Research on Non-Intrusive Load Decomposition Technology Based on Deep Learning Algorithm

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Abstract

Load identification is an important part of non-intrusive load decomposition to realize smart electricity consumption. The electricity consumption information of each consumer can be decomposed from the current change information of the main meter, so as to provide more refined and targeted information for electricity consumers. Power consumption management and dispatch services. This paper uses the current effective value and the harmonic component information after Fourier transform to propose a load decomposition algorithm based on a one-dimensional convolutional neural network. It uses similarity comparison to decompose the current information of each consumer and solves the problem of newly added users or the problem of using electrical appliances to retrain. It solves the problems that the current non-invasive load decomposition algorithm using one-dimensional convolution has low decomposition accuracy, new user appliances need to be retrained, and high complexity. It is found through experiments that the method proposed in this paper can also improve the accuracy of load decomposition to a certain extent, and the complexity is low.

Keywords: *Non-invasive load monitoring, deep learning, appliance status aggregation, smart grid*

I. Introduction

Smart power consumption is one of the important research directions of smart grid, among which load monitoring is its important function. Load monitoring can give the electricity consumption of various electric equipment, and on this basis, realize user-side energy management, electricity dispatch and other functions **错误!未找到引用源。**. Non-intrusive load monitoring (Non-intrusive load monitoring, NILM) is also called non-intrusive load disaggregation (Non-Intrusive Load Disaggregation, NILD [2]), which analyzes the total electricity meter data in a specific area, Relevant information can be obtained for each electrical load in the range, such as the number of loads, the type of each load, the working state and the corresponding energy consumption usage, etc. **错误!未找到引用源。**. NILM can use electrical appliances without entering the house or for the user. Under the premise of installing electric meters separately, it can realize the monitoring of users' electricity consumption, and provide users with corresponding electricity services more accurately through the analysis of electricity consumption behavior. It is important to improve the level of power supply services, save energy resources, and improve electricity efficiency. The practical significance of.

George Hart pioneered the concept of NILM [4]. The proposed monitor measures at the power interface, and determines the single switch that is turned on and off in the electrical load based on a detailed analysis of the current and voltage of the total load. The energy consumption of the equipment. This method can decompose electrical appliances from a small number of electrical appliances, and it is difficult to accurately decompose the electrical appliances in the case of a large number of electrical appliances. Therefore, scholars continue to propose to improve the decomposition effect by adding different load characteristics. Load characteristics mainly include steady-state characteristics, transient characteristics, and periodic characteristics of state transition characteristics. Among them, transient characteristics can be subdivided into transient power waveform characteristics, voltage noise characteristics, etc., and steady-state characteristics are subdivided into power steps. Characteristics, steady-state current waveform characteristics, etc. [5]. Through research, it is found that load decomposition by extracting more

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features has achieved good decomposition results.

With the development of artificial intelligence technology, technologies such as machine learning and deep learning have gradually been applied to non-intrusive load decomposition problems. This type of method does not require a high sampling rate, only uses low-end hardware to collect data, and learns load characteristics through deep neural networks, thereby establishing a corresponding load model for load identification and decomposition [6].The use of neural network methods avoids manual design of features, and makes it easier to analyze time series features, and has a certain improvement in decomposition accuracy [7]. At present, the research of deep learning in the application of non-intrusive load decomposition is one of the important directions now.

This article is based on the steady-state characteristics of electrical parameters and the characteristics of harmonic components, using a one-dimensional convolutional neural network method to decompose household appliances. Not only can the required electrical appliances be accurately decomposed, but also a good decomposition effect can be achieved by supplementing the electrical appliance signal library for different users' families without repeating training.

II. Non-Invasive Load Decomposition

Non-intrusive load monitoring is a typical time series analysis problem 错误!未找到引用源。. At a certain time t, the non-intrusive load decomposition can be expressed as follows:

$$F(p_t)= [P^1(t), P^2(t), \ldots, P^N(t)] + [e^1(t), e^2(t), \ldots, e^n(t)] \tag{1}$$

Among them, p_t is the total power of all electrical appliances collected by the meter at time t, $P^n(t)$ is the predicted power value of n electrical appliances at time t, and $e^n(t)$ is the measured value and predicted value of n electrical appliances The error.

A typical non-intrusive negative monitoring process includes data collection, data preprocessing, load decomposition and other steps [6]. If it is decomposed by deep learning methods, it is also necessary to build a network model.

2.1 Non-intrusive load decomposition model input electrical parameters

Load characteristics are an important factor for load decomposition, mainly to change the characteristics of voltage, current, and electric power to form electrical parameters that are conducive to extracting characteristics.

