H005 Well-Test Analysis Techniques Developed for the Waste Isolation Pilot Plant

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The Waste Isolation Pilot Plant (WIPP) is the U.S. Department of Energy's deep underground repository for transuranic radioactive wastes produced by the U.S. defence complex. The repository has been receiving waste for disposal since March 1999. The WIPP repository has been excavated 655 m below ground surface in Permian halite beds in the Delaware Basin in southeastern New Mexico (Figure 1). The Delaware Basin is an active area for oil and gas exploration and development in the U.S., and over 1000 wells have been drilled within 10 km of the WIPP site, over 850 since 1990.

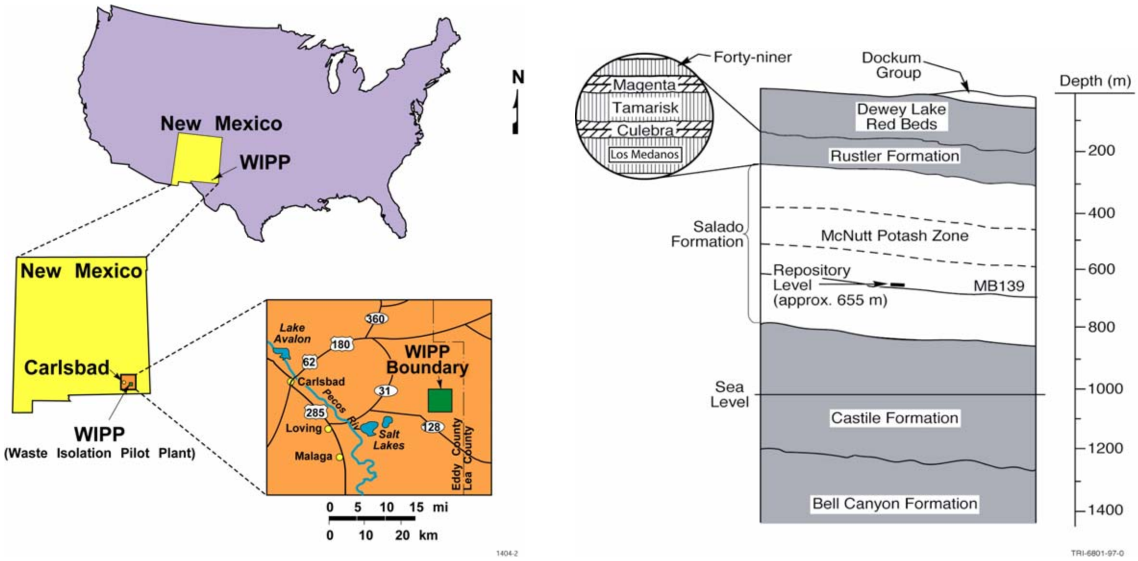

Figure 1. Location and stratigraphy of the WIPP site.

When the first exploratory borehole was drilled for the WIPP in 1974, drillers and oilfield service companies with experience in the area were used. As site-characterisation activities continued through the 1970s and 1980s, WIPP employed many techniques developed by the petroleum industry, including borehole geophysical logging, surface geophysical surveys (resistivity, seismic, CSAMT), well completion (perforation, acidisation), and well testing (DSTs). Oilfield casing, tubing, BOPs, packers, and bridge plugs became standard equipment at WIPP, and remain so to this day.

This paper concentrates on one aspect of site characterisation – the design and interpretation of well tests. Well tests provide the primary information for understanding groundwater flow and assessing the potential groundwater transport of radionuclides released from the repository through inadvertent human intrusion in the future. Well testing and well-test analysis is an area in which WIPP drew heavily from the petroleum industry, and is now poised to make a significant return contribution. Although the fluid of most concern at WIPP is water (or brine) instead of oil, petroleum-industry approaches to well testing and analysis were found to be more useful and advanced than those of the groundwater industry particularly in areas of skin effects, wellbore storage, and geometric models.

