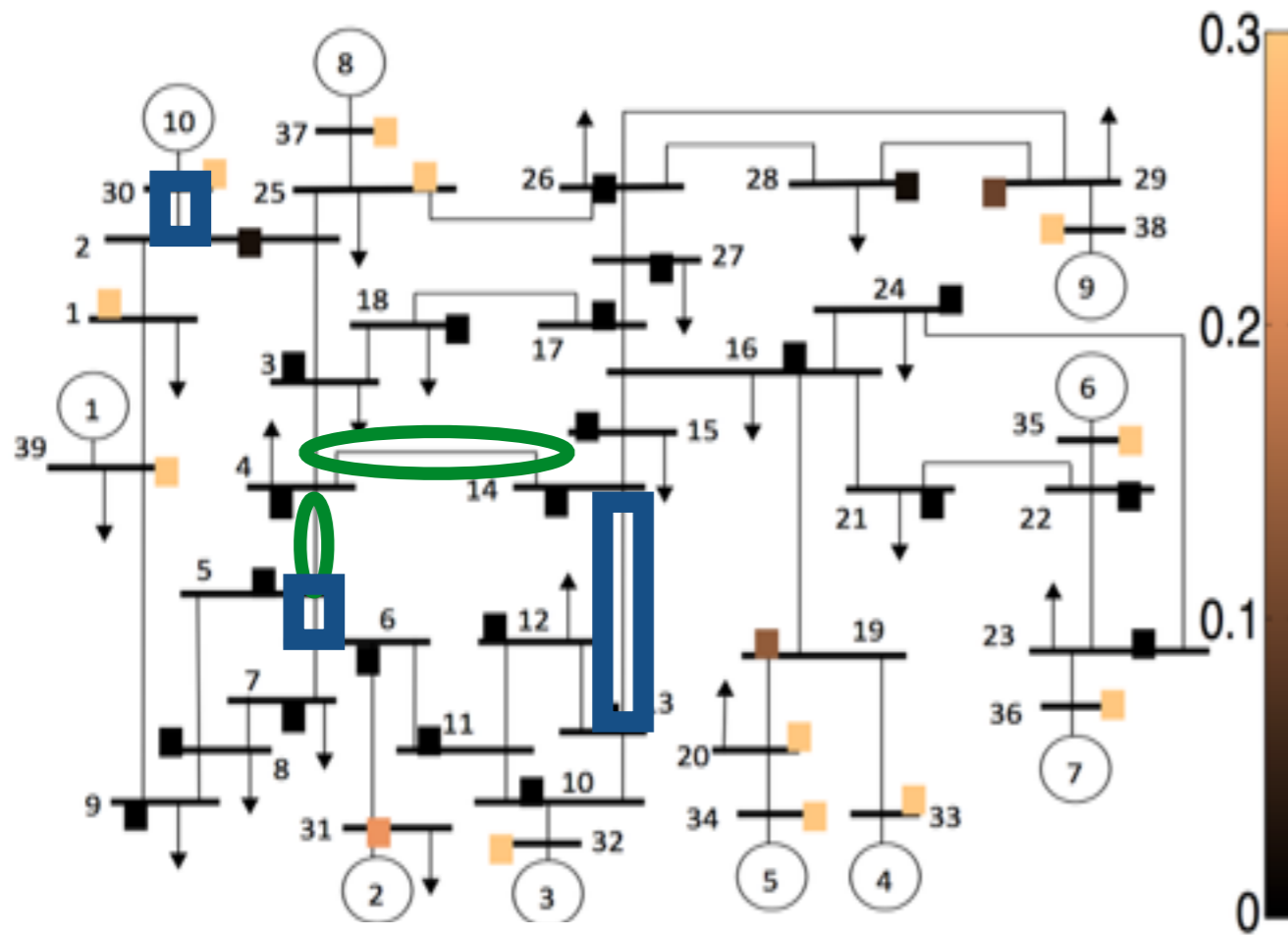
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