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An Artificial Intelligence Decision Support System for Unconventional Field Development Design

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Abstract

A comprehensive intelligent decision support system (IDSS) for unconventional field development design is presented in this paper. The proposed IDSS combines data-driven models with physics-based reservoir engineering methods and it is a stack of three AI layers: Predictive, Prescriptive and Cognitive. The predictive unit receives physical reservoir parameters as input and predicts the outcome for thousands of possible designs under different subsurface scenarios by using advanced machine learning and deep learning methods. The prescriptive unit searches between these outcomes and finds the most optimum solutions based on the project goals and risks using optimization techniques. Finally, the cognitive unit tries to understand the utility function of expert decision makers and finds the best solution from the optimum subset. For this paper, we focus on the predictive unit results.

Because of the time it takes to setup reservoir simulations, reservoir engineers can only test tens of well designs amongst thousands of possibilities for a particular project, which results in suboptimal outcome. Using the IDSS technology, we enable analyzing thousands of options in less than a week and consequently the optimum field development design can be achieved, which can decrease average cost per barrel of production by 15%.

This is the first study on a cognition-driven decision support system in the upstream oil and gas industry. Unlike conventional field development, for unconventional oil and gas fields the development process is a high-dimensional decision-making problem. In such problems, a cognition-driven DSS is a necessary tool for mitigating human error. The success of cognitive DSS, especially for a complex problem such as unconventional field development, paves the way towards wider usage of this technology in the oil and gas industry.

Introduction

A Decision Support System (DSS) is an information system used to support organizations and businesses to make informed decisions. If this system uses artificial intelligence (AI) techniques extensively, it is called Artificial Intelligence DSS (AIDSS) or Intelligence DSS (IDSS). Nowadays, DSS and IDSS systems are widely used in healthcare, finance, environment, security among many others. The oil and gas industry also utilizes DSS and IDSS for different purposes and business problems. Korovin and Kalayev (2015) listed some of the DSS systems in the oil and gas industry.

One of the important business problems in the upstream oil and gas industry is field development design and planning. Field development design is a collection of decisions to develop a previously explored area. These decisions are with respect to drilling location, number of wells, target depth, horizontal length, spacing between wells, well completion, amount and proportion of water and sand and many more. Clearly, thousands of different decision combinations can be made regarding all the mentioned factors. Each combination is a possible field development design or plan. Because of the sensitivity of the production to all of these factors, each decision has a profound effect on the overall design. Therefore, an expert must find an optimum design based on his/her objectives.

Although field development design is not a new problem in the oil and gas industry, the task becomes more challenging with the advent of unconventional resources, advanced hydraulic fracturing and horizontal drilling technologies. There is a significant difference between developing an unconventional field and a conventional one. Contrary to conventional wells, human decisions have huge influence on production of unconventional wells. Therefore, field development planning and design is a more important task for unconventional reservoirs. Additionally, the number of parameters in unconventional field development is much larger than the conventional ones. Finally, the geologic and economic uncertainties in unconventional fields are higher compared to their counterparts.

In summary, the problem of developing unconventional fields is a high-dimensional decision-making problem under high subsurface and economic uncertainties. In fact, because of the simultaneous presence of these two factors it is almost impossible for human experts to find the optimal solution for developing unconventional fields. Even finding a desirable suboptimal solution is challenging for an expert in this domain without using AI technologies and field development simulation tools.

In this paper, we propose an intelligent decision support system that leverages state of the art machine learning and optimization techniques to calculate solutions for a wide variety of user defined criterion, and provides a reduced set of field development design options for human expert to choose from. The benefits of such an intelligent decision support system for an expert are: reduced design time, best expected accuracy, and minimum cost per barrel of production that can be achieved for each well. In addition to the proposed IDSS, we introduce a new approach for production forecast that is based on the Decline Curve Analysis parameters (i.e. initial rate (qi), initial decline rate (di), and hyperbolic exponent (b)). As supported by the examples provided in the Results and Discussion section, the proposed approach also mitigates the effect of irregular and noisy production data, especially for the first year of production.

Theory and Methods

The success of a business or project depends on many factors such as planning, organizing, directing, and controlling (Turban et al., 2005). To do these functions successfully, managers are engaged in a continuous process of making decisions. In such situations, business managers are decision makers. Decision makers may deal with various types of decision problems, from daily operation to long-term company strategies. Decision makers in a company act at various levels. Also, decisions can be made by individuals or groups (Niu et al., 2008). Because of the importance of decision making, it is studied by many researchers from multiple disciplines (Dawes 1988; Hwang & Masud 1979; Simon 1979).

