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INFERRING WELL-TO-WELL CONNECTIVITY USING NONPARAMETRIC REGRESSION ON WELL HISTORIES

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ABSTRACT

In the past, well histories such as produced chloride concentration and injection rate data have been used to identify well-to-well relationships and thereby to recognize injection return flow paths in the reservoir. One of the difficulties in earlier approaches has been the need to make some kind of assumption of the expected form of the production histories. By using nonparametric regression, the need to assume a specific form of model is avoided, and a clearer vision of the relationships between reservoir parameters can be revealed. Data from Palinpinon-I field were analyzed using the approach and results were verified successfully against tracer test data and qualitative field observations.

1. INTRODUCTION

One of the most challenging reservoir engineering problems in the design of a geothermal development is the formulation of a strategy for reinjection. Due to the complexities of the geology in most geothermal reservoirs, which are usually found within fractured and heterogeneous volcanic rocks, it is common that injected fluids take apparently surprising paths through the reservoir and often show up rapidly and unexpectedly in production wells. Premature thermal breakthrough is a serious detriment to efficient recovery of the geothermal resource, and unfortunately has been a rather common occurrence in many geothermal fields (Horne, 1985).

Hence one of the most important tasks for a reservoir engineer designing a reinjection strategy for a given reservoir is to make an estimate of reservoir connectivity. Traditionally, this has been done by tracer testing, and a large number of papers have described field applications of this approach (for a recent example, see Fukuda, Akatsuka and Sarudate, 2006). Although effective, tracer testing has some disadvantages, namely:

1. It may be expensive.
2. The flow paths that become important during the production phase of the project may differ (because of differences in pressure fields) from the paths shown in tracer tests before the project began operation.
3. It may be hard to test all wells, because of the logistical costs of collecting samples, and because some wells may not receive tracer until a long time has passed.

For these reasons, it has also been popular to analyze the movement of fluids in the reservoir by monitoring the production of chloride, which changes as a function of time because the reinjected water is elevated in chloride concentration due to the separation of steam. The classic paper that illuminated this approach was Harper and Jordan (1985), which quantified the rate of return of reinjection water at Palinpinon-I field by analyzing chloride (among other variables).

In 1991, Urbino (Macario) and Horne used a correlation method to relate the chloride histories of production and injection wells, for example the well pair shown in Figure 1. This figure reveals a clear relationship between chloride injected at one location and the chloride produced at another. One of the variations of the approach was to subtract a linear-with-time trend from the data, which was an attempt to decipher short-term fluctuations from well histories that show a continuously increasing chloride concentration. The correlation approach was expanded further by Sullera and Horne (2001), who used wavelet decomposition to assist the illumination of the chloride fluctuations at different time resolutions.

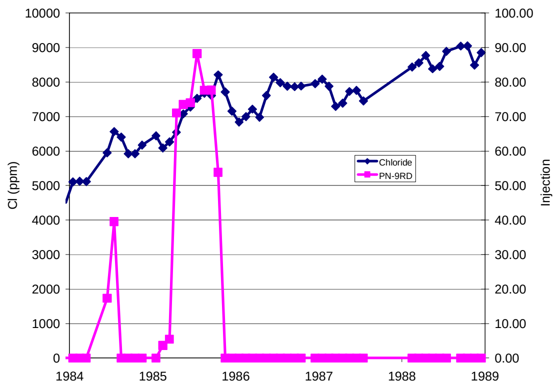

Figure 1: Example data from Palinpinon-I, showing chloride production in well OK-7 and injection rate of well PN-9RD, from Sullera and Horne (2001).

The basis of these approaches was to make assumptions as to the functional relationships between the input and output of chloride, for example:

$$Cl_p = a_0 + a_1 Q_{I1} + a_2 Q_{I2} + a_3 Q_{I3} + \ldots\ldots + a_n Q_{In} \tag{1}$$

where Cl_p = chloride concentration in production well, P

Q_{In} = mass flow rate into injection well I_n

a_n = linear coefficient of well I_n

a_0 = a constant associated with local initial chloride concentration

Another example model assumed a background trend of the chloride that increased in time:

$$Cl_p = a_0 + a_1 Q_{I1} + a_2 Q_{I2} + a_3 Q_{I3} + \ldots\ldots + a_n Q_{In} + bt \tag{2}$$

The methods proceeded by determining the best-fit values for the coefficients *a* and *b* that gave the best match to the observed data for produced chloride, given the histories of injection. The coefficients *a* were then directly identifiable as the magnitude of the connectivity between well pairs, a kind of "connection index".

