Degradation assessment of in-service aerial bundled cables in coastal areas leading to prognosis using infrared thermography

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Abstract
Of late, cross-linked polyethylene insulated aerial bundled cables have replaced conventional copper conductors being resistant to electricity pilferage, offer lower maintenance costs and reduced power losses. However, in coastal areas, aerial bundled cables experience frequent insulation breakdown causing sudden cable failures leading to unexpected power shutdowns. Condition monitoring, employing sophisticated diagnostic techniques, has thus become a major requirement of the energy sector. The reported research work utilizes infrared thermography as one such candidate NDT technique. A novel framework is proposed to investigate the progressive shift in the statistical parameters of the temperature distribution in aerial bundled cables’ insulation, as it degrades over time. The cumulative distribution function of pixel intensity data from a healthy/operational aerial bundled cable is first compared with a reported failed aerial bundled cable. A prominent difference in 0.9 cumulative distribution function values is observed in the temperature distributions. Therefore, 0.9 cumulative distribution function values are used for degradation quantification with respect to ageing. Degradation rates are then computed using periodically acquired thermographic data from operational aerial bundled cables, installed at two different locations in a coastal region, each subjected to different marine climate. The proposed technique proved effective in degradation rate assessment of insulation of operational aerial bundled cables. Consequently, the results achieved can also be utilized for remaining useful life prediction of these cables.

1 | INTRODUCTION

In electrical power transmission and distribution networks, health monitoring of power cables is a challenging task due to strong dependence on varying loading and environmental conditions [1]. The reliability of power distribution system is greatly influenced by power cables’ performance [2]. Insulated aerial bundled cables (ABCs) have exhibited good operational performance in many areas [3]. Additionally, these cables are also resistant to physical tampering making pilferage/line tapping impossible [4]. Of late, use of XLPE insulated ABCs has been enhanced in multiple micro-grids, due to prevention of electric pilferage [5].

Despite abovementioned benefits, the reliability of in-service ABCs, when subjected to changing climatic conditions, is not precisely known yet [6]. ABCs are reported to have a shorter lifespan when subjected to severe environmental conditions in coastal areas [4, 7]. The combined effect of high solar radiation intensity, high moisture content, and heavy electrical loads in coastal metropolises, stress the insulation of ABCs. Insulation Piercing Connectors (IPCs) used in ABCs [8] tend to create punctures in cable insulation thus making electrical contact. In addition to these punctures, minute cracks in the cable’s insulation become susceptible entry points for moisture and impurities to penetrate the ABC structure. Thermal loading caused due to diurnal variations in conjunction with changes in
levels of solar radiation, leads to continuous expansion/contraction of the penetrated moisture. Consequently, the internal pressure of the cables is raised during daytime and lowered at night. Unwarranted mechanical stresses are hence produced, aiding the growth of those micro-cracks with time which eventually leads to complete damage of the insulation. The penetrated moisture also corrodes the metal conductors lying under the insulation. This deterioration cannot be inspected visually. The phenomenon also expedites the thermal degradation process in the ABCs’ insulation, ultimately leading to cable failure.

Significant contributions are present in literature pertaining to cable degradation studies using numerical simulations and experimental assessments in lab environment. Zhiniu Xu et al. constructed a finite element numerical model for the temperature field of optic-electric composite submarine cable to monitor the insulation degradation effectively [10]. An integrated approach was presented by T. V. Santhosh et al. to predict the lifetime of instrumentation and control cables of Nuclear Power Plant by artificial neural network [11]. Neural network approach was also applied on XLPE insulated cables by L. Boukezzi et al. to predict accelerated thermal aging [12]. A. Levet studied the effect of Radiolytic ageing on insulation of control cables using mid-infrared spectroscopy and principal components analysis [13]. The Arrhenius equation is used by authors Zhong Zhang et al. and M. Rasoupoor et al. to calculate the residual life of XLPE cables based on the data obtained from experiments [2, 14]. D.F. Jingle Jabha et al. used acoustic emission technique for the failure prediction in XLPE power cables [15]. Anna Vykydalová et al. [16] developed a predictive model for the insulation degradation of polyethylene cable after performing artificial ageing.

