Capacitive Current calculation by a Recursive Least Square Method with Variable Forgetting Factors

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Abstract

Accurate detection capacitive current is the precondition of reasonable compensation capacity choice, extinction of arc, and leakage protection institution, and plays an important role in the safe operation of coal mine distribution network. This paper presents a new method on capacitive current estimation of a coal mine network. A capacitive current identification model of leakage test in noise environment is built; the variable forgetting factor recursive least square algorithm has preferable follow ability and high accuracy; adopting this least square algorithm as the means of system identification, a capacitive current identification method is established. This method can be easily realized as a part of the existing coal mine electrical equipment, and has highly engineering practical value; compared with traditional exponential weighted least square method, variable forgetting factor least square estimation of capacitive current is better in accuracy and convergence rate. Examples of coal mine distribution networks indicate that this new capacitive current calculation method has the characteristics of accuracy, speediness, and highly anti-jamming.

Keywords: coal mine distribution network, capacitive current, least square method, variable forgetting factor, identification

1. Introduction

The coal mine power supply system is a total cable network. According to research, the capacitive current of cable line is commonly from 25(three-core cable) to 50 (single core cables) times larger than that of the same length overhead line [1]-[3]. With the improvement of the coal mines modernization level and the increasing mining depth, the length of power cable lines is growing, which results in an increases of capacitive current for a coal mine distribution network [3]-[6]. Large capacitive current not only increases the risk of personal electric shock, but also makes it easier to produce leakage arc. Coal mine is a flammable and explosive environment with gas and coal dust, the increase of capacitive current affects the safety of coal mine distribution network operation [7]. Coal mine low-voltage network is equipped with zero-sequence reactor to compensate capacitive current; the compensation inductance of zero sequence reactors has to be regulated by the value of the system capacitive current [8]. Therefore, the coal mine capacitive current has to be measured accurately and safely, which has much significance for the rational choice of compensation capacity, arc extinction and leakage protection.

The existing measuring methods of capacitive currents are Alternating Current volt-ampere method [9] [10], additional low-frequency power method [11]-[13], resonance measurement method [14]-[15] in coal mine low voltage networks. Alternating Current volt-ampere method and resonance measurement method have some dangers; additional low-frequency power method has high precision from the principle's point of view, but the execution of injecting signal source is complex and much more difficult [16]. In addition, the most of existing methods are static measuring methods, and cannot realize the on-line capacitive current measurement of power networks. When the distribution network is running, capacitive current changes under the influence of external factors [17], so it can be detected regularly.

The coal mine electrical equipment almost have thick shell to meet explosion suppression and explosion protection [18]. If the capacitive current detection equipment are independent devices, the fussy connection modes have to be implemented, but the practical application effect of devices is not perfect.

Based on these, this paper presents a detection method of capacitive current by variable forgetting factor RLS (recursive least square) identification for coal mine distribution networks. Using daily leakage test data of coal mine power supply system, we can realize the advance estimate of capacitive current to ensure it is safe and accurate; this method can be combined with the existing intelligent feeder switch, which has highly engineering applicability.

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2. Improvement for Recursive Least Square Method with Weighted Forgetting Factors

For the discrete system, the least square format of the output from input is:

$$z(k) = \boldsymbol{h}^T(k)\boldsymbol{\theta} + e(k) \tag{1}$$

Where, $z(k)$ is the kth time observations value of output, $\boldsymbol{h}(k) = [h_1(k), h_2(k), \cdots, h_N(k)]^T$ is the sample vector, $\boldsymbol{\theta} = [\theta_1, \theta_2, \cdots, \theta_N]^T$ is the parameter vector for identification; $e(k)$ is the interference noise with zero average value.

