Prognostic Algorithm for Degradation Prediction of Aerial Bundled Cables in Coastal Areas

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***Abstract*— Cables are the crucial component in the electrical distribution system. Aerial Bundled Cables (ABCs) is a combination of insulated phase conductors bundled tightly together. They have replaced conventional cables due to simplicity in installation and being less prone to pilferage. However insulation degradation is a very common problem with ABCs especially when subjected to coastal environments. Due to bundled structure, the moisture penetrates within the cables. During electrical loading of the cable, this moisture starts deteriorating the cable insulation which eventually results in the cable failure. Actual Non-Destructive Testing (NDT) data from the installed in-service cable is acquired at different time instants to study the phenomena of insulation degradation w.r.t. time. A Particle Filter (PF) based prognostic approach is proposed in this paper to predict the insulation degradation for future time instants so that the cable can be replaced before the failure occurs. The proposed method will help the electrical maintenance managers to plan the replacement activity well in time to ensure uninterruptible/smooth electrical supply.**

Keywords-Infrared Thermography; degradation; stochastic; prognosis; health monitoring; future health prediction; Non-Destructive Testing

I. Introduction

Recent use of Aerial Bundled Cables (ABCs) over the traditional bare copper cables for overhead power distribution is an innovative concept [1]. These cables have an aluminum core covered with cross-linked polyethylene (XLPE) insulation. In comparison with conventional distribution system as shown in Fig. 1, ABCs are less prone to electricity pilferage and offer greater safety and reliability.

Figure 1. (a) Conventional Overhead system (b) Aerial Bundled Cable Overhead System.

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According to [2], the designed expected life of modern XLPE cables is significantly reduced in areas with high moisture and humidity content. Research has shown different ageing mechanisms involved the degradation of ABC network [1, 2] such as: Thermal ageing, electrical ageing, mechanical ageing and environmental ageing.

The electrical and thermal ageing are discussed in this paper. Penetration of moisture in the cable coupled with varying loads and temperatures cause puncturing the XLPE insulation. Especially in densely populated areas, cables are subjected to electrical load above rated currents and, in turn, temperatures. This temperature rise accelerates the chemical reaction of the insulator, as charge begins to pass through the insulator, resultantly aiding the insulation deterioration process [3]. In coastal areas, the high degree of moisture further exaggerates this effect. The daytime temperature variations or thermal fatigue in such areas are also very high which damage the ABC's insulation even rapidly [2]. The two common thermal ageing factors are: Ageing caused by constant temperature and ageing caused by thermal fatigue [4].

The first one is well known in the electrical industry known as Joule heating [5] which states that heat is generated when an electric current flows through a small, non-zero resistance. This heat then results in the degradation of the cable insulation. The second factor is due to the varying electrical loading on the cable. This leads to temperature changes within the cable called thermal cycling or fatigue [6]. This cyclic change in temperature leads to cyclic expansion and contraction of the cable which induces mechanical fatigue in the cables. Furthermore, use of non-standard clamps and connectors also contribute to the degradation of cable insulation [1].

The study of cable integrity and Remaining Useful Life (RUL) lies in the identification and characterization of prevalent degradation caused by ageing factors [2]. Degradation in various systems such as welded joints, electrical components and metallic pipelines is commonly measured using Thermography [7–9]. In the reported research work, this technique is used for degradation quantification of ABCs.

By design, all electrical cables have a rated power, current, voltage and temperature [1]. If the cable is operated at power levels exceeding the design parameters, the cable overheats resulting in degradation [10]. Such degradation, in turn, causes ageing and reduction in RUL Thermal images of ABCs can be

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used to study the temperature variations within different segments of the cable w.r.t. time. This temperature variation is a direct measure of the insulation degradation. Additionally, in coastal areas, sudden failures of ABCs have been reported. Such failures are attributed to high moisture content and varying temperatures. Nonexistence of degradation assessment attributes to non-availability of modern monitoring schemes and predictive models. Thus to avoid sudden failures of ABC and to keep the power networks operational, health monitoring and subsequent prognosis of ABC is required [11]. Therefore, need of the hour is to design a sophisticated prognostic scheme which can enable maintenance managers to undertake repair/ replacement actions well in time.

