ЖАРАТЫЛЫСТАНУ ЖӘНЕ ТЕХНИКАЛЫҚ ҒЫЛЫМДАР

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FORECASTING OIL PRODUCTION USING LSTM NETWORKS CONFINED TO DECLINE

Abstract. Natural resources are limited and very important in our industrial life and development. Oil is considered as the black gold and it is included in hundreds of industrial fields. Therefore, forecasting future oil production performance is an important aspect for oil industry. In this study, we proposed improvements to the existing deep learning model in order to overcome limitations associated with the original model. For evaluation purpose, proposed and original deep learning models were applied on a real case oil production data. The empirical results show that the proposed adjustments to the existing deep learning model achieves better forecasting accuracy.

Keywords: Oil Production Forecast, Long-Short Term Memory, Decline Curve Analysis.

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Аңдатпа. Табиғи ресурстар шектеулі және біздің өндірістік өмірімізде және дамуымызда өте маңызды. Мұнай қара алтын болып саналады және ол жүздеген өнеркәсіпте паидалынады. Сондықтан мұнай өндірісінің болашақтағы көрсеткіштерін болжау мұнай саласы үшін маңызды аспект болып табылады. Осы зерттеуде біз түпнұсқа модельмен байланысты шектеулерді еңсеру үшін қолданыстағы терең оқыту моделін жетілдіруді ұсындық. Мұнай өндірісінің нақты деректерінде бағалау мақсатында ұсынылған және түпнұсқалық терең оқыту модельдері қолданылды. Эмпирикалық нәтижелер қолданыстағы терең оқыту моделіне ұсынылған түзетулер болжамның дәлдігіне жететінін көрсетеді.

Түйін сөздер: Мұнай өндірісінің болжамы, ұзақ мерзімді жад, өндірістің төмендеу қисығын талдау.

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Аннотация. Природные ресурсы ограничены и очень важны в нашей промышленной жизни и развитии. Нефть считается черным золотом и используется в сотнях промышленных областях. Поэтому прогнозирование будущих показателей добычи нефти является важным аспектом для нефтяной промышленности. В этом исследовании мы предложили усовершенствования существующей модели глубокого обучения, чтобы преодолеть ограничения, связанные с исходной моделью. Для целей оценки предложенные и оригинальные модели глубокого обучения были применены на реальных данных добычи нефти. Эмпирические результаты показывают, что предлагаемые корректировки существующей модели глубокого обучения обеспечивают лучшую точность прогнозирования.

Ключевые слова: Прогноз добычи нефти, долгая краткосрочная память, анализ кривой падения добычи.

Introduction

Until the middle of the XIX century oil was produced in small quantities, mainly from shallow wells near its natural outlets to the surface of the earth. Since the second half of the XIX century demand for oil began to increase due to the widespread use of steam engines and the development of other industries, which posed complex problem of future oil production pattern. Historical and most common approach in solving this problem is Decline Curve Analysis (DCA) [1]. By identifying decline rate, DCA extrapolates past production in order to estimate expected production in the future. The main limitation of this tool is the linear statistical approach, which generally produce a poor fit on historical production data. Hence, in order to improve fitting curve, more accurate nonlinear model is required.

In the last couple of decades, deep learning models have been widely used with non-stationary data prediction, like economics, weather, stock price, and retail sales. Similarly, several studies in predicting oil production using deep learning algorithms such as Long Short-Term Memory (LSTM) were completed. However, despite its performance, deep learning models are still in infancy stage and requires further analysis in using during oil production prediction.

In this paper, we analyzed application of the existing deep learning model [2] on a real case oil field data from the western part of Kazakhstan, and compared to the proposed model which is a combination of traditional DCA and deep learning models. Empirical results showed that latter model outperformed its counterparts.

Related Works

In [3] it was demonstrated that using increased depths of LSTM networks improve overall performance of time series forecasting. Encouraged by these results authors in [2] developed Deep LSTM (DLSTM) network with stacked three LSTM blocks one after another in Petroleum Production Forecasting (Figure 1: Architecture of DLSTM recurrent network). The paper empirically shows that proposed model outperforms some other algorithms such as ARIMA, NEA, RNN, DGRU in describing the nonlinear relationship of petroleum time series data.

