Prediction of Capacitor's Accelerated Ageing Based on Advanced Measurements and Deep Neural Network Techniques

Hao Liu, Tim Claeys, Davy Pisssoort, *Senior Member, IEEE* and Guy A. E. Vandenbosch, *Fellow, IEEE*

Abstract— Capacitors are widely used in electronic systems and have a key function in EMC (electromagnetic compatibility) compliance. However, the ageing of capacitors results in an alteration of their parameters, which could pose a threat on the normal operation of systems as well as their EMC compliance. Normally, accelerated ageing is employed to shorten the experiment time. After the ageing, the capacitance and equivalent series resistance (ESR) are measured to evaluate the ageing process. In this paper, a new continuous characterization measurement set-up is implemented in which the accelerated ageing of the capacitors under test (CUTs) is continuously monitored during the overall accelerated ageing process. It significantly improves the continuity of the measurement and eliminates the errors attributed to the interrupting of the ageing process. This method is validated by comparing measurement results from the new measurement method with results of the conventional method. This was done by subjecting two types of film capacitors to thermal and electrical stress in order to evaluate the accelerated ageing effects. Furthermore, a conditional deep neural network with dropout technique is proposed to predict the accelerated ageing conditions of the capacitors. Instead of only forecasting the failure threshold, the proposed network is able to dynamically predict the accelerated ageing conditions at different elevated temperatures and voltages. This leads to a serious reduction of the total measurement time: from 1000h to 200h.

Index Terms— Capacitor accelerated ageing, Capacitance, ESR, Ageing prediction, Deep neural network, Dropout

I. INTRODUCTION

CAPACITORS are essential components in electronic devices. They are widely applied in RF circuits for coupling and decoupling, filtering and EMI/RFI suppression purposes. Therefore, they play a vital role in EMC performance. However, after a long-time operation, degradation mechanisms can have a significant negative impact on the capacitor parameters, such as the capacitance and the equivalent series resistance (ESR) [1, 2]. This impact possibly results in an EMC incompliance and even a malfunction. By monitoring the change of these parameters with time, it is possible to estimate the operational condition of the capacitors and to predict their life expectancy. Since the natural ageing of a capacitor takes a long time, accelerated ageing methods have been widely used.

In these methods capacitors are subject to a harsh environment, like high/low temperatures [3-5], overvoltage [4-6] to accelerate the ageing procedure without completely damaging the components.

Unfortunately, traditional accelerated ageing test methods are discontinuous. In a typical high-temperature ageing test, for instance, CUTs (Capacitors Under Test) are placed in a climate chamber and age in an accelerated way during a specific time, e.g. 1 day or 1 week, at elevated temperatures. In [4, 5] and [9] measurements were carried out only 6 times during the ageing tests of about 3000h and 1500h, respectively. The measurement interval was about 1 week in [2, 6, 8] and 1 day in [7]. These measurement time-intervals are comparable with the total ageing time. The few measured data only represent a variation trending instead of a full degradation characteristic of the capacitors. In these tests it is necessary to pause the accelerated ageing process before an after-ageing characterization can take place [4-8]. In this step, the climate chamber is cooled down to the ambient temperature and heated up afterwards to proceed the ageing process, which usually takes about 4 hours in total. This is because the cool-down and heat-up procedure needs to be gradual in order to avoid damaging the capacitors due to a sharp variation of temperature. This conventional method thus results in a discontinuity of the accelerated ageing process. Furthermore, the long-time interruption could result in a recovery of capacitance and ESR values, which is a non-wanted effect. Some of the online monitoring methods measure the ripple voltage across the capacitor and current through the capacitor to calculate the ESR value and capacitance [10-16]. These methods are generally applied to monitor the condition of the capacitor in normal operation, corresponding to a natural ageing process at ambient temperature (typical 25 °C), and the applied voltage is typically lower than the rated values. However, natural ageing obviously takes a very long time. As an alternative, accelerated ageing processes (using e.g. a climate chamber in combination with extra electrical stress) can be used to greatly shorten the overall testing time. Unfortunately, the on-site equipment used for natural ageing is not suitable for monitoring capacitors during the accelerated ageing process. As the capacitors need to be subjected to a harsh environment, such as high temperature, humidity and,

H. Liu and G. A. E. Vandenbosch are with the ESAT-TELEMIC research division, KU Leuven, Leuven 3001, Belgium (e-mail: hao.liu@esat.kuleuven.be; guy.vandenbosch@kuleuven.be).

