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Condition Monitoring of DC-Link Electrolytic Capacitors in PWM Power Converters Using OBL Method

Ahmed G. Abo-Khalil 1,2,*; Abdel-Rahman Al-Qawasmi 1,*; Ali M. Eltamaly 3,4,5; and B. G. Yu 6,*

1 Department of Electrical Engineering, College of Engineering, Majmaah University, Almajmaah 11952, Saudi Arabia
2 Department of Electrical Engineering, College of Engineering, Assuit University, Assuit 71515, Egypt
3 Saudi Electricity Company Chair in Power System Reliability and Security, King Saud University, Riyadh 11421, Saudi Arabia; eltamaly@ksu.edu.sa
4 Sustainable Energy Technologies Center, King Saud University, Riyadh 11421, Saudi Arabia
5 Electrical Engineering Department, Mansoura University, Mansoura 35516, Egypt
6 Division of Electrical, Electronic and Control Engineering, Kongju National University, Chungcheongnam-do 31080, Korea; bgyuyu@kongju.ac.kr
* Correspondence: a.abokhalil@mu.edu.sa (A.G.A.-K.); a.alQawasmi@mu.edu.sa (A.-R.A.-Q.)

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Abstract: Since the lifespan of an electrolytic capacitor is relatively short compared to other power semiconductor devices, the failure rate accounts for 60% and, thus, it is the most vulnerable component of the power conversion device. Therefore, the accurate measurement of the lifetime of an electrolytic capacitor is very important in ensuring the reliability of the entire system, including the capacitor. In this paper, an online failure detection method for a DC-link electrolytic capacitor in a back-to-back Pulse width Modulation (PWM) converter using the opposition-based learning particle swarm optimization-based Support Vector Regression (OPSO-SVR) technique is proposed. In this method, the capacitance and the DC-link capacitor power have been used in offline mode for SVR training and testing. During the offline mode, the SVR parameters have been optimized with the OPSO algorithm to use online to estimate the real value of the DC-link capacitor. The experimental results prove the superiority of the proposed technique over the SVR.

Keywords: electrolytic capacitors; opposition-based learning; lifetime estimation process

1. Introduction

Electrolytic capacitors are widely used in power conversion devices for the purpose of voltage smoothing due to their characteristics, but their lifespan is relatively short compared to other power semiconductor devices, which is a major factor in causing failure. The failure of the individual components will result in the failure of the power converter and the shutdown of the entire system in which it is incorporated, thus, requiring additional cost and time associated with the individual shutdown of the fault, as well as with the shutdown of the entire system. Therefore, it is indispensable to determine the lifetime of the part before the failure by continuously checking the state of components and to judge the life of the components before failure occurs. Among them, a failure diagnosis of the most frequently occurring electrolytic capacitors ensures the reliability of the whole system. The lifetime of an electrolytic capacitor can be predicted formally by the factors specified in the data sheet provided by the capacitor manufacturer, but the life expectancy of the electrolytic capacitor may vary due to factors such as the capacitor ripple current in the topology of use, and the change
in ambient temperature. There is a limit to accuracy, therefore, in order to ensure the reliability of the capacitor to determine the deterioration state of the electrolytic capacitor in advance, and, a fault diagnosis for continuously observing the current capacitor state is essential [1,2]. Figure 1 shows the failure distribution of different components in a static converter [3]. It is obvious that the electrolytic capacitor is the weakest element in the converters.

The lifetime of electrolytic capacitors is typically 1000 to 10,000 h in the case of operating under high temperatures, which is not long enough for most applications. The maximum temperature ratings are typically between +85 °C and +105 °C [4]. Figure 2 shows a typical capacitor characteristic at 105 °C; the capacitor lifetime is about 8000 h. To diagnose the reasons of electrolytic capacitor failure, the configuration of the capacitor should be introduced, as shown in Figure 3. Any aluminum electrolytic capacitor has two aluminum sheets and an electrolytic solution [5]. The aluminum electrolytic capacitor can be electrically represented as a series connection of capacitor, resistor, and inductor, as shown in Figure 4 [6].