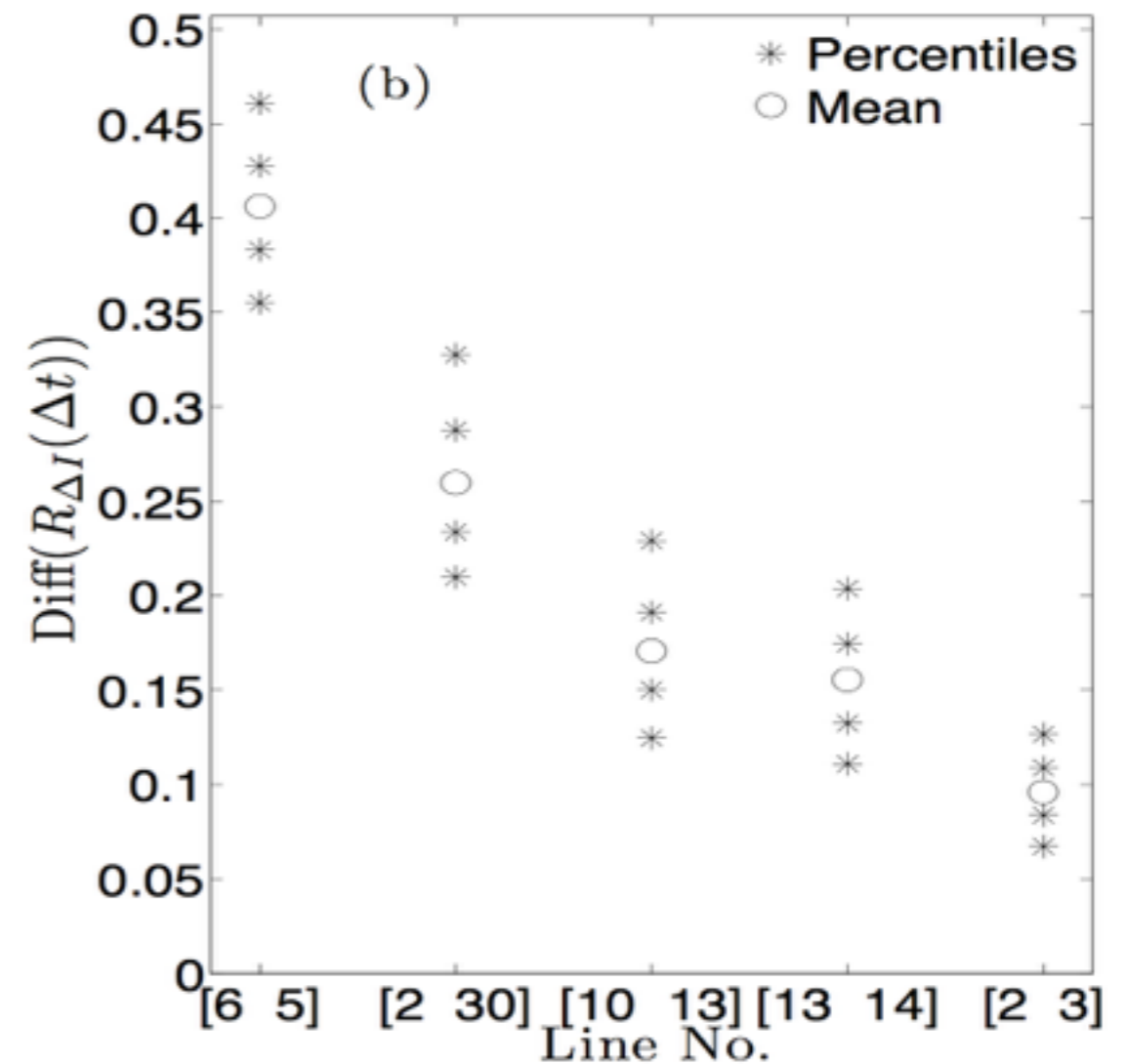
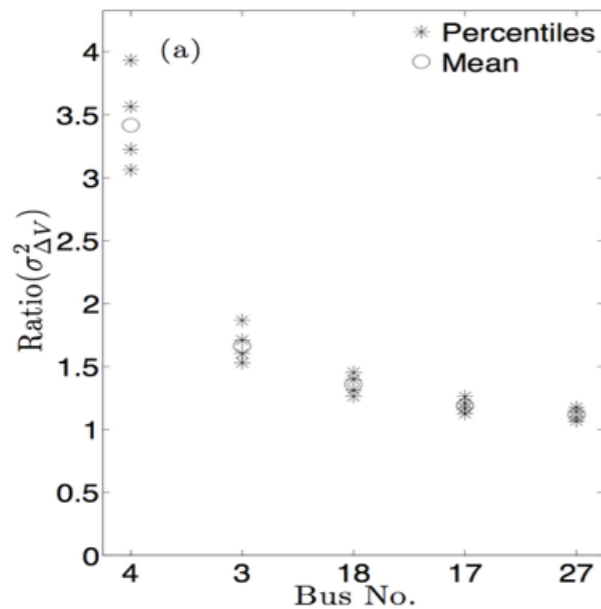
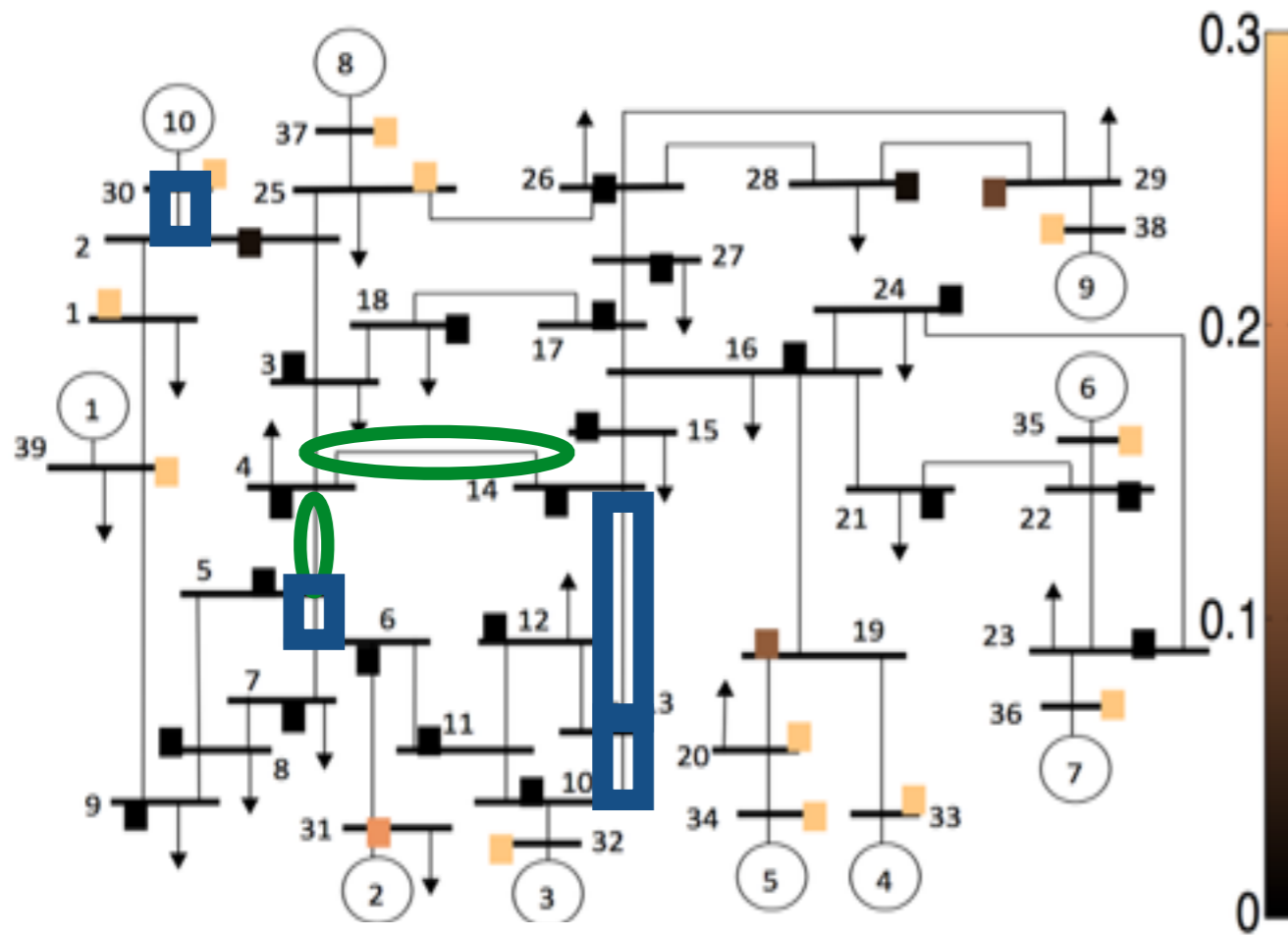
