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Modelling the degradation-rate of wooden utility poles in ground contact

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Wooden utility poles are used in power grids worldwide. Due to the large number of poles, models that can improve the inspection planning and renewal decisions for these components have the potential to yield considerable cost savings. In this paper, a widely used model for the degradation of wood in ground contact, the Timberlife model, is compared with inspection data from about 14,000 Scotch pine utility poles in the Norwegian power grid. This comparison shows that the original Timberlife model substantially underestimates the number of degraded creosote-treated poles relative to the inspection dataset. To address this, we propose an updated degradation model based on the existing Timberlife model and collected inspection data, using a Bayesian workflow. In the updated model, climate (i.e., precipitation and temperature), land type (i.e., forest, agricultural, or built-up area), and preservation treatment (i.e., creosote or CCA) are considered when predicting the degradation rate. Compared with the original Timberlife model, the updated models yield more accurate predictions of the number of degraded poles on a test set of collected inspection data.

Keywords: Wooden utility poles, degradation models, wood decay, rot, overhead power lines (OHLs), critical infrastructure, power distribution system, Markov chain Monte Carlo (MCMC), Bayesian workflow

1. Introduction

Many power grid companies prefer wooden utility poles due to their lower purchase and installation costs (Salman et al. 2020). There are, for instance, estimated to be between 120 and 200 million wooden utility poles in the US alone (Ryan et al. 2014). However, wood structures in ground contact are susceptible to degradation depending on factors such as precipitation, temperature, soil types, wood types, and preservative treatment (Anastasiades et al. 2024). Thus, the degradation rate will vary depending on the location of the poles.

Given the large number of wooden poles in the power grid, even minor improvements to inspection and renewal policies can yield substantial cost savings. Degradation models that help prioritize which poles to inspect or renew are thus valuable for grid companies.

One of the most used models for predicting the service life of wood structures is the Timberlife model (Anastasiades et al. 2024; van Niekerk et al. 2025; Pedersen and Istad 2024; Hundhausen et al. 2024). The Timberlife model was not explicitly developed for utility poles, but has been used to model the reliability of utility poles in, e.g., Australia (Ryan et al. 2016; 2014), Ireland (Hawchar et al. 2019), and the US (Salman et al. 2020). However, to the best of our knowledge, none of these previous studies have compared the Timberlife model's output with actual utility pole inspection data.

The Timberlife model is documented in (Wang et al. 2008) and is based on Australian field data and considers Australian climate and standards. In a recent paper Anastasiades et al. (2024) studied the applicability of the Timberlife model for predicting the service life of wood structures in the north-western part of Europe. Based on comparisons with test field data from Germany, they found it necessary to update the parameters in the original Timberline model and add a new parameter to account for soil type. This indicates that caution is required when applying the original Timberlife model outside Australia. Moreover, because the field data used in (Anastasiades et al. 2024) are limited to untreated test stakes (with dimensions ranging from 8×20 to 50×50mm), the applicability of this study for predicting the degradation rate of preservation-treated wooden poles is uncertain. There is thus a need for evaluating the applicability of the Timberlife model for modelling the degradation rate of wooden utility poles outside Australia, and to propose an updated model if the predictive accuracy proves poor.

The primary concern of this study is to make a degradation model suited for Norwegian grid owners. However, as preservation-treated wood in ground contact is used by utilities in other regions with a similar climate, e.g., the rest of Northern Europe and North America, and other industry sectors, this study is also relevant for a wider audience.

The remainder of this paper is organized as follows. Section 2 provides a brief introduction to the factors affecting wood degradation in ground contact and presents the original Timberlife model. Section 3 presents the inspection data used as the basis for the updated degradation models presented in Section 4. In Section 5, outputs from the proposed updated models are compared with test sets of the inspection data. This paper ends with some concluding remarks in Section 6.

2. Background

2.1 Factors affecting wood degradation

Wood degradation is mainly caused by fungi that digest moist wood, leading to rot. Factors governing fungal growth include moisture, oxygen, temperature, and nutrients (van Niekerk et al. 2021). These factors are often most pronounced in the ground-level zone of the pole.

