PROCEEDINGS, Thirty-Second Workshop on Geothermal Reservoir Engineering
Stanford University, Stanford, California, January 22-24, 2007
SGP-TR-183

ASSESSING UNCERTAINTY IN FUTURE PRESSURE CHANGES PREDICTED BY LUMPED-PARAMETER MODELS: A FIELD APPLICATION

Omer Inanc Tureyen, Hulya Sarak and Mustafa Onur

Department of Petroleum and Natural Gas Engineering
Istanbul Technical University, Buyukdere Caddesi
Istanbul, 34469, Turkey
e-mails: inanct@itu.edu.tr, hulya@itu.edu.tr and onur@itu.edu.tr

ABSTRACT

Lumped parameter models provide an attractive alternative to numerical modeling of geothermal reservoirs with the distinct advantage of having to deal with fewer modeling parameters. Hence when such models are used, the aim of the modeling work is then to determine the parameters that best describe the system often through history matching. Once the parameters of the model are determined, we proceed to make future predictions under given production scenarios. However, throughout the modeling work, it is very important to asses the uncertainty that arises from (i) "measurement" errors or noise in observed data, (ii) modeling errors, (iii) nonlinear relationship between model parameters and observed response and (iv) non-uniqueness of the problem. Furthermore, it is crucial that this uncertainty be reflected to the future predictions. Hence instead of dealing with a single deterministic response, one can analyze various possible outcomes of the future predictions.

In this work, we first introduce briefly two methods that can be used for predicting the uncertainty in future flow behavior predicted by lumped-parameter models; The Randomized Maximum Likelihood (RML) and the Ensemble Kalman Filter (EnKF). A synthetic application is given for comparing both methods. Then the RML is used to analyze the uncertainty regarding the future predictions of a lumped parameter model on a real field example. The field at study is the Balcova-Narlidere, a low temperature geothermal field located at the west coast of Turkey.

INTRODUCTION

Lumped-parameter models have been used for history matching and predicting pressure (or water level) changes in low-temperature geothermal systems in Iceland, Turkey, The Philippines, China, Mexico and other countries. Axellson *et al.* (2005) and Sarak *et al.* (2005) have presented several field applications of various lumped-parameter models to low-temperature geothermal systems. When lumped-parameter models are used, model parameters can be obtained by applying nonlinear least-squares estimation techniques in which measured field pressure (or water level) data are history matched to the corresponding model response (Axelsson, 1989, and Sarak *et al*., 2005). Then, by using history-matched models, the future performance (in terms of pressure changes or water levels) of the reservoir can be predicted for different production/re-injection scenarios to optimize the management of a given low-temperature geothermal system.

The ultimate goal in any geothermal reservoir study is to predict future performance and even more important to predict the uncertainty in future predictions under different management options. This is necessary to determine the production/re-injection practices that will provide sustainable exploitation of the geothermal system in consideration. Uncertainty in all future predictions of pressure changes is inherent due to (i) measurement errors or noise in observed data, (ii) modeling errors, (iii) span of the available observed data (pressure change data and production history), and (iv) nonlinear relationship between model parameters and observed response.

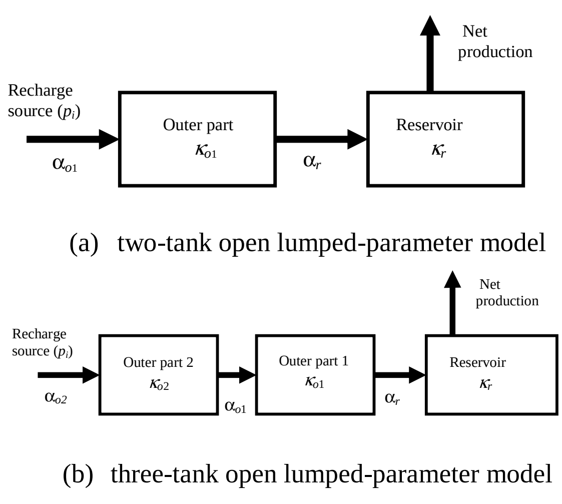
In this paper we discuss the uncertainty in performance predictions and provide a real field example. This is accomplished with a stochastic method of modeling that incorporates uncertainties both in the model and observed data to future performance predictions, the RML method. This method has been shown to be quite efficient for the assessment of uncertainty in performance predictions for nonlinear problems (Kitanidis *et al*., 1995; Oliver *et al.*, 1996; Liu and Oliver, 2003; Gao *et al.*, 2005). Onur and Tureyen (2006) have shown its detailed application regarding lumped-parameter modeling on synthetic examples.

The paper begins with a brief review of lumped-parameter models considered in this study. Then, history matching and performance prediction problems are discussed. We mainly focus on two methods; the RML and the EnKF. We have compared the two methods on a synthetic example provided by Onur and Tureyen (2006). Finally we apply the RML on a real field example.

LUMPED PARAMETER MODELING

The lumped-parameter modeling considered here is very similar in concept to the one presented originally by Axelsson (1989) and identical to the one presented later by Sarak *et al.* (2003a, 2003b, and 2005). As in these works, our lumped-parameter models are based on the conservation of mass only and hence are valid for low-temperature liquid reservoirs under the assumption that variations in temperature within the system can be neglected (i.e. the simulated systems are assumed to be isothermal).

Lumped-parameter modeling can be regarded as a highly simplified form of numerical modeling. In numerical models, a geothermal system is represented by many (>100 to 10^6) gridblocks. On the other hand, in lumped-parameter modeling, a geothermal system is represented by only a few homogeneous tanks and is visualized as consisting of mainly three parts: (1) the central part of the reservoir; (2) outer parts of the reservoir, and (3) the recharge source. The first two are treated as series of homogeneous tanks with average properties. The recharge (or constant pressure) source can be connected to the other parts of the reservoir or directly to the central part of the reservoir and is treated as a "point source" that recharges the system. If there is no connection to the recharge source, the model would be closed, otherwise would be open. Two different open lumped-parameter models are depicted in Fig. 1.



