Neural network prediction of the reservoir properties on the Kloštar oil field

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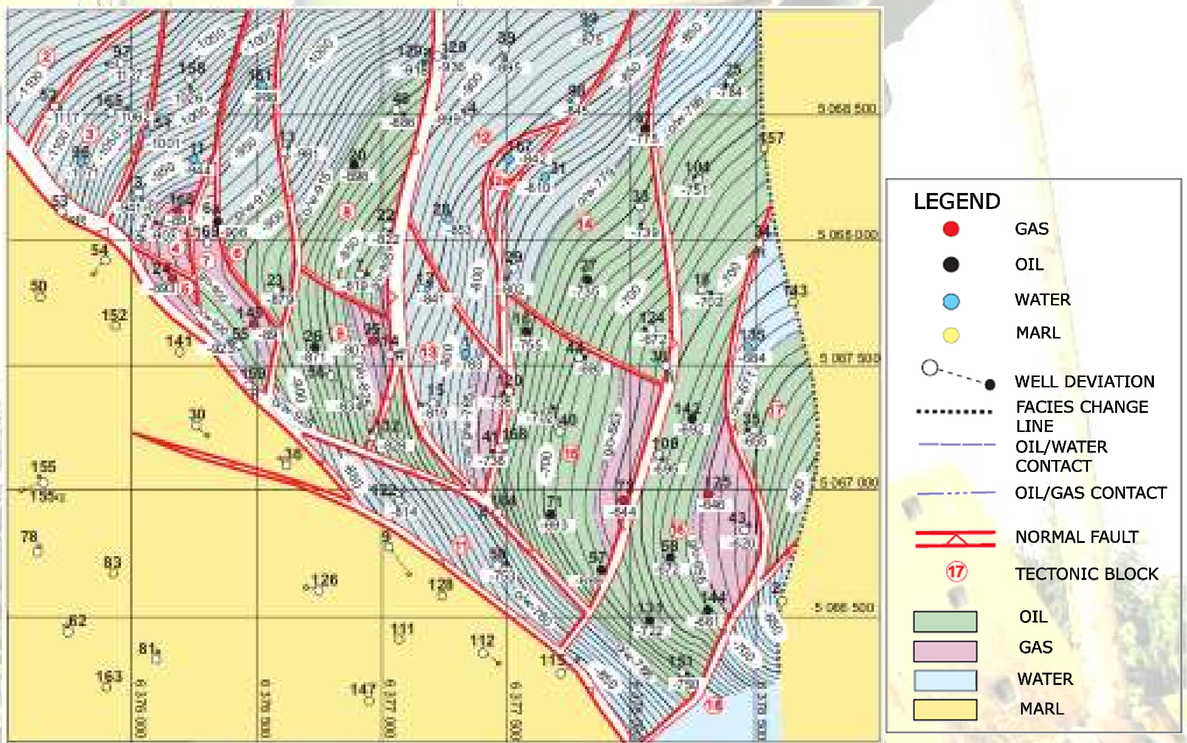
INTRODUCTION

