NEW PREDICTIVE MODELLING APPROACH TO URANIUM IN SITU RECOVERY

By

Jess Page, Minh Tran, Sam Mercer, Prajna Uddagiri, Rick Morgans, [2]Ben Jeuken,

WGA, Australia
[2]Boss Energy, Australia

Presenter and Corresponding Author

Jess Page
jpage@wga.com.au

ABSTRACT

Boss Energy are entering into an exciting new phase of development, with the Enhanced Feasibility Study completed in 2021, and the project on track for production of 2.45Mlb of U_3O_8. Boss Energy's Honeymoon project is supported by highly skilled hydrogeologists, geologists, and management with proven operational experience. To further enhance their position, Boss Energy, in collaboration with WGA, have identified an innovative approach to determine recovery of In-situ (Leach) Recovery (ISR) deposits from data available during exploration. Boss Energy and WGA were granted an Accelerated Discovery Initiative (ADI) grant by the South Australian Government to deliver this tool, which has the potential to be rolled out to other operations.

The tool takes information available at the exploration stage of the project to predict ISR decline curve and uranium extraction. The tool has the potential to assist operations in wellfield planning, and be integrated with process plant models for economic optimisation of uranium production. WGA have employed a machine learning approach' tool, based on review of literature, Honeymoon operational datasets, and current modelling methodology. Our key findings are:

- Application of our machine learning approach to predicting decline curve is novel. Although machine learning is used in adjacent applications, such as prediction of mineralisation, iron deposits, stratigraphy, and lithology within the vicinity of the uranium body, it has not been used to predict decline curves in uranium ISR.
- Our approach leverages faster and more simple algorithms than current modelling techniques to predict uranium recovery. Current practices in the industry require a detailed profile of the deposit and require significant computing power: Most of the models use Reactive Transport Modelling (RTM), which couples numerical models of the metallurgical and hydrodynamic processes occurring underground. These sophisticated models can produce and track production curves to a high level of integrity. The disadvantage is that these models use a high level of computing power to produce results, and since they require a detailed understanding of the spatial distribution of both physical and chemical properties within the deposit they can be very sensitive to this data.

We assessed and ranked the suitability of several machine learning models, and progressed a hybrid metallurgical, hydrodynamic and machine learning model, to leverage both known relationships, and the potential increase in accuracy provided by machine learning algorithms. We also identified a second approach that can be leveraged during operations to further boost the model. Systems, also known as compartment, model, which is a mathematical approach to describing material transmission across a system.The systems modelling approach may be used for near real time operational modelling, where the deployed model can learn from and react to the wellfield and plant data as it is collected

We have also identified the following opportunities which have the potential to improve production planning and well field development tooling:

- In this phase of works, the potential for this model to be used in wellfield planning was demonstrated by overlaying several decline curves. This could be further progressed to enhance productivity of the wellfield planning team, enabling them to focus on their core business through integration with a plant production model and operating costs, to create optimised wellfield planning, and operational setpoints, to maximise production and revenue.
- Given that the response of a heap leach extraction process is similar to an ISR profile, the modelling approaches proposed in this study could be used to more simply predict heap leach performance.
- The dataset generated by Boss Infill drilling during feasibility evaluation of the deposit contains extensive information (Borehole magnetic resonance tool, and density and neutron logs). This data will be very useful at later stages of the development to link to future production data.

This presentation will summarise the final project reporting and interactive model test interface, aligned with our commitment to the knowledge share requirements of our ADI grant.

Keywords: Uranium, ISR, Machine Learning, South Australia,

INTRODUCTION

Project Appreciation

Sedimentary uranium deposit evaluation for ISR is challenging due to the difficulty in determining reasonable prospects for eventual economic recovery input to reporting exploration results under the JORC Code 2012, and more so, difficulty in determining the proportion (if any) of the mineralisation that can be recovered by ISR methods and reported as a reserve. Boss Energy (Boss), in collaboration with WGA, have identified that there may be opportunities to improve the evaluation process by using novel methods such as machine learning (ML) in conjunction with other innovative tools in exploration. WGA and Boss have been granted an Accelerated Discovery Initiative (ADI) grant by the South Australian Government, to further develop this concept. If successful, this tool has the potential to be rolled out to other operations.
Boss own the Honeymoon site, which was previously owned by Uranium One and operated from 2012 to 2013. Boss has completed an Enhanced Feasibility Study (EFS) after an extensive test work program, on the restart of the Honeymoon In-situ Recovery (ISR) Project in the Curnamona district of South Australia. The existing Honeymoon processing facility will be re-developed and expanded, with fast-tracked production within 12 months and a target production of 2.45 Mlb/annum U3O8 by the second year of the expansion.

Project Objectives

The objective of this project is to deliver a ‘proof of concept’ geophysical data processing tool for sedimentary uranium deposit evaluation for recovery by In-situ Recovery (ISR) during Greenfields exploration.
The proposed geophysical data processing tool was initially projected to a machine learning model that uses the data from downhole geophysics logs, specifically new and innovative tools such as the borehole magnetic resonance tool in conjunction with density and neutron logs and onsite XRF data to derive the amenability for leaching of a deposit. The implementation of the tool has the potential to improve the exploration efficiency; reduce cost; and resources needed for exploration, hence reducing the overall exploration footprint. This ‘proof of concept’ study aimed to prove that advanced data analysis techniques can predict uranium recovery based on field data produced in a drilling program. This technology is enabled by the development of machine learning models to predict leach recovery, and ultimately, predict surface plant production from exploration drill hole geophysical and geochemical data. Rapid scenario generation using the developed technology will drive focus for further exploration programs.

