



Die Ressourcenuniversität. Seit 1765.

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# All-at-once Inversion Approach for MT on a Finite Difference Grid

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# Outline

1 Governing equations

2 1D case

3 Newton method

4 Lagrange multipliers

5 KKT system

6 Results

# Governing equations

## Curl-curl equation

- electrical field for 3D earth

$$\nabla \times \nabla \times \mathbf{E} + i\omega\mu_0\sigma\mathbf{E} = 0$$

## Helmholtz equation

- electrical field for 1D layered earth

$$\partial_{zz}^2 E_x(z) - i\omega\mu_0\sigma(z)E_x(z) = 0$$

## Formulation

- forward modelling:  $\mathbf{A}(\mathbf{m})\mathbf{u} = \mathbf{b}$ 
  - $\mathbf{A}$  – forward operator or system matrix
  - $\mathbf{m}$  – model parameter,  $\mathbf{m} = \log \sigma$
  - $\mathbf{b}$  – source terms and boundary values
  - $\mathbf{u}$  – real and imaginary parts of the electrical field and its first spatial derivative
- solution  $\mathbf{u}$  for the whole discretized region and different frequencies
- measurements only at the earth's surface for each frequency  $\rightarrow \mathbf{d}$
- compare modelled and measured data:  $\mathbf{r} = \mathbf{Q}\mathbf{u} - \mathbf{d}$   
projection matrix  $\mathbf{Q}$  is necessary

## Newton method

- nonlinear systems of equations
- linearisation of the optimisation problem
- solving a linear system of equations in each iteration
- first and second derivatives of objective function are used

# Lagrange multipliers

## Lagrangian

$$\mathcal{L}(\mathbf{u}, \mathbf{m}, \boldsymbol{\lambda}) = \frac{1}{2} \|\mathbf{Q}\mathbf{u} - \mathbf{d}\|^2 + \frac{\beta}{2} \|\mathbf{W}(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2 + \boldsymbol{\lambda}^T [\mathbf{A}(\mathbf{m})\mathbf{u} - \mathbf{b}] \rightarrow \min$$

gradient of the Lagrangian:  $\nabla \mathcal{L}$

$$\nabla \mathcal{L} = \begin{pmatrix} \mathcal{L}_{\mathbf{u}} \\ \mathcal{L}_{\mathbf{m}} \\ \mathcal{L}_{\boldsymbol{\lambda}} \end{pmatrix}$$

$$\begin{aligned} \mathcal{L}_{\mathbf{u}} &= \mathbf{Q}^T(\mathbf{Q}\mathbf{u} - \mathbf{d}) + \mathbf{A}^T \boldsymbol{\lambda} \\ \mathcal{L}_{\mathbf{m}} &= \beta \mathbf{W}^T \mathbf{W}(\mathbf{m} - \mathbf{m}_{\text{ref}}) + \mathbf{G}^T \boldsymbol{\lambda} \\ \mathcal{L}_{\boldsymbol{\lambda}} &= \mathbf{A}\mathbf{u} - \mathbf{b} \end{aligned}$$

with  $\mathbf{G} = \partial_m \mathbf{A} \cdot \mathbf{u}$

# Second derivatives of $\mathcal{L}$ , Hessian $\mathcal{H}_{kkt}$

## KKT system

$$\mathcal{H}_{kkt} \cdot \begin{pmatrix} \delta u \\ \delta m \\ \delta \lambda \end{pmatrix} = - \begin{pmatrix} \mathcal{L}_u \\ \mathcal{L}_m \\ \mathcal{L}_\lambda \end{pmatrix}$$

$$\begin{pmatrix} \mathcal{L}_{u,u} & \mathcal{L}_{u,m} & \mathcal{L}_{u,\lambda} \\ \mathcal{L}_{m,u} & \mathcal{L}_{m,m} & \mathcal{L}_{m,\lambda} \\ \mathcal{L}_{\lambda,u} & \mathcal{L}_{\lambda,m} & \mathcal{L}_{\lambda,\lambda} \end{pmatrix} \cdot \begin{pmatrix} \delta u \\ \delta m \\ \delta \lambda \end{pmatrix} = - \begin{pmatrix} \mathcal{L}_u \\ \mathcal{L}_m \\ \mathcal{L}_\lambda \end{pmatrix}$$

