ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0054

Research on Turbulence Calculation Model based on Machine Learning

Chuangen Zheng[1], Likang Zhao[1], Haiquan Zhong[1, *], Li Lin[2], Zhiyu Xu[3]

[1] State Key Laboratory of Oil and Gas Reservoir Geology and Exploitation, Southwest Petroleum University, Chengdu 610500, China

[2] Yunnan University of Finance and Economics, Kunming 650000, China

[3] Research Institute of Dilling and Production, Qinghai Oilfield Company, PetroChina, Dunhuang, Gansu 735301, China

[*]E-mail: swpuzhhq@126.com

Abstract

With the continuous development of the information age, machine learning technology has been continuously improved and applied in various aspects. Especially in the petroleum industry, it has become common to use computational fluid dynamics (CFD) technology to study multiphase flow problems. Due to the great development of machine learning, the fitting speed and accuracy of this technology are accelerated in the process of modeling and analysis. CFD technology consists of pre-processing, solver and post-processing. The solver stage is the core of CFD technology, and turbulence model analysis is the most valuable part in this stage, which has great room for improvement. This paper starts from turbulence analysis, based on machine learning, adds filters before iterative values are introduced into turbulence model, extracts similar features, and removes redundancy, and also puts forward the prospect of machine learning and turbulence model research.

Keywords

Machine Learning; CFD; Turbulence; Model Building; Accuracy.

1. Introduction

Turbulence is a state in which the fluid is disturbed in the flow process, which widely exists in nature [1]. When the fluid flow velocity is small, it presents a stratified flow state, and there is no interference between the layers. and the Reynolds number is small. When the flow velocity increases, the disturbance also increases, and the turbulence occurs between the flows in each layer, and the Reynolds number is large. Accurate turbulent flow simulation research is of great significance in engineering application. Accurate calculation results are also of great significance to practical engineering research, analysis and model optimization. However, due to its huge data and cumbersome calculation, the direct numerical simulation method [2] can not accurately solve the turbulence with high Reynolds number. Most of the flows encountered in the actual engineering research are turbulence, so it is of great significance to master the internal law of turbulence.

In recent years, with the rapid development of information technology, machine learning methods have also developed rapidly. And turbulence modeling has been more and more applied, including reconstruction of Reynolds average stress by machine learning method [3-4], subgrid model based on fully connected artificial neural network [5], deconvolution subgrid model based on machine learning [6] Spatiotemporal subgrid model based on cyclic neural network and Mori Zwanzig formula [7].

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0054

Therefore, starting from the classical turbulence average statistical method, this paper introduces machine learning to optimize the turbulence calculation model.

2. Machine Learning Overview

Machine learning, proposed by Arthur Samuel, is the most typical branch of artificial intelligence (AI) technology. It is usually considered as a discipline with strong intersection and wide application range. Now it has developed into a discipline covering the most extensive field of science. After years of continuous in-depth development, machine learning has formed a set of traditional model building process. It can analyze unknown data, establish a preliminary model, and then predict through the model [8]. Secondly, the mathematical optimization theory also provides a theoretical basis for machine learning model training. The optimal model is found by repeatedly screening the optimal value of the model output data.

At present, machine learning can be divided into supervised learning and unsupervised learning according to its learning system [9]. Figure 1 (a) shows supervised learning, which is to obtain the prediction curve by fitting the model of the known data set with the help of manpower, and then predict the data from the prediction curve. Figure 1 (b) shows unsupervised learning, which makes similar classification prediction on the original data without assistance. If the prediction answer is correct, the machine will be provided with "reward".

