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Harmonic Source Classification based on GRU Network

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Abstract: ***With the development of ultra-high voltage and smart grids, the issue of power grid harmonic pollution caused by nonlinear loads and equipment has become more prominent. Harmonic pollution leads to increased energy consumption and poses safety risks to the operation of the grid, resulting in significant economic losses. In the comprehensive management of grid harmonics, the classification of harmonic sources is an urgent issue that needs to be addressed. In this context, this paper proposes a harmonic source classification method based on the GRU network. This method utilizes the GRU model, which is capable of long-term memory, to extract inherent features from harmonic data for classification, achieving good classification results. It provides a necessary foundation for the effective implementation of harmonic analysis and management.***

Keywords: smart grid, GRU, harmonic suppression

1. Introduction

With the rapid development of ultra-high voltage and smart grids, the issue of harmonic pollution caused by nonlinear loads and devices has increasingly come to the fore. Equipment such as photovoltaic power stations, substations, converter stations, and power plants inject harmonics into the power grid, leading to waveform distortions in the system's current and consequently causing harmonic pollution in the grid. Harmonic pollution not only leads to energy and equipment consumption but, under certain "resonant" conditions, can also cause damage to key grid equipment, posing safety risks to the power system and resulting in substantial economic losses [1]. To address and prevent harmonic pollution issues, the first problem that needs to be resolved in the process of strengthening grid harmonic analysis and comprehensive management is the rapid and accurate localization of the sources of harmonics.

Currently, the research on harmonic classification and recognition has formed a relatively mature approach. The common methods for classification and recognition mainly include: traditional state estimation methods [2], SE methods combined with the least variance [3], continuous state estimation methods [4], methods based on active power [5], and methods based on the characteristics of distorted loads [6].

However, traditional research on harmonic classification and recognition tends to start from an electrotechnical perspective, generally based on mechanistic models. It mainly relies on methods such as equivalent circuit models, harmonic state estimation, or harmonic impedance. Due to the time-varying nature of harmonic sources and their characteristics that are difficult to measure directly, traditional classification and recognition methods often struggle to obtain sufficient predictive values for computation. Therefore, the introduction of methods based on deep neural networks aims to optimize traditional harmonic source detection and recognition methods, enhancing their performance. The adaptive, self-organizing, and pattern recognition capabilities of neural networks allow for the automatic identification of nonlinear relationships between input and output values—relationships that are often difficult to define or explain. This approach can obtain initial values of harmonic source parameters and significantly reduce the number of detection devices required by traditional classification and recognition methods.

The introduction of the Gated Recurrent Neural Network (GRU) was specifically aimed at better-capturing dependencies over long time steps within time series data[7]. It controls the flow of information through gates that are capable of learning. Among these, the GRU is a commonly used type of gated recurrent neural network.

In summary, the research objective of this paper is to address the issue of harmonic source identification using electric power quality monitoring data. The study focuses on the recognition of harmonic sources, starting from the perspective of statistics and machine learning. It aims to transcend traditional methods by employing a GRU-based model for the classification of harmonic sources, exploring the intrinsic patterns within the data to achieve rapid and accurate identification of harmonic sources. The prediction results will be evaluated using precision, recall, and F1 score metrics, providing a necessary foundation for the effective implementation of harmonic analysis and management.

2. Problem Formulation

2.1 Power Grid Harmonic Problem

Harmonics refers to the components obtained by decomposing a periodic non-sinusoidal electrical quantity, whose frequencies are integer multiples of the fundamental frequency. They are an important indicator of electric power quality. Harmonic pollution can lead to increased energy consumption and, in severe cases, may cause damage to key equipment in the power system, triggering significant safety issues and substantial losses. Harmonic distortion can result in a decline in electric power quality, affecting the efficiency and lifespan of electrical equipment. Classifying harmonic sources helps in addressing the specific causes of reduced power quality. On the other hand, uncontrolled harmonics may lead to overheating of electrical components, causing equipment failure or even fire hazards. Precise identification of harmonic sources is crucial for ensuring the reliability and safety of the system. By accurately classifying harmonic sources, power companies can optimize the operation of their systems, reduce energy losses, and save on operational costs. The sources of voltage harmonics and current harmonics in power systems mainly fall into the following categories [8]:

a) Electrical devices or power equipment containing rectifiers. Due to the unidirectional conduction characteristics of rectifying tubes, the input current waveform of the rectifier is non-sinusoidal, containing a large number of harmonic components.
b) Thyristor phase-controlled regulating devices. Due to the chopper conduction of thyristors, the voltage and current waveforms become non-sinusoidal, which contain a large number of harmonic components.
c) Electric arc furnaces and AC arc welding machines. Harmonic currents are generated due to the nonlinearity and variability of the equivalent impedance of the arc.
d) Equipment containing iron cores such as transformers and motors. The magnetization current waveform is distorted due to the nonlinearity of the iron core's magnetization curve.

Among various types of electrical equipment that inject harmonics into the power system, the most significant sources of harmonics are electrical devices, for example: photovoltaic power stations, power plants, substations, converter stations, electric arc furnaces, and electrified railways. The harmonic sources studied in this paper are aimed at these types of electrical equipment.

2.2 GRU

GRU is a variant structure of LSTM, in which GRU combines the input gate and forget gate of LSTM into an update gate and incorporates both the cell state and hidden state [9]. Compared to LSTM, the GRU neural network simplifies the three gates into an update gate and a reset gate, reducing the number of parameters required in the computation process [10]. Consequently, this reduction shortens the training time and accelerates the convergence speed. The reset gate and update gate in GRU are shown in Figure 1.

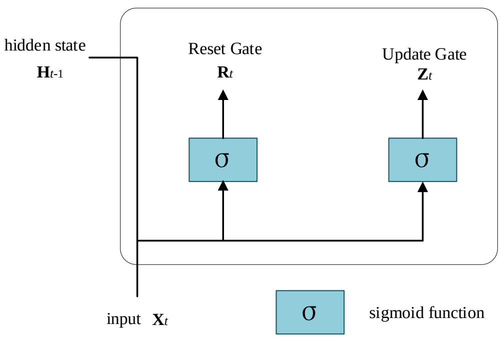

Figure 1: Reset and update gate in GRU

The computational steps of GRU are as follows:

For a given time step t, with the current input data as $\mathbf{X}_t$ and the hidden state from the previous time step as $\mathbf{H}_{t-1}$, the calculation formulas for the reset gate $\mathbf{R}_t$ and the update gate $\mathbf{Z}_t$ are as follows:

$$\mathrm{R}_t = \sigma(\mathbf{X}_t\mathbf{W}_{xr} + \mathbf{H}_{t-1}\mathbf{W}_{hr} + b_r) \quad (1)$$

$$\mathbf{Z}_t = \sigma(\mathbf{X}_t\mathbf{W}_{xz} + \mathbf{H}_{t-1}\mathbf{W}_{hz} + b_z) \quad (2)$$

Where Wxr, Wxz, Whr, Whz are weight parameters, and br, bz are bias parameters.

By combining the reset gate Rt with the conventional hidden state update mechanism, the candidate hidden state $\tilde{\mathbf{H}}_t$ for time step t is obtained.

$$\tilde{\mathbf{H}}_t = \tanh(\mathbf{X}_t\mathbf{W}_{xh} + (\mathbf{R}_t * \mathbf{H}_{t-1})\mathbf{W}_{hh} + b_h) \quad (3)$$

Where $\mathbf{W}_{xh}$ and $\mathbf{W}_{hh}$ are weight parameters, b_h is the bias parameter, the symbol * represents element-wise multiplication, and the tanh non-linear activation function is used to ensure the values in the candidate hidden state remain within the interval (-1, 1).

