On-Line Health Condition Monitoring of Power Connectors Focused on Predictive Maintenance

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***Abstract*—Electrical power connectors are critical points of electrical networks. Failure in high-voltage connectors may result in major power outages, safety risks and important economic consequences. Therefore, there is an imperious need to tackle such issue by developing suitable on-line condition monitoring strategies to minimize the aforementioned problems and to ease the application of predictive maintenance tasks. This work develops an on-line condition monitoring method to predict early failures in power connectors from data acquired on-line (electric current and voltage drop across the connector, and temperature) to determine the instantaneous value of the connector resistance, since it is used as a signature or indicator of its health condition. The proposed approach combines a parametric degradation model of the resistance of the connector, whose parameters are identified by means of the Markov chain Monte Carlo stochastic method, which also provides the confidence intervals of the electrical resistance. This fast approach allows an on-line diagnosis of the health condition of the connector, anticipating its failure and thus, easing the application of predictive maintenance plans. Laboratory results emulating the ageing conditions of the connectors prove the suitability and feasibility of the proposed approach, which could be applied to other power products and apparatus.**

***Index Terms*—Power connectors, parameter identification, on-line monitoring, contact resistance, condition monitoring, fault diagnosis, predictive maintenance.**

I. Introduction

ELECTRIC power connectors are the connection links in low-, medium,- and high-voltage power systems, thus being ubiquitous critical components. Although they are simple elements, connectors play a critical role in power systems and thus, any failure can lead to severe power outages with costly and catastrophic consequences [1]. However, power system operators try to offer a reliable, continuous and safe power delivery to customers, with the least possible service outages [2]. The increase of the electrical resistance of the connector is a sign of its degradation level, and thus, this parameter can be used as a signature or indicator of its health condition.

The electrical resistance of power connectors has two main components, the bulk resistance and the contact resistance. The bulk resistance is determined by the geometry and resistivity of the constitutive materials. The contact resistance includes the constriction resistance and the film resistance terms [3]. The contact resistance is influenced by different factors, including the pressure, roughness and state of the contact interfaces, or the presence of debris, dirt, oxides and poorly conductive films formed at the interface. As a consequence, an increase of the electrical resistance can be used as a reliable indicator of the connector degradation. This raise of the resistance increases the operating temperature, which in turn further increases the contact resistance. This vicious cycle overheats the connector, reducing its expected useful life [4]. Therefore, the long-time operation of the connector increases the electrical resistance due to the degradation mechanisms, thus negatively impacting the connector performance.

Two predominant processes govern the ageing of electrical connectors. First, the contact resistance may increase as a result of a low pressure contact between the connector and the conductor due to poor installation and/or peak and off-peak daily current cycles, generating contraction and expansion patterns, which tend to lose the contact. The chemical reactions occurring in the contact interfaces and specifically in the constriction areas contribute to generate non-conductive compounds, thus influencing the ageing behavior. Both ageing mechanisms occur simultaneously, thus increasing the electrical resistance of the connector [5]. According to [5], during ageing, electrical contacts experiment different stages, namely formation, relative stability and accelerated ageing, which are a consequence of physical changes and chemical reactions occurring at the constriction areas. The formation stage is characterized by the formation of a quite stable constriction area, whereas during the relative stability stage the resistance of the connector experiments a very small increase. Finally, the accelerated ageing stage is characterized by a fast increase of the resistance due to the combined effect of faster chemical processes and higher temperatures.

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The evolution of the contact resistance in electrical connectors and hence, the overall electrical resistance, is a fluctuating nonlinear non-monotonic process [6], thus being complex to analyze. Once the resistance of the connector exceeds a threshold value, it must be substituted to prevent any failure.

