Fast and Cost-Effective Mathematical Models for Hydrocarbon-Immiscible Water Alternating Gas Incremental Recovery Factor Prediction

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ABSTRACT: Predicting the incremental recovery factor with an enhanced oil recovery (EOR) technique is a very crucial task. It requires a significant investment and expert knowledge to evaluate the EOR incremental recovery factor, design a pilot, and upscale pilot result. Water-alternating-gas (WAG) injection is one of the proven EOR technologies, with an incremental recovery factor typically ranging from 5 to 10%. The current approach of evaluating the WAG process, using reservoir modeling, is a very time-consuming and costly task. The objective of this research is to develop a fast and cost-effective mathematical model for evaluating hydrocarbon-immiscible WAG (HC-IWAG) incremental recovery factor for medium-to-light oil in undersaturated reservoirs, designing WAG pilots, and upscaling pilot results. This integrated research involved WAG literature review, WAG modeling, and selected machine learning techniques. The selected machine learning techniques are stepwise regression and group method of data handling. First, the important parameters for the prediction of the WAG incremental recovery factor were selected. This includes reservoir properties, rock and fluid properties, and WAG injection scheme. Second, an extensive WAG and water flood modeling was carried out involving more than a thousand reservoir models. Third, WAG incremental recovery factor mathematical predictive models were developed and tested, using the group method of data handling and stepwise regression techniques. HC-IWAG incremental recovery factor mathematical models were developed with a coefficient of determination of about 0.75, using 13 predictors. The developed WAG predictive models are interpretable and user-friendly mathematical formulas. These developed models will help the subsurface teams in a variety of ways. They can be used to identify the best candidates for WAG injection, evaluate and optimize the WAG process, help design successful WAG pilots, and facilitate the upscaling of WAG pilot results to full-field scale. All this can be accomplished in a short time at a low cost and with reasonable accuracy.

INTRODUCTION

Due to the decline of oil production rate during the last decades, several exploration and production (E&P) companies started evaluating and implementing enhanced oil recovery (EOR) technologies. Water-alternating-gas (WAG) injection is one of the proven EOR technologies that have been implemented in several fields worldwide, with an incremental recovery factor typically ranging between 5 and 10%.1

The WAG injection process consists of injecting gas and water alternatively from the same injection well. CO2 and hydrocarbon gases are commonly used for the WAG process. WAG injection is a complex process, as demonstrated by many researchers.2,3 The complexity of the WAG process is related to the frequent change of fluid saturation.4,5

The current practice for evaluating the WAG injection process is using reservoir modeling, which is a very time-consuming and costly approach.2,6,7 The complexity of WAG modeling is related to both the modeling process itself and the complexity of the WAG process.2,3 The standard reservoir modeling approach starts by well and seismic data interpretation, generating structural and petrophysical models, building a three-dimensional (3D) static model, upscaling the fine grid static model, and history matching (HM) the developed reservoir model by tuning static and dynamic inputs. The history matching process requires several iterations between reservoir engineers and Geoscience team to achieve an acceptable HM quality. By the end of reservoir model history matching, a model prediction starts to evaluate different development scenarios. Because of the nonunique solution of a history matching process, the

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prediction profile is uncertain. With an increase in reservoir model complexity, the time and effort required for a reservoir study increase. Reservoir modeling uncertainty, related to the input data, modeling assumptions, data interpretation, selected modeling algorithms, and correlations, is one of the reservoir modeling challenges and limitations. Several attempts were proposed to handle reservoir model uncertainty; however, the proposed approaches are field-specific, time-consuming, and costly; require specific softwares, which are expensive; and are complex, especially for complex and large fields.

Due to the limitations of the WAG modeling approach, the development of alternative fast-effective analytical models was a necessity. Many authors attempted to develop analytical models to predict the WAG performance; however, the published work is field-specific, considers limited variables, is not validated with laboratory/pilot data, predicts WAG ultimate recovery factor but not the rate of WAG incremental recovery factor, and is applicable to WAG management instead of WAG recovery factor prediction.

The objective of this research work was to develop cost-effective mathematical models, based on WAG modeling and machine learning, which can be used as an alternative to reservoir modeling, using 13 predictors that cover rock properties, fluid properties, reservoir parameters, and WAG injection scheme parameters. The models are user-friendly mathematical formulas that relate the WAG incremental recovery factor to the selected 13 predictors, which can help the subsurface team screen the best WAG candidates, evaluate the WAG process with reasonable accuracy and within a short time, design the WAG pilot, and upscale the pilot results to full-field scale.

