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THE STUDY OF THE INTEGRATION OF PHYSICAL METHODS IN THE NEURAL NETWORK SOLUTION OF THE INVERSE PROBLEM OF EXPLORATION GEOPHYSICS WITH VARIABLE PHYSICAL PROPERTIES OF THE MEDIUM*

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Inverse problems of exploration geophysics

Inverse problems are the type of problems
when the system parameters are determined
from the observed data describing the system state.

The inverse problem of exploration geophysics consists
in reconstructing the spatial distribution of the properties
of the medium in the Earth's interior from measurements on its surface.

Features of inverse problem of exploration geophysics:

- ✓ Nonlinear
- ✓ Multi-parametrical
- ✓ High-dimensional
- ✓ ill-posed, ill-conditioned
- ✓ In general case do not have a direct numerical solution

Solution methods

Traditional solution methods:

- Optimization methods based on
  the multiple solution of the direct problem
  with the minimization of residuals in the space of the observed fields
  - ✓ High computational cost and low speed of work
  - ✓ Need for a good first approximation
  - ✓ Need to have a correct model for solving the direct problem
  - ✓ Small residual in the space of the observed quantities
    does not guarantee a small residual
    in the space of the determined parameters

Solution methods

Traditional solution methods:

- Matrix methods based on regularization
  - ✓ Need to choose the regularization parameter.
  - ✓ Linear method.

    It is necessary to perform nonlinear data preprocessing.

Solution methods

Neural network solution is considered as an alternative.

- ❑ Neural network solution
  - ✓ Free from the disadvantages of traditional methods
  - ✓ High computational cost when using machine learning methods are shifted from the stage of application of the computing system to the stage of its development, which increases the convenience of practical use of such a system.
  - ✓ The ill-posedness of inverse problems can "outweigh" the generalizing abilities of the neural networks, which leads to a deterioration in the quality of the solution.

Introduction

Solution methods

A general approach to reducing the ill-posedness of inverse problems is to use additional information:

- ❑ Response of the system to other types of external influences
  - ✓ Integration of geophysical methods (joint inversion) – simultaneous use of data from several geophysical methods.
- ❑ A priori knowledge about the system
  - ✓ Embedding physical equations in a machine learning methods – physics-informed neural networks
  - ✓ Domain specific data preprocessing
  - ✓ Accounting at the stage of creating a training dataset
  - ✓ Direct addition as input features to the neural network.

Introduction

Purpose of the study

In our previous studies, it was demonstrated
on a parameterization scheme with fixed layer properties
that the integration of geophysical methods gives better results
than using each of the methods separately.

The purpose of this study is to investigate:

- The effect of the integration of geophysical methods
for parametrization schemes with variable properties of the layers.
- An approach, based on addition of information
about the physical properties of the layers as input features

Problem statement

Neural network application scheme

Solution scheme for inverse problems of exploration geophysics:

- ❑ Define a parameterization scheme with a finite number of parameters
- ❑ Create a training data set:
  - For each training pattern
    - ✓ Set a random distribution of parameters on macrogrid
    - ✓ Calculate distribution of parameters on microgrid
    - ✓ Calculate field values by solving the direct problem using the finite difference method
- ❑ Train and neural networks on a training dataset
- ❑ Apply neural networks to the studied data

To use the integration of geophysical methods, it is necessary that the determined parameters of each method are the same.

Problem statement

Parameterization scheme

Description:

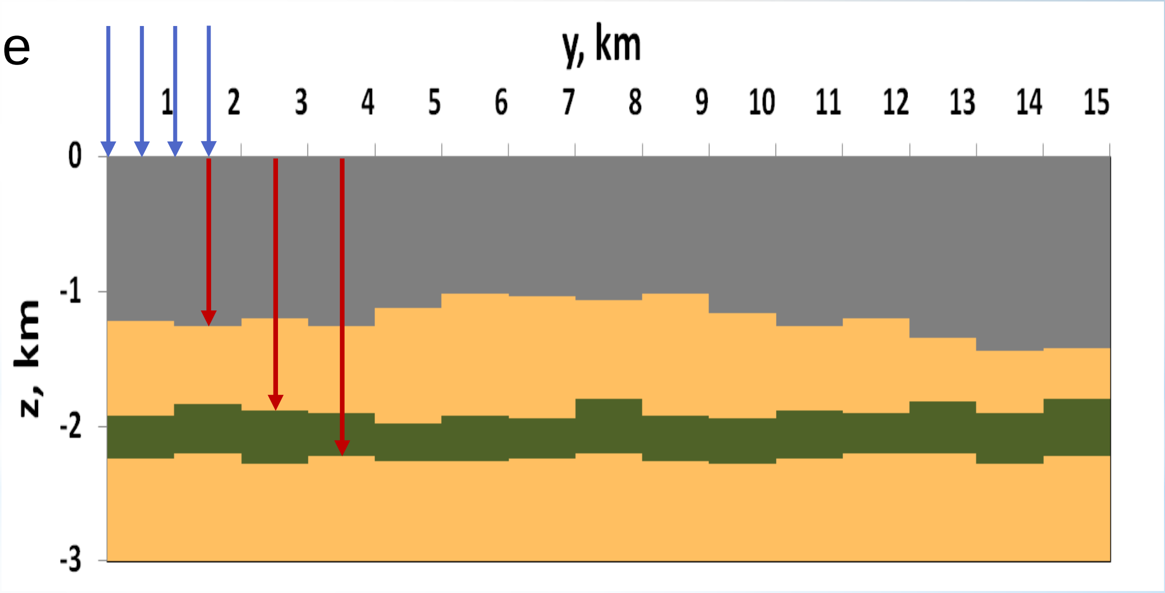
- Variable (determined) parameters
  - ✓ Depths of the lower boundaries of layers
- Calculated physical fields
  - ✓ Gravimetry (G)
  - ✓ Magnetometry (M)
  - ✓ Magnetotelluric sounding (MT)
- 2D model (section)
- 4 layers
  - ✓ The physical characteristics of the 2-nd and 4-th layers were the same
- The physical properties of the layers are fixed
  - ✓ Fixed / unfixed (variable) in the entire dataset
  - ✓ Fixed / unfixed (variable) within the section

