

Calibration of RMS based on hardware compensation method and Least Squares Support Vector Machine

Yan Huang^{1, a}, Anquan Deng^{1, b}, Tianyu Zhou^{2, c}, and Wu Zhu^{1, d, *}

¹Shanghai University of Electric Power, Shanghai 200090, China;

²Shanghai Urban Power Supply Company, Shanghai 200080, China;

^ailyahuang@163.com, ^b anquan_d@163.com, ^c550646555@qq.com, ^d zjmzwzsy@126.com

Keywords: RMS converter, nonlinear error, error calibration, hardware compensation method, Least Squares Vector Machine Algorithm.

Abstract: When the RMS measurement is performed on a wideband AC signal using a log-antilog operation circuit, a large nonlinear error is generated by the band limitation of the amplifier in the converter. Therefore, a new method for calibrating nonlinear errors using hardware calibration and software alignment is proposed. First, the hardware circuit with the voltage-frequency conversion chip VFC32 as the core is used for nonlinear calibration. The calibrated signal is then fitted using a least squares support vector machine. The test results show that the calibration accuracy can be achieved 0.014% within the frequency range of 50~20 × 10³Hz.

1. Introduction

With the rapid development of power electronics technology, high-frequency power electronic devices are increasingly used in power systems, these devices cause problems such as power waveform distortion and increase of harmonic components of power supplies in power systems ^[1], large errors occur when measuring with traditional measuring instruments. True RMS digital meters are widely used because they have the advantage of being able to measure any complex waveform without regard to the type and distortion of the waveform, as well as the advantages of high measurement accuracy, wide frequency range and fast response ^[2]. Considering accuracy, stability, linearity, and cost, a log-anti-log operational amplifier circuit is typically used to perform true RMS conversion. When the frequency of the measured signal increases, the operation circuit will generate nonlinear error due to the bandwidth limitation of the amplifier, to obtain a high-accuracy measurement result, nonlinear error calibration for the RMS conversion result is required.

There are two main methods for error calibration, namely hardware compensation method and software compensation method. The hardware compensation method is design an appropriate electronic circuit to calibrate the error according to the characteristics of the nonlinear error ^[3], but it is difficult to fully compensate, the application is limited, so it needs to be used together with software calibration. The software compensation method includes neural network method 、 Support Vector Machine (SVM) and so on. The most commonly used software calibration is the neural network and its improved algorithm, which can effectively calibrate nonlinear errors ^[4]. However, neural networks often have problems such as over-fitting and local minima when the sample is small ^[5]. SVM is based on the principle of minimizing structural risk, which can overcome the main shortcomings of neural networks and is suitable for solving practical problems such as small samples and nonlinearities ^[6]. However, the selection of parameters is difficult, and the traditional methods cannot accurately select parameters, resulting in poor fitting accuracy ^[7]. LSSVM is a new extension for SVM, with simple calculation, high fitting precision and fast calculation speed ^[8,9].

In this paper, a new method for wideband AC RMS calibration is proposed. The nonlinear error is double calibrated by hardware compensation method and least squares support vector machine (LSSVM).

2. The basic principle of hardware compensation method for calibrating nonlinear error

The RMS converter based on the log-anti-log converter has both gain error and nonlinear error, but the latter is the most important one ^[10]. When the frequency of the measured signal increases, it is limited by the bandwidth of the amplifier, and the nonlinear error increases in the measurement result.

Experiments were performed using a self-made RMS converter, four frequency points were selected: 5 kHz, 9 kHz, 14 kHz, and 19 kHz to measure the measurement errors at different frequencies. The measurement results are shown in Figure 1. It can be seen that at the same input voltage, the error becomes larger with the frequency increases. In addition, at the same frequency, the error increases as the input voltage increases. The output error is affected by the amplitude and frequency of the input voltage, according to this characteristic, a hardware calibration method is designed in this paper, the principle is shown in Figure 2.