Figure 1. Distribution of failure of power components [1].

Figure 2. Capacitor characteristics under high temperature [4].

Figure 3. The configuration of aluminum electrolytic capacitor.
Here, the generation of capacitance $C$ is generated at the anode and cathode, the internal resistance $R_s$ is represented by the resistance of the electrolyte and the insulating paper, and another small resistance configured in parallel with $C$ is due to the electrolyte leakage current. $L_S$ represents the equivalent series inductance.

The leak and deterioration of the electrolyte can be considered as the main eroding process in these capacitors by vapor diffusion through the seals. As a result of this deterioration, the capacitor’s internal ESR changes from the original value [7–10]. Until now, the failure signal diagnosis technique has been mostly fault-determined by determining the onset of abnormal signs when the ESR value of the electrolytic capacitor deteriorates more than twice as normal. In [11], a pulsating component voltage/current signal of a capacitor is modeled in a DC/DC converter by a bandpass filter (BPF) for a specific switching frequency range. References [12–14] proposed a method of estimating the capacitor ESR by recursive least squares (RLS) signal processing and Root-Mean-Square (RMS) operation after passing the pulsating voltage/current signal of the capacitor through the BPF, respectively. Beside this method, several algorithms, such as DFT (Discrete Fourier Transform) [15], Newton–Raphson [16], the least square method (LMS) [17], and the Laplace transform algorithm [18] were also proposed to calculate the capacitance or ESR to predict the capacitor lifetime by using the voltage/current injection method. As such, these methods are largely dependent on the signal processing of the BPF, which is cumbersome to know a specific switching frequency in advance for each PWM power converter, which must have a very large bandwidth. However, when the bandwidth of the filter is large, the size of the signal is reduced due to the influence of the capacitor’s impedance. Furthermore, as the higher order filter design is required, the filter coefficient and the hardware implementation are difficult.

Instead of injecting a voltage or current signal, it is possible to measure or calculate the capacitor ripple current based on the difference between the converter output current and inverter input current. The direct measuring of the capacitor current ripples is used in a few studies [19,20]. This method adds more hardware in the capacitor circuit, which adds complexity and cost. Moreover, using a toroidal core in measuring the capacitor ripple current adds extra parasitic inductance, which deteriorates the estimation of the capacitance.

To have more efficient lifetime estimation methods, several intelligent control approaches have been proposed in the signal injection techniques, such as Support Vector Regression [21,22], neural networks [23], and particle swarm optimization (PSO) [24]. To implement the neural network (ANN) method with accurate MPPT, the selection of neurons and layers should be large so that it takes more time in the training stage [25]. The Support Vector Machine (SVM) method has been proposed as a regression method to estimate the capacitance based on the sampling data of capacitance and the DC-link capacitor power. The SVM method is considered to have a significant advantage over ANN. SVM has a global and unique solution, while ANN can stick in multiple local minima. However, using fixed SVM parameters in a wide range and continuous variation of the capacitance results shows low estimation accuracy. Therefore, it is necessary to use an optimization algorithm to optimize the Support Vector Regression (SVR) parameters for the wide range capacitance.

To optimize the selection of these parameters, a genetic algorithm (GA) or PSO can be used. However, for the sake of simplicity, high-optimization performance, and fast convergence, PSO has significant merit over the other optimization techniques [26].

However, by using the Particle Swarm Optimization-Support Vector Regression (PSO-SVR) method, the population results have random manner due to the PSO-generated features. Therefore, it is not sufficient to use PSO alone to produce a precise result when it is used to tune the SVR parameters.
The opposition-based learning (OBL) method can be used to accelerate the process of optimizing the SVR parameters in different conditions and obtain knowledge about the corresponding global optimum. The proposed opposition-based learning particle swarm optimization (OPSO) is used to tune the SVR parameters to improve the capacitance estimation capability by comparing the obtained parameters from the SVR training and the parameters that are obtained from SVR with the opposite parameters. If the SVR with opposite parameters is better, these parameters are then used in the next step until the estimation process is done [27].

