Situational Awareness: Singular Value Methods for PMU Data Interpretation

Professor Chris DeMarco
Department of Electrical & Computer Engineering
University of Wisconsin-Madison
demarco@engr.wisc.edu

PSERC Tele-Seminar Series
March 2, 2010

Contributors & Acknowledgements

UW-Madison graduate student researcher on this work: Mr. Rafael Viloria, supported in part by PSERC project S-36, “Use of PMU Data to Increase Situational Awareness,”

Research has also been supported by the Bonneville Power Administration under contract number 00037890, “Voltage Stability Controls.”

Project lead Dmitry Kosterev; technical collaborator at BPA Eric Heredia.

Problem Motivation & Background

Synchronized "Phasor Measurement Unit" (PMU) familiar to most power engineers. Briefly, a PMU measures a windowed Fourier transform ("phasor") of the nominally sinusoidal voltages, currents, powers throughout grid.

GPS technology has facilitated precise, low-cost time synchronization of signals across large geographic distances. Today one can collect precisely synchronized measurements, at 30 or 60 Hz sampling rate, on a continental scale.

Problem Motivation & Background

So… utilities have (or will soon have) huge volumes of real-time & historic PMU data.

Refrain in our suddenly "Smart" Grid:
"How do we extract 'knowledge' from data?"

Personally, I prefer less grandiose formulation:
How do we compress PMU data, and use it to compute real-time performance metrics that improve grid control action?

Problem Motivation & Background

Need for reduction,feature extraction from voluminous data hardly unique to power industry.

Geological data processing, gene sequencing, bio-informatics, electronic commerce customer classification – all problems with similar features.

Long history of successful methods to achieve reduction and feature identification in huge data sets, particularly among other branches of the energy industry (i.e, oil companies).

Problem Motivation & Background: Late Breaking News

“ Sent: Friday, February 26, 2010 7:29 PM

To: NASPI Work Group Members

Subject: NERC-NASPI SynchroPhasor Data-Sharing Agreements Available

Dear NASPI Colleague --

I am pleased to announce that the new NERC-NASPI SynchroPhasor Data-Sharing Agreements have been completed and are available for your organization's review and signature. These agreements have been developed to cover the sharing of real-time synchrophasor data among data producers, data users and researchers. The lack of such agreements to date has been a major obstacle inhibiting the collection and sharing of phasor data for wide-area monitoring and situational awareness to improve bulk power system reliability.

….”

If it's Good Enough for Netflix

(…it should be good enough for critical national infrastructure)

The New York Times, December 10, 2008

Netflix Awards $50,000 for Progress in Contest

By Jenna Wortham

Netflix's challenge to the world's programmers to improve Cinematch… On Wednesday, Netflix awarded a group of computer scientists $50,000 for their entry, which upgraded Cinematch's suggestion abilities by more than 9 percent…

"Geeks like us get really excited about large-scale data problems that you can turn into knowledge," said Chris Volinsky, director of statistics research at AT&T Labs and a member of the winning team…

Mr. Volinsky's team and his Austrian counterparts focused on two main categories of algorithms. One, known as a nearest neighbor formula, generates recommendations based on shared tastes among users. The other, singular value decomposition, finds broader themes associated with favorites, like film genres and actors…

Data Algorithms & Prior PMU Work

As suggested in New York Times Netflix article, common "Swiss Army Knife" for treating large data sets in many fields has been Singular Value Decomposition (SVD) and related methods such as Principal Component Analysis (PCA).

Prior SVD and PCA Work in Power Systems

SVD methods used for noise reduction in PMU data, as a pre-filtering step for estimating oscillatory modes in grid electro-mechanical dynamics (M. Venkatasubramanian, PSerc project S-29).

PCA methods and its nonlinear variants employed for demand prediction in LMP market risk management (S. Deng, Pserc project M-17).

Synopsis of New Contribution

Premise in today's work: In characterizing quasi-steady state grid performance, SVD analysis particularly well suited to handling large PMU data sets.

Claim: *A windowed SVD computation on PMU data tracks a well-established performance metric, whose computation traditionally would require state estimation of operating point, with full network and load models.*

Method here offers a "model free," real-time indicator of quasi-steady state grid performance, particular relevant for control schemes to guard against voltage instability.

Singular Value Decomposition: General Background

Refresher on singular value decomposition

J *an ℓ xn matrix, rank m, is decomposed as*

$$\mathbf{J} = \mathbf{U}\,diag\{\sigma_1, \sigma_2, \ldots \sigma_m, 0, \ldots 0\}\mathbf{V}^*$$

where, **U** *and* **V** *are unitary matrices (i.e.,* $\mathbf{UU}^*$ *= Identity Matrix), and σ's are positive real numbers (case above illustrates both ℓ, n > m)*

