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Refracture candidate selection using hybrid simulation with neural network and data analysis techniques

Wang Yanfang, Saeed Salehi*

University of Louisiana at Lafayette, Lafayette, LA, USA

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ABSTRACT

By now very few analytical models have been developed to select well refracture candidates due to complicated multi-parameter relationships. In this study, we proposed a new method by merging mathematical data analysis with feed forward back propagation neural network utilizing post-fracturing data. The model preference is thereby based on the correlation coefficients of several selected independent variables against production performance.

The solution to this expense is a tool that can identify restimulation candidates quickly and economically. We employ two mathematical analysis techniques to filter several independent yet influential parameters as inputs. These parameters are supposed to be primary factors with high impact on potential production improvement. Then we use these well data to train an artificial neural network (ANN) to predict post-fracture production. The errors of the best samples should decrease consistently along with the training samples. A minimal error of the training sets is not necessary because over-fitting of the network could be memorizing rather than generalizing. The testing results showed that there is higher than 80% prediction accuracy, which is good enough for decision making. This methodology gives credible prediction results when it is applied in Zhongyuan oilfield and provides the operators with useful recommendations to make decisions for restimulation.

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1. Introduction

Hydraulic fracturing has been commonly used to accelerate production and improve ultimate recovery for decades. However, the fractured wells tend to be deficient due to the artificial fractures closure with time and differential pressure, which results in less conductivity of fracture into wells. In addition, many of the early fracture treatments resulted in wells which underperformed expectations, such as poor operational treatments, fracturing techniques and understanding (Vincent, 2012). Refracturing has been applied in underperformed fractured wells. For refracture candidate selection methods, each technique tends to select different wells for different reasons that may be valid, depending on specific reservoir characteristics. artificial neural networks have proven to be excellent predictive tools in various petroleum-engineering applications. Such applications include the prediction of fluid properties, well logging, well testing and horizontal drilling. Salehi et al. (2009) developed a neural network approach based on the parameters affecting casing collapse to estimate the potential collapse for the wells to be drilled and the current producing wells in the field. The output of the model predicted collapsed depth and casing collapse risk in the next 5 years. Fernandes and Petrobras (2012) used an artificial intelligence technology to classify the reservoir zones with different fluids from the observation of sufficient characteristics particular in well log data. Parada and Ertekin (2012) provided an artificial neural network methodology to build a high-performance neuro-simulation tool for screening improved oil recovery (IOR) methods. The tool also provided the flexibility to compare the hydrocarbon production for different sets of inputs, which facilitates comparison of various depletion strategies in the screening process as well. Centilmen et al. (1999) proposed a neuro-simulation technique that forms a bridge between an accurate reservoir simulator and a fully-trained predictive artificial neural network (ANN). This technique formed a fast predictive tool for optimizing the locations of the new wells in the reservoir. Bilgesu et al. (1998) designed a three-layer artificial neural network to define the relationship between the variables and predicted the condition of the bit. Nashawi and Sadiq (2000) presented an artificial neural network model to predict reasonably accurate values of the formation fracture gradient. They found out that this method was promising when comparing the results obtained from the model with those obtained from correlation. Shelley and Harri (2009) presented a method to evaluate the production associated with various hydraulic-fracturing scenarios and characteristics using data

* Corresponding author. Tel.: +1 337 482 6557.
E-mail addresses: wang.yanfang@gmail.com (W. Yanfang), saeads@gmail.com (S. Salehi).

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Nomenclature

ANN	artificial neural network
BP	back propagation
H	formation thickness (ft)
X_l	fracture length (ft)
S_o	oil saturation (%)
ϕ	effective porosity (%)
X_w	fracture width (ft)
K	permeability (%)
Q_{aff}	actual production rate after fracturing (stb/d)
Q_{beff}	production rate before fracturing (stb/d)
$Q_{pred-aff}$	predicted production rate after fracturing (stb/d)
$\Delta Q_{pred-aff}$	error between predicted and actual production rate after fracturing (stb/d)
X	value of the parameter to be normalized
$X_{\min}$, $X_{\max}$	minimum and maximum values respectively, of the parameter being normalized from the analyzed sample
x	input vector
y	hidden vector
w_{ij}	weight between input neuron and hidden neuron
w_i	weight between hidden neuron and output
Y	neural network output or prediction
f	sigmoid function
I_i	the ith input neuron
W_i	the weight of the ith neuron
n	the number of input neurons
E	error between actual and anticipated neural network output
ε	the tolerance value of error
x_{Multi}	the number of multiplications is x
$(x-1)_{Add}$	the number of addition is $x-1$