The exponential weighting RLS algorithm uses the quadratic sum of exponential weighting error as the guidelines function $\boldsymbol{J(\theta)}$:

$$J(\boldsymbol{\theta}) = \sum_{k=1}^{L} \lambda^{(L-k)}[e(k)]^2 = \sum_{k=1}^{L} \lambda^{(L-k)}[z(k) - \boldsymbol{h}^T(k)\boldsymbol{\theta}]^2 \tag{2}$$

Where, λ is the weighted forgetting factor, and $0 \le \lambda \le 1$, L is the number of iterations. RLS algorithm with exponential weighting is calculated as：

$$\begin{cases} \hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \boldsymbol{K}(k)[z(k) - \boldsymbol{h}^T(k)\hat{\boldsymbol{\theta}}(k-1)] \\ \boldsymbol{K}(k) = \boldsymbol{P}(k-1)\boldsymbol{h}(k)[\boldsymbol{h}^T(k)\hat{\boldsymbol{\theta}}(k-1)\boldsymbol{h}(k) + \lambda]^{-1} \\ \boldsymbol{P}(k) = \dfrac{1}{\lambda}[\boldsymbol{I} - \boldsymbol{K}(k)\boldsymbol{h}^T(k)]\boldsymbol{P}(k-1) \end{cases} \tag{3}$$

Among them, $\hat{\boldsymbol{\theta}}(k)$ is the estimated parameter vector at the time k; $\boldsymbol{K}(k)$ is the gain vector; $\boldsymbol{P}(k)$ is the error covariance matrix, and also is a symmetric matrix; $\boldsymbol{I}$ is a unit matrix. Forgetting factor λ is valued between 0.9 ~ 0.99 commonly.

The value of Weighted forgetting factor λ has a significant impact on the convergence speed and track performance for algorithm; the less λ value, the stronger tracking ability of weighted RLS algorithm for time-varying parameters, but the response of algorithm to noise is more sensitive at the same time. The larger λ value, the weaker tracking ability, but the algorithm is not sensitive to noise, and has a smaller convergence error of parameter estimation [19]-[20].

The forgetting factor λ of exponential weighting RLS algorithm once is selected, the iterative process is changeless. The ideal algorithm features are , in non-stationary condition, when the λ is small enough, a limited error in recent time can react only, so that the algorithm can quickly track non-stationary signal on local trends; in steady-state conditions, the λ can grow up to a large suitable value, so as to decrease the error in parameter estimation[21]. In order to achieve this adaptive adjustment, we introduce the variable forgetting factor [22].

$$\begin{cases} \lambda(k) = \lambda_{\min} + (1 - \lambda_{\min})^{2^{L(k)}} \\ L(k) = NINT[\rho e(k)^2] \end{cases} \tag{4}$$

In this equation, $\lambda(k)$ is the kth recurrence forgetting factor, $\lambda_{\min}$ is the minimum value of the forgetting factor, $e(k)$ is the estimated error, $e(k) = z(k) - \boldsymbol{h}^T(k)\hat{\boldsymbol{\theta}}(k-1)$, and ρ is the sensitive gain, which is used to control the rate of λ approaching to 1; the *NINT* refers to the smallest integer that can approach to $\rho e(k)^2$. When the estimated error $e(k)$ becomes infinite, the minimum value $\lambda_{\min}$ of forgetting factor can be obtained. When the $e(k)$ approaches to 0, then λ= 1. The error of each time is equal when λ= 1; that is to say, algorithm is without forgetting function or has the infinite memory function. According to many times of simulation results, the actual examples are $\lambda_{\min} = 0.7$, $\rho = 5$ in this paper.

Calculation formula for the variable forgetting factor RLS algorithm is:

$$\begin{cases} \hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \boldsymbol{K}(k)e(k) \\ \boldsymbol{K}(k) = \boldsymbol{P}(k-1)\boldsymbol{h}(k)[\boldsymbol{h}^T(k)\hat{\boldsymbol{\theta}}(k-1)\boldsymbol{h}(k) + \lambda(k)]^{-1} \\ \boldsymbol{P}(k) = \dfrac{1}{\lambda(k)}[\boldsymbol{I} - \boldsymbol{K}(k)\boldsymbol{h}^T(k)]\boldsymbol{P}(k-1) \\ e(k) = z(k) - \boldsymbol{h}^T(k)\hat{\boldsymbol{\theta}}(k-1) \end{cases} \tag{5}$$

Among them, $\hat{\boldsymbol{\theta}}(k)$ is a parameter estimate vector for the moment k; $\boldsymbol{K}(k)$ is a gain vector. $\boldsymbol{P}(k)$ is the error covariance matrix, and also is a symmetric matrix; $\boldsymbol{I}$ is a unit matrix.

