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Using AI to optimize the use of Gas Lift in Oil Wells

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Abstract

The growth of artificial intelligence technologies has opened the doors for solving complex challenges that previously were difficult to solve. The combination of AI, simulations and domain knowledge allow for the creation of fit-for-purpose solutions that are complex both mathematically and practically in operations. One such problem is the optimization of gas lift rates in real-time.

Typical gas lift optimization challenges in a field include the following:

- Real-time flow rate prediction of various phases
- Real-time wells performance
- Real-time pipeline network performance

The dynamic nature of the problem and the variability of the solution space makes it extremely hard for traditional simulation-based solutions to locate the optimal performance point in real-time. The computational requirement is massive and makes it difficult to perform these calculations at the “edge”. This is where combining simulations, human expertise, and machine learning technologies such as Deep Reinforcement Learning help build AI that can excel in rapidly computing optimized setpoints in complex domains. Using pioneering machine teaching methods combined with multiphase simulations we have built an AI to optimize gas lift rates in real-time.

Keywords
Gas Lift; AI; Bonsai; Brain; Two-Tank

Introduction

AI (artificial intelligence) is an important tool to apply to the gas lift problem because of various competing issues. Typically for each well there is an optimum gas lift flowrate which produces the maximum amount of oil. If there is too much gas, frictional pressure drop can cause the overall flowrate to drop and for some wells they will not flow at all, unless the gas lift is on. However, the optimum flowrate for individual wells may not be the global maximization of net profit. The optimization performed for this application calculates the net profit by considering the value of the oil revenue, the cost of fuel gas, the value of the net export gas, any penalties for over/under current gas nominations, and the cost of water disposal. Another complication is that in a typical field the actual gas lift rate to each well is not measured, only the gas lift valve position. This makes it more difficult for a typical operator to determine what the gas lift rate should be for each well, especially if there are hundreds of wells (3).

Bonsai is a low-code AI platform developed by Microsoft that simplifies machine teaching with deep reinforcement learning. Bonsai requires a simulator, a series of training exercises, and a way for the model to integrate into the Bonsai platform. The deployed product can either provide advisory or be utilized to perform direct control. This paper will discuss an application that was developed to optimize gas lift to maximize profitability of oil wells.

Methodology

For this application, the model simulates gas lift for 50 wells which are tied into four different separators each with a gas lift manifold for that pad. A simplified schematic is shown in Figure 1.

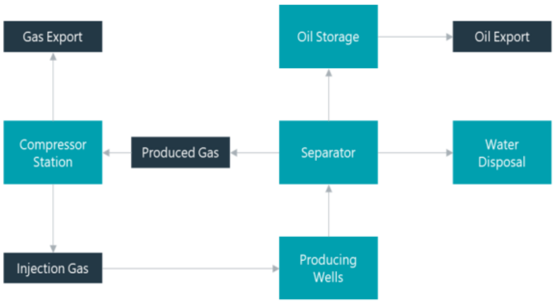

Figure 1: Simplified Schematic of the System

The wells selected for this pilot study are based on data from an actual field, where the wells performance was known over a full year and the reservoir pressure declines over time. The well model matched the field performance in terms of predicting the three-phase flowrates within 5%. More details about this model can be found in an upcoming paper (4). Over this 1-year period, the wells were modeled using a 'two-tank' reservoir model combined with a tubing model as this allowed us to match the field data. The two-tank model approach (2) is such that the formation is modeled as a set of two connected tanks so that production fluid flows from the far-field tank to the near-wellbore tank and thence into the wellbore. The tanks have fixed volumes, and pressure depletion is governed by the amount of production that has occurred. The far-field tank pressure depletes according to:

$$P_{res}(t) = P_{res}(t-\delta t) - \dot{m}_{tank}\frac{\delta t}{RP_{decay}}$$

and the near-wellbore tank pressure depletes according to:

$$P_{tank}(t) = P_{tank}(t-\delta t) - (\dot{m}_{prod} - \dot{m}_{tank})\frac{\delta t}{TP_{decay}}$$

Flowrates are modeled in terms of productivity indices. The far-field tank to near-wellbore tank mass rate is given by:

$$\frac{\dot{m}_{tank}}{\rho_{tank}} = PI_{res}(P_{res} - P_{tank})$$

The field data showed at times the operators had used too much gas lift which reduced production. In fact, with some types of wells with too much gas you can push the oil back into the reservoir. Also, the wells going to each pad were picked in different periods of field life, Early, Middle, and Late. The Early Life wells typically do not need gas lift for the first half of the year and then gas lift is needed after that. For late life wells, the requirement for gas lift will go down over time as the wells become depleted. For these conditions, the AI Model must also adjust the gas lift flowrates to compensate for these changing conditions.

