Reliability Evaluation of Underground Power Cables with Probabilistic Models

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***Abstract*—Underground power cables are one of the fundamental elements in power grids, but also one of the more difficult ones to monitor. Those cables are heavily affected by ionization, as well as thermal and mechanical stresses. At the same time, both pinpointing and repairing faults is very costly and time consuming. This has caused many power distribution companies to search for ways of predicting cable failures based on available historical data.**

In this paper, we investigate five different models estimating the probability of failures for in-service underground cables. In particular, we focus on a methodology for evaluating how well different models fit the historical data. In many practical cases, the amount of data available is very limited, and it is difficult to know how much confidence should one have in the goodness-of-fit results.

We use two goodness-of-fit measures, a commonly used one based on mean square error and a new one based on calculating the probability of generating the data from a given model. The corresponding results for a real data set can then be interpreted by comparing against confidence intervals obtained from synthetic data generated according to different models.

Our results show that the goodness-of-fit of several commonly used failure rate models, such as linear, piecewise linear and exponential, are virtually identical. In addition, they do not explain the data as well as a new model we introduce: piecewise constant.

I. Introduction

Electric power transmission and distribution networks consist of different types of cables, some of which have been installed more than 50 years ago, and some are newly added to the network. The major problem with these power cables is the lack of efficient condition monitoring methods [14].

Power outages, i.e. the unavailability of electricity supply due to faults, have many undesirable effects and are a high cost to the society as a whole. Loss of production, cost of repair, and customers' dissatisfaction are some of the important factors to be considered when analyzing the impact of outages. For institutions like hospitals, airports, and train stations, power outages can be disastrous.

There are many different reasons for power outages. According to a study by the Edison Electric Institute [10], 70 percent of power outages in the USA are weather related phenomena such as lightning, rain, snow, ice, etc. Another 11 percent of outages are caused by animals, such as birds, coming into contact with power lines. To reduce the impact of such incidents, many power electric companies are moving towards underground transmission and distribution lines. However, underground cables may also cause outages, most commonly due to insulation degradation and ruptures in conductors.

One drawback of underground cables is that the procedure for finding the exact place of failure is harder, since no visual inspection can be performed. In addition, even when a fault is localized, the process of digging the ground to reach the cable, and also repairing the cable, is more difficult and requires more skill than for aerial cables.

Many governing bodies are continuously increasing requirements put on distribution companies concerning the acceptable number and duration of power outages. In addition, in many areas of life, society is more and more relying on electrical power. Consequently, there is a great need for better methods to determine the condition of the in-service underground cables and their remaining useful life. In particular, it is important that those methods are cost effective.

In this paper, we analyze five different models to estimate the relationship between the age and failure rate in underground high voltage cables. In addition to commonly used models (linear, piecewise linear, and exponential), we also consider constant and piecewise constant models. In particular, we focus on the methodology for evaluating how well different models fit the data. As is common in this domain, the amount of data we have available is very limited, and it is difficult to know how much confidence should one have in the goodness-of-fit results.

We calculate the empirical failure rates based on real data of over fifty years of historical faults from a small European city. The data comes from historical databases at Halmstad Energi och Miljö (HEM Nät), one of the Swedish electricity distribution companies.

The remaining of this paper is structured as follows. Background and related work is presented in section 2. In section 3 we explain the proposed model evaluation methodology, and we describe our experiments and results in section 4. We summarize our contribution and discuss future work in section 5.

II. Background and Related Works

A mathematical model that represents the current condition of a cable is known as the state of the cable [13]. The state represents the condition of the cable at a given point in time. Owing to the fact that the cables are laid under the ground, their current state is not directly observable. Depending on the amount of available information, one can estimate the state in different ways, using different models. Clearly, if the information about the cables increases, the

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representing model becomes more precise. However, there is a tradeoff between the cost of collecting additional data and the benefits such data would provide.

There are mainly two methods for condition assessment of underground cables. The first is measuring the cables' condition by using different types of diagnostic and stress test analysis such as partial discharge (PD) and dielectric losses. The second is mining historical information such as age of the cables, and previous failures.