Real world degradation mechanisms are very complex and highly non-linear, and therefore cannot be exactly modelled in numerical computer simulations without simplifying assumptions. Field acquired NDT thermal data captures the degradation rate without any assumptions, and hence has a prowess compared to laboratory generated data. Given the limitations of laboratory and computer simulation environments, boundary conditions in laboratory cannot be exactly replicated in field, and hence laboratory based results will serve little purpose for validation.

The need of the hour is therefore to make use of real world NDT data for reliable damage quantification and degradation rate computation. In most condition monitoring practices implemented generally, only electrical parameters such as reduction in dielectric strength and insulation resistance are measured. These tests however, require the electrical cables to be disconnected from the main power line to accurately measure the electrical values [17]. These methods are well suited for checking degradation caused by electrical loading and cannot measure damage due to corrosion. The effects of severe environmental conditions are hence neglected in quantifying the combined effects on insulation degradation. In order to overcome this, sophisticated NDT based methods are recommended for accurate damage quantification of insulation in operational ABCs, beforehand [18]. Such methods can also be used for degradation rate computation and determining information pertaining to performance of ABCs under varying environmental and loading conditions. Therefore, need of the hour is to specify advanced in-situ degradation quantification methods for ABCs allowing energy companies to undertake pre-emptive maintenance, that is, before any untoward power shutdown occurs. A novel diagnosis scheme for ABCs installed in low voltage distribution networks in coastal areas, based on partial discharge evaluation has been presented by the authors in earlier publications [4, 7]. The temperature distribution generated in the ABCs’ insulation is another parameter that has the potential to evaluate the degree of insulation damage as the cable deteriorates with time in coastal environment.

In this paper, Infrared Thermographic data of operational ABCs having XLPE insulation, installed in the South Asian coastal regions, is processed. Acquired data is analysed using statistical techniques to find progressive degradation trends. Such a data driven degradation trend has the potential to predict incipient failures in the ABC infrastructure as well as estimate the remaining useful life of ABCs subjected to differing coastal climate severity. The proposed scheme will also help energy companies in adopting preventive maintenance strategies for electrical infrastructure leading to both asset management and cost savings.

The paper is divided into five sections. Upcoming section describes the detailed research methodology. The case study along with field data description is presented in the third section. Results and discussions are covered in the fourth section. Finally, fifth section concludes the paper.

2 | RESEARCH METHODOLOGY

This section comprehensively describes the steps leading to quantification of damage to the insulation of ABCs subjected to varying severity of coastal weather. Image segmentation is first performed on the captured thermal image to separate the potential region of interest (ROI) (i.e. cable insulation under study) and remove the background. Data normalization is then applied on the segmented image to compare the shift in pixel intensity distribution as the cable insulation degrades. Histogram of the normalized pixel intensity data is then computed. Finally, cumulative distributive function (CDF) is built to quantify the degradation in the cable’s insulation.

2.1 | Image segmentation

Image segmentation can be used to remove the unnecessary information like background data which is added at the time of data collection. Segmentation is performed by identifying the cable in the images using pixel-level or object-level properties [19].

The global thresholding segmentation technique, employed in this research work, categorizes pixels according to the range
of grey scale values and applies a single fixed criterion to all pixels in the image simultaneously [20]. Global thresholding segmentation separates the ROI (i.e. ABC cable segment under study) and removes the background from the captured thermal images.