T. Claeys and D. Pisssoort are with the M-Group, KU Leuven Bruges Campus, Brugge 8200, Belgium (e-mail: tim.claeys@kuleuven.be; davy.pisssoort@kuleuven.be).

especially, quite high voltages, a dedicated characterization method and measurement set-up needs to be developed. The normal probes or circuits used with the on-site equipment [10-12, 16] to extract the ripple voltage and current typically cannot withstand the harsh environment and would easily get broken.

For all these reasons, a new continuous measuring method is proposed and implemented. With this method, the CUTs are consistently placed inside the climate chamber and are continuously subject to the high temperature and/or high direct current (DC) voltage during the whole accelerated ageing procedure. Measurements start immediately at the beginning of the ageing process and are continuously repeated after short intervals of 1 h. In practice, since all steps in the measurement process take a very short time, about 1 min, the combined (accelerated ageing process + measurement of the CUT parameters) can be considered as non-stop. Furthermore, without long-term pause in the accelerated ageing process and the cool-down/heat-up steps of the climate chamber, the variations of the capacitance and ESR can be continuously monitored very precisely, yielding a good view on the ageing process. A prototype of an automated test setup for the accelerated ageing of capacitors was built to realize the newly introduced method. In the next step, the results of the continuous measurement process are used to predict the accelerated ageing conditions of capacitors.

In literature, the remaining useful life of a capacitor is mainly predicted by model-based and data-driven methods. Model-based methods capture the long-term evolution of the capacitors' degradation by mathematical models. The Arrhenius model and the Eyring model are two fundamental models to predict capacitor lifetime under thermal stress and electrical stress, respectively [17]. A degradation model is proposed for the capacitance loss attributed to the accelerated ageing process. The model is an exponential function of the applied voltage and temperature. The model parameters are identified by fitting the curves to the experiment data under different ageing test conditions [3]. A calendar-aging model [8] is developed based on the classical Eyring's law. It uses a heuristic capacitance loss model where the capacitance loss is a linear function of ageing time. The ageing time is an exponential function of the elevated temperature and applied voltages. Similarly, an estimated ageing model is developed based on the classical Eyring's law to quantify the charge/discharge ageing according to voltage, temperature, and RMS current [18]. In [19], the capacitance loss is faster at the beginning of the capacitor ageing, after which it turns into a low-rate loss phenomenon. In the developed empirical model, the ageing procedure was considered as a combination of two mechanisms with different time constants. An ageing model [20] was developed based on power-function acceleration factors. This model is more suitable for lifetime prediction of metallized polypropylene film capacitors (MPPFCs).

Compared to model-based methods, data-driven methods primarily focus on the measurement data rather than the complex mathematical models. ANNs (Artificial Neural Networks) have been applied to predict the remaining useful life of capacitors. For example, a residual lifetime prediction is

developed using linear regression and ANNs in [21]. Six factors are considered: temperature, ripple current, humidity, applied voltage, ESR and vibration. In [22], a BPNN (Back Propagation Neural Network) was developed to monitor the health states of capacitors based on the ESR values at different operating frequencies and temperatures. These researches only provide a predicted time point indicating the failure of the capacitors. Details of the ageing conditions over time, however, are not presented. In [23], a method was proposed based on fuzzy logic and neural networks, taking into account the electrical and environmental stresses prior to predicting the ageing conditions of the capacitors. A drawback of data-driven methods is that they are susceptible to noise in the measurement data, which results in overfitting issues and reduced prediction accuracy. The prediction results are usually point values. It is very hard to estimate the uncertainty and reliability of these models.

A Deep Neural Network (DNN) is a kind of artificial neural network with a multiple-layer architecture between the input and output [24]. It progressively extracts higher level features and significantly enlarges the capability of the neural network to deal with complex non-linear input-output relationships. Furthermore, due to the combinational power of the DNN architecture, there is more flexibility to change the input layers and the hidden layers. The hidden dense layers can be stacked to effectively learn features embedded within the data. The DNN architecture has been widely used in speech recognition [25], energy [26], and medical imaging [27].