Problem statement

Parameterization scheme

Properties:

- Geological section size
  - ✓ Depth- 3 km
  - ✓ Width -15 km



- Physical field measurement step
  - ✓ 0.5 km
  - ✓ 31 measurement points along the profile
- Step of changing the boundaries of geological layers
  - ✓ 1 km
  - ✓ 15 depth values for each layer
- The discreteness of changing the values of depths
  - ✓ 0.02 km

Problem statement

Properties of the layers

Layer	Description	Physical properties			Spatial properties		
		Density **σ**, kg/m³	Magnetization **μ**, A/m	Resistivity **ρ**, Ω·m	Upper bound, min-max, km	Lower bound, min-max, km	Thickness, min-max, km
1	Basalt	2 800 2 520 – 3 080	3 2.7 – 3.3	2 000 1 800 – 2 200	0	1 – 1.48	1 – 1.48
2	Terrigenous carbonate deposits of the Tunguska series	2 550 2 295 – 2 805	0.5 0.45 – 0.55	100 90 – 110	1 – 1.48	1.8 – 1.98	0.32 – 0.98
3	Gabbro-dolerites massive copper-nickel-platinum ores	3 000 2 700 – 3 300	0.9 0.81 – 0.99	1 000 900 – 1 100	1.8 – 1.98	2.2 – 2.28	0.22 – 0.48
4	Terrigenous carbonate deposits of the Tunguska series	2 550	0.5	100	2.2 – 2.28	—	—

Computational experiment

Dataset

- Dataset
  - Were obtained by numerical solution of the direct problem
  - Number of patterns — 10 000 patterns
  - Split into sets:

✓ Training set	70%	7 000 patterns
✓ Validation set	20%	2 000 patterns
✓ Test set	10%	1 000 patterns

Computational experiment

Data

- Data dimensionality
  - Output dimensionality
    - ✓ Inverse problem:
      *45 parameters = 3 layers * 15 values of layer boundary depth*
  - Input dimensionality
    - ✓ Gravimetry:
      *31 features = 1 field component * 31 measurement point (picket)*
    - ✓ Magnetometry:
      *31 features = 1 field component * 31 picket*
    - ✓ Magnetotelluric Sounding:
      *62 features = 2 field components * 1 frequency * 31 picket*
    - ✓ Physical properties of the layers:
      *3 or 45 (3*15) features for each geophysical method*

Computational experiment

Statement of computational experiment

The use of a priori information was carried out
by adding the values of the physical properties of the layers
as input features. In total - three features for each geophysical method.

When integrating geophysical methods, the data of two or three geophysical methods were simultaneously fed to the input of the NN:

- Individual use of geophysical methods
  - Gravimetry and magnetometry - 31 (31+3) features
  - Magnetotelluric Sounding – 62 (62+3) features
- Simultaneous use of data from two geophysical methods
  - 62 (62+6) or 93 (93+6) features
- Simultaneous use of data from all the three methods
  - 124 (124+9) features.

Computational experiment

Statement of computational experiment

Parameterization schemes:

- ❑ Properties fixed per data and fixed per section – **fdfs**
- ❑ Properties variable (unfixed) per data and fixed per section – **udfs**
- ❑ Properties variable (unfixed) per data and per section – **udus**