Condition monitoring involves a set of techniques focused to identify noticeable changes in a system, which indicate that a fault is being developed, so that, a warning of imminent failure must be generated, being the basis for applying failure detection approaches [7]. To this end, reliable measured data is required, from which health indicators can be obtained to assess the condition of the analyzed system [8]. Online condition monitoring is generating interest in low-voltage distribution networks [9], power transformers [10], circuit breakers [11], or power cables [12] among others. The development of reliable condition monitoring approaches for power connectors requires a deep knowledge of the failure mechanisms for on-line diagnosis of the condition of such devices so that when the behavior of the connectors drifts from the expected one, an appropriate action must be taken well before breakdown or severe deterioration occurs [13]. It is of vital importance detecting the faults in their early stage, when they are still developing. Incipient fault detection is of paramount importance in power systems, since such faults can lead to catastrophic consequences with huge economic losses. The detection and diagnose of incipient faults enables to apply predictive maintenance plans in power systems, thus minimizing associate failure risks and ensuring stable and reliable operation with minimum interruptions and outages, so that replacement of the failed component can be scheduled well before fault occurrence. However, incipient fault detection is still a challenging problem, since the subtle changes are difficult to detect and false alarm occurrence must be minimized [14]. Different methods can be applied for this purpose, including model-based approaches constructed from the physical laws governing the behavior of the analyzed systems, or based on probabilistic theories. Another possibility is by means of data-driven approaches, which require large amounts of system data, which are analyzed by means of suitable signal processing methods combined with machine learning algorithms [14].

The extensive application of low-cost sensors, wired and wireless communication systems and computational power facilitates the application of predictive maintenance approaches, although time-based and hands-on maintenance strategies are still commonly applied [15].

Accelerated degradation tests (ADTs) have been typically applied for evaluating the reliability and long-term performance of high reliability and long life products [16]. Due to their characteristics, it is difficult to have sufficient degradation and failure data in a reasonable time. ADTs are often accompanied of a statistical analysis of the data collected to analyze the degradation process [6]. Many works analyzing the long-term behavior of different products are based on ADTs [17]–[19]. However, this approach often requires testing several products simultaneously, so it can be expensive because of the required time, the associated human labor, the consumed energy, and the required materials. In addition, obtained results are usually specific for the tested products, thus lacking capability for generalization. Because of the aforementioned issues, this paper presents another alternative.

This work proposes a simple approach for on-line diagnosis of the health status of power connectors based on continuously monitoring their electrical resistance by measuring the voltage drop and the current flowing across the connectors and their temperature. Therefore, the current and past values of the electrical resistance are taken as signatures or an indicator of the health status of the connector. To this end, a parametric degradation model of the connector resistance is combined with the application of the Markov chain Monte Carlo (MCMC) method. MCMC is applied for identifying the most suitable values of the parameters of the resistance degradation model, according to the available experimental data, while also providing the confidence intervals of the electrical resistance, thus being possible to confine the expected future values of the resistance within the space defined by the confidence intervals. In the case that the measured value of the resistance falls between these intervals, it can be concluded that the connector operates under healthy conditions, otherwise, a warning signal should be activated. This strategy allows anticipating severe faults, thus limiting the consequences of the degradation of the connectors with time, and facilitating the application of predictive maintenance plans. The proposed approach is fast, being possible to be applied almost in real-time and can be adapted to many other power devices. In addition, the proposed method does not need performing accelerated ageing/degradation tests, which present many drawbacks, since they require long testing periods and intensive human labor, require large amounts of energy and thus, they result expensive.

Despite the key role of power connectors in power systems, there are few studies focusing on on-line monitoring of the health status of such components, this work contributing to this area.

II. Connector Resistance And Degradation Models

A. *On-line electrical resistance measurement*

As mentioned earlier, the resistance can be used as a reliable indicator of the health condition of power connectors. Typical values of this resistance is in the range of several units or tens of micro-Ohms, thus this being a challenging measurement. To this end, both the current I and the voltage drop ΔV across the connector terminals, as well as the phase shift φ between the voltage drop and the current are measured when the connector is energized, from which its resistance can be calculated as [20],

$$R_0 = \frac{\Delta V / I}{1+\alpha(T-20)} \cdot \cos\varphi \quad (1)$$

R_0 being the AC resistance of the connector measured at 20 ºC.

The AC resistance differs from the DC resistance due to the skin effect factor. However, due to the low frequency operation and the small size of the analyzed connectors, this difference is very small, although it tends to increase with the size of the connector. Since the resistance changes with temperature, (1) includes a temperature correction, where α is the resistivity temperature coefficient (0.004 °C^{-1} for both Al and Cu) and R_0 is the equivalent connector resistance when converted to 20ºC common reference. It is noted that the temperature coefficient of the analyzed bimetallic connectors is influenced by the quasi-metallic spots generated in the contact interface. Experimental results show that the temperature coefficient in (1) is better approximated by α = 0.0035 °C^{-1} because of this effect.

