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RISK ASSESSMENT OF DRILLING AND COMPLETION OPERATIONS IN PETROLEUM WELLS USING A MONTE CARLO AND A NEURAL NETWORK APPROACH

Dennis Kerr Coelho
Mauro Roisenberg
Paulo J. de Freitas Filho

Federal University of Santa Catarina
University Campus – Trindade
Florianópolis, SC, 88040-900, BRAZIL

Carlos Magno C. Jacinto

CENPES – Well Technology Engineering
PETROBRAS SA
Avenida Hum, Quadra 7, Ilha do Fundão
Rio de Janeiro, RJ, 21941-598, BRAZIL

ABSTRACT

This paper intends to show how two different methodologies, a Monte Carlo simulation method and a connectionist approach can be used to estimate the total time assessment in drilling and completion operations of oil wells in deep waters. The former approach performs a Monte Carlo simulation based on data from field operations. In the later one, correlations and regularities in parameters selected from a petroleum company database were detected using a competitive neural network, and then, a feedforward neural network was trained to estimate the average, standard deviation and total time wasted in the accomplishment of the well. At the end, the results obtained by both models are compared. The analyst could evaluate the precision of the estimated total-time based on geometric and technological parameters provided by the neural network tool, with those supplied by the traditional Monte Carlo method based on data of the drilling and completion operations.

1 INTRODUCTION

The total time taken in drilling and completion operations of oil and gas wells are subject to considerable uncertainty and risk factors, due to the limited knowledge concerning the geologic characteristics of the formation, technical difficulties and unexpected behavior of human operators (Jacinto 2002). More over, this time represents 70 to 80% of the final cost of the well due to high costs of daily rent of the drilling and completion rigs. The planning and risk assessment of these activities are hindered by unexpected events, such as kick (a bag of gas), lost of circulations and well collapse. Those events can cause the waste of time, increasing costs, decline of the production or even the loss of the well (Jacinto 2002).

Risk analysis and management of petroleum exploration ventures is growing worldwide and many international petroleum companies have improved their exploration performance by using principles of risk analysis in combination with new technologies (Harbaugh 1995, Rose 2001).

In this study we work with two different, but complementary approaches: a Monte Carlo simulation model and a connectionist methodology, in this case neural networks.

Nevertheless, the uncertainty in theory models and the great number of tasks involved in drilling and completion operations hinders the deployment of well-established risk analysis techniques.

The connectionist methodology seems to be a good alternative/complementary approach to the traditional Monte Carlo method to make risk analysis (Bishop 1995), by estimating the total operation time of the well in deep waters. By the use of many log cases present in most petroleum company databases, a neural network is capable to learn how to correlate “geometric” and “technological” parameters of a given well with the respective total distribution time of similar wells.

Because there are many uncertainties and risk factors involved in the operations, similar wells can take many different times for a given operation. In order to deal with this intrinsic uncertainty to that kind of problem, the hybrid connectionist architecture proposed in this work, outputs not only total estimation time, but also the uncertainty about the results in terms of average and standard deviation time of similar wells.

The next section presents a short description of oil and gas well engineering and tries to identify the uncertainty and risk factors present in the well accomplishment. A brief description of the Monte Carlo tool is presented in section 3. An analysis of the available data in the database and those selected to train the neural network architecture is shown in section 4. Section 5 is composed by the detailed description of the proposed hybrid neural architecture. A validation and the use of the concurrent models followed by the results of some experiments are show in section 6. Finally, our conclusions are presented and discussed.

2 DRILLING AND COMPLETION ENGINEERING AND RISK ANALYSIS

2.1 Drilling and Completion Operations

The development of a petroleum field includes many activities: drilling and completion of wells, installation of fluid collector systems (manifolds and flexible lines), construction and installation of a production unity (petroleum platform), installation of the production drain flow system (oil and gas pipelines, oil ships) (Jacinto 2002).

The drilling of an oil well is accomplished through a rig. The rocks are drilled by the action of the rotation and weight applied to an existent drill in the extremity of a drilling column. Rock fragments continually removed through a drilling fluid or mud. It is injected by pumps for the interior of the drilling column through the injection head (swivel) and comes back to the surface through the ring space formed between the walls of the well and the column. When certain depth is reached, the column is removed and a coating column goes down in the well. The space between the coating tubes and the walls of the well is cemented with the purpose of isolating the crossed rocks, allowing the progress of the drilling. In this way, the well is drilled in several phases, characterized by the different diameters of the bits (Jacinto 2002).