3. Identification Model Establishment on Capacitive Current Detection by Least Square

3.1 The Leakage Test

Chinese coal mine safety standards specify that artificial leakage trip test must be carried out on the low voltage leak detection device every day. Capacitive current detection can be completed during this daily artificial leakage. Artificial leakage test adds resistance on a phase in power supply system, which forms an artificial single-phase leakage, and detects whether the leakage protection device can reliably trip; the leakage test resistor is generally integrated into the mine feeder switch with other leakage detection modules together.

Circuit model of additional resistor leakage test for the coal mine power supply is shown in Figure 1, where R is additional resistance, which is added to phase A in branch 1; r_m and c_m respectively are insulation resistance and ground capacitance of the line *m*; u_{ag} 、u_{bg} 、u_{cg} are ground voltage of each phase; i_{alm} 、i_{blm} 、i_{clm} are each phase current of loads . u_A 、u_B 、u_C are the three phase voltage of power supply.

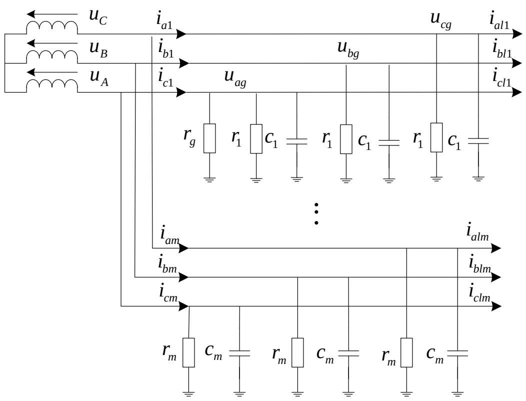


Figure 1: leakage test network of a coal mine power supply system

According to the circuit model of leakage test of Figure 1, the branch mathematical equation can be obtained:

$$i_0 = c\frac{du_0}{dt} + \frac{u_0}{r} + \frac{u_{ag}}{3r_g} \tag{6}$$

Where, u_0 is zero-sequence voltage, and $3u_0 = u_{ag} + u_{bg} + u_{cg}$; i_0 is zero-sequence current, and $3i_0 = i_a + i_b + i_c$; u_{ag} is ground voltage of additional resistance phase.

For normal branch with no additional resistor, the branch mathematical equation is:

$$i_0 = c\frac{du_0}{dt} + \frac{u_0}{r} \tag{7}$$

Although Equation (6) and Equation (7) are obtained in the neutral non-ground system; for a resonant network, the compensation arc access cannot change the structural models of each branch; the equations are still applied to describe the state of a resonance compensation network. Parameters *r* and *c* indicate the insulation characteristics of each branch after the leakage. As along as the parameters r and c are detected from Equations (6) and (7), then the capacitive current will be calculated easily

3.2 Parameters Identification Model

Equation (6) is a continuous time domain differential equation, using three sampling value of the points $(k-1)T_s$ 、 kT_s 、 $(k+1)T_s$ to express Equation (6); the discrete system identification model can be obtained:

$$i_0(k) = c\frac{u_0(k+1) - u_0(k-1)}{2T_s} + \frac{1}{r}u_0(k) + \frac{1}{3r_g}u_{ag}(k) + e(k) \tag{8}$$

In this equation, $i_0(k)$, $u_0(k)$, $u_{ag}(k)$ are respectively zero sequence current, zero sequence voltage, and phase to ground voltage of the additional resistor branch on time k ; T_s is the sampling interval. In the actual detection sampling process on signal i_0 , u_0 and u_{ag} , the checked signals can include random noise inevitably, as the influence of environment and testing means; assume that this is $e(k)$.

The Equation (8) is made as the insulation parameters identification equation of branches. Using variable forgetting factor RLS algorithm to identify it, the parameters r, c and r_g can be achieved online. Firstly, we express it as the least square format:

Order $z(k) = i_0(k)$, $h_1(k) = \dfrac{u_0(k+1) - u_0(k-1)}{2T_s}$, $h_2(k) = u_0(k)$, *local trends* $h_3(k) = u_{ag}(k)$, $\theta_1 = c$, $\theta_2 = \dfrac{1}{r}$, $\theta_3 = \dfrac{1}{3r_g}$; then, $\boldsymbol{\theta} = [\theta_1,\ \theta_1,\ \theta_3]^T$, $\boldsymbol{h}(k) = [h_1(k),\ h_2(k),\ h_3(k)]^T$.

