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Deep Learning-Based Prediction of the Cumulative Gas Production of the Montney Formation, Canada

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Summary

Many researches on cumulative gas production (CGP) prediction have been actively conducted due to the increasing interest in shale gas development. A typical method for predicting the CGP is a reservoir simulation which requires the detailed reservoir modelling procedure, such as the grid system for fractures, properties of shale gas reservoir, geomechanical information, and the hydraulic fracturing design including the spacing, half-length, conductivity, and geometry of fracture (Cipolla et al., 2010; Nguyen-Le and Shin, 2019). Also, the decline curve analysis (DCA) is widely used to predict the CGP of shale gas reservoir because it can be easily and quickly applied to CGP prediction (Hu et al., 2018). However, the prediction performance of DCA is poor if the production history is short, and there are many assumptions in equation parameters of various DCA methods (Tan et al., 2018).

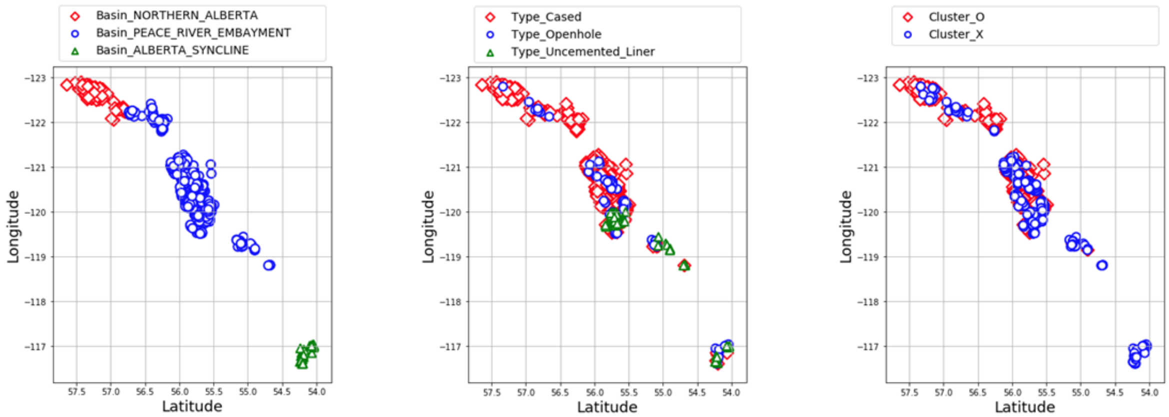
Deep learning (DL) models, such as artificial neural networks (ANN), convolution neural networks (CNN), long short-term memory (LSTM) networks, and CNN-LSTM hybrid networks (CNN+LSTM), is being applied to shale gas researches for predicting the CGP. Wang and Chen (2019) studied the ANN model for predicting the 12-month cumulative production of Montney formation using the well information, completion, and fracture treatment parameters. Luo et al. (2019) used an ANN model to identify the correlation between the 12-month cumulative production and the geological and completion parameters of Bakken formation. Lee et al. (2019) applied LSTM networks to construct the predictive model for future gas production using the more than 6 months of production data and the shut-in period as input parameters.

In this study, the DL models, such as ANN, 1-dimension CNN (1D-CNN), LSTM, and 1D-CNN-LSTM hybrid networks (1D-CNN+LSTM), were developed to predict the CGP (from 9-month to 36-month) using well information, the completion and fracture treatment parameters, and early production data (less than 6 months) in the Montney formation, Canada.

A comparison of the developed DL models revealed the 1D-CNN+LSTM model to have larger coefficient of determination (R^2) than those of the ANN, 1D-CNN, and LSTM models. The developed 1D-CNN+LSTM model may be used to evaluate the production performance of shale gas projects with short production history.

Data Pre-Processing

The Montney formation in British Columbia and Alberta, Canada consists of three basins (Northern Alberta, Peace River Embayment, and Alberta Syncline). A total of 1,000 dry gas wells in Montney formation were collected from AccuMap (IHS Markit, 2019) under the following conditions: horizontal well, cumulative oil and condensate production below 100 m^3, and amount of total proppant pumped more than 1 tonne (Fig. 1). Also, we investigated the true vertical depth (TVD), completion type (cased-hole, open-hole, and uncemented liner), stimulated length, total stage count, absence/presence of cluster, total cluster count, total proppant pumped, and total fluid (Fig. 1).



(a) **Basin** **(b) Completion type** **(c) Absence/presence of cluster**

Fig. 1. Well locations in Montney formation by the basin, completion type, and absence/presence of cluster.

