Joint Optimization of Vertical Component Gravity and P-wave First Arrivals by Simulated Annealing

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ABSTRACT

Joint seismic and gravity analyses of the San Emidio geothermal field in the northwest Basin and Range province of Nevada demonstrate that joint optimization changes interpretation outcomes. The prior 0.3-0.5 km deep basin interpretation gives way to a deeper than 1.3 km basin model. Kirchoff prestack depth migrations reveal that joint optimization ameliorates shallow velocity artifacts, flattening antiformal reflectors that could have been interpreted as folds. Furthermore, joint optimization provides a clearer picture of the rangefront fault.
by increasing the depth of constrained velocities, which improves reflector coherency at depth. This technique provides new insight when applied to existing datasets and could replace the existing strategy of forward modeling to match gravity data. We achieve stable joint optimization through simulated annealing, a global optimization algorithm that does not require an accurate initial model. Balancing the combined seismic-gravity objective function is accomplished by a new approach based on analysis of Pareto charts. Gravity modeling uses an efficient convolution model, while the basis of seismic modeling is the highly efficient Vidale eikonal equation traveltime generation technique. Synthetic tests show that joint optimization improves velocity-model accuracy and provides velocity control below the deepest headwave raypath. Restricted offset-range migration analysis provides insights into both pre-critical and gradient reflections in the dataset.
INTRODUCTION

The United States of America is the world leader in geothermal energy extraction, with current electrical generation capacity of 3,442 MW and 124 developing projects (Matek, 2014). The majority of these new developments are in the state of Nevada, due to a relatively thin crust that results in a high geothermal gradient (Blackwell et al., 2011). Matek (2014) states that only 40% of total geothermal production potential has thus far been realized in Nevada. Coolbaugh et al. (2006) estimate that half of the remaining potential resides in reservoirs with no obvious surface expression, commonly referred to as ‘blind’ systems (Cumming, 2009). Blind systems tend to occur in areas of high fracture density, producing high permeability (Vice, 2008; Colwell et al., 2012; Dering, 2013; Anderson, 2013; Kent, 2013; Mayhew, 2013; Jolie et al., 2015). Faulds et al. (2006) conducted a regional study and found that there is a high probability of finding geothermal systems at fault intersections. Louie et al. (2012) point out that due to resolution and depth of investigation constraints, seismic reflection imaging is the only geophysical method capable of precisely imaging fault intersections at production depths. The high cost of exploratory drilling campaigns and low success rates hamper new development, which can be remedied by geophysical investigations (Faulds et al., 2010; Louie et al., 2012; Harris, 2012).

One example of an active geothermal power plant where geophysical investigation has been applied is San Emidio, which is operated by U.S. Geothermal and is located roughly 100 km (60 miles) NNE of Reno, Nevada (Figure 1). San Emidio is situated just east of the transtensional Walker Lane in the extensional northern Basin and Range province. Rhodes (2012) describes the geothermal reservoir as being found in a right-stepping series of hard-linked, north-striking, west-dipping normal faults along the western flank of the
northern Lake Range. U.S. Geothermal has an installed energy production capacity of 12.75 megawatt electrical (MWe) at San Emidio, derived from a thermal anomaly at 520 m depth, with estimated total resource potential of 44 MWe (Rhodes, 2012; Matek, 2014). Eneva et al. (2011) discuss surficial temperature and subsidence anomalies that extend northward from the current production area, which suggests the possibility of another geothermal reservoir in the northern exploration area. In order to help guide exploratory drilling, U.S. Geothermal and Optim collected seismic and gravity data at San Emidio through a U.S. Deptartment of Energy American Recovery and Reinvestment Act project. Teplow et al. (2011) states that the project’s objective was to test the feasibility of utilizing geophysical techniques to identify large-aperture fractures at depth.

Sharp density and seismic velocity gradients are created by depositional and fault contacts of unlithified valley fill adjacent to crystalline bedrock (e.g., Abbott et al. (2001)). This complex structure produces rapid lateral velocity variations that preclude the use of standard seismic analysis routines used in sedimentary systems (Louie et al., 1988; Honjas and Pullammanappallil, 1997; Louie et al., 2012). Increased subsurface complexity demands more advanced migration algorithms, as well as increased velocity model accuracy. We utilize Kirchhoff prestack depth migration (KPSDM), which is able to handle structure with any range of dip within anti-aliasing parameterization, and is regarded as robust in the presence of complex velocity variations (Louie and Qin, 1991; Biondi et al., 2014). KPSDM is based on the Born, WKBJ, and far-field assumptions (Louie et al., 1988). As with any migration algorithm, using an accurate velocity model is essential, with particular importance on lateral velocity variations (Louie and Qin, 1991; Tieman, 1995; Luo and Hale, 2014). This is due to the way that KPSDM deforms short-wavelength reflectors around the long-wavelength velocity model. Pullammanappallil (1994) introduced seismic velocity
optimization using the simulated annealing algorithm (SA), which has proven success at sites with strong lateral velocity contrasts. Louie et al. (2012) discusses how the paired use of KPSDM and seismic SA has solved many of the problems inherent to imaging geothermal sites.

Teplow et al. (2011) produced a San Emidio line 6 velocity model using seismic SA (Figure 2). Converting the preexisting line 6 velocity model to a density model using the empirical velocity-to-density relationship of Gardner et al. (1974) followed by gravity modeling reveals a noticeable misfit; the total variation across line 6 is 17.15 mGal in the observed data, but only 10.25 mGal in gravity profile created from the velocity model (Figure 3). This suggests that including gravity in the velocity model building step would result in a different outcome. Vasco et al. (1996) show there can be many equivalent-error solutions in velocity optimization, which limits resolvability of complex structure and sharp velocity gradients. First-arrival SA shows great ambiguity at depths below the deepest raypath (Pullammanappallil, 1994), but density variations at much greater depths retain their influence on gravity measurements. Typically, gravity models are manually created to support seismic velocity models (e.g., O’Donnell Jr et al. (2001)). Including gravity constraints into the velocity-building step is one means of increasing the depth of constrained velocities and reducing nonuniqueness.