Singular Value Decomposition: General Background

Columns of **U** *serve as orthonormal basis vectors for range space of* **J;**

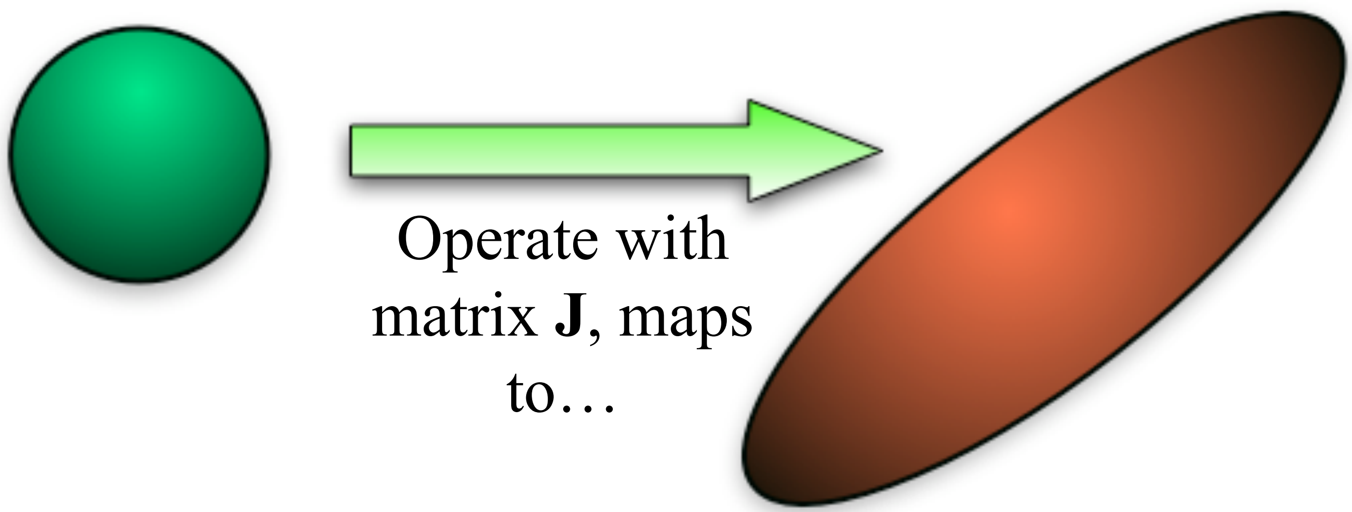
Columns of **V** *serve as orthonormal basis vectors for domain space of* **J;**

In applications where **J** *plays role of linear operator from input space to output space (e.g., multi-input, multi-output transfer function),* σ*'s describe gains along different directions.*

Singular Value Decomposition: General Background

Unit sphere in input space: Columns of **V** as basis vectors

Ellipse in output space, lengths of axes set by σ's. Columns of **U** as axes/basis vectors.



Singular Value Decomposition in Data Compression & Data Mining

- *Long-standing use of SVD in data handling.*
- *Basic idea: consider sequential acquisition (1,2, …k…) of a vector of "ℓ" measurements $\underline{m}[k]$*
- *For running window of length n, construct*

$$\mathbf{M}[k] := \left[\underline{m}[k-n+1], \underline{m}[k-n+2], \ldots \underline{m}[k]\right]$$

(*so* **M**[k] is dimension ℓ rows, n columns)

Simplest Interpretation Applying SVD to PMU Data

- *View PMU data as a time series "output," with vector of PMU measurements at time sample k comprising $\underline{m}[k]$. A window of such vectors composes matrix* **M**[k].

- *VERY simple idea: watch for degradation in operating condition to show up as changes in σ's and* **U**. *Initial efforts seek relation to an established performance metric, hence focus on the largest singular value and associated vector (but certainly could look at additional σ's)*

Interpreting PMU Data in SVD Perspective

Consider Quasi-steady-state, input-output view:

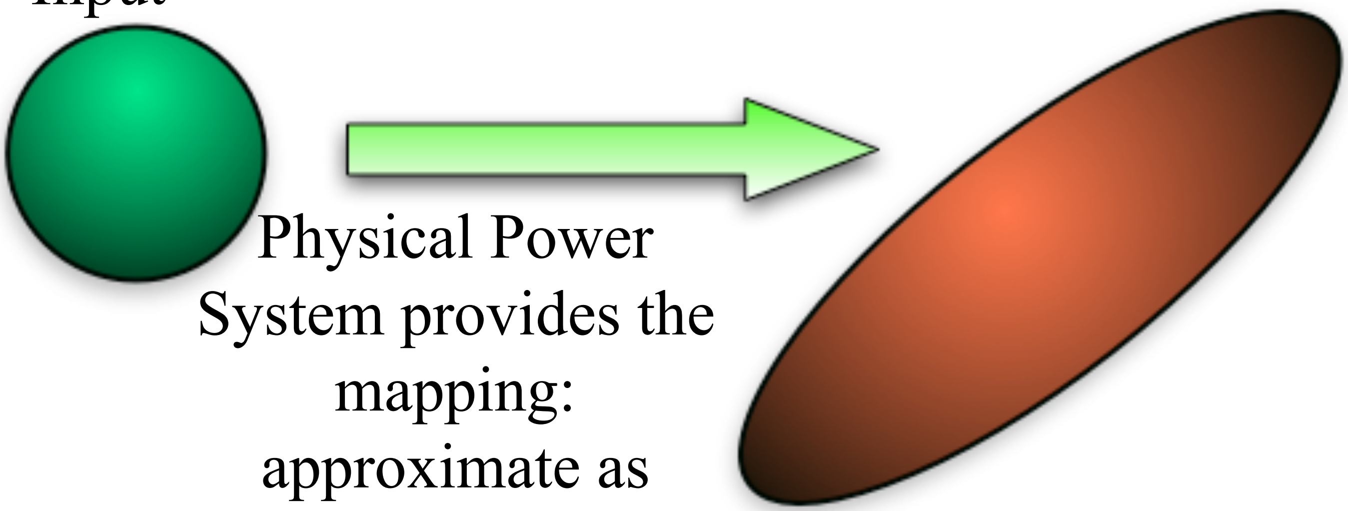
- *In power system, inputs are the continuously varying P-Q injections. Outputs are δ's and V's of PMU data. Mapping between them influenced by network switching, component failure, other structural changes.*

- *Injections have slowly varying component (daily load curve), and small magnitude, faster random variation. Random part looks like small variance filtered white noise(~ 1% demand magnitude).*

Next Level of Sophistication Interpreting SVD for PMU Data

Fast time-scale Random Variations in P-Q Injections as "Input"

Measured δ's and V's of PMU data as "Output"