A conditional deep neural network is proposed in this paper to dynamically predict the accelerated ageing conditions of capacitors. The dropout technique is used to make the network less sensitive to noise in the data and to prevent overfitting issues [28, 29]. A prediction interval is also applied to estimate the prediction uncertainty and improve the reliability of the predictions. In this study, the inputs of the network are the measurement data at the beginning stage of the accelerated ageing process, for instance, 0-200 h. The applied high temperature and voltage, as two conditional features, are the auxiliary inputs. The outputs are the ageing conditions of the capacitors, for example, for the time frame from 400h to the end of the ageing process. Furthermore, the well-trained conditional DNN with dropout is employed in an iterative way to predict the parameters of the capacitors for increasingly longer measurement times. For example, the first prediction is based on the measurements between 0 h and 50 h of measurement time, the second prediction is based on the measurements between 0 h and 100 h, etc. Once the predictions converge, it is reasonable to assume that sufficient measurement data have been obtained for a full prediction of the ageing conditions, and the measurements can be stopped. To the best knowledge of the authors, such a stop-criterion to be used in an accelerated ageing process of capacitors is nowhere available in literature.

The paper is structured as follows. In section II, the capacitors under test are discussed. Section III is dedicated to the automated test setup and the continuous monitoring method. The measurement results are discussed in section IV. Section V describes the proposed conditional DNN and the resulting

predictions. Based on this, in Section VI, the new stop criteria for the accelerated ageing measurement are presented. Finally, Section VII draws concluding remarks.

II. CAPACITORS UNDER TEST

The classical simple lumped parameter model for a capacitor consists of an ideal capacitor in series with an equivalent resistor. During the degradation process, the values of the capacitance and the ESR indicate the level of degradation since these values will noticeably shift when the capacitors are subject to an (accelerated) ageing process. There are two criteria indicating the end-of-life of capacitors: a) the ESR value reaches 2 times the initial value, b) the capacitance decreases in excess of 20% of the initial value [3]. An increased ESR results in more power dissipation and a decreased capacitance weakens the capability to handle ripple voltages. These two phenomena may trigger hazardous effects in the performance of circuits and systems. Capacitance deviation is defined as $\Delta C = (C(t) - C_0)/C_0$ where C_0 is the initial value before the ageing test and $C(t)$ is the measured value at time t during the ageing process. ESR deviation is defined as $\Delta ESR = ESR(t)/ESR_0$ where ESR_0 is the initial value before the ageing test and $ESR(t)$ is the measured value at time t during the ageing process.

In this paper, the CUTs are Polyethylene Terephthalate (PET) and Polypropylene (PP) film capacitors from different manufacturers. They are widely applied in electronic equipment for coupling, decoupling and filtering purposes. The 3 capacitors are described in more detail in Table I.

TABLE I
CAPACITORS UNDER TEST

Cap NO.	C1	C2	C3
Manufacturer	WIMA	WIMA	KEMET
Dielectric	PET	PP	PET
Rated Capacitance (C_R)	470 nF	3.3 nF	0.1 μ F
Max. Operating Temp. (T_R)	100 °C	100 °C	105 °C
Rated Voltage (U_R)	50 V	63 V	63 V

III. EXPERIMENTAL METHODOLOGY

In order to perform automatic measurements during the accelerated ageing, a dedicated experimental setup was developed. Its schematic representation is shown in Fig. 1. It contains a climate chamber, a dedicated PCB (Printed Circuit Board), an LCR meter, and an external power supply. The climate chamber is produced by Weiss Technik with a rated temperature range from -40 °C to 150 °C. The external power supply is used to overstress the capacitors electrically. The dedicated RF switching PCB was specifically designed to characterize multiple capacitors simultaneously during the accelerated ageing. It is controlled by a microcontroller and mainly contains RF switching relays (marked as S1, S2 and S3 shown in Fig. 1), and RF multiplexers which are employed to select one of the CUTs for measurement. The capacitors were connected to the PCB by high-temperature resistant and high-voltage resistant cables to reduce the measurement shift due to

the high temperature and voltage. The HM8118 LCR-meter is employed to measure the capacitance and ESR of the capacitors. In order to eliminate the effects of the long sensing wires, the kelvin 4-wire sensing method was applied. This configuration ensures the measured voltage exactly is the same as the voltage directly across the capacitor, which significantly improves the accuracy of the measurements. Note that the LCR meter was calibrated before the measurement in order to eliminate the unexpected effects of the multiplexer PCB.