$$\begin{pmatrix} \mathbf{Q}^T \mathbf{Q} & \mathbf{K} & \mathbf{A}^T \\ \mathbf{K}^T & \beta \mathbf{W}^T \mathbf{W} + \mathbf{R} & \mathbf{G}^T \\ \mathbf{A} & \mathbf{G} & \mathbf{0} \end{pmatrix} \cdot \begin{pmatrix} \delta u \\ \delta m \\ \delta \lambda \end{pmatrix} = - \begin{pmatrix} \mathcal{L}_u \\ \mathcal{L}_m \\ \mathcal{L}_\lambda \end{pmatrix}$$

$$\mathbf{G} = \partial_m \mathbf{A} \cdot \mathbf{u}, \quad \mathbf{K} = \partial_m \mathbf{A}^T \cdot \boldsymbol{\lambda}, \quad \mathbf{R} = \partial_m \mathbf{G}^T \cdot \boldsymbol{\lambda}$$

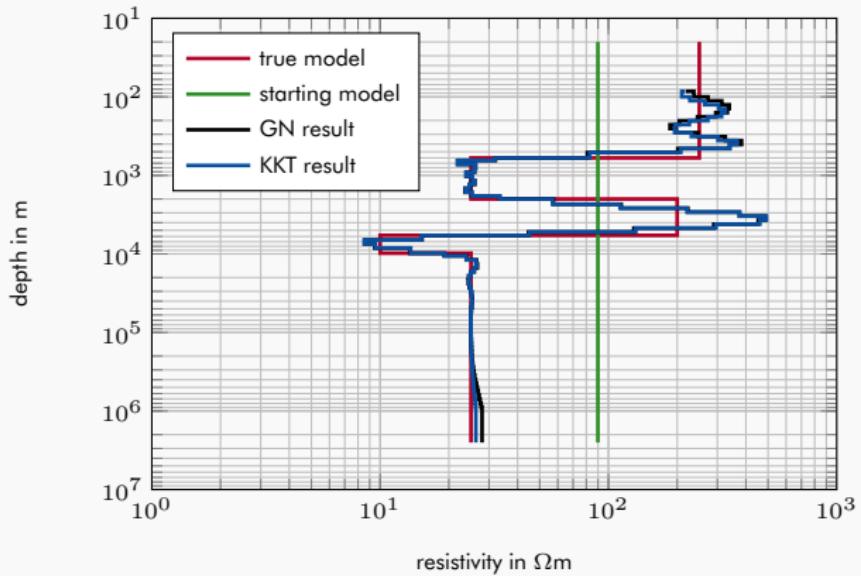
update after each iteration

$$\begin{pmatrix} \mathbf{u}_{n+1} \\ \mathbf{m}_{n+1} \\ \boldsymbol{\lambda}_{n+1} \end{pmatrix} = \begin{pmatrix} \mathbf{u}_n \\ \mathbf{m}_n \\ \boldsymbol{\lambda}_n \end{pmatrix} + \begin{pmatrix} \delta\mathbf{u} \\ \delta\mathbf{m} \\ \delta\boldsymbol{\lambda} \end{pmatrix}$$

- no forward problem has to be solved to get data for the new model

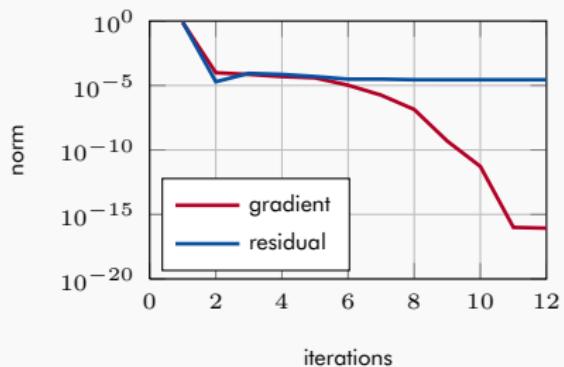
# Results

## Synthetic data

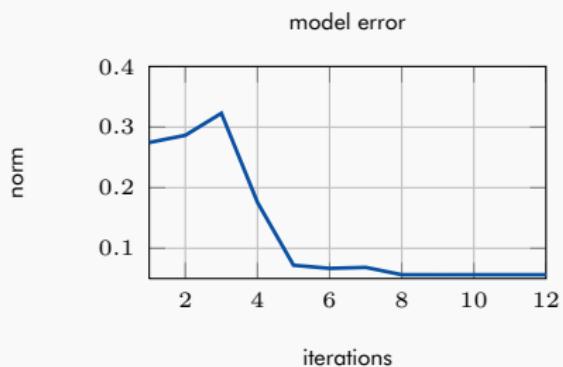


21 frequencies between  $10^{-4}$  and  $10^3$  Hz  
regularisation  $\beta = 4.5 \cdot 10^{-14}$

