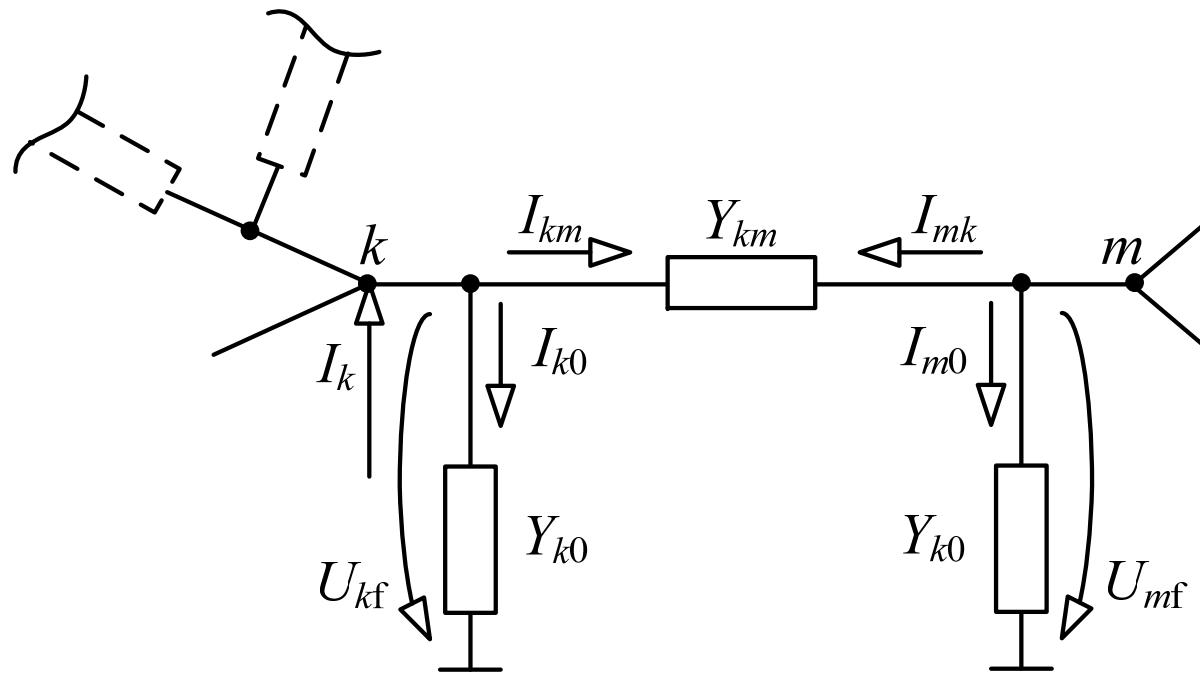


LOAD-FLOW CALCULATIONS IN MESHED SYSTEMS

Node voltage method

A system part with the node k and its neighbour



$$\hat{I}_k - \sum_{\substack{m=1 \\ m \neq k}}^n \hat{I}_{km} - \hat{I}_{k0} = 0$$

Currents

$$\hat{I}_{km} = (\hat{U}_{fk} - \hat{U}_{fm}) \hat{Y}_{km}$$

$$\hat{I}_{k0} = \hat{U}_{fk} \hat{Y}_{k0}$$

$$\hat{I}_k = \sum_{\substack{m=1 \\ m \neq k}}^n (\hat{U}_{fk} - \hat{U}_{fm}) \hat{Y}_{km} + \hat{U}_{fk} \hat{Y}_{k0}$$

$$\hat{I}_k = \hat{U}_{fk} \left(\sum_{\substack{m=1 \\ m \neq k}}^n \hat{Y}_{km} + \hat{Y}_{k0} \right) - \sum_{\substack{m=1 \\ m \neq k}}^n \hat{U}_{fm} \hat{Y}_{km}$$

Let's define the node self-admittance

$$\hat{Y}_{kk} = \sum_{\substack{m=1 \\ m \neq k}}^n \hat{Y}_{km} + \hat{Y}_{k0} = \sum_{\substack{m=0 \\ m \neq k}}^n \hat{Y}_{km}$$

