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Analysis and Research on Life Prediction System of Intelligent Energy Meter

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Abstract. A smart energy meter life prediction system is proposed to evaluate the actual state of the smart energy meter, predict life and complete quality control. A method combining single component modeling and partial module integral function simulation modeling is adopted. According to the sampling module and the metering module, a smart electric energy table simulation model is established by using a reasonable mathematical algorithm. The life influencing factors of each module of the smart energy meter are integrated and organized into a simulation model of the life prediction software of the smart energy meter. The smart meter measured data, the power meter measured data and the model simulation measured data are compared to verify the validity of the simulation model. The proposed method provides new technical support for the life prediction of smart energy meter.

1. Introduction

As an important part of the smart grid, the smart energy meter has been widely used in power generation, transmission, distribution and power consumption. It is a key carrier for the two-way real-time measurement, precise load control and power demand response. If the life of the smart energy meter is terminated prematurely, it will lead to various faults, such as burning of the energy meter, metering failure, etc., which will directly affect the vital interests of the grid enterprises and related consumers.

With the large-scale smart energy meter to the verification cycle period, if the cycle is rotated according to JJG 596-2012, it will inevitably cause a large number of energy meters that have not reached the end of their service life to be replaced, resulting in great waste of human and material resources. The remaining life prediction technology of smart energy meters is imperative. In this paper, a new prediction scheme is proposed for the service life of smart energy meter, and it can be realized to effectively complete the life prediction function of smart energy meter.

2. Overall analysis of electric energy meter life prediction model

Different types of smart energy meter internal structure, process design, device type, selected component parameters, etc., can be turned into 10 functional modules: LCD display module, clock timing module, metering module, current sampling module, voltage Sampling module, communication module, power module, security module, control module, and other modules, as shown in Figure 1.

The factors affecting the life of each module in the smart energy meter are different. For example, the life of the sampling part in the power module and the sampling metering module is closely related to the life of the components on the circuit board, and the life of the sampling metering model is affected by factors such as the quality of the chip package in addition to the life of the internal components. The main function of the influence error is the sampling module and the metering module.

Therefore, it is proposed to combine the single component modeling with the overall functional simulation modeling of some modules, mainly considering the module that directly affects the measurement accuracy of the smart energy meter from the sampling module and the measurement module. The intelligent electric energy table simulation model is established by using reasonable mathematical algorithm, and then the life-influencing factors of each module are integrated, and then compiled into a smart energy meter life prediction software simulation model.

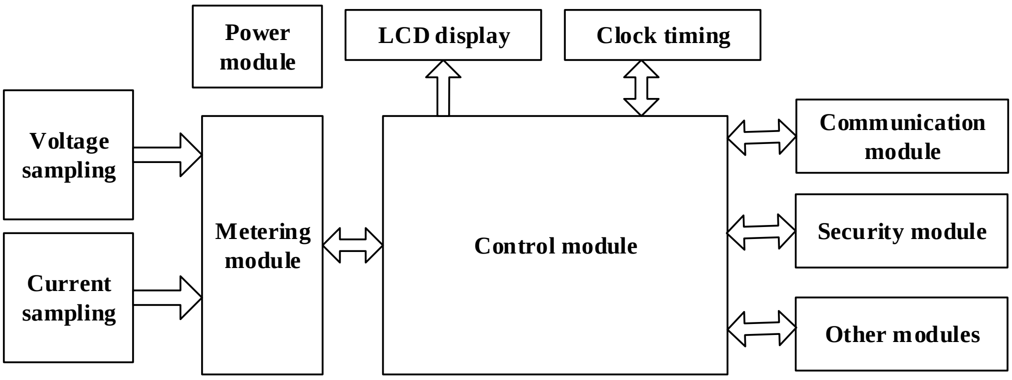

Figure 1. Basic module division of smart energy meter.

3. Establishment of life prediction model for smart energy meter

The sampling and metering module is the core module of the smart energy meter and is the key link in the life prediction model of the smart energy meter. The simulation model for building a smart energy meter is shown in Figure 2.