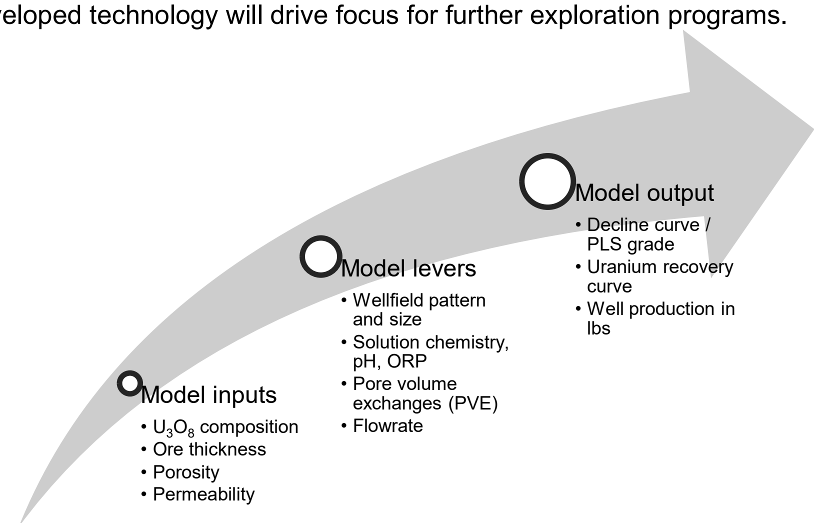

Figure 1: Proposed Geophysical Data Processing Tool Inputs, Levers, and Outputs

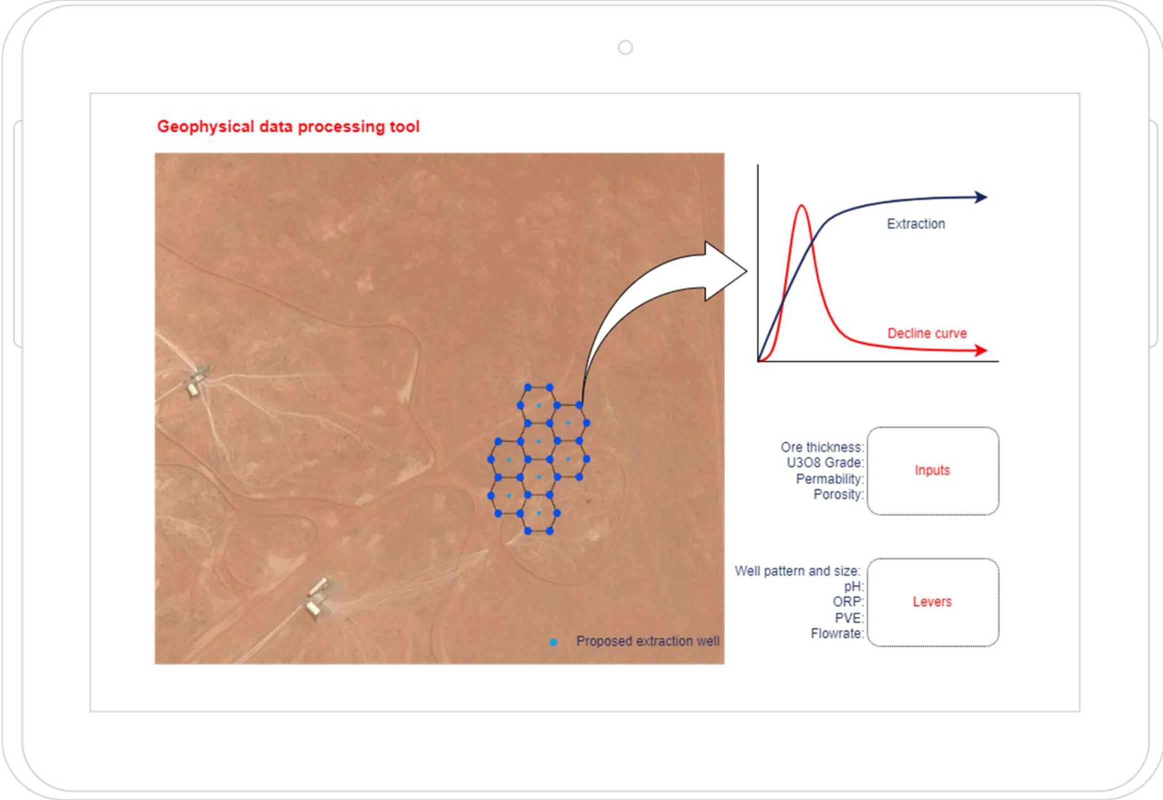

Figure 2: Idealised Version of The Tool Interface for A Single Well

The proposed tool will predict wellfield performance from exploration data for the Boss resource, and the methodology for tool development could be deployed on other operational sites. That is, although the tuned model parameters may be specific to the Boss Honeymoon mineralisation, the model development algorithm may be able to be rapidly deployed and tuned at other sites

METHODOLOGY

- ISR methodolgy
- ML applications
- Kinetics
- Key drivers

- Operational data
- Drilling data
- Database

- Gap analysis

- Application of ML to predict recovery
- Prototype dashboard

- Interim findings shared at Global Uranium Conference 2022, Final findigns at Alta 2023
- Recommentations and Opportunities

Research

Information gathering and literature review, including data, publications, operational information were collected, consolidated, and reviewed, including:

- Literature review on ISR modelling, including available data on other operational sites
- Review on Honeymoon operations historic datasets and modelling
- Machine learning applications to ISR and similar applications

As model development progresses the key model inputs and outputs will be further defined, and Honeymoon operations data collection gap analysis will be delivered, to inform recommendations for data collection for future operations.

Data Aggregation

The data framework has been developed as a basis for predictive modelling. Boss have historical and recent data, including drillhole collars, downhole geophysics, PFN data, water bores and screen depths, lithology, analytical results and well construction data which currently exists in a SQL server database. Available data has been transferred, using scripts where possible to increase efficiency, into a standardised format and loaded in a secure AWS database. The data that is not included in the current SQL database, including data still in excel sheets, may also be included in the database. The key features of the data aggregation include:

- The database schema has been developed that will enable use in future operations
- An aggregated dataset for modelling has been produced. As modelling is developed, additional iterations of data cleaning, and interpolation may be required
- Statistical analysis of data to better understand data and inform data cleansing requirements
- Development of a data framework and database for machine learning

LITERATURE REVIEW

Overview of ISR Mining

In Situ Recovery (ISR) mining methods are applicable to scenarios where the orebody is straddled between two impermeable layers, allowing for either acidic or alkaline leaching solution to be injected and recovered from the orebody. In uranium ISR, the acidic or alkaline solution is injected in the orebody via injection wells where the solution contacts and dissolves the uranium ore. The Pregnant Leach Solution (PLS) is recovered using pumps in extraction wells and sent to a processing plant for further extraction and purification of the uranium, as shown in Figure 3 below. To ensure the leaching fluid is contained within the mining zone, water quality in monitoring wells is analysed and mediating actions to taken if required.

