Research on Non-intrusive Residential Electric Load Identification System Based on SOPC

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Abstract. The high-precision identification of the non-intrusive residential electrical load is an essential technology to realize the intelligentization of the power grid. Due to its low input cost and easy maintenance, this technology has received much attention at home and abroad. In order to improve the accuracy of load identification, this paper proposes a non-intrusive residential electric load monitoring equipment based on system on a programmable chip (SOPC), which is focused on hardware system design, characteristic parameters optimizing and BP neural network algorithm optimization. The feasibility of the system was verified by experimental simulation and tests. The results of experiment show that the method used for hardware design can not only improve the speed of system and most closely match the actual running state of electrical appliances in testing circumstances, but it can also realize the function of load identification rapidly and accurately under the condition of the given residential electricity.

1. Introduction

At present, the traditional power industry is moving towards a new model of intelligence [1]. In 2009, the State Grid of China developed a smart grid development plan. After several years of development, smart meters and smart household appliances were also popularized nationwide. In the smart grid system, the monitoring method is one of the important factors that restricts the development of the smart grid. Therefore, real-time monitoring of the electrical quality has practical significance for the development of the new power grid.

Common electrical load monitoring methods include invasive load monitoring and non-intrusive load monitoring [2]. The traditional electric load monitoring method is intrusive in the sense that it requires to install a sensor on each load monitored. The technology of monitoring has high precision, which can achieve accurate monitoring of target loads, but it requires high hardware and maintenance costs. And it is difficult to implement widely. The non-intrusive method refers to installing monitoring equipment on the power input port, and to achieving the purpose of monitoring the electrical appliances by identifying the energy consumption of the electrical loads. Compared with traditional method, it has advantages of low economic input, convenient maintenance, excluding user privacy and easy to popularize, but comprehensive identification accuracy of loads needs to be improved. With the development of intelligent load monitoring technology, the systems of non-intrusive load identification have become a hot topic in academic research at home and abroad. The optimization of load identification method mainly includes the following aspects: date acquisition equipment, identification features and recognition algorithms. In the design of hardware system, the literature [3-4]
analyzed the defects of the existing data monitoring capabilities of the existing load monitoring devices in China. ARM and FPGA were used to build the hardware platform, which made the data processing and storage speed improve. In the literature [5-6], the advantages and disadvantages of steady-state and transient characteristics in load identification are analyzed in the selection of load characteristics, and the method of using current and current harmonic characteristics is proposed. In the literature [7-9], the neural network model is used for optimization and training in the selection of algorithm models, and the problem of low load recognition rate is solved at the algorithm level. Based on the Hidden Markov Model and its extended model, the literature [10-11] reduces the computational complexity of the traditional hidden Markov model algorithm and improves the computational efficiency. Reference [12] proposes a circuit-level energy measurement method that overcomes the problems that small or variable power devices cannot monitor. All of the above methods are tested by using a simple combination of electrical appliances and it is difficult to apply them to complex electrical combinations. Therefore, the comprehensive recognition performance is low and it is difficult to popularize it. So a non-intrusive residential electric load identification system based on SOPC is proposed in this paper. To improve the performance of processing complex data and comprehensive identification accuracy, it presents three major approaches: extracting eight electrical characteristics of load as feature quantity, using four-layer BP neural network for training recognition and optimizing the algorithm model parameters.

2. Hardware design of load monitoring and identification system

The extraction of load characteristics requires a tremendous amount of computation and extremely fast computing. In view of the pressure considerations of the ARM chip alone, the Xilinx integrated FPGA+ARM series chip ZYNQ 7020 is selected for the system to collecting data, processing data and extend additional function. In the hardware design of the system, four parts of data acquisition module, data processing module, data transmission module and data display module are mainly set. The overall block diagram of the system is shown in Fig 1.

![Figure 1. Block diagram of SOPC hardware implementation internal system.](image)

2.1. Data Acquisition Module

The module captures the unknown load current and voltage signals through the transformer, and uses the front-end conditioning circuit to perform preliminary processing on the original signal, and then performs equal-cycle sampling on the collected signal through the high-precision sampling circuit.
To ensure that the original data are sufficient, the system adopts the sampling period which is ten times the cycle of sampled signal. In addition, the module is embedded with a digital frequency measuring circuit and directly connected to the output end of the front-end conditioning circuit to observe the fluctuation of the output frequency signal at any time. The block diagram of the module system is shown in Fig 2:

![Block Diagram](image)

**Figure 2.** System diagram of data acquisition module.

2.2. Data Processing Module

The module uses the ARM chip to process the digital signal outputted by the data acquisition module through the digital filter circuit to remove noise and other disturbing signals. The digital logic operation circuit is used to calculate the electrical characteristic value of the desired signal by using the Verilog programming language, then transmit it to the DDR for data storage.

