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Automated control on natural gas pipelines using deep learning algorithms

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ABSTRACT

Natural gas has been recognized as a promising resource for urban energy system due to the less air pollution and a reliable supply transported along pipelines. A simplified physical model is established in this paper, which simulates the direct correlation of compressor operations and the inlet flux at each station to be the theoretical foundation of pipeline control. The deep neural network is designed then, with the corresponding input features and output results connected via certain hidden layers representing the complex hydraulic processes occurred along the pipeline. After training and network tuning using practical operation data, the trained model is shown to be effective in predicting the inlet flux at certain station as a consequence of certain operations on the compressors, which is essentially needed for the controllers in an urban energy controlling center.

Keywords: Natural gas pipeline, automated control, deep learning, compressor operation

NONMENCLATURE

Abbreviations	
DL	Deep Learning
Symbols	
CB	Compressor Boolean
W	Weight
f	Activation Function
o	Output
L	Loss
b	Bias

1. INTRODUCTION

With the continuous development of the human society, the demand for energy is increasing and public concerns are rising on the air pollution problems caused by the utilization of coal and oil. The energy industry is now looking for clean resources, in which natural gas, including shale gas, has attracted increasing attentions as a relative clean energy with a promising reserves worth exploitation. Natural gas is becoming an important supporting energy for economic development and pipeline transportation has been recognized as an irreplaceable manner to transport natural gas (including associated gas produced by oil field) from production site or processing plant to urban gas distribution center or industrial enterprise users. Except for the lower transportation cost, pipeline transportation of natural gas is more preferred mainly due to the easier management and remote centralized controlling. Long distance pipelines, as the backbone of energy network, can deepen the link between energy-producing areas and economically-developed areas, to achieve the mutual benefit and win-win situation.

The whole world is stepping into the Era of Industry 4.0, while new techniques including Big Data, Internet of Things and Artificial Intelligence are changing every aspect of our daily life. Such trend has brought new challenges as well as opportunities to the petroleum industry, in both terms of promoting intelligent production and improving the management efficiency. A much larger amount data can be available, as well as a much stronger data simulation technique with the aid of machine learning or deep learning. In regard of natural gas pipelines, an intelligent integrated management system has been established with the help of intelligent mobile terminals, intelligent sensing devices, electronic tags and other tools, while the process parameter acquisition systems, data storage and data transmission systems have been introduced to provide the real-tome data to the control center, in order to feed the automated control system.

In this paper, two representative long-distance natural gas pipelines are selected to construct a simplified physical model, in which the pipeline control is identified as to adjust the inlet flux at certain stations by operating on the compressors along the whole pipelines. The input features and output results are then determined for the deep neural networks, which are further trained and tuned to achieve an optimized prediction. A large amount of operation data available by the integrated digital pipeline management system, and prediction results using the model trained from the randomly selected data meet well with the testing data.

2. PHYSICAL MODEL

Pipeline 1 is a representative long-distance energy channel to introduce foreign natural gas resources into China, and it is the longest natural gas pipeline with the largest engineering amount in the world. The pipeline starts from the first station A, passing through 15 provinces, autonomous regions and cities, 192 county-level units, and ends in station I. Pipeline 2 is another major energy channel in China, going through 10 provinces, autonomous regions and cities and ends in station P. 9 stations were constructed along Pipeline 1, while 7 stations were constructed along Pipeline 2. Different numbers of compressors have been installed in each station, to control the transportation through the whole pipeline, and to adjust the distribution of natural gas to various destinations. The number of compressors installed in each station is listed in Table 1 and 2, and totally 33 compressors are inclusive in Pipeline 1 and 26 compressors are inclusive in Pipeline 2.

Station	Number of compressors
A	4
B	4
C	3
D	4
E	4
F	3
G	4
H	4
I	3

Table 1 General information of the Pipeline 1

Station	Number of compressors
J	4
K	4
L	3
M	4
N	4
O	3
P	4

Table 2 General information of the Pipeline 2

For a given pipeline, inlet flux at each station is believed to be directly relevant with the operation of all the compressors, e.g. running or stopping, if the initial flux is fixed and no other change is performed. In practical production, the central controlling team indeed control and optimize the gas distribution along the pipeline by opening or closing certain selected compressors. As an exploratory study, a simplified physical model is established in this study, considering the direct relevance between the inlet flux at two stations and the operation of all the 59 compressors as the theoretical foundation of pipeline controlling. In another word, the inlet flux at station A and P are affected by the opening and closing operations in the compressors along the pipeline, and the purpose of our automated control is to predict the flux after the operations, and to suggest the controller possible consequences.

