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Assessment of Big Data Analytics Based Ensemble Estimator Module for the Real-Time Prediction of Reservoir Recovery Factor

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Abstract

Production of oil & gas depends upon the recoverable amount of hydrocarbon existing beneath the underlying reservoir. Reservoir recovery factor provides of the production potential of ‘proven reservoirs’ which helps the planning of field development and production. Estimation of reservoir recovery factor, with a good degree of accuracy, is still a challenging task for engineers due to the high level of uncertainty, large inexactness, noise, and high dimensionality associated with reservoir measurements. In this paper, we propose a big data-driven ‘ensemble estimator’ (E2) module, comprising of wavelet associated ensemble models for the estimation of reservoir recovery factor. All the ensemble models in E2 were trained on big reservoir data and tested with unknown reservoir data samples obtained from U.S.A. oil & gas fields. Bagging and Random forest ensembles have been utilized to correlate several reservoir properties with reservoir recovery factor. Further, E2 utilizes Relief algorithm to understand the significance of reservoir properties effecting the recovery factor of a reservoir. The proposed E2 module has provided impressive estimation results for the determination of reservoir recovery factor with minimum prediction error. Random forest has given the highest coefficient of correlation (R^2=0.9592) and minimum estimation errors viz. mean absolute error (MAE=0.0234) and root mean square error (RMSE=0.0687). The performance of the proposed E2 module was also compared with conventional estimators viz. Radial basis function, Multilayer perceptron, Regression tree and Support vector regression. The experimental results have demonstrated the supremacy of E2 over conventional learners for the estimation of reservoir recovery factor.

Introduction

Recovery factor provides the estimation of recoverable hydrocarbon existing in the proven reservoirs. Geologists and engineers usually assess the reservoir potential with reasonable certainty under existing economic conditions and available technology. Accurate knowledge about reservoir extent and rate of recovery acts as a guideline for proper planning of hydrocarbon production. Normally, reservoir data are complex, nonlinear, multidimensional and noisy in nature due to heterogeneity. The heterogeneous attribute of hydrocarbon reservoir makes the estimation of recovery factor difficult. Several reservoir variables influence the recovery factor which increases the chances of error significantly. Therefore, advanced techniques are required which can easily minimize the error, handle complex reservoir data and estimate reservoir recovery factor efficiently.

Researchers have made several efforts to establish correlations between reservoir rock properties and recovery factors. American Petroleum Institute (API) (1967) correlated reservoir rock characteristics and the properties of produced fluid with oil recovery factors. API conducted a special investigation to establish the relationship between the oil recovery factor and the well spacing for dolomite, limestone and sandstone formations. Craze et al. (1945) performed a factual study to understand the effects of well spacing on oil recovery using API datasets and suggested important parameters that affect the reservoir recovery factors under consideration. Arps and Roberts (1955) concluded that the ultimate recovery factor is directly proportional to oil gravity excluding the higher solution gas/oil ratio. They also suggested that lithofacies of producing formation and relative permeability have a high influence on recovery factor. Gutherie et al. (1955) used multiple correlation analysis to calculate recovery factor for sandstone reservoirs having water drive mechanism. Musket (1946) established that recovery factors have an inverse relationship with oil viscosity while direct with gas solubility due to oil shrinkage phenomena during hydrocarbons production. API Bulletin D14 (1967) proposed empirical correlations for depletion drive, water driven and solution gas driven reservoirs. It was also specified that the proposed correlations could estimate recovery factors for reservoirs having similar characteristics or behavior. However, in practicality, reservoirs having similar values of OOIP didn't occur naturally. In 1985, API Bulletin D14 (2nd Ed.) gathered actual oil & gas fields data to improve study on oil recovery as compared to 1st edition. Gulstad (1995) applied multiple linear regression for the estimation of recovery factor of Carbonate and Sandstone reservoirs having water drive or solution gas drive mechanism. Oseh and Omtara (2014) estimated the recovery factor of Niger delta using a multilinear regression model. Onolemhemhen and Isehunwa, (2016) proposed an empirical model for the estimation of recovery factor of depletion and water driven reservoir in Niger Delta. All the above-mentioned correlations have limitations and shortcomings owing to complex reservoir data. Therefore, advanced computational techniques are required to estimate the reservoir recovery factor more accurately and efficiently.

