

Predicting production performance of Coalbed Methane reservoirs with Long Short-Term Memory Networks

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Abstract. Coalbed Methane (CBM) is a clean and highly efficient energy source. The prediction of its production performance is difficult because of the complex geological conditions and exploitation processes. The CBM well deliquification always has a long duration. Therefore, long-term prediction is more instructive than short-term prediction for fracturing treatment parameters. But there is a long-term dependence problem in the time series prediction. Therefore, in this paper long short-term memory networks (LSTM) are proposed to overcome the problem. The experimental results show that in the case of similar accuracy, the LSTM predict longer than artificial neural networks. And the LSTM are more accurate than the artificial neural networks in the same output time period.

1. Introduction

Coalbed Methane (CBM) is one of the unconventional gas resources. The development and utilization of CBM are beneficial to relieve the tense situation of conventional oil and gas supply, ensure the safety of coal production and protect the atmospheric environment. At Present, there is still a gap between the performance of CBM wells and the target of the rapid development of CBM industry in China [1]. Predicting production performance of CBM reservoirs is the basis of the design of CBM extraction, which is of great significance to the efficient mining of CBM wells. However, prediction of gas production from the CBM reservoirs is difficult due to the complex mechanisms of storage and transport and many influenced factors.

Several theories and methods have been studied to predict production of oil and gas. The main theories and methods include Arps decline curve method [2], reservoir simulation [3], Weng's model [4], type curve analysis [5], gray forecasting model [6] and artificial neural network (ANN) [7]. Most of these methods are good at short-term production prediction. But the CBM well deliquification usually has a long duration. At present, the method for long-term production prediction of CBM wells is still need to study.

The performance of the CBM well is influenced by geological factors and engineering factors. The operation parameters and gas production values constitute time series. Recurrent Neural Networks (RNN) has been utilized in many field to predict time series [8-11]. But the shortcomings of overfitting and the exploding gradient commonly seen when training recurrent networks. In 1997, Sepp Hochreiter



and Jürgen Schmidhuber [12] proposed Long short-term memory networks (LSTM). And Felix Gers' team improved it in 2000 [13]. LSTM is an improved RNN which can overcome the shortcomings.

This study focuses on predicting production performance of CBM reservoirs with LSTM. This paper is organized as follows. First, the model of the LSTM is presented. Second, experiments are executed with real data from CBM wells. Finally, the results are discussed and analyzed.

2. LSTM model

LSTM has been applied on learning latent task-specific features across many domains [14-16]. The biggest difference between a simple RNN and a LSTM is the hidden layer. LSTM takes a more complex memory block to replac the hidden node. But there was a weakness of the original LSTM networks in processing continual input streams. Gers et al. [13] proposed an improved memory structure to avoid the memory cells degenerating into common hidden nodes. Therefore, figure 1 is the structure of our LSTM memory block.

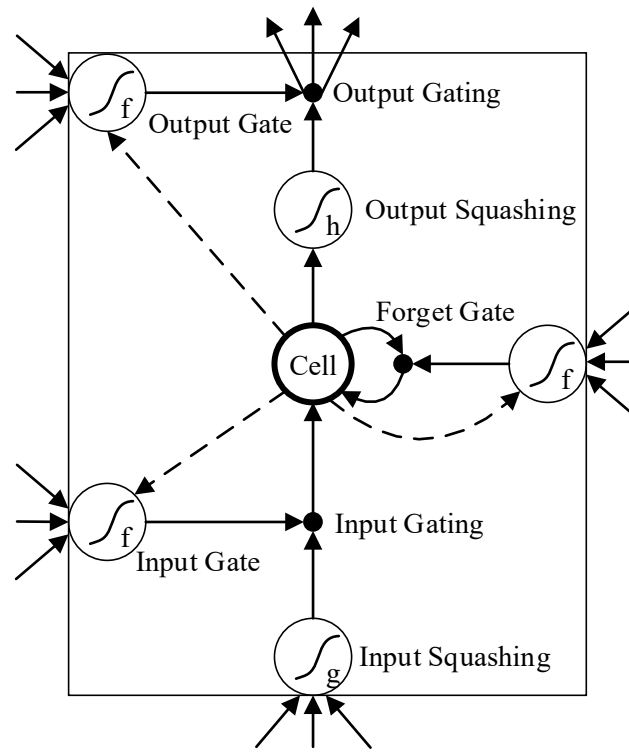


Figure 1. LSTM memory block with one cell [13].

The LSTM memory block has three gates and two squash units besides one cell. Using backpropagation through time (BPTT) gradient calculation as the method of backward pass, the equations for a recurrent neural network are as follows.

