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W. Trainor-Guitton, G. Hoversten, G. Nordquist, R. Mellors, R. Intani

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Value of information analysis using geothermal field data: accounting for multiple interpretations & determining new drilling locations

Whitney J. Trainor-Guitton[1], G. Michael Hoversten[2], Gregg Nordquist[3], & Rindu Grahabhakti Intani[3]*

[1]formerly Lawrence Livermore National Laboratory; presently Colorado School of Mines, wtrainor@gmail.com

[2]Chevron Energy Technology Company, San Ramon, CA, [3]Chevron Geothermal Power Indonesia, Jakarta, Indonesia

Summary

We present a value of information analysis for MT data for locating high steam flow regions of a geothermal resource. The high electrical conductivity feature in volcanic geothermal settings, known as the clay cap, can be indicative of geothermal alteration occurring just above the resource. We demonstrate how two alternative interpretations of the clay cap from one 3D electrical conductivity model can be used to estimate the value of geophysical information. Our results indicate that the final VOI estimate depends on the different interpretations of the clay cap and the assigned prior probability of steam flow magnitude. Additionally, we demonstrate how these VOI evaluations can be used to guide future drilling locations.

Introduction

How well does geophysical data improve our geothermal prospecting decisions? How much is this information worth? These types of questions can be addressed using the value of information (VOI) method. VOI quantifies how relevant any particular information source is, given a decision with an uncertain outcome; thus, the estimated VOI can be used to justify the purchase of additional data when exploring for geothermal resources. The contributions presented in this paper are twofold. First, our work illustrates the implementation of a VOI that utilizes an existing dataset of steam flow measurements to deduce trends between steam flow and electrical conductivity. The second set of results presented here demonstrates how the VOI evaluations can serve as a guide on deciding where to drill new production wells in undeveloped areas.

The Darajat Geothermal Field

Darajat is a vapor geothermal field located in West Java, Indonesia. First production from the field was started in 1994 and additional capacity was added in 2000 and 2007 to bring the total production capacity to 271 MW from three power plants. Please refer to Rejeki et al. (2010) for geologic and modeling background. Specifically, we utilize two datasets from Darajat: steam flow rates and a 3D electrical conductivity model that has been constructed from MT (magnetotellurics) data. The steam flow measurements are the average production over one year for 27 different wells. Four of these wells were drilled near to or outside of the geothermal field and are characterized by production rates of < 5kg/s. The distribution of the data is plotted on Figure 1.

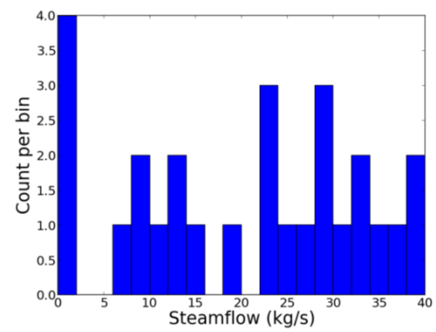

Figure 1: Steam flow data set: average production of 27 wells

For this VOI demonstration, we categorized the *steam flow magnitude* into seven groups or bins, represented by θ_i:

$$\theta_i \;\; i \in \begin{cases} 7, & \theta \geq 30\ kg/s \\ 6 & 25 \leq \theta < 30\ \text{kg/s} \\ 5' & 20 \leq \theta < 25\ \text{kg/s} \\ 4, & 15 \leq \theta < 20\ \text{kg/s} \\ 3, & 10 \leq \theta < 15\ \text{kg/s} \\ 2, & 5 \leq \theta < 10\ \text{kg/s} \\ 1, & 0 \leq \theta < 5\ \text{kg/s} \end{cases} \tag{1}$$

We define our prior uncertainty with respect to steam flow production using these steam flow categories. Table 1 summarizes the probability of occurrence for each of the categories ($\Pr(\Theta=\theta_i)$) (a) according to the data and (b) a hypothetical prior probability that will be used later for the VOI analysis (for demonstration purposes, not related to Darajat). These probabilities should be derived from expert opinion and all other data available for the particular site.