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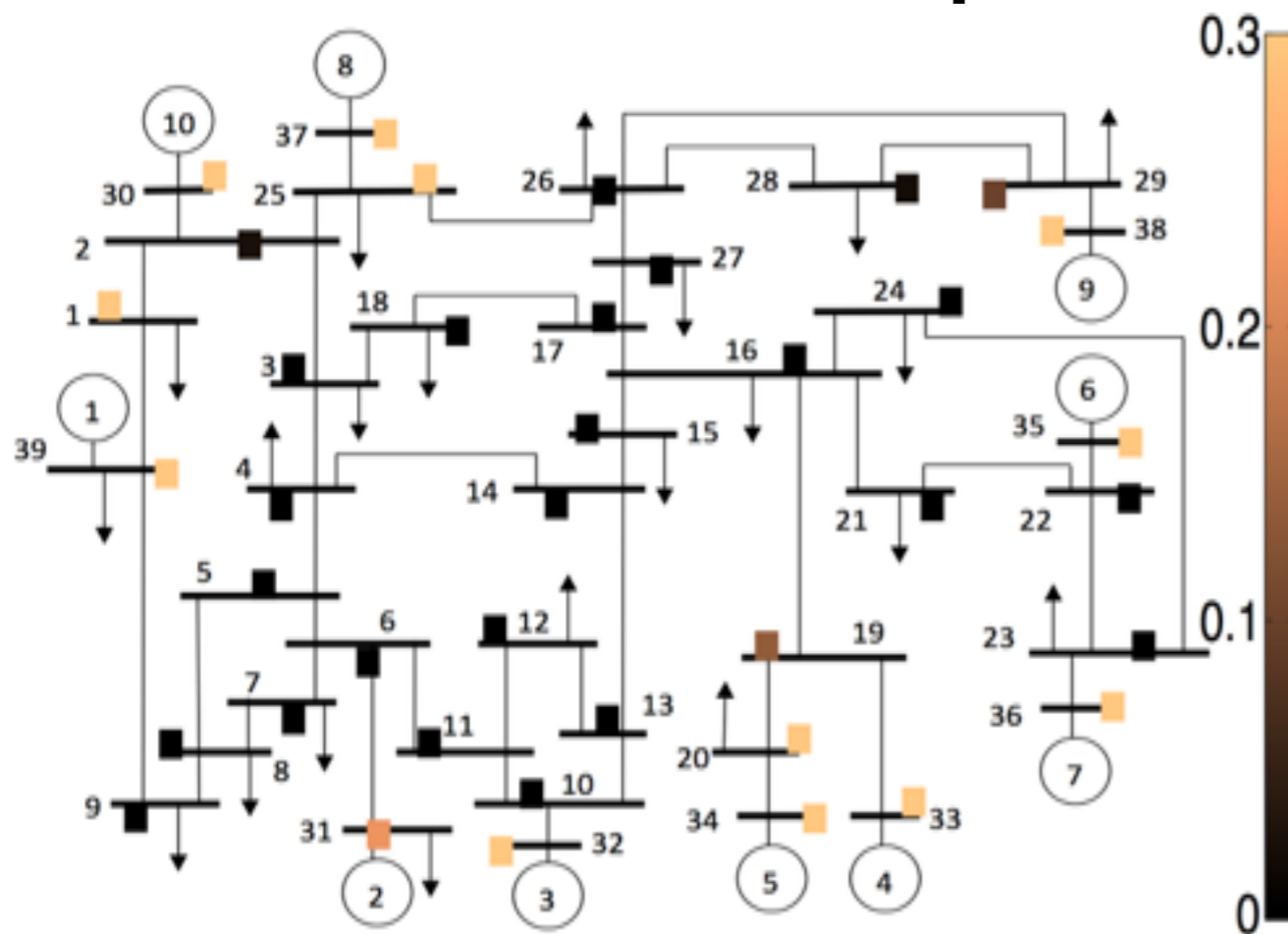
