Improving Recovery in The Yates Field Using Dynamic Feedback Loop based on Physics-Informed Artificial Intelligence

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Abstract

We present a robust control system and methodology for physics-informed artificial intelligence (PAI) used to optimize and improve oil recovery, demonstrated in the Yates Field operated by the Kinder Morgan CO2 company. The system consists of a robust control system (referred to as Dynamic Feedback Loop, or DFL) equipped with novel hydrocarbon sensors that measure oil concentration and other parameters continuously and simultaneously on a set of producing wells. The goal of this system is to optimize operational parameters (e.g. choke valve settings, injection rates) to reach specific target metrics of production (e.g. maximizing produced oil while minimizing produced gas).

The key element of our approach is the use of a multi-layer artificial neural network (deep neural network, or DNN, to be specific) that extracts physics-based parameters from the real-time measurements and predicts relevant parameters of the DFL control system. DNNs are prone to overfitting in training, making them ineffective in unfamiliar or challenging situations outside the training dataset. To overcome this problem, we have developed a physics-informed robust neural network technique, where the reservoir physics and sensor data are used to train DNN representations of the key physical parameters. Typically, only simplified physical models are developed using available geostatic or historical production data. Also, due to the dynamic nature of these systems, the accuracy of the models often changes over time. To improve predictive capability of the model, we combine the DNN with the system-theoretic robust control concepts based on physics with a model uncertainty formulation. The concept was first validated using a combination of simulations, isolated sensor data and analyses based on sets of historic production data.

A study using historic production data on Kinder Morgan's Yates Field Unit (YFU) 4045 Pilot (3 producing wells) indicates application of the DFL system results in an increase in cumulative production of up to 35% per year, compared to what is obtained through a traditional (fixed-point) control system. Currently, the DFL is being field-tested on a different set of wells in the Yates Field, instrumented with the novel hydrocarbon sensors that generate continuous and simultaneous production data.

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Introduction

Problem statement

The main objective of the work described in this paper is the development of a predictive analytical tool for oil reservoir management. Oil & gas reservoirs can be considered as complex dynamical physical systems interacting with the environment through a finite set of inputs and outputs, i.e. through the wellbores accessing the reservoir. The dynamic behavior of the system is in general time-varying and contains non-linearities or non-linear components. Examples of system inputs are fluid injections (flow rates of injected species) and wellhead choke valve settings (pressure and/or flow rate control); outputs typically consist of the production fluid flow rates (oil, water and gas).

As such these systems can be modeled and managed using concepts from control theory [1], [2]. Optimization of these systems consists of maximizing (or minimizing) an objective function or metric; in this case, such function could for example be the cumulative amount of oil produced over time, discounted by the total amount of gas and/or water over time. Due to the complexity and size of the systems, the large number of time-dependent parameters and variables, and the often limited quantitative knowledge and understanding of these parameters and variables, reservoir management is a demanding proposition [3], [4], and automation of the processes involved a challenging task.

In our control theory representation, automated system optimization would consist in a control strategy or algorithm that continuously generates the optimal set of controls (system inputs, e.g. fluid injections or wellhead choke valve pressure/flow rates) to produce the optimal value of the objective function. Successful optimization will result in increased production of the oil resource while minimizing the unwanted and/or environmentally detrimental by-products such as excess gas and water. Two main issues are thought to have prevented widespread implementation of automated control systems in the current US oil & gas industry, and instead made the industry continue to rely on heuristics and human expert knowledge and intuition:

1. The lack of real-time, relevant, high-resolution data (i.e. the system outputs, the instantaneous flow rates of the various fluid components at the wellhead), and as a consequence of this, the lack of instant decision-making tools that would lead towards smart reservoir automation.

2. The large uncertainty and limited accuracy typically present in physical reservoir modeling, as a result of the complex nature and often limited or sparse knowledge of relevant parameters in these systems.

In this work we propose to directly address and overcome these issues. On the first point above (1): we are testing and utilizing a high-performance fluid monitoring system enabled by an innovative hydrocarbon sensing technology (NeoTek Energy's DirectRead® technology) which produces real-time, high-resolution production data on each monitored well. More details on these sensor systems and the data it produces are provided in a subsequent section below.

With regard to the second point (2): we have developed a robust control methodology based on physics-informed artificial intelligence (PAI), which addresses the issue of model uncertainty in a systematic way.

Physics-informed Artificial Intelligence

Classical robust control theory approaches (i.e. non-AI based) tend to fall short in cases with large numbers of variables, and equally large numbers of parameters and parametric uncertainty in the models used for most real-world systems, as well as cases with non-linearities in the system. On the other hand, as the progress in AI technology has made it all but ubiquitous in daily life, and in recent years it also has been adopted in the oil and gas industry to address a wide variety of problems and applications [5, 6], AI is a natural candidate to consider as part of our robust control/reservoir management problem.

However, given the model uncertainty mentioned before the use of standard state-of-the-art AI-techniques would likely require an unreasonably large amount of training data for any algorithm or strategy to be successful. Our PAI methodology incorporates a physics-based model of the dynamic system, which is being used to train a deep neural network (DNN), as well as impose constraints on its outputs. This results in a greatly reduced need for training data. Also, as the DNN is used in real-time in a closed-loop feedback configuration (DFL) to estimate model parameters as well as model uncertainty, it will be able to (self-)report when the DNN can no longer be relied upon and needs to be retrained, for instance in a situation where the dynamic behavior of the system has significantly changed from the one used initially to train the DNN.

Therefore, we believe our PAI concept and DFL system exploit the 'best of both worlds' (robust control theory and AI) and provide the appropriate tools to address the problem of control of complex dynamic systems (such as the oilfield).

The Yates Field

The Yates Field is a mature and well-studied field in the Permian Basin in West-Texas (Figure 1). It is the second largest conventional recovery field in Texas, and is a naturally fractured reservoir, with in particular the East Side area being highly fractured and characterized by high porosity and permeability. This has allowed a large portion of the East Side production to be driven by gas-oil gravity drainage (GOGD) during primary recovery. Gas injection, and gas assisted GOGD, has typically been applied for secondary recovery (in contrast, in the West Side area water flooding was the main method for secondary recovery). Kinder Morgan's YFU4045 Pilot is located in the East Side (Figure 1, left insert) and has been the subject of a study and test of hydrocarbon miscible injection [7].

To validate the feasibility and effectiveness of our approach, a simulation was performed of a DFL system on this pilot, with gas injection data and historic production data from the three producing wells (YFU4002, YFU4063 and YFU4064) used to tune the physical reservoir model (which was applied to train the DNN). The main results described and discussed in this paper are based on this simulation and what-if analysis. In a second phase of the study, the DFL system is being tested real-time in the field. High-resolution sensor systems have been installed on a different unit (YFU2421) in the Yates Field (located about 2 miles from the YFU4045 Pilot) and the field testing is currently ongoing.

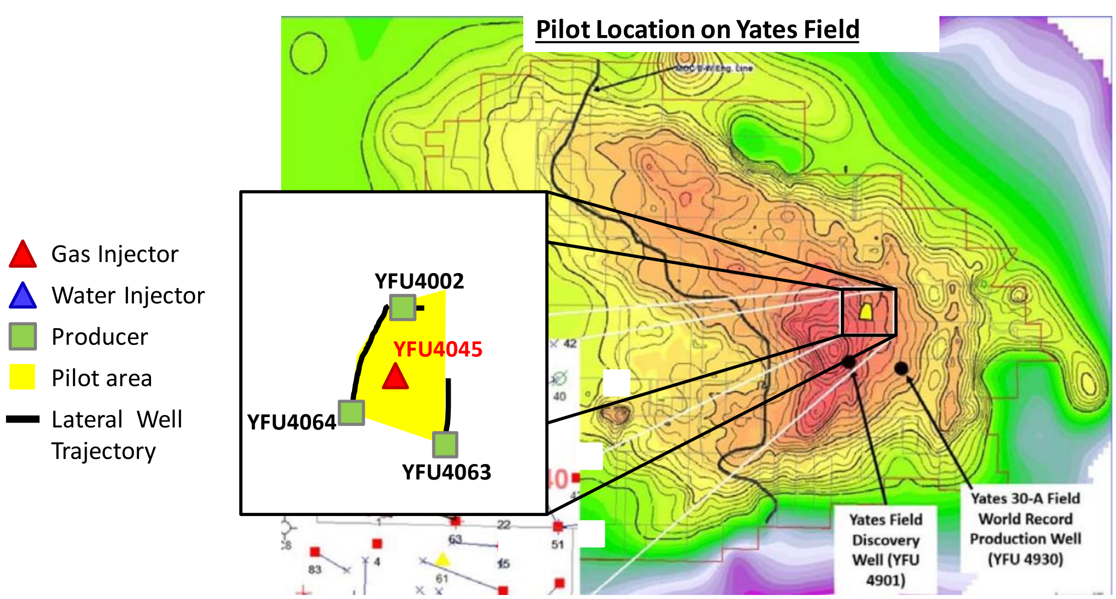

Figure 1: Map of the Yates Field in West-Texas and location of the YFU4045 Pilot (adapted from [7])

High-resolution oil production data through direct hydrocarbon sensing

To validate our approach in the field novel multi-sensor systems are employed which generate real-time oil-water-gas compositional (fluid concentrations) and output flow rate data. They are based on and built around NeoTek Energy's DirectRead® chemical sensing technology, in combination with a set of physical sensors (differential pressure, density, pressure, temperature) and are capable of directly detecting very small changes in oil concentration (of the order of 0.1%) in complex, high-velocity multiphase flow.

Figure 2 shows a conceptual drawing of the sensor system we are using, as well as a photograph of a system installed in the field. These relatively low-cost systems (Gas-Oil Ratio Analyzers, or GORA's) are customized for the Yates Field and designed to provide continuous measurements of metrics of interest, such as the gas-oil ratio (which is of high importance in gas flooded fields). The systems are typically deployed on the surface near the wellhead, in a bypass loop parallel to the outgoing pipeline, in order to enable activation and deactivation of the systems without interfering with the production. They are powered by batteries charged by photovoltaic cells, or by grid power when available.