3. DEEP LEARNING ALGORITHM

3.1 Network construction

As discussed above, key factors controlling the pipeline operation are the opening and closing of compressors in each station, and the goal of the pipeline control is to adjust the inlet flux at specific stations. Two deep neural networks are designed for each pipeline respectively, with the Compressor Boolean value (represented by CB) as the input features (1 represents opening, and 0 represents closing), and the flux at station A and P as the output result. Several hidden layers are placed between the input and regression layer, in which the activation function is introduced to simulate the complex hydraulic processes along the whole pipeline. In order to approach the underneath complex mathematical correlations previously described using nonlinear functions, a large of nodes are needed in each hidden layer to construct a long linear combination.

As the number of input features is larger than that of the output result, the data used for training and testing should reach a certain size to avoid overfitting. In this paper, we totally obtained 1339 operation data points, e.g. the operation record of each compressor and the value at each station in 1339 days. 90% of the data is randomly selected as the training data to feed the network, while the other 10% of the data is used as the ground-truth in the testing.

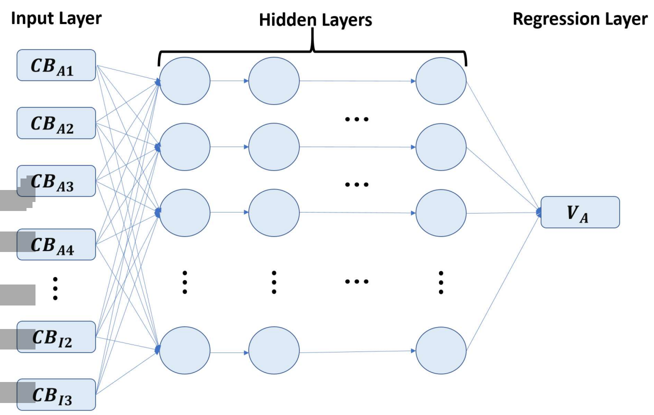

Figure 1 Deep neural network for Pipeline 1

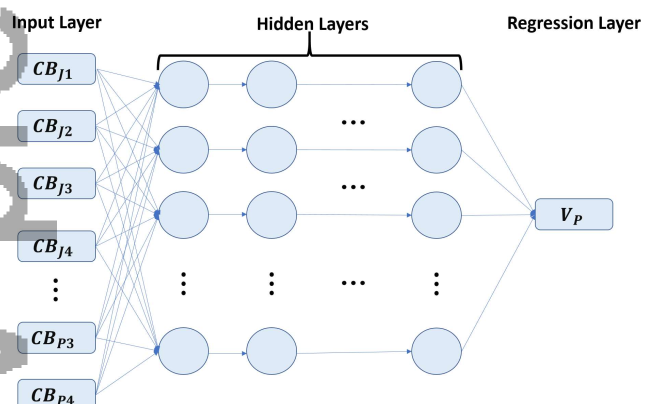

Figure 2 Deep neural network for Pipeline 2

3.2 *Deep Learning Techniques*

The visibility of using deep learning algorithm to control pipeline operation relies on the assumption that the trained linear combination of all the input features (key factors) can represent closely to the complex hydraulic process in the transportation. Based on that, the following simulation process can be constructed to determine the numerical correlation of the input and output features.

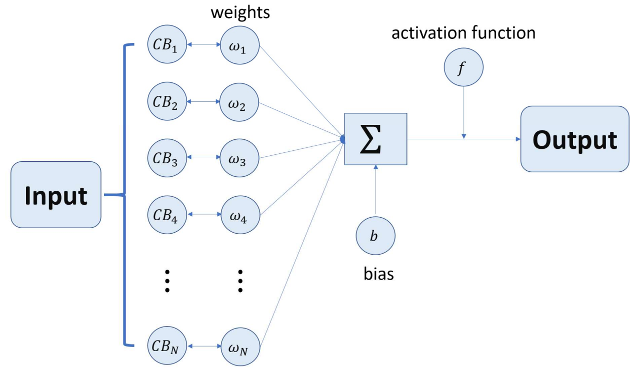

Figure 3 The simulation process in each node

As shown in Figure 3, the output of each node, y_i, can be calculated by the following equation as a function of input data vector CB_i,

$$y_i = f_i(W_i * CB_i + b_i),$$

where W_i denotes the weight vector, b_i denotes the bias introduced and f_i denotes the activation function selected in this node. The output of one hidden layer is the input of the next one, and this relation can be formulated as the following function if three hidden layers are taken into account:

$$o = f_3(W_3 * f_2(W_2 * f_1(W_1 * x_1 + b_1) + b_2) + b_3),$$

where f_1, f_2 and f_3 denote the activation function used in each layer respectively. Generally, the activation function can be the same for each hidden layer, but there has also been argument that combination of various activation functions can improve the prediction performance.

