Environmental monitoring of leaks using time-lapsed long electrode electrical resistivity

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A B S T R A C T
Highly industrialized areas pose challenges for surface electrical resistivity characterization due to metallic infrastructure. The infrastructure is typically more conductive than the desired targets and will mask the deeper subsurface information. The risk of this occurring may be minimized if steel-cased wells are used as long electrodes in the area near the target. We demonstrate a method of using long electrodes to electrically monitor a simulated leak from an underground storage tank with both synthetic examples and a field demonstration. Although the method of using long electrodes has been proposed by others, no time-lapse resistivity data have been collected, modeled, and analyzed within a nuclear waste tank farm environment. Therefore, the main objective of this work was to test whether the long electrode method using steel-cased wells can be employed to spatially and temporally track simulated leaks in a highly industrialized setting. A secondary objective was to apply a time-lapse regularization procedure in the inverse modeling code, similar to the 4D tomography approach by Kim et al. (2009), and to test the procedure’s effect on the quality of the outcome regarding plume intensity and position.

For the synthetic examples, a simple target of varying electrical properties was placed beneath different types of layers of low resistivity to simulate the effects of the infrastructure. Both surface and long electrodes were tested on the synthetic domain, and the test cases covered a variety of survey parameters including low and high electrode density, noise, array type, and the explicit location of the wells relative to the target. All data were processed in four dimensions, where the regularization procedure was applied in both the time and space domains. The synthetic test case showed that the long electrode resistivity method could detect relative changes in resistivity that was commensurate with the differing target properties. The surface electrodes, on the other hand, had a more difficult time matching the original target’s footprint unless the electrodes were distributed at a greater density on the surface. The simulated tank leak in the field experiment was conducted by injecting a high conductivity fluid in a perforated well within the S tank farm at the Hanford Site, and the resistivity measurements were made before and after the leak test. The field results showed a lowered resistivity feature develops south of the injection site after cessation of the injections. The parameter used in the time-lapsed inversion had a strong influence on the differences in inverted resistivity between the pre- and post-injection datasets, but the interpretation of the target was consistent across all values of the parameter. The long electrode electrical resistivity monitoring (ERM) method may provide a tool for near real-time monitoring of leaking underground storage tanks given a sufficient density of wells.

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1. Introduction

The Hanford Site in southeastern Washington has 177 underground liquid waste storage tanks with nearly 210×10^6 L of highly radioactive legacy waste generated from plutonium production for nuclear weapons. Of these, 67 single-shelled tanks are known or suspected as having leaked, possibly releasing an estimated 4×10^6 L of radioactive fluids into the vadose zone (Gephart and Lundgren, 1998).

The Department of Energy has conducted liquid waste retrieval from the single-shelled tanks for several years to help reduce the risk from the aging tanks (Walker and Cavallaro, 1996). The waste is transferred to safer double-shelled tanks for interim storage. Eventually all waste will be converted to a stable waste form, with the original plans calling for remediation at a waste treatment and immobilization plant (WTP). However newer plans have been reformulated to send low activity waste that would otherwise have gone to the WTP to supplemental treatment by other means, such as bulk vitrification (Brooks et al., 2006; Nassif et al., 2008).

The waste tanks are grouped together in number of tank farms, which are highly complex industrial areas with below ground piping.
networks, distribution manifolds and divergence boxes needed to move the waste from the generating plant to specific tanks, electricity distribution networks, and other waste retrieval infrastructure (Haberman, 1995). Routine leak detection is conducted either through liquid level monitoring inside the tank or soil monitoring outside the tank. Unfortunately, intra-tank monitoring is not reliable during liquid waste retrieval due to the nature of the retrieval operations and changing liquid levels.

Remote sensing ex-tank methods are also used within the tank farms for routine characterization and retrieval monitoring. Steel-cased leak detection wells are placed around each tank for use by down-hole geophysical logging tools, including spectral gamma and neutron logging (Gee et al., 2007). Unless multiple tools are used, however, it would take several days to log all wells around a tank.

Instantaneous leak detection during retrieval is impossible with the borehole logging methods. Additionally, these borehole tools have limited volume sensing capabilities (Koizumi et al., 1994), making them susceptible to missing a leak.

Surface-based electrical resistivity monitoring (ERM) has the potential to overcome these issues. ERM refers to using the temporal information from repeated electrical resistivity surveys to infer fluid movement over time. This author has used the terminology of electrical resistivity characterization (ERC) elsewhere to describe a single snapshot of resistivity to simply map the spatial distribution of resistivity targets (see Rucker et al., 2009a; 2010). Ramirez et al. (1996) and Daily et al. (2004a) described several ERM methodologies that could be used around a leaky tank, including the incorporation of steel-cased wells as long electrodes. The tests used a series of nested borehole electrodes shorted together to form a long electrode analog around a partially buried steel tank. Geophysical experiments in Ward and Gee (2000) and Barnett et al. (2003) described several injection experiments at different test facilities on the Hanford site, where steel-cased wells as electrodes were used for the high-resolution resistivity method. Ramirez et al. (2001) also showed an example of using long electrodes from the injection experiment at same the test facilities. Burke (2006) and Schofield (2006) described a time series-based transfer resistance monitoring technology with long electrodes around storage tanks using the patented methodology by Fink (2006). Rucker et al. (2010) demonstrated that long electrode ERC can be used to define the spatial distribution of historical leaks in an actual tank farm at Hanford.