Joint seismic-gravity optimization is the most successful and best-studied technique that incorporates two geophysical datasets to arrive at one solution. Models produced by the simultaneous optimization of multiple datasets are often more geologically realistic than models constrained by a single type of data (Roy et al., 2005). Rovetta et al. (2013) demonstrate that joint seismic-gravity optimization improves seismic imaging in areas with rapid lateral velocity variation. San Emidio is a prime location to test joint seismic-gravity
optimization, not only because of untapped resource potential and an outstanding dataset, but also due to a sharp density and velocity contrast at the alluvium-bedrock contact. However, joint optimization using the SA algorithm is a surmountable goal, as it is often difficult to get models to converge. Difficulties stem from the choice of an objective function that balances seismic and gravity constraints and the determination of an effective cooling schedule (Basu and Frazer, 1990; Sen and Stoffa, 2013).

Our hypothesis is that obtaining a stable joint optimization algorithm will lead to more accurate seismic velocity models. Improved velocity models increases interpretability of migrations by enhancing the resolvability of structure at depth through increased focusing of deep reflectors. This outcome could positively impact geothermal drilling success rates in the Great Basin.

Seismic and Gravity Data Processing

Optim collected seismic line 6 in 2010, which is very close to the geothermal production zone (Figure 1). Shot records for line 6 have a maximum offset of 3,220 m and a receiver spacing of 17 m (55 ft). Optim stacked ten 8-100 Hz Vibroseis sweeps at each shot point, followed by cross-correlation with the source sweep as described in Cambois (2000). We made nearly 10,000 first arrival picks on raw, unfiltered records (Figure 4), followed by trial velocity modeling using the seismic SA optimization of SeisOpt® ProTM. We made first arrival picks in the center peak of the Klauder wavelet that results from Vibroseis source correlation. Careful inspection of plotted calculated and observed traveltimes on AGC-gained wiggle trace shot records with interior and exterior muting revealed areas where we picked inconsistent data, such as shallow diffractions, pre-arrival sweep correlation artifacts,
and shot-to-shot cycle skipping. In order to determine if our models are under- or over-fit, we compute $\chi^2$ values by taking the ratio of the travelt ime model RMS error and the measurement error. We estimated the measurement error from the summed geometry, timing, processing, and picking errors, which we determined to be 6.7 ms. Removal of picks in problem areas reduced the number of picks by 30%, greatly reducing the amount of inconsistent data (Figure 5). $\chi^2$ values for the initial and final runs are 2.3 and 0.97, respectively; obtaining a $\chi^2$ value of 2.3 indicates the data are underfit, while a value 0.97 implies a very slight overfit (Van Avendonk et al., 2001). Empirically determined migration processing parameters are based on the effectiveness of suppressing surface/air wave amplitudes, while preserving steeply dipping fault reflections. Prior to migration, we applied a time-squared gain function, 20-40 Hz Butterworth bandpass filter, high-cut dip filter centered at 25 Hz with a corner velocity of 1,400 m/s, 200 ms AGC gain window, and 0.5 s raised cosine Hanning window. After migration, we used a frequency recovery filter, 3-by-3 Laplacian smoother, and clipped amplitude at twice the RMS value of the whole migrated section.

MWH Geosurveys collected 726 vertical component gravity measurements in 2008 (Figure 1). The Bouguer-anomaly contours mapped in Teplow et al. (2011) in the vicinity of seismic line 6 have a near constant north-south; this suggests that extracting a 2D gravity profile along seismic line 6 will yield a useful 2D gravity analysis in the dip direction. Gravity station selection is based on proximity to seismic line 6, resulting in 16 equidistant data points with a spacing of 205 m. Three extra virtual stations on the western end of line 6 are provided by linear interpolation of nearest measured points. MWH Geo-Surveys applied drift and tidal corrections on the order of 0.2 mGal and determined inner-ring terrain and elevation corrections in the field. Due to the way that our optimization automatically han-
dles topographic corrections on smaller scales, inner-ring corrections are not needed here, where the 2D topographic profile is representative of the nearby 3D topography. When conducting a gravity survey, precise topographic measurements are critical to proper gravitational modeling; an error of 1 m in vertical elevation can result in a change of 0.3 mGal (Telford and Sheriff, 1990). We used elevation data from line 6 SEG-Y trace headers with a precision of 1 foot (0.3 m). Gravity stations are not located directly on the seismic line, but relative elevation changes are preserved; these errors are assumed to be within the 1 foot measurement error. MWH Geo-Surveys applied Bouguer corrections using a density of 2.5 g/cc, which is close to measured basement densities in this region (Drakos, 2007; Mankhemthong, 2008). For $\chi^2$ analysis, we assume the combined average measurement error to be 0.15 mGal.

THEORY

SeisOpt® Pro™ Velocity Modeling

Optim’s SeisOpt® Pro™ produces velocity models by seismic SA optimization and deterministic traveltime modeling. The seismic SA algorithm of SeisOpt® Pro™ updates by a Monte Carlo approach and does not require an accurate initial model (Pullammanappallil, 1994). When optimization commences, seismic SA initially explores the entire model space. Across many iterations, the SA algorithm gradually changes into a local optimization to begin exploiting a narrow region. Due to the fact that first-arrival refraction methods only return traveltime values above the deepest raypath, model extension populates the rest of our rectangular cross-section model space. Generating isotime contour plots tests the validity of model extension. Extension by downward linear interpolation from velocity
elements along the deepest raypath to the laterally translated deepest velocity element of the model creates a concave bedrock profile, resulting in generated traveltimes arriving too early. In order to rectify this issue, a manual and ad hoc lateral extension strategy produces a velocity model with a flat bedrock interface extending west towards the valley axis.