Bonsai is asked to set the overall gas lift rate per manifold and then this rate is split between the wells based on the gas lift valve position of each well which is also set by Bonsai. The best practice was found to allow Bonsai to not set the actual valve position but the change in the valve position in a manner more like a controller. Bonsai is trained based on attempting to optimize the net profit over a period over 180 days of simulated time (this is done to capture the natural decline in the wells). The system is trained using scenarios where various combinations of wells (wells turned on and off), network pressure, and gas nominations are provided to the model. Also, some wells will benefit more from gas lift than others and so if there is a shortage of gas, the gas lift is routed preferentially to those wells.

Results & Discussion

Microsoft's name for the AI application is the Brain. The best practice in Brain Design is to break the application into concepts. In this case, 5 concepts were used. Each pad was given its own concept and the pads had anywhere between 8 and 16 wells where the Brain controlled the change in the gas lift position. Then there was an overall concept which balanced overall gas lift per pad to balance the gas generation overall. The brain learns by practicing and for this application it required approximately 100,000,000 iterations total. Note each concept is trained individually. Each training run started with an initial starting condition (snapshot). The model would then simulate the 180 days of behavior during which time the wells decline, and various modifications were made to the state (wells on/off – network pressure changes). The changes were saved in a scenario file, where the state could be changed every 12 hours. A combination of 6 starting states and 13 scenarios were used for the training, where Bonsai would rotate through the various 78 combinations of starting state and scenarios (one combo for each training run). The brain then picks the best neural net weights which provide the greatest cumulative profit for the sum of the 78 scenario/snapshots. Figure 2 shows trends of gas volumetric rate, oil rate, gas penalty rate and total net profit with time with AI assisted production. The plots show improvements to gas and liquid production, reduction in gas penalty and increases to the net daily profit.

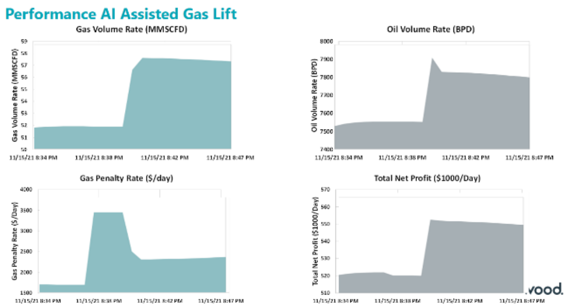

Figure 3: AI Assisted Gas Lift Performance tracking

Bonsai trains the brain in the cloud using containers which contain the model/config files and the snapshots and scenarios. It spins up the required number of simulators for each case (1) (this project would use 18 to 50 simulators at once). Bonsai then tells the model which snapshots to start with and which scenarios to run. At each specified interval, the model would provide the calculated state of the system (flowrates into the well pad separator, pressures, temperatures) and Bonsai provides the next setpoints. Note, we do not provide the model with individual well flowrate information because this may not be available in the field. So, the models need to be robust and always provide accurate results and not crash. Next, they must be fast, typically one 180- day training simulation requires 100 seconds of computer time.

In general, the system can optimize the overall profitability by 5 to 10%. However more importantly, it can determine when and how much gas lift it should provide in a well's life. In some of the scenarios/snapshots, the field was started up from a shutdown and the trained Brain was able to startup the wells to the optimized gas lift setting. So, this means that the system cannot only optimize but it can help the operator adjust for any type of operation in the field.

Conclusion

This presentation will demonstrate that trained Bonsai brain can increase the profitably of gas lifted wells and is able to manage when conditions in the field change. More importantly it can provide recommendations (for gas injection rates) which are better than the best operator can do on every shift. Finally, this presentation will show that the lessons learned in developing this application can be applied to a wide range of applications in the oil field such as compressor optimization and slugging control, etc.

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