The condition of power cables can be measured in two ways: using on-site testing [6], [7], [9] or laboratory testing [16]. On-site testing is performed directly on the in-service cables. In the laboratory testing, first, a new cable undergoes accelerated aging processes to simulate the condition of aged cables, which are then analyzed. In both of these methods the amount of PD, oil analysis, and bulk properties of insulation, e.g. tang δ measurement, are used to determine the cables condition. The tang δ measurement is a diagnostic test conducted on cables' insulation to measure their deterioration. In fact, the tang δ measurement is used as the loss factor of the insulation material which will increase during the aging process. The assessment of the in-service cables should be performed every 3-5 years and the results classify the investigated cables into different categories based on which future maintenance can be performed. Both of these measurements are very costly and complex processes.

The historical data analysis is usually performed in one of the two ways. The first is based on Crow-AMSAA and reliability growth model [1], [2], [8], [14]. Based on the time duration between each recorded failure in the system, historical failures are modeled using a Weibull distribution. This Weibull model is then used to estimate the time to the next failure, usually in the whole system, i.e., for all underground cables, without any distinction between aged and new cables. In other words, all the cables are considered to be in the same condition, regardless of their age, type, and other factors.

In the second historical data analysis method, in addition to the previous failures, other information such as age, and insulation condition are used to model failure rate [11], [12], [18]. Bloom et al. [3], [4] used historical data for age and number of previous failures as "observable condition"; and experts' judgment for insulation degradation condition, environmental stressor, and effect of the previous failures as "unobservable conditions". By using the historical data and the experts' knowledge they modeled the changes in cables' condition probabilistically, i.e., given the current state of a cable, what is the probability of different cable states in the future. Of all the factors used in their work, only age and historical failure rate are extracted from actual data, and all the rest of the information is based on the experts' judgment.

The failure rate model is usually used for estimating the expected number of future failures. One important aspect is that future failures are influenced by the replacement strategy employed, which is one of the possible solutions for electric power companies to reduce the number of outages. Replacement actions, also known as rejuvenation, is the procedure of replacing the old and faulty parts with new cables. There has been some research analyzing how the replacement of old cables reduces the number of expected failures and improves reliability, for example [11] and [12], however, the majority of work in the field does not take rejuvenation into account.

In general, there are three types of underground cables widely used in distribution power grids [5]:

- Oil-Filled cable
- Paper Insulated Lead Cover cable (PILC)
- Cross-linked Polyethylene cable (XLPE)

Before development of XLPE cables in 1993, PILC cables were the most common installed underground power cables [15]. Their estimated expected lifetime is declared to be around 40 years [17], but they have been used for more than that in many transmission and distribution grids. In these grids, the problem of degradation of underground cables due to aging is becoming more and more severe.

The old Paper Insulated Lead Cover (PILC) cables, which are of main concern in this study, are heavily affected by a number of factors such as ionization, thermal breakdown as well as electrical and mechanical stresses [5]. Since the paper insulation is made of cellulose, the quality of the insulation degrades over time and causes more frequent breakdowns. One way to decrease the corrosion speed and cable fragility is to fill the paper insulation with oil.

There are several important factors that accelerate the aging process in PILC cables. The ones most commonly mentioned in the literature are cyclic overloading, thermal breakdown, PD, irregular load pattern, direct or indirect spiking, inadequate depth in the ground, and very low temperature.

Cable joints, which are part of the underground cables, can also cause outages in the network. The jointing is the act of reconstructing two cables to become one. It is used when a longer cable is needed or when a part of an old cable is replaced with a new cable. A joint is usually the weakest part of an underground cable and it is affected by three types of stressors: thermal, electrical, and mechanical stress. Mechanical stress and water ingress are the main causes of failures in cable joints [5]. The fault in the joints might affect the conductor, insulation, or sheath. The sheath of the joints get corroded due to overloading and the chemicals present in the soil over a period of time. This increases the chance of moisture seepage into the joint, which subsequently causes failure.

In this work, we only use available historical data to compute failure rate. This approach is not as accurate as performing direct measurements on individual cables, but is often preferred in practice since mining the available data to find a model is significantly cheaper than performing laboratory or field tests.

III. Methodology

It is well known that by analyzing historical information of cables inventory, it is possible to predict the future failures in cables with some degree of accuracy. One common example is modeling the failure rate for a particular type of cables. We use historical data from a small European city to estimate the parameters of the model. This model can then be used to predict future faults for different cables.

In particular, in this paper we focus on the failure rate for PILC underground cables at a certain age. Note that there are several other factors affecting failure rate variation in cables, such as number of joints, history of previous failures, environmental stressors, usage patterns, manufacturer and cable type, etc. Here, however, we only consider the age and the number of historical faults to estimate failure rate.