**Velocity to Density Conversion**

Our joint optimization scheme is predicated upon observations that density tends to be non-linearly proportional to seismic velocity. Brocher (2005) provides an excellent overview of available velocity-density relationships (Figure 6). Ludwig et al. (1970) produced the Nafe-Drake curve, which is valid for all rock types with a $v_p$ range of 1.5 km/s to 8.5 km/s. Gardner et al. (1974) derived the most widely used equation, which is valid for sedimentary rocks with $v_p$ from 1.5 km/s to 6.1 km/s. Christensen and Mooney (1995) and Godfrey et al. (1997) provide linear relationships for crystalline rocks at 10 km depth, with $v_p$ ranges of 5.5 km/s to 7.5 km/s and 5.9 km/s to 7.1 km/s, respectively. We chose the Gardner relationship for providing the most reasonable densities when extrapolated to velocities below 1.5 km/s; the minimum velocity for our optimization is 0.5 km/s.

**Forward Modeling Algorithms**

Sen and Stoffa (2013) posit that fully understanding the limitations and assumptions inherent to forward modeling is the most important step in developing a successful optimization algorithm. Monte Carlo optimizations can require hundreds of thousands of iterations, necessitating the use of an efficient forward modeling scheme. Furthermore, due to the large variety of models encountered, forward modeling algorithms must be robust and resilient
to artifacts. The setting for our San Emidio line 6 models is a 2D cartesian coordinate space \((x, z)\), where \(x\) is defined as distance easting and \(z\) as depth. Each element in the model space has dimensions of 55 ft by 55 ft \((17 \text{ m} \times 17 \text{ m})\), with the origin defined as the shallowest western corner element.

The deterministic Vidale method generates our traveltime models through a finite-difference solution to the eikonal equation (Vidale, 1988). Visual examination of isotime contour plots shows that our traveltime model remains stable amidst the most extreme velocity gradients encountered during optimization.

Gravity modeling must be compatible with the model space of the Vidale method and meet the demands of being both efficient and robust. Our gravity model obtains a 3D gravitational response from 2D density models, which Fedi et al. (1998) term 2.5D modeling. Telford and Sherif (1990) point out that this type of extrapolation is only valid when variation in and out of the plane is minimal; examining directional gravity gradients shows this to be a reasonable assumption. The derivation and verification of our gravity model can be found in Reeder et al. (2014). One difference between our final model and the one shown in Reeder et al. (2014) is that the gravity model used in this study employs the line integral method of Talwani et al. (1959) instead of infinite cylinders, which provides a minor accuracy improvement.

Hubbert (1948) showed that the vertical component of an arbitrary polygon’s gravitational response is given by a line integral along the boundaries with respect to the angle \(\theta\), which is measured from the positive (downward) \(z\)-axis to the positive (eastern) \(x\)-axis. The integral can be decomposed into \(n\) separate integrals from the points A to B, where \(n\) is the number of polygon vertices (Equation 1). Our numerical implementation follows
Talwani et al. (1959).

\[ g_z = 2G \rho \sum_{i=1}^{n} \int_{A_i}^{B_i} z \, d\theta = 2G \rho \sum_{i=1}^{n} \int_{A_i}^{B_i} \frac{\alpha_i \tan \theta_i \tan \phi_i}{\tan \phi_i - \tan \theta_i} \, d\theta \] (1)

Simulated Annealing Algorithm

The SA technique has been applied to a wide variety of optimization problems, including direction-finding circuit design, chemical processing, facility layout, pattern recognition, and wavefield inversion (Basu and Frazer, 1990; Suman and Kumar, 2005). SA takes its name from the annealing process of petrology and metallurgy, which describes crystal formation in a cooling melt. In contrast to local optimization algorithms, SA probabilistically accepts models with higher error than prior models; this mechanism allows the algorithm to escape local minima. One of the benefits of this technique is that it does not depend on an accurate initial model, which is very useful in areas of complex geology with limited a priori information, and precludes interpreter bias.

The idea of probabilistic acceptance of higher error models during optimization was first put forth by Metropolis et al. (1953). More than thirty years later, Kirkpatrick et al. (1983) and Černý (1985) independently took the idea one step further by slowly decreasing the probabilistic acceptance chance, which is colloquially known as lowering the temperature. Szu and Hartley (1987) and Beaty et al. (2002) improved efficiency with ‘fast’ SA, which draws new models from a Cauchy-Lorentz distribution instead of a Gaussian distribution. Next, Zhang et al. (1997) and Ingber (1993) presented ‘very fast’ SA, which narrows the range of possible models through iterations. Chunduru et al. (1997) utilize a hybrid SA optimization technique that occasionally draws a new model using gradient descent. Yang et al. (2002) present ‘improved very fast’ SA, which utilizes a ‘double judge’ error-checking
rule to prevent joint optimization objective function errors when using ‘very fast’ SA. Our implementation of the generalized SA algorithm follows the outline of Pullammanappallil (1994), who first applied this optimization technique to first arrival traveltime tomography; implementation of fast SA could be a further development.

The maximum model cross-section depth of 1,526 m (5,005 ft) is based on a-priori information of maximum bedrock depth from wells. The allowed velocity range of 0.5 km/s to 6.5 km/s comes from previous velocity modeling results and rock physics estimations (Teplow et al., 2011). Before optimization commences, each model element is populated with a random velocity. The temperature, which controls the probabilistic acceptance rate, initially starts above the liquidus; above this temperature, all new models are accepted, regardless of their error. The initial, randomized velocity model cycles through a set number of iterations at supraliquidus temperatures to achieve a state of high disorder prior to cooling (Pullammanappallil, 1994). The velocity model is converted into a density model using our extended Gardner’s relationship (Figure 6). Starting traveltime and gravity models are obtained, followed by calculation of RMS error $\sigma$ as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n_x} (x_{\text{observed}} - x_{\text{calculated}})^2}{n_x}}$$

