The Study on Void Fraction Prediction of Gas-liquid Two Phase Flow Based on Convolutional Neural Network

Zhe Kan *, Xinyang Liu
School of Information and Control Engineering
Liaoning Petrochemical University, Fushun, China
*Corresponding author email: kanzhe@lnpu.edu.cn

Abstract. For the gas-liquid two phase flow in the horizontal pipeline, at the center angle the void fraction of the different liquid phases is calculated with the finite element simulation software, and then a soft measurement model of the void fraction is established. By comparing with traditional recursive augmented least squares (RELS), particle swarm optimization (PSO), and simulated annealing-based PSO, the void fraction soft measurement model is identified and calculated separately. The segmentation optimization results of PSO based on simulated annealing have higher accuracy and stability than RELS and PSO, but as the number of center angles increases, the relative accuracy and stability of the system will deteriorate. And the characteristic is not conducive to the calculation and analysis of data results. By combining the actual model, the convolutional neural network weight update algorithm is added to the LSTM, and the RNN-LSTM convolutional neural network is used to predict the void fraction of the second half the region. It improves the effect of RNN gradient problem on learning ability and improves learning ability. Through comparison, it is found that the convolutional neural network based on RNN-LSTM has a better prediction effect, improves the accuracy and stability of the system, and provides a new method for the measured void fraction of twophase flow.

1. Introduction
Void fraction is an important parameter in the measurement of two phase flow. It is widely present in the chemical and petroleum fields, and is particularly important for process optimization in production processes, flow measurement and control, and personal safety of operators [1]. In actual industrial production, the traditional soft sensor model method based on a single model has the problems of high model training complexity, poor matching of process characteristics and low prediction accuracy. With the continuous development of soft sensor theory, more and more attention has been paid to the soft sensor model method based on multiple models. By adding the prediction results of multiple models, the prediction accuracy and generalization ability of the model are improved. Literature [2] has achieved a good prediction of the water content of oil-water two phase flow, but the samples taken are too few and not convincing enough; the number of clusters output by the radiation propagation cluster depends on the input bias parameter p[3], and is not mentioned in the text.

In this paper, the finite element simulation of the adopted model is carried out, and the relationship between the model parameter (void fraction) to be identified and the known physical parameter (center angle) is established through the theoretical model to obtain the soft measurement model of the void fraction. Through simulation experiments, it is found that using traditional RELS [4] to identify the soft sensor model of void fraction will greatly reduce the accuracy and stability of the system, because
the change of the centre angle does not apply to the entire model. It is improved accuracy and stability of the system by analysis of the distributional data samples properties and segmental optimization, and the soft measurement model of void fraction is used the particle swarm algorithm (PSO)[5]. But the relative accuracy and stability of the system deteriorated need continue to increase as the circularity angle. This is because the basic PSO is easy to fall into the influence caused by local optimization; PSO based on simulated annealing [6] solves the problem that PSO easily falls into local optimization during the calculation process, reduces the influence of the change of the center angle on the measurement result, and improves the accuracy and stability of the system. However, when the center angle is large, there will be a large system error and fluctuation. In order to further improve the accuracy and stability of the system and solve the problems of small model applicability, insufficient global search capability and unsatisfactory prediction results in the prediction process, a convolutional neural network based on RNN-LSTM is used to predict the void fraction. The weight update algorithm in the convolutional neural network is added to the LSTM, which improves the influence of the RNN gradient problem on learning ability and improves learning ability. Simulation experiments show that this method has higher system accuracy and stability than the first three methods.

Research done in this article:
Part1: establish the simulation model of the capacitive sensor through the finite element simulation software;
Part2: use LSTM convolutional neural network to improve RNN;
Part 3: Compare the prediction effects of the four methods through simulation research;
Part 4: draw conclusions.

2. Gas-liquid two phase flow measurement model

2.1 Schematic diagram of gas-liquid two phase stratified flow
When the horizontal pipeline is filled with gas and liquid two kinds of media, stratification will occur, with the lower density above and the higher density below. Figure 1 shows the stratification of two different media, gas and liquid. Assuming that the density of the gas is less than the density of the liquid, the center angle $\beta$ corresponds to the liquid part, and the rest is the gas part.

![Fig.1 Schematic diagram of gas-liquid stratified flow](image)

2.2 Finite element simulation model
According to the model of the toroidal capacitance sensor, we use the finite element simulation software [7] to establish a similar model for the experiment, as shown in figure 2. In the picture, two ring electrodes are sheathed on the outside of the pipe, one is the excitation electrode and the other is the receiving electrode. The outer side of the electrode is a shielding cover, the purpose is to shield the magnetic field and other signal interference. The medium in the lower part of the pipe is a liquid, here we set its relative dielectric constant to 2.5, and the upper part is gas, we set its relative dielectric constant to 1, and it is assumed that the relative dielectric constant will remain unchanged during the measurement process. Solve and record the centre angle and void fraction using finite element simulation software, and establish the relationship between the model parameters (void fraction) to be
identified and the known physical parameters (centre angle) through the theoretical model to obtain the soft sensor model of the void fraction.