A widely used method for dealing with categorical data, such as basin, completion type, and absence/presence of cluster, is one-hot encoding that is to create the new categorical features that can have the values 0 and 1 (Müller and Guido, 2016). In this study, the basins, completion type, and absence/presence of cluster were converted to eight categorical features by performing one-hot encoding.

To eliminate the effects of shut-in period during production, the time-step was calculated by considering the production hours in each month, then the CGPs at the 1-, 3-, 6-, 9-, 12-, 15-, 18-, 21-, 24-, 27-, 30-, 33-, and 36-month were estimated using linear interpolation, which is to construct new data points within the range of a discrete set of known data points

In this study, the all CGPs, total stage count, total cluster count, total proppant pumped, and total fluid are adjusted per unit stimulated length for fair comparison of productivity because longer well gives higher production, and we considered the slope between CGP per length at the 1-month (CGP_1M/L), CGP per length at the 3-month (CGP_3M/L), and CGP per length at the 6-month (CGP_6M/L) as additional variables as follows:

$$Slope\_3M\_1M = ((CGP\_3M/L) - (CGP\_1M/L))/2 \tag{1}$$

$$Slope\_6M\_1M = ((CGP\_6M/L) - (CGP\_1M/L))/5 \tag{2}$$

$$Slope\_6M\_3M = ((CGP\_6M/L) - (CGP\_3M/L))/3 \tag{3}$$

The TVD, total stage count per length (Stage/L), total cluster count per length (Cluster/L), total proppant pumped per length (Proppant/L), total fluid per length (Fluid/L), eight categorical features, CGP_1M/L, CGP_3M/L, CGP_6M/L, Slope_3M_1M, Slope_6M_1M, and Slope_6M_3M are selected as nineteen input variables. The dataset was divided into 80% of the train set and 20% of the test set. In addition, all variables were normalized using the minimum and maximum values.

Development of Deep Learning Models and Conclusions

The DL is implemented in Python 3.6 using Pandas, Numpy, and Keras. Fig. 2 shows the architecture of DL models (ANN, 1D-CNN, LSTM, and 1D-CNN+LSTM) used in this study. The k-fold cross validation and grid search process for hyperparameter tuning were performed to optimize the DL models. The minimum mean absolute error and mean squared error or the maximum R^2 were used to determine the optimal values of the hyperparameters and the k of k-fold cross validation was assumed to be four.

Table 1 shows the results of hyperparameter tuning of the DL models for predicting CGP. Various DL models were developed, and the R^2 values of the developed models were compared, as shown in Fig. 3. A comparison of the developed models for predicting CGP per length at the 36-month (CGP_36M/L) revealed the R^2 (test set) of the 1D-CNN+LSTM (0.9147) model to be larger than that of the LSTM (0.9102), 1D-CNN (0.9070), and ANN (0.9121) models. Therefore, the optimal DL model for predicting CGP is 1D-CNN+LSTM model.

The developed 1D-CNN+LSTM model may be used to evaluate the production performance of shale gas projects with short production history.

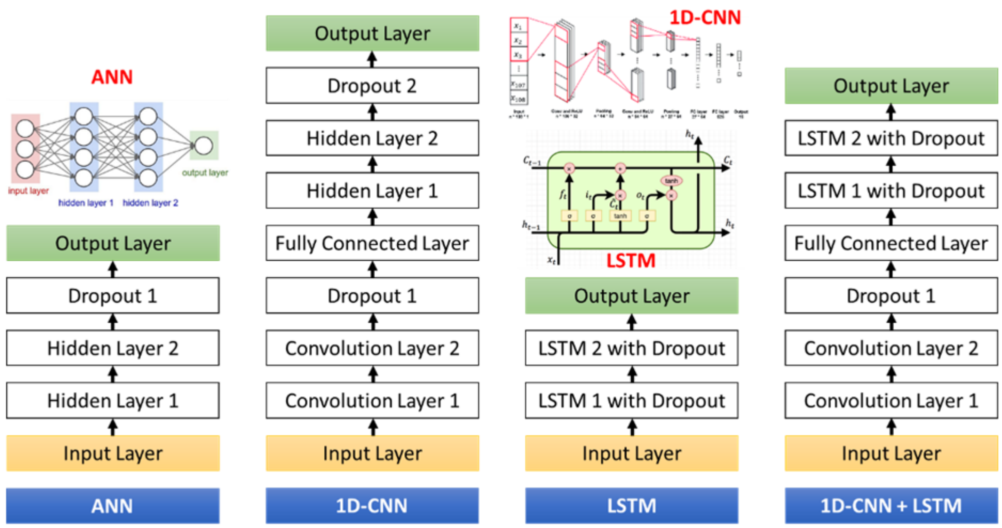
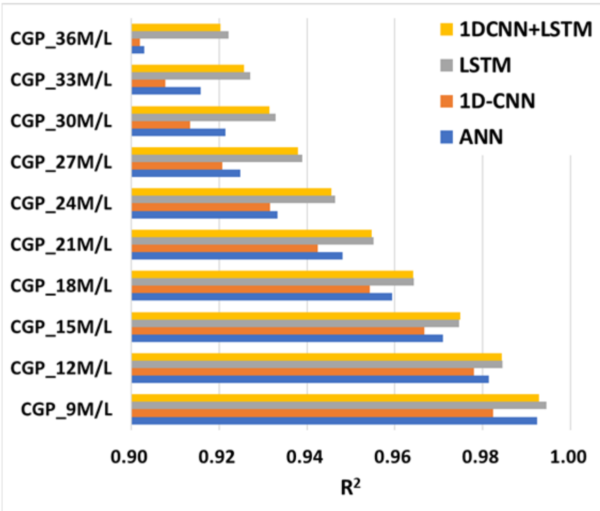