A. Combined Thermal and Electrical Ageing Test

In the combined thermal and electrical ageing test, an

Fig. 1. Principle schematic of the experiment setup.

elevated temperature and a high electrical voltage are applied to accelerate the ageing process. The temperature was gradually increased in steps of 25 °C until the pre-determined temperature limit was obtained. This gradual heating procedure lasted for 2 h and was used to avoid fast thermal cycling stress or thermal shocks due to a sharp increase in temperature [2]. Since a too high temperature could immediately damage the capacitors in the test, the upper temperature limit was set at 120 °C, according to the rated operational temperature of the CUTs. Likewise, also the electrical voltage should not be too high, or the CUTs are immediately damaged. Therefore, the applied voltage was set at 1 – 1.4 times the rated values. Note that a 1 k Ω resistor was put in series in order to limit the charging and discharging current.

B. Compared with discontinuous method

In order to verify the experimental procedure explained in the previous sections, the results of a few runs with this procedure were compared with the results of the conventional discontinuous procedure. The CUTs were the capacitors presented in Table I. The test environment was set at 85 °C, 85% RH (relative humidity), and 0.7 U_R . The whole accelerated ageing test lasted about 6 weeks. The time interval of the discontinuous measurement was set at about 2 days. Fig. 2 compares the conventional discontinuous method and the proposed new continuous monitoring method. The new method shows results very consistent with the conventional method. This validates our proposed accelerated aging measuring method. Note already that the capacitance and ESR values of the C1 capacitors rapidly decrease and increase after 200h,

respectively, see Fig. 2, suggesting that they are proceeding towards failure after 200 h, while the capacitance and ESR values of the C2 capacitors drop fast in the beginning of the 200 h and then further gradually decrease. Any large variation in ESR indicates the failure of the PP capacitors. The C3 capacitors have the same dielectric (PET) as the C1 ones and display similar variations, except that the capacitance and ESR values show a rapid decrease and increase at around 400 h, respectively. The measurement results based on the discontinuous method are plotted in symbolized line where the slope value of the line is representative of the increase/decrease rate of the capacitance and ESR. In Fig. 2, the variation trending is similar, but the increase/decrease rates of the discontinuous method are lower than those of continuous method. This phenomenon might be attributed to the aforementioned long-time interruption of the ageing process which leads to a recovery in the capacitors. This issue can result in misestimation of the ageing conditions of the capacitors, and it can be eliminated by the continuous method. Note also that, instead of a few points for the discontinuous method, we obtain a complete curve for the new proposed continuous method, resulting in a more detailed and precise description of the ageing effects.

IV. MEASUREMENT RESULTS AND DISCUSSION

In Section III, the usefulness of the new continuous measurement procedure was shown. In the next test, the widely used film capacitors with PET and PP dielectrics are put under 6 kinds of harsh environments, with temperatures 100 °C and 120 °C, and voltages 1 U_R , 1.2 U_R , 1.4 U_R . Since the temperature of the climate chamber is fixed during an ageing

Fig. 2. Comparison between the conventional discontinuous method and the proposed continuous monitoring method, (i) and (ii) are C1 capacitors, (iii) and (iv) are C2 capacitors, (v) and (vi) are C3 capacitors.

test, in total 2*1000 h (about 12 weeks) is needed to cover these 6 environments. Considering that C1 and C3 have the same dielectric, C1 and C2 were selected as representative for PET and PP dielectric capacitors. To be specific, two batches of 6 capacitors (12 in total) were tested simultaneously in order to provide statistical data: C1 capacitors with PET dielectric and C2 capacitors with PP dielectric. The relative humidity was uncontrolled since the temperature was 100 °C or higher. The total ageing time was 960 hours.

C. Capacitance Deviation

Fig. 3 shows the capacitance deviation during the complete ageing test. There is a decreasing trend for both the PET and PP dielectrics. This is explained by that fact that in the beginning the electrons obtain energy and speed up which results in an increase of electrical flux as well as dielectric constant. However, if even more energy is obtained, even going over the

Fig. 3. Capacitance and ESR deviation for PET and PP dielectric capacitors, for the temperatures 100 °C and 120 °C (marked by _100 and _120, respectively) and the applied DC voltages 1, 1.2 and 1.4 (marked by _1, _1.2, and _1.4, respectively)

limit which bonds the electrons with the parent atom, more and more electrons are generated, and macromolecules start to break down, leading to a chain-reaction [3, 4]. At that moment, breakdown and partial discharge might occur due to the elevated voltage. The chain-reaction and self-heating phenomenon result in the rapid decrease of the capacitance. Eventually, the C1 and C2 type capacitors show around 7% - 26% and 5% - 15% degradation in capacitance values, respectively. It is obvious that capacitance degradation becomes more severe when the capacitors are subject to higher thermal and DC electrical stress.