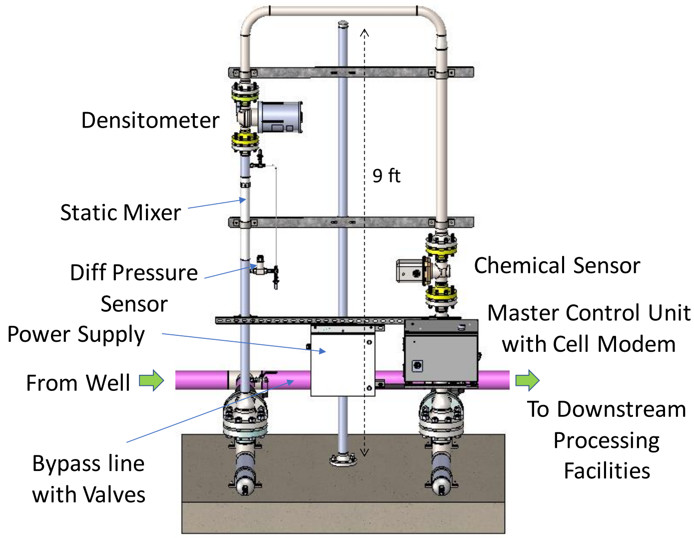

Figure 2: Gas-Oil-Ratio Analyzer (GORA) conceptual drawing and photograph of system installed in the field.

Data is transmitted using the cellular network and processed in a real-time database system. Raw data produced by each GORA system is converted into values for the output quantities at a typical rate of 1 sample per 10 seconds. The reported output quantities are volumetric concentration of oil (as a percentage of the total fluid, i.e. both gas and liquid), volumetric gas-to-oil ratio, or 'GOR' (in the typical industry units of standard cubic feet per barrel, or scf/bbl), oil flow rate (in barrels/day, bbld), gas flow rate at process and/or standard conditions (in cubic feet per day or standard cubic feet per day), gas volume fraction (a dimensionless number between 0 and 1), pressure (in psi) and temperature (F).

Sample data from a prototype GORA system installed on a well in the Yates Field is shown in Figure 3. As can be observed from the data, this well is operated using an intermittent 'shut-in' and 'reactivation' schedule, as a result of the well being subject to 'gas coning' (as discussed below). Figure 4 shows a zoom in of the data, illustrating the high temporal density and dynamic behavior the sensors are able to capture. It is focused on a short two-hour period of time right after the well is reactivated (period between t = 3025 hours and t = 3027 hours). A typical behavior upon reactivation is observed: a short peak of gas (high GOR period) is followed by about a half hour or mostly liquid flow (high oil vol%, low GOR), finally followed by a steadier regime of low oil volume fraction and intermediate GOR.

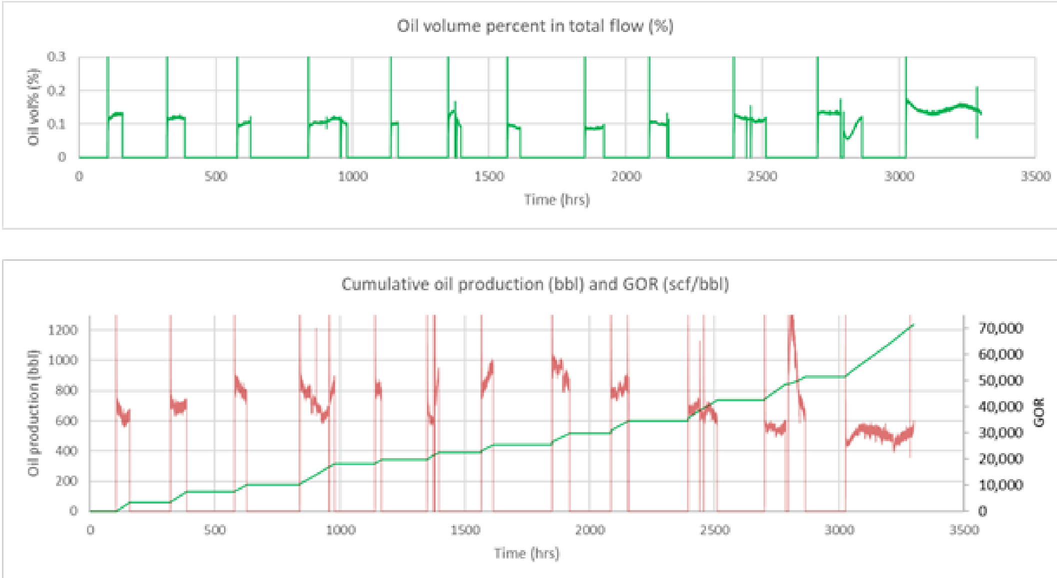

Figure 3: oil volume %, GOR and cumulative oil production data over a time period of about four and a half months acquired by a prototype GORA system (installed on a well that is periodically activated and deactivated – an example of an 'open loop' control strategy).

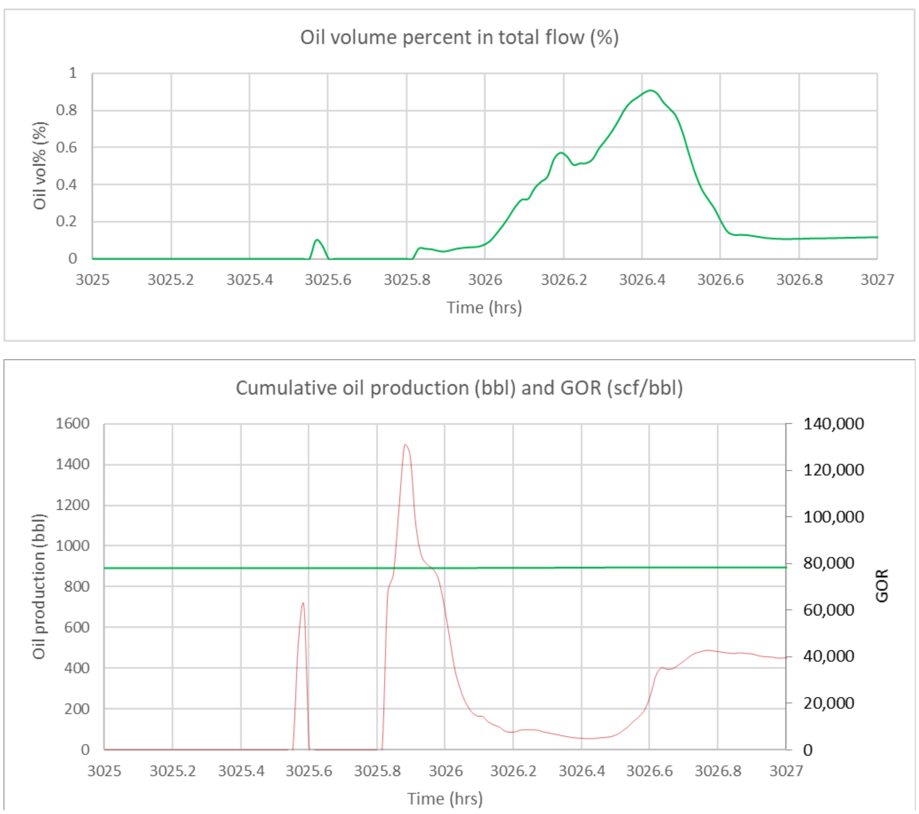

Figure 4: Detail (a time period of 2 hours, during a 'reactivation' step).

Approach and methods

PAI concepts: theory

We have developed a methodology for incorporating physics into artificial intelligence (AI) techniques to provide rapid and accurate insights into future performance of dynamic non-linear systems. The key element of the proposed approach has been to develop multi-layer artificial neural networks (i.e. deep neural networks, or DNNs) that employ physics-based parameters and can predict key variables indicating the states and/or performance of the system based on the real-time measurements.

DNNs are powerful learning models that allow computational models of multiple processing layers to learn and represent data with multiple levels of abstraction, thus implicitly capturing intricate structures of large-scale data. DNNs have shown promising results in a wide range of supervised and unsupervised machine learning tasks. However, the task of training DNNs to accurately identify a nonlinear map from a few potentially very high-dimensional input and output data pairs is very challenging due to the large solution spaces. DNNs are easy to overfit in training, making it difficult to respond effectively to unfamiliar or challenging situations outside the dataset.

To overcome this problem, we have developed a physics-informed robust neural networks technique where the physics and data are used to train DNN representations of the key physical parameters. In many cases pertaining to the modeling of physical systems, there exist a vast amount of prior knowledge such as physical laws developed from first principles that govern the dynamics of a system, or phenomenologically-derived relationships, or other rules originating from the insights of domain experts.

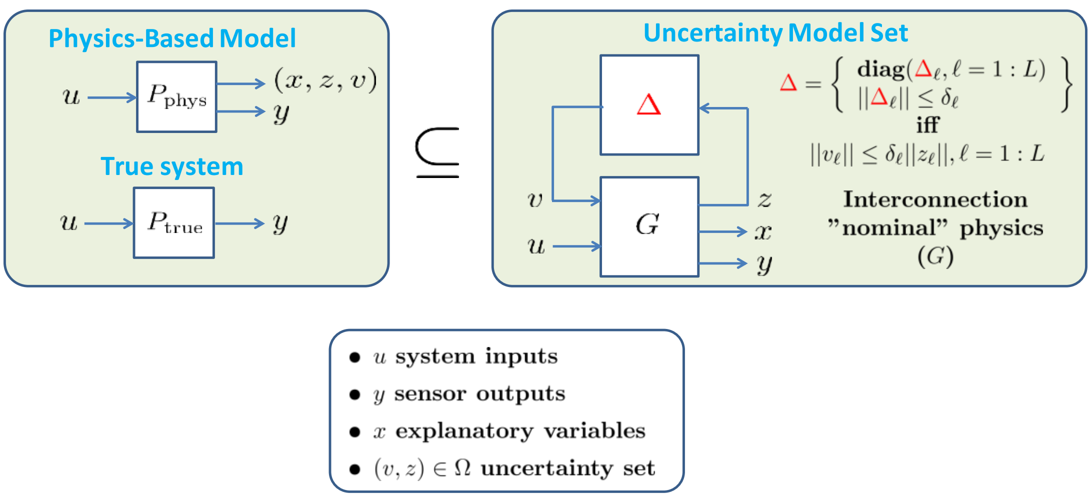

Figure 5: System model with model uncertainty formulation.

The method developed in this program uses the prior knowledge as a regularization agent that constrains the space of admissible solutions to a manageable size [8]. In this way, the output from the neural networks is enforced by the physics equations. In most cases in real-world problems, and particularly in the field of oil reservoir modeling, only approximate models exist. In addition, due to the dynamic nature of systems, the accuracy of those models often changes over time. These model uncertainties can significantly degrade the predictive capability of the DNN. To address this, we used system-theoretic robust control ideas [9, 10] as illustrated in Figure 5 and Figure 6, combined with DNNs to achieve robust performance.

