A Multivariate State Estimation Technique and Multilayer Forward Neural Network Framework on Steam Turbine Valve Flow Curve Simulation

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Abstract. The Multivariate State Estimation Technique (MSET) is firstly implemented as the fault detection technique for monitoring parameters of the steam turbine valve. Second, healthy operation states are remained to form a preliminary dataset for the valve curve simulation. Then, the Forward neural network (FNN) based piecewise linear fitting method is used to simulate the steam turbine valve flow curve. With a MSET-FNN framework proposed, the simulation accuracy will be enhanced by removing the unhealthy operational states. In addition, the simulation process will gain a speed up with the utilization of GPU.

1. Introduction
A massive volume of data stored in the Supervisory Information System (SIS) and Distributed Control System (DCS) [1] is formed during the operation of thermal power units. This enables analysts to do data mining in the power units. Among them, simulation of the steam turbine valve flow curve is one that is of great significance to effectively improve the steam turbine operation and avoid negative coordination among power units. It is because 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.

The MSET is a technique for real-time process monitoring [2-3]. Studies show that MSET can detect the fault of equipment of power plant by comparing the residuals with the threshold [4-6]. Therefore, it can also be used in the fault detection for steam turbine valve. Traditionally, the flow characteristics are obtained through field test. Recently, a series of online analysis using big data methods have been proposed. Huang Yanhao et al. [7] provided the basic framework of developing big data technology in the power system simulation domain. Li Cunwen [8] improved the K-Medoids algorithm and proposed a multiple linear regression method for steam turbine flow characteristics analysis. Shang Xingyu et al. [9] used BP neural network to simulate the relationship between the valve position and the steam flow. Zou Baochan et al. [10] 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.

This paper proposes a MSET-FNN framework to improve the steam turbine valve flow curve simulation. The MSET is firstly implemented as the fault detection technique for monitoring parameters of the steam turbine valve. Second, healthy operation states are remained to form a preliminary dataset for the valve curve simulation. Then, the FNN based piecewise linear fitting method is used to simulate the steam turbine valve flow curve. With a MSET-FNN framework
proposed, the simulation accuracy will be enhanced by removing the unhealthy operational states. In addition, the simulation process will gain a speed up with the utilization of GPU.

2. MSET
MSET is an advanced pattern recognition technology that generates an estimate of current health. Firstly, by constructing a process memory matrix \( D \) from the normal data, MSET learns the state of normal operation of multi-dimensional measurement points. Secondly, by comparing the real-time operation data with the process memory matrix, MSET completed the judgment of whether a certain measurement point is operating normally.

Some conceptions involved in MSET include the process memory matrix \( D \), the system state or observation \( X_{obs} \) and the estimate \( X_{est} \). The data matrix defined by MSET, shown in the equation (1) has \( m \) parameters, and each parameter has \( N \) time steps. Each column of the matrix is the time series values from \( t_1 \) to \( t_N \) of one parameter \( x_i \). Each row of the matrix lists the values of all the parameters from \( x_1 \) to \( x_m \) at one time \( t_i \). We call each column an observation or state of the product at the corresponding time because it contains all of the monitored parameters of the product.

\[
D = \begin{bmatrix}
x_1(t_1) & \cdots & x_1(t_N) \\
\vdots & \ddots & \vdots \\
x_m(t_1) & \cdots & x_m(t_N)
\end{bmatrix} = [X(t_1), \ldots, X(t_N)]
\]  

(1)

The state or observation \( X_{obs} \) of the system at time \( t_j \) is represented by a vector \( X(t_j) \) or \( X_{obs}(t_j) \) of length \( m \), where \( m \) is the number of monitored parameters of the product.

\[
X(t_j) = [x_1(t_j), x_2(t_j), \ldots, x_m(t_j)]^T
\]

(2)

To account for as many working conditions as possible, expert experience should be utilized to collect normal operating data during a wide range of time. Therefore, \( D \) could cover the full dynamic range of the monitoring parameters under normal system operation.