(a) two-tank open lumped-parameter model

(b) three-tank open lumped-parameter model

Figure 1. Two different lumped-parameter models.

The model shown in Fig. 1(a) represents a two-tank open lumped model, where the first tank, in which production/injection occurs, represents the innermost (or central) part of the geothermal system. The changes in pressure in this part are monitored and production/injection rates are recorded. In the second tank, representing the outer part of the reservoir that is connected to the recharge source, there is neither production nor injection and it recharges the central reservoir. Fluid production causes the pressure in the reservoir to decline, which results in water influx from the outer to the central part of the reservoir. The recharge source represents the outermost part of the geothermal system.

When using the lumped-parameter models considered in this work (Fig. 1), the simulated model (output) response represents pressure or water level changes for an observation well for a given net production history (input). The number of model parameters increases as the number of tanks or the complexity of the lumped model increases.

Here and throughout, α represents the recharge constant between the tanks in kg/(bar-s), κ represents the storage capacity (or coefficient) of a tank in kg/bar, and p_i represents the initial pressure of the recharge source in bar. The geothermal system is assumed to be in hydrodynamic equilibrium initially; i.e., the initial pressure, p_i, is uniform in the system. Further details about the lumped-parameter models used in this study can be found in Sarak *et al.* (2003a, b, and 2005).

HISTORY-MATCHING PROBLEM

After a period of production from a geothermal reservoir, and based on the production/injection rate history given, a lumped-parameter model can be matched to the observed pressure (or water level) data to obtain the parameters of that particular model. Different methods for matching the observed data exist in the literature. In this paper we look at the RML method and the EnKF method and provide a brief comparison.

The Randomized Maximum Likelihood (RML) Method

Here and throughout, $\boldsymbol{d}_{obs}$ refers to the vector of measured or observed pressure change or water level data, and contains all N_d measurements that will be used for estimating the model parameters through nonlinear regression. We let $\boldsymbol{C}_D$ be the N_dxN_d symmetric positive-definite covariance matrix for pressure change measurement errors, and assume that measurement errors for pressure data are Gaussian with mean zero (vector) and covariance matrix $\boldsymbol{C}_D$ [i.e., $N(\mathbf{0}, \boldsymbol{C}_D)$]. $N(\mathbf{0}, \boldsymbol{C}_D)$ represents a normal distribution with mean zero and covariance matrix $\boldsymbol{C}_D$. Throughout, a boldface capital letter denotes a matrix, while a boldface lower case letter denotes a column vector.

Letting $\boldsymbol{e}$ denote the N_d-dimensional vector of errors for observed data and $\boldsymbol{m}=(m_1,m_2,\cdots,m_M)^T$ denote the vector of unknown model parameters that are estimated, it follows that

$$\boldsymbol{d_{obs}} = \boldsymbol{f}(\boldsymbol{m})+\boldsymbol{e} \quad (1)$$

Here $\boldsymbol{f}$ refers to the N_d-dimensional vector of computed pressure change or water level data from a considered lumped model, for a given $\boldsymbol{m}$. M represents the total number of unknown model parameters.

As noted above, $\boldsymbol{e}$ is $N(\boldsymbol{0}, \boldsymbol{C}_D)$. Thus, the likelihood function for the model conditional to observed data is given by (Bard, 1974)

$$L(\boldsymbol{m}|\boldsymbol{d}_{obs}) \propto \exp\left\{-\frac{1}{2}\left[\boldsymbol{d}_{obs}-\boldsymbol{f}(\boldsymbol{m})\right]^T \boldsymbol{C}_D^{-1}\left[\boldsymbol{d}_{obs}-\boldsymbol{f}(\boldsymbol{m})\right]\right\} \quad (2)$$

where the superscripts "*T*" and "-1" represent transpose of a vector and inverse of a matrix, respectively. The maximum likelihood estimate of $\boldsymbol{m}$, which honors measured pressure data, is obtained by maximizing Eq. 2, or equivalently, minimizing the objective function $O(\boldsymbol{m})$ given by

$$O(\boldsymbol{m})=\left[\boldsymbol{d}_{obs}-\boldsymbol{f}(\boldsymbol{m})\right]^T \boldsymbol{C}_D^{-1}\left[\boldsymbol{d}_{obs}-\boldsymbol{f}(\boldsymbol{m})\right] \quad (3)$$

The lumped-parameter model responses are nonlinear with respect to the model parameters. Thus, Eq. 3 calls for nonlinear minimization techniques. Over the past, we have found that the gradient based algorithms such as the Levenberg-Marquardt method based on a restricted procedure described by Fletcher (1987) is quite efficient to minimize Eq. 3.

In the RML sampling procedure of Eq. 2, a conditional realization of model parameters to observed data can be generated as follows: **(i)** provide an initial guess of the model parameter vector $\boldsymbol{m}$, **(ii)** add noise to the observed data (i.e., a realization of observed data) by $\boldsymbol{d}_{uc}=\boldsymbol{d}_{obs}+\boldsymbol{C}_D^{1/2}\boldsymbol{z}_u$, where $\boldsymbol{z}_u$ is an N_d-dimensional vector of independent standard random normal deviates. In the applications considered in this paper, $\boldsymbol{C}_D^{1/2}$ is a diagonal matrix with entries equal to the square roots of the corresponding diagonal entries of $\boldsymbol{C}_D$; **(iii)** generate a conditional realization of the model parameter vector $\boldsymbol{m}_r^*$ by minimizing Eq. 3 with $\boldsymbol{d}_{obs}$ replaced by $\boldsymbol{d}_{uc}$; **(iv)** check to see if the estimated model parameter vector $\boldsymbol{m}_r^*$ gives an acceptable match of the data.

To generate n conditional realizations, we repeat the procedure described by items (**i**) through (**iv**) n times. After n acceptable realizations of the model parameter vector, $\boldsymbol{m}_r^*$, for r=1,2,…,n, are generated, we can predict n realizations of the future response using these n $\boldsymbol{m}_r^*$ realizations in the lumped-parameter model considered for a given future production scenario. Then, we can characterize the uncertainty in the predicted response by constructing the histogram and/or cumulative frequency based on these n realizations of the predicted responses at any given prediction time t_i such that $t_i > t_{N_d}$.

