Recent Development in Application of Artificial Intelligence in Petroleum Engineering

Shahab D. Mohaghegh
West Virginia University & Intelligent Solutions, Inc.

Introduction

With the recent interest and enthusiasm in the industry toward smart wells, intelligent fields and real-time analysis and interpretation of large amounts of data for process optimization, our industry's need for powerful, robust and intelligent tools has significantly increased. Operations such as asset evaluation, 3-D and 4-D seismic data interpretation, complex multi-lateral drilling design and implementation, log interpretation, the building of geologic models, well test design, implementation and interpretation, reservoir modeling, and simulation are being integrated in order to result in comprehensive reservoir management. In recent years, artificial intelligence, in its many integrated flavors from neural networks to genetic optimization to fuzzy logic, has been making solid steps toward becoming more and more accepted in the main stream of the oil and gas industry. In a recent set of JPT articles[1-3], fundamentals of these technologies were discussed. This article will cover some of the most recent and advance uses of intelligent systems in our industry and discusses their potential role in our industry's future.

Based on the recent developments, it is becoming clear that our industry has realized the immense potential that is offered by intelligent systems. Our daily life as petroleum professionals is full of battling highly complex and dynamic problems and making high-stakes decisions. The industry has realized that the huge amounts of data that have been gathered throughout the years can now be used as a learning tool for our business and can help us increase the bottom-line. Moreover, with the advent of new sensors that are permanently placed in the wellbore, very large amounts of data that carry important and vital information about the state of production are now available. In order to make the most of these exotic hardware tools one must have access to proper software to process the data in real time. A simple search in the techniques that are available to scientists and professionals will show that intelligent systems in their many flavors are the only viable techniques that are capable of bringing real time analysis and decision making power to these new hardware. It is a well known fact that most sophisticated hardware tools are nothing more than expensive toys if they are not coupled with the right scientific technique and software that can effectively analyze what they produce. A search of the available commercial intelligent software tools for the oil and gas industry indicates that although there are some software applications that barely scratch the surface of the capabilities of the intelligent systems (and must be commended for their contributions), the software tool that can effectively implement intelligent systems in our industry has not yet made it to the commercial market.

Integrated Intelligent Systems

Today intelligent systems are used in our industry in a wide variety of areas. They cover higher level issues and analyses, from predicting the natural gas production in the United States for the next 15 years[4-5] and decision making at the management level while dealing with incomplete evidence[6] to more everyday technical issues that concerns geo-scientists and engineers such as drilling[7], reservoir characterization[8-11], production engineering issues[12-13], well treatment[14-15], and surface facilities[16], to name a few. In this article, three of these applications will be reviewed to demonstrate the diversity of the issues and the power of intelligent systems techniques that address them.

Intelligent systems can be used to address many types of problems that are encountered in our industry. They can be divided into several categories:

1. Fully data driven. These types of problems use vast amounts of data in order to model the dynamics of a system. This is mainly an empirical approach. Problems such as developing synthetic well logs, reservoir characterization by correlating logs to seismic and core data, and, forecasting U.S. natural gas production are examples.
2. Fully rule based. These are a set of decision making problems in which expert knowledge must be used. Well log interpretation and identification of best enhanced recovery method are good examples.
3. Optimization. These problems are concerned with finding the best set of operational conditions to achieve specific results in a highly complex, non-linear and dynamic problems. Examples include surface facility optimization for increasing oil rate and history matching.
4. Data-Knowledge Fusion. These are problems that integrates data with expert knowledge in order to address complex issues such as selecting stimulation candidates and identifying best practices.

The limit of applicability of intelligent systems in the oil and gas industry is the imagination of the professionals that use them. Like any other analytical technique, intelligent systems have limitations. It is important to understand the limitations of these techniques in order to increase the probability of their success and their efficiency. As an example, let's consider the group of techniques in intelligent systems that are developed based on data, such as neural networks. These systems are vulnerable to insufficient data. In other words, the major limitation of such techniques is that they cannot be efficiently developed in cases that data is scarce. A major question then will arise, "how much data is enough?" This is a question that, although it seems to be quite simple, does not have a straight forward answer.

Data, Data, Data

The question "How much data is enough?" can only be answered in the context of the problem that is being addressed. What might be enough data in one problem may not be enough for another problem. The amount of data required for modeling the behavior of a system is controlled by its complexity (rule of thumb is that more complicated problems require more data simply because in the case of complex system more data is required in order to have a true statistical representation of the system behavior). If data is considered a snap shot of reality, or a "formalized representation of facts" as defined in the U.S. department of Justice's web site, then the amount of data that is required to statistically cover a reasonable representation of a system will increase proportionally with the system's complexity. If we take the number of independent variables required for modeling a system (the number of columns in a spreadsheet) as an indication of the system's complexity, then the number of instances of the system's behavior(the number of rows in a spreadsheet) required for developing an intelligent system will be directly proportional to the number of variables. Simply put, as the number of variables in the data sets grows, so should the number of cases or records.

Although not all intelligent systems are fully data driven, this paper mainly concentrates on the paradigms that are used for modeling purposes and known as data driven solutions. Although this makes neural network the main focus, developing successful neural models require the use of fuzzy logic and genetic optimizations. It has been shown that an integrated use of fuzzy cluster analysis and fuzzy combinatorial analysis[14] plays a vital role in developing successful neural network models. While fuzzy combinatorial analysis identifies the most optimum set of independent variables that must be used during the modeling process, fuzzy cluster analysis ensures that training, calibration, and verification data sets are statistically representative of the system behavior. More than a decade of experience in developing intelligent models for the oil and gas industry has proven that these are the two most important integration techniques that are required for successful neural modeling of complex systems. All other issues such as network architecture, activation function selection, tuning of parameters such as learning rate and momentum, although important, pale when compared to these two integration techniques during the model building process.

Once we identify intelligent systems as the main tool for solving a certain problem we are making an important but implicit assumption. We are assuming that all the intricacies, non-linearity, and complexity of the system behavior (that we are trying to model for prediction purposes) can be represented through data that can be collected, and that we either have or can acquire such data. Furthermore, we are assuming that the sample data that is going to be used as the basis for modeling is statistically representative of the system.

When data become the most important component of the modeling process certain issues need to be addressed. Many databases suffer from missing data that are represented by holes in the data matrix. In cases that data are hard to come by, being able to patch the holes in a database in a way that does not harm the integrity of the entire database can prove to be very valuable. Currently the only way to deal with such a problem is statistical averaging, a technique that leaves a lot to be desired. The next issue is outliers. One needs to be able to identify and deal with outliers in the database. Domain expertise can help in identifying anomalies in the data and passing judgment regarding whether an anomaly is an outlier or an important but unique behavior that needs to be considered.

In the next sections three recent applications of intelligent systems in oil and gas related problems are briefly covered. For more detail on these applications please refer to the provided references.

Forecasting U.S. Natural Gas Production

Predicting energy production and consumption is an elusive task. Nevertheless, it is an important piece of information that contributes to policy making, financial, industrial, and residential energy market; and energy management at all levels. Therefore, being able to reasonably forecast U.S. natural gas production can be a significant contribution.

In 2001, for the first time artificial neural networks were used to build a predictive model (Texas A&M Model) to forecast U.S. natural gas production[4]. In 2004 a new predictive model was introduced[5] (WVU Model) that was developed using a hybrid intelligent system. The new model was a significant enhancement over the 2001 model for two major reasons. First, unlike the 2001 model, the new model did not use "gas price" as an input to the model in order to compute U.S. natural gas production. The argument was that if the price of natural gas could be predicted for a particular year in future (using some kind of method), the same can be used to predict U.S. natural gas production since these two variables behave equally chaotically. The second enhancement of the new model had to do with the fact that it used ranges of the variables as input into the model rather than using crisp numbers. Since each of the input variables into the new model had to be a prediction, it made much more sense to incorporate the uncertainty associated with these inputs into the model. Therefore, the results of the new model for forecasting U.S. natural gas production were probability distributions rather than crisp values.