Hence for k^{th} node current

$$\hat{I}_k = \hat{U}_{fk} \hat{Y}_{kk} - \sum_{\substack{m=1 \\ m \neq k}}^n \hat{U}_{fm} \hat{Y}_{km}$$

$$\hat{I}_k = \sum_{m=1}^n \hat{U}_{fm} \hat{Y}_{(k,m)}$$

Matrix expression

$$(\hat{I}) = (\hat{Y})(\hat{U}_f) \quad \sqrt{3}(\hat{I}) = (\hat{Y})(\hat{U})$$

Regular admittance matrix

$$(\hat{U}_f) = (\hat{Y})^{-1}(\hat{I}) = (\hat{Z})(\hat{I})$$

Singular admittance matrix – node voltage x (1 ÷ n-1) defined

$$\begin{pmatrix} (\hat{I}_x) \\ (\hat{I}_y) \end{pmatrix} = \begin{pmatrix} (\hat{Y}_A) & (\hat{Y}_B) \\ (\hat{Y}_B)^T & (\hat{Y}_D) \end{pmatrix} \begin{pmatrix} (\hat{U}_{fx}) \\ (\hat{U}_{fy}) \end{pmatrix}$$

Hence

$$\begin{pmatrix} \hat{\mathbf{I}}_x \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{Y}}_A \end{pmatrix} \begin{pmatrix} \hat{\mathbf{U}}_{fx} \end{pmatrix} + \begin{pmatrix} \hat{\mathbf{Y}}_B \end{pmatrix} \begin{pmatrix} \hat{\mathbf{U}}_{fy} \end{pmatrix}$$

$$\begin{pmatrix} \hat{\mathbf{I}}_y \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{Y}}_B \end{pmatrix}^T \begin{pmatrix} \hat{\mathbf{U}}_{fx} \end{pmatrix} + \begin{pmatrix} \hat{\mathbf{Y}}_D \end{pmatrix} \begin{pmatrix} \hat{\mathbf{U}}_{fy} \end{pmatrix}$$

Let's calculate $\begin{pmatrix} \hat{\mathbf{I}}_x \end{pmatrix}, \begin{pmatrix} \hat{\mathbf{U}}_{fy} \end{pmatrix}$

$$\begin{pmatrix} \hat{\mathbf{U}}_{fy} \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{Y}}_D \end{pmatrix}^{-1} \begin{pmatrix} \hat{\mathbf{I}}_y \end{pmatrix} - \begin{pmatrix} \hat{\mathbf{Y}}_D \end{pmatrix}^{-1} \begin{pmatrix} \hat{\mathbf{Y}}_B \end{pmatrix}^T \begin{pmatrix} \hat{\mathbf{U}}_{fx} \end{pmatrix}$$

Gauss-Seidel method

- iterative method for non-linear equations
- not always a good convergence

Basic idea

$$f(\mathbf{x}) = 0$$

Rewritten

$$\mathbf{x} = \mathbf{g}(\mathbf{x})$$

If $\mathbf{x}^{(k)}$ is the estimation in k^{th} step, the next iteration is

$$\mathbf{x}^{(k+1)} = \mathbf{g}(\mathbf{x}^{(k)})$$

We continue until two following iterations difference is smaller than the prescribed precision ε

$$\left| \mathbf{x}^{(k+1)} - \mathbf{x}^{(k)} \right| \leq \varepsilon$$

Sometimes the convergence can be improved by the acceleration factor α ($\alpha < 1$ or $\alpha > 1$)

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \alpha \left(\mathbf{g}(\mathbf{x}^{(k)}) - \mathbf{x}^{(k)} \right)$$

The system of n equations with n unknowns

$$f_1(x_1, x_2, \dots, x_n) = c_1$$

$$f_2(x_1, x_2, \dots, x_n) = c_2$$

.....

$$f_n(x_1, x_2, \dots, x_n) = c_n$$

Each unknown is expressed from one equation

$$x_1 = c_1 + g_1(x_1, x_2, \dots, x_n)$$

$$x_2 = c_2 + g_2(x_1, x_2, \dots, x_n)$$

.....

$$x_n = c_n + g_n(x_1, x_2, \dots, x_n)$$

Gauss: k^{th} iteration from $(k-1)^{\text{th}}$ approximation

$$x_m^{(k)} = c_m + g_m(x_1^{(k-1)}, x_2^{(k-1)}, \dots, x_{m-1}^{(k-1)}, x_m^{(k-1)}, \dots, x_n^{(k-1)})$$

Gauss-Seidel: for k^{th} iteration calculation also k^{th} approximations from previous equations are used

$$x_m^{(k)} = c_m + g_m(x_1^{(k)}, x_2^{(k)}, \dots, x_{m-1}^{(k)}, x_m^{(k-1)}, \dots, x_n^{(k-1)})$$

Convergence is tested for each variable separately.