Therefore, in accordance with the format of least square of parameter estimation, the insulation parameter identification model is as follow:

$$z(k) = \boldsymbol{h}^T(k)\theta + \boldsymbol{e}(k) \tag{9}$$

after sampling, the data of L points is used to calculate by introducing the above expression equation into variable forgetting factor RLS algorithm Equation (5), through recursive operating, so that we can get the results of parameter identification.

For these without leakage (without additional test resistor) branches, just ordering $\theta_3 = 0$ of the above algorithm, its least square calculation procedures are the same as the additional resistor branch in a leakage test.

Variable forgetting factor RLS algorithm is a recursive algorithm, and the initial state needs to be selected. The initial values of the estimated parameter and error covariance matrix are in follow:

$$\begin{cases}\hat{\boldsymbol{\theta}}(0)=\boldsymbol{\varepsilon}\\ \boldsymbol{P}(0)=\alpha\boldsymbol{I}\end{cases} \tag{10}$$

In the equation, ε is the sufficiently small real vector, and α is a sufficiently large real. After a certain number of recurrences, the satisfied results can be achieved.

4. Establishment of Capacitive Current Detection Algorithm

4.1 Capacitive Current Detection Algorithm

The algorithm procedure based on Variable forgetting factor RLS algorithm of capacitive current in coal network is shown in Figure 2. During leakage test, add the testing resistor and start identification algorithm including sample zero-sequence current i_{0i} of branches, zero-sequence voltage u_0 and phase to ground voltage u_{ag} of additional resistor line; and then make a recurrence to parameter identification in accordance with variable forgetting factor RLS algorithm; then move forward a sampling interval, and continue to the next recursive calculation of insulation parameter. Repeat this course multiple times; the insulation resistance r_m and ground capacitance of each branch can all be obtained.

After obtaining r_m and c_m, it is easier to estimate capacitive current I_{cm} of each branch, the total capacitance C_Σ and the total capacitive current $I_{C\Sigma}$ of system; if system voltage is U, they are as follow:

$$I_{cm}=\omega c_m U \tag{11}$$

$$C_\Sigma=\sum c_m \tag{12}$$

$$I_{c\Sigma}=\omega C_\Sigma U \tag{13}$$

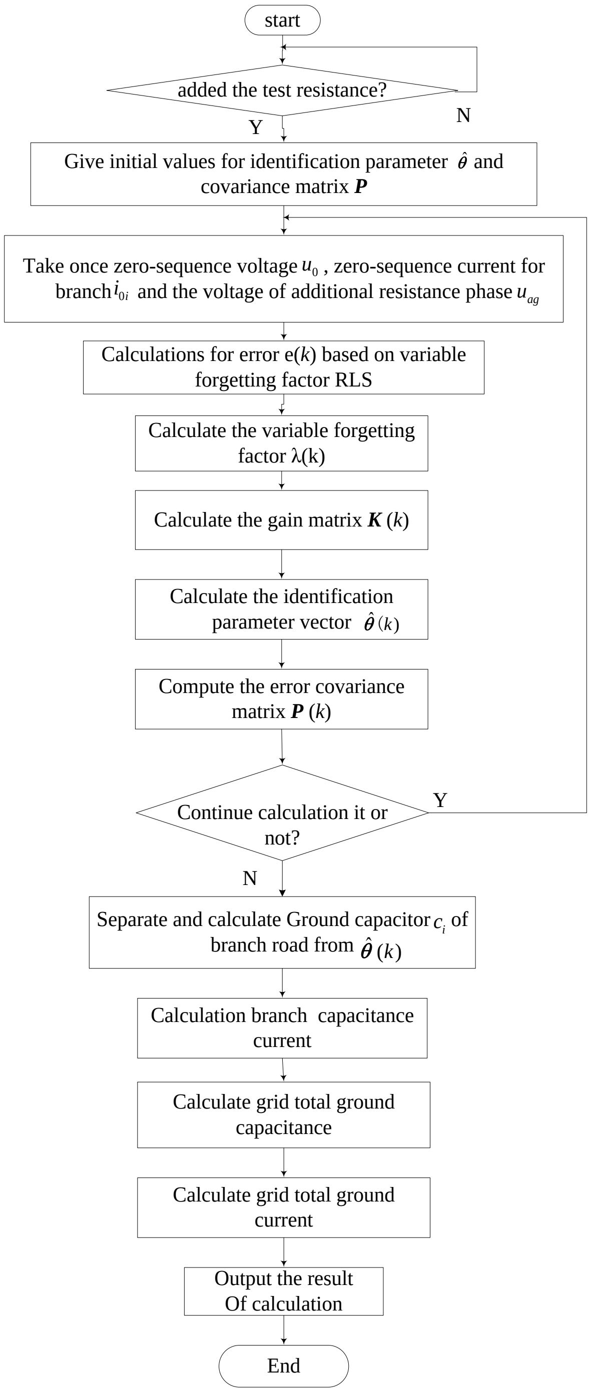


Figure 2: flow chart of capacitive current identification

The steps of capacitive current detection algorithm are as following:

Step1: Judge whether the Leakage test resistor has been attached, if it did, go to step2, to implement the parameter identification process; otherwise, repeat step1, continue to detect whether there exists leakage test.

Step2: Assign initial values for the recognition parameter $\hat{\boldsymbol{q}}$ and the covariance matrix $\boldsymbol{P}$.

Step3: Get zero-sequence voltage u_0, zero-sequence current i_0 and the ground voltage u_{ag} of additional resistor phase.

Step4: Calculate the estimated error $e(k)$, in accordance with variable forgetting factor algorithm (equation5).

Step5: Calculate the variable forgetting factor $\lambda(k)$, according to the equation(4)

Step6: Calculate the gain matrix $\boldsymbol{K}(k)$, identification parameter vector $\hat{\boldsymbol{\theta}}(k)$ and error covariance matrix $\boldsymbol{P}(k)$ successively, according to the algorithm of variable forgetting factor (equation5).

Step7: Judge whether to continue recurrence identification calculation; if it needs, go to step3, to continue identification of parameters; if not, the identification recurrence process is over, then execute sequentially.

Step8: Separate the branch ground capacitance c_i from the identification parameter vector $\hat{\boldsymbol{\theta}}(k)$.

Step9: According to Equation (11), calculate the branch capacitive current I_{cm}.

Step10: According to Equation (12), calculate the total capacitance C_Σ of the power supply system.

Step11: According to Equation (13) calculate the total Capacitive current $I_{C\Sigma}$ of the power supply system.

Step 12: Output the results.

4.2 The Discuss of Algorithm Data Window

In order to confirm the suitable data window of variable forgetting factors RLS algorithm, we consider the accessible maxim data scope, convergence of algorithm, and the accuracy of identification results. In the standard of coal mine explosion proof leakage protection relay, the action time of selective leakage protection device is set as 30ms, which means the leakage device in good condition can operate in 30ms. The capacitive current is detected during artificial leakage test every day. Zero sequence voltage, zero sequence current and ground voltage are used to recognize capacitive current, and the time that these signals examined do not exceed 30ms after the leakage test resistor is added. So the accessible maxim data scope cannot exceed this 30ms, and, conservative consideration, the data in a cycle after leakage test resistor added are selected as the data for capacitive current identification; that is to say, the identification data window can be 20ms.

In addition, consider from convergence speed of recurrence, if sampling frequency is fixed; only the algorithm data window is large enough, and there are sufficient samples, the variable forgetting factor RLS algorithm can converge totally during data window. Substantial simulations and experiment indicate that the slowest speed convergence course of capacitive current identification algorithm does not exceed half of a cycle, that means the identified capacitive current value is close to real value after half of a cycle. From the identification speed, the data window can be selected as slightly larger than half of a cycle. But considering actual situation where there are interferences, in order to ensure the accuracy of identification results, the larger sampling data quantity, the higher identification parameters accuracy. We adopt the way of data sampling redundancy; the data window is selected as 20ms time scope ultimately after the leakage resistor is added.