To estimate failure rate we need to have access to historical databases containing information such as installation year, date of previous failures, and the age of the cable at the time of failure. Furthermore, to calculate the proportion of faulty cables over total cables, we need to know the total length of all the in-service cables during each year.

The process of calculating the failure rate, estimating model parameters, and finally, evaluation of the results is described below, as shown in Figure 1.

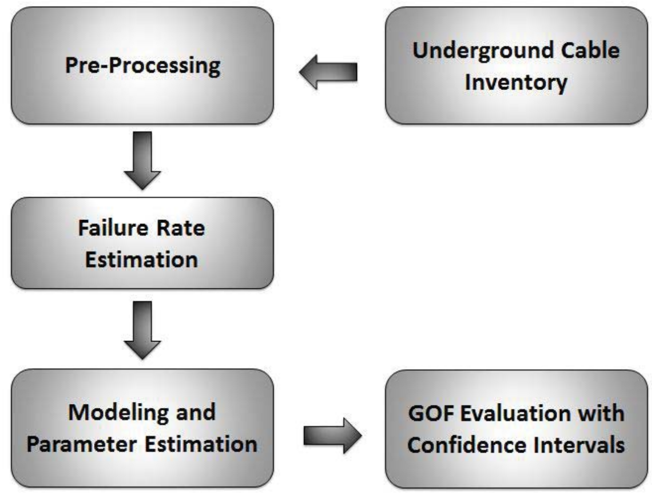

Fig. 1. Overview of the model creation and evaluation process.

A. Pre-processing

Due to the requirements explained above and the available databases, we have selected cable inventory data set. This data set contains historical information about both the in-service and destroyed cables that have been installed since 1908 in Halmstad power distribution grid. Each cable is described with a unique ID and the transmission line to which it belongs, as well as additional information such as insulation type, conductor size, installation year, length, etc. In this work, we only analyze in-service high-voltage PILC cables.

A transmission line between two cable boxes consists of a number of cables. According to the data set, the total number of high-voltage transmission lines containing PILC cable is about 500.

The cables in a line may have different installation years. We assume that the initial installation year of the line is the earliest installation year among all cables in the group.

In addition to length of in-service cables, we require information about past failures. In our case the historical failure database could not be directly linked to the cable information, since the two use different asset identifiers. Therefore, to identify past failures, we use the assumption that *short* cables in any given line are artifacts of previous repairs. Therefore, we consider each cable of length smaller than 20 meters to correspond to a failure in the line. The failure is assumed to have taken place in the year of the installation of the short cable, and to take place in the oldest cable within this line. Those assumptions are not fully accurate, but we have confirmed, through discussions with domain experts, that they are realistic.

B. Failure rate estimation

Failure rate is the frequency with which a system or component fails within a given unit of time. This definition can be naturally extended to a population of systems, for example a network of cables. In this work we consider the number of failures per year per kilometer. The general equation for the empirical failure rate is:

$$FR = \frac{N}{L},$$

where N is the number of failures in a year and L is the total length of in-service cables.

There are many factors that influence the failure rate, however, in this work we only focus on cable age (understood as the number of years between installation of the cable and the time of the failure). It is a well-known fact that the likelihood of failure changes with age. Therefore, we express the empirical failure rate for underground cables at age α as the total number of failure that happened to cables at age α, denoted $N(\alpha)$, divided by the total length of cables that were in-service at age α, denoted $L(\alpha)$:

$$FR(\alpha) = \frac{N(\alpha)}{L(\alpha)}.$$

Among several factors affecting failure rate, we only consider the factors that can be estimated from the historical databases we have access to: installation year of each cable (age), length, voltage class (high voltage or low voltage), and failure history: number of failures, and age at time of failure.

C. Modeling and parameter estimation

A failure function, $\lambda(\alpha)$, is a function that describes changes in failure rate depending on age. Figure 2 shows a commonly used model that represents the failure function known as the bathtub curve [11]. The model begins with a high failure rate (infant mortality), followed by fairly constant failure rate (useful life). Finally, the failure rate increases again as the component reaches the end of its life (wear-out).