Newton-Raphson method

- the most often method for non-linear equations
- it uses Taylor polynomial
- it converts non-linear equations solution to linear equations solution, gradually higher precision of the estimation

Basic idea

$$f(x) = c$$

If $x^{(0)}$ is the initial estimation and $\Delta x^{(0)}$ is the difference from the right solution, then

$$f(x^{(0)} + \Delta x^{(0)}) = c$$

Expansion to the Taylor series

$$f(x^{(0)}) + \left(\frac{df}{dx}\right)^{(0)} \Delta x^{(0)} + \frac{1}{2!} \left(\frac{d^2f}{dx^2}\right)^{(0)} (\Delta x^{(0)})^2 + \dots = c$$

Higher orders neglecting (linearization)

$$\Delta \mathbf{c}^{(0)} \approx \left(\frac{d\mathbf{f}}{d\mathbf{x}} \right)^{(0)} \Delta \mathbf{x}^{(0)}$$

where

$$\Delta \mathbf{c}^{(0)} = \mathbf{c} - \mathbf{f}(\mathbf{x}^{(0)})$$

is called “defect”.

Adding $\Delta \mathbf{x}^{(0)}$ to the initial estimation gives the second approximation

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} + \frac{\Delta \mathbf{c}^{(0)}}{\left(\frac{d\mathbf{f}}{d\mathbf{x}} \right)^{(0)}}$$

(Note: impossible if the derivative equals zero)

The same relation in the next steps give the method algorithm:

$$\Delta \mathbf{c}^{(k)} = \mathbf{c} - \mathbf{f}(\mathbf{x}^{(k)})$$

$$\Delta \mathbf{x}^{(k)} = \frac{\Delta \mathbf{c}^{(k)}}{\left(\frac{d\mathbf{f}}{d\mathbf{x}} \right)^{(k)}}$$

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \Delta \mathbf{x}^{(k)}$$

$$\Delta \mathbf{c}^{(k+1)} = \mathbf{c} - \mathbf{f}(\mathbf{x}^{(k+1)})$$

The system of n equations with n unknowns

$$f_1(x_1, x_2, \dots, x_n) = c_1$$

$$f_2(x_1, x_2, \dots, x_n) = c_2$$

.....

$$f_n(x_1, x_2, \dots, x_n) = c_n$$

Expansion to the Taylor series

$$(f_1)^{(0)} + \left(\frac{\partial f_1}{\partial x_1}\right)^{(0)} \Delta x_1^{(0)} + \left(\frac{\partial f_1}{\partial x_2}\right)^{(0)} \Delta x_2^{(0)} + \dots + \left(\frac{\partial f_1}{\partial x_n}\right)^{(0)} \Delta x_n^{(0)} = c_1$$

$$(f_2)^{(0)} + \left(\frac{\partial f_2}{\partial x_1}\right)^{(0)} \Delta x_1^{(0)} + \left(\frac{\partial f_2}{\partial x_2}\right)^{(0)} \Delta x_2^{(0)} + \dots + \left(\frac{\partial f_2}{\partial x_n}\right)^{(0)} \Delta x_n^{(0)} = c_2$$

.....

$$(\mathbf{f}_n)^{(0)} + \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_1} \right)^{(0)} \Delta \mathbf{x}_1^{(0)} + \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_2} \right)^{(0)} \Delta \mathbf{x}_2^{(0)} + \dots + \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_n} \right)^{(0)} \Delta \mathbf{x}_n^{(0)} = \mathbf{c}_n$$