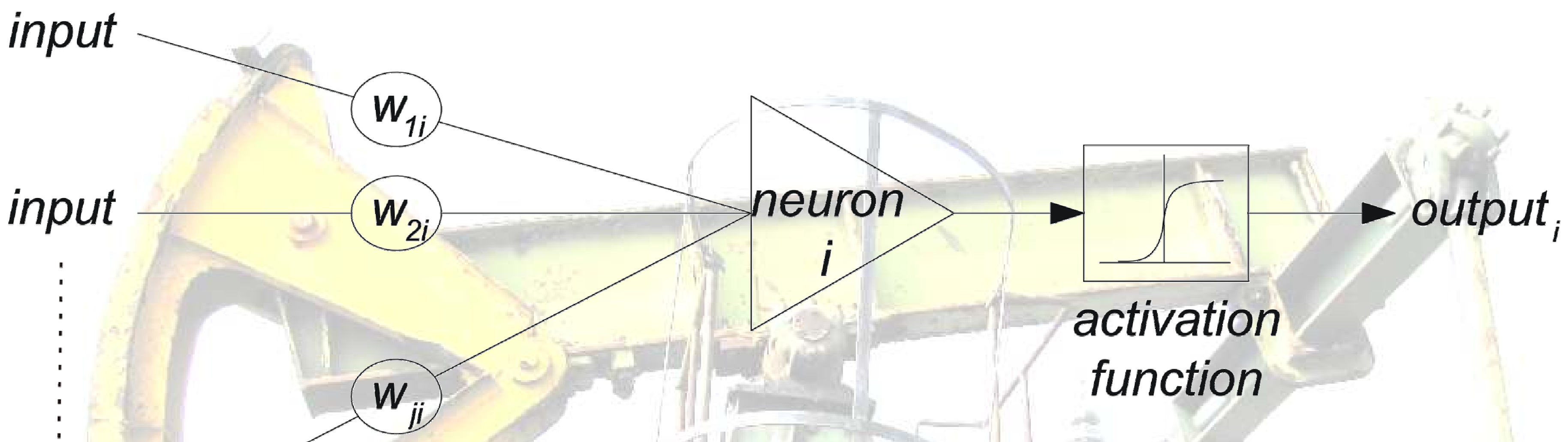
PETROLEUM GEOLOGY SETTINGS

Hydrocarbon baring units:

- Basement of the Tertiary system
- Middle Miocene series
- **Upper Miocene series**
  - **“I. sandstone series”**
  - **“II. sandstone series”**



