Bayesian Estimates of Transmission Line Outage Rates That Consider Line Dependencies

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Abstract

- Transmission line outages are inevitable for a power system and the data is limited.
- Paper proposed a Bayesian hierarchical model that leverages line dependencies to better estimate outage rates of individual transmission lines from limited outage data.
- The Bayesian model produces more accurate individual line outage rates, as well as estimates of the uncertainty of these rates even when the available data is less.

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Introduction

- Transmission line outage rates are foundational for many reliability calculations, but in historical data the counts of outages for the more reliable lines are low, and estimated individual line outage rates are highly uncertain.
- Ways in which individual transmission lines are partially similar, including their length, rating, geographical location, and their proximity.
- This paper leverage these partial similarities with a Bayesian hierarchical method to improve the estimation of line outage rates from historical data.

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Introduction

- The conventional method of estimating annual line outages have high variance and for many line outages we have very less data
- One method to mitigate the problem of data is to group lines by line voltages, length, area etc.
- To exploit the partial dependencies of line outage rates, paper proposes a Bayesian hierarchical method to estimate outage rates of individual transmission lines. In particular, the method can leverage the multiple partial dependencies in line length, rating, network proximity, and geographical area to give better outage rates of individual lines.

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Introduction

The model proposes :

- Estimates annual outage rates for individual transmission lines more accurately by leveraging partial similarities between line
- Has performance better than the conventional method of simply dividing the number of outages by the number of years observed, especially when the data is limited.
- Instead of pooling lines with one characteristic in common, gives a way to combine multiple partial similarities between lines.
- Shows that line length and rated voltage correlate with line outage rate, but the correlation is not strong.

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Literature review

- Bayesian approaches encode uncertainty in uncertain parameters such as outage rates as random variables.
- Bayes theorem is used to combine data with prior distributions that describe initial knowledge of the uncertainty. The prior distributions are updated with the available data to give a posterior distribution that describes the uncertainty in the parameter values given all the available data.
- Bayesian methods are ideal for problems with limited data (such as estimation of outage rates), where it is necessary to use all the information available.

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Modelling line dependencies

Historical Outage Data

- Data consist of transmission line outage by North American utility (Bonneville Power Administration) for 14 years since 1994.
- Data include the sending end and receiving end bus name of outaged lines, voltage rating, length, outage time, district and other information.
- There are 549 outages in the data with rated voltage of 69,115,230,287,345 and 500KV
- Excluded 1000KV HVDC line and momentary outages.
- If a line fails several times it's counted as one.

Modelling line dependencies

Data exploration

- Initially used the conventional method of dividing the number of outages by number of years.
- After pooling the overall data the mean and standard deviation comes out to be 0.6 and 0.7 respectively.
- The variance to mean ratio comes out to be 1.2 showing overdispersion.

Modelling line dependencies

Scaling line length and voltage ratings

The line lengths and voltage ratings are transformed and scaled so that their magnitudes and variations are scale-free and comparable.

$$x_L = \frac{ln\mathbf{L}}{scale(ln\mathbf{L})} \tag{1}$$

scale(z) = meadian(z-median(z))

$$x_V = \frac{\mathbf{V}/SD(\mathbf{V})}{scale(\mathbf{V}/SD(\mathbf{V}))} \tag{2}$$

It is usually considered that the line length and voltage rating have a positive correlation, but the correlation is weak: the Pearson correlation coefficient is 0.34

Modelling line dependencies

Line proximity

- The proximity of lines is quantified by the weighted sum of two kernels.
- The first kernel is based on districts. Lines in the same district are more likely to experience the same weather conditions.
- The second kernel is based on network distance in terms of line length, which, to some extent, reflects both geographic proximity and the physical and engineering interactions in the power grid.

Modelling line dependencies

Line proximity - District

There are 12 districts, and districts for each line are represented by a feature vector $\phi_{dis} \in \{0, 1\}^{12}$ whose coordinates correspond to the districts, and are set to 1 for each district crossed by that line, and to 0 otherwise. We define district kernel as :

$$\Sigma_1 = exp(-\| \phi_{dis}(i) - \phi_{dis}(j) \|_2{}^2 - I_{i \neq j}) \tag{3}$$

where $\| . \|$ stands for two norm and $I_{i \neq j}$ is an indicator function. The kernel Σ_1 forms a correlation matrix since it is positive definite.

Modelling line dependencies

Line proximity - Network distance

The network distance between lines L_i and L_j along the network lines is defined as :
d_{ij} = d(L_i,L_j) = minimum length in miles of a network path joining midpoint of L_i to midpoint of L_j .
The distance of line to itself is zero and the distance of a line to a neighboring line with at least one bus in common is half of the total length of the two lines.

$$\Sigma_2 = exp[-\frac{d(L_i, L_j)}{2}] \quad (4)$$

As d(L_i, L_i)=0, the diagonal elements of Σ_2 are one.