$n_x$ represents the total number of measurements. Seismic and gravity error values are calculated separately. The velocity model is perturbed by setting a random rectangular region of the model to a random velocity. Afterwards, the updated velocity model is converted to a density model and new energies are calculated. The standard and conditional model acceptance criteria are given as follows:

$$\text{if } (\sigma_{ns} < \sigma_{os}) \text{ AND } (\sigma_{ng} < \sigma_{og})$$

$$\text{elseif } e^{\frac{(\sigma_{ns} - \sigma_{os})^q(\sigma_{os} - \sigma_{ns})}{T_s}} > \text{rand}[0, 1] < e^{\frac{(\sigma_{ng} - \sigma_{og})^q(\sigma_{og} - \sigma_{ng})}{T_g}}$$
Where rand[0,1] is a random number from 0 to 1; $\sigma_{ns}$ and $\sigma_{ng}$ represent the ‘daughter’ model errors for seismic and gravity, respectively; $\sigma_{os}$ and $\sigma_{og}$ are the ‘parent’ errors; $\sigma_{ss}$ and $\sigma_{sg}$ are the ‘successful’ errors; $T_s$ and $T_g$ are the temperatures; and $q$ is an even whole number that is determined empirically. If either of the aforementioned logical expressions are true, the daughter errors and models replace the parent. $\sigma_{ss}$ and $\sigma_{sg}$ equal the measurement error in seismic and gravity data, which is also used in the stopping criteria; setting $\sigma_{ss}$ and $\sigma_{sg}$ equal to less than measurement errors would allow $\chi^2$ values less than 1, which would permit model over-fitting (Van Avendonk et al., 2001). Finally, the algorithm checks all stopping criteria; these include maximum number of iterations, successful error, minimum temperature, and maximum number of successive model rejections. If no stopping criteria are met, the cooling schedule is exercised and the algorithm loops back to the model perturbation step. This process continues until a stopping criteria is met.

**Simulated Annealing Parameters**

The most impactful component of a joint optimization is the objective function (Roy et al., 2005). This is where Tikonov regularization can be implemented, such as damping (Snieder and Trampert, 2000), smoothness (Constable et al., 1987; Boulanger and Chouteau, 2001; Vermeesch et al., 2009; Berger et al., 2011; Lelièvre et al., 2012), or structural similarity (Xiao et al., 2011; Teranishi et al., 2012; Haber and Holtzman Gazit, 2013). These additional types of regularization are further areas for development of our joint optimization algorithm.

The temperatures, $T_s$ and $T_g$, are in the denominator of the exponentials; as $T_s$ and $T_g$ decrease, the probability of both exponentials being greater than rand[0,1] tends towards zero. The seismic temperature ($T_s$) is converted into a gravity temperature ($T_g$) at each
The conversion factor is determined through a novel calibration technique that uses Pareto charts (Figure 7). Suman and Kumar (2005) provide a comprehensive overview of Pareto optimization. In this application, the Pareto chart shows whether the seismic or gravity component of the objective function is dominating the optimization. We empirically deduced that seismic-gravity objective function balance occurs when gravity temperatures \( T_g \) are equal to the iteration-equivalent seismic temperatures \( T_s \) divided by 100,000 (Figure 7b). This parameter is hereby referred to as \( T_{\text{conv}} \).

The value of \( T_{\text{conv}} \) is dependent on the ratio of the dimensionalities of the time data space over the gravity data space, which has proportionality to the ratio of optimization convergence rates. The time data space consists of 5,550 picks made on 193 receivers with a first arrival time range of 1,189 ms and a first-arrival-pick precision of 6.7 ms; this gives a time data space dimensionality of 190,089,157. The gravity data space has 16 stations, with an observed measurement range of 17.15 mGal and estimated precision of 0.15 mGal, resulting in a gravity data space dimensionality of 1,829. This produces a time-gravity data space dimensionality of 103,912, which is close to our empirically-determined value of \( T_{\text{conv}} \). We created the gravity model presented in Reeder et al. (2014) to ensure that the dimensionality of the time and gravity model spaces were similar; in this case, both model spaces have a dimensionality of 17,745, which is the product of 195 easting elements and 91 depth elements. This equation may be a good benchmark for \( T_{\text{conv}} \):

\[
T_{\text{conv}} = \frac{(#\text{receivers})(#\text{picks})(\text{first arrival range})(\text{gravity measurement precision})}{(#\text{stations})(\text{gravity data range})(\text{first arrival pick precision})}
\]  

(5)

The cooling schedule, which controls the probabilistic acceptance criteria, consists of an initial temperature, temperature reduction scheme, critical temperature, and minimum temperature. The choice of an effective cooling schedule is very important; for example,
Basu and Frazer (1990) show that it is cost-effective to use 80% of the total computation budget on determining the critical temperature alone. Lee and Lee (2013) conclude that there is still work to be done towards an analytical determination of an optimal starting temperature, but as long as the initial temperature is set sufficiently high, achieving the global minima is possible. The effective temperature range is mapped utilizing ideas taken from Basu and Frazer (1990). Short tests (1,000 iterations) over a discretized temperature series ranging from $10^{100}$ to $\sim 0$ establish the liquidus and solidus (Figure 8). The liquidus boundary occurs at $T_s$ of $10^{5.5}$, while the solidus – where probabilistic acceptance tends to zero – is located at $T_s$ of $10^{2.6}$.

The critical temperature is a fixed temperature across many iterations that occurs just before reaching the solidus. For single objective functions, Basu and Frazer (1990) present a very effective method of critical temperature determination, in which a series of tests are run at static temperatures to find where error is minimized. However, their method is not effective for a joint seismic-gravity objective function. Our final joint optimization critical temperature of $T_s$ equal to $10^{2.8}$ is deduced empirically by exploring values slightly above the solidus; this value is model-dependent, and must be derived again when new observations are used. Upon discovery of the critical temperature, similar testing is carried out for the value of $q$ that minimizes error, which is equal to 2 for all SA and joint SA runs in this paper.

