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# Presenting a Graphical Tool to Predict the Drilling Rate of Penetration through Intelligent Approaches

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## Abstract

The prediction of drilling rate is one of the important issue because of its role in minimizing drilling costs to optimize the drilling process. Field data analysis is a key element in reducing costs and improving drilling operations. Furthermore, developing field information analysis tools and providing prediction models are two alternatives to improve drilling operations. When a drilling system is deployed, there are only a few limited parameters which can be controlled and changed. In general, the main purpose of this research is to apply intelligent techniques and provide graphical tools for predicting drilling performance. For this purpose, a database of field data such as well depth, drill weight, drill speed, drill chuck, weight on the hook and the torque was established from one of the southern fields of Iran. In this research, two different types of graphical tools were proposed to predict the drilling rate of penetration as well as to calculate the cost per foot, using a fuzzy neural network and Neuro-fuzzy approaches. The goals of the economic evaluation are the drill performance and the cost-per-foot calculation. The results showed that a good correlation coefficient ( $R=0.94$ ) was obtained to predict the penetration rate using the neural network. In order to improve the findings, the fuzzy neural network method was applied. The results demonstrated that a very good relationship with high precision having a coefficient of determination ( $R^2=0.99$ ) was obtained and thereby it depicted a significant improvement in the accuracy of the prediction models.

**Keywords:** Drilling Rate, Prediction, Cost Per Foot, Neural Network, Fuzzy-neural Network, Graphical Software

## Introduction

Evaluation of drilling performance plays a major role in drilling operations productivity as well as drilling costs [1]. With respect to minimizing the costs, field data should be gathered and monitored precisely, leading to apply highly accurate data analysis tools. Using predictive models and results from field data analyses, it is possible to take effective measures in which the project could be managed appropriately to attain the most desirable and efficient results. Through the optimization process of the drilling operation, the parameter of the Rate of Penetration (ROP) is one of the most important factors. It directly contributes to the success of the project. This parameter is related to formation properties, fluid rheology, weight on bit, bit rotational speed, bit type, well deviation, bit hydraulic, etc.

Another essential parameter affecting the drilling effectiveness is the cost per foot of drilling. This is in association with whole drilling costs while it is close relation with bit price and rate of penetration. Some valuable attempts were made to present equations for predicting ROP and cost per foot of drilling [2-5].

This paper presents an approach to achieve predictive empirical models to evaluate drilling operation performance (rate of penetration and cost estimation) using neural networks and neuro-fuzzy methods in one of the Iranian oilfields. It finally results in a graphical tool provided by applying Graphical User Interface (GUI) tools in MATLAB software.

## Research Methods

Artificial neural networks (ANNs) or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute

animal brains [1]. Such systems “learn” to perform tasks by considering examples, generally without being programmed with any task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as “cat” or “no cat” and using the results to identify cats in other images. They do this without any prior knowledge about cats, e.g. that they have fur, tails, whiskers and cat-like faces. Instead, they automatically generate identifying characteristics from the learning material that they process.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it, and then signal additional artificial neurons can be connected to it.

In common ANN implementations, the signal at a connection between artificial neurons is a real number, and the output of each artificial neuron is computed by some non-linear function of the sum of its inputs. The connections between artificial neurons are called ‘edges’. Artificial neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that the signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first layer (the input layer), to the last

layer (the output layer), possibly after traversing the layers multiple times.

The original goal of the ANN approach was to solve problems in the same way that a human brain would. However, over time, attention moved to performing specific tasks, leading to deviations from biology. ANNs have been used on a variety of tasks, including engineering problems such as petroleum engineering and drilling operations as it is used in this paper.

Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as the fuzzy neural network (FNN) or neuro-fuzzy system (NFS) in the literature. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules.

The strength of neuro-fuzzy systems involves two

contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. The neuro-fuzzy in fuzzy modeling research field is divided into two areas: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdani model; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model.

### Modeling Approach and Results

Primarily, a database was compiled from field observation of drilling operation in one of the Iranian oilfields. The database was then analyzed via the neural network and neuro-fuzzy techniques. With that regard, MATLAB software was utilized.

By using Graphical User Interface (GUI) tool in software, a graphical tool was designed to evaluate the rate of penetration and cost estimation in a specified drilling project.

Figure 1, for instance, illustrates a neuro-fuzzy structure of the problem.

Figure 2 shows a snapshot of designed graphical tool using GUI in MATLAB software. Using this tool, a user can easily calculate ROP and cost per foot of drilling for each arbitrary drilling case.

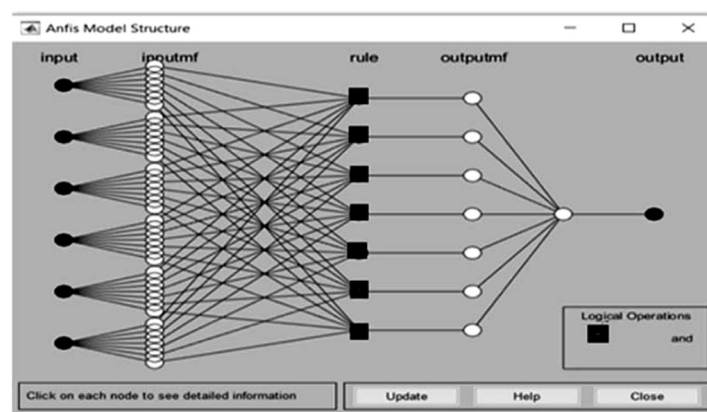


Figure 1: A Schematic of a neuro-fuzzy structure of the problem.

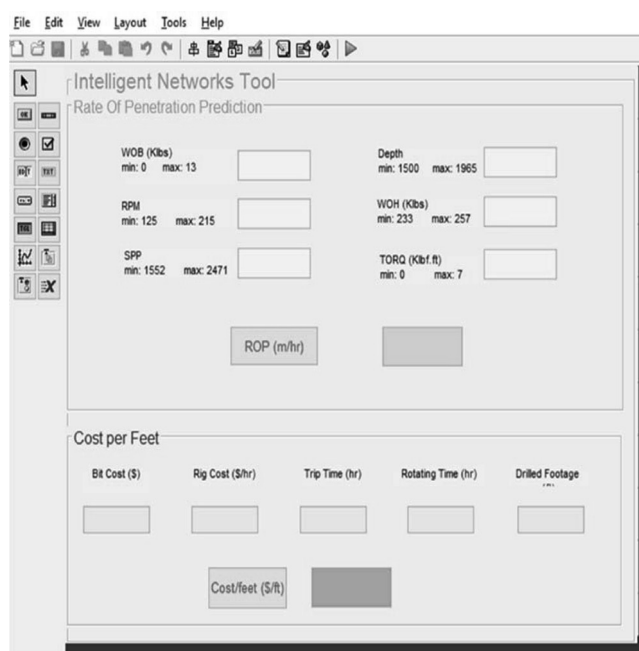


Figure 2: An illustration of the designed graphical tool.

## Conclusions

Primarily, a database from drilling field data, in one of the southern Iranian oilfields, was established. The database was then analyzed through intelligent techniques to ultimately yield some equations and a graphical tool for calculating and predicting the rate of penetration and cost of drilling. The results showed a very good relation between measured and predicted ROP using the neural network and neuro-fuzzy approaches with  $R^2=0.879$  and  $R^2=0.889$ , respectively. Finally, a graphical tool using Graphical User Interface (GUI) in MATLAB software was provided to easily predict both ROP and cost per foot of drilling.

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