Because of the need to quantify flow through the ultra-low-permeability halite host rock and interbedded fractured anhydrites, however, WIPP was forced to go beyond the petroleum industry's state of the art in well testing and test analysis. At the nanoDarcy permeability level, waiting for the ideal antecedent test conditions assumed by analytical solutions to develop takes much too long to be practicable. Hence, we have developed a numerical approach to well-test interpretation that allows any borehole flow and/or pressure history to be incorporated in test analysis. This approach can be applied equally well to the common problem of not wanting to take wells off production to perform a well test. All that is required is knowledge of the rate (or pressure) history of the well and a measurable change in the rate. Including factors such as pressure-dependent wellbore storage and temperature effects in the analysis is trivial. We have also moved beyond the limitations of having to assume an integer dimension of flow (linear, radial, or spherical) in our analyses. This is particularly helpful in fractured rocks, which may exhibit non-integer flow dimensions.

We have developed a well-test-analysis code, nSIGHTS (n-dimensional statistical inverse graphic hydraulic-test simulator), that incorporates the capabilities discussed above with advanced inversion and uncertainty analysis capabilities. nSIGHTS can simulate any kind or combination of well test(s) in a single-phase system. Non-test events or periods can be included in the simulation by specifying pressures and/or rates. nSIGHTS was designed to facilitate a new approach to well-test analysis that provides quantitative information about model and parameter uncertainty.

The analysis of well-test data using nSIGHTS follows five basic steps (Figure 2): (1) Conceptual model identification, (2) estimation of initial values, (3) applying inverse methods to define the combinations of fitting parameters that match the well test behavior, (4) perturbation analysis to check for parameter correlations and intersection of the minima from different constraints, and (5) estimating the contributions of non-fitting parameters.

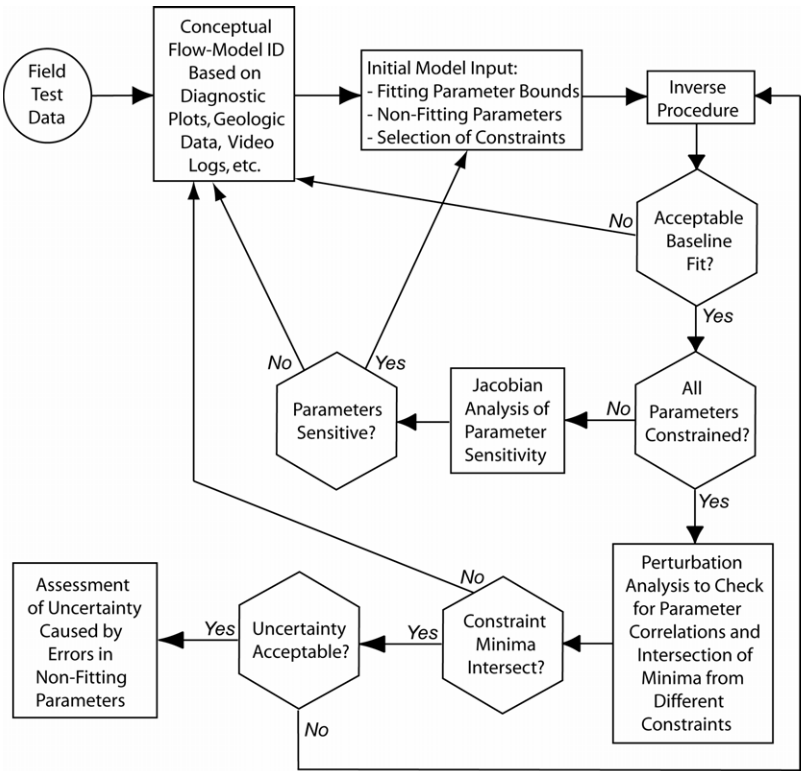

Figure 2. Flow chart of analysis methodology.

The first step in the analysis procedure outlined in Figure 2 is conceptual model identification, which is often the greatest source of uncertainty in the parameter-estimation process. Diagnostic plots (e.g., the pressure derivative of Bourdet et al. (1989) and the flow-dimension diagnostic plots of Beauheim et al. (2004)), geologic data, video logs, and any other available information are used to identify an initial conceptual model for simulation.