The use of a priori information – **ai**

Computational experiment

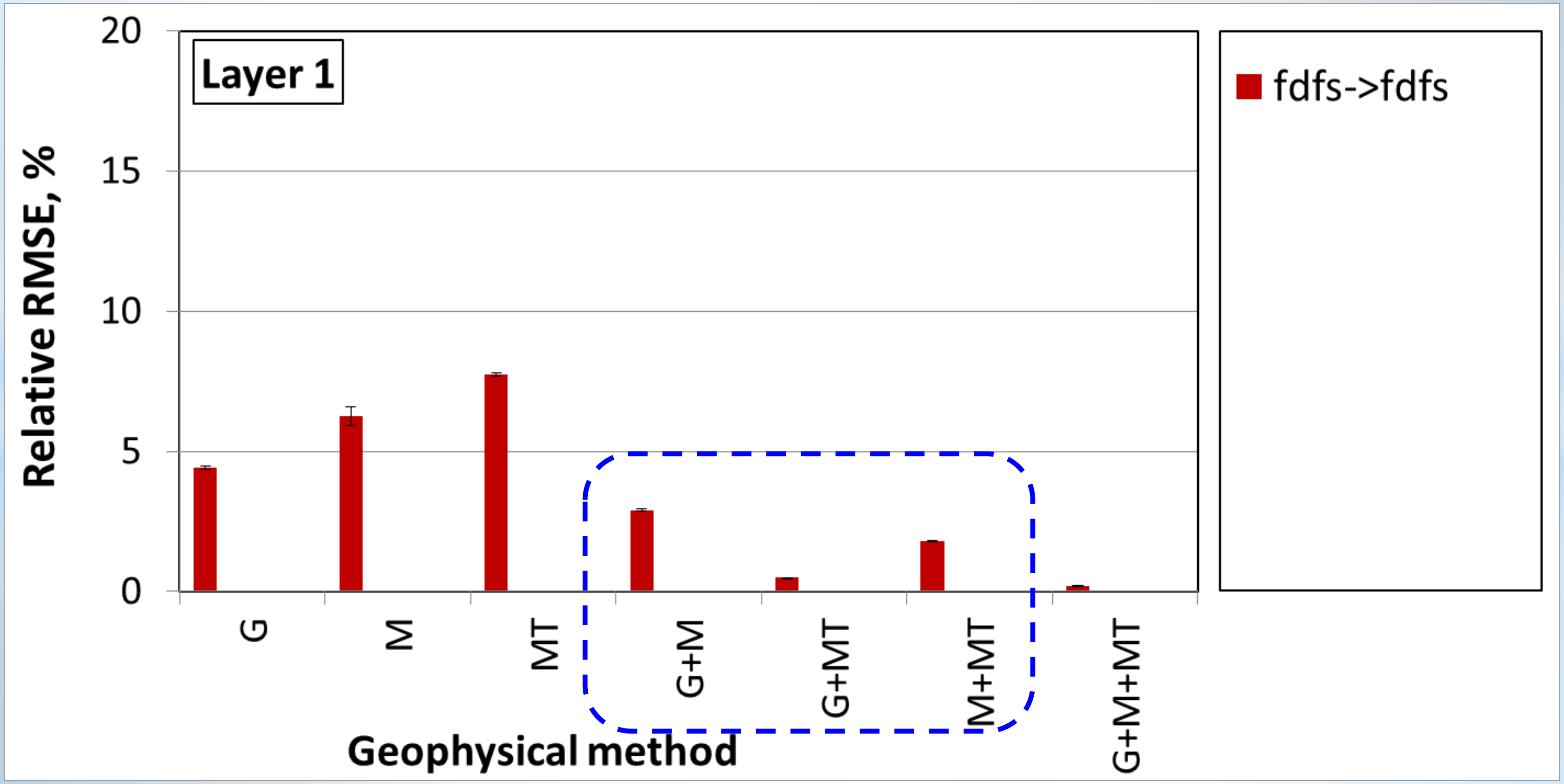
Use of neural networks

- Architecture:
  - Multilayer perceptron
  - 1 hidden layer - 32 neurons
  - Activation function:
    - ✓ hidden layer – sigmoid
    - ✓ output layer: linear – for regression approach
sigmoid – for classification approach
- Prevent overfitting - early stopping method
  - Stop training after 500 epochs
with no improvement on the validation set
- Weights initialization
  - Each neural network was trained 5 times
with various initial weights values.
  - The statistic indexes of the results of application of the 5 networks were averaged

