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A SIMPLIFIED METHOD OF TREND REMOVAL TO DETERMINE NOISE OBSERVED DURING A SUPERCAPACITOR'S DISCHARGING

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A new method of trend removal is proposed. This is a simplified method based on Empirical Mode Decomposition (EMD). The method was applied for voltage time series observed during supercapacitor discharging process. It assured the determination of an additive noise component after subtracting the identified trend component. We analyzed voltage time series observed between the terminals of the supercapacitor when discharged by a loading resistance *R*. The steps of the proposed method are presented in detail. The results are compared with the results obtained for polynomial approximation. Statistical parameters (kurtosis, skewness) of the histograms of the identified noise component were estimated to evaluate the quality of the proposed detrending method. The method was adjusted to the analyzed data by selecting a parameter of the applied envelope function of the EMD method. We conclude that the proposed method is faster and more efficient for detecting the additive noise component than the competitive polynomial approximation. The identified noise component may be used to evaluate the State of Health of tested supercapacitors and therefore requires fast algorithms with efficient detection.

Keywords: noise; trend removal; supercapacitor; histogram; empirical mode decomposition.

1. Introduction

Random time series are often recorded when a slowly changing component (trend) disturbs their further analysis, especially at low frequency ranges. This effect is observed in various experiments and data [1-3]. Therefore, new and efficient methods are required to analyze random data generated in recently developed new electronic devices and structures. A simplified method of trend removal to determine the random component generated in supercapacitor structures during the discharging process is proposed. That random component may be used to determine the State of Health of the investigated specimen [4].

The supercapacitor is an electrostatic double-layer capacitor (EDLC) with capacitance values much higher (e.g., hundreds of Farads) than other commercial capacitors, but may operate at lower voltage limits. This device accepts and delivers charge much faster than the competing element – the battery, and therefore may be applied in mobile electronic systems or other power supply units. Unfortunately, these elements are sensitive to any overheating or excessive voltage during charging which accelerate aging processes. Therefore, we consider using noise generated in the EDLC structures as a tool of determining the State of Health of these energy-storing elements. The same method of applying noise was used to detect the state of charge of batteries [5]. Noise generated within the EDLC structure should comprise $1/f$ and white noise components having normal distribution as predicted elsewhere [6].

Voltage fluctuations observed across the loading resistance connected to the terminals of the charged EDLC comprise a close to exponentially decaying voltage (trend) with an additive noise component. Its equivalent circuit model consists of a few *RC* branches with successively increasing time constants and therefore we cannot use a simple approximation of the trend by exponential function to identify noise component [7–9]. It is possible to stand out at least two branches with the lowest time constants but it is not sufficient to determine the trend component by applying exponential decaying approximation (some of the time constants depend on the EDLC polarizing voltage). In Fig. 1 we can see an exemplary discharging curve of the investigated EDLC having two dominant time constants (the first one determines discharging to about 6 000 s and the second one after about 10 000 s). When a selected time constant *RC* determines exponential discharging the observed voltage U versus time t is a straight line in semi-log scale. Additive noise component is visible in the presented data at Fig. 1 having logarithmic scale of OY axis when the recorded voltage drops to relatively low voltage (e.g., below $U = 10^{-2}$ V).

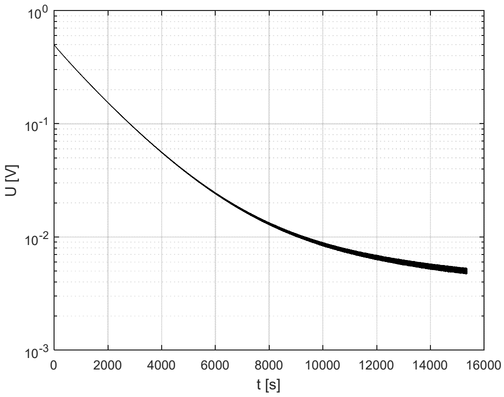

Fig. 1. Voltage recorded between the terminals of the tested EDLC, and having capacitance $C = 8$ F, when discharged by loading resistance $R = 200\ \Omega$ with two dominant time constants; the OY axis has logarithmic scale for better visualization of the time constants, the EDLC was charged to 0.5 V.

