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# Connectionist model for predicting minimum gas miscibility pressure: Application to gas injection process

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## HIGHLIGHTS

- Handling extensive MMP dataset with LSSVM approaches.
- Developed approach has lower parameters than other intelligent based models.
- Determination of MMP through gas injection by means of new intelligent approaches.
- Sensitivity of the evolved approaches explicated in details.

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## ABSTRACT

Improving the recovery factor of conventional oil reservoirs is not a far-fetched target when injecting miscible gases is discussed in technical Enhanced Oil Recovery (EOR) plan. Considering the leading role that Minimum Miscible Pressure (MMP) factor plays in the scenario of a miscible gas injection, and the significant impact that it does have on the sweep efficiency of the injected gas is inevitable. Because of the expensive, difficult and time consuming laboratory techniques which are used to obtain the MMP, concluding a quick, robust and cheap solution to measure the MMP has been turned into petroleum researchers' priorities. In the current study, Least Square Support Vector Machine (LS-SVM) and evolutionary algorithms (for example, Genetic Algorithm (GA) and Imperialist Competitive Algorithm), both addressed in previous literatures, have been employed to estimate the MMP. A set of laboratorial data accessible in the open literature was gained to test the reliability of the proposed HGAPSO-LSSVM model which its generated results have been compared with the other proposed intelligent approaches. Moreover, the performances of both implemented solutions certify statistically the strong potential of models in prediction of the MMP.



## 1. Introduction

Gas injection, particularly remarked with $CO_2$ flooding, is a common technique of EOR classified into secondary oil recovery in conventional oil reserves which either technically, through elevating the rate of recovery factor about 15–25%, or environmentally, in terms of storing gases such as $CO_2$ and $N_2$ in the reservoirs, is beneficial [1].

Design of gas injection projects depends intensely on the amount MMP which affects deeply the rate of local displacement efficiency from $CO_2$. MMP is defined as the lowest pressure in which a crude oil and a solvent develop a dynamical miscibility [2–6]. By reaching to the MMP, the displacement is piston-like and the oil recovery is 100% at 1 pore volume of the injected gas, if the displacement process is represented as a one dimensional, two-phase, dispersion-free flow [2–4].

Optimum displacement efficiency of gas flooding happens at displacement pressures greater than MMP where multiple-contact miscibility between the reservoir fluid and the injected gas can be observed [7].

Thanks to serious made attempts in the area of MMP prediction for hydrocarbon (i.e. C1 and C2) and $CO_2$ gases, several precious conclusions and technical issues have been drawn and observed. For instance, applying the high values of MMP increases the

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**Nomenclatures**

*Acronyms*

| | |
|---|---|
| ANOVA | Analysis Of Variance |
| EOR | Enhanced Oil Recovery |
| GA | Genetic Algorithm |
| MMP | Minimum Miscibility Pressure |
| MSE | Mean Squared Error |

*Variables*

| | |
|---|---|
| $C_i$ | hydrocarbon component (e.g., $i = 1$ refers to methane) |
| $c_1$, $c_2$ | trust parameters |
| Int. | intermediate components |
| Mw | Molecular Weight |
| $T$ | reservoir temperature |
| $T_c$ | critical temperature |
| $R^2$ | coefficient of determination |
| Vol. | volatile components |

relevant operational costs while it provides the miscibility development in different processes of vaporizing, condensing and combination of both. In the other hand, low values of MMP decrease the efficiency of the miscible displacement process. Thus, precise assessment of the MMP can potentially result in major economic paybacks [6–11].

The expensive and time-consuming rising bubble apparatus (RBA), slim tube displacement, and pressure composition diagrams are the miscibility evaluator techniques using the parameters with the greatest impacts on the MMP such as the oil composition, oil temperature, and gas composition. To overcome the monetary and time hurdles, substantial cheap and rapid Multiple-contact experiments for slim-tube tests have been suggested although their incapability in determining the MMP for a vaporizing or condensing drive restrictions their utilization for EOR schemes [12,13].

