

ECEN 667

Power System Stability

Lecture 21: Modal Analysis

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Announcements



- Read Chapter 8
- Homework 7 is posted; due on Tuesday Nov 28
- Final is as per TAMU schedule. That is, Friday Dec 8 from 3 to 5pm

Single Machine Infinite Bus

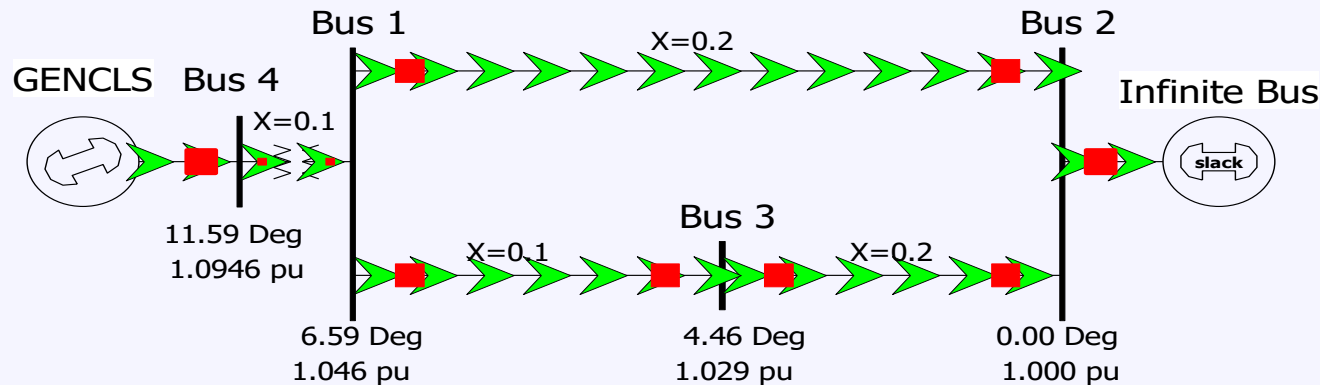


- A quite useful analysis technique is to consider the small signal stability associated with a single generator connected to the rest of the system through an equivalent transmission line
- Driving point impedance looking into the system is used to calculate the equivalent line's impedance
 - The Z_{ii} value can be calculated quite quickly using sparse vector methods
- Rest of the system is assumed to be an infinite bus with its voltage set to match the generator's real and reactive power injection and voltage

Small SMIB Example



- As a small example, consider the 4 bus system shown below, in which bus 2 really is an infinite bus



- To get the SMIB for bus 4, first calculate Z_{44}

$$Y_{bus} = j \begin{bmatrix} -25 & 0 & 10 & 10 \\ 0 & 1 & 0 & 0 \\ 10 & 0 & -15 & 0 \\ 10 & 0 & 0 & -13.33 \end{bmatrix} \rightarrow Z_{44} = j0.1269$$

Z_{44} is Z_{th} in parallel with $jX'_{d,4}$ (which is $j0.3$) so Z_{th} is $j0.22$

Example: Bus 4 with GENROU Model



- The eigenvalues can be calculated for any set of generator models
- This example replaces the bus 4 generator classical machine with a GENROU model
 - There are now six eigenvalues, with the dominate response coming from the electro-mechanical mode with a frequency of 1.83 Hz, and damping of 6.92%

Generator Information (on Generator MVA Base)

	Real Part	Imag Part	Magnitude	Damping Ratio	Damped Freq (Hz)	Damped Period (Sec)	Undamped Freq (Hz)	Machine Angle	Machin
1	-21.2494	0.0000	21.2494	1.0000	0.0000		3.3819	0.0159	
2	-0.8016	11.5521	11.5798	0.0692	1.8386	0.5439	1.8430	0.7055	
3	-0.8016	-11.5521	11.5798	0.0692	-1.8386	-0.5439	1.8430	0.7055	
4	-14.2252	0.0000	14.2252	1.0000	0.0000		2.2640	0.0044	
5	-3.7124	0.0000	3.7124	1.0000	0.0000		0.5909	0.0154	
6	-0.4231	0.0000	0.4231	1.0000	0.0000		0.0673	0.0027	

Example: Bus 4 with GENROU Model and Exciter



- Adding an relatively slow EXST1 exciter adds additional states (with $K_A=200$, $T_A=0.2$)
 - As the initial reactive power output of the generator is decreased, the system becomes unstable

Generator SMIB Eigenvalue Information

Bus Number: 4
Bus Name: Bus 4
ID: 1
Status: Closed
Area Name: Home (1)

Generator Information (on Generator MVA Base)