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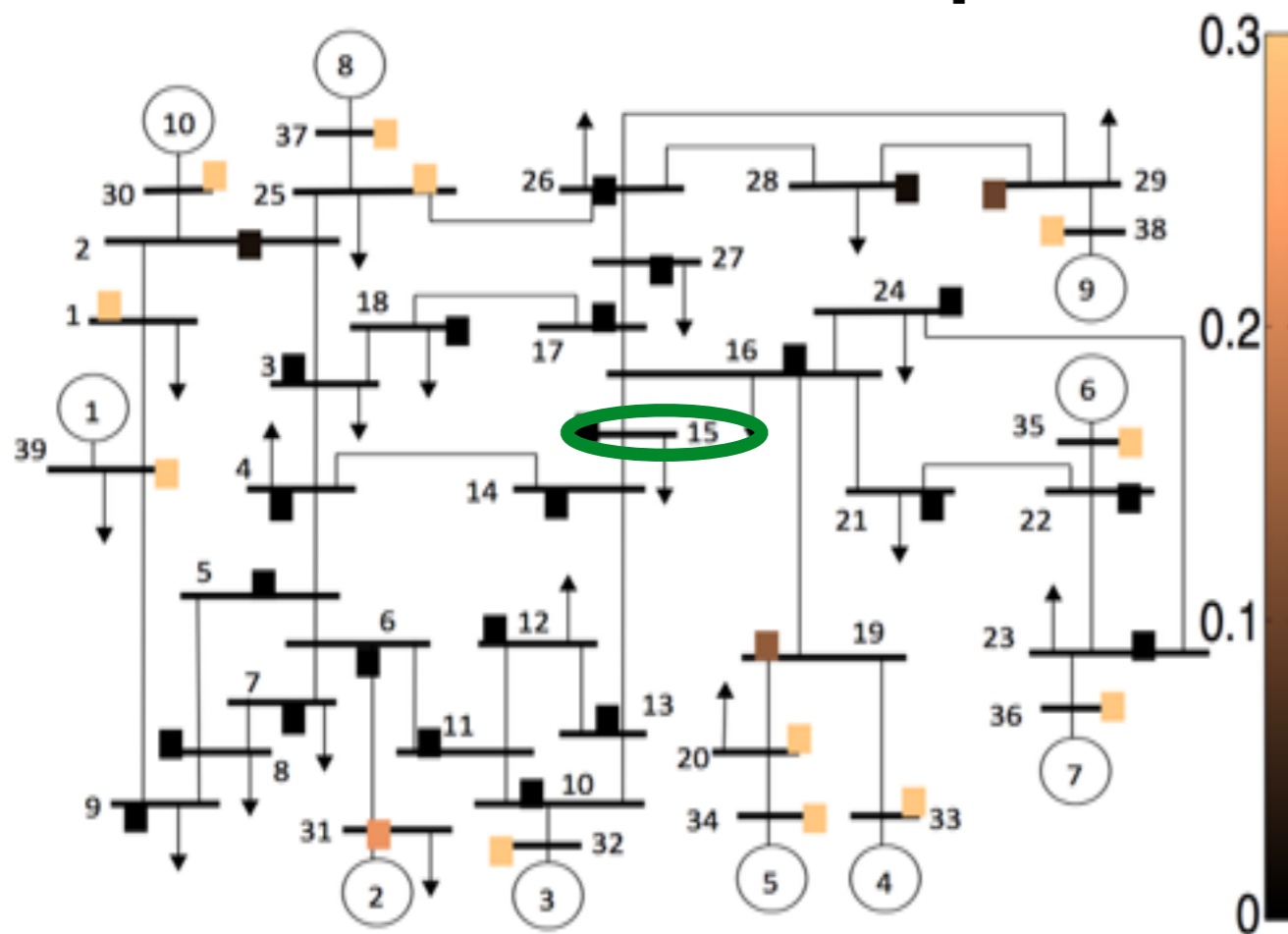