A general decision-making process involves four phases: *Intelligence*, *Design*, *Choice*, and *Implementation (*Simon, 1977). Decision making, by its nature, is a cognitive process, involving different cognitive tasks, such as collecting information, evaluating situation, generating and selecting alternatives, and implementing solutions. Decision making is never error-proof, as decision makers are prone to their cognitive biases. Therefore, decision support systems (DSS) are often used by decision makers in order to minimize their cognitive errors and maximize the performance of actions (Niu et al., 2008).

Gorry and Scott-Morton (1971) defined DSS as interactive computer-based systems which help decision makers utilize *data* and *models* to solve ill-structured problems. A subsequent classic definition of DSS, provided by Keen and Scott-Morton (1978), is that DSS couples the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions (Niu et al., 2008). As Niu et al. (2008) mentioned, a DSS is intended to support, rather than replace, decision makers' role in solving problems. Decision makers' capabilities are extended through using DSS, particularly in ill-structured decision situations.

One of the ill-structured problem in the oil and gas industry is unconventional field development design. Because of too many influencing factors as well as high uncertainty, usually decision making is not linear for this type of problems.

To find the most optimum field development design, our proposed IDSS uses three stacked layers of artificial intelligence methods (Figure 1). These AI levels, from bottom to top are: Predictive Unit, Optimization Unit, and Cognitive Unit. After talking to hundreds of oil and gas industry experts and testing tens of different decision-making architectures, a comprehensive IDSS for this purpose was designed (Figure 2).

In this paper, components of this IDSS for unconventional field development planning and design are discussed first. Then, we focus our attention on the first component of this system, which is the predictive unit and show how integrating petroleum engineering concepts can help build a robust predictive model.