We have observed that voltage fluctuations (identified additive noise) can exhibit some relatively fast changes in intensity as presented in Fig. 2 (e.g., at the moments around 5 700 s or 6 100 s). These brisk changes may result from charge redistribution as suggested in the model of noise generation elsewhere [6] and its occurrence may be induced by aging, activating local changes in the electrode/electrolyte interface. These changes are responsible for the observed modulations of intensity of the noise component at selected time intervals. In our paper we propose a simplified method for fast trend determination which takes into account the additive noise component having properties as those presented in Fig. 2 and may be performed automatically, without requiring a decision by human beings while running the applied algorithm.

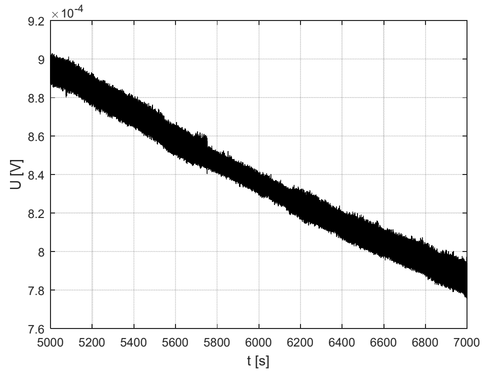

Fig. 2. Voltage fluctuations superimposed on the discharging voltage curve observed between the terminals of the tested EDLC at selected time intervals from Fig. 1.

2. The Proposed Method

The proposed method applies EMD decomposition [10], but is much less computationally demanding and therefore should be much faster and may be performed by a portable computing device. The EMD decomposition of the exemplary signal comprising of $8 \cdot 10^6$ recorded samples can take tens of minutes using MATLAB software installed on a contemporary personal computer. The trend component is determined from the intrinsic mode functions as presented elsewhere [10]. This operation requires a human decision to run the algorithm. Therefore, we propose to modify the suggested EMD method when the trend is similar to the observed during supercapacitor's discharging (Fig. 1) by eliminating the necessity of selecting any parameters by a human being while running the algorithm. One parameter has to be selected before the analysis by applying the EMD method.

We assume in the proposed method that the trend is determined by formula:

$$m(t) = (e_u(t) + e_l(t))/2\,, \qquad (1)$$

where: $m(t)$ is the trend component, $e_u(t)$ and $e_l(t)$ are upper and lower envelopes of the observed discharging curve. The resulting trend component determined by this method for exemplary data (Fig. 1) is presented in Fig. 3. The upper and lower envelopes, marked as black solid lines (Fig. 3) were evaluated by MATLAB function *envelope* with the specified parameter n which has to be selected. This function determined the envelopes using a spline interpolation over local minima for the $e_l(t)$ function or local maxima for the $e_u(t)$ function separated by at least n samples within the recorded time series [11]. We called the function *envelope* by using the input arguments [*yupper*, *ylower*] = *envelope*(U, n, '*peak*'), where *yupper* and *ylower* are upper $e_u(t)$ and lower $e_l(t)$ envelopes of the signal U. The parameter '*peak*' determines a use of spline interpolation. The spline function [12] is a function defined piecewise by polynomials of relatively low degrees and may be used by applying another software than MATLAB. This solution is preferred in interpolation problems, because it gives quite a small interpolation error by using low degree polynomials for the spline functions. It avoids Runge's phenomenon [12] when too high degrees of polynomials may induce oscillations between the measurement points. The proposed spline interpolation seems to be a good choice when the trend is close to exponential decay function. The trend approximation method by the eq. (1) is very simple when we determine both envelopes.

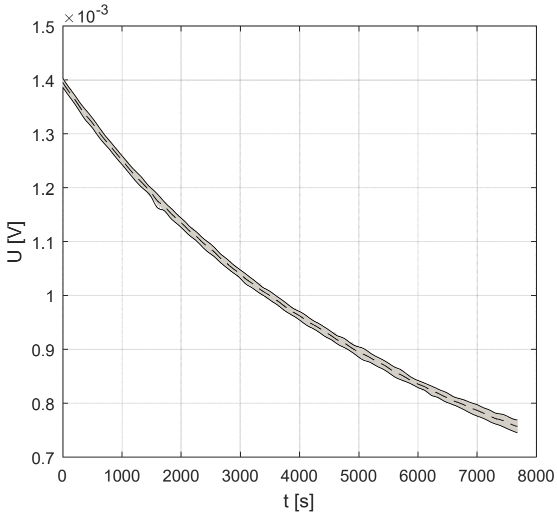

Fig. 3. Illustration of the proposed method of trend detection: the trend component (dashed line) was determined as the mean value of the upper and lower envelopes (solid outer lines); the recorded voltage fluctuations (additive noise) are incorporated into the area (grey colour) between the envelopes.