Table 1. Notation

D_0	Diameter of pole at installation, e.g., $t = 0$, [mm]
$d_{t,i}, d_{t,e}$	Degradation depth at time t due to internal (i) and external (e) degradation, respectively [mm].
δ_t	Share of cross-section that is degraded at time t, i.e., $\delta = (2d_t)/D_0$
k_c	Parameter considering the precipitation and temperature in the area where the pole is located
k_a	Alternative climate parameter, based on monthly climate data.
k_s	Parameter considering the soil type to which the wood is exposed
k_w	Parameter corresponding to the durability of the used wood types. *
r	Degradation rate of wood [mm/year]. *
R_y, R_m	Annual and monthly precipitation, respectively [mm/year] and [mm/month]
T_y, T_m	Annual and monthly average temperature, respectively [°C]
t	Time since installation of utility pole [years]
t_{lag}	Time-lag before degradation starts
ξ	Time-lag parameter
a	Intercept for the linear degradation model [mm]
C	CCA-equivalent coefficient

* For the parameters k_w and r, the subscripts $core$, $heart$, and sap refer to different parts of the cross-section of the wood pole: corewood, heartwood, and sapwood, respectively. The subscript tr and un indicate whether the wood is treated or untreated.

Based on inspections of wooden poles in the Norwegian power grid, Refanaes et al. (2006) found that degradation mainly occurs between 45 cm below ground level and about 15 cm above ground level. Moreover, as the bending force due to wind load is often highest at ground level, the degradation of the utility poles at the ground level is of great concern to grid owners (Yu et al., 2016).

In Norway, Scots pine (Pinus sylvestris) is the predominant choice for utility poles. Utility poles in Norway have traditionally been treated with preservatives such as copper-chromium-arsenic (CCA) or creosote. While Norwegian legislation currently prohibits the use of these substances for new poles, due to their adverse effects on human health and the environment, poles that are potential candidates for renewal are still predominantly CCA- and creosote-treated. Information on the allowed preservatives and required retention levels for use in the Nordic countries is provided by the Nordic Wood Preservation Council (NWPC 2025).

2.2 The Timberlife model for in-ground degradation.

The Timberlife report (Wang et al. 2008) for degradation in ground contact presents an idealized model for degradation depth at time t, d_t, based on a degradation time-lag, t_{lag}, and a degradation rate, r. Thus:

$$d_t = r\left(t - t_{lag}\right) \mathbf{1}_{\{t>t_{lag}\}} \,, \qquad (1)$$

where $\mathbf{1}_{\{\cdot\}}$ denotes the indicator function, which equals 1 if the argument is true and 0 otherwise. Further, $r = k_w k_c$, and $t_{lag} = \xi r^{-0.95}$ (Wang et al. 2008). The parameter k_w represents the durability class of the wood type used, k_c represents the climate at the location of the pole, and ξ is a time-lag parameter. Values for k_w for the different wood durability classes are given in (Wang et al. 2008). The durability classes of the different wood types are specified in (Standards Australia 2005). As Scots pine is a softwood of durability class 4, the parameters defined for this durability class are used in the remainder of this paper.

The climate parameter, k_c, is calculated using the following formula (Wang et al. 2008):

$$k_c = f\left(R_y\right)^{0.3} g\left(T_y\right)^{0.2}. \qquad (2)$$

Where R_y er is the annual precipitation, and T_y is the annual average temperature. Moreover, $f(R_y)$ is calculated using the formula:

$$f\left(R_y\right) = 10\,\left[1 - exp\left(-0.001\,\left(R_y - 250\right)\right)\right] , \qquad (3)$$

and $g\left(T_y\right)$ is found by:

$$g\left(T_y\right) = \begin{cases} 0 & if \quad T_y \le 5°\text{C} \\ -1 + 0.2T_y & if \quad 5°\text{C} < T_y \le 20°\text{C} \\ -25 + 1.4T_y & if \quad T_y > 20°\text{C} \end{cases} . \qquad (4)$$

However, the degradation rate is not homogeneous through the cross-section of the poles. In the Timberlife model the wooden pole cross-section is divided into three layers: corewood, heartwood, and sapwood. Different models for how degradation progresses through these layers of the poles' cross-section are presented in Ch. 1 of (Wang et al. 2008). The two degradation models that are relevant for the Norwegian utility poles are degradation of treated softwood poles starting on the outside of the poles and progressing inwards (referred to as external degradation in the remainder of this paper) and degradation starting in the center of the poles and progressing outwards (referred to as internal degradation).