This approach was reasonably successful, and was shown by Urbino (Macario) and Horne (1991) to be qualitatively consistent with the results of tracer tests.

Nonetheless, a philosophical difficulty with this style of analysis is the requirement to make assumptions of the mathematical form of the model, such as Eq. (1) or (2). The reservoir physics may result in the relationships being something other than simple forms. This is a weakness of the approach.

In an attempt to address this weakness, we investigated the use of nonparametric regression. The fundamental idea of nonparametric regression is to match the data without making assumptions about the underlying form of the relationships. In fact, a major advantage of the approach is that the nature of the relationship is revealed in the process. The magnitude of the connectivities can also be estimated, and these values are then useful for reinjection analysis and design.

In the sections that follow, the nonparametric regression method known as ACE will be described, and an example of its application to data from Palinpinon-I will be shown.

2. NONPARAMETRIC 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. An example of its use will be shown here to illustrate how it works.

In this example, a synthetic data set was generated so that the effectiveness of the method in recovering the underlying model could be determined. The original data are shown in Figure 2.

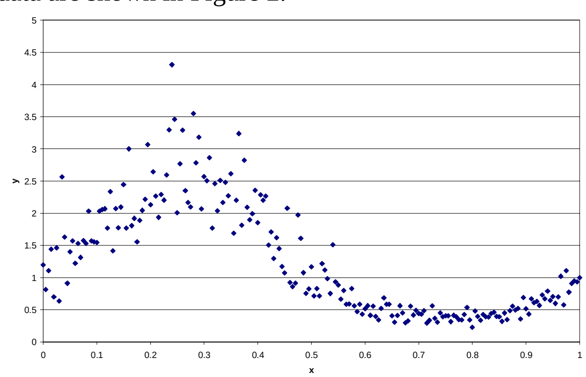

Figure 2: Test data set, generated with the expression ln y = sin 2πx.

These data were generated using the following expression:

$$y_j = \exp\left[\sin(2\pi x_j) + \frac{\varepsilon_j}{2}\right] \qquad (1 \le j \le 200), \tag{3}$$

where x_j is drawn from a uniform distribution U(0, 1) and ε_j is independently drawn from a standard normal distribution N(0, 1). It should be noted that the underlying model for these data is:

$$\ln y_j = \sin(2\pi x_j) \tag{4}$$

Hence the functional forms of both y and x functions are nonlinear.

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

$$g^*(y) = \sum_{i=1}^{p} f_i^*(x_i) + e^* \qquad (5)$$

where e^* is the remaining error not captured by the functional form, and which is assumed to be normally distributed.

Figure 3 shows the inferred relationship $g(y)$ as a function of y, compared to the form used to create the data original (which was ln y). Figure 4 shows the inferred relationship $f(x)$ as a function of x, compared to the form used to create the data original (which was sin $2\pi x$). Finally, Figure 5 shows the match of the "model" to the observed data. The remarkable capability of the ACE method to separate the individual behaviors is revealed in this example.

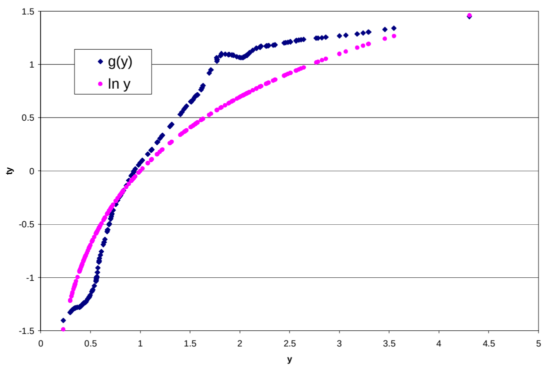

Figure 3: Inferred functional form g(y) of output signal, compared to original generating expression ln y.

