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Modern Methods of Machine Learning Application as a Tool for Oil Production Forecasting

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Современные методы применения машинного обучения как инструмента прогнозирования добычи нефти

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Oil production forecasting plays an important role in efficient oil field development. This helps to adjust the current field development system. Detailed and accurate forecasting of oil production levels is necessary to assess the economic and technological efficiency of oil field development. Forecasting production levels can be performed in various ways, using special software (tNavigator, etc.). Commonly, it involves lengthy calculations, for rapid production levels forecast, it is possible to use other tools, as machine learning.
Machine learning and artificial intelligence application in the oil and gas industry has become increasingly popular in recent years, as by using historical production data, it is possible to forecast oil/liquid production levels. In addition, similar deposits with resembling geological characteristics and exploitation history can be used for the same purposes.
In addition to machine learning and artificial intelligence application as a forecasting tool, it is possible to use decline curve analysis.
Considering the importance of forecasting in terms of a strategic planning perspective, a wide range of methods have been proposed to obtain accurate forecasts based on available data and computing power. This article provides a comprehensive analysis of the tools used for long-term oil production forecasting, including machine learning algorithms and decline curve analysis (DCA), in particular. This article presents the results of applying the long and short-term memory model and its applicability on a candidate well.

Ключевые слова:
прогнозирование добычи, машинное обучение, кривая падения давления, искусственный интеллект, сеть с долговременной и кратковременной памятью.

Прогнозирование добычи нефти играет важную роль в эффективной разработке месторождения нефти. Это помогает скорректировать действующую систему разработки месторождения. Детальное и точное прогнозирование уровня добычи нефти необходимо для оценки экономической и технологической эффективности разработки месторождения нефти. Прогнозирование уровня добычи можно осуществить различными способами. Одним из таких может быть использование специального программного обеспечения (tNavigator и др.). Использование данного программного обеспечения иногда сопряжено с длительными расчетами, поэтому для оперативного прогнозирования уровня добычи возможно использование других инструментов, таких как машинное обучение.
Использование машинного обучения и искусственного интеллекта в нефтегазовой отрасли приобретает все большую популярность в последние годы, поскольку, используя исторические данные по добыче, возможно прогнозирование уровней добычи нефти/жидкости. Кроме того, для аналогичных целей могут быть использованы аналогичные месторождения со схожими геологическими характеристиками и историей эксплуатации.
Помимо использования машинного обучения и искусственного интеллекта, в качестве инструмента прогнозирования возможно применение анализ кривой падения.
Учитывая важность прогнозирования с точки зрения стратегического планирования, предлагается широкий спектр методов для получения точных прогнозов, основанных на характере доступных данных и вычислительной мощности. В данной статье представлен всесторонний анализ инструментов, используемых для долгосрочного прогнозирования добычи нефти, включая алгоритмы машинного обучения и анализ кривой падения добычи (DCA). Представлены результаты применения модели с долговременной и кратковременной памятью и ее практическая применимость на примере ее использования на скважине кандидате.

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Introduction

Oil production forecasting plays an important role in energy planning and decision making in the oil industry [1–3].

Considering the importance of oil production forecasting, various methods have been developed to provide forecasts based on available historical data.

One of the methods is Decline curve analysis (DCA) based on the following fact: while developing an oil field, the production level decreases that could be described by using regularities.

The analysis of the pressure decline curve allows to make a fairly accurate prediction due to the large number of analytical curves describing the nature of decline in production. One of the advantages of the forecasting method is the small amount of input data required.

Advanced data-based approaches such as machine learning (ML) and artificial intelligence (AI) have become increasingly popular in recent years. These approaches allow to make the parameters forecasting on the basis of studied regularities and interrelations of development parameters.

A one-dimensional long short-term memory (LSTM) model is considered and proposed, the main purpose of which is to calculate single-stage and multi-stage production forecasts.

At present, a large number of research in machine learning to perform various oil and gas production goals have been carried out. For example, the research of M. Berihun [4] used feed-forward neural networks to model the flow of oil, gas and water. Data collected from a field located in the Malay Basin were used to evaluate the model performance. Random combinations of input parameters (e.g., water injection rate, water injection pressure, etc.) were selected to establish the relations between production and injection well parameters. The results showed that this type of feature extraction significantly improves the model performance and gives the root-mean-square error (RMSE) and the highest coefficient of determination when the model is trained using Bayesian regularization.

S.M. Berneti and M. Shahbazyan [5] proposed a model based on the Imperialist competitive algorithm (ICA) to optimize the initial weight of feed-forward neural networks and to predict the oil flow rate from the wells in one of the Iranian oil fields in the northern Persian Gulf. The authors proposed the ICA-ANN (artificial neural network) model as a cheaper and faster alternative to multiphase flow meter [6]. The ICA-ANN model with two input parameters (temperature and pressure) gave the most accurate flow predictions with a RMS error of 0.0123 and an R^2 efficiency factor of 0.97. In a similar study A. Payaman, S. Salavati [7], the following input parameters for the neural network were used: pressure, choke size and the ratio of produced gas to oil (GF). Later, the forecasts were compared with the known empirical dependencies [8-12] used for predicting the flow of two-phase fluid through a wellhead choke.

The authors P. Zhang, M. Zhao [13] in their research applied a back propagation neural network (BP) together with logging data and production history to predict oil and water flow rate. The input dataset was initially divided into three parts (static data, dynamic data and spatio-temporal dependencies) to account for the different effects of fluid flow in the reservoir rock and tubing string. The authors developed a Voronoi diagram to analyse the spatio-temporal dependencies between wells at the field level. The result showed, that the error in predicting oil flow rate is less than 7 % and water flow rate is within 5 %.

The LSTM model was built and trained to forecast oil production in a Chinese oil field with 5 production and 4 injection wells [14]. According to the analysis, the model was mostly influenced by the amount of remaining recoverable reserves and wellhead pressure. The root mean square error (RMSE) and mean absolute percentage error (MAPE) of the LSTM model were small with values of 0.985 and 0.035, respectively.

