

# **LE/ESSE 2640:**

# **Adjustment calculus**

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# **Lecture 9: Non-linear Parametric Adjustment**

# Non-linear parametric adjustment

- Functional models

- The math function:  $L = F(X)$
- Observation equations:  $l + v = F(\hat{x})$
- Residual equations:  $v = \hat{l} - l = F(\hat{x}) - l$

# Non-linear parametric adjustment

- Stochastic models
  - $\mathbf{L} \sim N(\bar{\mathbf{l}}, \Sigma_{LL})$
  - $\mathbf{L}$  : Observation vector (Variable)
  - $\bar{\mathbf{l}}$ : the expectation of  $\mathbf{l}$
  - $\Sigma_{LL}$ : variance and covariance of  $\mathbf{L}$
  - $Q = \frac{1}{\sigma_0^2} \Sigma_{LL}$ : the cofactor matrix
  - $P = \sigma_0^2 \Sigma_{LL}^{-1}$ : the weight matrix

# Non-linear parametric adjustment

- Least squares solutions
  - Find such  $\hat{\mathbf{x}}$  that the cost function:  $\phi = \mathbf{v}^T P \mathbf{v}$  min

# Non-linear parametric adjustment

- $\phi = \mathbf{v}^T P \mathbf{v} \quad \mathbf{v} = \hat{\mathbf{l}} - \mathbf{l} = F(\hat{\mathbf{x}}) - \mathbf{l}$
- Linearization at the initial values
- $\hat{\mathbf{l}} = F(\hat{\mathbf{x}}^0) + \frac{\partial F}{\partial \hat{\mathbf{x}}} \big|_{\hat{\mathbf{x}}=\hat{\mathbf{x}}^0} \delta \hat{\mathbf{x}}$
- Recall the linear case:  $\hat{\mathbf{l}} = A\hat{\mathbf{x}} + \mathbf{C}$ ,  $\hat{\mathbf{x}} = N^{-1}A^T P(\mathbf{l} - \mathbf{C})$
- $A = \frac{\partial F}{\partial \hat{\mathbf{x}}} \big|_{\hat{\mathbf{x}}=\hat{\mathbf{x}}^0} \quad \mathbf{C} = F(\hat{\mathbf{x}}^0)$
- $\delta \hat{\mathbf{x}} = N^{-1}A^T P[\mathbf{l} - F(\hat{\mathbf{x}}^0)]$

# Non-linear parametric adjustment

- $\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + \delta\hat{\mathbf{x}}$
- $\mathbf{v} = F(\hat{\mathbf{x}}^0) + \frac{\partial F}{\partial \hat{\mathbf{x}}} \big|_{\hat{\mathbf{x}}=\hat{\mathbf{x}}^0} \delta\hat{\mathbf{x}} - \mathbf{l}$
- $\mathbf{v} = J\delta\hat{\mathbf{x}} - [\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\mathbf{v} = A\delta\hat{\mathbf{x}} - [\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\hat{\sigma}_0^2 = \frac{\mathbf{v}^T P \mathbf{v}}{n-m}$

# Variance-covariance matrices

- Quantities:  $\boldsymbol{l}$  (observations),  $\hat{\boldsymbol{x}}$  (parameters),  $\boldsymbol{v}$  (residuals),  $\hat{\boldsymbol{l}}$  (adjusted observations)

	$\boldsymbol{l}$	$\hat{\boldsymbol{x}}$	$\boldsymbol{v}$	$\hat{\boldsymbol{l}}$
$\boldsymbol{l}$	$\Sigma_{ll}$			
$\hat{\boldsymbol{x}}$				
$\boldsymbol{v}$				
$\hat{\boldsymbol{l}}$				



# Variance-covariance matrices

- Derivation of variance-covariance matrices
  - Express the quantities as functions of measurement vector
  - Derivation of variance-covariance matrices based on error propagation

# Variance-covariance matrices

- Express the quantities as functions of measurement vector
- $\mathbf{l} = \mathbf{l}$
- $\delta \hat{\mathbf{x}} = N^{-1} A^T P [\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + \delta \hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + N^{-1} A^T P [\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\mathbf{v} = A \delta \hat{\mathbf{x}} - [\mathbf{l} - F(\hat{\mathbf{x}}^0)] = (A N^{-1} A^T P - \mathbf{I}) [\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\hat{\mathbf{l}} = \mathbf{l} + \mathbf{v} = \mathbf{l} + (A N^{-1} A^T P - \mathbf{I}) [\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\hat{\mathbf{l}} = \mathbf{l} + \mathbf{v} = A N^{-1} A^T P \mathbf{l} - (A N^{-1} A^T P - \mathbf{I}) F(\hat{\mathbf{x}}^0)$

