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OIL PRODUCTION PREDICTION USING WELL TEST DATA

In this paper, the oil production forecasting method by using data obtained from virtual pressure gauges is proposed. The proposed method is based on the deep learning constructed by the combination of 3 convolution layers of CNN.

Consider a time series $\{x(t_i)\}$ and $\{y(t_i)\}$ are given. And assume that $x(t_i)$ is a m dimensional vector of input features and $y(t_i)$ is a n dimensional vector of output features. The forecasting the sequences of output features of length l_0 using the sequences of input features of length l_i is required. The CNN maps an input sequence $x(t_k), ..., x(t_{k+l_i-1})$ to the output sequence $\hat{y}(t_{k+l_i}), ..., \hat{y}(t_{k+l-1})$ for $k = 0, ..., N$ via activation functions. By iteratively updating the weights of the transformation functions, the minimization of a loss function is conducting, which penalizes the distance between the output and the target sequences. The proposed CNN model architecture has the following blocks (fig. 1).

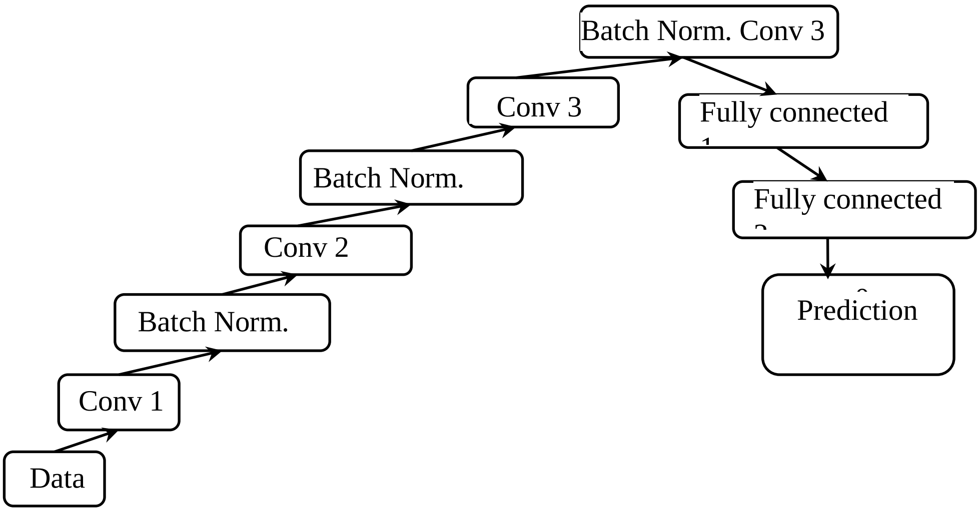

Fig. 1. Deep learning approach for oil production forecasting

The implementation of the method is conducted on the Python and Tensorflow. In this study, for implementation and experiments, the data taken from https://github.com/nikolai-andrianov/VFM/. These data are data obtained from *virtual pressure gauges* to predict oil production and describes the flow rate of the liquid and gas. The flow rate in the dataset is recorded by every 1 second and DateTime, Pressure (bar), Temperature (degC), Qo (m3/day), Qw (m3/day), Qg (m3/day) are features of the dataset. The data in a dataset is represented by time series as a flow. The prediction model is constructed based on improved CNN algorithm. The detection accuracy and test results for various metrics of the improved CNN model are shown in table.

Table

Prediction results of proposed CNN

Prediction model	Train loss	Test loss	Train accuracy	Test accuracy
Proposed 3 layer CNN	0.36	0.37	0.752	0.736

As shown from the results of experiments in Table 1, the improved CNN have produced well results. The experiments are conducted by changing the parameters and for the obtaining optimal results from CNN the network details of the proposed model is constructed are as follows: 1) Deep CNN with 3 conv layers 2) 4712 row for train data, 3142 rows for test data is used, number of input features m = 1, . . . , 7 and number of output features n = 1. 3) Cross entropy loss function and Adam optimizer with batch size of 64 and number epochs equal to 60000, dropout = 0.2, learning_rate = 0.001. 4) A number of filters in first conv layer is 16, in second conv layer is 14, in third conv layer is 8, the number of neurons in the fully connected layer is 40.

In this work, as mentioned above, adding various layers to the proposed CNN model very high results are obtained. So, the training of the proposed in this study the CNN model is conducted very good, and according to the Train Loss parameter, the loss parameter achieved 0.36 value, according to train accuracy parameter the network is trained with 0.752 accuracies. Here during testing is also a good result achieved. Thus, the Test loss and Test accuracy parameters of the model has obtained the 0.37 and 0.736 values, respectively. It seems here, that the training and testing of the proposed model are conducted very well. There is not big jumping between training and testing phases. As in the training phase the model is trained with the high accuracy, in the test phase it also is predicted the points with high accuracy. The prediction accuracy of the proposed CNN model is visualized in Figure 2.

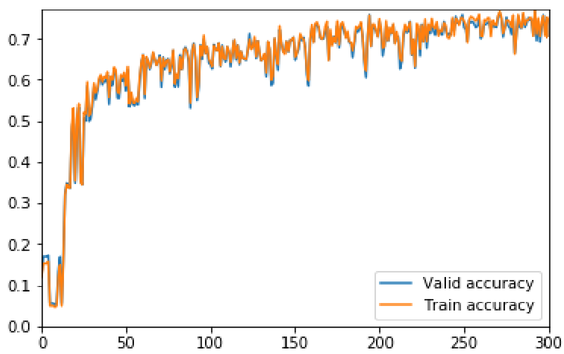

Fig. 2. Prediction accuracy of proposed CNN

Here the training curve is the almost complete overlap of the validation curve. In good prediction models, the dynamics of the validation line must be in the direction of the train line and should be as close to it as possible.

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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