The temperature of the connector cannot be used alone as a fault indicator because it depends on several variables such as the ambient temperature, the electrical current level that flows through the connector, or meteorological variables (wind speed, solar radiation, ice or rain). Therefore, for using the temperature as an indicator of the connector condition, a complex thermal model would be required. Due to this complexity, and the need to measure other variables (rain, wind speed, etc.) this paper avoids applying this method.

B. Oxidation Multi Spot Resistance Degradation Model

To predict the future value and the evolution with time of the connector resistance, a suitable model is required. The multi spot resistance degradation parametric model presented in [21] is selected in this paper due to its simplicity, small number of parameters to identify and satisfactory results. It assumes an increase with time of the contact resistance because of the development under fretting conditions of non-conductive oxide films at the contact interface and a uniform distribution of the contact spots. According to [21], the two-parameter, i.e., $\theta = (R_0,\tau)$, resistance degradation model determining the evolution with time of the connector resistance, taking into account the oxidation process for uniformly distributed multi-spot contacts can be written as,

$$\hat{R}(t,R_0,\tau)=\frac{R_0}{\left(1-\sqrt{t/\tau}\right)^2\cdot\left(1+t/\tau\right)} \tag{2}$$

where $\hat{R}$ is the electrical resistance estimated by the model, t is the time measured from the installation of the connector, R_0 is its initial resistance corrected to 20ºC, and τ is the maximum life time, since it produces a zero-value in the denominator of (2). Fig. 1 shows the evolution with time of the resistance according to (2).

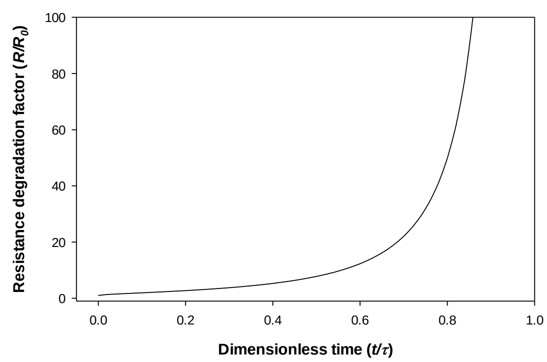


Fig. 1. Oxidation multi spot resistance degradation model.

III. Markov Chain Monte Carlo Simulations

Markov chain Monte Carlo (MCMC) are stochastic methods allowing to obtain parameter estimates for complex models, for which standard estimation methods are extremely difficult to apply. In this paper the role of MCMC is to identify the parameters $\theta = (R_0,\tau)$ of the multi-dimensional distribution function corresponding to the contact resistance $\hat{R}(t,R_0,\tau)$ described by (2).

MCMC iteratively generates random samples to characterize the parameters of the distribution of interest [22]. MCMC methods include different sampling algorithms from a given complex multi-dimensional probability distribution [23]. They build a Markov chain having the chosen multi-dimensional distribution as its equilibrium distribution. Markov chains are stochastic models which define a sequence or collection of random variables moving from one estate to another one. The probability to move from one state to the subsequent one only depends on the current state and elapsed time, but it is independent of the sequence of preceding states. By recording states from the chain it is possible to generate a sample of such distribution. When including more steps in the Markov chain, the distribution of the sample tends to match more accurately the actual desired distribution. Markov chains are guided random walks through the space of parameters describing all feasible values of such parameters, although some values have more probability to be generated than others (it depends on the prior information of the experimental data provided by the user). Therefore, Markov chains tend to sample from the more likely sample space regions. Although different algorithms are available to implement MCMC, the Metropolis–Hastings (MH) algorithm (see Fig. 2) is among the most popular [22], [24], [25]. MH is a statistical sampling method that generates the Markov chain, thus allowing to generate as many samples as required in the random sequence. The Markov chain is often initialized by sampling from a two-dimensional uniform prior distribution $P(\theta)$ with upper and lower bounds u_b and l_b, respectively [26]. It is assumed that when increasing the sample size, the probability density functions built by the Markov chain tend to converge to the actual distribution [25].

MCMC is focused to approximate from a sampling of prior distribution $P(\theta)$, the posterior probability density function (PDF) of the model parameters $\theta = (R_0,\tau)$, which is a conditional probability function depending on the measured resistance data R, i.e., $P(\theta|R)$. Finally, via Monte Carlo integration, summary statistics are generated from the randomly generated samples to describe the distribution of the parameters [27].