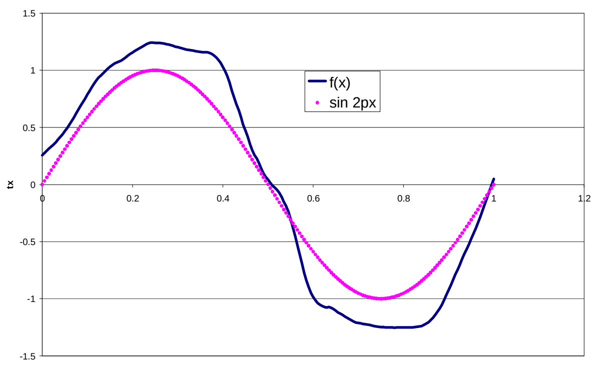

Figure 4: Inferred functional form f(x) of output signal, compared to original generating expression sin 2πx.

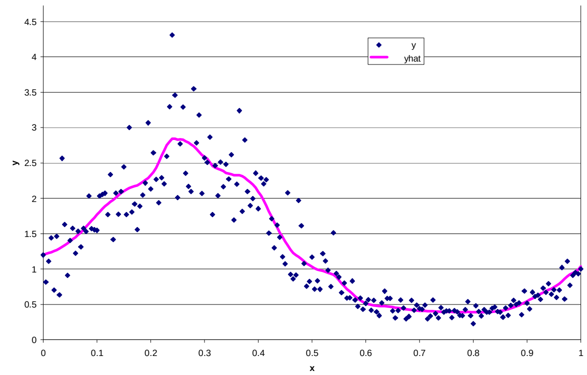

Figure 5: Extracted model response, fitted to original data.

It should be noted that the ACE method can be applied with more than one independent x variable. Hence 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).

3. APPLICATION TO PALINPINON-I CHLORIDE DATA

Having introduced the ACE approach, it is clear that this method offers advantages over the inherently "parametric" approaches used earlier by Urbino (Macario) and Horne (1991) and Sullera and Horne (2001). It is no longer necessary to make any explicit or implicit assumptions about how the input and out variables depend on each other. To compare the approaches, we reexamined the same data set used in these two earlier studies, namely the production and injection histories of Palinpinon-I field over the period between 1983 and 1989.

Typical results are shown for well OK-7 in Figures 6 and 7, and for well PN-17D in Figures 8 and 9. Figure 6 can be compared to the original data shown in Figure 1. Looking first at Figure 6, which has been simplified by including only the functions due to time (red line) and due to well PN-9RD (pink squares), it can be seen that the ACE procedure extracts a simpler picture of the relationships between input and output signals. Importantly, the time dependence is not linear, as was assumed in the earlier studies. The details of the PN-9RD function are somewhat deceptive, as the well was not injecting for much of the time. Hence it is the magnitude of the positive values of the transform function that indicate the degree of connection between this well and OK-7. Figure 7 adds the transform functions for all of the injection wells – the relative sizes of their positive components shows their connectivity to well OK-7. Figures 8 and 9 show the same kinds of data for well PN-17D, revealing an almost linear dependence on time in this case.