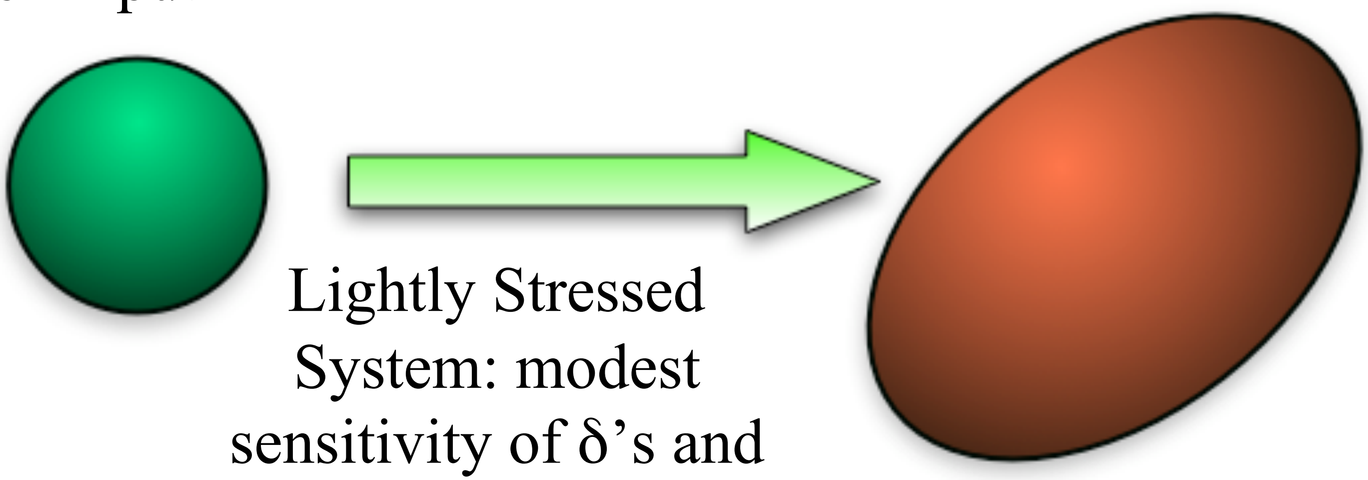


Physical Power System provides the mapping: approximate as PF Jacobian Inverse in Taylor Expansion

Next Level of Sophistication Interpreting SVD for PMU Data

Variations in P-Q Injections as "Input"

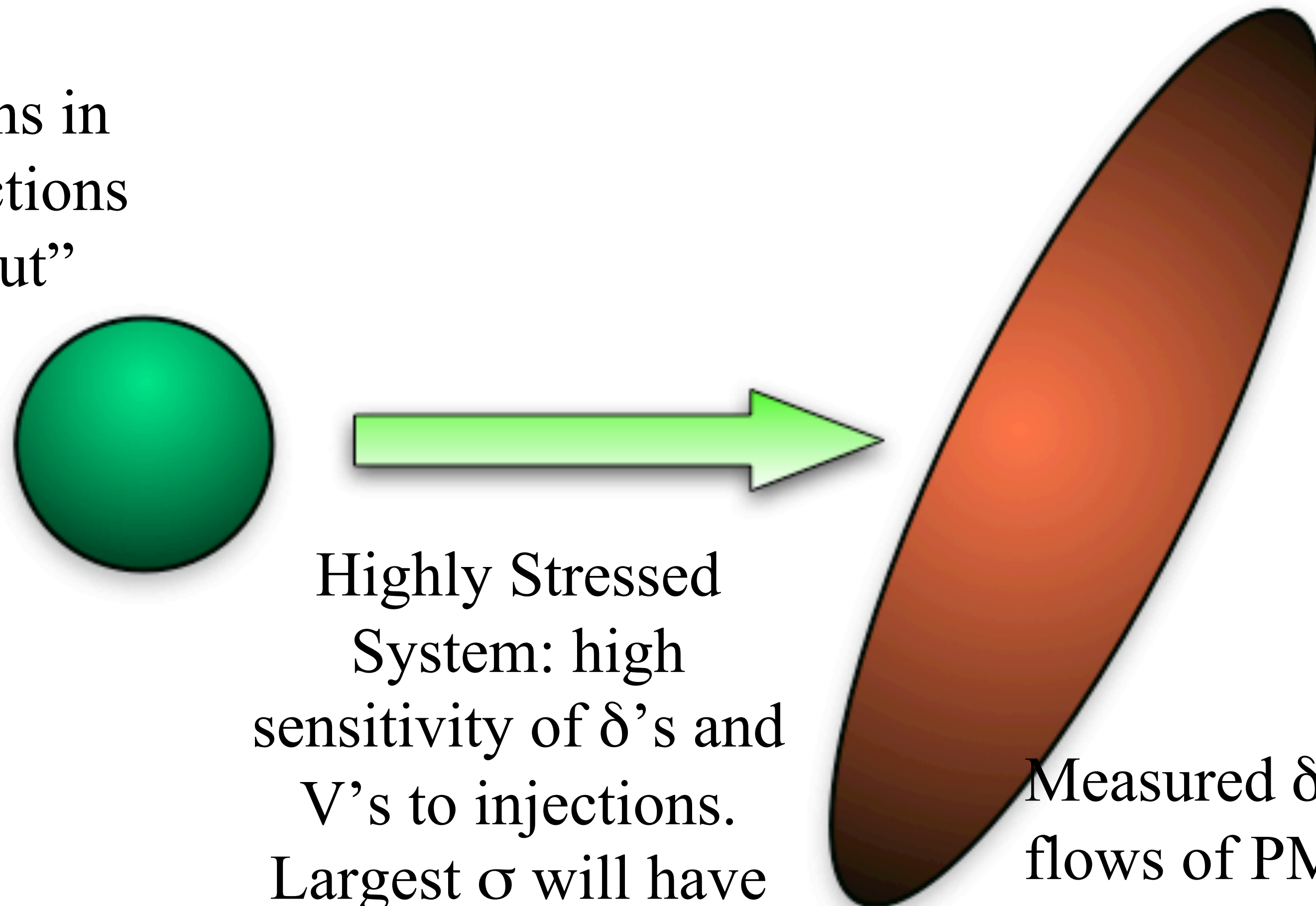
Measured δ's and V's of PMU data as "Output"