The time-lag for treated softwood subject to internal degradation is (Wang et al. 2008):

$$t_{lag,core,tr} = 4\xi r_{core,un}^{-0.95} + 45C \,, \qquad (5)$$

where $r_{core,un}$ is the degradation rate of untreated sapwood, and C is a CCA-equivalent coefficient. See (Wang et al. 2008) for how to calculate the CCA-equivalent coefficient based on the CCA or creosote retention level. The corresponding formula for the time-lag for external degradation is:

$$t_{lag,sap,tr} = \xi r_{tr,sap}^{-0.95} + 15C \,, \qquad (6)$$

where $r_{tr,sap} = \left(k_{w,sap,un} k_c\right)/(1 + 45C)$.

In a recent paper, Anastasiades et al. (2024) adapted the original Timberlife to a North European context based on field data from Germany. In this paper, updated model parameters and the addition of a soil factor, k_s, are proposed. The updated model parameters from (Anastasiades et al. 2024) and the original Timberlife parameter from (Wang et al. 2008) are listed in Table 2. Other wood-related parameters used when applying the Timberlife model in this paper are presented in Table 3.

Table 2: Timberlife parameters for softwood of durability class 4.

Parameter	(Wang et al. 2008)	(Anastasiades et al. 2024)
$k_{w,core}$	2.72	1.20
$k_{w,heart}$	1.36	0.60
$k_{w,sap}$	5.44	1.00
k_s	NA	3.0 * 4.0 **
ξ	5.5	4.0 * 1.0 **

* for soils with "little organic material"
** for soils with "a lot of organic material"

Table 3: Other wood-related parameters.

Parameter	Value	Source
Dry* Scotch pine sapwood density	$480\ kg/m^3$	(NWPC 2017)
creosote retention	$135\ kg/m^3$	(NWPC 2004)
CCA retention	$12\ kg/m^3$	(NWPC 2004)
C_{CCA}	0.90	(Wang et al. 2008)
$C_{creosote}$	1.97	(Wang et al. 2008)

* 12% moisture content

2.3 Accounting for variability

As acknowledged by Wang et al. (2008), there is significant variability in the degradation rate of wood. To account for this, Wang et al. (2008) propose modeling the variability of k_c and k_w as two-parameter Weibull distributions. Based on field data analysis, they find the coefficient of variation $(CV) = 0.90$ for k_w for wood of durability class 4, and $CV = 0.55$ for k_c. Moreover, Wang et al. (2008) assert that $CV = 1.2$ can be used as a first-order approximation of the variability of degradation depth for wood of durability class 4. Anastasiades et al. (2024) do not provide parameters for modelling the variability of the degradation rate.

3. Exploration of Inspection Data

To assess the applicability of the Timberlife model for predicting the degradation depth of treated Scotch pine utility poles, model outputs have been compared with inspection data collected from three different geographical areas in the south-eastern part of Norway. When collecting this data, all poles in some selected overhead line (OHL) segments were subject to visual inspection. All poles with $t \geq 15$ years have been subject to Resistograph measurements at ground level to detect internal degradation. Poles with $t < 15$ years have thus been excluded from the dataset. Poles with unknown installation year or unknown geographical location have also been excluded. For poles where degradation has been identified, data on the original cross-section diameter and the height of the degraded area above the ground level have been recorded. For poles where external degradation has been identified, the degradation depth has been calculated by: $d_{t,e} = (D_0 - D_{t,e})/2$, where D_0 is the initial pole cross-section, and $D_{t,e}$ is the cross-section of non-degraded wood of the pole at the inspection time. For poles where internal degradation has been identified, the degradation depth has been calculated by: $d_{t,i} = \frac{D_0}{2} - shell_{min}$, where $shell_{min}$ is the smallest of the measured distances from the outer