Figure 1 shows the prediction of the WVU model until year 2020. The verification dataset (blind data) used during this development was U.S. natural gas production from year 1998 to 2002, while 20 percent of the remaining data was used in calibrating the model and therefore was not used during the model development.

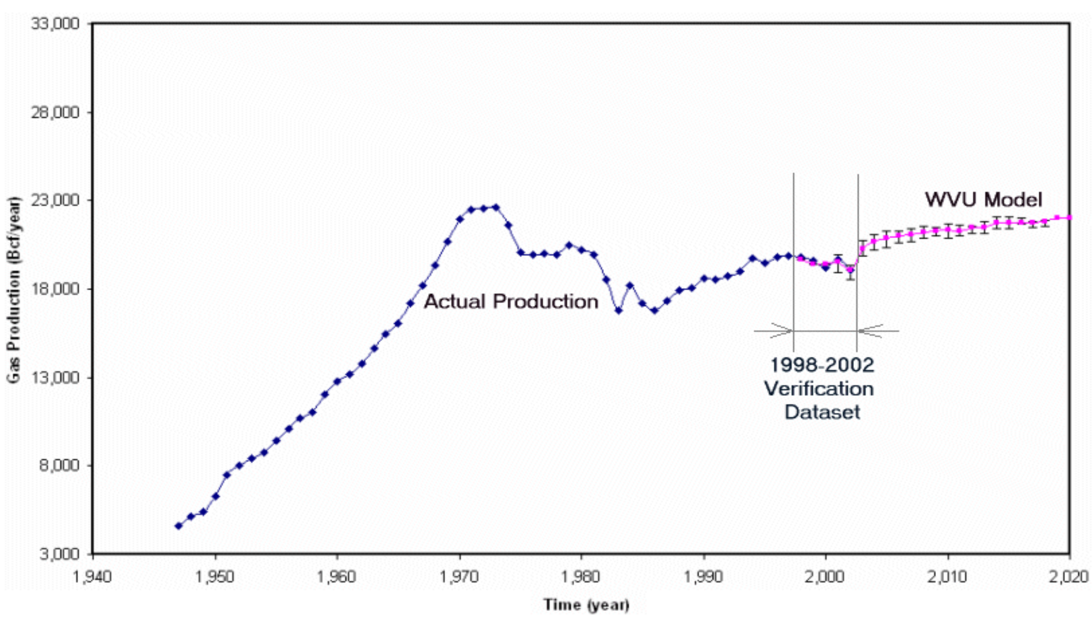

Figure 1. WVU model forecasts U.S. Natural Gas production into year 2020.

Figure 2 shows the difference in forecasting using different models. The new WVU model performs closer to the Texas A&M Model than the stochastic model and one developed and used by Energy Information Agency of the U.S. Department of Energy. The new model provides a more optimistic production scenario than the other model in early years but a more pessimistic forecast further into the future.

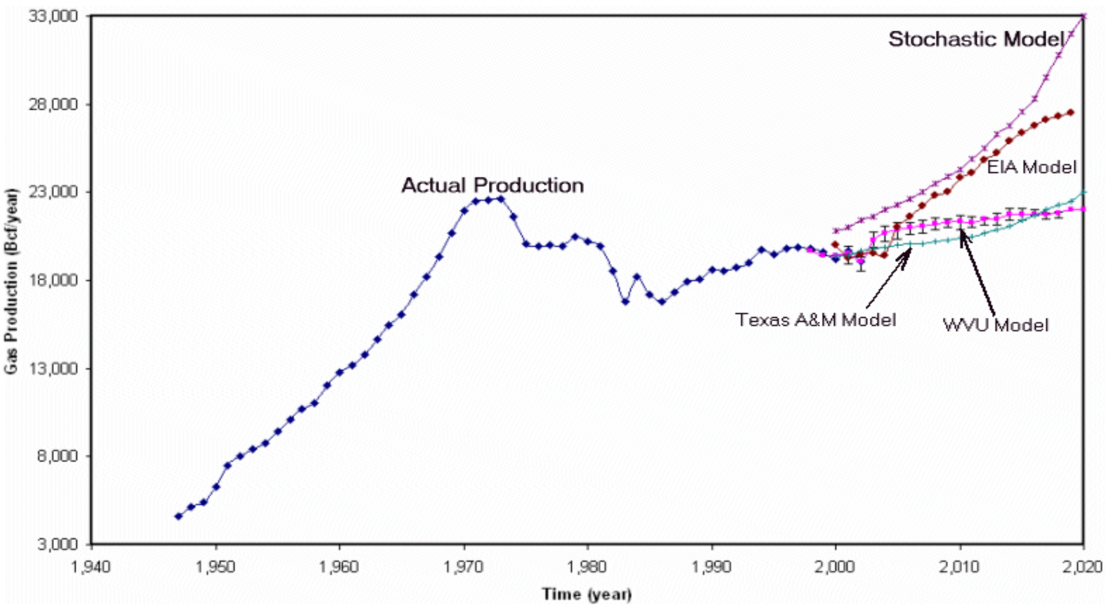

Figure 2. Comparison of WVU model with existing models.

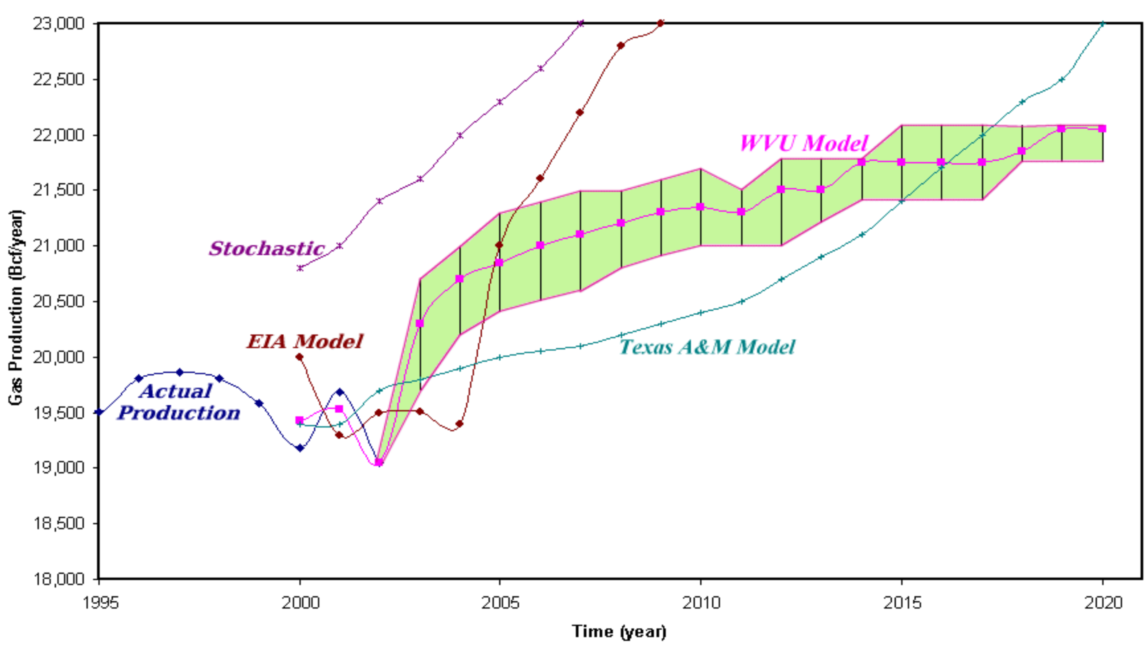

Figure 3. A closer look at the comparison of WVU model with existing models.

In Figure 3, a closer look at the differences in WVU's model prediction with the existing models is displayed. The new WVU model was built using a particular neural network architecture, known as recurrent neural networks. Recurrent networks are used for building models from time-series data. The input variables used in the development of the new WVU model were:

1. US natural gas production from previous year;
2. Growth Domestic Product;
3. US Population;
4. Average Depth of Oil & Gas Exploratory Wells;
5. Annual Gas Depletion Rate;

One of the major characteristics of the models that are constructed using intelligent systems is their organic nature. This means that as new information becomes available, year after year, these models can be retrained to learn from the data that has become available in order to forecast the future even better. Therefore, these models have the potential to grow and get better with time, hence the term organic.

