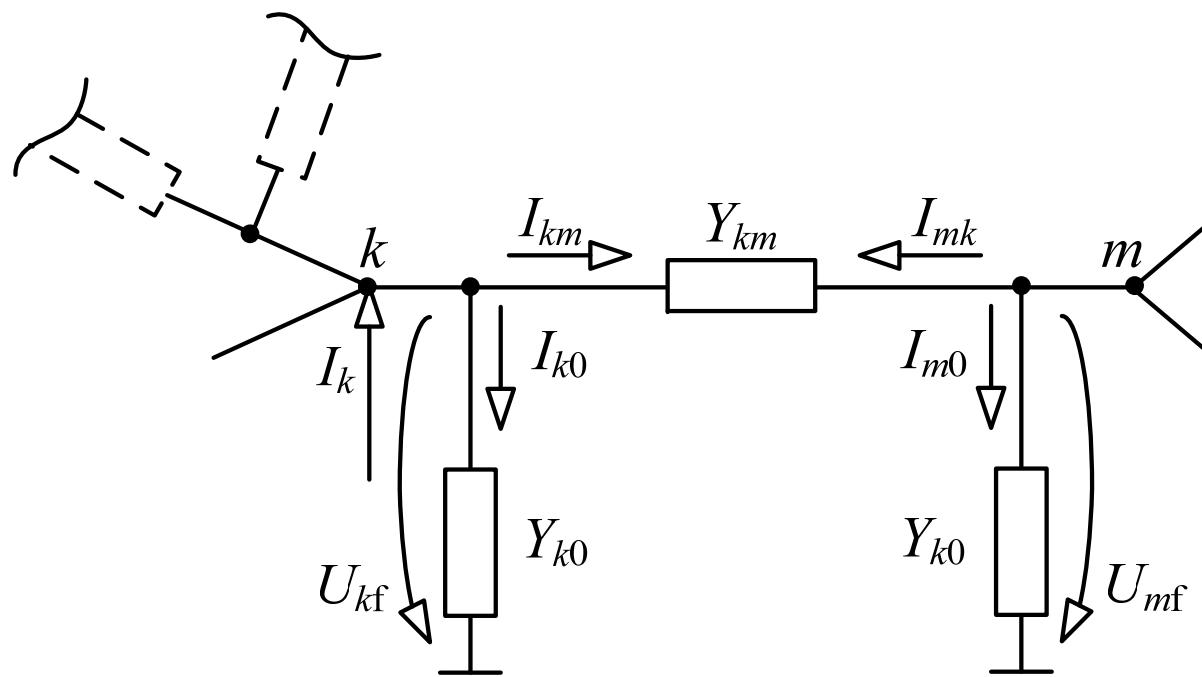


# LOAD-FLOW CALCULATIONS IN MESHED SYSTEMS

## Node voltage method

A system part with the node  $k$  and its direct neighbour  $m$



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

## 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 (adm. matrix diagonal element)

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

Node mutual admittance (non-diagonal element)

$$\hat{Y}_{(k,m)} = -\hat{Y}_{km}$$

Hence for  $k^{\text{th}}$  node current

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

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

Matrix expression

$$\begin{pmatrix} \hat{I} \end{pmatrix} = \begin{pmatrix} \hat{Y} \end{pmatrix} \begin{pmatrix} \hat{U}_f \end{pmatrix} \quad \sqrt{3} \begin{pmatrix} \hat{I} \end{pmatrix} = \begin{pmatrix} \hat{Y} \end{pmatrix} \begin{pmatrix} \hat{U} \end{pmatrix}$$

Regular admittance matrix (there is at least one non-zero element  $\hat{Y}_{k0}$ )

$$\begin{pmatrix} \hat{U}_f \end{pmatrix} = \begin{pmatrix} \hat{Y} \end{pmatrix}^{-1} \begin{pmatrix} \hat{I} \end{pmatrix} = \begin{pmatrix} \hat{Z} \end{pmatrix} \begin{pmatrix} \hat{I} \end{pmatrix}$$