modeling and optimization technologies such as artificial neural networks and genetic algorithm. Fang et al. (1992) used GA for petrophysics application where they applied it for porosity and permeability determination. Huang (2002) used an integrated neural-fuzzy-genetic algorithm to predict permeability from well logs. Yashodhan et al. (2012) provided a methodology using a neural network drilling parameter optimization system to ensure maximum run length from all bits and downhole tools at the highest possible penetration rates (ROP). Tran et al. (2002) used a novel GA method for fracturing design optimization.

Application of the neural network system for restimulation candidate selection has been reported in the literature. Reese et al. (1994) reviewed different applications of refracture stimulation and conducted a study of the stimulation process and interpreted field data where refracturing had been applied. Mohaghegh et al. (1998, 2000) developed a methodology that used several artificial neural networks and genetic algorithm routines to help engineers select restimulation candidates based on available data. This methodology was applied to oilfield for refract jobs or chemical restimulations. Shelley and Halliburton (1999) investigated an ANN analysis of well restimulation candidate selection in Red Oak field. Public information such as geographical location, surface elevation, initial and current reservoir pressure estimates, perforation location, initial completion procedures, refracture procedures, and current production were used as inputs to train networks. The combination of BP network with genetic algorithm allowed creating proper architecture. Saeedi et al. (2007) studied candidate selection for polymer gels treatments in Arbuckle formation. They only used pretreatment well data as input parameters: the neural network they developed could predict accurately the post-treatment cumulative oil production of the well with satisfied error. But in the study of variables significance, they only compared the results from sensitivity analysis with conventional logic. Mohaghegh et al. (2002) studied 150 well restimulations in the Codell formation, DJ Basin. They applied data mining study to optimize candidate selection and identify successful practices. Similarly, in Oberwinkler and Economides (2003), data mining was applied for selecting promising refracture candidates. That method combined self-organizing maps with neural networks, which gained very strong learning skills. This method had another advantage that it could provide sufficient and efficient explanation of the prediction results. But these methods were considered time-consuming and complicated, for example if one particular parameter dataset was not available, the conclusions obtained from all the available parameters could be unreliable because the potential inter influence. Reeves et al. (2000) evaluated refracturing and provided guidelines to engineers with respect to refracture stimulation design and commercial viability. Refracture stimulation treatments in tight formations require increased fracture length, and refracture treatments conducted in wells in permeable reservoirs require increased fracture conductivity to be commercially successful. They used reservoir simulation techniques such as virtual intelligence and type-curve techniques. However, when reservoir simulation techniques were used, it was necessary to add noise data to replicate actual field condition.

Zhongyuan oilfield features low gas reservoir pressure, long perforation distance and bad well condition. Hydraulic fracturing had been operated in the oilfield, but the predicted productivity after fracturing was far from actual results due to limited data, inaccurate models and parameters as well as uncertainty of hydraulic fracturing mechanisms. However, there is sufficient remaining recoverable reserves and formation energy in that area. Therefore, due to geological characteristics of Zhongyuan oilfield, general hydraulically fracturing techniques to stimulate the whole target interval could not be successfully applied on that oilfield. Zeng (2004) provided a set of layering and chosen fracturing technique, including evaluation technique of target formation, tools of mechanical separating-layer. In Zeng Yuchen (2005), he investigated CO_2 fracturing stimulation on 5 wells in Zhongyuan oilfield. This method brought success through the cooperation with Schlumberger. However, few investigations have been conducted on refracture candidate selection on that oilfield. Improvement of restimulation production efficiency requires accurately selecting candidate wells for treatment optimization. Based on the well data obtained from that oilfield, in this work, the nonlinear interrelationship between some parameters from different kinds of reports was analyzed. A productivity prediction model of optimizing refracture design was established. This step helped to identify the most promising wells for refracture treatments out of the large amount of possible candidates (underperforming treatments). The prediction results for that oilfield turned out to be promising. This can be further investigated for actual restimulation optimization design. The goal of the model building is not only to create a proper model for well refracture candidate selection using a suite of available input parameters, but to measure and improve the model quality and to find a ranking for selected well refracture candidates with respect to their predicted potential for production improvement using the model.

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