Table 1: Prior probabilities of steam flow categories $\Pr(\Theta=\theta_i)$) according to the data and other projections

↓Steam Flow Rate (kg/s)	a) % steam flow data in each category	b) Alternate prior $Pr(\Theta=\theta_i)$
$30< \theta_i$	26%	10%
$25\leq \theta_{i\ i}\leq 30$	15%	10%
$20\leq \theta_i\leq 25$	15%	10%
$15 \leq \theta_i\leq 20$	7%	10%
$10 \leq \theta_i\leq 15$	11%	10%
$5 \leq \theta_i\leq 10$	11%	10%
$\theta_i \leq 5$	15%	40%

The MT data used for this analysis consists of 85 remote referenced stations which were distributed over and outside the boundaries of the Darajat geothermal field. The data were collected in 1996-97 and 2004 and were used to interpret the distribution and extensions of the electrically conductive clay cap beyond the first development area (Rejeki et al., 2010). We use the conductivity model (which overlies the steam flow measurements) to determine possible relationships between the electrical conductivity property and the steam flow magnitude. Typically, the distribution and characteristics of the high conductivity layer can be used to estimate the likely location and margins of the geothermal system (Cumming, 2009). We attempt to assess whether the thickness and conductivity information of the clay cap can be used to distinguish between higher and lower steam flow (Ussher et al., 2000).

Establishing several possible relationships between conductance and steam flow

We define a conductivity threshold of σ=0.12 S/m in order to delineate the location and thickness of the clay cap. Thus, a top and bottom surface is defined where the electrical conductivity begins to decrease from the threshold value of σ=0.12 S/m. The resulting cap is pictured in Figure 2.

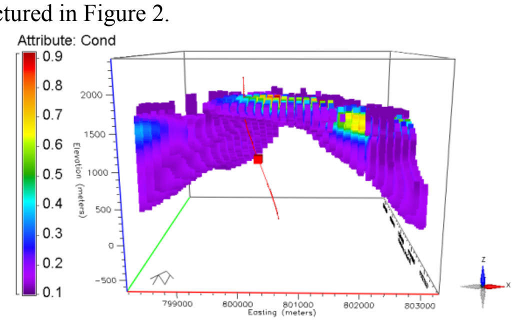

Figure 2: Clay cap defined by 0.12 S/m threshold and Well 15 (path in red) and its midpoint (red square).

Next, we determine which conductivity locations within the clay cap can be associated with the steam flow measurements. We suggest that steam flow measurements closer to the cap are more likely to influence the electrical conductivities and geometry of the clay cap. Therefore, we expect a stronger relationship between the steam flow measurements that are closer to the clay cap. We define 750m as the maximum distance between a steam flow measurement and any point within the clay cap. We choose this distance because it represents the lower quartile of all distances between the clay cap conductivities and steam flow locations.

Fifteen of the 27 steam flow measurements locations were within the maximum threshold of 750m. The statistics of the conductance's and their "collocated" steam flow categories are plotted in the box plot of Figure 3, where the steam flow categories median conductance is plotted in red, the quartile range is represented by the blue box, the "whiskers" (dashed lines) represent the standard deviations. With the exception of the highest steam flow (>30kg/s) and the 15-20 kg/s category, generally lower conductance values correlate with higher steam flow rates. The highest steam flow category has the largest range and most conductance data points, as expected since wells are preferentially sampled to high steam flow areas. Also, the 3 wells with the highest rates are located near the clay cap margin, where it thickens significantly. Conversely, the 15-20 kg/s category has only 10 data points. The negative correlation of steam flow with conductance (which is dominated by the thickness) is expected since greater temperatures (>200˚C) are often shallower over the center of the geothermal field. The shallow high temperatures tend to thin the conductive layer due to the highly conductive smectite clays altering into more resistive illitic or chloritic clays (Ussher et al., 2000).