Although the method has been proposed by others, no ERM data have been collected and analyzed within the Hanford tank farm environment. Therefore, the main objective of this work was to test whether the long electrode ERM method, with steel-cased wells, can be used to spatially and temporally track simulated leaks in an industrialized (or nuclear) tank farm setting. A secondary objective was to employ a time-lapse regularization procedure in the inverse modeling code, similar to the 4D tomography approach by Kim et al. (2009), and to test the procedure’s effect on the quality of the outcome regarding plume intensity and position.

To test the hypothesis that ERM is capable of monitoring for leaks from a nuclear waste tank, a set of synthetic test cases as well as a full-scale field experiment were conducted. The synthetic test cases used ERM to track the evolution of a simple target in a domain that included 1) an overlying conductive surface layer and 2) a set of distributed pipes to mimic the infrastructure. Both surface and long electrode surveys were tested to demonstrate the ability of long electrodes to monitor plumes in complex environments. The synthetic test cases were run with a variety of survey parameters such as array type, measurement noise, and electrode density and position to evaluate their effects on the ability to image the synthetic plume. The field experiment included the acquisition of resistivity data collected as independent snapshots before and after a series of simulated leaks from tank S102 in the S Tank farm of the Hanford Site. To test the time-lapse regularization procedure, the snapshots from both field and synthetically derived data were inverted together using a smooth regularization method in both the time and space domains.

Given the speed of field data acquisition on a limited subset of wells and the availability of highly efficient computational platforms, the method could conceptually be applied in near real-time to monitor for leaks during waste retrieval. Alternatively, the concept of long-term environmental monitoring with time-lapsed long electrode imaging could be used at industrial facilities where a sufficient number of wells exist (e.g., refineries or fuel depots), or for larger spatial applications such as the monitoring of secondary recovery of oil or carbon sequestration (e.g., Daily et al., 2004b).

2. Site description

The S tank farm is located in the southern portion of the 200 West Area of Hanford’s central plateau (Fig. 1). The S tank farm is one of 12 on the Hanford Site and is bordered by the SY tank farm on the northeast corner and the SX tank farm to the south. The tank farm is organized such that the underground tanks are aligned in rows with three tanks per row and centers spaced approximately 30 m apart. Numbering of the tanks start with S101 in the northeast corner of the farm and S112 is in the southwest corner. The tanks are approximately 23 m in diameter with a capacity of 2870 m³ (758,000 gal).

The S and SX tank farms contain aqueous waste generated from chemical processing that was conducted in the S plant from 1952 to 1966 (Agniew, 1997). In general, highly acidic waste streams were over neutralized with sodium hydroxide and routed to tanks for storage. The high pH resulted in the formation of precipitates of uranium, heavy metals, and strontium-90 that eventually settled to the bottom of the tanks. Sophisticated inventory models were later developed to help understand specific risks from known leaks from the tanks in these farms. Lichtner and Felmy (2003) developed inventories for tanks SX108, SX109, and SX115 and showed extremely high concentrations of sodium (19.2 mol/L) and nitrates (5.46 mol/L) for SX115. At the S tank farm, only S104 is suspected to have leaked, with volume estimates of 91 × 10³ L and nitrate concentrations of 3.04 mol/L (Khaleel et al., 2007).

3. Geology

The Hanford Site is located within the Pasco Basin of the Columbia Plateau in southeastern Washington State. The plateau is a broad plain that is underlain by a thick sequence of basalt flows (the Columbia River Basalt Group) more than 3000 m thick (Paillet and Kim, 1987). The basalt flows have been folded and faulted, creating broad structural and topographic basins.

Sediments underlying the Hanford Site are glacial–fluvial as a result of great floods that swept through the Columbia Basin during the past 15,000 years (Gee et al., 2007). Fig. 2 shows a cross section from two borehole logs and describes stratigraphic sequences taken from west to east through the S tank farm area (cross section identified in Fig. 1); the figure was modified from Johnson and Chou (1998). The major formations from top to bottom include a Pleistocene-age Hanford formation resulting from the catastrophic flood deposits of glacial Lake Missoula, a Pliocene-age calcified paleosol Cold Creek unit, and the Pliocene-age Ringold formation consisting of overbank deposits from the ancestral Columbia River (Zachara et al., 2007).