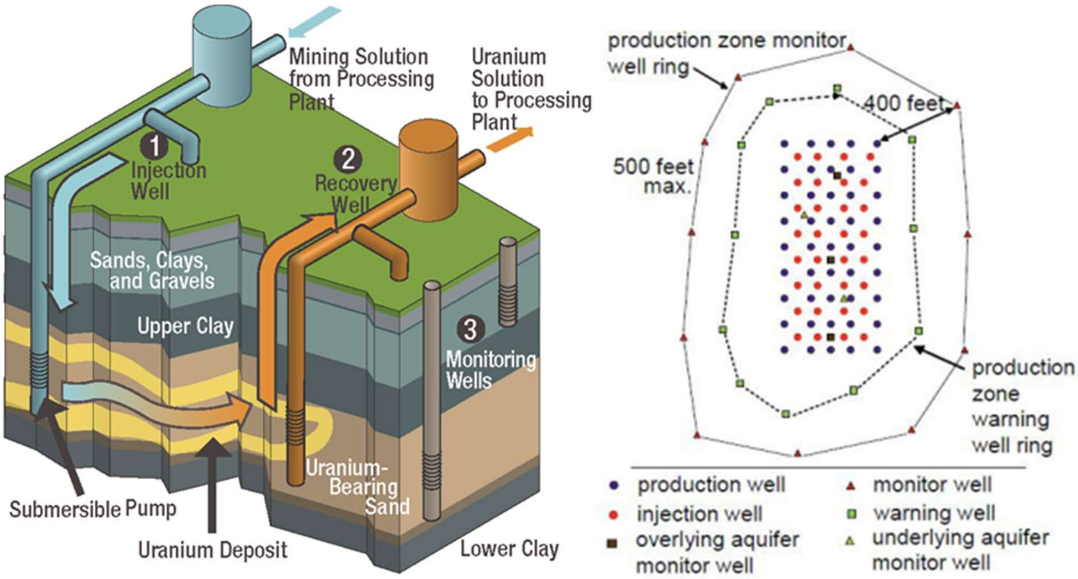

Figure 3: Uranium ISL Mining Method and Wellfield Layout [1] [2]

Unlike conventional open cut mining, the uranium is extracted entirely in-situ. This approach to mining is cost-effective and low impact to the surrounding environment [3] [4]. The leaching process occurs underground, and the extent and process chemistry are only measurable at the extraction wells. The PLS chemistry is used by operators to control and optimise production [5]. The layout of injection and extraction wells is typically aligned with one of the 'spot' patterns shown in Figure 4. After a period of operation, the wells may be switched from injection to extraction to establish new path lines and boost recovery from the pattern.

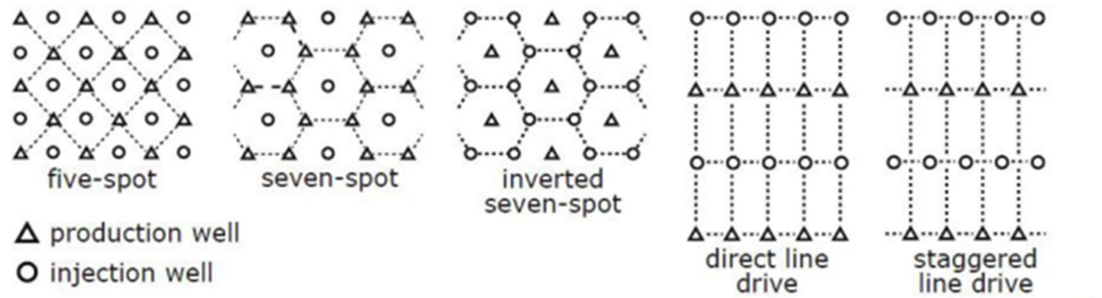

Figure 4: Well Field Pattern Layout Nomenclature [2]

Modelling ISR Production

Uranium PLS grade curves, know often in industry as Decline Curves (as the uranium grade typically declines over time), are typically obtained from a kinetic model of the ISR process. The key operational output metrics are permeability, leachability, and the predicted uranium production curve. This information enables the operators to plan and optimise the overall production process. In the case of greenfield exploration, an accurate prediction of production can be used to gauge the the initial economic and commercial value of the project. Predictive models capture the following characteristics and dynamics of the system:

- Geochemical reactions
- Kinetics of primary and secondary reactions associated with the injected chemicals
- Hydrodynamic transportation properties

These variables are coupled together, and the governing system of equations is solved to generate a Decline Curve. This modelling approach is described as reactive transport modelling [6] which has been applied to systems with geochemical and aquifer properties, and reviewed by various authors [7] [8] [9]. This model has been used to predict the PLS curve [6] using operational parameters associated with leaching reaction kinetics, aquifer properties and wellfield configurations [10].

Reactive transport modelling of ISR [6] is based on rigorous numerical models of all physical processes, from the fluid flow dynamics through to the geological properties of uranium bearing sand and the chemical processes occurring at the fluid-solid interface. Previous work has shown that the production curve can be predicted to a high level of fidelity but at the cost of increasing the complexity of the overall model [11] [12]. Disadvantages of this kind of modelling include both the computational power required to perform it, and the detailed inputs required including a complete three-dimensional model of the orebody. In general, the uncertainty in the ISR extraction extent is mainly attributed to uncertainty in the 3D geological model, and when used as a key input to 3D reactive transport ISR modelling, can result in execution of computationally expensive statistical methods [13] [14].

Fundamental to the modelling ISR process and the overall objective of generating a useful PLS curve require the understanding of the underlining metallurgical processing occurring during the in-situ leaching, reviewed in the following sections.

Metallurgical Processes

The rate and extent of uranium extraction from the host ore body by the applied solution is influenced by several mineralogy and metallurgical factors:

- Uranium mineralogy, oxidation state and ore composition
- Solution composition and impurity precipitation
- Acid concentration measured as pH
- Oxidation Reduction Potential (ORP)
- Temperature
- Pressure
- Solution residence time

The impact on the leaching kinetics of uranium concentration in the ore, acid concentration, ORP, temperature and leach duration are described in the following generic kinetic equations. The effects of these variables are interdependent and should be considered collectively. The rate coefficients ko, and exponents to pH and ORP, can be derived from literature or empirically from test data.

Table 1: Kinetic Equations Describing Uranium and Gangue Dissolution

General Leaching Rate Law	$\frac{dX}{dt} = \mathrm{k}(T)\mathrm{f}(C)w(1-X)$	**Equation 1**
Arrhenius Equation	$\mathrm{k}(T) = \mathrm{k}_0 \exp\left(\frac{-Ea}{R}\left(\frac{1}{T} - \frac{1}{T_o}\right)\right)$	**Equation 2**
Concentration function for uranium mineral dissolution	$\mathrm{f}(C) = [H^+]^a[ORP]^b$	**Equation 3**
Concentration function for gangue dissolution	$\mathrm{f}(C) = [H^+]$	**Equation 4**
Topology function	$\mathrm{w}(1-X) = (1-X)^{\phi}$	**Equation 5**

Table 2: Combined Kinetic Equation for Uranium Dissolution

General Leaching Rate Law	$\frac{dX}{dt} = \mathrm{k}_0 \exp\left(\frac{-Ea}{R}\left(\frac{1}{T} - \frac{1}{T_o}\right)\right)[H^+]^a[ORP]^b(1-X)^{\phi}$	**Equation 6**

Table 3: Descriptions of Kinetic Parameters

SYMBOL	DESCRIPTION	UNITS
a	pH coefficient	**-**
b	ORP coefficient	**-**
$-Ea$	Activation energy	**kJ/mol**
$[H^+]$	Hydrogen ion concentration	**M**
k_0	Reaction rate constant, or Rate coefficient	**Order dependent**
ORP	Oxidation Reduction Potential (ORP)	**mV**
ϕ	Phi – reaction order, or topology factor	**-**
R	Universal gas constant	**J/K.mol**
T	Temperature	**K**
T_o	Temperature at standard conditions	**K**
X	Conversion extent, or Extraction	**%**

The topology function in the general leach equation is typically used for heap leach kinetic evaluation and accounts for the changing surface area over time, with a parameter phi ϕ that varies to account for the complexity of leaching from the heap leach material which is not spherical or uniform size. The value of phi is between 0.5 and 2 for a heap leach kinetic function [15].