# Variance-covariance matrices

- Derivation of variance-covariance matrices based on error propagation
- $\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + \delta\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + N^{-1}A^T P[\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- Derive  $\Sigma_{\hat{\mathbf{x}}\hat{\mathbf{x}}}$ , given  $\Sigma_{ll}$
- $$\begin{aligned}\Sigma_{\hat{\mathbf{x}}\hat{\mathbf{x}}} &= (N^{-1}A^T P)\Sigma_{ll}(N^{-1}A^T P)^T \\ &= N^{-1}A^T P\sigma_0^2 P^{-1}P A N^{-1} \\ &= \sigma_0^2 N^{-1}A^T P A N^{-1} = \sigma_0^2 N^{-1}\end{aligned}$$

# Variance-covariance matrices

- $\mathbf{v} = A\delta\hat{\mathbf{x}} - [\mathbf{l} - F(\hat{\mathbf{x}}^0)] = (AN^{-1}A^T P - \mathbf{I})[\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\begin{aligned}\Sigma_{\mathbf{v}\mathbf{v}} &= (AN^{-1}A^T P - \mathbf{I})\Sigma_{ll}(AN^{-1}A^T P - \mathbf{I})^T \\ &= (AN^{-1}A^T P - \mathbf{I})\sigma_0^2 P^{-1}(AN^{-1}A^T P - \mathbf{I})^T \\ &= \sigma_0^2 (AN^{-1}A^T - P^{-1})(PAN^{-1}A^T - \mathbf{I}) \\ &= \sigma_0^2 (AN^{-1}A^T P AN^{-1}A^T - P^{-1}PAN^{-1}A^T - AN^{-1}A^T + P^{-1}) \\ &= \sigma_0^2 (AN^{-1}A^T - AN^{-1}A^T - AN^{-1}A^T + P^{-1})\end{aligned}$

$$\Sigma_{\mathbf{v}\mathbf{v}} = \sigma_0^2 P^{-1} - \sigma_0^2 AN^{-1}A^T$$

$$\Sigma_{\mathbf{v}\mathbf{v}} = \Sigma_{ll} - \sigma_0^2 AN^{-1}A^T$$

# Variance-covariance matrices

- $\hat{l} = AN^{-1}A^TPl - (AN^{-1}A^TP - I)F(\hat{x}^0)$
- $$\begin{aligned}\Sigma_{\hat{l}\hat{l}} &= (AN^{-1}A^TP)\Sigma_{ll}(AN^{-1}A^TP)^T \\ &= (AN^{-1}A^TP)\sigma_0^2P^{-1}(AN^{-1}A^TP)^T \\ &= \sigma_0^2AN^{-1}A^TPAN^{-1}A^T \\ &= \sigma_0^2AN^{-1}A^T\end{aligned}$$

# Variance-covariance matrices

- $\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + \delta\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + N^{-1}A^T P[l - F(\hat{\mathbf{x}}^0)]$
- Derive  $\Sigma_{l\hat{\mathbf{x}}}$ ,  $\Sigma_{\hat{\mathbf{x}}l}$  given  $\Sigma_{ll}$
- $\Sigma_{\hat{\mathbf{x}}l} = (N^{-1}A^T P)\Sigma_{ll} = N^{-1}A^T P\sigma_0^2 P^{-1}$
- $\Sigma_{\hat{\mathbf{x}}l} = \sigma_0^2 N^{-1}A^T$
- $\Sigma_{l\hat{\mathbf{x}}} = \Sigma_{\hat{\mathbf{x}}l}^T = \sigma_0^2 AN^{-1}$

# Variance-covariance matrices

- $\mathbf{v} = (AN^{-1}A^T P - \mathbf{I})[\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- Derive  $\Sigma_{l\mathbf{v}}$ ,  $\Sigma_{\mathbf{v}l}$  given  $\Sigma_{ll}$
- $$\begin{aligned}\Sigma_{\mathbf{v}l} &= (AN^{-1}A^T P - \mathbf{I})\Sigma_{ll} \\ &= (AN^{-1}A^T P - \mathbf{I})\sigma_0^2 P^{-1} \\ &= \sigma_0^2 AN^{-1}A^T - \sigma_0^2 P^{-1} \\ &= \sigma_0^2 AN^{-1}A^T - \Sigma_{ll}\end{aligned}$$

$$\Sigma_{l\mathbf{v}} = \Sigma_{\mathbf{v}l}^T = \sigma_0^2 AN^{-1}A^T - \Sigma_{ll}$$