Modelling line dependencies

Line proximity - Combining two kernels

The network proximity Σ is the weighted sum of above two kernels:

$$\Sigma = w\Sigma_1 + (1-w)\Sigma_2 \tag{5}$$

Where $0 < w < 1$. For example, if the two kernels are equally important, then $w = 0.5$

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The Bayesian Hierarchical Model

- We assume that the outage count follows a Poisson distribution :

$$N_i \sim Poisson(\lambda_i t_i), \qquad i = 1, \ldots, n \tag{6}$$

where N_i is the outage count for line i over t_i years,λ_i is the annual outage rate, and n is the number of lines.

- We assume that the outage rates λ_i follows a Gamma distribution:

$$\lambda_i \sim Gamma(\alpha, \alpha/\mu_i), \qquad i = 1, \ldots, n \tag{7}$$

The mean outage rate μ_i is modeled via a linear regression model with correlated lines.

The Bayesian Hierarchical Model

- The linear regression model assumes the predicted variable is normally distributed, but μ_i is positive and may have a large range of values, so μ_i is transformed by a log function :

$$\ln \boldsymbol{\mu} = \beta_0 + \beta_L x_L + \beta_V x_V \tag{8}$$

  Where μ, β_0 are column vector

- β_0 follows a multi variable normal distribution

$$\beta_0 \sim \mathcal{N}(m1, \sigma^2(w\Sigma_1 + (1-w)\Sigma_2)) \tag{9}$$

- Line dependencies are captured by the covariance matrix of this multivariate normal distribution, σ^2 is a scalar which controls the magnitude of the covariance and w controls the weights of the two kernels.

The Bayesian Hierarchical Model

- The parameters α, β_V , β_L , w, σ^2 and m will be estimated using prior distributions in combination with the data as described below. The prior distributions are:

$$
\begin{aligned}
\alpha &\sim \text{Half Normal}(0.7, 8^2) \\
m &\sim \mathit{Normal}(-1.5, 5^2) \\
\sigma^2 &\sim \text{Half Normal}(0, 0.5^2) \\
\beta_L &\sim \mathit{Normal}(0.13, 5^2) \\
\beta_V &\sim \mathit{Normal}(0.12, 5^2) \\
w &\sim \mathit{Beta}(1, 1)
\end{aligned}
\tag{10}
$$

- These priors are set to ensure that the parameters have a reasonable range and/or mean when compared to our knowledge about the system.

The Bayesian Hierarchical Model

Summary of Bayesian model

- We now summarize the Bayesian hierarchical model. The Bayesian hierarchical model is specified by (6,7,8,9) together with the prior distribution of the parameters (10). Note that the partial dependencies between the lines are expressed in (8,9).
- The model parameters, including the outage rates λ, are :

$$\theta = (\lambda, \mu, \beta_0, \alpha, \beta_L, \beta_V, m, w) \tag{11}$$

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The Bayesian Hierarchical Model

Summary of Bayesian model

- The objective is to estimate the posterior distribution of the parameters $\Pr(\theta|\boldsymbol{N})$ that is informed by the line outage counts $\boldsymbol{N}$.
- By Bayes' theorem, the posterior distribution :

$$\Pr(\theta|\boldsymbol{N}) = \frac{\Pr(\boldsymbol{N}|\theta) \times \Pr(\theta)}{\Pr(\boldsymbol{N})} \tag{12}$$

The Bayesian Hierarchical Model

Summary of Bayesian model

- Normalization can be applied later, it is sufficient to calculate the unnormalized numerator of (12). We can exploit the dependencies in the hierarchical model (7,8,9) to get parameters :

$$\Pr(\boldsymbol{N}|\theta) = \Pr(\boldsymbol{N}|\lambda) = \prod_i \Pr(N_i|\lambda_i) \tag{13}$$

$$\Pr(\theta) = \prod_i \Pr(\lambda_i|\alpha, \mu_i) \Pr(\boldsymbol{\mu}|\beta_0, \beta_L, \beta_V) \Pr(\beta_0|m, w) \times \Pr(\alpha) \Pr(\beta_L) \Pr(\beta_V) \Pr(m) \Pr(w) \tag{14}$$

so that

$$\Pr(\boldsymbol{\theta}|\boldsymbol{N}) \propto \Pr(\boldsymbol{N}|\theta) \Pr(\theta)$$

$\propto \prod_i \Pr(N_i|\lambda_i) \prod_i \Pr(\lambda_i|\alpha, \mu_i) \Pr(\boldsymbol{\mu}|\beta_0, \beta_L, \beta_V) \Pr(\beta_0|m, w) \times$
$\Pr(\alpha) \Pr(\beta_L) \Pr(\beta_V) \Pr(m) \Pr(w)$ (15)

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Bayesian processing on real data

Sampling Process

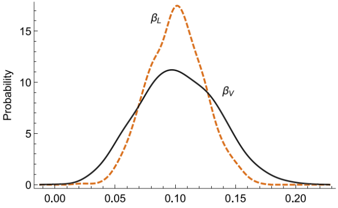
The Bayesian hierarchical model described in the previous section is applied to the historical outage data

