

Reference station weighting and frame optimality in minimally constrained networks

C. Kotsakis

Department of Geodesy and Surveying
Aristotle University of Thessaloniki
Thessaloniki, Greece



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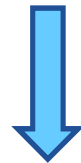


Introduction

- ❑ **Reference frame densification through network adjustment:** a key geodetic task
- ❑ Different solution schemes exist for solving this problem
- ❑ This paper is concerned with the use of minimal constraints (MCs) over a number of reference stations

Study's rationale

Usual form of MCs $\mathbf{E}(\mathbf{x} - \mathbf{x}^{\text{ext}}) = \mathbf{0}$



Generalized form of MCs $\mathbf{E}\mathbf{P}_x(\mathbf{x} - \mathbf{x}^{\text{ext}}) = \mathbf{0}$

Un-resolved issue: choice of the weight matrix

Example

Usual form of
NNT/NNR conditions

$$\sum_i (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

$$\sum_i \mathbf{x}_i^0 \times (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

Weighted form of
NNT/NNR conditions

$$\sum_i p_i (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

$$\sum_i \mathbf{x}_i^0 \times p_i (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

This is a simplified scheme assuming a diagonal weight matrix

(*) $p_i=0$ or $p_i=1$ is often considered as a 'weighting' choice

Example

Usual form of
NNT/NNR conditions

$$\sum_i (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

$$\sum_i \mathbf{x}_i^0 \times (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

Weighted form of
NNT/NNR conditions

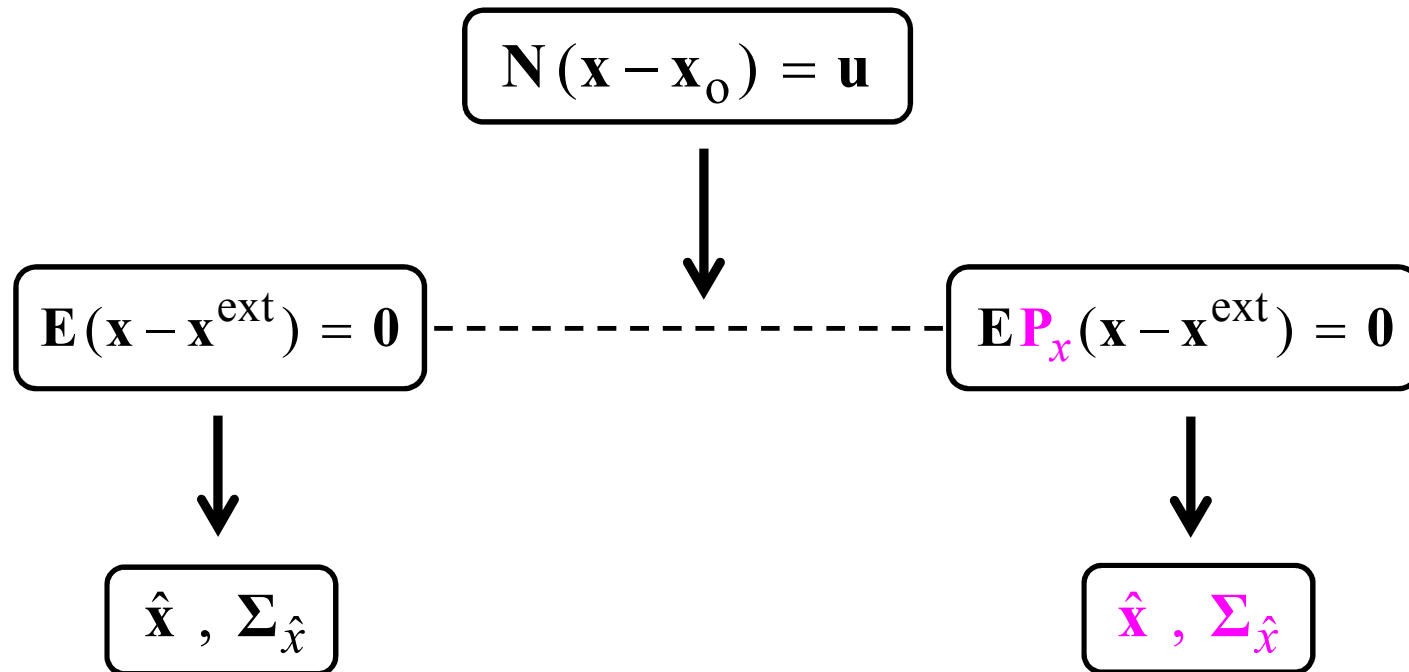
$$\sum_i \mathbf{P}_i (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) = \mathbf{0}$$

$$\sum_i \mathbf{x}_i^0 \times \left(\mathbf{P}_i (\mathbf{x}_i - \mathbf{x}_i^{\text{ext}}) \right) = \mathbf{0}$$

