Improved Workflow for 3D Inverse Modeling of Magnetotelluric Data: Examples from Five Geothermal Systems

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Keywords

magnetotellurics, geothermal energy, 3D inversion, geophysical inverse theory

ABSTRACT

Magnetotellurics (MT) is now an important geophysical tool for imaging complex geothermal energy systems, but retrieving realistic three-dimensional (3D) resistivity models is challenging, and computationally intensive. To ameliorate this situation, we develop a sequenced MT inversion workflow that formalizes and improves upon concepts introduced by Rosenkjaer & Oldenberg (2012). We test the performance and reliability of our workflow using five 3D MT datasets from geothermal fields in the United States (Coso, Raft River) and Iceland (Krafla, Hengill and Krysuvik). We compare inversion results from the standard and sequenced workflows for each experiment, and find that the sequenced workflow always retrieves a better-fitting model, specifically at lower frequencies, which is geologically consistent and representative of a high temperature geothermal system. It also uses fewer computational resources.

1. INTRODUCTION

Modeling resistivity is difficult when sparse MT data are used to constrain 3D high-temperature geothermal resources. 3D MT models often contain 1,000 times more unknown parameters compared with 2D MT. This fact of scale is driving a shift toward parallelized-computation to decrease the time required for the modeling phase of geophysical exploration. However, in current practice, computational cost is still a limiting factor. For example, Hersir et al. (2013) reduced the number of nodes in a 3D MT model of Krysuvik geothermal field in Iceland because of large computational demands, a choice that ultimately decreased interior model resolution by over 50%. Simpson & Bahr (2005) describes this reality as “the trade-off between computational economy and precision”, but we find this is only half the story when using field MT data; in fact, the standard approach to 3D MT inversion for geothermal surveying may systematically fail to model lower frequency data (< 0.1 Hz).

We define the ‘standard approach’ as using 3D mesh designs adapted from the 2D mesh design principles of Weaver (1994), documented in Simpson & Bahr (2005), and inverting the full bandwidth of data starting from a homogeneous resistivity model or one that contains a priori information.

We define ‘computational cost’ in the same way modern supercomputing clusters define burden – as the product of model nodes, processors used, and total runtime. Cost and efficiency are essential to users of serial MT simulators because runtimes for large models are on the order of weeks. For parallel code users, total runtime is less important than the financial or opportunity costs of running a job on a PC cluster in a sub-optimal manner.

In an effort to economize 3D inversion, Rosenkjaer & Oldenburg (2012) proposed a sequenced workflow concept wherein the full MT dataset is divided into frequency bands and inverted piecewise using different model grids. By sequentially inverting the data and using the result of the previous step as a starting model for the subsequent step, the

Figure 1. Sequenced workflow diagram

authors suggest reductions in total computational cost can be achieved.

Our prime objective is to test the sequenced workflow hypothesis using five real 3D MT datasets. We use Electromagnetic Geological Mapper (EMGeo) to invert the data. EMGeo is a parallelized 3D finite difference (FD) non-linear conjugate gradients (NLCG) minimization algorithm (Newman & Alumbaugh, 2000), with a pre-conditioner described in Newman & Boggs (2004). Obviously our results do not apply universally; however, given the popularity of FD methods across the MT community, we believe our method and guidelines could be realistically ported to many of the other popular 3D MT inversion packages (e.g., Haber, 2000; Siripunvaraporn et al., 2005a; Siripunvaraporn & Egbert, 2009; Avdeev & Avdeeva 2009; Siripunvaraporn et al., 2011; Kelbert et al., 2014; others reviewed in Avdeeva, 2008 and Siripunvaraporn, 2011). An argument can also be made for optimizing the workflow for finite element based methods given their recent advances (e.g., Key & Owall, 2011), and because these routines can be even more computationally-demanding than FD inverse modeling algorithms (Newman, 2013).

Section 2 describes the proposed method (i.e. sequenced workflow) along with the inversion settings. Section 3 describes the five MT data experiments used in this analysis. Our results (Section 4) focus on model convergence and structural resolution, not field interpretation, but some cursory results will be discussed. We place our results in the context of previous work and refer the reader to these studies for further description of the geothermal systems themselves. Using multiple MT datasets we find that following the prescribed sequenced workflow for inversion uses fewer computational resources than the standard approach, and also retrieves a better-fitting 3D solution and corresponding resistivity model of the geothermal system. In an a priori sense, these benchmarks are critical to operators looking for accurate resource information at low cost.