Research Methods

The choice of LSTM neural networks for long-term oil production forecasting in this study is explained by the fact that the neural network allows capturing temporal dependencies in sequential data.

A new class of neural networks, Recurrent Neural Networks (RNN), was introduced in the 1980s and specifically designed to solve time series problems [16–18]. The unique architecture belonging to RNNs allows them to store information over successive time steps, which makes them suitable for sequential data. During the training process, RNNs use a back propagation of error over time algorithm that allows weight correction by calculating gradients. Despite the advantages offered by RNN models for solving problems including sequences, gradient vanishing makes training increasingly inefficient over long time intervals of dependencies [19].

To reduce the limitations of RNN models, a more sophisticated variant, LSTM, was introduced [20]. Unlike RNN analogues, LSTM networks can capture long-term dependencies in sequential data and efficiently remember extended temporal relations, avoiding problems with derivatives. An inner solution to the problem is to use a Constant error carousel (CEC) in the model, which ensures the error signals to be stored in each unit cell, allowing gradients to be saved in long sequences [21, 22].

Cross-validation time series and hyperparameter tuning

Machine learning uses a separate dataset to evaluate model performance [23–25]. To understand if the model generalizes and calculates the forecasted values effectively, the model performance is evaluated on a validation dataset during training.

In machine learning, there are various types of validation methods [26–29] used to evaluate model behavior. The selection criteria depend on the specific type of data being processed and its size. Traditional validation methods, such as standard k-fold cross-validation and simple holdout validation methods, cannot always be used with data that are time-dependent. In contrast to these methods, time series cross-validation saves the data temporal order and is well suited for chronological type data [30].

Figure 1 explains the basic principle of cross-checking. The points are the oil production in a particular month. The blue points are used by the model for training. The red points are the result of oil production forecast. Initially, the dataset from the first iteration is used (1st iteration – the model trained until 01.11.2017). After calculation of all forecast points in the model, the number of test points is increased by one (2nd iteration – the model trained until 01.12.2018), and the values are calculated again. This sequence of actions is continued for all points in the forecast horizon, and at each step the mean arithmetic deviation (MAE) is used to estimate the difference between the real and forecasted moment. At the end, all errors are averaged to assess the model behaviour as new data becomes available. The procedure simulates a real-world scenario where new monthly oil production data are regularly added to historical data, and the model is to adapt changing regularities as new data become available.

This methodology allows fine-tuning of critical hyperparameters including window size, number of epochs and units in the LSTM architecture. Various algorithms available to select the optimal combination of hyperparameters significantly improve the forecasting performance of the model [31–36].

Performance evaluation values

Evaluating the performance of the applied model is important to understand the quality of the forecasting model used [37, 38].

Root mean square error (RMSE) is a standard criterion used to evaluate the quality of performance by quantifying the average error between observed and forecasted values [39]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(O_i - P_i\right)^2}. \tag{1}$$

The arithmetic mean deviation is another effective measure for estimating a regression model:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - P_i\right|. \tag{2}$$

Another important value for estimating a regression model is the mean square logarithmic error (MSLE), particularly effective for datasets following an exponential trend [40].

$$\mathrm{MSLE} = \frac{1}{n}\sum_{i=1}^{n}\left(\log\left(\mathrm{O_i}+1\right) - \log\left(P_i+1\right)\right)^2. \tag{3}$$

Results

This study used the data from the production well of oil field *X* of Western Siberia. Fig. 2 shows the oil and water production profile for the period from January, 1 2003 to November, 1 2020.

The red points on the production curve correspond to periods of workover/ well servicing (ESP isolation reduction, ESP voltage cut-off, reaching full capacity, etc.). The downtime periods ranged from 11 to 481 h and, as can be seen from the graph, they typically coincide with failures in fluid production.

To start prediction with the LSTM model, it was necessary to determine the right number of hyperparameters such as number of segments, number of epochs and window size.

To select the optimal number of epochs, window size and number of segments, the arithmetic mean deviation for various combinations of these parameters was calculated.

Figure 3 shows the values of the arithmetic mean deviation for each of hyperparameters as vertical bars, and the value of the arithmetic mean deviation is indicated on the horizontal axis. It is worth noting that the deviation decreases as the complexity of the LSTM model increases. Considering the graph, we can conclude that as the number of hyperparameters increases, the accuracy of model prediction increases, also with increasing window size there is a decrease in the arithmetic mean deviation for several combinations of the units and epochs number.

The graph analysis showed that to obtain the most accurate forecast, a model with the number of epochs equal to 100 and the number of segments equal to 128 should be used. After determining the combination of these hyperparameters, it was necessary to determine the optimal window size. For this purpose, the absolute error was calculated for each window size at each time interval (Fig. 4).

Having determined the necessary hyperparameters, the given LSTM model was used to forecast oil production levels 36 months ahead. Three different approaches were used for production rate modeling. The first method (one-dimensional one-step model) meant that having forecasted the production one month ahead, the next forecasting step did not use the value calculated by the LSTM model, but the real-world value. Summing up, the following conclusion can be made that real data is necessary when forecasting production levels of this type (Fig. 5).

The difference between the second approach (recursive forecasting) and the first one was the following: when forecasting at the second time step the model was trained on the value forecasted at the first time step. Thus, after several time steps, the model was trained on its previously forecasted values (Fig. 6).

For production level forecast using the third method (one-dimensional multi-step model), the production profile was calculated for 36 months (Fig. 7).

Each forecasted production profile was compared to the actual data, and the errors of each method were calculated: 1st method: RMSE = 22.48, MAE = 18.43, and MSLE = 0.52; 2nd method: RMSE = 30.46, MAE = 24.00, and MSLE = 0.71; 3rd method: RMSE = 31.72, MAE = 25.21, and MSLE = 1.03. Each model was also evaluated for possibility to overestimate or underestimate the values.

Figure 8 shows the scatter diagram of monthly forecasts and actual data for the stated period with Pearson correlation coefficient equal to 0.66. A large cluster of points above the line passing through the origin with a slope of 1 is a clear sign of oil production overestimation. In addition, in the same figure we can see a comparison of historical and forecasted cumulative oil production for the period. At the end of the period, the model overestimates the cumulative actual data by 480 t.