Selection of the parameter n in the proposed method is crucial for accurate detrending. Its value cannot be too small because a low frequency component will be attenuated. It cannot be too high at the same time because the trend component will not be determined accurately. The influence of n selection for power spectral density and a histogram of additive noise component identified after detrending is presented for exemplary experimental results in the next section. The analyzed voltage time series were similar in numerous experiments with the as-prepared and aged EDLCs when recorded during discharging through the selected loading resistance. We have observed intermittent changes in noise intensity within consecutive time intervals.

3. Detrending Results

We have applied the proposed method for voltage time series recorded while discharging the EDLC of capacitance $C = 8$ F by loading resistance $R = 200\ \Omega$. The measurement set-up comprised of low-noise voltage amplifier (Stanford Research Systems, model SR560) and data acquisition board (National Instruments, model NI4431). Power spectral density of background noise, observed at fully discharged supercapacitor, was at least ten times lower than the power spectral densities of the identified noise during discharging. Exemplary data are presented in Fig. 2. The parameter n of the function *envelope* available in MATLAB software was selected by repeated attempts. When $n = 100\,000$ we observed reasonable trend approximation. Similar results were observed for n being even a few times smaller. This issue will be discussed in depth further. At the same time, polynomial approximation was performed using *polyfit* and *polyval* MATLAB functions. Experimentally we set the 6$^{\text{th}}$ order polynomial, which gave us the most accurate results.

We can identify the differences in time records of the determined noise components (Fig. 4) by both proposed methods (e.g., at $t = 1700$ s, $t = 2500$ s). The power spectral densities $S_u(f)$ of the determined voltage fluctuations exhibit the main difference at low frequency ranges (Fig. 5). Detrending using polynomial approximation attenuates low frequency components and therefore the newly proposed method is more relevant to identifying noise generated in the EDLC and to using the determined noise to evaluate State of Health of the tested EDLCs. Power spectral densities $S_u(f)$ were estimated by using Welch method and averaging over 30 spectra.

Figure 6 presents histograms of the exemplary identified voltage fluctuations (Fig. 4). We may see that the histogram of the noise component determined by the proposed method seems to be closer to Gaussian distribution than the second one achieved using polynomial approximation due to more straight lines of the estimated histogram (normal distribution comprises two straight lines for the selected OY and OX axes in the Fig. 6). Table 1 presents the statistical parameters (skewness and kurtosis) of the recorded voltage noise samples presented in Fig. 4. We may say that the proposed detrending method identified noise component having distribution more close to normal distribution – skewness and kurtosis are slightly closer to the values observed for normal distribution. The difference is rather tiny between the methods when we consider the selected statistical parameters only. A more vivid difference was observed for power spectral densities $S_u(f)$. At the lowest frequency component ($f = 4{\cdot}10^{-3}$ Hz) the difference between $S_u(f)$ estimated for both noise time series using two detrending methods (Fig. 4) exceeds a factor of two (Fig. 5).

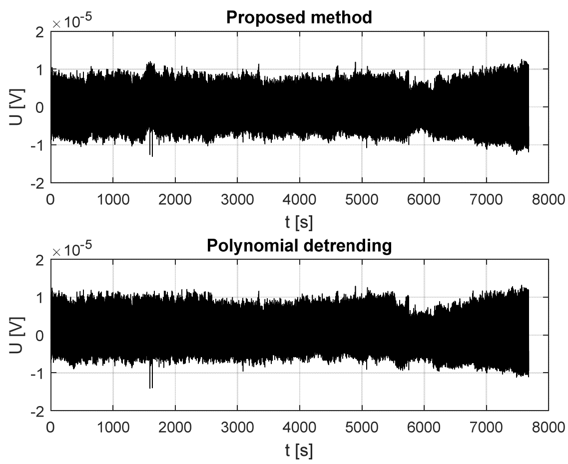

Fig. 4. Voltage fluctuations detected by two selected detrending methods: the proposed method utilizing envelopes determined by the MATLAB function *envelope* applying the specified parameter $n = 100\,000$ (top) and the 6th order polynomial approximation by using functions *polyfit* and *polyval* (bottom).