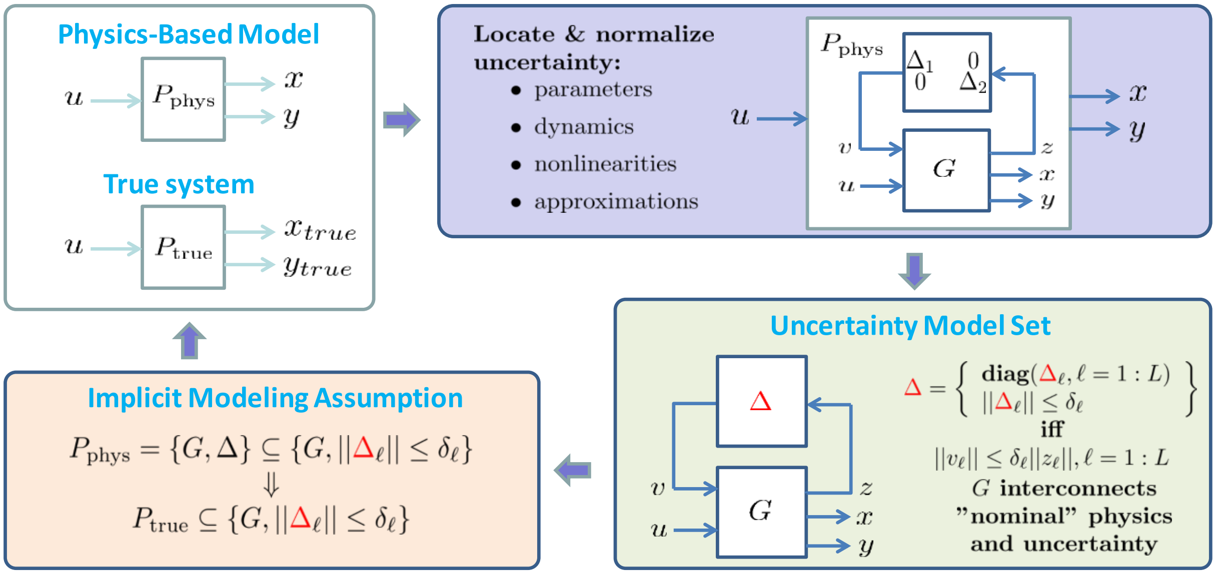

Figure 6: Building a physics-based model uncertainty structure.

Here, x denote key explanatory variables, y the measurements (sensor data), u is a control input, z and v are inputs and outputs of the modeled uncertainties, Δ, and G is the interconnection system matrix. The loss function that we have used to train the DNNs is given below:

$$\text{L} = \|(\hat{z}, \hat{x}, y) - G(\hat{v}, u)\|^2 + \|\hat{x} - x\|^2 + \|(\hat{z}, \hat{v}) - (z, v)\|^2$$

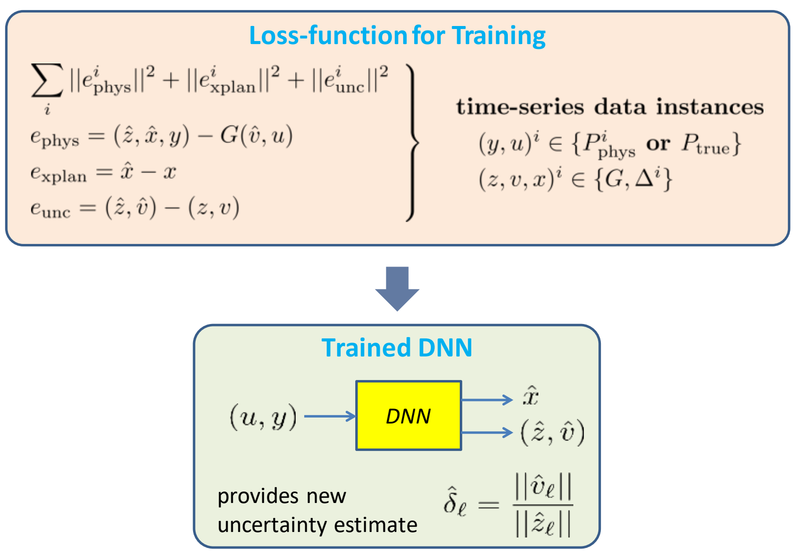

Figure 7: Training of DNN

In this expression, the variables $\hat{x}$, $\hat{z}$, $\hat{v}$ are the estimates for x, z, v produced by the DNN. The goal is to find a set of parameters in the neural network that minimizes the loss function. In this setting, the neural networks are constrained to respect any symmetry, invariance, or conservation principles originating from the physical laws that govern the observed data, as modeled by general time-dependent and nonlinear partial differential equations. Therefore, the trained networks approximate the solution to the physical equations. Moreover, the predicted input/output of the uncertainties indicate whether the prediction is guaranteed to be within a certain bound for admissible uncertainties.

As architecture for the DNN, we initially tested a simple feed-forward network [8]. However, due to the difficulty in measuring the model parameters in practice, supervised learning approaches that require labeled datasets are not suitable. Therefore, we selected instead an autoencoder network [11]. The autoencoder (Figure 8) is a feedforward neural network with a hidden layer that represents the latent variables. The network is trained in unsupervised manner to reconstruct its input and learn the model parameters.

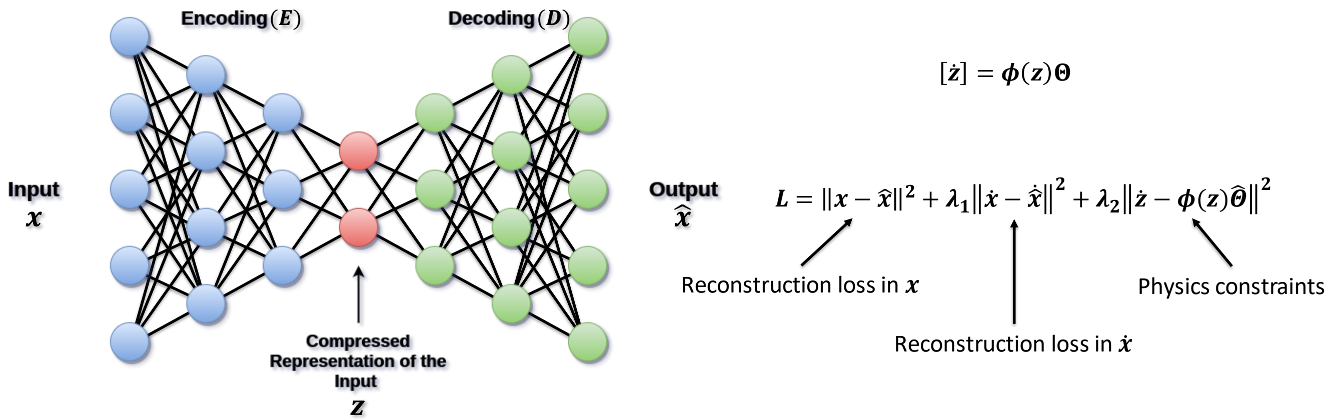

Figure 8: Autoencoder DNN architecture

The trained DNN will be used in a feedback loop as described in subsequent sections, with effective control algorithms to achieve robustness to system variations and uncertainty, reduction of response to noises and disturbances, and optimality of the dynamic response. First though we will discuss the physical reservoir models used in this study.

Physical models of the reservoir

We have examined a number of relatively simple reservoir models for application in our PAI concept. The first is the well-known CRM model. The second is a new model developed by our team describing gravity-driven moveable oil-gas interfaces (‘1D gas coning model’). Both approaches can be combined to obtain a modified CRM-like model. Finally, a multi-well extension to the gravity-driven model was selected to best capture the behavior of the Yates YFU4045 Pilot wells (as well as other, similar operations in Kinder Morgan’s Yates Field).

CRM Reservoir Model

We initially explored the Capacitance-resistive Model (CRM) as a reservoir model to validate the proposed approach. The CRM is an inter-well connectivity model that characterizes the time-dependent effects of injection wells on production well [12]. It can be used to optimize injection rates for maximum oil production. The governing differential equation of the CRM is given by:

$$\tau_{ij}\frac{dx_{ij}}{dt} = -x_{ij}(t) + f_{ij}u_j(t) - \frac{dp_i}{dt}\tau_{ij}J_{ij}$$

Here:

x_{ij}: production rate at production well *i* that corresponds only to the injection well *j*.
u_j: injection rate at injection well *j*.
p_i: bottomhole pressure at production well *i*.
τ: time constant, $\tau = cV_p/J$, where c is compressibility and V_p is pore volume.
f: inter-well connectivity (distribution), $f_{ij} \geq 0$ and $\sum_{i=1}^{N_x} f_{ij} \leq 1$.
J: productivity index.

The CRM equation above contains a sum of three terms: the first accounts for exponential decline as in primary recovery production, the second contains injection rate, and the third covers the effect of the change in bottom hole pressure (BHP). The equation is based on the change in average pressure of a constant volume surrounding producers. The pressure change is due to the producer's rate and inflow from neighboring injectors [13]. In general, producer BHP does not change much. Hence, to start our study with the simplest, yet most effective model, we ignored the third term [12].

We used an empirical oil-cut model to compute oil production [14]. This model uses a power-law relationship between the instantaneous water–oil ratio and cumulative-water injected. Therefore, fractional flow of oil can be written as [14]:

$$f(t) = \frac{1}{1 + \alpha CI^{\beta}} \qquad \text{where } CI = \sum_{j=1}^{N_I} \int_{t_0}^{t} u_j(t) dt$$

We used the CRM with nominal parameters to generate datasets for offline DNN training. We then perturbed the inter-well connectivity of the nominal model and used it as a real system.

Gas and Water Coning During Oil Production

When oil is being produced from a well, it results in a pressure drop that moves the gas zone towards the wellbore, forming a cone-shaped gas oil boundary as shown in Figure 9 [15]. As production rate is increased, the height of the cone also increases until at a certain production rate gas flows into the well through the well perforations. This phenomenon is referred to as gas coning. Gas coning pose a significant issue in many oil field applications as it significantly reduces oil production, increase cost of the production operation and has a direct effect on the overall recovery efficiency of the oil reservoirs. (The phenomenon of water coning is similar).

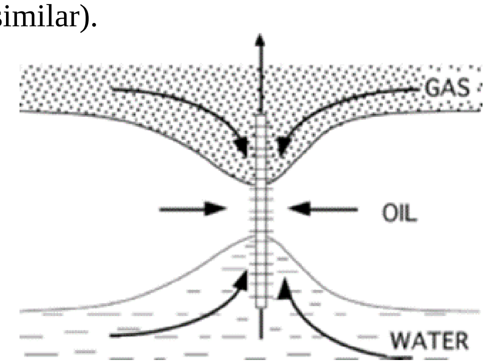

Figure 9: A producing well subject to gas and water coning (from [15]).