Prudhoe Bay Surface Facility Modeling

Prudhoe Bay has approximately 800 producing wells flowing to eight remote, three-phase separation facilities (flow stations and gathering centers). High-pressure gas is discharged from these facilities into a cross–country pipeline system flowing to a central compression plant. Figure 4 illustrates the gas transit network between the separation facilities and the inlet to the compression plant.

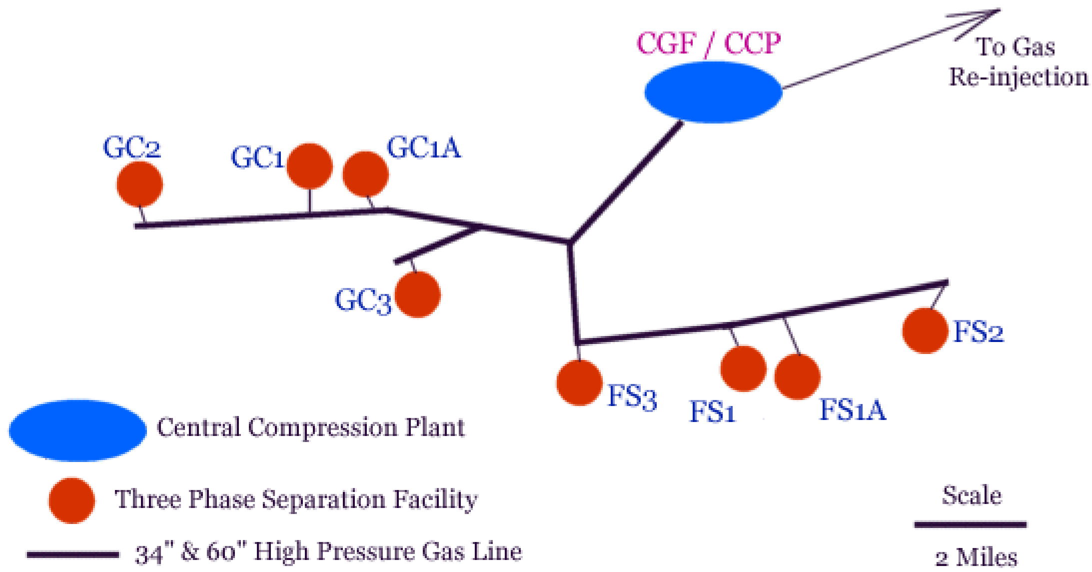

Figure 4. Simplified Overview of the Gas Transit Line system.

Fuel gas supply (at the flow stations and gathering centers) and artificial lift gas supply for the lift gas compressors at GC1 are taken off the gas transit line upstream of the compression plant. This reduces the feed gas rate and pressure at the inlet to the compression plant.

Gas feeding the central compression plant is processed to produce natural gas liquids and miscible injectant. Residue gas from the process is compressed further for reinjection into the reservoir to provide pressure support.

Ambient temperature has a dominant effect on compressor efficiency and hence total gas handling capacity and subsequent oil production. Figure 5 illustrates the range of daily average temperatures from 1990-2000, and the actual daily average for 2001 and 2002. Observed temperature variations during a 24-hour period can be as high as 40 degrees Fahrenheit.

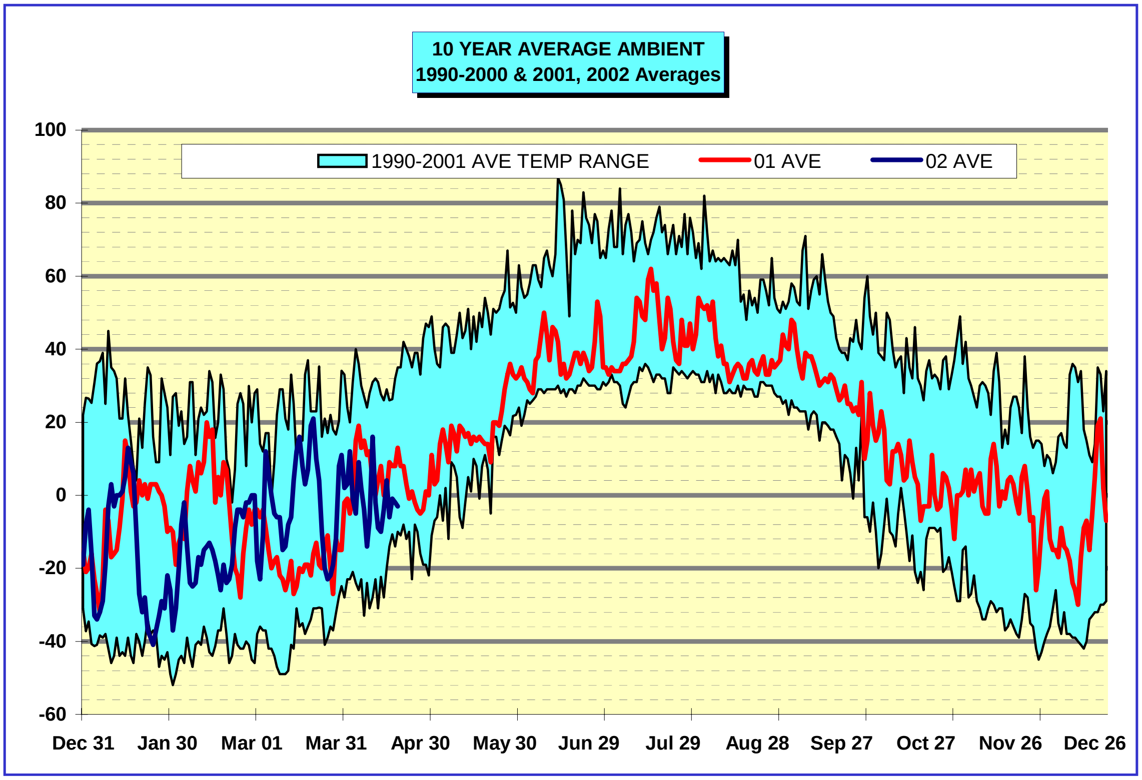

Figure 5. Historical daily average ambient temperature range.

Figure 6 is a curve fit of total shipped gas rate to the compression plant versus ambient temperature for 2001. A significant reduction in gas handling capacity is observed at ambient temperatures above 0°F. Individual well GOR ranges between 800 scf/stb and 35,000 scf/stb, with the lower GOR wells in the water-flood area of the field and higher GORs in the gravity drainage area. Gas compression capacity is the major bottleneck to production at Prudhoe Bay and typically field oil rate will be maximized by preferentially producing the lowest GOR wells.

As the ambient temperature increases from 0 and 40°F, the maximum (or "marginal") GOR in the field decreases from approximately 35,000 to 28,000 scf/stb. A temperature swing from 0 to 40°F in one day equates to an approximate oil volume reduction of 40,000 bbls, or 1000 bopd per °F rise in temperature.