**Kirchhoff Prestack Depth Migration Algorithm**

The most straightforward way to judge the quality of two velocity models is by comparing the magnitude of traveltime misfits. However, a lower error does not necessarily mean a
velocity model is better. Comparing coherency of migrated seismic sections allows further analysis of velocity model quality. The Kirchhoff prestack depth migration (KPSDM) code aaRGkmig.c creates our seismic images (Louie, 2014, Personal Comm.). KPSDM has proven effectiveness in areas with sharp lateral velocity variations (Louie et al., 1988; Louie and Qin, 1991; Honjas and Pullammanappallil, 1997; Chávez-Pérez et al., 1998; Louie et al., 2012). KPSDM has been described as a ray-equation back-projection inversion of the acoustic wave field (Louie et al., 1988). Three assumptions are inherent to this technique: the Born approximation, the WKBJ approximation, and the far field assumption. The Born approximation assumes that reflections are caused by rapid variation in material properties and data only include primary reflections. The WKBJ approximation, also known as the geometric optics approximation, implies seismic energy propagates along infinitely high-frequency rays through material with properties that vary slowly (Robinson, 1986). This facilitates solving the wave equation and grants low-frequency energy unrealistic sensitivity to thin refractors (Brown, 1982). The far field assumption implies receivers are at least two wavelengths away from sources, which precludes the inclusion of complex near-field diffraction interactions.

Our KPSDM code is derived from codes developed by Chávez-Pérez et al. (1998), Chávez-Pérez and Louie (1998), Kanbur et al. (2000), Abbott et al. (2001), Mela and Louie (2001), Louie et al. (2002), and Stern et al. (2015). Our code includes operator anti-aliasing as described by Lumley et al. (1994), the obliquity factor of Claerbout (1985), and the kirchfast speedup described in Claerbout (1997). Setting the Lumley (1994) operator anti-aliasing distance parameter equal to the shot spacing (220 ft or 67 m) produces less noisy migrations than using the receiver spacing (55 ft or 17 m). We generate traveltime planes using the algorithm described in Vidale (1988). Since migration resolution is equivalent to
the resolution of input traveltime planes, we conduct testing to ensure image aliasing does not occur. Preferred model dimensions are 195 easting elements by 91 depth elements. Each element is square with dimensions of 55 ft by 55 ft (17 m by 17 m). After migration, we apply the rho filter of Thorson and Claerbout (1984), which consists of two time-derivatives followed by a 180° phase shift; this is colloquially known as a frequency recovery filter. We then smooth the migration image with a 3 by 3 averaging kernel. This combination acts to suppress low-frequency summation artifacts and short-wavelength noise, while preserving reflectors of interest.

RESULTS

Synthetic Testing

Comparisons between seismic SA optimization and joint seismic-gravity SA optimization are made using synthetics, but these tests do not make use the same proprietary seismic SA features of SeisOpt® Pro™. Synthetic testing shows how joint optimization further constrains velocity models. The synthetic velocity model consists of a bedrock interface with two downward steps (Figure 9a). Gardner’s relation converts the synthetic velocity model into a density model. Synthetic gravity data are generated using the synthetic density model, followed by density optimization using SA (Figure 9b). Traveltime optimization is performed on the generated synthetic traveltimes (Figure 9c). Joint optimization is used to obtain a velocity-density model from the synthetic traveltimes and gravity model (Figure 9d).

Gravity optimization alone successfully recovered the shallow structure and general trend of down-to-the-west bedrock (Figure 9b-1) with an RMS error of 0.41 mGal. However,
gravity optimization produces a velocity-equivalent inversion of –43% near the bottom of the model (Figure 9b-2). Seismic optimization alone produces a model with insufficiently high velocities that are diffused through the model space, a very strong velocity inversion on the east side of –87% (Figure 9c-1), and an RMS error of 33.7 ms (Figure 9c). The shallow velocity inversion on the east side of the velocity model is below the deepest ray (Figure 9c-2); typically, everything below the deepest ray would be clipped and the empty elements in the remaining rectangular model space would be populated by model extension. Qualitatively, joint optimization most successfully recovered the synthetic model and had the lightest velocity inversion of –10% (Figure 9d-1). However, the joint optimization model shows higher RMS errors of 2.56 mGal and 102.6 ms (Figure 9d). These results are an example of how the joint optimization produces more realistic and useful models than the stand-alone seismic and gravity optimizations, but yields higher RMS error.

**San Emidio Optimization Results**

Our results come from one seismic line collected at one geothermal field. Our goal with these results is to show a positive test of our hypothesis, not a thorough examination of San Emidio’s geothermal potential. The geologic setting of our survey is typical of most geothermal resources in the Great Basin, suggesting general applicability of this method.

*First Arrival Traveltime Optimization Velocity Model*

The velocity model based solely on first-arrival traveltime optimization shows a flat basin floor (Figure 10A), shallow velocity pull-up (Figure 10B2), and a rather jagged sediment-bedrock interface that generally dips to the west at 30° (Figure 10D1). The RMS error for this model is 6.5 ms; this gives a $\chi^2$ value of 0.97, indicating these data are slightly
overfit (Figure 5). We converted this velocity model into a density model, which resulted in a $\chi^2$ value of 16.5, indicating this model very poorly fits gravity data (Figure 3). The velocity gradient is very sharp on the western side of the velocity model at 1.4 km depth; this region was populated by manual lateral model extension (Figure 10A). This sharp gradient corresponds to a concave and highly coherent basin-floor reflector (Figure 10A). Shallow reflectors on the west side of the migration are less coherent (Figure 10B1). Antiformal deformation of a shallow reflector is congruent with the shallow velocity pull-up (Figure 10B2).

