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A NEW LOOK AT WELL-TO-WELL CORRELATIONS USING NONPARAMETRIC, NONLINEAR REGRESSION

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ABSTRACT

In this paper a nonparametric regression method, Alternating Conditional Expectation (ACE), was applied to production data from the Palinpinon field in the Philippines. The method reveals an interesting nonlinear correlation between the injected flow rate and produced concentration for a number of injector-producer pairs. In order to evaluate the ACE approach, we applied it to a subset of the Palinpinon data set and checked the results by using cross-validation. The nonparametric transformations produced by ACE were used to predict future concentration values. The predictions were compared to measured values with satisfactory results in some cases - for other cases the predictions were not good.

The approach presented here takes a simplified view of the physical model describing flow through fractures with time-varying flow rate and concentration. The shortcomings of the approach are discussed and alternative ways of using ACE to reveal the well-to-well connectivity are suggested.

INTRODUCTION

In geothermal field exploitation, the main objective is to provide a balance between obtaining maximum productivity from the wells and at the same time, prolonging the economic life of the reservoir. Presently, the developer relies on a variety of ways ranging from experimental methods to numerical simulation to help ensure that the field is being managed safely and efficiently. Depending on field response, appropriate development strategies and field management policies are instituted and modified.

In this study, production histories for chloride concentration were correlated to injection rate histories based on nonparametric regression to establish well-to-well connectivity. The method of inferring well connectivity by this approach can be conducted with routinely measured production and geochemical data which does not require operational disruption that would be needed with the typical tracer test. Attaining an understanding of the connections between wells is very useful in designing a strategy for brine injection, and predicting where thermal breakthroughs are likely to occur (Horne and Szucs, 2007, Villacorte et al. 2010).

Analytical approaches have been presented in numerous works and in different mathematical forms. This can be seen in the classic paper of Harper and Jordan (1985) who quantified the rate of return of injection water at Palinpinon in the Southern Negros Geothermal Production Field (SNGPF) based on chloride histories. Later, mathematical analysis of Palinpinon's chloride histories was carried out by Urbino and Horne (1991) using a linear regression method; and by Sullera and Horne (2001) who used wavelet decomposition. A well-to-well correlation technique based on nonparametric nonlinear regression (ACE) was discussed by Horne and Szucs (2007) and Villacorte et al. (2010). All of the studies analyzed chloride production histories from wells in the Palinpinon field to infer well connectivity. The results were verified qualitatively by comparison with tracer tests results. However, these methods have shown a weakness in that an assumption of the mathematical form of the connection model is required. This could mean imposing reservoir relationships that may not be extrapolated validly into the future.

The first objective of this work was to examine possibility of verifying the results from ACE by cross-validation, using the Palinpinon data set; and secondly to suggest an alternative way of using ACE to reveal the well-to-well connectivity.

NONPARAMETRIC NONLINEAR REGRESSION - ACE

The ACE (alternating conditional expectation) method was presented by Breiman and Friedman (1985) as a nonparametric approach to modeling data without knowing the model in advance. Non-parametric models differ from parametric models in that the model structure is not specified *a priori* but is instead determined from data.

The ACE method works by inferring a decomposition of the signal in the following form:

$$g^*(y) = \sum_{i=1}^{p} f_i^*(x_i) + e^* \qquad (1)$$

where e^* is the remaining error not captured by the functional form and which is assumed to be normally distributed. It is important to note that $g(y)$ and $f_i(x)$ are not known in advance but are extracted as a result of the algorithm. Since f_i and g represent any smooth function, Equation (1) defines a nonlinear mapping from the inputs, x_i, to the outputs, y. This property along with the nonparametric assumption makes ACE a very powerful tool for data fitting. The predictive capacity of the results, however, depends on how the inputs and outputs are defined, whether Equation (1) can fully capture the input-output relationship, and the amount of information contained in the provided data. When there is marginally sufficient data, the predictive results are highly susceptible to noise.

Since the ACE method can be applied with more than one independent x variable, it is a very suitable way of investigating the relationships between outputs (for example, chloride production at a well) and inputs (for example, injection rates at many other wells). Horne and Szucs (2007) and Villacorte et al. (2010) applied the ACE approach to analyze chloride production histories from the Palinpinon field in the Philippines, and showed good success in predicting the independently measured tracer returns, when there was sufficient transient character in the data.