Soft computation techniques such as genetic algorithm (GA), fuzzy logic, artificial neural networks (ANNs) and Support vector regression (SVR) have gained popularity in the field of petroleum for detection, optimization, identification and estimation of various properties (Anifowose, 2017; Tewari and Dwivedi, 2018a, Tewari and Dwivedi 2018b). ANNs and SVR have given remarkable results in case of reservoir characterization, lithofacies identification, the classification of drill pipe stuck up, anomaly detection etc. (Anifowose, 2017; Tewari and Dwivedi, 2018a, Tewari and Dwivedi 2018b). However, ANNs suffers from shortcomings such as overfitting, stuck up in local minima, lack of proper architectural guideline, large number of parameters etc. whereas, SVR is found to be unstable (plasticity dilemma) and failed to handle the problem of imbalanced data (Zhang and Ma, 2012; Tewari and Dwivedi, 2018b). To overcome abovementioned issues multiple-learner-system such as Ensemble methods, a committee of machines etc. were proposed in the literature (Polikar, 2006). Ensemble methods are multiple-learner-system that combines the decision of several supervised learners together to provide a final solution for the assigned classification or regression problem. This paper proposes an Ensemble Estimator (E2) Module for estimation of the reservoir recovery factor from reservoir data collected from U.S.A. oil & gas field. The objectives of this research work are given below.

- To develop a robust estimation module for determination of reservoir recovery factor.
- To investigate the performance of existing learners with the proposed module.
- To recognize and properly address the problem of uncertainty, inexactness, high dimensionality and noise associated with reservoir data.

- To evaluate the degree of dependence of various reservoir properties for example relative permeability, OOIP, net pay thickness, porosity etc., on the estimation of reservoir recovery factor.
- To provide guidelines for the application of proposed ensemble learners for the estimation of reservoir recovery factor.

The aim of this research work is to develop Ensemble methods based estimator module in combination with wavelet filters, Relief algorithm and GA for the assessment of reservoir recovery factor with the optimum number of reservoir parameters. The proposed estimation module has also been compared with Radial Basis Function regressor (RBFR), Regression Tree (RT), Multilayer Perceptron (MLP), and SVR to evaluate its performance for the estimation of reservoir recovery factor.

