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Development of Inverse Modeling Techniques for Geothermal Applications

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Earth Sciences Division

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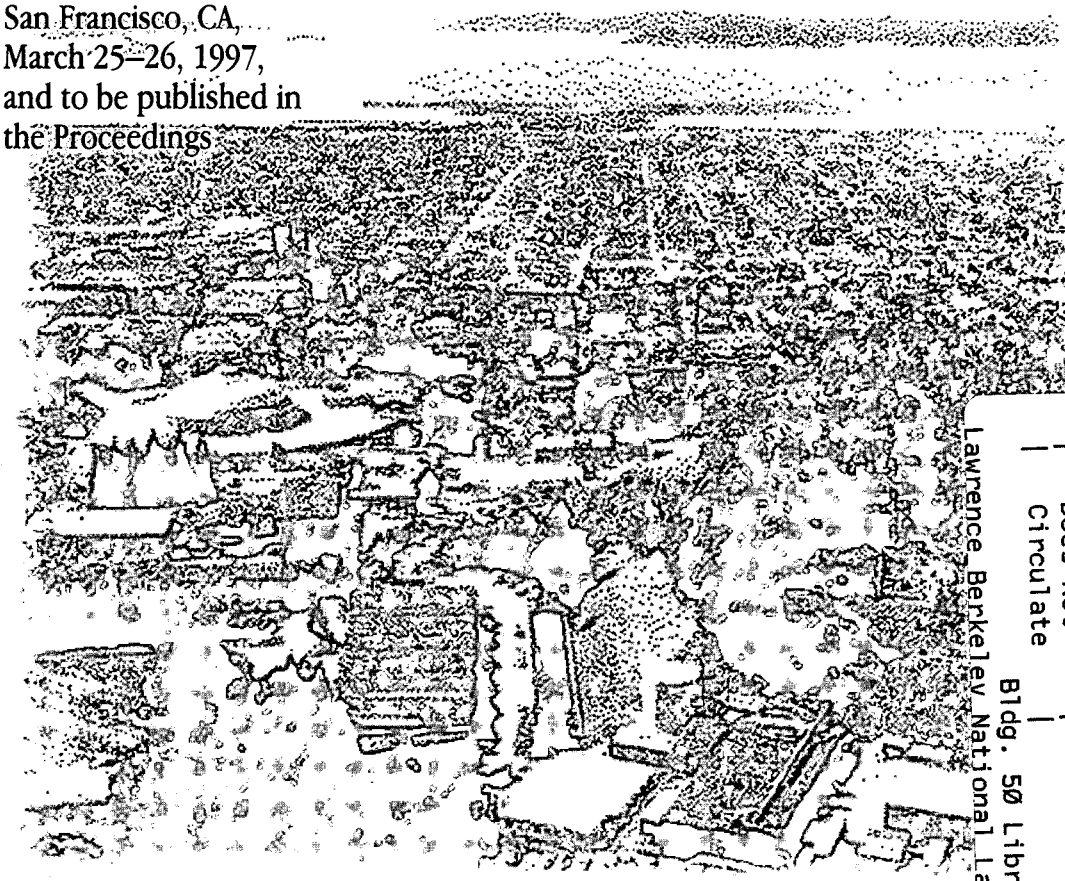

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DEVELOPMENT OF INVERSE MODELING TECHNIQUES FOR GEOTHERMAL APPLICATIONS

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ABSTRACT

We have developed inverse modeling capabilities for the non-isothermal, multiphase, multicomponent numerical simulator TOUGH2 to facilitate automatic history matching and parameter estimation based on data obtained during testing and exploitation of geothermal fields. The ITOUGH2 code allows one to estimate TOUGH2 input parameters based on any type of observation for which a corresponding simulation output can be calculated. In addition, a detailed residual and error analysis is performed, and the uncertainty of model predictions can be evaluated. One of the advantages of inverse modeling is that it overcomes the time and labor intensive tedium of trial-and-error model calibration. Furthermore, the estimated parameters refer directly to the numerical model used for the subsequent predictions and optimization studies. This paper describes the methodology of inverse modeling and demonstrates an application of the method to data from a synthetic geothermal reservoir. We also illustrate its use for the optimization of fluid reinjection into a partly depleted reservoir.