Much of the historical contamination in the 200 Areas at Hanford is confined to the Hanford formation, with the exception of the more conservative compounds such as nitrate, and pertechnetate (TeO₄⁻); these compounds may travel to the water table (approximately 80 m below ground surface) in a relatively short period of time. Locally at the S and SX tank farms, the Hanford formation can be divided into subunits based on loose boundaries of coarse and fine grained fractions. These subunits are described from top to bottom (and shown in Fig. 2): Subunit H1b is the uppermost stratigraphic unit in
the tank farm area, but is completely missing beneath the tank farm due to removal during construction and replacement by a reworked sand and gravel backfill (Reidel and Chamness, 2007). In surrounding boreholes this subunit H1b ranges from a few meters in thickness to the east and up to 12 m to the west. Below this subunit lies subunit H1a, which consists predominantly of an interstratified silt to very fine sands and ranges in thickness from 0 m in the farm (due to removal) to about 9 to 12 m outside the farm. Subunit H1 is a coarse unit dominated by gravel to gravelly sand and ranges in thickness from 1 m to nearly 10 m beneath the tank farm. Particle size results from several wells around the site show averages of approximately 30% gravel, 66% sand, and only 4% mud for H1 compared to the materials directly above and below it that average <1% gravel, 90% sand, and 9% mud (Reidel and Chamness, 2007). The bottom lying subunit H2 consists primarily of interstratified silty sands and thins from about 22 m on the east to approximately 10 m on the west side of the farm. Johnson and Chou (1998) suggest that this thinning may signify some scouring on top of the subunit.

Fig. 1. Location of the S tank farm on the Hanford Site.

Fig. 2. Geologic cross section through the center of S tank farm (modified from Johnson and Chou, 1998).
4. Numerical modeling

The three dimensional inversion of long electrode data is similar to that presented in Loke and Dahlin (2002) and Loke et al. (2003), with either the L2 norm smoothness constrained least squares that aims to minimize the square of the misfit between the measured and modeled data (deGroot Hedlin and Constable, 1990; Ellis and Oldenburg, 1994):

$$\left(j^2 I_i + \lambda_i W^T W \right) \Delta r_i = j^2 R g_i - \lambda_i W^T W r_{i-1}$$

(1)

or the L1 norm that minimizes the sum of the absolute value of the misfit:

$$\left(j^2 R g_i + \lambda_i W^T R_m W \right) \Delta r_i = j^2 R g_i - \lambda_i W^T R_m W r_{i-1}$$

(2)

where $g$ is the data misfit vector containing the difference between the measured and modeled data, $J$ is the Jacobian matrix of partial derivatives, $W$ is the spatial roughness filter, $R_g$ and $R_m$ are the weighting matrices to equate model misfit and model roughness, $\Delta r_i$ is the change in model parameters for the ith iteration, $r_i$ is the model parameters for the previous iteration, $l$, and $\lambda_i$ is the Lagrangian spatial dampening factor. The logarithms of the model resistivity and measured apparent resistivity values are used as the model parameters and data respectively in the above equations. For this work, we invoked the L2 norm smoothness constrained least squares model.

Accommodating long electrodes in commercial resistivity modeling codes can be accomplished easily by taking advantage of the existing code structure. Although the long electrodes act as linear sources and receivers, they can be modeled with a point source on the surface and by assigning to the long electrode's position a series of very conductive cells of uniform value, say 0.01 $\Omega$ m, to simulate a metallic well. The current source is located at a node and the adjacent four cells are assigned the low resistivity values (Fig. 3a). The high contrast between the well's resistivity and that of the surrounding medium can cause adverse effects in the numerical model such as accuracy and stability. In order to reduce the effects of this problem, the forward model mesh is discretized more finely relative to the inverse model mesh so that a more gradual transition of electrical resistivity occurs between the well and the host medium.

An example of the capability of the resistivity code is demonstrated by placing a single long electrode in a 100 $\Omega$ m background. The numerical results of transfer resistance using the finite difference method are compared to an analytic solution of an infinite conductor of infinitesimal diameter (from Johnston et al., 1987; Warrick and Rojano, 1999):

$$R = \frac{V}{I} = \frac{\rho}{4 \pi b} \ln \left[ \frac{r^2 + b^2} {r^2 + b^2} \right]^{0.5} + b$$

(3)

where $\rho$ is the resistivity of the background, $b$ is the length of the long electrode (or well) extending from the surface of the earth and $r$ is the distance between the center of the well and the potential measurement location at the surface of the earth. The electrode-to-ground contact resistance is assumed to be constant for the length of the well. Eq. (3) can be shown to revert to the solution of a homogeneous half-space for point electrodes, as $b \to 0$. For the numerical modeling, the length of the long electrode was simulated as 44 m, which is typical of the wells in Hanford's tank farms. The transfer resistance results in Fig. 3b show that the resistivities between 0.01 and 0.001 $\Omega$ m assigned to the long electrode produce the most accurate results. Specifically for this example, the resistivity of 0.006 $\Omega$ m is the most accurate with a difference of less than 4% from the analytic values for the entire distance of 1 to 50 m away from the well. The differences are likely partially due to the assumptions of the infinite conductor and infinitesimal diameter for the analytic solution compared to the finite conductor and diameter for the numerical models.

