Application of Multi-layer Forward Neural Network based Piecewise Linear Regression in Simulation of Steam Turbine Valve Flow Curve

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Abstract: In this paper, the piecewise linear function regression method based on FNN (Forward neural network)-ReLU (Rectified linear units) is used to simulate the flow curve of steam turbine valve. In the big data scenario, this method could accelerate the fitting process using GPU, as well as improve the accuracy by increasing the hidden layer of the neural network. In addition, the number of segments is auto-determined and manually chosen initial break point avoided. Applying the method to simulate the relationship between the valve position and the steam flow in a 330M power unit in Shandong, the result shows a higher fitting accuracy with lower time consumption.

1. Introduction

A massive volume of data is formed during the operation of thermal power units, which makes available the analysis to the flow characteristics of steam turbine valves. Simulation of the valve flow curve which represents the relationship between the valve position and the steam flow is of great significance to effectively improve the steam turbine operation and avoid negative coordination among power units. If the flow curve of the steam turbine valve misrepresents the actual steam flow characteristics, the unit's primary frequency control capability might be insufficient and the direction of the valve adjustment will be misleading.

Traditionally, the flow characteristics are obtained through field test. However, due to the low simulation model capacity and data update infrequency, a series of online analysis using big data methods have been proposed. Shan Guangxian et al. [1] outlined the data warehouse, data mining technology and their application prospects in power systems. Huang Yanhao et al. [2] provided the basic framework of developing big data technology in the power system simulation domain. Gao Yajie et al. [3] used statistics to identify the actual steam turbine valve flow characteristics and optimized the steam turbine regulation. Wang Gang et al. [4] applied a multiple linear regression to the identification of the flow characteristic parameters of steam turbine regulating valves. Li Cunwen [5] improved the K-Medoids algorithm and proposed a multiple linear regression method for steam turbine flow characteristics analysis. Shang Xingyu et al. [6] used BP neural network to simulate the relationship between the valve position and the steam flow. Zou Baochan et al. [7] applied neural network during the processing of flow characteristics data and identified an optimal steam turbine's valve flow curve regulation using the least square method.

The piecewise linear function regression method based on FNN-ReLU [8] is used to simulate the flow curve of steam turbine valve under a deep learning scenario. It has the advantage of high training
speed utilizing GPU devices and enables a construction of deeper network thereby improving the fitting accuracy. In addition, the number of segments is auto-determined and manually chosen initial break point avoided. Applying the method in a 330M power unit of Shandong province, the result shows a higher fitting accuracy with lower time consumption.

2. Steam Turbine Valve’s Characteristics Field Test

The traditional steam turbine valve flow characteristics field tests are divided into the single valve control mode and sequence valve control mode. For the single control mode, the control methods of DEH (Digital electric hydraulic) system should be switched to the single valve mode and stabilize the unit load. Then, control instruction will be reduced at a certain rate and boiler adjusted so that the pressure and temperature of the main steam remain stable. For the sequence control mode, the operator need to adjust every valve of the steam turbine sequentially and record the pressure, temperature, flow of the main steam as well as regulating stage pressure of all the valves. Flugelformula is put into use during the simulation of flow characteristic curve, as follows:

$$ G = A \sqrt{\frac{2k}{k-1}} p_0' \rho_0' (\varepsilon_n^2 - \varepsilon_n^{k+1}) $$

\( G \) is the main steam flow, \( A \) is the outlet area of nozzle, \( p_0' \) is the stem pressure of nozzle inlet and \( \rho_0' \) is the steam density of nozzle inlet. Pressure ratio is \( \varepsilon_n = \frac{p_1}{p_0} \), where \( p_1 \) is the nozzle back pressure, \( k \) is the adiabatic exponent.

Due to the need to operate in the field, the traditional steam flow curve simulation method has three shortcomings. Firstly, the flow characteristics are obtained under specific operating conditions of the boiler, however, the working parameters of the boiler usually change dynamically in actual operation. Therefore, it is difficult to completely maintain the ideal test state. At the same time, the steam turbine will also be adjusted dynamically, which causes further deviation of the flow characteristic curve obtained by the field test. Secondly, the data from during field test is limited resulting in a lower fitting model capacity, which is not able to dig out the true characteristics of the valve. This means that a large amount of data in SIS (Supervisory information system) and DCS (Distributed control system) can’t be deeply mined. Thirdly, the field test requires a person to go to the site for operation causing a low frequency test, so when the valve characteristics changes, the original fitting model might be no longer applicable.