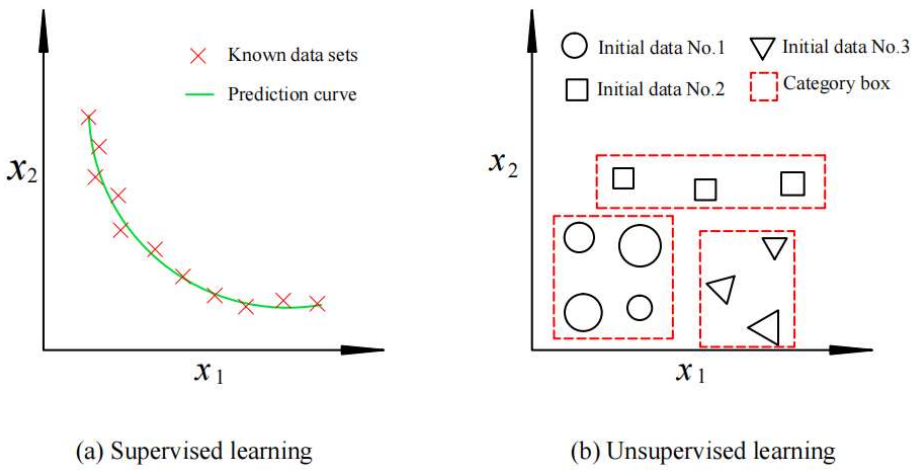

Figure 1. Machine Learning Classification

3. Turbulence Theory

The study of turbulence model started very early in China, but due to the complexity and randomness of turbulence, the turbulence theory has not yet formed a mature system. Chen et al[10] proposed the constrained turbulence large eddy simulation method, and she zhensu et al[11] proposed a new model (SED-SL) based on structural ensemble dynamics, He et al[12] elaborated the turbulence spatiotemporal correlation and dynamic coupling model under the two reference systems of Euler and Lagrange. Through the continuous research of turbulence theory, scholars have deepened their understanding of turbulence, but the essence of turbulence has not been measured by a set of basic physical laws.

Through long-term observation and measurement of turbulence, it is found that the reason why turbulence is mixed is due to the randomness of its flow. Because of its random phenomenon, only through a large number of experiments, one discrete data point is obtained each time, and the statistical average method is used to fit the "decisive" results. At present, there are three statistical average methods in turbulence theory: time average method, volume average method and probability average method.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0054

3.1 Time-averaged Method

The Cartesian coordinate system (Figure 2) is drawn by taking a fixed point in the turbulent flow field, taking the time scale as the horizontal coordinate and the instantaneous velocity of the point as the vertical coordinate:

$$\overline{\mu}(x_1\ x_2\ x_3)=\frac{1}{T}\int_{t_0}^{t_0+T}\tilde{\mu}_i(x_1\ x_2\ x_3\ t)dt \tag{1}$$

Where $\tilde{\mu}_i(x_1\ x_2\ x_3\ t)$ is the result of any experiment. The starting time t_0 is arbitrary and independent of the time interval. The average value itself cannot be a time function. Therefore, the time average method can only be used to discuss the steady turbulent flow.

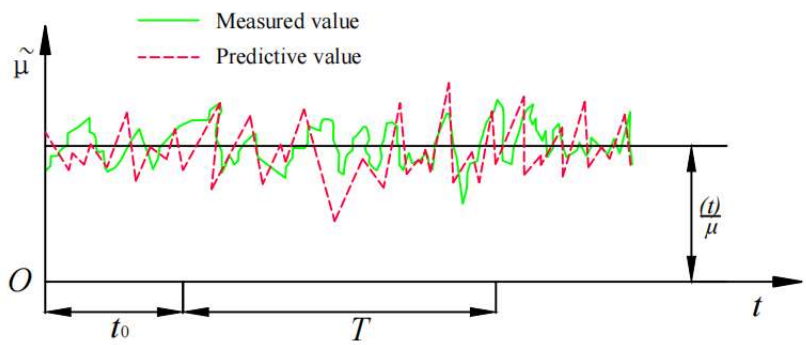

Figure 2. Relation curve between instantaneous speed and time at a fixed point

3.2 Body-average Method

The randomness of turbulence is reflected not only in time, but also in spatial distribution. The Cartesian coordinate system is drawn with the volume relative position scale as the abscissa and the instantaneous velocity of the point as the ordinate (Figure. 3). The mathematical expression (2) of the volume averaging method is:

$$\overline{V}_i(t)=\frac{1}{\tau}\iiint_{\tau}\tilde{V}_i(\xi\ \eta\ \zeta\ t)d\xi d\eta d\zeta \tag{2}$$

The body-mean method is only applicable to describe the turbulent flow field that is uniform for the body mean, which can be an indefinite flow field.

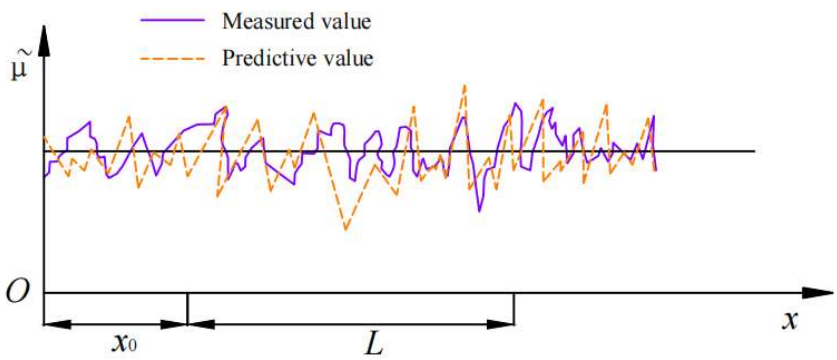

Figure 3. Instantaneous Velocity Versus Axis Displacement Curve

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0054

3.3 Probabilistic Averaging Method

The time averaging method and volume averaging method are only applicable to relatively special turbulent flow field models. For general unsteady and non-uniform turbulence, the general averaging method of random variables, i.e. ensemble averaging method, is generally adopted. Its meaning is to make arithmetic average of repeated experimental results. The mathematical expression of probability averaging method (3) is:

$$\overline{V}_i\left(x_1\ x_2\ x_3\ t\right)=\lim_{N\to\infty}\frac{1}{N}\sum_{k=1}^{N}\widetilde{V}_i\left(x_1\ x_2\ x_3\ t\right) \tag{3}$$

where $\widetilde{V}_i\left(x_1\ x_2\ x_3\ t\right)$ is the flow field distribution function of the K-th experiment, and N is the number of repeated tests.