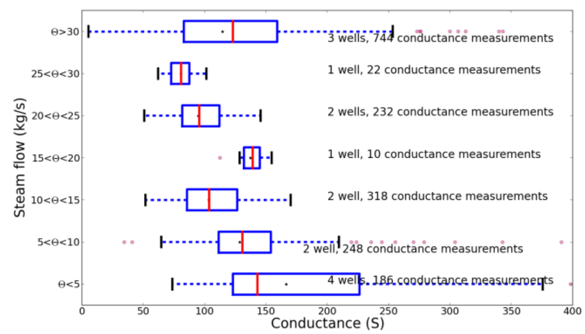

Figure 3: Box-whisker plot showing the median (red), interquartile range (solid blue) and variance (dashed blue) of conductance measurements "collocated" with the 7 different steam flow categories. From clay cap interpreted with the 0.12 S/m threshold.

Figure 4 displays the conductance measurements behind the statistics of Figure 3. For each of the steam flow categories, the counts per bin of the collocated conductance measures are demonstrated in the histogram. The data likelihood (Equation 2) uses these counts to determine how likely a conductance bin (represented by g_j) is given that the steam flow category (θ_i) associated with it is known:

$$Pr(G = g_j|\Theta = \theta_i) = \frac{c_{ij}}{\sum_i c_{ij}} \qquad (2)$$

$$i = \{1,2,3,4,5,6,7\}\ j = 1, \dots, J$$

where c_{ij} represents the count in conductance bin j in steam flow category i. The denominator, $\sum_i c_{ij}$, represents normalization by the sum of all data points in a particular conductance bin (j) across all the steam flow categories (i). For example, in conductance bin 40-50S (j=5), the likelihood for $\theta_i > 30$ is $Pr(G = g_{j=2}|\Theta = \theta_{i=1}) = \frac{13}{14} =$

93% because another steam flow category ($5 < \theta_i \leq 10$) is also associated with this conductance: $Pr\big(G = g_{j=4} | \Theta = \theta_{i=6}\big) = \frac{1}{14} = 7\%$.

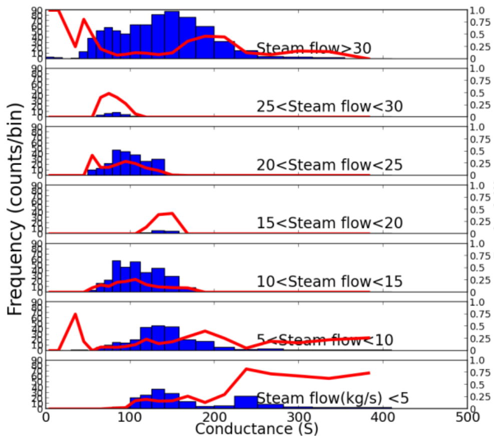

Figure 4: Counts (bars) and posteriors (red lines) for the clay cap interpretations defined at 0.12 S/m. The sum of the posterior across the steam flow categories (vertically for each conductance bin) equals 100%.

Next, we want to establish the information posterior which establishes a "misinterpretation rate" or how uniquely a conductance bin can distinguish between any of the steam flow categories θ_i. According to Bayes law, the posterior $Pr\big(\Theta = \theta_i | G = g_j\big)$ in Eq. 3 below is equal to the product of the prior probability $Pr(\Theta = \theta_i)$ and the likelihood $Pr\big(G = g_j | \Theta = \theta_i\big)$ scaled by the marginal $Pr\big(G = g_j\big)$:

$$Pr\big(\Theta = \theta_i | G = g_j\big) \dots \tag{3}$$

$$= \frac{Pr(\Theta = \theta_i) Pr\big(G = g_j | \Theta = \theta_i\big)}{\sum_{k=1}^{7} Pr(\Theta = \theta_k)\, Pr\big(G = g_j | \Theta = \theta_k\big)} \dots$$

$$= \frac{Pr(\Theta = \theta_i) Pr\big(G = g_j | \Theta = \theta_i\big)}{Pr\big(G = g_j\big)}$$

$$i = \{1,2,3,4,5,6,7\}\; j = 1, \dots, J$$

The posterior is the solid colored lines in Figure 4. When the posterior is close to 1 (right hand y-axis label) in any particular conductance bin, this indicates that conductance is more reliable in determining the steam flow magnitude. The posteriors in Figure 4 were calculated using the prior according to the data (Table 1a).