In contrast to the previous case, the recursive forecasting clearly underestimates the cumulative oil production. When analyzing fig. 9, 758 t of underestimated cumulative production can be noted. In addition, the diagram shows scattered data points with a correlation coefficient of Pearson 0.4.

The one-dimensional multistep model overestimates cumulative oil production by 530 t. In this case, a more scattered plot can be observed with a Pearson correlation coefficient of – 0.22 (Fig. 10), indicating a negative correlation between the variables.

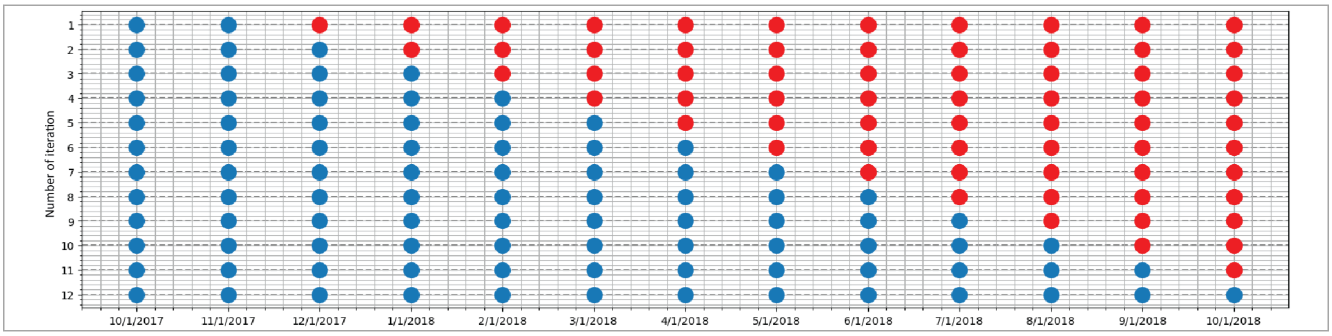

Fig. 1. Cross-validation of time series with increasing window size Номер итерации - Number of iteration