2.3. Data Recognition Module

The module is connected to the data processing module through the Axi4 bus, and the feature values of the collected electrical appliances are firstly optimized, then the data are normalized and preprocessed, and then input into the neural network algorithm model constructed by the design for identification. Finally, the training model is transplanted into the SOPC system through C++ for hardware implementation.

2.4. Data Transmission Module

The module uses the WiFi for two-way transmission and matches with the data display module, which not only facilitates the end user to view the working state of the appliance, but also directly transmits the data to the power company to realize analysis of the finer-grained load monitoring data.

3. Extraction of steady-state characteristics of residential load

The steady-state characteristic of the load refers to the electrical characteristics of the appliance when it is in a steady state, which reflects the power consumption information under real-time conditions. Non-intrusive feature extraction refers to obtaining the steady state eigenvalue under each characteristic parameter through the digital logic operation based on the collected voltage, current and other data, which is necessary for the load identification. This study uses the steady-state characteristics of seven household appliances as samples, including voltage rms, current rms, active power, apparent power, reactive power, power factor, current total harmonic distortion and voltage total harmonic distortion, to establish a residential electricity load database.
3.1. Selecting steady-state characters

According to the sampled data, the discretized voltage rms \( U_{\text{rms}} \) and the current rms \( I_{\text{rms}} \) are calculated as follows:

\[
U_{\text{rms}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} u^2(n)}
\]

\[
I_{\text{rms}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} i^2(n)}
\]

“\( N \)” represents the number of sampling points in a single sampling period, and “\( u \)” and “\( i \)” are the sampling voltage and current value. The expressions for calculating the active power \( (P) \) and the apparent power \( (S) \) are as follows:

\[
S = U_{\text{rms}} I_{\text{rms}}
\]

\[
P = \frac{1}{N} \sum_{n=1}^{N} u(n)i(n)
\]

The reactive power represents the part of the power in the AC circuit that is reversibly converted due to the presence of reactive components (referred to as pure inductance or pure capacitance). In the sinusoidal AC system, the calculation formula is as follows:

\[
Q = \sqrt{S^2 - P^2}
\]

The power factor (PF) is a coefficient that measures the efficiency of electrical equipment. In alternating current, the cosine of the phase difference between voltage and current is called the power factor, which is represented by the symbol \( \text{COS} \Phi \). In terms of value, the power factor is the ratio of active power to apparent power:

\[
\text{COS} \Phi = P / S
\]

Total harmonic distortion rate is a performance parameter that characterizes the degree of waveform distortion relative to sine wave. Divided into harmonic voltage distortion rate \( (THD_v) \) and harmonic current distortion rate \( (THD_i) \), the formula is as follows:

\[
THD_v = U_{h} / U_1 \times 100\%
\]

\[
THD_i = I_{h} / I_1 \times 100\%
\]

Among them, \( U_h \) and \( I_h \) represent the total amount of harmonic voltage and harmonic current, \( U_1 \) and \( I_1 \) are expressed respectively as the effective value of the fundamental voltage and the effective value of the fundamental current.

3.2. Establishment of Characteristic Matrix

Due to the difference in electrical characteristics during the use of various appliances, this can be used to achieve decomposition of the electrical load directly. The sensitivity of diverse characteristic parameters on electrical identification is also different. For instance, in the identification of large-scale appliances, the effects of active power and reactive power are obvious, but not in low-power appliances. So building a recognition library of electrical characteristics to train algorithms is an important means to improve load identification, which includes different types of electric information. According to eight characteristic parameters, the collected load characteristics can be expressed in the form of a matrix as follows:
In the actual sampling, the selection of the number of sampling points \((N)\) is artificially set according to the experimental needs, but in order to avoid over-fitting in the data training process, the actual selection of the sampling points is not infinite.