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

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

$$\hat{I}_y = (\hat{Y}_B)^T \hat{U}_{fx} + \hat{Y}_D \hat{U}_{fy}$$

Let's calculate  $\hat{I}_x$ ,  $\hat{U}_{fy}$

$$\hat{U}_{fy} = (\hat{Y}_D)^{-1} \hat{I}_y - (\hat{Y}_D)^{-1} (\hat{Y}_B)^T \hat{U}_{fx}$$

## Gauss-Seidel method

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

### Basic idea

$$f(x) = 0$$

Rewritten

$$x = g(x)$$

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

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

We continue until two following iterations difference is smaller than the prescribed precision  $\varepsilon$

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

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

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

### 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:  $k^{\text{th}}$  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  $k^{\text{th}}$  iteration calculation also  $k^{\text{th}}$  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

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

## Taylor series

$$f(x)|_{x_0} = \sum_{k=0}^{\infty} \frac{\left(\frac{df(x_0)}{dx}\right)^{(k)}}{k!} (x - x_0)^k$$

Expansion to the Taylor series

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

Higher orders neglecting (linearization)

$$\Delta c^{(0)} \approx \left(\frac{df}{dx}\right)^{(0)} \Delta x^{(0)}$$

where

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

is called “defect”.

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

$$x^{(1)} = x^{(0)} + \frac{\Delta c^{(0)}}{\left(\frac{df}{dx}\right)^{(0)}}$$

(Note: impossible if the derivative equals zero)

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

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

$$\Delta x^{(k)} = \frac{\Delta c^{(k)}}{\left(\frac{df}{dx}\right)^{(k)}}$$

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

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

## 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

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

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

.....

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

## Matrix expression

$$\begin{pmatrix} c_1 - (f_1)^{(0)} \\ c_2 - (f_2)^{(0)} \\ \vdots \\ c_n - (f_n)^{(0)} \end{pmatrix} = \begin{pmatrix} \left( \frac{\partial f_1}{\partial x_1} \right)^{(0)} & \left( \frac{\partial f_1}{\partial x_2} \right)^{(0)} & \cdots & \left( \frac{\partial f_1}{\partial x_n} \right)^{(0)} \\ \left( \frac{\partial f_2}{\partial x_1} \right)^{(0)} & \left( \frac{\partial f_2}{\partial x_2} \right)^{(0)} & \cdots & \left( \frac{\partial f_2}{\partial x_n} \right)^{(0)} \\ \vdots & \vdots & \vdots & \vdots \\ \left( \frac{\partial f_n}{\partial x_1} \right)^{(0)} & \left( \frac{\partial f_n}{\partial x_2} \right)^{(0)} & \cdots & \left( \frac{\partial f_n}{\partial x_n} \right)^{(0)} \end{pmatrix} \cdot \begin{pmatrix} \Delta x_1^{(0)} \\ \Delta x_2^{(0)} \\ \vdots \\ \Delta x_n^{(0)} \end{pmatrix}$$

in short

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

Hence

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

The method algorithm:

$$\Delta C^{(k)} = \begin{pmatrix} c_1 - (f_1)^{(k)} \\ c_2 - (f_2)^{(k)} \\ \vdots \\ c_n - (f_n)^{(k)} \end{pmatrix}$$

$$\Delta X^{(k)} = J^{(k)}^{-1} \cdot \Delta C^{(k)}$$

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

$$\left( \Delta C^{(k+1)} \right) = \begin{pmatrix} c_1 - (f_1)^{(k+1)} \\ c_2 - (f_2)^{(k+1)} \\ \vdots \\ c_n - (f_n)^{(k+1)} \end{pmatrix} \quad \text{where} \quad \left( \Delta X^{(k)} \right) = \begin{pmatrix} \Delta x_1^{(k)} \\ \Delta x_2^{(k)} \\ \vdots \\ \Delta x_n^{(k)} \end{pmatrix}$$