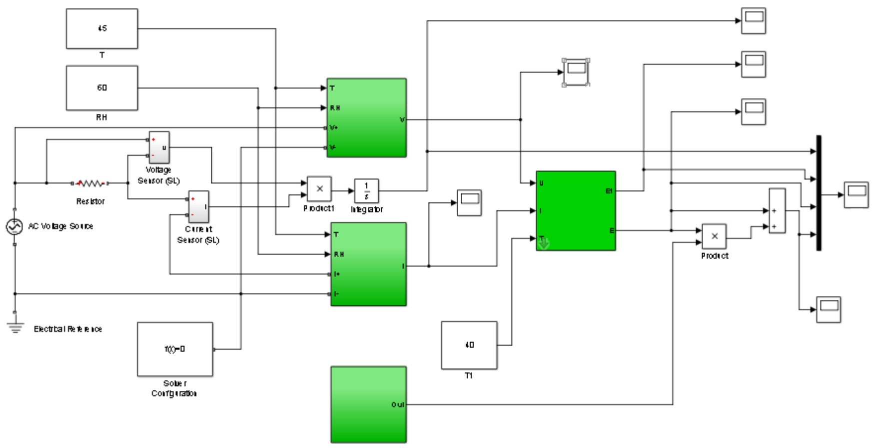

Figure 2. Intelligent electric energy meter simulation model.

It mainly includes three parts: voltage sampling, current sampling and metering chip. The life prediction simulation models of these three parts are quite different, which leads to the complexity of the module life prediction model.

3.1. Voltage sampling module setup

The sampling part of the sampling and metering module separately samples the voltage and current, and the voltage sampling circuit is mainly stepped down by the voltage divider of the resistor and

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sampled by the capacitor filter. Voltage sampling requires the effect of ambient temperature on the resistance of the resistor.

Its output voltage value is:

$$V_{2p} = \frac{R_{14}}{R_{14} + R_1 + R_2 + \cdots + R_{12}} \times U \tag{1}$$

The voltage sampling part mainly converts the 220V AC voltage into a small voltage signal through a resistor divider network. The biggest advantage of using the resistor network is that the linearity is good and the cost is low. The disadvantage is that electrical isolation cannot be achieved.

The voltage module mainly uses a voltage division network. Since the voltage in the main circuit is generally high, it is not suitable for direct acquisition and processing. Therefore, the voltage in the main circuit needs to be divided by a resistor and capacitor filtered to reduce the voltage to a certain value is then applied to the voltage channel of the metering chip.

3.2. Current sampling module setup

The current sampling circuit first converts a large current into a small voltage signal through a manganese copper shunt, and then sends a small voltage signal to the metering chip to calculate the electrical energy. Current sampling, like voltage sampling, needs to consider the effect of ambient temperature and humidity on the resistance of the manganese-copper shunt.

The current sampling part passes through the manganese copper shunt, and the manganese copper shunt uses the manganese copper piece as the shunt resistor Rs. When the large current i(t) flows, a corresponding proportional weak voltage Ui(t) is generated, and the mathematical expression is :

$$U_{i(t)} = i\left(t\right)\ R \tag{2}$$

The small signal Ui(t) is sent to the multiplier of the energy metering section as a measure of i(t) flowing through the meter. Compared with ordinary current transformers, it has the advantages of good linearity and small temperature coefficient.

The function of the current collecting module is mainly to convert the current of the main circuit into a voltage applied to the current channel of the metering chip, and the capacitor around the resistor acts as a bypass and filtering. The function of R1 is equivalent to a manganese copper shunt, which functions to convert the current signal into a voltage signal, and the function of the resistance model is realized by programming.

3.3. Metering module establishment

The energy metering part mainly calculates the active energy in the t time by sampling the voltage and the sampling current. The instantaneous power p(t) per unit time is defined as:

$$p\left(t\right) = u\left(t\right) i\left(t\right) \tag{3}$$

Where u(t) and i(t) are the voltage applied across the powered device and the current flowing through the device, respectively. The electrical energy consumed by the electrical equipment is defined as the integral of the instantaneous power p(t) over time:

$$W = \int_0^T p(t)dt = \int_0^T u(t)i(t)dt \tag{4}$$

Discretization of Equation 4 yields:

$$W=[\sum_{k=1}^{N} u(t_k) i(t_k)\Delta t] \tag{5}$$

Where u(tk) and i(tk) are the sampled values of u(t) and i(t) at time tk, respectively; Δt is the sampling interval of the electronic meter; n is the actual number of sampling points. It can be seen from the above formula that the core of the energy metering is u(tk)i(tk), which is to achieve the multiplication of voltage and current. The voltage and current multiplication can be achieved by a multiplier.

The metering module mainly simulates the basic principle of the metering chip, that is, through the product of the instantaneous voltage and current, and then integrates it to calculate the electric energy, and the modeling of the part also establishes a sub-module of the influence of the ambient temperature on the crystal frequency. It is used to simulate the influence of clock deviation on metering chip energy metering in actual operating environment.

3.4. Error neural network expert system module establishment

In order to obtain the basic error obtained after extracting the smart meter sample for simulation modeling, it is necessary to perform curve fitting on the experimental error data. The simulation of this part is fitted to the error data by a neural network.