To perform a 4D inversion that accommodates both time and space domains, we take the approach demonstrated by Kim et al. (2009). The time domain is incorporated directly into the regularization procedure by modifying Eq. (1):

$$\left(j^2 I_i + l (W^T W + \alpha M^T M) \right) \Delta r_i = j^2 R g_i - \lambda_i (W^T W + \alpha M^T M) r_{i-1}$$

(4)

where $M$ is the difference matrix applied across the time models with only the diagonal and one sub diagonal elements having values of 1 and -1, respectively. Similar in concept to the spatial roughness filter, the temporal roughness filter, $M$, minimizes the difference in the resistivity of each model cell and the corresponding cell for the next temporal model. The time-lapsed regularization parameter, $\alpha$, is the temporal...
damping factor that gives the relative importance weight for minimizing the change in the resistivity between one temporal model and the next model. Eq. (4) assumes the electrical resistivity varies smoothly in time and space, and the degree of smoothness in time is controlled through $\alpha$ by the user. Higher values of $\alpha$ will result in time-lapsed inverted models that are more similar to one another. A value of zero for the time lapsed parameter equates to no time regularization.

5. Synthetic test cases

We demonstrated the applicability of ERM in an industrial setting using synthetic test cases with a simple target, similar to the models presented in Rucker et al. (2010). The first trial was to conduct a surface-based electrode resistivity survey over a domain for pre- and post-injection examples to understand the limitations of the method in complex environments. The second trial was to conduct models with long electrodes. The synthetic cases for the surface electrode models explored a variety of settings, including electrode density (electrodes spaced at 6 m or 10 m over a grid), array type (pole–pole or dipole–dipole), addition of noise (0 or 2% added to the apparent resistivity data), and the type of near surface conductive layer (solid layer or distributed pipes) that would act as the feature to add complexity to represent the industrial setting. The near surface conductive layer was 0.25 m thick, located 1 m below ground surface, with a resistivity of 0.01 $\Omega\text{m}$. It should be noted, however, that the numerical equations do not accurately depict subsurface metallic items because they do not explicitly account for the interfacial polarization between the metal and the adjacent electrolytic fluids. Wait (1982) accommodated such problems analytically with a boundary condition that accounts for a secondary potential field from an idealized cylindrical metallic body. The numerical work presented here, therefore, is an approximation to the pipe problem.

5.1. Surface electrode models

For the base case representing the pre-injection time, the background resistivity was set to 100 $\Omega\text{m}$ with domain dimensions of 60 m in all directions. For the post-injection example, the simple target was placed at the depth between 10 and 15 m below ground surface with resistivity of 1 $\Omega\text{m}$. The target dimensions were 15 × 15 m and placed slightly off center towards the northeast. Fig. 4a shows the example domain with the near surface conductive layer and target. To represent the pipes explicitly, linear conductive features with resistivity values of 0.01 $\Omega\text{m}$, running parallel to the $x$ or $y$ axes, were placed at the 1 m depth (Fig. 5a). Square blocks of low resistivity larger than the simulated diameter of the pipes were also placed at the intersection of pipes to represent valves and junction boxes used at the Hanford Site.

The surface model trial included a forward modeling component to calculate the apparent resistivities and an inverse modeling component to calculate the estimated true resistivity given the simulated measured values from the forward modeling. The forward modeling was conducted with RES3DMODx64 (Geotomo Software, Malaysia), which is the version of the software manufacturer's forward modeling suite that can accommodate point and long electrodes. The domain for the forward model was divided into 116 finite difference blocks in both $x$ and $y$ directions, and 28 telescoping layers. The surface electrodes were distributed evenly across the surface and the acquisition campaign included collecting data as a full three dimensional set. The 4D time lapsed resistivity inverse modeling was accomplished with RES3DINx64, a 64 bit parallel-processing code (Geotomo Software, Malaysia). The value for the time-lapsed regularization parameter, $\alpha$, was fixed at 0.001 for all examples.

Table 1 lists the eight example cases run with the surface electrodes along with the corresponding figure that shows the inverse modeling results. The first set of synthetic models included a solid conductive layer, no noise, pole–pole array, and two sets of electrode densities: 10 m separation and 6 m separation over the surface grid. Fig. 4a shows a schematic of the domain with target and the inversion results are presented in Fig. 4b–g. The percent difference was a simple calculation between pre- and post-injection using the method presented in Rucker et al. (2009b). The percent difference was calculated on a cell-by-cell basis and negative percent differences reflect areas becoming more conductive. A first glance between the

![Fig. 4. Synthetic models of ERM using surface electrodes, a) model schematic, b) pre-injection inverse model results with conductive layer, no target, and low resolution surface electrode coverage, c) post-injection inverse model results with near surface layer, target, and low resolution surface electrode coverage, d) percent difference between pre- and post-injection, e) through g) repeat with high resolution surface electrode coverage. Model details are summarized in Table 1.](Image)
pre- and post-injection domains shows little differences between the two examples. Fig. 4d and g, however, shows quantitatively that there are resistivity changes within the domain due to the addition of the simple target. The figure focuses on the regions that become the most conductive after injection by eliminating all values with a percent change greater than about $-0.75\%$. The result is a target that encompasses nearly the entire northeast quadrant of the uppermost layers for the low density electrode configuration. The original target footprint is drawn on the surface for direct comparison. The higher density electrode configuration represents the target with higher fidelity, but there appears to be some noisy values in the northeast quadrant. The conclusion for these two tests is target reconstruction can be conducted, but a high density set of electrodes are needed to overcome the conductive surface layer.