General Info | A Matrix | Eigenvalues

	Real Part	Imag Part	Magnitude	Damping Ratio	Damped Freq (Hz)	Damped Period (Sec)	Undamped Freq (Hz)	Machine A
1	-0.4932	11.1230	11.1339	0.0443	1.7703	0.5649	1.7720	(
2	-0.4932	-11.1230	11.1339	0.0443	-1.7703	-0.5649	1.7720	(
3	-1.0000	0.0000	1.0000	1.0000	0.0000		0.1592	(
4	-2.6767	0.0000	2.6767	1.0000	0.0000		0.4260	(
5	-3.3713	-7.2794	8.0222	0.4202	-1.1586	-0.8631	1.2768	(
6	-3.3713	7.2794	8.0222	0.4202	1.1586	0.8631	1.2768	(
7	-14.5740	0.0000	14.5740	1.0000	0.0000		2.3195	(
8	-21.2347	0.0000	21.2347	1.0000	0.0000		3.3796	(

Case is saved as B4_GENROU_Sat_SMIB

Example: Bus 4 with GENROU Model and Exciter



- With $Q_4 = 25$ Mvar the eigenvalues are

	Real Part ▼	Imag Part	Magnitude	Damping Ratio	Damped Freq (Hz)	Damped Period (Sec)	Undamped Freq (Hz)	Machine A
1	-0.1239	-10.3955	10.3962	0.0119	-1.6545	-0.6044	1.6546	(
2	-0.1239	10.3955	10.3962	0.0119	1.6545	0.6044	1.6546	(
3	-1.0000	0.0000	1.0000	1.0000	0.0000		0.1592	(
4	-2.6586	0.0000	2.6586	1.0000	0.0000		0.4231	(
5	-3.5938	-6.8580	7.7426	0.4642	-1.0915	-0.9162	1.2323	(
6	-3.5938	6.8580	7.7426	0.4642	1.0915	0.9162	1.2323	(
7	-14.5078	0.0000	14.5078	1.0000	0.0000		2.3090	(
8	-21.4739	0.0000	21.4739	1.0000	0.0000		3.4177	(

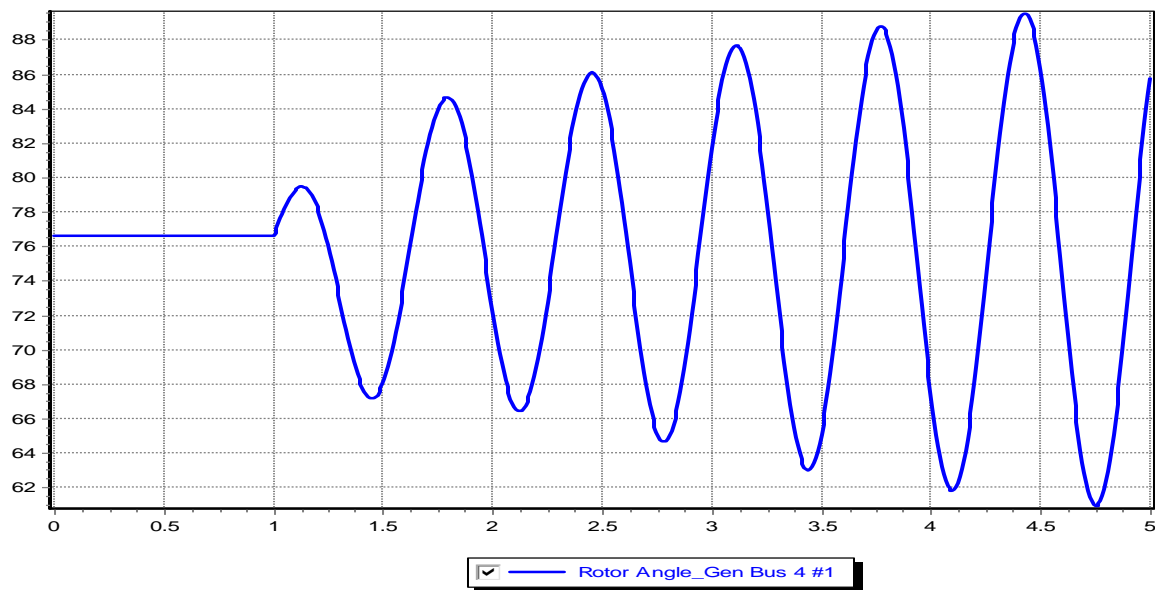
- And with $Q_4=0$ Mvar the eigenvalues are

