ASSESSMENT OF URANIUM RECOVERY BY ISR MODELING

Vladimir Ugorets, SRK Consulting (USA)

Numerical modeling has a variety of applications within the life cycle of an in-situ recovery (ISR) type mine. In terms of ISR projects, mine planning, operational optimization, and restoration are distinctly different phases in the mine life cycle with very different objectives. Our recent experience with uranium ISR projects in development suggests each objective can be approached with a single comprehensive numerical model that accounts for both groundwater flow and reactive transport analysis and, in doing so, improves economic performance of the mining project. When generated early in the project development phase, the numerical model provides a full life cycle framework and operational parameters for the ISR mine. This paper focuses on the application of these numerical modeling techniques to mine planning and optimization of resource recovery.

Background

In 2008, the authors began a detailed technical review of the Khiagda uranium deposit in Buryatia (Russia). More than 9 years of recovery data from the existing pilot test operation were used for assessment of uranium productions from four major paleochannels. Part of the project scope included independent interpretation of the pilot test data and characterization of the sequential development of the deposit at a commercial scale. The authors gained access to site-specific physical and chemical performance data that are not typically available for contemporary uranium ISR projects in development. These data form the basis of the modeling discussion described in this paper.

Objectives

The physical and chemical aspects associated with uranium ISR are complex and evaluation of subsurface processes in complex hydrogeological and geochemical setting can be very difficult. Nevertheless, for the purpose of predictive modeling, this complexity can be reduced to a relatively few fundamental processes. The accuracy of estimation can be improved by incorporating our knowledge of these fundamental processes, however imperfect this knowledge may be. The primary objectives of a model-based approach to ISR projects are:

- To improve accuracy in extrapolating uranium extraction over time; and
- To account for changes in performance parameters (thickness, uranium grade, sulfide content, well-field design parameters, etc.) when estimating extraction in different locations.

Methodology

Given the technical data available from the active ISR project, the authors applied a streamline analysis approach to modeling based on research conducted by the US Bureau of Mines (Peterson, 1985; Schmidt et al., 1981). With this approach, the 2-dimensional (2D) well-field problem is reduced to a single 1-dimensional (1D) problem with steps as follow:

- Data assessment and streamline analysis;
- Flow path and reactive transport analysis; and
- Predictive modeling.

The ISR model uses an analytical model (e.g., *ISRFlow* developed by K.A.Peterson) for streamline analysis and geochemical modeling software *PHREEQC* (Parkhurst and Appelo, 1999) for simulation of the change in uranium concentration in the pregnant leach solution (PLS) through time. Initial uranium recovery data were required for ISR model calibration.

The purpose of the stream analysis is to define the flow field that drives solute transport. The streamlines were generated using a 2D steady-state groundwater model simulating flow induced by pumping and injection and assuming that total pumping and injection rates are balanced. Each streamline was characterized by a flow rate and a breakthrough time.

The next step is to simulate reactive transport along the representative flow paths generated from the streamline analysis. To simplify data processing, a single "tube" (i.e., reaction path), consisting of 20 to 100 cells was used to represent all flow paths in a given problem and a uniform time step was assigned to all cells. Each individual cell selected for output constitutes an observation point that represents the endpoint of a flow path.

The reactive transport model simulates the different geochemical reactions, including uraninite oxidation, pyrite oxidation, dissolution of limonite (goethite), cation exchange, and solution buffering of pH. The output from *PHREEQC* consists of concentration values through time for selected cells, which represent flow paths to recovery wells. These concentration histories can be integrated in a way that represents the change in uranium concentration over time for the variable PLS extracted from a single recovery well or a group of recovery wells over time. This was accomplished by calculating weighted- average concentrations using weighting factors from the flow-path analysis. The weighted-average concentration history was then used to calculate uranium recovery rate and cumulative uranium recovery.

The orebody can be subdivided into row or hexagonal cells for predictive modeling depending on its configuration. Productivity values (uranium resource per area) need to be calculated for each of the predictive blocks based on the 3-D resource block model.

Predictive ISR models for both row blocks and hexagonal cells were developed to predict production schedule based on average values of hydraulic conductivity, thickness of productive aquifer, width of orebody (for row blocks), pumping rate of recovery well, and orebody productivity.

Findings

Based on streamline analysis and the ISR reactive transport model, uranium recovery calculations were conducted for predictive row blocks and hexagonal cells by varying productivity values. Results of these predictive runs include:

- Uranium concentration in PLS vs. time;
- Uranium extraction (in tonnes) vs. time; and
- Percent of uranium recovery vs. time, and simulated as function of ore productivity.