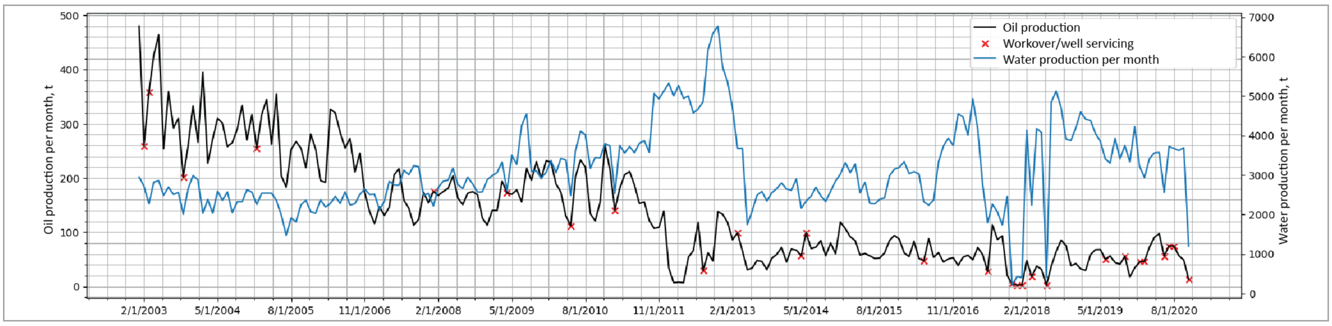

Fig. 2. Oil/water production profile of the well

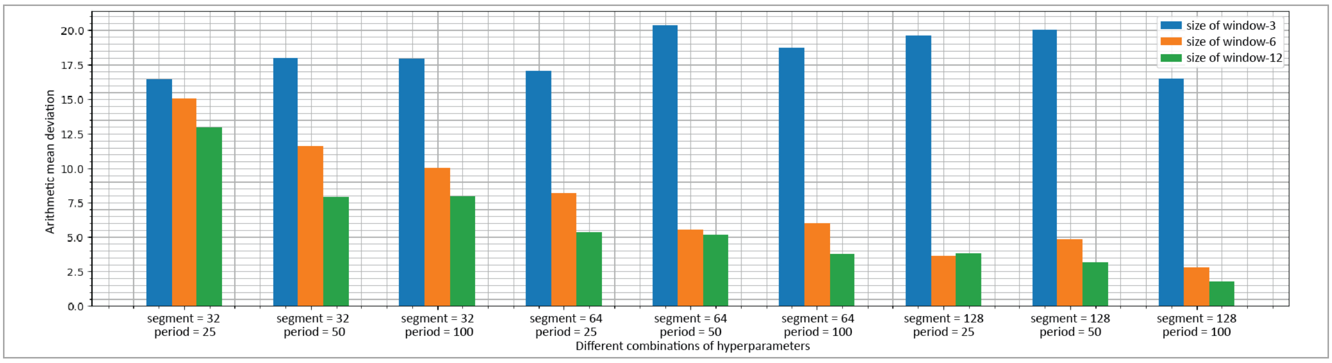

Fig. 3. Arithmetic mean deviation for each combination of hyperparameters

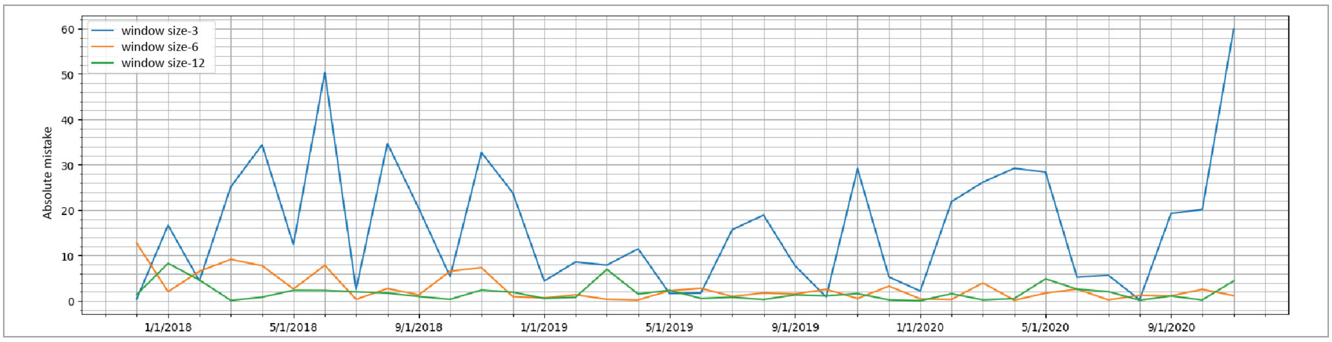

Fig. 4. Window size selection

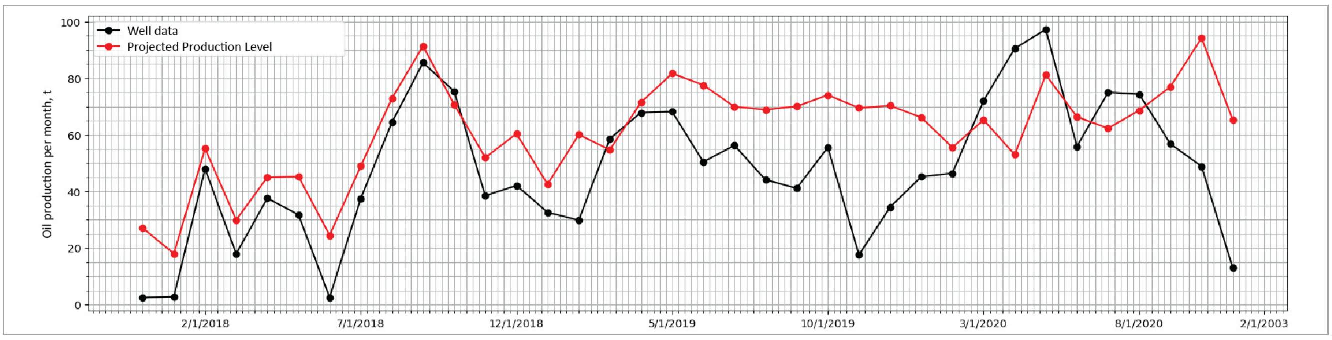

Fig. 5. Forecasting with a one-dimensional one-step model

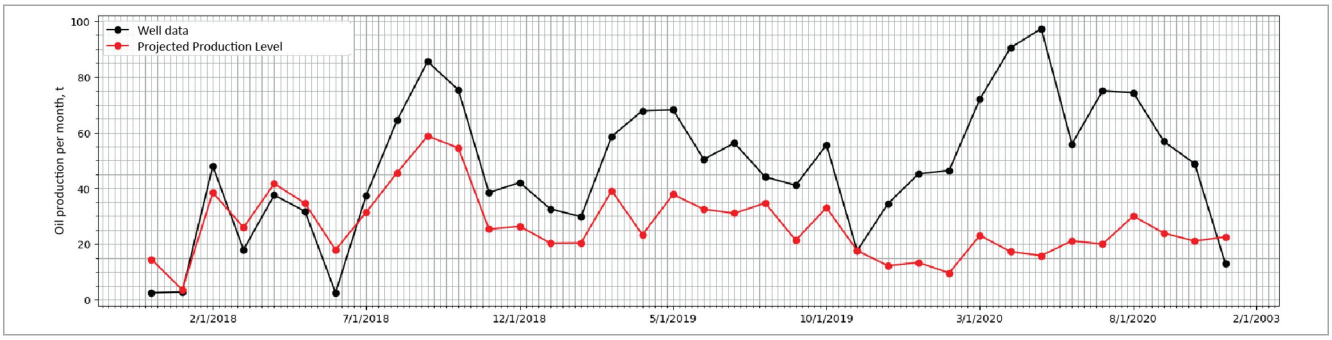

Fig. 6. Recursive forecasting

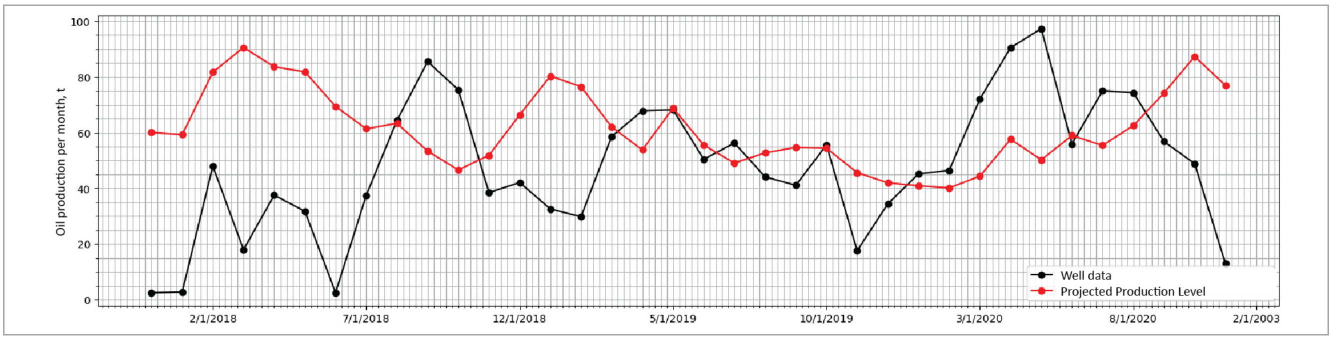

Fig. 7. Forecasting with a one-dimensional multi-step model

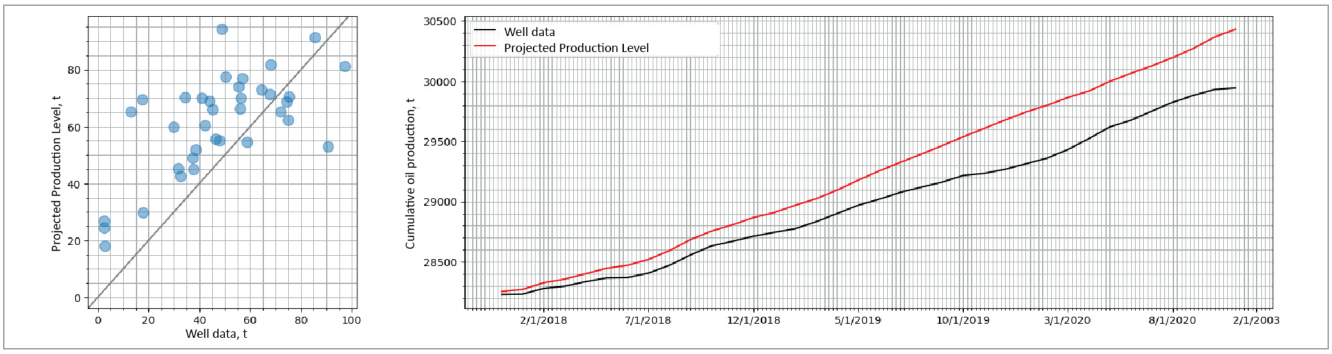

Fig. 8. Scatter diagram in one-dimensional one-step model

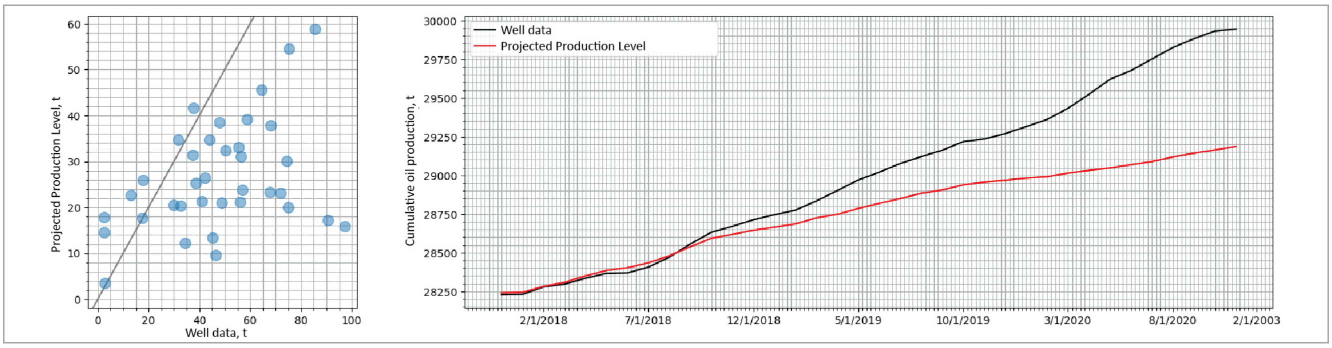

Fig. 9. Scatter diagram for recursive forecasting

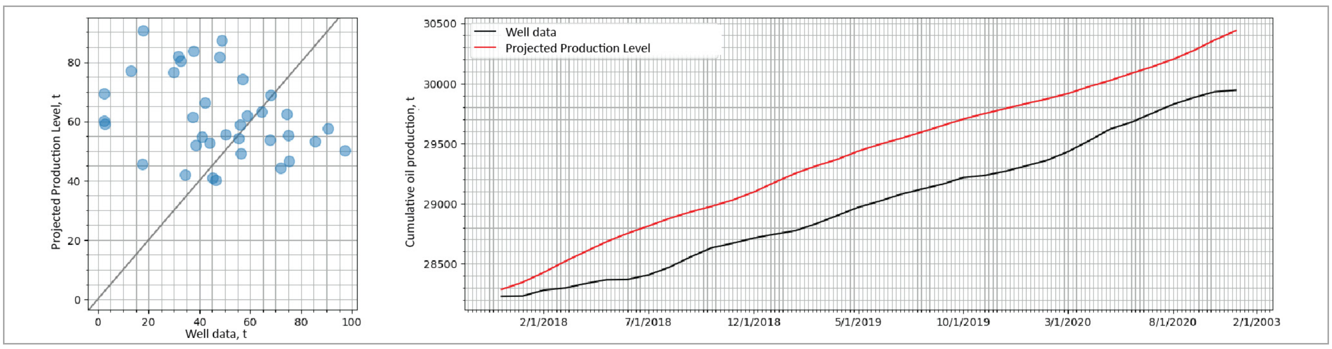

Fig. 10. Scatter diagram in a one-dimensional multistep model

Conclusion

1. The aim of the study was to use machine learning algorithms, specifically LSTM, to conduct long-term oil production forecasts. The methodology included the use of cross-validation of time series with varying window size to determine the optimal combination of hyperparameters for the LSTM model.

2. The results of the study showed that the one-dimensional one-step bidirectional LSTM model demonstrated significantly lower error rates compared to the recursive one-step forecast model and the multistep forecast model. However, it is important to realize that the one-dimensional one-step bidirectional LSTM model has practical limitations. During forecast, input and output pairs are generated using actual data. This aspect should be taken into account when evaluating its applicability in real scenarios.

3. On the other hand, the recursive model showed a tendency to underestimate values over the three-year period. This characteristic implies a risk proneness, being potentially reliable in future decision-making of an oil and gas company.

4. Future trends could include the study of multidimensional forecasting models as dynamic data. This extension could improve forecast accuracy by additional relevant factors.