	Real Part ▼	Imag Part	Magnitude	Damping Ratio	Damped Freq (Hz)	Damped Period (Sec)	Undamped Freq (Hz)	Machine A
1	0.2704	-9.5336	9.5374	-0.0283	-1.5173	-0.6591	1.5179	(
2	0.2704	9.5336	9.5374	-0.0283	1.5173	0.6591	1.5179	(
3	-1.0000	0.0000	1.0000	1.0000	0.0000		0.1592	(
4	-3.0137	0.0000	3.0137	1.0000	0.0000		0.4796	(
5	-3.6849	-6.4281	7.4094	0.4973	-1.0231	-0.9775	1.1792	(
6	-3.6849	6.4281	7.4094	0.4973	1.0231	0.9775	1.1792	(
7	-14.4234	0.0000	14.4234	1.0000	0.0000		2.2956	(
8	-21.6978	0.0000	21.6978	1.0000	0.0000		3.4533	(

Example: Bus 4 with GENROU Model and Exciter



- Graph shows response following a short fault when Q4 is 0 Mvar



- This motivates trying to get additional insight into how to increase system damping, which is the goal of modal analysis

Modal Analysis - Comments



- Modal analysis (analysis of small signal stability through eigenvalue analysis) is at the core of SSA software
- In Modal Analysis one looks at:
 - Eigenvalues
 - Eigenvectors (left or right)
 - Participation factors
 - Mode shape
- Power System Stabilizer (PSS) design in a multi-machine context is done using modal analysis method.

Goal is to determine how the various parameters affect the response of the system

Eigenvalues, Right Eigenvectors



- For an n by n matrix \mathbf{A} the eigenvalues of \mathbf{A} are the roots of the characteristic equation:

$$\det[\mathbf{A} - \lambda\mathbf{I}] = |\mathbf{A} - \lambda\mathbf{I}| = 0$$

- Assume $\lambda_1 \dots \lambda_n$ as distinct (no repeated eigenvalues).
- For each eigenvalue λ_i there exists an eigenvector such that:

$$\mathbf{A}\mathbf{v}_i = \lambda_i\mathbf{v}_i$$

- \mathbf{v}_i is called a right eigenvector
- If λ_i is complex, then \mathbf{v}_i has complex entries

Left Eigenvectors



- For each eigenvalue λ_i there exists a left eigenvector \mathbf{w}_i such that:

$$\mathbf{w}_i^t \mathbf{A} = \mathbf{w}_i^t \lambda_i$$

- Equivalently, the left eigenvector is the right eigenvector of \mathbf{A}^T ; that is,

$$\mathbf{A}^t \mathbf{w}_i = \lambda_i \mathbf{w}_i$$

Eigenvector Properties



- The right and left eigenvectors are orthogonal i.e.

$$\mathbf{w}_i^t \mathbf{v}_i \neq 0, \mathbf{w}_i^t \mathbf{v}_j = 0 \quad (i \neq j)$$

- We can normalize the eigenvectors so that:

$$\mathbf{w}_i^t \mathbf{v}_i = 1, \mathbf{w}_i^t \mathbf{v}_j = 0 \quad (i \neq j)$$

Eigenvector Example



$$\mathbf{A} = \begin{bmatrix} 1 & 4 \\ 3 & 2 \end{bmatrix}, |\mathbf{A} - \lambda \mathbf{I}| = 0 \Rightarrow \begin{vmatrix} 1 - \lambda & 4 \\ 3 & 2 - \lambda \end{vmatrix} = 0$$

$$\lambda^2 - 3\lambda - 10 = 0 \Rightarrow \lambda_{1,2} = \frac{3 \pm \sqrt{(3)^2 + 4(10)}}{2} = \frac{3 \pm \sqrt{49}}{2} = 5, -2$$

Right Eigenvectors $\lambda_1 = 5$

$$\mathbf{A}\mathbf{v}_1 = 5\mathbf{v}_1 \Rightarrow \mathbf{v}_1 = \begin{bmatrix} v_{11} \\ v_{21} \end{bmatrix} \Rightarrow \begin{aligned} v_{11} + 4v_{21} &= 5v_{11} \\ 3v_{11} + 2v_{21} &= 5v_{21} \end{aligned} \quad \text{choose } v_{21} = 1 \Rightarrow v_{11} = 1$$

Similarly,

$$\lambda_2 = -2 \Rightarrow \mathbf{v}_2 = \begin{bmatrix} 4 \\ -3 \end{bmatrix}$$

$$\mathbf{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Eigenvector Example