The second step in the analysis process is determining initial values for model input. Values must be determined for two types of parameters: 1) non-fitting parameters (e.g., borehole radius, flow rate, borehole pressure history, fluid density, etc.); and 2) fitting parameters (e.g., hydraulic conductivity, specific storage, static formation pressure, flow dimension (geometry), etc.). The non-fitting parameter values are determined directly from field measurements, equipment configurations, laboratory measurements, etc. Initial estimates of the fitting-parameter values are made using standard analytical techniques such as type-curve matching and straight-line analysis, and upper and lower bounds on the values are specified based on experience. Some parameters can be either fitting or non-fitting, depending on the type of test that is performed. Test-zone compressibility, for example, must be fixed (non-fitting) when analysing a pulse test but can be a fitting parameter in the analysis of a pressure-buildup/falloff test. A parameter is specified as non-fitting when it cannot be constrained as a fitting parameter. Constraints to be used in fitting are also defined at this stage. The constraints are simply the different data plots to be matched by the fitting algorithm. These plots typically include some or all of the following data types: pressure, pressure derivative, cumulative production, and flow rates. The data are used to make specialised plots in an attempt to maximise sensitivity to the fitting parameters and combine parameter correlations such that relatively unique estimates of the fitting parameters are obtained.

The third step in the analysis procedure is to run the inverse code (nSIGHTS). Standard optimisation algorithms (Simplex, Levenberg-Marquardt) are used to identify values of the fitting parameters that provide the best match to the test data. If an acceptable match is not obtained at this stage, the conceptual model and/or the model input should be re-evaluated. If an acceptable match has been obtained, the analyst should verify that all optimised parameters lie within their specified ranges, not at a prescribed limit. If the model fit is good but a parameter is at its allowed limit, the model may not be sensitive to that parameter. A Jacobian analysis will reveal whether or not the model is sensitive to that parameter. If it is not sensitive, the conceptual model may be revised to remove that parameter. If it is sensitive, the specified bounds for it may need to be expanded.

Once an acceptable baseline fit with well-constrained parameters has been found, perturbation analysis is performed. The baseline-fit parameter values are randomly perturbed a specified number of times and the problem is re-optimised for each perturbation to investigate the uniqueness of the solution. This process will show which parameters are correlated and, when performed with different constraints specified, will show whether or not the different constraints have intersecting minima. If the constraints do not have intersecting minima, the conceptual model may be missing an important feature and should be revisited. If the minima intersect, the acceptability of the uncertainty should be determined. If the uncertainty is considered too great, alternative constraints should be used in the inverse procedure.

Finally, nSIGHTS utilises a Latin Hypercube sampling routine in a process to quantify the degree to which non-fitting parameter values affect the fitting-parameter values. Error distributions (normal, log-normal, uniform, etc.) are specified for each of the non-fitting parameters. The non-fitting parameters are then sampled a specified number of times and the fitting parameters are optimised for each sampled set. The result is a distribution of fitting-parameter values that reflect both the uncertainty due to correlations among fitting parameters and correlations between fitting and non-fitting parameters.

A constant-pressure flow test followed by a pressure-buildup test provides an example. Figure 3 shows the data from this test sequence. The flow rate during the constant-pressure period and the pressure buildup and derivative data were used to constrain the solution. Figure 4 shows the minima obtained from perturbation analysis when only flow rate was used as a constraint, when only the pressure derivative was used as a constraint, and when both the flow and pressure data were combined as a constraint. The minimum for the combined constraint is seen to be the intersection of the individual constraint minima. The pressure and the flow data are complementary constraints given that this intersection is small relative to the ranges of the individual constraints. Thus, the uncertainty is reduced.

Figure 5 shows the match obtained to the flow-rate data, demonstrating nSIGHTS' ability to match complicated test responses. Figure 6 shows an example from another test of non-intersecting minima from different constraints, indicating inadequacy of the conceptual model.