Overfitting is hard to avoid in deep learning research, especially for our over parametric neural network with a much larger size of input features than the output results. A nearly perfect performance can be achieved for the training data using the trained model, but the performance could be too bad to be accepted for verification of the testing data. A common solution to prevent over-fitting problem is to reduce the degree of freedom in the model training via certain constraints.

It can be easily referred from Figure 3 that the performance of the proposed deep learning algorithm is significantly affected by the weight parameters, and a proper initialization of the latter can be helpful for an efficient and robust network construction and convergence rate in training. Gradient vanishing or exploding may occur, if input variance increases too fast due to the overestimated weight initialization, and the training will fail with no convergence in that case. On the contrary, the model complexity may be damaged and the network performance is bad if the input variance drops quickly to an extremely small value, which is mainly caused by the underestimated weight parameters in the initialization. Xavier initialization, the most common used approach to generate the initial weight distribution, can be modeled by the following equation as:

$$\begin{aligned} var(y) = var(w_1 * CB_1 + w_2 * CB_2 + \ldots + w_n * CB_n \\ + b) \\ = var(w_1) * var(CB_1) + var(w_2) \\ * var(CB_2) + \ldots + var(w_n) \\ * var(CB_n) \overset{(1)}{=} n * var(w_i) \\ * var(CB_i), \end{aligned}$$

where the equation (1) is only meaningful if all the weights w_i and input parameters CB_i are assumed to be identity distributed. The input and output variance of one layer shall keep the same and a Gaussian distribution of weight parameter is expected.

Dropout is another technique common used to avoid overfitting, by discarding certain nodes and their related conenctions in the hidden layers to reduce the network freedom. This approach is also involved in our algorithm, and the dropout probability is set to be 10% in our design.

3.3 Training and tuning

As the index indicating the performance of the trained model, loss function is often calculated in the training. In practice, the following formation of loss function is verified to be efficient in overcoming overfitting problems. The large weights can be penalized by modifying the loss function with an additional regularization term proportional to the L2 norm of the weights,

$$L = \frac{1}{N} \sum_{n=1}^{N} \left| o - \hat{o} \right|^2 + \lambda |\mathbf{W}|_2^2,$$

where L is the loss function, o and $\hat{o}$ represent the operation data and output prediction respectively, $\mathbf{W}$ is the weight vector, and λ determines the penalization on the possible large weights.

After tracking the change of loss function L, hyper-parameters in the network can be tuned to obtain an optimized result. 5 hidden layers are preferred in Network 1 while 4 hidden layers are preferred in Network 2. The number of nodes in each layer is selected as 200, and the activation function is using “ReLU”. The loss function decreasing curve in the training process using this set of hyper-parameters is illustrated in Figure 4, and it can be easily referred that the network performance is quite good with a rapid convergence of loss function.

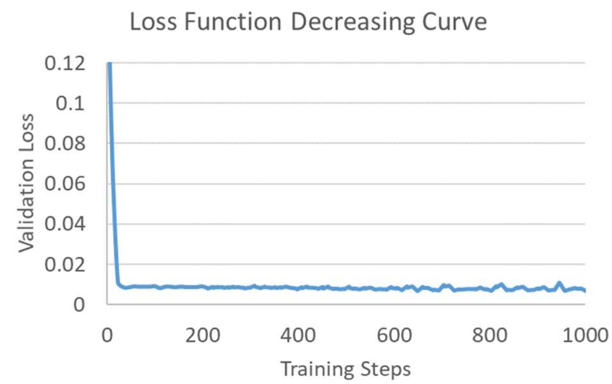

Figure 4 Loss function decreasing curve using this set of hyper-parameters

3.4 Results

The trained model is expected to be applied in predicting the inlet flux at station A and P for different operation plans on the compressors along the pipelines. In order to verify the performance of the trained model, the operation plan is selected to be the same as the practical operations in January, 2017 and January 2018, when the operation data is complete and reliable.

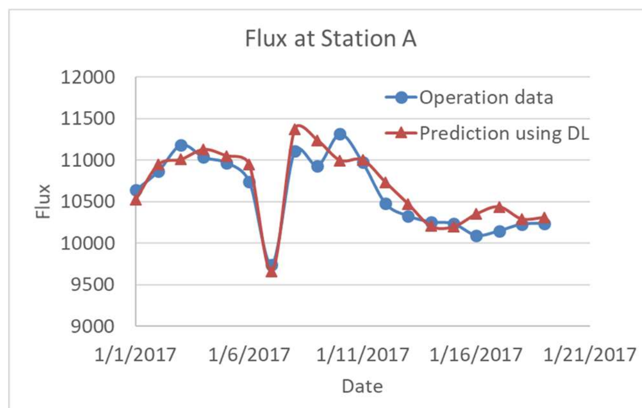

Figure 5 Comparison of operation data and prediction results using deep learning algorithm for the inlet flux at Station A in January, 2017 (unit: m^3/h)