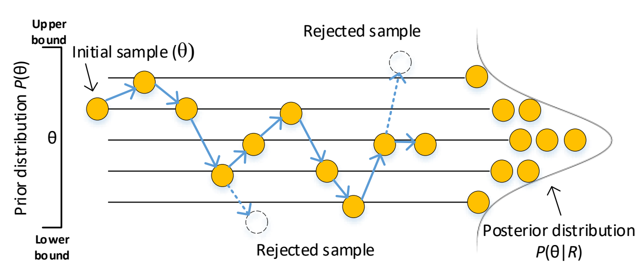


Fig. 2. Construction of the Markov chain by the Metropolis-Hastings algorithm. Adapted from [25].

A. Initial Parameter estimation

Parameters R_0 and τ are estimated from measurements of the contact resistance by applying the Markov Chain Monte Carlo

(MCMC) method in combination with the *fminsearch* function from Matlab®, which finds the minimum of an unconstrained multivariable function using a derivative-free method [28]. The *fminsearch* function returns the initial estimates or seed values of the parameter estimates $\hat{\theta}_{ini} = (R_0, \tau)_{ini}$ and the sum of squares (*sos*) of the error function, which are required by the MCMC algorithm. The definitive values of the parameters $\hat{\theta}_{def} = (R_0, \tau)_{def}$ are provided by the MCMC algorithm.

MCMC provides many estimated pairs (R_0,τ), thus enabling generating confidence intervals for the parameters being estimated. The *fminsearch* function from Matlab® outputs the sum of the squares of the error function as in (3), calculated as the squared difference between the measured contact resistance R and the one provided by the model, i.e., $\hat{R}$ as in (2). The sum of squares function, *sos*, is expressed as,

$$sos = \sum_{i=1}^{n} [R(t_i) - \hat{R}(t_i)]^2 \qquad (3)$$

$R(t_i)$ and $\hat{R}(t_i)$ being, respectively, the contact resistance measured at time $t = t_i$, and the contact resistance calculated by means of (2), whereas n is the number of acquired data points.

MCMC simulations require, as inputs, the initial estimates of the parameters $\hat{\theta}_{ini} = (R_0, \tau)_{ini}$, and the covariance matrix of the parameter estimates $\hat{\theta}$, which is calculated from the initial estimate of the error variance $\hat{\sigma}_\varepsilon^2$, since MCMC requires to know the variance of each parameter. According to [29], $\hat{\sigma}_\varepsilon^2$ can be calculated as,

$$\hat{\sigma}_\varepsilon^2 = sos/(n-p) = \frac{1}{n-p} \sum_{i=1}^{n} [R(t_i) - \hat{R}(t_i)]^2 \qquad (4)$$

sos being the residual sum of squares of the error function and p the number of parameters in the regression model, two in the analyzed case. The covariance matrix of the parameter estimates can be calculated as,

$$\mathrm{cov}(\hat{\theta}) = \hat{\sigma}_\varepsilon^2 (X_i' \cdot X_i)^{-1} \qquad (5)$$

where X and X' are, respectively, the Jacobian or first-order partial derivatives matrix and its transposed matrix, which from (2) results in,

$$X_i = \partial \hat{R}(t_i, \hat{\theta}) / \partial \theta = \left[\partial \hat{R}(t_i, \hat{\theta}) / \partial R_0 \quad \partial \hat{R}(t_i, \hat{\theta}) / \partial \tau \right] \qquad (6)$$

B. Proposed approach summary

Fig. 3 summarizes the steps of the approach proposed in this paper. First, on-line data (temperature, voltage drop and current) are acquired, from which the resistance of the connector is obtained. The past data is fitted using the resistance degradation model given by (2), the parameters of the model and the confidence intervals being determined by means of MCMC simulations. Finally, the current measured value of the electrical resistance is compared against the prediction performed by the model as detailed in Fig. 4, in order to diagnose the health condition of the connector.

Fig. 4 explains how the proposed approach works. It shows the tendency of the evolution electrical resistance in one connector (connector #5) and the fitting of the model according to the parameters identified by the MCMC algorithm, along with the calculated confidence intervals. It allows diagnosing the health status of the connector, which is done by comparing the current value of the electrical resistance with the value estimated by the model. The blue line and "x" symbols in Fig. 4 are the past measured values of the electrical resistance, the black line represents the fitted model according to (2), and the pink line and "x" symbol represents the current measured value of the resistance. In the case that the current measured value of the resistance falls between the confidence intervals, it is assumed that the connector behaves well, otherwise an alarm is triggered. In this latter case, if during the consecutive measurements corresponding to a pre-established time interval the resistance falls outside the confidence intervals, a warning indicating that the connector must be replaced must be generated.