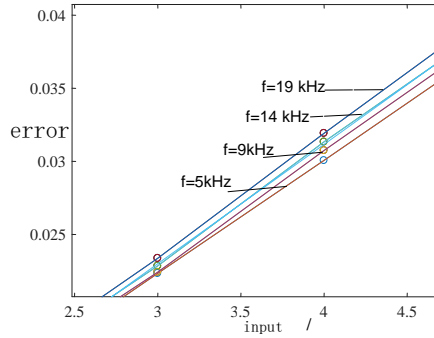


Fig.1 The error curve varies with frequency and voltage

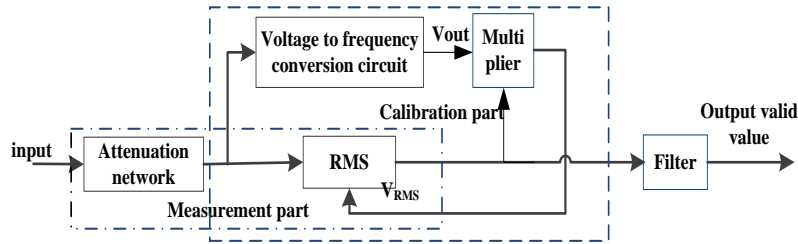


Fig.2 Hardware calibration schematic diagram

The core of the frequency compensation circuit is the voltage-to-frequency conversion component named VFC32. VFC32 will convert to the voltage value V_o according to the frequency of the input signal, and divide the voltage to obtain V_{out} as the coefficient multiplied with the result measured by the original RMS measurement system by the multiplier AD734, and then the multiplied result is used as the feedback amount to adjust the RMS measurement system to output true RMS conversion results with better linearity. In this way, the nonlinear error caused by the input voltage amplitude and frequency is compensated and calibrated at the same time. The schematic diagram of the voltage-frequency conversion circuit is shown in Figure 3.

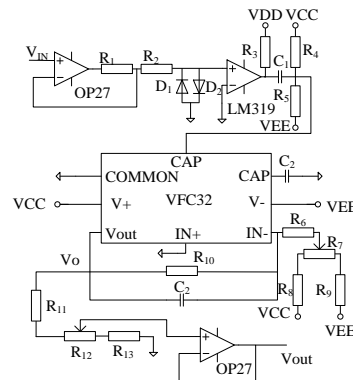


Fig.3. Schematic diagram of voltage frequency conversion circuit

The high frequency AC signal is converted into a standard input pulse with an amplitude of 5V after being processed by peripheral circuits such include OP27 and LM319, the VFC32 internal trigger is triggered after the input is differentiated by C_1 , R_5 and R_6 , access to the reference current source, charge C_2 (increase the output voltage V_o); C_2 charging time is fixed, therefore, if the input pulse frequency is lower, the discharge time is longer and the output voltage is lower. The output voltage value is determined by C_3 and R_7 .

$$V_o = R_7 \times 0.25\text{mA} \quad (1)$$

In the above formula: V_o is the output voltage of VFC32. If we set the output voltage full value is 10V, then R_7 takes 40K Ω .

$$C_3 = \frac{33000\text{pF}}{f_{\text{FS}}(\text{kHz})} - 30\text{pF} \quad (2)$$

In the above formula: f_{FS} is the full scale frequency, take 20KHz. When R_7 takes 40K Ω and the input is 50Hz~20KHz, $C_3=1.6\text{nF}$ is calculated according to formula (2). After determining the circuit parameters, input 1V, 50Hz~20KHz signal, and get the conversion result shown in Table 1.

Table.1 The Voltage frequency conversion results

Input signal frequency /kHz	The output voltage V
1	0.48
5	2.4
10	4.8
20	9.6

3. Nonlinear compensation based on LSSVM .

3.1 Fundamental

Since the hardware compensation method is difficult to fully compensate, it is necessary to linearly fit the measurement results through an algorithm to achieve higher accuracy. The calibration principle based on LSSVM is shown in Figure 4.