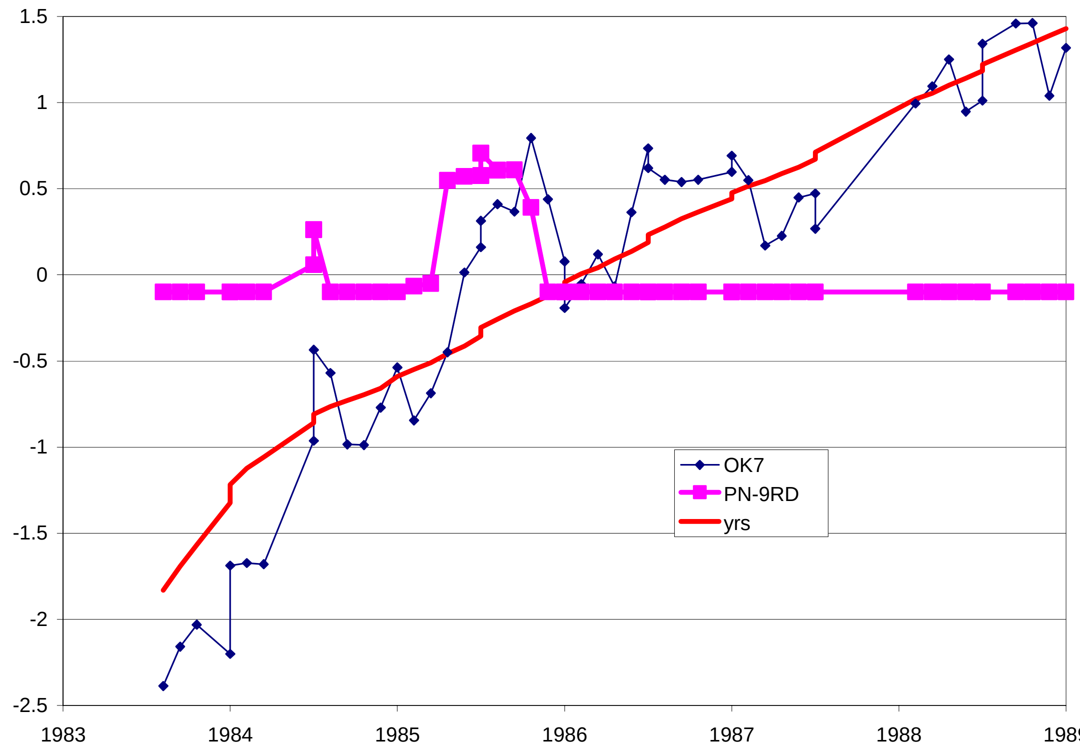

Figure 6: Extracted model functions from OK-7 data (thin line), showing dependence on time (red line), and dependence on injection into PN-9RD (pink squares).

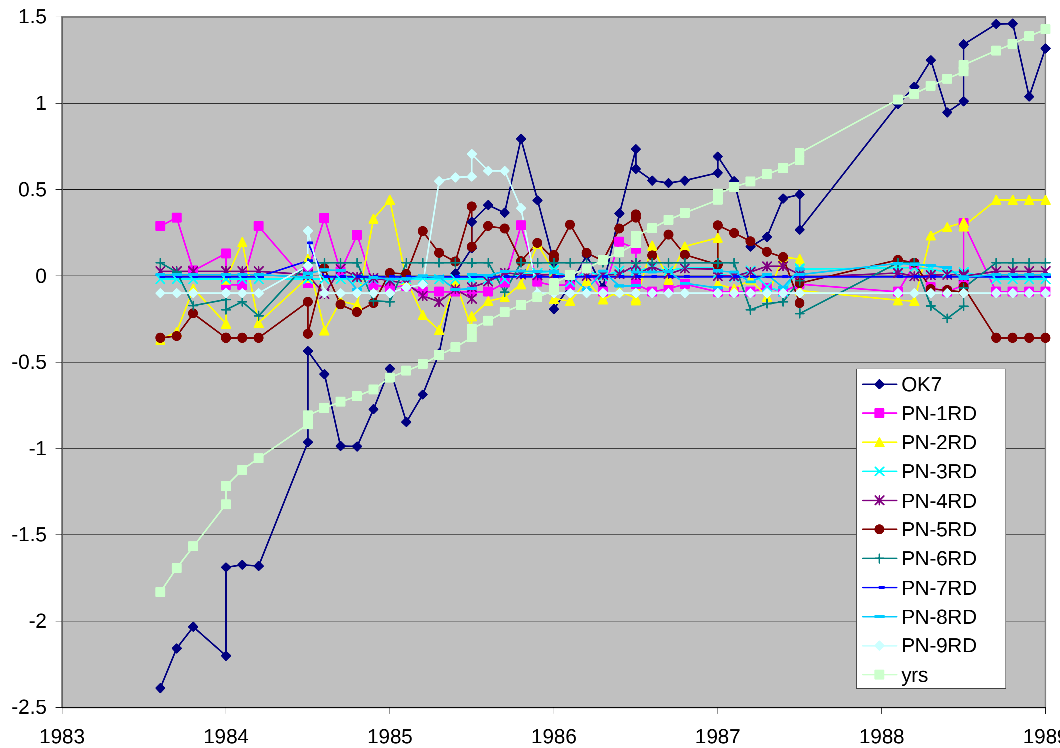

Figure 7: Extracted model functions from OK-7 data, showing dependence on time, and dependence on injection into all injection wells.