Fig. 5 shows the results of running a similar set of tests to those in Fig. 4, but with a pipe layer that does not completely envelop the near surface in low conductivity values. Both low (Fig. 5b–d) and high (figures e–g) density surface electrodes were tested and the results from the high density electrodes appears to reconstruct the target slightly better than the low density electrode simulation. The last example for the set was to add a 2% noise to the apparent resistivity forward calculations for both pre- and post-injection data. The noise was added independently to each set, and the results of Fig. 5h–j show that, again, the target can be reconstructed with reasonable fidelity with this specific example of using a high density set of electrodes. One item to note, however, is the range of percent difference for the pipe example of Fig. 5 versus that of Fig. 4. Although the high end of the percent difference range is commensurate in both example sets (7 to 10% for the noise-free examples), the low end of the range is much lower for the pipe example (at $-30\%$ for the noise-free example).

Additionally, to present the same sized target in all percent difference figures (all targets in Figs. 4 and 5 are approximately 10,000 m$^3$), the opacity for the pipe example was quite low and narrow given the full range of values. For example, the opacity for Fig. 5g starts at $-15\%$, which is midway through the range as opposed to starting at 10% of

<table>
<thead>
<tr>
<th>Case</th>
<th>Electrode type</th>
<th>Array</th>
<th>Infrastructure representation</th>
<th>Electrode distribution</th>
<th>Noise</th>
<th>Figure number</th>
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<tr>
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<td>Yes (2%)</td>
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<td>Yes (2%)</td>
<td>8k-l</td>
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</tbody>
</table>

PP = pole–pole; DD = dipole–dipole.
the range as in Fig. 4g. To find targets then, one must have an appreciation for the size of the target to be expected from the survey.

The last set of examples for the surface electrodes included a dipole–dipole survey with the high density electrode configuration. The dipole–dipole data were collected in-line (as opposed to cross-line) along 11 lines in the north–south direction and 11 lines in the east–west direction, with a constant dipole spacing of 6 m, and maximum dipole separation of eight dipole lengths. The dipole–dipole example sets included a surface conductive layer (presented in Fig. 6a) and a pipe layer (presented in Fig. 6e). The dipole–dipole array has a limited depth of investigation to about 20% of the dipole separation. Results of running the forward and inverse models show in general that the method can find the top of the target with high fidelity even with noise. The reconstruction of the target’s depth actually appears to be better resolved compared to the pole–pole results. To capture the entire target, however, the method of acquisition would definitely need to encompass a larger area with more electrodes. In tank farm environments at Hanford, increasing the footprint of the electrode distribution is rarely an option because of physical boundaries. The pole–pole method allows a greater depth of investigation with a smaller footprint, with the realization that resolution of target features may suffer.

5.2. Long electrode models

The second trial included a long electrode time-lapsed inversion example to demonstrate the advantage of using wells as electrodes in infrastructure-rich areas. For this example, three snapshots were conducted: a baseline (or pre-injection) with no target, an interim injection period with the target having a resistivity of 10 Ωm, and a post-injection target of 1 Ωm. The injection creates a target that resides at the depths of 10 to 15 m below ground surface for the

Fig. 6. Continuation of surface electrode synthetic models using a dipole–dipole array with a continuous conductive layer and a pipe layer. Model details are summarized in Table 1.
duration of the injection, with dimensions of 15 × 15 m. To image the
targets, 20 long electrodes were distributed somewhat randomly
throughout the domain, with a stipulation that a minimum of 5 m
between electrodes and two electrodes through the target (see
Fig. 7a). The two electrodes were removed from the target and placed
elsewhere in the domain in low electrode density coverage areas
for additional tests. The long electrodes were 44 m in length, with
a diameter of 0.1 m and resistivity of 0.006 Ωm. The spatial density
of long electrodes (200 m²/electrode) for the model was meant to
replicate that of a typical Hanford tank farm.

The pole–pole array was used for all simulations. The pole–pole
(PP) array has the least number of combinations for a truly
three-dimensional acquisition methodology, compared to the pole–dipole
(PD) and dipole–dipole arrays (DD). The numbers of possible
combinations (C) for each of these arrays are:

\[ C_{PP} = \binom{n}{2} \quad (4) \]

\[ C_{PD} = 3 \cdot \binom{n}{3} \quad (5) \]

\[ C_{DD} = 3 \cdot \binom{n}{4} \quad (6) \]

where \( n \) is the number of electrodes and the parentheses represents
the combinatorial function of \( n!/(n-k)!k! \). For 20 electrodes, the
number of data values for the pole–pole array is 190 versus 14,535
values for dipole–dipole. Granted, not all dipole–dipole combinations
are viable, especially those with extremely large geometric factors
and those in the null-field geometry, where both potential electrodes
are placed on the same voltage potential. However, an extremely large
number of combinations may be prohibitive where the dynamics
of the plume may be evolving quickly.

