A Novel Method for Power Quality Disturbance Detection Based on LSTM Network Model Residuals

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Abstract. In order to accurately detect the time when the disturbance of power quality (PQ) occurs and the variation of voltage amplitude, a novel method of power quality disturbance detection that is based on the residual of the long short-term memory (LSTM) network model is proposed. Firstly, an offline model is developed based on historical voltage signals from a power grid under the normal condition by using the LSTM theory. Then, in order to detect PQ events online, the grid voltage signal is taken as the input of the model to obtain the residual component between the input signal and the normal signal. Finally, the amplitude change of the residual component reflects the amplitude change of the voltage. The starting and ending time and duration of the disturbance are located by detecting the mutation points of the residual component. Experiments on simulation data and engineering data show that the proposed method can well reflect the amplitude change when the voltage is disturbed, and the disturbance positioning accuracy is high.

1. Introduction
The instability and complexity of PQ disturbance are always the challenge and emphasis for scholars [1]. Most of the existing signal analysis methods are based on time-frequency domain, including Short-Time Fourier transform (STFT) [2], Hilbert-Huang transform (HHT) [3], Wavelet transform (WT) [4], S-transform (ST) [5], etc. When analyzing in the time-frequency domain, if the detected signal contains harmonics and inter-harmonics close to its frequency, the detection accuracy will be affected. In recent years, some scholars have proposed a PQ disturbance detection method based on the time domain model, using the residual sequence of the AutoRegressive (AR) model [6] to detect the mutation points of the disturbance signal. However, there are no strictly stationary signals in the power system, AR model cannot be directly applied to the analysis of non-stationary signals. Therefore, this paper proposes a novel method of PQ disturbance detection based on the residual of LSTM network model. The LSTM network is used to model the normal voltage signal. Then the measured signal is used as input, and the expected normal voltage is obtained by tracking the hidden information of the measured signal. The residual sequence is generated by subtracting the expected signals from the measured signals. The amplitude change of the residual sequence reflects the amplitude change of the voltage signal. The mutation points in the residual sequence are used to detect the occurrence time and duration of the disturbance. Experiments on simulated signals and measured signals of the power grid show that the mutation points in the residual sequence of the LSTM network model can indicate the moment of fault initialization and fault clearing of the power grid, and its amplitude changes can well reflect the voltage changes. Compared with traditional time-frequency
analysis method, the proposed method has less computation and a good prospect for engineering application.

2. Power Quality Disturbance Detection Method Based on LSTM Network

2.1. LSTM Network

LSTM network performs well on time series forecasting problems. The structure of recurrent layer neurons in LSTM network is shown in Figure 1.

![Figure 1. Neurons in the LSTM recurrent layer.](image)

The training process of LSTM network is as follows:

a. Prepare the training data set $T$

b. Calculate the output value of the recurrent layer

In Figure 1, the input vector $X_t$ and the output vector $H_{t-1}$ of the recurrent layer at $t-1$ will act simultaneously on the input gate $I_t$, the forget gate $F_t$, and the output gate $O_t$ in each neuron of the recurrent layer. The sigmoid function is used for all three gating, and the value domain of the function is $(0,1)$. Multiplication of the gating function with another vector can control the output ratio of the vector, so it plays a control role of information.

At time $t$, $H_t$ is expressed as

$$H_t = O_t \odot \tanh(C_t)$$  \hspace{1cm} (1)

In equation (1), $\odot$ represents the multiplication of the corresponding items of the two matrices. $C_t$ is the memory value stored in the neuron at time $t$. $C_t$ is weighted and updated with time, so the information at different times has the same impact on the current. $C_t$ is shown in equation (2). $O_t$ determines how much of the memory value in $C_t$ can be output.

$$C_t = F_t \odot C_{t-1} + I_t \odot \tanh(W_{cx}X_t + W_{ch}H_{t-1} + b_c)$$  \hspace{1cm} (2)

$F_t$ controls the output ratio of $C_{t-1}$, $I_t$ controls the output ratio of the input value. $O_t$, $F_t$ and $I_t$ are expressed as equations (3) to (5).

$$O_t = \sigma(W_{ox}X_t + W_{oh}H_{t-1} + b_o)$$  \hspace{1cm} (3)

$$F_t = \sigma(W_{fx}X_t + W_{fh}H_{t-1} + b_f)$$  \hspace{1cm} (4)

$$I_t = \sigma(W_{ix}X_t + W_{ih}H_{t-1} + b_i)$$  \hspace{1cm} (5)

In equations (2) to (5), $\sigma$ is the sigmoid function. $W_{ix}$, $W_{ih}$, $b_i$, $W_{fx}$, $W_{fh}$, $b_f$, $W_{ox}$, $W_{oh}$, $b_o$, $W_{cx}$, $W_{ch}$, $b_c$ are the weight matrix and bias of input gate, forget gate, output gate and memory unit respectively.

c. Calculate the error $E$ between the predicted value and the true value inversely

$$E = \sum_i (h_i - \hat{h}_i)^2$$  \hspace{1cm} (6)
In equation (6), $h$ represents the truth value, $\hat{h}$ represents the predicted value.

d. Calculate the gradient of the output layer weight and the output layer bias
If $E$ reaches the error threshold or the network training times reaches the maximum number of iterations, stop training.