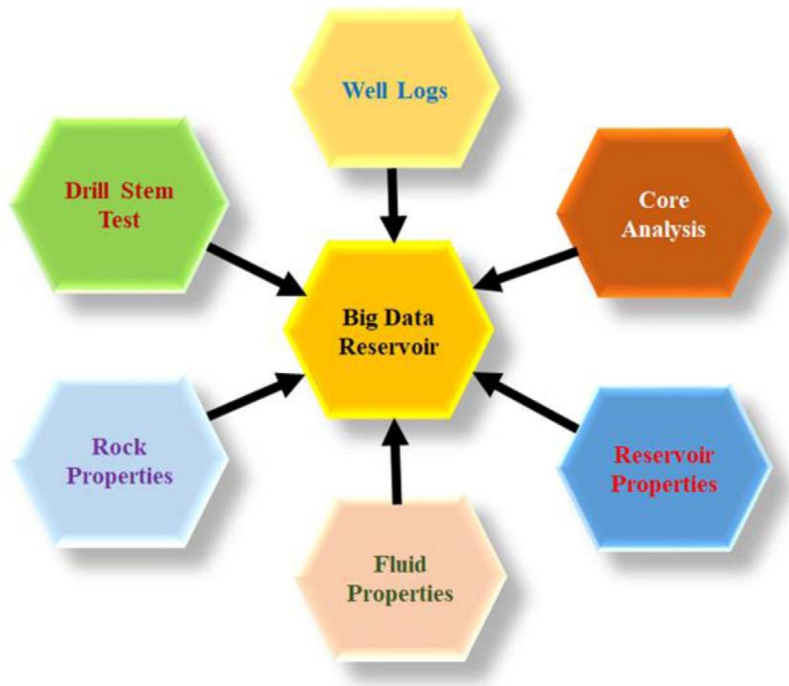

Figure 1—Big input data reservoir collected from different sources for the estimation of reservoir recovery factor.

Ensemble Methods

Ensemble approach is the latest development in the field of machine learning for pattern recognition and big data analytics. Ensemble methods are specially designed to fulfill the requirements of petroleum data analytics viz. feature selection, incremental learning for real-time streaming data, fusion of heterogeneous data from different sources, handling imbalanced data, learning from non-stationary environment etc. (Zhang and Ma, 2012). Ensemble algorithms are inspired by real-world practical situations where the decisions of experts are better than a single expert for a particular task. It combines the decision of several supervised learners together to achieve higher classification and regression accuracy. Ensemble methods focus on bias and variance of input sensor data which have a direct influence on estimation accuracy. It trains several supervise learners simultaneously on a fixed bias of input data and then combines the decisions in such a way that reduces the associated variance of data while information content remains unaffected (Polikar, 2006). Dietterich (2000) mathematically proved that multiple-learner-system viz. Ensemble methods are superior to a single learner system. Ensemble methods are made up of three main segments viz. data selection (diversity in data), training of base learners and combining decision of base learners. Decisions of base learners are combined together using several combination strategies such as majority voting rule, weighted majority voting, Algebraic combiners, Borda count etc.(Zhang and Ma, 2012). Supervised algorithms are found to be more stable in sense of memory plasticity dilemma when used as base learners such as SVR. Ensemble approach can be implemented in several ways such as random selection or sampling of input training data and feature space, manipulation of error function etc. Several ensemble methods have been reported with diverse architectures such as Bagging, Random forest, Random subspace, Stacking generalization, Adaboost etc. In this study, Bagging and Random forest algorithms have been tested for the estimation of recovery factor from reservoir data.

Bagging: Bagging ensemble is also known as Bootstrap Aggregating because it combines the benefits of boosting and aggregating techniques (Breiman et al., 1996). It generates random independent samples with replacement utilizing boosting technique for simultaneously training of base learners (Skurichina et al., 2002). Later, decisions of base learners are combined together using various aggregating techniques viz. majority voting rule or averaging the decisions of base learners.

Random forest: Random forest is a prolongation of Bagging ensemble. Random forest algorithm has certain advantages such as handling of prediction and classification tasks, lesser training and fast prediction time, less number of tuning parameters, built-in assessment of generalization error, easy processing of high dimensional data, found suitable for small as well as large datasets etc. Random forest utilizes decision trees as a base learner for pattern recognition problems. It constructs a swarm of decision trees using bootstrap samples during the training phase and outputs the average prediction of decision trees. It also provides a good estimate of prediction error as out-of-bag error and error rate (Breiman et al., 2001).

Table 1—Distribution of data used for research work (Gulstand, 1995).

S. No.	Type of reservoir	Number of data points
1.	Water drive for Sandstone reservoirs	128 samples
2.	Water drive for Carbonate reservoirs	30 samples
3.	Solution gas drive (at the bubble point) for Sandstone reservoirs	139 samples
4.	Solution gas drive (at the bubble point) for Carbonate reservoirs	70 samples

Table 2—List of reservoir parameters used for Solution drive and Water drive mechanisms for recovery factor estimation.