$$\left( J^{(k)} \right) = \begin{pmatrix} \left( \frac{\partial f_1}{\partial x_1} \right)^{(k)} & \left( \frac{\partial f_1}{\partial x_2} \right)^{(k)} & \cdots & \left( \frac{\partial f_1}{\partial x_n} \right)^{(k)} \\ \left( \frac{\partial f_2}{\partial x_1} \right)^{(k)} & \left( \frac{\partial f_2}{\partial x_2} \right)^{(k)} & \cdots & \left( \frac{\partial f_2}{\partial x_n} \right)^{(k)} \\ \vdots & \vdots & \vdots & \vdots \\ \left( \frac{\partial f_n}{\partial x_1} \right)^{(k)} & \left( \frac{\partial f_n}{\partial x_2} \right)^{(k)} & \cdots & \left( \frac{\partial f_n}{\partial x_n} \right)^{(k)} \end{pmatrix}$$

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

## Load Flow solution

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

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

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

$$\hat{S}_k = \hat{U}_k \sum_{m=1}^n \hat{U}_m^* \hat{Y}_{(k,m)}^*$$

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

$$\begin{pmatrix} \hat{\mathbf{S}}_1 \\ \dots \\ \hat{\mathbf{S}}_k \\ \dots \\ \hat{\mathbf{S}}_n \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{U}}_1 & 0 & 0 & 0 & 0 \\ 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \hat{\mathbf{U}}_k & 0 & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \hat{\mathbf{U}}_n \end{pmatrix} \cdot \begin{pmatrix} \hat{\mathbf{Y}}_{(1,1)}^* & \dots & \dots & \dots & \hat{\mathbf{Y}}_{(1,n)}^* \\ \dots & \dots & \dots & \dots & \dots \\ \hat{\mathbf{Y}}_{(k,1)}^* & \dots & \hat{\mathbf{Y}}_{(k,k)}^* & \dots & \hat{\mathbf{Y}}_{(k,n)}^* \\ \dots & \dots & \dots & \dots & \dots \\ \hat{\mathbf{Y}}_{(n,1)}^* & \dots & \dots & \dots & \hat{\mathbf{Y}}_{(n,n)}^* \end{pmatrix} \cdot \begin{pmatrix} \hat{\mathbf{U}}_1^* \\ \dots \\ \hat{\mathbf{U}}_k^* \\ \dots \\ \hat{\mathbf{U}}_n^* \end{pmatrix}$$

- powers defined → nonlinearity

Aim: to calculate  $\mathbf{P}, \mathbf{Q}, \mathbf{U}, \delta$  in nodes and branches

Note: Assumption of symmetrical system and its loading → single phase models.

## Node types

Node power		Node voltage phasor components	
defined	to be calculated	defined	to be calculated
–	$P, Q$	$U, \vartheta$	–
$P, Q$	–	–	$U, \vartheta$
$P$	$Q$	$U$	$\vartheta$
$Q$	$P$	$\vartheta$	$U$

slack (swing bus) – „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 ( $U, \vartheta$  for loads;  $\vartheta$  for generators)
- control – here no changes ( $U$  for slack and generators), they change in optimization procedures

## Calculations in relative values

### Denominated values

$$\hat{S} = 3\hat{U}_f \hat{I}^* = \sqrt{3}\hat{U}\hat{I}^* \quad \hat{U}_f = \hat{Z}\hat{I} \quad \hat{U} = \sqrt{3}\hat{Z}\hat{I}$$

### Base values

$$\hat{S}_v = \sqrt{3}\hat{U}_v \hat{I}_v^*$$

$$\hat{Z}_v = \frac{\hat{U}_v}{\sqrt{3}\hat{I}_v} = \frac{\hat{U}_v}{\sqrt{3}\left(\frac{\hat{S}_v}{\sqrt{3}\hat{U}_v}\right)^*} = \frac{U_v^2}{\hat{S}_v^*}$$

