Leveraging Machine Learning for Electromagnetic Inversion and Uncertainty Quantification: Application for Critical Mineral Exploration

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1 Introduction

- Climate changes have a lot of impact on our lives.
- Extensive research on renewable energy.
- Renewable energy depends on minerals like copper, lithium, nickel, cobalt and aluminum.

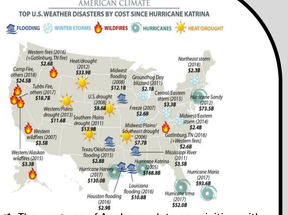
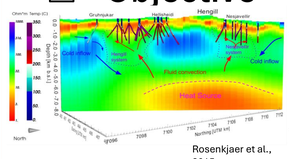


Fig1: The progress of AusLamp data acquisition with emphasis on the East Tenant region.

2 Objective



Rosenkjaer et al., 2015

Fig 2: Picture of resistivity model from MT data inversion showing geothermal production systems.

- Electromagnetic (EM) methods are key in mineral exploration and geothermal energy.
- Growing demand for geothermal energy and critical minerals will boost EM data use.
- Finding an alternative approach that accurately and efficiently samples from the posterior probability distribution.
- Explore the feasibility of using Invertible Neural Network to solve EM inverse problems and quantity uncertainties.

3 Motivation

- UQ enhances inversion for better risk analysis and decision making.
- Traditional inversions yield a single model, restricting uncertainty assessment.
- Efficient high-dimensional sampling (Posterior probability Density) methods are needed.
- Propose the use of Invertible Neural Networks.
- Apply INN to MT data from East Tennant, Australia

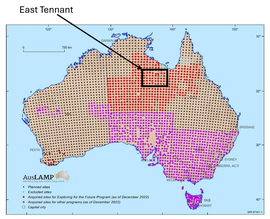


Fig 3: The progress of AusLamp data acquisition with emphasis on the East Tenant region.

4 Methods

- INN works with Bayes' theorem and normalizing flows.
- Mapping is learnt in the forward direction
- Training-free backward mapping.
- Added latent variable guarantees bijectivity.

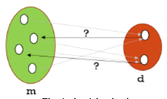


Fig 4: Ambiguity in mapping

$$p_x(x) = P_z(f(x))|detDf(X)|$$
$$P_X(x) = P_z(Z)|detDZ|$$
$$P_z(Z)|detDZ|$$
$$P_Z(Z)|det\frac{\partial_z}{\partial_x}|$$

Fig 5: Bijective Mapping INN

$$p(m|d_{obs}) = \frac{p(d_{obs}|m)p(m)}{p(d_{obs})}$$

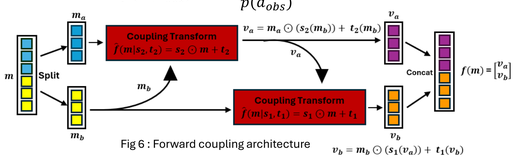


Fig 6 : Forward coupling architecture

$$v_a = m_a \odot (s_2(m_b)) + t_2(m_b)$$
$$v_b = m_b \odot (s_1(v_a)) + t_1(v_b)$$

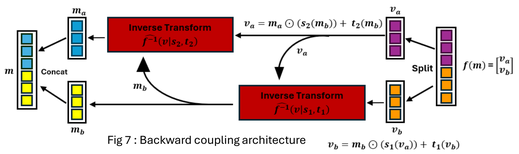


Fig 7 : Backward coupling architecture

$$v_a = m_a \odot (s_2(m_b)) + t_2(m_b)$$
$$v_b = m_b \odot (s_1(v_a)) + t_1(v_b)$$

- INN splits the input into 2 halves.
- Each half goes through an affine transformation.
- The results are concatenated to produce the output.
- For inversion, each half goes through inverse transformation.
- The results are concatenated to produce the inputs in the backward direction.
- This produces the inversion.