Several interpretations of the clay cap (a 3D feature) are possible and may result in different estimates of the effectiveness of the MT technique to detect electrically conductive targets, which can be indicative of potential geothermal resources. We repeat the above using a threshold of 0.10 S/m. The statistics of the conductance's associated with the 7 different steam flow categories are displayed in Figure 5. Figure 5 compared to Figure 3 has a smaller range of conductance for the highest steam flow category but also shows a similar negative correlation of steam flow and conductance. The higher conductivity threshold (Figure 4) results in a thinner clay cap, thus smaller conductance values (10-250S) and outliers >300S, whereas conductance's in Figure 5 are ~40-250S and no outliers >300S.

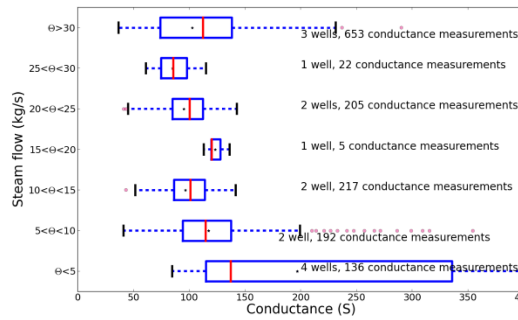

Figure 5: Box and whisker plot showing the median (red), interquartile range (solid blue) and variance (dashed blue) of conductance "collocated" with the 7 different steam flow categories. From clay cap interpreted with the 0.10 S/m threshold.

Value of Information Results using Different Clay Cap Interpretations

VOI estimates the possible increase in expected utility by gathering information before making a decision, such as where or if to drill a production well (Pratt et al., 1995). In its simplest form, the VOI equation can be expressed as:

$$VOI = \max\big(V_{with\ information} - V_{prior}, 0\,\big) \tag{4}$$

where V is the value, the metric used to quantify the outcome of a decision. The simplest decision in geothermal exploration is "to drill or not" for one particular location (represented by *a=1,2* respectively). Therefore, for our example, value is the revenue gained minus the costs incurred for any particular decision action taken. Table 2 represents **hypothetical**, monetary values that could represent relative gains or losses for the 7 steam flow categories θ_i.

V_{prior} uses the outcomes of Table 2 and quantifies the best the decision-makers can do with the current uncertainty (no MT data has been collected).

$$V_{prior} = \max_a \left(\sum_{i=1}^{7} Pr(\Theta = \theta_i) v_a(\theta_i) \right) \; a = 1,2 \tag{5}$$

Value of information analysis using geothermal field data

Table 2: Nominal value outcomes for the 2 decision options (columns) and 7 possible steam flow categories (rows).

Decision option→ ↓Steam Flow Rate (kg/s)	$v_{a=1}^{(t)}(\theta_i)$ **a = 1** (drill under cap)	$v_{a=2}^{(t)}(\theta_i)$ **a = 2** (do nothing)
$30 \leq \theta_i$	\$700,000	\$0
$25 \leq \theta_i$ $_i\leq 30$	\$300,000	\$0
$20 \leq \theta_i \leq 25$	\$125,00	\$0
$15 \leq \theta_i \leq 20$	\$40,000	\$0
$10 \leq \theta_i \leq 15$	\$0	\$0
$5 \leq \theta_i \leq 10$	-\$200,000	\$0
$\theta_i \leq 5$	-\$500,000	\$0

Next, the value with MT information is calculated using the misinterpretation rate (posterior of Eqn. 3)

$$V_{imperfect} = \sum_{j=1}^{J} \Pr(G = g_j) \ldots \left\{ \max_a \left[\sum_{i=1}^{7} Pr(\Theta = \theta_i | G = g_j) v_a(\theta_i) \right] \right\} \quad (6)$$