The detailed application of the RML method specific to the lumped parameter models can be found in Onur and Tureyen (2006).

The Ensemble Kalman Filter (EnKF) Method

The EnKF method specific to history matching observed data from oil and gas fields can be found in the literature (Zafari and Reynolds, 2005; Gu and Oliver, 2006). In this study we have applied their algorithmic approach to the lumped parameter models. Hence we explain the EnKF method specific to lumped parameter models.

In the EnKF method, we start off with constructing a state vector $\boldsymbol{y}$ at any given time t^k as shown in Eq. 4.

$$\boldsymbol{y}=\left[\boldsymbol{m}^T\boldsymbol{d}^T\right]^T \quad (4)$$

Here the state vector is composed of both the model parameters ($\boldsymbol{m}$) and the model response ($\boldsymbol{d}=\boldsymbol{f}(\boldsymbol{m})$). The dimension of the state vector $\boldsymbol{y}$ is $N_y=M+N_d$. It is also possible to write $\boldsymbol{d}$ using Eq. 5.

$$\boldsymbol{d} = \boldsymbol{H}\boldsymbol{y} \quad (5)$$

$\boldsymbol{H}$ is a matrix with only 0 and 1 as its components, $\boldsymbol{H}=[\boldsymbol{0}|\boldsymbol{I}]$. Here $\boldsymbol{0}$ is a $N_d \times M$ matrix with 0 entries and $\boldsymbol{I}$ is an identity matrix with dimensions of $N_d \times N_d$. The only purpose of using the matrix $\boldsymbol{H}$ is to extract $\boldsymbol{d}$ out of the state vector $\boldsymbol{y}$.

A state vector specific to a two tank open model would be:

$$\boldsymbol{y}=\left[\alpha_{\boldsymbol{r}},\kappa_{\boldsymbol{r}},\alpha_{\boldsymbol{o}1},\kappa_{\boldsymbol{o}1},\boldsymbol{d}(\alpha_{\boldsymbol{r}},\kappa_{\boldsymbol{r}},\alpha_{\boldsymbol{o}1},\kappa_{\boldsymbol{o}1})\right]^T \quad (6)$$

Initially, at t=0, before any data is assimilated, a large number of state vectors is generated, $\boldsymbol{y}_1$, $\boldsymbol{y}_2$, …, $\boldsymbol{y}_{Ne}$, from some prior model where N_e is the total number of state vectors which is also referred to as the number of ensembles. At this point only the model parameters in the state vectors are generated from some prior distribution. The corresponding $\boldsymbol{d}$**'**s are then computed (using the model parameters for each ensemble) at the time where the first data is observed. Then an updating is performed from time level k to k+1 using the following equation:

$$y_j^{k+1} = y_j^k + K_e\left(d_j^{obs,uc} - Hy_j^k\right) \quad \left(j = 1,\ldots,N_e\right) \tag{7}$$

Here, the superscript k indicates the time level, j indicates the j^{th} ensemble, $d_j^{obs,uc}$ is an unconditional realization of the observed data vector for the j^{th} ensemble. This unconditional realization is generated by adding noise to d_{obs}. A different noise is added for each ensemble through the following relationship:

$$d_j^{obs,uc} = d_{obs} + e \tag{8}$$

K_e is the Kalman gain and is computed as:

$$K_e = C_{Y,e}^k H^T\left(HC_{Y,e}^k H^T + C_D\right)^{-1} \tag{9}$$

The $C_{Y,e}$ corresponds to the covariance matrix of the state vector y. The $C_{Y,e}$ covariance matrix can be computed using the ensembles. Any component of the state vector covariance matrix is determined from:

$$c_{m,l} = \frac{1}{N_e - 1}\sum_{j=1}^{N_e}\left(x_{m,j} - \overline{x}_m\right)\left(x_{l,j} - \overline{x}_l\right) \quad \left(m,l = 1,2,\ldots,N_y\right) \tag{10}$$

The subscripts m and l refer to the m^{th} and l^{th} entries in the covariance matrix. $x_{m,j}$ and $x_{l,j}$ correspond to the m^{th} and l^{th} variables for the j^{th} ensemble. $\overline{x}_m$ and $\overline{x}_l$ are the means that are calculated across the ensembles.

The updating is repeated until all data available are assimilated.

Application of the EnKF method on a synthetic example

To demonstrate the EnKF method on lumped-parameter models, we use the same synthetic example given by Onur and Tureyen (2006). The true field in their example was represented by a 2-tank open model. The true model response (in this application, the pressure change) was corrupted by adding noise from a $N(0,0.49)$ to simulate a real case. Hence the observed pressure change to be used in the application is now the corrupted pressure change. We further assume that we know the level of noise (the variance=0.49 bar^2). The corrupted pressure change data represent our observed data (d_{obs}) and contain 193 data points. The observed pressure data are shown in Fig. 2 by solid blue circular data points, whereas the true pressure change data are shown by a solid blue curve. The net production rate history is shown as the black solid curve in Fig. 2 and is assumed to contain no errors.

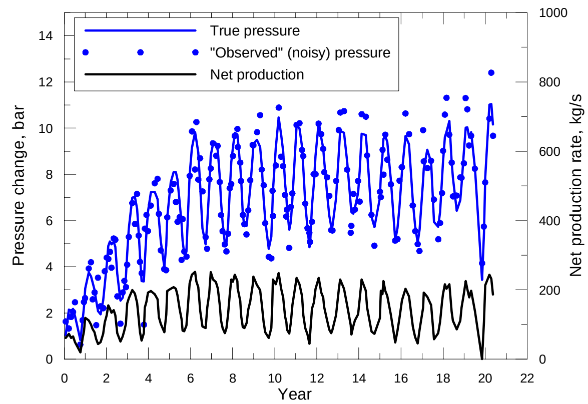


Figure 2. True and observed (noisy) pressure change data and net production rate history.