The various model simulations are summarized in Table 1 and the
results for the simple conductive layer with and without noise are
shown in Fig. 7b–h. The results from time-lapsed long electrode

![Fig. 7. Synthetic models of ERM using long electrodes, a) schematic of electrodes with target, b) resistivity contours for a 10 Ωm target, representing an interim injection period, c) resistivity contours for a 1 Ωm target representing a post-injection period, d) percent difference between pre-injection base case and no target to that of the interim injection with a target of 10 Ωm, e) percent difference between pre-injection base case and no target to that of the post-injection with a target of 1 Ωm, f) percent difference between pre-injection and target of 10 Ωm with 2% noise added, g) percent difference between pre-injection and target of 1 Ωm with 2% noise.](image-url)
inversion are presented as contour plots of resistivity of the uppermost layer (layer thickness = 1.4 m) of the model in Fig. 7b and c. Rucker et al. (2010) demonstrated that the long electrode inversion results typically have a funnel shape, where the low resistivity target has the largest footprint at the surface. The intensity of the target decreases with depth likely due to a modeling artifact when incorporating wells with finite resistivity, in this case 0.006 Ωm. Based on the finite conductivity of the well in the model, the current density along the length of the well decreases with depth. It is suspected that the vertical information is lost because all target information is assumed to exist at the highest current density.

Fig. 7d compares the interim 10 Ωm target to the baseline and shows a decrease in resistivity by up to one percent where the original target existed (the original target is outlined for an easy comparison with the inverse model results). Theoretically, the resistivity decrease should be 90%, but the smoothing in both time and space, combined with the near surface conductive infrastructure, are the likely reasons for a weakened target. Unlike the surface electrode example, the long electrode places the target in its correct position, but is generally confined to the location of the wells. Fig. 7e compares the 1 Ωm target to the baseline, with the target intensity increasing to 3.4% change from background. When 2% noise is added to the apparent resistivity, the results in Fig. 7f and g for the 10 and 1 Ωm target, respectively, shows reasonable fidelity with higher intensity changes and elongated features outside of the target footprint, compared to the simulation with no noise.

The remaining set of long electrode synthetic models is shown in Fig. 8. These models cover a conductive layer and an overlying pipe layer, well placement in or out of the target, and noise. The weakest performance was by the model with an overlying conductive layer with wells outside of the target, presented in Fig. 8a and b, with target intensities lower than the previous models in Fig. 7. Noise added to the data allowed the intensity to increase, but with the target's center to be to the right of the actual location, as shown in Fig. 8c and d. The last set of plots from Fig. 8e–l show the results with a pipe layer, repeating the scenarios of electrodes in and out of the target and with noise added to the apparent resistivity. These models performed much better than the overlying conductive layer in reproducing the target's location. When noise is considered, the targets appear more smooth than without noise.

6. Field methods

6.1. Leak injection test

A series of tank leaks were simulated in the S tank farm around tank S102 to test the effectiveness of several resistivity based geophysical methods to quantify these leaks (Rucker et al., 2007). The leak injection system included the use of a well, originally designated as a leak detection monitoring well (located at the 10 o'clock position around tank S102), for injection of the tank waste simulant. The well was converted from a leak detection well to an injection well by perforating the 15 cm diameter carbon steel pipe from 15 to 33 m below ground surface and plugging the well below the perforated zone. The perforated zone was designed to simulate a leak from the tank bottom. The simulated waste consisted of a 25% (by volume, or 250,000 ppm) sodium thiosulfate pentahydrate solution with a specific gravity of approximately 1.138 at a temperature of 23.1 °C. The simulant had electrical properties similar to the radioactive waste stored in underground tanks, which was estimated to be

![Fig. 8. Long electrode case models showing percent difference for different survey parameters. Model details are summarized in Table 1.](image-url)
approximately 0.08 Ωm. The electrical properties of the solution were not measured explicitly for this test, but estimated from tabulated values of Weast (1986). Schön (1996) also shows similar sodium compounds with equivalent resistivity values. A series of ten simulated leaks occurred over a 3 month period with a total $51 \times 10^3$ L of solution injected into the subsurface. Table 2 lists the details of the injection schedule with volumes and flow rates.

6.2. Resistivity monitoring

Prior to the leaks, a long electrode electrical resistivity survey was conducted in the S tank farm to establish a baseline condition for comparison with the post leak test condition. The survey included resistivity measurements on the steel-cased wells using a SuperSting R8 resistivity data acquisition system (Advanced Geosciences, Inc. Austin, TX). Data acquisition took approximately 40 min to complete a full reciprocal data set on 32 wells with a measurement time of 3.6 s per cycle and two cycles per reading. The survey design, acquisition, and processing methodology was similar to the long electrode characterization conducted by Rucker et al. (2010) in the T tank farm, where the wells were used as both current transmission and voltage receiving electrodes. The pole–pole configuration was used, and the remote electrodes were located approximately 1500 m away in nearly opposite directions. The steel-cased monitoring wells were dispersed near the footprint of the northern tanks S101 through S106. The monitoring wells were typically less than 42 m in length, with the water table at approximately 70 m below ground surface.