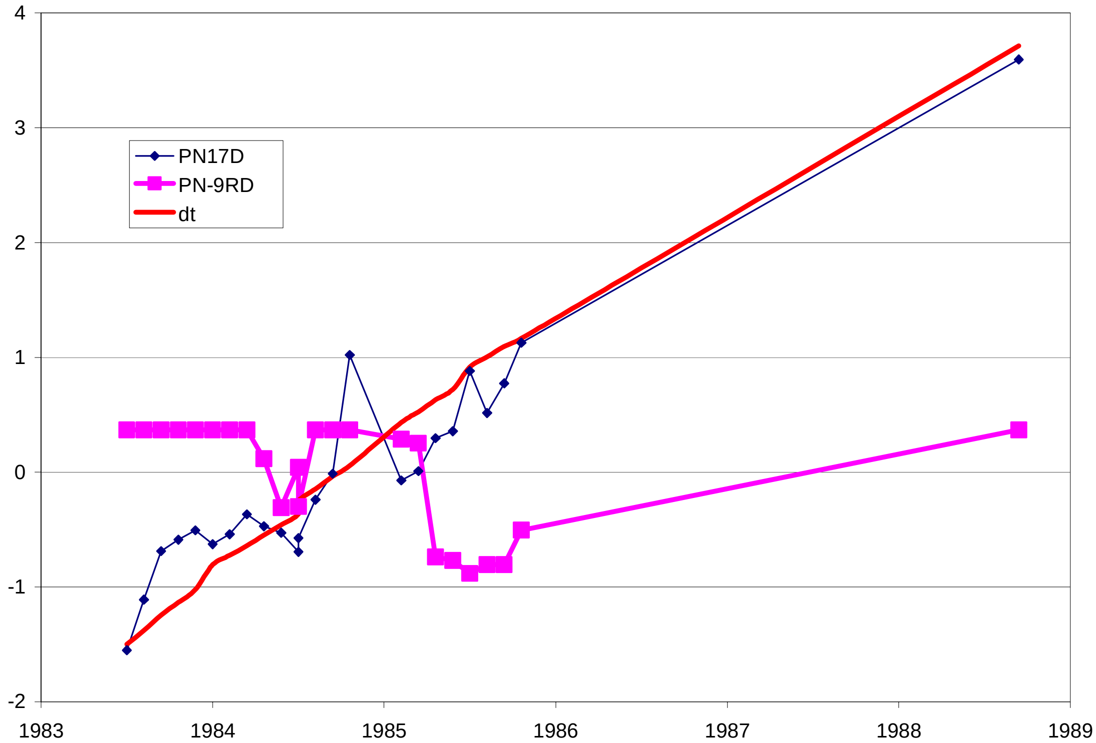

Figure 8: Extracted model functions from PN-17D data (thin line), showing dependence on time (red line), and dependence on injection into PN-9RD (pink squares).