INTRODUCTION

Numerical modeling is an essential tool for the study of basic multiphase flow processes in geothermal reservoirs. Moreover, simulation of future field performance can be used to design, analyze, and optimize various operational scenarios. The latter requires that site-specific, model-related parameters are available on the scale of interest. Inverse modeling can be used to determine effective model parameters by using quantitative information from well tests and past field performance and minimizing the differences between model results and field observations.

Inverse modeling greatly enhances the interpretative potential of numerical reservoir simulations. It can be applied in several modes, providing useful information for three different reservoir management problems. First, it can be used to design and optimize a well testing program for reservoir characterization. The ability of a proposed design to identify hydrogeologic parameters such as the permeability of productive features can be assessed by performing inversions of synthetically generated data. Such an approach is described in detail in Finsterle and Pruess (1996).

The second mode of application is the analysis of the actual data from laboratory and field tests, or data obtained during field exploitation. An example that illustrates the analysis of laboratory data from a graywacke core plug from The Geysers Coring Project is given in Finsterle and Persoff (1996). Also a synthetic field example is discussed below.

Thirdly, the minimization algorithms developed for automatic model calibration can also be used to optimize certain aspects of field operation, e.g., injection rates can be determined such that the thermal output in adjacent production wells is maximized for minimal injection costs. An illustrative example is discussed below. It is important to realize that this type of analysis requires detailed knowledge about actual and hypothetical costs associated with field operations, and - more important - a model of the geothermal reservoir that is able to accurately predict the system behavior for a variety of injection and production scenarios. Optimizing reservoir operations requires conducting a thorough characterization of the geothermal field, which in turn must be based on a good test design. All aspects are supported by inverse modeling.

In this paper we give a brief introduction to the main concepts of inverse modeling. A synthetic example is provided to demonstrate the main application of the method, i.e., automatic calibration of a numerical model of the geothermal reservoir to production data (history matching). We then discuss the possibilities and limitations of using inverse modeling techniques for the optimization of a field operation such as water injection into a partly depleted geothermal reservoir.

INVERSE MODELING THEORY

The core of an inverse modeling code is an accurate, efficient and robust simulation program which solves the forward problem. We use TOUGH2 (Pruess, 1991) to simulate fluid and heat flow in a geothermal reservoir. A summary description of the TOUGH2

version used in geothermal applications can be found in Finsterle et al. (1997).

The determination of reservoir properties from performance data, such as pressures, temperatures, enthalpies, and flow rates, is referred to as the inverse problem. The indirect approach to inverse modeling consists of minimizing some norm of the differences between the observed and simulated field responses which are assembled in the residual vector $\mathbf{r}$ with elements

$$r_i = z_i^* - z_i(\mathbf{p}) \tag{1}$$

Here z_i^* is an observation (e.g., pressure, temperature, flow rate, etc.) at a given point in space and time, and z_i is the corresponding simulator prediction, which depends on the vector $\mathbf{p}$ of all unknown or uncertain model parameters, including initial and boundary conditions. Since the residual vector $\mathbf{r}$ comprises observations of different units and accuracy, we introduce a vector $\mathbf{y}$ with the residual weighted by the inverse of the standard deviation σ_i:

$$y_i = r_i/\sigma_i \tag{2}$$

Depending on assumptions about the error structure of the residuals, different norms of $\mathbf{y}$ may be chosen:

$$\|\mathbf{y}\|_\beta = \left(\sum |y_i|^\beta\right)^{1/\beta} \tag{3}$$

If the error structure of the residuals is assumed Gaussian and described by a covariance matrix $\mathbf{C}_{zz}$, the L_2-norm ($\beta = 2$) seems appropriate, and the objective function S to be minimized is the sum of the squared weighted residuals:

$$S = \mathbf{r}^T \mathbf{C}_{zz}^{-1} \mathbf{r} = \sum_{i=1}^{m} \left(\frac{r_i}{\sigma_i}\right)^2 \tag{4}$$

where m is the total number of observations. In maximum likelihood theory, it is shown that minimizing S is equivalent to maximizing the probability of reproducing the observed system state.