Prognosis of cables encompasses the prediction of future health state based on historical monitoring and cable conditions. The future health states are predicted using two different approaches widely established in the literature: Model – based approach and data-driven approach. The prediction of future health states using data driven approach is more reliable as the approach captures all the degradation factors in actual settings. Traditionally, the Stress vs Number of cycles to failure (S-N) curves are used for estimating life and maintenance planning of electrical infrastructure [7]. Neural Network based approaches are also popular; one such model was applied on XLPE insulated cables by L. Boukezzi et al. to predict accelerated thermal aging [12]. Another novel approach for fatigue life prediction was developed by Amiri & Khonsari showing a relationship between initial temperature R_0 and temperature at multiple load values N_f supported by experimentally calculated coefficients [7]. However, most of these contemporary methods are model-based and do not inherently incorporate the underlying environmental effects.

To counter this limitation, statistical models are used for useful life predictions. Historical database, generated over a certain period, can be used for the analysis and prediction of failure rate. To predict degradation, methods such as Bayes' filter technique can be used as it effectively handles the stochastic nature of the degradation. Sequential Monte Carlo (SMC) based Particle Filter (PF) is a highly compatible model for nonlinear state transitions and Non-Gaussian noise distributions [13]. Detailed discussion related to these models is given in [13-16]. In [13], MC based PF model has been used for the prediction of flaw growth in aircraft wing using historical data from in-service Airbus A310 aircraft. In [14], another SMC based method has been developed to incorporate uncertainties from the environment thereby improving the prediction of crack growth in metallic structures. Similar model has also been used for the prediction of RUL of steam generator tubing [15]. Another probabilistic approach for corrosion and fatigue crack growth in aluminum alloys in aqueous environments has been developed in [16].

In the reported work, SMC based PF [13] is reformulated for the prognosis of ABCs installed in coastal areas of developing countries. Use of actual historical data captured through Thermal Imaging camera (TIC) at multiple instances in the proposed scheme improves the accuracy of the proposed prognosis model. Accurate predictions will consequently enable electrical utility companies to design improved pre-emptive maintenance strategies.

II. Methodology

Statistical framework is implemented in the proposed approach due to the uncertainty involved in cable degradation. For determining insulation degradation, a feature is required that can differentiate between a healthy cable and a degraded cable. A novel feature i.e. Thermal degradation parameter (TDP) will be used in this study for characterizing XLPE insulation degradation. TDP is equivalent to the temperature of the cable per unit ampere current. It is based on the principle of joule heating process i.e. the passage of an electric current through a conductor produces heat. It is a major parameter in the proposed framework that determines the insulation degradation of the cable.

$$TDP = \frac{Temperature\ of\ Cable\ (°C)}{Load\ on\ Cable\ (A)} \quad (1)$$

Bayesian filtering approach is used in which TDP i.e. Temperature per unit current $(°C/A)$ is treated as the state t_k, where k is the week number i.e. k = 1, 2, 3, ...,, K ('K' is the number of weeks till which the measurements are available) and m_k is the measurement acquired during that week (states with additive noise). For prediction, all the previous measurements $m_{1:k}$ are known. Therefore, the conditional probability also known as posterior density $p(t_k \mid m_{1:k})$ can be estimated from the prior density $p(t_k \mid t_{k-1})$ and the likelihood density $p(m_k \mid t_k)$ using the Bayes' theorem [13] as shown in Eq. (2).

$$p(t_k \mid m_{1:k}) = \frac{p(m_k|t_k).p(t_k|m_{1:k-1})}{p(m_k|m_{1:k-1})} \quad (2)$$