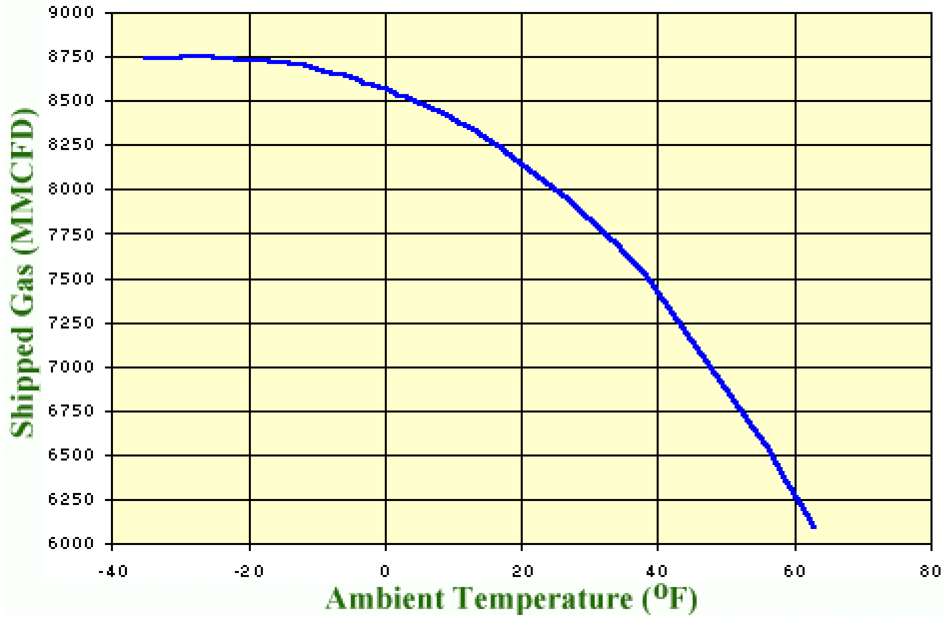

Figure 6. Shipped Gas versus Ambient Temperature in 2001

The reduction in achievable oil rate, per degree Fahrenheit increase in temperature, increases with ambient temperature. This is due, in part, to the increase in the slope of the curve of shipped gas versus temperature, and also to the reduction in limiting or “marginal” GOR as gas capacity decreases. At higher temperatures, larger gas cuts are required at lower GORs to stay within compression limits.

As ambient temperature rises, the inlet pressure at the compression plant increases. High inlet pressure can create backpressures at the separation facilities that will cause flaring. This is not environmentally acceptable and is avoided by cutting gas production. However, sometimes, ambient temperatures change so rapidly that significant gas cuts are necessary to avoid flaring. A similar problem occurs if a compressor experiences unexpected mechanical failure.

The ability to optimize the facilities in response to ambient temperature swings, compressor failures, or planned maintenance is a major business driver for this project. Proactive management of gas production also reduces unnecessary emissions.

As part of a two-stage process to maximize total oil rate under a variety of field conditions it is first necessary to understand the relationship between the inlet gas rate and pressure at the central compression plant and the gas rates and discharge pressures into the gas transit line system at each of the separation facilities. Therefore, the first stage of this study was to build an intelligent model that is capable of accurately predicting the state of this dynamic and complex system in real time basis.

Figures 7 and 8 show the accuracy of the predictive models that were built for the central compression plant. In these figures it is shown that both pressure and rate can be predicted with reasonable accuracy.

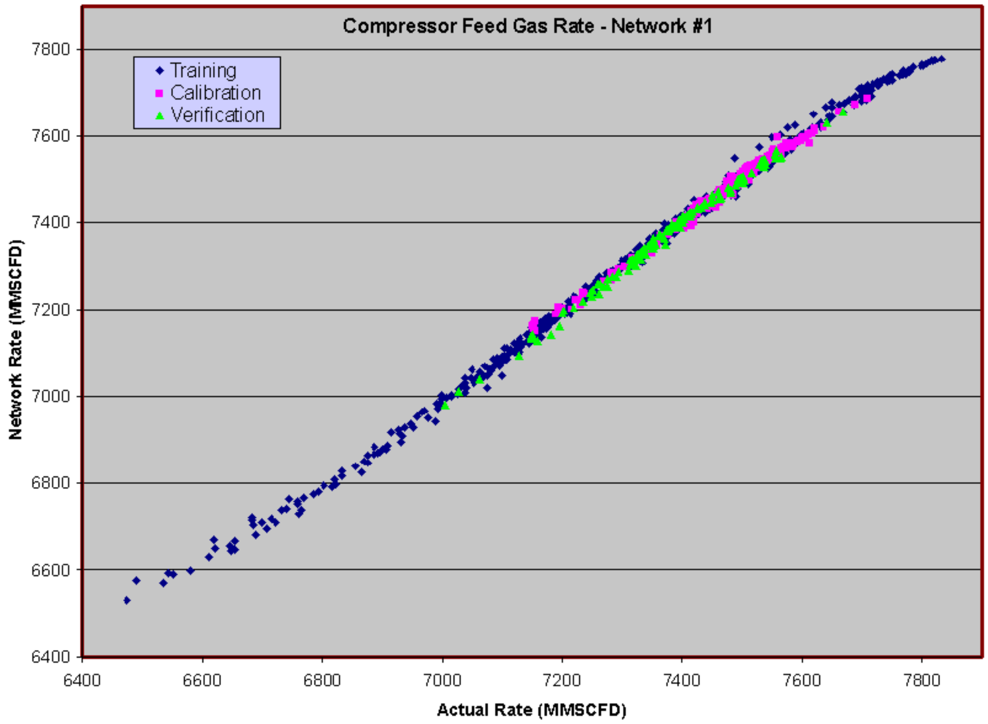

Figure 7. Cross plot for Compressor Feed Gas Rate, network model #1.

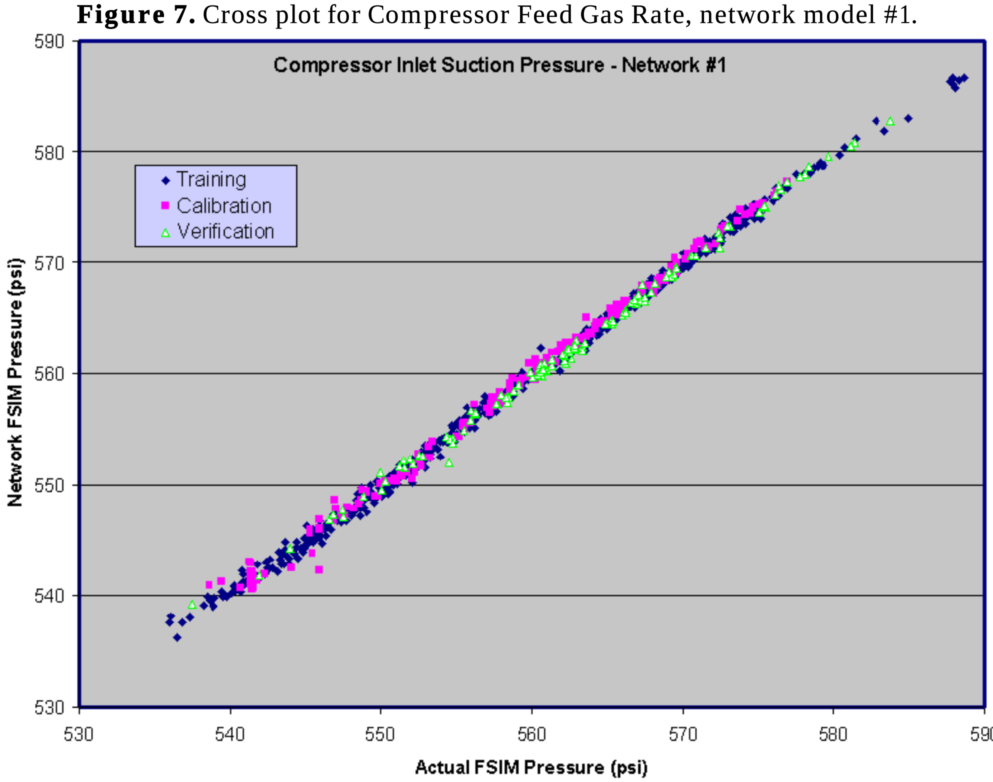

Figure 8. Cross plot for Compressor Inlet Suction Pressure, network model #1.

Field oil rate will be impacted by the manner in which gas is distributed between facilities. A state-of-the-art genetic algorithm-based optimization tool will then be built based on the neural network models in order to optimize the oil rate. The goal of the optimization tool is to determine the gas discharge rates and pressures at each separation facility that will maximize field oil rate at a given ambient temperature, using curves of oil versus gas at each facility.