2.1. Forward pass

The three gates are nonlinear summation units. The activation function 'f' for the three gates is the logistic sigmoid. In order to control the result between 0 (gate closed) and 1 (gate open). They collection the input data x_t at time step t and the output data h_{t-1} at time step $t-1$. Equation (1), equation (2) and equation (3) correspond to input gate, forget gate and output gate, respectively.

$$i_t = \sigma(W^{xi}x_t^l + W^{hi}h_{t-1}^l + b_i) \quad (1)$$

$$f_t = \sigma(W^{xf}x_t + W^{hf}h_{t-1} + b_f) \quad (2)$$

$$o_t = \sigma(W^{xo}x_t + W^{ho}h_{t-1} + b_o) \quad (3)$$

where, W^{xi} is the weight of the connection from x_t to input gate, W^{hi} is the weight of the connection from h_{t-1} to input gate, W^{xf} is the weight of the connection from x_t to forget gate, W^{hf} is the weight of the connection from h_{t-1} to forget gate, W^{xo} is the weight of the connection from x_t to output gate, W^{ho} is the weight of the connection from h_{t-1} to output gate. And b_i , b_f and b_o are the bias of input gate, forget gate and output gate, respectively.

The activation function ‘g’ and ‘h’ for two squash units are usually tanh. Therefore, the output g_t of input squashing is shown as Equation (4). The output of output squashing is $\tanh(s_t)$.

$$g_t = \tanh(W^{xg}x_t + W^{hg}h_{t-1} + b_g) \quad (4)$$

where, W^{xg} is the weight of the connection from x_t to input squashing, W^{hg} is the weight of the connection from h_{t-1} to output squashing, b_g is the bias of the cell, s_t is the state of the cell at time step t .

Both of the input gating and the output gating execute Hadama product function. In another word, the filled circle means Hadama product in figure 1. The update of cell states is following equation (5). Input gating and output gating accomplish the calculation of $i_t \circ g_t$ and equation (6), respectively.

$$s_t = s_{t-1} \circ f_t + i_t \circ g_t \quad (5)$$

$$h_t = o_t \circ \tanh(s_t) \quad (6)$$

2.2. Backward pass

The weights update according to minimizing the total Square error during a time T. Therefore, the Object function is

$$L_N = \frac{1}{2} \sum_{l=1}^N \sum_{t=0}^T \|o^l(t) - y^l(t)\|^2 \quad (7)$$

Then to take its partial respect to weights and biases.

3. Application

In order to study the predictive effect of the LSTM model on CBM production, an artificial neural network (ANN) model with 10 hidden nodes is utilized to accomplish the contrast test. The Junggar Basin in Xinjiang Province, China contains abundant CBM resources. The LSTM model and ANN model have been applied to this area. For example, the main reservoir and treatment parameters for well X are listed in Table 1. The bottom hole pressure (BHP) and casing pressure are shown as figure 2. The CBM production is shown as figure 3. The date of the data is between 2014.12.38 and 2017.12.24. In another word, it is totally 1103 days.

Table 1. Reservoir and treatment parameters.

Deep of Coalbed (m)	Thick of Coalbed (m)	Pump diameter (mm)	Pump setting depth (m)
816.989	15	44	972.90
866.989	10		
929.989	27		

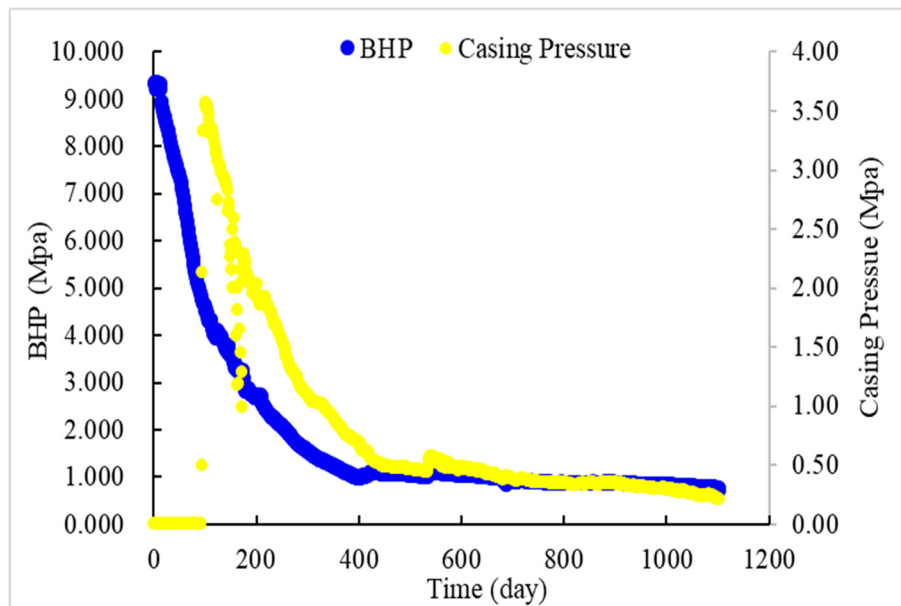


Figure 2. BHP and casing pressure of well X.