3. Piecewise Linear Regression in Simulation of Steam Turbine Valve Flow Curve

3.1 Neural Network

ANN (Artificial neural network) is a computational model that mimics the structure and function of biological neural networks. It continuously updates the neurons in each layer of the network through the gradient descent method. ANN is mostly used for estimating or approximating complex functions. Among different structures, the FNN is the most common in use. It utilizes a unidirectional multilayer structure.
FNN is a feedforward network with the structure of single input, output layer and multi hidden layer. For each layer, FNN has multiple neurons, of which the specific structure is as follows:

$ x_i $ and $ y_i $ are the inputs and outputs of FNN, $ w_i $ is the weight for each neuron, and $ f(.) $ represents the activation function. ReLU is used as the activation function (equation 2) for the FNN based piecewise linear regression model.

$$ f(x) = \max(0, x) $$

Due to the sparse structure of the ReLU function, the neural network does not have to activate all the neurons during the output process. Compared to Sigmoid and Tanh activation function, ReLU has no upper and lower bounds, so there will be no saturation of neurons during training. At the same time, because the derivative of ReLU function is constant, the training process will not suffer from gradient vanishing, which makes available a deeper network structure.

### 3.2 FNN-ReLU based Piecewise Linear Regression Model

Using piecewise linear function regression using a deep learning framework is of great significance to valve flow curve simulation. This is because the linear regression of a single function is too simple, resulting in low fitting accuracy. It also means that a huge amount of data can be utilized. In addition, the traditional piecewise linear regression method has the defects of connection point judgment,
manual setting of segments number and slow fitting speed. According to Meitetsu [8], if the ReLU activation function is put into use in FNN for the \((n - 1)\)th layer and adding them element-wisely, the segment number is determined by the number of neurons of that layer. Let the number of neurons in the \((n - 1)\)th layer be \(n\), then the potential number of segments is \(n + 1\).

\[ y = (1, ..., 1)^T(W^T x) + c_h \]  

(3)

where: (1) \(x\) represents the output value of the hidden layer, which is \((h_1, h_2, h_3, h_4)\) in Fig 4. These variables are activated by the ReLU function; \(W^T\) is the weight matrix for the last layer with the dimension of \(4 \times 1\); \(c_h\) is a constant value. In order to make the network enable to do a piecewise linear fitting, the output values of the last second layer need to be directly added. That is why the vectors \((1, 1, 1, 1)^T\) and \((h_1, h_2, h_3, h_4)\) are multiplied.

4. Dataset and experimental results

The proposed model is applied to a 330MW power unit in Shandong Province for experiments. As shown in Fig 5, the x-axis of the curve is the valve position instruction, and y-axis stands for the steam flow. In order to improve the fitting accuracy, the number of hidden layers can be increased. Here, we use 4 hidden layers and set the \((n - 1)\)th layer of 7 neurons so the potential segments will be 8. To accelerate the training process, we use Pytorch with GPU as the deep learning framework and set the batch number to 128 as well as using ADAM (Adaptive Moment Estimation) for parameter optimization. From the experiment result, we can find that: (1) FNN-ReLU based piecewise linear regression model can accurately fits the steam turbine valve flow well with an \(R_{MSRE} \) of 0.027; (2) the linear segments are 5, which is auto-determined during the optimization process; (3) compared to CPU, the training time is greatly reduced by more than 200% with GPU.
5. Conclusion
In this paper, the FNN-ReLU based piecewise linear function regression model is used to simulate the flow curve of steam turbine valve. The experiment result shows that it improves the accuracy with a multilayer network structure and accelerates the fitting process of the valve flow curve using GPU. In addition, the network enables the self-determination of the linear segments, therefore, make it more flexible compared to the traditional piecewise linear regression method.

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