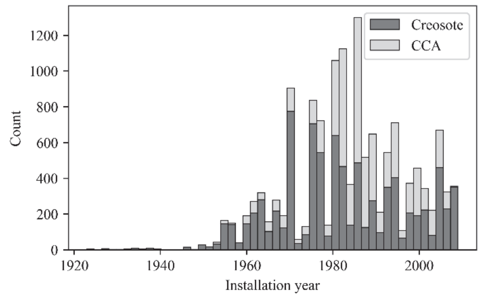

Fig. 1 The age distribution and preservation treatment of the poles in the inspection dataset.

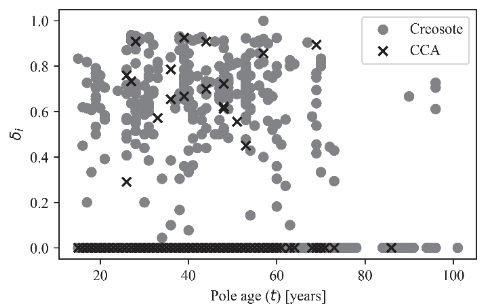

Fig. 2 Share of the pole cross-section affected by internal degradation (δ_i) in the inspection dataset.

diameter of the pole to decayed wood internally in the pole.

Fig. 1 shows the age distribution of the poles in the dataset. Fig. 2 shows the share of pole cross-section affected by internal degradation at time t, $\delta_i = (2d_{t,i})/D_0$. As the focus of this study is degradation in ground contact, only poles where rot has occurred below 0.15 m above ground level are considered.

As there are examples of relatively young poles in Fig. 2 with considerable degradation, it seems reasonable to assume that some of the poles in the inspected OHLs have previously been replaced. However, information on the number of replaced poles in the inspected OHLs is not available. Another observation from Fig. 2 is that relatively few of the poles have $\delta_i < 0.5$. This may be because uncovering internal degradation from Resistograph measurements can be challenging when the degraded area is small. Based on this, it seems reasonable to assume that the degradation rate is higher than the inspection data indicates, as some poles with a high degradation rate were likely replaced before the inspection, and some poles with incipient degradation were likely not uncovered.

Fig. 3 shows poles where external degradation has been identified. In contrast with Fig. 2, it is apparent that few of the poles where external degradation has been identified have $\delta_e = \frac{(2d_{t,e})}{D_0} > 0.5$. This may be because, as the degradation rate in treated sapwood is normally much lower than in core and heartwood (Wang et al. 2008), few poles in the dataset have reached a high δ_e at the time of the inspection. Secondly, as external degradation is relatively easy to observe, it seems reasonable to assume that some replacements were made before the inspection data used in this dataset were collected. Moreover, recommendations have been made that poles with a residual bending moment below 75% of their initial strength, corresponding to $\delta_e >$ 0.09, should be replaced (Nordnes et al. 2011). However, as the inspection interval for OHLs can be up to 10 years (Merz et al. 2024), some poles with δ_e above the recommended level are expected in the dataset.

Another observation is that internal degradation has been identified primarily in creosote-treated poles. In contrast, external degradation has been observed on both creosote- and CCA-treated poles.

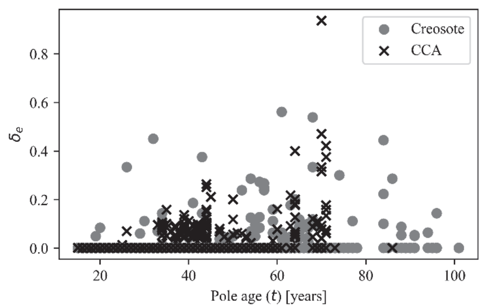

Fig. 3 Share of the pole cross-section affected by external degradation (δ_e) in the inspection dataset.