One month after the cessation of the injection testing, a follow-on resistivity survey was completed on the same wells used in the pre-injection survey. Fig. 9 shows the scatter of the measured data for the pre- and post-injection, with data presented as apparent resistivity. The apparent resistivity was calculated the same as if it were a point electrode on the surface. The pre-injection data in Fig. 9a shows low scatter among reciprocal measurements, whereas the post-injection reciprocal measurements exhibited higher scatter. The reciprocal error was used as a means for data rejection, with those data outside the 5% range eliminated from the dataset. Of the 992 combinations, 46 were rejected for high reciprocal errors. Fig. 9c shows the scatter of pre- to post-injection apparent resistivity data. The data within Fig. 9c were used for inverse modeling.

7. Field results

Fig. 10 shows the results of the time-lapsed long electrode inversion of the S tank farm leak injection test. The data are presented as contour plots of the uppermost layer in the model; the thickness of the upper layer was 2.1 m. The modeling was conducted on a Dell PowerEdge R900 with 4 quadcore Xeon 2.93 GHz processors. The inversion modeling for the two snapshots typically finished in less than 70 min with six iterations and a final RMS less than 15%. The size of the computer was much larger than necessary to run the long electrode inversion model. Its use was due to availability and the fact that the long-electrode module was developed for 64-bit platforms. The memory requirements for this particular problem were less than 1 GB of RAM, with an inverse model domain of 34 cells by 27 cells, by 14 layers.

The top four models, Fig. 10a–d, show the logarithm of electrical resistivity for two snapshots of differing time-lapsed parameter values. Fig. 10a and b represent the before and after leak injection test results with $\alpha = 0.001$, and Fig. 10c and d represent before and after with

<table>
<thead>
<tr>
<th>Activity</th>
<th>Start date/time</th>
<th>Stop date/time</th>
<th>Approximate leak rate (l/h)</th>
<th>Operating duration (h)</th>
<th>Approximate volume (l)</th>
<th>Approximate cumulative volume (l)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leak 1</td>
<td>1/20/06</td>
<td>2/06</td>
<td>40</td>
<td>300</td>
<td>12,000</td>
<td>12,000</td>
</tr>
<tr>
<td>Leak 2</td>
<td>2/13/06</td>
<td>2/18/06</td>
<td>60</td>
<td>119</td>
<td>7140</td>
<td>19,140</td>
</tr>
<tr>
<td>Leak 3</td>
<td>3/7/06</td>
<td>3/15/06</td>
<td>20</td>
<td>194</td>
<td>3860</td>
<td>23,000</td>
</tr>
<tr>
<td>Leak 4</td>
<td>3/21/06</td>
<td>3/23/06</td>
<td>80</td>
<td>50</td>
<td>3970</td>
<td>28,970</td>
</tr>
<tr>
<td>Leak 5</td>
<td>4/12/06</td>
<td>4/14/06</td>
<td>80</td>
<td>50</td>
<td>4000</td>
<td>30,970</td>
</tr>
<tr>
<td>Leak 6</td>
<td>4/19/06</td>
<td>4/23/06</td>
<td>40</td>
<td>100</td>
<td>3970</td>
<td>34,940</td>
</tr>
<tr>
<td>Leak 7</td>
<td>4/27/06</td>
<td>5/2/06</td>
<td>40</td>
<td>117</td>
<td>4680</td>
<td>39,620</td>
</tr>
<tr>
<td>Leak 8</td>
<td>5/8/06</td>
<td>5/11/06</td>
<td>60</td>
<td>68</td>
<td>4160</td>
<td>43,720</td>
</tr>
<tr>
<td>Leak 9</td>
<td>5/15/06</td>
<td>5/19/06</td>
<td>60</td>
<td>63</td>
<td>3760</td>
<td>47,580</td>
</tr>
<tr>
<td>Leak 10</td>
<td>5/23/06</td>
<td>5/25/06</td>
<td>80</td>
<td>49</td>
<td>3880</td>
<td>51,380</td>
</tr>
</tbody>
</table>
α = 0.1. In each figure, the lower left and right hand corners have been blanked to remove resistivity data. The blanking was based on the absence of wells in the area and the extremely low sensitivity of those cells to the final resistivity distribution.

The pre-injection results in Fig. 10a and c show a low resistivity target north of tank S104 and extending west-southwest across S105. From historical characterization records and inventory reports, it is likely that tank S104 lost approximately 91 × 10^3 L of highly saline waste to the subsurface and the pre-injection assessment is mapping the footprint of the leak. Furthermore, the dipping subunits identified in the geologic assessment may be a driving force behind the westward migration. The post-injection results in Fig. 10b and d show a slight decrease in resistivity near the injection well (square symbol) at the northwest corner of S102.

