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Good wells make better stimulation candidates: An evidence-based analysis

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A B S T R A C T

Effective candidate selection is an important consideration in planning successful stimulation campaigns. Identifying "high potential" wells—those that would provide the largest incremental production—has been the subject of several studies, some of which have suggested that stimulation of better producers is a good practice to maximize stimulation benefits. An evidence-based investigation of this idea is lacking and is the subject of this study. This paper hypothesizes that a positive correlation exists between a well's oil production performance and its stimulation incremental oil production. We tested this hypothesis by investigating three independent methods: (1) analysis of aggregate results of case studies in the literature, (2) analysis of production and workover data from four mature Permian Basin San Andres leases, and (3) analysis of the simulation results from a tuned reservoir model. The results confirmed the existence and statistical significance of a positive correlation between pre-stimulation oil rate and stimulation incremental oil production. In our field-scale reservoir simulation model, we used pre-stimulation oil rate to rank stimulation candidates, which identified more than 80% of the top candidates. We recommend prioritizing wells that exhibit high oil production for stimulation in order to statistically increase the likelihood of maximized workover benefits.

1. Introduction

Well stimulation refers to any treatment performed to restore or improve the productivity of an oil/gas well. The purpose of well stimulation is to enhance oil/gas field economics through faster and higher hydrocarbon delivery without significant investment (Economides and Nolte, 2000; Schechter, 1992). Candidate selection, i.e. identifying wells that would provide the largest incremental production, is an integral part of the stimulation workflow. Well stimulation optimization and effective candidate selection strategies have been the subject of numerous studies. Table 1 summarizes selected studies on candidate selection, the proposed candidate selection techniques, and a summary of the results and conclusions. More than ten candidate selection strategies have been practiced and documented using actual field data, analytical models, and reservoir simulation models. These techniques include well-test-driven techniques (e.g., well performance analysis, identification of formation damage source and severity), production data analysis techniques (e.g., production comparison with nearby wells), and computerized optimization techniques (e.g., Artificial Neural Networks and Genetic Algorithms). Artificial intelligence methods have introduced a powerful tool to solve nonlinear production optimization problems. Due to the complex and nonlinear nature of production optimization problems, the relationship between the inputs (e.g., geology, drilling, completion, workover), and the output (production enhancement) are often not known and mathematical modeling is, therefore, not an option. It that regard, data-driven artificial intelligence methods are excellent tools for pattern recognition and nonlinear, multidimensional interpolation, and could help reveal complex relationships between input and output parameters (Holdaway, 2014).

Despite the considerable effort devoted to this problem, there is no general agreement on the optimal candidate selection strategy. Moore and Ramakrishnan (2006) concluded that no selection criteria can be universally applied, and a reservoir-specific selection criteria should be formulated based on the existing experience for each field. Zoveidavianpoor et al. (2012a) reviewed conventional candidate selection techniques for hydraulic fracturing and reported that candidate selection is not a straightforward procedure because it lacks an agreed-upon approach to identify stimulation candidates across different geological settings. Reeves et al. (1999a) applied three different candidate selection techniques and showed that each technique provides a completely different list of candidate wells, indicating the uncertainty involved with each technique. The complex nature of this problem and the lack of agreement among various candidate selection techniques can be associated with (1) the considerable amount of data required to accurately determine the sources of well impairment and to identify the optimal remedial action, (2) the variations in the performance of each reservoir stimulation technique, and (3) the uncertainty of operational

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Table 1
Selected publications on well stimulation optimization with focus on candidate selection.