2. SEQUENCED WORKFLOW

We propose segmenting the 3D MT inversion process into two steps. First, the low frequency band (<1 Hz) is inverted on a coarse model mesh. A prescription for mesh design is given below. After fitting the low frequency data (root mean squared, $RMS < 2$), the resulting model is refined, or reparameterized, onto a finer mesh. In the second step, all data are inverted using the refined coarse solution as a starting model. 1 Hz is chosen somewhat arbitrarily as the dividing frequency, although MT data collected to image geothermal or environmental targets (on the order of a few kilometers depth) commonly straddle ~ 1 Hz.

The remainder of this section describes how we tune the inversion settings to reliably generate accurate solutions that converge efficiently and mitigate user-inflicted bias.

Total Model Size

Model boundaries adversely affect interior model parameters when they are located too close to MT receivers, a modeling phenomenon that originates from lateral homogeneous Dirichlet boundary conditions. Weaver (1994) states that boundary effects are no longer apparent at a distance of three skin depths, where skin depth is calculated using the lowest inverted frequency. At the model interior, signal amplitude of a lateral boundary effect originating at a distance of three skin depths is approximately $1/e^3$ or five percent of the forward solution's field amplitude. Expansion of the total model footprint to five skin depths from boundary to receiver generates some additional costs, but is often warranted in geologic environments where a priori understanding of penetration depth often underestimates reality. In the vertical direction, model space should extend a few skin depths into the Earth based on the lowest inverted frequency and also incorporate an air layer to pad the Earth model.

FD Node Separation

The volume of interest in a typical high-temperature geothermal survey extends down to capture the transition from electrically conductive hydrothermal-alteration products (i.e., smectite-zeolite clays) into the underlying and relatively more resistive core of the geothermal reservoir (Pellerin et al., 1996). In some cases this volume also includes a shallow electrically conductive heat source at its base. Model space is discretized using a Cartesian parameterization with uniform FD node separations throughout the volume of interest in the neighborhood of the MT array. Uniform node spacing ensures maximum accuracy when modeling important targets.

Beyond the model interior, horizontal node separation increases at 20% out to the lateral model boundary (3-5 skin depths away), while within the model interior node separation is kept constant. Vertical node separation may modestly change near topography (see below), but is uniform 1 – 8 km below the topographic surface, growing at 20 % beyond this zone.

For the experiments considered in this work, the coarse inversion mesh ranged from 50 to 80 nodes in each dimension, while the fine or standard mesh used 90 to 150 nodes in each dimension.

Topography

Changes in elevation and bathymetry on the order of less than 100 m are known to distort MT signals induced within deeper conductive structures (Jiracek, 1990). In effect, this phenomenon restricts model parameterization at the surface of the model where one must accurately model topography using a fine discretization. We propose using a uniform 50 m vertical node separation from 500 m above the highest elevation to 500 m below the lowest land or bathymetric surface. Above this interval, in the air, we grow at 30 % to pad the area of interest. Below the topographic interval, vertical node separation grows at a rate of 20 % until node separation equals the uniform increment.

Model Refinement

The issue of topography also appears during the reparameterization phase of the proposed workflow – when coarse topography is refined. Care must be taken to replace those cells lying immediately below the topographic surface, which were masked with resistive air values during the first inversion step because topography was discretized using large lateral FD separations. This becomes exceedingly important when static shift effects are not filtered out of 3D MT data prior to inverting.

During refinement, if the exact resistivity value from a neighboring coarse mesh node is assigned to a new node the result is a gradient artifact in the final resistivity model at the location of the new node. To avoid these artifacts, new FD node values should be based on the interpolated or average resistivity gradient of the coarse model.

Starting Model

Starting models are known to bias geophysical inversion, specifically when dominant structural features are included. To minimize this source of bias, we propose using an homogeneous starting model that encompasses topography and bathymetry, treating air and water with appropriate resistivity values. We validate the sensitivity of a particular model feature by repeating the inversion experiment using different starting models, and then comparing the results.