This is a simplified scheme assuming a block-diagonal weight matrix

(*) $\mathbf{P}_i = (\text{diag}\boldsymbol{\Sigma}_{i,\text{ext}})^{-1}$ or $\mathbf{P}_i = (\boldsymbol{\Sigma}_{i,\text{ext}})^{-1}$ has been suggested
but never rigorously justified as a weighting choice

“Classic” vs. “generalized” MCs



Can we get an **improved MC solution** through a justified choice of the weight matrix?

Crucial restrictions in MC-based frame optimality

(under current un-weighted scheme)

- (1) The realized frame through a network adjustment is optimized only at the stations **participating** in the MCs
(what about the other network stations?)
- (2) The optimality of the realized frame considers only the **data noise effect** in the estimated coordinates
(what about the “datum noise” effect?)

What do “classic” MCs optimize?

Rank-deficient NEQs

$$\mathbf{N}(\mathbf{x} - \mathbf{x}_0) = \mathbf{u}$$

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \quad \text{Reference stations}$$

MCs applied to the reference stations:

$$\mathbf{E}_1(\mathbf{x}_1 - \mathbf{x}_1^{\text{ext}}) = \mathbf{0}$$

Optimized covariance matrix of MC solution

$$\Sigma_{\hat{x}} = \mathbf{N}^{-} = \begin{bmatrix} \Sigma_{\hat{x}_1} & \Sigma_{\hat{x}_1, \hat{x}_2} \\ \Sigma_{\hat{x}_2, \hat{x}_1} & \Sigma_{\hat{x}_2} \end{bmatrix}$$

Minimum trace

Data noise effect

Consider the generalizations: (1/2)

Rank-deficient NEQs

$$\mathbf{N}(\mathbf{x} - \mathbf{x}_0) = \mathbf{u}$$

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \quad \text{Reference stations}$$

MCs applied to the reference stations:

$$\mathbf{L}_1(\mathbf{x}_1 - \mathbf{x}_1^{\text{ext}}) = \mathbf{0}$$

Optimized covariance matrix of MC solution

$$\Sigma_{\hat{x}} = \mathbf{N}^{-} = \begin{bmatrix} \Sigma_{\hat{x}_1} & \Sigma_{\hat{x}_1, \hat{x}_2} \\ \Sigma_{\hat{x}_2, \hat{x}_1} & \Sigma_{\hat{x}_2} \end{bmatrix}$$

Data noise effect

Minimum trace

or

Minimum trace

Consider the generalizations: (2/2)

Rank-deficient NEQs

$$\mathbf{N}(\mathbf{x} - \mathbf{x}_0) = \mathbf{u}$$

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \quad \text{Reference stations}$$

MCs applied to the reference stations:

$$\mathbf{L}_1(\mathbf{x}_1 - \mathbf{x}_1^{\text{ext}}) = \mathbf{0}$$

Optimized covariance matrix of MC solution

$$\Sigma_{\hat{x}} = \mathbf{N}^{-} + \tilde{\Sigma}_{\hat{x}} = \begin{bmatrix} \Sigma_{\hat{x}_1} & \Sigma_{\hat{x}_1, \hat{x}_2} \\ \Sigma_{\hat{x}_2, \hat{x}_1} & \Sigma_{\hat{x}_2} \end{bmatrix}$$

Data noise effect
Datum noise effect

Minimum trace

or

Minimum trace

or

Minimum trace

Formulation of the problem

Rank-deficient NEQs

$$\mathbf{N}(\mathbf{x} - \mathbf{x}_0) = \mathbf{u}$$

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix}$$

Reference stations

Prior information for reference stations:

$$\mathbf{x}_1^{\text{ext}}, \Sigma_{x_1}^{\text{ext}}$$

Datum definition by an arbitrary set of MCs

$$\mathbf{H}_1(\mathbf{x}_1 - \mathbf{x}_1^{\text{ext}}) = \mathbf{0}$$

Optimization problem to be solved

$\Sigma_{\hat{x}}$ \rightarrow CV matrix of MC solution

$$\min_{\mathbf{H}_1} \text{trace}(\mathbf{S} \Sigma_{\hat{x}} \mathbf{S}^T)$$

CV matrix of MC solution

$$\begin{aligned}\mathbf{N}(\mathbf{x} - \mathbf{x}_0) &= \mathbf{u} \\ \mathbf{H}(\mathbf{x} - \mathbf{x}_0) &= \mathbf{c}\end{aligned}$$