For solving reservoir management problems, where a cost function is to be minimized, the L_1-norm ($\beta = 1$) is chosen, in which the sum of the absolute residuals is minimized. In this case, the "data" z_i^* to be matched are zero for expenses, and a large number for profits.

Due to strong nonlinearities in the functions $z_i(\mathbf{p})$, an iterative procedure is required to minimize the objective function S. The Levenberg-Marquardt modification of the Gauss-Newton algorithm (Levenberg, 1944; Marquardt, 1963) has been found to be suitable for our purposes. The basic idea of this method is to move in the parameter space along the steepest descent direction far from the minimum, switching continuously to the Gauss-Newton algorithm as the minimum is approached. This is achieved by decreasing a scalar λ_k, known as the Levenberg parameter, after a successful iteration, but increasing it if an uphill step is taken. The following system of equations is solved for $\Delta\mathbf{p}_k$ at an iteration labeled k:

$$(\mathbf{J}_k^T \mathbf{C}_{zz}^{-1} \mathbf{J}_k + \lambda_k \mathbf{D}_k)\Delta\mathbf{p}_k = -\mathbf{J}_k^T \mathbf{C}_{zz}^{-1} \mathbf{r}_k \tag{5}$$

Here, $\mathbf{J}$ is the sensitivity matrix with elements $J_{ij} = -\partial r_i/\partial p_j = \partial z_i/\partial p_j$. It relates a change in an observable to a corresponding change in a hydrological parameter. $\mathbf{D}$ denotes a matrix of order n (n being the number of parameters to be estimated) with elements equivalent to the diagonal elements of matrix $(\mathbf{J}_k^T \mathbf{C}_{zz}^{-1} \mathbf{J}_k)$. The improved parameter set at iteration level $k+1$ is calculated:

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \Delta\mathbf{p}_k \tag{6}$$

While the Levenberg-Marquardt algorithm is especially efficient for solving non-linear least-squares problems, it can also be used for the minimization of L_1-norms when using larger values for λ_k.

Under the assumption of normality and linearity, a detailed error analysis of the final residuals and the estimated parameters can be conducted (for details see Finsterle and Pruess (1995)). For example, the covariance matrix of the estimated parameter set is given by:

$$\mathbf{C}_{pp} = s_0^2 \left(\mathbf{J}^T \mathbf{C}_{zz}^{-1} \mathbf{J}\right)^{-1} \tag{7}$$

where s_0^2 is the estimated error variance given by:

$$s_0^2 = \frac{\mathbf{r}^T \mathbf{C}_{zz}^{-1} \mathbf{r}}{m-n} \tag{8}$$

As a byproduct of calculating the Jacobian matrix $\mathbf{J}$, one can qualitatively examine the contribution of each data point to the solution of the inverse problem as well as the total parameter sensitivity.

The inverse modeling formulation outlined above is implemented in a computer program named ITOUGH2 (Finsterle, 1997).

HISTORY MATCHING

The purpose of this section is to illustrate the use of the proposed methodology for the characterization of geothermal reservoirs. ITOUGH2 provides the flexibility to take advantage of almost any type of data collected during well testing or field exploitation. For the sake of simplicity and reproducibility, we will analyze a synthetic case.

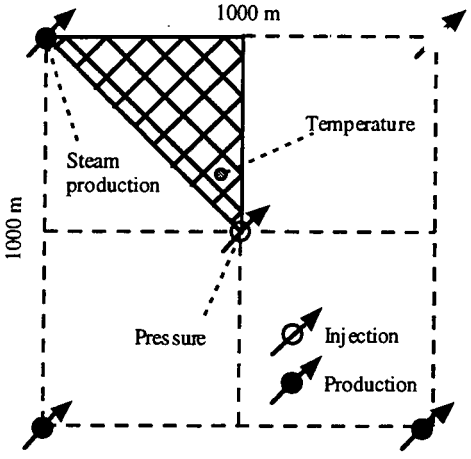

Figure 1. Five-spot well pattern with grid for modeling 1/8 symmetric domain. Observation points and type of data measured is also indicated.