Regularization

To stabilize the inversion, a smoothing criterion or Tikhonov regularization operator is included in the objective function (Tikhonov & Arsenin, 1977). Specifically, we initialize from a regularization parameter value (λ) of 1.25, and then make 50% reductions in λ when the NLCG algorithm stalls in its line search. This relaxation approach successfully imaged the Coso geothermal field method (Newman et al., 2008). λ is reset after model refinement because the second part of the sequenced workflow is essentially a new inversion.

3. DATA

MT data transfer functions relate components of the measured horizontal EM fields to a 2x2 complex impedance tensor (Z) in the Fourier domain. The present study considers five real 3D MT datasets, each containing between 101 and 138 stations. The survey areas range in size from 39 km² (Coso) up to a few hundred square kilometers (Krysuvik; Hengill). In general, the inverted bandwidth is four or five decades, 200—0.01 Hz. Only off-diagonal impedance tensor elements (Z_{xy} , Z_{yx}) are inverted for the present experiments (see below). We decimate the Z_{xy} and Z_{yx} transfer functions to 3 or 4 samples per decade, and mask the data points that we know are contaminated by noise. We assign data weights for the inversion using a relative impedance measure of 5% of the amplitude of the impedance tensor component.

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Recently, the role of the on-diagonal impedance tensor elements (Z_{xx} and Z_{yy}) in the 3D imaging process has gained attention (Newman et al., 2008; Patro & Egbert, 2011; Rosenkjaer, 2011; Rosenkjaer & Oldenburg, 2012; Jones et al., 2013; Tietze & Ritter, 2013). One observation of these works is that as on-diagonal element amplitudes approach off-diagonal element amplitudes on-diagonal variances naturally collapse to real errors, and full tensor analysis becomes critical. From our experience, imaging noisy on-diagonal tensor data does not significantly change the interpretation of important geothermal structure within several kilometers of the surface accessible by drilling. Clearly, in cases where on-diagonal component amplitudes are large at high frequencies, full tensor analysis becomes necessary even to retrieve models above drill depth. Further work will explore how modeling is affected by full tensor weighting measures.

Figure 2. Final Xzy (a,c) and Yzx (b,d) phase misfits for 3-D MT inversion experiments at Coso (A), Raft River (B), Krafla (C), Hengill (D) and Krysuvik (E). Results for standard workflow (a, b) poorly fit the low frequency data relative to the sequenced workflow results (c, d).

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For the five datasets we investigated, the Z_{xx} and Z_{yy} components showed low relative amplitudes over the penetration length of interest (<3 km). For example, 85% of the Krafla data had on-diagonal to off-diagonal amplitude ratios less than 1:10; 80 % of the higher amplitude on-diagonal data were below 0.1 Hz. Therefore, inverting and interpreting the upper 3 km using only Z_{xy} and Z_{yx} appears warranted. Given the observation that on-diagonal amplitudes generally increase with decreasing frequency (i.e., increasing penetration length), it is clear that full tensor analysis would be required to accurately model the deep roots (>6 km) of these high temperature 3D geothermal systems.

Coso

Coso geothermal system, located in the Walker Lane/ Eastern California Shear Zone, produces fluids in excess of 250°C from a permeable reservoir 1–3 km below the surface. Newman et al. (2008) inverts 125 MT soundings recorded in the Coso area during 2003–2005 (Wannamaker et al., 2004). The authors construct a complex resistivity

model of the buried two-phase geothermal field by 2D and 3D inversion. We used 101 stations from this dataset. Masking was applied to the low frequency (<0.1 Hz) Z_{yx} data, because of a potential contamination from the Bonnaville Power Authority DC intertie transmission line. The DC intertie runs N-S from north of Los Angeles to The Dalles, OR, inducing a strong magnetic field oriented E-W in the Coso area. Wannamaker et al. (2004) used distant remote reference MT observatories at Parkfield, CA and Socorro, NM to eliminate this far-reaching noise source; however, we observe non-physical Z_{yx} phase trends at low frequencies in the post-processed data, which were not analyzed in their inversion.

Raft River

Characterization of the geothermal field at Raft River, Idaho is part of an on-going Enhanced Geothermal System demonstration project sponsored by the US Department of Energy to assess the viability of well stimulation and thermal stress as a means of increasing subsurface permeability (Bradford et al., 2013). To characterize the Raft River site, Maris et al. (2012) modeled the electrical resistivity distribution of the Raft River geothermal field in Southern Idaho using 105 MT stations in a 3D array. We invert the same dataset used by Maris et al. (2012).