In their application of RML, Onur and Tureyen (2006) have used three types of lumped models; 2-tank closed, 2-tank open and a 3-tank closed model. In this study, in order to make a comparison between RML and EnKF, the same lumped parameter models are used.

For 2-tank closed, 2-tank open and 3-tank closed models, the state vectors to be used in the EnKF method can be given as:

$$y = \begin{bmatrix} \alpha_r \\ \kappa_r \\ \kappa_{o1} \\ d \end{bmatrix}, \quad y = \begin{bmatrix} \alpha_r \\ \alpha_{o1} \\ \kappa_r \\ \kappa_{o1} \\ d \end{bmatrix}, \quad y = \begin{bmatrix} \alpha_r \\ \alpha_{o1} \\ \kappa_r \\ \kappa_{o1} \\ \kappa_{o2} \\ d \end{bmatrix} \tag{11}$$

respectively.

In this synthetic application of the EnKF, we consider 1000 ensembles. The initial α's have been generated from $N(50,225)$ and the κ's from $N(1\times10^{10},9\times10^{18})$. These represent the prior models used in this example. The updating of the state vector is performed for all 193 data points. For the 1000 ensembles, we generate 1000 different $d^{obs,uc}$ by adding uncorrelated noise to d^{obs} from $N(0,0.49)$.

As mentioned in the previous section, the EnKF works by assimilating one data at a time. Each time a new data point is assimilated, the forward model is run from t^k to t^{k+1} where t^k represents the present time and t^{k+1} represents the time of next data assimilation. However, in our case we can not perform the forward run from t^k to t^{k+1} because of the variable rate history. The lumped parameter models that are used in this study are based on the analytical solutions using the Duhamel's principle to handle the variable-rate history. Hence, each time a data point is assimilated, instead of running the model from t^k to t^{k+1} we run the model from t^0 to t^{k+1} where t^0 represents t=0.

Figs. 3-5 represent the match to the observed data obtained from the first 20 years and future predictions until 45 years. Once again we have used the same rate scenario as of Onur and Tureyen (2006) for the future predictions.

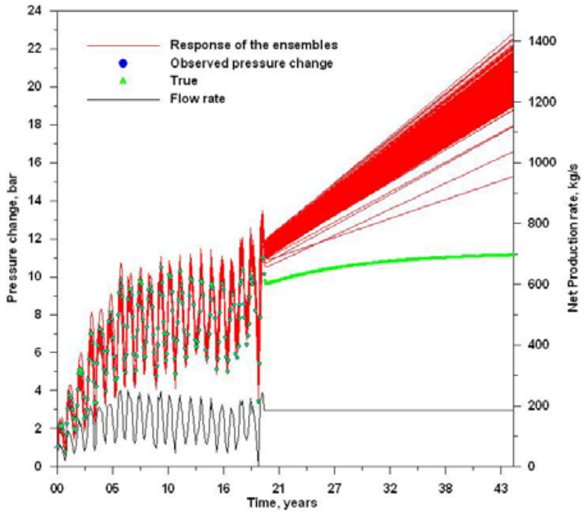


Figure 3. Predicted pressure change by EnKF, 2-tank closed model.

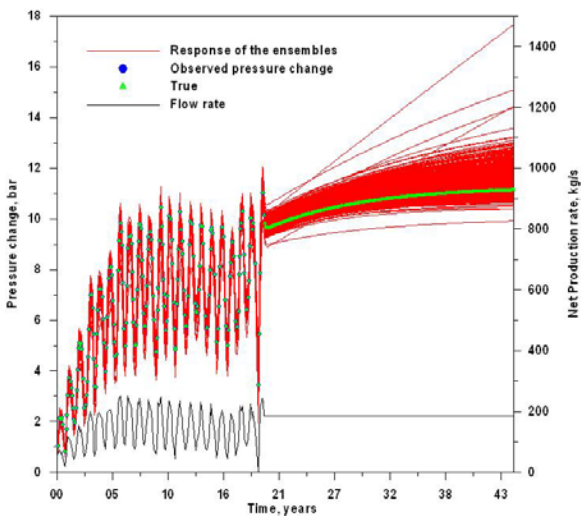


Figure 4. Predicted pressure change by EnKF, 2-tank open model.

The results of Fig. 3 indicates that the performance predicted with the 2-tank closed model is biased; all ensembles result in pressure changes greater than the truth. Fig. 4 represents the results of the 2-tank open model (which is the correct model). In this case, the truth lies within the band of predictions. Finally Fig. 5 represents the results of the 3-tank closed model. Just as in the case with the 2-tank closed model, the prediction band fails to contain the truth.

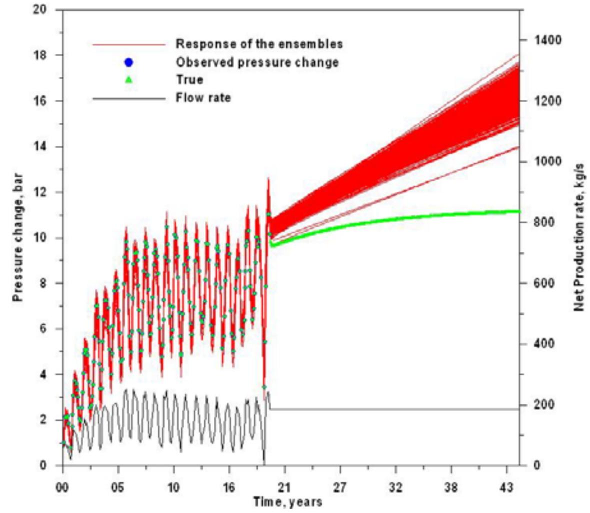


Figure 5. Predicted pressure change by EnKF, 3-tank closed model.

We make a comparison on the model parameters obtained by the RML (Onur and Tureyen, 2006) and the EnKF methods. The results of RML application can be summarized in Table 1. The mean of the model parameters obtained from the 1000 ensembles in EnKF is given in Table 2. Both in Tables 1 and 2, the numbers in parentheses indicate the 95% confidence intervals for the specific model parameters.