When finishing the drilling, it begins a new stage of operations designed to prepare the well, so it can produce in safe and economic conditions during its useful life: the completion. In this phase, the valves in the head of the well that control the flow of petroleum are installed. The well is conditioned and shelled, and the production column is installed. Then the production of petroleum can begin (Jacinto 2002).

2.2 Risk Analysis

Risk connotes the possibility of loss and the chance or probability of that loss. Modern risk analysis utilizes principles of statistics, probability theory and utility theory (Jain 1991, Bedford 2001 and, Vose 2001). In oil exploration there are many aspects of risk. Risk and uncertainty are associated with drilling operations, with field development and with production. In this paper we are going to concentrate on those elements of risk associated to the drilling and completion of individual wells (Jacinto 2002). If the operations needed to drill and complete a given well go without problems, the total time is usually short. In the other hand, if the same well has a fill setbacks, failures, accidents and even if workovers occurs, such as, equipment failure, drill breaks, wall tumbling or a well blowout, the total time could be much longer than expected. So, when forecasting the total time, it must be expressed by a probability distribution, instead of a single number.

The components of a well drilling and completion time, are often difficult to define with any degree of exactitude, and the failure sources can be blunder, systematic or random, associated with operation, equipment, material, geology or workmanship (Harbaugh 1995).

3 THE MONTE CARLO METHOD FOR RISK EVALUATION

Because of the probabilistic nature associated with the time of drilling and completion operations, to estimate the necessary time to rent all the required rigs, is considered a complex task. The scenario where the analyst takes decisions is full of uncertainties for nearly every action. Therefore, several of them are risky decisions.

One of the most traditional techniques to deal with decision and risk analysis under uncertainty is modeling and simulation using the Monte Carlo method. Considering the assumption that the analyst can associate a theoretical random distribution, which better describes every operation in the process, it is possible to model and simulate the system by random sampling from the input distributions. In this case, the defined functions are related to the time to conclude each drilling and completion operation. In its great majority, these are random variables (Law 1991, Jain 1991, Bedford 2001, Vose 2001 and, Evans 2002).

For this research, we developed a customized simulation tool (*E&P Risk*) that allows the estimation of the total time necessary to execute all needed operations. Before performing the simulation, the analyst should define the representative distribution for each operation. In the *E&P Risk* suite, this can be done by searching the operation time from the corporate data base and performing a fitting process using a built in tool. For every operation, an input distribution can be adopted and fed in the model.

Taking into account the Central Limit Theorem and that the operations are assumed independent, the resulting sum of the operation time will be approximately Normally distributed, providing no variable dominates the uncertainty of the sum (Jain 1991 and, Bedford 2001).

At the end of the simulation, after generating hundreds or even thousands of samplings of the operation time, an estimation of the total time is presented as a confidence interval for the mean total time and also an exposition to risk histogram, with the indication of some desired percentiles to better support the decisions (Figure 1).

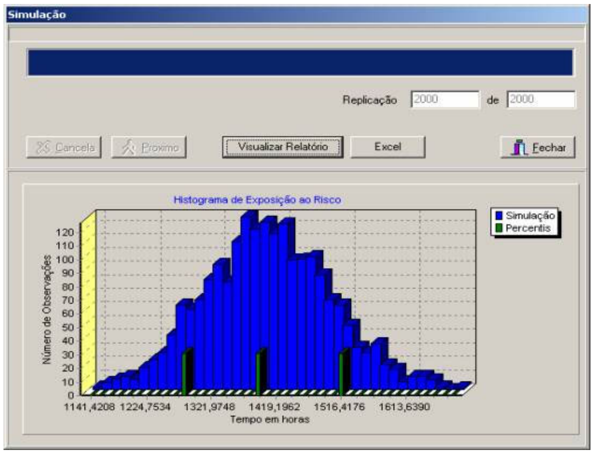

Figure 1: Exposition to Risk Histogram

As the histogram and their related results (estimated total time and cost) are presented, the decision maker can now use those values to take a decision and/or use then to refine it after confronting it with those obtained with the aid of complementary approaches like the one we are going to explain in the next topic.

4 DATA MINING AND THE NEURAL NETWORK EVALUATION

An alternative to guesswork the total time of a novel well, is to use the history of previous perforated wells and, correlate its geological, technological and geometric features with the time spent in these operations.

The database used in this research refers to drilling and completion operations of petroleum wells and has about 3100 registers with 37 fields each. One of the biggest challenges in this work was to select relevant data to guesswork. The activities developed in this stage of the research are mainly related to the analysis of the available data and the selection of those that can be correlated with the time for a given operation. A series of experiments were driven using the available data and the data analysis tools. There were analyzed fields that carried geological, technological and geometric information as input parameters related with the time of a given well operation.