- Left eigenvectors

$$\lambda_1 = 5 \quad \mathbf{w}_1^t \mathbf{A} = \mathbf{w}_1^t 5 \Rightarrow [w_{11} \quad w_{21}] \begin{bmatrix} 1 & 4 \\ 3 & 2 \end{bmatrix} = 5[w_{11} \quad w_{21}]$$

$$\begin{aligned} w_{11} + 3w_{21} &= 5w_{11} \\ 4w_{11} + 2w_{21} &= 5w_{21} \end{aligned} \Rightarrow \text{Let } w_{21} = 4, \text{ then } w_{11} = 3$$

$$\mathbf{w}_1 = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \quad \lambda_2 = -2 \Rightarrow \mathbf{w}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$\mathbf{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \mathbf{v}_2 = \begin{bmatrix} 4 \\ -3 \end{bmatrix} \quad \mathbf{w}_1 = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \quad \mathbf{w}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$\text{Verify } \mathbf{w}_1^t \mathbf{v}_1 = 7, \quad \mathbf{w}_2^t \mathbf{v}_2 = 7, \quad \mathbf{w}_2^t \mathbf{v}_1 = 0, \quad \mathbf{w}_1^t \mathbf{v}_2 = 0$$

We would like to make $\mathbf{w}_i^t \mathbf{v}_i = 1$.

This can be done in many ways.

Eigenvector Example



$$\text{Let } \mathbf{W} = \frac{1}{7} \begin{bmatrix} 3 & 1 \\ 4 & -1 \end{bmatrix}$$

$$\text{Then } \mathbf{W}^T \mathbf{V} = \mathbf{I}$$

$$\text{Verify } \frac{1}{7} \begin{bmatrix} 3 & 4 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 4 \\ 1 & -3 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

- It can be verified that $\mathbf{W}^T = \mathbf{V}^{-1}$.
- The left and right eigenvectors are used in computing the participation factor matrix.

Modal Matrices



- The deviation away from an equilibrium point can be defined as

$$\Delta \dot{\mathbf{x}} = \mathbf{A} \Delta \mathbf{x}$$

- From this equation it is difficult to determine how parameters in \mathbf{A} affect a particular \mathbf{x} because of the variable coupling
- To decouple the problem first define the matrices of the right and left eigenvectors (the modal matrices)

$$\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n] \quad \& \quad \mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n]$$

$$\mathbf{A} \mathbf{V} = \mathbf{V} \mathbf{\Lambda} \quad \text{when} \quad \mathbf{\Lambda} = \text{Diag}(\lambda_i)$$

Modal Matrices



- It follows that

$$\mathbf{V}^{-1}\mathbf{A}\mathbf{V} = \mathbf{\Lambda}$$

- To decouple the variables define \mathbf{z} so

$$\Delta\mathbf{x} = \mathbf{V}\mathbf{z} \rightarrow \Delta\dot{\mathbf{x}} = \mathbf{V}\dot{\mathbf{z}} = \mathbf{A}\Delta\mathbf{x} = \mathbf{A}\mathbf{V}\mathbf{z}$$

- Then

$$\dot{\mathbf{z}} = \mathbf{V}^{-1}\mathbf{A}\mathbf{V}\mathbf{z} = \mathbf{W}\mathbf{A}\mathbf{V}\mathbf{z} = \mathbf{\Lambda}\mathbf{z}$$

- Since $\mathbf{\Lambda}$ is diagonal, the equations are now uncoupled with

$$\dot{z}_i = \lambda_i z_i$$

- So $\Delta\mathbf{x}(t) = \mathbf{V}\mathbf{z}(t)$

Example



- Assume the previous system with

$$\mathbf{A} = \begin{bmatrix} 1 & 4 \\ 3 & 2 \end{bmatrix}$$

$$\mathbf{V} = \begin{bmatrix} 1 & 4 \\ 1 & -3 \end{bmatrix}$$

$$\mathbf{V}^{-1}\mathbf{A}\mathbf{V} = \begin{bmatrix} 5 & 0 \\ 0 & -2 \end{bmatrix}$$

Modal Matrices



- Thus the response can be written in terms of the individual eigenvalues and right eigenvectors as

$$\Delta \mathbf{x}(t) = \sum_{i=1}^n \mathbf{v}_i z_i(0) e^{\lambda_i t}$$

Note, we are requiring that the eigenvalues be distinct!

- Furthermore with

$$\Delta \mathbf{x} = \mathbf{VZ} \Rightarrow \mathbf{z} = \mathbf{V}^{-1} \mathbf{x} = \mathbf{W}^T \mathbf{x}$$

- So $\mathbf{z}(t)$ can be written as using the left eigenvectors as

$$\mathbf{z}(t) = \mathbf{W}^t \mathbf{x}(t) = [\mathbf{w}_1 \ \mathbf{w}_2 \ \dots \ \mathbf{w}_n]^t \begin{bmatrix} x_1(t) \\ \vdots \\ x_n(t) \end{bmatrix}$$

Modal Matrices



- We can then write the response $\mathbf{x}(t)$ in terms of the modes of the system

$$z_i(t) = w_i^t x(t)$$

$$z_i(0) = w_i^t x(0) \triangleq c_i$$

$$\text{so } \mathbf{x}(t) = \sum_{i=1}^n \mathbf{v}_i c_i e^{\lambda_i t}$$

$$\text{Expanding } \Delta x_i(t) = v_{i1} c_1 e^{\lambda_1 t} + v_{i2} c_2 e^{\lambda_2 t} + \dots v_{in} c_n e^{\lambda_n t}$$