Results

Inverse problem solution

Dependence of the quality of the solution on input data

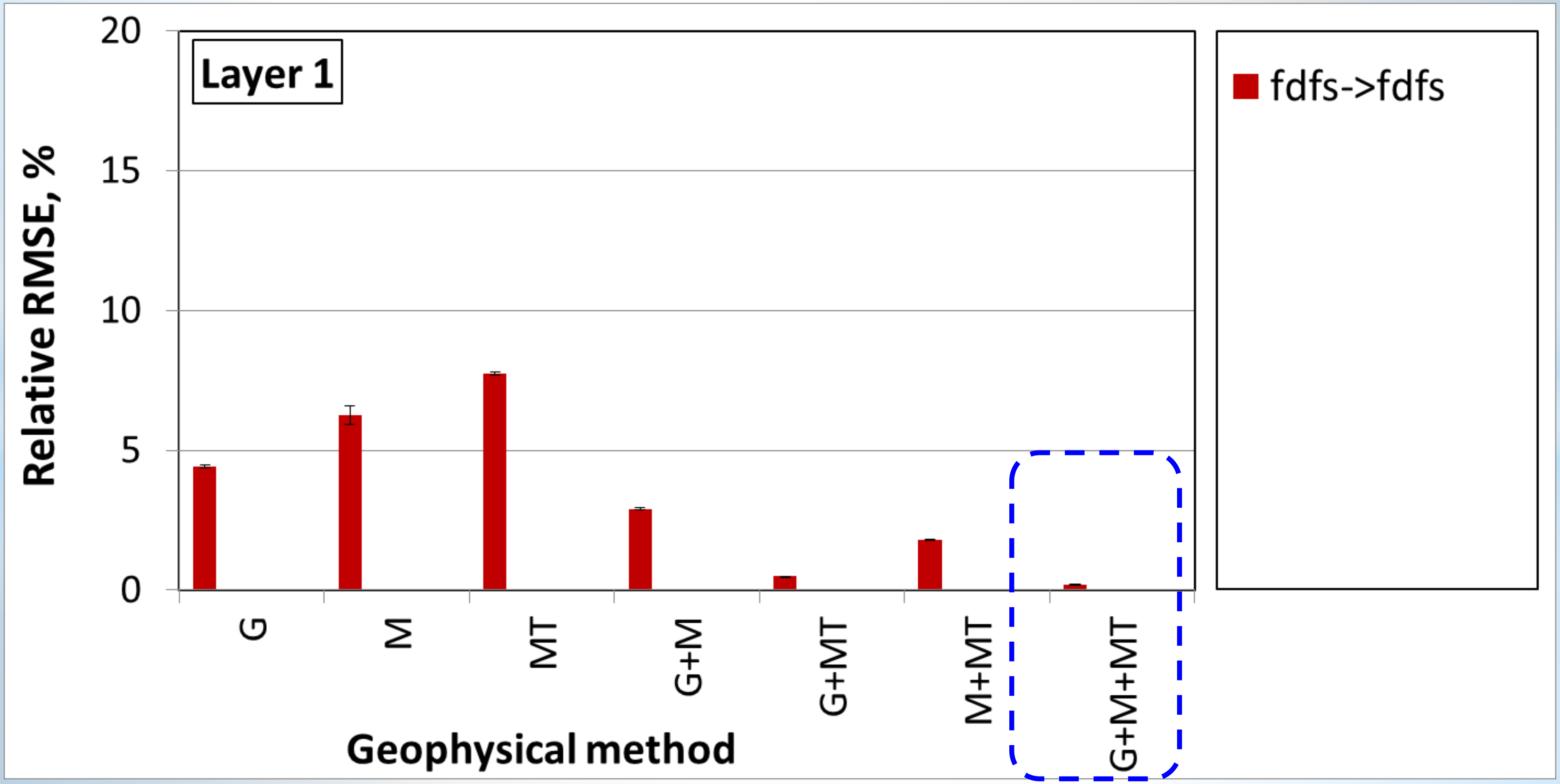


Simultaneous use of data from any geophysical methods improve recovery quality compared to the individual use of data from any of them.