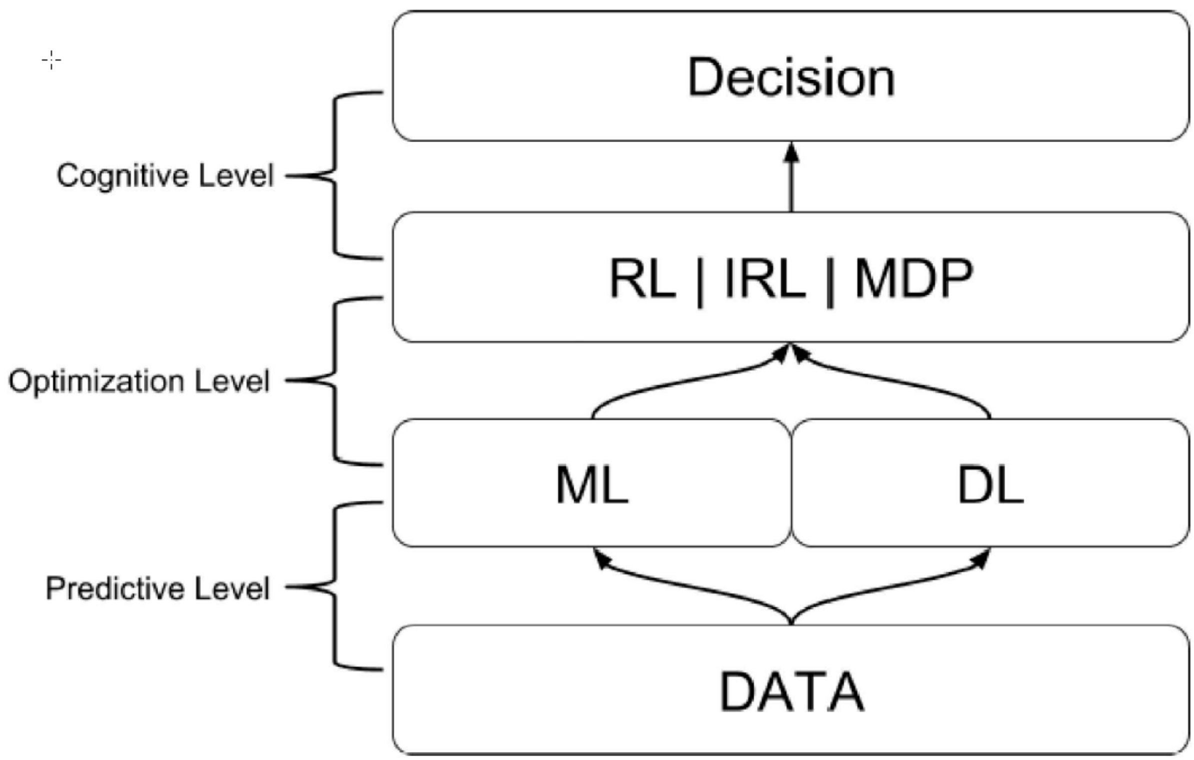

Figure 1. Three levels of artificial intelligence methods in our proposed IDSS.

Predictive Model

Predictive model is the basis for an intelligent decision support system. To make the best decision, a decision maker should make accurate predictions and forecast the outcome of each decision. In the case of field development design, the outcome of each design should be predicted quickly and accurately. Methods such as numerical reservoir simulations can predict the outcome of each design accurately enough (provided good reservoir and geological models are available), but they are extremely slow. As mentioned before, a typical field development design should analyze tens of thousands of different development scenarios in hundreds of different geological settings (and probably market conditions). Regardless of model making efforts, the prediction of these scenarios takes months if not years using numerical reservoir simulators. It is not surprising that only 25% of the field development projects are being done using numerical reservoir simulators (Gilman and Ozgen, 2013). In a separate research, we found that this number is even less when it comes to developing unconventional resources. The forecast speed is only one of the issues with numerical reservoir simulators. The amount of required data for building geological and reservoir models, limited number of experts in the field, and unknown physics of fluid flow in unconventional tight reservoirs are among other reasons.

An alternative for predicting the performance of field development design is using statistical models as well as single-well models. Unlike numerical reservoir simulators, these tools are fast, yet inaccurate.