The global thresholding segmentation is achieved by allocating the value of 1 to all high pixel intensity areas representing the ROI, and 0 to all pixel intensity areas representing the unwanted background, in the captured thermal image, as given in Equation (1) [19]. This step converts the thermal image to a binary configuration, which aids in reducing complexity of data and eases the process of classification.

\[
b(x,y) = \begin{cases} 
1, & f_i(x,y) > \tau \\
0, & f_i(x,y) < \tau 
\end{cases} \quad (1)
\]

In Equation (1), \(f_i(x,y)\) is the \(i\)th pixel in the thermal image matrix \(f(x,y)\), \(\tau\) is the specified threshold value which helps discriminate regions of the threshold image (either the ROI or unwanted background) and \(b(x,y)\) is the required segmented image matrix. Otsu’s thresholding method was used in this research, to compute the threshold for each image. The technique uses the variance between clusters as the criterion to select the optimal threshold value \(\tau\), for discriminating between ROI and unwanted background [20]. The process of global thresholding segmentation using the Otsu technique applied on a raw thermal image to separate the ROI is shown in Figure 1. The white region in Figure 1b represents the ROI (cable segment) while the black region represents the unwanted background.

The temperature-energy distribution in the ROI (cable segment under study) is then recomputed by multiplying the original raw image matrix \(f(x,y)\) with the segmented image matrix \(b(x,y)\), as given in Equation (2). This produces the final segmented image matrix \(g(x,y)\), containing only the required information pertaining to the temperature-energy distribution in the cable segment under study (ROI).

\[
g(x_i,y_i) = f(x_i,y_i) \times b(x_i,y_i) \quad (2)
\]

### 2.2 Data normalization

As the cable insulation degrades, the maximum and minimum temperatures in each of the periodically captured thermal images change over time. In order to compare the variation in the temperature-energy distribution of the degrading cable’s insulation, each of the periodically collected segmented image matrices \(g(x,y)\), are normalized. This is achieved using min–max normalization, which maps the temperature information in each thermal image to range spanning from 0 to 1 [21]. The min–max normalized segmented image matrix \(g'(x,y)\) is computed using Equation (3).

\[
g'(x_i,y_i) = \frac{g(x_i,y_i) - \min (g(x,y))}{\max (g(x,y)) - \min (g(x,y))} \quad (3)
\]

Where \(g'(x_i,y_i)\) is the \(i\)th pixel in the normalized segmented image matrix \(g'(x,y)\), whereas, \(g(x,y)\) is the non-normalized segmented image matrix.

### 2.3 Histogram and cumulative distribution function computation

The shift in the thermal energy distribution in the ABC’s insulation as it degrades over time, can be observed well using histogram representation of the normalized segmented image matrices. Histograms are hence computed processing periodically collected thermal data from degrading ABCs. The total thermal energy under each histogram is normalized to 1, so that the shift in the thermal energy distribution with respect to the proportion of pixels can be compared. The cumulative thermal energy content in each of the normalized histograms can also be represented as CDF. CDFs are hence computed processing the normalized histograms of all the periodically collected data from degrading ABCs, and analysed for suitable degradation trend.

### 3 CASE STUDY

Karachi, Pakistan is a metropolitan city, located in the coastal region of South Asia. Being the industrial hub of Pakistan and...
also densely populated, a reliable power distribution network is its prime requirement. ABCs have replaced conventional bare conductors in many low voltage (LV) power distribution networks of Karachi, to help curb electricity pilferage. The responsible maintenance agency Karachi Electric, has also reported significant reduction in maintenance costs, power losses and tripping incidents due to use of ABCs [22]. The ABC infrastructure recently installed in the area is shown in Figure 2a. These cables have rated voltage of 0.6/1 kV with maximum bearing load of 215 A.

Health diagnosis of the ABCs has however, been a challenge for the energy company since multiple unexpected cable failures have been reported in areas installed with ABCs, near the coastal belt, leading to unplanned shutdowns. ABCs installed near the coastal belt of Karachi, experience rapid thermal degradation and insulation fracture of the insulation. Actual damaged ABCs uninstalled from the distribution network of Karachi is displayed in Figure 2b. Effective damage assessment techniques are hence required for ABCs to prevent unexpected power outages and plan preventive maintenance activities well in time.