Irrelevant weight matrix \mathbf{W}

$$\hat{\mathbf{x}} = \mathbf{x}_0 + (\mathbf{N} + \mathbf{H}^T \mathbf{H})^{-1} (\mathbf{u} + \mathbf{H}^T \mathbf{c})$$

General form

$$\Sigma_{\hat{\mathbf{x}}} = \Sigma_{\hat{\mathbf{x}}}^{\text{obs}} + \Sigma_{\hat{\mathbf{x}}}^{\text{mc}}$$

Data noise effect
(due to errors within \mathbf{u})

Datum noise effect
(due to errors within \mathbf{c})

CV matrix of MC solution

$$\mathbf{N}(\mathbf{x} - \mathbf{x}_0) = \mathbf{u}$$

$$\mathbf{H}(\mathbf{x} - \mathbf{x}_0) = \mathbf{c}^{(*)}$$



Irrelevant weight matrix \mathbf{W}

$$\hat{\mathbf{x}} = \mathbf{x}_0 + (\mathbf{N} + \mathbf{H}^T \mathbf{H})^{-1} (\mathbf{u} + \mathbf{H}^T \mathbf{c})$$

General form

$$\Sigma_{\hat{\mathbf{x}}} = \Sigma_{\hat{\mathbf{x}}}^{\text{obs}} + \Sigma_{\hat{\mathbf{x}}}^{\text{mc}}$$

Data noise effect
(due to errors within \mathbf{u})

Datum noise effect
(due to errors within \mathbf{c})

(*) in this study we have that:

$$\mathbf{H} = [\mathbf{H}_1 \quad \mathbf{0}]$$

$$\mathbf{c} = \mathbf{H}_1 (\mathbf{x}_1^{\text{ext}} - \mathbf{x}_1^0)$$

Basic equations

$$\begin{aligned} \mathbf{N}(\mathbf{x} - \mathbf{x}_0) &= \mathbf{u} \\ \mathbf{H}(\mathbf{x} - \mathbf{x}_0) &= \mathbf{c} \end{aligned}$$



$$\hat{\mathbf{x}} = \mathbf{x}_0 + (\mathbf{N} + \mathbf{H}^T \mathbf{H})^{-1} (\mathbf{u} + \mathbf{H}^T \mathbf{c})$$

General form

$$\Sigma_{\hat{\mathbf{x}}} = \Sigma_{\hat{\mathbf{x}}}^{\text{obs}} + \Sigma_{\hat{\mathbf{x}}}^{\text{mc}}$$

error CV propagation &
well-known algebraic properties
from MC theory

$$\Sigma_{\hat{\mathbf{x}}}^{\text{obs}} = (\mathbf{N} + \mathbf{H}^T \mathbf{H})^{-1} - \mathbf{E}^T (\mathbf{H} \mathbf{E}^T)^{-1} (\mathbf{E} \mathbf{H}^T)^{-1} \mathbf{E}$$

$$\Sigma_{\hat{\mathbf{x}}}^{\text{mc}} = \mathbf{E}^T \underbrace{(\mathbf{H} \mathbf{E}^T)^{-1} \Sigma_c (\mathbf{E} \mathbf{H}^T)^{-1}}_{\Sigma_\theta} \mathbf{E}$$

$$\Sigma_\theta$$

$$(*) \Sigma_c = \mathbf{H}_1 \Sigma_{x_1}^{\text{ext}} \mathbf{H}_1^T$$

Basic equations

$$\begin{aligned} \mathbf{N}(\mathbf{x} - \mathbf{x}_0) &= \mathbf{u} \\ \mathbf{H}(\mathbf{x} - \mathbf{x}_0) &= \mathbf{c} \end{aligned}$$



$$\hat{\mathbf{x}} = \mathbf{x}_0 + (\mathbf{N} + \mathbf{H}^T \mathbf{H})^{-1} (\mathbf{u} + \mathbf{H}^T \mathbf{c})$$