Here, the posterior accounts for how often one may correctly and incorrectly infer a steam flow category given the conductance. The posterior is used as weights when averaging the outcome of each alternative. Since the decision is made after conductivity data has been collected, the best alternative ($\max_a$) is chosen. Lastly, $V_{imperfect}$ is weighted by the marginal probability $\Pr(G = g_j)$. Table 3 contains all the $VOI_{imperfect}$ results, where $VOI_{imperfect}$=~\$11,000 when the prior is based on the steam flow data. However, this increases to \$48,775 for the alternate prior (Table 1b): MT will have more value if there is a larger chance for drilling a "dry hole." The $VOI_{imperfect}$ results for the 0.1 S/m clay cap threshold are higher when the prior probability for 30kg/s is higher, reflecting how the conductance for this category has less overlap with the others (Figure 5). This reverses for the alternate prior.

Table 3: Table of nominal $V_{imperfect}$ and $VOI_{imperfect}$ for the 2 clay cap interpretations (columns) for 2 different priors (rows).

Prior Probability:	Clay Cap defined by threshold:	0.12 Siemens/m	0.10 Siemens/m
According to data	V_{prior}	\$151,550	\$151,550
	$V_{imperfect}$	\$162,580	\$171,500
	$VOI_{imperfect}$	***\$11,030***	***\$19,950***
Alternate prior	V_{prior}	\$0	\$0
	$V_{imperfect}$	\$48,775	\$37,090
	$VOI_{imperfect}$	***\$48,775***	***\$37,090***

Using posterior to determine the next location to drill

The next set of results demonstrates how the information posteriors $Pr(\Theta = \theta_i | G = g_j)$ can be used to help determine new locations for drilling that may have higher likelihood of success. Figure 6 depicts the conductance map of the Darajat field, and Figure 7 is the corresponding probability map for encountering steam flow >15 kg/s. This is derived from the information posterior (Eqn. 3) by summing the posterior for the top four steam flow categories. By integrating insights from this type of map with other available data, new drilling locations and targets can be assessed for chance of success.

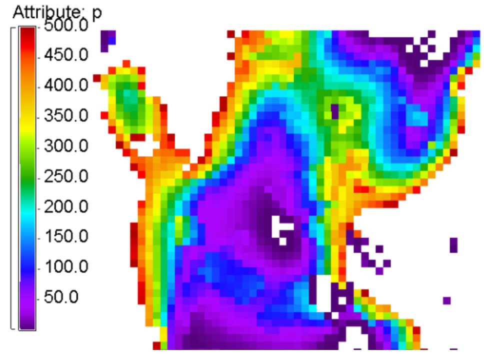

Figure 6: Conductance (S) of clay cap interpreted with 0.12 S/m threshold (plane view).

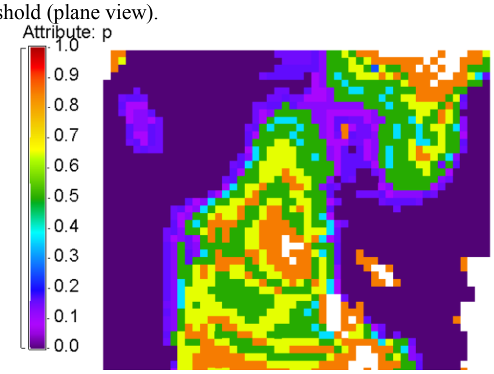

Figure 7: $Pr(\Theta > 30 | G = g_j)$): Probability of θ> 15 kg/s given conductance of Figure 6 and posterior calculated from Figure 4.

Conclusions

Our methodology estimates the prediction power of MT given a collocated steam flow dataset. Previous VOI methodologies used synthetic data for the exploration geothermal problem (Trainor-Guitton et al., 2014). This study defines the reliability of MT field data to predict a particular steam flow category by using observed field production rates which are approximately collocated with the geophysical data. We also demonstrate how the posterior probabilities can guide future well locations by using the past performance of MT to locate high steam flow. We appreciate funding from the DOE Geothermal Technologies Office. This research was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract No. DE-AC52-07NA27344. LLNL-CONF-666823.