We consider a two-dimensional five-spot production-injection problem (Figure 1) previously studied by Pruess (1991) and Pruess and Wu (1993). The problem specifications correspond to conditions typically encountered in deeper zones of two-phase geothermal reservoirs. The medium is assumed to be fractured with embedded impermeable matrix blocks in the shape of cubes with side lengths of 50 m. The permeable volume fraction is 2 % with an intrinsic porosity of 50 %. Reservoir thickness is 305 m. Water with an enthalpy of 500 kJ/kg is injected at a rate of 8 kg/s. Production occurs against a prescribed bottomhole pressure of 90 bars with a productivity index of 5×10^{-12} m^3.

We assume that pressure measurements are taken in the injection well, temperature is measured in an observation well, and the vapor flux is recorded at the production well assuming a pressure of 8 bars and a temperature of 170 °C at the steam-liquid separator.

TOUGH2 is run in forward mode to generate synthetic data for five years of field performance history, and random noise is added to simulate measurement errors. Subsequently, the model is automatically calibrated against these observations in order to determine certain input parameters considered unknown or uncertain. The parameters include the logarithm of the effective fracture permeability, fracture spacing and the initial reservoir temperature. The true, initial and estimated parameter sets are shown in Table 1. The calculated pressures, temperatures, and steam flow rates are shown in Figure 2. The squares are the synthetically generated data, the dash-dotted lines represent the simulation result with the initial parameter set, and the solid line is the automatically obtained match. The true parameter set is identified very accurately within 8 ITOUGH2 iterations.

Table 1. Five-Spot Well Pattern: True, Initial, and Estimated Parameter Set

Parameter	True Value	Initial Guess	Best Estimate
log (perm. [m^2])	-14.2	-13.5	-14.2
fracture spacing [m]	50.0	20.0	48.1
temperature [°C]	300.0	270.0	299.2

In this system, steam generation and thus thermal power output declines after about 2.5 years of production, and is reduced to less than a third of the initial production after 5 years. Concurrently, temperature in the vicinity of the injection well start to decrease as a result of fluid injection and local boiling, leading to lower pressures. Increasing injection rates may help maintain steam production, provided that the enthalpy of the produced fluid does not decline significantly, as will be discussed in the following section.

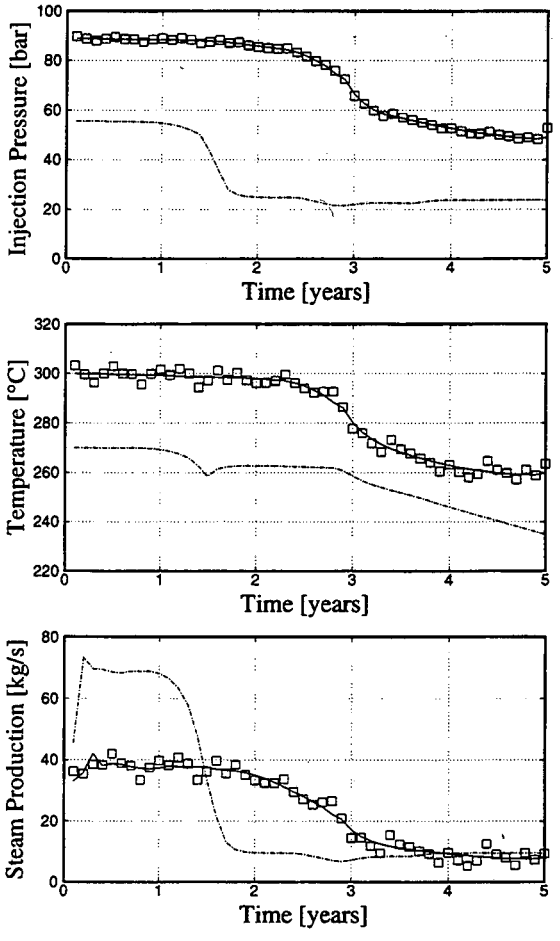

Figure 2. Five-spot well pattern: Automatic history matching of pressure data in the injection well, temperature data in the observation well, and steam flux data at the separator. Squares represent the synthetically generated data. Dash-dotted and solid lines are the calculated system response with the initial and final parameter set, respectively.