Fig. 2. Architecture of deep learning models used in this study.

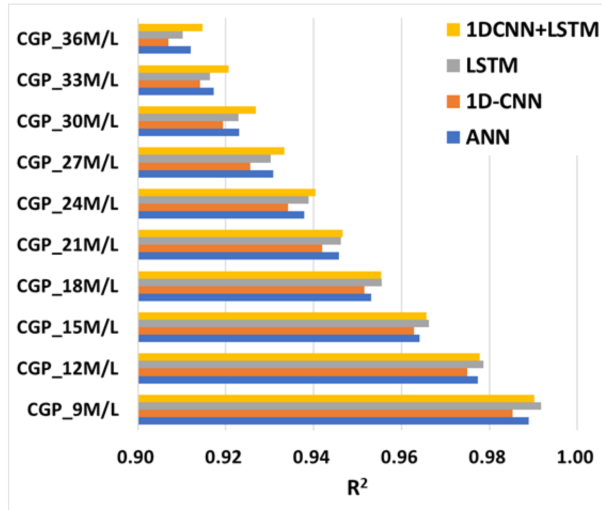
Table 1. Optimal values of hyperparameters for DL models

ANN	1D-CNN	LSTM	1D-CNN+LSTM
• Neurons of HL 1 = 60 • Neurons of HL 2 = 20 • Drop = 0.0 • AF of HL 1 = 'Selu' • AF of HL 2 = 'Selu' • Lr = 0.0008	• Neurons of CL 1 = 110 • Neurons of CL 2 = 130 • Neurons of HL 1 = 10 • Neurons of HL 2 = 40 • Drop 1= 0.3 • Drop 2 = 0.5 • AF of CL 1 = 'Selu' • AF of CL 2 = 'Relu' • AF of HL 1 = 'Elu' • AF of HL 2 = 'Selu' • Lr = 0.0006	• Neurons of LSTM 1 = 90 • Neurons of LSTM 2 = 5 • Drop of LSTM 1= 0.0 • Drop of LSTM 2= 0.1 • Recurrent Drop of LSTM 1= 0.3 • Recurrent Drop of LSTM 2= 0.5 • Lr = 0.0007	• Neurons of CL 1 = 30 • Neurons of CL 2 = 90 • Neurons of LSTM 1 = 150 • Neurons of LSTM 2 = 90 • Drop 1= 0.1 • Drop of LSTM 1= 0.1 • Drop of LSTM 2= 0.3 • Recurrent Drop of LSTM 1= 0.1 • Recurrent Drop of LSTM 2= 0.0 • AF of CL 1 = 'Elu' • AF of CL 2 = 'Relu' • Lr = 0.0008

* hidden layer (HL), convolution layer (CL), dropout (Drop), activation function (AF), learning rate (Lr)
* 'Relu' = rectified linear unit, 'Elu' = exponential linear unit, and 'Selu' = scaled exponential linear unit



(a) Train set



(b) Test set

Fig. 3. Comparison of the R^2 at various DL models for predicting CGP per length at the 9-, 12-, 15-, 18-, 21-, 24-, 27-, 30-, 33-, 36-month.

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