## Synthetic data – inversion process

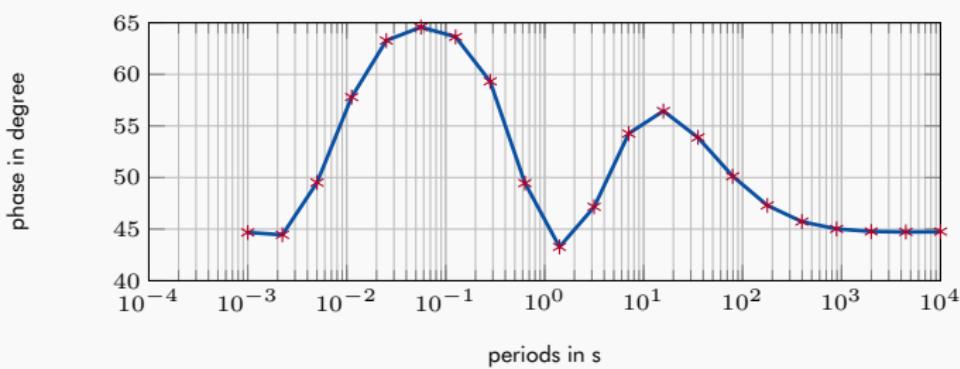
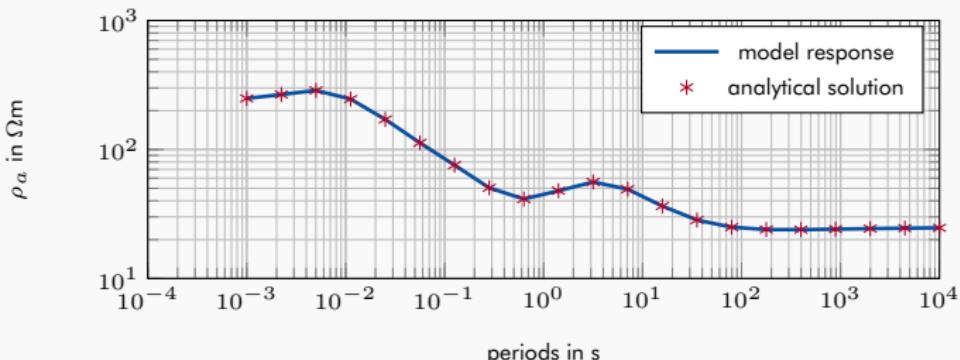