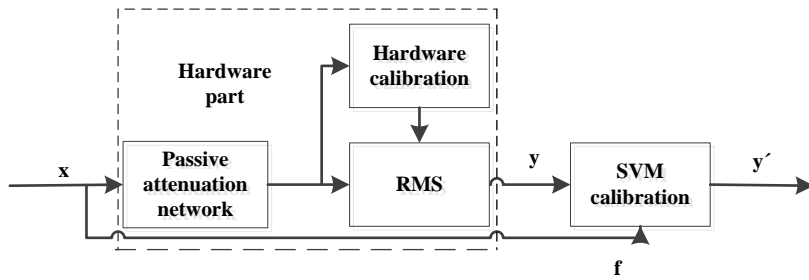


Fig.4.The calibration schematic diagram based on LSSVM

Assume that the characteristics of the instrument are:

$$y = g(x, f) \quad (3)$$

Where: $g(x, f)$ ——a nonlinear function

x -- input voltage;

y -- the hardware circuit of the output voltage;

f -- the frequency of input signal ;

Since $g(x)$ is a nonlinear function, there is a certain nonlinear error in the measurement result, and the hardware calibration cannot be fully calibrated. in order to compensate for the nonlinearity, the y can be passed through a compensation part. the characteristic function of the compensation part is:

$$y' = G(y, f) \quad (4)$$

Where: y' is the output after compensation. To make the compensated output ideal, then:

$$G(y, f) = g^{-1}(x, f) \quad (5)$$

$$y' = g^{-1}(x, f) = x \quad (6)$$

When the frequency changes, the coefficient of $G(y, f)$ is not constant over the entire measurement frequency range, but it is a function related to frequency. Therefore, the inverse function in equation (5) is a very complicated mathematical model, which is difficult to express with a specific function, but the nonlinear relationship can be expressed as close as possible by the SVM model.

3.2 LSSVM calibration model

According to the SVM principle, k sets of samples are known:

$$(x_1, y_1), (x_2, y_2), \dots, (x_i, y_i), \dots, (x_k, y_k)$$

The nonlinear transformation $x \rightarrow \varphi(x)$ is used to map the input from the original low-dimensional space to the high-dimensional feature space (Hilbert space), so the linearly inseparable sample set in the low-dimensional space can be linearized return in this feature space. Constructing the optimal decision function in this high-dimensional feature space is:

$$g(x) = \frac{1}{2} \omega^T * \varphi(x) + b \quad (7)$$

Where: $\omega^T * \varphi(x)$ is the inner product of the vectors ω^T and $\varphi(x)$; b indicates the amount of paranoia, and $b \in \mathbb{R}$. When the $f^*(x)$ plane supports the vector distance maximization, the plane is the plane to be found. According to this goal, the introduction of the slack variable ξ_i can establish the following optimization goals:

$$\min \frac{1}{2} \omega^T * \omega + C \sum_{i=1}^k (\xi_i + \xi_i^*) \quad (8)$$

The constraints are:

$$\begin{cases} y_i - \omega^T \varphi(x_i) - b \leq \varepsilon + \xi_i \\ \omega^T \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \end{cases} \quad (9)$$

Where C is the penalty coefficient, the larger the greater the penalty for the sample which the training error bigger than ε ; ε is the loss function parameter, and the error requirement of the regression function is specified, the smaller the ε is, the smaller the error of the regression function is, and the higher the regression precision is.

LSSVM transforms the inequality constraint in the SVM into an equality constraint, and the optimization problem is transformed into the optimal solution of the following formula:

$$\min \frac{1}{2} \omega^T \omega + \frac{1}{2} \gamma \sum_{i=1}^k \xi_i^2 \quad (10)$$

$$\text{s.t.} \quad y_i = \omega^T \varphi(x_i) + b + \xi_i \quad (11)$$

Where: ξ_i^2 is the regression error of the nonlinear system, γ is a positive real number, can adjust the system regression error, the larger they, the smaller the error, but the calculation amount becomes correspondingly larger.