FLIR® E40 thermal imaging camera is used in this study for data acquisition to capture the temperature-energy distributions generated in the insulation of in-service, degrading ABCs. Prior to each data acquisition session, the camera was calibrated. ‘Lava’ palette mode was selected while the temperature range was set to 20–120°C. There was no service interruption and the ABCs were kept energized during the data acquisition.

All thermal images of the cables were captured at night to avoid effects of sunlight. Furthermore, all images were captured between 2000 and 2200 h’s time of the day, in every testing instant, allowing valid comparison of the data collected. To avoid inaccuracy caused by atmospheric conditions, the distance between the camera and the ABC surface was kept consistent at 5–6 inches, at horizontal angle. It was also ensured that no smog or fog was present at the time of data acquisition. At each testing instant, thermal images were taken at six predefined and fixed sample points along the length of the ABC, as shown in Figure 3. At each of these six test locations, three thermal images were taken to cater for the data acquisition error and mean image is then used for degradation assessment for each of the six test locations. Finally, the overall degradation index of the cable at a particular measurement instant is the average of the degradation parameters computed at the six test locations. The detailed measurements are tabulated in Table 1.

Two different areas in Karachi were chosen for periodic thermographic data acquisition. The ABCs installed in these areas were subjected to different severity of coastal conditions. Moreover, data from an energized but failed cable was also collected from a third site in Karachi:

SITE-I: Located in the metropolis centre, this site is 7 km from the sea. Humidity and wind levels recorded are relatively low in this area. ABC was installed at this site in April 2016 while the electrical load maintained on average is 120 A.

SITE-II: This site is right next to the sea hence the installed ABC is directly exposed to the shore. Gale and high moisture content is recorded here hence, corrosion of metallic structures installed at this site is significantly faster. ABC at this location was replaced in January 2019 and progressive degradation of this cable is analysed. The average electrical load maintained on the line is 134 A.

SITE-III: During the selected data collection time period, an ABC insulation failure was reported at a third site on 23 October 2018. From the sea shore, this site is approximately 8 km away. The cable was tested in lab prior installation by K-Electric and was operating at nominal loading and stress conditions. Thermal data acquisition was performed here while the failed cable was still kept energized. Acquired thermal data values from the failed cable are used as a reference in the reported study. 277 weeks was the recorded service life of this cable from date of installation [4].

4 | RESULTS

A comprehensive comparative analysis is provided in this section, between the thermal energy distributions in the histograms of the periodically collected thermal data from in-service ABCs at Site I, Site II and Site III. The progressive shift in the CDF values in the periodically collected thermal data from degrading ABCs at both sites is also investigated.
TABLE 1 0.9 CDF values computed at all six data acquisition points displayed in Figure 3 along the cable length

| Site   | Date       | Segment B     | Segment C     |
|--------|------------|---------------|---------------|
|        |            | Start | Middle | End   | Start | Middle | End   | Mean  |
| Site I | 13-Jul-2018| 0.6245 | 0.6696 | 0.6954| 0.6747| 0.6954 | 0.6095| 0.6615|
|        | 07-Aug-2018| 0.6767 | 0.6873 | 0.6933| 0.6862| 0.6873 | 0.6933| 0.6874|
|        | 20-Oct-2018| 0.6793 | 0.7528 | 0.6637| 0.7081| 0.719  | 0.6977| 0.7034|
|        | 04-Nov-2018| 0.6780 | 0.7613 | 0.6624| 0.7319| 0.6892 | 0.7176| 0.7067|
|        | 01-Dec-2019| 0.7127 | 0.7728 | 0.7326| 0.7603| 0.7555 | 0.692 | 0.7331|
|        | 08-Jan-2019| 0.7281 | 0.7675 | 0.7084| 0.7011| 0.7731 | 0.7692| 0.7412|
|        | 19-Mar-2019| 0.7478 | 0.7381 | 0.7205| 0.7314| 0.7407 | 0.7842| 0.7438|
|        | 15-Apr-2019| 0.7398 | 0.7734 | 0.7289| 0.7314| 0.7182 | 0.7472| 0.7452|
| Site II| 25-Jan-2019| 0.5316 | 0.6791 | 0.6156| 0.6443| 0.6123 | 0.5267| 0.6300|
|        | 16-Mar-2019| 0.6636 | 0.6609 | 0.6667| 0.7191| 0.6286 | 0.6455| 0.6707|
|        | 22-Apr-2019| 0.7121 | 0.6805 | 0.7109| 0.7303| 0.6941 | 0.6297| 0.6929|
|        | 04-May-2019| 0.7468 | 0.7149 | 0.7124| 0.7472| 0.7113 | 0.701  | 0.7195|
| Site III | Faulty cable | –     | –     | 0.8665| –     | –     | –     | 0.8665|