Uranium extraction is a diffusion process, and therefore the overall rate is proportional to the rate of diffusion through the solution layer adjacent to the solid surface [16]. The kinetic model can be combined with physical factors that impact leaching, such as particle size, and permeability, which may have equivalent proxies for ISR compared to the traditional slurry leach modelling kinetics. A key challenge with modelling the kinetics of ISR extraction is that while the injection and production solution chemistry is monitored, the profile of the solution chemistry within the ore body cannot be monitored in real time.

Uranium Mineralogy and Oxidation State

The mineralogy and oxidation state of uranium influence the kinetics and leachability of the deposit. Mineralogy by QEMSCAM on samples submitted to ANSTO as part of the Honeymoon Field Leach Trial (FLT) study identified that most of the uranium present in the orebody is a uranium phosphate mineral in tetravalent form U(IV) [17]. The key uranium mineral was tristramite. $(Ca,U,Fe)(PO_4,SO_4).2H_2O$, with other uranium minerals not able to be identified due to small grain size and phase intergrowth. Tristramite is known to occur in association with sulphides, which presents as pyrite in the Honeymoon ore.

Tetravalent uranium must be oxidised to hexavalent uranium for dissolution to occur. An oxidant, hydrogen peroxide, is added to the solution prior to wellfield injection to indirectly oxidise the uranium by first oxidising ferrous to ferric, as described in the reactions below. The magnitude of the ratio of ferrous to ferric is measured using an ORP probe, and for typical conditions the logarithmic relationship can be described by the Nernst equation. ANSTO test work has shown that maintaining the ORP around 450mV, in conjunction with low pH, is effective at uranium dissolution for the Honeymoon ore [17], and typically satisfactory for most ores [18].

The concentration of iron in the solution is maintained by a combination of iron dissolution from the ore and iron sulphate injection into the solution. The total iron concentration and the ferric/ferrous ratio are both important to extraction. Higher iron content will mean higher oxidant addition required to maintain a target ORP. High ORP, more than 475mV, was shown to cause high oxidant consumption in the Honeymoon ore, likely due to pyrite oxidation since oxidant consumption increased with increasing feed sulphide content.

Table 4: Uranium Dissolution Chemical Reactions

Ferric oxidation	$2\ Fe^{2+} + H_2O_2 + 2H^+$	"	$2Fe^{3+} + 2H_2O$	**Equation 7**
Tetravalent uranium oxidation to hexavalent uranium	$UO_2 + 2Fe^{3+}$	"	$UO_2^{2+} + 2Fe^{2+}$	**Equation 8**
Uranyl sulphate formation	$UO_2^{2+} + 3SO_2^{2-}$	"	$[UO_2(SO_4)_3]^{4+}$	**Equation 9**
Pyrite dissolution	$FeS_2 + 8H_2O + 14Fe^{3+}$	"	$15Fe^{2+} + 2SO4^{2-} + 16H^+$	**Equation 10**

Acid Concentration, Solution Composition and Gypsum

Acid added to the solution is consumed in the dissolution of the ore, and consumption is largely driven by gangue concentration since these are typically at much higher concentrations than the uranium minerals. Acid consumption is a key economic driver in the ISR uranium production process, and addition rates are optimised based on evaluation of uranium extraction, acid costs and gangue dissolution, which can impact operability from precipitated impurities, risk product quality and increase oxidant consumption. Mineralogy by ANSTO showed that varying amounts of clay phases such as kaolinite were present, while the main silicate gangue material was quartz [17]. Complex aluminosilicates, if dissolved, may precipitate as a gel [16], causing plugging, reduced permeability and reduced access to ore and uranium extraction.

A pH of 1.5 was recommended by ANSTO for the Honeymoon ore [17], with higher pH having a negative impact on dissolution, and increasing the risk of ferric precipitation [18]. Gypsum precipitation was found to be minimised by maintaining low pH, ORP>490mV, and Cl >8.5g/L.

Sulphuric acid is added to the solution prior to injection, and the pH of the injection and production streams are typically monitored.

Solution Residence Time, Temperature and Pressure

The rate of diffusion is inversely proportional to the square root of the rate of motion of the phases relative to each other [16]. In ISR, the ore is stationary, and the fluid moves past the ore, at a rate determined by the pumping rate, and influenced by the permeability of the ore body. The solution residence time is often normalized to a ‘Pore Volume (PV)’, which is simply the time taken to circulate a volume of solution that is equal to the volume of formation within the leaching pattern multiplied by the effective porosity. Uranium recovery of a pattern is typically tracked in ISR against the number of ‘Pore Volume Exchanges (PVE)’ as opposed to time. Diffusion is negatively impacted by formation of slimes and gypsum.

Temperature increases the rate of dissolution of uranium and gangue minerals according to the Arrhenius equation. In ISR, the temperature in not typically controlled. Target ORP, pH, and residence time must be evaluated in conjunction with operational temperature to optimise the process.

Hydrodynamic Processes

Fluid flow dynamics, or hydrodynamics, must be incorporated into ISR process models since the dynamics of the leaching solution from the injection channel to the path taken to reach the extraction channel influence access to ore and overall recovery [19] [20]. The cross section of flow paths from the two injection wells to the extraction well is shown in Figure 5. With the inclusion of hydrodynamics in 1D, 2D or 3D, the resulting model can predict performance at multiple injection points with different flow rates and inhomogeneous material properties associated with geology of the mine site, including porosity and permeability. The inclusion of fluid dynamics increases in the complexity of model, and computing power required to solve the model.