References

1. Petrakov D.G. et al. Standards for Selection of Surfactant Compositions used in Completion and Stimulation Fluids. International Journal of Engineering, 2023, vol. 36, no. 9, pp. 1605-1610. DOI: 10.5829/IJE.2023.36.09C.03
2. Aghaei H. et al. Density-dependent relationship between changes in ultrasonic wave velocities, effective stress, and petrophysical-elastic properties of sandstone. Ultrasonics, 2023, vol. 132, 106985 p. DOI: 10.1016/j.ultras.2023.106985
3. Petrakov D.G., Penkov G.M., Zolotukhin A.B. Experimental study on the effect of rock pressure on sandstone permeability. Zapiski Gornogo institute, 2022, vol. 254, pp. 244-251. DOI: 10.31897/PMI.2022.24
4. Negash B.M., Yaw A.D. Artificial neural network based production forecasting for a hydrocarbon reservoir under water injection. Petroleum Exploration and Development, 2020, T. 47, no. 2, pp. 383-392. DOI: 10.1016/S1876-3804(20)60055-6
5. Berneti S.M., Shahbazian M. An imperialist competitive algorithm artificial neural network method to predict oil flow rate of the wells. International journal of computer applications, 2011, vol. 26, no. 10, pp. 47-50. DOI: 10.5120/3137-4326
6. Falcone G., Alimonti C. The challenges of multiphase flow metering: today and beyond. International Conference on Offshore Mechanics and Arctic Engineering, 2007, vol. 42681, pp. 823-834. DOI: 10.1115/OMAE2007-29527
7. Mirzaei-Paiaman A., Salavati S. The application of artificial neural networks for the prediction of oil production flow rate. Energy Sources, Part A: Recovery, utilization, and environmental effects, 2012, vol. 34, no. 19, pp. 1834-1843. DOI: 10.1080/15567036.2010.492386
8. Gilbert W.E. Flowing and Gas-Lift Well Performance. Drilling and Production Practice, 1954, vol. 13, pp. 126-157.
9. Baxendell P.B. Bean performance-lake wells. Shell Internal Report. Houston, TX: Shell Oil, 1957.
10. Ros N.C.J. An analysis of critical simultaneous gas/liquid flow through a restriction and its application to flowmetering. Applied Scientific Research, 1960, vol. 9, pp. 374-388. DOI: 10.1007/BF00382215
11. Achong L.B. Revised bean and performance formula for Lake Maracaibo wells. Shell Internal Report. Houston, TX: Shell Oil Co, 1961.
12. Mirzaei-Paiaman A., Salavati S. A new empirical correlation for sonic simultaneous flow of oil and gas through wellhead chokes for Persian oil fields. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2013, vol. 35, no. 9, pp. 817-825. DOI: 10.1080/15567031003773304
13. Zhang P.Y., Meng-Meng Z. The Application of BP Neural Network In Oil-Field. TELKOMNIKA Indonesian Journal of Electrical Engineering, 2013, vol. 11, no. 9, pp. 527-75283. DOI: 10.11591/telkomnika.v11i9.3280
14. Liu W., Liu W.D., Gu J. Forecasting oil production using ensemble empirical model decomposition based Long Short-Term Memory neural network. Journal of Petroleum Science and Engineering, 2020, vol. 189, 107013 p. DOI: 10.1016/j.petrol.2020.107013
15. Ali P.J.M. et al. Data normalization and standardization: a technical report. Mach Learn Tech Rep, 2014, vol. 1, no. 1, pp. 1-6. DOI: 10.13140/RG.2.2.28948.04489
16. Rumelhart D.E., Hinton G.E., Williams R.J. Learning representations by back-propagating errors. Nature, 1986, vol. 323, no. 6088, pp. 533-536. DOI: 10.1038/323533a0
17. Werbos P.J. Generalization of backpropagation with application to a recurrent gas market model. Neural networks, 1988, vol. 1, no. 4, pp. 339-356. DOI: 10.1016/0893-6080(88)90007-X
18. Elman J.L. Finding structure in time. Cognitive science, 1990, vol. 14, no. 2, pp. 179-211. DOI: 10.1016/0364-0213(90)90002-E
19. Bengio Y., Simard P., Frasconi P. Learning long-term dependencies with gradient descent is difficult. IEEE transactions on neural networks, 1994, vol. 5, no. 2, pp. 157-166. DOI: 10.1109/72.279181
20. Hochreiter S., Schmidhuber J. Long short-term memory. Neural computation, 1997, vol. 9, no. 8, pp. 1735-1780. DOI: 10.1162/neco.1997.9.8.1735
21. Gers F.A., Schmidhuber J., Cummins F. Learning to forget: Continual prediction with LSTM. Neural computation, 2000, vol. 12, no. 10, pp. 2451-2471. DOI: 10.1162/089976600300015015
22. Staudemeyer R.C., Morris E.R. Understanding LSTM--a tutorial into long short-term memory recurrent neural networks. arXiv preprint arXiv:1909.09586, 2019. DOI: 10.48550/arXiv.1909.09586
23. Understanding LSTM networks by Colah accessed at Understanding LSTM Networks -- colah's blog.
24. Werbos P.J. Backpropagation through time: what it does and how to do it, Proceedings of the IEEE, 1990, vol. 78, no. 10, pp. 1550-1560. DOI: 10.1109/5.58337
25. Kohavi R. et al. A study of cross-validation and bootstrap for accuracy estimation and model selection. Ijcai, 1995, vol. 14, no. 2, pp. 1137-1145.
26. Berrar D. et al. Cross-Validation, 2019. DOI: 10.1016/B978-0-12-809633-8.20349-X
27. Kee E. et al. A Comparative Analysis of Cross-Validation Techniques for a Smart and Lean Pick-and-Place Solution with Deep Learning. Electronics, 2023, vol. 12, no. 11, 2371 p. DOI: 10.3390/electronics12112371
28. Little M.A. et al. Using and understanding cross-validation strategies. Perspectives on Saeb et al. GigaScience, 2017, vol. 6, no. 5, gix020 p. DOI: 10.1093/gigascience/gix020
29. Falessi D. et al. On the need of preserving order of data when validating within-project defect classifiers. Empirical Software Engineering, 2020, vol. 25, pp. 4805-4830. DOI: 10.1007/s10664-020-09868-x
30. Suradhaniwar S. et al. Time series forecasting of univariate agrometeorological data: a comparative performance evaluation via one-step and multi-step ahead forecasting strategies. Sensors, 2021, vol. 21, no. 7, pp. 2430. DOI: 10.3390/s21072430
31. Zhang X., Zhang X. Optimal model averaging based on forward-validation. Journal of Econometrics, 2022. DOI: 10.1016/j.jeconom.2022.03.010
32. Radzi S.F.M. et al. Hyperparameter tuning and pipeline optimization via grid search method and tree-based autoML in breast cancer prediction. Journal of personalized medicine, 2021, vol. 11, no. 10, 978 p. DOI: 10.3390/jpm11100978
33. Belete D.M., Huchaiah M.D. Grid search in hyperparameter optimization of machine learning models for prediction of HIV/AIDS test results. International Journal of Computers and Applications, 2022, vol. 44, no. 9, pp. 875-886. DOI: 10.1080/1206212X.2021.1974663
34. Shekar B.H., Dagnew G. Grid search-based hyperparameter tuning and classification of microarray cancer data. 2019 second international conference on advanced computational and communication paradigms (ICACCP), IEEE, 2019, pp. 1-8. DOI: 10.1109/ICACCP.2019.8882943
35. Bergstra J., Bengio Y. Random search for hyper-parameter optimization. Journal of machine learning research, 2012, vol. 13, no. 2. DOI: 10.5555/2188385.2188395
36. Liashchynskyi P., Liashchynskyi P. Grid search, random search, genetic algorithm: a big comparison for NAS. arXiv preprint arXiv:1912.06059, 2019 DOI: 10.48550/arXiv.1912.06059
37. St-Aubin P., Agard B. Precision and Reliability of Forecasts Performance Metrics. Forecasting, 2022, vol. 4, no. 4, pp. 882-903. DOI: 10.3390/forecast4040048
38. Cerqueira V., Torgo L., Mozetič I. Evaluating time series forecasting models: An empirical study on performance estimation methods. Machine Learning, 2020, vol. 109, pp. 1997-2028. DOI: 10.1007/s10994-020-05910-7
39. Chai T., Draxler R.R. Root mean square error (RMSE) or mean absolute error (MAE)? - Arguments against avoiding RMSE in the literature. Geoscientific model development, 2014, vol. 7, no. 3, pp. 1247-1250. DOI: 10.5194/gmd-7-1247-2014
40. Park Y.H. Concise logarithmic loss function for robust training of anomaly detection model. arXiv preprint arXiv:2201.05748, 2022. DOI: 10.48550/arXiv.2201.05748