In this paper, an AC voltage component that has a frequency of 30 Hz, which is lower than the line frequency, and an amplitude of 10 V is injected into the DC-link voltage reference, which causes the real DC-link voltage to oscillate with the same frequency. The effect of the injected AC component is negligible because the number of the cycles of the injected voltage is short. The resulting AC voltage ripple component is then extracted using a BPF to estimate the DC-link capacitance using the OPSO-SVR method with tunable parameters by using opposition-based learning (OBL). The kernel function in SVR is used to estimate the capacitance based on the sampling data and SVR parameters, which are obtained from the offline training process. The proposed algorithm is validated by the experimental results.

2. Capacitance Lifetime Monitoring

In the AC–DC–AC converter steady-state condition, the DC-link voltage stays constant except for switching frequency-related ripple components. To estimate the capacitor circuit parameters, the available information from the constant DC-voltage is not enough to use. Therefore, injecting a low frequency signal to the reference voltage is required to estimate the capacitance during the disturbance. The injected component into the constant DC-link voltage is as follows:

\[ v_{dc,\text{ripple}}^* = V_{ac} \sin \omega_{in} t \]  

To guarantee an accurate capacitance estimation, the DC-link voltage with the injected AC voltage should be controlled precisely. Therefore, a feedforward component needs to be added to the conventional DC-link voltage controller. When the PWM converter loss is neglected, the input and output power of the DC-link can be expressed as:

\[ \frac{C}{2} \frac{dv_{dc}^2}{dt} = p_{in} - p_{out} \]  

Equation (2) is used to estimate the DC-link capacitance by calculating the two sides of the equation as follows:

\[ p_{in} = \frac{3}{2} \left( v_{e d}^* r_d^* + v_{e q}^* q_d^* \right) \]  

\[ p_{out} = \frac{3}{2} \left( v_{ds}^* r_{ds}^* + v_{qs}^* q_{qs}^* \right) \]

If \( r_d^* = r_d^* = 0 \) for the unity power factor control of the line side, then:

\[ p_{in} = \frac{3}{2} E_{d} \]  

From (2) through (5), the feedforward component of the q-axis current reference is as follows:

\[ i_{q,\text{ff}} = \frac{2}{3E} \left( \frac{C}{2} \frac{dv_{dc}^2}{dt} + p_{out} \right) \]
The total reference DC-link voltage is given as:

\[ v_{dc}^* = V_{dc0}^* + v_{dc,ripple}^* = V_{dc0}^* + V_{ac} \sin \omega_{in} t \]  

(7)

By substituting the DC-link Equation of (7) in (6), and assuming that \( V_{dc0}^* \gg V_{ac} \), then:

\[ \frac{dv_{dc}^2}{dt} = 2 \omega_{in} V_{dc0}^* V_{ac} \cos \omega_{in} t \]  

(8)

Thus, by substituting the square derivative of the DC-link voltage from (8) into (6), the feedforward component of the q-axis current reference is expressed as:

\[ i_{q,f,f} = \frac{2}{3E} \left( \omega_{in} C V_{dc0}^* V_{ac} \cos \omega_{in} t + p_{out} \right) \]  

(9)

Figure 5 shows the control block diagram of the AC/DC/AC PWM converter. The controller consists of a DC-link voltage control loop and two current control loops. The q-axis current is determined by the DC-link voltage controller, while the d-axis current controller determines the output current power factor. The output current of the converter is controlled in phase with the mains voltage and can be controlled at almost unity power factor. The DC-link voltage is controlled by the current of the axis q corresponding to the active power, and the current of the axis d, corresponding to the reactive power, controls the power factor. Under load conditions, it is important to control the DC-link with a constant reference voltage while the current reference of the q axis changes, depending on the actual power component. By injecting the low frequency voltage component into the reference voltage of the DC-link, the q-axis reference of the converter and the actual current includes ripple components of the same frequency.

Figure 5. Control block diagram of DC/AC PWM converter.