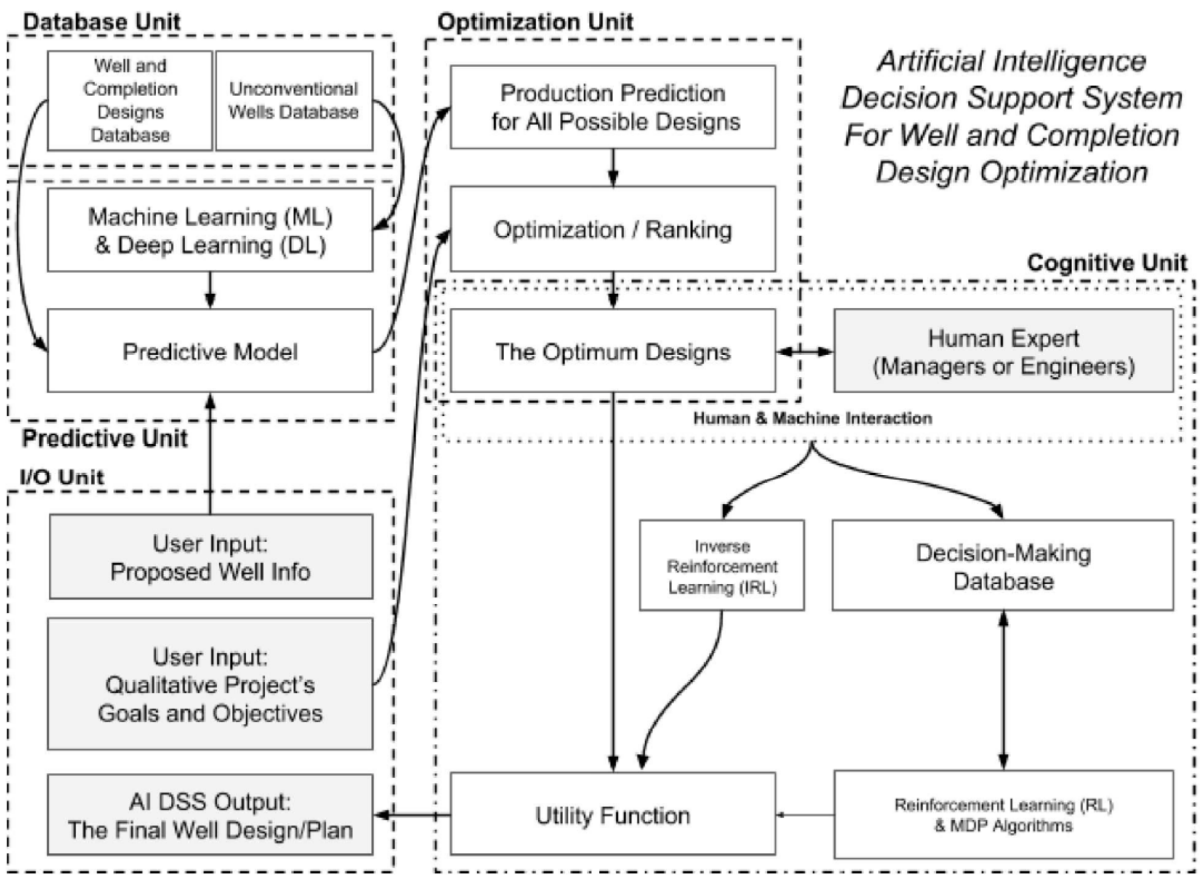

Figure 2. Detailed flowchart of our Intelligent Decision Support System for Field Development Design (a pending patent).

A powerful tool for having fast and accurate predictions is machine learning. Machine learning models can predict the outcome of tens of thousands of field development designs in different geological and economic settings in few hours. Provided clean and reliable data, the accuracy of these models can surpass the accuracy of numerical reservoir simulators since they make their predictions on the real data and with no simplifying assumptions.

The objective of these models is simply predicting EUR (Estimated Ultimate Recovery), 6-month, or 1-year cumulative production of a well (or a pad) before drilling, using data from previously drilled wells. It is a typical regression problem in machine learning. In recent years, engineers tried simple techniques such as multi-linear regression methods to make such predictive models. Although, these models are easy to understand, they generally suffer from poor accuracy. Machine learning models such as tree-based, random forest, and boosting models have provided more accurate predictions in recent years. Our study showed that models such as XGBoost (Chen and Guestrin, 2016) can reach up to less than 15% error in complex basins such as DJ Basin. In addition to machine learning models, deep learning models were tested for the same task.

As mentioned, clean data has significant effect on the performance of machine learning and deep learning models. Although, we expected that processing the completion data to be the most challenging, we find that cleaning production data is by far a more challenging task. Note that production is not an input data, but the target data in our predictive model. In addition to fluid flow complexity in unconventional wells, other factors such as unexpected well maintenance and tools installation as well as different production strategies make this data very noisy in the first year of production (Muralidharan and Joshi, 2018). Because of these problems, most machine learning predictive models fail in predicting 6-month or 1-year cumulative production. Furthermore, note that one should make separate models for 6-months, 1-year, and EUR productions. Production data is in the form of time-series with monthly productions. These machine learning models calculate accumulative production from the time-series data and train different models based on 6-months, 1-year, and EUR productions.

In this paper, we propose a novel approach in our predictive model by using the petroleum engineering knowledge and by modeling the production of 3541 wells (all in DJ Basin) using Decline Curve Analysis (DCA) (Arps, 1944).

DCA models are regressions for historical production data (Tan et al., 2018). Arps (1944) defined three types of decline curve models: exponential, harmonic, and hyperbolic decline curves. The hyperbolic model can be considered as a generic model (Belyadi et al., 2017) and is widely used for the unconventional wells and reservoirs. Equation (1) shows a hyperbolic model.

$$q(t) = \frac{q_i}{(1 + bd_i t)^{1/b}} \quad \text{Equation (1)}$$

where,

q = current production rate,

t = cumulative time,

q_i = initial production rate,

di = initial decline rate,

b = hyperbolic exponent.

In our predictive model, instead of targeting cumulative production values, we predict the performance of each well by its DCA parameters (i.e. initial rate (qi), initial decline rate (di), and hyperbolic exponent (b)). This approach also mitigates the effect of irregular and noisy production data, especially for the first year of production.