When using the Timberlife model on the inspection dataset, the climate coefficient, k_c, has been calculated using Eq. (2) and data from the Norwegian standard climate normals for the period 1991-2020 (Tveito 2021). As this climate dataset has a spatial resolution of 1x1 km, linear interpolation was used to approximate the annual average temperature, T_y, and precipitation, R_y, for each pole.

Further, the AR50 land resources database, which covers the whole of mainland Norway (Heggem et al. 2019), has been used as a proxy for accounting for differences in the soil type at the location of the individual poles. The relevant land types in this study are *agricultural*, *forest,* and *built-up area*. As the AR50 database contains only polygons of areas larger than 1.5 hectares, the land type for some poles has probably been misclassified. However, the number of misclassified land types appears to be few and is not expected to affect the analysis performed in this study.

Table 4 shows that only the prediction from the original Timberlife model (Wang et al. 2008) for the number of degraded CCA-treated poles is approximately in line with the number of degraded poles uncovered in the inspection data. In this analysis, we have assumed that the pole cross-section is evenly divided into corewood, heartwood, and sapwood. When performing this comparison, internally degraded poles with $0.5 \leq \delta_i \leq 0.95$ and externally degraded poles $d_t \geq 2mm$ and $\delta \leq 0.15$ have been included. Comparisons between the inspection data and the Timberlife model, when variability in k_w and k_c is accounted for, are shown in Fig. 5.

Table 4 Comparison of the number of degraded poles uncovered in inspection data and prediction from Timberlife models.

Treatment	**n**	**Insp. data**	**(Wang et al. 2008)**	**(Anastasiades et al. 2024)***
Internal degradation ($\mathbf{0.5 \leq \delta_i \leq 0.95}$)				
creosote	8525	257	0	5
CCA	5483	17	26	317
External degradation ($\boldsymbol{\delta_e \leq 0.15, d_t \geq 2}$mm)				
creosote	8525	59	0	7
CCA	5483	121	139	293

*In this study, all poles belonging to land type *agricultural* have been assigned k_s and ξ parameters for soil with "a lot of organic material", while the remainder of the poles have been assigned parameters for soil with "little organic material".

Looking more closely at the results of the comparison between the inspection data and the Timberlife predictions, other challenges become apparent.

1) While, according to Eq. (4) from the Timberlife-model, pole degradation is not possible when $T_y \leq$ 5°C, degradation has been identified in several poles where the annual average temperature is substantially lower.
2) Assuming a retention level of the creosote-treated poles according to the requirements given in (NWPC 2004), $C_{creosot} = 1.97$, resulting in the shortest possible time-lag for internal degradation to be:

$$\lim_{r \to \infty} t_{lag,tr,sap}(r) = 45C_{creosot} = 88.65\ years \quad (7)$$

   This is substantially higher than the age of several of the poles where internal degradation has been uncovered (as shown in Fig. 2).
3) Statistical analysis of the training dataset indicates that the effect of land type differs depending on the treatment of the poles (as shown in Table 5).

Table 5. p-values of two-sided Binomial tests with the null-hypothesis that the land type does not affect degradation.

Treatment	**Land type** Agri.	Forest	Built.
Internal degradation			
creosote	$1 \cdot 10^{-5}$	$3 \cdot 10^{-3}$	0.92
CCA	1.00	0.86	0.58
External degradation			
creosote	0.06	0.05	0.22
CCA	0.39	$2 \cdot 10^{-5}$	$5 \cdot 10^{-12}$

4. Updated Degradation Models

Based on the data exploration the following adjustments to the original Timberlife model are proposed in this paper:

- Introduction of a climate factor that allows degradation to occur in locations with $T_y <$ 5°C.
- Introduction of land type as an explanatory variable,

- Update of the model parameters based on a Bayesian approach.