D. ESR Deviation

Fig. 4 presents the ESR deviation during the ageing. The C1 type capacitors with a PET dielectric show a gradual increase with ageing time. This typical tendency is a result of 1) loss of the metallization film layers due to corrosion because of the moisture and 2) surge currents when breakdowns and partial discharges occur within the capacitors. The final ESR is about 1.3 - 2.2 times the initial value. However, the C2 type capacitors with a PP dielectric show a totally different trend. The ESR values gradually decreases and eventually reach values of about 0.7 - 0.45 times the initial value. This is caused by the electrons speeding up and thus the increasing electrical

flux under high temperature [4, 5]. Regarding the ageing effects due to the DC electrical stress, the measurement results show different characteristics. In general, the ESR values of the PP dielectric capacitors show more decrease with the increase of the DC electrical stress, while the ESR values of the PET dielectric capacitors show an increase. The dissipation factor is closely related to the ESR value [7]. Therefore, typically more energy is dissipated when the ESR value increases.

V. CONDITIONAL DNN WITH DROPOUT

In this paper, the DNN network was implemented using the following software: Keras API v2.30, written in Python v3.7.0, and on top of the TensorFlow framework v2.0.0 [30].

A. Architecture of conditional DNN

The architecture of the proposed conditional DNN is depicted in Fig. 4. The main functionality of the network is to predict the accelerated ageing conditions of the capacitors at specific high temperature (T) and voltage (V). To be specific, in this paper, the 0-200h ageing data and the applied T and V are the inputs and the 401-960h ageing results are the outputs. As seen in Fig. 4, the 200h ageing data are at the layer 1 level and the T and V input are at the layer_2 level. The reasons for this are as follows. If the two parameters T and V are put at the input layer level 1, this input layer has 202 neurons, and the temperature and voltage represent only 2 neurons. Their actual impact could be overruled due to the relatively low proportion (2:200). This problem is addressed by considering the T and V parameters as 2 new conditional input parameters. This is the advantage of working with multi-layers.

The 0-200h measurement data thus go into the Input layer_1 and firstly pass through the MLP_1 (Multi-Layer Perceptron) which has 10 outputs. Then the 2 conditional features (T and V) are added conveniently after passing through an individual MLP_2. The outputs from MLP_1 and MLP_2 are thus merged into a new layer (Merged layer) and eventually pass through MLP_3 to generate an output representative of the accelerated ageing conditions of the capacitors after 400h.

The details of the proposed conditional deep neural network architecture with dropout technique are given in Table II. Note that the MLP_2 has 4 neurons in Layer2 which means that the 2 conditional features are mapped into 4 neurons to enlarge the weights of T and V . The Output layer has 560 neurons representative of the capacitor accelerated ageing condition

Fig. 4. Architecture of the proposed conditional DNN

data in the range of 401-960h. The activation functions are ReLU (Rectified Linear Unit) functions except in the output layer which implements a Hyperbolic Tangent (TanH) function [30].

B. Dropout technique to prevent overfitting

Overfitting problems occur when there are noise and unexpected behavior in the measurement data. Network neurons develop co-dependency amongst each other during training which suppresses the individual power of each neuron. An overfitted model could result in an unreliable prediction with low accuracy. To prevent these overfitting issues, the dropout technique is applied in this study. Instead of training all the neurons, it randomly drops out neurons (hidden or visible) in a fully-connected neural network, shown as the grey-crossed neurons in Fig. 4, during training in each iteration [28]. In this case, it is equivalent to training different networks in each iteration. The dropout technique averages the effects of all the different networks and reduces the overfitting issues. In this study, the dropouts are added right after the MLP_1 and MLP_3, as indicated in Table II. The dropout rate in the dropout technique is set to 30%. This value is a compromise [29]. If the dropout rate is too small, the network is changed too little and the dropout technique does not work satisfactory. If the rate is too large, the network drops too many neurons and the training procedure results in a bad learning result.

