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IMPLEMENTATION OF SUPPORT VECTOR MACHINES FOR PREDICTION OF PVT PROPERTIES IN CRUDE OIL SYSTEMS

For the development of advanced strategies of the oil reservoir, the importance of the accurate prediction of the PVT (pressure-volume-temperature) features is great. .In the paper, Support Vector Regression (SVR) machine learning method is used for the prediction of Pb which is one of the most important parameter of Pressure-Volume-Temperature (PVT) properties in oil fields.

The accurate determination of the PVT properties of the reservoir fluids, such as bubble point pressure (Pb), solution gas-oil ratio (Rs) and oil formation volume factor (Bob), is necessary for the formation evaluation of hydrocarbon reserves, reservoir performance, material balance calculations, well test analysis, numerical reservoir simulations calculations. Ideally, the PVT properties can be obtained by laboratory PVT tests. Or estimated by using equations of state (EOS) and empirical correlations [1]. Exists is a sufficiently large number of correlation equations characterizing the oils of a various oilfield. The correlation functions of the following authors are most popular: Standing (1947); Vasquez and Beggs (1980); Al-Marhoun (1988); Dokla and Osman (1988); Labedi (1992); Beggs and Robinson (1975); Glaso (1980) and etc [2]. There is a need for the development of new approaches to improve predictions because empiric correlations are usually unsatisfactory in the prediction of PVT properties. In this case, there is a need for methods of machine learning or deepth learning [3].

In this model P_b was presented as function of four input parameters: solution gas–oil ratio (R_s) reservoir temperature (T), oil gravity (γ_o), and gas relative density (γ_g). The functional dependence of these parameters can be expressed as follows:

$$\boldsymbol{P}_b = F\left(T, \gamma_o, \gamma_g, \boldsymbol{R}_s\right).$$

The experiments have been conducted with applying selected RBF nuclear function of SVR on Middle East dataset in literature [1].

Experiments were conducted using python programming language (jupyter notebook) on Linux OS (Ubuntu Desktop 16.04) with 1.7GB RAM, Intel(R) Core(TM) i5-2400, 64bit prosessor, 3.10GHz CPU properties. MATlab is used for visualize of results.

In this work 160 oil samples of Middle East oil were used for research [1]. 112 samples of this dataset was used for training and 48 samples was used for testing. In order to get high accuracy, dataset was scaled in [0,1] range, and applied k-cross validation.

The SVR-RBF model implementation is shown in Fig. 1.

```
Imput: dataset as D[i,j] # a matrix with 160 rows and 5 columns
Output: predicted Pb values # a matrix with 48 rows and 1 columns
import modules #import modules.
    for i=1 to 160
      for j=1 to 5
    begin
scale Di,j;# scale dataset.
    end.
    for i=1 to 112
      for j=1 to 5
    begin
    D1=Di,j; #split from dataset for training end.
    for i=113 to 160
      for j=1 to 4
D2=Di,j;# split from dataset for testing
    end.
Train D1;# train SVR on D1.
Test D2;# testing on D2.
Evaluate (MAE, RMSE, R^2); # calculate evaluation metrics.
Print(MAE, RMSE, R^2); #print evaluation metrics.
Plot D2. # visualization of results.
```

Fig. 1. Steps for the RBF nuclear function of SVR

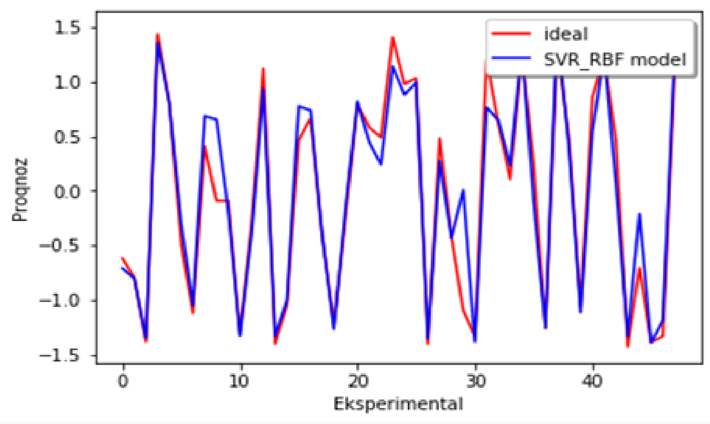

Fig. 2. The performance of SVR-RBF in P_b prediction

Three kernel functions of SVR (SVR-RBF nuclear function, SVR-linear nuclear, SVR-polynomial nuclear) were used to evaluate model. The performance of SVR-RBF in Pb prediction for the Middle East oil is shown in Fig. 2.

Three statistical quality indicators (correlation coefficient- R2, root mean square error- RMSE and mean absolute error- MAE) were used to predict Pb. The comparative analysis of the gained results has been conducted with five (Standing, Dokla & Osman, Macarcy & El-Batononey, Khairy, Petrosky & Farshad) exist empiric correlations (table 1). Graph plots of the mean absolute error (MEA) versus the correlation coefficients (R2) for modeling schemes are shown in Fig. 3 for predicting Pb.

correlation	MAE	RMSE	R^2
Standing	0.164	0.217	0.973
Dokla & Osman	0.290	0.380	0.820
Macarcy & El-Batononey	0.221	0.297	0.886
Khairy	0.565	0.688	0.509
Petrosky & Farshad	0.137	0.178	0.967
SVR-RBF	**0.136**	**0.197**	**0.985**

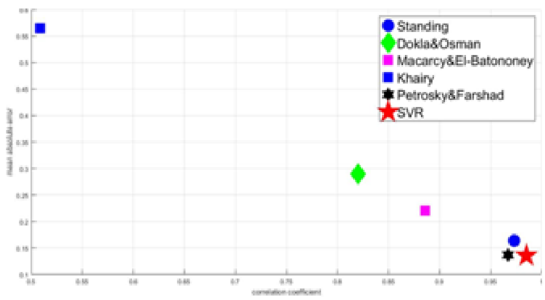

Figure 3. the mean absolute error (MEA) versus the correlation coefficients (R^2) for modeling scheme.

SVR RBF kernel function showed high accuracy (highest correlation coefficient, lowest root mean square error and mean absolute error) to predict P_b than others. At the end of the analysis it was clear that suggested model showed more accuracy result with 0.985 correlation coefficient than other correlations.

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DIGITAL ON-AIR BROADCASTING SYSTEM'S NOISE IMMUNITY LEVEL ESTIMATION METHOD, BASED ON CONSTELLATION DIAGRAM IMAGES

The following text contains information on the method of increasing the level of noise immunity for digital broadcasting systems and on estimating the noise immunity of DVB-T2 standard systems based on the image of constellation diagrams.

For estimation of digital on-air broadcasting systems (DTV) quality is decided to measure the number of basic parameters. First of all, one needs to understand, whether the signal strength at the receiver is sufficient, because signal reception quality directly depends of it. If the level is low, it means, that there is no reliable reception, therefore, there is no sound and image. One of the important parameters of digital systems is MER (Modulation Error Ratio), it can be correlated with the signal / noise ratio in analog communication systems. Third parameter is BER (Bit Error Ratio). It describes occurrence frequency of mistaken-