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Developing a novel workflow for natural gas lift optimization using advanced support vector machine

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ABSTRACT

Natural Gas Lift (NGL) is one of the most attractive methods to enhance oil recovery. In this method, oil is produced using gas from the gas region either adjacent or far from the oil layer. The reservoir simulation software should be run many times to optimize the NGL process. This is practically impossible due to time-consuming simulation of an actual reservoir. In this study, support vector machine (SVM) was used to overcome the problem. The reservoir simulation software was replaced by the trained SVM. Through this, each run only takes a few seconds. The process was optimized for a real field using particle swarm optimization (PSO) and genetic algorithm (GA). The optimum SVM parameters were determined by the PSO algorithm. Taguchi experiment design was used to determine optimum GA and PSO parameters.

1. Introduction

Natural gas lift (NGL) is one of the improved oil recovery (IOR) methods. NGL is used as an alternative for artificial gas lift (Khamehchi et al., 2009; Khamehchi et al., 2011; Hamedi et al., 2011; Khishvand and Khamehchi, 2012). In this method, the gas of gas cap or an adjacent gas layer enters an annulus through perforations made into the wall of this region. The gas produced through perforations enters the tubing through the Inflow Control Valve (ICV). The next steps are similar to artificial gas lift. Fig. 1 illustrates the process. The concept of "natural gas lift" was first introduced by Kumar et al. when several oil wells in NLM field in India were closed (Kumar et al., 1999). Thereafter, NGL has been successfully used (Al-Kasim et al., 2002; Betancourt et al., 2002; Dabiri Nezhad and Sheikh Darani, 2008; Jin et al., 2005; Konopczynski and Tolan, 2007; Nagib et al., 2011; Peringod et al., 2011; Warren et al., 2009; Xueqing et al., 2012; Youl et al., 2010; Zorbalas et al., 2007). Rashidi and Khamechi optimized the gas input rate for a short period of two years for a synthetic reservoir using genetic algorithm (GA) (Rashidi and Khamehchi, 2012). In most cases, production optimization (i.e. sensitivity analysis) has been carried out for ICV size and the process has been assumed to be independent of the wellhead and other parameters (Peringod et al., 2011). Many parameters including the number, size and location of ICV installation, tubing ID, wellhead pressure and minimum perforation distance from the stand-off point should be selected for long-term optimization of NGL. According to literature, only one ICV is required to be installed on the oil layer perforation (Barreto and Schiozer, 2014).

There is no study on long-term optimization of the NGL process in a real field. In fact, it is often impossible due to the time-consuming process. Well and reservoir models should be coupled for long-term optimization. Then, the optimization algorithm will find the optimal solution using the integrated model. The simulator (well and reservoir models) should be run thousands of times to find the optimal solution. For real reservoirs with a large number of grids, each execution of the model using a simulator is time-consuming. Therefore, optimization of these reservoirs takes a long time and even it becomes impossible in some cases. To overcome this drawback, a proxy model can be used to decrease the number of simulator runs and required time to find optimum answer (Rasouli et al., 2015). A proxy model is a mathematical equation which replaces the simulator to mimic the relation between the inputs and outputs. The use of a proxy will reduce accuracy while reducing the time required to get simulator results.

