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Improving computational efficiency of forward modelling for ground-based time-domain electromagnetic data using neural networks

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Inversion of large-scale time-domain electromagnetic surveys is a time consuming and computationally expensive task. Probabilistic or deterministic methodologies, such as Monte Carlo inversion or Gauss-Newton methods, require repeated calculation of forward responses, and, dependent on methodology and survey size, the number of forward responses can reach from thousands to millions. In this study, we propose a machine learning based forward modelling approach in order to significantly decrease the time required to calculate the forward responses, and thus also inversion time. We employ a fully-connected feed-forward neural network to approximate the forward modelling process. For training of the network, we generated 93,500 forward responses using AarhusInv with resistivity models derived from 9 surveys at different locations in Denmark, representing a Quaternary geological setting. The resistivity models are discretized into 30 layers with logarithmically increasing thicknesses down to 300 m, and ranges from 1 to 1,000 Ω·m. The forward responses, were modelled with 14 gates/decade from 10^{-7} s to 10^{-2} s. To ensure better network convergence, the input resistivity models are normalized after logarithmically transforming them. Furthermore, the network target outputs, i.e. forward responses, are globally normalized, where each gate is normalized in relation to the maximum and minimum values of the respective gates. This ensures each gate is prioritized equally.

The network performance is evaluated on a test set derived from a separate survey containing 5,978 resistivity models, by directly comparing the neural network based forward responses to the AarhusInv forward responses. The performance is exceptionally good, with 99.32% of all gates accurate to within 3% relative error, which is comparable to data uncertainty. The time derivatives of the generated forward models, dB/dt, are also computed by convolving a transmitter waveform. The dB/dt performance is 86.2%, but is improved to an accuracy of 98.02% within 3% error by post-processing the forward responses using a local smoothing algorithm. The low dynamic range of the target outputs induces rounding/truncation errors, which leads to jagging, and therefore increasing the error when the waveform is applied to the un-processed forward responses. However, the 1.98% of the gates that exceed the 3% error after post-processing lie within typical data uncertainty, ensuring the suitability for use in inversion schemes.

The proposed forward modelling strategy is up to 17 times faster than commonly used accurate modelling methods, and may be incorporated into either deterministic or probabilistic inversion algorithms, allowing for significantly faster inversion of large datasets.

A TEM system having a 40 m × 40 m central loop configuration was selected for this study. However, in principle, any geometry can be applied. Additionally, the proposed scheme can be extended for other systems, such as airborne EM systems by considering the altitude as an extra input parameter.