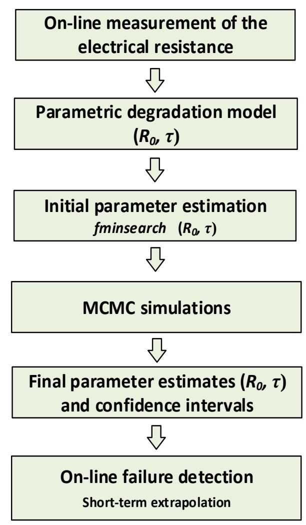


Fig. 3. Proposed on-line health condition monitoring approach.

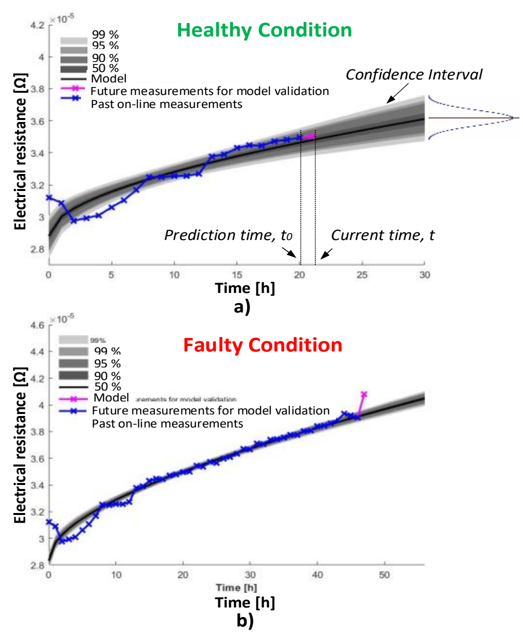


Fig. 4. On-line condition monitoring approach suggested in this paper, including the electrical resistance degradation model fitted according to (2), and the 50%, 90%, 95% and 99% confidence intervals plotted as area bands, representing the predictive probability limits due to the uncertainty in the parameters values. a) Healthy condition. b) Fault condition.

IV. The Tested Connectors and Experimental Setup

A. *The Tested Connectors*

Medium voltage connectors are usually made of copper or aluminum. They are designed for providing a stable and reliable electrical connection between two conductors. To this end, such elements must generate very reduced power losses [30], [31], i.e., they must offer very low electrical resistance. Medium voltage grids typically use compression connectors, because compression is a simple technique producing a relatively low contact resistance and reliable electrical connection.

This work analyzes the behavior of bimetallic copper-aluminum ICAU120 aluminum-copper compression connectors from SBI Connectors, which are intended for 120 mm^2 aluminum conductors. In these connectors, aluminum and copper are joined by friction welding. The barrel of the connector is compressed by using of a hexagonal crimping machine. To improve the contact between the aluminum conductor and the barrel of the connector, contact grease withstanding 140ºC was applied to the inner barrel surface.

The developments done in this work, as well as the presented experimental results are a means to validate the feasibility to apply this approach in substation connectors by means of the *SmartConnector* project, whose details are found in [32]. It includes the substation connector itself, a set of miniature sensors (temperature, voltage drop and current), a thermal energy harvesting unit, and wireless communications.

Medium voltage connectors instead of substation connectors have been used to experimentally validate the condition monitoring approach proposed in this paper since the useful life of the former is shorter, thus allowing a drastic reduction of testing time, technician hours, power requirements and overall cost.

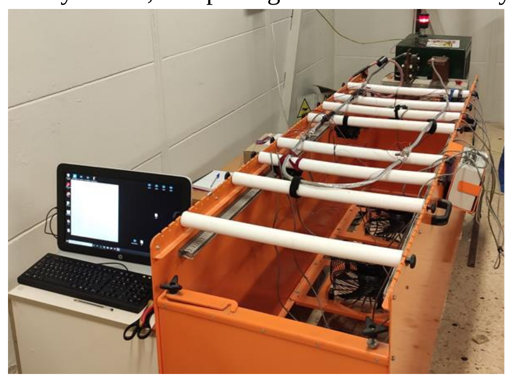
B. *Accelerated degradation by means of heat cycle tests*

Experimental heat cycle tests following the IEC 61238-1-3:2018 standard [5] were carried out to accelerate the degradation of the connectors and to obtain experimental data to corroborate the accuracy and usefulness of the proposed approach. In a real application data should come from the on-line measurements of the *SmartConnector* instead from the heat cycle tests.