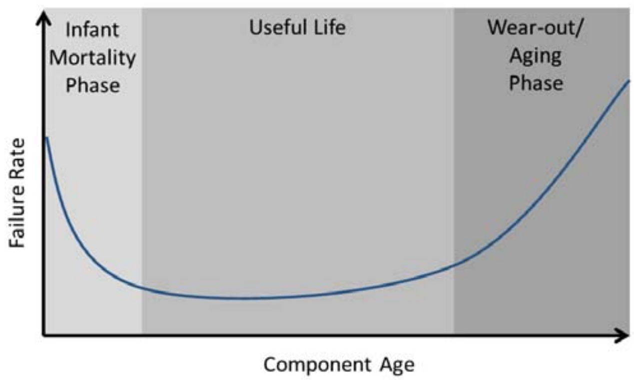

Fig. 2. Bathtub curve of typical failure rate for components.

When discussing power cables, we are particularly interested in modeling the "wear-out" time and the effects of aging process on failure rate. It is commonly believed that the failure rate increases as cables get older.

Our goal is to find an appropriate failure function $\lambda(\alpha)$. To this end, we investigate five different models and evaluate how well, the empirical failure rates fit each model. Observe that we do not specifically consider the "infant mortality" period in this analysis.

We have decided to perform experiments using five different failure functions. The three commonly used models in statistical analysis are linear, piecewise linear, and exponential. In addition to these, we have also investigated constant and piecewise constant models.

Constant: This model is described by a constant line with the failure rate equal to $\lambda(\alpha) = \mu$, where μ is the mean failure rate value of all the empirical data points $FR(\alpha)$.

Piecewise constant: This model is constructed by two constant lines at different values, μ_1 and μ_2, where μ_1 is the mean failure rate before T_{pwc} and μ_2 is the mean failure rate after T_{pwc}.

$$\lambda(\alpha) = \begin{cases} \mu_1 & \text{if } T_{pwc} \leq \alpha \\ \mu_2 & \text{if } T_{pwc} > \alpha \end{cases}$$

Linear: The linear model is specified by a linear function with two parameters: slope m_l and intercept b_l. In this model, the increment of failure rate between two consecutive time points is constant.

$$\lambda(\alpha) = m_l(\alpha) + b_l$$

Piecewise linear: This model represent the failure rate to be constant at the beginning up to age T_{pwl}, and then failure rate grows linearly with slop m_{pwl}. Therefore, the function is specified by three parameters, the constant failure rate b_{pwl}, the time which failure rate starts to increase linearly T_{pwl}, and the slop m_{pwl} of the line.

$$\lambda(\alpha) = \begin{cases} b_{pwl} & \text{if } T_{pwl} \leq \alpha \\ m_{pwl} \cdot (\alpha - T_{pwl}) + b_{pwl} & \text{if } T_{pwl} > \alpha \end{cases}$$

Exponential: this distribution is described by the function:

$$\lambda(\alpha) = \beta \cdot e^{\beta \cdot \alpha}$$

For each model, the corresponding parameters are calculated by Levenberg-Marquardt optimization algorithm implemented in Python `scipy` library, minimizing the mean square error.

After parameter estimation, we need to evaluate how well do the empirical data points fit each model. This can be done by using different goodness-of-fit measures.

D. GOF evaluation

In this study we employ two goodness-of-fit measures; the first is based on calculating the *probability of generating the data* from a given model (PGD); the second is based on *mean square error* between the data and the model (MSE).

In the PGD measure, for each age, the value of the failure function $\lambda(\alpha)$ at that age is considered to be the mean value of a normal distribution. The variance of this normal distribution is computed from the empirical data points. At each age, the cumulative probability function is used to calculate the probability that a given data point belongs to the normal distribution centered around the failure function. Finally, the calculated probabilities for each age are multiplied together to give the value of GOF for that model. The higher this probability is, the better the data points fit the model.

However, the resulting numbers are very small and difficult to analyze, and thus we use the negative logarithm (base 10) of those values to make them easier to interpret. Therefore, the lower the value of the GOF, the better the empirical failure rates fit the model under consideration.

$$GOF_{PGD} = \\ -\,log_{10} \prod_{\alpha} P(x \leq FR_\alpha | FR_\alpha \in X_i \sim (\mu = \lambda(\alpha), \sigma^2))$$

The MSE GOF measure is the sum of squared differences between each data point and the value of the failure function at corresponding age. Also in this case, the lower the GOF value the better the data points fit the model under consideration.

$$GOF_{MSE} = \frac{1}{n} \sum_{\alpha} (FR(\alpha) - \lambda(\alpha))^2$$

where *n* is the number of data points.