Figures 9 and 10 show the PVT behavior of separation facility FS2 based on the data collected during the operation of the entire surface facility. This data has been clustered using a fuzzy c-mean clustering algorithm for modeling preparation.

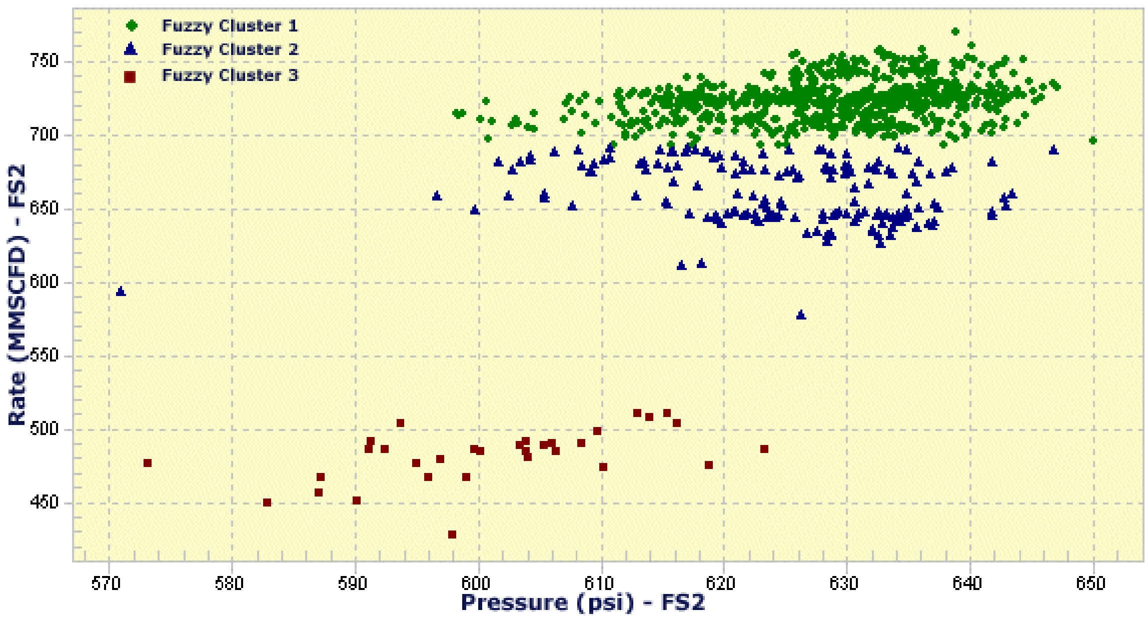

Figure 9. Clustered Pressure-Volume behavior of FS2 separation facility.

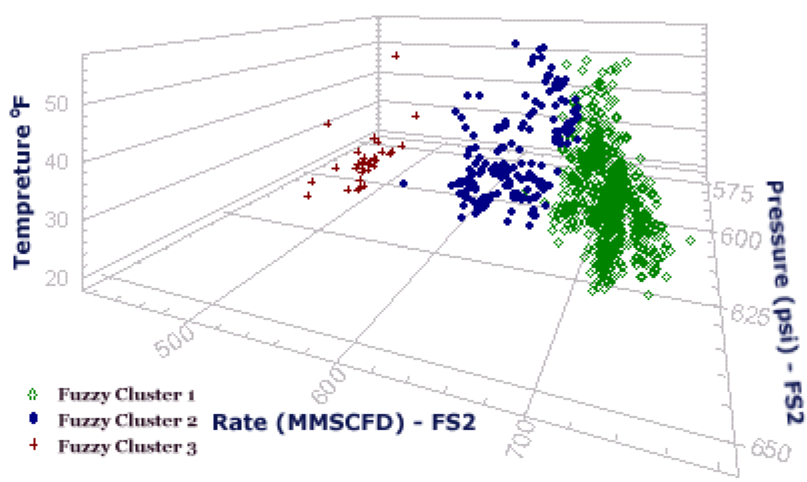

Figure 10. Clustered Pressure-Volume-Temperature behavior of FS2 separation facility.

Looking at Figure 4, one can see that separation facility FS2 is connected to separation facility FS1A. As was mentioned before, the dynamic system model for this complex surface facility included a collection of several smaller but co-dependent models. The model developed for the separation facility can predict the rate at FS2 as a function of all the parameters that directly influence its behavior. Figures 11 and 12 show the behavior of the FS2 rate as a function of temperature as well as the rate in separation facility FS1A.

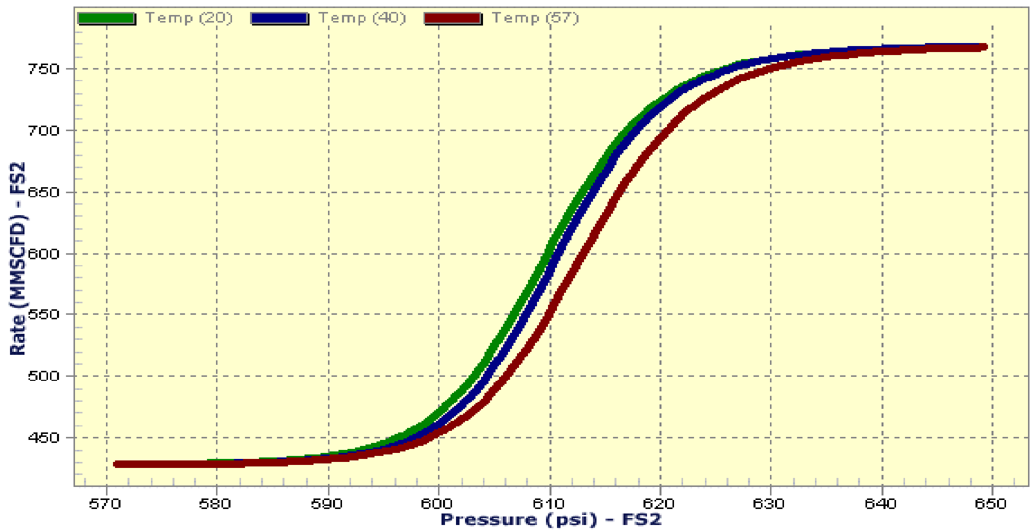

Figure 11. FS2 rate behavior as a function of pressure @ FS2 and temperature.

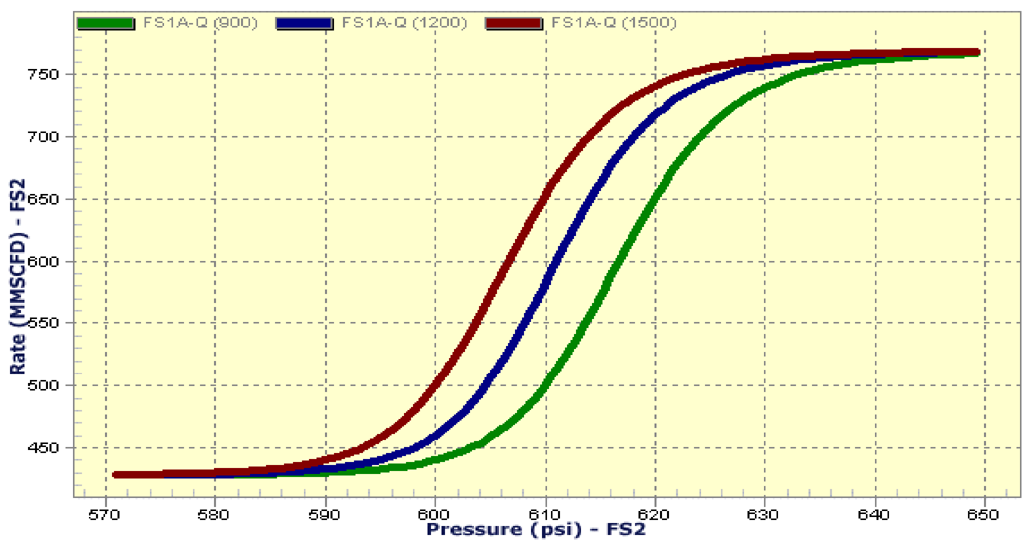

Figure 12. FS2 rate behavior as a function of pressure @ FS2 and FS1A rate.