gradient  $\|\nabla \mathcal{L}\|$  and residual norm



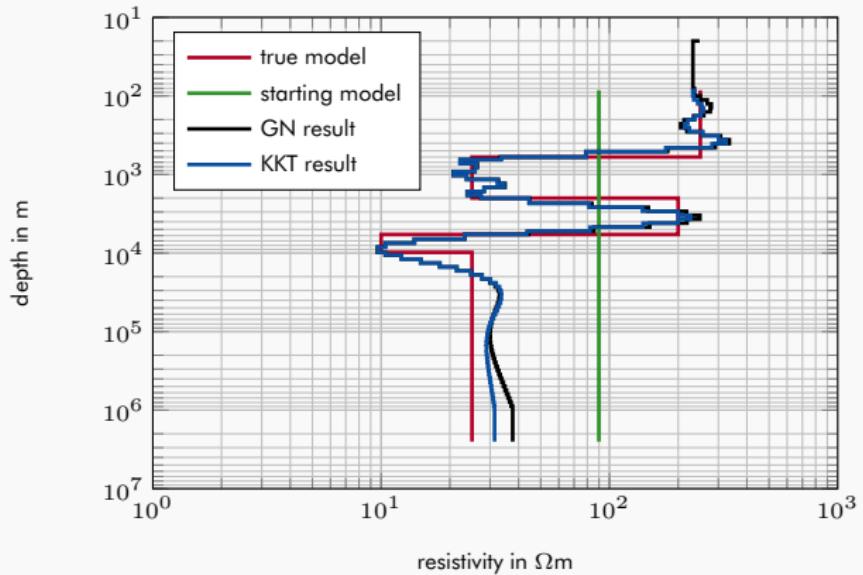
model parameter residual norm

# Sounding curves



# Results

## Synthetic data with noise

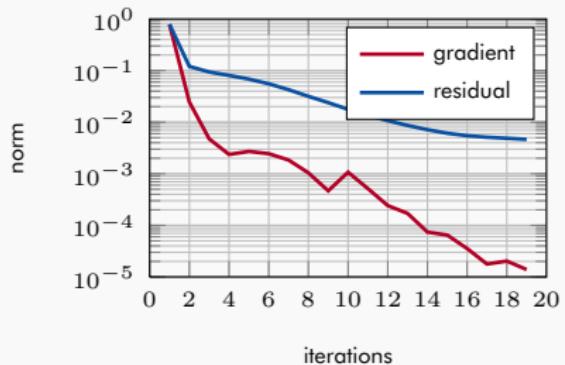


21 frequencies between  $10^{-4}$  and  $10^3$  Hz

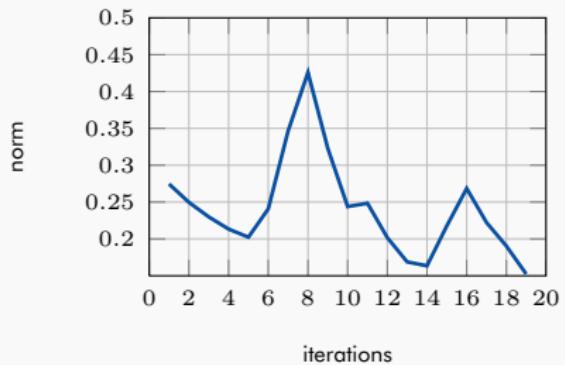
regularisation  $\beta = 0.45^{\text{iteration}} \cdot 10^{-4}$

# Results

## Synthetic data with noise – inversion process

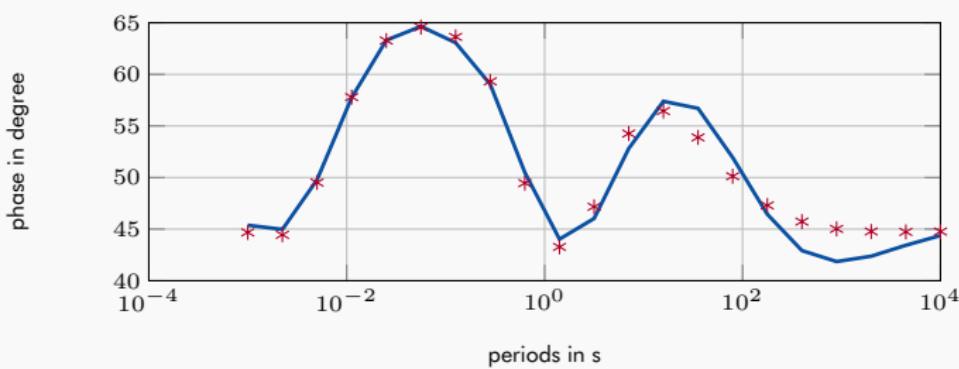
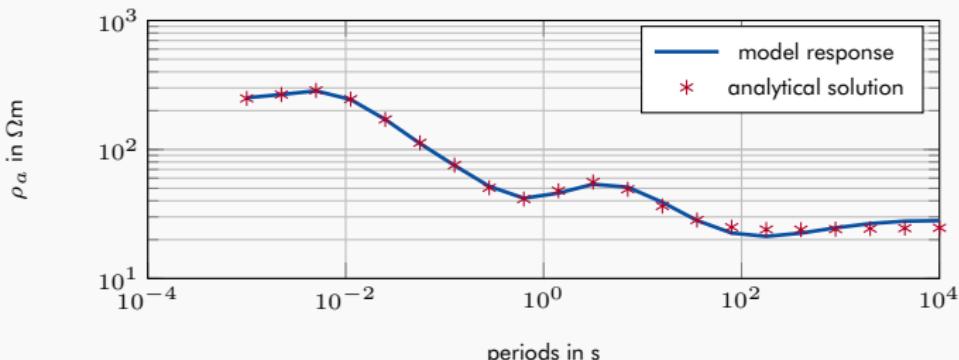