S. No.	Variables	Units	Minimum	Maximum	Rank	Weight
1.	Original-oil-in-place at initial pressure as reported by the operator (OOIP)	STB/NAF	57	2146	1	0.062355
2.	Calculated (OOIPcal)	STB/NAF	55.29	212.47	2	0.056851
3.	Rock permeability to air (K)	Darcies	0.1	2970	3	0.036505
4.	Oil viscosity at bubble point (Ubp)	Centipoise	0	80	4	0.028659
5.	Oil viscosity at Abandonment pressure (Uoa)	Centipoise	0	150	5	0.024084
6.	Oil viscosity at initial pressure (Uoi)	Centipoise	0.1	92	6	0.022439
7.	Net pay thickness (h)	ft	0	1100	7	0.020911
8.	k/Uob ratio	Dimensionless	0.05	4500	8	0.017914
9.	Oil Gravity (API)	API	14	54	9	0.015224
10.	Oil Formation Volume Factor (Bo)	RB/STB	80	7707	10	0.006191
11.	Temperature (T)	Degree F	72	270	11	0.001694
12.	Water viscosity (Uw)	Centipoise	0.012	1.3690	12	0.000827
13.	Oil Formation Volume Factor at abandonment pressure (Boa)	RB/STB	0	2.75	13	0.000471
14.	Pressure at the end of Primary (Pep)	psig	10	6000	14	0.000167
15.	Effective Porosity (Por)	%	0.0180	120	15	0.000049
16.	Pressure ratio (Pb/Pa)	Dimensionless	0.63	500	16	-0.00272
17.	Initial reservoir pressure (Pi)	psig	14	9030	17	-0.00371

S. No.	Variables	Units	Minimum	Maximum	Rank	Weight
18.	Solution gas ratio at abandonment pressure (Rsa)	SCF/STB	0	2741	18	-0.00395
19.	Bo at bubble point pressure (Bob)	RB/STB	0	3.2	19	-0.00443
20.	Connate water saturation (Sw)	fraction	0	0.7	20	-0.00475
21.	Solution gas ratio at bubble point (Rsb)	SCF/STB	0	3539	21	-0.00772
22.	Solution gas ratio at initial reservoir pressure (Rsi)	SCF/STB	0	3539	22	-0.00801
23.	Bo at initial pressure (Boi)	STB/NAF	1.034	2.9	23	-0.01152
24.	Recovery Factor (RF)	STB/NAF	0	908	Nil	Nil

Experimental Evaluation

The experimental data used for this research work were acquired from the literature (Gulstad, 1995; Craze and Buckley 1945). The dataset contains original 367 reservoirs of Sandstone and Carbonate lithological character, out of which 209 reservoirs have a dominant solution gas drive mechanism while 158 reservoirs yield through water drive mechanism as listed in Table 1. The reservoir parameters used for this study are listed in Table 2. The computational architecture of the proposed E2 module has been implemented using WEKA and MATLAB, which are well-established platforms for machine learning and data mining (Hall et al., 2009; Tewari and Dwivedi, 2018b).

Ensemble Estimator Module

The proposed E2 module is inspired from earlier reported intelligent ADD framework to handle complex reservoir data (Tewari and Dwivedi, 2018a). The proposed module consists up of three computational layers viz. the preprocessing layer, model development layer and post-processing layer. In preprocessing layer, resampling was done to eradicate any data sample having missing values. Further, resampled data was normalized to reduce the dominance of samples having large values. After normalization, Haar wavelet was utilized to reduce the noise associated with reservoir data followed by feature extraction using Relief algorithm (Dwivedi and Singh, 2006; Dwivedi et al., 2008; Dwivedi and Singh, 2009a; Dwivedi and Singh, 2009b). Relief algorithm also helps to understand the relevance and contribution of each input predictor variable for the estimation of reservoir recovery factor (Tewari and Dwivedi, 2018a). It allocates rank and importance predictor weight to each reservoir variable according to their contributions in pattern recognition of reservoir recovery factor. Training samples were considered randomly after feature extraction to generate 10 sets of training (70%) and testing (30%) datasets using 10-fold cross-validation technique to reduce the chances of overfitting. The performance of machine learning models depends upon the quality, reliability and amount of training data.