### Relative values

$$\hat{s} \cdot S_v = \sqrt{3} \cdot \hat{u} \cdot U_v \cdot \hat{i}^* \cdot I_v^*$$

$$\underline{\hat{s} = \hat{u} \cdot \hat{i}^*}$$

$$\hat{u} \cdot U_v = \sqrt{3} \cdot \hat{z} \cdot Z_v \cdot \hat{i} \cdot I_v$$

$$\underline{\hat{u} = \hat{z} \cdot \hat{i}}$$

## Node current (single phase)

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

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

## Node power

$$p_i + jq_i = \hat{u}_i \cdot \hat{i}_i^* \quad \hat{i}_i = \frac{p_i - jq_i}{\hat{u}_i^*}$$

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  $U, \delta$ :

$$\hat{u}_i^{(k+1)} = \frac{\frac{p_i - j q_i}{\hat{u}_i^{*(k)}} + \sum_{\substack{j=1 \\ j \neq i}}^n \hat{y}_{ij} \hat{u}_j^{(k)}}{\sum_{\substack{j=0 \\ j \neq i}}^n \hat{y}_{ij}}$$

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

Solution for  $P$ :

$$p_i^{(k+1)} = \operatorname{Re} \left\{ \hat{u}_i^{*(k)} \left[ \hat{u}_i^{(k)} \sum_{\substack{j=0 \\ j \neq i}}^n \hat{y}_{ij} - \sum_{\substack{j=1 \\ j \neq i}}^n \hat{y}_{ij} \hat{u}_j^{(k)} \right] \right\}$$

Solution for Q:

$$q_i^{(k+1)} = -\operatorname{Im} \left\{ \hat{u}_i^{*(k)} \left[ \hat{u}_i^{(k)} \sum_{\substack{j=0 \\ j \neq i}}^n \hat{y}_{ij} - \sum_{\substack{j=1 \\ j \neq i}}^n \hat{y}_{ij} \hat{u}_j^{(k)} \right] \right\}$$

Admittance matrix elements

$$\hat{y}_{(i,i)} = \sum_{\substack{j=0 \\ j \neq i}}^n \hat{y}_{ij} \quad \hat{y}_{(i,j)} = -\hat{y}_{ij}$$

PQ:  $U, \delta$  slack known  $\rightarrow 2(n-1)$  unknown

$$\hat{u}_i^{(k+1)} = f(p_i, q_i, \hat{u}_j^{(k)})$$

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

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

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

### Newton-Raphson Power Flow Solution

$$\hat{S}_i = \hat{U}_i \sum_{j=1}^n \hat{U}_j^* \hat{Y}_{(i,j)}^* = U_i^2 \hat{Y}_{(i,i)}^* + \hat{U}_i \sum_{\substack{j=1 \\ j \neq i}}^n \hat{U}_j^* \hat{Y}_{(i,j)}^*$$

$$\hat{S}_i = f_i(\hat{U})$$

### Exponential form

$$\hat{S}_i = P_i + jQ_i \quad \hat{U}_i = U_i e^{j\delta_i} \quad \hat{Y}_{(i,j)} = Y_{(i,j)} e^{j\theta_{(i,j)}}$$

$$\hat{S}_i = U_i e^{j\delta_i} \sum_{j=1}^n U_j Y_{(i,j)} e^{-j(\delta_j + \theta_{(i,j)})}$$

Power separated into the real and imaginary part

$$P_i = \sum_{j=1}^n U_i U_j Y_{(i,j)} \cos(\delta_i - \delta_j - \theta_{(i,j)})$$

$$Q_i = \sum_{j=1}^n U_i U_j Y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

→ 2 equations for each PQ node, 1 equation for each PU node

The power changes are expressed (linearization)

$$\Delta \hat{S}_i = \sum_{j=1}^n \left( \frac{\partial \hat{S}_i}{\partial \delta_j} \Delta \delta_j + \frac{\partial \hat{S}_i}{\partial U_j} \Delta U_j \right)$$

$$\Delta P_i = \sum_{j=1}^n \left( \frac{\partial P_i}{\partial \delta_j} \Delta \delta_j + \frac{\partial P_i}{\partial U_j} \Delta U_j \right)$$

$$\Delta Q_i = \sum_{j=1}^n \left( \frac{\partial Q_i}{\partial \delta_j} \Delta \delta_j + \frac{\partial Q_i}{\partial U_j} \Delta U_j \right)$$