Matrix expression

$$\begin{pmatrix} \mathbf{c}_1 - (\mathbf{f}_1^{(0)}) \\ \mathbf{c}_1 - (\mathbf{f}_2^{(0)}) \\ \vdots \\ \mathbf{c}_n - (\mathbf{f}_n^{(0)}) \end{pmatrix} = \begin{pmatrix} \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_1} \right)^{(0)} & \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_2} \right)^{(0)} & \dots & \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_n} \right)^{(0)} \\ \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{x}_1} \right)^{(0)} & \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{x}_2} \right)^{(0)} & \dots & \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{x}_n} \right)^{(0)} \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_1} \right)^{(0)} & \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_2} \right)^{(0)} & \dots & \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_n} \right)^{(0)} \end{pmatrix} \cdot \begin{pmatrix} \Delta \mathbf{x}_1^{(0)} \\ \Delta \mathbf{x}_2^{(0)} \\ \vdots \\ \Delta \mathbf{x}_n^{(0)} \end{pmatrix}$$

in short

$$(\Delta \mathbf{C}^{(0)}) = (\mathbf{J}^{(0)}) \cdot (\Delta \mathbf{X}^{(0)})$$

Hence

$$\left(\Delta X^{(0)}\right) = \left(J^{(0)}\right)^{-1} \cdot \left(\Delta C^{(0)}\right)$$

The method algorithm:

$$\left(\Delta C^{(k)}\right) = \begin{pmatrix} c_1 - (f_1^{(k)}) \\ c_1 - (f_2^{(k)}) \\ \vdots \\ c_n - (f_n^{(k)}) \end{pmatrix}$$

$$\left(\Delta X^{(k)}\right) = \left(J^{(k)}\right) \cdot \left(\Delta C^{(k)}\right)$$

$$\left(X^{(k+1)}\right) = \left(X^{(k)}\right) + \left(\Delta X^{(k)}\right)$$

$$(\Delta \mathbf{C}^{(k+1)}) = \begin{pmatrix} \mathbf{c}_1 - (\mathbf{f}_1^{(k+1)}) \\ \mathbf{c}_1 - (\mathbf{f}_2^{(k+1)}) \\ \vdots \\ \mathbf{c}_n - (\mathbf{f}_n^{(k+1)}) \end{pmatrix} \quad \text{where} \quad (\Delta \mathbf{X}^{(k)}) = \begin{pmatrix} \Delta \mathbf{x}_1^{(k)} \\ \Delta \mathbf{x}_2^{(k)} \\ \vdots \\ \Delta \mathbf{x}_n^{(k)} \end{pmatrix}$$

$$(\mathbf{J}^{(k)}) = \begin{pmatrix} \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_1} \right)^{(k)} & \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_2} \right)^{(k)} & \dots & \left(\frac{\partial \mathbf{f}_1}{\partial \mathbf{x}_n} \right)^{(k)} \\ \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{x}_1} \right)^{(k)} & \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{x}_2} \right)^{(k)} & \dots & \left(\frac{\partial \mathbf{f}_2}{\partial \mathbf{x}_n} \right)^{(k)} \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_1} \right)^{(k)} & \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_2} \right)^{(k)} & \dots & \left(\frac{\partial \mathbf{f}_n}{\partial \mathbf{x}_n} \right)^{(k)} \end{pmatrix}$$

$(\mathbf{J}^{(k)})$ – Jakobi matrix, regularity assumption

Load Flow solution

U-I equations system can be extended to voltage-power dependence

$$\hat{I}_k = \sum_{m=1}^n \hat{U}_{fm} \hat{Y}_{km}$$

$$\hat{S}_k = 3\hat{S}_{fk} = 3\hat{U}_{fk} \hat{I}_k^* = 3\hat{U}_{fk} \sum_{m=1}^n \hat{U}_{fm}^* \hat{Y}_{km}^*$$

$$\hat{S}_k = \hat{U}_k \sum_{m=1}^n \hat{U}_m^* \hat{Y}_{km}^*$$

$$\left(\hat{S}\right) = \left(\hat{U}_{\text{diag}}\right) \left(\hat{Y}^*\right) \left(\hat{U}^*\right)$$

$$\begin{pmatrix} \hat{S}_1 \\ \dots \\ \hat{S}_k \\ \dots \\ \hat{S}_n \end{pmatrix} = \begin{pmatrix} \hat{U}_1 & 0 & 0 & 0 & 0 \\ 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \hat{U}_k & 0 & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \hat{U}_n \end{pmatrix} \cdot \begin{pmatrix} \hat{Y}_{11}^* & \dots & \dots & \dots & \hat{Y}_{1n}^* \\ \dots & \dots & \dots & \dots & \dots \\ \hat{Y}_{k1}^* & \dots & \hat{Y}_{kk}^* & \dots & \hat{Y}_{kn}^* \\ \dots & \dots & \dots & \dots & \dots \\ \hat{Y}_{n1}^* & \dots & \dots & \dots & \hat{Y}_{nn}^* \end{pmatrix} \cdot \begin{pmatrix} \hat{U}_1^* \\ \dots \\ \hat{U}_k^* \\ \dots \\ \hat{U}_n^* \end{pmatrix}$$