In the model development layer, processed input reservoir data were applied for training and testing of Ensemble methods viz. Bagging and Random forest. A cluster of hundred SVRs was utilized as base learner's algorithm in Bagging ensemble. The hyperplane parameters of SVR were optimized separately using Genetic algorithm to obtain the generalized performance of Ensemble methodology. However, a cluster of hundred Decision trees was used as base learners for Random forest in place of SVRs. The performance of the proposed module was evaluated using three statistical parameters as given below.

A. Coefficient of correlation (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(RF_m - RF_p\right)^2}{\sum_{i=1}^{n}\left[RF_m - \frac{1}{n}\sum_{i=1}^{n}\left(RF_m\right)\right]_i^2} \tag{1}$$

B. Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RF_m - RF_p\right)^2} \tag{2}$$

C. Mean absolute error (MAE):

$$MAPE = \frac{1}{n}\sum_{i=0}^{n}\left|\frac{\left|RF_m - RF_p\right|}{RF_m}\right| \tag{3}$$

where RFm is measured recovery factor whereas RFp is predicted one. The coefficient of correlation (R^2) is a good measure of the estimation capability of machine learning estimators. Value of R^2 varies from 0 to 1, where value nearer to one indicates good estimation results. RMSE and MAPE are widely accepted error evaluating criteria for estimation model and utilized in findings. The performance of E2 was also compared with other popular machine learning techniques such as RBFR, RT, MLP, and SVR to show the superiority of the E2 module.

In post-processing layer, the optimally tuned Ensemble model was tested on unseen or new data samples to evaluate its effectiveness and robustness. The optimum model parameters were saved during model development layer. The optimized E2 module can be employed to predict the recovery factor for any type of reservoir formations.