# Variance-covariance matrices

- $\hat{l} = AN^{-1}A^TPl - (AN^{-1}A^TP - I)F(\hat{x}^0)$
- Derive  $\Sigma_{l\hat{l}}, \Sigma_{\hat{l}l}$  given  $\Sigma_{ll}$
- $$\begin{aligned}\Sigma_{\hat{l}l} &= (AN^{-1}A^TP)\Sigma_{ll} \\ &= (AN^{-1}A^TP)\sigma_0^2P^{-1} \\ &= \sigma_0^2AN^{-1}A^T\end{aligned}$$

$$\Sigma_{l\hat{l}} = \Sigma_{\hat{l}l}^T = \sigma_0^2AN^{-1}A^T$$



# Variance-covariance matrices

- $\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + \delta\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + N^{-1}A^T P[l - F(\hat{\mathbf{x}}^0)]$
- $\mathbf{v} = (AN^{-1}A^T P - I)[l - F(\hat{\mathbf{x}}^0)]$
- Derive  $\Sigma_{\mathbf{v}\hat{\mathbf{x}}}$ ,  $\Sigma_{\hat{\mathbf{x}}\mathbf{v}}$  given  $\Sigma_{ll}$
- $$\begin{aligned}\Sigma_{\hat{\mathbf{x}}\mathbf{v}} &= (N^{-1}A^T P)\Sigma_{ll}\left((AN^{-1}A^T P - I)\right)^T \\ &= (N^{-1}A^T P)\sigma_0^2 P^{-1}(PAN^{-1}A^T - I) \\ &= \sigma_0^2 N^{-1}A^T P A N^{-1}A^T - \sigma_0^2 N^{-1}A^T \\ &= \mathbf{0}\end{aligned}$$
- $\Sigma_{\mathbf{v}\hat{\mathbf{x}}} = \mathbf{0}$

# Variance-covariance matrices

- $\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + \delta\hat{\mathbf{x}} = \hat{\mathbf{x}}^0 + N^{-1}A^T P[\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\hat{\mathbf{l}} = AN^{-1}A^T P\mathbf{l} - (AN^{-1}A^T P - \mathbf{I})F(\hat{\mathbf{x}}^0)$
- Derive  $\Sigma_{\hat{\mathbf{l}}\hat{\mathbf{x}}}$ ,  $\Sigma_{\hat{\mathbf{x}}\hat{\mathbf{l}}}$  given  $\Sigma_{\mathbf{ll}}$
- $$\begin{aligned}\Sigma_{\hat{\mathbf{x}}\hat{\mathbf{l}}} &= (N^{-1}A^T P)\Sigma_{\mathbf{ll}}(AN^{-1}A^T P)^T \\ &= (N^{-1}A^T P)\sigma_0^2 P^{-1}P AN^{-1}A^T \\ &= \sigma_0^2 N^{-1}A^T P AN^{-1}A^T \\ &= \sigma_0^2 N^{-1}A^T\end{aligned}$$
- $\Sigma_{\hat{\mathbf{l}}\hat{\mathbf{x}}} = \sigma_0^2 AN^{-1}$

# Variance-covariance matrices

- $\mathbf{v} = (AN^{-1}A^T P - \mathbf{I})[\mathbf{l} - F(\hat{\mathbf{x}}^0)]$
- $\hat{\mathbf{l}} = AN^{-1}A^T P \mathbf{l} - (AN^{-1}A^T P - \mathbf{I})F(\hat{\mathbf{x}}^0)$
- Derive  $\Sigma_{\mathbf{v}\hat{\mathbf{l}}}$ ,  $\Sigma_{\hat{\mathbf{l}}\mathbf{v}}$  given  $\Sigma_{\mathbf{ll}}$
- $$\begin{aligned}\Sigma_{\hat{\mathbf{l}}\mathbf{v}} &= (AN^{-1}A^T P)\Sigma_{\mathbf{ll}}((AN^{-1}A^T P - \mathbf{I}))^T \\ &= (AN^{-1}A^T P)\sigma_0^2 P^{-1}(PAN^{-1}A^T - \mathbf{I}) \\ &= \sigma_0^2 AN^{-1}A^T PAN^{-1}A^T - \sigma_0^2 AN^{-1}A^T \\ &= \mathbf{0}\end{aligned}$$
- $\Sigma_{\mathbf{v}\hat{\mathbf{l}}} = \mathbf{0}$

# Variance-covariance matrices

- Quantities:  $\mathbf{l}$  (observations),  $\hat{\mathbf{x}}$  (parameters),  $\mathbf{v}$  (residuals),  $\hat{\mathbf{l}}$  (adjusted observations)

	$\mathbf{l}$	$\hat{\mathbf{x}}$	$\mathbf{v}$	$\hat{\mathbf{l}}$
$\mathbf{l}$	$\Sigma_{ll}$	$\sigma_0^2 AN^{-1}$	$\sigma_0^2 AN^{-1}A^T - \Sigma_{ll}$	$\sigma_0^2 AN^{-1}A^T$
$\hat{\mathbf{x}}$	$\sigma_0^2 N^{-1}A^T$	$\sigma_0^2 N^{-1}$	$\mathbf{0}$	$\sigma_0^2 N^{-1}A^T$
$\mathbf{v}$	$\sigma_0^2 AN^{-1}A^T - \Sigma_{ll}$	$\mathbf{0}$	$\Sigma_{ll} - \sigma_0^2 AN^{-1}A^T$	$\mathbf{0}$
$\hat{\mathbf{l}}$	$\sigma_0^2 AN^{-1}A^T$	$\sigma_0^2 AN^{-1}$	$\mathbf{0}$	$\sigma_0^2 AN^{-1}A^T$