Библиографический список

1. Standards for Selection of Surfactant Compositions used in Completion and Stimulation Fluids / D.G. Petrakov [et al.] // International Journal of Engineering. – 2023. – Т. 36, № 9. – P. 1605–1610. DOI: 10.5829/IJE.2023.36.09C.03
2. Density-dependent relationship between changes in ultrasonic wave velocities, effective stress, and petrophysical-elastic properties of sandstone / H. Aghaei [et al.] // Ultrasonics. – 2023. – Т. 132. – P. 106985. DOI: 10.1016/j.ultras.2023.106985
3. Petrakov, D.G. Experimental study on the effect of rock pressure on sandstone permeability / D.G. Petrakov, G.M. Penkov, A.B. Zolotukhin // Записки Горного института. – 2022. – Т. 254. – С. 244–251. DOI: 10.31897/PMI.2022.24

4. Negash, B.M. Artificial neural network based production forecasting for a hydrocarbon reservoir under water injection / B.M. Negash, A.D. Yaw // Petroleum Exploration and Development. – 2020. – T. 47, № 2. – P. 383–392. DOI: 10.1016/S1876-3804(20)60055-6
5. Berneti, S.M. An imperialist competitive algorithm artificial neural network method to predict oil flow rate of the wells / S.M. Berneti, M. Shahbazian // International journal of computer applications. – 2011. – T. 26, № 10. – P. 47–50. DOI: 10.5120/3137-4326
6. Falcone, G. The challenges of multiphase flow metering: today and beyond / G. Falcone, C. Alimonti // International Conference on Offshore Mechanics and Arctic Engineering. – 2007. – T. 42681. – P. 823–834. DOI: 10.1115/OMAE2007-29527
7. Mirzaei-Paiaman, A. The application of artificial neural networks for the prediction of oil production flow rate / A. Mirzaei-Paiaman, S. Salavati // Energy Sources, Part A: Recovery, utilization, and environmental effects. – 2012. – T. 34, № 19. – P. 1834–1843. DOI: 10.1080/15567036.2010.492386
8. Gilbert, W.E. Flowing and Gas-Lift Well Performance / W.E. Gilbert // Drilling and Production Practice. – 1954. – T. 13. – P. 126–157.
9. Baxendell, P.B. Bean performance-lake wells. Shell Internal Report / P.B. Baxendell. – Houston, TX: Shell Oil. – 1957.
10. Ros, N.C.J. An analysis of critical simultaneous gas/liquid flow through a restriction and its application to flowmetering / N.C.J. Ros // Applied Scientific Research. – 1960. – T. 9. – P. 374–388. DOI: 10.1007/BF00382215
11. Achong, L.B. Revised bean and performance formula for Lake Maracaibo wells. Shell Internal Report / L.B. Achong. – Houston, TX: Shell Oil Co. – 1961.
12. Mirzaei-Paiaman, A. A new empirical correlation for sonic simultaneous flow of oil and gas through wellhead chokes for Persian oil fields / A. Mirzaei-Paiaman, S. Salavati // Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. – 2013. – T. 35. № 9. – P. 817–825. DOI: 10.1080/15567031003773304
13. Zhang, P.Y. The Application of BP Neural Network In Oil-Field / P.Y. Zhang, Z. Meng-Meng // TELKOMNIKA Indonesian Journal of Electrical Engineering. – 2013. – T. 11. – №. 9. – P. 527-75283. DOI: 10.11591/telkomnika.v11i9.3280
14. Liu, W. Forecasting oil production using ensemble empirical model decomposition based Long Short-Term Memory neural network / W. Liu, W.D. Liu, J. Gu // Journal of Petroleum Science and Engineering. – 2020. – T. 189. – C. 107013. DOI: 10.1016/j.petrol.2020.107013
15. Data normalization and standardization: a technical report / P.J.M. Ali [et al.] // Mach Learn Tech Rep. – 2014. – T. 1, № 1. – P. 1–6. DOI: 10.13140/RG.2.2.28948.04489
16. Rumelhart, D.E. Learning representations by back-propagating errors / D.E. Rumelhart, G.E. Hinton, R.J. Williams // Nature. – 1986. – T. 323, № 6088. – P. 533–536. DOI: 10.1038/323533a0
17. Werbos, P.J. Generalization of backpropagation with application to a recurrent gas market model / P.J. Werbos // Neural networks. – 1988. – T. 1, №. 4. – P. 339–356. DOI: 10.1016/0893-6080(88)90007-X
18. Elman, J.L. Finding structure in time / J.L. Elman // Cognitive science. – 1990. – T. 14, № 2. – P. 179–211. DOI: 10.1016/0364-0213(90)90002-E
19. Bengio, Y. Learning long-term dependencies with gradient descent is difficult / Y. Bengio, P. Simard, P. Frasconi // IEEE transactions on neural networks. – 1994. – T. 5, № 2. – P. 157–166. DOI: 10.1109/72.279181