## Complete equation description

$$\begin{pmatrix} \Delta P_2^{(k)} \\ \dots \\ \Delta P_n^{(k)} \\ \Delta Q_2^{(k)} \\ \dots \\ \Delta Q_n^{(k)} \end{pmatrix} = \begin{pmatrix} \frac{\partial P_2}{\partial \delta_2}^{(k)} & \dots & \frac{\partial P_2}{\partial \delta_n}^{(k)} & \frac{\partial P_2}{\partial U_2}^{(k)} & \dots & \frac{\partial P_2}{\partial U_n}^{(k)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial P_n}{\partial \delta_2}^{(k)} & \dots & \frac{\partial P_n}{\partial \delta_n}^{(k)} & \frac{\partial P_n}{\partial U_2}^{(k)} & \dots & \frac{\partial P_n}{\partial U_n}^{(k)} \\ \frac{\partial Q_2}{\partial \delta_2}^{(k)} & \dots & \frac{\partial Q_2}{\partial \delta_n}^{(k)} & \frac{\partial Q_2}{\partial U_2}^{(k)} & \dots & \frac{\partial Q_2}{\partial U_n}^{(k)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \frac{\partial Q_n}{\partial \delta_2}^{(k)} & \dots & \frac{\partial Q_n}{\partial \delta_n}^{(k)} & \frac{\partial Q_n}{\partial U_2}^{(k)} & \dots & \frac{\partial Q_n}{\partial U_n}^{(k)} \end{pmatrix} \cdot \begin{pmatrix} \Delta \delta_2^{(k)} \\ \dots \\ \Delta \delta_n^{(k)} \\ \Delta U_2^{(k)} \\ \dots \\ \Delta U_n^{(k)} \end{pmatrix}$$

More compact equations form

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

$$(J) = \begin{pmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial U} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial U} \end{pmatrix} = \begin{pmatrix} J_1 & J_2 \\ J_3 & J_4 \end{pmatrix}$$

Equations number for  $n$  nodes,  $s$  slacks,  $m$  PU nodes,  $p$  PQ nodes ( $n = s + m + p$ ):

$$\Delta P \times (n-s), \Delta Q \times (n-s-m)$$

$$P_i = \sum_{j=1}^n U_i U_j Y_{(i,j)} \cos(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{\substack{j=1 \\ j \neq i}}^n U_i U_j Y_{(i,j)} \sin(-\delta_i + \delta_j + \theta_{(i,j)})$$

$$\frac{\partial P_i}{\partial \delta_j} = U_i U_j Y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)}) \quad j \neq i$$

$$\frac{\partial P_i}{\partial U_i} = 2U_i Y_{(i,i)} \cos(\theta_{(i,i)}) + \sum_{\substack{j=1 \\ j \neq i}}^n U_j Y_{(i,j)} \cos(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial P_i}{\partial U_j} = U_i Y_{(i,j)} \cos(\delta_i - \delta_j - \theta_{(i,j)}) \quad j \neq i$$

$$Q_i = \sum_{j=1}^n U_i U_j Y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial Q_i}{\partial \delta_i} = \sum_{\substack{j=1 \\ j \neq i}}^n U_i U_j Y_{(i,j)} \cos(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial Q_i}{\partial \delta_j} = -U_i U_j Y_{(i,j)} \cos(\delta_i - \delta_j - \theta_{(i,j)}) \quad j \neq i$$

$$\frac{\partial Q_i}{\partial U_i} = -2 U_i Y_{(i,i)} \sin(\theta_{(i,i)}) + \sum_{\substack{j=1 \\ j \neq i}}^n U_j Y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial Q_i}{\partial U_j} = U_i Y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)}) \quad j \neq i$$

## Iterative solution idea

$$\begin{pmatrix} \delta \\ U \end{pmatrix}_k$$

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

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

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

## Decoupled Power Flow Solution

Transmission system: higher ration X/R for power lines

Couplings  $\Delta P \sim \Delta \delta$ ,  $\Delta Q \sim \Delta U$  stronger than  $\Delta P \sim \Delta U$ ,  $\Delta Q \sim \Delta \delta$ .