- powers defined \rightarrow nonlinearity

Aim: to calculate **P**, **Q**, **U**, δ in nodes and branches

Node types

Node power		Node voltage phasor components	
defined	to be calculated	defined	to be calculated
–	P, Q	U, ϑ	–
P, Q	–	–	U, ϑ
P	Q	U	ϑ
Q	P	ϑ	U

slack – „balance node“, balance P, Q for losses, as a huge system, large generation

PQ – loads

PU – generators, controlled voltage

Quantities

- fixed – requirements (P,Q for loads; P for generators)
- state – independent variables (U, δ for loads; δ for generators)
- control – here no changes (U for slack and generators), they change in optimization procedures

Node current (single phase)

$$\hat{I}_i = \hat{U}_i \sum_{\substack{j=0 \\ j \neq i}}^n \hat{Y}_{ij} - \sum_{\substack{j=1 \\ j \neq i}}^n \hat{Y}_{ij} \hat{U}_j$$

Node power

$$P_i + jQ_i = \hat{U}_i \hat{I}_i^*$$

$$\hat{I}_i = \frac{P_i - jQ_i}{\hat{U}_i^*}$$

hence

$$\frac{P_i - jQ_i}{\hat{U}_i^*} = \hat{U}_i \sum_{\substack{j=0 \\ j \neq i}}^n \hat{Y}_{ij} - \sum_{\substack{j=1 \\ j \neq i}}^n \hat{Y}_{ij} \hat{U}_j$$

Gauss-Seidel Power Flow Solution

Solution for U, δ :

$$\hat{U}_i^{(k+1)} = \frac{\frac{P_i - jQ_i}{\hat{U}_i^{*(k)}} + \sum_{\substack{j=1 \\ j \neq i}}^n \hat{Y}_{ij} \hat{U}_j^{(k)}}{\sum_{\substack{j=0 \\ j \neq i}}^n \hat{Y}_{ij}}$$

(note: for loads $P, Q < 0$)

Solution for P:

$$P_i^{(k+1)} = \text{Re} \left\{ \hat{U}_i^{*(k)} \left[\hat{U}_i^{(k)} \sum_{\substack{j=0 \\ j \neq i}}^n \hat{Y}_{ij} - \sum_{\substack{j=1 \\ j \neq i}}^n \hat{Y}_{ij} \hat{U}_j^{(k)} \right] \right\}$$

Solution for Q:

$$Q_i^{(k+1)} = -\text{Im} \left\{ \hat{U}_i^{*(k)} \left[\hat{U}_i^{(k)} \sum_{\substack{j=0 \\ j \neq i}}^n \hat{Y}_{ij} - \sum_{\substack{j=1 \\ j \neq i}}^n \hat{Y}_{ij} \hat{U}_j^{(k)} \right] \right\}$$

Admittance matrix diagonal elements

$$\sum_{\substack{j=0 \\ j \neq i}}^n \hat{Y}_{ij} = \hat{Y}_{ii}$$

Slack voltage known $\rightarrow 2(n-1)$ equations

PQ: $\hat{U}_i^{(k+1)} = f(P_i, Q_i, \hat{U}_j^{(k)})$

PU: $Q_i^{(k+1)} = f(\hat{U}_i^{(k)}, \hat{U}_j^{(k)})$

$$\hat{U}_i^{(k+1)} = f(P_i, Q_i^{(k+1)}, \hat{U}_j^{(k)})$$

imaginary part taken, real part to be calculated

$$\left(e_i^{(k+1)}\right)^2 + \left(f_i^{(k+1)}\right)^2 = \left|\hat{U}_i\right|^2$$