The next step is to use MSET for dynamic modelling. To determine whether parameters of the \( X_{obs} \) is under an unhealthy state, every absolute value of the residual between \( X_{obs} \) and the predicted value \( X_{est} \) is calculated and compared with the residual under healthy state, namely:

\[
\varepsilon = |X_{obs} - X_{est}|
\]

(3)

Here, \( X_{est} = D_{m \times N} \cdot W_{n \times 1} \), “\( \cdot \)” is matrix multiplication. This formula indicates that the predicted value comes from the extraction of historical information, because \( X_{est} = w_1 X(t_1) + w_2 x_2 + \ldots + w_N X(t_N) \). Among them: \( W_{n \times 1} \) can be determined by minimizing the sum of squares of the residual vector \( \varepsilon \). So there is the following formula:

\[
W = (D^T \otimes D)^{-1}(D^T \otimes X_{obs})
\]

(4)

where \( \otimes \) represents a non-linear operator between matrices or between matrices and vectors. For the general matrix product “\( \cdot \)”, there may exist a multicollinearity, which make the matrix not invertible. Therefore, in order to be able to get \( W \), \( \otimes \) generally chooses Euclidean distance as a nonlinear operator instead of “\( \cdot \)”. So the specific expression for \( \otimes \) is as follows:

\[
\otimes(X, Y) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2}
\]

(5)

Finally, by comparing \( \varepsilon \) from \( X_{obs} \) with the residual threshold vector \( \varepsilon^* \) under healthy conditions, we can judge whether a given parameter in \( X \) is unhealthy or not.

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

3.1. Neural Network
FNN is a feed forward 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:
Fig1. FNN neuron structure

where $x_i$ 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 6) for the FNN based piecewise linear regression model.

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

(6)

Fig2. ReLU activation function

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 based Piecewise Linear Regression Model

Using piecewise linear function regression based on 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 [11], 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 $n + 1$.

The mathematical form [11] for the last layer of the model is:

$$y = (1, ..., 1)^T(W^T x) + c_h$$

(7)
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.

3.3. Numerical Experiment

The FNN based piecewise linear regression model is applied to a 330MW power unit in Shandong Province for experiments. Main steam flow/pressure/temperature, post-valve pressure, valve flow and valve position are chosen as the parameters for inputs \(x\). In Fig 4, the x-axis of the curve is the valve position instruction given other parameters unchanged, 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.

![Fig4. FNN-ReLU fitted steam flow curve of turbine valve](image)

4. MSET-FNN Framework

Steps are as follows to form a whole MSET-FNN framework:

Step1. Choose main steam flow/pressure/temperature, post-valve pressure, valve flow and valve position as \(X_{obs}\) for steam turbine valve simulation.

Step2. Using expert knowledge, the normal operation of the valve under various working conditions are formed as the training set for MSET to build process memory matrix \(D\).

Step3. Split the training set into two parts. Take one part to build \(D\) and the other as \(X_{train}\) to calculate a benchmark \(\varepsilon^*\). Compare the \(\varepsilon\) from new observed data \(X_{obs}\) with \(\varepsilon^*\) to judge which of the parameters in \(X_{obs}\) is a fault.

Step4. Remove the data of time-period during which shows fault warning in the observations. The data left then is prepared for feeding into the FNN to make simulations.

Step5. Use ReLU as the activation function and ADAM for optimization. The loss function here is \(R_{MSRE}\):

\[
R_{MSRE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}
\]

Step6. After the FNN model trained, adjust valve position from 0 to 100 while making other inputs unchanged to get a simulation of the steam turbine valve curve.
5. Conclusion
We proposed a MSET-FNN framework to improve the steam turbine valve curve simulation. During the entire workflow, MSET is used as a data filter to build a preliminary training data set for FNN learning. The FNN based piecewise linear fitting method is used to simulate the steam turbine valve flow curve. With this framework, the simulation accuracy will be enhanced by removing the unhealthy operational states. In addition, the simulation process will gain a speed up with the utilization of GPU.

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