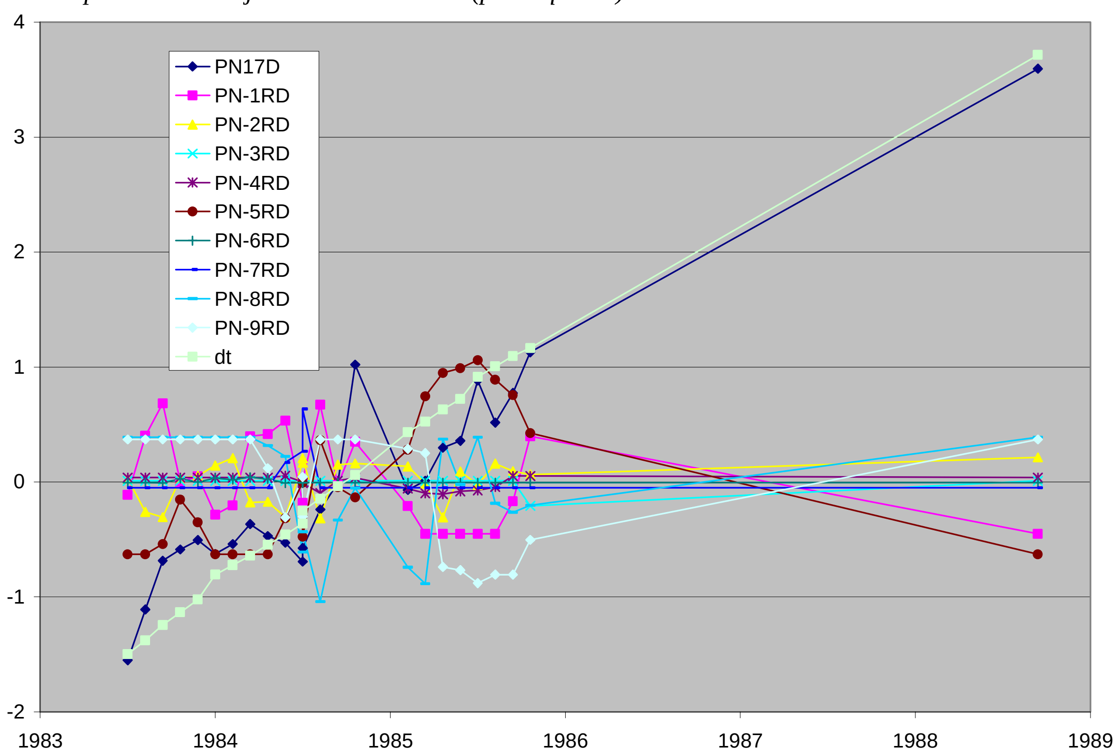

Figure 9: Extracted model functions from PN-17D data, showing dependence on time, and dependence on injection into all injection wells.

Based on the transform functions shown in Figures 7 and 9, we can compute a "connection index" for well-to-well connectivity. We experimented with different ways to do this, and eventually decided on an index defined as:

$$I_i = \frac{1}{n}\sum_{j=1}^{n}\left| f_i(x_i(t_j)\right| \qquad (6)$$

These indices are listed in Table 1, and illustrated graphically in Figures 10 and 11. Figure 10 includes the overall dependence on time, to reveal the size of the impact of reinjection at each production well (the total length of the bar). Individual bar segments in Figure 10 indicate the strength of the connections from specific injection wells. These same connection strengths are shown in Figure 11, allowing a quick visualization of the largest connections – the ones most likely to result in thermal breakthrough.

Table 1: Connection indices based on the average absolute magnitude of the ACE derived transform functions $f_i(x_i)$. These same data are shown graphically in Figures 10 and 11.

	PN-1RD	*PN-2RD*	*PN-3RD*	*PN-4RD*	*PN-5RD*	*PN-6RD*	*PN-7RD*	*PN-8RD*	*PN-9RD*	*dt*
OK7	0.10	0.19	0.03	0.03	0.20	0.10	0.01	0.03	0.16	0.69
OK9D	0.07	0.17	0.27	0.19	0.38	0.01	0.04	0.05	0.17	0.74
OK10D	0.10	0.17	0.28	0.20	0.12	0.17	0.16	0.13	0.11	0.56
PN15D	0.06	0.06	0.04	0.27	0.13	0.03	0.10	0.01	0.06	0.93
PN16D	0.04	0.02	0.14	0.05	0.03	0.03	0.01	0.07	0.03	0.84
PN17D	0.33	0.16	0.02	0.05	0.54	0.01	0.09	0.40	0.43	0.85
PN18D	0.05	0.23	0.06	0.12	0.16	0.04	0.02	0.09	0.02	0.69
PN19D	0.09	0.06	0.41	0.08	0.11	0.07	0.01	0.14	0.03	0.88
PN21D	0.02	0.04	0.27	0.47	0.25	0.03	0.00	0.03	0.00	0.88
PN23D	0.04	0.10	0.14	0.08	0.05	0.06	0.00	0.08	0.04	0.78
PN24D	0.06	0.08	0.19	0.20	0.08	0.10	0.03	0.24	0.13	0.79
PN26D	0.28	0.11	0.04	0.07	0.28	0.05	0.03	0.11	0.07	0.76
PN27D	0.08	0.12	0.07	0.22	0.23	0.03	0.02	0.02	0.16	0.88
PN28	0.13	0.15	0.10	0.08	0.08	0.00	0.00	0.14	0.00	0.74
PN29D	0.06	0.12	0.08	0.06	0.05	0.09	0.01	0.05	0.11	0.76
PN30D	0.05	0.10	0.29	0.11	0.22	0.02	0.01	0.22	0.02	0.57
PN31D	0.05	0.06	0.07	0.11	0.11	0.04	0.02	0.11	0.11	0.84