5. Simulation Verification

5.1 Establishment of Simulation Model

An 1140V coal mine distribution network is setup by MATLAB; it is shown in Figure 3. Coal mine power supply system is generally total cable networks. This 1140V system is a mixing net using radiation mode of connection and main line mode of connection, and there are four branch lines; each line has several segments, and, for example, the third line l_3 has 3 segments from l_{31} to l_{33}. In Figure 3, the feeder switches of each line are not shown, and the load is behind the arrow. The cross sectional area and length of each segments are labelled on the line, such as the L11-70-800 denotes the cross sectional area of L11 is 70mm^2, and length is 800m. These 1140V system has three kinds of cross-sectional area lines; they are 16mm^2, 50mm^2, 70mm^2. For 70mm^2 line, the resistance r per unit length, the inductance L per unit length and the ground capacitance c per unit for each sectional area lines are : $\mathrm{r} = 0.27\Omega/km$, $\mathrm{L} = 0.34mH/km$, $c = 0.29\mu F/km$; for line 50mm^2, the resistance r per unit length, the inductance L per unit length and the ground capacitance c per unit for each sectional area lines are $\mathrm{r} = 0.39\Omega/km$, $\mathrm{L} = 0.36mH/km$, $c = 0.26\mu F/km$; for line 16mm^2, the resistance r per unit length, the inductance L per unit length and the ground capacitance c per unit for each sectional area lines are : $\mathrm{r} = 1.24\Omega/km$, $\mathrm{L} = 0.40mH/km$, $c = 0.21\mu F/km$.

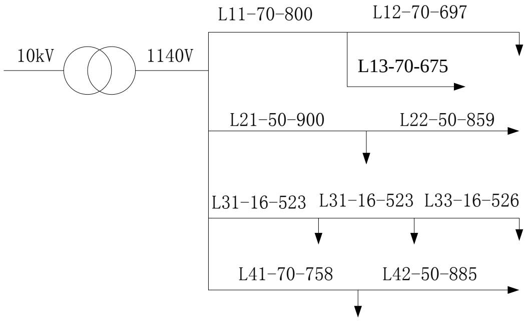


Figure 3: 1140V Mine power supply system

The simulation is completed by MATLAB. Firstly the 1140V mine power supply system model is made by applying MATLAB model file, and then we simulate the leakage fault, and record the zero sequence current waveform. Secondly, we use the M file of MATLAB to write the software of capacitive current detection based on variable forgetting factor recursive least squares; the detection software gives a processing to record waveform of zero sequence current, the zero sequence voltage, and then achieves the branch of the capacitive current and total network capacitance current.

The actual signal detection is often accomplished under the situation with interference noise. The sampling signals are the signals with noise. For the simulation verification of capacitive current identification, noise condition is needed; only like this, the simulation can more approach the reliability and be reasonable. So we inject noise signals in simulation to verify the anti-interference ability of a capacitive current identification method. The injected white noise frequency is 0-4kHz, and its signal-to- noise ratio is 20dB. In this paper we give the simulation results with the situation whose sampling number per cycle is 256.

5.2 Identified Results Analysis Compared with Conventional RLS

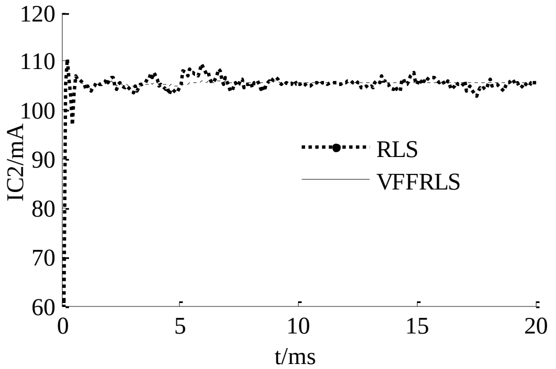
In order to research the effectiveness of parameter identification method based on variable forgetting factor RLS algorithm, we use exponentially weighted RLS algorithm for parameter identification, so this least squares method is the better one in traditional methods; by comparison with the results of exponentially weighted RLS parameter identification method, the proposed variable forgetting factor RLS parameter identification methods can be evaluated. In the simulation, traditional exponentially weighted RLS algorithm sets forgetting factor as 0.91, initial identification value of the parameter as $\hat{\boldsymbol{\theta}}(0)=\mathbf{0}$, initial covariance matrix as $\boldsymbol{P}(0)=10^8\boldsymbol{I}$ ($\boldsymbol{I}$ is the unit Matrix), and the others as the same with variable forgetting factor RLS algorithm's.