A detailed analysis of inverse modeling results including a discussion of parameter sensitivities is given for a similar, albeit more complex example in Finsterle et al. (1997). The purpose of this example is simply to illustrate the history matching capabilities of ITOUGH2 and to introduce the simulation problem used for the subsequent optimization study. Recall, however, that calibration is an important step in any study that is based on predictive modeling.

OPTIMIZATION OF FLUID INJECTION

As mentioned above, Figure 2 shows the general characteristics of a partially depleted geothermal field with reservoir pressure decline and a gradual decrease in steam production. Fluid injection has been proposed as a means to extend the life of geothermal resources.

In the example given, during the first five years water was injected at a constant rate of 8 kg/s. The question arises at which rate fluid should be injected in the future to maintain or even increase thermal energy output. Provided that liquid injection actually increases fluid production, there is obviously a tradeoff between higher returns from increased power generation versus the costs associated with the reinjection. This leads to an optimization problem that can be solved using the methodology outlined in the previous section.

Evaluating and optimizing the economics of developing and managing a geothermal field involves consideration of a complex interplay of factors, including capital investments, operating expenses, and revenues. Not only the amount of expenses and revenues but also their timing can have large impacts on project economics. Matters are complicated by the fact that future reservoir performance and future economic factors are both subject to uncertainty. Analyses of geothermal project economics usually employ probabilistic concepts and sophisticated models of cash flow analysis, but tend to be highly simplistic in their representation of reservoir processes which drive production behavior and injection performance (Sanyal et al., 1989; Martono, 1995).

Inverse modeling by means of ITOUGH2 offers a capability to integrate financial analysis and optimization with detailed reservoir modeling. In what follows this is illustrated with a synthetic example which intentionally uses a very simplistic cost function. Our objective is to convey the concept of an "integrated" optimization, in which a detailed process model of reservoir performance is combined with a consideration of economic cost and revenue factors in a fully coupled manner.

The following simplistic cost function has been chosen to demonstrate the proposed approach:

$$S = \sum_{\Delta t} \left(q_{inj} \cdot c_{inj} - q_v \cdot h_v \cdot f \cdot c_{elec} + q_l \cdot c_l \right) \cdot \Delta t \qquad (9)$$

Here, q_{inj} is the injection rate [kg/s] to be determined which is multiplied by the specific costs c_{inj} [$/kg] to yield the costs for the injected water. q_v and h_v are the vapor production rate and enthalpy, respectively, the product of which is the thermal energy produced per time unit.

In the model considered, the thermal output is multiplied by a factor $f = 0.25$ to yield the electric power output which then can be multiplied by the specific price for electric energy c_{elec}. Since the latter is a gain, it is subtracted from the injection costs. Finally, we add a penalty term to minimize liquid production q_l. Assigning a relatively large value for the hypothetical costs c_l favors a mode of operation that would produce high-enthalpy fluid. The specific costs are time dependent, and are therefore integrated over the entire prediction period (e.g., 30 years) to yield a total cost estimate.

Note that q_{inj} is both the input parameter to be optimized and part of the cost function to be minimized. Production rates q_v and q_l and steam enthalpy h_v are the result of a TOUGH2 simulation, i.e., they depend not only on q_{inj} but also on all the model parameters either prescribed or estimated by inverse modeling. It is this dependence that makes site characterization, model development, and calibration crucial steps in solving management problems by means of reservoir simulation.

It should also be realized that Eq. (9) proposed here can be extended to include more sophisticated cost functions and additional costs and profits which may depend on both input parameters and output variables in a non-linear fashion.

The example discussed below is based on specific injection costs c_{inj} of 200 $/acre-ft (which may include pumping and water treatment costs), an energy price of 0.05 $/kWh, and a hypothetical cost of 0.01 $/kg to penalize liquid production.