- So c_i is a scalar that represents the magnitude of excitation of the i^{th} mode from the initial conditions

Numerical example



$$\begin{bmatrix} \Delta \dot{x}_1 \\ \Delta \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 8 & -2 \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \end{bmatrix}, \Delta \mathbf{x}(0) = \begin{bmatrix} 1 \\ -4 \end{bmatrix}$$

Eigenvalues are $\lambda_1 = -4$, $\lambda_2 = 2$

$$\text{Eigenvectors are } \mathbf{v}_1 = \begin{bmatrix} 1 \\ -4 \end{bmatrix}, \mathbf{v}_2 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\text{Modal matrix } \mathbf{V} = \begin{bmatrix} 1 & 1 \\ -4 & 2 \end{bmatrix}$$

$$\text{Normalize so } \mathbf{V} = \begin{bmatrix} 0.2425 & 0.4472 \\ -0.9701 & 0.8944 \end{bmatrix}$$

Numerical example (contd)



Left eigenvector matrix is:

$$\mathbf{W}^T = \mathbf{V}^{-1} = \begin{bmatrix} 1.3745 & -0.6872 \\ 1.4908 & 0.3727 \end{bmatrix}$$

$$\dot{\mathbf{z}} = \mathbf{W}^T \mathbf{A} \mathbf{V} \mathbf{z}$$

$$\begin{bmatrix} \dot{z}_1 \\ \dot{z}_2 \end{bmatrix} = \begin{bmatrix} -4 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

Numerical example (contd)



$$\dot{z}_1 = -4z_1, \quad \mathbf{z}(0) = V^{-1}\mathbf{x}(0)$$

$$\dot{z}_2 = 2z_2, \quad \begin{bmatrix} z_1(0) \\ z_2(0) \end{bmatrix} = \begin{bmatrix} 4.123 \\ 0 \end{bmatrix}$$

$$z_1(t) = z_1(0)e^{-4t}; \quad z_2(t) = z_2(0)e^{2t}, \quad \mathbf{C} = \mathbf{W}^T \mathbf{x}(0) = \begin{bmatrix} 4.123 \\ 0 \end{bmatrix}$$

$$\mathbf{x} = \mathbf{V}\mathbf{z}$$

$$\begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ -4 & 2 \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix}$$

Because of the initial condition, the 2nd mode does not get excited

$$= c_1 \begin{bmatrix} 0.2425 \\ -0.9701 \end{bmatrix} z_1(t) + c_2 \begin{bmatrix} 0.4472 \\ 0.8944 \end{bmatrix} z_2(t) = \sum_{i=1}^2 c_i \mathbf{v}_i z_i(0) e^{\lambda_i t}$$

Mode Shape, Sensitivity and Participation Factors



- So we have

$$\mathbf{x}(t) = \mathbf{V}\mathbf{z}(t), \quad \mathbf{z}(t) = \mathbf{W}^t \mathbf{x}(t)$$

- $\mathbf{x}(t)$ are the original state variables, $\mathbf{z}(t)$ are the transformed variables so that each variable is associated with only one mode.
- From the first equation the right eigenvector gives the “mode shape” i.e. relative activity of state variables when a particular mode is excited.
- For example the degree of activity of state variable x_k in v_i mode is given by the element V_{ki} of the the right eigenvector matrix \mathbf{V}

Mode Shape, Sensitivity and Participation Factors



- The magnitude of elements of \mathbf{v}_i give the extent of activities of n state variables in the i^{th} mode and angles of elements (if complex) give phase displacements of the state variables with regard to the mode.
- The left eigenvector \mathbf{w}_i identifies which combination of original state variables display only the i^{th} mode.

Eigenvalue Parameter Sensitivity



- To derive the sensitivity of the eigenvalues to the parameters recall $\mathbf{A}\mathbf{v}_i = \lambda_i\mathbf{v}_i$; take the partial derivative with respect to A_{kj} by using the chain rule

$$\frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i + \mathbf{A} \frac{\partial \mathbf{v}_i}{\partial A_{kj}} = \frac{\partial \lambda_i}{\partial A_{kj}} \mathbf{v}_i + \lambda_i \frac{\partial \mathbf{v}_i}{\partial A_{kj}}$$

Multiply by \mathbf{w}_i^t

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i + \mathbf{w}_i^t \mathbf{A} \frac{\partial \mathbf{v}_i}{\partial A_{kj}} = \mathbf{w}_i^t \frac{\partial \lambda_i}{\partial A_{kj}} \mathbf{v}_i + \mathbf{w}_i^t \lambda_i \frac{\partial \mathbf{v}_i}{\partial A_{kj}}$$