To conduct the heat cycle tests, an electrical loop was installed, which includes seven ICAU120 Al-Cu medium-voltage connectors and 120 mm^2 aluminium alloy conductor, as shown in Fig. 5. Wire equalizers were used to measure the voltage drop across the connectors, since they allow improving the contact resistance measurement accuracy by equalizing or averaging the voltage distribution at the measuring points.

Before running the experiment, the initial or reference value of the DC resistance of all connectors was measured by applying four-wire or Kelvin method, using a calibrated digital micro-ohmmeter (Micro Centurion II from RayTech). Next, the heat cycle tests were carried out. The power frequency electric current in the loop was measured by using a Rogowski coil (500LFxB from CWT; 0.06 mV/A). During such tests the voltage drop across the outer terminals of all connectors and the electrical current in the loop were acquired by means of a NI USB-6202 DAQ instrument, which includes 8 differential inputs using a sample frequency of one sample every six seconds, which allows calculating the resistance of the connectors every 6 seconds. T-type thermocouples and a thermocouple data acquisition module (USB TC-08 from Omega) were used to acquire the temperature in order to correct the resistance of the connectors to 20ºC by applying (1).

The recommended operating temperature of the conductor is below 90 ºC. However, to accelerate the degradation process, the heat cycle tests were performed at 120ºC during approximately 92.5 h, completing a total of 140 heat cycles.



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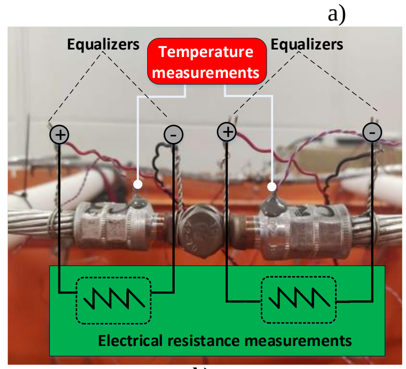


b) c)

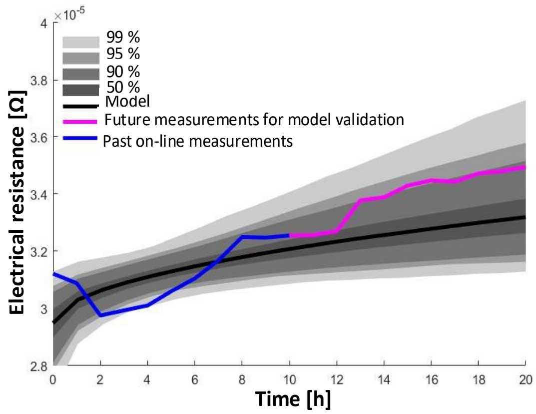
Fig. 5. a) Electrical loop for the temperature cycle tests. b) Contact resistance measurement by using wire equalizers. c) ICAU120 Al-Cu medium voltage connectors.

V. Experimental Results and On-Line Condition Monitoring Approach Assessment

A. *Experimental evaluation of the MCMC-based on-line condition monitoring approach.*

This section evaluates the performance of the proposed condition monitoring approach. To this end the experimental results of the seven analyzed connectors collected during the accelerated heat cycle tests are presented and compared against the results provided by the MCMC-based degradation model. A total of 5000 MCMC iterations were conducted to obtain suitable results by applying the proposed approach.

Fig. 6 shows the temporal evolution of the on-line measurements of the contact resistance of connector #5. These results are plotted in intervals of ten test hours. As explained, the MCMC method identifies the most suitable parameter values (R_0,τ) of the parametric degradation model and the confidence intervals representing the predictive probability limits due to the parameter uncertainty. If the current value of the resistance falls between the confidence intervals, it is considered that the connector is working as expected, otherwise an alarm signal must be generated. In this last case, if during the consecutive measurements corresponding to a pre-established time interval the resistance falls outside the confidence intervals, a warning indicating that the connector must be replaced should be generated. When the measured values are outside of confidence intervals but below the model line (black line), the connector is in the formation phase, so it must not be considered as faulty. Results presented in Fig. 7 for connector #5 indicate that according to the model, the connector behaves well until hour 40, since the new measured resistances (pink line) fall within the confidence intervals. However, according to Fig. 7.d, from hour 45 on, the new values of the resistance surpasses the confidence intervals, thus indicating an anomalous behavior of the connector.