ARTIFICIAL NEURAL NETWORKS

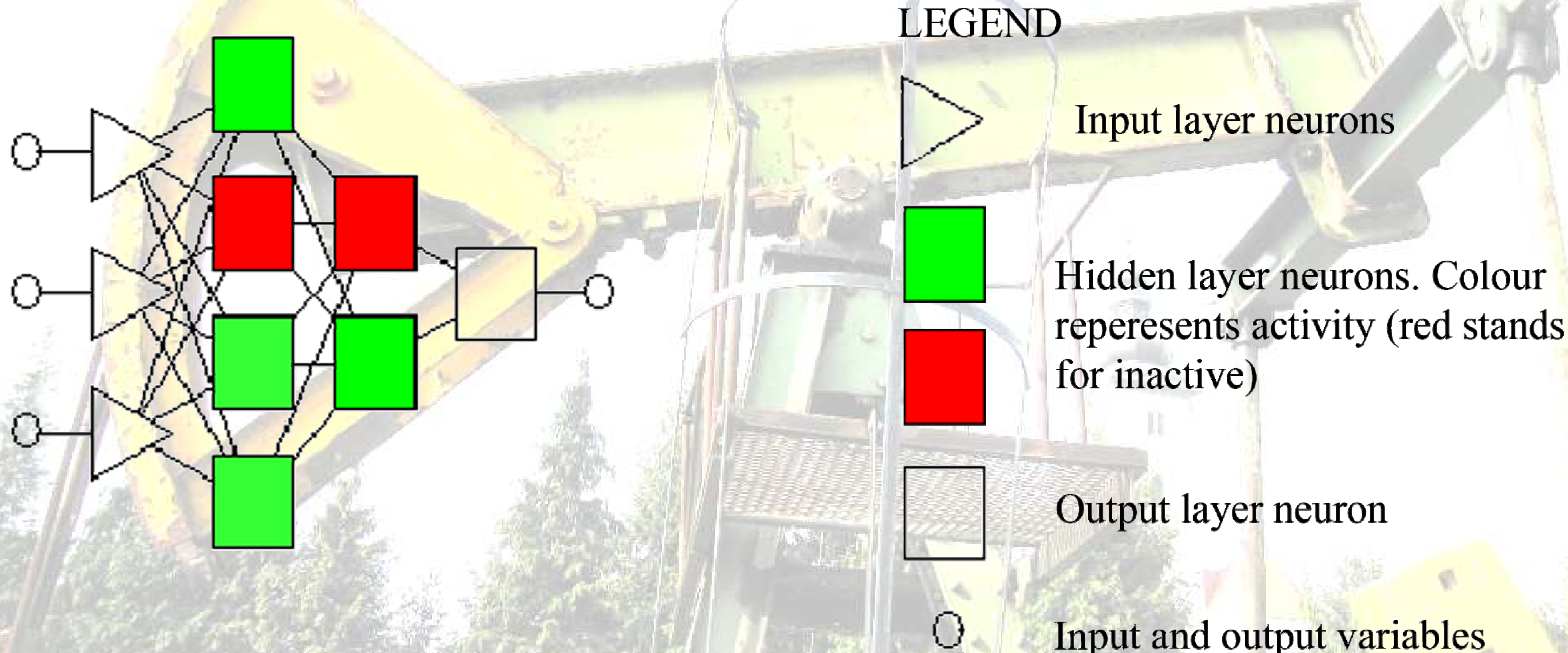


$$u_i = \sum_{j=1}^{n} (w_{ji} \cdot input_j) \qquad output_i = F(u_i \cdot t_i)$$

ARTIFICIAL NEURAL NETWORKS

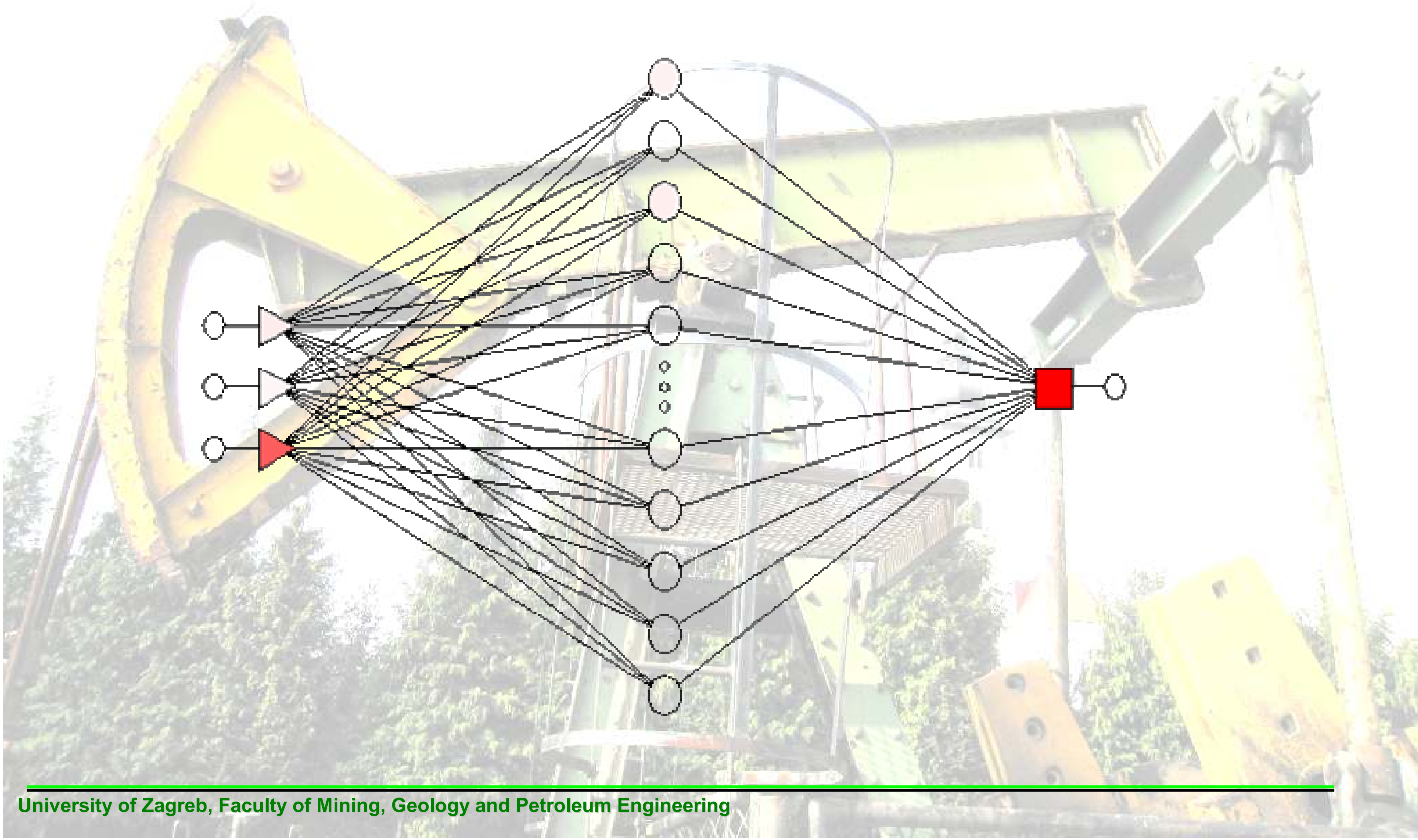
Two types of neural networks were used:

-multi layer perceptron (MLP) neural network



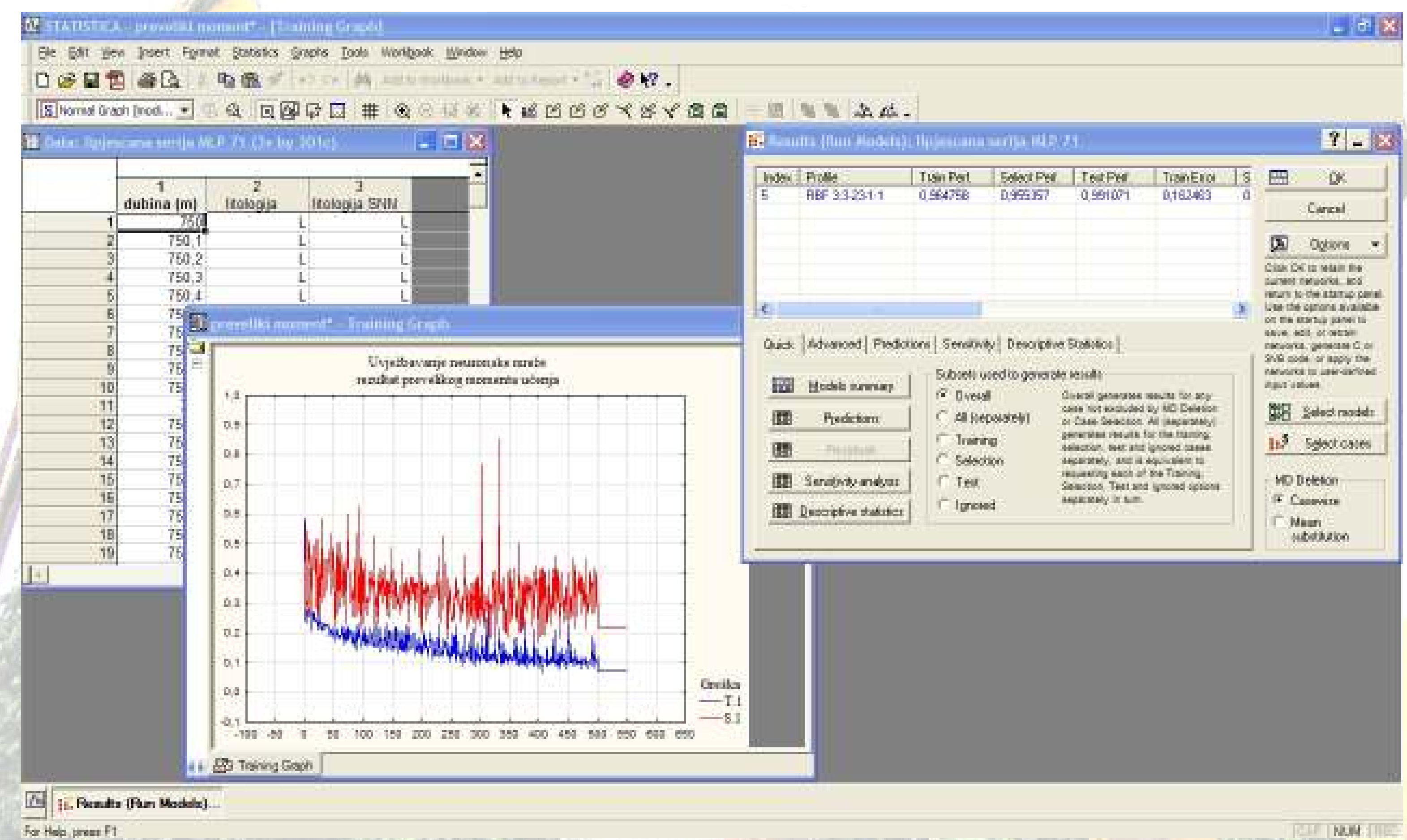
ARTIFICIAL NEURAL NETWORKS

-radial basis function (RBF) neural network



DATA ANALYSIS

Program package: StatSoft STATISTICA 7



DATA ANALYSIS

- Data from two wells were analyzed:
    - Well Klo-A
    - Well Klo-B
- Important factors for successful training of an artificial neural network:
    - Number of hidden layers and number of neurons within each of this layers
    - Selection of the best suited training algorithm
    - Number of epochs
    - Learning rate (momentum)

DATA ANALYSIS

LITHOLOGY PREDICTION

- **Input data:**
  - **Spontaneous potential (SP) curve**
  - **Resistivity curves**
    - **R_{16}**
    - **R_{64}**
  - **Traditionally determined lithology**
- **Lithology was defined as a categorical variable represented as either sandstone (1) or marl (0)**

DATA ANALYSIS

LITHOLOGY PREDICTION-RESULTS

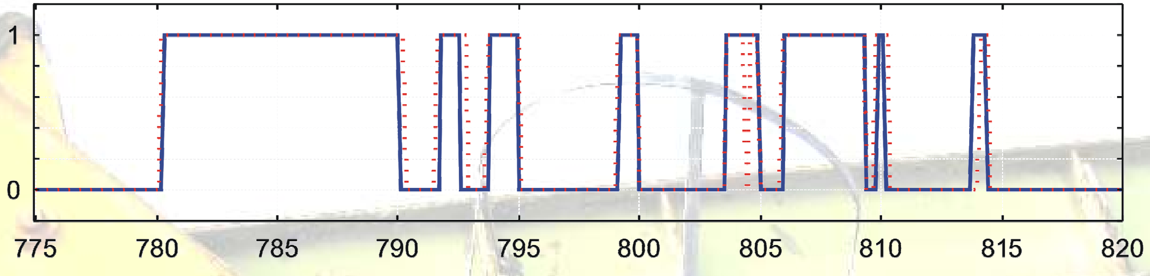
Neural network type and properties	Well	Training error[a]	Selection error[a]
RBF 3–31–1	Klo-A	0.152942	0.172753
MLP 3–4–6–3–1	Klo-A	0.31438	0.133478
RBF 3–13–1	Klo-B	0.156621	0.149185
MLP 3–6–4–2–1	Klo-B	0.255012	0.214935

[a]Error value ranges from 0 to 1, where 0 represents 100% success of prediction, i.e., no error.