The element-wise multiplication of $\mathbf{R}_t$ and $\mathbf{H}_{t-1}$ can reduce the influence of previous states. Whenever the terms in the reset gate $\mathbf{R}_t$ approach 1, we revert to a regular recurrent neural network. For all terms in the reset gate $\mathbf{R}_t$ that is close to 0, the candidate hidden state is the result of a multilayer perceptron with $\mathbf{X}_t$ as the input.

The above calculation results are only the candidate hidden states, but they still need to be combined with the effect of the update gate $\mathbf{Z}_t$. The new hidden state $\mathbf{H}_t$ largely comes from the old state $\mathbf{H}_{t-1}$ and the new candidate state $\tilde{\mathbf{H}}_t$. Below is the final update formula for the Gated Recurrent Unit.

$$\mathbf{H}_t = \mathbf{Z}_t * \mathbf{H}_{t-1} + (1 - \mathbf{Z}_t) * \tilde{\mathbf{H}}_t \quad (4)$$

Whenever the update gate $\mathbf{Z}_t$ approaches 1, the model tends to retain the old state. At this time, the information from $\mathbf{X}_t$ is essentially ignored, effectively skipping over the time step t in the dependency chain. Conversely, when $\mathbf{Z}_t$ approaches 0, the new hidden state $\mathbf{H}_t$ will be close to the candidate state. These designs can help address the issue of vanishing gradients in recurrent neural networks and better capture dependencies over long sequences of time steps. For instance, if the update gate of all time steps in an entire subsequence is close to 1, regardless of the sequence length, the old hidden state from the starting time step of the sequence can easily be retained and passed to the end of the sequence.

In summary, the Gated Recurrent Unit possesses two significant features:

(a) The reset gate helps capture short-term dependencies within a sequence.
(b) The update gate aids in capturing long-term dependencies within a sequence.

3. Experimental Scheme

3.1 Data Analysis

Approximately 1000 sample data points were collected for each of the nine types of harmonic sources, which include: electric vehicle charging stations, electric heating systems, electrified railways, wind farms, photovoltaic power stations, urban rail transit, converter substations grid-side outputs, converter stations AC outputs, and rolling mills, comprising nine types of harmonic source data. These nine types of harmonic sources are correspondingly assigned to labels 0-8, as shown in Table 1.

Table 1: Nine harmonic sources

Types of Harmonic Sources	*Label*
Electric Vehicle Charging Stations	0
electric heating systems	1
electrified railways	2
wind farms	3
photovoltaic power stations	4
urban rail transit	5
converter substations grid-side outputs	6
converter stations AC outputs	7
rolling mills	8

One sample data point is collected every three minutes for each category, totaling 9000 data points. Approximately 20% of the data (about 1800 data points) is uniformly extracted as the test set, 900 data points as the validation set, and 6300 data points as the training set. The data set partitioning is shown in Table 2

Table 2: Data set partitioning

dataset	*quantity*	*quantity*
training set	6300	70%
test set	1800	20%
Validation set	900	10%

Each data point contains 72 feature values, which are the higher-order harmonics of the three-phase current at various moments. Upon comparison, the arrangement and direction of the higher-order harmonics within the same category are generally consistent. Moreover, since higher-order harmonics possess a sequential order, it is appropriate to use the GRU model for classification.

3.2 Model Building

The harmonic source classification problem is modeled and designed based on the deep learning model GRU, with the modeling architecture shown in Figure 2.

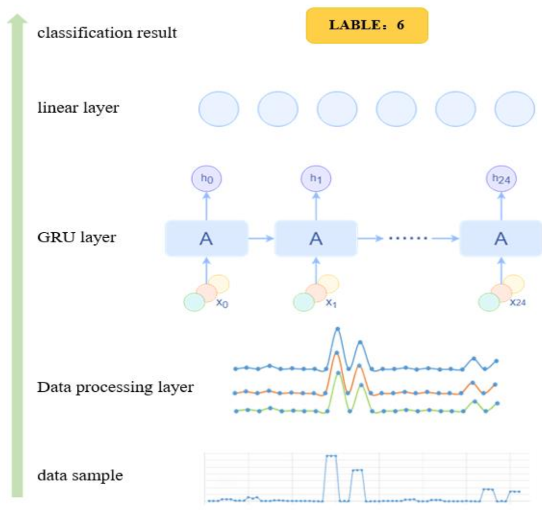

Figure 2: Model architecture diagram

The model consists of three parts: the data processing layer, the GRU layer, and the linear layer. The optimization algorithm used is Stochastic Gradient Descent (SGD).