In the first example we try to determine a constant injection rate which minimizes the total costs over a 30-year production period. Since only one parameter is considered, the total costs can be evaluated for the entire range of reasonable injection rates, i.e., no minimization algorithm is needed. Figure 3 shows the individual cost contributions and the total cost as a function of injection rate. Since we are only interested in relative costs, no currency unit is indicated in all plots showing costs. Steam production and thus energy return increases almost

linearly with injection rate, and is about 3.5 times higher for q_{inj} = 11.6 kg/s (the optimum injection rate) as compared to the scenario with no fluid injection, and 30 % higher as compared to the base case with an injection rate of 8 kg/s. If injection rate is further increased, however, liquid water enters the production well, and the enthalpy of the steam declines, reducing the thermal output of the well. It is obvious that the liquid produced from the reservoir can be replenished to the point at which thermal breakthrough occurs. The injection costs and penalty function are insignificant in this example, but make the minimum more pronounced. In conclusion, the solution to the optimization problem is almost completely governed by the hydrogeology of the reservoir. Only non-linear cost and penalty functions would greatly affect the optimum injection rate.

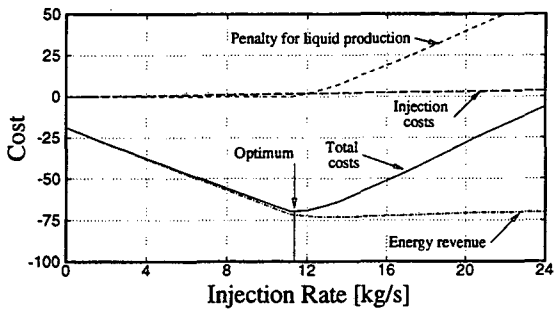

Figure 3. Injection optimization: Injection costs and energy return as a function of injection rate calculated for a 30-year period. The total costs to be minimized also contains a penalty cost for liquid production.

In the second example we try to further reduce costs by allowing the injection rate to vary with time. We arbitrarily subdivide the 30-year production period into three 10-year intervals, and determine three injection rates, one for each period. This optimization problem is solved by using the minimization algorithm mentioned above. We discuss the result of this optimization by comparing it with a no-injection scenario, the base case scenario (injection at a constant rate of 8 kg/s), the previously obtained solution (constant rate of 11.6 kg/s), and a high injection rate of 32 kg/s which is not an optimum. Since the minimum of the total cost is almost identical with the maximum of steam production, we can take the predicted steam flux at the separator as an indication of total system performance, where the profit is the area under the curve multiplied by the steam enthalpy of 2769 kJ/kg and the steam price (i.e., $f \cdot c_{elec}$). Recall that injection costs and the costs from producing low-enthalpy fluid, which are not directly seen in the plot of steam production, are taken into account when determining the optimum injection rate.

Figure 4 shows the five different injection scenarios and the resulting steam production as a function of time. If injection is stopped after five years, steam production ceases almost completely within another few years. Continuous injection at 8 kg/s supplies enough fluid that steam production is maintained at about 9 kg/s. The optimum constant injection rate of 11.6 kg/s determined in the previous case increases the steam production by about 30 %, but is limited by thermal breakthrough at the end of the production period. To demonstrate the effect more clearly, injection at a higher than the optimum constant rate, e.g., 32 kg/s, is considered, resulting in a higher production for about 7 years. However, this is followed by a sharp decline so that on a 30 year time frame significantly more energy can be produced with the smaller injection rate. The high injection rate is also associated with high injection costs and large quantities of liquid produced at the wellhead. Finally, if variable injection rates are specified as determined by the optimization algorithm, the overall energy production can be further increased with only moderately higher injection costs. The three injection rates are 18.4, 13.4, and 8.9 kg/s for the 5-15, 15-25, and 25-35 year injection period, respectively. The average injection rate is 13.6 kg/s, i.e., injection costs are increased by only about 17 % compared to the optimum value obtained with a constant rate of 11.6 kg/s. Recall that injection costs are minor compared to the increase in revenue from steam production for the assumed specific costs.