Based on these graphs and assuming target of 80% of uranium recovery, the data points for time of 80% of recovery as function of productivity were fit with polynomial regression analysis with the following best fit curves:

$$T_{80\%} = a + b \times P + c \times P^2 \qquad (1)$$

where:

$T_{80\%}$ = time of 80% of recovery (years);

P = productivity of orebody, (kg/m^2).

Based on the relationship $T_{80\%} = f(P)$ expressed above in equation (1) and shown in Figure 1, the time required to achieve 80 % recovery for each of the blocks within orebody was calculated.

The annual uranium production from each predictive block were calculated using the formula:

$$U_{annual} = (P \times A \times 0.8) / T_{80\%} \qquad (2)$$

where:

$T_{80\%}$ = time of 80% of recovery (years);

P = productivity of orebody (kg/m^2); and
A = area of the block (m^2).

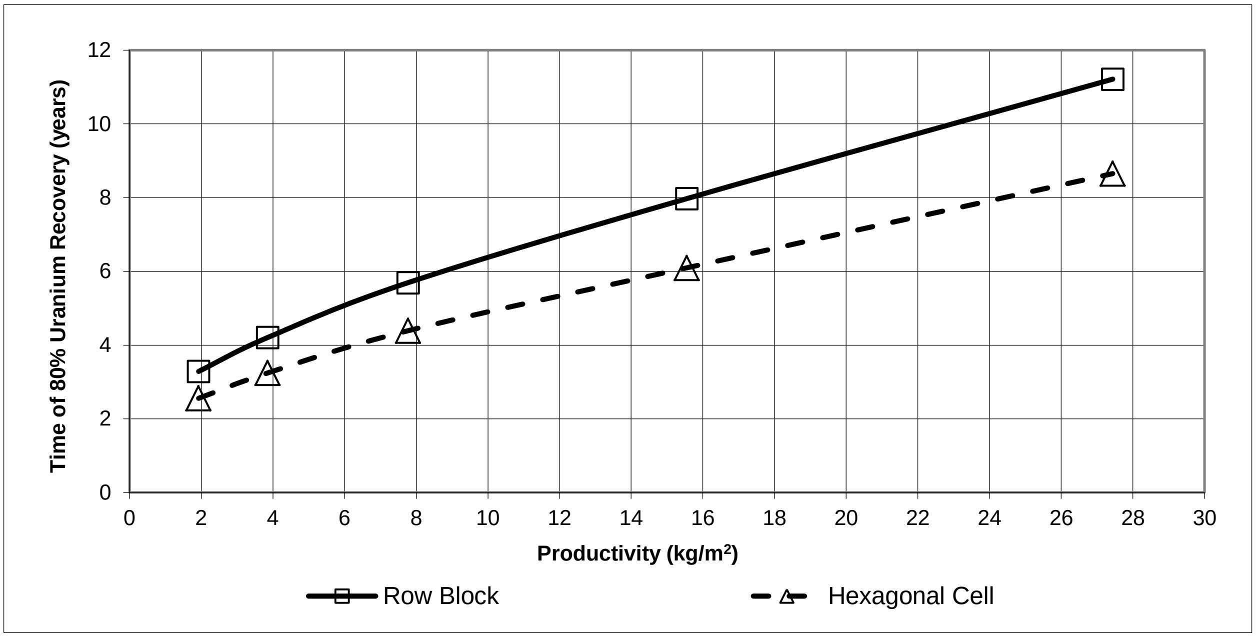

Figure 1.
Relationship between time of 80% of recovery as a function of productivity.

The average uranium concentration in PLS from each predictive block was calculated by formula:

$$C_{average} = (U_{annual} \times 1000) / (Q \times 24 \times 365) \qquad (3)$$

where:
$C_{average}$ = average uranium concentration within time of 80% of recovery (mg/L);
U_{annual} = annual uranium production from each predictive block (kg/year); and
Q = Total PLS extracting rate from the block (m^3/hour).

A production schedule was developed for entire deposit based on data relative to annual recovery from each predictive block considering a) uranium production target, b) plant capacity to process PLS, and c) requirements for uranium concentration in PLS. Similar ISR modeling approach can be used to optimize well field design and distance between recovery and injection wells.

Conclusions

Although the Khiagda example is an acid ISR process, the numerical modeling as described above can be directly applied to alkaline ISR processes common in the United States as well.

This model-based approach can be used during the mine development phase to layout well field patterns, create general well field operational parameters, predict time of recovery in individual well patterns, and schedule and optimize well field operation to improve the economic benefit of the resource. Likewise, a similar model-based approach can predict and aid in optimization of post-mining well field restoration through analysis of those reactions utilized in the restoration process: groundwater sweeps, reverse osmosis groundwater treatment, and injection of alkaline or reducing solutions into the production aquifer. If developed early in the mine life cycle, the intelligence of the model will increase over time creating a dynamic tool for continued efficient operation of the ISR facility.