Finally, it is important to note that, while GOF results can be compared directly, it is often difficult to properly interpret the results, especially when the data is of limited quantity (and also quality) and it does not fit any of the models perfectly. Therefore, we propose a way to interpret the results by comparing the obtained GOF measures with expected GOF and confidence intervals, estimated using synthetic data.

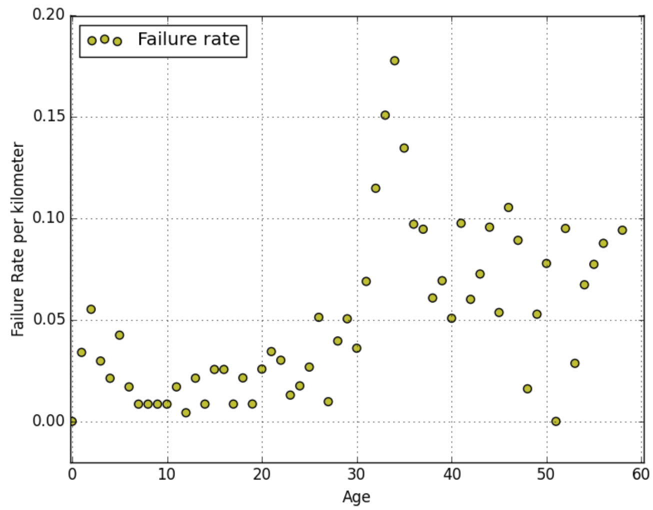

Fig. 3. Empirical failure rate per kilometer as function of age, for high voltage PILC cables.

For each model, a number of synthetic data sets are generated by drawing random points from a normal distributions with mean equal to the failure function at each age and variance computed from the empirical data points. The synthetic data sets should have the same number of points as the empirical data points. The PGD and MSE GOF are computed between each synthetic data set and the corresponding model, confidence intervals are derived based on the variance of the GOF values. The GOF of the synthetic data sets generated by one model are also compared to all other models in order to determine how well a data set generated from model A fits model B. These comparisons will help us draw conclusions about the how well the empirical data points fit each of the proposed models.

IV. Results and Discussion

The result of calculating empirical failure rates at each age, for high voltage PILC cables, is shown in Figure 3. The horizontal axis represents the cable age at time of failure and the vertical axis represents the failure rate λ (per kilometer).

By comparing this result with Figure 2 it is possible to extract three lifetime phases. The empirical data starts with higher failure rates at ages 1-6, the “infant mortality” period. It then continues with a period of low and fairly constant rates during ages 7-19, the “useful life”. And finally, the higher failure rates start again from age 20, the “wear-out” phase. However, there are also some differences from the bathtub curve, the most clear ones being the peak at ages around 30 years, and the shape of the wear-out phase.

The parameters for constant, piecewise constant, linear, piecewise linear, and exponential models were estimated from the empirical data. Each resulting model is shown in Figure 4. The resulting parameter for the constant model is $\mu = 0.052$, and for the piecewise constant model are $\mu1 = 0.023$, $\mu2 = 0.082$, and $T_{pwc} = 30$. The parameters for the linear model are $m_l = 0.0013$, and $b_l = 0.0128$. For the piecewise linear $b_{pwl} = 0.0231$, $m_{pwl} = 0.00147$, and $T_{pwl} = 0.00695$. For the exponential model, the parameter β is equal to 0.0254.

To compare the results of GOF between different models, first we generated 100 synthetic data sets based on each model, and then measured the PGD and MSE between each randomly generated data set and all the models. In Figure 5, one randomly generated data set is shown for each model. Then, for each group of 100 generated data sets, we found the mean value of all calculated GOF to all models and the corresponding 95 percent confidence interval.

We performed the PGD and MSE tests for all combination of synthetic data sets and models. In this case, data sets A, B, C, D, and E are the 100 randomly generated data sets from constant, piecewise constant, linear, piecewise linear, and exponential models respectively. The results of GOF tests based on PGD and MSE are presented in Table I and Table II. For example, the result of PGD GOF test of the data generated from constant model (A) with respect to the linear model (C) is 43.8960 ± 0.6276.

From the GOF results presented in Table I and Table II, several observations can be made, as follows.

As expected, the best GOF results are obtained when the data set is compared to the model which generated it. For example, Data A fits model A better than any other model. These correspond to the diagonal entries in Table I and Table II.

The results of GOF measurements from fitting each generated synthetic data with the same model (diagonal of the tables) does not show any statistically significant differences. This verifies that performing this type of comparison between synthetic data and models is systematically correct, i.e., the result of comparing model A with synthetic data A is as good as comparing model B with synthetic data B.