The insulation degradation prediction is more challenging once the future measurements are not available. The predictive density $p(t_{K+F}|m_{1:k})$ can then be computed as:

$$p(t_{K+F}|m_{1:k}) = \int p(t_k|m_k).\prod_{F=K+1}^{K+F} p(t_F|t_{F-1})dt_F \quad (3)$$

where, the term t_{K+F} represents the future state at $K+F$ instants ('F' is the total number of predicted states). SMC based PF is used in the study as it is compatible with non-linear state transition models as well as with Non-Gaussian noise probability density functions (PDFs) [13, 15]. In PF, the posterior PDF is expressed in terms of samples and their associated weights at each instant. Let Ns be the total number of samples that are drawn from importance density, t_k^i are the set of support points with associated weights w_k^i where $i=1:N_s$. (N_s is equal to 1000 samples). The weights are normalized such that $\sum w_k^i = 1$. The joint posterior density at location 'k' can be approximated as:

$$p(t_k \mid m_k) \approx \sum_{i=1}^{N_s} w_k^i \delta(t_k - t_k^i) \tag{4}$$

The samples can be drawn from importance density $q(t_{1:k} \mid m_{1:k})$ and the weights can be assigned by using:

$$w_k^i \propto \frac{p(t_{1:k}^i \mid m_{1:k})}{q(t_{1:k}^i \mid m_{1:k})} \tag{5}$$

The overall scheme of the proposed PF algorithm is shown in Fig. 2 as:

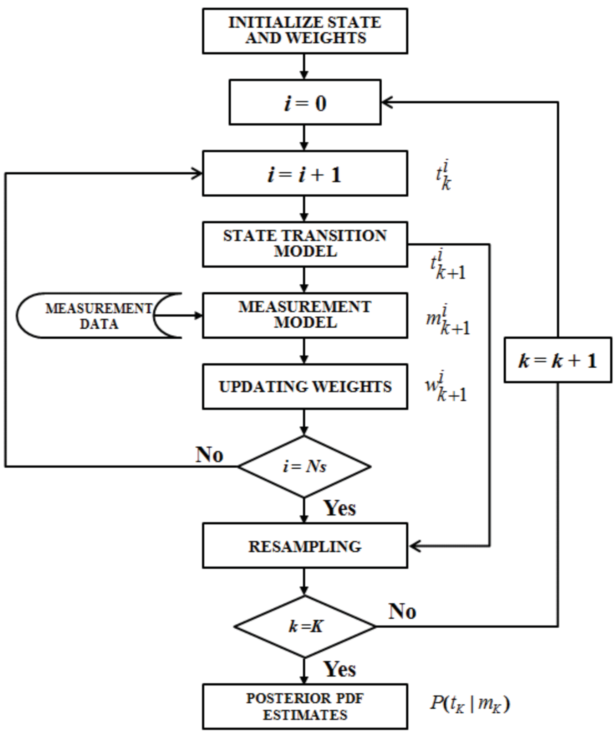

Figure 2. PF framework

The state transition model used in this study is an exponential model as shown in (6):

$$p(t_k \mid t_{k-1}) = e^{-\frac{\|t_k - t_{k-1}\|^a}{a}} \tag{7}$$

where a is the parameter which controls the variability in the states. The measurement model used is the J^{th} order polynomial as shown in (7):

$$m_k = \sum_{j=1}^{J} p_j t^j \tag{7}$$

The polynomial coefficients p are calculated from the training database of known states and corresponding measurements.

III. CASE STUDY

ABCs in coastal areas have exhibited rapid degradation than those installed in non-coastal areas. In this research, coastal areas of Pakistan were selected for Non-destructive data acquisition. Aluminum XLPE insulated ABC is being used in these areas to supply electrical power. An example of XLPE insulated ABC is shown in Fig. 3.

Figure 3. Sample ABCs

TIC FLIR E40 has been used for thermography of the in-service ABC. The specifications of TIC FLIR E40 are tabulated in Table I.

TABLE I. SPECIFICATIONS OF FLIR E40

Characteristic	Detail
Temperature range	-4°F to 1202°F (-20°C to 650°C)
Frame Rate	60Hz
Field of view/min focus distance	25° x 19°/1.31ft (0.4m)
Resolution	19,200 pixels (160 x 120) Infrared resolution
Accuracy	± 2% (reliable temperature measurement)
Thermal sensitivity	<0.07°C at 30°C

The thermographic results from TIC are used to assess the degradation of the cable. Two spans of ABCs are selected for data acquisition i.e. Span B & C. Due to long length of each span and limited field of view (minimum focus distance) of the TIC, the span is further divided into smaller segments (start, middle and end segment of cable) as displayed in Fig. 4. Thermal Imaging was then performed at each of these smaller segments on monthly basis to generate historical health monitoring database. A total of six images (three images for each span B & C) were captured at each instant.