The proposed detrending method requires the selection of a parameter n equal to the number of samples separating local maxima for the $e_u(t)$ function or local minima for $e_l(t)$ function which are used to establish envelope functions by spline approximation [11]. We have run numerous computations to establish how accurately this parameter should be selected to secure acceptable results. We can conclude that its selection may be quite arbitrary to secure acceptable detrending results.

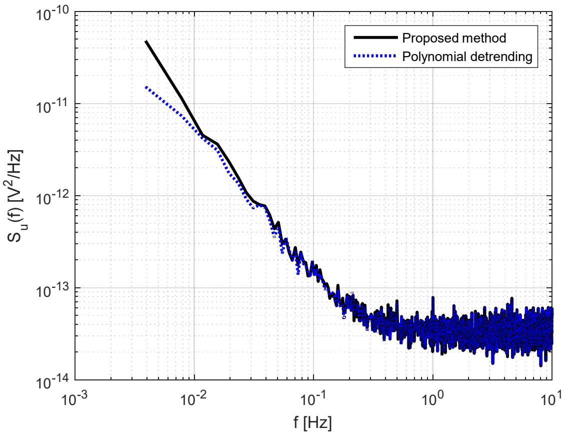

Fig. 5. Power spectral densities of additive voltage noise time series presented in Fig. 4 and detected by two selected detrending methods: the proposed method utilizing envelopes determined by the MATLAB function *envelope* applying the specified parameter n = 100 000 and the 6th order polynomial approximation using functions *polyfit* and *polyval*.

Table 1. Statistical parameters of signals presented in the Fig. 4 in comparison to the Gaussian noise.

		Statistical parameter	
		Skewness	**Kurtosis**
Signal	**Proposed method**	0.51	3.71
	Polynomial detrending	0.52	3.91
	Gaussian noise	0	3

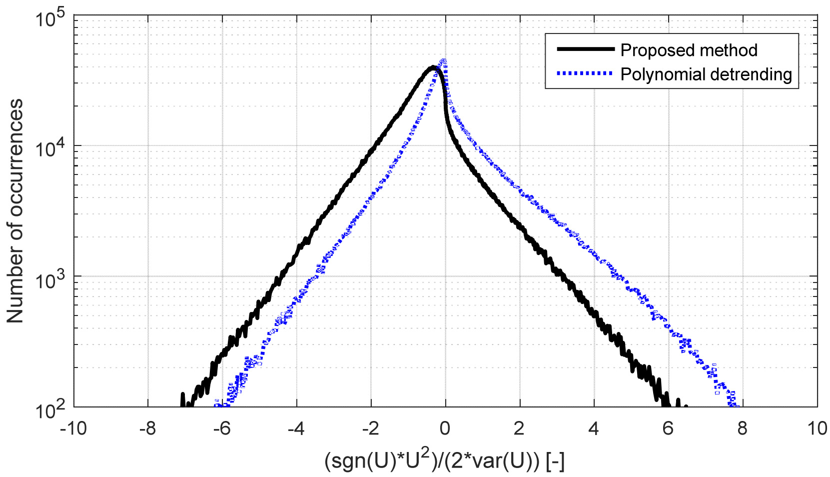

Fig. 6. Histograms of additive voltage noise time series presented in Fig. 4 and detected by two selected detrending methods: the proposed method utilizing envelopes determined by the MATLAB function *envelope* applying the specified parameter n = 100 000 and the 6th order polynomial approximation by using MATLAB functions *polyfit* and *polyval*.

Figure 7 shows the power spectral densities of the signals obtained by the proposed detrending procedure to the exemplary discharging curve (Fig. 1) at selected values of the parameter *n*. We observed that relatively similar results of $S_u(f)$, except of the lowest frequency component at $f = 4{\cdot}10^{-3}$ Hz, were achieved when *n* exceeded 100 000. When *n* was lower than 100 000 we observed serious attenuation of low frequency components and a formation of additional low frequency components (e.g., around $f = 3{\cdot}10^{-2}$ Hz for $n = 10\,000$ or around $f = 2{\cdot}10^{-1}$ Hz for $n = 1\,000$). These new components result from a similar effect as Runge's phenomenon [12] when the approximated time series are too short to avoid some slowly changing intermittences.

We see that there is a correlation between the recorded number of samples and the maximal acceptable *n* value. The longer recorded time series mean lower frequency *f* of the estimated power spectral density $S_u(f)$ at the same estimation error determined by number of averaged spectra. For lower frequency *f* we may then apply greater n values.