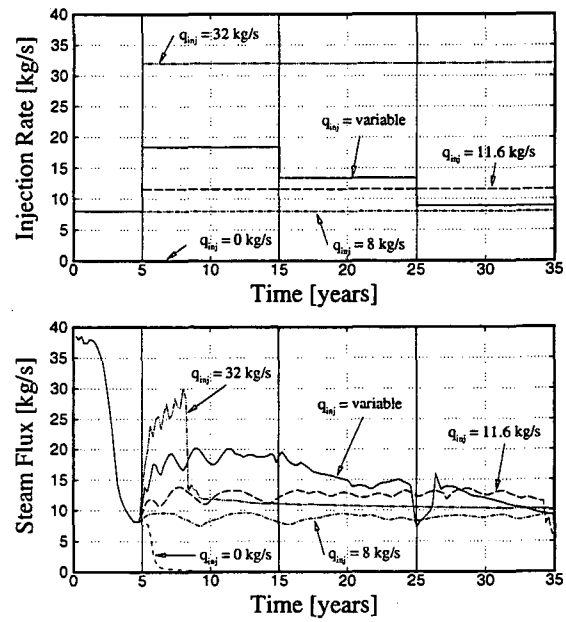

Figure 4. Injection optimization: Steam production at separator as a function of time for five different fluid injection scenarios shown in the upper panel.

The optimum injection rates are declining with time. High injection rates seem acceptable at early times when reservoir temperatures are high. At later time, it is not only the shortage of fluid but also of thermal energy that limits steam production. Note the short period of temperature decline and enhanced liquid production near t= 25 years, which leads to a reduction of the proposed injection rate for the final period.

From this last observation and the system behavior as seen with the high injection rate it becomes obvious that the solution depends on the time frame used for optimization. Short-term solutions tend to favor large injection rates whereas lower injection rates are considered optimal if energy production has to be sustained over longer time periods.

We want to point out that the oscillations seen in Figure 4 are due to finite space discretization employed in the numerical simulations. These effects are particularly severe in problems with coupled thermal and phase fronts as in our case. For a detailed discussion of this problem the reader is referred to Pruess et al. (1987).

CALIBRATION AND OPTIMIZATION

We have mentioned in the previous section that the optimum injection rate is strongly dependent on the production rate and steam enthalpy, and for the case studied here, is only mildly influenced by the costs associated with fluid injection, liquid production and energy prices as long as they are in realistic proportions to each other. While the actual profit obviously depends on the details of the economic model, the optimum at which the total costs are minimized is virtually governed by the time at which unwanted thermal interference occurs in the production well. In other words, the accuracy of the simulation model is essential for the outcome of the optimization study.

To clarify this point, we define and evaluate a measure of the uncertainty associated with the cost prediction. Errors in the calculated cost result from (i) simplifications and systematic errors in the conceptual model of the geothermal reservoir, (ii) uncertainties in the model parameters, (iii) variations in the injection rates, and (iv) simplifications in the cost function and uncertainties in the cost factors. Issue (i) is by far the most important one because errors in the conceptual model usually have a strong impact on predictions, resulting in systematic errors much larger in magnitude than errors from the other sources.

Note that accurate simulation of water injection into geothermal reservoirs is a challenging task. Complex coupled processes of fluid and heat flow in heterogeneous, fractured formations must be modeled, and the flow problem has to be solved in a stable and efficient manner. The issues arising when modeling water injection into vapor-dominated reservoirs are discussed in a companion paper (Pruess et al., 1997).

The second largest source of prediction errors is the uncertainty associated with the hydrogeologic input parameters used in the model. Recall that model-related parameters may be estimated using inverse modeling, and that estimates of their uncertainties are calculated based on Eq. (7). We have studied the impact of parameter uncertainties on the calculated total cost by means of Monte Carlo simulations. A standard deviation of 0.3, 10 m, and 5 °C was assigned to the three parameters log(k), fracture spacing and initial reservoir temperature, respectively, and 300 TOUGH2 simulations have been performed based on randomly generated parameter sets. As a result of these simulations, a probability distribution (histogram) of the total costs can be drawn. This distribution is compared to the result of a similar Monte Carlo simulation, where the injection rate is considered variable with a standard deviation of 1 kg/s. A comparison of the two histograms is an indication of the relative importance of parameter uncertainty versus the uncertainty in the optimum injection rate. Note that a more rigorous study would imply solving the optimization problem for each Monte Carlo realization of the hydrogeologic parameters, giving the actual range of injection rates as a result of parameter uncertainty.