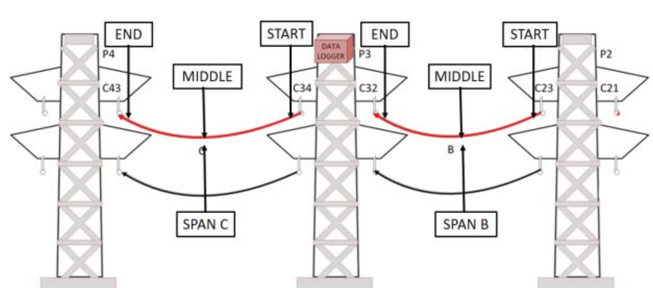

Figure 4. Nomenclature used for data collection

Thermal Images of ABC were then analyzed and corresponding absolute temperatures of cable were computed. The data used in the reported research is acquired at six different time instants. At every time instant, load (current) on ABC was varying due to variable consumer usage. It was necessary to balance the loading effect, so that the recorded thermal data at different instants and load conditions could be compared. The effect of load was nullified at corresponding instant on respective cable using the TDP. Reference TDP for newly installed in service cable is also determined in order to compare a healthy cable with a degraded cable. An example of the TDP data used in the proposed study (corresponding to the instant of July 2018) is tabulated in Table II as:

TABLE II. TDP DATA OF JULY 2018

Thermal Degradation Parameter ($^{\circ}C/A$)			
	Start segment	*Middle segment*	*End segment*
Cable Span B	0.5797	0.5713	0.5688
Cable Span C	0.5726	0.5733	0.5800

Due to the penetration of moisture in the bundled cable, insulation degradation occurs eventually resulting in failure. ABC is taut and fixed to the connectors between two distant poles. One end of the cable is fixed to connector on one pole while the other end is fixed to the connector on another pole. These points act as point of entry (POE) for moisture/humidity as cable is open near the connectors as displayed in Fig. 5. The moisture content in the cable along with the heat generated due to current deteriorates the insulation over time.

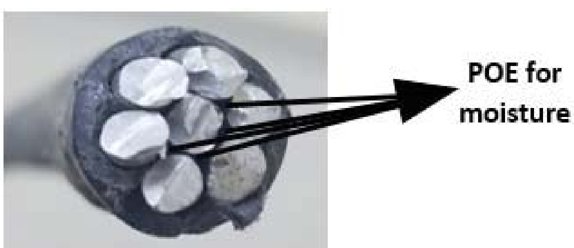

Figure 5. POE for moisture in ABC

IV. RESULTS & DISCUSSION

Thermographic data of ABC acquired at different instants on monthly basis starting from May 2017 till February 2019 is used in this study. This data was then transformed into TDP as discussed in the methodology section. Cubic spline interpolation was used in order to obtain data on weekly basis. The available data of 90 weeks was then divided into training and validation phase. Data corresponding to 82 weeks was used as training segment whereas the remaining 8 weeks data was used for validation of the proposed scheme. The proposed PF based prognosis scheme is applied individually on each span and their corresponding segments as discussed in the case study. The results in Fig. 6–8 are showing the predictions of cable span B whereas Fig. 9–11 are showing the prediction results of cable span C.