Reference	Location/Field	Technique	Summary and Findings
Xiong and Holditch, 1995	theoretical	fuzzy logic	Eight fuzzy evaluators are developed to improve decision-making of candidate selection, treatment type selection, and fluid and additive selection.
Shelley, 1999; Shelley et al., 1998	Red-Oak field, OK; Red Deer Creek field, TX	Artificial Neural Networks (ANNs)	The commonly available well and reservoir characteristics and the production response to past stimulations are used to evaluate recompletion and re-stimulation potential in the remaining wells.
Zarei et al., 2014	simulation, anonymous field	Genetic Algorithms (GA)	Long-term effect of workovers is emphasized. GA and engineer-guided GA are used to allocate limited stimulation resources and to determine optimal workover timing.
Reeves et al., 2000, 1999a, 1999b	Green River, Piceance, East TX, & TX Gulf Coast Basins	production data comparison; ANNs & GA; type curve matching	Top candidates ranked by each analytical method are unique to that method, indicating the uncertainty of each method. Stimulation of underperforming wells (production data comparison) is less effective than ANNs or GAs.
Nitters et al., 2000	theoretical	structured candidate selection	Candidate wells are selected by comparing actual performance and theoretical potential. The sources of poor performance are identified to help with treatment selection and design.
Kartoatmodjo et al., 2007	simulation, Bokor field, East Malaysia	risk-based candidate selection	Risk likelihood and severity are evaluated to reflect potential monetary and time loss. Risk analysis is performed using Monte-Carlo simulation to select optimal candidates.
Krasey, 1988	Pembina field, Alberta, Canada	high-grading candidate selection	Pressure transient analysis is used to measure the skin factor. Stimulation candidates are ranked by comparing stabilized production rate before and after skin removal.
Jennings, 1991	P/6 gas field, The Netherlands	high-productivity wells	High-productivity wells possess most critical characteristics related to stimulation success, e.g. fast payout. The notion that little benefit comes from stimulating good wells is wrong.
Nnanna and Ajienka, 2005, 2009	Niger Delta, Nigeria	formation damage identification	Identification of damage radius and its components can help in choosing right candidates for acid stimulation.
Sinson et al., 1988	theoretical	constrained nonlinear optimization	For stimulation economics optimization, an objective function is formulated to reflect the relationship between reservoir and well characteristics, treatment type and design.

Other Relevant Works:
fuzzy logic (Hashemi et al., 2012; Zoveidavianpoor et al., 2012b; Zoveidavianpoor and Gharibi, 2016); constrained nonlinear optimization (Ugbenyen et al., 2011); Artificial Neural Networks (Mohaghegh et al., 2001; Popa et al., 2005); identifying sub-performing wells and analyzing sources of impairment (Afolabi et al., 2008; Sencenbaugh et al., 2001; Strong et al., 1997); detailed analysis of well and reservoir characteristics and operator's field experience (Moore and Ramakrishnan, 2006).

parameters during well stimulation.

Researchers have intimated that stimulation of "good producers" may provide better results when compared to the more complex analytical models. Reeves et al. (2000) applied various candidate selection techniques to a field-scale reservoir simulation model. They concluded that while some techniques can identify a majority of top stimulation candidates, the techniques are inferior when compared to selecting better producers as stimulation candidates. Shelley (1999) concluded that wells with higher production rates are generally the best candidates for recompletion. Jennings (1991) noted that high deliverability wells benefit from fast payout time and effective well cleanup, making them attractive candidates for stimulation. Table 2 shows a list of studies that have supported the stimulation of good producers. These studies are mainly based on analytical or simulation models and present a very limited number of case studies; therefore, they lack sufficient field data to establish a compelling case.

In this study, we applied correlation analysis to several stimulation datasets to verify a correlation between pre-stimulation oil rate and the stimulation incremental oil production, and to measure the strength of such correlation. Based on the analysis, we proposed a new candidate selection method that imposes significantly smaller cost and time of analysis. Finally, we used a field-scale reservoir simulation model to test the field applicability and performance of the proposed candidate screening criterion.

2. Definitions

A good producer is defined as a well that when compared to other producers, has relatively higher oil/gas production rates. A good stimulation candidate is a well that when compared to other producers, would deliver larger incremental oil/gas production if stimulated. These definitions are selected because of their simplicity and ease of use; they can be readily applied to various production datasets to identify good producers and good stimulation candidates without the

Table 2
Selected publications supporting stimulation of good producers.

Reference	Technique	Observation/Conclusion
Ely et al., 2000	production performance comparison; pattern recognition technology; type curve matching	Best producers are often best candidates for stimulation; however, stimulation of such wells is performed reluctantly because of the risk of losing production from an excellent well.
Sencenbaugh et al., 2001	performance-based screening; large-scale field implementation	After re-stimulation of 110 wells, the need for re-stimulation of better producers was recognized, and those producers were added to the list of potential candidates.
Moore and Ramakrishnan, 2006	performance-based screening; evaluation of successful and unsuccessful case histories	Candidate selection in the past has focused on underperforming wells. This approach has yielded disappointing results. Eliminating the under-performing well is recommended as a candidate screening criterion.
Ugbenyen et al., 2011	analytical modeling; nonlinear optimization	Analytical models are applied to determine an optimal candidate selection strategy. Results show that the stimulation benefits are higher when pre-stimulation productions are higher.