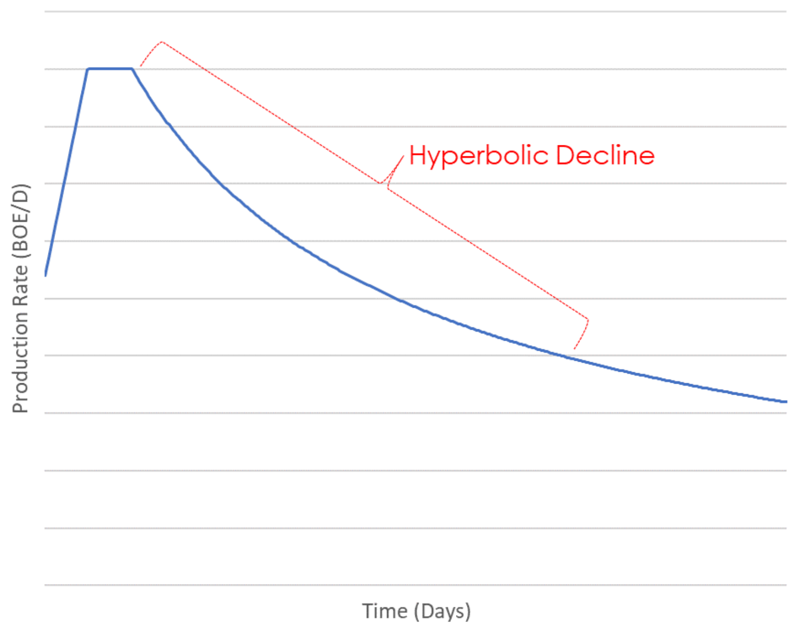

Figure 3. A typical decline curve for the DJ basin wells. In this study, we model the hyperbolic decline part of the curve.

Optimization Model

The second step in every decision-making process is prescriptive analysis or in other words optimization. The optimization in decision making is a process of rejecting undesirable outcomes, then ranking the optimum outcomes based on predefined objectives. A successful optimization model should take uncertainty, in this case geological and market uncertainty, into account and rank optimum field development designs.

The optimization model consists of 4 different parts: outcome of each design (output of the predictive model), geological uncertainty model, market uncertainty model, and project general goals. The first three parts are self-explanatory. The general goal needs more clarification.

Before emerging of unconventional resources, oil and gas projects were mostly long-term investments by large companies. The unconventional resources changed the landscape of investment in the oil and gas industry too. Nowadays, many operators with different sizes make investments in development of unconventional fields. While small operators and private equity firms look at unconventional projects as short-term investments, large companies are still trying to acquire more long-term investments. Some companies have access to huge amounts of financial resources and can perform enormous development projects, while others are exploring best options with their limited budgets. Therefore, different players in the unconventional oil and gas projects have different interests and one size does not fit all. Increasing number of wells versus size of hydraulic fracturing can have different short- and long-term effects. Every decision maker must define a general goal for their projects, which aligns better with a specific design and not others. Moreover, general goals can include risk tolerance. Therefore, even two companies with the same goal can have different optimal designs, because their risk tolerance levels are different. It is the task of optimization models to match the best design (from its outcomes) with the project goals. In another word, the optimization models can be considered as initial ranking functions. Generally, in the unconventional projects, metrics such as IP90 (production in the first 90 days), IP180 (production in the first 180 days), EUR (Estimated Ultimate Recovery), IRR (Internal Rate of Return), project budget, etc. are being used as ranking functions.

Although companies and professionals in the oil and gas industry can define their project goals, the decision making is still not a linear process. Therefore, a simple ranking function cannot help them with the final decision making. As we describe in the next section, the cognitive model for decision making is more complex than a multi-factor ranking function. Thus, the optimization unit is not the final unit in our suggested intelligent decision support system.

Cognitive Model

Behind every business or personal decision making, there is a function called Utility Function. This function, that could be simple or complex, is responsible for ranking options and finding the most optimum one. Unfortunately, in complex problems such as field development design, no expert can give a mathematical form of this function to computer for its decision making. Fortunately, computers can derive these functions if they are provided with enough decision-making examples from human experts and consistent human judgements. Artificial intelligence techniques such as Inverse Reinforcement Learning (IRL) algorithms can observe an expert in different situations for a period of time and derive the utility function behind his decisions. As an example, preferring an optimum design to another one can help IRL algorithms reveal the underlying utility function. In addition to getting enough examples from an expert, the system should help him/her with providing consistent judgements. Therefore, instead of overwhelming the expert with too many options, the optimization unit only suggests a few options to an expert for interaction and final decision making.