2.2. Power Quality Disturbance Detection Based on Residual Sequence of LSTM Network Model

2.2.1. Offline modeling. The process of offline modeling is as follows:
Step 1: Obtain the required signals. Using the equations in [7], the PQ disturbance signals include voltage swells, voltage sags, voltage interrupts and oscillatory transients.
Step 2: Generate the required training set. Take $m$ normal voltage signals of the power grid to form a training set $T$, and divide each training sample according to a sliding time window with length $k$, which can be expressed as equation (7):

$$X_i = \begin{bmatrix} x_{i,1} & x_{i,2} & \cdots & x_{i,k} \\ x_{i,2} & x_{i,3} & \cdots & x_{i,k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i,N-k} & x_{i,N-k+1} & \cdots & x_{i,N-1} \end{bmatrix}, \quad Y_i = \begin{bmatrix} x_{i,k+1} \\ x_{i,k+2} \\ \vdots \\ x_{i,N} \end{bmatrix}$$

In equation (7), the number $N$ is the length of the signal, The input of the $i$-th training sample is represented by $X_i$, and the output of the $i$-th training sample is represented by $Y_i$, where $i=1, 2, ..., m$. The training set $T$ is expressed as $T=\{(X_1,Y_1),(X_2,Y_2),\cdots,(X_m,Y_m)\}$. Each row in the matrix $X_i$ represents a sliding time window, and the $j$-th sliding time window of $X_i$ can be expressed as $X_{i,j}=(x_{i,j},x_{i,j+1},\cdots,x_{i,j+k})$, where $j=1, 2, ..., N-k$.
Step 3: Modeling of signal tracking model. Input $T$ into the network for training. Each time $X_{i,j}$ is used as input, the predicted data $x_{j+k}$ of the sliding time window is output. After many experiments, the optimal parameters are determined and the required model is obtained.

2.2.2. Event detection. The process of event detection is as follows:
Step 1: Obtain the expected normal voltage signals. After the model is established, the first sliding window $X_{i,1}(x_{i,1},x_{i,2},\cdots,x_{i,k})$ of the measured signal is used as the input to obtain the output $x_{k+1}$, and then $x_{k+1}$ is added to the next sliding window $X_{i,2}(x_{i,2},x_{i,3},\cdots,x_{i,k+1})$ to obtain $x_{k+2}$. In this way, the expected normal voltage signal are obtained.
Step 2: Extract the residual component. Since the model cannot adapt to the sudden change caused by the disturbance quickly, subtracting the measured voltage from the expected voltage will produce some relatively large estimation errors $r$ at the sampling points where the disturbance occurs. The estimated error $r$ is the residual sequence of the model.
Step 3: Detection and localization. The sampling moment corresponding to the mutation point of the residual sequence is the moment of fault initialization and fault clearing in the power grid. The amplitude change of the model residual sequence can determine the voltage change when the disturbance occurs.

3. Experiment and Analysis

3.1. Simulated Data
To prove that the proposed method is effective, LSTM network and AR model are used to detect the voltage swells, voltage sags, voltage interrupts, and oscillatory transients. The fundamental frequency is set to 50 Hz, and the sampling frequency is set to 3200 Hz. A total of 20 cycles of signals are
collected, the total length is 1280 $\Delta t$, and the sampling interval $\Delta t = 0.3125$ms. The LSTM method was used for training and the following parameters were finally determined after several experiments: the length of sliding time window $k$ was 32; the number of recurrent layers was 3; each layer had 100 neurons; the maximum number of iterations was 1000; the learning rate was 0.005.

Voltage swells is shown in Figure 2(a). The disturbance occurs at $741 \Delta t$, and ends in $1141 \Delta t$, the duration is $400 \Delta t$, and the actual increase in voltage is 17.8%. Figure 2(b) and Figure 2(c) show the residual sequence and voltage changes of the two models. Figure 2(b) shows that the start and end times of the disturbance detected by the residual sequence of the LSTM network model are $742 \Delta t$ and $1141 \Delta t$, the duration is 399 $\Delta t$, and the voltage rise is about 0.1785 p.u. (17.85%). Figure 2(c) shows that the start and end times of the disturbance detected by the residual sequence of the AR model are $743 \Delta t$ and $1141 \Delta t$, the duration is 398 $\Delta t$, and the voltage rise is about 0.2163 p.u. (21.63%).

Voltage sags is shown in Figure 3(a). The disturbance occurs at $236 \Delta t$, and ends in $858 \Delta t$, the duration is $622 \Delta t$, and the actual drop is 19.69%. Figure 3(b) and Figure 3(c) show the residual sequence and voltage changes of the two models. Figure 3(b) shows that the starting and ending time of the disturbance detected by the residual sequence of the LSTM network model are $237 \Delta t$ and $858 \Delta t$, the duration is 621 $\Delta t$, and the voltage drop is about 0.1968 p.u. (19.68%). Figure 3(c) shows that the starting and ending time of the disturbance detected by the residual sequence of the AR model are $237 \Delta t$ and $858 \Delta t$, the duration is 621 $\Delta t$, and the voltage drop is about 0.1617 p.u. (16.67%).