Furthermore, the model shows that the take-off gas for fuel gas and at GC1 for gas-lift play practically no role on the rate at FS2, given all other pressures and rates stay constant. This can be clearly seen from Figures 13 and 14. Looking at the facility schematic shown in Figure 4, this prediction of the intelligent model makes sense.

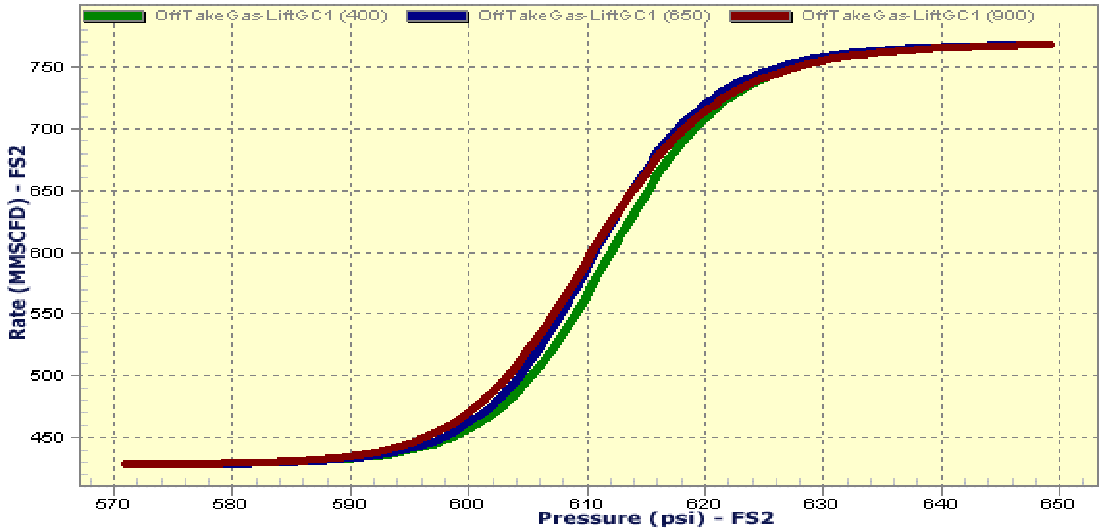

Figure 13. FS2 rate behavior as a function of pressure @ FS2 and Off-take for gas lift.

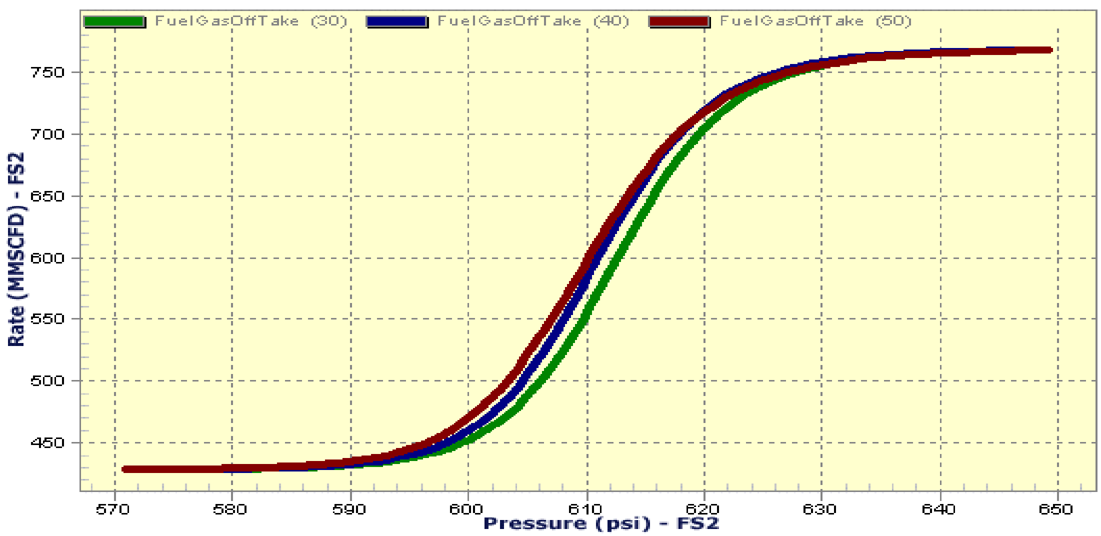

Figure 14. FS2 rate behavior as a function of pressure @ FS2 and fuel gas off-take.

Similar graphs for a separation facility that is in an entirely different situation are shown in the following figures. Separation facility GC3 is directly influenced by pressure and rate from the central compression plant and the separation facilities FS3 and GC1A as well as the ambient temperature. Figures 15 and 16 are the field data collected for GC3 at different temperatures. Please note that the data shown in these figures have been collected while the surface facility was online and the rate and pressure in all facilities were continuously changing. Figure 17 shows the modeled pressure-rate behavior of GC3 as a function temperature while all other variables remain constant.

Figures 18 and 19 show the model behavior as rates in central compression plant and the separation facility GC1A change. Gas capacity constraints start to affect oil production at about 0°F, with increasing impact as the temperature increases.

The estimated benefit of this tool for optimizing oil rate during temperature swings and equipment maintenance is 1-2 MBOPD for 75% of the year.

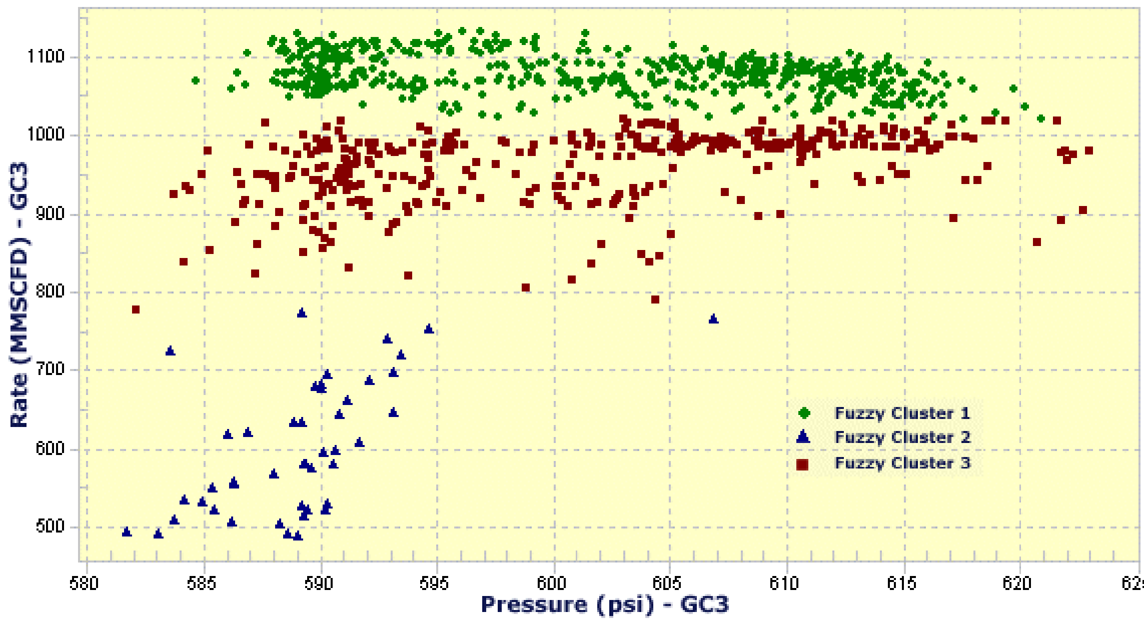

Figure 15. Clustered Pressure-Volume behavior of GC3 separation facility.