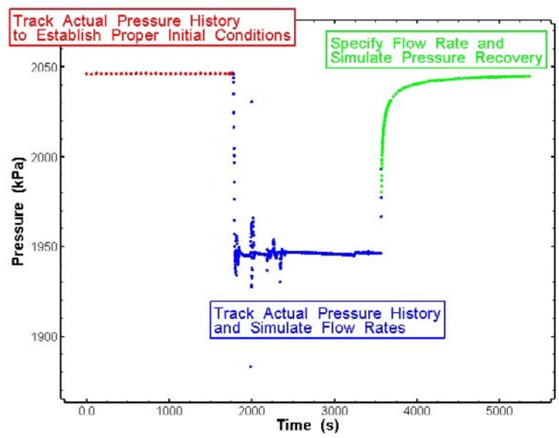

Figure 3. Constant-pressure flow and buildup test data.

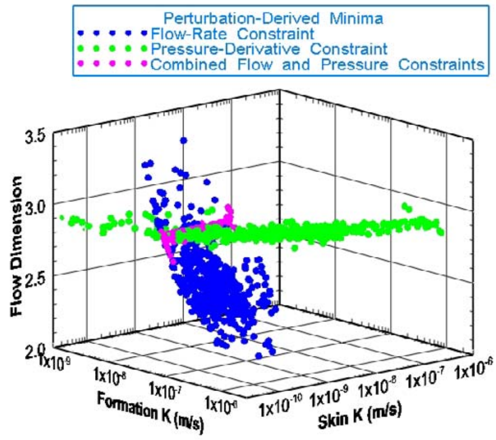

Figure 4. Minima derived for different constraints from perturbation analysis.

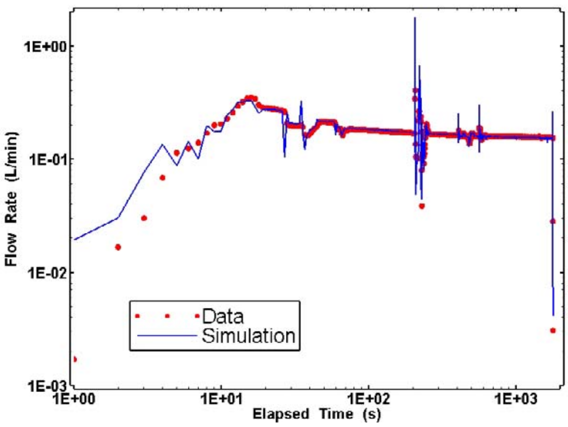

Figure 5. Baseline fit to flow-rate data using all constraints.

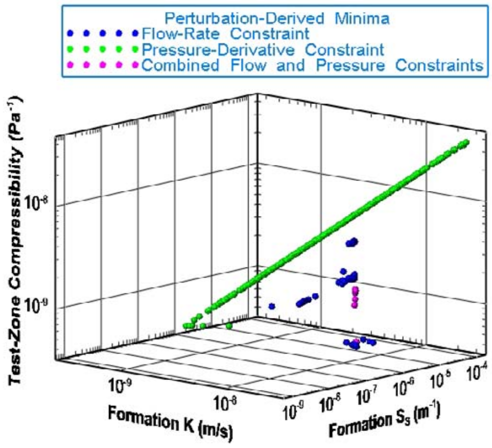

Figure 6. Non-intersecting minima from different constraints.

The statistical tools described above are most beneficial when applied before and during a well test – when applied after the fact, you often only discover things that make you wish the test(s) had been conducted differently. The basic strategy for test design is to find "complementary" constraints, i.e., constraints that exhibit different (ideally, positive and negative) correlations for each pair of fitting parameters. This can often be accomplished simply by applying different types of transforms to a single data set, such as first and second derivatives.

In summary, we have developed a new analysis code and methodology for well-test interpretation that allows model and parameter uncertainties to be investigated and quantified using various statistical techniques. An understanding of the causes of uncertainties permits a more intelligent approach to hydraulic-test design, implementation, and analysis. Rationales for test duration, data-acquisition rates, and pressure/flow-rate resolution can be developed from the specific objectives of a test. Using the statistics as a design tool, optimal constraints can be identified before testing begins. Real-time analysis can then be used to determine when the test objectives have been met. Maximum information is obtained in minimal time, saving time and money and ensuring that the necessary information has actually been obtained before testing is terminated.

References

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