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i + \mathbf{w}_i^t [\mathbf{A} - \lambda_i \mathbf{I}] \frac{\partial \mathbf{v}_i}{\partial A_{kj}} = \mathbf{w}_i^t \frac{\partial \lambda_i}{\partial A_{kj}} \mathbf{v}_i$$

Eigenvalue Parameter Sensitivity



- This is simplified by noting that $\mathbf{w}_i^t (\mathbf{A} - \lambda_i \mathbf{I}) = 0$ by the definition of \mathbf{w}_i being a left eigenvector
- Therefore

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i = \frac{\partial \lambda_i}{\partial A_{kj}}$$

- Since all elements of $\frac{\partial \mathbf{A}}{\partial A_{kj}}$ are zero, except the k^{th} row, j^{th} column is 1
- Thus $\frac{\partial \lambda_i}{\partial A_{kj}} = W_{ki} V_{ji}$

Sensitivity Example



- In the previous example we had

$$\mathbf{A} = \begin{bmatrix} 1 & 4 \\ 3 & 2 \end{bmatrix}, \quad \lambda_{1,2} = 5, -2, \quad \mathbf{V} = \begin{bmatrix} 1 & 4 \\ 1 & -3 \end{bmatrix}, \quad \mathbf{W} = \frac{1}{7} \begin{bmatrix} 3 & 1 \\ 4 & -1 \end{bmatrix}$$

- Then the sensitivity of λ_1 and λ_2 to changes in \mathbf{A} are

$$\frac{\partial \lambda_i}{\partial A_{kj}} = W_{ki} V_{ji} \rightarrow \frac{\partial \lambda_1}{\partial \mathbf{A}} = \frac{1}{7} \begin{bmatrix} 3 & 3 \\ 4 & 4 \end{bmatrix}, \quad \frac{\partial \lambda_2}{\partial \mathbf{A}} = \frac{1}{7} \begin{bmatrix} 4 & -3 \\ -4 & 3 \end{bmatrix}$$

- For example with $\hat{\mathbf{A}} = \begin{bmatrix} 1 & 4 \\ 3 & 3 \end{bmatrix}$, $\hat{\lambda}_{1,2} = 5.61, -1.61$,

Eigenvalue Parameter Sensitivity



- This is simplified by noting that $\mathbf{w}_i^t (\mathbf{A} - \lambda_i \mathbf{I}) = 0$ by the definition of \mathbf{w}_i being a left eigenvector
- Therefore

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i = \frac{\partial \lambda_i}{\partial A_{kj}}$$

- Since all elements of $\frac{\partial \mathbf{A}}{\partial A_{kj}}$ are zero, except the k^{th} row, j^{th} column is 1
- Thus $\frac{\partial \lambda_i}{\partial A_{kj}} = W_{ki} V_{ji}$

Eigenvalue Parameter Sensitivity



- To derive the sensitivity of the eigenvalues to the parameters recall $\mathbf{A}\mathbf{v}_i = \lambda_i\mathbf{v}_i$; take the partial derivative with respect to A_{kj} by using the chain rule

$$\frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i + \mathbf{A} \frac{\partial \mathbf{v}_i}{\partial A_{kj}} = \frac{\partial \lambda_i}{\partial A_{kj}} \mathbf{v}_i + \lambda_i \frac{\partial \mathbf{v}_i}{\partial A_{kj}}$$

Multiply by \mathbf{w}_i^t

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i + \mathbf{w}_i^t \mathbf{A} \frac{\partial \mathbf{v}_i}{\partial A_{kj}} = \mathbf{w}_i^t \frac{\partial \lambda_i}{\partial A_{kj}} \mathbf{v}_i + \mathbf{w}_i^t \lambda_i \frac{\partial \mathbf{v}_i}{\partial A_{kj}}$$

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i + \mathbf{w}_i^t [\mathbf{A} - \lambda_i \mathbf{I}] \frac{\partial \mathbf{v}_i}{\partial A_{kj}} = \mathbf{w}_i^t \frac{\partial \lambda_i}{\partial A_{kj}} \mathbf{v}_i$$

Eigenvalue Parameter Sensitivity



- This is simplified by noting that $\mathbf{w}_i^t (\mathbf{A} - \lambda_i \mathbf{I}) = 0$ by the definition of \mathbf{w}_i being a left eigenvector
- Therefore

$$\mathbf{w}_i^t \frac{\partial \mathbf{A}}{\partial A_{kj}} \mathbf{v}_i = \frac{\partial \lambda_i}{\partial A_{kj}}$$