## MACHINE LEARNING

Machine learning, by definition, is a branch of computer science that enables computers to learn from data, using a different type of algorithm. Machine learning helps in automating decision making, studying patterns, and making a prediction based on available data. The machine learning process can be either supervised or unsupervised. In supervised machine learning, the program is trained based on a predefined set of data. The trained program is then used, which then facilitates the program to be able to draw an accurate conclusion with new data. In unsupervised machine learning, the program finds relationships and hidden patterns given a set of data, i.e., a list of vectors.

The most popular approaches/algorithms in machine learning are artificial neural networks and genetic algorithms.

Artificial neural networks (ANN) are a computing system, which was inspired by brain neural networks. ANN is a nonlinear function approximator, which determines the relationship between the dependent variable and input vectors. The fundamental elements in the neural network are neurons. Neurons are mathematical functions that transform the input data using weights, activations functions, and a set of linear operations such as summations and multiplications. A collection of multiple neurons forms a layer, and the collection of interconnected layers forms the neural networks.

Two machine learning techniques were selected for the development of the WAG incremental recovery factor mathematical models. The selected machine learning techniques are stepwise regression and group method of data handling.

**Stepwise Regression.** Regression is a statistical technique to determine the relationship between two or more variables. The output vector is a dependent variable that is related to one or multiple independent variables. The most straightforward form of regression technique is linear regression. Despite its simplicity, linear regression may not be adequate for a complex nonlinear problem. Hence, nonlinear regression might be required for complex and nonlinear problems. Stepwise regression is a technique that aims to select the model through a step-by-step procedure. Predictors are added or removed based on their importance using statistical significance. The outcome of this process will be a single regression model. A stepwise approach is either through backward or forward propagation. The common progression is the forward approach.

However, few published research papers demonstrated that stepwise regression has multiple drawbacks related to overfitting. It was also found to underestimate the importance of a few features during model construction.

**Group Method of Data Handling.** Group method of data handling is one of the supervised feed-forward self-organizing neural network algorithms. It produces a model looking at the input predictors and the response only. The original vectors are used to build the first neural network layer, using an iterative polynomial regression procedure, with each layer feeding its output vectors to the next layer. The GMDH external criterion preserves superior neurons within each layer for successive generations, yielding an optimum neural network structure.

The structure of the GMDH network is developed based on the predefined criterion, which discards noneffective nodes using a layer-by-layer pruning process.

The GMDH polynomial regression equations are produced using only effective predictors. The quadratic polynomial regression equation developed first by Ivakhnenko is shown in eq 1

\[
y = a + bx_i + cx_j + dx_i^2 + ex_j^2 + fx_i x_j
\]

Here, \(y\) is the output vector; \((x_i, x_j)\) is a pair of input vectors; and \(a, b, c, d, e, \) and \(f\) are the coefficients of the polynomial regression model. These coefficients are determined during the model training process.

**Equation 2** shows the vector—matrix relationship of the GMDH method.

\[
X = \left[ \begin{array}{ccc} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{array} \right] \rightarrow Z = \left[ \begin{array}{ccc} x_{11} & \cdots & x_{1(m-1)/2} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{n(m-1)/2} \end{array} \right] \rightarrow Y \\
\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}
\]

(2)

where \(X\) is a matrix of input vectors and \(Y\) is the response vector.

## RESEARCH METHODOLOGY

To develop HC-IWAG incremental recovery factor mathematical models, the following steps were followed:

- Perform WAG literature review, including WAG modeling and optimization, WAG pilot design and upscaling, and important factors affecting WAG recovery.
- Select the important parameters that demonstrated an impact on WAG recovery, based on literature review, and previously published research work.
- Perform design of experiment (DOE) using two-level full factorial design (FFD), using the selected WAG parameters. The DOE was performed using nine parameters; however, the initial gas–oil ratio was varied afterward, ensuring that the bubble point pressure is lower than the initial reservoir pressure for the constructed undersaturated oil reservoir models,

- Generate and simulate 512 and 512 reservoir models for HC-IWAG and waterflooding processes, respectively,

- Generate a database that consists of the selected 10 predictors, reservoir pressure, pore volume of injected water at WAG start-up, hydrocarbon pore volume of injected gas, and WAG incremental recovery factor,

- Develop a WAG incremental recovery factor using stepwise regression and group method of data handling (GMDH) machine learning techniques. The objective of choosing the two machine learning techniques was to develop mathematical models that are easy to use and calibrate by the subsurface team.