Hence, reducing the required cost and time, in addition to improve the rate of precision and increase the cases of feasibility known as the incentives of working hard on developing alternate techniques such as mathematical models to predict the MMP of gas–oil system [14–16].

As a result, a number of correlations about the prediction of gas–oil MMP have been introduced in the literature. Based on what Benham, Dowden and Kunzmanl did for enriched natural gas MMP, Holm and Josendal (1974) proposed an adaptation for temperature [17]. 1985 is the year that Orr and Silva [18] upraised a model requiring a more complete data on crude oil compositions and Riedel [19] proposed an addition to Benham et al. (1959) model adding compositional effects which results in reducing the amount of error for MMP prediction [17–19].

The analytical models are based on the PVT behaviour of fluids. Such models not only need a characterization procedure of the heavy fraction but also group contribution methods to estimate the critical parameters of the pure components [20]. Moreover, the kij for any cubic EoS routinely used to perform MMP calculations can be estimated by the method developed by Jaubert and Privat [21].

Statistical models are the other attractive field of research, but inflexible presumptions such as linearity, sample size, and continuity block meeting the satisfying goal [7,11,22–25].

After all, great efforts have been put forth to make practical the usage of artificial intelligence based solutions in the estimation of the MMP. In this research, two absolutely different sorts of the referred methods have been applied to predict the MMP according to the Temperature ($T$), Molecular Weight (MW) of the C5 + and Vol./Int. Firstly, GA-LSSVM has been conducted which is an extremely robust technique in comparison with the other methods. Technically, gaining from a few numbers of parameters, having a simple structure and low rate of complexity causes generally running in a shorter time as an analogy which has been drawn between SVM family the other intelligent solutions. Then, a hybrid of LSSVM and Particle Swarm Optimization (PSO), hybrid particle swarm optimization and genetic algorithm (HGAPSO) and Imperialist Competitive Algorithm (ICA) has been follow in the second part of the methodology. The effectiveness of the proposed approaches in predicting experimental gas–oil MMP from the literatures [11,13,24,26–43] has been investigated. The generated results indicate this fact that the implemented models have a better exactness compared with the conventional solutions and tests. Based on the statistical indexes, it was revealed that the HGAPSO-LSSVM is also more reliable than the LSSVM hybrid.

## 2. Least Square Support Vector Machine (LS-SVM)

The original Least Square Support Vector Machine (LSSVM) model was proposed by Suykens and Vandewalle in 1999 dedicated to the first type of support vector machine (SVM) for function estimation and regression. As known for scholars, overfitting one can have with neural networks, svm or ls-svm. To avoid it for svm or ls-svm one applies e.g. 10-fold cross-validation. Consider given inputs $Xi$ (Temperature ($T$), Molecular Weight (MW) of the C5 + and Vol./Int.) and output $Yi$ (Minimum Miscible Pressure (MMP)) time series. Generally, Least Square Support Vector Machine (LSSVM) nonlinear function can be represent as below [44–46]:

$$f(x) = w^T x + b \tag{1}$$

where $f$ depicts the connection between the target variable (Minimum Miscible Pressure (MMP)) and input variables (Temperature ($T$), Molecular Weight (MW) of the C5 + and Vol./Int.), $w$ act for the m-dimensional weight vector, $\varphi$ play the mapping function which plans $x$ into the m-dimensional characteristic vector and $b$ stands for the bias term [44–50].

Owning to the principle of topology minimization, the regression problem may be determined by mulling over the tortuosity of function a fitting error as following expression [45–50]:

$$\mathrm{Min}\ \mathrm{J}(w,e) = \frac{1}{2} w^T w + \gamma \sum_{k=1}^{m} e_k^2 \tag{2}$$

whereas following constraints should be considered [45–50]:

$$y_k = w^T \varphi(x_k) + b + e_k,\ \ k = 1, 2, \ldots, m \tag{3}$$

where $\gamma$ represents the margin parameter and $e_k$ stands for the error variable for $x_k$ [45–50].

Refer for the derivations directly to the LS-SVM work by Suykens [45,46], Least Square SVM regression expressed as follow as [45–50]:

$$f(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{4}$$