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A LSSVM approach for determining well placement and conning phenomena in horizontal wells

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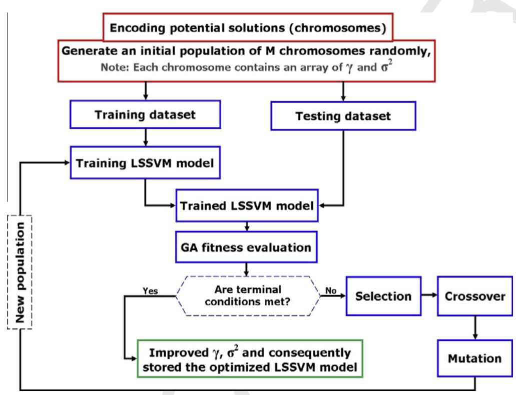
HIGHLIGHTS

- Developing easy-to-use model to estimate the optimum well placement in horizontal oil wells.
- Comparing performance of the conventional methods versus proposed GA-LSSVM method.
- Handling precise breakthrough time data in horizontal oil wells by GA-LSSVM method.

GRAPHICAL ABSTRACT



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ABSTRACT

Knowledge of the breakthrough time is very significant for effective oil well management and for extending the oil production time of the well without the presence of water or free gas. The importance lies in the fact that once water or gas has broken through, the fluid distribution and the fluid relative permeabilities in the system will change. Accordingly, applying robust predictive models in this area to arrive at an appropriate prediction of breakthrough times as well as optimum horizontal well placement in homogeneous and anisotropic reservoirs as a function of rate and density difference ratio is of great interest in oil and gas production system. The current study plays emphasis on applying the predictive model with the aim of the LSSVM (least square support vector machine) to estimate breakthrough time and optimum fractional well placement. Genetic algorithm (GA) was utilized to choose and optimize hyper parameters (γ and σ^2) which are embedded in LSSVM model. Utilization of this model showed high competence of the applied model in terms of correlation coefficient (R^2) of 0.9999 and 0.9999, mean squared error (MSE) of 0.000000142 and 0.000000622 from actual values for estimated dimensionless breakthrough time and optimum fractional well placement, respectively.

1. Introduction

Water and/or gas coning encountered in several oil wells is a serious problem which results in lower oil production rates, lower oil recovery and increased lifting cost. Therefore, in order to control the coning phenomena, many researchers have investigated the mechanism and developed methods to calculate critical rate, predict breakthrough time and reduce water cut [1–19]. These works deal with estimating the simultaneous water and gas breakthrough time and the optimum location of horizontal well in the presence of both gas cap and aquifer using rigorous and complicated

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Nomenclature

Abbreviation

AARD	average absolute relative deviation
GA	genetic algorithm
GOC	gas oil contact
LM	Levenberg–Marquardt
LSSVM	least square support vector machine
MSE	mean square error
M-SIMPSA	Simplex Simulated Annealing Algorithm
QP	quadratic programming
RBF	Radial Basis Function
SLT	statistical learning theory
SRM	structural risk minimization
SVM	support vector machine

Variables

$\overline{y^{\text{actual}}}$	average of the observed experimental data
y_i^{actual}	*i*th target
$y_i^{\text{predicted}}$	*i*th output
e_k	regression error
α_k	Lagrange multipliers
B_{opt}	optimum fractional well placement
D_b^{opt}	optimum distance above the WOC, ft
h	formation thickness, m
k_h	horizontal permeability, md
k_v	vertical permeability, md
L	horizontal well length, ft
N	number of data points
ϕ	density difference ratio
q_D	dimensionless flow rate
Q_O	oil flow rate, STB/day
R^2	coefficient of determination
t_{DBT}	dimensionless breakthrough time
μ_o	oil viscosity, cp
ρ_g	gas density, lb/ft^3
ρ_o	oil density, lb/ft^3
ρ_w	water density, lb/ft^3
ϕ	porosity, fraction
ψ	density difference ratio
b	bias term
ω	weight vector
γ	regularization parameter

methods. Their research investigated several issues such as critical rate and/or breakthrough time calculations.

It was found that the maximum water-free oil production rate corresponds to the critical rate and the breakthrough time which represents the period required by bottom water to reach the well's oil perforations [20]. If oil production rate is above this critical value, water breakthrough occurs [20]. After breakthrough, the water phase may dominate the total production rate to the extent that further operation of the well becomes economically not valuable and the well must be shut down [4,14–15,18,21–32].

Kabir et al. [33] proposed two depletion strategies to improve recovery of the remaining oil. In the first option, a conventional horizontal is completed below the gas/oil contact (GOC). Once the well waters out, the well is recompleted in the gas zone. Completion occurs either at the crest for a small gas-cap reservoir or at the GOC, inducing reverse cone, for reservoirs with thick-gas columns.

Recently, Bahadori [34] suggested new dimensionless correlation for estimation optimum fractional well placement and relevant dimensionless breakthrough time through horizontal wells. The aforementioned correlation can predict optimum fractional well placement and corresponding breakthrough time with good degree of accuracy. However, this correlation cannot be applicable and updateable for other reservoir. In other words, the developed correlation cannot adjusted for using in other homogenous and heterogeneous reservoirs.

This study deals with the usability of least square-SVM paradigm, as a simplification of conventional SVM, to predict the optimum fractional well placement and relevant dimensionless breakthrough time through horizontal wells. Tremendous actual data banks [14,34–36] were used for evolving our new method. Genetic algorithm (GA) was coupled with the aforementioned LSSVM as an optimization theme for indicating of hyper parameters. To the best of our knowledge, no record for modeling of optimum well placement for horizontal wells in general by SVM or LSSVM approaches was found in the literature.

2. Theory

2.1. Least-squares-SVM

Vapnik was a first research who introduced support vector machine (SVM) [37], is a sort of intelligent approaches. SVM is a very effective approach and has been used widely for classification, regression and pattern recognition [38]. The principle idea of SVM is transforming the nonlinear input area to a high-dimensional properties area and finds a hyper plane via a nonlinear mapping [39].

This novel approach is based upon the statistical learning theory (SLT) and the structural risk minimization (SRM) concepts [40]. SVMs obtain the solution via solving the quadratic programming (QP), and the solution returned is global (or even unique) instead of many local ones, unlike other regression techniques such as neural networks, as QP problem is a convex function [41]. However, this approach may be time-consuming and difficult as it entails the solution of a set of nonlinear equations (quadratic program). Suykens and Vandewalle [42] proposed least squares-support vector machine (LSSVM) models as an alternate formulation of SVM regression. LSSVM enjoys similar advantages as SVM, in addition it requires solving a set of only linear equations (linear programming) instead of a quadratic programming (QP) problem, which is computationally simpler and makes the problem easier to deal with.

The formulation of LSSVM for nonlinear function estimation is expressed as follows. Given training set $\{x_k, y_k\}, k = 1, 2, \ldots, N$, where $x_k \in \mathbb{R}^n$ is the k'th input data in input space and $y_k \in \mathbb{R}$ is output value for given value of specific input variable (i.e. x_k) and N refers to the number of the training samples. Using nonlinear function $\varphi(\cdot)$, which maps the training set in input space to the high (and possibly infinite) dimensional space, the following regression model is constructed:

$$y = \omega^T \varphi(x) + b \quad \text{with} \quad \omega \in \mathbb{R}^{n_h}, \quad b \in \mathbb{R}, \quad \varphi(\cdot) \in \mathbb{R}^n \to \mathbb{R}^{n_h} \tag{1}$$