Krafla

138 MT soundings were acquired to image the Krafla volcanic system and NNE-SSW trending fissure swarm located in NE Iceland during several campaigns between 2004 and 2006. Gasperikova et al. (2011) reports 3D modeling results of the Krafla and Hengill MT datasets; including interpretation of an electrically conductive feature at Krafla as being related to the magma that was intersected by the deep Iceland Deep Drilling Project (IDDP) well. Forthcoming work compares different 3D Krafla and Hengill MT inversions using three different codes: MT3DInv (Haber et al., 2000); WSINV3DMT (Siripunvaraporn et al., 2005); and EMGeo. We invert 112 stations from this Krafla dataset.

Hengill

We invert 138 MT soundings from Hengill, one of the largest geothermal systems in Iceland, which were collected by different research groups from 2000—2006. Gasperikova et al. (2011), Arnason et al. (2010), Rosenkjaer (2011) and Rosenkjaer & Oldenburg (2012) each invert a subset of the Hengill MT dataset and deliver interpretations of the major structural features.

Krysuvik

3D MT field data recorded over a geothermal field in the Krysuvik area of the Reykjanes peninsula in SW Iceland were analyzed and interpreted by Hersir et al. (2013). We invert the same 102 station dataset.

4. INVERSION & MODELING RESULTS

Inversion experiments were executed using the massively-parallelized EMGeo algorithm, typically using ~4,000 core processors of Hopper Cray XE6 (1280×10^{15} floating point operations per second; 217 TB memory) located at Lawrence Berkeley National Laboratory's National Energy Research Scientific Computing Center (NERSC). On Hopper, solving the sequenced problem with final (fine) mesh dimensions of $120 \times 120 \times 120$ (on average) required a total runtime of 2-6 hours. Alternatively, we executed some of the inversions on 240 processors of a local Dell C6100 cluster (5.6×10^{12} floating point operations per second; 1056 GB memory). Running on our local cluster, the sequenced problem commonly required 4-6 days.

We find that sequenced workflow retrieves a better-fitting model in all experiments. Figure 2 shows final model misfit to the recorded phase data for the five datasets. We compare the standard workflow result with the sequenced workflow result for each experiment. We only compare phase because it is more sensitive to changes in subsurface resistivity. Predicted phase misfits for the standard approach commonly range from ± 10 –25 degrees across the low frequency band. When we use the sequenced workflow we effectively reduce these errors to ± 5 degrees, which is a generally acceptable tolerance for MT modeling.

Based on the results presented one might argue that the standard workflow solutions for Krafla, Hengill and Krysuvik actually would converge to the low frequency data if they were allowed to continue iterating. In reality, all three Iceland standard workflow runs repeatedly stalled out in the NLG line search despite reducing λ ; this is the criterion for inversion termination.

In some cases, the result of the first part of sequenced workflow (i.e., the coarse model) predicts statically shifted responses at some stations. We observe that these statics are removed during the second part of the workflow, in effect improving near-surface accuracy.

We find that sequenced workflow is also more efficient. Figure 3 summarizes model convergence (RMS) as a function of computational cost for both standard and sequenced workflow inversions that were run for each experiment. The sequenced workflow is less costly for every experiment, with cost savings being as high as 50% in the case of Coso. The Krafla, Hengill and Krysuvik standard inversions failed to converge so no cost-savings was determined.

Lastly, we find that running the coarse part of the sequenced workflow costs approximately 1% of the full sequenced inversion cost. Also, there was no observed advantage to running the coarse inversion below an RMS=2 in terms of the cost of the second part of the workflow.

5. DISCUSSION

We use our results from 3D inverse modeling of the Krafla data to illustrate the ramifications of interpreting a model that poorly fits data below 1 Hz (Figure 4). The model generated from standard inversion workflow does not contain any information about the electrically conductive pathway that Gasperikova et al. (2011) interpreted as the conduit that supplied the magma encountered by the deep IDDP well. It also fails to image the relatively more resistive fractured reservoir at 1–3 km depth. Using the sequenced workflow inversion we retrieve a geologically consistent model of a high temperature geothermal system, which images both the magmatic conduit and the resistive core of the geothermal reservoir. In fact the coarse model also clearly retrieves these two features despite its lack of near surface resolution and unrealistic smoothness. This is remarkable because we used ten times more resources in the standard workflow compared to the coarse part of the sequenced inversion.