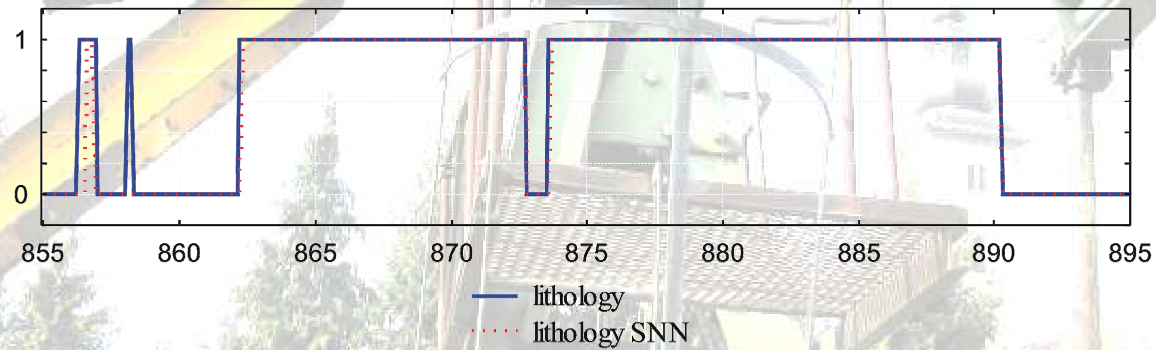
DATA ANALYSIS

LITHOLOGY PREDICTION-RESULTS

MLP neural network training in “I. sandstone series” – Klo-A



MLP neural network prediction in “II. sandstone series” – Klo-A

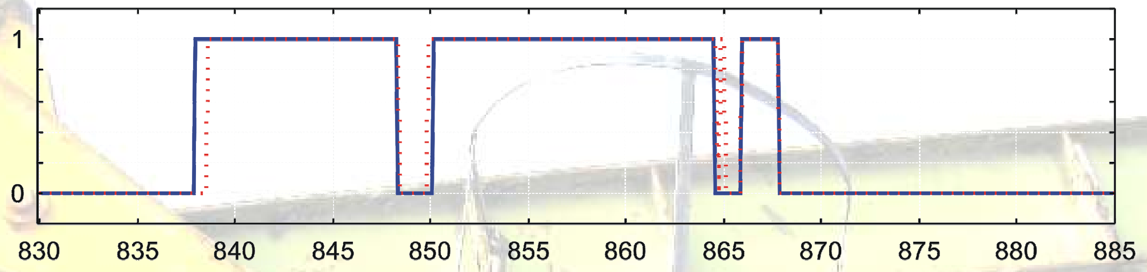


Neural network type and properties	Well	Training error	Selection error
MLP 3–4–6–3–1	Klo-A	0.31438	0.133478

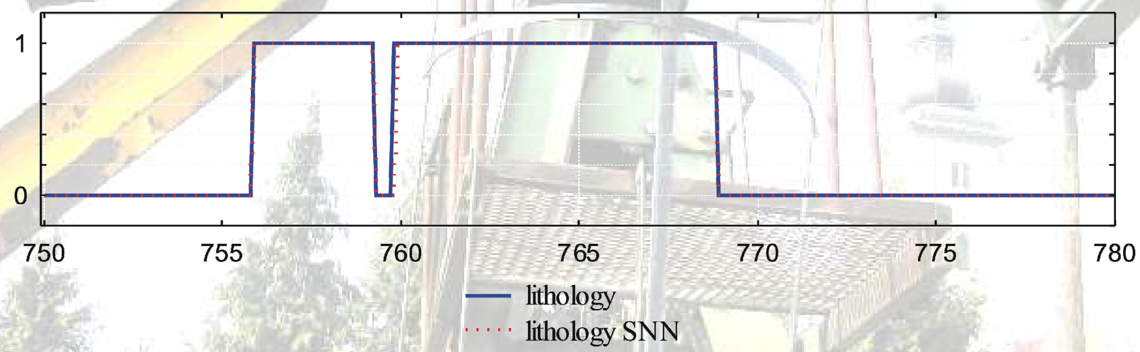
DATA ANALYSIS

LITHOLOGY PREDICTION-RESULTS

RBF neural network training in “II. sandstone series” – Klo-B



RBF neural network training in “I. sandstone series” – Klo-B



Neural network type and properties	Well	Training error	Selection error
RBF 3–13–1	Klo-B	0.156621	0.149185