Hydrodynamics are governed by the following dynamic equations [21]:

- Mass conversation law
- Diffusion equation
- The constitutive relationship
- Darcy law

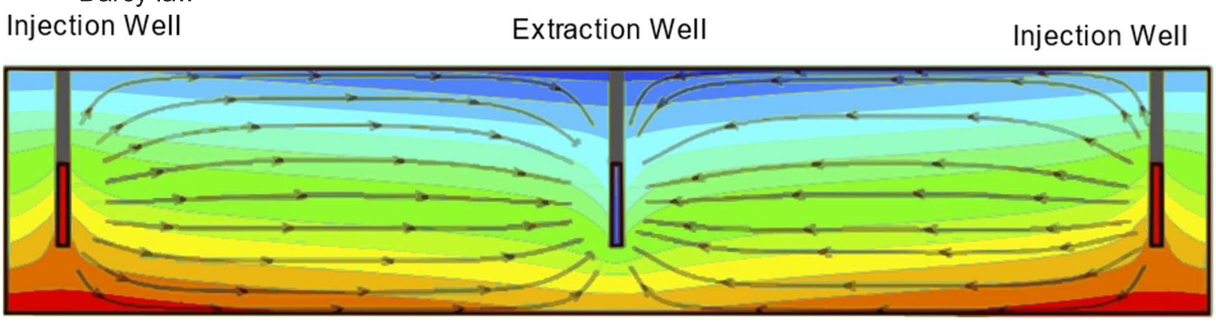

Figure 5: 2D Cross Section View of Flow Path Lines [11]

Ideally, the flow through the orebody would resemble a plug flow reactor (PFR), which would produce the highest grade PLS in the lowest volume of extraction fluid. The PLS grade curves generated by operations resemble residence time distribution (RTD) of tanks in series, which describes a cascade of n tanks in series and accounts for effects such as dead zones, non-ideal back mixing, and/or bypassing effects [22]. The term tau used in the equations below to determine the distribution, is equivalent to the total pore volumes passed. The gamma function can be applied to the RTD function to permit an analytical solution, as shown in Equation 12. The conversion and PLS grade can be defined from the segregated model that combines the kinetic and RTD equations in Equation 13.

Table 5: Residence Time Distribution (RTD) Modelling

Tanks in series, where n is an integer [22]	$RTD(t)$	=	$\frac{t^{n-1}}{(n-1)!}\left(\frac{n}{\tau}\right).e^{\left\{-\frac{t\,n}{\tau}\right\}}$	**Equation 11**
Tanks in series, where n is any decimal number [22]	$RTD(t)$	=	$\frac{t^{n-1}}{\Gamma(n)}\left(\frac{n}{\tau}\right).e^{\left\{-\frac{t\,n}{\tau}\right\}}$	**Equation 12**
Mean conversion X for mixed kinetic X(t) and RTD E(T) function [23]	$\frac{d\bar{X}}{\mathrm{dt}}$	=	$X(t).E(t)$	**Equation 13**

Current Practice in Uranium ISR Modelling

ISR uranium producers have developed and applied custom models for ISR wellfield production. These models typically use a theoretical basis including:

- Reaction kinetics
- Residence time modelling
- Reactive transport modelling
- User selected wellfield patterns, well spacing radius, and dimensions, that describe the pattern area

Boss have developed a theoretical/empirical model to describe the kinetics of wellfield extraction, with output shown in Figure 6. This typical wellfield output profile has a sharp initial peak followed by a long decay tail [24]. The grey and orange lines represent the measured data and the green and blue lines the modelled results, both in terms of uranium concentration in the PLS and uranium extraction as a function of PVs treated.

This theoretical/empirical approach works well for performing wells but does not consider all operational factors that may influence the recovery. The limitations of the modelling are:

- Variation in ore body composition means using averages for kinetic modelling may produce misleading results. This is because the orebody genesis contributes greatly to the high spatial variability in the chemical kinetics, which in turn affects the shape and accuracy of the PLS model [25].
- Limited data for validation of the model.

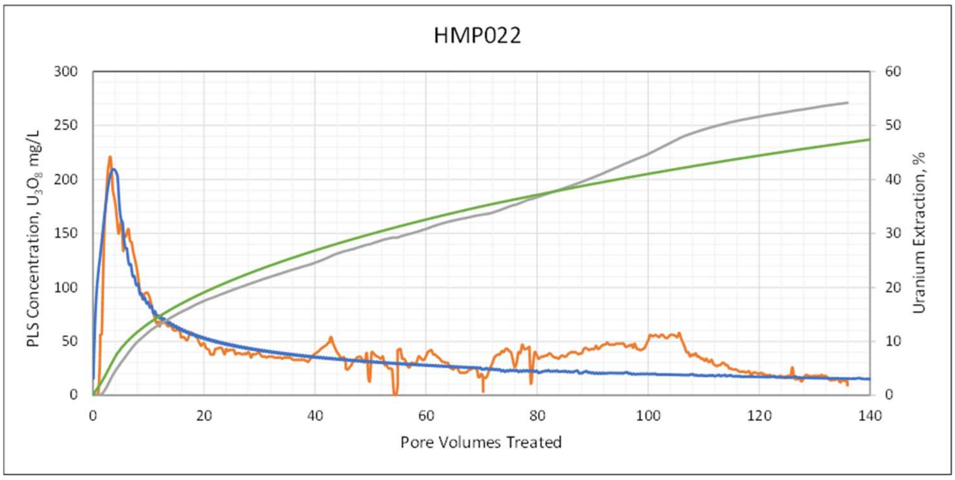

Figure 6: Typical Wellfield Output Profile with Sharp Initial Peak Followed by a Long Decay Tail [24]

KATCO mine, the world's largest ISR mine, have used reactive transport software HYTEC developed by MINES ParisTech [26], to simulate and predict the PLS curve [6]. The tool is written in C++ with the system solved using iterative numerical methods. In this application, the model's parameters were based on known and assumed operational leaching kinetics, aquifer properties, and wellfield configurations [21]. These model's parameters, for example leaching kinetic and aquifer properties, are not time invariant which implies new system parameters will need to be used to recalibrate the model. Although HYTEC allows for easy manual tuning upon deviation of the model from operational data, it is still a tedious exercise to recalibrate the multiple individual patterns for a given wellfield during the mining exploitation phase.
Due to the need to continuously re-adjust the model parameters of HYTEC code, HYSR was created which a graphical user interface (GUI) to the program to provide a friendlier user experience to mine operators, and clear presentation in the output of the program [6]. The GUI does not require initial or boundary conditions and imports a block model or well specifications [27].
These models can be used in short term and long-term planning, as well as to assess the environmental footprint of an ISR mining site to minimise environmental impact [27].

Other Similar Processes

Non-Uranium ISR
ISR mining is also employed in copper and gold recovery. A recent scoping study on reactive transport modelling of copper ISR demonstrated that a full reactive transport model was developed using the COMSOL Multiphysics package to full scale simulations of the whole ore body [10]. The model included modelling existing underground workings as 2D fractures, and parametric studies at the block scale with a five spot well field design. The parametric models allowed the investigation of the key factors affecting PLS recovery, and the full-scale simulations shows a practical modelling example of how to use Reactive Transport Modelling (RTM) for production prediction, albeit without calibration from ongoing production data.

Heap Leach
In heap leaching ore is typically crushed and stacked as it comes out of the mine without any additional grinding like traditional mining flowsheets. A leach solution is then applied to the ore surface and permeates through the ore pile using gravity to be collected in a sump. Weeks or months elapse before the solution is reapplied to the heap. Due to the permeation of leaching solution through ore, this presents similar physical interactions as ISR but on different timescales. Physical models accounting for the kinetics of the ore are typically in the forms described in Table 1 and will be applicable to ISR.
In the heap bioleaching process, the system has been model using three fundamentals intercoupled subprocess including chemical reactions, temperature, and bacterial activity [29]. Additionally, Kalman filter was added (i.e., a recursive estimator method) to estimate the system time varying system parameters. In an application setting, the initial model derived from first principles did not work very well. A solution is to add empirical adjustments to the equations to add in the missing dynamics.