Here, a closer look at the ACE transformations reveals an interesting nonlinear correlation between the injected flow rate and produced concentration for a number of injector-producer pairs. In order to verify the validity of the ACE model, we applied it to subset of the Palinpinon data set and checked the results by using cross-validation.

The sections that will follow will present examples of cross-validation results and interpretations of the ACE transforms.

CASE RESULTS AND DISCUSSIONS

Injection and production rates of 18 wells from the Palinpinon field were investigated in this study. The results from four of those wells are shown in this paper - two good cases and two bad cases.

In Figure 1 we see each of the inferred transformations $f_i(x_i)$ (tx in the figure) for well OK-7. It is clear, based on Equation (1), that the output (captured in $g(y)$), is most dependent on input x_{10} which represented time in this case. Each of the other inputs, x_1 through x_9, denotes the injection rate. Thus, the results in Figure 1 show how the contribution of each injector to the output concentration varies with the injection rate. It seems likely that this type of information would be useful for field management.

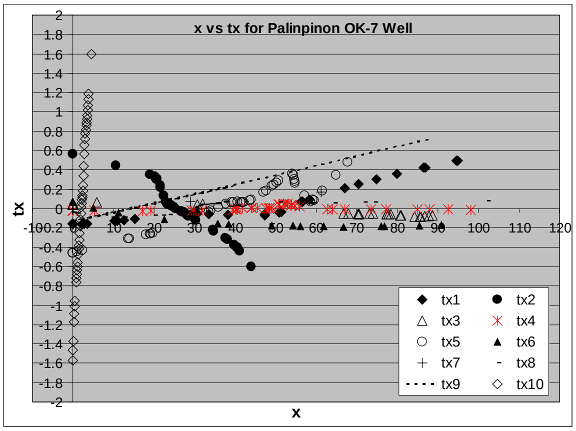

Figure 1: Extracted model functions from OK-7 well data.

A way of validating how representative the ACE results were, was to use cross-validation. Following that approach, part of the data set was used for estimation, and then the estimated transformations were used to predict the rest of the data.

Figure 2 has 53 data values from well OK-7. For the cross-validation the last nine data values were disregarded in the estimation and then predicted independently using the transformations obtained from ACE. The results look promising as shown in Figure 2 (*y_est* are the predictions and *y_meas* are the actual measurements).

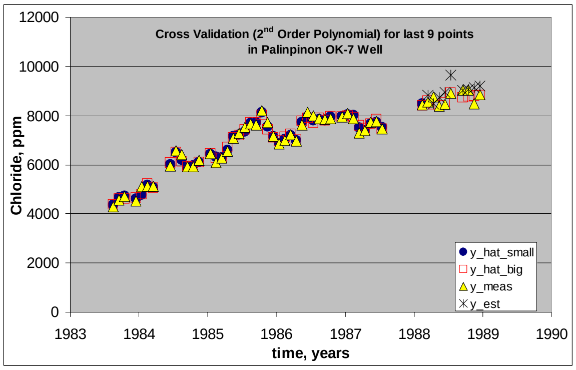

Figure 2: Cross validation results for OK-7 well.

A second example is shown in Figures 3 and 4 where the data for production well PN-16D was analyzed. In this case, the time input is left out of Figure 3, although it was highly influential. What was especially noteworthy, in both of the aforementioned examples, was that ACE found a strong negative correlation between the output concentration in PN-16D and OK-7, and injection into PN-2RD (represented by tx2). This indicates that increasing the injection into PN-2RD may effectively reduce the amount of flow going towards PN-16D and OK-7. Note also that PN-8RD (tx8) seems to be especially well connected to PN-16D as represented by the strong positive correlation seen in Figure 3.