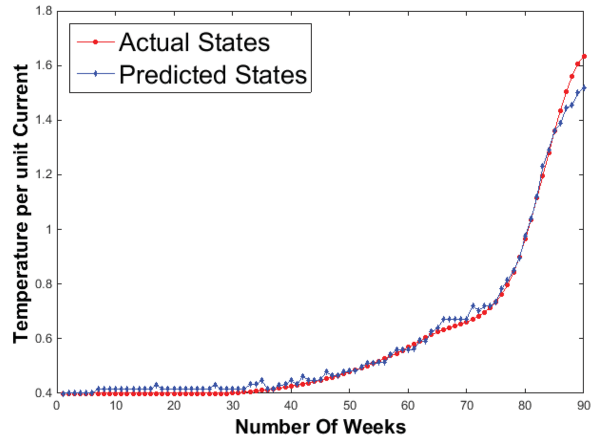

Figure 6. Actual vs. predicted states of Span B (start segment)

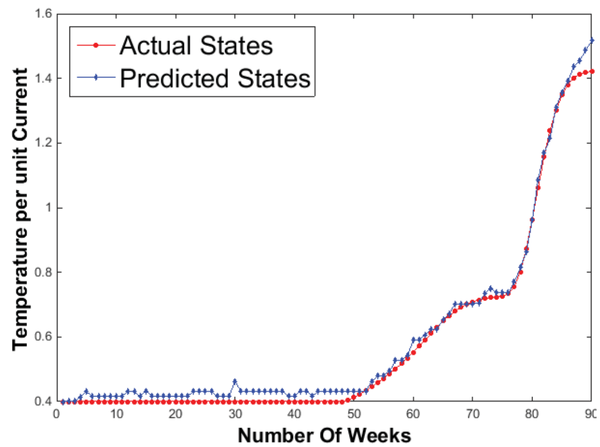

Figure 7. Actual vs. predicted states of Span B (Middle segment

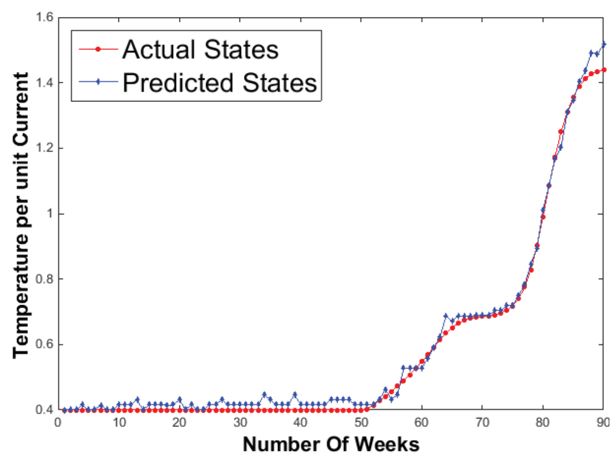

Figure 8. Actual vs. predicted states of Span B (End segment)

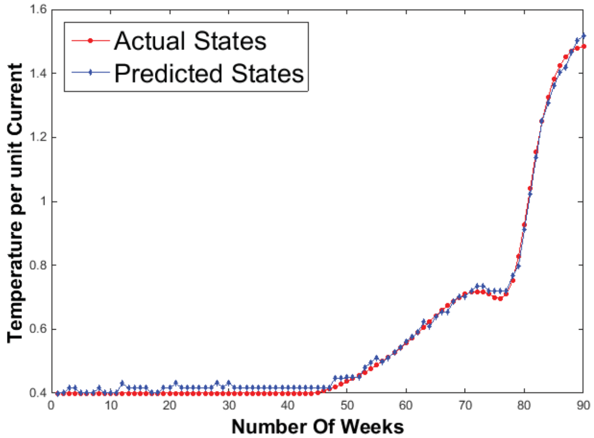

Figure 9. Actual vs. predicted states of Span C (Start segment)

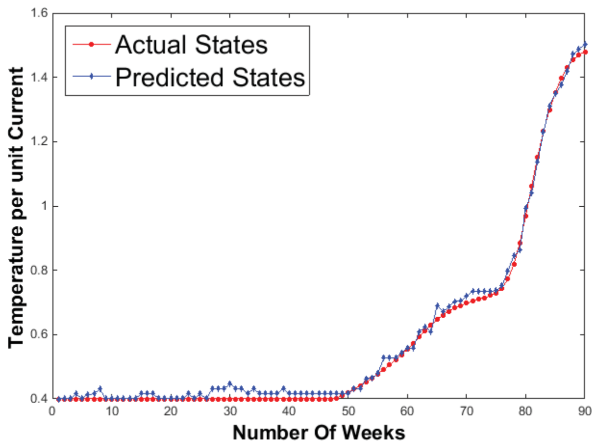

Figure 10. Actual vs. predicted states of Span C (Middle segment)