Results and Discussion

To get the best predictive model, production data of 3541 wells in DJ basin were transformed into DCA space. Figure 4 and Figure 5 illustrate the estimated DCA parameters in a 3D semi-log plot. As it suggests, there is no apparent correlation between initial production rate (qi) and initial decline rate (di). It means that the initial production individually cannot represent how good or bad a well will be in future. It is an important result for predictive models. Factors like IP90 (Initial Production – 90 days) and IP180 (Initial Production - 180 days) might suggest higher production in short term, but they don't necessarily mean successful ultimate recovery (EUR). Unfortunately, we see many predictive models for unconventional wells that aim predicting IP90, IP180 or similar measures and suggesting completion optimization based on those short-term and initial production factors.

Also, Figure 5 shows that there is a weak correlation between initial production rate (qi) and hyperbolic exponent (b). Unlike previous plots, initial decline rate (di) versus b factors (b) shows a significant correlation. It suggests that initial decline rate (d_i) and hyperbolic exponent (b), which is more of a long-term factor, have some underlying correlation. Simply put, high initial decline rate means higher b. To understand this correlation, it is important to have a basic understanding of the hyperbolic exponent (b). Generally, b affects long-term production, where t is large, while it does not make that much difference in short-time production. On the other hand, initial decline rate affects the short-term (or initial) rate. Therefore, it seems a higher decline rate might suggest a bad well, but ultimately it produces more in long term.

For the next step, we tried to see if the DCA parameters can be predicted using a machine learning model. Information such as drilling data (e.g. location, measured depth, target formation, horizontal length, etc.), completion data (e.g. completion type, perforation length, amount of proppant, amount of water, etc.), and geological data as well as DCA data for more than 3400 wells were collected and cleaned. Figure 6 shows a few of completion parameters vs qi, di, b (DCA parameters).

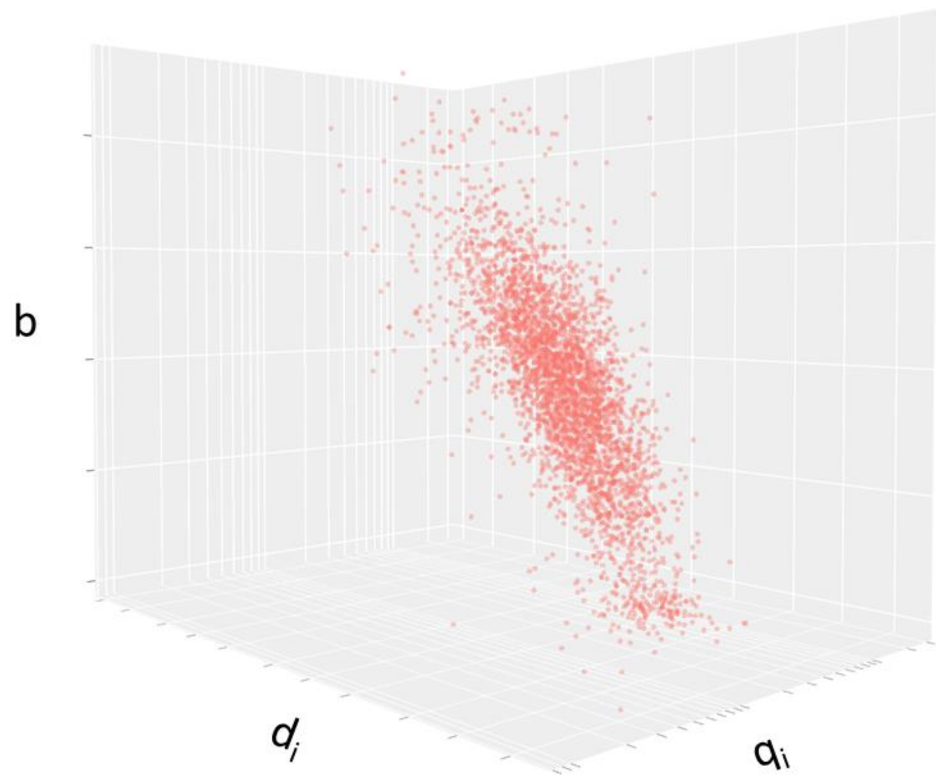

Figure 4. DCA parameters (qi, di, and b) for 3541 wells.