In solving the optimization problem of equation (8), the linear regression coefficient ω is likely to have a very high dimensional or even an infinite dimension, so the problem is transformed into its dual space, and create a Langrange equation.

$$L(\omega, b, \xi, a) = \frac{1}{2} \omega^T \omega + \gamma \sum_{i=1}^k \xi_i^2 - \sum_{i=1}^k a_i [\omega^T \varphi(x_i) + b + \xi_i - y_i] \quad (12)$$

a_i is the Langeland multiplier.

According to the Karush-Kuhn-Tucker condition, Introducing the Mercer condition, the solution of equation (12) is transformed into solving the equations in equation (14):

$$\begin{pmatrix} 0 & X^T \\ X & \Psi + \gamma^{-1}E \end{pmatrix} \begin{pmatrix} b \\ a \end{pmatrix} = \begin{pmatrix} 0 \\ Y \end{pmatrix} \quad (13)$$

Where $X = (1, \dots, 1, -1)^T$, $\Psi = \varphi(x)^T \varphi(x_i)$ is a kernel function that conforms to the Mercer condition. The final model for LSSVM is:

$$g(x) = \sum_{i=1}^k a_i K(x_i, x) + b \quad (14)$$

Where: $K(x_i, x)$ is the kernel function.

3.3 Calibration step

The basic steps of RMS nonlinear error calibration based on LSSVM in this paper are as follows:

- (1) Identify relevant training and test samples and parameters that affect the linearity of the measurement.
- (2) To construct a suitable kernel function, we use the radial basis kernel function $K(x_i, x) = \exp(-\frac{|x-x_i|^2}{2\delta^2})$ in this paper.
- (3) Determine the optimal penalty coefficient C , and the kernel function parameter δ .
- (4) The resulting output values are modeled using the resulting optimal LSSVM parameters.

4. Experimental verification

In order to verify the effectiveness of the proposed scheme, we use the self-made AC voltage true RMS converter with the input AC signal which frequency is 50Hz~ 20kHz, the test results are first corrected by hardware circuits, and then model the test data by support vector machine for nonlinear calibration. The AC voltage reference is provided by the FLUKE5502A multi-function calibrator and the converter output is measured using the FLUKE8846A.

The first step is the hardware calibration section. Put the measured value of the RMS converter into the calibration circuit and select 10 kHz for debugging. When the maximum error of the measured result at 10 kHz is adjusted to approximately 4×10^{-4} , the measured results at other input frequencies are shown in Table 2.

Table 2 The comparison before and after hardware calibration

Input value	5kHz		9kHz		14kHz		19kHz	
	Before	after	Before	after	Before	after	Before	after
1.0000	0.999557	1.000141	0.999465	1.000189	0.999414	1.000299	0.999303	1.000341
2.0000	1.999533	2.000295	1.999303	2.000291	1.999140	2.000400	1.999050	2.000521
3.0000	2.999629	3.000395	2.999309	3.000316	2.999376	3.000396	2.999332	3.000496
4.0000	3.999690	4.000247	3.999683	4.000262	3.999690	4.000272	3.999496	4.000342

It can be found from the above table that for each input, a certain error will be generated after the RMS conversion, and the error is significantly reduced after the hardware compensation calibration.

The second step is to apply the LSSVM model to nonlinearly calibrate the output value after hardware compensation calibration. Some results are shown in Table 3.

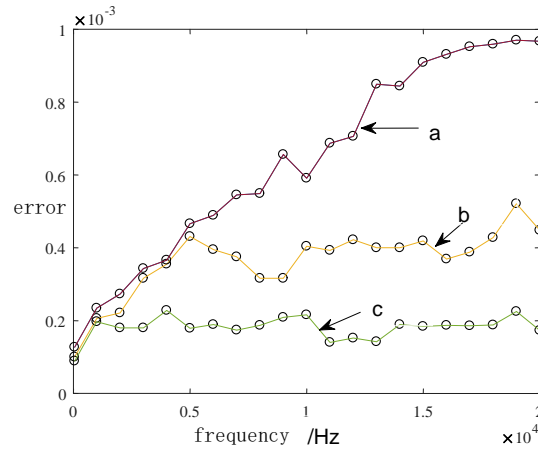
Table.3 The comparison before and after LSSVM calibration