Table 1. Estimated model parameters by history-matching of observed data with three different lumped-parameter models using the RML method (Onur and Tureyen, 2006).

Model Parameters	**True parameter values (2-tank open)**	**Estimated parameters for lumped-models**		
		2-tank closed	2-tank open	3-tank closed
κ_r (kg/bar)	$8.9\text{x}10^7$	$9.5\text{x}10^7$ ($\pm1.2\text{x}10^7$)	$8.9\text{x}10^7$ ($\pm1.3\text{x}10^7$)	$8.9\text{x}10^7$ ($\pm1.3\text{x}10^7$)
α_r (kg/bar-s)	30	27.9 (±1.0)	30.6 (±1.7)	30.6 (±2.1)
κ_{o1} (kg/bar)	$1.1\text{x}10^{10}$	$2.4\text{x}10^{10}$ ($\pm2.1\text{x}10^9$)	$1.2\text{x}10^{10}$ ($\pm3.1\text{x}10^9$)	$1.2\text{x}10^{10}$ ($\pm6.5\text{x}10^9$)
α_{o1} (kg/bar-s)	37	-	31.0 (±6.1)	31.0 (±43)
κ_{o2} (kg/bar)	-	-	-	$2.9\text{ x}10^{13}$ ($\pm1.3\text{x}10^{17}$)

Comparing Tables 1 and 2, shows that the results for the 2-tank closed and the 3-tank closed system are rather different. Although not shown here, the future predictions of the RML are also different from Figs. 3 and 5.

Table 2. The mean of the model parameters obtained by EnKF for with three different lumped-parameter models.

Model Parameters	True parameter values (2-tank open)	Estimated parameters for lumped-models		
		2-tank closed	2-tank open	3-tank closed
κ_r (kg/bar)	8.9x10^7	3.34x10^7 (±2.4 x10^7)	7.9x10^7 (±2.12x10^7)	7.55x10^7 (±2.18x10^7)
α_r (kg/bar-s)	30	32.72 (±2.72)	30.36 (±2.52)	30.88 (±2.5)
κ_{o1} (kg/bar)	1.1x10^{10}	1.6x10^{10} (±2 x10^9)	1.2x10^{10} (±3.4x10^9)	1.12x10^{10} (±3x10^9)
α_{o1} (kg/bar-s)	37	-	33.57 (±8.42)	57.02 (±27.62)
κ_{o2} (kg/bar)	-	-	-	1.4 x10^{10} (±4.6 x10^9)

Furthermore, Fig. 5, displays an unexpected behavior. Even though the number of model parameters has increased, the band of uncertainty seems to have decreased when we compare with the predictions of the 2-tank open model (Fig. 4). The RML, on the other hand, shows (Onur and Tureyen, 2006) an increase in the uncertainty band, which would be expected. This may be caused because of the difference in the parameter κ_{o2}, where the EnKF provides a much lower value, with a much lower confidence interval. Because of this, in Fig. 5 we observe much higher pressure drops, high enough not to include the true model.

On the other hand, the EnKF 2-tank open model results seem to be consistent with that of RML, except the confidence intervals seem to be slightly higher in the EnKF method. Also the band of uncertainty seems to be a little larger than the RML as well.

At this point, if there exists no mistake with our implementation of the EnKF, it is not clear to us, why the EnKF, provides, different results than RML. However, it is worthwhile to mention one of the sensitivities that we have performed. We once again work with the 3-tank closed model, however, this time we provide a different prior model. In this case for each parameter, we use a uniform distribution with means equal to the results of the RML method provided in Table 1. Fig. 6 displays the future predictions. Now the results are very similar to the RML results. As expected, the uncertainty band has increased and contains the truth.

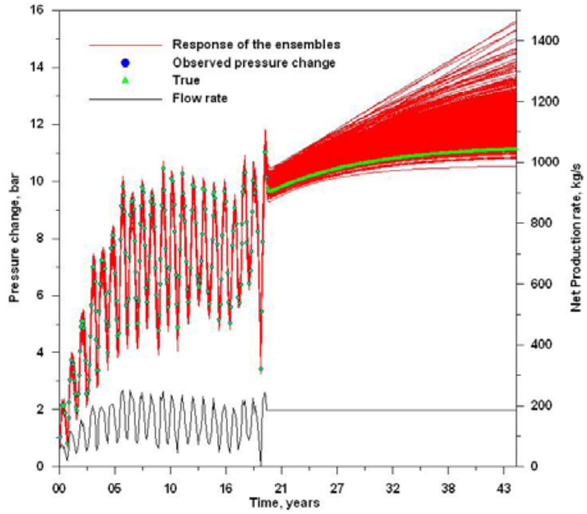


Figure 6. Predicted pressure change by EnKF, 3-tank closed model with different prior model.

Table 3 illustrates a comparison between the model parameters obtained by different prior models using the EnKF and the RML. As it is clear, in this case, the results are very similar to that of RML.

Table 3. A comparison of model parameters obtained by RML, EnKF and EnKF with different prior model for the 3-tank closed model.

Model Parameters	3-tank closed		
	RML	EnKF	EnKF with different prior model
κ_r (kg/bar)	8.9x10^7 (±1.3x10^7)	7.55x10^7 (±2.18x10^7)	8.99x10^7 (±1.44x10^7)
α_r (kg/bar-s)	30.6 (±2.1)	30.88 (±2.5)	30.37 (±2.04)
κ_{o1} (kg/bar)	1.2x10^{10} (±6.5x10^9)	1.12x10^{10} (±3x10^9)	1.31x10^{10} (±4.0x10^9)
α_{o1} (kg/bar-s)	31.0 (±43)	57.02 (±27.62)	28.51 (±9.26)
κ_{o2} (kg/bar)	2.9 x10^{13} (±1.3x10^{17})	1.4 x10^{10} (±4.6 x10^9)	3.03 x10^{13} (±3.2x10^{13})

Many more sensitivities have been performed (not shown here) regarding the effects of the prior model. We have seen that the results are quite sensitive to which prior model we use. The EnKF for some prior models, seems to get stuck in some local minima. At this point we can not explain why this is so. More research needs to be conducted on this subject. We are continuing with our research regarding this topic. However, as a general conclusion so far, we can state that the RML is a very robust technique suitable for history matching lumped parameter models. Hence in the real field application we present in the next section we use the RML method for determining model parameters.