20. Hochreiter, S. Long short-term memory / S. Hochreiter, J. Schmidhuber // Neural computation. – 1997. – T. 9, № 8. – P. 1735–1780. DOI: 10.1162/neco.1997.9.8.1735
21. Gers, F.A. Learning to forget: Continual prediction with LSTM / F.A. Gers, J. Schmidhuber, F. Cummins // Neural computation. – 2000. – T. 12, № 10. – P. 2451–2471. DOI: 10.1162/089976600300015015
22. Staudemeyer, R.C. Understanding LSTM--a tutorial into long short-term memory recurrent neural networks / R.C. Staudemeyer, E.R. Morris // arXiv preprint arXiv:1909.09586. – 2019. DOI: 10.48550/arXiv.1909.09586
23. Understanding LSTM networks by Colah accessed at Understanding LSTM Networks -- colah's blog.
24. Werbos, P.J. Backpropagation through time: what it does and how to do it / P.J. Werbos // Proceedings of the IEEE. – 1990. – T. 78, № 10. – P. 1550–1560. DOI: 10.1109/5.58337
25. A study of cross-validation and bootstrap for accuracy estimation and model selection / R. Kohavi [et al.] // Ijcai. – 1995. – T. 14, № 2. – P. 1137–1145.
26. Cross-Validation / Berrar D. [et al.]. – 2019. DOI: 10.1016/B978-0-12-809633-8.20349-X
27. A Comparative Analysis of Cross-Validation Techniques for a Smart and Lean Pick-and-Place Solution with Deep Learning / E. Kee [et al.] // Electronics. – 2023. – T. 12, № 11. – P. 2371. DOI: 10.3390/electronics12112371
28. Using and understanding cross-validation strategies. Perspectives on Saeb et al / M.A. Little [et al.] // GigaScience. – 2017. – T. 6, № 5. – C. gix020. DOI: 10.1093/gigascience/gix020
29. On the need of preserving order of data when validating within-project defect classifiers / D. Falessi [et al.] // Empirical Software Engineering. – 2020. – T. 25. – P. 4805–4830. DOI: 10.1007/s10664-020-09868-x
30. Time series forecasting of univariate agrometeorological data: a comparative performance evaluation via one-step and multi-step ahead forecasting strategies / S. Suradhaniwar [et al.] // Sensors. – 2021. – T. 21, № 7. – P. 2430. DOI: 10.3390/s21072430.
31. Zhang, X. Optimal model averaging based on forward-validation / X. Zhang, X. Zhang // Journal of Econometrics. – 2022. DOI: 10.1016/j.jeconom.2022.03.010
32. Hyperparameter tuning and pipeline optimization via grid search method and tree-based autoML in breast cancer prediction / S.F.M. Radzi [et al.] // Journal of personalized medicine. – 2021. – T. 11, № 10. – P. 978. DOI: 10.3390/jpm11100978
33. Belete, D.M. Grid search in hyperparameter optimization of machine learning models for prediction of HIV/AIDS test results / D.M. Belete, M.D. Huchaiah // International Journal of Computers and Applications. – 2022. – T. 44, № 9. – P. 875–886. DOI: 10.1080/1206212X.2021.1974663
34. Shekar, B.H. Grid search-based hyperparameter tuning and classification of microarray cancer data / B.H. Shekar, G. Dagnew // 2019 second international conference on advanced computational and communication paradigms (ICACCP). – IEEE, 2019. – C. 1–8. DOI: 10.1109/ICACCP.2019.8882943
35. Bergstra, J. Random search for hyper-parameter optimization / J. Bergstra, Y. Bengio // Journal of machine learning research. – 2012. – T. 13, № 2. DOI: 10.5555/2188385.2188395
36. Liashchynskyi, P. Grid search, random search, genetic algorithm: a big comparison for NAS / P. Liashchynskyi, P. Liashchynskyi // arXiv preprint arXiv:1912.06059. – 2019. DOI: 10.48550/arXiv.1912.06059
37. St-Aubin, P. Precision and Reliability of Forecasts Performance Metrics / P. St-Aubin, B. Agard // Forecasting. – 2022. – T. 4, № 4. – P. 882–903. DOI: 10.3390/forecast4040048
38. Cerqueira, V. Evaluating time series forecasting models: An empirical study on performance estimation methods / V. Cerqueira, L. Torgo, I. Mozetič // Machine Learning. – 2020. – T. 109. – P. 1997–2028. DOI: 10.1007/s10994-020-05910-7
39. Chai, T. Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature / T. Chai, R.R. Draxler // Geoscientific model development. – 2014. – T. 7, № 3. – P. 1247–1250. DOI: 10.5194/gmd-7-1247-2014
40. Park, Y.H. Concise logarithmic loss function for robust training of anomaly detection model / Y.H. Park // arXiv preprint arXiv:2201.05748. – 2022. DOI: 10.48550/arXiv.2201.05748

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