Lightly Stressed System: modest sensitivity of δ's and V's to injections. Largest σ will have moderate magnitude

Next Level of Sophistication
Interpreting SVD for PMU Data

Variations in
P-Q Injections
as “Input”



Highly Stressed
System: high
sensitivity of δ’s and
V’s to injections.
Largest σ will have
very large magnitude

Measured δ’s ,V’s,
flows of PMU data
as “Output”

Relation to Traditional Voltage Instability Metric

- *Voltage instability problem inspired voluminous literature and range of methods in 80's and 90's.*

- *Details vary, but most shared basic viewpoint – quasi-steady state input changes drive variation in operating point. "Degree of stability" degrades (perhaps as measured through eigenstructure of linearized dynamics), until stability is lost. "Path" of state divergence after stability lost often manifested predominantly as voltage decline - hence **VOLTAGE** instability.*

Relation to Traditional Voltage Instability Metric

- *In mathematical terms, scenario described above is a bifurcation.*

- *Wide range of bifurcation phenomena possible. Simplest appearing to "fit" observed voltage instability phenomena is saddle node bifurcation – quasi-static motion of operating point for linearized dynamics looses stability via eigenvalue passing through zero.*

Relation to Traditional Voltage Instability Metric

Power system linearized dynamics depend on operating point through power flow Jacobian. Hence, subject to all simplifying assumptions above, performance metric indicating proximity to voltage instability emerges:

Track smallest singular value of power flow Jacobian matrix as operating point varies.

Among early works making this observation –
A. Tiranuchit, R.J. Thomas, "A Posturing Strategy against Voltage Instabilities in Electric Power Systems," IEEE Trans. Power Sys, 1988.

Relation to Traditional Voltage Instability Metric

Perhaps obvious, but useful to note:

1/ [Smallest singular value of power flow Jacobian]

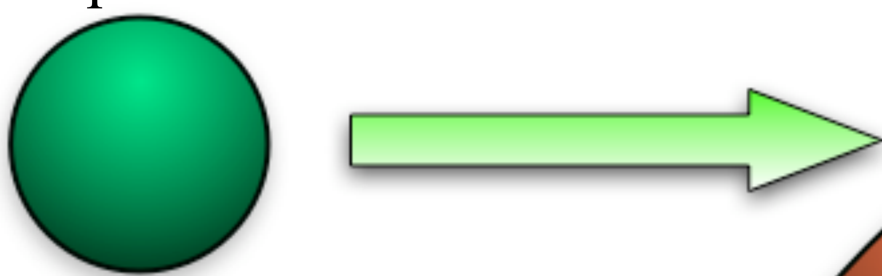
=

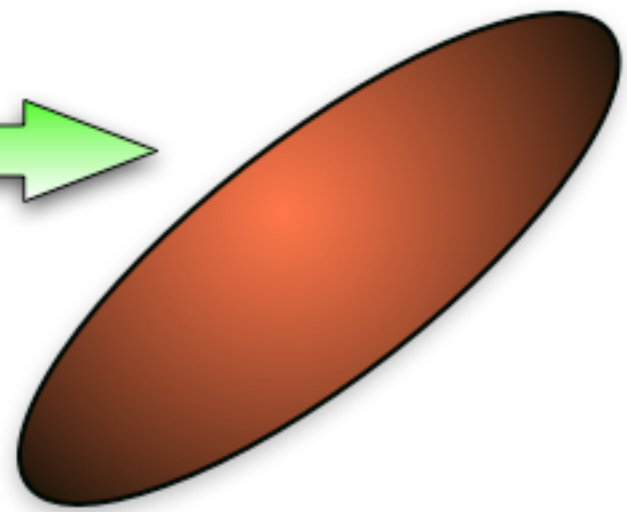
Largest singular value power flow Jacobian inverse

Recall Conceptual Picture Earlier – PMU Role of Power Flow Jacobian

Fast time-scale Random Variations in P-Q Injections as “Input”

Measured δ’s and V’s of PMU data as “Output”





Physical Power System provides the mapping: approximate as

PF Jacobian Inverse

Caveats and Practical Issues

- *PMU deployment expanding, but still expect only a modest subset of all phasor angles and voltages (i.e., PMU's measurement density modest % of all bulk power system buses)*

- *So mapping we actually get is only a* ***subset of the rows*** *of the Power Flow Jacobian Inverse.*

  (Aside: this framework may also offer a very tractable formulation for optimizing measurement placement/observability).

Computational Experiments in Synthetically Generated Data

First: IEEE 14 and 118 bus test systems, in a MATLAB power flow:

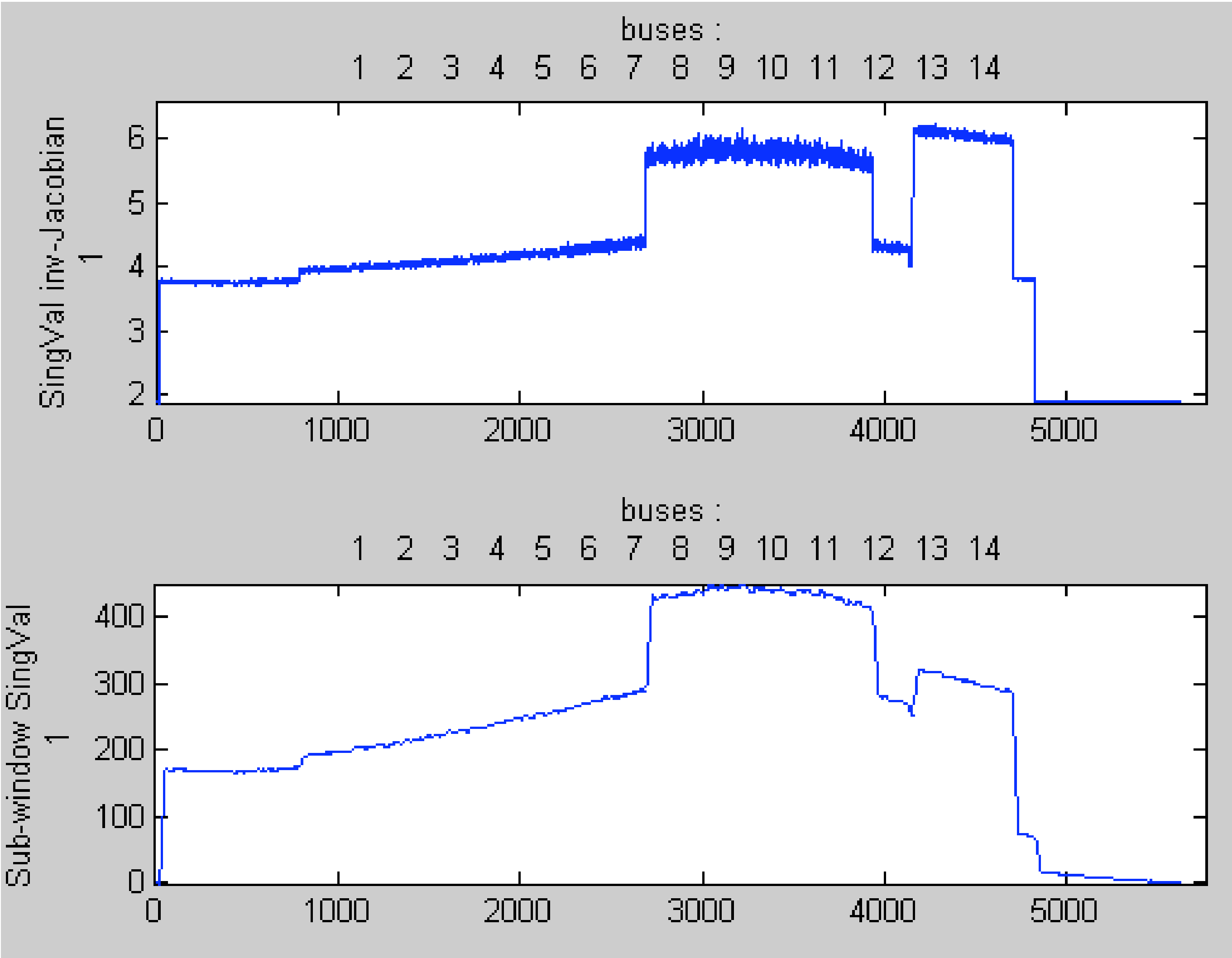
- *Construct sequential power flow computation;*
- *"Drive" computation by time sampled loads & generation dispatch, along 24 demand curve, with 1% random load variation superimposed (computation to follow uses 15 sec sampling interval, 5760 samples per 24 hours);*
- *"Stress" system by randomly chosen switching in and out of lines over 24 study period;*
- *For (subset of buses) record angles and voltage magnitudes as hypothetical PMU measurements;*

Computational Experiments in Synthetically Generated Data

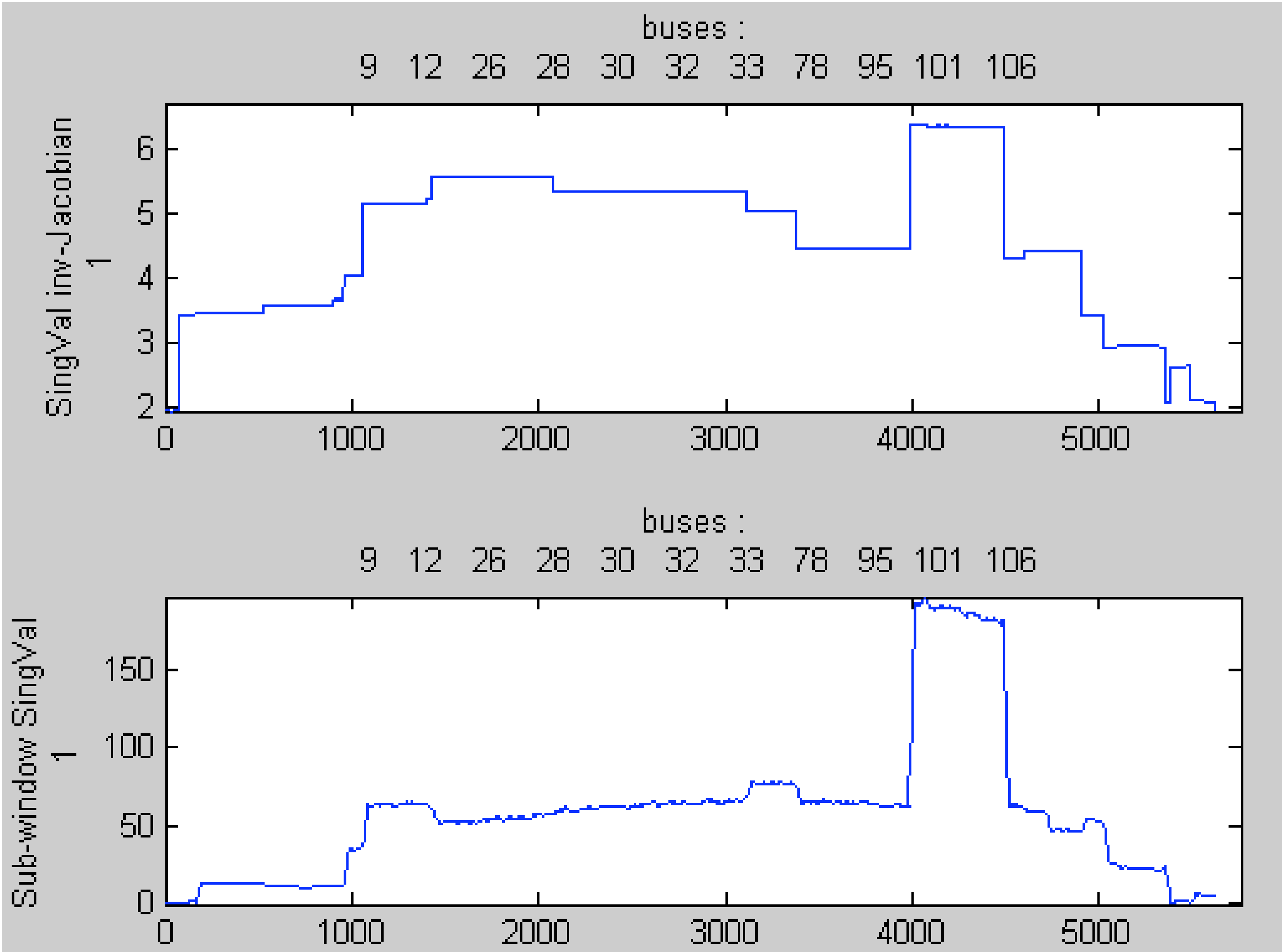
For IEEE 14 and 118 bus scenarios described on previous page, we'll test our hypothesis by comparing plots of:

- *Largest singular value of windowed PMU measurement matrix (labeled as "Sub-window SingVal" in plots to follow);*
- *Largest singular value of computed from appropriate rows of PF Jacobian inverse (labeled as "SingVal inv-Jacobian" in plots to follow)*

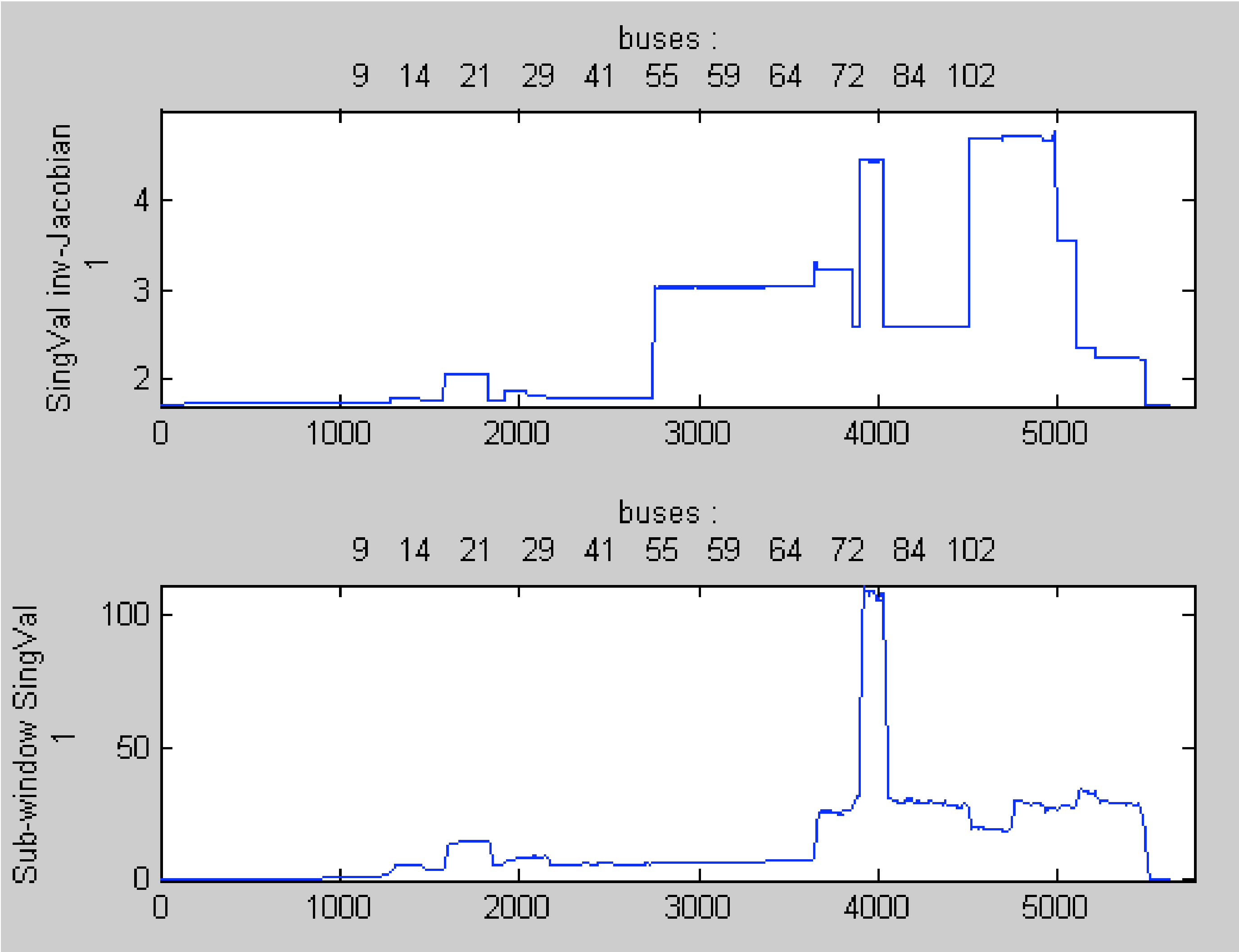
IEEE 14 Bus Experiment – Idealized Limit of PMU at Every Bus



IEEE 118 Bus Experiment – PMU Penetration 11 out of 118 Buses



IEEE 118 Bus Experiment – PMU Penetration 11 out of 118 Buses



Power Flow based Computational Experiments for Larger Systems

- *Next goal in computational experiments - generate time-sequenced power flows in more realistic model, with increased system stress and corresponding control actions (e.g., cap switching) for known scenario.*