Input value	5kHz		9kHz		14kHz		19kHz	
	Before	after	Before	after	Before	after	Before	after
1.0000	1.000141	1.000135	1.000189	1.000185	1.000299	1.000189	1.000341	1.000176
2.0000	2.000295	2.000170	2.000291	2.000239	2.000400	2.000187	2.000521	2.000147
3.0000	3.000395	3.000228	3.000316	3.000210	3.000396	3.000187	3.000496	3.000224
4.0000	4.000247	4.000179	4.000262	4.000159	4.000272	4.000110	4.000342	4.000116

At a frequency between 50 Hz and 20 kHz, 21 points were selected to compare the error of the results before calibration, after hardware calibration, and after LSSVM calibration based on hardware calibration, as shown in Figure 4.

Table.4 The comparison of measurement error before and after calibration

	5kHz	9kHz	14kHz	19kHz
before	4.66×10^{-4}	6.96×10^{-4}	8.49×10^{-4}	9.59×10^{-4}
after hardware calibration	3.95×10^{-4}	3.16×10^{-4}	4×10^{-4}	5.21×10^{-4}
After LSSVM calibration	2.28×10^{-4}	2.39×10^{-4}	1.89×10^{-4}	2.24×10^{-4}



a is the curve of the measurement system error changed with the frequency before calibration
b is the curve of the measurement system error changed with frequency after the hardware calibration
c is the curve of the measurement system error changed with frequency after calibration by hardware and LSSVM

Fig.5.The comparison diagram of calibration results

5. Summary

This paper proposes a new RMS nonlinear error method, which first performs hardware compensation and then models and fits based on LSSVM. The experimental results show that the error can be less than 1.4×10^{-4} when the AC voltage is measured at 50Hz~20kHz, and the error tends to be stable with increasing frequency. It provides a new method for nonlinear error calibration of wideband AC RMS converters and has a good application prospect.

References

- [1] Tian Yefei. 2017 Measure techniques for the TRMS of high frequency noise current signal. *Automation and Instrumentation*. Vol. 1(72-73).
- [2] Gao Rui. 2010. True RMS Frequency Compensation Algorithm and Improved Measurement System Based on RMS/DC Conversion Method. *Machinery and Electronics*. Vol. 5(70-73).
- [3] Tang Chao, Li Shiping. 2007. Development and research of calibration of nonlinear technology. *Electronic Measurement Technology*. Vol. 30(1-4).

- [4] Yuan Chuming, Liao Shenghua, Liu Yi, Zhang Gang, Chen Youping. 2012. Intensity Compensation and Nonlinear Correction of Optical Fiber Sensor Using Neural Network *Instrument Technique and Sensor*. Vol.2(108-110).
- [5] Peng Jishen, Yu Jingzhe, Xia Naigin. 2011. Approaches to Non- linearity Compensation of Copper Resistor Based on Neural Network in Temperature Measurement. *Computer Measurement and Control*. Vol.19(243-245).
- [6] Wang Yongxiang, Chen Guochu. 2016. Short-term wind power prediction based on IAFSA optimization SVM. *Electrical Measurement and Instrumentation*. Vol.53 (80-84).
- [7] Gao Dawei, Liu Jianling. 2014. Software Design and Study of Humidity Sensor SVM Temperature Compensation. *Instrument Technique and Sensor*. Vol.12(7-9+12).
- [8] Liu Yang, Jiang Qing, Sang Yingping. 2013. Application of Least Squares Support Vector Machine in Dynamic Weighing System. *Instrument Technique and Sensor*. Vol.12(170+172).
- [9] Qiao Aimin, He Bexia, Zhang Wei. 2013. The Power-sensed Sensor Temperature Error Compensation Based on LS-SVM and Embedded Technology *Chinese Journal of Sensors and Actuators*. Vol.26(637-642)
- [10] Zhu Wu, Zhang Jiamin. 2006. Study on the Method of Auto-calibration for Curves Family of Wide Band RMS Convertor. *Chinese Journal of Scientific Instrument*. Vol.27(505-507).