The selected fields in the database, which later on were used as inputs of the neural network model, are:

1. **Type of Operation:** Specifies precisely what kind of drilling or completion was made - Exploratory Drilling, Production Drilling, Restoration, Completion, Maintenance Evaluation, etc.
2. **Well Fluid:** Specifies what kind of hydrocarbon is produced in the well – Gas, Oil, Unknown;
3. **Type of Well:** Specifies if the well is a Production or Injection Well;
4. **Lateral Goal Distance:** Is a geometric parameter that specifies the distance between the axis of the rig and the goal (petroleum reservoir), including an inclined space, that increases the risk of the operations;
5. **Water Sheet:** Another geometric parameter that specifies the distance between the surface and the bottom of the sea and that correlates with the type of the rig and the time of the operations;
6. **Petroleum Field:** A geological parameter related with the kind, the hardness and the thickness of rocks that must be perforated;
7. **Rig Type:** A technological parameter that specifies how sophisticated must be the rig to operates in the well;
8. **Final Depth of the Drill:** Specifies how deep the reservoir is and correlates with the number of drilling phases.

Our first attempt to use neural network to forecast the total time using the above data, as input parameters, lead to a very restrictive performance. The objective of these experiments was to determine the learning and generalization capacity of a *feedforward* artificial neural network on the real data of operations in oil wells. An initial step was to separate the data by “Type of Operation” fed and to train a different neural net for each “Type of Operation”. With this, we intended to facilitate the learning of neural nets and obtain more precise results. As the first conclusion of this initial analysis, a very big variability was observed in the total time of operations of the database, even for a same operation type. This variability is related to the risk and uncertainty embedded in operations and did appear in extremely similar and even in the same well.

In this way, the capacity of the net to forecast was extremely harmed, supplying a medium value of total drilling time, but without giving to the user the notion of the quality of the results which are influenced by this great variability. To deal with this problem and appropriately represent the embedded risk, it was necessary a neural network architecture capable to model, not only the total time estimative, but also the probability distribution of the operations total time.

5 HYBRID NEURAL NETWORK ARCHITECTURE

In order to deal with an and represent the risk of drilling and completion operation, a hybrid neural approach was developed. In this architecture we used two neural network models and a probabilistic neuron as output of the architecture. This approach tried to reach two objectives: the first one, was to do an initial treatment in the input data, classifying them in clusters of input parameters for similar wells. Its architecture can be seeing in Figure 2.

A competitive unsupervised learning neural network does this. Later on, a *feedforward* neural network was trained with the clustering information a long with the geometric, technological and geological input parameters.

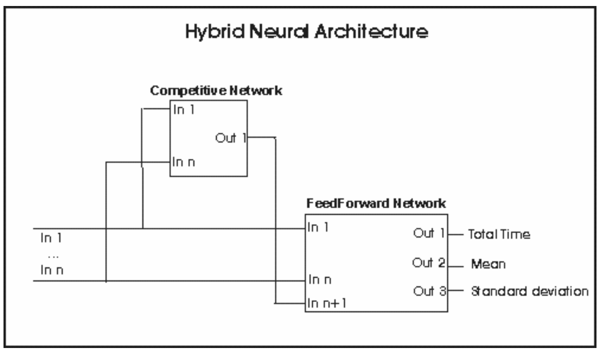

Figure 2: Schematic View of the Hybrid Neural Network Architecture.

This supplies, as an output, the total time, the average total time and the standard deviation of the group of wells in the cluster. So, the user can have a notion of the "quality" of the results and evaluate the risk and uncertainties involved in perforating the well.

The second goal to be reached by this hybrid approach was to make possible the classification of a never previously seen well.

5.1 Competitive Neural Network Module

The competitive neural network used in our proposal is a simple competitive network as shown in Figure 3. This network has two totally connected layers, and the output layer is a competitive one (Haykin 1998). When an example is presented to the network, the winner neuron, i.e., that with the greater activation value, represents the related cluster with the input parameters.

During the training, the clustering capability is enhanced through the use of a bias in each neuron whose value is decreased each time the neuron wins the competition.