The data processing layer is responsible for importing the data, and dividing it into three parts: training set, validation set, and test set. It also batches the data and shuffles it randomly to improve accuracy. Each piece of data is treated as a time series, with the three phases of electrical current, A, B, and C, each considered as a feature, and each higher-order harmonic as a time step. Thus, the input data is a sequence with 3 features and 24 time steps. Once the data processing is complete, it enters the main body of the model for training.

The GRU layer, serving as the core of the entire model, has update and reset gates that are highly suitable for extracting features from time series. The processed data is fed into the GRU for trained learning, extracting features contained within the harmonic data. The parameter design for the GRU layer is as follows: feature dimension is 3; dimension of the hidden states is 32; number of GRU layers is 1; dimensions of the input data's shape is (seq_len=24, batch=64, input_size=3). The parameter settings of the model are shown in Table 3.

Table 3: The Parameter Settings of the Model

Parameter	*Value*
Feature dimension	3
Hidden layer state dimension	32
Number of GRU layers	1
Dimensions of the input data	(24,64,3)

The linear layer takes the harmonic features extracted by the GRU as input, with the aim of this layer being to output class ification of the features. The model employs cross-entropy to measure model loss, calculates the loss function, and defines an optimizer, choosing SGD as the optimization algorithm, with the number of iterations set to 500.

4. Experimental Results and Analysis

4.1 Training Process

The training model is implemented through programming on the Pytorch platform. The training environment is as follows. The processor model is Intel(R) Core(TM) i5-6200U CPU @ 2.30GHz, with a processor base frequency of 2.40 GHz, a nd a memory capacity of 8 GB. The experimental parameter settings are shown in Table 4.

Table 4: Experimental Parameter Settings

Parameter	*Value*
epoch	500
learning rate	0.005
batch size	64

4.2 Training results and analysis

At the end of the experiment, the test set was fed into the trained model, resulting in an accuracy of 98.7%. By invoking the classification report function from sklearn, an analysis of metrics such as precision, recall, and f1-score for the GRU classification model can be obtained, and the metric results are shown in Table 5.

Table 5: Evaluation index results of GRU model

Label	*Precision*	*Recall*	*F1-Score*
0	0.9953	1	0.9976
1	0.9958	0.9713	0.9834
2	0.9817	0.9907	0.9862
3	1	1	1
4	0.9865	0.9399	0.9626
5	0.9953	0.9953	0.9953
6	1	1	1
7	1	1	1
8	0.9316	0.9909	0.9604

The average precision and recall rates of the GRU classification model are both above 98%, with the identification accuracy for labels 3, 6, and 7, which correspond to wind farms, converter substation grid-side outputs, and converter station AC outputs harmonic sources, reaching 100%. The prediction results show that the model has a good ability to distinguish between positive and negative samples, with an average f1-score result exceeding 98%, indicating good stability of the classification model.

5. Summary

This paper applies the GRU model, a deep learning algorithm suitable for processing time-series data, to the classification of harmonic sources. The GRU model not only overcomes the defect of gradient explosion that is prone to occur in RNNs but is also more streamlined compared to LSTM, which speeds up training, reduces convergence time, and yields training results that are not significantly different from those of LSTM. The GRU model extracts abstract features from harmonic data and classifies them through a linear layer, achieving satisfactory classification results. This model enables the classification and identification of nine types of harmonic sources, providing a necessary foundation for the effective implementation of harmonic analysis and management.

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