Except the constant model (model A) which is statistically very different from the rest of the models, the result of pairwise comparison between a GOF test in synthetic data generated by a model but fitting with another model, and a result of GOF test in the other combination of this two models, is not significantly different. For example, GOF between data B and model D, is not significantly different than the GOF between data D and model B.

There is no statistically significant difference between GOF of the data points, neither the empirical nor synthetic, between linear, piecewise linear, and exponential models. That is, the GOF results are within the respective confidence interval obtained from the synthetic data. This indicates that those three models are virtually identical.

Nonetheless, the real data seems to fit the piecewise constant model better than the other models. This suggests that the failure rate could be modeled by two constant lines; low failure rate up to age 30 and higher failure rate after that. This does not confirm the assumption that the failure rate increases monotonically as a function of age. This observation is quite surprising, and we believe it deserves

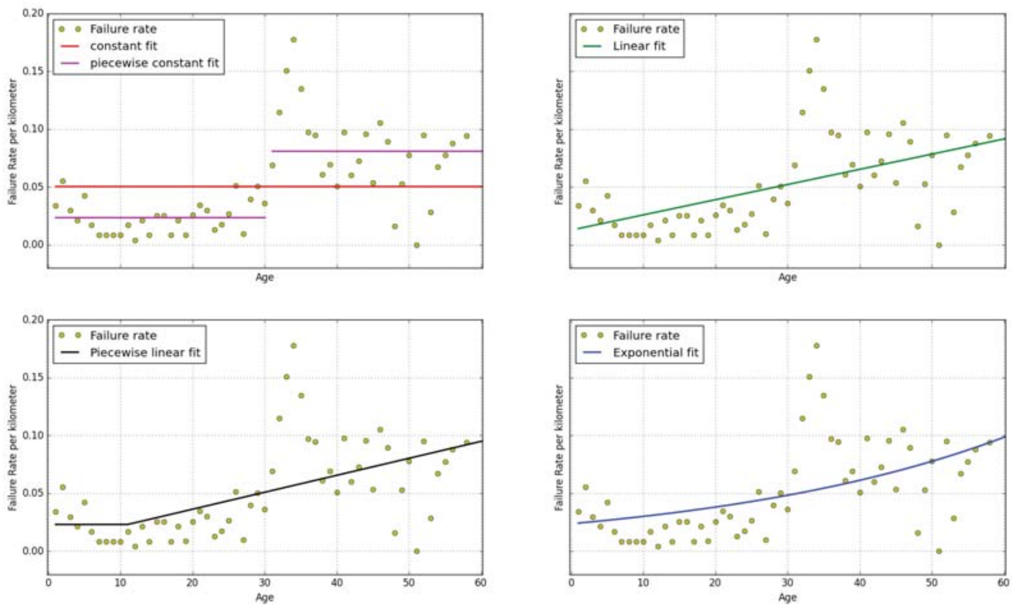

Fig. 4. Five different failure rate models, fitted to the empirical data.

further analysis in the future.

This result might be caused by several factors. First, the very high values of failure rate at ages between 32 and 35 years affect other models more than the piecewise constant model. Second, the input data set and the in-use information is not enough to uniquely and with confidence identify the best model. Therefore, other information should also be taken into the account. Third, we did not considered the affect of repair and replacement of cables on failure rate estimation. In fact, the process of rejuvenation of the underground cables prevents the failure rates from becoming too high, especially after experiencing number of failures (in our case after age of 40 years or so).

V. Conclusion and Future Work

In this paper we have presented some of the characteristics of power grid cables, especially PILC underground cables, which are used in many power transmission and distribution networks. We have also discussed the main challenges regarding fault prediction for these cables.

We have introduced five different probabilistic models for predicting failure rate depending on cable age, and evaluated how well does each of these models fit the real-world, historical fault data. We have employed two different goodness-of-fit measurements, one based on mean square error and one based on probability of generating the data.

In order to compare the GOF measures between various models, a new methodology is presented. The GOF test results are interpreted by generating 100 synthetic data sets for each model, and estimating the corresponding confidence intervals. Then, pairwise comparisons are performed between each model and synthetic data sets.

According to the result of GOF from PGD and MSE tests, the linear, piecewise linear, and exponential models do not show significant difference. On the other hand, the piecewise constant model fits the failure rates better, in a statistically significant way, than other models.