5.2 Feedforward Neural Network Module

The *feedforward* neural network module receives, as inputs, the cluster in which the well is classified and the "conventional" input parameters. The outputs of this module are the predicted total time, the average total time for the well class and the standard deviation of the class. In this proposal, 3 layers neural network were used. That net

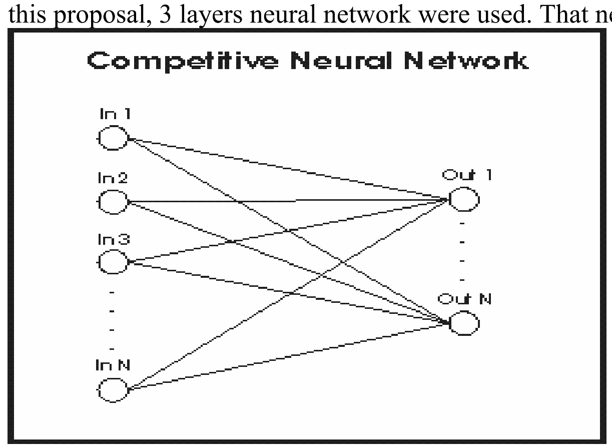

Figure 3: Compet itive Neural Network Module.

was trained using the *backpropagation* algorithm (Haykin 1998).

5.3 Probabilistic Neuron

The average total time and the standard deviation output neurons of the *feedforward* neural module send its output signals to a probabilistic neuron. The probabilistic neuron is a stochastic neuron where the activation function has a probabilistic interpretation. The output of the neuron can be +1 or –1, but the decision of which value will be send to the output, is probabilistic, i.e., it obeys a probability distribution. This distribution is governed by the average and standard deviation inputs (Jacinto 2002).

For simplicity, in this work the activation function of the probabilistic neuron was the Normal function, but the Lognormal function seems also to be a good choice. With this output, the neural model is completed and an internal Monte Carlo simulation was run. The output data is used to make a distribution diagram, showing the variability of the total time, illustrating the embedded risks in the drilling of the well.

6 VALIDATION AND USE OF THE CONCURRENT MODELS

In order to validate the proposed methodology, some initial tests were done. Taken into account the same data base, we proceed to estimate the total time, applying both, the Monte Carlo simulation and the Neural Network approach.

This is a type of concurrent validation where the total time x, guessed by the connectionist tool, is considered into the Normal distribution obtained by the Monte Carlo simulator (Figure 4). We try to answer the following question: "what is the risk to obtain a time greater than x?

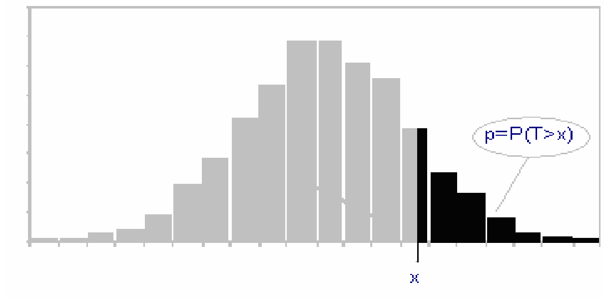

Figure 4. Total time Forecasting as a Frequency Distribution.

Collecting a sample of operational data time, we fed the Monte Carlo model considering 2000 replications and obtained the following results:

- Minimum Total Time: 1131.70 hours;
- Maximum Total Time: 1701.32 hours
- Mean total Time: 1401.04 hours
- Standard Deviation: 91.28 hours

Figure 5 shows the obtained exposition to risk histogram for the Monte Carlo simulation.

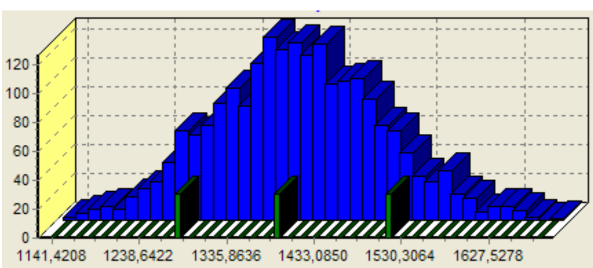

Figure 5: Exposition to Risk Histogram for the Case Study

Considering the same database, we got data and fed the Neural Network tool. We ran over similar wells and the following results are obtained:

- Type of Operation: Exploratory Drilling
- Number of Competitive Neurons: 14
- Training Cases: 171
- Validation Cases: 57

Feedforward Module training results:

- Average Total Time (hours): 1543.01 hours
- Standard Deviation: 369.71 hours

The result seems to be very useful, since the Total Time estimated by the Neural Network fits inside the interval provided by the Monte Carlo simulation. In the case of this example, very close to the P90 percentile (Figure 6).