gradient  $\|\nabla \mathcal{L}\|$  and residual norm



model parameter residual norm

# Sounding curves



# Outlook

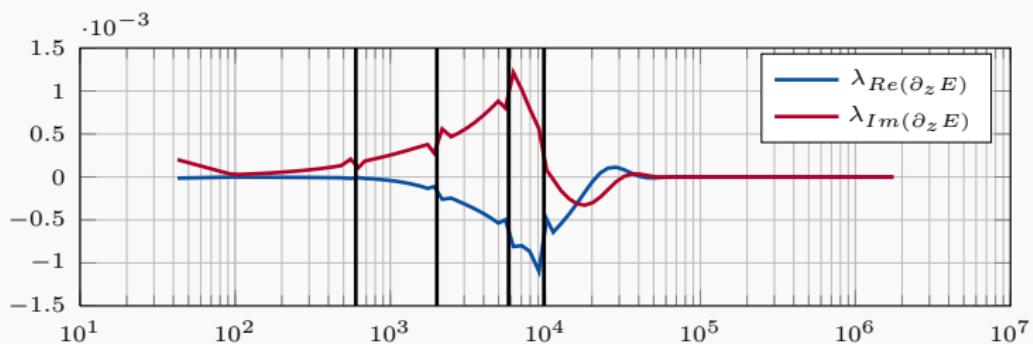
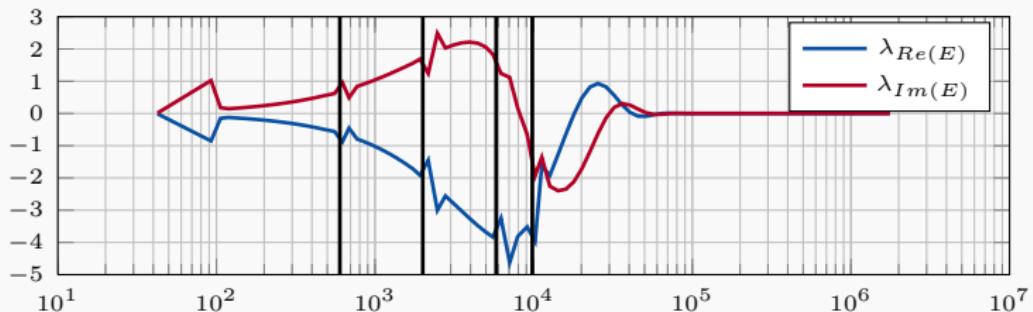
- 2D magnetotelluric problem
- 3D magnetotelluric problem

Thank you for your attention!

## References

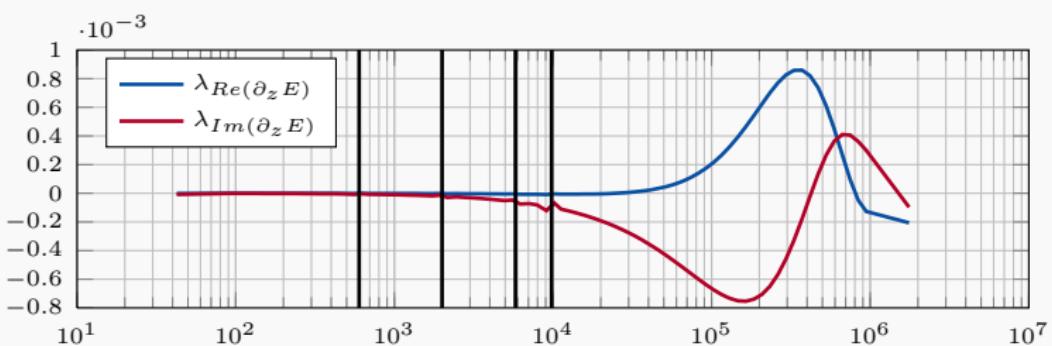
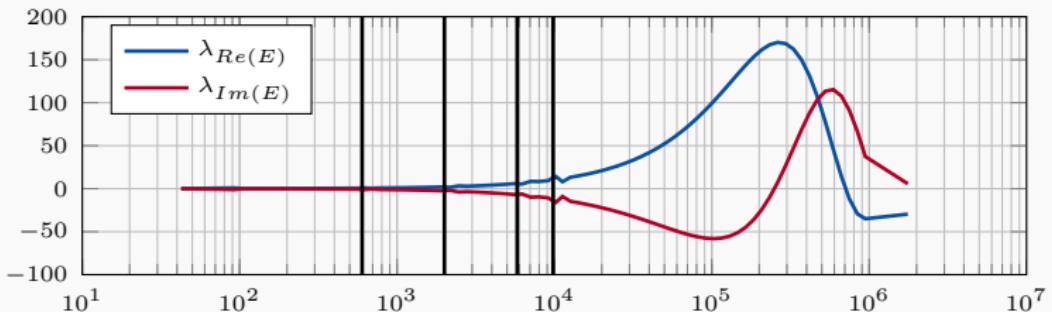
Haber, E., Asher, U. M., Oldenburg, D., On optimization techniques for solving nonlinear inverse problems, Inverse Problems 16, 2000.

# Behaviour of Lagrange multipliers



frequency=0.14 Hz

# Behaviour of Lagrange multipliers



frequency=0.0001 Hz

## Regularisation parameter noisy data