Results

Inverse problem solution

Dependence of the quality of the solution on input data

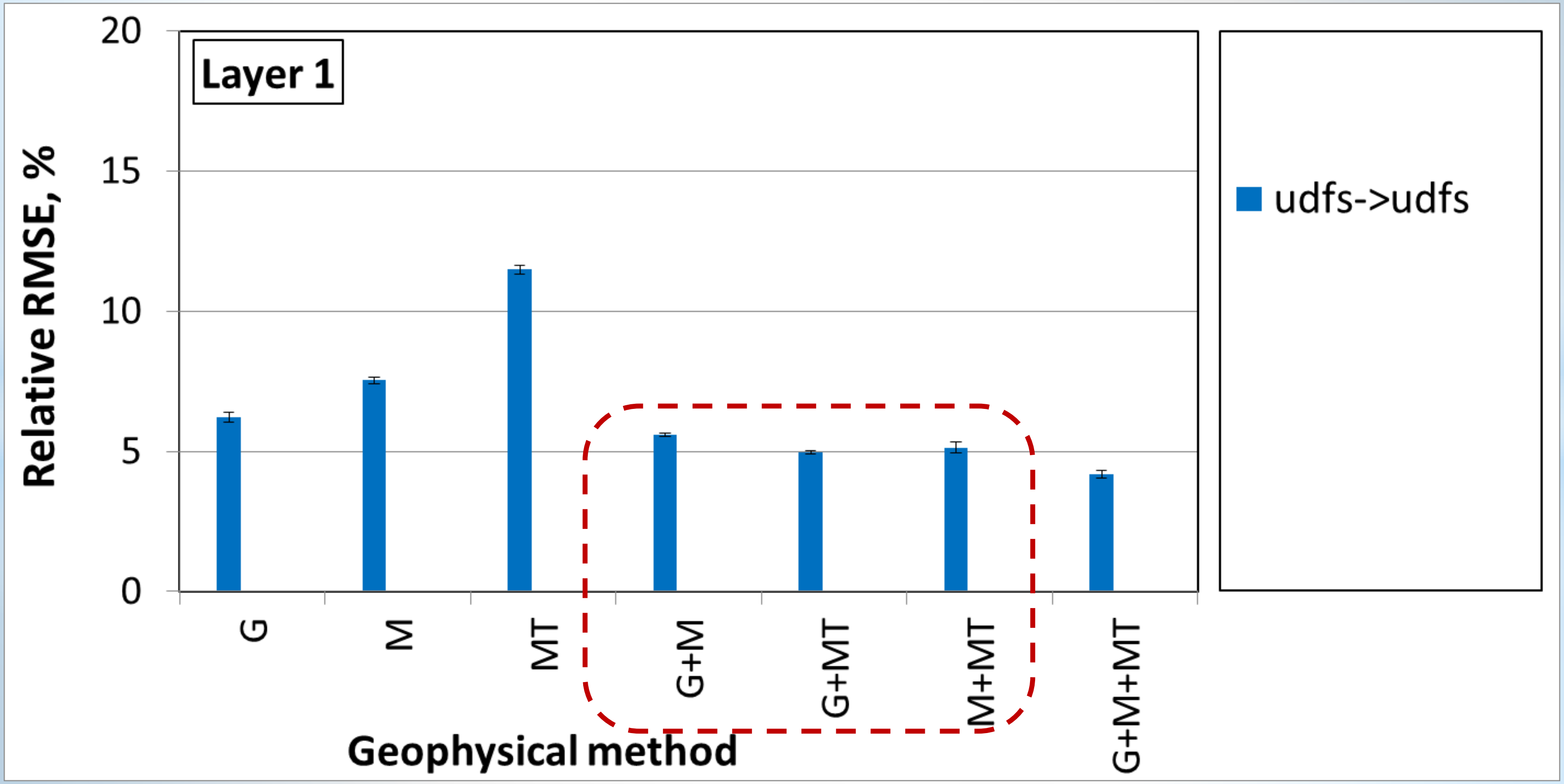


The best result was provided by simultaneous use of the data from all the three geophysical methods.

Results

Inverse problem solution

Dependence of the quality of the solution on input data



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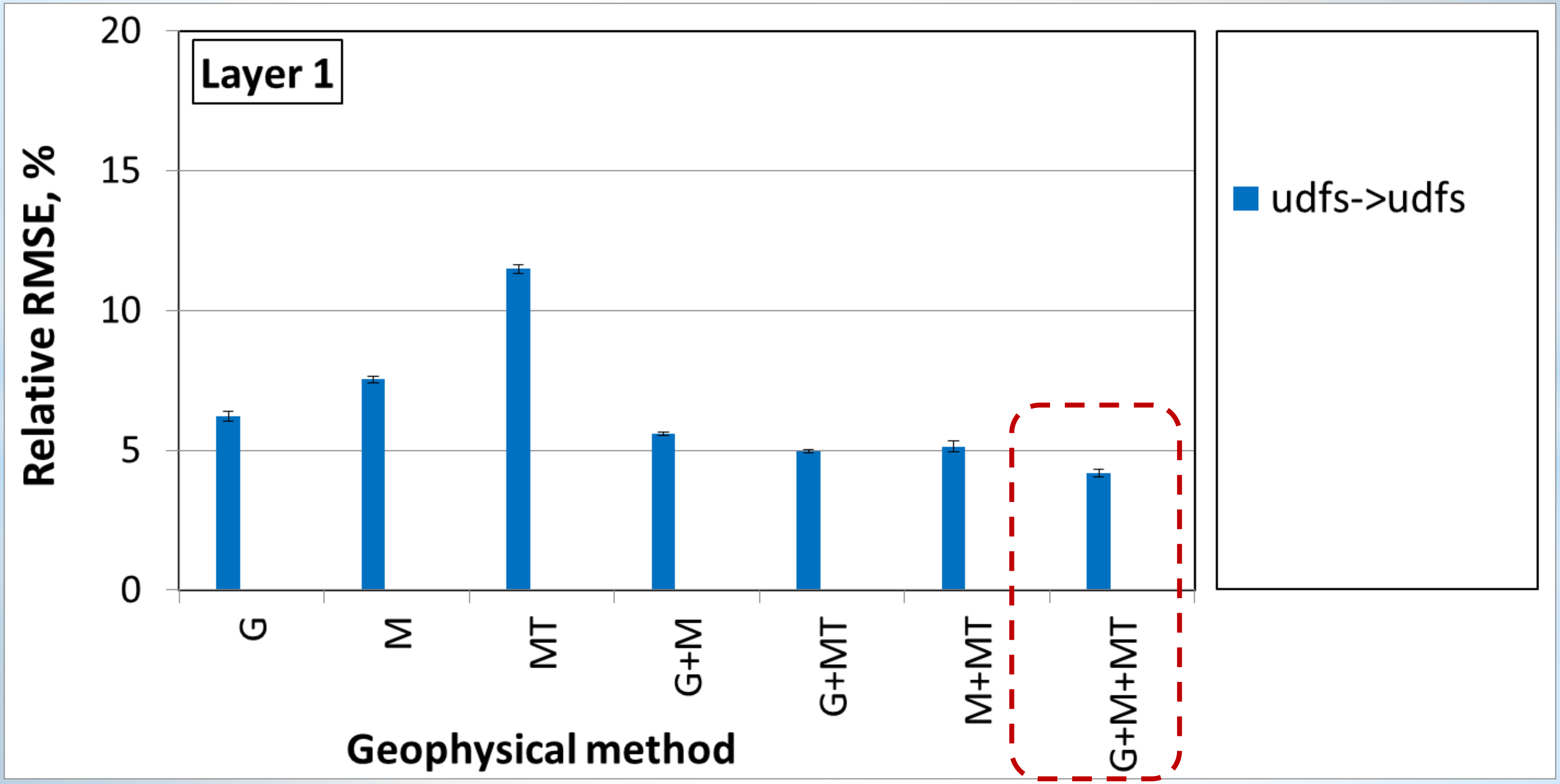