4. Application of Machine Learning to Turbulence Models

4.1 Model Building

Through the above discussion, because the turbulent flow field depends on experimental data for manual verification and data analysis, its workload is very huge and unrealistic. Because it is difficult to meet the experimental conditions of each experiment, the physical model is established through machine learning. At the same time, it is feasible to modify the model through the existing experimental data to realize the analysis of the turbulence model of the machine.

Under the given initial conditions, that is, at the beginning of the initial flow field, each iteration of the turbulence statistical average method will be introduced into the machine through the solver for learning. The machine improves the establishment of the model through learning and calculates the convergent solution with the optimal model (Figure 4). Due to the mutual feedback of data in each iteration, the convergence process is very slow, but its stability and accuracy are very high.

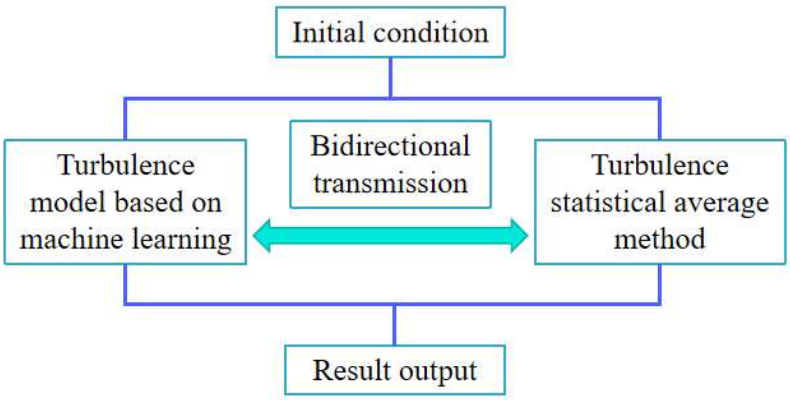

Figure 4. Model Flow Chart

4.2 Model Optimization

In the process of model construction, the machine mainly includes data processing, feature selection, determination of model framework and parameter optimization [13]. Each aspect involves a very complex research field.

In the research of data processing, the initial data required by the machine will be obtained directly through turbulence numerical calculation. However, with the accumulation of time, the amount of data obtained increases sharply, and the characteristics of data decrease. If the original turbulence numerical data are still used directly, the training effect of the model will be greatly reduced. In order to ensure the characteristics of the data, we can add filters to filter similar and redundant data when

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0054

the turbulence numerical data is transmitted to the machine. The improved flow chart is shown in Figure 5.

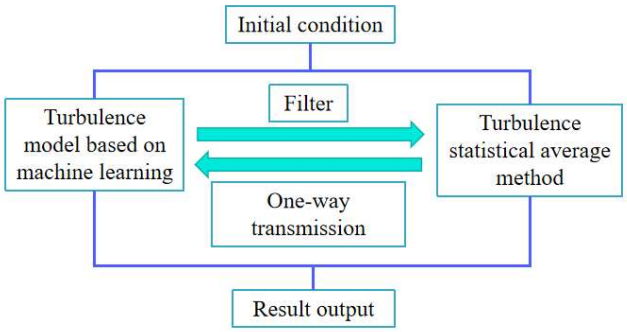

Figure 5. Improved Model Flow Chart

In the study of feature selection, it is consistent with the numerical data of turbulence. Too many feature sets not only have little effect on model training, but also greatly improve the requirements of machines. The redundant and abnormal feature sets in the convergence process will even interfere with the machine learning algorithm and reduce the performance of the model. In order to avoid too many useless feature sets, there have been relevant studies in China. Commonly used algorithms include filtering method, packaging method and embedding method [14]. In addition, while selecting features, the correlation between data values and features should be comprehensively considered. During feature collection, pay attention to the consistency of feature quantization standards to avoid model deformity caused by the alienation of quantization standards.