The percent change in resistivity between pre- and post-injection surveys with α = 0.001 was more significant than α = 0.1, and Fig. 10e and f show these differences quantitatively. Both sets of models show a logical placement of the lowered resistivity near the injection well and both show a similar shape to the distribution of positive and negative changes (a percent change of zero is distinguished by a solid contour line). The similarity ends, however, with the intensity of those changes as indicated by the associated color scales. The smaller
α parameter represented in Fig. 10e shows that the scale of change was much greater than that associated with the larger α parameter. Fig. 11 shows the pre- and post-injection resistivity values for a model cell 8 m to the south of the injection well for a full range of α values. The lowest value for the modeling was zero, and was placed on the log scale plot as a matter of convenience. As α increases, the resistivity curves converge towards a single value (approx. 119 Ωm) and the percent difference between the pre- and post-injection model results nears zero. The time regularization appears to affect the pre-injection resistivity modeling much greater than the post-injection modeling at this cell. An inspection of behavior of different cells around the entire domain shows that the behavior can be wildly different for the shape of the pre- and post-injection curves, as they may change directions and cross as the α time-lapsed parameter increases. The cell we chose for Fig. 11 happens to be relatively well behaved. The common thread throughout the domain, however, is that the percent change in all cells tends toward zero as α increases.

8. Discussion and conclusions

ERM was demonstrated in a complex industrial settings on two examples, including a set of synthetic test cases and an actual field experiment. The synthetic cases were meant to show the expected outcome from known conditions and replicate the same layout as Rucker et al. (2010) with both surface and long electrodes. The work was expanded here, however, to include a wider range of scenarios. The field experiment was used to test the viability of ERM to monitor leaks from the underground storage tanks during retrieval from single-shelled tanks using long electrodes. The field resistivity test was conducted at the S tank farm on the Hanford Site to track the movement of an injected saline tracer into the vadose zone. Hanford has been the focus of several surface based resistivity projects in the past to map contaminant plumes resulting from direct disposal of liquid waste to the ground (Rucker et al., 2009c; Rucker and Fink, 2007). The Hanford Site is generally well suited for the technique given the contrast between the resistive host sands and conductive waste. The long electrode technique was chosen specifically for the present field study due to the highly complex nature of the focus area, with its vast amounts of metallic infrastructure that could potentially interfere with surface electrode measurements.

The time-lapsed study incorporated a time regularization scheme in the inverse model to smooth the variability across multiple snapshots. The time-lapsed parameter, α, controls the degree of temporal smoothing with larger values decreasing the expected variability. For the synthetic test cases, the α was fixed at 0.001 for all models. The results of the synthetic cases with surface electrodes showed the method could see a change in electrical properties even with a near surface conductive layer. This is a vast improvement over the results in Rucker et al. (2010), where a single snapshot using ERC with surface electrodes could not distinguish the target from the infrastructure. The ERM performed better at identifying a target when noise was low and electrode density was high. The long electrode ERM was also capable of placing the target in the correct location with a lower density of electrodes. The method appears to be more sensitive to noise than the surface electrode method, and care must be used to select good data for entry to the inverse model.

The inverse modeling of the field experiment with long electrodes was conducted by examining the effect of α on the model outcome. The results showed that the time-lapsed parameter can have a dramatic effect on the intensity of the changes. Small values of α provided minimal restriction and the pre- and post-injection values at select cells were seen to differ by a factor of 10 or more near the injection site. Larger values of α were seen to restrain those differences. Consistently throughout the domain, as the time-lapsed parameter increased, the percent difference between pre- and post-injection converged towards zero.

Although the intensity varied greatly, the shape of the target was relatively consistent for all models for the field study. The injection of a highly saline solution into the vadose zone caused a lowered resistivity feature to appear moving to the south from the injection site. This consistency in shape and location for multiple models reinforces the hypothesis that long electrodes can be used to monitor dynamic events of the subsurface. Unfortunately, understanding those results in a hydrogeologic framework will be difficult. Since the long electrode technique destroys vertical information and the regularization in both space and time smoothes the degree of resistivity from one point to the next, calibration of the resistivity data will be tenuous if laboratory petrophysical models have been developed to convert the temporal changes in resistivity to changes in moisture content or contaminant concentration. Singha and Gorelick (2006) and Rucker (2010) summarized the complications of calibrating results in this manner, including the mismatch in scale between measurement modalities and decreased sensitivity of the resistivity method away from the electrodes. They conclude that the field-scale relations between electrical resistivity and the hydrogeological parameter must be site, survey, and inversion specific.

As for a near real-time monitoring tool, the time lapsed long electrode resistivity method has the potential to turn around information quickly. An eight-channel acquisition system can conceivably acquire data on 32 wells in approximately 12 min without reciprocals. A system where the channel count is equal to the number of electrodes would minimize the total time needed to acquire data. The processing time, however, is currently the limiting factor and a one-hour old model is the quickest turnaround observed. As computing platforms become larger, together with the development of more efficient highly parallel computational algorithms (e.g., Loke et al., 2010), the time needed to conduct this step will also reduce. In the mean time, simple time series measurements of transfer resistance on multiple long electrode pairs is the fastest leak detection method deployed at Hanford (Burke, 2006).

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References