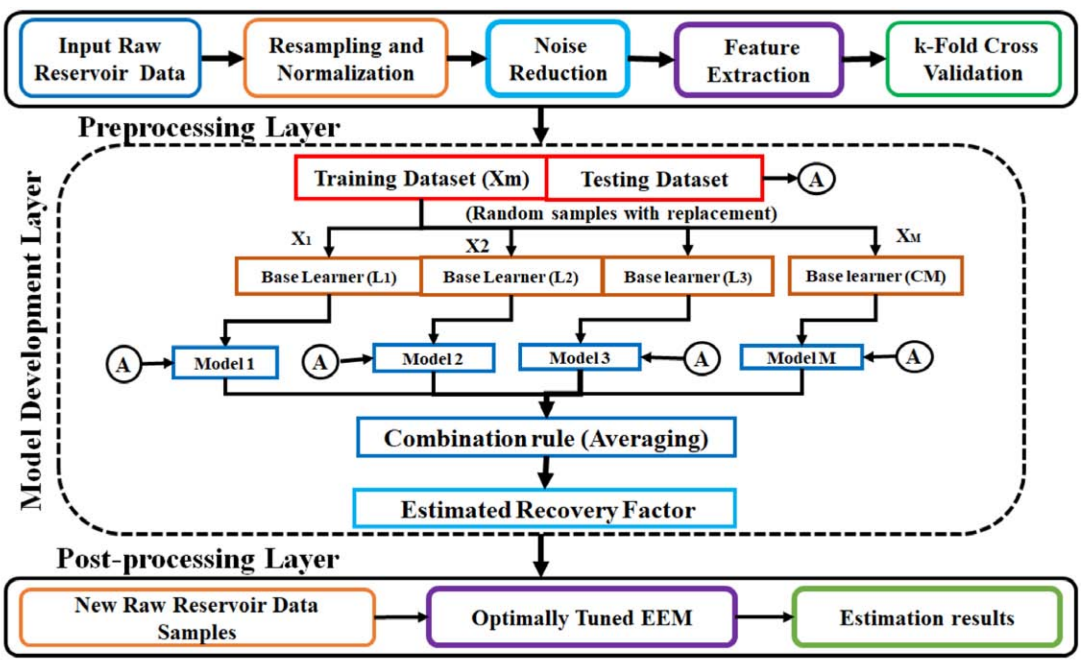

Figure 2—The proposed Ensemble Estimator Module based on Bagging ensemble for the estimation of reservoir recovery factor.

Results and discussion

The real-field reservoir data utilized in the research were found to be complex, nonlinear, noisy, and highly dimensional in nature. Heterogeneous nature of hydrocarbon reservoir contributes to complexity, nonlinearly and uncertainty in all the reservoir measurements. However, there are no standard tools or techniques available in present scenario that can measure the reservoir heterogeneity or its influence on other reservoir properties. Therefore, twenty-three reservoir measurements, acquired from different sources, have been used as variables in the input data for correlating recovery factor of the reservoir as shown in Table 1 and Fig. 1. The input data utilized in this study were real performance data of U.S.A. oil and gas fields as shown in Table 1 and Table 2. The input data were collected from well logs, core analysis, sensors, and drill stem tests performed during real field operations. It was observed from the collected data that reservoirs having water drive production show a higher rate of recovery as compared to reservoirs containing solution or gas cap drives. The input reservoir data suffer from the issue of high dimensionality that increases the computational cost of the proposed E2 module for the estimation of reservoir recovery factor. E2 utilizes Relief algorithm for the reduction of dimensionality of input data and understands the importance of each input variables for the estimation of recovery factor. It ranked the applied features or input variables according to their contribution in pattern recognition for reservoir recovery factor as shown in Table 2 and Fig. 3 (K=70). It was found that original-oil-in-place had the highest contribution to the estimation of reservoir recovery factor whereas effective porosity had lesser contribution. Input variables having negative weights were eliminated from the input dataset. Out of twenty-three reservoir variables, only fifteen variables were found suitable for our purpose. Original-oil-in-place, relative permeability, oil viscosity, net pay thickness, and oil gravity were top five contributing features or variables identified by Relief algorithm for the estimation of reservoir recovery factor.

The performance of machine learning models depends upon the quality, reliability and amount of training data. The input reservoir data were resampled, normalized, de-noised, and compressed in preprocessing layer. The processed data were distributed into the training and testing sets using the 10-fold cross-validation technique to reduce the chances of overfitting. In the model development layer, parameters of base learners were optimized separately to achieve the maximum regression accuracy and to minimize estimation error. Ensemble methods also reduce the variance associated with decisions of base learners in final estimation results of recovery factor. The optimum parameters of ensemble methods were saved for post-processing layer (Bagging-SVR, C=100, Gamma=0.001, epsilon=0.01, kernel=Radial Basis Function, Base learners =100; Random forest-Decision tree, base learners =100, random split = yes, out-of-bag-estimation=yes). Random forest has achieved highest estimation accuracy followed by Bagging ensemble (Random forest-Decision tree, R^2=0.9592, MAE=0.01023, and RMSE=0.0465; Bagging-SVR, R^2=0.9345, MAE=0.0234, and RMSE=0.0687). The performance of Ensemble methods was also compared with other popular machine learning models as shown in Table 3. The optimally tuned Ensemble model was tested on additional unseen or new reservoir data samples in the post-processing layer to evaluate the robustness of proposed E2.