Machine Learning Methods

Artificial intelligence and machine learning have been instrumental in driving technical advances across many industries in the past 10 years. This has been driven by both large computing resources available to companies such as Google and Microsoft, as well as the availability of large datasets. In some domains, such as image recognition or speech recognition, (deep) machine learning is a solved problem and real-world applications abound. This growing trend has led to a suite of accessible machine learning methods and tooling applicable to mineral exploration and extraction processes.

Machine learning is a data driven approach to process modelling, used to solve regression or classification problems, where a target variable or class from a training dataset is inferred from a set of input variables. Once the training process is completed and validated, the model can be used to predict new targets from new input variables.

There was no literature found in the application of machine learning to predict the PLS curve of the ISR process. Several examples of ML application in geology assessments were reviewed, including ML to predict mineralisation, iron deposits, stratigraphy, and lithology within the vicinity of the uranium body [28]. Another application of ML was using downhole measurements to learn filtration coefficients, which is used as model input parameter to the ISR model [29].

The complexity of machine learning methods can vary from simple, such as linear or logistic regression, through to very complex and computationally intensive methods such as deep neural networks, where large amounts of input data are fitted with the target labelled data.

The quality and ability to generalise (give accurate predictions when used with new data that it has not been trained on) of supervised models depends on the quality and quantity of the data available ideally a large data set will assist in the training the model to an acceptable degree of accuracy for deployment of the model.

The dataset provided by Boss contains 48 Decline Curves, which is insufficient amount of data to model the PLS curve purely using machine learning method. With small data sets such as in this project, machine learning can overfit [30]. To reduce the risk of overfit, the machine learning problem can be constrained with extra information. Constraining the model can be done by regularisation [31], or by explicitly including constraints based on the underlying geophysical and chemical problem.

Table 6 lists several supervised learning methods considered for this project. They are assessed in terms of:

- complexity - how much computational effort is required in fitting the model
- accuracy - is the model, once fitted, able to accurately represent the process
- interpretability - are the parameters of the model able to be related easily to physical processes
- applicability - can we use this model in this project

Table 6: ML Techniques Ranked for Suitability to ISR Process Modelling

MODELLING TECHNIQUE	COMPLEXITY	ACCURACY	INTERPRETABILITY	APPLICABILITY
System Modelling	**Low**	**Medium**	**High**	**Yes**
Support Vector Regression	Low	Medium	Medium	Yes
Random Forest Regression	Medium	High	Medium	Yes
XGBoost Regression	Medium	High	Medium	Yes
Deep Neural Network Regression	Very High	High	Low	No
Time Series	Low	Medium	High	Yes
Adaptive Models	Low-medium	Medium	High	Yes

DATA AGGREATION

Data from several sources was aggregated into a database in preparation for modelling. The purpose of data aggregation was to both assess the quantity and quality of the data and identify any gaps in knowledge.

Two key datasets were provided:

- BIF (Boss In-fill drilling data)
- Historical production data, including 3 wellfields – 16 patterns each, 48 Decline Curves

The historic operations data is key to understanding what the key outputs that operations require to plan, operate, and optimise production. Key information includes

- Calculated PLS grade decline curve and extraction
- Resource estimate of uranium in pounds
- Injection and extraction solution chemistry and flow (NTU, ORP, pH, composition, Flow)
- Pore volume

The following gaps were identified and represent opportunities to improve the model in future applications of the model:

- There is currently no way to use the extensive information contained in the BIF data (Borehole magnetic resonance tool, and density and neutron logs), as it was not obtained in the historical wellfields. This data will be useful in future applications of the predictive tool.
- Resource estimate of other key elements and mineralogy for the existing dataset were not available. This data may inform other aspects of the ore amenability to leaching and improve the prediction.
- Porosity, ore thickness, and wellfield area, and pattern, which are used to derive the pore volume was not available. Pore volume was provided in the historic data without the input data.

The dataset provided by Boss Energy contains 48 PLS curves, which is insufficient amount of data to model the PLS curve purely using machine learning method. With exclusion of data where there is no flow, or backflow, this data set reduces further. To prevent overfitting, the model must be constrained by regularisation [31] or by available information such as kinetics, hydrodynamics, and ore body characterisation.

MODELLING SELECTION AND METHODOLOGY

Model Selection

Because of the limited data sets available, and the sensitivity of complex machine learning approaches to overfitting on small data sets, a hybrid approach to modelling was progressed through to development. Two different lumped parameter models were proposed:

- System modelling – using a compartment modelling approach to generates the correct shape predicted curve, with simple but potentially not interpretable parameters.
- Mixed kinetic and RTD model – this model leverages theory and interpretable parameters in a simple model.
- The mixed kinetic – ML model was selected to go forward to development into a predictive model, because it has directly interpretable parameters that enable the user to understand the impact of key mineralisation characteristics, well construction and injection solution chemistry.

The inclusion of theoretical-empirical models in the kinetic-ML model introduced rigidity to the model, which in some cases resulted in lower accuracy results when compared to the highly flexible systems modelling approach. System modelling allowed more flexibility in shape of curves produced, which enabled it to fit historical decline curves that had operational issues, and skew parameters. The systems model was not taken forward in this project because the model does not meet the objective of the study which was to produce a predictive model from data at the exploration stage, and parameters are not directly interpretable. Systems modelling is a more suitable approach for near real time operational modelling, where the deployed model can learn from and react to operational issues on the fly.

Modelling Methodology

The mixed kinetic- ML model leverages the kinetic equations, and known residence time distribution (RTD) functions, to find the kinetic rate constants that are used for prediction. This approach was selected since:

- The inclusion of theoretical modelling maintains impact of key operational levers on the predictive model, such as lixiviant composition, and wellfield patterns.
- Use of machine learning models to derive functions for the rate constants will leverage a greater portion of the data provided than conventional regression, and therefore has the potential to produce higher accuracy predictions than achievable with the theoretical modelling.

Fitting kinetic models to noisy data can be difficult, and it can be necessary to move from simple least squared loss functions to more sophisticated techniques that reduce the influence of outliers, penalise model complexity and find globally optimal solutions [32] [33].
The proposed model methodology will use error minimisation, 'curve fit', across all tests to find the kinetic equation constants, k1, a1, b1, phi, described in Equation 1 to Equation 5, and the residence time distribution constants N and tau described in Equation 11 to Equation 13. The RTD input n, theoretical number of tanks in series, will change with each well, i.e., poor flow will be characterised by back mixing, and short circuiting. Machine learning will be used in conjunction with all available data to derive the 'functions' for the constants. Feature importance is used in the derivation of the machine learning models to develop the understanding of the key drivers on the ISR process.