3. Capacitance Estimation Using OPSO-SVFR

The proposed capacitance estimation algorithm was applied in two steps: opposition particle swarm optimization (OPSO), and parameters selection for SVM (Support Vector Machine) with OPSO. These two steps were performed on the input data of capacitance and the DC-link capacitor power. The two phases are discussed in Sections 3.1 and 3.2.
3.1. Support Vector Regression (SVR)

SVM is an alternative learning method for Multi-Layer Perceptron Classifiers that minimizes structural risks, maps patterns into higher-dimensional feature spaces, and provides optimal identification. SVM, using the statistical learning method, minimizes structural errors, unlike conventional classification techniques, such as principal component analysis (PCA) and neural networks [27–30]. For this reason, SVM has been successfully implemented in various fields, such as prediction, classification, and regression.

Support Vector Regression (SVR) has been extended to regression problems by introducing an insensitive loss function to SVM regression models, while SVM has been applied to the prediction of classification problems [31]. The SVM provides an optimal separation plane (hyperplane) to solve the classification problem. The reasons why SVM attracts attention are as follows: firstly, it is easy to interpret the results because it is based on a clear rationale; secondly, it can achieve a higher level of accuracy than neural networks in practical applications, such as classification and regression.

The choice of a subset of functions is an important issue when creating a regression analysis system to construct a regression model based on SVM. It is important to minimize the number of input functions that produce optimum predictions and models with less computationally intensive calculations. The use of a subset of small and appropriate characteristics can facilitate the implementation of regression decisions. The appropriate adjustment for the SVR parameters can improve the regression accuracy. Selecting the kernel function, kernel parameters, and the penalty factors are very important factors in the SVR design. Therefore, the proper selection of the subsets of functions and the parameter settings of the model have a significant impact on the regression accuracy. The selection of the characteristic subsets affects the appropriate parameters of the kernel, so it is best to obtain the subset of features and the SVR parameters at the same time.

As mentioned earlier, SVR is a regression method for predicting an unknown function between the inputs and outputs by using the training data. When the system input/output relationship is obtained in the offline process, a prediction of the output value based on the obtained relation can be obtained in the online process. The input and output data for offline training are given as \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\), where \(x_i\) and \(y_i\) are input and output vectors, and \(n\) is the number of training data. The general function of SVR is as follows [32]:

\[
f(x) = (w \cdot \Phi(x)) + b
\]  

where \((\cdot)\) is the vector dot product. The slack variables (\(\xi\) and \(\xi^*\)), which minimize the empirical risk, are expressed as [24]:

\[
R_{\text{reg}}(f) = \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} \Gamma(f(x_i) - y_i)
\]  

where \(\Gamma(\cdot)\) is the cost function, and \(C\) is the penalty factor that controls how much variation is allowed for the training data and the complexity term of the model (\(||w||^2\)). The slack variable is introduced so that the estimation problem can be determined even if training data exists.

The optimization solution is expressed by subject to \(0 \leq \alpha_i \leq C, 0 \leq \alpha^*_i \leq C\)

\[
f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha^*_i). (\phi(x_i) \cdot \phi(x)) + b
\]

Through the introduction of the kernel function, the regression function of Equation (12) is represented by Equation (13)

\[
f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha^*_i). K(x_i, x) + b
\]
where \( K(x_i, x_j) = \Phi(x_i)^T \Phi(x_j) \) is the kernel function. The bias term \( b \) can be calculated as follows:

\[
b = \text{mean} \left( \sum_{i=1}^{n} y_i - (a_i - a_i^*) \cdot K(x_i, x) \right)
\] (14)

The radial base function (RBF) is selected to solve the problem as follows:

\[
K(x_i, x) = \exp\left(\frac{-|x_i - x|^2}{\sigma^2}\right)
\] (15)

3.2. The O-Particle Swarm Optimization

The particle swarm optimization (PSO) algorithm is one of the optimization techniques that was inspired by the social behavior of animals, and was proposed in 1995 by J. Kennedy and R. Eberhart [33]. Just as bio populations, such as ants and bees, share information about each individual’s experience to find food and travel to the optimal location, the PSO algorithm makes it possible to find the optimal solution by balancing each other’s variables. The PSO algorithm has the disadvantage of being prone to the local minimum, but unlike other search algorithms, it can use global optimization for large and complex functions, such as evolutionary operations, and perform better than evolutionary operations. Due to its high speed, it has recently attracted much attention and has been applied to various fields that are difficult to solve with existing algorithms [34,35].