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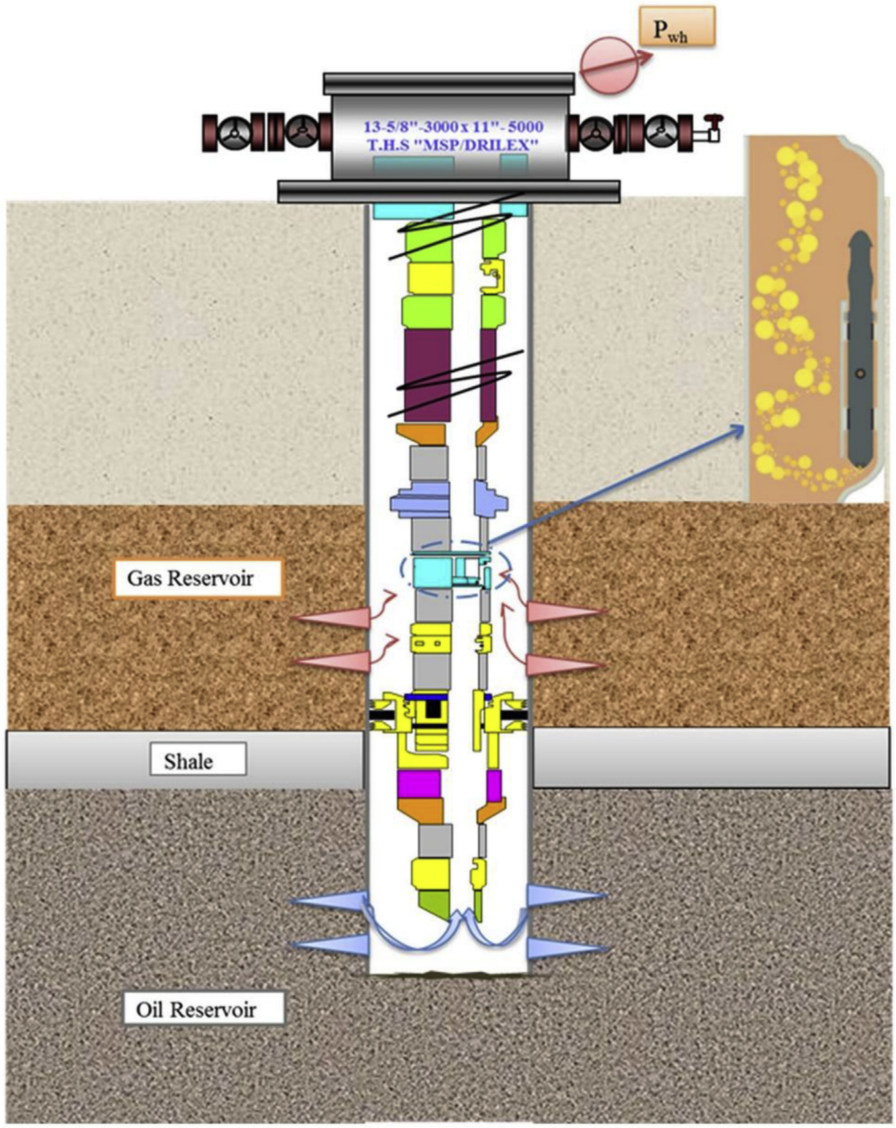

Fig. 1. A view of natural gas lift process.

There are different methods to create such a proxy including support vector machine, genetic programming, artificial neural network, least square support vector machine, co-active neuro-fuzzy inference system, etc. For this purpose, the simulator is run for a specific number of times. Based on the inputs and resulting output parameters, a proxy model is created to approximate the simulator's behavior. The resulting proxy model is capable of generating outputs using inputs and allows long-term optimization. In this study, SVM is used due to support vector machines privileged generalization performance in regression and classification. A proxy model is developed for a particular field using SVM. Then, the optimal parameters controlling the simulator are determined by coupling SVM with optimization algorithms.

2. Theoretical background

The theoretical background of SVM and optimization algorithm that will be used in this study are briefly discussed below. For more details, the readers may refer to the cited literature.

2.1. Support vector machines

SVM as a machine learning tool was first introduced by Vapnik for classification purposes (Vapnik, 1995). The generalized SVM can be used for regression and it is called Support Vector Regression (SVR) (Cortes and Vapnik, 1995). SVM transfers the input vectors into a higher-dimensional space using a nonlinear mapping method. It considers a hyper-plane with the highest margin between linearly separable classes using a separation method. The operations in this high dimensional space are performed using kernel functions. SVR can be generally formulated as follows (Suykens et al., 2002):

$$f(x) = \langle w, \Phi(x) \rangle + b \tag{1}$$

which

$\Phi(x)$: Nonlinear function to mapping x into n-dimensional feature space
w: weight vector
b: bias term