4. Optimizing algorithm based on BP neural network

BP neural network algorithm is one of the most widely used neural network algorithm models. It is a multi-layer network algorithm for signal forward propagation and error back-propagation. Its basic structure is shown in Figure 3:

![Figure 3. Basic structure diagram of BP neural network.](image)

According to the structure diagram, during the process of forward propagation, the state of the \((2 < l < L)\) layer neurons \(Z^{(l)}\) and the output value of the activation function \(a^{(l)}\) are:

\[
Z^{(l)} = W^{(l)} a^{(l-1)} + A^{(l)}
\]

\[
a^{(l)} = f(Z^{(l)})
\]

Among them, the \(w\) transfer weight is expressed, \(A_{dd}\) indicating the offset between the layers. For the realization of forward algorithm, how to determine and becomes the core of the problem. And the cost function is used in the error back-propagation algorithm, and the specific formula is as follows:

\[
E_{i} = \frac{1}{L} \sum_{k=1}^{L} (y^{(i)}_{k} - o^{(i)}_{k})^{2}
\]

\(y^{(i)}_{k}\) and \(o^{(i)}_{k}\) refer to the value of ideal output and actual output of the neural network, respectively. The cost error is directly compared to determine if the weights and offsets are within reasonable limits. The parameters are updated by the gradient descent method until the requirements are met, and then the optimal weight value can be determined. The following uses the simplest sample operation to introduce the parameter update method:

\[
W^{(n+1)} = W^{(n)} - \mu \frac{\partial E_{i}}{\partial W^{(n)}}
\]
The “n” represents the iterations of algorithm. The essence of back propagation networks is that make the change of weights become little by gradient descent method and finally attain the minimal error.

There is no specific theory for the design of the hidden layer of the neural network and the number of neurons to refer to. According to the actual experimental situation, the complexity of the network is designed from being simple to complex. According to the results of many experiments, four layers are finally designed in the network structure. The number of neurons in each layer is selected as shown in Table 1:

| Layer     | Neuron count |
|-----------|--------------|
| Input     | 9            |
| Layer 1   | 60           |
| Layer 2   | 60           |
| Output    | 8            |

In addition to setting the above parameters, in order to reduce the forecast error and mean square error of the BP neural network algorithm, the Sigmoid function and the Relu function are selected on the node transfer function of the hidden layer and the output layer. In order to speed up the training process of the network, the training data are pre-processed firstly, and then the input value is normalized to the range of interval (0, 1) according to the expected output value. Finally, output of the network is inversely normalized to verify the accurate rate of the network.

5. Conclusion

In the aspect of algorithm, BP neural network algorithm under supervised learning mode is adopted in the system. The data of established database are used for model training and verification, which are normalized and randomly processed by script. Eighty percent of the data are used as the training set of the model, and twenty percent of the data are the validation set for the model. The trained algorithm model is verified by the verification set, and the neural network toolbox called Matlab is used to construct and verify the algorithm model. The specific steps include calling Newff to build the structure of the BP neural network and setting various related parameters, calling the train function to train the constructed network, and using the Sim function to verify the data of the verification set. Before the experiment, in order to realize the effective algorithm identification of the load, the load was tagged by the method of on-hot code. The specific load and label used in the experiment are shown in Table 2:

| Load type                  | Label set         |
|----------------------------|-------------------|
| Desktop                    | [0000001]         |
| Fluorescent lamp(36W)      | [0000010]         |
| Fan                        | [0001000]         |
| Signal generator           | [0001000]         |
| mobile phone charging      | [0010000]         |
| Drinking fountain          | [0100000]         |
| Filament lamp(25W)         | [1000000]         |

According to the actual experimental situation, the complex recognition effect of the neural network is shown in Table 3:
Table 3. Comprehensive Recognition Rate of System.

| Experimental combination | Recognition rate (%) |
|--------------------------|----------------------|
| One kind                 | 99.98                |
| Two kinds                | 99.76                |
| Three kinds              | 99.51                |
| Four kinds               | 98.83                |
| Five kinds               | 98.54                |
| Six kinds                | 98.13                |
| Seven kinds              | 97.83                |

It can be seen from Table 3 that the recognition rate of the identification system of this paper is stable at 99.5% or more for the combination of the following three appliances, and the comprehensive recognition rate for the combination of four or more appliances is reduced. When the electrical combination reaches seven, the recognition rate still reaches 97.83%. In terms of iterations and convergence tolerance, the performance of the system is superior to the algorithm proposed in the literature [9]. Therefore, the system has certain application value and reference value in the construction of smart grid.

6. Acknowledgments

This work was financially supported by Project of Science and Technology Department of Sichuan Province (2017GZ0307) fund and Graduate Innovation Research Project of Southwest Minzu University (CX2019SZ11) fund.

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