3. Based on RNN-LSTM convolutional neural network

3.1 Recurrent neural network (RNN) model
Recurrent neural network (RNN) is a type of recurrent neural network that takes sequence data as input, performs recursion in the evolution direction of the sequence, and all nodes (recurrent units) are connected in a chain.

![RNN working principle](image)

X is a vector, which is the feature vector of a certain data, as the input layer. U is the parameter matrix from the input layer to the hidden layer. S is a vector of hidden layers. V is the parameter matrix from the hidden layer to the output layer. O is the vector of the output layer, and W is expanded according to the timeline, which is the weight matrix between each time point. The reason why RNN can solve the sequence problem is that it can remember the information at each moment. The hidden layer at each moment is determined not only by the input layer at that moment, but also by the hidden layer at the previous moment.

3.2 Improvement of RNN by LSTM convolutional neural network
Although the gradient problem of RNN has been solved[8] to some extent by LSTM [9], it is still not enough. The reason is that it can handle fewer orders of magnitude, but it will still be difficult for longer sequences. Therefore, we still need to find a new method to solve this problem. Here we use the LSTM convolution [10] neural network to improve the RNN, mainly adding the weight update algorithm in the convolutional neural network to the LSTM. The influence of the RNN gradient problem on learning ability is improved, and the learning ability and the accuracy of prediction data are improved.

3.2.1 LSTM
All RNNs have a chained form of repeating neural network modules. In a standard RNN, this repeated module has only a very simple structure, such as a tanh layer. LSTM has the same structure, but the repeated modules have a different structure, as shown in figure 4. Unlike a single neural network layer, there are four, including three σ and a tanh, interacting in a very special way.
In figure 4, we can simply understand the working principle of the repeating module in LSTM: the vector is transmitted from one point operation to another point operation via the neural network layer, and finally distributed to different locations through replication.

The calculation process of the repeat module is as follows:

1. Determine discard information
   \[ f_t = \sigma(W_f \cdot [H_{t-1}, x_t] + b_f) \]
   \[ i_t = \sigma(W_i \cdot [H_{t-1}, x_t] + b_i) \]

2. Confirm the updated information
   \[ \tilde{C}_t = \text{tanh}(W_c \cdot [H_{t-1}, x_t] + b_c) \]

3. Update cell status
   \[ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \]

4. Output information
   \[ O_t = \sigma(W_o \cdot [H_{t-1}, x_t] + b_o) \]
   \[ H_t = O_t \cdot \text{tanh}(C_t) \]

### 3.2.2 Convolutional neural network weight update

In the CNN, the convolution kernel can be regarded as the weight in the artificial neural network, and the sampling layer is essentially a convolution operation, which updates the weight [11] of the convolution layer in CNN. Then combined with LSTM is applied in the traditional RNN algorithm.

The process of solving the weight update of the convolutional layer in CNN is as follows:

1. For each feature map of the convolutional layer output:
   \[ x_{ij}^l = F \left( \sum_{k \in M_{ij}} x_{ij}^{l-1} \ast k_{ij}^l + b_{ij} \right) \]

2. Calculated sensitivity:
   \[ \delta_{ij}^l = \delta_{ij}^{l-1} W_{ij}^{l-1} \ast F'(u^l) = \beta_{ij}^{l-1} \text{up}(\delta_{ij}^{l-1}) \ast F'(u^l) \]
   here \( \ast \) means multiplying each element, ‘up’ means up sampling operation.

3. Calculate the partial derivative of the error cost function for the bias b:
   \[ \frac{\partial E}{\partial b_l} = \sum_{ij} (\delta_{ij})_{l,ij} \]

4. Calculate the partial derivative of the error cost function for the convolution kernel k:
   \[ \frac{\partial E}{\partial k_l} = \sum_{ij} (\delta_{ij})_{l,ij} (\rho_{ij})_{l,ij} \]
   \((\rho_{ij})_{l,ij}\) is the convolution of \( x_{ij}^l \) when doing convolution with \( k_{ij} \), \((u, v)\) is the centre of the patch, and the value of \((u, v)\) position in the feature map is output.

The process of updating the weight of the down-sampling layer in CNN:

1. For each feature map of the convolutional layer output:
   \[ x_{ij}^l = F \left( \theta_{down}(x_{ij}^{l-1}) + b_{ij} \right) \]
   ‘down’ means down sampling.

2. Calculated sensitivity:
   \[ \delta_{ij}^l = \delta_{ij}^{l-1} W_{ij}^{l-1} \ast F'(u^l) = F'(u^l) \circ \text{conv2}(\delta_{ij}^{l-1}, \text{rot180}(k_{ij}^{l-1})), 'full' \]

3. Calculate the partial derivative of the error cost function for the bias b:
   \[ \frac{\partial E}{\partial b_l} = \sum_{ij} (\delta_{ij})_{l,ij} \]
4. Simulation experiment and comparison
This experiment is to learn and simulate the data by using Matlab. Since this article discusses the relationship between the centre angle and the void fraction, the time series is replaced by the centre angle. Through the simulation of the previous three methods, we found that when the centre angle is greater than 180°, the soft measurement model of void fraction is no longer applicable, therefore, LSTM convolutional neural network is used to improve the RNN, and the algorithm is used to learn the void fraction data with a centre angle of less than 180°, and the predicted data of the void fraction with a centre angle of more than 180° is obtained.