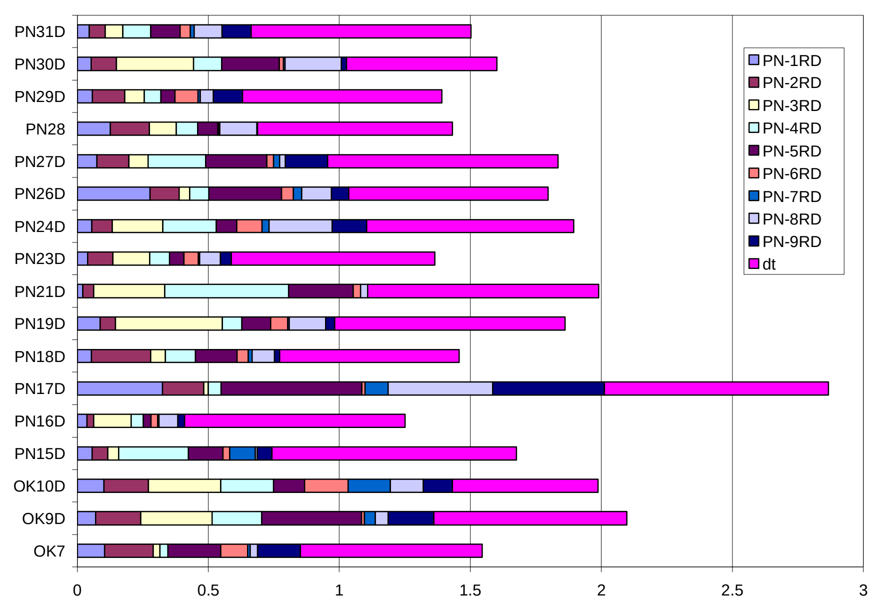

Figure 10: Summary of "connection indices" based on ACE function magnitudes. Total length of bars indicate impact on well of reinjection returns. Rightmost element represents time dependence.

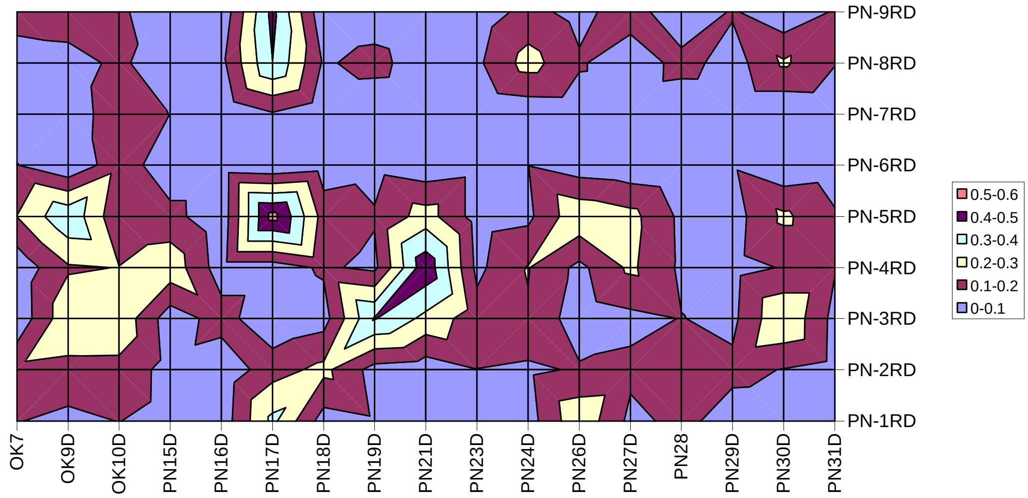

Figure 11: Summary of "connection indices" based on ACE functions, showing magnitude of well to well connections.

4. COMPARISONS TO TRACER TESTS

We can compute these connection indices using ACE, but do they have physical meaning compared to actual fluid movements in the reservoir? One way this can be investigated is by comparing the indices to well-to-well connectivity measurements obtained by other approaches. Fortunately, a series of tracer tests conducted at Palinpinon-I allowed us to make such a comparison.