The maximum production rate without the coning is called the **critical rate**. Attaining the critical rate is a very practical problem. It is also important to know the location of the gas-oil contact surface for oil recovery from horizontal wells. However, very few studies have been reported on the water/gas-oil coning behavior [15]. To reduce the coning problem, field operators occasionally shut in the wells to equalize pressure and fluid saturations back to static conditions.

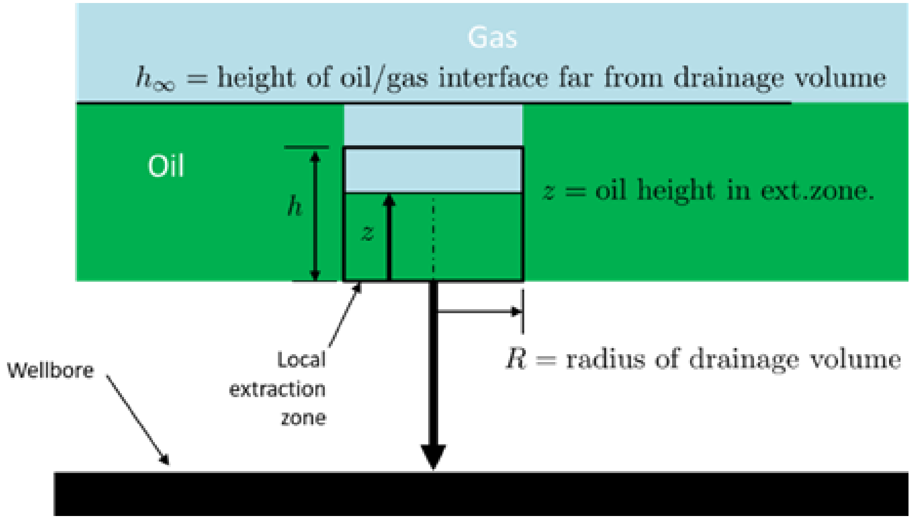

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Figure 10: 1D model for coning.

1D Gas Coning Model

As gas coning is generally a concern in the Yates Field (which is currently operated as a CO_2 flood), we developed a model that captures the phenomenon of gas coning as shown in the schematic in Figure 10. The model considers the drainage volume of the wellbore, which is assumed to be cylindrical in shape, as a control volume. As the production rate is increased, the downward dynamic force due to the wellbore lowers the gas-oil interface to a certain level where the dynamic force is balanced by the weight of oil below this point. The rate of change in the volume of oil in the control volume can be expressed as the difference between the volume rate of oil flowing into the zone and the volume rate of oil flowing out of the zone. The physical equations can be written as:

$$\pi R^2 \dot{z} = q_{in} - q_{out}$$
$$q_{in} = a\Delta\rho g(h_\infty - z)$$
$$q_{out} = q\min\left(\frac{z}{h}, 1\right)$$
$$y = q\min\left(\frac{z}{h}, 1\right)$$

Here, R is the radius of drainage volume, z is oil height in the extraction zone, a is the volume rate per unit pressure drop, $\Delta\rho$ is the density difference between oil and gas, g is the acceleration of gravity, h_∞ is the height of oil/gas interface far from the drainage volume, and h is the height of the drainage volume. Note that a includes the effect of gas viscosity and formation permeability near the perforation.

Figure 11 shows the volumetric oil concentration in total production from the well. The top row shows the data obtained by a GORA sensor system at a test well in the Yates field (YFU 3902) and the bottom row shows the outputs from the calibrated coning model. We observe from both the sensor data and the model outputs that the oil concentration gradually decreases while the well is open. After a few days of shut-in period, pressure and fluid saturations are restored and approach static conditions. This shows that the coning model captures the dominant behavior of the well production. This calibrated model was used as a nominal model to test our approach.

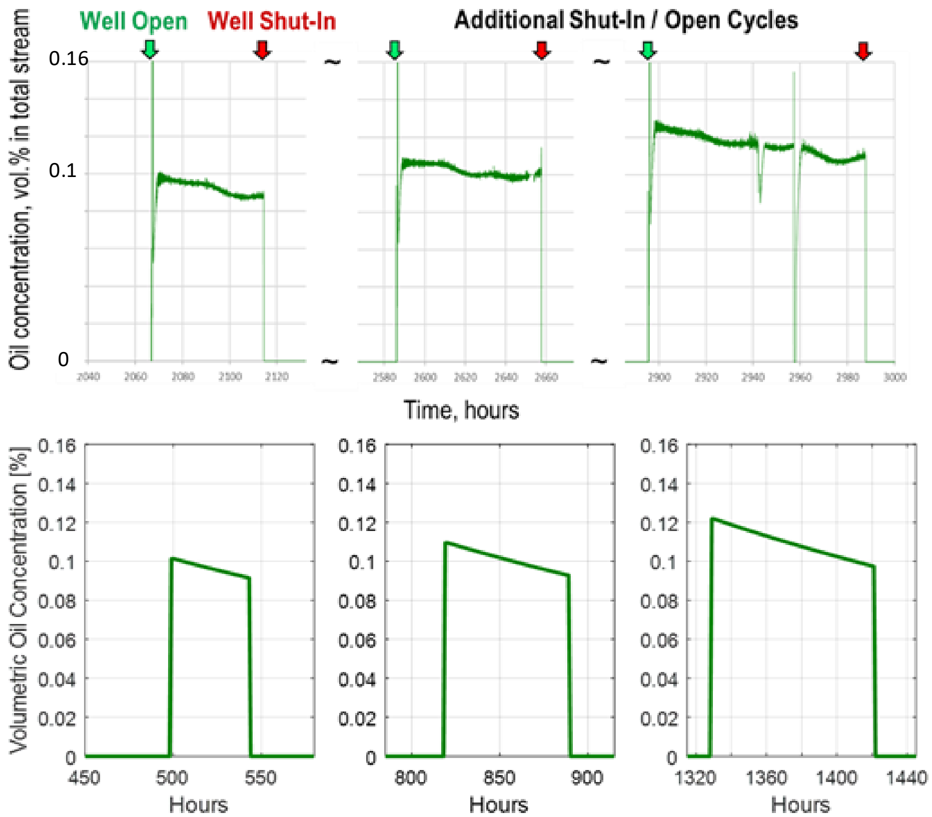

Figure 11: Volumetric oil concentration in total production. Top: GORA measurements in the Yates field, Bottom: Calibrated coning model.

Model with structured uncertainties

Defining a normalized variable $x = \frac{z}{h}$, the equations above can be re-written as:

$$\dot{x} = \alpha - \beta x - \gamma q \min(x, 1) = \Theta^T \phi(x)$$
$$y = q \min(x, 1)$$

where $\alpha = \frac{a \Delta \rho g h_\infty}{\pi R^2 h}$, $\beta = \frac{a \Delta \rho g}{\pi R^2}$, $\gamma = \frac{1}{\pi R^2 h}$, $\Theta = [\alpha, \beta, \gamma]^T$, and $\phi(x) = [I, -x, q\min(x, 1)]^T$.

If there are uncertainties in the model parameters, i.e. $\Theta = \bar{\Theta} + \tilde{\Theta}$, we can re-write the equations as:

$$\dot{x} = \left(\bar{\Theta} + \tilde{\Theta}\right)^T \phi(x) = \bar{\Theta}^T \phi(x) + v$$

Here, $v = \tilde{\Theta}^T \phi(x)$. With this formulation, the coning model with structured uncertainty is shown in Figure 12. In the diagram, the input to the uncertainty block is $z = \phi(x)$, and the structured uncertainty block is defined as $\Delta = \mathrm{diag}(\Theta - \bar{\Theta}) = \mathrm{diag}\left([\tilde{\alpha}, \tilde{\beta}, \tilde{\gamma}]\right)$, where $|\tilde{\alpha}| \le \delta_\alpha, |\tilde{\beta}| \le \delta_\beta, |\tilde{\gamma}| \le \delta_\gamma$.

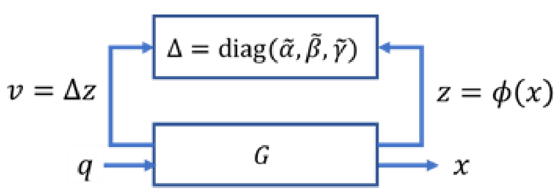

Figure 12: Coning model with structured uncertainty.

CRM + Coning Model

The CRM model describing the inter-connectivity between the wells and the coning model describing the well production at individual wells can be combined to obtain a model of the entire reservoir system with multiple wells, as shown in Figure 13. We note that T and F are matrices with q and u vectors. The number of wells can easily be extended with this model, and it was initially used to validate the DFL concept using simulations.

However, though applicable to most conventional (water) flooded fields, we found the model not entirely adequate for the gas-assisted, gas-oil gravity drainage (GOGD) driven wells in the YFU4045 test field [7]. Therefore, we updated the model specifically for a multi-well GOGD case as described next.

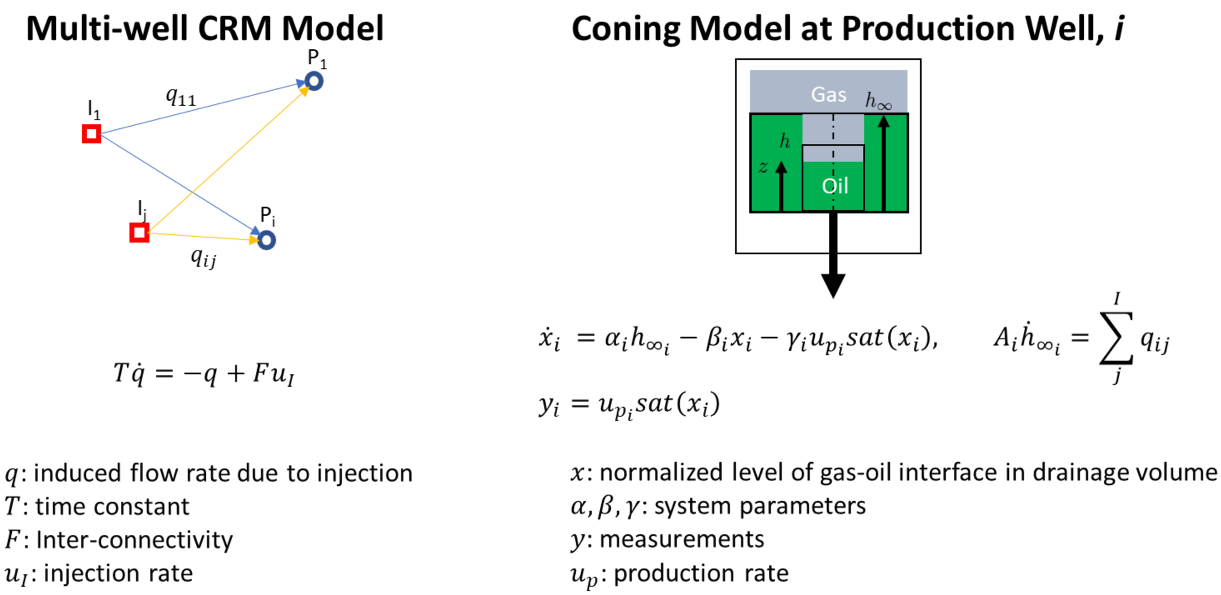

Figure 13: CRM and coning model combined.