Therefore the Jakobi matrix can be simplified:

$$\begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix} = \begin{pmatrix} \frac{\partial P}{\partial \delta} & 0 \\ 0 & \frac{\partial Q}{\partial U} \end{pmatrix} \begin{pmatrix} \Delta \delta \\ \Delta U \end{pmatrix} = \begin{pmatrix} J_1 & 0 \\ 0 & J_4 \end{pmatrix} \begin{pmatrix} \Delta \delta \\ \Delta U \end{pmatrix}$$

So called “Decoupled problem” needs usually less time for calculation.

More iterations but quicker matrix calculations. (Number of operation for lin. equations system solution increases quicker than linearly.)

2 systems are solved sequentially in each step.

Convergence precise, only the change of Jakobi matrix, i.e. iteration steps.

Approximate solution only in case of simplified relations for P, Q.

## Ideal power line ( $R = 0, G = 0$ )

$$P_{ij} = \frac{U_i U_j}{X_{ij}} \sin \delta_{ij} \quad Q_{ij} = \frac{U_i^2}{X_{ij}} - \frac{U_i U_j}{X_{ij}} \cos \delta_{ij} - U_i^2 \cdot \frac{B}{2}$$

$$\frac{\partial P_{ij}}{\partial \delta_{ij}} = \frac{U_i U_j}{X_{ij}} \cos \delta_{ij} \quad \frac{\partial Q_{ij}}{\partial \delta_{ij}} = \frac{U_i U_j}{X_{ij}} \sin \delta_{ij}$$

$$\frac{\partial P_{ij}}{\partial U_i} = \frac{U_j}{X_{ij}} \sin \delta_{ij} \quad \frac{\partial Q_{ij}}{\partial U_j} = \frac{2U_i - U_j \cos \delta_{ij}}{X_{ij}}$$

For little loaded lines ( $\delta_{ij} \rightarrow 0$ ) decoupling precise enough.

$$\frac{\partial P_{ij}}{\partial \delta_{ij}} = \frac{U_i U_j}{X_{ij}} \quad \frac{\partial Q_{ij}}{\partial \delta_{ij}} = 0$$

$$\frac{\partial P_{ij}}{\partial U_i} = 0 \quad \frac{\partial Q_{ij}}{\partial U_i} = \frac{2U_i - U_j}{X_{ij}}$$

The next simplifications reduce calculating  $\mathbf{J}_1$  and  $\mathbf{J}_4$  each iteration.

### Fast Decoupled Power Flow Solution

$$\frac{\partial p_i}{\partial \delta_i} = \sum_{\substack{j=1 \\ j \neq i}}^n u_i u_j y_{(i,j)} \sin(-\delta_i + \delta_j + \theta_{(i,j)})$$

$$q_i = \sum_{j=1}^n u_i u_j y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial p_i}{\partial \delta_i} = \sum_{j=1}^n u_i u_j y_{(i,j)} \sin(-\delta_i + \delta_j + \theta_{(i,j)}) - u_i^2 y_{(i,i)} \sin(\theta_{(i,j)})$$

$$\frac{\partial p_i}{\partial \delta_i} = q_i - u_i^2 y_{(i,i)} \sin(\theta_{(i,j)}) = q_i - u_i^2 B_{(i,i)}$$

$$B_{(i,i)} = y_{(i,i)} \sin(\theta_{(i,j)}) = \text{Im}\{y_{(i,i)}\}$$

Usually  $B_{(i,i)} \gg q_i$  and  $u_i^2 \approx u_i$

$$\frac{\partial p_i}{\partial \delta_i} = -u_i B_{(i,i)}$$

---

$$\frac{\partial p_i}{\partial \delta_j} = u_i u_j y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