FIELD APPLICATION

The application of the RML method on synthetic examples of lumped parameter models for geothermal reservoirs have been successfully performed by Onur and Tureyen (2006) Here, we extend the application of RML method to a real field. The field at study is the Balcova-Narlidere Geothermal Field. This field is known as the oldest geothermal system in Turkey and is situated 10km west of Izmir. The geothermal water with a temperature ranging from 80°C to 140°C is produced from the wells with depths ranging from 48.5m to 1100m.

The application of RML will be performed on the data collected from one of the wells in the field. The data consists of net rate (production rate – injection rate) information starting from 01/01/2000 and corresponding water level data starting from 17/06/2001. All data have been collected until 10/11/2005. Here it is important to note that the net rate history is obtained from the entire field whereas the water level data is collected only from a single well. Fig. 7 illustrates the collected data to be used in the RML application.

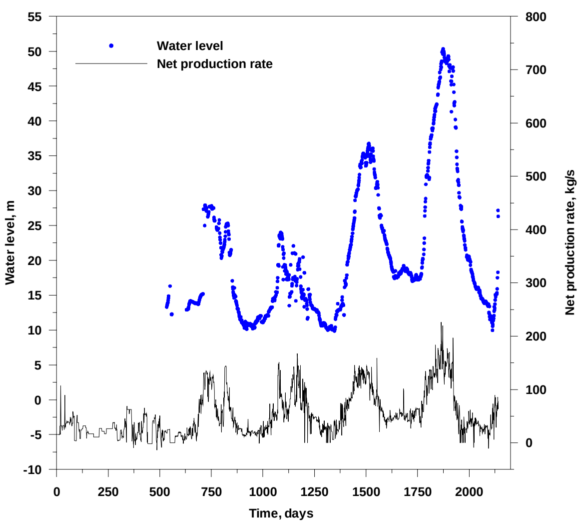


Figure 7. Observed rate and water level data.

The RML method has been performed on the above data for 5 different lumped parameter models (1 tank open model, 2 tank open/closed models and 3 tank open/closed models). For each model 100 realizations of matched responses are generated and the results are compared.

During the application, the water levels have been converted to pressure changes. Hence all computations are performed on the pressure changes, but results in the graphs are given in terms of water levels. The realizations of the observed data is obtained by adding random noise from a $N(0,0.8125)$ distribution. The pressure change data is treated stationary and hence the variance of the noise is obtained as the deviation from the overall mean. In other words, first the mean of the pressure change signal is computed. Then the variance of the entire signal is determined based on this mean.

Once the history matching is complete we make future predictions with the optimal model parameters. The rate history for the future 10 years is obtained by taking the rates of the last year of the matching period and increasing them by %20 each year.

Figs 8-12 illustrate the history matching period and the future 10 year predictions for the 1 tank open model, 2 tank closed/open models and 3 tank closed/open models respectively. The blue circled points in the figures represent the observed water level data, the solid red lines represent the results of 100 simulations and finally the solid black line represents the net flow rate.

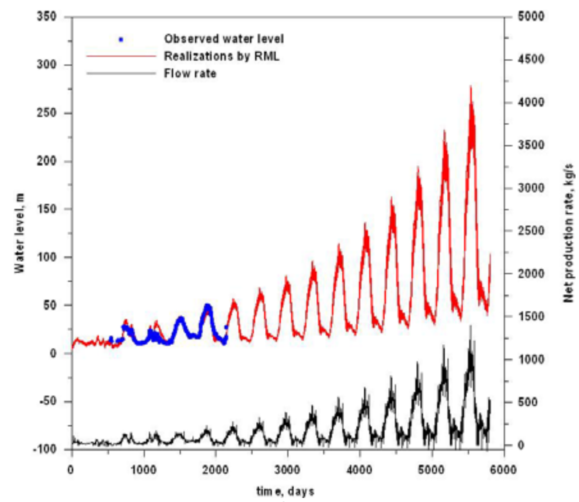


Figure 8. Realizations of predicted pressure change generated by RML, 1-tank open model.

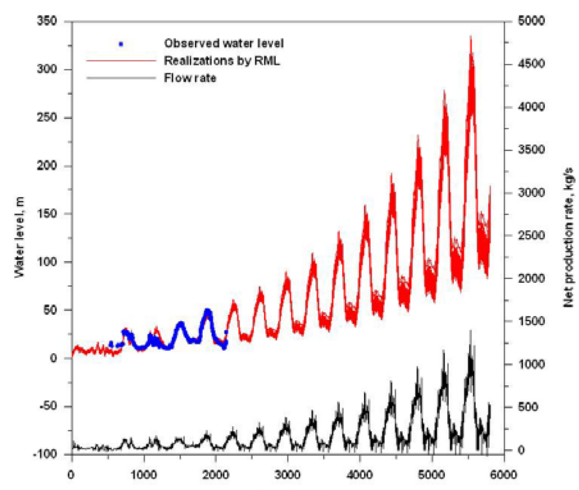


Figure 9. Realizations of predicted pressure change generated by RML, 2-tank closed model.

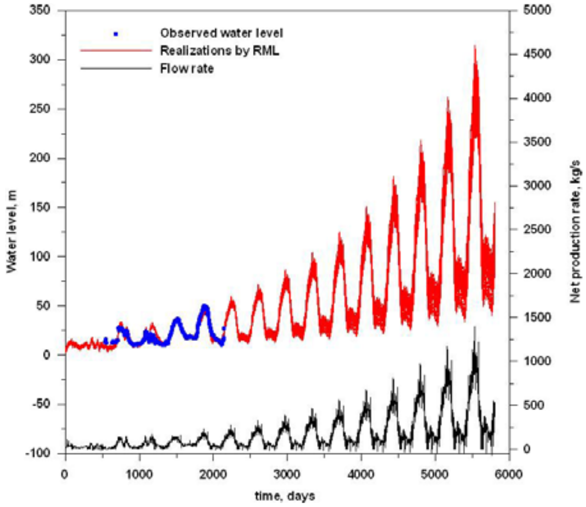


Figure 10. Realizations of predicted pressure change generated by RML, 2-tank open model.