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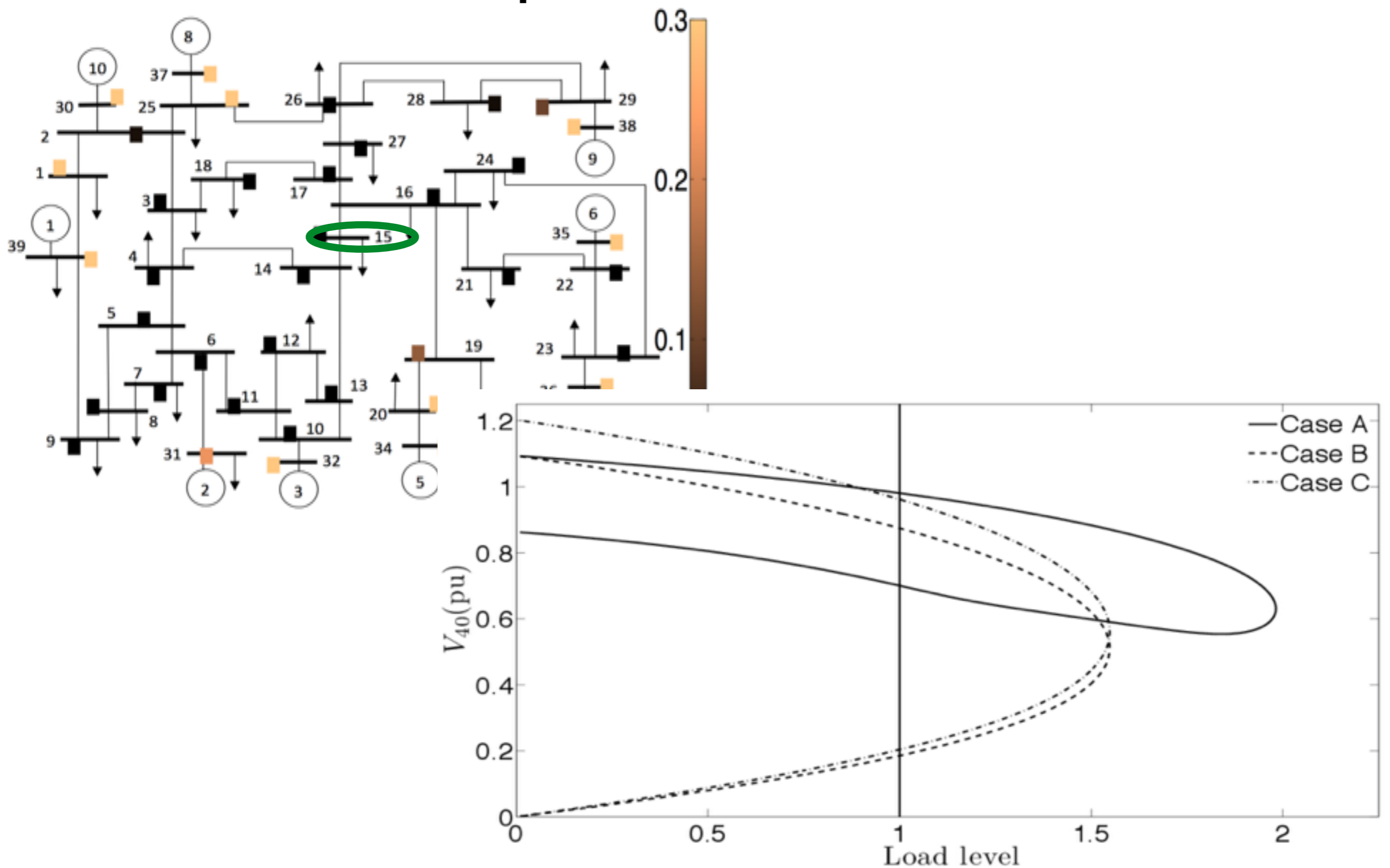