Figure 4 and Figure 5 are the capacitive current recognition results of branch 2 and branch 4 in 1140V coal mine network. Leakage test resistance R_g is 22kΩ. and R_g is added on branch 1. In Figure 4 and Figure 5, IC2 and IC4 respectively represent ground capacitance current of branch2 and branch4. In order to evaluate the following speed and identification accuracy of identification algorithm for ground capacitive current recognition process, absolute relative errors of identification parameters are used to measure the algorithm's accuracy. In Figure 4 and Figure 5, eIC2 and eIC4 respectively represent the absolute value of ground capacitive current relative errors of branch2 and branch4. From the results of identification, we can see

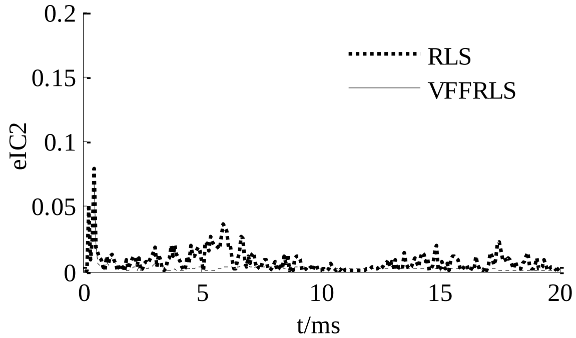
1). Within about 1 / 8 of cycle, the speed that the variable forgetting factor RLS algorithm follows the true value is similar to the speed of traditional exponentially weighted RLS algorithm during capacitive current identification course. At the initial stage of recursion, the identification results of the traditional weighting RLS and variable forgetting factor RLS can both follow the true value at a faster rate.

2). It can be seen from the error curves, although convergence rates of the two algorithms for parameter identification are almost similar, the parameter adjustment errors of variable forgetting factor RLS are significantly less than the exponentially weighted RLS method, after identification follows truth value. This is the effect of the introduction of variable forgetting factor. After weight vector fully follows up to the parameter, the variable forgetting factor $\lambda(k)$ can increase quickly, which decreases the errors of steady state process. For the exponentially weighted RLS parameters, during the error decrease in the convergence process, the forgetting factor λ remains unchanged, and its small values make it sensitive to noise, so the estimated error is large.

3). In a half cycle after adding a resistor, the identification results of variable forgetting factor RLS are basically convergent, and the convergence is stable. We can use one cycle data after adding resistance to identify the capacitive current of system