DATA ANALYSIS

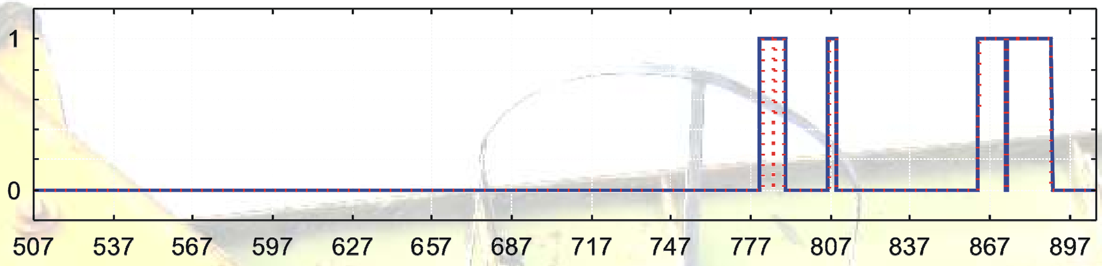
HYDROCARBON SATURATION PREDICTION

- Input data:
  - Spontaneous potential (SP) curve
  - Resistivity curves
    - R_{16}
    - R_{64}
  - Traditionally determined lithology
  - Traditionally determined hydrocarbon saturation
- Lithology was defined as a categorical variable represented as either sandstone (1) or marl (0)
- Hydrocarbon saturation was also defined as a categorical value of hydrocarbon saturated (1) and unsaturated (0)

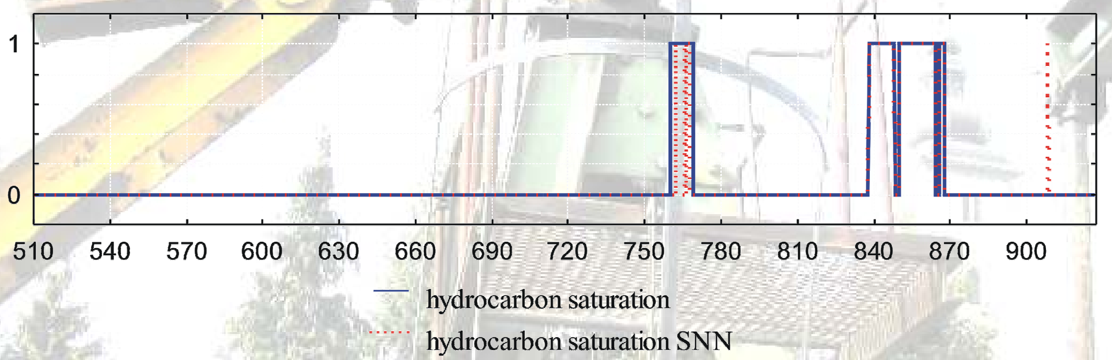
DATA ANALYSIS

HYDROCARBON SATURATION PREDICTION

MLP neural network training in Klo-A



MLP neural network prediction in Klo-B



Neural network type and properties	Training error	Selection error
MLP 5–6–8–1	0.056897	0.091173

CONCLUSIONS

•When determining lithological component in wells Klo-A and Klo-B with RBF and MLP neural networks, we achieved excellent correspondence between true and predicted values.

•Prediction of hydrocarbon saturation in well Klo-B with a neural network trained in well Klo-A gave excellent correspondence between real and predicted values.

•Our results show the great potential of neural networks' application in petroleum geology research, where they could be used to quickly acquire results from well logs, to obtain vertical and lateral correlation of such logs, and to solve other petroleum geology problems.

CONCLUSIONS

THANK YOU FOR YOUR ATTENTION!