- *Efforts under way to modify power flow tools to more easily accomplish time sequenced studies, with very large number of samples over period of interest (perhaps down to 2 seconds, so 43,200 power flow solutions for 24 hr study).*

Power Flow Based Computational Experiment in Larger System

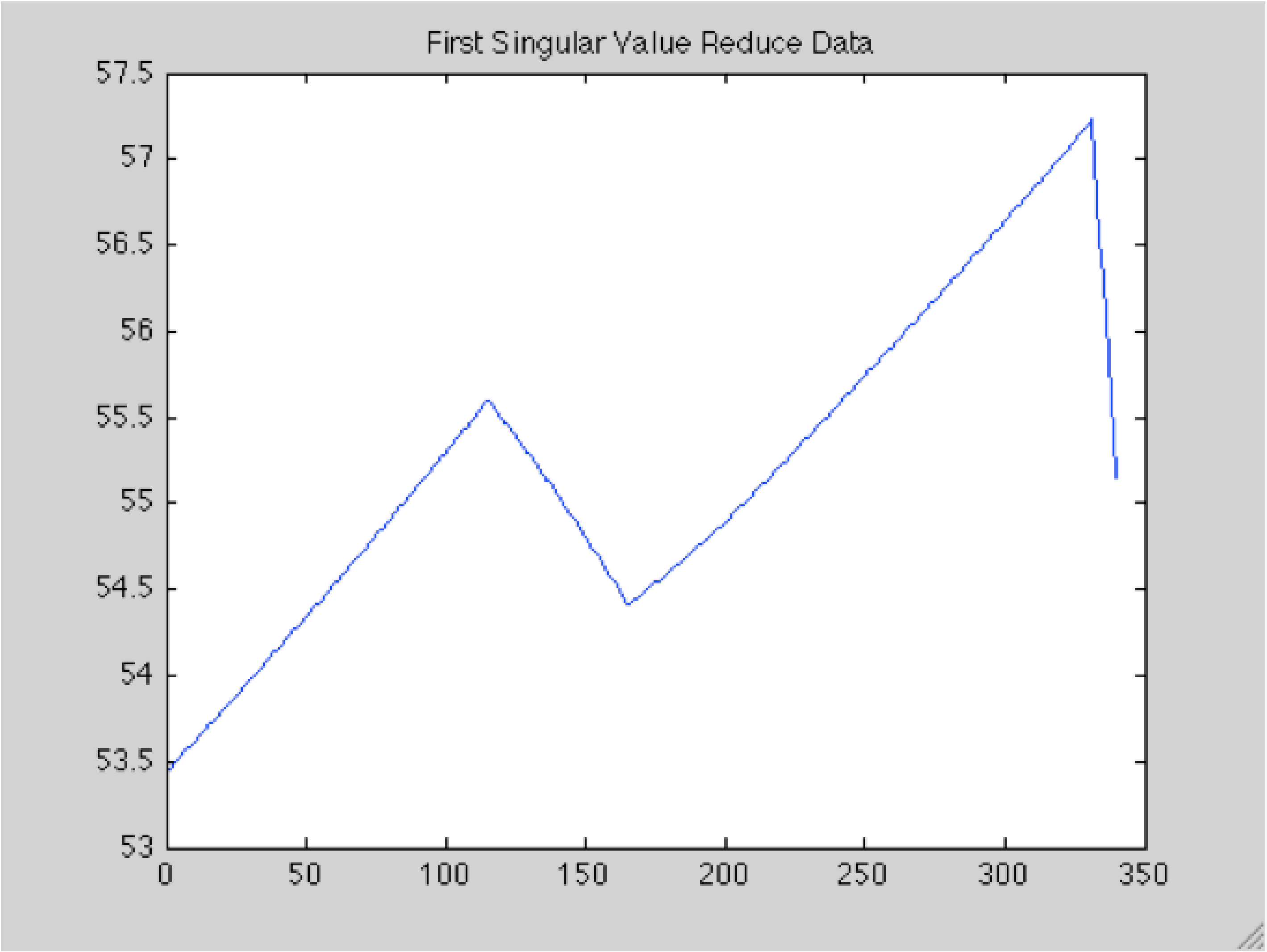
- *Bonneville Power Administration collaborator, Mr. Eric Heredia, (painstakingly!) constructed 350-sample study (as we await improved time-sequenced solution tools).*

- *Study system is synthetic WECC case, gradually stressed with increasing north-to-south transfers.*

- *All tap changers and cap-switching blocked, until a mid-study correction point, at which a number of voltage control actions applied.*