Figure 5 shows the two histograms. The one in bold represents the distribution as a result of uncertainty in the hydrogeologic parameters, and the thin line columns show the distribution due to uncertainties in the injection rates. The minimum cost as determined above is indicated at -174. Reservoir conditions more favorable than the ones used during the optimization may actually lower the total costs. On the other hand, many parameter combinations lead to significantly higher costs if injection occurs at the presumably optimum rate. These parameter sets usually have a lower permeability and/or reservoir temperature than expected. There is a considerable risk that the reinjection rate is sub-optimal, and that the operation is less profitable than expected, as indicated by the 90 % percentile which indicates that 10 % of the 300 Monte Carlo simulations realized costs above -26 monetary units.

The distribution discussed above is compared to the one that results from uncertainty in the injection rate. Since the mean of the injection rate is taken to be the optimum one for the best estimate parameter set, costs are always higher when perturbing the optimum pumping schedule (both increasing and decreasing the injection rate leads to higher costs). Nevertheless, the uncertainty in the cost estimate is bounded with a

90 % percentile at -147 which is relatively close to the minimum cost.

The analysis presented here is qualitative in nature. It was performed to illustrate the significance of reservoir characterization. Model calibration is important because errors in the parameters are a major source of prediction uncertainty. Again, test design and data analysis using inverse modeling can reduce the uncertainty in the estimated parameters, leading to more reliable model predictions which justify the use of automatic minimization routines for the determination of optimum reinjection schedules.

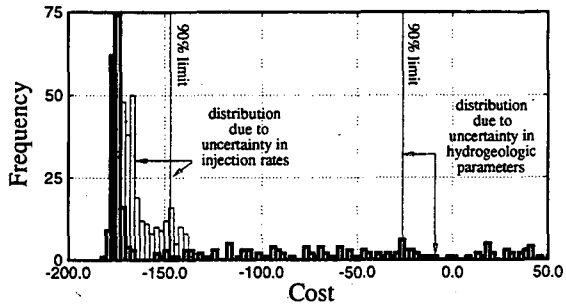

Figure 5. Uncertainty analysis: Cost distributions determined by Monte Carlo simulations reflecting prediction uncertainty as a result of uncertainty in the hydrogeologic parameters (bold line columns) and due to uncertainty in the injection rate (thin line columns).

CONCLUDING REMARKS

The purpose of this paper was to show the flexibility of an inverse modeling approach for automatic history matching and the estimation of model parameters by performing a joint inversion of all available data. In addition to automatic model calibration, the ITOUGH2 code provides a number of semi-quantitative measures to study parameter sensitivities, correlations between parameters and observations, prediction uncertainties, total parameter sensitivities, and the potential benefit from taking measurements of a certain kind and in a certain location. This information is useful for the design and optimization of reservoir characterization and monitoring programs.

The advantage of inverse modeling procedures is that they overcome the time and labor-intensive tedium of trial-and-error model calibration. Effective, model-related parameters are automatically determined on the scale of interest. This ensures that the reliability of subsequent predictions can be improved if they are based on the same or a consistent conceptual model of the geothermal reservoir.

We also demonstrated the use of inverse modeling techniques for the optimization of a reinjection operation. Injection rates have been automatically determined to maximize energy production while avoiding potential drawbacks from thermal degradation and liquid breakthrough at the production well. It was shown that such an optimization study requires an accurate simulation model, i.e., sophisticated process modeling and calibration are the key issues that need to be addressed when using numerical simulations to support reservoir management.

This study was performed using a generic model of the geothermal reservoir, and a very simplistic economic model for calculating the cost function. However, the sophisticated process description of the TOUGH2 simulator along with automatic model calibration capabilities provide the basis for a reliable prediction of the geothermal reservoir behavior. The output of a site-specific process model can and should be linked to a detailed economic model for a combined optimization which takes into account the interaction between field operations and fluid and heat flow in the reservoir.

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