The results from Table 1 reflect that the residual sequence of the LSTM network model is very sensitive to disturbance. Compared with the AR model, the LSTM network can more detect the starting and ending time and duration of the disturbance accurately. The amplitude change of the residual sequence of the LSTM network can reflect the change of the voltage amplitude. The tracking sensitivity of LSTM is higher than that of AR model, which proves the effectiveness of the proposed method.

| Type of disturbance | Detection error of start point (ms) | Detection error of end point (ms) | Detection error of amplitude (%) |
|---------------------|-------------------------------------|----------------------------------|---------------------------------|
|                     | LSTM | AR | LSTM | AR | LSTM | AR |
| Voltage swells      | 0.3125 | 0.625 | 0 | 0 | 0.05 | 3.83 |
| Voltage sags        | 0.3125 | 0.3125 | 0 | 0 | 0.01 | 3.52 |

Figure 4 and Figure 5 show the detection of voltage interrupts and oscillatory transients using the proposed method.
The actual start time of voltage interrupts is 923 $\Delta t$, the end time is 1029 $\Delta t$, and the duration is 106 $\Delta t$. The actual start time of oscillatory transients is 394 $\Delta t$, the end time is 432 $\Delta t$, and the duration is 38 $\Delta t$. From Figure 4 and Figure 5, we know that the residual sequence of the LSTM network exhibits significant singularities. The mutation points in the time domain are the starting and ending time of the disturbance. The mutation points in the residual sequence of the LSTM network model can be locate the starting and ending time of the disturbance accurately.

3.2. Engineering Case

The proposed method is used to analyse the monitoring data of the wave recorder of a substation in Northwest China. The cause of the disturbance is that there is a short circuit between the phases of the line during the operation of the system, which causes the current to rise sharply, causing the voltage sags in the A-phase and B-phase of the 110kV bus voltage. The fundamental frequency is 50Hz, the data sampling frequency is 3200Hz. A total of 20 cycles of signals are collected. The length of signal is 1280 $\Delta t$, sampling interval $\Delta t = 0.3125$ms.

The measured signals of the three-phase voltage on the bus side of the power grid are shown by Figure 6. The start time of the A-phase disturbance is 639 $\Delta t$, the end time is 881 $\Delta t$, the duration is 242 $\Delta t$, and the actual sag is 0.1875p.u. (18.75%). The start time of the B-phase disturbance is 642 $\Delta t$, the end time is 867 $\Delta t$, the duration is 225 $\Delta t$, and the actual sag is 0.2385p.u. (23.85%).

![Figure 6. Three-phase voltage signals of 110kV bus.](image)

After normalizing the voltage data of A-phase and B-phase, we use the method proposed in Section 2 for detection. The residual sequence and amplitude prediction results of phase A and phase B are shown in Figure 7 and Figure 8.

![Figure 7. Detection of Ua.](image)

![Figure 8. Detection of Ub.](image)

Figure 7(b) and Figure 8(b) show that the non-linear and impulsive loads in the power grid produce some harmonics. The A-phase voltage disturbance detected by the residual error of the LSTM network model occurs at 642 $\Delta t$, the end time is 886 $\Delta t$, the duration is 244 $\Delta t$, and the voltage drop is about
0.1626 p.u. (16.26%). The B-phase voltage disturbance occurs at $644\Delta t$, the end time is $886\Delta t$, the duration is $242\Delta t$, and the voltage drop is about 0.1945 p.u. (19.45%).

Table 2. Detection results of engineering data.

| Voltage phase | Detection error of start point (ms) | Detection error of end point (ms) | Detection error of amplitude (%) |
|---------------|-------------------------------------|----------------------------------|---------------------------------|
| Ua            | 0.9375                              | 1.5625                           | 2.49                            |
| Ub            | 0.625                               | 0                                | 4.4                             |

The results in Table 2 show that the proposed method is also applicable to engineering signals, and the voltage amplitude change information can be obtained through the amplitude change of the residual sequence accurately. The starting and ending time of PQ disturbance can be precisely located by detecting the mutation points in the time-domain residual sequence.

4. Conclusion
This paper proposes a novel method of PQ disturbance detection based on the residual of LSTM model. Firstly, the LSTM network is used to model and estimate the normal voltage signal. Then the measured signal is used as the input to generate a residual sequence to detect the mutation point of the disturbance signal. Experiments with engineering data and simulation data show that this method can not only accurately locate disturbances, but also detect voltage amplitude changes, which proves the practicability and effectiveness. Since the signal used for modeling in the proposed method does not consider the influence of noise, the detection of mutation point in the voltage waveform still has defects and needs to be further improved in subsequent work.

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