- Test the predictive models using 30% of the WAG modeling data, which was not used in training and validating the predictive model.

- Test the predictive models using published WAG laboratory experiment for a field in India.20

## RESERVOIR MODEL INPUT AND THE SELECTED PARAMETERS RANGES

A reservoir model that consists of two producers and two injectors was used in this reservoir study. Figure 1 shows the permeability distribution of a study reservoir model.

Table 1 summarizes the reservoir input data used during this WAG research study. The original model is a light oil undersaturated sandstone reservoir, with an average permeability of approximately 40 md and porosity of 0.15. The selected variables were updated based on the design of experiment. A total of 512 simulation models were generated for waterflooding. Similarly, 512 simulation models were generated for WAG injection. The study parameters used to develop the WAG incremental recovery factor are summarized in Table 2.

![Figure 1. Permeability distribution for the field used in this research.](image)

![Figure 2. Stepwise regression WAG incremental recovery factor prediction model training results.](image)
Training and Testing. A prediction model was achieved after multiple iterations with a coefficient of determination ($R^2$) of 0.764 for the training set. Figure 2 summarizes the results of the WAG incremental recovery factor model from the stepwise regression method.

The stepwise regression model for WAG incremental recovery factor prediction is shown in eq 3:

$$\text{WAG Incr. RF} = 0.678629 + 1.52161 \times P_{13}^{1/3} \times P_{12}^{1/3} \times P_{11}^{1/3}$$

$$\quad + (51.2051)P_{12}^{1/3} + (-0.56029)P_{11}^{1/3} + 80.8539P_{10}^{1/3} + 0.44602P_{9}^{1/3} + (-2.3262)P_{8}^{1/3} + (-0.329361)$$

$$\quad + 1.753P_{7}^{1/3} + (-64.3765)P_{6}^{1/3} + (-1.34369)P_{5}^{1/3} + (-0.344998)P_{4}^{1/3} + (-0.818857)P_{3}^{1/3} + 2.15251P_{2}^{1/3} + 1.28477P_{1}^{1/3}$$

$$\quad + (-7.17222)P_{0}^{1/3} + (-3.55374)P_{-1}^{1/3} + (0.22168)P_{-2}^{1/3} + (5.2274)P_{-3}^{1/3} + (0.252146)P_{-4}^{1/3} + 0.370326P_{-5}^{1/3}$$

$$\quad + 6.59739P_{-6}^{1/3} + (-0.239071)P_{-7}^{1/3} + (0.678629) + (1.52161)$$

(3)

where $P_1$ to $P_{13}$ are the 13 predictors used in this study.

Group Method of Data Handling Predictive Model Training and Testing. The generated WAG modeling data was divided, similarly to stepwise regression, into training and validation data sets; 70% of the data was used for training the GMDH prediction model, while the remaining 30% was used for testing the model. The developed WAG incremental recovery factor, from the GMDH technique, was achieved after multiple iterations with a coefficient of determination of 0.753 for the training set.

Table 4 and Figure 3 summarize the results of the WAG incremental recovery factor model from the GMDH method. The GMDH model for WAG incremental recovery factor prediction is shown in eq 4:

$$\text{WAG Incr. RF} = 0.0471175 + 0.0632519P_1 + 0.470784P_2 \quad (4)$$

Again, $P_1$ to $P_2$ are the 13 predictors used in this study, where $A, B, C, D, \ldots$ and $P$ are variables described in Table 3.

WAG Predictive Model Testing. WAG incremental recovery factor models were tested using the WAG modeling test dataset, which is 30% of total WAG simulation data. A blind test, using the WAG laboratory experiment for a field located in India, was then performed to assess the prediction capability of the developed HC-IWAG models. WAG laboratory experiment data is shared in Appendix A. Data in Appendix A was extracted from the published conference paper by Ramachandran et al. (Table 4).