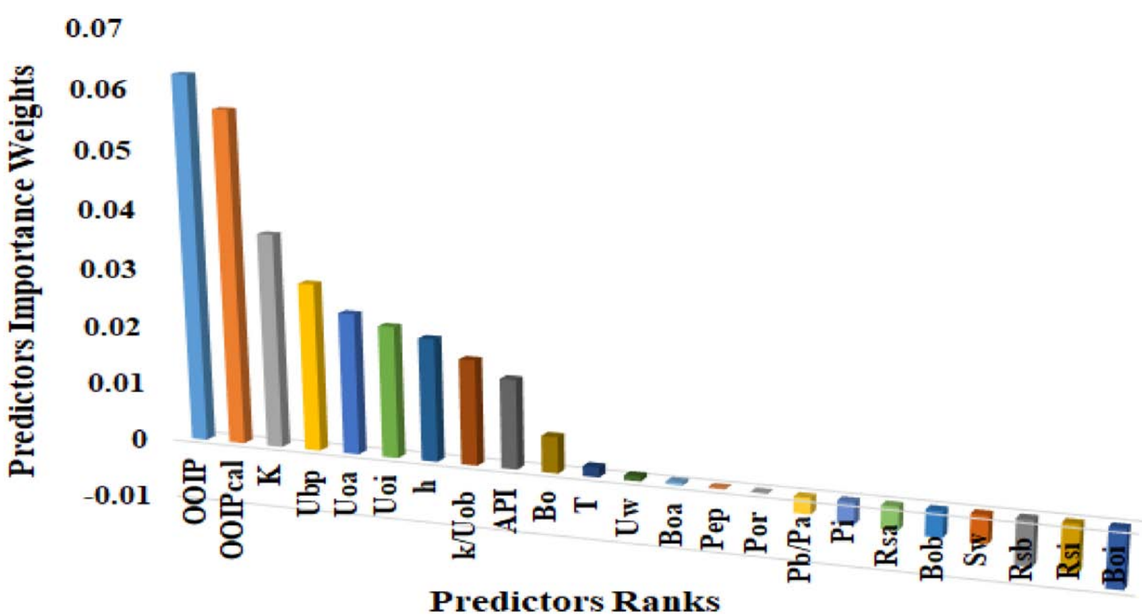

Figure 3—Input reservoir variables are arranged in increasing order of their predictor importance weights.

Table 3—The comparison of different machine learning algorithms utilized for the estimation of reservoir recovery factor.

S. No.	Learning Algorithm	R^2	MAE	RMSE
1.	RBFR	0.5946	0.0759	0.1207
2.	RT	0.5709	0.0753	0.1196
3.	MLP	0.6256	0.077	0.1177
4.	SVR	0.8154	0.0547	0.0841
5.	Bagging	0.9345	0.0234	0.0687
6.	Random Forest	0.9592	0.01023	0.0465

Conclusion

A novel computational module (E2) based on Ensemble methods has been proposed for the estimation of reservoir recovery factor. The performance of four other popular supervised algorithms is also compared with the proposed module. Random forest has achieved the highest estimation accuracy as compared to other machine learning algorithm. This study also suggests that original-oil-in-place has a major influence on the reservoir recovery factor in pattern recognition whereas effective porosity has relatively lesser contribution. The contributions of this research work are given below.

- E2 has successfully handled complex reservoir data and estimated the information of reservoir recovery factor.
- Fifteen reservoir variables are identified as important elements that contribute to recovery factor estimation.
- Original-oil-in-place, relative permeability, oil viscosity, net pay thickness, and oil gravity are identified as top five contributing elements influencing reservoir recovery factor.
- The proposed E2 framework has been designed to handle complexity added due to the heterogeneous behavior of the reservoir.
- In the study, E2 has emerged as the robust and reliable estimator for extracting information from complex reservoir data.

The results clearly indicate that Ensemble methods can be utilized to estimate the reservoir recovery factor and have the potential for solving the real oil & gas field's problems. The three computational layers described in this research work are important to handle nonlinearity, noise, and high dimensionality of reservoir data to achieve more generalize performance of Ensemble models. This study has increased the possibilities of interdisciplinary work in petroleum engineering domain.

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