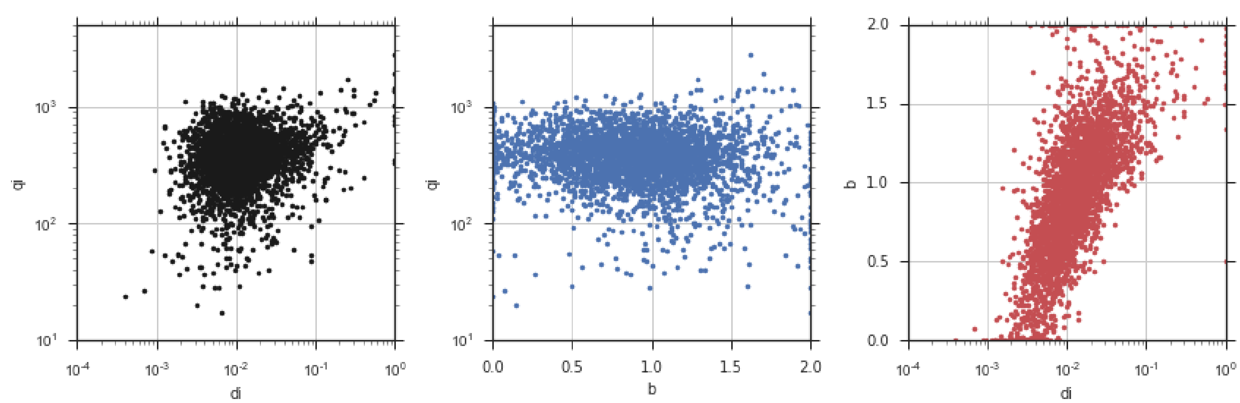

Figure 5. DCA parameters (qi, di, and b) for 3541 wells.