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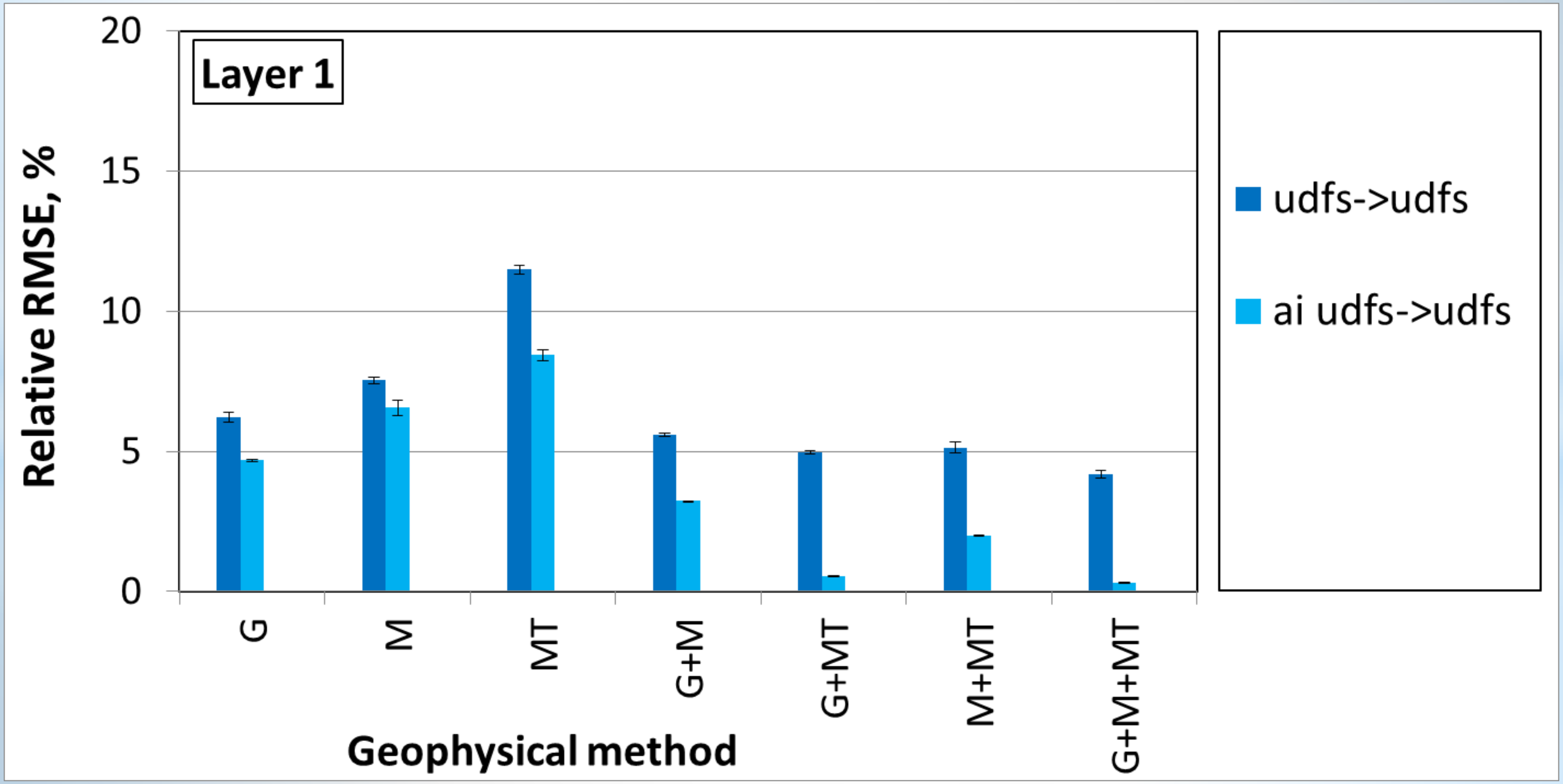
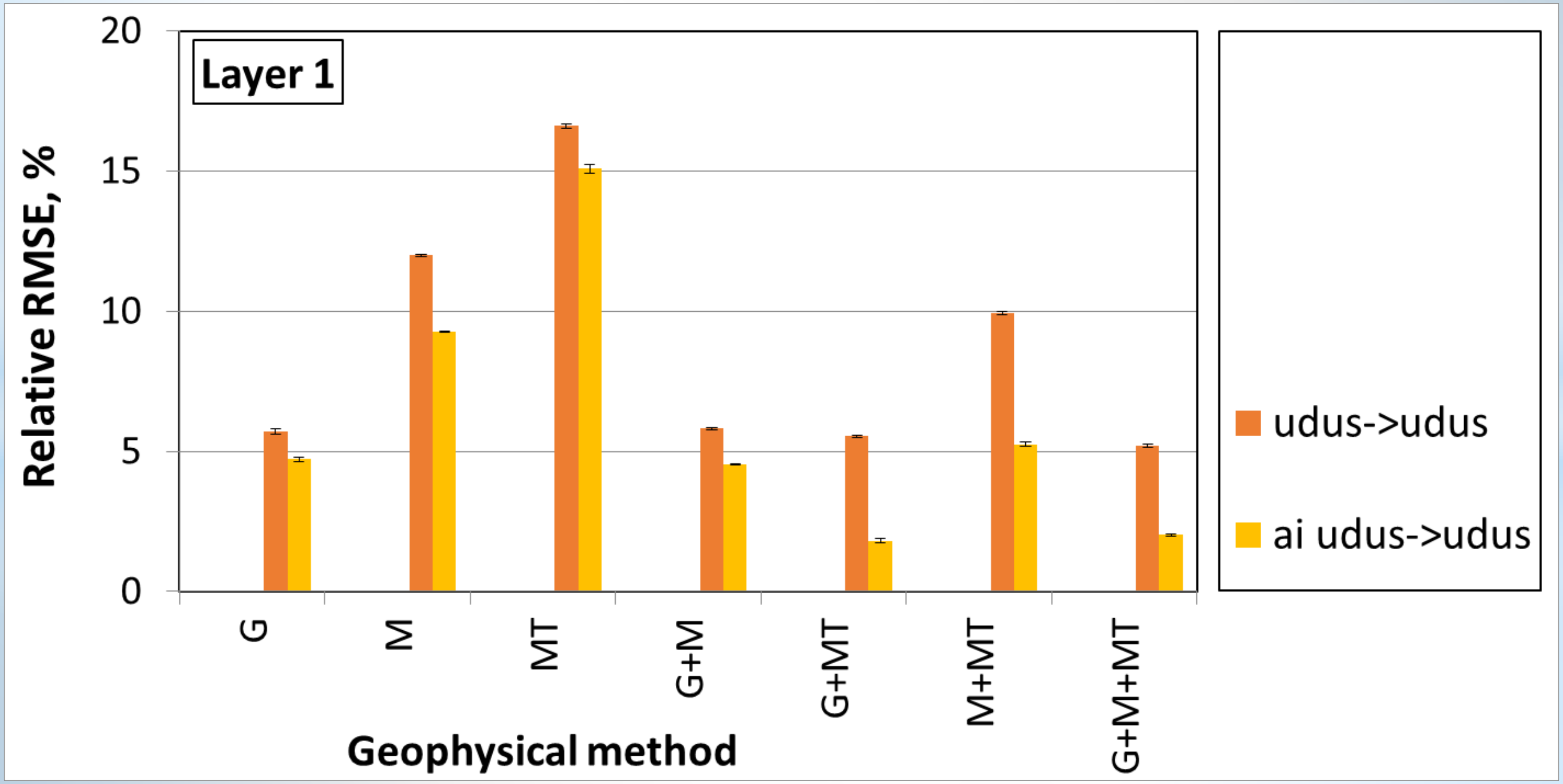