This result was quite surprising, since we expected that the failure rate to be an increasing function of age. This could be explained by the fact that the faulty cable sections are

TABLE I
Goodness-of-fit measurement by using PGD test

(-Log10 ∏ cdf)	Data A	Data B	Data C	Data D	Data E	Real Data
Constant (Model: A)	38.8769 ±0.5209	43.4234 ±0.6310	42.0862 ±0.6638	42.9481 ±0.6564	42.7505 ±0.6278	43.6205
P.W. Constant (Model: B)	46.9932 ±0.6820	38.4123 ±0.5535	39.8806 ±0.6393	39.4594 ±0.5502	40.8079 ±0.5812	32.9166
Linear (Model: C)	43.8960 ±0.6276	39.2477 ±0.4468	37.8395 ±0.5524	37.0250 ±0.4749	38.0640 ±0.5256	37.0885
P.W. Linear (Model: D)	44.4949 ±0.6098	39.0726 ±0.5864	37.7932 ±0.5307	37.3312 ±0.5280	38.2944 ±0.5902	36.4592
Exponential (Model: E)	42.7155 ±0.6604	39.7050 ±0.5764	37.9634 ±0.4783	37.3717 ±0.4866	37.7189 ±0.4820	37.8377

TABLE II
Goodness-of-fit measurement by using MSE test

(1+e3 mse)	Data A	Data B	Data C	Data D	Data E	Real Data
Constant (Model: A)	1.2409 ±0.0455	1.6574 ±0.0585	1.5392 ±0.0623	1.6216 ±0.0613	1.5937 ±0.0590	1.6408
P.W. Constant (Model: B)	1.9951 ±0.0632	1.2550 ±0.0486	1.3805 ±0.0601	1.3414 ±0.0502	1.4503 ±0.0523	0.8647
Linear (Model: C)	1.7007 ±0.0577	1.3124 ±0.0407	1.1822 ±0.0483	1.1088 ±0.0423	1.1880 ±0.0457	1.2345
P.W. Linear (Model: D)	1.7557 ±0.0570	1.2952 ±0.0520	1.1784 ±0.0460	1.1429 ±0.0467	1.2106 ±0.0517	1.2184
Exponential (Model: E)	1.6032 ±0.0608	1.3525 ±0.0532	1.1819 ±0.0427	1.1278 ±0.0435	1.1592 ±0.0421	1.3008

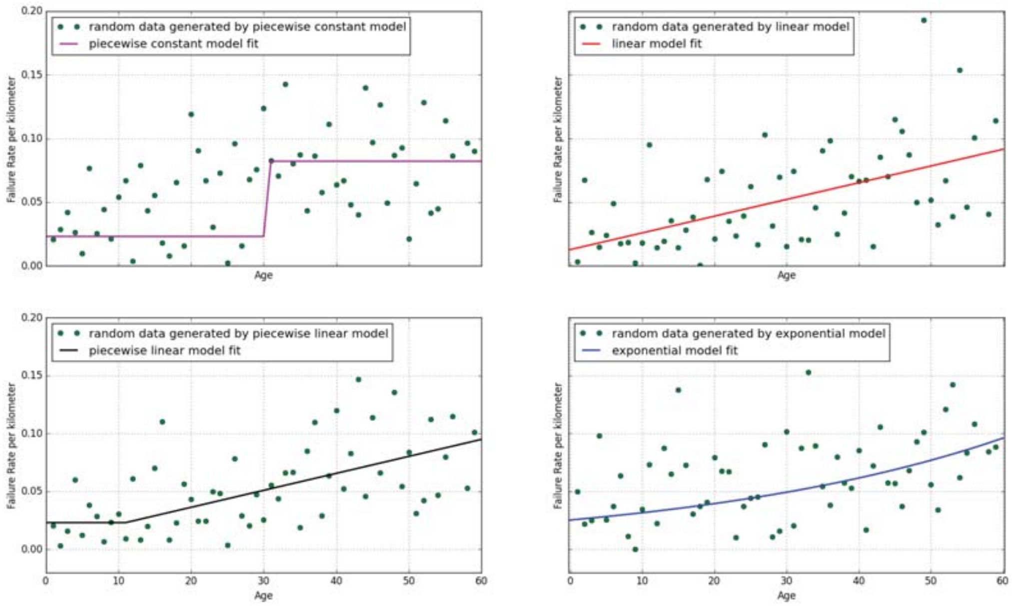

Fig. 5. Synthetic data generated based on different models

continuously replaced by new cables. In fact, the replacement strategy in the underground cables is something we plan to look into in the future in more detail.