4.3 Determination of the Model Framework

The determination of model framework is an important parameter affecting the efficiency of machine learning and the accuracy of turbulence numerical prediction. At present, the main model frameworks at home and abroad include Gaussian process, deep neural network, Single-layer/shallow neural network and tree model. In the process of data fitting between machine and solver, the following three key points must be paid attention to:

1) The turbulence numerical data collected in each iteration must be consistent with the quantitative standard of the special collection, otherwise abnormal values will appear, resulting in the decline of the accuracy of the model. Too many abnormal values will also directly lead to machine learning to establish a wrong empirical model.

2) In the operation of the model algorithm, the stability of the algorithm must be fully considered. Since the establishment of the model is based on the continuous collection and optimization of experimental data, the predicted values cannot be consistent with the actual values. This leads to small errors in each iteration.

3) In fact, for the machine model that explicitly changes the subgrid stress or Reynolds stress, although the error fluctuation is very small, the flow field will be significantly amplified in the continuous iterative accumulation. Therefore, a correction function is needed for model control. For example, Wu et al[15] proposed a method to measure the model conditions. Explicit data drives Reynolds stress and tries to enhance the stability of the model by establishing linear and nonlinear models. Although scientists have conducted in-depth research on this aspect, they still have not found a general physical law to define the specific method to improve the stability, This research field needs further development and improvement.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0054

5. Conclusion

The rapid development of machine learning promotes fluid mechanics, injects fresh blood into fluid mechanics, and opens a new research direction for its development. Starting from the complexity of turbulence calculation, in order to find a fast solution, this paper proposes to combine with machine learning to obtain a mathematical model, which is still based on the initial experimental data to establish the original model. The fitting rate of machine learning is accelerated through machine supervised learning, continuous communication between turbulence numerical data and machine, and filter miscellaneous numerical values and feature sets. The future development of intelligent hydrodynamics should not only learn from the new methods and theories of machine learning and even artificial intelligence. Through interdisciplinary and coordinated development, and in combination with the practical needs of engineering problems and life problems, overcome the prominent scientific problems in the field of fluid mechanics and the bottleneck problems faced by engineering design.

References

[1] Johnson P L. A physics-inspired alternative to spatial filtering for large-eddy simulations of turbulent flows[J]. Journal of Fluid Mechanics, 2022, 934.

[2] Li X L, Fu D X, Ma Y W, et al. Direct numerical simulation of compressible turbulent flows[J]. Acta Mechanica Sinica, 2010, 26(6): 795-806.

[3] Ling J, Kurzawski A, Templeton J. Reynolds averaged turbulence modelling using deep neural networks with embedded invariance[J]. Journal of Fluid Mechanics, 2016, 807: 155-166.

[4] Duraisamy K, Iaccarino G, Xiao H. Turbulence modeling in the age of data[J]. Annual Review of Fluid Mechanics, 2019, 51: 357-377.

[5] Gamahara M, Hattori Y. Searching for turbulence models by artificial neural network[J]. Physical Review Fluids, 2017, 2(5): 054604.

[6] Maulik R, San O, Rasheed A, et al. Data-driven deconvolution for large eddy simulations of Kraichnan turbulence[J]. Physics of Fluids, 2018, 30(12): 125109.

[7] Ma C, Wang J. Model reduction with memory and the machine learning of dynamical systems[J]. arXiv preprint arXiv:1808.04258, 2018.

[8] Du Yu Perceptual computing of human pose and gesture based on deep learning [D] Zhejiang: Zhejiang University, 2017.

[9] Dimiduk D M, Holm E A, Niezgoda S R. Perspectives on the impact of machine learning, deep learning, and artificial intelligence on materials, processes, and structures engineering[J]. Integrating Materials and Manufacturing Innovation, 2018, 7(3): 157-172.

[10] CHEN S,XIA Z,PEI S,et al.Reynolds-stress-constrained large-eddy simulation of wall-bounded turbulent flows[J]. Journal of Fluid Mechanics,2012,703:1-28.

[11] She zhensu, Tang fan, Xiao Structural ensemble dynamics theory for engineering turbulenc models [J] Acta Aerodynamica Sinica, 2019,37 (1): 1-18.

[12] HE G,JIN G, YANG Y.Space-time correlations and dynamiccoupling in turbulent flows[J].Annual Review of Fluid Mechanics,2017,49:51-70.

[13] Zhang Weiwei, Zhu Linyang, Liu Yilang, et al. Progresses in the application of machine learning in turbulence modeling [J] Acta Aerodynamica Sinica, 2019,37 (03): 444-454.

[14] Guyon I, Elisseeff A. An introduction to feature extraction[M]. Feature extraction. Springer, Berlin, Heidelberg, 2006: 1-25.

[15] WU J L,XIAO H,SUN R,et al.Reynolds averaged Navier- Stokes equations with explicit data-driven Reynolds stress closure can be ill-conditioned[J].Journal of Fluid Mechanics, 2019,869:553-586.