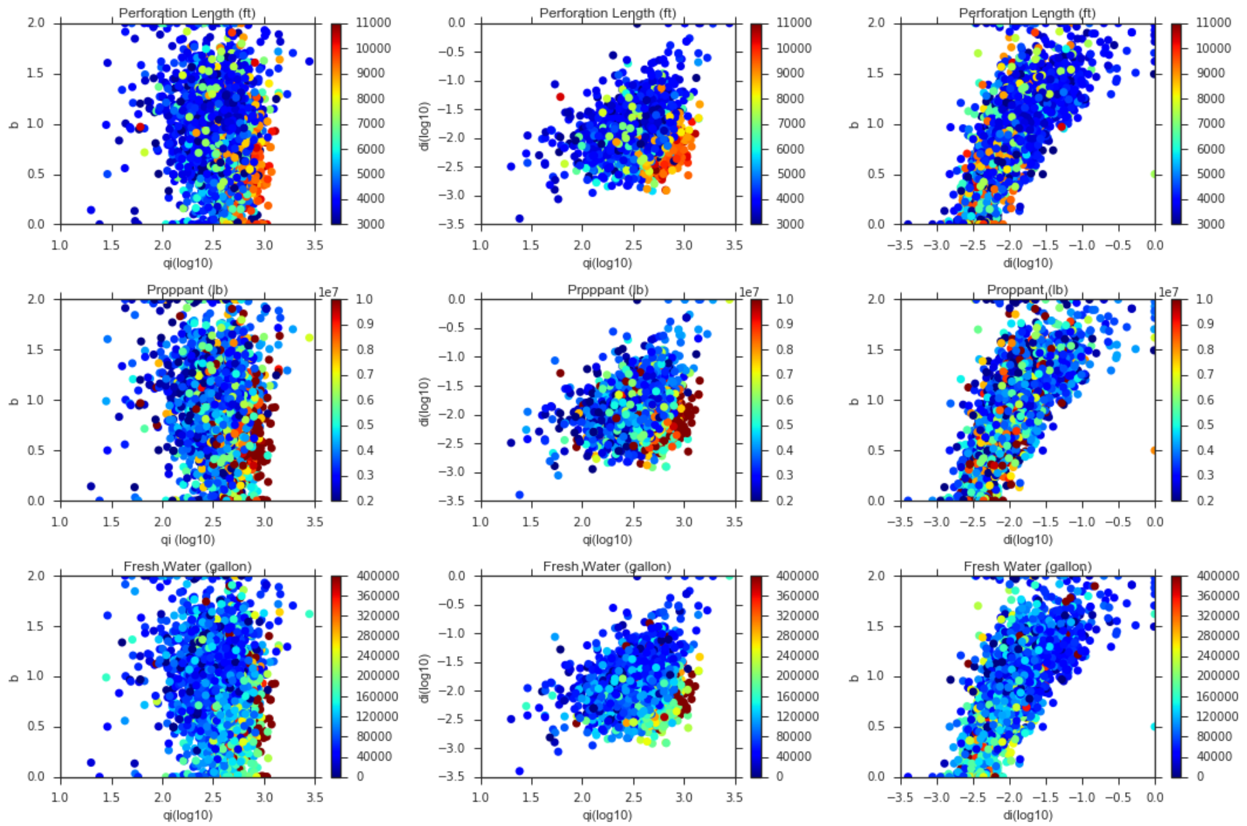

Figure 6. A few completion parameters vs qi, di, and b.

As Figure 6 suggests, design parameters such as perforation length, proppant, and fresh water have direct effect on production parameters qi and di. It seems that these parameters do not have a significant effect on b. We suspect that geological parameters and natural reservoir properties might have an effect on b which is more like a long-term production parameter. This hypothesis needs more investigation and research.

Also, to do a simple feasibility test, we selected a limited number of input parameters and predicted qi, di, and b. Figure 7 shows the preliminary results for a XGBoost model (Chen and Guestrin, 2016).

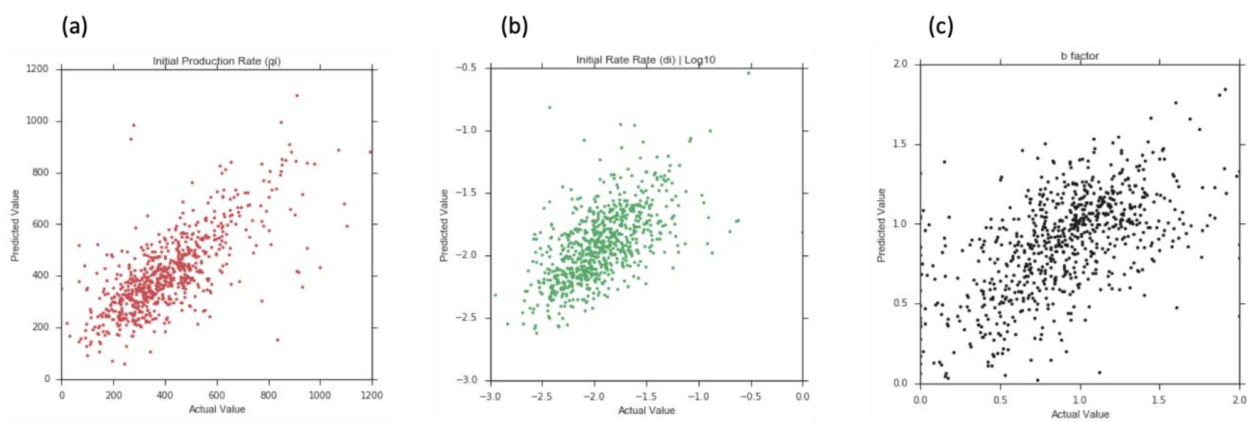

Figure 7. Predicted DCA parameters vs their actual values.

Overall, the gradient boosting model could estimate DCA parameters very well with a limited set of data. Also, the initial test suggests that qi is the best predicted parameter and b factor is the worst predicted parameter. It is consistent with our expectations (see Figure 6) and the discussion of influence of geology on b factor. Again, because b has a long-term effect on production, and since short-term production is more important for unconventional wells, less accurate estimation of b does not have huge effect on the plan that we choose.

With a robust predictive model, the next step is to do prediction for a wide range of drilling and completion options and find the most optimum outcomes. This is the task of our future research.

Conclusions

We made the case for an intelligent decision support system that can be used effectively for unconventional field development design and planning. After an extensive research on IDSS for other applications, we outlined main components of an IDSS for helping an expert to find the most optimum field design. The main components of this IDDS are Predictive model, Optimization/Prescriptive model, and Cognitive model. Technologies such as machine learning and deep learning can be used to build a robust predictive model. Optimization under subsurface and market uncertainties is necessary before any recommendation. At last, we showed the necessity of a cognitive model for supporting the final decision. Such system benefits from reinforcement learning and inverse reinforcement learning algorithms.

This is an ongoing research and the future reports and papers will illustrate more applications of this system for unconventional projects.

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