$$e_i^{(k+1)} = \sqrt{\left|\hat{U}_i\right|^2 - \left(f_i^{(k+1)}\right)^2}$$

Newton-Raphson Power Flow Solution

$$\hat{S}_k = \hat{U}_k \sum_{m=1}^n \hat{U}_m^* \hat{Y}_{km}^* = U_k^2 \hat{Y}_{kk}^* + \hat{U}_k \sum_{\substack{m=1 \\ m \neq k}}^n \hat{U}_m^* \hat{Y}_{km}^*$$

$$\hat{S}_k = f_k \left(\left(\hat{U} \right) \right)$$

Exponential form

$$\hat{S}_k = P_k + jQ_k \quad \hat{U}_k = U_k e^{j\theta_k} \quad \hat{Y}_{km} = Y_{km} e^{j\theta_{km}}$$

$$\hat{S}_k = U_k e^{j\theta_k} \sum_{m=1}^n U_m Y_{km} e^{-j(\theta_m + \theta_{km})}$$

Power separated into the real and imaginary part

$$P_k = \sum_{m=1}^n U_k U_m Y_{km} \cos(\vartheta_k - \vartheta_m - \theta_{km})$$

$$Q_k = \sum_{m=1}^n U_k U_m Y_{km} \sin(\vartheta_k - \vartheta_m - \theta_{km})$$

The power changes are expressed

$$\Delta \hat{S}_k = \sum_{m=1}^n \left(\frac{\partial \hat{S}_k}{\partial \vartheta_m} \Delta \vartheta_m + \frac{\partial \hat{S}_k}{\partial U_m} \Delta U_m \right)$$

$$\Delta P_k = \sum_{m=1}^n \left(\frac{\partial P_k}{\partial \vartheta_m} \Delta \vartheta_m + \frac{\partial P_k}{\partial U_m} \Delta U_m \right)$$

$$\Delta Q_k = \sum_{m=1}^n \left(\frac{\partial Q_k}{\partial \vartheta_m} \Delta \vartheta_m + \frac{\partial Q_k}{\partial U_m} \Delta U_m \right)$$