C. Evaluation standards

The prediction errors are evaluated by the following parameters: root mean square error (RMSE), mean absolute deviation (MAE), and R-Squared (R^2), calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{N-1}} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^N (x_i - \hat{x}_i)}{N} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad (3)$$

where N is the number of output results, x_i are the actual outputs, $\hat{x}_i$ are the predicted outputs, $\bar{x}$ is the mean of actuals.

TABLE II
DNN ARCHITECTURE INFORMATION

Items	Parameters
Input layer_1	200 neurons
MLP_1	Layer1 (500 neurons) Layer2 (Dropout (0.3)) Layer3 (10 neurons)
Input layer_2	2 neurons
MLP_2	Layer1 (12 neurons) Layer2 (4 neurons)
Merged layer	14 neurons
MLP_3	Layer1 (100 neurons) Layer2 (Dropout (0.3)) Layer3 (500 neurons) Layer4 (Dropout (0.3))
Output layer	560 neurons

D. Prediction results

The datasets of the PET capacitors, shown in Fig. 3, were employed to train the proposed conditional neural network, except the 100_1.2 dataset, which was used to assess the prediction. The training results with and without the dropout are presented in Fig. 5, where the 120_1.2 dataset was selected as example. The predictions with and without dropout were compared to illustrate the advantages of the dropout technique, see Fig. 6. The training errors without dropout are slightly lower than those with dropout technique as shown in Table III. However, it is obvious from the results that the DNN with dropout efficiently overcomes the over-fitting issue and improves the prediction accuracy. This can also be verified by comparing the prediction errors in Table III, where the DNN with dropout has high R-Squared values 0.91 and 0.87 while the DNN without dropout has values 0.58 and 0.65. These well-matched prediction results also validate the proposed conditional DNN.

E. Prediction intervals

Predictions coming from the neural network are specific values instead of an interval. Consequently, as such, the prediction uncertainty or confidence cannot be estimated. Actually, the neural network with dropout enabled generates different outputs every forward pass for the same input. The outputs for several times can be presented using the concept of a Gaussian distribution [29]. In order to obtain the prediction intervals (PI), the conditional DNN with dropout is thus iteratively employed to return a set of predictions for the same input data. The distribution of the prediction results is used to calculate the prediction intervals. The iteration number can be set as large as required, but at the cost of an increased calculation time. Hence, in this work the iteration number was set as 50. This number has shown to result in a good performance [30].

TABLE III
TRAINING AND PREDICTION ERRORS BY CONDITIONAL DNN

		Training Errors		Prediction Errors	
		Dropout	without	with	Without
ΔC	RMSE		0.0015	0.0021	0.0074
	MAE		0.0013	0.0018	0.0057
	R^2		0.98	0.94	0.58
ΔESR	RMSE		0.027	0.032	0.055
	MAE		0.022	0.026	0.029
	R^2		0.95	0.92	0.65

TABLE IV
PREDICTION ERRORS WITH AND WITHOUT PREDICATION INTERVAL

	Prediction Errors	Without PI	With PI
ΔC	RMSE	0.0026	4.5E-4
	MAE	0.0022	3.8E-4
	R^2	0.91	0.98
ΔESR	RMSE	0.037	0.0026
	MAE	0.0016	0.0021
	R^2	0.87	0.99

The 50 predicted results present a quasi-normal distribution, as shown in Fig. 7 for the predicted capacitor ageing results at 960h. The fitted Gaussian PDF (probability density function) is well matched, which indeed verifies the gaussian-distribution property of the predicted data. The mean of the 50 predictions can be taken as the finally predicted result. This method

Fig. 5. Training plots of ΔC and ΔESR by proposed neural network architecture with and without dropout technique (i) ΔC without dropout (ii) ΔC with dropout (iii) ΔESR without dropout (iv) ΔESR with dropout

Fig. 6. Predictions of ΔC and ΔESR by Neural network architecture with and without dropout techniques.

dramatically boosts the prediction accuracy, as shown in Table IV and Fig. 8, where the right rotated figure illustrates the probability density of the predicted ageing results at 960h. The low RMSE and MAE values, and the high R^2 value in Table III and Table IV, clearly verify the advantages of the dropout technique and PI, procedures which have not been used in literature yet. The proposed DNN architecture largely improves the accuracy and reliability of the predictions.