In practice, 3D MT models are orders of magnitude larger than typical 2D problems and contain millions of unknown parameters. At this scale, there are a few experimental design factors that can lead to solution bias, inefficient model-data convergence, or in some cases a lack of convergence.

One of the most important inversion design aspects is model parameterization. When the inverted bandwidth is broad (3-5 decades) it is difficult to optimize the interior FD node separation. Standard workflow results indicate that it is challenging to fit low frequency data using a finely sampled model mesh, probably because the data are oversampled. This ultimately translates to inefficiencies in the standard inversion's descent path, and in some cases (e.g., Krafla, Hengill and Krysuvik) forces the inversion to stall before reaching an acceptable minimum. The sequenced workflow addresses this issue by linking the results of two different model parameterizations. This is not unlike the multifrequency joint inversion problem (e.g., Key et al., 2009), in which one must find a way to strike a balance between fitting data of competing wavelength.

Figure 3. Comparison of convergence efficiency for standard workflow inversion (black) and sequenced workflow inversion (red). The sequenced workflow curves are separated into coarse (dashed) and fine (solid) parts. Note that cost is plotted on a log scale.

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A second important design aspect concerns the starting model. In this paper, we only show inversion results from 10 Ohm-m homogeneous starting models that include topography and nearby bodies of water. However, we also used 30 Ohm-m and 100 Ohm-m starting models to understand the robustness of a particular modeled feature. We recommend this approach because introducing ad hoc resistivity structure, unless determined through a different geoscientific technique, is known to bias 3D modeling due to the inherent degree of nonuniqueness in MT inversion.

Figure 4. Final result comparison from 3-D inversion of MT data recorded at Krafla geothermal field retrieved using (A) standard workflow and (B) sequenced workflow. The standard model retrieves neither the resistive core of the geothermal reservoir, nor the strong electrically conductive ascending pipe feature interpreted as the source of the magma encountered in the deep IDDP well.

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6. CONCLUSIONS

According to our results from five different high-temperature geothermal MT surveys, the proposed sequenced workflow for 3D FD MT inversion improves both the accuracy and efficiency of the inversion process. Siripunvaraporn (2011) describes how 3D MT inversion is limited by three factors: processor technology, the form of the mathematical algorithm, and the form of the forward modeling scheme. In this paper we showed how workflow optimization could also improve 3D MT inversion.

ACKNOWLEDGEMENTS

The authors thank Michael Commer, Erika Gasperikova, and an anonymous reviewer for their helpful suggestions and insight; the Iceland GeoSurvey for sharing data from Krafla, Hengill and Krysuvik geothermal fields; and Phil Wannamaker for sharing data from Raft River geothermal field. This work was carried out at Lawrence Berkeley National Laboratory with funding provided by the Department of Energy Geothermal Program Office under contract GT-480010-19823-10, and Office of Basic Energy Sciences under contract DE-AC02-05CH11231.

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Figure 1. Sequenced workflow diagram

Figure 2. Final Zxy (a,c) and Zyx (b,d) phase misfits for 3-D MT inversion experiments at Coso (A), Raft River (B), Krafla (C), Hengill (D) and Krysuvik (E). Results for standard workflow (a, b) poorly fit the low frequency data relative to the sequenced workflow results (c, d).

A. Coso

B. Raft River

C. Krafla

D. Hengill

E. Krysuvik

Figure 3. Comparison of convergence efficiency for standard workflow inversion (black) and sequenced workflow inversion (red). The sequenced workflow curves are separated into coarse (dashed) and fine (solid) parts. Note that cost is plotted on a log scale.

Figure 4. Final result comparison from 3-D inversion of MT data recorded at Krafla geothermal field retrieved using (A) standard workflow and (B) sequenced workflow. The standard model retrieves neither the resistive core of the geothermal reservoir, nor the strong electrically conductive ascending pipe feature interpreted as the source of the magma encountered in the deep IDDP well.