FIGURE 4 Thermographic images of ABC. (a) Energized healthy ABC showing insulation intact, (b) energized failed ABC portraying swollen insulation

As the ABCs insulation progressively degrades, the thermal energy of the cable rises. This characteristic is well observed in Figure 4 in which the temperature distribution in a healthy in-service ABC at Site I and failed ABC at Site III is compared. The temperature range is also observed to shift towards higher value in the degradation data, periodically acquired at both sites, as the cable increasingly deteriorates.

For each captured raw thermal image, step wise scheme listed in Section 2 was applied. Each raw image was processed using Otsu based image segmentation to extract the required ROI (i.e. cable segment under study). Subsequently, the unwanted background was removed, as discussed in Section 2.2. The binary segmented image was then multiplied by the original raw image to re-compute the temperature-energy distribution in the ROI, as explained in Equation (2). The segmented image matrix \( g(x, y) \) was then normalized using min–max technique given in Equation (3), to compute the \( g'(x, y) \) matrix.

The \( g'(x, y) \) matrix maps the thermal energy distribution in each thermal image to a common 0 to 1 scale. Histogram of the \( g'(x, y) \) matrix represents the thermal energy distribution amongst the population of pixels in the ROI. Therefore, in the final step, histogram is computed with normalized frequencies so that its cumulative thermal energy equals 1.

Figures 5 and 6 display the histogram representation of thermal energy distributions in the periodically collected data from the start section of segment B in installed ABCs at Site I and Site II, respectively. A shift in distribution over time towards higher thermal energy divulges the progressive degradation in the cable under testing. Hence, as the cables progressively degrades at both sites, the thermal energy distribution gradually shifts towards the higher energy side. Similar shift was also observed in the histograms of the periodically collected data from the other sample points along the cable length (i.e. middle and end sections) at both sites.

In order to quantify the shift in thermal energy distribution, various statistical parameters (including mean, standard deviation, coefficient of variation, entropy, skewness and kurtosis) were investigated, however, no reasonable trend was found. The cumulative thermal energy in each processed image was hence computed. Figures 7 and 8 display the CDF plots computed processing periodically collected thermal degradation data from Site I and Site II, respectively. In the CDF plots, a prominent increasing trend in the normalized thermal energy values corresponding to 0.9 CDF is observed, as the cables degrade over time.

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The 0.9 CDF thermal energy parameter represents the thermal energy greater than 90% of pixels in image $g(x, y)$, as formulated in Equation (4).

$$0.9 \text{ CDF} = P[g(x_i, y_i) \leq 0.9].$$

In July 2018, the 0.9 CDF value for ABC at Site I was 0.62 (taken at week 146 after installation) whereas for the newly installed ABC at Site II, 0.9 CDF value was 0.53 in January 2019. The 0.9 CDF value for failed cable is much higher and is found to be 0.86. In Figures 7 and 8, the 0.9 CDF parameter is observed to progressively shift towards higher thermal energy value with increasing damage to the cable. A similar shift was also observed in 0.9 CDF values of the other cable segments (i.e. middle and end sections of span B, and start, middle and end sections of span C) at both sites, as tabulated in Table 1. Mean 0.9 CDF at a particular measurement instant is the average of degradation parameters computed at the six test locations. The averaging of six readings will also cater for data acquisition error.