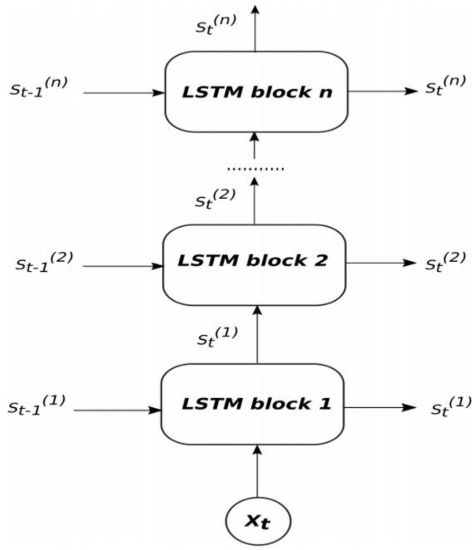

Figure 1: Architecture of DLSTM recurrent network

However, two major concerns of this model should be noticed. First one is an evaluation of a model accuracy using testing data set (original data is split into train and test sets). Authors created data batches using certain time lag period and predicted next time series data using the last batch from the dataset (Figure 2: Included evaluation approach). This is not the best approach in validating the model, since the assumption of using unseen data during the testing stage is not valid anymore. The second drawback of the proposed model is the fact that known trend of any oil production data, which is decline over the time, is not captured in the model. This can result in unrealistic output over the long-term forecasting (Figure 3: DLSTM output results).

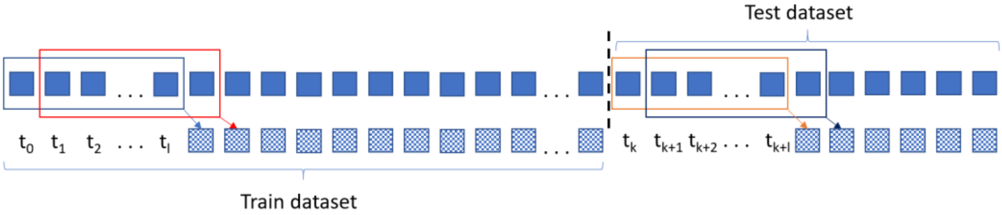

Figure 2: Included evaluation approach

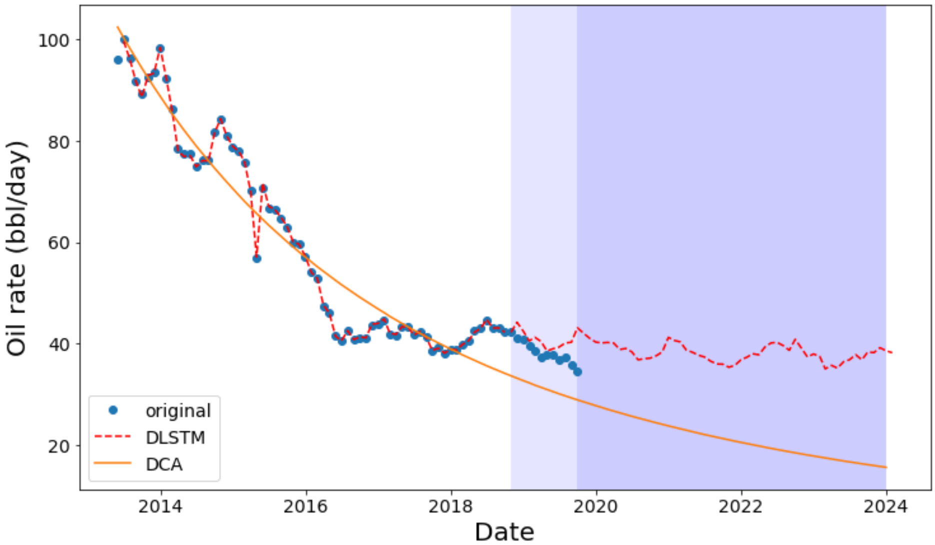

Figure 3: DLSTM output results

Proposed Model

The main reason why DLSTM Model fails in following decline trend is the fact that during removing the trend of historical production curve difference of consecutive data was applied. This approach does not constrain the general curve to decline over the time. In the proposed model, constrain to decline is achieved by taking the difference between production data and general exponential decline, and only then apply DLSTM model. Therefore, deviation of historical production data from general decline curve is modelled.