Multi-well GOGD Model

In many areas in the Yates Field, gas injection is currently used to maintain the gas cap and as the reservoir is highly fractured, the production wells are highly interconnected. In such cases, oil production is mostly driven by gas-oil gravity drainage (GOGD). An updated multi-well model based on GOGD is shown in Figure 14. In the updated model, the difference in the height of gas-oil interface, h_∞, drives the flow between the wells. The net flow from producer j to producer i can be written as:

$$q_{ij} = c_{ij}(h_{\infty,j} - h_{\infty,i})$$

Here, the parameter c_{ij} depends on the geostatic properties as well as fluid properties between the wells, such as permeability, viscosity, and density. At each producer, h_∞ can be changed due to the net flow of oil, and the production of oil causes the gas-oil interface to descend. This can be expressed as:

$$A_i \dot{h}_{\infty,i} = \sum_k q_{ik} - u_{p,i} sat(x_i)$$

The model for oil production is the same as in the coning model described earlier.

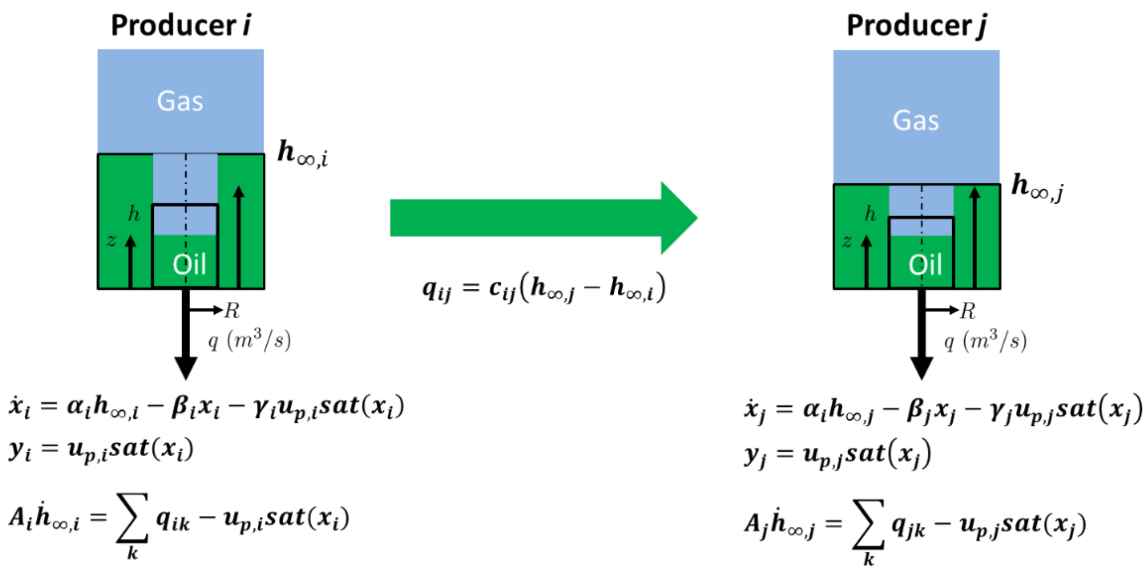

Figure 14: The updated multi-well GOGD model as applicable to the Yates field test.

Figure 15 shows responses to a ‘bump test’ of the multi-well model consisting of three production wells. The plots on the top row show the control signals (well flow rates) and the second-row plots show the changes in h_∞ over time. In this simulation, each well is first separately ‘activated’ for a period of time (while the others are ‘de-activated’ or shut-in); later, there is overlap imposed during subsequent activation periods. Due to the flow between the wells, we can see that h_∞ of each well converges. The third and fourth row plots show the normalized height of the gas-oil interface in the drainage volume and the oil production, respectively.

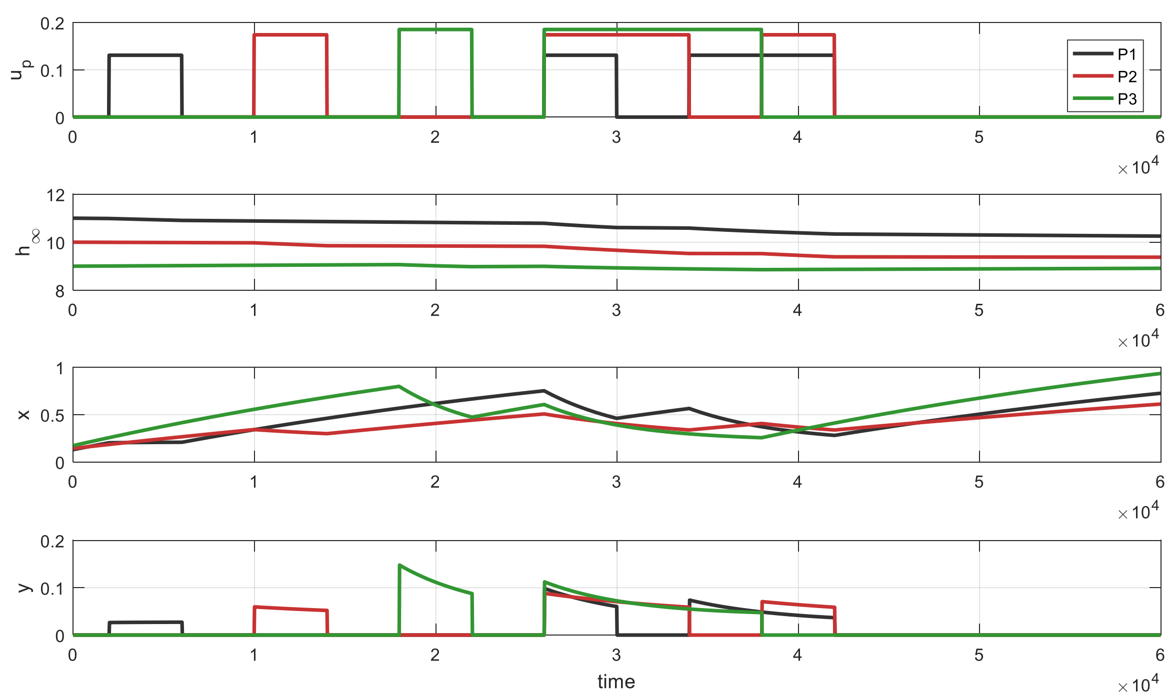

Figure 15: Responses to the bump test of the multi-well model.

Dynamic Feedback Loop (DFL) with DNN

Production optimization of an oil reservoir requires an understanding of the dynamic behavior of the reservoir. We will demonstrate the efficacy of applying system physics and an upper bound on model uncertainty to train a deep neural network (DNN) to generate reliable estimates of the states and uncertain parameters of the system using the DFL.

The development of NeoTek Energy's low-cost sensor systems has enabled us to obtain large volumes of real-time data. To take advantage of this high-resolution data, we have developed a dynamic feedback loop (DFL) that provides rapid and accurate insights into future performance of the dynamic system and optimizes control inputs to maximize economic oil recovery. The DFL will also operate with sparser, lower-resolution data (such as produced by test separators) but we expect the overall benefit to increase with the time resolution of the data, as the system will be able to adjust and adapt itself to changing conditions more rapidly.

The schematic of the DFL is shown in

Figure 16. Initially, the deep neural network (DNN) is trained off-line with the dataset generated from a nominal model of the oil reservoir. The DNN is then trained to produce the estimates of the key variables and uncertainty variables based on the control inputs and the measurement data. Here, the key variables include variables representing the states, characteristics, and/or performance of the system. If the nominal model used for DNN training is accurate, the estimates of the key variables would be reliable. However, if the model is inaccurate or the system is changed, the prediction error is likely to increase. For this reason, the DNN produces uncertainty estimates together with the key variables. The uncertainty variables indicate if the level of model uncertainty is admissible. If the model uncertainty is too large, it means that the training dataset does not represent the actual system well. Therefore, the outputs from the trained DNN would be inaccurate. In this case, the model must be updated, and the DNN needs to be re-trained with the updated model.

The trained DNN is deployed in the field for on-line control. The DNN takes real-time measurements collected from the reservoir and provides the outputs to the optimizer. Utilizing the information, the optimizer generates the optimal control inputs to maximize oil production and feeds them to the actual reservoir system (or to an operator to make the changes).

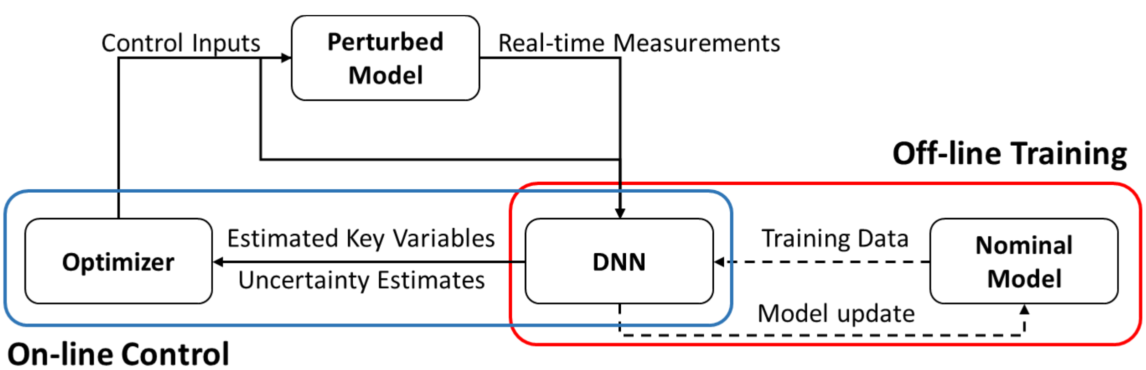

Figure 16: Schematic of the dynamic feedback closed-loop reservoir management system.