RESULTS

The mixed kinetic – ML model was developed using the following approach:

- An algebraic solution to mixed kinetic-RTD model was produced
- Model equation was fit to the decline curve data set, to obtain a set of k0, N and tau to describe the kinetic and flow pattern of the decline curves
- The key mineralisation and injection solution chemistry drivers for the parameters k0, n and tau were investigated using machine learning. The most important features, were:
  - Resource estimation: The uranium resource drives the size of the decline curve peak,
  - U3O8 in injection solution: The BLS grade will boost the PLS grade
  - pH: Acidity impacts rate of uranium dissolution
  - ORP: Uranium oxidation is required to leach
  - Potassium: Potassium is likely desorbed from clay in the ISR leach process under the leaching conditions. The extent of potassium in the injection liquor and PLS may be an indication of the effectiveness of the leach.
  - Turbidity: The concentration of dissolved solids may impact precipitation, permeability, and fluid flow paths.
- Machine learning models were developed to predicted k0, n and tau across the decline curve data set, using gaussian, SVR, linear and decision tree. The key findings were:
  - Number of theoretical tanks was shown to be typically between 1.5 and 2. This produces a response consistent with flow bypassing, which is consistent with an understanding of complex ISR flow paths. Higher n would imply the system is approaching perfect mixing, which is unlikely for ISR.
  - Mean residence time, tau, was in the range 25-30 days. This implies that the peak of PLS grade occurs in this timeframe, which aligns with operational experience.
  - k0 the kinetic coefficient was in the range 5.10-5.12 x 10^{-5} L/mol/h which is a reasonable order of magnitude for uranium dissolution.
- The accuracy of the models was inspected visually and using the mean squared error. An example of a curve fit is shown in Figure 7.
- The kinetic parameters a, b and k were interrogated and adjusted to ensure the response of the decline curve met understanding of the metallurgical fundamentals

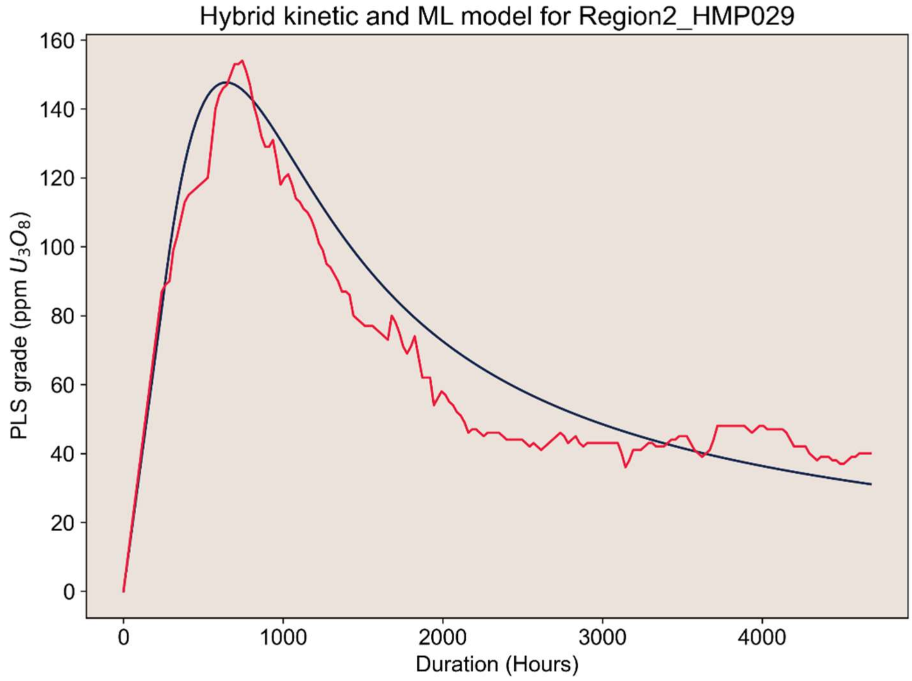

Figure 7: Mixed kinetic- ML model fit to historic well HMP029. This is a test data decline curve, meaning it's data was not used to train the model

The model was deployed in an interactive dashboard in MS Excel, to enable users to adjust mineralisation, well construction and injection solution characteristics, to determine PLS grade and extraction over time, shown in Figure 8.
To demonstrate the potential of the model to simplify wellfield planning, several decline curves were overlayed and the aggregate PLS grade calculated over time. The resulting aggregated uranium grade in the PLS and total flowrate are shown in Figure 9.

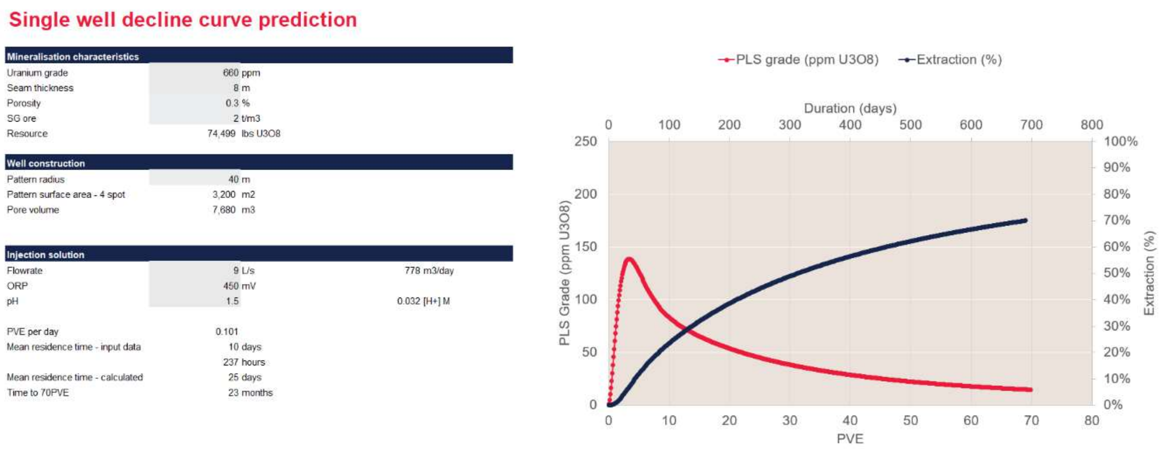

Figure 8: Mixed Kinetic – Machine Model deployed in Excel. mineralisation, well construction and injection solution characteristics, can be adjusted to determine PLS grade and extraction over time