Complete equation description

$$\begin{bmatrix} \Delta R_1 \\ \Delta P_2 \\ \Delta P_{n-1} \\ \Delta P_n \\ \Delta Q_1 \\ \Delta Q_2 \\ \Delta Q_{n-1} \\ \Delta Q_n \end{bmatrix} = \begin{bmatrix} \frac{\partial R_1}{\partial \mathcal{G}_1} & \frac{\partial R_1}{\partial \mathcal{G}_2} & \frac{\partial R_1}{\partial \mathcal{G}_{n-1}} & \frac{\partial R_1}{\partial \mathcal{G}_n} & \frac{\partial R_1}{\partial U_1} & \frac{\partial R_1}{\partial U_2} & \frac{\partial R_1}{\partial U_{n-1}} & \frac{\partial R_1}{\partial U_n} \\ \frac{\partial P_2}{\partial \mathcal{G}_1} & \frac{\partial P_2}{\partial \mathcal{G}_2} & \frac{\partial P_2}{\partial \mathcal{G}_{n-1}} & \frac{\partial P_2}{\partial \mathcal{G}_n} & \frac{\partial P_2}{\partial U_1} & \frac{\partial P_2}{\partial U_2} & \frac{\partial P_2}{\partial U_{n-1}} & \frac{\partial P_2}{\partial U_n} \\ \frac{\partial P_{n-1}}{\partial \mathcal{G}_1} & \frac{\partial P_{n-1}}{\partial \mathcal{G}_2} & \frac{\partial P_{n-1}}{\partial \mathcal{G}_{n-1}} & \frac{\partial P_{n-1}}{\partial \mathcal{G}_n} & \frac{\partial P_{n-1}}{\partial U_1} & \frac{\partial P_{n-1}}{\partial U_2} & \frac{\partial P_{n-1}}{\partial U_{n-1}} & \frac{\partial P_{n-1}}{\partial U_n} \\ \frac{\partial P_n}{\partial \mathcal{G}_1} & \frac{\partial P_n}{\partial \mathcal{G}_2} & \frac{\partial P_n}{\partial \mathcal{G}_{n-1}} & \frac{\partial P_n}{\partial \mathcal{G}_n} & \frac{\partial P_n}{\partial U_1} & \frac{\partial P_n}{\partial U_2} & \frac{\partial P_n}{\partial U_{n-1}} & \frac{\partial P_n}{\partial U_n} \\ \frac{\partial Q_1}{\partial \mathcal{G}_1} & \frac{\partial Q_1}{\partial \mathcal{G}_2} & \frac{\partial Q_1}{\partial \mathcal{G}_{n-1}} & \frac{\partial Q_1}{\partial \mathcal{G}_n} & \frac{\partial Q_1}{\partial U_1} & \frac{\partial Q_1}{\partial U_2} & \frac{\partial Q_1}{\partial U_{n-1}} & \frac{\partial Q_1}{\partial U_n} \\ \frac{\partial Q_2}{\partial \mathcal{G}_1} & \frac{\partial Q_2}{\partial \mathcal{G}_2} & \frac{\partial Q_2}{\partial \mathcal{G}_{n-1}} & \frac{\partial Q_2}{\partial \mathcal{G}_n} & \frac{\partial Q_2}{\partial U_1} & \frac{\partial Q_2}{\partial U_2} & \frac{\partial Q_2}{\partial U_{n-1}} & \frac{\partial Q_2}{\partial U_n} \\ \frac{\partial Q_{n-1}}{\partial \mathcal{G}_1} & \frac{\partial Q_{n-1}}{\partial \mathcal{G}_2} & \frac{\partial Q_{n-1}}{\partial \mathcal{G}_{n-1}} & \frac{\partial Q_{n-1}}{\partial \mathcal{G}_n} & \frac{\partial Q_{n-1}}{\partial U_1} & \frac{\partial Q_{n-1}}{\partial U_2} & \frac{\partial Q_{n-1}}{\partial U_{n-1}} & \frac{\partial Q_{n-1}}{\partial U_n} \\ \frac{\partial Q_n}{\partial \mathcal{G}_1} & \frac{\partial Q_n}{\partial \mathcal{G}_2} & \frac{\partial Q_n}{\partial \mathcal{G}_{n-1}} & \frac{\partial Q_n}{\partial \mathcal{G}_n} & \frac{\partial Q_n}{\partial U_1} & \frac{\partial Q_n}{\partial U_2} & \frac{\partial Q_n}{\partial U_{n-1}} & \frac{\partial Q_n}{\partial U_n} \end{bmatrix} \begin{bmatrix} \Delta \mathcal{G}_1 \\ \Delta \mathcal{G}_2 \\ \Delta \mathcal{G}_{n-1} \\ \Delta \mathcal{G}_n \\ \Delta U_1 \\ \Delta U_2 \\ \Delta U_{n-1} \\ \Delta U_n \end{bmatrix}$$

More compact equations form

$$\begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix} = \begin{pmatrix} \frac{\partial P}{\partial \vartheta} & \frac{\partial P}{\partial U} \\ \frac{\partial Q}{\partial \vartheta} & \frac{\partial Q}{\partial U} \end{pmatrix} \begin{pmatrix} \Delta \vartheta \\ \Delta U \end{pmatrix}$$

$$(J) = \begin{pmatrix} \frac{\partial P}{\partial \vartheta} & \frac{\partial P}{\partial U} \\ \frac{\partial Q}{\partial \vartheta} & \frac{\partial Q}{\partial U} \end{pmatrix} = \begin{pmatrix} H & K \\ L & M \end{pmatrix}$$

Iterative solution idea

$$\begin{pmatrix} \vartheta \\ \mathbf{U} \end{pmatrix}_k$$

$$\text{defect} \begin{pmatrix} \Delta \mathbf{P} \\ \Delta \mathbf{Q} \end{pmatrix}$$

$$\begin{pmatrix} \Delta \vartheta \\ \Delta \mathbf{U} \end{pmatrix} = (\mathbf{J})^{-1} \begin{pmatrix} \Delta \mathbf{P} \\ \Delta \mathbf{Q} \end{pmatrix}$$

$$\begin{pmatrix} \vartheta \\ \mathbf{U} \end{pmatrix}_{k+1} = \begin{pmatrix} \vartheta \\ \mathbf{U} \end{pmatrix}_k + \begin{pmatrix} \Delta \vartheta \\ \Delta \mathbf{U} \end{pmatrix}$$