Results

YFU4045 Pilot: simulation and analysis

We used the historic production data from late-2016 to mid-2017 of the YFU4045 Pilot to validate and tune our previously described multi-well GOGD model. The tuned model was used to implement and test the proposed DFL for an initial analysis and validation of the entire concept.

Model Tuning with Historic Production Data

The historic data used originates from Kinder-Morgan's study where the effect of miscible injection on the reservoir production was examined [7]. In the study, a hydrocarbon miscible (HCM) injectant (Y-Grade) was used in a single pilot injection well to mobilize remaining oil in the gas cap and accelerate gravity drainage. During the pilot, well tests of nearby producing wells, gas and oil sampling, and chromatographic analysis were performed.

Based on the reservoir and wellbore characteristics required for a successful HCM injection test, Yates Field Unit (YFU) 4045, a CO2 injection well was chosen as the HCM pilot injection well to conduct the test. The YFU4045 injector is bounded by three oil producing wells (YFU 4002, 4063, 4064), as shown in Figure 17.

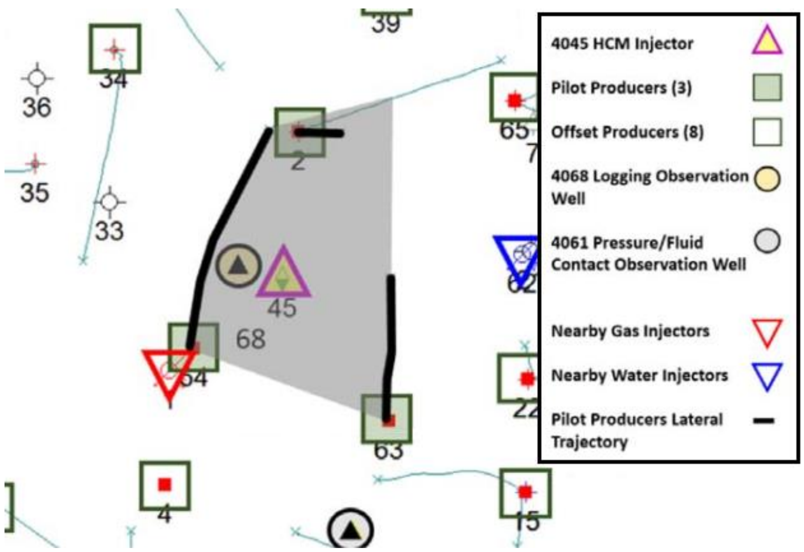

Figure 17: Pilot injector (YFU4045) & offset wells (YFU 4002, 4063, 4053) in the Yates field (from [7]).

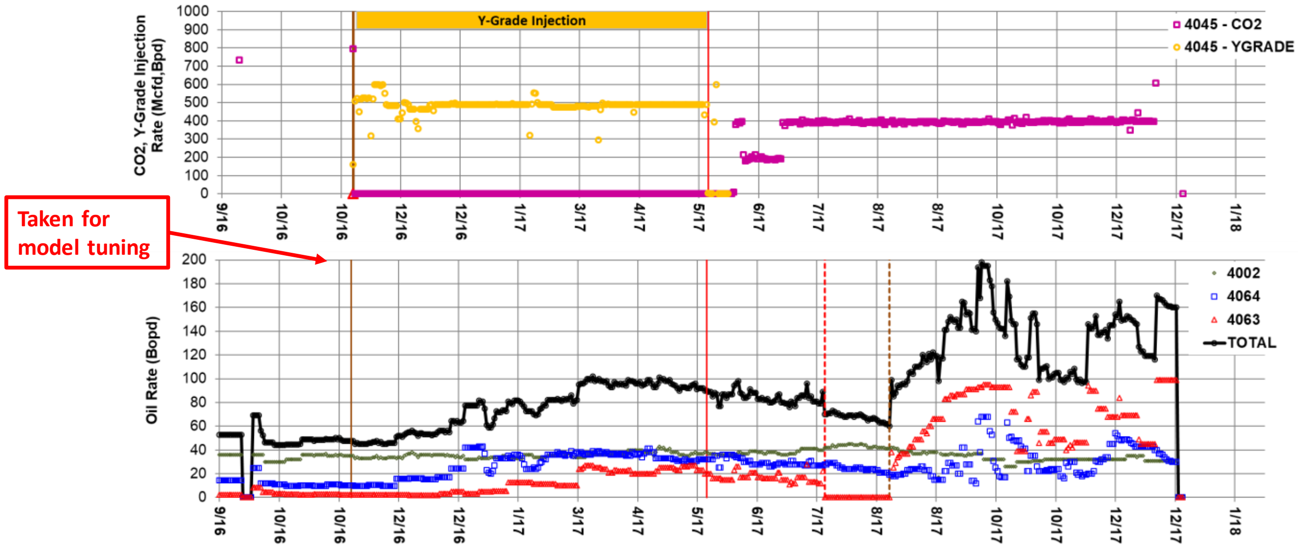

Figure 18: YFU4045 HCM pilot well production & injection rates (adapted from [7]).

The initial phase of the HCM injection test included injection of pure Y-Grade into the YFU4045 injector for six months and testing and analyzing the three offset producers. The oil production response has been favorable, with the oil rate impacted by the Y-Grade injection, as shown in

Figure 18. YFU 4064 was the first of the pilot producers to exhibit incremental oil response after around 30 days of Y-Grade injection. YFU 4063 responded after around 80 days. YFU 4002 saw much slower and more muted response, suggesting that most of the injectant was sweeping in the direction of the YFU 4063 and 4064.

After completing the six-months of Y-Grade injection, several tests were conducted to determine the feasibility of injecting Y-Grade/CO2 mixtures, and chase CO2 gas injection began. In Oct 2016, YFU 4063 began experiencing severe operational problems due to flowline/test vessel freezing due to its high CO2 content and low temperatures, resulting in reduced rates.

Model parameters were tuned to match as closely as possible the individual well oil production rates. As shown in

Figure 18, the reliability of the data became questionable after the Y-grade injection period due to the operational problems. Therefore, we mainly used the data during the six-months of Y-grade injection period.

Figure 19 shows the comparison of the model output with the field data. In the figure, the red lines represent the field data and the black lines represent the model output. It is shown that the model reasonably fits the incremental oil recovery during the injection. Although the dominant behavior is captured with the model, there is a non-negligible error in the oil production rate. The differences between the model and the data could be caused by unmodelled physics, measurement errors, noise, or un-recorded total production rates at the producing well. These errors are expected to be reduced if GORA sensors are installed and provide additional production information, including GOR and control input for each producer.

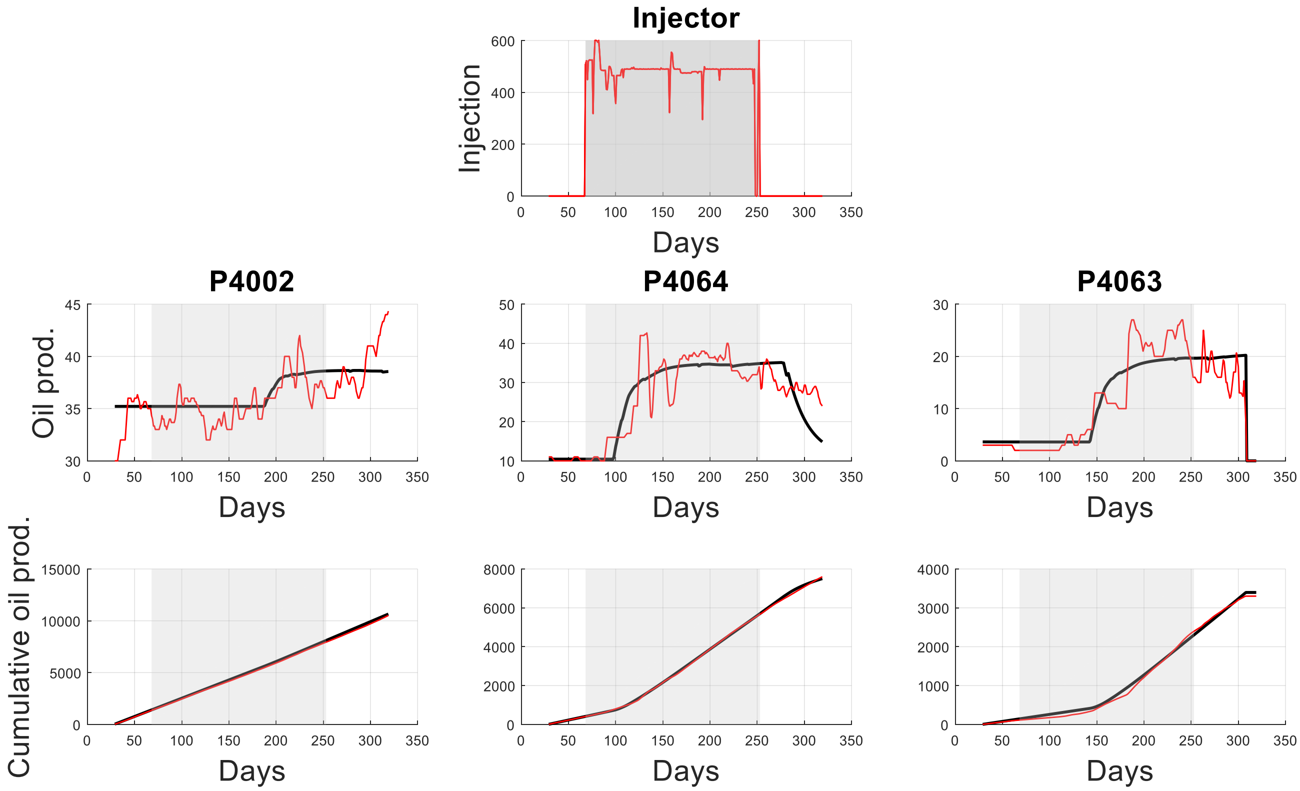

Figure 19: Comparison of model output with field data (Red: data, Black: model).

Implementation of Dynamic Feedback Loop

We tested the autoencoder type DNN trained to estimate the parameters of the multi-well reservoir model with the data from the tuned model. The model data was generated based on the oil field injection data.