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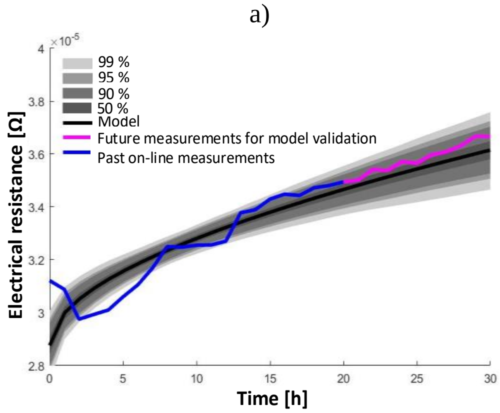

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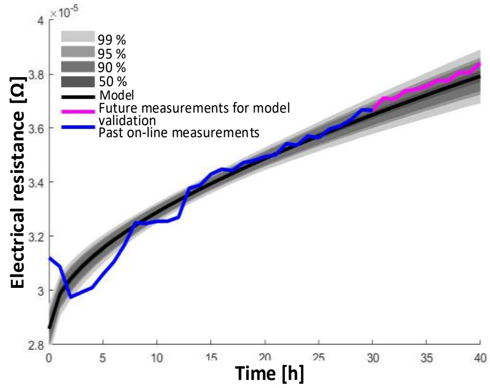

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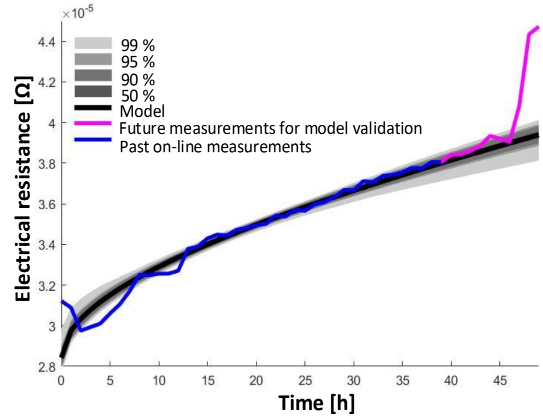

d)

Fig. 6. Results of the MCMC-based condition monitoring approach presented in this paper. Predictions made at hours 10, 20, 30 and 40 of the accelerated heat cycle tests for connector #5. Past on-line measurements (blue line), future measurements (pink line) and the predictions made by the fitted model (black line) used for model validation and confidence intervals (99%,95%, 90% and 50%). Prediction made by the model after a) 10 h b) 20 h c) 30 h d) 40h.

B. Results summary

This section describes the experimental results achieved through the heat cycle test of the analyzed connectors.

Results reported in Fig. 7 show that the behavior of connectors #1, #5 and #6 starts failing around hour 45, connectors #2, #4 and #7 still do not fail at hour 60, whereas connector #3 starts failing around hour 55.

As 5000 MCMC iterations were performed, the MCMC algorithm returns a probability density function of the parameters R_0 and τ, so their mean value is calculated, which is shown in Table I at hour 40 of the heat cycle tests. Table I also displays the coefficients of determination R^2 between the adjusted model and experimental data to prove the accuracy of the model in representing the experimental data. The coefficient of determination of connector #7 is low because this is the only connector that at hour 40 is at the beginning of the relativity stability phase or at the end of the formation phase, as shown in Fig. 7. Therefore, its resistance is stable with no noticeable increment, thus presenting a stable behavior with no symptoms of degradation, as corroborated by the results, which show that the measured value of the resistance is always below the prediction of the model. The results shown in Fig. 7 and the high determination coefficients presented in Table I prove the suitability and accuracy of the proposed fault diagnosis method.

TABLE I
Model Parameters at Hour 40

Connector	#1	#2	#3	#4	#5	#6	#7
R_0 [Ω]	2.4E-05	3.3E-05	3.1E-05	2.5E-05	2.9E-05	3.0E-05	2.5E-05
τ [h]	714285.7	3169.3	2631.6	2325.6	1875.4	769.2	4412.9
R^2	0.968	0.924	0.997	0.994	0.999	0.999	0.508

The procedure presented in this paper requires, in average, a computational effort of about 5 seconds using an Inter(R) Xeon(r) CPU E5-2620 0 @ 2.00GHz with 64 Mb RAM memory.