- Since all elements of $\frac{\partial \mathbf{A}}{\partial A_{kj}}$ are zero, except the k^{th} row, j^{th} column is 1
- Thus $\frac{\partial \lambda_i}{\partial A_{kj}} = W_{ki} V_{ji}$

Sensitivity Example



- In the previous example we had

$$\mathbf{A} = \begin{bmatrix} 1 & 4 \\ 3 & 2 \end{bmatrix}, \quad \lambda_{1,2} = 5, -2, \quad \mathbf{V} = \begin{bmatrix} 1 & 4 \\ 1 & -3 \end{bmatrix}, \quad \mathbf{W} = \frac{1}{7} \begin{bmatrix} 3 & 1 \\ 4 & -1 \end{bmatrix}$$

- Then the sensitivity of λ_1 and λ_2 to changes in \mathbf{A} are

$$\frac{\partial \lambda_i}{\partial A_{kj}} = W_{ki} V_{ji} \rightarrow \frac{\partial \lambda_1}{\partial \mathbf{A}} = \frac{1}{7} \begin{bmatrix} 3 & 3 \\ 4 & 4 \end{bmatrix}, \quad \frac{\partial \lambda_2}{\partial \mathbf{A}} = \frac{1}{7} \begin{bmatrix} 4 & -3 \\ -4 & 3 \end{bmatrix}$$

- For example with $\hat{\mathbf{A}} = \begin{bmatrix} 1 & 4 \\ 3 & 2.1 \end{bmatrix}$, $\hat{\lambda}_{1,2} = 5.057, -1.957$

Participation Factors



- The participation factors, P_{ki} , are used to determine how much the k^{th} state variable participates in the i^{th} mode

$$P_{ki} = V_{ki} W_{ki}$$

- The sum of the participation factors for any mode or any variable sum to 1
- The participation factors are quite useful in relating the eigenvalues to portions of a model

Participation Factors



- For the previous example with $P_{ki} = V_{ki} W_{ik}$ and

$$\mathbf{A} = \begin{bmatrix} 1 & 4 \\ 3 & 2 \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} 1 & 4 \\ 1 & -3 \end{bmatrix}, \quad \mathbf{W} = \frac{1}{7} \begin{bmatrix} 3 & 1 \\ 4 & -1 \end{bmatrix}$$

- We get

$$\mathbf{P} = \frac{1}{7} \begin{bmatrix} 3 & 4 \\ 4 & 3 \end{bmatrix}$$

PowerWorld SMIB Participation Factors



- The magnitudes of the participation factors are shown on the PowerWorld SMIB dialog
- The below values are shown for the four bus example with $Q_4 = 0$

Generator SMIB Eigenvalue Information

Bus Number: 4
 Bus Name: Bus 4
 ID: 1
 Area Name: Home (1)

Generator Information (on Generator MVA Base)

General Info | A Matrix | Eigenvalues

	Real Part	Imag Part	Magnitude	Damping Ratio	Damped Freq (Hz)	Damped Period (Sec)	Undamped Freq (Hz)	Machine Angle	Machine Speed w	Machine Eqp	Machine PsiDp	Machine PsiQpp	Machine Edp	Exciter EField before limit	Exciter VF
1	0.2704	-9.5336	9.5374	-0.0283	-1.5173	-0.6591	1.5179	0.6920	0.6810	0.1642	0.0250	0.0137	0.0139	0.1714	0.0000
2	0.2704	9.5336	9.5374	-0.0283	1.5173	0.6591	1.5179	0.6920	0.6810	0.1642	0.0250	0.0137	0.0139	0.1714	0.0000
3	-1.0000	0.0000	1.0000	1.0000	0.0000		0.1592	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
4	-3.0137	0.0000	3.0137	1.0000	0.0000		0.4796	0.0071	0.0098	0.0573	0.0011	0.1263	0.9865	0.0865	0.0000
5	-3.6849	-6.4281	7.4094	0.4973	-1.0231	-0.9775	1.1792	0.1643	0.1764	0.6494	0.0534	0.0350	0.0964	0.7120	0.0000
6	-3.6849	6.4281	7.4094	0.4973	1.0231	0.9775	1.1792	0.1643	0.1764	0.6494	0.0534	0.0350	0.0964	0.7120	0.0000
7	-14.4234	0.0000	14.4234	1.0000	0.0000		2.2956	0.0054	0.0049	0.0219	0.9995	0.0013	0.0028	0.0226	0.0000
8	-21.6978	0.0000	21.6978	1.0000	0.0000		3.4533	0.0030	0.0037	0.0009	0.0006	0.9971	0.0762	0.0011	0.0000