In this work we have only considered the failure rate based on the age and the total number of previous failures. However, from the available data set, we can obtain the effects of failure rate based on other factors such as the number of joints, history of previous failures, geographical location, etc. For example, we can cluster cables based on the number of joints per kilometer, and then calculate the failure rate for cables at each cluster. Therefore, by adding more information to the failure rate estimation we can have a better interpretation of the cables failure rate variation over age.

The probabilistic model can also be updated by considering additional information such as load patterns, temperature, and effects of replacement. By exploiting useful information one can determine the condition of in-service equipment, and better plan the scheduling maintenance. Consequently, instead of unplanned outages, power distribution companies can have planned outages, which are shorter and less disruptive.

References

[1] H. P. Barringer. Use Crow-AMSAA reliability growth plots to forecast future system failures. *Second Annual International Maintenance Excellence*, 2006.

[2] Paul Barringer. Predict failures: Crow-AMSAA 101 and Weibull 101. *Proceedings of IMEC*, 2004.

[3] J. A. Bloom et al. Guidelines for intelligent asset replacement, vol.3, underground distribution cables. Technical report, EPRI, Palo Alto, CA, 2005.

[4] Jeremy A. Bloom, Charles Feinstein, and Peter Morris. Optimal replacement of underground distribution cables. In *Power Systems Conference and Exposition*, pages 389–393. IEEE, 2006.

[5] R. M. Bucci, R. V. Rebbapragada, A. J. McElroy, E. A. Chebli, and S. Driller. Failure prediction of underground distribution feeder cables. *IEEE Transactions on Power Delivery*, 9(4):1943–1955, 1994.

[6] P Cichecki, E Gulski, JJ Smit, and RA Jongen. Statistical analysis of transmission power cables condition data. *Proceedings of the 16th International Symposium on High Voltage Engineering*, pages 851–856, 2009.

[7] Piotr Cichecki, R Jongen, Edward Gulski, Johan J Smit, Ben Quak, Frank Petzold, and F Vries. Statistical approach in power cables diagnostic data analysis. *IEEE Transactions on Dielectrics and Electrical Insulation*, 15(6):1559–1569, 2008.

[8] J. Y. Gill. *Forecasting Underground Electric Cable Faults Using the Crow-AMSAA Model*. Engineering Information Transfer, 2011.

[9] E. Gulski, J. J. Smit, F. J. Wester, and J. W. van Doeland. Condition assessment of high voltage power cables. In *International Conference on Power System Technology*, volume 2, pages 1661–1666. IEEE, 2004.

[10] Edison Electric Institute. The many causes of power failures. Available online, 2013.

[11] RA Jongen, PHF Morshuis, E Gulski, JJ Smit, J Maksymiuk, and ALJ Janssen. Application of statistical methods for making maintenance decisions within power utilities. *IEEE electrical insulation magazine, 22,(6)*, 2006.

[12] RA Jongen, PHF Morshuis, JJ Smit, ALJ Janssen, and E Gulski. Failure analysis of in service failed resin cable joints by means of a statistical approach. In *Electrical Insulation and Dielectric Phenomena, 2006 IEEE Conference on*, pages 517–520. IEEE, 2006.

[13] R. Keefe. Cable reliability management strategies. Technical Report CA:2004.1002257, EPRI, 2004.

[14] E. L. Mariut and E. Helerea. Enhancing reliability for medium voltage underground power lines. *7th International Symposium on Advanced Topics in Electrical Engineering (ATEE)*, pages 1–6, 2011.

[15] Harry Orton. History of underground power cables. *Electrical Insulation Magazine, IEEE*, 29(4):52–57, 2013.

[16] Cristina Stancu, Petru V Notingher, and Mihai Gabriel Plopeanu. Electrical lifetime estimation of underground power cables. *Journal of International Scientific Publications: Materials, Methods & Technologies*, 6(part 1):165–178, 2012.

[17] Zairul Aida Abu Zarim and Tashia Marie Anthony. HV cable diagnostics. In *International Conference on Condition Monitoring and Diagnosis*, pages 1151–1155. IEEE, 2012.

[18] Yujia Zhou and Richard E Brown. A practical method for cable failure rate modeling. In *Transmission and Distribution Conference and Exhibition, 2005/2006 IEEE PES*, pages 794–798. IEEE, 2006.