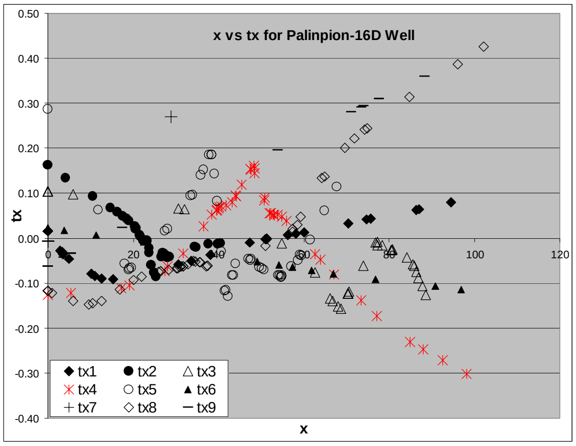

Figure 3: Extracted model functions from PN-16D well data.

PN-16D had 47 data values. In order to apply cross-validation, five data values were deleted. The cross-validation results are shown in Figure 4. Again a relatively good fit was seen between the observed and predicted values.

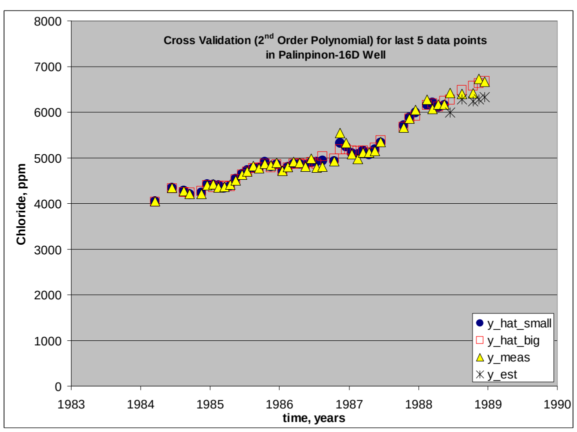

Figure 4: Cross validation results for PN-16D well.

Examples from two additional production wells, OK-10D and OK-9, are shown in Figures 5 through 8.

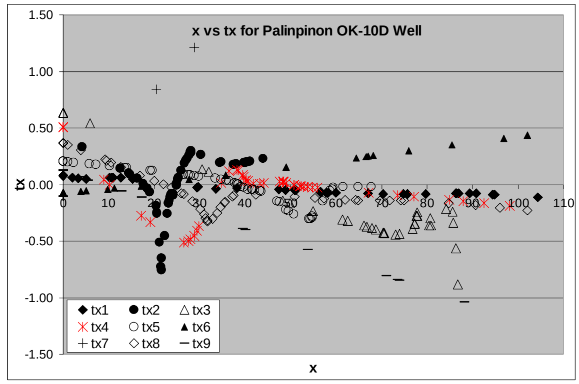

Figure 5: Extracted model functions from OK-10D well data.

Well OK-10D had 55 data values. All but the last five data values were used for estimation. The results are shown in Figure 6.

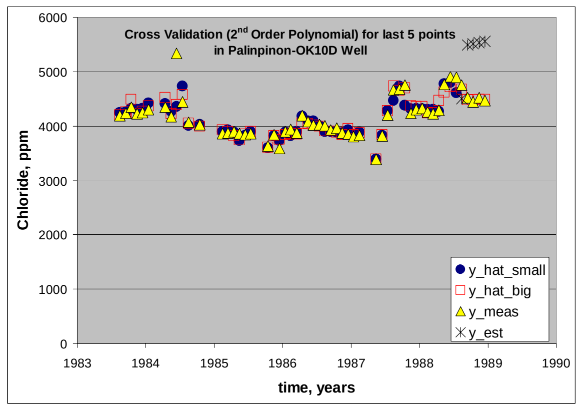

Figure 6: Cross validation results for OK-10D well.

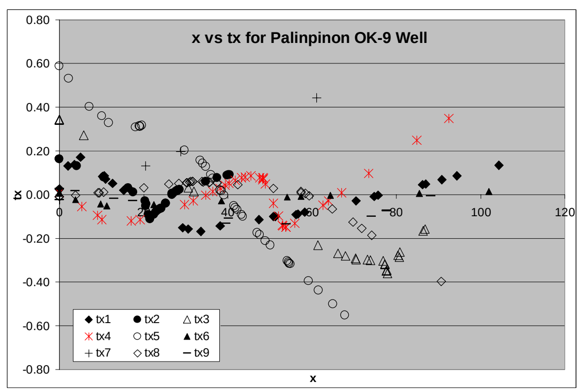

Figure 7: Extracted model functions from OK-9 well data.