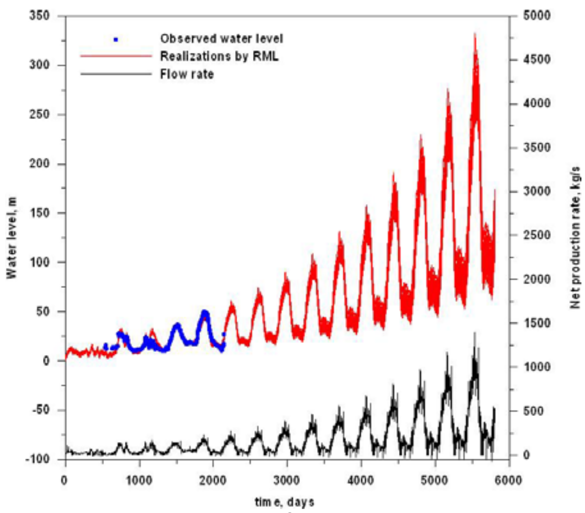


Figure 11. Realizations of predicted pressure change generated by RML, 3-tank closed model.

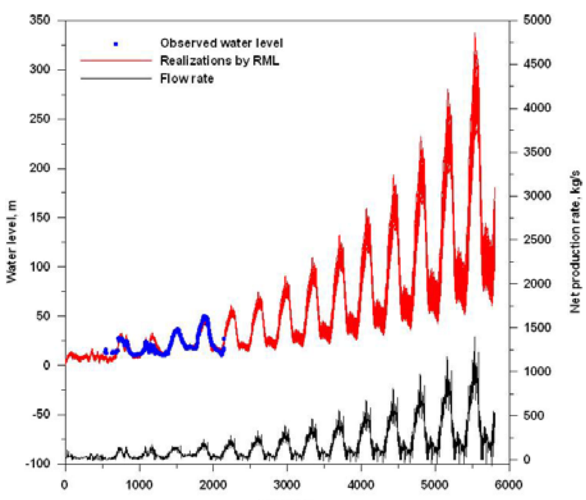


Figure 12. Realizations of predicted pressure change generated by RML, 3-tank open model.

Based on the results provided by the Figs 8-12, we can conclude that the band of the predictions (or the uncertainty in predictions) is narrowest for the 1 tank-open model and widest for the 2 tank open model.

Table 4 summarizes the history matched parameters and various statistics (95% confidence intervals and RMS). All these parameters and their statistics have been obtained by averaging the results of 100 realizations. An inspection of the RMS values indicate that they are all almost the same and can be considered close to the actual noise that was added to the observed data for generating realizations of the data. The confidence intervals in this case will probably be the discriminating measure for the best model that represents the actual system. κ_{o1} and α_{o1} for the 2-tank open model, κ_{o1}, α_{o1} and κ_{o2} for the 3-tank closed model and α_{o1}, κ_{o2} and α_{o2} for the 3-tank open model are unacceptable due to their high confidence intervals (Here our definition is that an estimate of a parameter is acceptable if its confidence interval range is less than 95% of the estimated value itself). Hence they can immediately be ruled out as candidates for describing the Balcova-Narlidere geothermal field.

Table 4. Estimated model parameters by history-matching of observed data with five different lumped-parameter models.

Model Parameters	Estimated parameters for lumped-models				
	1-tank open	2-tank closed	2-tank open	3-tank closed	3-tank closed
κ_r (kg/bar)	8.4×10^{7} ($\pm1.2\text{x}10^{7}$)	7.4×10^{7} ($\pm1.2\text{x}10^{7}$)	8.0×10^{7} ($\pm1.3\text{x}10^{7}$)	7.7×10^{7} ($\pm1.4\text{x}10^{7}$)	7.6×10^{7} ($\pm1.8\text{x}10^{7}$)
α_r (kg/bar-s)	44.2 (±2.43)	47.2 (±2.74)	46.2 (±2.91)	46.2 (±12.9)	46.4 (±4.55)
κ_{o1} (kg/bar)	--	1.5×10^{10} ($\pm3.7\text{x}10^{9}$)	1.8×10^{12} ($\pm1.8\text{x}10^{14}$)	2.1×10^{10} ($\pm6.6\text{x}10^{10}$)	2.2×10^{10} ($\pm1.2\text{x}10^{10}$)
α_{o1} (kg/bar-s)	--	--	10.6 ($\pm1.1\text{x}10^{6}$)	2.9 ($\pm2.9\text{x}10^{5}$)	0.823 (±823.0)
κ_{o2} (kg/bar)	--	--	--	3.0×10^{13} ($\pm9.0\text{x}10^{19}$)	8.5×10^{13} ($\pm3.4\text{x}10^{17}$)
α_{o2} (kg/bar-s)	--	--	--	--	622.5 ($\pm1.2\text{x}10^{7}$)
RMS (bar)	0.99	0.97	0.98	0.97	0.97

The reason for obtaining such wide confidence intervals for the above mentioned model parameters can be explained as follows: The observed data do not show significant sensitivity to these parameters. Hence the uncertainty regarding these parameters are large.

Based on the above observations, since the RMS values are relatively close to each other, we compare the confidence intervals for the parameters of the 1-tank open model and the 2-tank closed model. The 1-

tank open model in this case seems to best represent the real field due to the lower confidence intervals of the model parameters.

To better represent the response differences of the different models, Fig. 13 illustrates the box and whisker plot of the responses at 5750 days. The highest water level is reached with the 2-tank closed model. This is expected since, the system is closed. The largest band of uncertainty on the other hand is provided by the 2-tank open model. It is interesting to see that the model chosen to represent the real field has the narrowest band of uncertainty and provides the smallest water level at the same time.