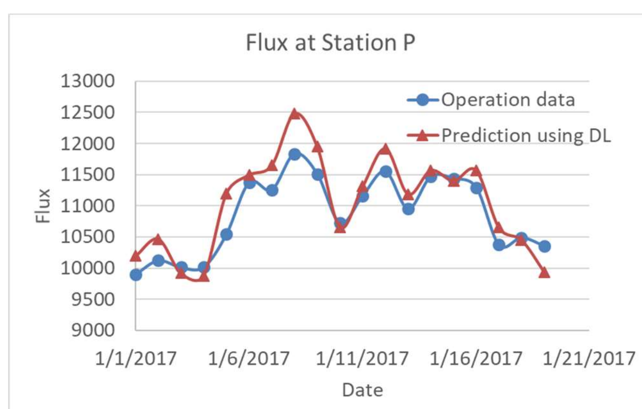

Figure 6 Comparison of operation data and prediction results using deep learning algorithm for the inlet flux at Station P in January, 2017 (unit: m^3/h)

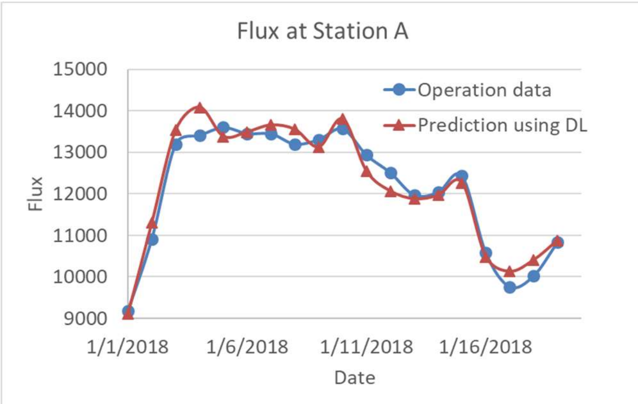

Figure 7 Comparison of operation data and prediction results using deep learning algorithm for the inlet flux at Station A in January, 2018 (unit: m^3/h)

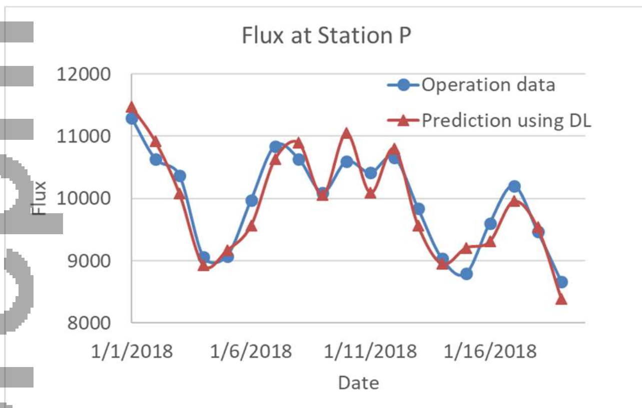

Figure 8 Comparison of operation data and prediction results using deep learning algorithm for the inlet flux at Station P in January, 2018 (unit: m^3/h)

As shown in the Figures 5-8, the predictions of trained model meet well with the ground truth, operation data. The variance is hard to be fully eliminated and overfitting is prevented. Based on the network performance, it can be guaranteed that the assumption of direct relevance between compressor operation and station inlet flux is valid, and the idea of predicting the consequence of pipeline controlling using deep learning algorithm is applicable.

4. DISCUSSION AND CONCLUSIONS

A deep learning algorithm is developed in this paper, starting from the problem identification, to network construction and hyper-parameter tuning, and the output prediction of inlet flux at certain station can be considered by the pipeline controller in the designing of pipeline controlling plans on compressor operations. The simplified physical model of pipeline control is verified to be effective in representing the complex hydraulic processes along the pipeline, and the corresponding input and output feature selections are confirmed to be suitable. The good agreement between the prediction results and practical operation data proves the well-tuned network structure and parameters, which convince us that the trained model can provide a reliable guess on the inlet flux at specific stations. The complex hydraulic and optimization modeling and simulation in previous pipeline management can be avoided with the aid of deep learning algorithms, which significantly accelerates the controlling processes.

However, it is still worth mentioning that this research is still an exploratory study and there is still distance between the simplified physical model and realistic integrated pipeline controlling systems. More factors are involved in the practical operations other than compressor opening or stopping, and the network structure can be more complex with more features taken into consideration, for example, distance between the stations and pressure after the compressor. It is happy to state that the extension of the proposed deep neural network is not difficult, while more tuning is expected in case of complex correlations underneath the newly-involved parameters.

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