The PSO algorithm represents individual potential solutions as particles, and the number is initially determined by the dimension setting. The initialization and updates of PSO are randomly done in each calculation step using the standard PSO. An improvement for the random behavior of the standard PSO is obtained by initializing the swarm based on the opposite numbers. A comparison between the position and velocity components using the standard PSO and the opposition PSO is then done to select the optimum position and velocity.

The \( i^{th} \) \( d \)-dimensional particle is characterized by its location vector \( p_i^t = p_{i1}^t, p_{i2}^t, \ldots, p_{id}^t \) and its speed vector \( v_i^t = v_{i1}^t, v_{i2}^t, \ldots, v_{id}^t \). Each particle knows its best personal location \( p_{i, \text{Best}}^t \) and the entire population’s best global solution \( P_{\text{Best}}^t \). The position of the population at iteration \( t \) is \( p_t = p_{1t}, p_{2t}, \ldots, p_{Nt} \), where \( N \) is the population size. Each particle updates its location according to Equations (16) and (17):

\[
v_{i}^{t+1} = w v_i^t + c_1 r_1 (p_{i, \text{Best}}^t - p_i^t) + c_2 r_2 (P_{\text{Best}}^t - p_i^t)
\] (16)

where \( r_1 \) and \( r_2 \) are random functions in the range of [0, 1], \( c_1 \) and \( c_2 \) are personal and social learning factors, and \( w \) is the inertia weight.

\[
p_{i}^{t+1} = p_i^t + v_{i}^{t+1}, \quad i = 1, 2, 3, \ldots, N
\] (17)

The constriction coefficients introduced in [34] are used to set \( c_1 \) and \( c_2 \):

\[
x = \frac{2}{\varphi - 1 + \sqrt{\varphi^2 - 4\varphi}}
\] (18)

\[
c_1 = x\varphi_1, \quad c_2 = x\varphi_2
\] (19)

where \( \varphi = \varphi_1 + \varphi_2 > 4 \). The optimization process is terminated when the best global solution results in a permissible fitness using the opposite PSO. The opposition-based population initialization technique is shown in the flowchart in Figure 6, which is used in initializing and updating the position and velocity components instead of random initialization.
This capacitor lifetime is ended when its value deteriorates to 1950 \( \mu F \).

### 3.3. Capacitance Estimation Using OPSO-SVR

The optimum voltage estimation using the OPSO-SVR method can be described in steps as follows:

- Enter the original data for estimation, known as the data preparation step.
- Initialize and update the particles using standard PSO and then repeat the same step using the opposite numbers.
- Update the position and velocity components by using standard and opposition PSO formulas to get the accurate SVR parameters.
- Perform an offline training process for SVR with training samples assessing each particle fitness value of the OPSO for the SVR.
- Update each particle velocity and position until the termination condition is satisfied.
- Construct and retrain the SVR estimation model based on the optimal parameters.

For each sample, \( BPF[|P_{in} - P_{out}|] \) is the input of the SVR estimator, which is calculated from the source currents, voltages, and the DC-link voltage, while the estimated capacitance \( \hat{C} \) is the output, as shown in Figure 7.

\[
\begin{align*}
V_{dc} & \\
V_a, b, c & \\
e_{a, b, c} & \\
i_a, b, c & \\
i_{a, b, c} & \\
\end{align*}
\]

**Figure 7.** The structure of capacitance estimation process.

In this paper, it was assumed that the initial nominal value of the capacitor was 3950 \( \mu F \). This capacitor lifetime is ended when its value deteriorates to 1950 \( \mu F \). In order to use OPSO-SVR to check the capacitance value during the system operation, it was necessary to collect a number of training data between the initial and final values.