2.1.1 Effective value of current

The magnitude and direction of the alternating current will change periodically with time. Assuming that the alternating current is I, the effective value of the alternating current

$$I^\tau = \frac{I}{\sqrt{2}} \tag{2}$$

2.1.2 Harmonic component

Harmonic component refers to the integral multiple component of the Fourier series of the electrical quantity in one period whose order is greater than 1.

Assuming that the collected current can be represented by the sine function y=Asin(wx+φ), the Fourier series can be written as the following formula:

$$f(t) = \frac{a_0}{2} + a_1\cos(wt) + b_1\sin(wt) + a_2\cos(2wt) + b_2\sin(2wt) + \cdots$$

$$=\frac{a_0}{2}+\sum_{n=1}^{\infty}[a_n\cos(nwt)+b_n\sin(nwt)] \tag{3}$$

Among them, a_n and b_n are harmonic components.

$$a_n=\frac{2}{T}\int_{t0}^{t0+T}f(t)\cos(nwt)dt$$
$$b_n=\frac{2}{T}\int_{t0}^{t0+T}f(t)\sin(nwt)dt \tag{4}$$

2.2 Load decomposition model based on effective value and harmonic components

The important difference between this paper and the existing non-intrusive load decomposition model algorithm lies in the data selection. Some scholars make use of the differences in the working modes of users' electrical appliances and use the differences in the working hours of different electrical appliances to decompose. However, because there are too many working modes of multiple electrical appliances, thousands of working modes can be arranged and combined, so the decomposition effect is not good. Another alternative data is to decompose by the effective value of the current. Since the effective value of the current will have a transition edge when the electrical appliance starts to work, different electrical appliances have different magnitudes of the effective value of the current jump. Therefore, it can be resolved by the difference of the transition edge. Using this kind of data can effectively obtain useful information, but the amount of data information is not enough, and there are too few values for reference in the decomposition, which is prone to error decomposition.

Therefore, based on previous experience, we add high-frequency harmonic components after the effective value, and compare the similarity of load decomposition as a whole data. High-frequency components often have more effective information, and different electrical appliances have different high-frequency harmonic component data at the transition edge. According to the difference between the harmonic components before and after a certain time, determine which electrical appliance is working. Changes in patterns.

In this paper, the current amount of a cycle is sampled, and the sampling cycle is 20ms/time. Assuming that ln is the effective value obtained by the nth sampling, and ln is the harmonic component obtained by the nth sampling, the data Y for this article can be expressed as:

$$\mathrm{Y}=[I_1+I_2+\cdots+I_n]+[l_1+l_2+\cdots+l_n] \tag{5}$$

2.3 Load decomposition evaluation index

Non-invasive load decomposition involves multiple steps, and any step will affect the final decomposition effect. The main evaluation indicators are as follows:

1) The accuracy of the results of load decomposition;

The main indicators of the accuracy of load decomposition recognition are:

① Mean Absolute Error (MAE) is used to evaluate the decomposition effect at a certain time. Suppose g_t is the real power consumed by a certain electrical appliance at time t, and Pt is a certain decomposed power after load decomposition. Use electrical power.

$$\mathrm{MAE}=\frac{1}{T}\sum_{t=1}^{T}|P_t-g_t| \tag{6}$$

② The integrated signal error (Signal Aggregrate Error, ASE) is used to evaluate the decomposition effect over a period of time.

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$$\mathrm{SAE} = \frac{P-P^*}{P} \tag{7}$$

In the above formula, P is the power consumption value of P in a period of time, and P* is the power consumption in a period of time after load decomposition.

2) The stability of the recognition effect;

3) The generalization ability and scalability of the recognition algorithm.

III Load decomposition based on one-dimensional convolutional neural network

3.1 Convolutional neural network

Convolutional neural network (CNN) is a multi-layer supervised learning neural network consisting of a convolutional layer, a pooling layer, and a fully connected layer. Among them, the convolutional layer is used to advance the feature information; the pooling layer is used for downsampling to reduce the amount of data while retaining effective features as much as possible; the fully connected layer obtains the activated feature information value. Compared with other deep neural networks, convolutional neural networks share the characteristics of weights, which can simplify the network structure and have better adaptability, and can achieve classification and recognition tasks.

3.2 One-dimensional convolutional neural network

One-dimensional convolutional neural network (1D convolutional neural network, 1D-CNN) is a convolutional neural network that can extract temporal features from time series [8].

The input and output of one-dimensional convolution is a vector, and the convolution kernel slides in one-dimensional space, and outputs another vector through the operation of the vector and the convolution kernel.

In this paper, one-dimensional convolution is used for feature extraction. Due to the small amount of data, in order to better ensure the characteristics of the data, the pooling process is removed and the convolutional layer is directly followed by the fully connected layer to improve the accuracy of the features.