**Joint Seismic-Gravity Optimization Velocity Model**

Joint optimization provides a velocity model section without the false deep, sharp basin floor (Figure 11A), minor velocity inversions (Figures 11B1 and D2), and a smooth, convex bedrock profile (Figure 11C). The RMS error for gravity is 1.25 mGal and 27 ms for seismic traveltimes; this gives a $\chi^2$ value of 4, indicating that this velocity model underfits first arrival data (Figure 5). The velocity-equivalent density model gives a $\chi^2$ value of 5.4, suggesting the model is underfitting gravity data (Figure 3). Plotting traveltime residuals vs. offset (e.g., Van Avendonk et al. (2001)) reveals that shallow velocities are too slow, velocities at depth are too fast, and the deepest velocities are too slow. On the westernmost side, velocities consistent with sedimentary rock extend from the surface to the bottom of the velocity model; this suggests the basin is deeper than 1.5 km (Figure 11A). Reflectors on the west side of the migration are straight and coherent (Figure 11B1). The sediment-bedrock velocity interface has a westward dip of 20° on the eastern margin, which gradually increases to a dip of 60° near the center of the model (Figure 11C). This velocity gradient is congruent with a very coherent reflector (Figures 11B2 and C). Velocity inversions occur in valley fill at 0.5 km depth on the west side (–25%) and at 1.2 km depth in the bedrock.
(−16%) (Figures 11B1 and D2). In this migration, the shallow antiformal reflector observed in the first arrival traveltime optimization migration is flat (Figure 11B2). The truncated shallow reflector on the east side is now intersected by subtle reflectors that dip westward at 45° (Figure 11D1). These dipping reflectors transition to horizontal westward forming a highly coherent, long-wavelength deep reflector (Figure 11D2).

**Restricted Offset Range Migrations**

Restricted offset-range migrations of the first arrival traveltime optimization (Figure 10) and jointly optimized (Figure 11) velocity models reveal which offset ranges the reflector energy in our final migration images is coming from (Figure 12). Empirically, there are three discernible effective offset ranges; the ‘near’ offset range of 0 m to 1.5 km (Figure 12a/d); the ‘mid’ offset range of 1.5 km to 2.0 km (Figure 12b/e); and the ‘far’ offset range of 2.0 km to 3.2 km (Figure 12c/f).

The near-offset migrations contain the deep valley reflector (Figure 12a-A/d-A), deep basement reflector (Figure 12a-D₂/d-D₂), and minor shallow reflector energy (Figures 12a-B₁/d-B₁, 12a-B₂/d-B₂, and 12a-D₁/d-D₁). Both mid-offset migrations display a high-amplitude concave reflector in the center; trace-wise polarity-randomization analysis of Harlan et al. (1984) shows that this is a migration artifact (Figure 12b-H/e-H). The mid-offset migrations also show part of the deep basement reflector energy (Figure 12b-D₂/e-D₂), continuous shallow reflector energy (Figure 12b-B₂/e-B₂), and a smooth, concave shallow reflector (Figure 12b-C/e-C). The first arrival traveltime optimization model’s far-offset migration is dominated by the highly sinuous shallow reflector energy (Figure 12c-B₂) that transitions eastward into the smooth shallow reflector (Figure 12c-C), and dims westward.
towards the shallow valley reflectors (Figure 12c-B₁). The jointly optimized far-offset migration is balanced between shallow and deep energy (Figure 12f-B₂/f-D₂). Shallow reflectors are more coherent across all offsets in offset migrations produced from the jointly optimized model (Figures 12d-B₁/C, 12e-B₁/C, and 12f-B₁/C). The deep basement reflector is also present in all offset migrations (Figures 12d-D₂, 12e-D₂, and 12f-D₂).

**DISCUSSION**

**Interpretations**

The flat valley floor interpretation that would naturally come from the SeisOpt® Pro™ (Figure 10) velocity model results is poorly supported by seismic data, as that region of the velocity model is below the deepest headwave raypath. For the SeisOpt® Pro™ results, the deep valley velocity gradient is purely a function of arbitrary lateral model extension from the deepest raypath. Since we observed that creating a concave refractor using vertical model extension produces arrival times that are too early, the bedrock interface is most likely not shallowing substantially on the west side of the velocity model. Reflectors in this area are arcuate in the migration using the SeisOpt® Pro™ velocity model (Figure 10). The added deep velocity control from gravity in the joint optimization results in a velocity model that shows the valley being at least 1.5 km deep (Figure 11). The reflectors in this region also become flat and coherent when the jointly optimized velocity model is used for migration, which is expected for undeformed Tertiary sediments (Figure 11). Most of the energy in these reflectors comes from robust near-offset data (Figures 12a-A and 12d-A). However, these deep reflectors are present across the jointly optimized velocity model restricted offset range migrations (Figure 12d-e-f/A), but the same is not true for the SeisOpt® Pro™
velocity model restricted offset range migrations (Figure 12a-b-c/A). The deep valley model that results from joint optimization conflicts with the prior shallow valley interpretation of Rhodes (2012), who was basing his interpretations on surficial geologic mapping. Our new interpretation could be validated by conducting a seismic survey with greater maximum offset or comparing to well log data. Matlick (1995) reports that Chevron’s Kosmos 1-8 well, located 700 m north of the western edge of line 6, did not encounter Mesozoic basement rock (Nightingale formation) at target well depth of 1,223 m.

Convex velocity pull-ups in the first arrival traveltime optimization velocity model translates to antiformal reflectors in the corresponding migration (Figure 10). Incidentally, a similar velocity pull-up is observed in the synthetic traveltime optimization, because velocities are spread along sparse rays in all of these cases (Figure 9). Vasco et al. (1996) show that sharp velocity interfaces can be equivalently represented by models with lower magnitude velocity gradients that diffuse velocity contrasts over a broader region. This antiformal reflector is flattened when the jointly optimized velocity model is used for migration (Figure 11B2), and this reflector becomes observed across all offset ranges (Figure 12d-e-f/B2).