The results for well OK-9 are shown in Figure 8. Estimation was done using 35 out of 44 available data points.

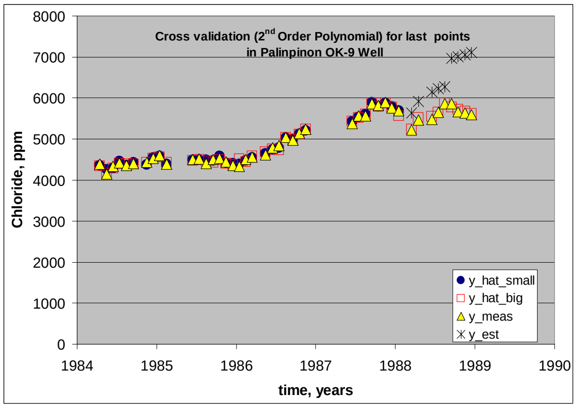

Figure 8: Cross validation results for OK-9 well.

The meanings of the nonlinear transformations in Figures 5 and 7 could be interpreted in a similar manner as before. However, the cross-validation results were not as good for these cases. The reason for this may well be that the prediction data for these second two cases deviated from the linearly growing trend seen in the estimation section. The predicted values depended on this average trend to a large extent, through their relation to the time values. Therefore, this may be an obstacle that needs to be overcome to enable more robust application of the ACE model.

We speculate that the ACE prediction method might be more effective if the time were converted into cumulative flow between wells. This can be shown to reduce the variability in tracer impulse returns for simple flow models, under variable flow rate conditions (Juliusson and Horne, 2011). Finally, it might be practical to correlate the produced concentration to injected concentrations with a few time lags (a kind of nonlinear convolution model). These possibilities will be addressed in future work.

CONCLUSION

We have applied the ACE algorithm to injection-production data and given additional interpretation of its output. The ACE nonparametric method shows promise to estimate well-to-well connectivity. This has been verified by successful cross-validation applications at Palinpinon field. However the predictions were compared to measured values with satisfactory results only in some cases - for other cases the predictions were not good. So it can be said that ACE is flexible but it still has relatively poor predictive power. We infer from this lack of success that the definition of the correlation function may need modification. For example, we know that there is a time lag between the productions and injections, but in this study, we assumed instantaneous responses. It is also important that the data contain sufficient information to restrict the ACE transformations, which are very flexible by definition.

These results show that care must be taken in the choice of regression models. It is important to understand the physics of the problem to be able to choose a regression model of appropriate complexity. Choosing too complex a model can lead to deceivingly good data estimates based on a large number of parameters with poor predictive capacity.

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REFERENCES

Breiman L. and Friedman J.H. (1985), "Estimating Optimal Transformations for Multiple Regression and Correlation," *Journal of American Statistical Association*, **80**, p. 580-619.

Harper, R.T. and Jordan, O.T. (1985), "Geochemical Changes in Response to Production and Reinjection for Palinpinon-1 Geothermal Field, Negros Oriental, Philippines," *New Zealand Geothermal Workshop*, p. 39-44.

Horne, R.N. and Szucs, P. (2007), "Inferring Well-to-Well Connectivity Using Nonparametric Regression on Well Histories," *Thirty-Second Workshop on Geothermal Reservoir Engineering*.

Juliusson, E., and Horne, R.N. (2011), "Analyzing Tracer Tests Under Variable Flow Rate Injection and Production," *Thirty-Sixth Workshop on Geothermal Reservoir Engineering*.

Sullera M. Ma. and Horne R. N. (2001), "Inferring Injection Returns from Chloride Monitoring Data", *Geothermics*, **30**, p. 591-616.

Villacorte, J.D., Malate, R.C.M. and Horne, R.N. (2010) "Application of Nonparametric Regression on Well Histories of Geothermal Production Fields in the Philippines," *World Geothermal Congress, Bali, Indonesia.*