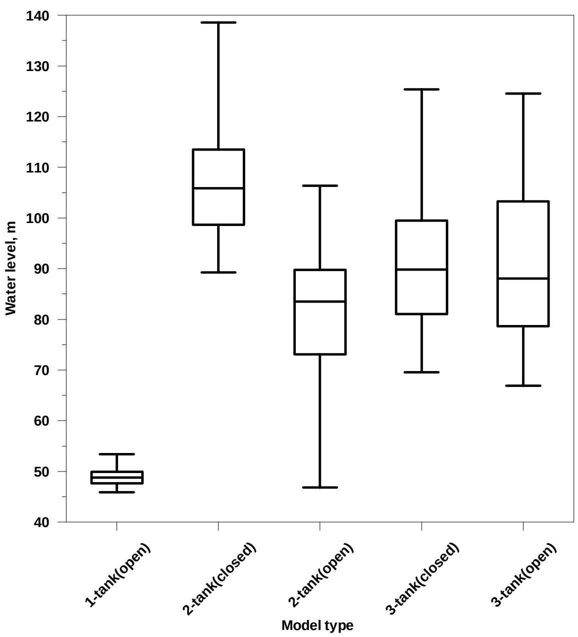


Figure 13. Box and whisker plot of water levels for five different models at 5750 days.

All the production wells in Balcova-Narlidere field are operated by pumps set in the wellbores. The pumps in the wells are installed at an average depth of 150 m from the surface. For safe and efficient operation of the wellbore pumps to avoid a possible cavitation a minimum liquid level above the pump must be maintained. This minimum liquid level is recommended to be 30 m in wells above the pumps. Therefore, the water level is allowed to drop to 120 m in wells unless the installation depths of the pumps are changed. Thus the pump depths are limiting constraints in operation of the field. The water level should not drop below 120 m in wells. Otherwise the pumps at the present installation depths will not be functional. Based on this, according to the model that we believe best represents the system (1-tank open model), the wells will be operational until around 4400 days based on the rate scenario that is provided in Fig. 8.

CONCLUSIONS

On the basis of this study, the following specific conclusions can be stated:

(i) The EnKF method has been implemented for history matching lumped parameter models and is compared with the RML.

(ii) The EnKF method seems to be sensitive for different prior models. We need to investigate further into knowing why.

(iii) Preliminary results show that RML is a more robust method for lumped parameter models.

(iv) The RML method has successfully been implemented to real field data.

(v) Based on the RML results, the authors believe that the Balcova-Narlidere geothermal system can best be represented by a 1-tank open model.

(vi) The uncertainty analysis shows that the uncertainty band in the predictions is also lowest with the 1-tank open model.

(vii) Based on the 1-tank open model, if the flow rates are increased by 20% each year, the pump facilities can manage the field for about 6 more years.

ACKNOWLEDGEMENTS

We would like to thank Assist. Prof. Niyazi Aksoy for providing the field data.

REFERENCES

Axelsson, G. (1989), "Simulation of Pressure Response Data From Geothermal Reservoirs by Lumped Parameter Models," *14th Workshop on Geothermal Reservoir Engineering*, Stanford University, USA, 257-263.

Axelsson, G., Björnsson, G., and Quijano, J.E. (2005), "Reliability of Lumped Parameter Modeling of Pressure Changes in Geothermal Reservoirs," proceedings, World Geothermal Congress 2005, Antalya, Turkey 24-29 April.

Bard, Y. (1974), *Nonlinear Parameter Estimation*, Academic Press, San Diego, CA, USA, 340 pp.

Fletcher, R. (1987), *Practical Methods of Optimization*, John Wiley & Sons, New York City, NY, USA, 101.

Gao, G., Zafari, M., Reynolds, A.C. (2005), "Quantifying Uncertainty for the PUNQ-S3 Problem in a Bayesian Setting With RML and EnKF," *proceedings the 2005 SPE Reservoir Simulation and Symposium*, Houston, Texas, USA, 31 January-2 Febrauary.

Gu, Y. and Oliver, D.S. (2006), "The Ensemble Kalman Filter for Continuous Updating of Reservoir Simulation Models", *Journal of Energy Resources Technology*, 128, 79-87.

Kitanidis, P.K. (1995), "Quasi-linear Geostatistical Theory for Inversing," *Water Resources Research*, 31 (10), 2411-2419.

Liu, N. and Oliver, D.S. (2003), "Evaluation of Monte Carlo Methods for Assessing Uncertainty," *SPE Journal* (June), 188-195.

Oliver, D.S., He, N., and Reynolds, A.C. (1996), "Conditioning Permeability Fields to Pressure Data," proceedings of 5th European Conference on the Mathematics of Oil Recovery, Leoben, Austria, 3-6 September.

Onur, M., and Tureyen, O.I., (2006), "Assessing Uncertainty in Future Pressure Changes Predicted by Lumped-Parameter Models for Low-Temperature Geothermal Systems" *proceedings 31st Stanford Workshop on Geothermal Reservoir Engineering*, Stanford University, USA, 30 Jan. – 1 Feb.

Sarak, H, Onur, M., Satman, A. (2003a), "New Lumped Parameter Models for Simulation of Low-Temperature Geothermal Reservoirs," *proceedings 28th Stanford Workshop on Geothermal Reservoir Engineering*, Stanford University, USA, 27-29 Jan.

Sarak, H., Onur, M., and Satman, A. (2003b), "Applications of Lumped Parameter Models for Simulation of Low-Temperature Geothermal Systems," *proceedings 28th Stanford Workshop on Geothermal Reservoir Engineering*, Stanford University, USA, 27-29 Jan.

Sarak, H, Onur, M., and Satman, A. (2005), "Lumped- Parameter Models for Low-Temperature Geothermal Reservoirs and Their application," *Geothermics*, **34**, 728-755.

Zafari, M. and Reynolds, A.C. (2005), "Assesing the Uncertainty in Reservoir Description and Performance Predictions With the Ensemble Kalman Filter" *proceedings the 2005 SPE Annual Technical Conference and Exhibition*, Dallas, Texas, USA, 9-12 October.