VI. NEW STOP-CRITERION FOR ACCELERATED AGEING EXPERIMENT

It is proved in Section V that the proposed conditional DNN algorithm accurately predicts the accelerated ageing conditions of the capacitors based on the first 200h ageing data. In practice, this means that we can stop the accelerated ageing experiment after 200h, after which the “future” ageing conditions can be predicted based on the proposed conditional DNN. This already saves a large amount of measurement time compared to a full accelerated ageing experiment, which usually takes 1000h.

However, it is possible to go one step further by using a new stop-criterion for the accelerated ageing experiment. The

Fig. 7. Prediction distribution of ΔC (i) and ΔESR (ii) at 960h.

Fig. 8. ΔC (i) and ΔESR (ii) predicted results with prediction interval. principle schematic for this new stop-criterion is given in Fig. 9. It works as follows. In a first step, the measurement is performed over the time interval 0-50h. These data are imported into the well-trained neural network Cond_ANN_50 to produce a prediction for the time interval 401-960h (=560 values stored in Data (0)). In a second step, the measurement is continued over the time interval 50-100h. These data are added to the 0-50h data, and the new and longer string of data is imported into the well-trained neural network Cond_ANN_100 to produce another prediction for the same time interval as in step 1, 401-960h (=560 values stored in Data (1)). In a third step, Data (0) and Data (1) are compared. The prediction is considered as reliable and the accelerated ageing test is terminated if the comparison is well matched (90% in this paper, based on equation (3)). However, if the agreement is not satisfactory, the measurement proceeds for another 100h, generating a longer input string of data, which produces a prediction stored in Data (2), which can be compared to Data (1). A cycle is thus started up ending at the moment that the agreement is satisfactory.

In this paper, the prediction results based on the Input_50h, Input_100h, and Input_200h data are given in Fig. 10. The prediction errors are presented in Table V. Large R^2 values

TABLE V
PREDICTION ERRORS FOR DIFFERENT INPUTS

Prediction Errors	Input_200h	Input_100h	Input_50h
ΔC	RMSE	4.5E-4	7.4E-4
	MAE	3.8E-4	6.1E-4
	R^2	0.98	0.96
ΔESR	RMSE	0.0026	0.012
	MAE	0.0021	0.0106
	R^2	0.99	0.94

Fig. 9. Principle schematic of the new stop-criterion for accelerated ageing test. Note that the different-length input data are marked by Input_50h, Input_100h, ..., Input_100*N h. The networks with respect to the different input data are marked by _50, _100, ..., _100*N.

indicate accurate predictions. For the new stop-criterion, the comparison between the predictions as a result of the different inputs is given in Table VI. The well-matched results show the high reliability of the predictions. Hence, the accelerated ageing measurement can actually already be stopped at 100h and the accelerated ageing characteristics of the capacitors up to 960h can be predicted accurately.

Fig. 10. Prediction comparison of ΔC (i) and ΔESR (ii) for different-length inputs.

Note that although in principle, also the discontinuous method could be used in the prediction, the fact that in practice it has far fewer measuring points impedes this. This is clearly seen in the validation, see Fig. 2. While the results of the comparison itself are quite satisfying, the discontinuous method produces at most only one point per 50 hours measuring time, whereas the continuous method produces one measuring point per hour. For a measuring time of 200 h, this results in 5 points versus 201 points, respectively. It is obvious that any DNN based on only 5 points will be inferior to a DNN based on 201 points.

TABLE VI
COMPARISON BETWEEN DIFFERENT INPUTS

Input length	Matching results
Input_100h vs Input_200h	0.98
Input_50h vs Input_100h	0.96

VII. CONCLUSIONS

In this paper, first, a continuous monitoring method for accelerated ageing effects on capacitors was proposed and validated by comparing it with the conventional discontinuous method. The proposed method provides more detailed and precise information with respect to the accelerated ageing conditions of the capacitors. In practice, two kinds of film capacitors with PET and PP dielectrics were subject to both thermal and electrical stress in the accelerated ageing process. The capacitance and ESR values were continuously measured to evaluate the accelerated ageing effects. Second, a conditional DNN with dropout technique was proposed to actually predict the accelerated ageing conditions. By introducing the concept of the prediction interval, the prediction accuracy is highly improved. Based on the DNN predictions, a new stop criterion was proposed, which is able to drastically reduce the necessary measurement time from a typical 1000h to a more practical 200 h, or even less.

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