As shown in the synthetic models, density optimization was most effective at recovering shallow structure (Figure 9b). The flattening of this shallow reflector demonstrates that including gravity constraints in the velocity optimization improves the resolvability of shallow velocity structure. This constraint is caused by the decay of gravity sensitivity as the inverse of the distance squared; gravity models are very sensitive to shallow density model elements. Furthermore, shallow reflectors on the western side of the model are more straight and coherent when the joint optimization velocity model is used for migration (Figure 11B1). Restricted offset range migrations reveal that the sinuous shallow reflectors are primarily found in offsets greater than 1.5 km; this suggests that these reflectors may just
be migrated refraction energy instead of true reflectors (Figures 12b-B₂ and 12c-B₂). This also helps explain the sensitivity of the antiformal reflectors to the input velocity model (Figures 10B₂ and 11B₂).

On the contrary, the presence of this reflector is well-established by drilling; Matlick (1995) states that Phillips ST-1 intersected the sediment-basalt contact roughly 250 m south of line 6 at an easting of 1.7 km and depth of 485 m. This lithological contact is found within 75 m of the shallow reflector in both of our migrations (Figures 10B₁ and 11B₁). The sensitivity of these reflectors to the velocity model and minor presence in near-offset migrations suggests that this contact may be gradational in nature, which produces pseudoreflections or diving waves.

However, the reflector is partially visible in the near offset migration for the joint optimization model, which may be evidence for improved shallow velocity model accuracy (Figure 12d-B₂). The sinuous reflector at 0.5 km depth and 2.5 km easting is most coherent in the migration using the jointly optimized velocity model, in which this reflector corresponds to a sharp velocity gradient (Figure 11C). This shallow reflector is incoherent in the first arrival traveltine optimization migration (Figure 10C), and is not congruent with sharp velocity gradients. The robustness of this reflector is supported by presence in the near offset migrations (Figures 12a-B₁ and 12d-B₁). This is further evidence that joint optimization improves shallow regions of velocity models. Typically, smoothing shallow reflectors can be accomplished by manual refinement of the velocity model or by migration velocity analysis; using joint optimization removes the need for this step, saving human interaction time.

Applying knowledge of the well control given by Phillips ST-1 reveals that the reflector
at B2 and C is very likely the alluvium-basalt interface. The stratigraphic column suggests that the next deeper reflector should be a basalt-tuff interface, followed by a tuff-basement reflector. None of the migrations demonstrate the basalt-tuff reflector, due to the fact that theoretically it is a weakly negative impedance contrast. Mayhew (2013) also could not differentiate the basalts and tuffs in seismic migrations at nearby Astor Pass; this seismic facies was verified by subsequent drilling.

However, evidence for the basement interface is observed. The first line of evidence are reflection terminations in both the first arrival traveltime optimization and jointly optimized velocity model migrations at the depth-projected position of the mapped surficial rangefront fault (Figures 10D1 and 11D1). Following the surficial fault projection deeper reveals a strong, slightly concave reflector that appears offset (Figure 11d2). The deep reflector interpreted to be the tuff-basement contact is poorly resolved in the migration that uses SeisOpt® Pro™ velocity models (Figures 10D2 and 11D2). Examining the restricted offset migrations makes the increase in coherency much more obvious (Figure 12). This region is situated below the deepest first-arrival raypath, and is therefore poorly constrained by first-arrival velocity modeling alone; this indicates that joint optimization produces a more accurate velocity model at depth, which helps focus the seismic image below the basalt refractor.

Two velocity inversions are observed in the jointly optimized velocity model (Figure 11B1, D2). The shallow rectangular velocity inversion at B1 corresponds to flat reflectors in the migration image (Figure 11B1). These flat reflectors are not very coherent in the first arrival traveltime optimization (Figure 10B1) migration. Most of this shallow velocity inversion is below the deepest raypath, but these shallow elements are sensitive to the gravity component of the the joint optimization; this suggests that this shallow ve-
locity inversion may be real. Assuming that the shallow reflector discussed earlier is the sediment-basalt contact, the deep velocity inversion at the bottom of the jointly optimized velocity model is situated stratigraphically in the Mesozoic section (Figure 11D$_2$). This velocity inversion is below the deepest raypath and is relatively poorly constrained in the gravity model. For these reasons, this velocity inversion is most likely an artifact of joint optimization. Implementing regularization could resolve this artifact. In the end, the deep velocity inversion does not have a meaningful impact on the resultant migration image (Figure 11D$_2$).

Previous researchers in the Pyramid Lake area have shown that blind geothermal systems tend to exist on north-northeast trending normal faults in highly faulted areas, such as fault intersections and fault tips (Drakos, 2007; Vice, 2008; Rhodes, 2012; Mayhew, 2013; Anderson, 2013). Phillips ST-1 intersected a major fault 200 m south of line 6 at an easting of 1.7 km and depth of 588 m. This fault is not well-resolved in our migration images (Figures 10B$_2$ and 11B$_2$). However, Mayhew (2013) states that the Pyramid sequence rocks that this fault cuts are too permeable to focus fluid motion through faults; he suggests that the real target should be fault intersections in the Mesozoic basement. The migration that uses a velocity model produced by joint optimization imaged a fault offset in the basement rock (Figure 11D$_2$). Reflector truncations around the area of 1,200 m (3,900 ft) easting and 1.1 km depth in migrations using velocity models produced by first arrival traveltime optimization and joint optimization could be produced by a fault contact of Tertiary sediments adjacent to volcanic rocks (Figures 10 and 11). This fault could be the basement conduit for fluids that Mayhew (2013) suggests looking for.