![Error analysis chart based on RNN-LSTM convolutional neural network](image1)

Fig.5 Error analysis chart based on RNN-LSTM convolutional neural network

![Data inspection results](image2)

Fig.6 Data inspection results

It can be seen from figure 5 that after 1,800 network trainings, the RNN-LSTM convolutional neural network operation error is close to 1.4x10-3. Figure 6 is the result obtained by learning and predicting 12 sets of data. It can be seen that the error between the predicted value (Predictive_value) and the actual value (Actual_value) is small, and this method improves the accuracy of the predicted result.

![Identification result of void fraction](image3)

Fig.7 Identification result of void fraction
It can be seen from figure 7 that the data obtained by using soft measurements of RELS, PSO and PSO based on simulated annealing, the change trend of the data is almost the same as the theoretical value, but through figure 8 we can clearly see that the error is relatively large, especially when the centre angle is greater than 180°, the error of the measurement results of RELS and PSO will increase significantly. Although the error of PSO based on simulated annealing is smaller than that of RELS and PSO, when the centre angle is within a certain angle range, the stability of the system is not good, resulting in a certain fluctuation in the predicted results. These phenomena are caused by the shortcomings of their algorithms. Based on the RNN-LSTM convolutional neural network, the predicted value of the void fraction (black curve) and the theoretical value (blue curve) almost overlap, and the forecast data error and error fluctuation are smaller, which shows that the method has a higher accuracy and stability.

5. Conclusion
The weight update algorithm in the convolutional neural network is added to the LSTM, and the void fraction is predicted by using the convolutional neural network based on RNN-LSTM. Simulation experiments show that compared with RELS, basic PSO and PSO based on simulated annealing, the prediction data obtained by the algorithm is closer to the theoretical value, and solves the problems of small model applicability, insufficient global search ability and unsatisfactory prediction results in the identification process of the first three optimization algorithms. At the same time, it also improves the impact of RNN gradient problems on learning ability, and improves learning ability and accuracy of prediction data. It can better realize the prediction of the void fraction of gas-liquid two phase flow, which greatly improves the accuracy and stability of the prediction system. It is of great significance for process optimization, flow measurement and control, and personal safety during the production process, and provides a new method for the measurement of two phase flow void fraction.

Acknowledgments
This work was supported by the General Project of the Liaoning Province Education Department (L2020019), China.

References
[1] Hewitt G F. Measurement for Two-phase Flow Parameters. London: Academic Press, 1978
[2] Xin Zhao, Ningde Jin, Weibo Li. Soft measurement method of phase content of oil-water two phase flow[J]. Journal of Chemical Industry and Engineering, 2005(10):1875-1879.
[3] Kaijun Wang, Junying Zhang, Dan Li, et al. Adaptive affine propagation clustering[J]. Journal of Automation, 2007, 33(12): 1242-1246.
[4] Dongqing Wang. Recursive augmented least squares identification method based on auxiliary model [J]. Control Theory and Applications, 2009, 26(01): 51-56.
[5] Xiaoliu Zhu, Weili Xiong, Baoguo Xu. QDPSO algorithm based on simulated annealing technology[J].Computer Engineering,2007(15):209-210.

[6] Changtao Wang, Xiaotong Sun, Zhonghua Han, Yi Zhu. Research on building pipeline layout based on adaptive simulated annealing PSO algorithm[J]. Journal of System Simulation, 2018, 30(05): 1941-1949.

[7] Yanli Zhang. Simulation study of a new type of electric compensation electrode based on Ansoft Maxwell's calculated capacitance[D]. Qingdao University, 2015.

[8] Zelong Li, Chunjie Yang, Wenhui Liu, Heng Zhou, Yuxuan Li. Prediction of silicon content in molten iron based on LSTM-RNN model[J]. Journal of Chemical Engineering, 2018,69(03):992-997.

[9] Ping Yang, Dan Wang, Zijian Kang, Tong Li, Lihua Fu, Yueren Yu. Prediction Model of Paroxysmal Atrial Fibrillation Based on Pattern Recognition and Integrated CNN-LSTM[J]. Journal of Zhejiang University (Engineering Science Edition), 2020, 54(05): 1039-1048.

[10] Chuanjun Pang, Jianming Yu, Changyou Feng, Yan Liu, Yefeng Jiang. Power load clustering modeling and characteristic analysis based on LSTM automatic encoder [J/OL]. Power system automation: 1-11[2020-06-20]

[11] Kun Xiao. Multi-layer convolutional neural network deep learning algorithm portability analysis[J/OL]. Journal of Harbin Engineering University: 1-6[2020-06-21].