Artificial neural networks simulate certain structures and functions of biological neural networks, which are composed of artificial neurons that mimic biological neurons. The input-output relationship of multi-input single-output neurons is:

$$y=f\,(\sum_{i=1}^{n} w_i x_i - \theta) \tag{6}$$

Where y is the neuron output, f is the output transformation function, or the activation function, xi is the i-th input of the neuron, wi is the connection weight, and θ is the threshold of the neuron.

Neurons are connected by a certain topological structure to form a neural network, and different connections form different neural networks. The basic structure of a neural network can generally be summarized as a weighted summation part, a linear dynamic part and a non-linear function mapping part, wherein the weighted summation part is:

$$v_i(t) = \sum_{j=1}^{n} a_{ij} y_j(t) + \sum_{k=1}^{m} b_{ik} u_k(t) + w_i \tag{7}$$

Or written in vector form:

$$V(t) = Ay(t) + Bu(t) + W \tag{8}$$

The state processing part can be described by a transfer function as:

$$Xi(s) = H(s)Vi(s) \tag{9}$$

Wherein H(s) can generally take the form: H(s)=1, H(s)=1/s, H(s)=1/1+Ts, and the like.

The nonlinear part is:

$$y_i = g(x_i) \tag{10}$$

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In the formula, the function g generally takes a sigmoid function, a threshold function, a tangent function, and the like.

When H(s)=1, a static network is available:

$$\begin{aligned} x(t) &= Ay(t) + Bu(t) + W \\ y(t) &= g(x(t)) \end{aligned} \tag{11}$$

Take H(s)=1/1+Ts, then get the dynamic network:

$$\begin{aligned} Tx(t) + x(t) &= Ay(t) + Bu(t) + W \\ g(t) &= g(x(t)) \end{aligned} \tag{12}$$

The information processing and transmission in the network is realized by the connection right of the network structure, and the connection weight is obtained through a fixed network topology and following certain rules and learning algorithms.

4. Energy meter life prediction model verification

The experiment was conducted under different resistive loads. Under different loads, simultaneously record the instantaneous voltage, instantaneous current and instantaneous power of the smart energy meter, and simultaneously record the instantaneous data with a high-precision power analyzer. The data recorded by the power meter is used to calculate the resistance, so as to compare with the simulation results.

Table 1 is the data measured by the smart energy meter in the test. The test measures the current, voltage and electric power of the main circuit under different load conditions.

Table 1. Smart Energy Meter Experimental Measurement Data Sheet.

Smart energy meter	Voltage(V)	Current (A)	Active power (kW)
load 1	221.03	1.8057	0.3990
load 2	220.8	4.6297	1.0217
load 3	221.13	7.3193	1.6181
load 4	222.93	10.0697	2.2446

The experimental data of the power analyzer is used to calculate the total resistance of the main circuit, and the calculated resistance is used to bring in the model established by Simulink to verify the accuracy of the model. Table 2 shows the data measured by the power analyzer.

Table 2. Power meter experimental data.

Smart energy meter	Voltage(V)	Current (A)	Active power (kW)
load 1	220.39	1.8065	0.3981
load 2	219.84	4.6268	1.0162
load 3	219.8	7.3127	1.6071
load 4	221.53	10.0837	2.2301

When the simulation model is built, the simulation is performed with the main circuit with four different loads. In the case of load 1, when the settlement resistance is 122Ω, the sampling simulation result is shown in Fig. 3. Also record other load simulation results.

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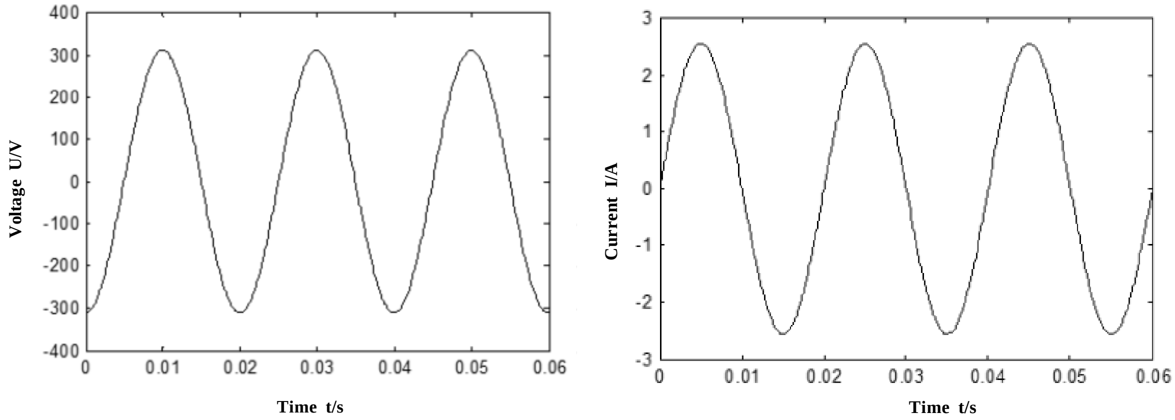

(a) Voltage sampling (b) Current sampling

Figure 3. Simulation waveform with load 1.