Tables 5 and 6 and Figures 4 and 5 show the WAG predictive models testing results. The results indicate that the developed WAG incremental recovery factor models, from both GMDH and stepwise regression methods, are effective when compared with the test dataset. However, the stepwise regression model shows a better prediction performance than the GMDH model for this study.

Table 2. Study Parameters Ranges used in the Design of Experiment

| input variable                  | minimum value | maximum value |
|---------------------------------|---------------|---------------|
| horizontal permeability (md)    | 50            | 1000          |
| permeability anisotropy ($K_h/K_v$) | 0.01          | 1             |
| oil API gravity                 | 25            | 50            |
| gas specific gravity (cp)       | 0.55          | 0.9           |
| water viscosity (cp)            | 0.1           | 1             |
| land coefficient                | 1             | 6             |
| ratio $S_{wi}/S_{wr}$           | 0.2           | 1             |
| WAG ratio                       | 3:1           | 1:5           |
| WAG cycle (month)               | 2             | 24            |
| solution GOR (SCF/STB)          | 350–2000, added post DOE to limit the research work to undersaturated reservoirs only |
and stepwise regression techniques, have reasonable predictability (∼80%). Hence, use of these models can save the WAG modeling time and cut the WAG project cost. Developing reservoir simulation models for WAG evaluation purposes may not reduce the uncertainty on WAG prediction results due to the uncertainty associated with the modeling input and modeling process (Table 7).

### Results and Discussion

For the development of the WAG incremental recovery factor mathematical models, 13 input predictors were selected. The 13 predictors are horizontal reservoir permeability, vertical reservoir permeability, oil gravity, gas gravity, water viscosity, ratio of the residual oil saturation to gas over the residual oil saturation to water, trapped gas saturation, WAG cycle, WAG pore volume of injected gas, WAG pore volume of injected water at WAG start-up, and hydrocarbon volume of injected gas.

The simulated 512 WAG reservoir models demonstrated that WAG incremental recovery factor is typically between 5 and 15% but, however, up to 30% incremental recovery factor was observed from few reservoir models.

A proportion of 70% of the simulated WAG data was used for training WAG incremental recovery factor models, and 30% of the data was used for testing the developed prediction models. The sensitivity on the training—testing split ratio was performed, leading to similar results as the base case split (70 and 30% for training WAG incremental recovery factor models, and 30% of the WAG modeling dataset).

The development of HC-IWAG incremental recovery factor mathematical predictive models with a reasonable accuracy was achieved by the use of neural network-based mathematical predictive models. The effectiveness of the neural network-based mathematical predictive models was further validated by the GMDH model and stepwise regression model testing parameters (Table 5).
achieved, based on WAG modeling and the selected machine learning techniques. The models were tested using WAG modeling test data, which is 30% of the total used WAG modeling data, and a WAG laboratory experiment for a field in India. Stepwise regression and GMDH techniques showed similar model accuracy; however, stepwise regression model is simpler compared to the GMDH model. The capability of stepwise regression technique to develop a predictive model with high accuracy was proven by several researchers.28−32

The developed HC-IWAG models are mathematical expressions that relate the WAG incremental recovery factor to the 13 input parameters. These mathematical models are expected to help the subsurface team screen the best candidates for the WAG process based on their expected WAG incremental recovery factor, conduct feasibility studies by generating preliminary incremental production profiles, evaluate and optimize WAG injection performance for the HC-IWAG process with reasonable accuracy, design a WAG pilot, and upscale the results from WAG pilot or laboratory experiments to the full-field scale. The developed WAG predictive models can be calibrated using the WAG pilot results prior to results upsaling.

Table 7. Prediction Model Input Vectors

| $P_1$ | horizontal permeability (md) |
| $P_2$ | permeability anisotropy (fraction) |
| $P_3$ | API |
| $P_4$ | gas gravity |
| $P_5$ | water viscosity (cp) |
| $P_6$ | $S_{og}$ (fraction) |
| $P_7$ | land coefficient |
| $P_8$ | WAG cycle (months) |
| $P_9$ | solution gas–oil ratio (Sm³/Sm³) |
| $P_{10}$ | WAG ratio |
| $P_{11}$ | pore volume of injected water at WAG start-up (fraction) |
| $P_{12}$ | reservoir pressure (bars) |
| $P_{13}$ | hydrocarbon pore volume of injected gas (fraction) |
The developed WAG predictive mathematical models are expected to overcome few of the limitations of the WAG evaluation current tool (i.e., reservoir modeling), including cutting the cost and the duration of the WAG project evaluation, accelerating the decision making, and incorporating input data uncertainty by running several prediction scenarios within a limited time.