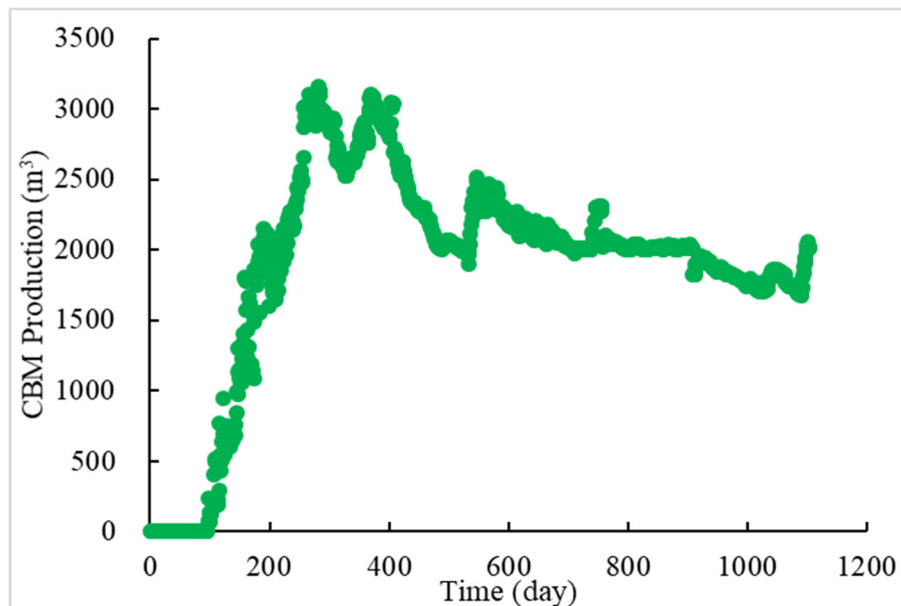


Figure 3. CBM production of well X.

4. Results and discussion

With twenty days interval, the predictive time length was increased and the accuracy of the prediction was compared. The testing data was the next training data according to the days interval. The set of predictive time length was $\{20, 40, 60, \dots, 200\}$. Finally, the average accuracy of each models in every predictive time length was the experiment result as shown in figure 4.

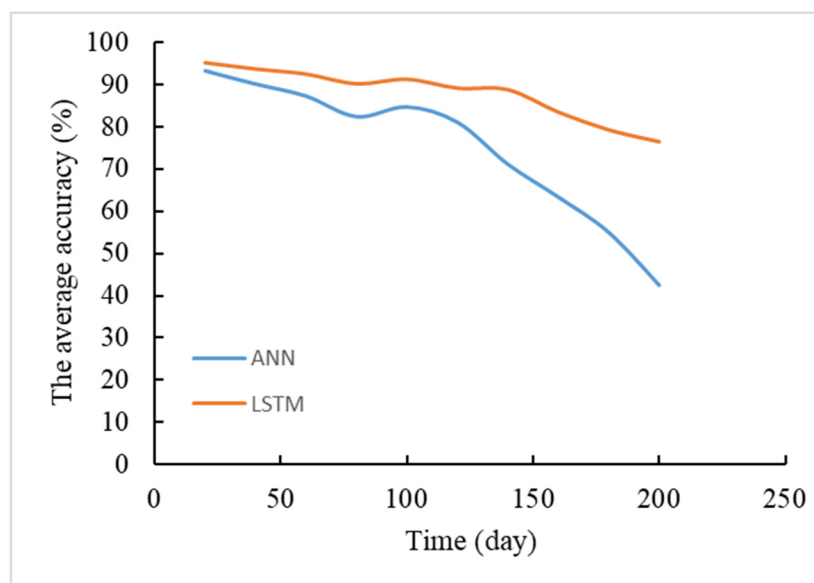


Figure 4. The average accuracy of each models in every predictive time length.

Obviously, both of the average accuracy of two models were decreased with longer predictive time length. And the predict effect of LSTM model always preceded the ANN model. For the results of ten predictive time length, the average accuracy of LSTM was 12.91% higher than ANN model. In addition, the same experiment was executed with 23 CBM wells data. Although the result of accuracy was different, the change rule was consistent.

5. Conclusions

The LSTM model presented in this paper have been useful in long-term prediction of the production performance of CBM reservoirs. We have demonstrated the benefits of the simulation with case studies, and draw the following conclusions:

- (1) With the same predictive time length, the accuracy of LSTM model is obviously higher than ANN model. The LSTM model has presented some advantages on dealing with mass data.
- (2) With the same accuracy, the LSTM model could predict longer term production. The LSTM model is also good at learning time series.

In a word, LSTM is a method to predict long-term CBM wells production performance. It will provide the guidance for the design and construction of CBM wells.

Acknowledgments

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