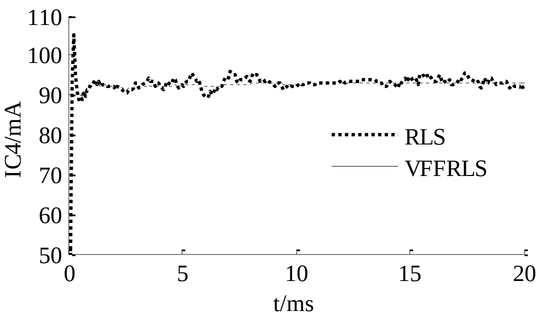


(a) Capacitive current

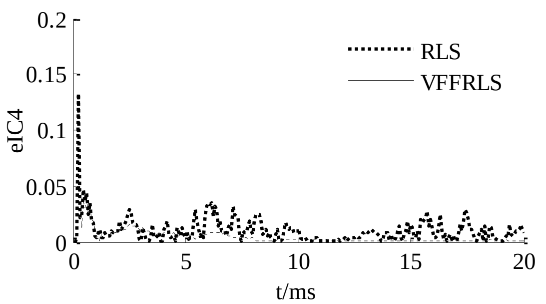


(b) Absolute error

Figure 4: Capacitive current identification results of branch2



(a) Capacitive current



(b) Absolute error

Figure 5: Capacitive current identification results of branch4

5.3 Capacitive Current Results Demonstration

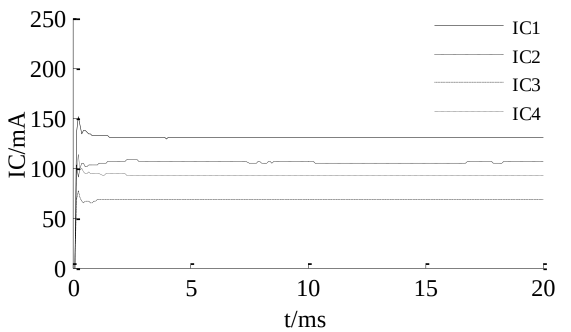
In order to verify the capacitive current identification accuracy with variable forgetting factor RLS, the 1140V coal mine distribution network is used as the example to simulate. The actual sampling signal is often affected by factors such as noise interference; in order to detect the noise resistance of algorithm proposed, the noise with signal-to-noise ratio SNR = 20 dB is injected .Capacitive current recursive curves of each branch are shown in Figure 5 (a), and the error curves are shown in Figure 5 (b);IC*i* (*i*=1, 2, 3, 4) denotes the capacitive current of the *i*th branch; eIC*i* (*i*=1, 2, 3, 4) denotes the capacitive current absolute error of the *i*th branch

As can be seen from Figure 5, in 1/4 cycle at the beginning of the identification, capacitive current has basically followed the true value. In 1/2 cycle at the beginning of the identification, identification results are convergent. Within the second half of cycle, the capacitive current is almost unchanged. Although capacitive current relative errors are large, at first the recognition stage, this duration is short. Identification data window is chosen with a cycle, so this can satisfy the demands of convergence and accuracy for parameter identification.

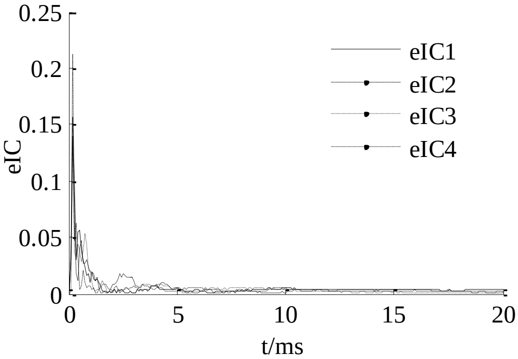
The average value of the capacitive current in the second half cycle of Identification curve is the final calculated capacitive current value. The calculated values of capacitive current corresponding to Figure 6 are shown in Table 1, where IC*i* (i=1, 2, 3, 4) denotse the capacitor current of the ith branch.

As it can be seen from Table 1, the maximum capacitive current identification error (branch 3) is -0.34%. Through the recognition results in Table 1, the total capacitive current can be calculated, it is 196.16mA, and its error is -0.11% with actual value 396.81mA.

Therefore, differences of the each branch capacitive current identification value with actual value are very small, and the differences of total capacitive current is also so follow:



(a) Capacitive current



(b) Absolute error

Figure 6: Capacitive current identification results

Table 1: Results of Capacitive current detection

capacitive current of each branch	IC_1	IC_2	IC_3	IC_4	IC_Σ
actual value/mA	130.20	105.40	68.20	93.00	396.82
identification value / mA	130.11	105.30	67.97	92.98	396.36
relative error	-0.08%	-0.10%	-0.34%	-0.024%	-0.11%

6. Conclusions

Effective test of capacitive current is of great value for the coal mine distribution network safe operation. This paper presents a capacitive current online identification method for the coal mine low voltage power supply system. The least square identification model on capacitive current is established; estimation method of capacitive current by variable forgetting factor Least Square is obtained; the accuracy and reliability of this new method is verified by an actual coal mine distribution. Characteristics of methods are embodied in these points:

1). Using the daily leakage test data, capacitive current estimation can be realized in advance; it can be easily embedded in an existing underground electrical equipment as a part, and has highly engineering practical value.

2). Compared with traditional exponential weighted least square method, variable forgetting factor least square estimation of capacitive current is better in accuracy and convergence rate; when the system appears large disturbances, it can also estimate capacitive current of systems accurately.

3). The time of capacitive current identification algorithm is 1 cycle approximately; in the end of the leakage test, the real time estimation of capacitive current can be realized fleetly and safely.

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