Direct addition of information
about the physical properties of the layers as input features
makes it possible to improve the quality of the solution.

Results

Inverse problem solution

Dependence of the quality of the solution on input data



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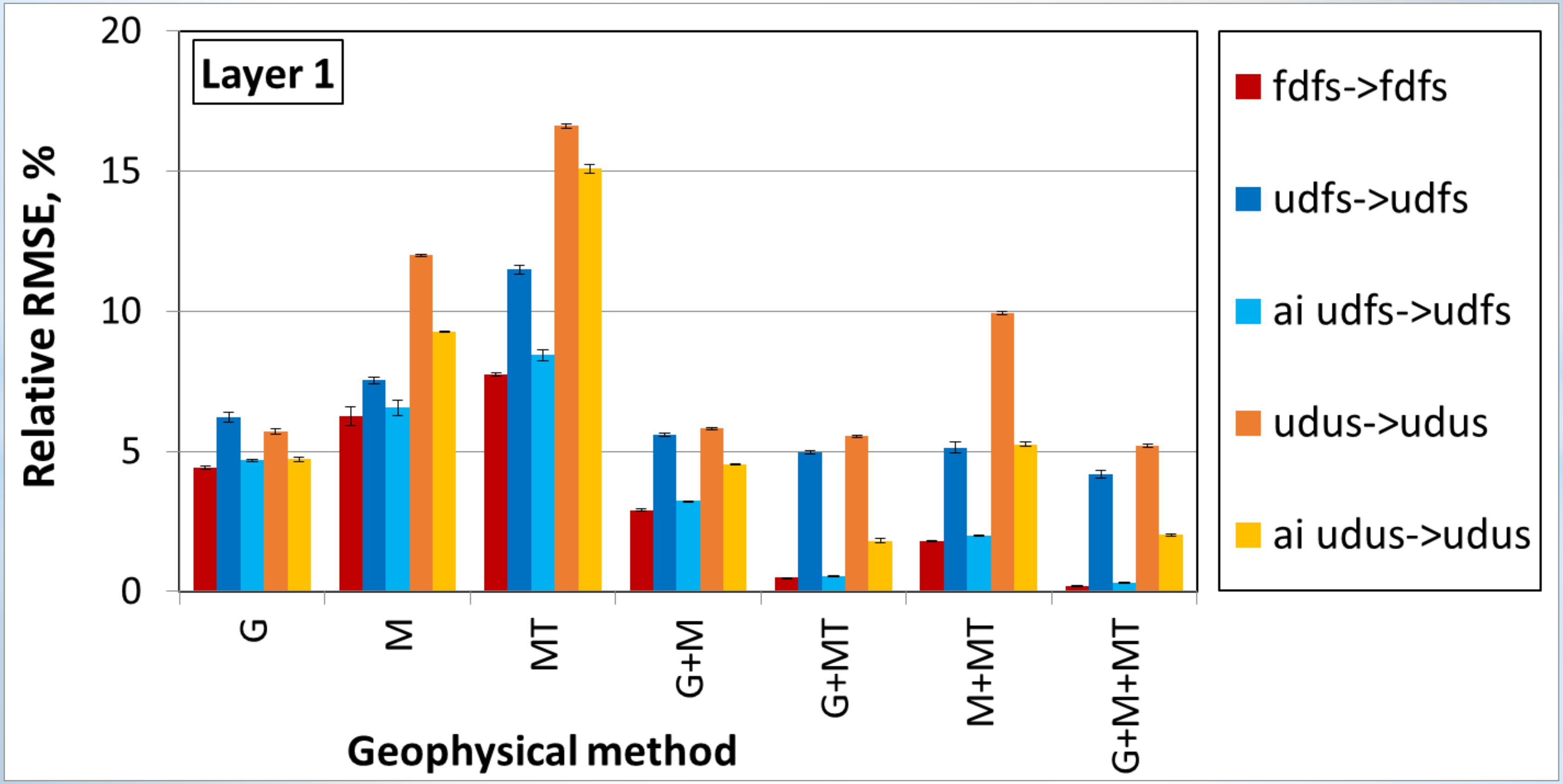
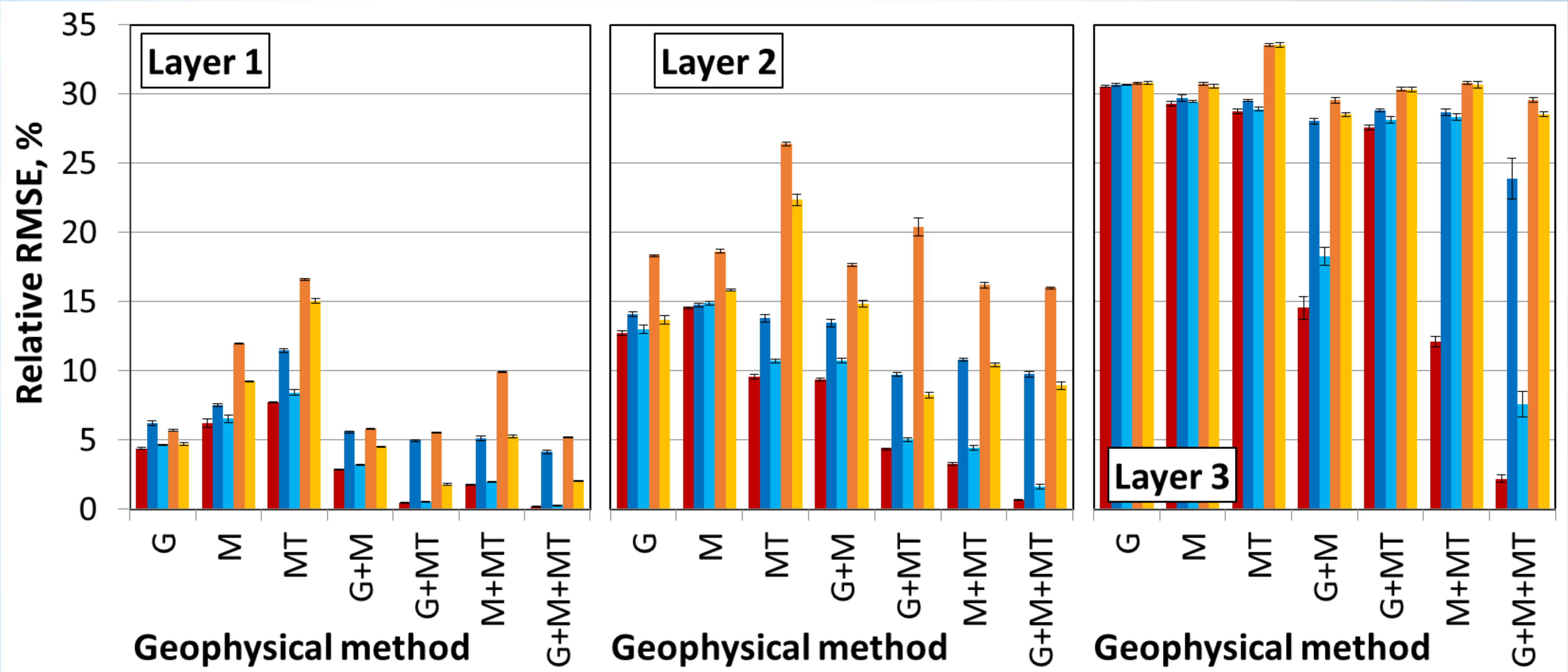


Indirect introduction of *a priori* information
through the use of a narrower parameterization scheme
makes it possible to improve the quality of the solution.

Results

Inverse problem solution

Dependence of the quality of the solution on input data



All observed effects are valid for all layers

Conclusions

- The use of *a priori* information in the neural network solution of inverse problems of exploration geophysics gives a positive effect:
  - ✓ Direct addition of information about the physical properties of the layers as input features makes it possible to improve the quality of the solution.
  - ✓ Indirect introduction of *a priori* information through the use of a narrower parameterization scheme shows a better result of the solution compared to using a more universal parameterization scheme.

Conclusions

- Data integration of different geophysical methods gives a positive effect for all considered parameterization schemes:
  - ✓ Simultaneous use of data from any two geophysical methods improves the quality of the solution compared to the individual use of data from any of them.
  - ✓ The best result was provided by simultaneous use of the data from all the three geophysical methods.
  - ✓ This effect is also observed when directly adding information about the physical properties of the layers as input features.

Thank you
for your attention!