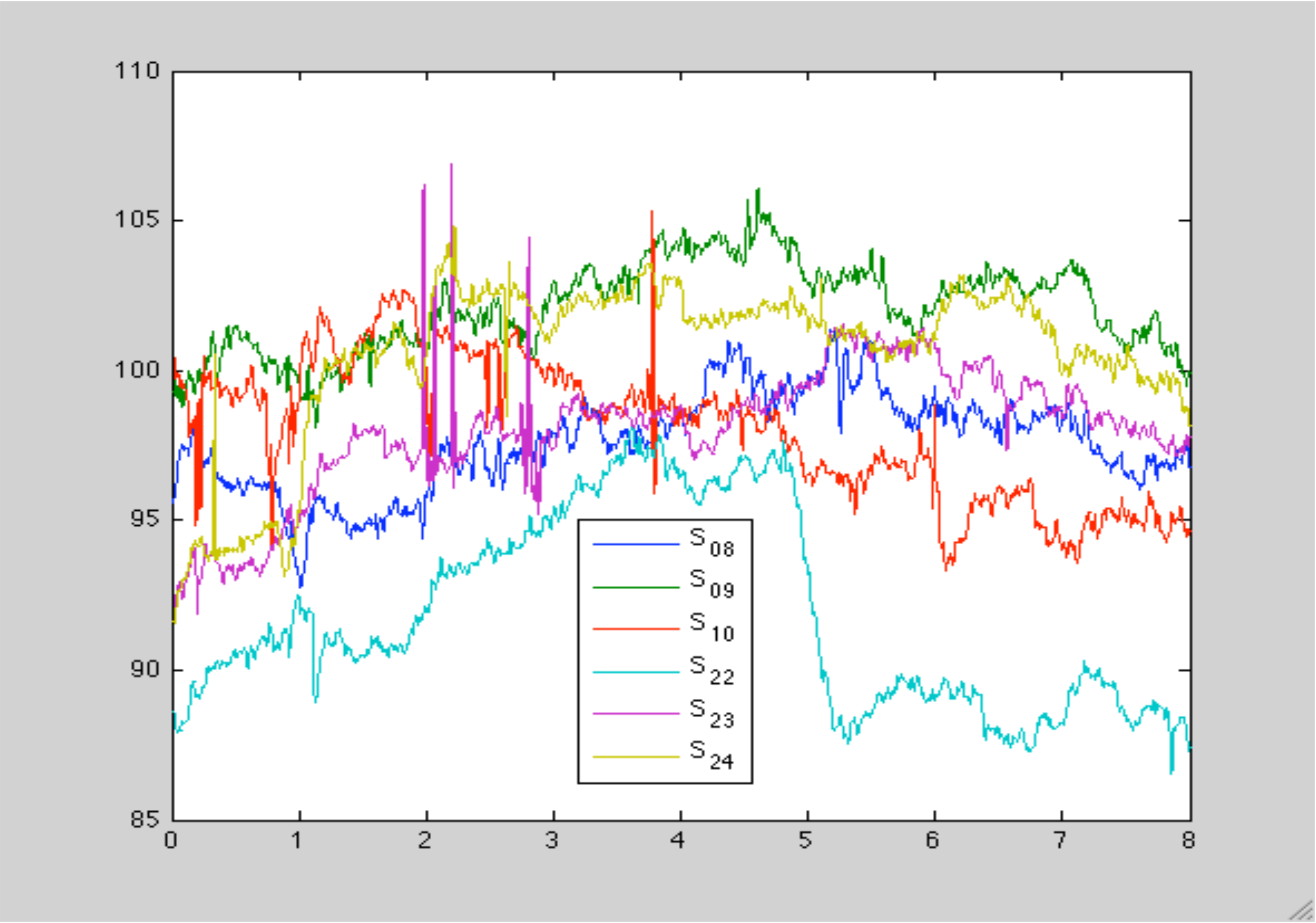
- *"Stress metric" (i.e., first singular value vs. time) should: gradually increase, drop at midpoint, increase to near-loss of PF solution, & "drop to solvability" at end…*

Power Flow Based Computational Experiment in Larger System



Real-World: SVD tests on historic PMU data sets courtesy of BPA

- *Plot to follow shows six eight-hour "days," with color coded largest singular value versus time.*
- *Vertical axis: Largest singular value computed on windowed measurement set (52 PMU measurement channels used, sampled @ 30 Hz, window length ~150 samples).*
- *Horizontal axis: Time in hours, starting from 11:00 AM as "zero hour"*



110
105
100
95
90
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0
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6
7
8
S_{08}
S_{09}
S_{10}
S_{22}
S_{23}
S_{24}

Information from Singular Vector: Which Measurements Influential?

- *As part of singular value decomposition, one also obtains singular vectors: in notation of earlier slides, the columns of the* **U** *matrix.*

- *By definition, each column has unit length (2-norm equal to 1). Size of entries of* $\mathbf{U}_1$ *show degree of contribution to largest singular value.*

- *Rough first test: for the 52 measurements in data set here, flagged a measurement as "influential" if magnitude exceeded 1.5/sqrt(52). Result seems to correlate well with engineering experience as to which PMUs are "important" measurement points.*

Interpretation & Questions Raised

- Data scaling: when mixing PMU measurements of physically different quantities, their relative scaling strongly influences their contribution to singular values.

- For example, natural to keep voltages in pu, while for MW line flows standard base of 1000 MVA seems natural (but clearly arbitrary!);

- But then angles: Degrees? (no – too large numerically – angles unrealistically dominate significance!); Radians? (better, but initial experience suggests may be a little “small” – less significance than seems realistic); Historic baseline average? (appealing, but subjective)

Next Steps

Data Scaling Issues:

- Model based approach: run SVD analysis on synthetic PMU data generated from power flow studies. Correlate SVD scaling and thresholds with trusted analytic indicators available in full power flow (e.g. conditioning and sensitivities from power flow Jacobian)

- Statistical learning approach: use large number of historic data sets, with ranking of degree of system stress during these periods, to learn statistics of svd behavior, and thresholds of transitions to unacceptable operating conditions.

Next Steps

Data Drop-out Filtering Issues:

- Inevitable that a geographically distributed measurement system (PMUs) will be subject to communication loss/data dropouts, other bad data. Seek optimal estimation/filtering to reduce these effects.

- Yet unusual line switching and other transient events produce points that ***are*** significant, ***should*** be reflected in performance metric, and ***perhaps*** influence control.

- Adds challenge to filtering problem - avoid throwing baby out with the bath water.

Next Steps

Data Reduction Issues

- Common historic use of SVD is as data compression tool - ignore data associated with singular values below some tolerance (aside: this technique historically was competitor to jpeg in image data compression).

- Our very crude first tests, with high standards of fidelity, and no filtering to remove outliers, suggest fairly modest compression gains with real-world PMU data sets.

- But ***much*** more could be done in data compression. To best knowledge of this researcher, appears a missed opportunity in design of PMU data concentrators.