A combination between 1950 \( \mu F \) and 500 \( \mu F \) was used to obtain the required training data between 3950 and 1950 \( \mu F \) and its corresponding capacitor power, as shown in Table 1. Figure 8 shows the regression response of the trained data.
Figure 9 shows the flowchart of the proposed method. First, a suitable set of sampling data $(x_j, y_j)$ were specified. The SVR parameters were computed through the offline process. Then, the optimized parameters were used online for any DC-link capacitor power $x$ to estimate the unknown capacitance value.

Figure 8 shows the regression model of the trained data.

**Table 1. Training Data.**

|       | Measured Value $[\mu F]$ | SVR Estimated Value $[\mu F]$ | OPSO-SVR Estimated Value $[\mu F]$ |
|-------|---------------------------|------------------------------|----------------------------------|
| A     | 3789                      | 3786                         | 3787                             |
| B     | 3323                      | 3320                         | 3320                             |
| C     | 2857                      | 2855                         | 2856                             |
| D     | 2394                      | 2393                         | 2395                             |
| E     | 1928                      | 1922                         | 1924                             |

Figure 9. Capacitance estimation process using opposition-based learning particle swarm optimization-based Support Vector Regression (OPSO-SVR).
4. Experimental Results

For validating the performance of the proposed OPSO-SVR algorithm, an experimental setup was implemented on a reduced scale in a laboratory, of which, the configuration is shown in Figure 10.

The reference DC-link voltage with the AC-injected component is shown in Figure 11. The amplitude of the injected component was 10 V and the frequency was 30 Hz. Figure 12a,b shows the control performance of the converter d- and q-axis currents, which can be considered satisfactory.

![System configuration diagram](image)

**Figure 10.** System configuration.

![Reference and real DC-link voltage with the 30 Hz component](image)

**Figure 11.** Reference and real DC-link voltage with the 30 Hz component.

![Real and reference currents](image)

**Figure 12.** Real and reference currents (a) q-axis current control, (b) d-axis current control.
The measured AC power component of the DC-link capacitor and its filtered waveform are shown in Figure 13a,b. The bandpass filter with a cut-off frequency of 30 Hz was used to pass the 30 Hz power component, as shown in Figure 13b. The estimation process in two different capacitances was performed and shown in Figure 14a. For case D, for example, the expected capacitance was 2.395 μF, which had only an error of + 0.042 [%] in comparison and can also be compared with the measured value in Table 1.

\[
\hat{C} = 2395 \, \mu\text{F}
\]

This also shows that the expected rate of rapid change in capacity was fast. For further investigation of OPSO-SVR accuracy, a set of random values of capacitance estimation were implemented under five different power levels; Table 2 shows the calculation of the mean, maximum, minimum, and standard deviation. To confirm the superiority of OPSO-SVR over the SVR method, Figure 15 shows that the proposed method was faster than SVR, which made it better for online capacitance estimation.
Table 2. Capacitance monitoring error.

| Measured Capacitance [μF] | Power in = 1 kW | Power in = 1.5 kW | Power in = 2 kW | Power in = 2.5 kW | Power in = 3 kW | Mean | Max | Min | STD |
|---------------------------|----------------|-------------------|----------------|-------------------|----------------|------|-----|-----|-----|
|                           | Error | Error | Error | Error | Error |                  |      |     |     |     |
| 3789                      | 0.08% | 0.09% | 0.14% | 0.125% | 0.11% | 0.14%            | 0.14% | 0.09% | 0.00037 |     |
| 3323                      | 0.07% | 0.13% | 0.2%  | 0.05%  | 0.09% | 0.09%            | 0.00169477 | 0.13% | 0.03% | 0.0045 |
| 2857                      | 0.1%  | 0.09% | 0.15% | 0.1%   | 0.08% | 0.08%            | 0.000960228 | 0.15% | 0.08% | 0.0004 |
| 2394                      | 0.1%  | 0.085%| 0.115%| 0.14%  | 0.075%| 0.14%            | 0.001053874 | 0.14% | 0.075%| 0.00023 |
| 1928                      | 0.112%| 0.13% | 0.12% | 0.09%  | 0.085%| 0.002759459      | 0.13% | 0.085%| 0.0195 |

Figure 15. Capacitance estimation using SVR and OPSO-SVR.