- The posterior distributions (15) of the parameters (11) can be evaluated numerically by repeated sampling from the distribution with a Monte Carlo Markov Chain (MCMC) algorithm.
- Software Stan was used, which implements MCMC as Hamiltonian Monte Carlo (HMC)

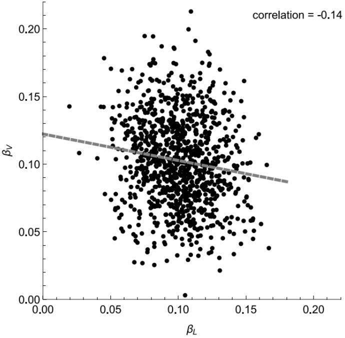
Bayesian processing on real data

Results of Bayesian estimates

- The posterior distributions of L and V and their correlation, we see a very weak correlation which is reasonable as x_L and x_V have very weak correlation.



(a) Distribution of β_L and β_V



(b) Scatter plot and co relation of β_L and β_V

Bayesian processing on real data

Results of Bayesian estimates

- The conventional method estimates the outage rate with the sample mean. The standard deviation of the sample mean can be estimated as $s/\sqrt{n}$, where s is the sample standard deviation, and n is the sample size.
- The standard deviation of the Bayesian estimator is typically smaller than the conventional estimator, especially when the data is limited to one year.
- The median ratio of standard deviations is 0.66 for one year of data, while the median ratio is 0.93 for 14 years of data.
- the Bayes estimator using one year of data achieves the same standard deviation as the conventional estimator using 2.30 years of data $(1/(0.662)=2.30)$.
- One advantage of the Bayesian method is that it provides a principled way of making line outage rates with no observed outages.

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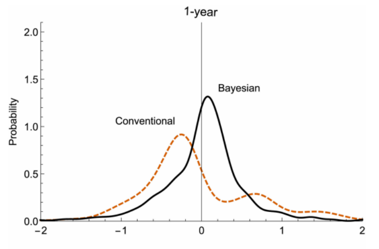
Test Bayesian estimate on synthetic data

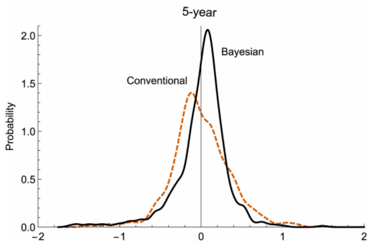
- Build a generative model for synthetic datasets of arbitrary size, so the data are not limited in size, and the ground truth values are known.
- Then test the Bayesian hierarchical model and the conventional estimates on the synthetic data.
- Generate three datasets with different sizes so that we have the equivalents of 1-year, 5-year, and 100-year data.

Test Bayesian estimate on synthetic data

- The less the data the wider the histogram, as the data increases the two modes merges into one.
- For 1-year data, the standard deviation of the error is 0.6 for Bayesian estimates and 0.9 for conventional estimates; for 5-year data, the standard deviation is 0.3 for Bayesian estimates and 0.4 for conventional estimates.



(a) Distributions of point estimation errors of Bayes estimates and conventional estimates using 1-year data



(b) Distributions of point estimation errors of Bayes estimates and conventional estimates using 5-year data

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Conclusion

- We use a Bayesian hierarchical model to improve the estimation of annual outage rates for individual transmission lines.
- This Bayesian method incorporates several types of dependencies between lines and is applied to real outage data and tested with synthetic data.
- For the shorter observation periods with the lower outage counts, the Bayesian estimates perform better than the conventional estimates.
- Our Bayesian hierarchical model offers an improvement over the conventional estimates for two reasons.
    - The Bayesian method can appropriately capture our prior knowledge of the parameter uncertainties with prior distributions.
    - The model is hierarchical and models the dependence between lines, information about multiple partial commonalities can be appropriately shared across similar lines.

Conclusion

- For correlated line with respect to the geographical dependencies we model these line dependencies as a covariance matrix in the Bayesian hierarchical model.
- The covariance matrix is the weighted sum of two kernels that represent geographic district commonalities and network line proximity, respectively
- The results for our data are that individual line outage rates are only partially correlated with the line length or the voltage rating. Therefore, it is more reasonable to consider the outage rate for a whole line instead of the rate per mile.
- When data is limited, which is generally true for power system outage data, Bayesian estimates have smaller uncertainty than conventional estimates.

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Conclusion

- With a specific acceptable standard deviation, the proposed Bayesian method needs less data than the conventional method.
- For example, if utilities need two years of data using the conventional method to estimate line outage rates with a given uncertainty, they typically only need one year of data using the proposed Bayesian method to obtain an outage rate estimate that meets the same uncertainty requirement

Improvements

- Further advantage could be gained by including other factors such as average wind speed or altitude.
- The proposed Bayesian method can naturally be extended to investigate line outage rates for specific causes.