During the early life of the field, PNOC-EDC conducted a number of tracer test campaigns at Palinpinon, as described by Urbino, Zaide, Malate, and Bueza (1986). These tracer test records showed the transit time of the tracers from one well to another, as well as the total fraction of the tracer recovered. We used the reciprocal of the transit time as an indicator of the connectivity, based on the premise that a fast (short) transit time represents a strong connection.

Figure 12 shows the results of the tracer test with injection into PN-1RD, compared to the connectivity from well PN-1RD estimated in the ACE analysis. The results are very consistent.

Figure 13 shows a similar comparison in the case of PN-9RD, which was a test that showed many more positive returns of tracer. Again the results are consistent, although not perfectly so.

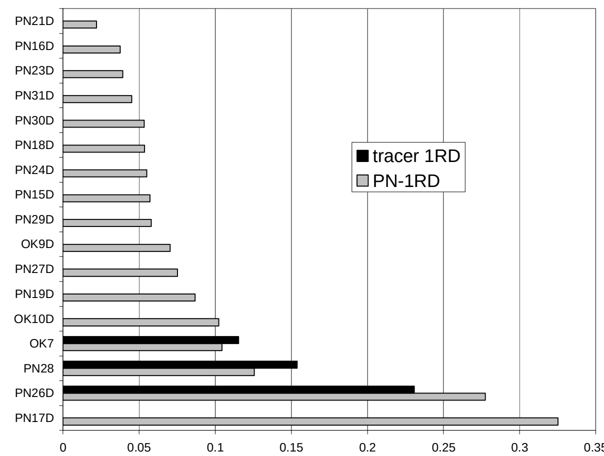

Figure 12: Comparison of connection indices from injector PN-1RD, compared to results of tracer test into PN-1RD (inverse of arrival time).

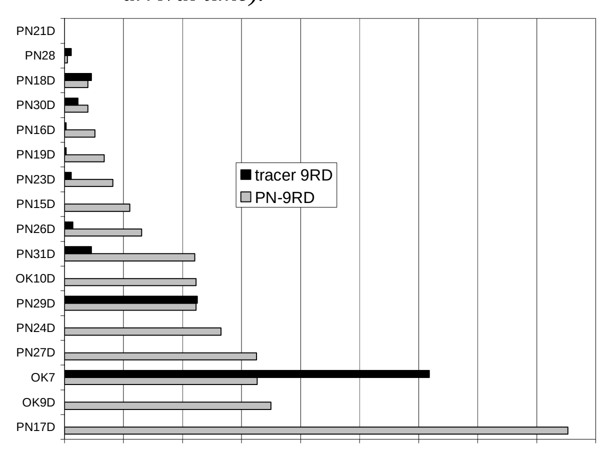

Figure 13: Comparison of connection indices from injector PN-9RD, compared to results of tracer test into PN-9RD (inverse of arrival time).

5. DISCUSSION

As a demonstration of the approach, the application of the ACE method to Palinpinon-I data of production well chloride as a function of reinjection well injection rate showed that the well-to-well connectivity indices computed in this way are consistent with tracer test results. The advantage of inferring well connectivity by this approach is that it can be done with routinely measured production and geochemical data and does not require the expense and operational disruption that would be needed with a tracer test. In addition, it is also an important advantage that the well configuration is in normal operational condition, whereas during a tracer test there is often a worry that the flow paths may be influenced by the configuration of the wells during the test itself.

The procedure shown here is applicable to other kinds of data, for example pressure, enthalpy, flow rate and any number of geochemical species. The more kinds of data included, the better the chance of capturing the interwell dependencies. The data set used here provided promising results, even though the fact that the injection wells were often shut in completely during this time frame is not optimal for the analysis.

6. CONCLUSION

The ACE nonparametric regression method is a useful way to make estimates of well-to-well interrelationships. The application of the approach to historical data from Palinpinon-I geothermal field in the Philippines yielded results that were consistent with tracer testing of the reservoir.

The approach may also be usefully applied to other forms of production data, to reveal reservoir connectivity.

Knowledge of the connectivity is of very significant value during the design of a reinjection strategy.

7. ACKNOWLEDGEMENTS

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