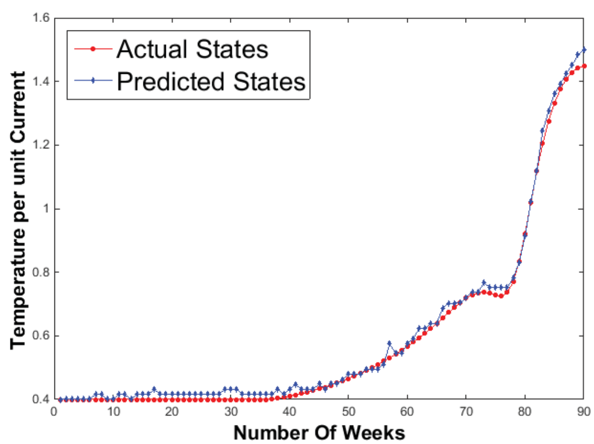

Figure 11. Actual vs. predicted states of Span C (End segment)

The prediction results displayed in Fig. 6-11 is clearly show the efficacy of the proposed prognostic technique for ABC cables. The proposed algorithm, when applied on actual historical data, precisely follows the trend of the actual states. Thus this technique can be used effectively in order to determine the future health states of the ABCs. The errors between the predicted and actual state is computed at each time instant. the error is the difference between the actual and predicted states. These errors for cable span B & C are tabulated in Table III & IV respectively.

TABLE III. CABLE SEGMENT B – PREDICITON ERRORS

Weeks after Training Period	Start	Middle	End
1	-0.0331	0.0260	0.0482
2	-0.0221	-0.0089	-0.0003
3	-0.0011	-0.0074	0.0108
4	0.0480	-0.0116	-0.0128
5	0.0597	-0.0340	-0.0226
6	0.1070	-0.0417	-0.0650
7	0.1064	-0.0676	-0.0528
8	0.1156	-0.0953	-0.0802

TABLE IV. CABLE SEGMENT C – PREDICTION ERRORS

Weeks after Training Period	Start	Middle	End
1	-0.0001	0.0038	-0.0392
2	0.0181	-0.0128	-0.0316
3	0.0220	0.0049	-0.0282
4	0.0197	0.0220	-0.0175
5	0.0328	0.0118	-0.0176
6	0.0032	-0.0175	-0.0225
7	-0.0248	-0.0177	-0.0408
8	-0.0330	-0.0247	-0.0497

A quantitative metric known as Root Mean Square Error (RMSE) for each cable span is also calculated using (8):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (t_{actual} - t_{predicted})_i^2}{n}} \tag{8}$$

Where n is the total number of segments corresponding to *start segment, middle segment* and *end* segment (n=3) The RMSE using (7) of the degradation prediction of cable span B & C at eight instants after the training period are tabulated in Table V as:

TABLE V. RMSE IN DEGRADATION PREDICTION

Root Mean Square Error (℃/A)		
Weeks after Training Period	***Cable Span B***	***Cable Span C***
1	0.0369	0.0227
2	0.0138	0.0223
3	0.0076	0.0208
4	0.0295	0.0198
5	0.0418	0.0225
6	0.0762	0.0166
7	0.0789	0.0294
8	0.0981	0.0373

V. CONCLUSION & FUTURE WORK

The prediction method in the degradation of the XLPE insulation of ABC is proposed. In this method, the thermal imaging data of actual in-service cable is used. Thermal degradation parameter (TDP) is extracted from the acquired data. Due to the stochastic nature of degradation, PF framework is used to determine the future health state of the ABC insulation. The results and lower prediction errors demonstrate the efficacy of the proposed technique. The degradation prediction method can also be used to determine the RUL of ABC. This work can be further improved by incorporating the fatigue models i.e. Electrical and Thermal fatigue model in the prediction scheme.

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