Rhodes (2012) mapped a surficial down-to-the-west normal fault 100 m beyond the eastern edge of our model space. Assuming this fault has a 60° dip that projects into the
surface, the bedrock interface dips too shallowly in both of our velocity models (Figures 10 and 11). The easternmost edge of the velocity model has very low fold and is poorly constrained, particularly at depth. When gravity constraints are added, a deep reflector is observed dipping to the west (Figure 11) that could be projected to the surface location of the rangefront fault in Rhodes (2012). This reflector is concave and flattens westward from 45° to 0° from Figure 11D1 to Figure 11D2, suggesting that this normal fault is listric. This reflector shows a breach in coherency at 2 km easting and 1.3 km depth, which could indicate another fault that cuts the basement rock. Given that the Oligocene and Miocene sections dip to the east at 20°, the hydrothermal fluids could be concentrated in this deep fault before following stratigraphic boundaries up and to the west. Upon reaching the Tertiary clastic section, the fluids could be rising up, creating the current production zone discovered by Phillips ST-1. This production zone is located within the region of gradational velocity suggested by pseudoreflections (Figure 11B2).

Implications

The efficiency of joint optimization is comparable to that of SeisOpt® Pro™. First arrival traveltime optimization using SeisOpt® Pro™ took 16 hours. We completed the joint optimization in roughly 20 hours. We greatly improved the efficiency of the joint optimization by the inclusion of Matlab MEX codes, which takes advantage of the C language, and by vectorization of ‘for’ loops. Further efficiency improvement can be obtained by porting our optimization to C.

Comparing the RMS error of the jointly optimized velocity model to first arrival travelt ime optimization reveals that joint optimization produces higher RMS error. Traveltime
RMS errors are 6.5 ms for first arrival traveltime optimization and 27 ms for our joint optimization. First arrival traveltime optimization produces a velocity model with a $\chi^2$ value below unity, while joint optimization underfit data. Using this criterion, SeisOpt® ProTM performed better. Lower RMS errors might be achieved with the joint optimization by also optimizing the coefficients of the velocity-to-density conversion polynomial; it is possible that using the Gardner relationship causes inconsistencies between the gravity and seismic datasets. For example, the velocity-to-density function should account for variations with depth. The lack of spatial variation in the relationship may also explain trends in the traveltime residual vs. offset plot. However, similar results are observed in the synthetic models, which use a flawless velocity-to-density conversion; the synthetic velocity optimization has an RMS error of 33.7 ms, while the synthetic joint optimization has a traveltime RMS error of 102.6 ms. This indicates that adding gravity constraints comes at the cost of traveltime RMS error. Qualitatively comparing the optimized synthetic velocity models and Kirchhoff migrations suggests that joint optimization produces superior results to traveltime optimization alone, which suggests that RMS error is not the only indicator of relative velocity model quality and utility.

Our method of using Pareto charts to calibrate joint optimization objective functions applies to many optimization problems beyond just geophysics. The technique that we described can be explored by anyone experiencing difficulty obtaining a convergent joint optimization. The logical next step would be to automate this process by examining how well the trend of the Pareto chart matches a linear fit. Furthermore, a nonlinear seismic-to-gravity temperature conversion could be superior to a linear one. The way that we mapped the solidus and liquidus is a very straightforward method to create the outline of a cooling schedule, particularly the initial and final temperatures. Here, we determined the critical
temperature ($T_{\text{conv}}$) empirically by testing temperatures just above the solidus. We showed that the time-gravity data space dimensionality is close to our empirically determined value of $T_{\text{conv}}$, which may serve as a good benchmark. This is an area of ongoing research, and may one day be determinable analytically.

The improvements to seismic imaging demonstrated in this paper can influence new development at San Emidio. U.S. Geothermal has the added ability to compare velocity model results with both the known stratigraphic section and proprietary well data to tie lithologic contacts to reflectors. Furthermore, a more accurate velocity-to-density conversion can be calibrated by looking at sonic and density logs collected by Chevron in the 70’s that we did not have access to; this relationship could also include an extra term to account for variation with depth. Using a data-driven velocity-density relationship could reduce seismic-gravity data inconsistency and refine seismic imaging even further. Imaging may also be improved by using a more advanced reflection imaging algorithm, such as reverse time migration. Our results shed light on the lateral position of three faults, including one in the Mesozoic basement; that fault would be an ideal target according to Mayhew (2013). We showed that the valley is at least 1,500 m (4,900 ft) deep, which was not indicated by previous velocity models (Teplow et al., 2011; Rhodes, 2012).

The joint optimization procedure can also positively impact geothermal exploration worldwide. This technique should be tried anywhere that difficult seismic imaging is encountered. First, velocity models should be converted to density models and gravity profiles computed; if these profiles match gravity as they are, joint optimization might not result in a different outcome. Second, off-line gravity gradients must be examined to check if cylindrical symmetry is a valid assumption. The old strategy of forward-modeling density models to match gravity data could be replaced by our joint optimization technique, removing the
CONCLUSIONS

We presented a stable, convergent joint seismic-gravity optimization algorithm. Seismic migrations that use velocity models produced by first arrival traveltime optimization may have shallow velocity pull-ups, which joint optimization flattens out. Synthetic modeling demonstrates that joint optimization produces more accurate results than standalone seismic optimization. Jointly optimized velocity models are constrained below the deepest first-arrival raypath, which improves coherency of reflectors at depth. In this case, deeper velocity control reveals that the basin at San Emidio is deeper than 1,500 m (4,900 ft), which conflicts with the prior shallow basin interpretation. The migration using our jointly optimized velocity model shows stronger evidence for the rangefront fault than does the migration using the first arrival traveltime optimization velocity model. Joint optimization produces velocity models that are more useful though they have higher RMS error, and has similar computing requirements.

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REFERENCES


Faulds, J., M. Coolbaugh, and V. Bouchot, 2010, Characterizing structural controls of


Honjas, W., and S. K. Pullammanappallil, 1997, Predicting shallow Earth structure within the Dixie Valley geothermal field, Dixie Valley, Nevada, using a non-linear velocity opti-


Kent, T., 2013, Comparing Deformation at Soda Lake Geothermal Field from GPS and 3D Seismic: Master’s Thesis, University of Nevada - Reno. ProQuest. 41 pg. #1540191.


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