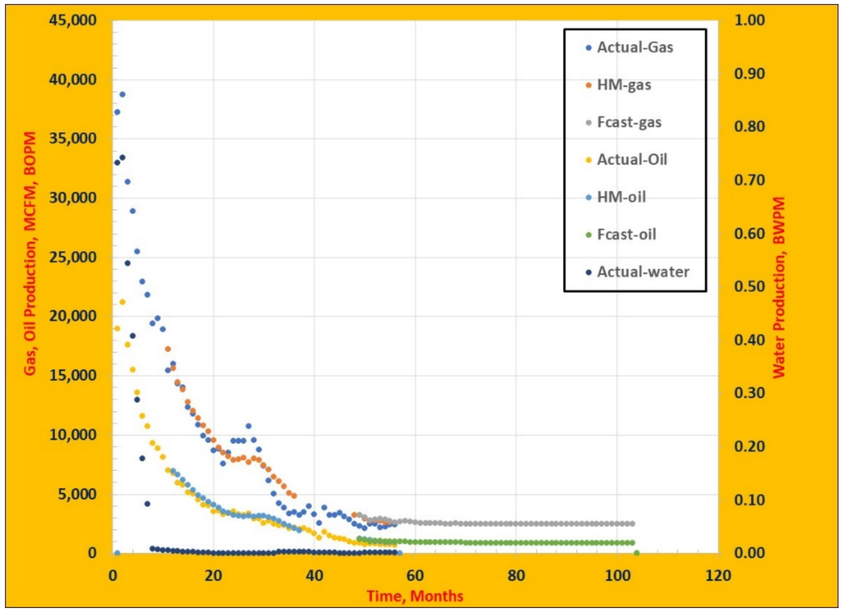
Anatomy of Data Analytics, Machine Learning and Deep Learning -- Demystified – Part V



In this article Deep Learning methods are extended to decline curve forecasting, one of the most common reservoir engineering challenges. The adjacent figure is an example prediction using Long-short Term Memory (LSTM) method.

The Densely connected feed forward networks used so far in the previous examples has one drawback in that they do not have any memory. Each input shown to them is processed independently, with no state kept in between inputs. However, in order to process a time series (e.g. decline curve), a full representation is needed by maintaining an internal model of what is being processed, built from past information and constantly updating as new information comes in. Recurrent Neural Network (RNN) is specialized precisely for that. It processes sequences by iterating through the sequence elements and maintaining a state containing information relative to what it has seen so far. LSTMs, a specialized form of recurrent neural network model, are capable of automatically learning features from sequence data, support multiple-variate data, and can output a variable length sequences that can be used for multi-step forecasting. There are many types of LSTM models that can be used for each specific type of time series forecasting problem. They are described below.

Vanilla LSTM

Simple RNNs suffers from the fact that it cannot retain all previous information while processing a particular step due to vanishing gradient problem, an effect that is similar to what is observed with non-recurrent networks causing the network to eventually become untrainable. LSTM circumvents this problem by adding a means to carry information across many timesteps, like a conveyor belt running in parallel for any information to jump in and out at any step thereby preventing older signals from gradually vanishing during processing. The parameters can be further tuned and dropout rates added to improve the performance of LSTM.

Stacked LSTM

Multiple hidden LSTM layers can be stacked one on top of another in what is referred to as a Stacked LSTM model. Thus the capacity of the network is increased without overfitting the data.

BiDirectional LSTM

Bidirectional LSTM exploits the order sensitivity of RNN i.e. RNN can process the timesteps of the input sequence in order either going forward or backward but not both. On some sequence prediction problems, it can be beneficial to allow the LSTM model to learn the input sequence both forward and backwards and concatenate both interpretations.

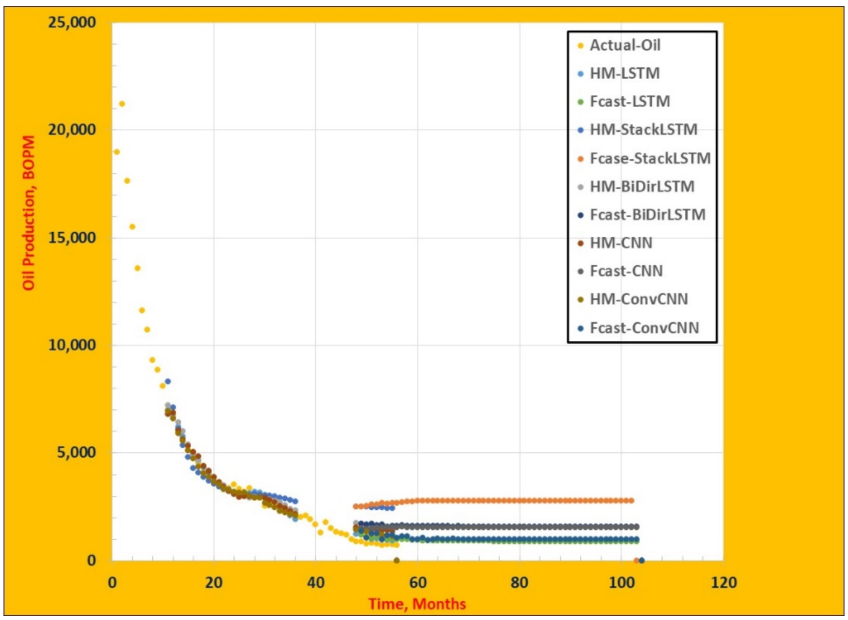
Convolution Neural Network LSTM (CNN-LSTM)

A convolutional neural network (CNN), is a type of neural network developed for working with two-dimensional image data. The CNN can be very effective at automatically extracting and learning features from one-dimensional sequence data such as univariate time series data. A CNN model can be used in a hybrid model with an LSTM backend where the CNN is used to interpret subsequences of input that together are provided as a sequence to an LSTM model to interpret. This hybrid model is called a CNN-LSTM.

ConvLSTM

A type of LSTM related to the CNN-LSTM is the ConvLSTM, where the convolutional reading of input is built directly into each LSTM unit. The ConvLSTM was developed for reading two-dimensional spatial-temporal data, but can be adapted for use with univariate/multivariate time series forecasting.

Sample Dataset – Eagle Ford



The dataset used is around 55 months of production of a typical Eagle Ford well. The well has all three phase production as well as well head pressures. This time series data is split in 2/3rd and 1/3rd, where the first part of the data is used to train the model whereas the remaining part is used to hind cast and gauge how good the model did in reproducing the data. Finally, the trained model is used to forecast time series for another 55 months of production. The LSTM methods discussed above are sequentially implemented to train, hindcast and forecast, for comparison. Unlike other decline curve methods used in the unconventional production forecast, these methods are not based on general trend fitting and physics is accounted for implicitly. However, it has the same drawback in that it assumes same operational conditions will be continued in the future. The *n_steps* parameter of the model which represents the number of previous steps used to forecast the next step was varied to investigate the quality of the forecast. Clearly, the performances differ indicating that the model parameters need to be tuned during the training process to improve their forecasting accuracy.

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