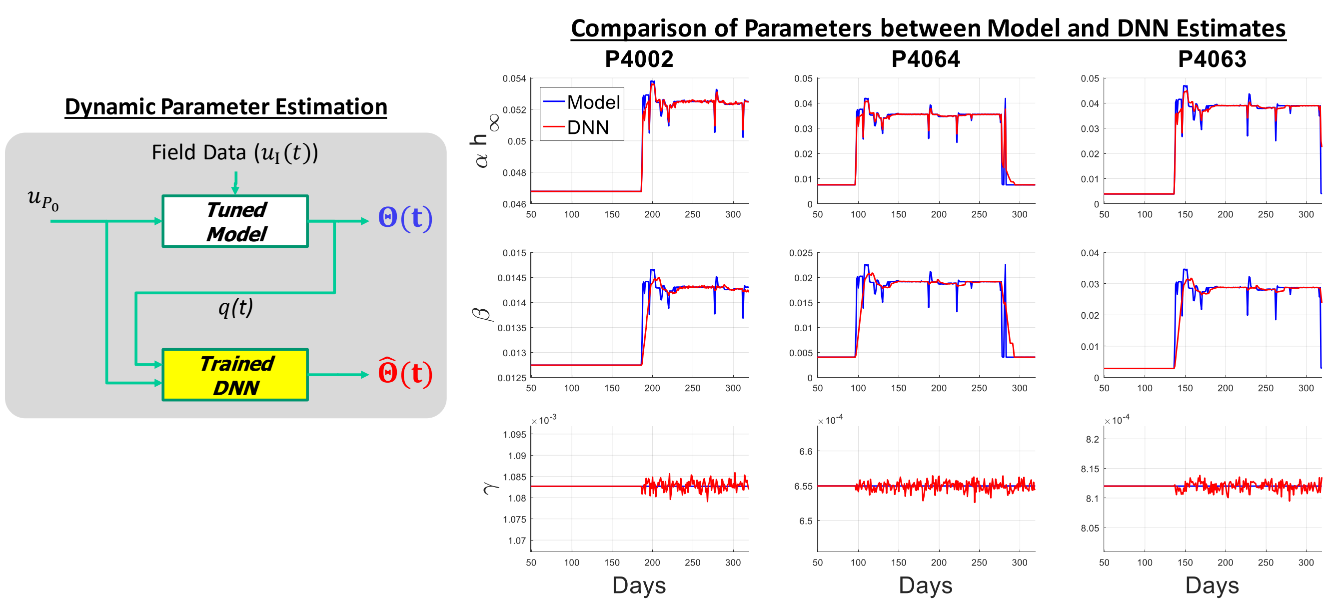

Figure 20: Comparison of physical parameters/state between the model and the DNN estimates (Black: model, Red: DNN estimates).

Figure 20 shows the comparison of parameters/state between the model and the DNN estimates. The black lines represent the actual values of the parameters/state generated from the tuned model and the red lines represent the estimated values from the DNN. The figure shows the DNN produces reasonable estimates of the time-varying parameters.

The schematic of DFL for the initial analysis is shown in Figure 21 (left bottom diagram). Based on the injection data from the historic dataset and the control inputs, the tuned model produces the oil production rates. The trained DNN estimates the physical parameters, $(\alpha h_{\infty}, \beta, \gamma)$, for each producer. The controller uses the estimated physical model parameters to dynamically compute the optimal production rate.

The oil production from the DFL system and the oil production from the open-loop system can now be compared, as shown in Figure 21. The open-loop system represents the current reservoir management approach, in which an optimal set of control inputs (e.g. choke valve settings, injection rates) is selected, based on expertise and best estimates from existing data, and maintained throughout the period of time under consideration. In the DFL system on the other hand, the control inputs are continuously adjusted by the trained DNN using the incoming sensor data. The black lines represent the open-loop system and the blue lines represent the DFL. It is shown that the use of DFL significantly improves the cumulative oil production, by an amount of 34.7% over a year.

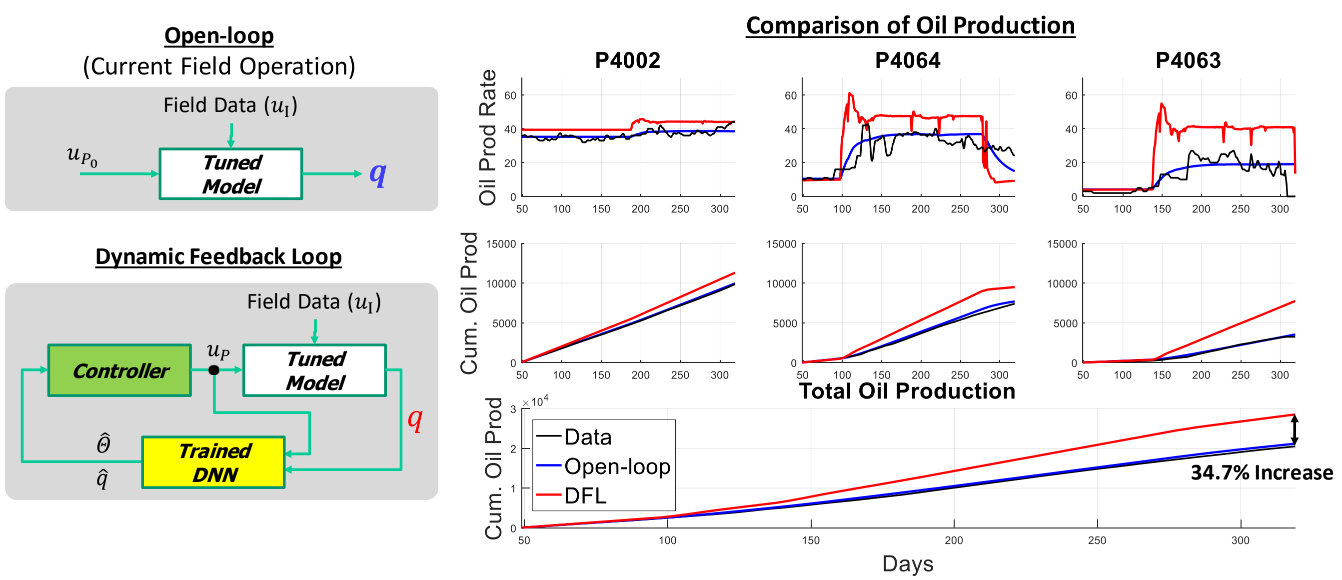

Figure 21: Dynamic feedback loop used for initial analysis.

Estimation accuracy and model falsification

The estimation accuracy of the model parameters depends on the training sets used for the DNN. The (red colored) data shown in Figure 20 was produced by a DNN with the (non-perturbed) model included in the training dataset. A typical issue with AI and DNN's is the tendency to produce poor results when the incoming data does not lie within the training set, resulting in a need for very large training datasets, covering the largest possible space. In our DFL approach, a model falsification criterium can be implemented through the uncertainty formulation and continuously tested against during operation. In case the model would be falsified (e.g. when the incoming data would lie far outside the training set produced by the model, implicating the current model is no longer valid), the controller can for instance be designed to fall back on open-loop control, or raise a flag indicating the need for a model update and re-training the DNN, thus making the system overall very robust to these issues.

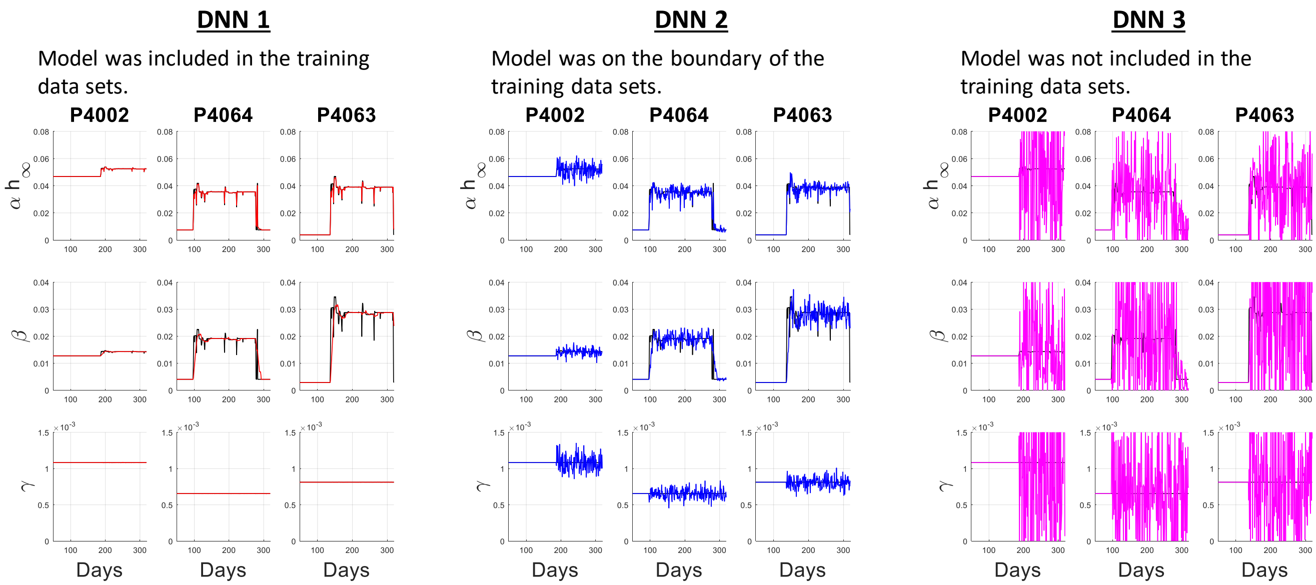

Figure 22: Three cases, with from left-to-right decreasing estimation accuracy of the model parameters