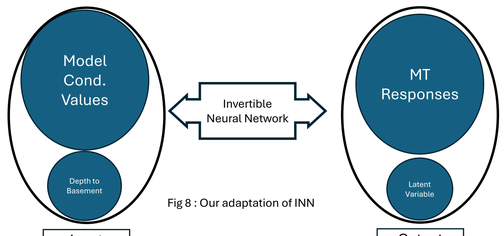


Fig 8 : Our adaptation of INN

5 Airborne Electromagnetic Result

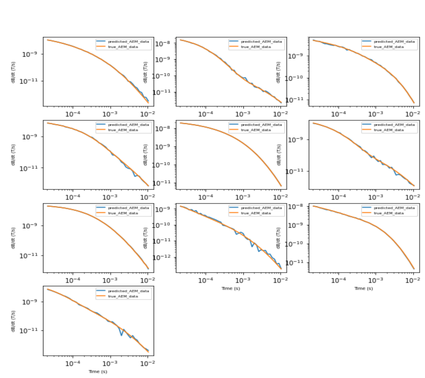


Fig 9: Predicted AEM data

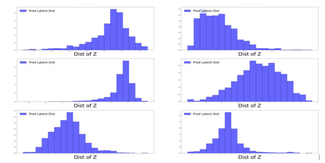


Fig 10: Distribution of the latent variable

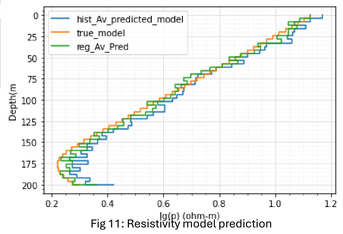


Fig 11: Resistivity model prediction

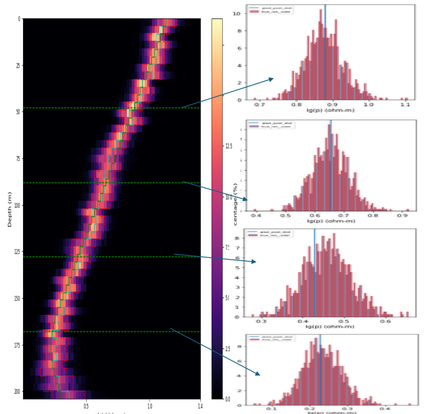
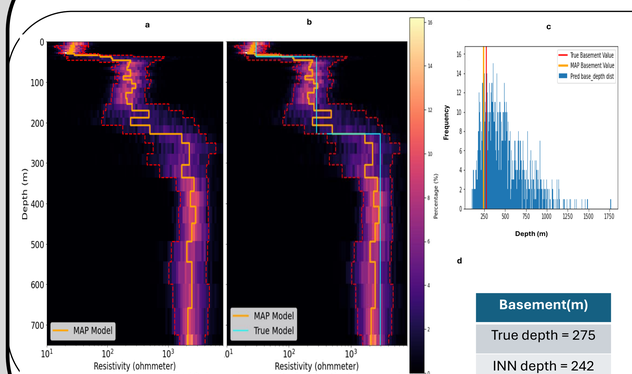


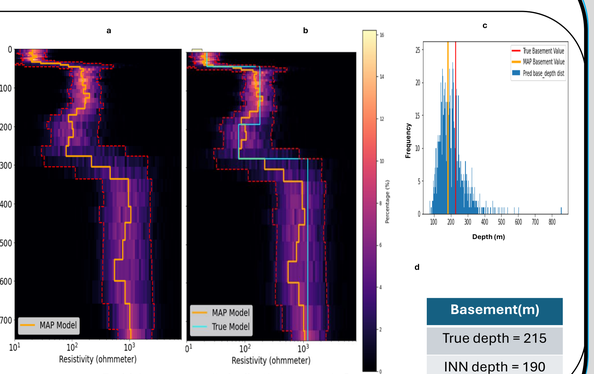
Fig 12: Posterior distributions of resistivity models

6 Synthetic MT Inversions



Basement(m)
True depth = 275
INN depth = 242

Fig 13: Inversion results for Synthetic example 1



Basement(m)
True depth = 215
INN depth = 190

Fig 14: Inversion results for Synthetic example 2

7 Field MT Inversion Results

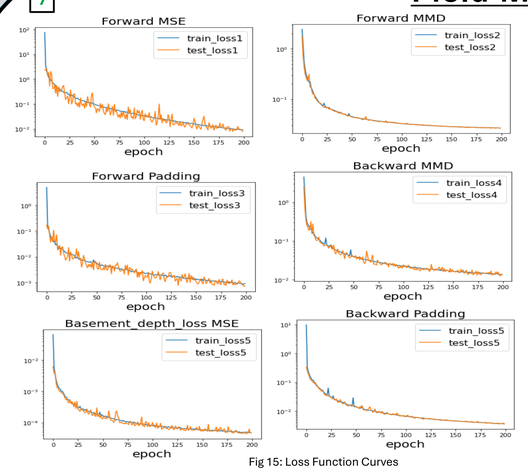
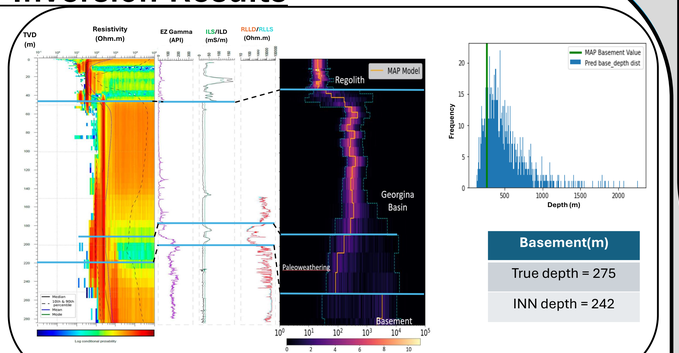