OK Save Cancel Help Print

Case is saved as B4_GENROU_Sat_SMIB_QZero

Measurement Based Modal Analysis



- With the advent of large numbers of PMUs, measurement based SSA is increasingly used
 - The goal is to determine the damping associated with the dominant oscillatory modes in the system
 - Approaches seek to approximate a sampled signal by a series of exponential functions (usually damped sinusoids)
- Several techniques are available with Prony analysis the oldest
 - Method, which was developed by Gaspard Riche de Prony, dates to 1795; power system applications from about 1980's
- Here we'll consider a newer alternative, based on the variable projection method

Some Useful References



- J.F. Hauer, C.J. Demeure, and L.L. Scharf, "Initial results in Prony analysis of power system response signals," *IEEE Trans. Power Systems*, vol.5, pp 80-89, Feb 1990
- D.J. Trudnowski, J.M. Johnson, and J.F. Hauer, "Making Prony analysis more accurate using multiple signals," *IEEE Trans. Power Systems*, vol.14, pp.226-231, Feb 1999
- A. Borden, B.C. Lesieutre, J. Gronquist, "Power System Modal Analysis Tool Developed for Industry Use," *Proc. 2013 North American Power Symposium*, Manhattan, KS, Sept. 2013

Variable Projection Method (VPM)



- Idea of all techniques is to approximate a signal, $y_{\text{org}}(t)$, by the sum of other, simpler signals (basis functions)
 - Basis functions are usually exponentials, with linear and quadratic functions also added to detrend the signal
 - Properties of the original signal can be quantified from basis function properties (such as frequency and damping)
 - Signal is considered over an interval with $t=0$ at the beginning
- Approaches work by sampling the original signal $y_{\text{org}}(t)$
- Vector \mathbf{y} consists of m uniformly sampled points from $y_{\text{org}}(t)$ at a sampling value of ΔT , starting with $t=0$, with values y_j for $j=1 \dots m$
 - Times are then $t_j = (j-1)\Delta T$

Variable Projection Method (VPM)



- At each time point j , where $t_j = (j-1)\Delta T$ the approximation of y_j is

$$\hat{y}_j(\boldsymbol{\alpha}) = \sum_{i=1}^n b_i \phi_i(t_j, \boldsymbol{\alpha})$$

where $\boldsymbol{\alpha}$ is a vector with the real and imaginary eigenvalue components, with $\phi_i(t_j, \boldsymbol{\alpha}) = e^{\alpha_i t_j}$ for α_i corresponding to a real eigenvalue, and

$$\phi_i(t_j, \boldsymbol{\alpha}) = e^{\alpha_i t_j} \cos(\alpha_{i+1} t_j) \text{ and } \phi_{i+1}(t_j, \boldsymbol{\alpha}) = e^{\alpha_i t_j} \sin(\alpha_{i+1} t_j)$$

for a complex eigenvector value

Variable Projection Method (VPM)



- Error (residual) value at each point j is

$$r_j(t_j, \boldsymbol{\alpha}) = y_j - \hat{y}_j(t_j, \boldsymbol{\alpha})$$

— $\boldsymbol{\alpha}$ is the vector containing the optimization variables

- Function being minimized is

$$\frac{1}{2} \sum_{j=1}^m (y_j - \hat{y}_j(t_j, \boldsymbol{\alpha}))^2 = \frac{1}{2} \|\mathbf{r}(\boldsymbol{\alpha})\|_2^2$$

$\mathbf{r}(\boldsymbol{\alpha})$ is the residual vector

Method iteratively changes $\boldsymbol{\alpha}$ to reduce the minimization function

Variable Projection Method (VPM)



- A key insight of the variable projection method is that

$$\hat{\mathbf{y}}(\boldsymbol{\alpha}) = \boldsymbol{\Phi}(\boldsymbol{\alpha})\mathbf{b}$$

And then the residual is minimized by selecting

$$\mathbf{b} = \boldsymbol{\Phi}(\boldsymbol{\alpha})^+ \mathbf{y}$$

where $\boldsymbol{\Phi}(\boldsymbol{\alpha})$ is the m by n matrix with values

$\Phi_{ji}(\boldsymbol{\alpha}) = e^{\alpha_i t_j}$ if α_i corresponds to a real eigenvalue,

and $\Phi_{ji}(\boldsymbol{\alpha}) = e^{\alpha_i t_j} \cos(\alpha_{i+1} t_j)$ and $\Phi_{ji+1}(\boldsymbol{\alpha}) = e^{\alpha_i t_j} \sin(\alpha_{i+1} t_j)$

for a complex eigenvalue; $t_j = (j-1)\Delta T$

Finally, $\boldsymbol{\Phi}(\boldsymbol{\alpha})^+$ is the pseudoinverse of $\boldsymbol{\Phi}(\boldsymbol{\alpha})$