Figure 6 demonstrates the expected application of the WAG incremental recovery factor developed models.

### Table 8. WAG Laboratory Experiment Data

| $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ | $P_8$ | $P_{10}$ | $P_{11}$ | $P_{12}$ | $P_{13}$ | WAG Incr. RF |
|-------|-------|-------|-------|-------|-------|-------|-------|---------|---------|---------|---------|-------------|
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.00        | 0           |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.03        | 1.95        |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.04        | 3.32        |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.08        | 5.27        |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.09        | 8.17        |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.12        | 10.17       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.14        | 12.87       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.19        | 13.47       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.26        | 13.67       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.35        | 13.67       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.40        | 13.27       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.48        | 15.07       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.53        | 15.07       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.61        | 15.07       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.68        | 15.07       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.74        | 14.67       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.80        | 15.07       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.88        | 14.97       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 0.94        | 14.97       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 1.01        | 15.17       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 1.08        | 14.77       |
| 200   | 0.1   | 47    | 1.14  | 0.22  | 0.16  | 6     | 1     | 178     | 1       | 0.7     | 280     | 1.23        | 14.97       |

$P_2$ (vertical-to-horizontal permeability ratio) was assumed 0.1.

The developed WAG predictive mathematical models are expected to overcome few of the limitations of the WAG evaluation current tool (i.e., reservoir modeling), including cutting the cost and the duration of the WAG project evaluation, accelerating the decision making, and incorporating input data uncertainty by running several prediction scenarios within a limited time.

Figure 6 demonstrates the expected application of the WAG incremental recovery factor developed models.

## CONCLUSIONS

It is known that although reservoir modeling is the current tool for predicting WAG incremental recovery factor, it is very costly and time-consuming. In addition, it may also have a high degree of uncertainty. Hence, many studies are planned toward developing analytical models. However, published WAG recovery factor analytical models are limited to the prediction of WAG ultimate recovery factor without predicting the rate of WAG recovery, predicting WAG recovery factor instead of WAG incremental recovery factor, or applicable to WAG management rather than WAG incremental recovery factor prediction.

In this study, WAG incremental recovery factor predictive models were developed with a coefficient of determination ranging from 0.75 to 0.766 for stepwise regression and GMDH techniques, respectively. Even though stepwise regression and GMDH techniques showed similar prediction model accuracies, the stepwise regression mathematical model is simpler compared to the GMDH mathematical model. Here, 13 parameters that captured different input domains (rock and fluid properties, reservoir, and WAG injection scheme) were used for the development of WAG predictive models.

Once the models were developed, a blind test was performed using a WAG laboratory experiment to evaluate their predictive capability. The results demonstrated a good predictability of the developed models, with $R^2$ of 0.8 and 0.81 for stepwise regression and GMDH, respectively.

In this work, it was also shown that the developed predictive models are user-friendly mathematical expressions that relate the WAG incremental recovery factor to the input data. Therefore, these predictive hydrocarbon-immiscible WAG
models are expected to help reservoir engineers screen the best candidates for the WAG process, run a WAG feasibility study, and evaluate full-field WAG with reasonable accuracy. Furthermore, these models can also help engineers not only design WAG pilot location but also facilitate the upscaling of WAG pilot results to the full-field scale. The developed WAG models are applicable to medium-to-light undersaturated oil reservoirs.

**APPENDIX A**

See Table 8

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**NOMENCLATURE**

API oil gravity

D depth (ft)

EOR enhanced oil recovery

FVF formation volume factor (RBBL/STB or Rm³/Sm³)

GOR gas–oil ratio (SCF/STB)

HCVP hydrocarbon pore volume injected (fraction)

K reservoir horizontal permeability (md)

Kv reservoir vertical permeability (md)

n total number of observations

m number of input vectors to the data mining method

P reservoir pressure (psi)

RF recovery factor (%)

Rs solution gas–oil ratio

T reservoir temperature (°C)

WAG water alternating gas

WAG Incr. RF incremental WAG recovery factor

WPVI water pore volume injected

μ oil viscosity (cp)

γ gas gravity

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