# Can we find trends that would not show up in mean values?



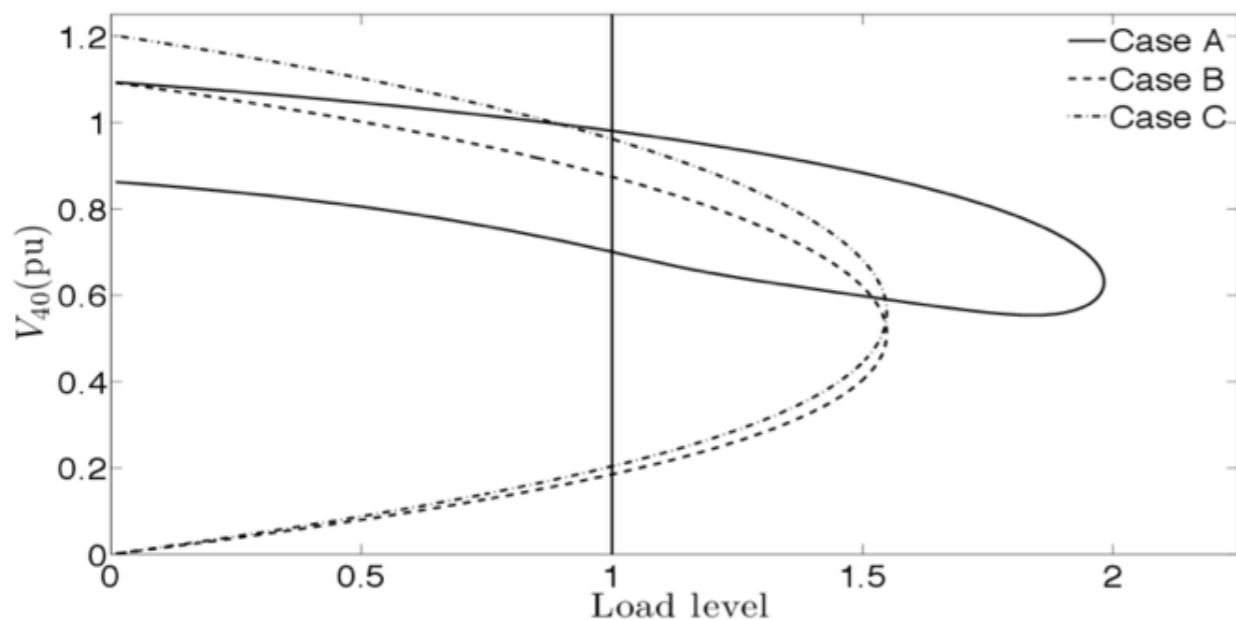
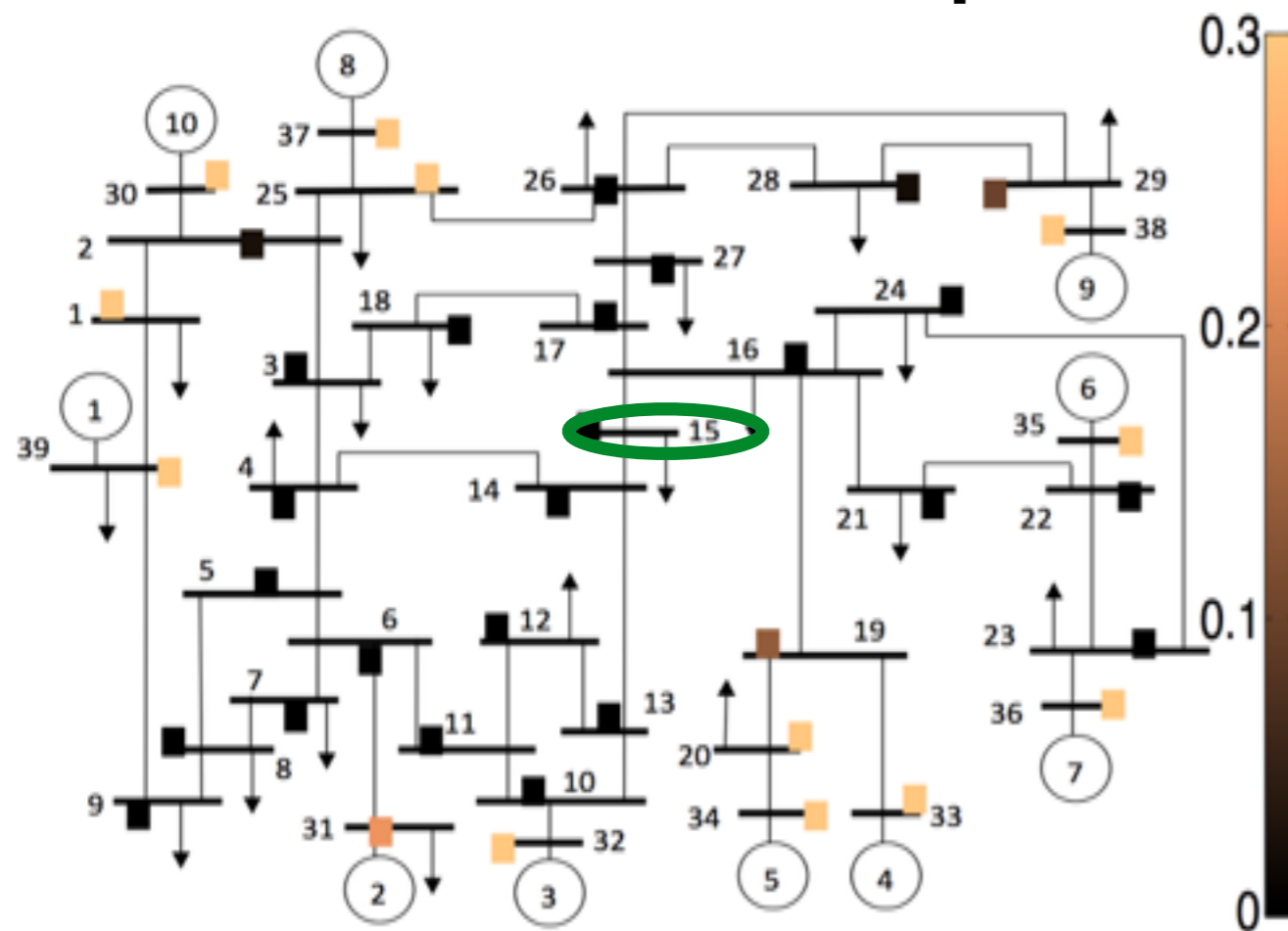
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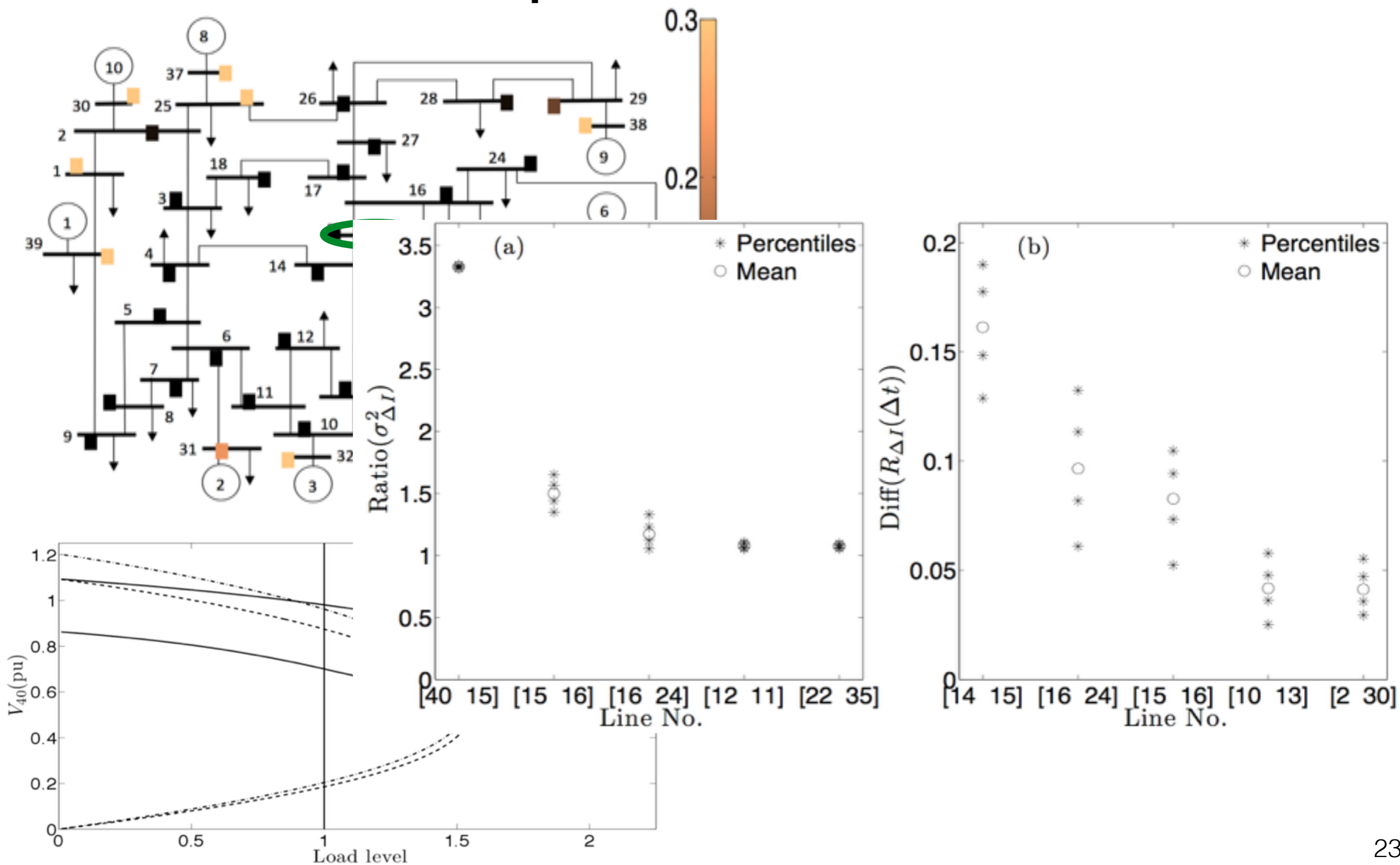


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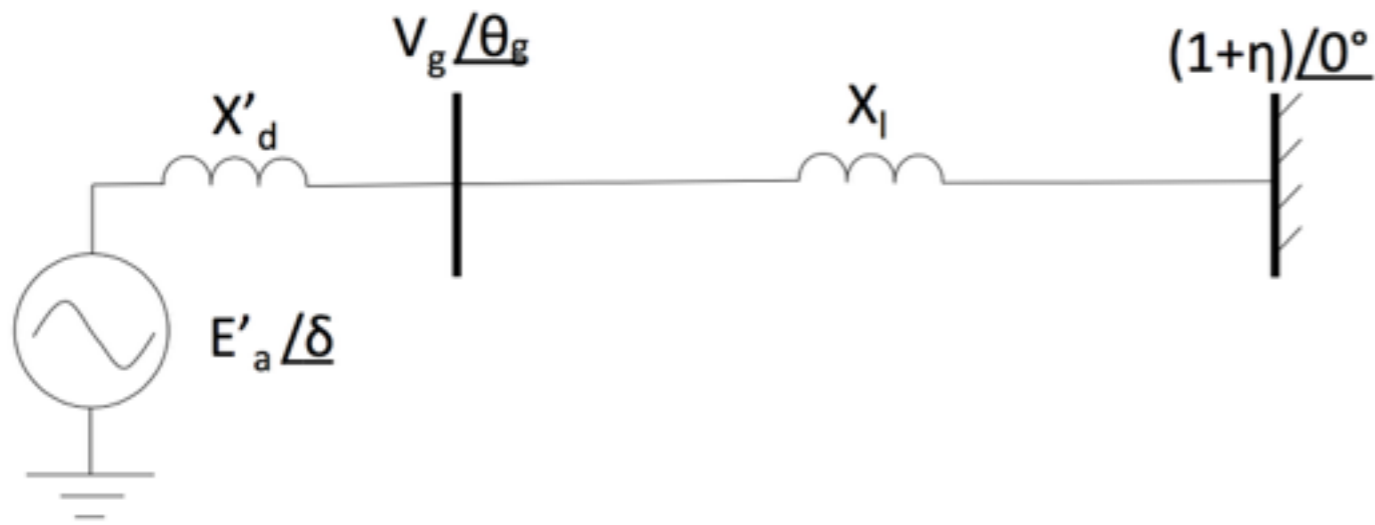