In addition, it was noticeable that the speed and the accuracy of the SVR algorithm was less than OPSO-SVR, as the latter method tuned the SVR parameters in every step to achieve the correct value faster.

The estimated capacitance, the capacitance power variation, and the derivative of the DC-link voltage in the steady state condition are shown in Figure 16a–c. The estimation error for the SVR algorithm was about 0.35%, while the estimation error was 0.28% in OPSO-SVR for the same conditions.

Figure 16. Capacitance estimation in steady state: (a) estimated capacitance, (b) \( BPF\{|P_{in} - P_{out}|\} \), (c) \( BPF\{0.5 dr^2_{dc}/dt\} \).

The SVR and OPSO-SVR estimation performance for different capacitance readings is concluded in Figure 17. In Figure 18, the estimation error of Table 2 is drawn to show the percentage error in different load powers. The estimation accuracy for both methods was acceptable and close to the real value.
which adds no cost to the power and control circuits. The proposed algorithm is based on injecting a low-frequency voltage component to the DC-link reference voltage and then extracting the fluctuated capacitor power, which determines the deterioration state of the capacitor. This algorithm is based on the OPSO-SVR technique by determining a relationship between the capacitor value and its power. The validity of the algorithm was verified through experiments on various experimental conditions, and the variation of the estimation error was analyzed according to the capacitance measurement environment. The experimental results confirmed that the capacitance estimation was a low estimation error, which was well below 0.2%, making this method effective for detecting the state of an electrolytic capacitor in the PWM converter system. The proposed algorithm can be implemented by software without adding or replacing hardware, which adds no cost to the power and control circuits. Therefore, it can be considered as low cost, and it can be directly applied to commercially-produced converters and sensors, which adds no cost to the power and control circuits. The proposed algorithm is based on using a digital controller to estimate the capacitor lifetime without any additional hardware or sensors.

5. Conclusions

This paper presented an online method to detect the deterioration condition and lifetime for electrolytic capacitors in AC–DC–AC converters. The main advantage of the proposed algorithm is the use of a digital controller to estimate the capacitor lifetime without any additional hardware or sensors, which adds no cost to the power and control circuits. The proposed algorithm is based on injecting a low-frequency voltage component to the DC-link reference voltage and then extracting the fluctuated capacitor power, which determines the deterioration state of the capacitor. This algorithm is based on the OPSO-SVR technique by determining a relationship between the capacitor value and its power. The validity of the algorithm was verified through experiments on various experimental conditions, and the variation of the estimation error was analyzed according to the capacitance measurement environment. The experimental results confirmed that the capacitance estimation was a low estimation error, which was well below 0.2%, making this method effective for detecting the state of an electrolytic capacitor in the PWM converter system. The proposed algorithm can be implemented by software.
without adding or replacing hardware. Therefore, it can be considered as low cost, and it can be
directly applied to commercially-produced converters and existing converters, which are versatile
technologies. Moreover, this method has more advantages, as information about the DC-link ripple
current is not necessary because it depends on the estimation of the capacitor power and the change in
the DC-link voltage.

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Nomenclature

\[ V_{ac} \] the peak voltage of the injected AC voltage
\[ \omega_{in} \] the angular frequency
\[ C \] the DC-link capacitance
\[ R_{\text{leak}} \] Capacitor leakage resistance
\[ v_{dc} \] the DC-link voltage
\[ p_{in} \] the line side converter input power
\[ p_{out} \] the load side converter output power
\[ v_{d}, v_{q} \] the line side d-q axis voltages
\[ i_{d}, i_{q} \] the line side d-q axis currents
\[ v_{ds}, v_{qs} \] the load side d-q axis voltages
\[ i_{ds}, i_{qs} \] the load side d-q axis currents
\[ E \] the magnitude of the source voltage
\[ W \] the weight vector
\[ B \] the bias
\[ \Phi \] the nonlinear function
\[ r_1 \text{ and } r_2 \] random functions
\[ \varepsilon \] the variance
\[ c_1 \text{ and } c_2 \] personal and social learning factors
\[ w \] the inertia weight

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