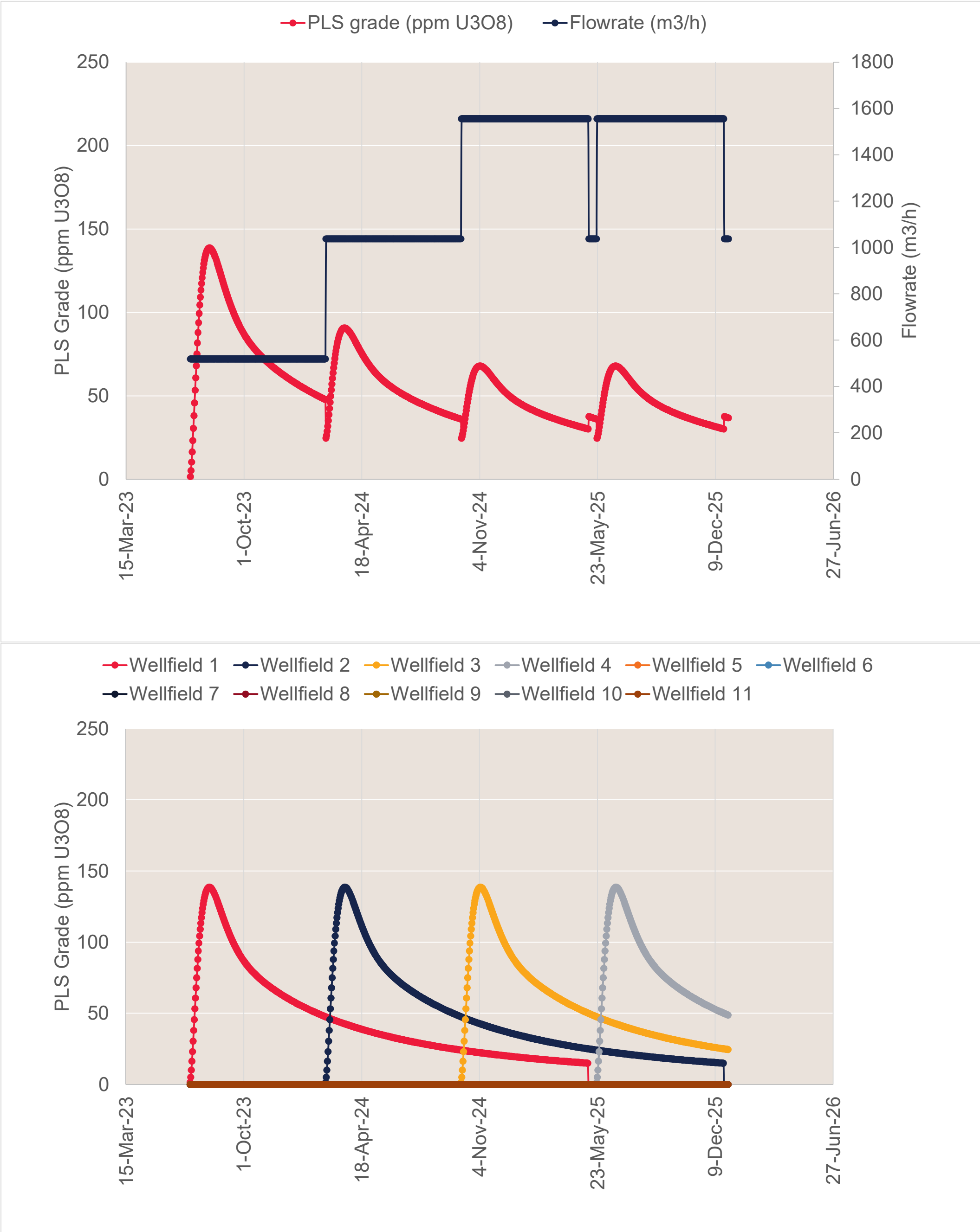

Figure 9: To demonstrate the potential of the model to simplify wellfield planning, several decline curves were overlayed and the aggregate PLS grade calculated over time

OPPORTUNITIES

Integration of New Innovative Exploration Tools
Borehole magnetic resonance tool, and density and neutron log data can be used to further train and tune the model as operational data relating to those wells becomes available. Given the additional information and potentially higher accuracy of these instruments in assessing the mineralisation, the use of these inputs in model tuning may result in a higher accuracy decline curve and extraction rate. This approach is applicable to other ISR amenable uranium deposits.

Wellfield Planning and Cost Optimisation
In this phase of works, the potential for this model to be used in wellfield planning was demonstrated by overlaying several decline curves. This could be further progressed to:

- Optimise number of patterns and wellfields online using an automated algorithm
- Integration with a plant production model to maximise production
- Integration with a plant production model and operating costs to create optimised wellfield planning, and operational setpoints, to maximise revenue

The development of a streamlined model that leverages automation of the wellfield planning and production forecast, will enhance productivity of the wellfield planning team, enabling them to focus on their core business.

Real Time PLS Grade and Extraction Forecast During Operations Using the Systems Modelling Approach

The systems modelling approach may be used for near real time operational modelling, where the deployed model can learn from and react to the wellfield and plant data as it is collected. Since mineralisation characteristics, permeability, gangue composition and operational approach may change over time, the model will experience drift. This issue can be outcome by updating the well system parameters (α, β, μ, N). There are various adaptive filtering techniques which could be implemented to automate the process of updating of the system parameters α, β, μ, and N. A recommended approach is the use of Kalman filter, which has successfully been used in an SIR epidemiological model, which shares similar system characteristics as ISR.

In the implementation of the systems modelling technique for each well, the initial system parameters can be estimated by using machine learning utilising well construction characteristics, injection chemistry, and flowrates. During ISR operation, operational data such as PLS and BLS assay data, pump speed and pressure, real time flowrates, can then be used to map operational values to the model system parameters, adjusting and correcting for drift in the model.

In an operational setting, there are multiple cells or patterns that are individually modelled. The process of auto-adjusting the individual well system parameters to match the changes to the ISR operational conditions can be automated. The result is a more accurate prediction of the well PLS curve in a production setting.

Implementation in Heap Leach Modelling

Given that the response of a heap leach extraction process is similar to an ISR profile, the modelling approaches proposed in this study could be used to predict heap leach performance.

CONCLUSION

WGA and Boss' joint study into the development of a novel tool to predict the amenability of a deposit to ISR met the key project objects:

- A model was developed to predict the extent of uranium extraction and PLS grade over time from data available during exploration. This model also has the potential to be used for wellfield planning and cost optimisation, and operational control, at Honeymoon and other sites, and could be deployed in other similar processes such as heap leach.
- Knowledge share of the project discoveries at the Global Uranium Conference 2022 and Alta 2023.
- The project was completed within budget and ahead of schedule.
- The development of an interactive tool exceeded the expectations of the original scope of the ADI grant to deliver a 'proof of concept' geophysical data processing tool for sedimentary uranium deposit evaluation for ISR during Greenfields exploration.

The development of the model was supported by a thorough review of literature, Honeymoon historic operational datasets, and current modelling methodology, as well as a robust understanding of the process enabled by collaboration of experts from Boss and WGA.

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