Usually  $\delta_i \approx \delta_j$ ,  $u_j \approx 1$

$$\frac{\partial p_i}{\partial \delta_j} = u_i y_{(i,j)} \sin(-\theta_{(i,j)}) \quad B_{(i,j)} = y_{(i,j)} \sin(\theta_{(i,j)}) = \text{Im}\{y_{(i,j)}\}$$

$$\frac{\partial p_i}{\partial \delta_j} = -u_i B_{(i,j)}$$

---

$$\frac{\partial q_i}{\partial u_i} = -2u_i y_{(i,i)} \sin(\theta_{(i,i)}) + \sum_{\substack{j=1 \\ j \neq i}}^n u_j y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

$$q_i = \sum_{j=1}^n u_i u_j y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial q_i}{\partial u_i} = -u_i y_{(i,i)} \sin(\theta_{(i,i)}) + \sum_{j=1}^n u_j y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

$$\frac{\partial q_i}{\partial u_i} = -u_i y_{(i,i)} \sin(\theta_{(i,i)}) + q_i$$

**Usually**  $B_{(i,i)} = y_{(i,i)} \sin(\theta_{(i,i)}) = \text{Im}\{y_{(i,i)}\} \gg q_i$

$$\frac{\partial q_i}{\partial u_i} = -u_i B_{(i,i)}$$


---

$$\frac{\partial q_i}{\partial u_j} = u_i y_{(i,j)} \sin(\delta_i - \delta_j - \theta_{(i,j)})$$

Usually  $\delta_i \approx \delta_j$

$$\frac{\partial q_i}{\partial u_j} = u_i y_{(i,j)} \sin(-\theta_{(i,j)})$$

$$\frac{\partial q_i}{\partial u_j} = -u_i B_{(i,j)}$$


---

$$\begin{pmatrix} \frac{\Delta p}{u} \\ \frac{\Delta q}{u} \end{pmatrix} = - \begin{pmatrix} B' & 0 \\ 0 & B'' \end{pmatrix} \begin{pmatrix} \Delta \delta \\ \Delta u \end{pmatrix}$$

$$\begin{pmatrix} \Delta \delta \\ \Delta u \end{pmatrix} = - \begin{pmatrix} B'^{-1} & 0 \\ 0 & B''^{-1} \end{pmatrix} \begin{pmatrix} \frac{\Delta p}{u} \\ \frac{\Delta q}{u} \end{pmatrix}$$

$B'$  and  $B''$  are imaginary parts of the adm. matrix (in p.u.), their inversion is calculated only once. (Note: Division by voltages element by element.)

## DC Power Flow

Relative values. Assumptions:

$$u_i \approx u_j \approx 1$$

$$\sin \delta_{ij} \approx \delta_{ij}$$

$$b_{ij} = -\frac{1}{X_{ij}}$$

$$P_{ij} = \frac{U_i U_j}{X_{ij}} \sin \delta_{ij}$$

$$p_{ij} \cdot S_v = \frac{u_i \cdot U_v \cdot u_j \cdot U_v}{x_{ij} \cdot Z_v} \sin \delta_{ij}$$

$$p_{ij} = \frac{u_i \cdot u_j}{X_{ij}} \sin \delta_{ij} \Rightarrow p_{ij} = \frac{\delta_{ij}}{X_{ij}} = \frac{\delta_i - \delta_j}{X_{ij}}$$

## Matrix

$$p_i = \sum_{\substack{j=1 \\ j \neq i}}^n \frac{\delta_i - \delta_j}{X_{ij}} = \delta_i \sum_{\substack{j=1 \\ j \neq i}}^n \frac{1}{X_{ij}} - \sum_{\substack{j=1 \\ j \neq i}}^n \frac{\delta_j}{X_{ij}}$$

$$p_i = \delta_i b'_{(i,i)} + \sum_{\substack{j=1 \\ j \neq i}}^n \delta_j b'_{(i,j)}$$

$$(p) = (b')(\delta)$$

Only longitudinal reactances  $\rightarrow b'$  singular. 1 node as a reference with  $\delta = 0 \rightarrow$  matrix  $b''$  smaller by one order.

(DC model doesn't calculate losses, thus slack not needed but an angle reference yes.)

$$(\delta) = (b'')^{-1}(p)$$

$$(u) = (g)^{-1}(i)$$