In addition to that, for making fair evaluation model accuracy was estimated using mismatch between unseen test data and pure predicted output as shown in the Figure 4: Proposed evaluation approach below.

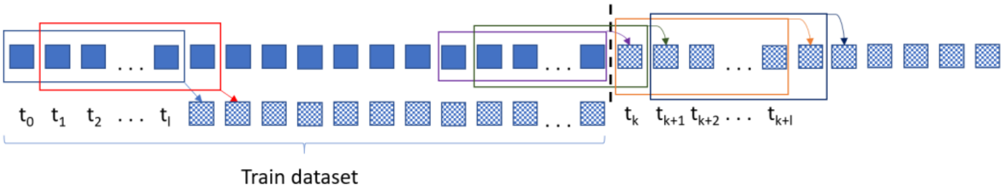

Figure 4: Proposed evaluation approach

Experimental Results

After de-trending historical production data using overall decline and applying DLSTM model explained in [2], it is possible to achieve better fit to the test datasets. At the same time, future predictions from DCA-DLSM model follow general trend of conventional decline pattern (Figure 5: Proposed DCA-DLSTM output results).

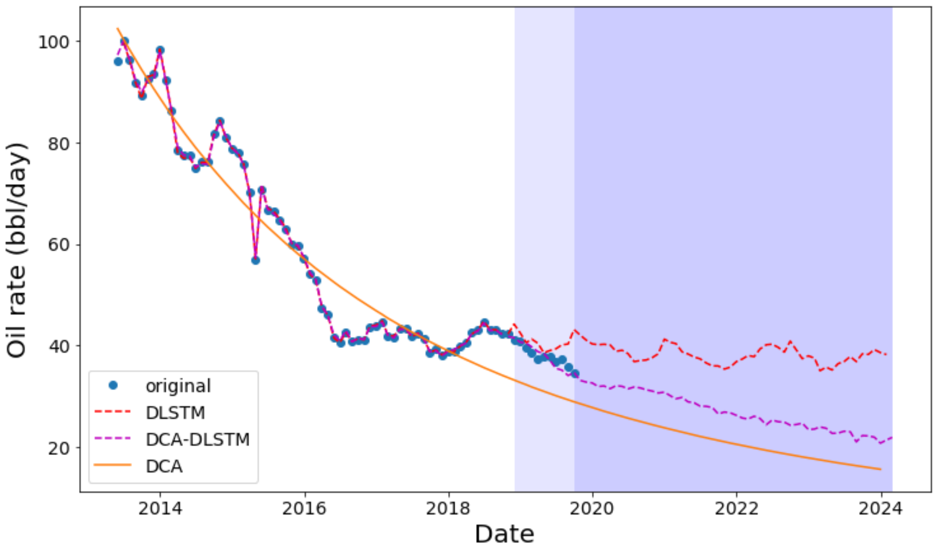

Figure 5: Proposed DCA-DLSTM output results

To control the learning process and evaluation accuracy of the proposed method, the root means square error (RMSE) was used. The RMSE is a frequently used measure of the differences between values (sample or population values) predicted by a model and the values observed [4]. It represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences.

$$E_{RMSE} = \sqrt{\frac{1}{n}\sum(y-\hat{y})^2}$$

Table 1: Forecasting accuracy

Forecasting Model	**RMSE**
DCA	5.8
DLSTM	3.65
DCA-DLSTM	**0.53**

As can be seen from the Table 1*: Forecasting accuracy*, in the assessment of oil production forecasting, the effectiveness of the DCA-DLSTM model is better than other algorithms.

Conclusion

In this paper we discussed existing experiments conducted using recurrent neural networks (DLSTM), which can capture the nonlinear relationship between the system's input and output labels. However, it is limited in controlling overall decline trend of the oil production time series data. Therefore, we developed better prediction model, which is based on combination of traditional DCA and described DLSTM. The results show that the accurate prediction and learning performance of proposed model outperformed its counterparts.

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