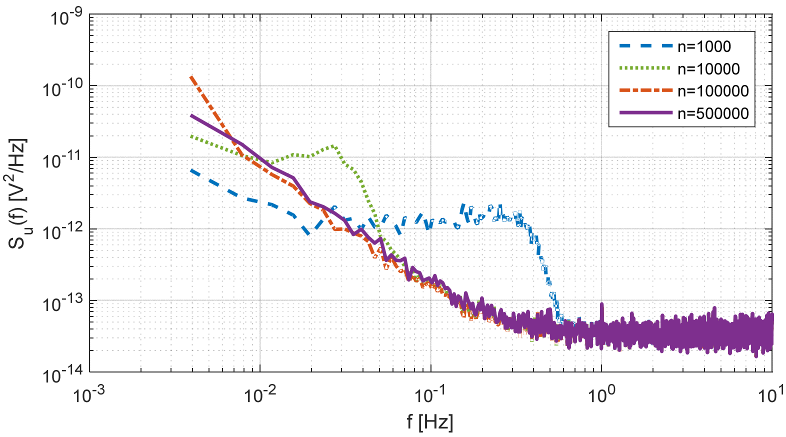

Fig. 7. Power spectral densities of noise component of the signal (Fig. 1) detrended by the proposed method and using the selected values of the parameter *n*.

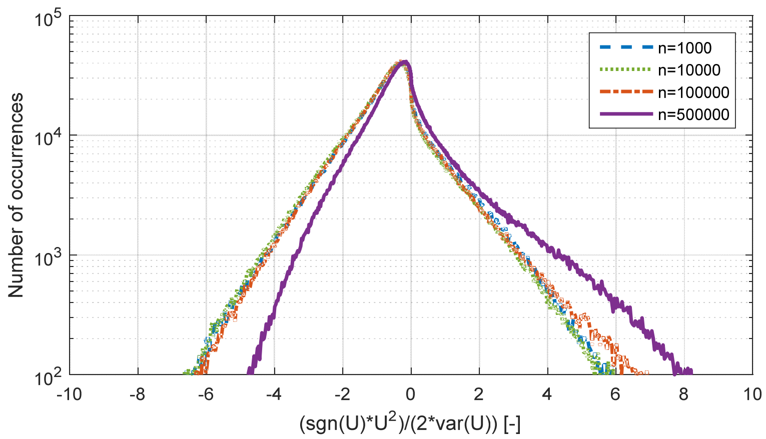

Fig. 8. Histograms of noise component of the signal (Fig. 1) detrended by the proposed method and using the selected values of the parameter *n*.

On the other hand, the too high value of *n* results in the too rough approximation of trend component and the determined noise component is not accurate, especially at the lowest frequency range. This is proved by histograms estimated using the same data and parameter n as for the presented power spectral densities (Fig. 8). When $n = 500\,000$ the histogram was much more deformed than other histograms for lower n. The histograms are similar when n does not exceed 100 000.

In our case the reasonable selection is $n = 100\,000$ but other values even two or three times smaller or larger may be accepted as well. We should underline that the selected range of acceptable values of the parameter n depends on sampling frequency ($f_s = 1024$ Hz in the reported case) and bandwidths of the measured noise components ($1/f$ noise and white noise). Parameter n may be optimized by applying an algorithm with a penalty function. Unfortunately, the results may be unclear because of wide range of acceptable n values and available limited length of the analysed electrochemical noise time series, necessary to reduce random error.

We may conclude that a more thorough analysis should determine the acceptable range of n values when f_s and a number of the collected samples are set. Then, the proposed method may be used fully automatically for the specimens having different capacitance.

4. Conclusions

We consider a problem of additive noise component detection from the voltage recorded between the terminals of the EDLC during discharging experiments. The noise component may be used to determine the State of Health of the tested EDLC when exposed to aging but it requires decent detection. A new method, based on the MATLAB *envelope* function and using spline approximation, was proposed. The method requires the selection of the parameter n expressing the number of samples separating local extrema in the analyzed voltage time series and used for spline interpolation. We presented how the parameter n may be selected to get good results of noise component detection. The proposed method identified additive noise component in a better way than the previously used method based on polynomial approximation. The main difference was observed at low frequency ranges. We have applied the 6th order polynomial because at higher orders Runge effect was observed and at lower order approximation was too rough.

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