Table 3 shows the simulation results of the voltage, current and power of the main circuit measured by Matlab modeling and simulation.

Table 3. Intelligent electric energy meter simulation data average.

Smart energy meter	Voltage(V)	Current (A)	Active power (kW)
load 1	221.03	1.8057	0.3965
load 2	220.80	4.6297	1.0189
load 3	221.13	7.3093	1.6094
load 4	222.93	10.0697	2.2053

In the test, the results measured by the smart energy meter are compared with those measured by the power meter, as shown in Fig. 4. The simulation results are compared with the results measured by the power meter in the test, as shown in Figure 5.

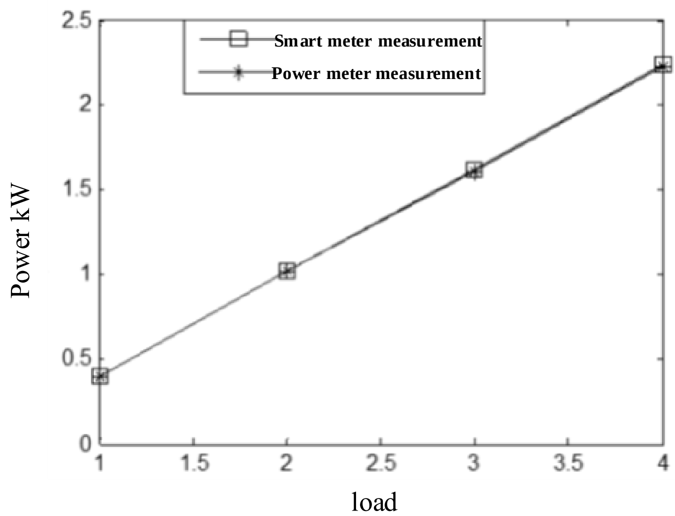

Figure 4. Comparison between the measured results of the smart energy meter and the measured results of the power meter.

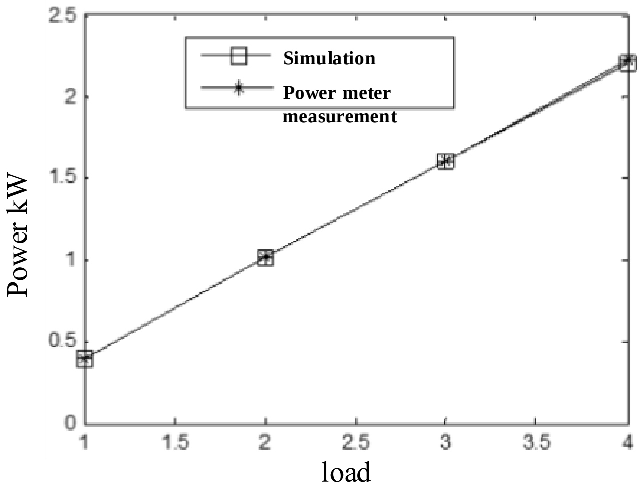

Figure 5. Comparison of the results measured by the power meter with the simulation results.

As shown in Figure 4, the data measured by the smart energy meter is always larger than the data measured by the power analyzer. The calculated power deviation rate is 0.27% with load 1 and 0.54% with load 2. The power deviation rate was 0.68% at 3 o'clock and 0.65% at 4 min.

As shown in Fig. 5, the data obtained by the simulation is compared with the data measured by the power analyzer, and the power deviation rate is 0.40% when the load is loaded, and the power deviation rate is 0.27% when the load is 2, and the power deviation is when the load is 3 The rate was 0.14%, and the power deviation rate was 1.11% with load 4.

5. Conclusion

The intelligent electric energy meter is the key link between the enterprise and the user. It is an important equipment to ensure the accurate measurement of electric energy. The prediction of the life of the smart energy meter is predicted by the life of each module in the electric energy meter. This paper proposes a smart meter life prediction scheme, which is modeled by voltage sampling, current sampling, and metrology and basic error neural network. Experiments were performed to verify the validity of the model under different resistive loads. The proposed life prediction system of smart energy meter provides a new idea and method for life prediction of electric energy meter.

Acknowledgments

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