Self-adjusted multi-sensor information fusion electric energy measuring based on neural networks

ZhuFeng Li¹, Yang Li²

¹College of Application Physics and material, WuYi Univ. 529020 jiangmeng Guangdong China
²Student, College of Biological Sciences, State university of Minnesota. 55401 st.paul Minnesota United States

Abstract: In this article, self-adjusted Multi-sensor Information Fusion measuring method of electric energy based on neural networks has been thoroughly given. This paper studies the method of automatic error correction of electric power measurement also. The effective learning algorithm of the neural network based on gradient algorithm and Newton algorithm is combined with the LEA discriminant method. The results show that the method can improve the learning efficiency. The hardware model of adaptive real-time fast power measurement is constructed by using DSP device. The experimental results show that the adaptive power measurement model is better than the traditional power meter.

KeyWords: neural networks、power energy measuring、self-adjusted、DSP

1 Introduction

High precision measurement of electric energy in complex field environment is an urgent problem that has not been solved. Such as temperature -30 - +40 °C, humidity of 40% - 80%, frequency, voltage, current, power factor, external magnetic field, waveform distortion, voltage line loss and so on. These factors seriously affect the accuracy of electrical energy measurement. The economic loss caused by inaccurate measurement of electric energy can only be artificially estimated, which is unscientific and unfair. The failure of the metering device can not be found in time and non manual. Fault can only be detected when waiting for cycle check, Resulting in time delays and economic losses. How to improve the measurement error of the electric power measurement device in a complex and changeable environment, It is of great significance to realize the real-time intelligent correction, to improve the accuracy of the electric energy meter in the complex and changeable environment, and to carry out the intelligent diagnosis of the fault of the metering device. The multi sensor information fusion based on the optimized neural network can effectively correct the influence of the environment on the electric energy measurement, and can realize the real-time, dynamic and high-precision intelligent electric energy measurement[1]. Optimization of neural network is to determine a reasonable neural network structure, the optimal neural network weight learning algorithm. According to the actual situation, the establishment of a reasonable data sample library of environmental factors and power relations, measuring device status information and fault classification samples. It is of great academic and practical value to realize the accurate measurement and fault diagnosis of electric field measurement device[2,3,4].

2 In the complex scene, basic principle of electric energy measurement and fault diagnosis by the optimization of multi sensor information fusion based on neural network method

Based on the optimized neural network and multi sensor information fusion, electric energy measurement and fault diagnosis system scheme is shown in figure 1. The voltage transformer transforms the high voltage into a smaller voltage V. The current transformer transforms the high current into a small current I. The electrical power P can be obtained by multiplying the voltage V’ with the current I’. According to the measurement results of multi sensors for field environment (temperature, humidity, voltage, frequency, current, power factor, magnetic field, waveform distortion, voltage line loss, etc.), real time and error corrected power P’ can be obtained by neural network computing. P’ multiplied by time t is the result of electrical energy E.

The neural network needs to be optimized and trained before use. The sample database that maps the actual data relationship needs to be collected to built. Firstly, the fitness function of the network structure is established. Then, based on the genetic algorithm to optimize the weights of neural network, the neural network structure is optimized, To search for a reasonable neural network structure for the application of...
multi sensor information fusion in complex field environment. According to the state information (power, current, voltage, power factor, line loss, etc.), real-time fault diagnosis of electric energy measurement device can be completed by neural network. Creeping, large line loss and disconnection are part of the fault state information. Neural network needs to complete information fusion learning, clustering learning, finally realize the diagnosis function[5,6].

3 Optimization methods of neural network structure

According to the complexity of the specific problems, the appropriate neural network structure can be selected, that is, to ensure the network of data induction, but also can save resources and time. The number of nodes in the input layer is determined by the physical quantity of the detection. The number of nodes in the output layer is determined according to the number of outputs. It is difficult to determine the number of hidden nodes. Considering the network capacity and function approximation, the number of hidden units should be chosen more. However, considering the generalization ability of the network, the number of hidden units should not be too much. So the number of hidden units should have the best value. The initial number of hidden units should be given first, and then the correlation pruning algorithm is used to reduce the number of hidden nodes until the number of hidden nodes is determined. Finally, the number of nodes of hidden units with less and reasonable number is determined. The initial number of hidden units is determined by subtractive clustering method[7].

The method of determining the initial number of hidden units (subtractive clustering method).

Set m dimensional space n data points (X1, X2, ..., Xn), subtractive clustering process is as below. First, for each point Xi of the data set, the density index is calculated. The highest density data X0 is the first cluster center.

\[ D_0 = \sum_{i=1}^{n} \exp \left[ \frac{1}{\| x_i - x_0 \|^2} \right] \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 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\[ f(x) = (1 + e^{-x})^{-1}. \]

The response function of the output notes is linear.