5 | DISCUSSION

Thermal stress variations occur in installed ABCs’ causes repeated expansion and contraction of the cable’s insulation leading to micro-crack growth. Moisture and impurities ingress through these cracks, causing corrosion of the sheathed conductors. Corrosion of the conductors increases the conductor resistance, causing temperature to rise when current flows. Such heat dissipation increases thermal stresses on the insulation, which
further aggravates insulation rupture. Such insulation degradation phenomenon is clearly depicted in pixel intensities of acquired thermal images. Accordingly, mean 0.9 CDF value of the acquired images show an increasing trend due to progressive insulation degradation at both sites as shown in Table 1. However, difference in degradation rates in ABCs installed at Site I and Site II is due to variation in the environmental conditions the cables are subjected to. The 0.9 CDF parameter value obtained from cable at Site II approaches the 0.9 CDF value of failed cable at higher rate as compared to Site I, due to harsher conditions at Site II. Higher degradation rate of cables at Site II is attributed to greater proximity with the sea shore, where high wind speeds and high moisture content is observed. ABC insulation is known to rapidly degrade under such severe environmental/weather conditions [5].

Thermal data acquisition activity at Site I was once again performed on 19 June 2020 (at week 247), to assess the cable health at that time. The thermal analysis revealed a mean 0.9 CDF value of 0.82 indicating that the cable condition is approaching the failed state.
To develop a predictive model for computation of degree of insulation damage with respect to time, Site I degradation trend was analysed. The mean values tabulated in Table 1 provide an overall index of degradation at each data acquisition instant. These mean values are curve fitted using smoothing spline function in MATLAB. The ‘fitted’ function is then used to extrapolate the degradation trend to the value of reported failed cable to forecast time to failure, as shown in Figure 9. The reported prediction technique highlights that the ABC installed at Site I will fail 127 weeks from 13 July 2018, that is, when the first thermal measurement was taken. Prior life recorded was 146 weeks, that is, from installation to first measurement. The accumulated service life is hence equivalent to 273 weeks. Since Site I and III (failed cable) were in close vicinity of each other [4], the prediction results of Site I can be compared to the recorded service life of ABC at Site III, that is, 277 weeks. This validates the efficacy of the reported degradation prediction model.

In order to improve the proposed prediction model, degradation data acquired from multiple locations and increased number of thermal signature instances from failed but operational ABCs can be incorporated. It is however, significant to mention that the 0.9 CDF value works very well as a health assessment index throughout the functional life of the cable.

6 | CONCLUSION AND FUTURE WORK

In this paper, a novel and effective health diagnostics framework is proposed for ABCs deployed in coastal regions, using infrared thermography. It is based on the realization that the thermal energy distribution in the ABC’s insulation shifts towards higher range, as the cable degrades over time. Hence CDF plots of the thermographic data were investigated for feature extraction. A considerable increasing trend was found in the 0.9 CDF parameter value with progressive degradation of the cable’s insulation. The proposed technique has displayed effectiveness in insulation damage quantification of ABCs subjected to varying degrees of coastal climate. The use of real in-service thermal degradation data in this research adds value as compared to many conventional laboratory based testing methods [10, 14]. It is pertinent that the effect of environmental factors, contributing to cable deterioration, is already encapsulated within the acquired thermal data. The novel data acquisition scheme, image processing and degradation trend assessment can hence be extended for condition monitoring of in-service electrical infrastructure. Implementation of the proposed health diagnostics scheme will enable improved maintenance practices; ultimately leading to better power distribution reliability and cost savings.

The proposed research framework can also be extended for health assessment of IPCs and associated mechanical fixtures that are used as supporting elements in the ABC installed in distribution networks. Remaining Useful Life prediction models can also be developed for ABCs installed in coastal areas like using particle filter (Bayesian Sequential Monte Carlo) algorithms [23–25]. This will enable prediction of any incipient cable failure and assist in performing repair/replacement activities beforehand ensuring uninterrupted power distribution.

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