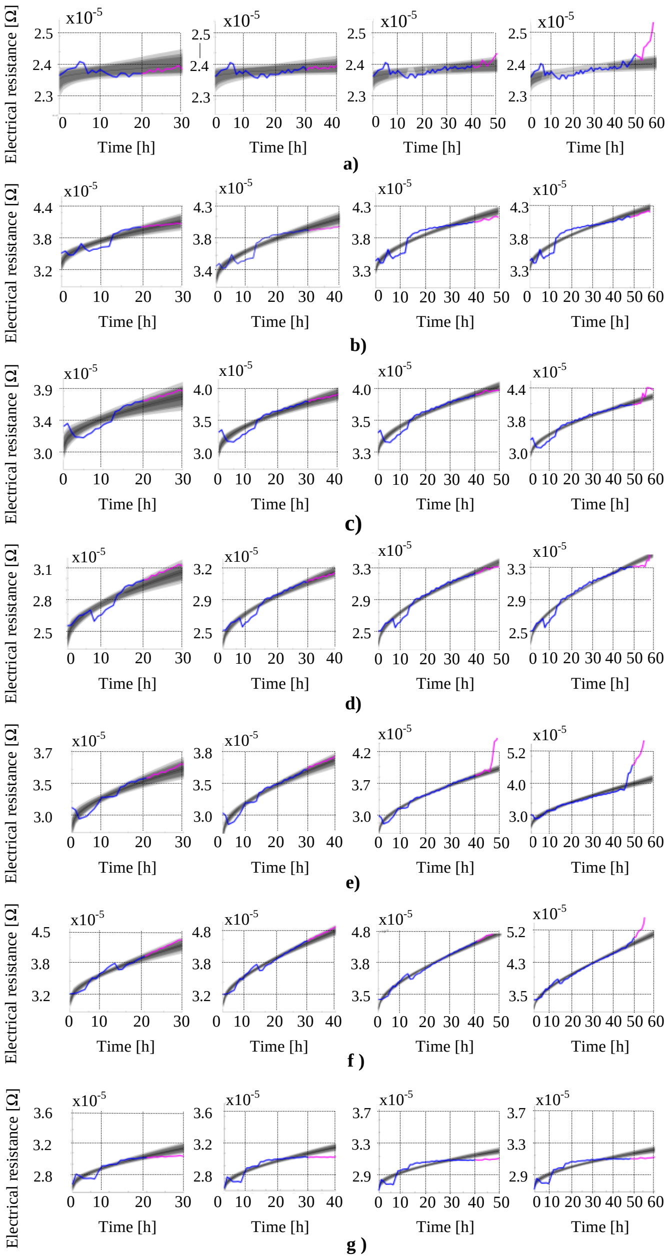

Fig. 7. MCMC-based condition monitoring approach validation during the 100 h of the accelerated heat cycle tests for all connectors (#1 - #7). Model predictions against experimental data during the 100h of the heat cycle tests for all the connector from 20 h to 50 h every 10 hours (#1 - #7). a) Connector #1. b) Connector #2. c) Connector #3. d) Connector #4. e) Connector #5. f) Connector #6. g) Connector #7.

VI. Conclusions

This paper has presented and verified by means of a thorough experimental plan an on-line condition monitoring method to detect early failures of power connectors. To this end, the electrical resistance of the connector must be continuously monitored, since it is used as a signature of the health condition of the connector. It is obtained from on-line measurements of the temperature, the voltage drop and the current flowing across the connectors. An outstanding advantage of the proposed approach is that it allows avoiding to perform previous degradation tests to the connectors, thus simplifying the requirements, minimizing power consumption and operator intervention. The proposed approach is based on a parametric degradation model of the connector resistance, whose parameters are identified by applying the Markov chain Monte Carlo (MCMC) method, which also determines the confidence intervals of the electrical resistance. Therefore, when the measure value of the resistance falls within the intervals, it is concluded that the connector behaves well, otherwise a warning signal is activated. This approach allows anticipating severe faults, thus preventing the connectors and the installation from major failures, while facilitating to apply predictive maintenance plans. Finally, the proposed approach can be applied for on-line condition monitoring of many other elements and devices.

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