Fig 15: Loss Function Curves



Basement(m)
True depth = 275
INN depth = 242

Fig 17: Inversion results for Field Station ET008

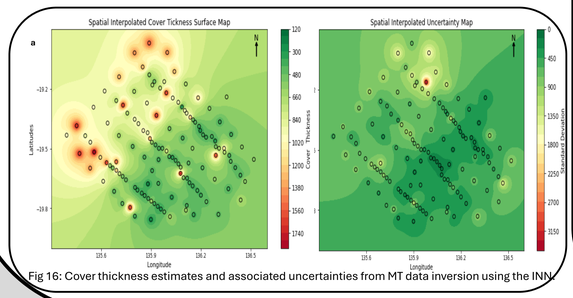
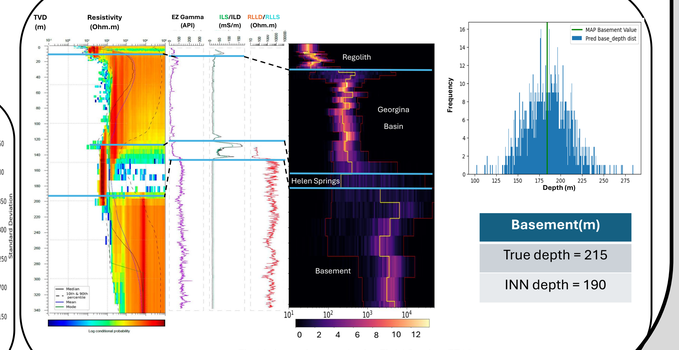


Fig 16: Cover thickness estimates and associated uncertainties from MT data inversion using the INN



Basement(m)
True depth = 215
INN depth = 190

Fig 18: Inversion results for Field Station ET10n

8 Preliminary 2D Synthetic results

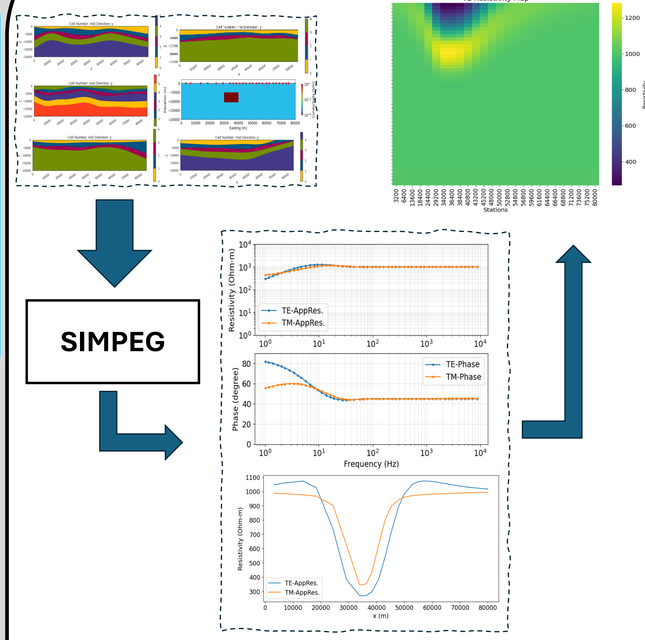


Fig 19: Data Generation Steps for 2D training using Invertible Neural Network

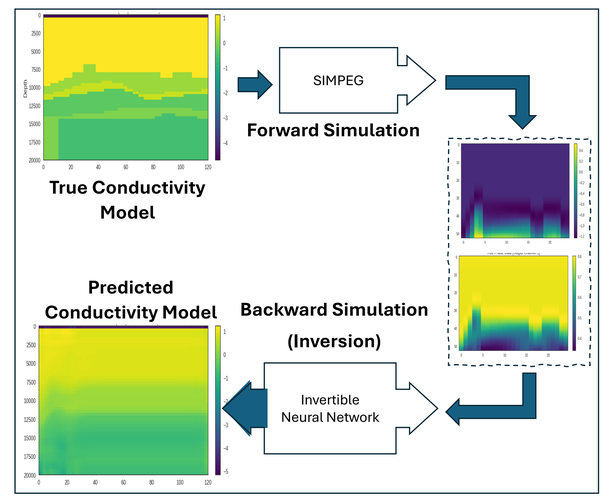


Fig 20: Inversion results for 2D Synthetic MT data

9 Conclusion and Summary

- INN learns the forward process and obtains the inverse process 'for free'.
- Efficiently and effectively draws from the posterior distribution to characterize the associated uncertainties.
- The generation of the INN posteriors is computationally very cheap compared to other Bayesian approaches.
- Future work involves applying INN for a full 2D and 3D MT field inversion.

10 References

- Gasperikova et al., 2015, Resistivity characterization of the Krafla and Hengill geothermal fields through 3D MT inverse modelling.
- Jiang et al., 2023, Probabilistic inversion of audio frequency magnetotelluric data and application to cover thickness estimation for mineral exploration in Australia.