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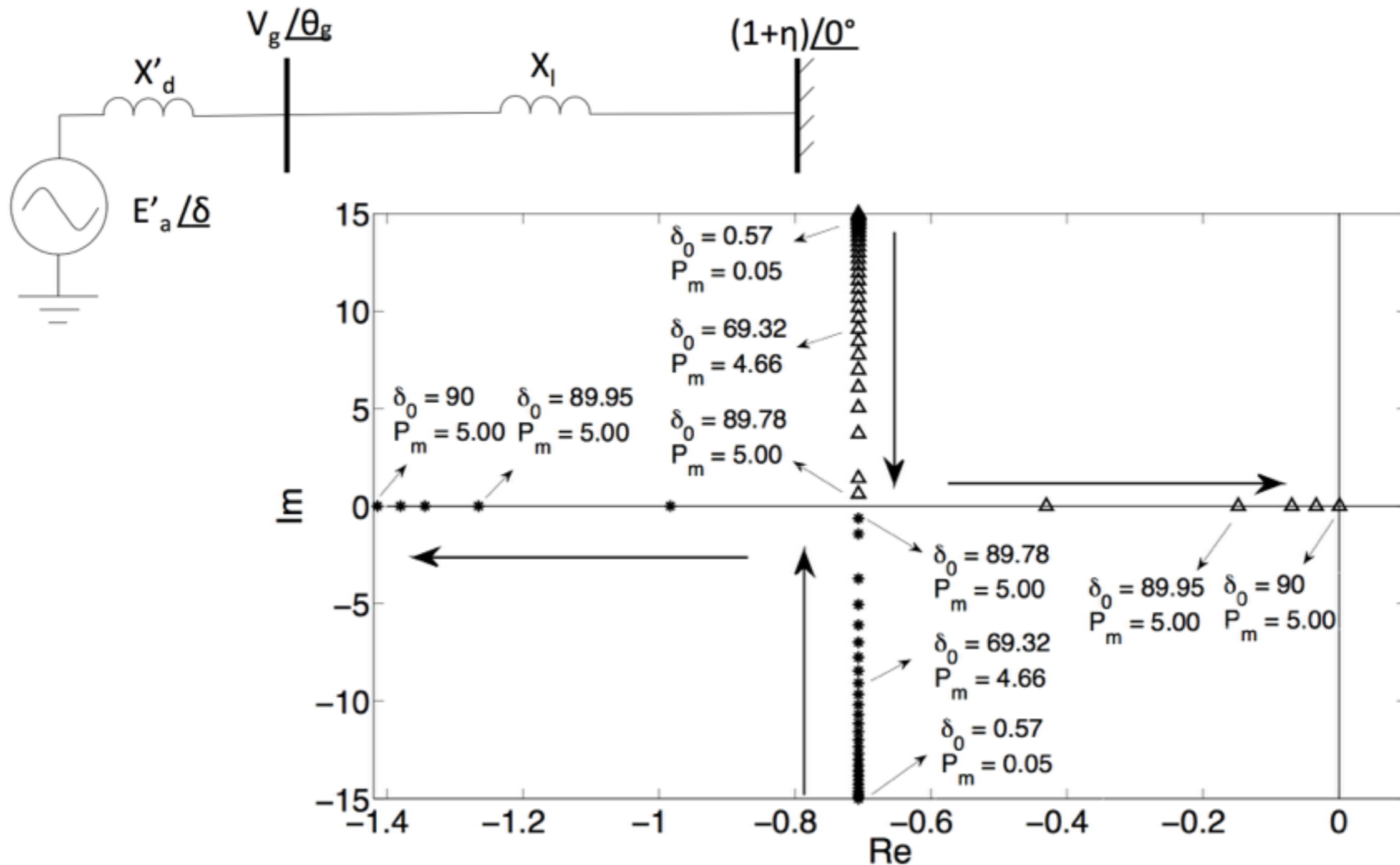


Why not just monitor critical  
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- Autocorrelations of **currents near generators** (particularly smaller ones) are generally good indicators of system-wide stability issues (e.g., inter-area oscillations—Hopf bifurcation)
- Frequently, fluctuations can **identify the locations** of emerging problems in the network

# Statistical Early Warning Signs of Instability in Synchrophasor Data



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