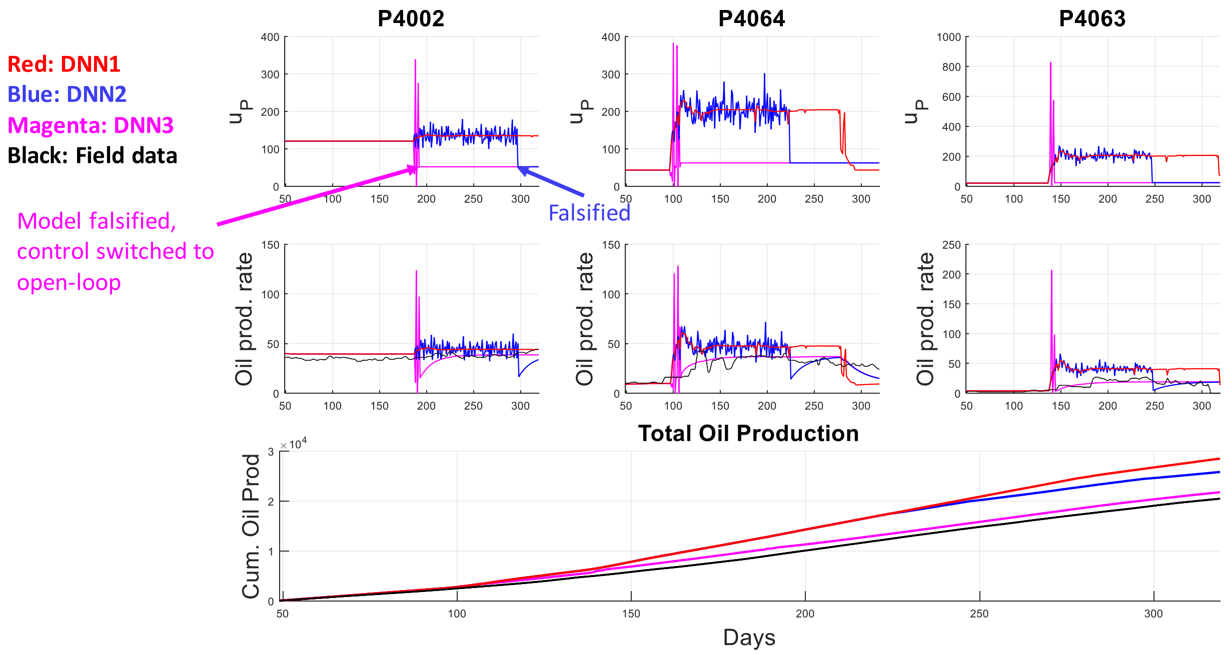

Figure 23: System performance for the three scenarios in Figure 22 (with the black-colored data representing the field data, which was produced in open-loop mode)

This is illustrated by Figure 22 andFigure 23, which depict the model parameter estimates and system performance for three different scenarios: a first one (red-colored data), with the unperturbed model within the training dataset (good estimation accuracy), a second one (blue-colored data), with the unperturbed model at the boundary of the training dataset (moderate estimation accuracy), and a third one (magenta-colored data), with the model outside of the training data (very poor estimation accuracy). In all cases, the system performance exceeds the performance obtained in open-loop operation, as a result of the continuous application of the falsification criterium in the feedback loop.

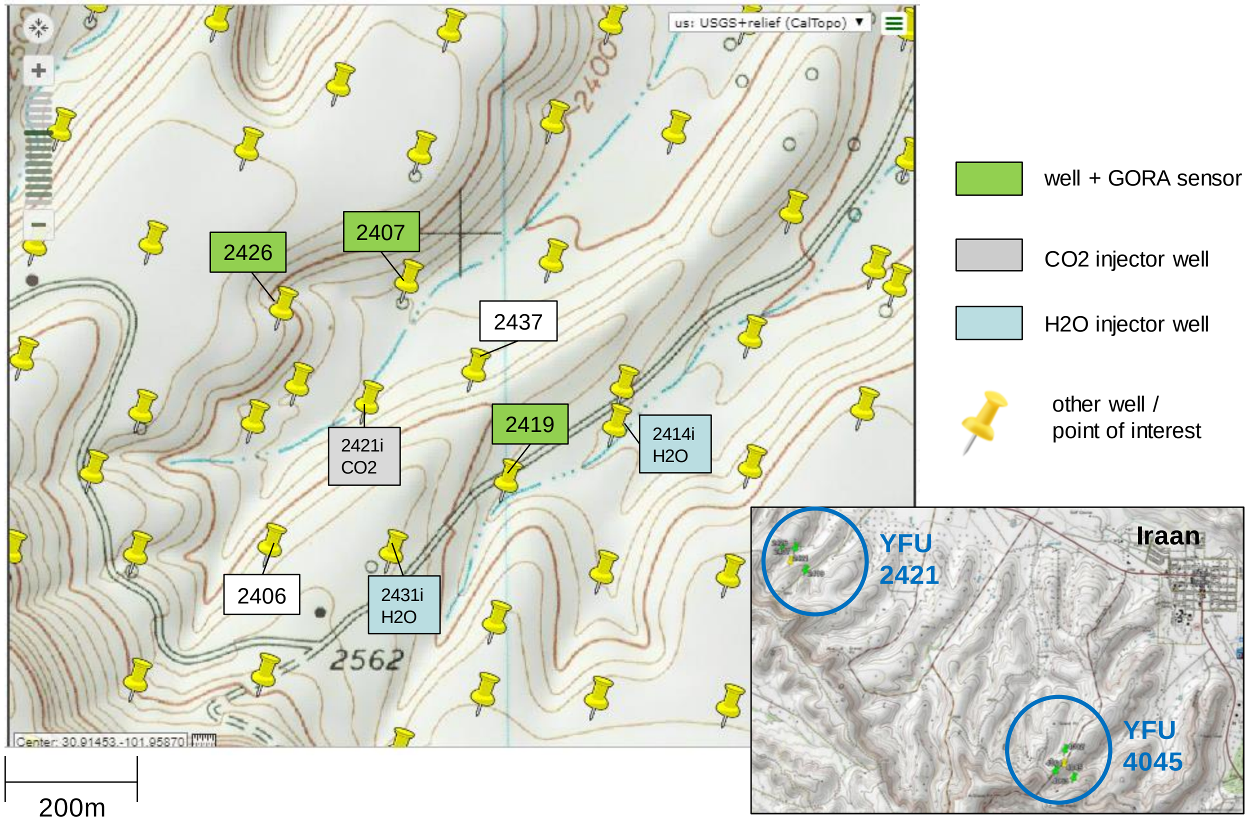

Figure 24: YFU2421 field test site with GORA instrumented wells (YFU2421 is located about 2 miles away from YFU4045)

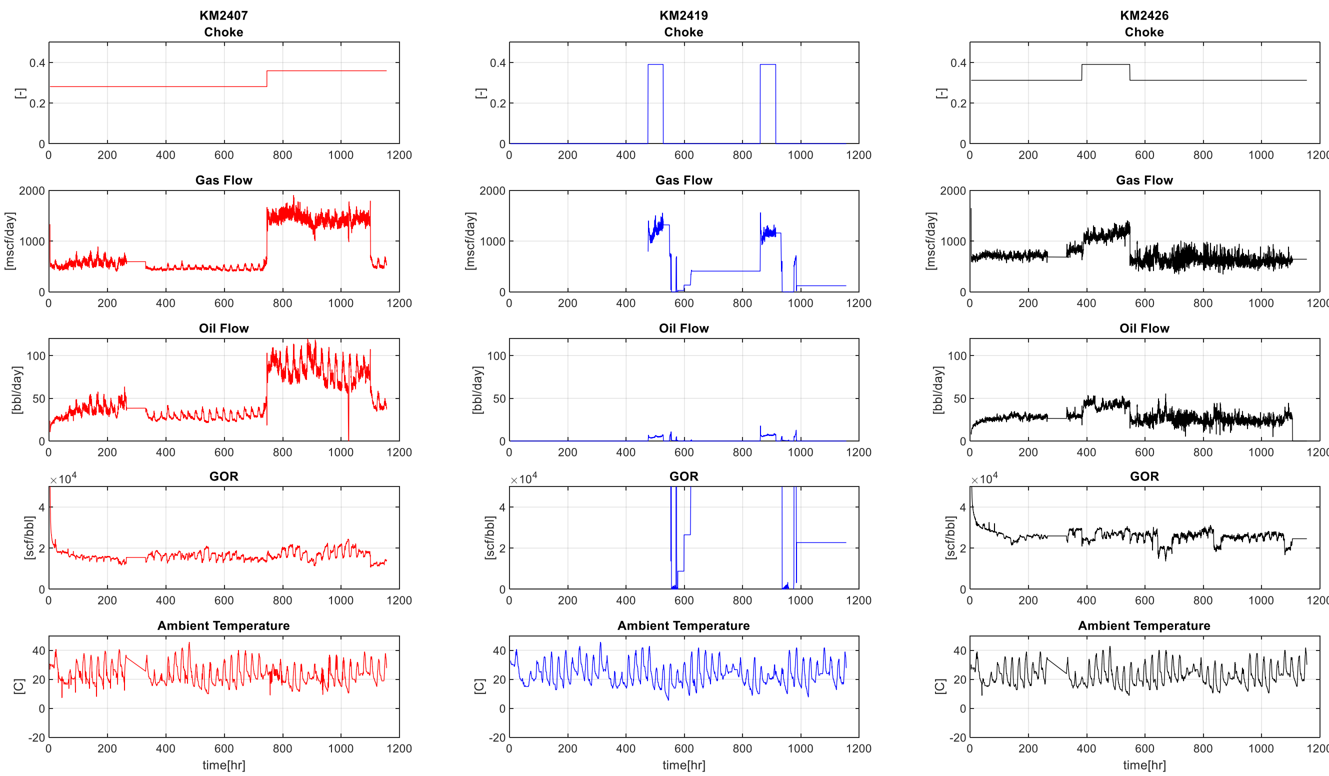

Figure 25: High-resolution GORA data on the YFU2407 (red), YFU2419 (blue) and YFU2426 (black) wells. Plots from top to bottom: choke valve setting, gas flow rate, oil flow rate, GOR and temperature

YFU2421 Pilot: high-resolution data

After initial validation using the YFU4045 Pilot historic data and the promising simulation results, the DFL system is being field tested in real-time. The test site and test wells are located around the YFU2421 (gas) injecting well. YFU2407, YFU2419 and YFU2426 are the producing wells (see Figure 24).

The first step in designing and implementing the DFL is again to tune the model to the data acquired after a series of 'bump tests'. As shown in Figure 25, which depicts the high-resolution production data produced by the GORA systems, the first of these tests consists of a sequence of changes in the respective choke valve settings of the three producing wells. This process is currently ongoing; upon completion, the autoencoder DNN will be trained, the robust controller designed and the DFL implemented for field testing and experimental validation.

Conclusion

We propose a novel method to address oil reservoir management based on physics-informed Artificial Intelligence (AI). A dynamic feedback closed-loop control system with a deep neural net (DNN) was developed for multiple-well operation and optimization. A new reservoir model was developed to capture the dominant behavior of producing wells driven by (gas assisted) gas-oil gravity drainage (GOGD), as seen in many portions of the Yates Field. The DNN was trained with datasets from a set of models with perturbed model parameters. Simulation results show that the performance of the system in terms of net profit improves by using the state estimates provided by the DNN. In addition, the profit was further improved by dynamically updating the control based on the uncertainty estimates. An annual improvement in cumulative oil production of up to 35% is predicted. The DFL concept is currently being field tested for further validation.

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