3.3 Non-invasive load decomposition network model

As shown in Figure 1, the one-dimensional neural network structure used in this article is a five-layer convolutional layer and a fully connected layer.

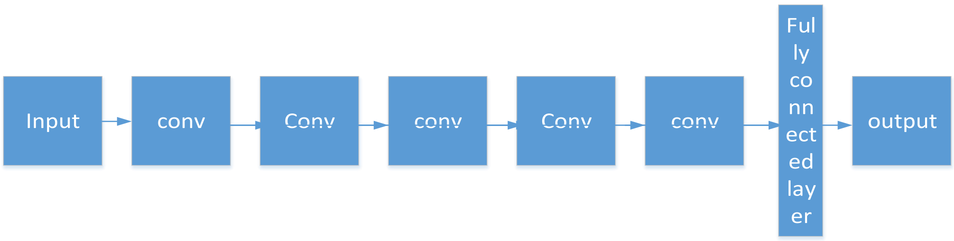

Fig 1: The neural network structure diagram used in this article

The input signal is a one-dimensional signal with a size of 1×230, which is composed of the effective value of the current at a certain moment and harmonic components.

In the inference process, the 64-bit data features are compared for similarity to finally determine which category they belong to.

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IV. Experiment

4.1 Data collection

At present, the data that power companies can collect mainly include: current, voltage, electrical power and frequency. These basic physical parameters can be obtained through simple calculations to obtain active power, power factor, reactive power, effective value, harmonic components and energy consumption. And other equipment parameters [9].

AS shown in Figure 2 and Figure 3 in this experiment, we use the BLUED dataset. The BLUED dataset contains high-frequency (12 kHz) household-level data from a single American household within approximately 8 days. The data set also contains a list of events involving every device in the household that changes state each time (such as turning on a microwave oven). Each second includes 60 cycles, and each cycle has 15,000 sampling points to obtain the current sinusoidal waveform. Through this, the effective value of the current and harmonic components can be calculated.

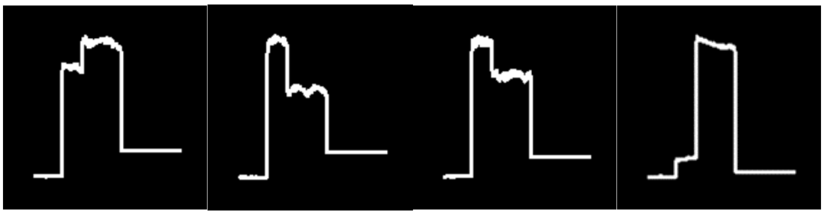

Fig 2: Jumping edge of different electrical appliances

Fig 3: Harmonics of different appliances

4.2 Analysis of results

The input of the one-dimensional neural network is a one-dimensional array composed of the effective value of the current plus the harmonic components; the output is the electrical appliance category. After processing the Blued data, the dimensions of the processed data obtained are 'labels.npy': (338, 4, 53); 'dataset.npy': (338, 4, 1, 230, 1). Expand the above data dimensions to obtain 1352 data with dimensions of 230. The first 9 dimensions of each data are the difference between the frequency domain feature vectors before and after the electrical switching occurs, and the last 221 dimension is the relevant current or voltage signal during the switching process. Change situation (jump edge).In the 1352 data, the first and second categories accounted for the vast majority, and the sum of the two accounted for more than 88%. In the first 20 categories, the number of data items included in each category are: 901, 295, 11, 7, 71, 9, 9, 4, 1, 1, 2, 1, 0, 1, 1, 1, 0, 1, 1, 1. Take the first and second types of data as a single data set to train the two-class model, and the accuracy can reach more than 82%. Among them, the accuracy of training the model using the first 9-dimensional data is slightly higher, at 83%; the accuracy of training the model using the 221-dimensional data is 82%. Take the first, second, and fifth types of data as one type, and all the remaining data as one type, and create a 4-category data set. The accuracy of training the model with the first 9-dimensional data is about 70%, and the accuracy of training the model with the latter 221-dimensional data is 71%.

V. Summary

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This paper uses 1D-CNN to construct a non-intrusive load decomposition model based on the current effective value and harmonic components obtained from current sampling data, and obtains a good decomposition effect. The training model obtained has good scalability and generalization. Ability. The specific features are summarized as follows: Firstly, Obtain experimental data which are effective value of current and harmonic component: Second, Targeted construction of 1D-CNN model; Third, According to the user's electrical appliances, there is no need to retrain, just adjust the inference data set.

Finally, through the analysis of the experimental results, it can be known that the decomposition accuracy rate of the method in this paper is about 70%. Compared with the traditional neural network method, it avoids the frequent training process and saves time for targeted load decomposition.

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