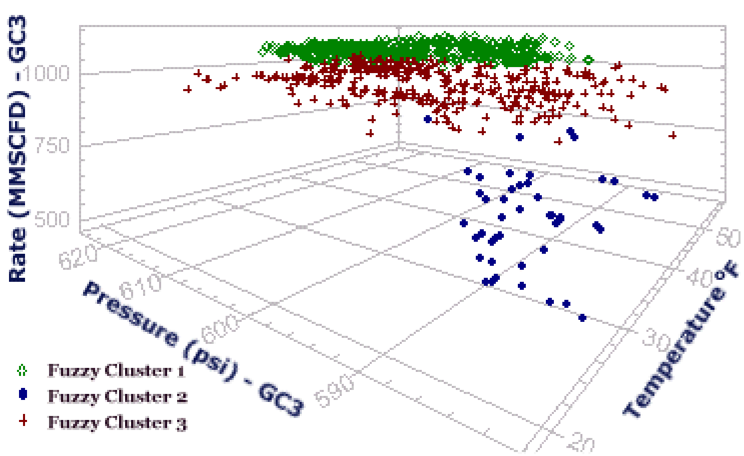

Figure 16. Clustered Pressure-Volume-Temperature behavior of GC3 separation facility.

The above results show the complexity of the system being modeled as well as the power of the hybrid intelligent systems that make modeling of such a complex and non-linear system possible. Using conventional simulation techniques proves to be inadequate for a system as large and complex as the one mentioned here. The mere number of facilities, pipe sizes and fittings, and the rigors associated with modeling each component and coupling them all together at the end make it a difficult task. Hybrid intelligent systems on the other hand, when handled properly and with the right set of software tools, can implicitly count for all the intricacies of such a complex system as long as the collected data set is representative of the system and process behavior.

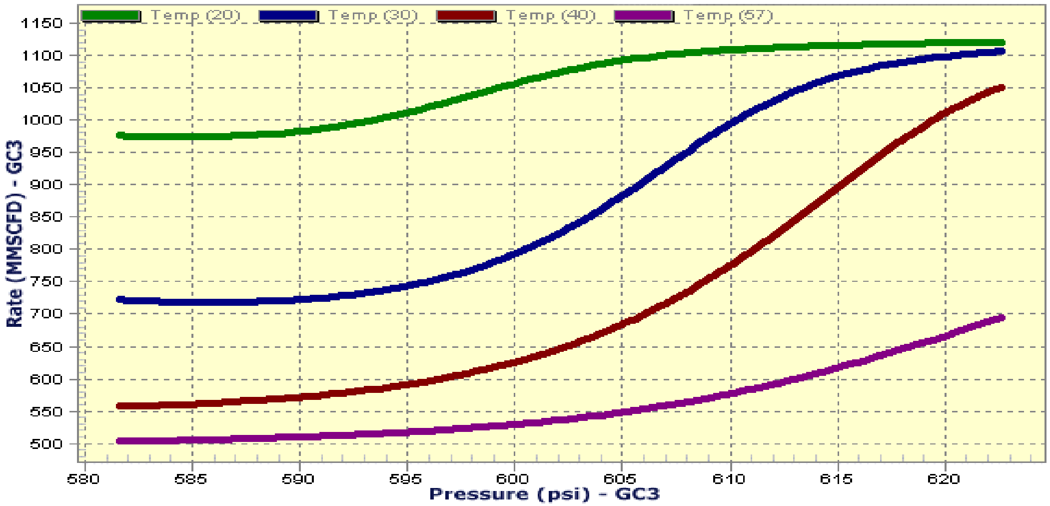

Figure 17. GC3 rate behavior as a function of pressure @ GC3 and Temperature.

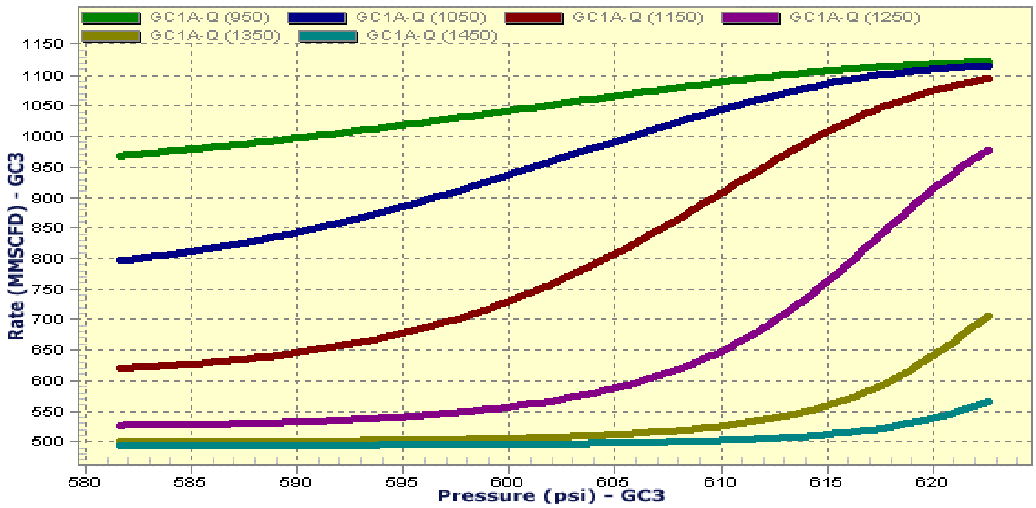

Figure 18. GC3 rate behavior as a function of pressure @ GC3 and GC1A rate.

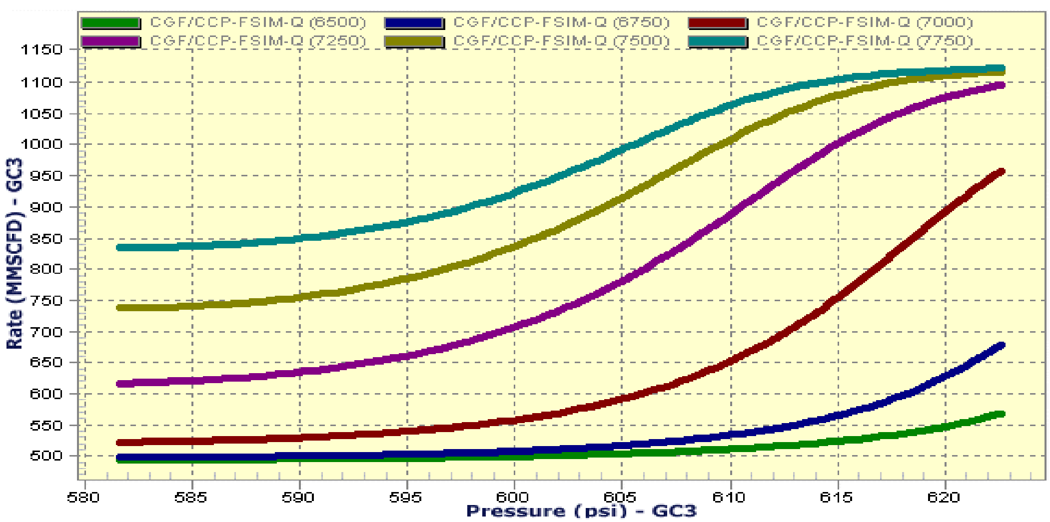

Figure 19. GC3 rate behavior as a function of pressure @ GC3 and CCP rate.

It is interesting that for the two models that were demonstrated above, only 20% of the available field data was used for modeling purposes and the remaining 80% of the data was used to validate the models. This markedly increases the confidence that is associated with the applicability and robustness of the model.

Reservoir Characterization of Cotton Valley Formation, East Texas

The Cotton Valley formation in East Texas is known for its heterogeneity as well as for the fact that the well logs and reservoir characteristics are non-correlatable from well to well[17]. In a recent study[10], hybrid intelligent systems were used to characterize the Cotton Valley formation by developing synthetic magnetic resonance logs from conventional logs. This technique is capable of providing a better image of the reservoir properties' (effective porosity, fluid saturation, and permeability) special distribution and more realistic reserve estimation at a much lower cost.