General form

$$\Sigma_{\hat{\mathbf{x}}} = \Sigma_{\hat{\mathbf{x}}}^{\text{obs}} + \Sigma_{\hat{\mathbf{x}}}^{\text{mc}}$$

error CV propagation &
well-known algebraic properties
from MC theory

$$\Sigma_{\hat{\mathbf{x}}}^{\text{obs}} = (\mathbf{N} + \mathbf{H}^T \Sigma_c^{-1} \mathbf{H})^{-1} - \mathbf{E}^T (\mathbf{H} \mathbf{E}^T)^{-1} \Sigma_c (\mathbf{E} \mathbf{H}^T)^{-1} \mathbf{E}$$

$$\Sigma_{\hat{\mathbf{x}}}^{\text{mc}} = \mathbf{E}^T \underbrace{(\mathbf{H} \mathbf{E}^T)^{-1} \Sigma_c (\mathbf{E} \mathbf{H}^T)^{-1}}_{\Sigma_\theta} \mathbf{E}$$

$$\Sigma_\theta$$

$$(*) \Sigma_c = \mathbf{H}_1 \Sigma_{x_1}^{\text{ext}} \mathbf{H}_1^T$$

Problem solution

Frame/network optimality principle

$$\min_{\mathbf{H}_1} \text{trace} \left(\boldsymbol{\Sigma}_{\hat{\mathbf{x}}}^{\text{obs}} + \lambda \boldsymbol{\Sigma}_{\hat{\mathbf{x}}}^{\text{mc}} \right)$$

Optimal MC matrix (applied to the reference stations)

$$\mathbf{H}_1 = \mathbf{E}_1 \left(\mathbf{Q}_{11} + \lambda \boldsymbol{\Sigma}_{x_1}^{\text{ext}} \right)^{-1}$$



$$(\mathbf{N} + \mathbf{E}^T \mathbf{E})^{-1} = \begin{array}{c} \begin{array}{cc} \mathbf{x}_1 & \mathbf{x}_2 \\ \hline \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \hline \mathbf{Q}_{12}^T & \mathbf{Q}_{22} \end{array} \\ \mathbf{x}_1 \\ \mathbf{x}_2 \end{array}$$

see Kotsakis (2013, JGeod) for proofs

Problem solution

Frame/network optimality principle

$$\min_{\mathbf{H}_1} \text{trace} \left(\mathbf{S} \boldsymbol{\Sigma}_{\hat{x}}^{\text{obs}} \mathbf{S}^T + \lambda \mathbf{S} \boldsymbol{\Sigma}_{\hat{x}}^{\text{mc}} \mathbf{S}^T \right)$$

\mathbf{S} is a 'station selection matrix'

Optimal MC matrix (applied to the reference stations)

$$\mathbf{H}_1 = \mathbf{E}_1 \left(\mathbf{Q}_{11} + \lambda \boldsymbol{\Sigma}_{x_1}^{\text{ext}} \right)^{-1}$$



$$(\mathbf{N} + \mathbf{S}^T \mathbf{S} \mathbf{E}^T \mathbf{E} \mathbf{S}^T \mathbf{S})^{-1} = \begin{bmatrix} \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \mathbf{Q}_{12}^T & \mathbf{Q}_{22} \end{bmatrix} \begin{matrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{matrix}$$

see Kotsakis (2013, JGeod) for proofs

Minimization of the datum noise effect

Frame/network optimality principle	Objective	Optimal MC matrix
$\min_{\mathbf{H}_1} \text{trace} \left(\boldsymbol{\Sigma}_{\hat{x}}^{\text{mc}} \right)$	over all network stations	$\mathbf{H}_1 = \mathbf{E}_1 \left(\boldsymbol{\Sigma}_{x_1}^{\text{ext}} \right)^{-1}$
$\min_{\mathbf{H}_1} \text{trace} \left(\mathbf{S} \boldsymbol{\Sigma}_{\hat{x}}^{\text{mc}} \mathbf{S}^T \right)$	over a subset of network stations	$\mathbf{H}_1 = \mathbf{E}_1 \left(\boldsymbol{\Sigma}_{x_1}^{\text{ext}} \right)^{-1}$ <p style="color: red; text-align: center;">Independent of \mathbf{S} !</p>