Formula (4) is the error energy function. That is, the output vector \( y_I = (y_{11}, y_{12}, \ldots, y_{1L}) \) subtracts the actual output vector of the output layer unit \( y_I = (y_{21}, y_{22}, \ldots, y_{2L}) \).

The error is squared and added.

\[ E = \frac{1}{2} \sum_{i=1}^{J} \left( \sum_{j=1}^{M} v_{rj} f(J_i) (\sum_{l=1}^{L} u_{lj} x_{lj} + O_j) - b_{ih} \right)^2 + \frac{1}{2} \sigma^2 \]  

(4)

By adjusting the weights \( \{w_{ij}\} \), \( \{v_{jt}\} \) and the number of hidden layer nodes \( Q \), the number of network connection weights, the error energy function \( E(w) \) can reach the minimum, to realize the optimization of the network selection. Then E is a function of \( w \), \( E = E(w) \). [12, 13, 14]

### 4.1 Steepest gradient descent learning algorithm

\( W \) is a vector, \( E \) is a multivariate function. Through the network learning, \( w \) value can be determined, at this time the function E to achieve the minimum value. Gradient \( G(w) \) is vector. If \( E(w) \) produces the largest change, the corresponding direction is \( G(w) \). The mode is the maximum change rate of \( E(w) \) at M point. Vector \( G(w) \) is the gradient of the number field \( E(w) \) at the point. 

\[ \nabla E \]

is the Hamilton operator.

The gradient descent learning algorithm is shown as follows. The initial position \( W(k) \) is chosen randomly, and the moving direction and step size of \( W(k+1) \) are determined according to the gradient of \( W(k) \) point, so that the error function \( E(W(k+1)) \) is decreased rapidly than \( E(W(k)) \). Then \( W(k+1) \) is used as the starting point and the steepest descent method is used repeat to determine the \( W(k+2) \). Finally, the point \( W(k+n) \), which form the smallest \( E(W(k)) \), is found as the solution of the neural network weights. The iterative formula of steepest descent learning algorithm is formula (5). A \( k \) is a positive number, also known as the step size. At each iteration, a \( k \) is determined by the one dimensional linear search. The steepest gradient descent learning method decreased rapidly at the early stage of learning, and learning in the later there will be a severe vibration phenomenon that the learning speed is very slow, because two times the search direction of the adjacent gradient algorithm is orthogonal, the search process will appear "seesaw" phenomenon. Therefore, in the later stage of learning the Newton method is used.

\[ W(k+1) = W(k) - a(k) \nabla E(W(k)) \]  

(5)

Newton iteration method

According to the BP neural network in Figure 2, the weights of BP neural network can satisfy the solution of nonlinear equations. The nonlinear equations are formula (6).

\[ \sum_{j=1}^{M} v_{rj} f(J_i) (\sum_{l=1}^{L} u_{lj} x_{lj} + O_j) - b_{ih} = 0 \]  

(6)

\( (i=1, 2, \ldots, L) \), \( (r=1, 2, \ldots, R) \).
dislocation, to accumulate, the ratio, known as the

dislocation plus CRDA method.

\[ R(k) = \sum_{i=0}^{n} E(W(k-i)) \]

When \( R(k) \rightarrow 1 \), the gradient iteration method can be
considered as a "seesaw state", and the gradient
algorithm is replaced by the Newton iteration method.

Formula(8) is the combination of gradient method and
Newton method. When \( R(k) > 1 + \varepsilon; \varepsilon \) is a small positive
number greater than 0, \( \lambda_k = 1 \) is used and gradient
iteration method is adopted. When \( R(k) = 1 + \varepsilon; \lambda_k = 0 \) is
selected, using Newton iterative method[29,30,31,32]. The selection of epsilon will affect
the iterative steps of the gradient iteration method. The

\[ W(k+1) = W(k) - \lambda_k \frac{\partial E(W(k))}{\partial W} \]

smaller the epsilon is, the more the gradient method is
used to iterate, and the higher the accuracy of judging the
gradient iteration failure, the longer the computation
time of the machine. Thus, by using the CRDA method,
the point at the end of the gradient iteration method falls
into the convergent domain of the Newton iterative
method to be used. The effective combination of gradient
iteration method and Newton iteration method is
achieved.

\[ W(k+1) = W(k) - \lambda_k [F(W(k))]^T F(W(k)) \]