Table 1: Clusters Found

Clusters	N° of Classified Cases
0	7
1	17
2	17
3	12
4	14
5	12
6	22
7	15
8	24
9	4
10	16
11	8
12	45
13	11
14	4

RMS of the clustering: 0,0273

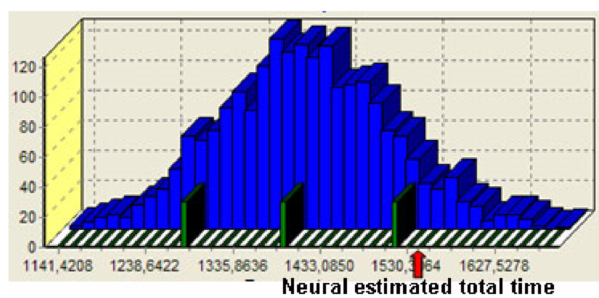

Figure 6: The Neural Estimated Total Time within the Monte Carlo Distribution Result

7 FINAL REMARKS

Risk assessment is an important constituent in the development process of a well installation. Well drilling and completion operations, especially in deep waters, are very risky and uncertain operations, subject to great variability.

Conventional *feedforward* neural network model usually gives a single number as response to the input parameters. In this work we have proposed a hybrid model with competitive *feedforward* and probabilistic neurons, in order to represent the uncertainty of the process. Using the models developed in this study, the Total Time for well drilling and completion operations is estimated.

Despite the promising results of the neural network tool, we believe that the methodology must be complemented with traditional simulation, qualitative or semi-quantitative risk assessment techniques, particularly for the purpose of risk identification. This approach offers to the analyst more information to deal with the decision making process. On one hand, the expected Total Time is based on low level information supplied by the operation time. On the other hand, he or she can consider higher level information (geological, technological and geometric data) as a base to predict the Total Time.

Salability of results is probably the key justification when considering the use of more than one technique to express and to convince yourself and others about the results, especially when dealing with risk decisions under uncertainty. Most people are skeptical of simulation results simply because they do not understand the technique or the final result. Sometimes, as shown in this study, it is helpful to use two or more techniques simultaneously to verify and validate the results of each one.

Our approach is towards a broader investigation that aims to evaluate the performance of this technique for more test cases and under other aspects of drilling and completion operations, as the continuous improvement in drilling performance, reducing the risks as new wells of the same type are perforated by the same team.

REFERENCES

Jacinto, C. M. C. 2002. Modelagem e simulação do risco na perfuração e completação de poços de petróleo e gás em águas profundas. M.S. Dissertation. UFF, BRAZIL.

Harbaugh, J. W., Davis, J. C., and Wendebourg. C. 1995. Computing. Risk for oil prospects: Principles and programs. Pergamon. UK.

Rose, P., 2001. Risk analysis and management of petroleum exploration ventures. AAPG Methods in exploration Series, No. 12. AAPG. USA.

Bishop, C. M. 1995. Neural networks for pattern recognition. Oxford University. UK.

Haykin S. 1998. *Neural networks: A comprehensive foundation.* McMillan College. USA.

Law, A. M., 1991. Simulation modeling and analysis., 2nd Edition, McGraw-Hill, New York, USA,.

Jain, R. 1991. *The art of computer systems performance analysis: Techniques for experimental design, measurement, simulation, and modeling*. John Wiley & Sons Inc, New York, USA.

Bedford, T., and Cooke, R. 2001. *Probabilistic risk analysis: foundations and methods*. Cambridge University Press.

Vose, D. 2001. *Risk analysis: a quantitative guide, 2nd Edition*, John Willey & Sons.

Evans, J. R., and Olson, D. *2002. Introduction to simulation and risk analysis. 2nd Edition*, Prentice Hall.

AUTHOR BIOGRAPHIES

DENNIS KERR COELHO is a MS candidate at the Department of Computer Science at Federal University of Santa Catarina (UFSC), Brazil. His e-mail address is <dennis@inf.ufsc.br>

MAURO ROISENBERG is an associate professor at the Department of Computer Science at Federal University of Santa Catarina (UFSC), Brazil. He received a Doctoral degree in electrical engineering from UFSC in 1998. His research interests include simulation and artificial intelligence. His e-mail address is <mauro@inf.ufsc.br>.

PAULO J. FREITAS FILHO is an assistant professor in the Department of Computer Science at Federal University of Santa Catarina (UFSC), Brazil. His research interests include simulation of computer systems for performance improvement, risk modeling and simulation, analysis for input modeling and output analysis. He is a member of SCS – Society for Computer Simulation, SBC – Brazilian Society for Computers. His e-mail address is <freitas@inf.ufsc.br>.

CARLOS MAGNO C. JACINTO is a Petrobras SA. (Brazilian Energy Company) employee about 17 years. He is a doctorate candidate in COPPE – UFRJ. His research interests include risk modeling and simulation, performance improvement, failure prediction and artificial intelligence; all applied in Well Technology Engineering. His e-mail address is <cmcj@petrobras.com.br>.