The study area included a total of 26 wells. Magnetic resonance logs were available from only six wells while the other 20 wells had conventional logs but no magnetic resonance logs. Figure 20 demonstrates the relative location of the wells. In this figure wells with magnetic resonance logs are shown with red circles and are named MR-1, MR-2, etc. Wells that have no magnetic resonance logs are shown with blue asterisks and are named W-1, W-2, etc. The idea is to use the six wells that have MRI logs and develop a series of intelligent models for Cotton Valley's effective porosity, fluid saturation and permeability. The inputs to the model would be well location and conventional logs such as gamma ray, SP, induction, and density. Upon completion of the development process, techniques such as kriging can be used in order to develop a special distribution of these reservoir characteristics throughout the domain where the intelligent model is applicable. One of the major contributions of this study is that MRI cannot be performed on cased wells, while many of the conventional logs used in this methodology are available from most of the wells in a field.

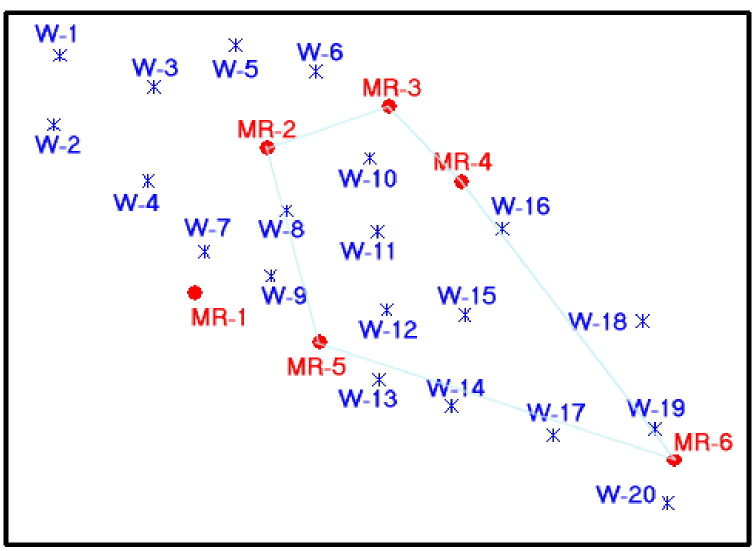

Figure 20. Relative location of wells used in the study.

The intelligent model for this study is developed by using five of the wells, MR-2, through MR-6. The MRI logs from well MR-1 are used as blind well data in order to validate the applicability of the intelligent model to other wells in the field. Furthermore, since well MR-1 is on the edge of the section of the field being studied, and is somewhat outside of the interpolation area relative to wells MR-2 through MR-6, it would push the envelope on accurate modeling. This is due to the fact that the verification is done outside of the domain where modeling has been performed. Therefore, one may claim that in a situation such as the one being demonstrated here, the intelligent, predictive model is capable of extrapolation as well as interpolation. The term extrapolation is used here as a special extrapolation rather than an extrapolation of the log characteristics.

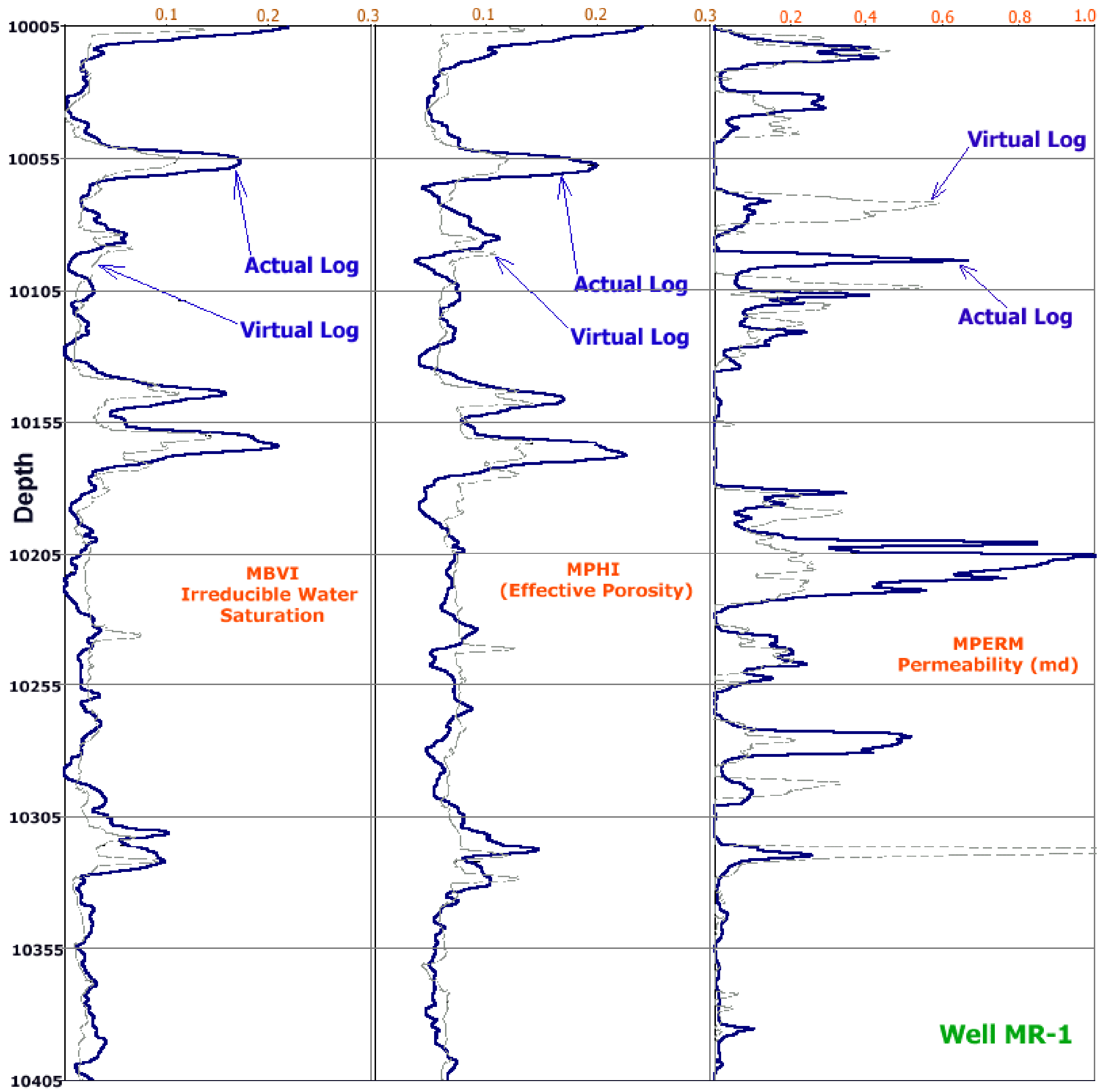

Figure 21. Actual and modeled MRI logs for Well MR-1.

Figure 21 shows the actual and virtual magnetic resonance logs (MPHI - effective porosity, and MBVI - irreducible water saturation) for well MR – 1. The logs shown in Figures 18 were used to estimate reserve for this formation. Using the virtual magnetic resonance logs, the estimated reserves were calculated to be 138,630 MSCF/Acre, while using the actual magnetic resonance logs, the calculated reserve estimates were 139,324 MSCF/Acre for the 400ft of pay in this well. The difference between the two estimated reserves is about 0.5%. The small difference in the calculated estimated reserves based on virtual and actual magnetic resonance logs demonstrates that operators can use this methodology effectively to reach reserve estimates with much greater accuracy at a fraction of the cost. This will allow operators to make better reserve management and operational decisions possible.

Concluding Remarks

More than a decade has passed since intelligent systems were first applied in our industry. During this period many problems have been successfully addressed. Our industry still awaits the commercialization of software applications that can bring the power of integrated intelligent systems into the main stream of the oil and gas profession. Implementation of integrated intelligent system in our daily problem solving efforts is only a matter time. Companies that recognize the importance of investing in this technology now will be the vanguards that will rip its benefits sooner than others. Future of this technology in our industry has never been brighter.

Acknowledgement

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