Minimization of the datum noise effect

$$\Sigma_{\hat{x}}^{mc} = \begin{bmatrix} \Sigma_{\hat{x}_1}^{mc} & \Sigma_{\hat{x}_1, \hat{x}_2}^{mc} \\ \Sigma_{\hat{x}_2, \hat{x}_1}^{mc} & \Sigma_{\hat{x}_2}^{mc} \end{bmatrix}$$

Minimum trace
 or
Minimum trace
 or
Minimum trace

Equivalent to the **optimal ‘frame alignment’ principle**

$$\Sigma_{\hat{x}}^{mc} = \mathbf{E}^T \Sigma_{\theta} \mathbf{E} \quad \longrightarrow \quad \boxed{\min_{\mathbf{H}_1} \text{trace}(\Sigma_{\theta})}$$

where Σ_{θ} expresses the accuracy of the (non-estimable) frame parameters from the adopted MCs and reference stations

$$\Sigma_{\theta} = (\mathbf{H}_1 \mathbf{E}_1^T)^{-1} \mathbf{H}_1 \Sigma_{x_1}^{\text{ext}} \mathbf{H}_1^T (\mathbf{E}_1 \mathbf{H}_1^T)^{-1}$$

Minimization of the **data noise** effect

Frame/network optimality principle	Objective	Optimal MC matrix
$\min_{\mathbf{H}_1} \text{trace} \left(\boldsymbol{\Sigma}_{\hat{x}}^{\text{obs}} \right)$	over all network stations	$(\mathbf{N} + \mathbf{E}^T \mathbf{E})^{-1} = \left[\begin{array}{c c} \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \hline \mathbf{Q}_{12}^T & \mathbf{Q}_{22} \end{array} \right]$ $\mathbf{H}_1 = \mathbf{E}_1 (\mathbf{Q}_{11})^{-1}$
$\min_{\mathbf{H}_1} \text{trace} \left(\mathbf{S} \boldsymbol{\Sigma}_{\hat{x}}^{\text{obs}} \mathbf{S}^T \right)$	over a subset of network stations	$(\mathbf{N} + \mathbf{S}^T \mathbf{S} \mathbf{E}^T \mathbf{E} \mathbf{S}^T \mathbf{S})^{-1} = \left[\begin{array}{c c} \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \hline \mathbf{Q}_{12}^T & \mathbf{Q}_{22} \end{array} \right]$

Minimization of the data noise effect

Frame/network optimality principle	Optimal MC matrix	Objective
$\min_{\mathbf{H}_1} \text{trace} \left(\mathbf{S} \boldsymbol{\Sigma}_{\hat{\mathbf{x}}}^{\text{obs}} \mathbf{S}^T \right)$ <div style="border: 1px solid black; border-radius: 15px; padding: 10px; width: fit-content; margin: 10px auto;"> $\mathbf{H}_1 = \mathbf{E}_1 (\mathbf{Q}_{11})^{-1}$ </div>	<div style="border: 1px solid black; border-radius: 15px; padding: 10px; width: fit-content; margin: 10px auto;"> $\mathbf{H}_1 = \mathbf{E}_1$ </div>	<p>over the reference stations</p> $\mathbf{S} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \end{bmatrix}$
$(\mathbf{N} + \mathbf{S}^T \mathbf{S} \mathbf{E}^T \mathbf{E} \mathbf{S}^T \mathbf{S})^{-1} = \begin{matrix} & \mathbf{x}_1 & \mathbf{x}_2 \\ \mathbf{x}_1 & \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \mathbf{x}_2 & \mathbf{Q}_{12}^T & \mathbf{Q}_{22} \end{matrix}$	<div style="border: 1px solid black; border-radius: 15px; padding: 10px; width: fit-content; margin: 10px auto;"> $\mathbf{H}_1 = \mathbf{E}_1 \mathbf{N}_{12} \mathbf{N}_{22}^{-2} \mathbf{N}_{12}^T$ </div>	<p>over the 'new' stations</p> $\mathbf{S} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \end{bmatrix}$

Conclusions

- ❑ Different MC weighting schemes lead to different types of frame optimality
- ❑ Reference station weighting can be used to optimize the accuracy of a MC solution in terms of
 - the data and/or datum noise effects
 - the network stations over which these effects are considered
- ❑ Numerical testing is still required to assess the differences from MC weighting schemes in geodetic network adjustment problems

Thanks for your attention !