5 DSP technology is adopted to realize
the real-time fast measurement of
electric energy

Digital signal processor DSP (Digital Signal Processing)
is particularly suitable for digital signal processing
operations, the main feature is that real-time and rapid
implementation of a variety of digital signal processing
algorithms. DSP devices work well in common
convolution, filtering, FFT and matrix operations. The
DSP device produced by the American Simulated
company ADSP-21060 is designed for high performance
multiprocessing applications such as medical imaging,
3D graphics acceleration, radar, electronic signal
processing, etc. It represents the best performing 32 bit
DSP chip at present. ADSP-21060 is a high performance
floating-point DSP chip, the super Harvard architecture,
with four independent bus (two data bus, a program bus
and a I/O bus); 4M memory, with DMA controller and I/O
processor, allowing flexible and high speed data transmission
without overhead, the rate is 240Mbytes/s can provide; and 16
32 bit processor interface; multi channel serial port with
40Mbit/s. In this paper, the DSP devices are used to receive
the data of various environmental sensors and perform neural
network calculation. The corrected power value is calculated,
and then the electric energy is calculated by the integral
calculation of power and time. All the control and operation
are completed by DSP, and the adaptive measurement of
electric energy is realized. The neural network weights are
obtained by using gradient Newton combined learning method.

6 Experimental results

| Error precision | Maximum number of learning steps | The steepest descent gradient algorithm | The ordinary gradient Newton method | CRDA method |
|-----------------|---------------------------------|----------------------------------------|---------------------------------|-------------|
|                 | Number of learning steps | Convergence ratio | Total learning steps | Convergence ratio | The number of step gradient | The number of step Newton | Total learning steps | Convergence ratio | The number of step gradient | The number of step Newton |
| 0.1             | 2000                    | 177                        | 80%                      | 99                       | 100%                      | 94                       | 5                       | 96                       | 100%                      | 88                       | 8                       |
| 0.01            | 4000                    | 499                        | 90%                      | 297                      | 85%                       | 291                      | 6                       | 102                      | 92%                       | 90                       | 12                      |
| 0.001           | 8000                    | 1221                       | 86%                      | 460                      | 95%                       | 448                      | 12                      | 119                      | 98%                       | 91                       | 28                      |

The experimental results of different algorithms are shown in
table 1.

Repeated studies by Random selection of initial values are
completed 100 times, and average results are shown in table
1. We can see from the experimental results of table 1. The
CRDA method to judge the tonsure Newton algorithm
significantly reduced the number of learning steps, improve
the rate of convergence. The effectiveness of this method is
demonstrated. The experimental impact experiment of
electric power adaptive measuring instrument based on neural
network is carried out. The error of adaptive watt hour meter
and general electric energy meter is measured by 0.02 level
standard watt hour meter, and the change of the error of two
types of watt hour meter is compared with the change of
environment quantity. The result is shown in table 2. From the
experimental results of Table 2, it can be seen that the error
of electric energy measurement in general electric energy meter
will cause great additional error when the environment
changes. However, the added error of the adaptive energy
meter when the environment changes is very small. It
basically matches the standard electric energy meter to
measure the electric energy. The validity of neural network based adaptive measurement method for electric power is verified.

7 Conclusion

The adaptive measurement method of power and energy based on neural network can effectively modify its own measurement errors adaptively and in real-time in complex environment. Real time intelligent correction is realized to improve the accuracy of the meter in complex environment. In the neural network learning, the CRDA method is used to reduce the point at the end of the gradient iteration method into the convergent domain of the Newton iterative method to be used, and the gradient iteration method and the Newton iteration method are combined effectively. The adaptive electric energy measurement method will effectively change the traditional principle and calibration method of electric energy measurement, and improve the accuracy, range of application and environmental impact resistance of the meter. This method is of great significance.

8 Reference

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Zhufeng Li . 1965. men . Senior laboratory technician. Master. Mainly engaging in physical experiment , electronic measuring technology and neural net research. Undertake 2 scientific and technological projects in Jiangmen city, 4 research projects funded by Wuyi University. More than 30 papers were published. Communicate address: 207# College of Application Physics and material,WuYi Univ. Jiangmeng Guangdong China . Zip code: 529020,Telephone: 0750-3299401(o) Email: zhufenglee@126.com

Yang Li . 1991. men .born in harbin china . In 2016, the Bachelor's degree has been awarded from college of life science , state university of Minnesota United States . Studying and internship in state university of Minnesota United States now . Mainly engaging in life science , Genetic engineering , physics , chemical and light application research .In 2017, 1 invention patents were awarded from People's Republic of China. ranking fourth,The patent number is “ZL 201310695565.1”. 3 papers were published.