Three variants of degradation models for treated utility poles of Scots pine are presented in this section: 1) internal degradation of creosote-treated poles, 2) external degradation of creosote-treated poles, and 3) external degradation of CCA-treated poles. A variant for internal degradation of CCA-treated poles has not been developed due to the low number of such poles identified in the inspection dataset.

4.1 Alternative climate parameter, k_a

We propose the following alternative climate parameter to allow degradation in locations where $T_y \leq 5$°C, but the temperature is > 5°C in parts of the year:

$$T_a = \frac{1}{n} \sum_{i=1}^{12} T_{m,i} \, \mathbf{1}_{\{T_{m,i} > 5°\mathrm{C}\}} \tag{8}$$

$$R_a = \frac{12}{n} \sum_{i=1}^{12} R_{m,i} \, \mathbf{1}_{\{T_{m,i} > 5°\mathrm{C}\}} \tag{9}$$

where $T_{m,i}$ and $R_{m,i}$ are the monthly average temperature and precipitation in month $i \in [1,12]$, respectively, and n is the number of months with average temperature > 5°C. Moreover, the alternative climate parameter is found through:

$$k_a = \left(\frac{n}{12}\right) f(R_a)^{0.3} \, g(T_a)^{0.2} \tag{10}$$

4.2 Updated model for internal degradation

This sub-section describes the development of an updated model for internal degradation. A subset of the inspection data ($n = 6917$) containing only creosote-treated poles from two geographical areas was used as a training dataset. Another subset of the inspection data containing creosote-treated poles from a third geographical location was set aside as a test dataset ($n = 1608$).

As we have only one observation per pole, updating the complete Timberlife model, which accounts for different degradation rates and time-lags as degradation progresses through the layers of the pole, is challenging. We have thus chosen to simplify the original Timberlife model into the following linear model:

$$d_t^* = rt - a \,, \tag{11}$$

where d_t^* is a latent variable representing a modelled degradation depth at time t, and $d_t = d_t^* \mathbf{1}_{\{d_t^* > 0\}}$ is the observed degradation depth. Further, t is the age of the utility pole, a is the intercept of the linear model, i.e., $a = -d_{t=0}^*$, and r is the degradation rate in $mm/year$. Moreover, we assume that the inspection method used is not sufficiently capable of detecting poles with $\delta_i \leq 0.5$ and that poles with $\delta_i \geq 0.95$ have been renewed before the inspection.

4.2.1 Finding priors for the updated model.

Based on Ch. 7 in (Wang et al. 2008), we assume that r is Weibull distributed, i.e., $r \sim Weibull(s, \lambda)$. The probability density function (PDF) for the Weibull distribution is:

$$f(x; s, \lambda) = \frac{s}{\lambda}\left(\frac{x}{\lambda}\right)^{s-1} exp\left(-\left(\frac{x}{\lambda}\right)^{s}\right), \tag{12}$$

where s is the shape parameter, and λ is the scale parameter. As the coefficient of variation (CV) of the Weibull distribution depends only on the shape parameter, s can be found by using a root finding algorithm to solve:

$$CV^2 = \frac{\Gamma\left(1+\frac{2}{s}\right) - \left(\Gamma\left(1+\frac{1}{s}\right)\right)^2}{\left(\Gamma\left(1+\frac{1}{s}\right)\right)^2}, \tag{13}$$

where $\Gamma(\cdot)$ is the gamma-function. Further, the scale parameter can be found by:

$$\lambda = \frac{\bar{r}}{\Gamma\left(1+\frac{1}{s}\right)}, \tag{14}$$

where $\bar{r}$ is the mean degradation rate. Moreover, we assume $CV = 1.2$, as suggested in (Wang et al. 2008, 63), and use the original deterministic Timberlife model for finding the mean degradation rate, i.e., $\bar{r} = k_{w,core} k_a$. Using the pole in the training dataset with the median climate coefficient we find that $\bar{r} = 1.0$. Further, we use Eq. (14) and (13) to find the shape and scale parameters for the prior distribution of r, denoted λ_W and s_W, respectively.

4.2.2 Approximating the intercept, a

We assume that the intercept, a, is a deterministic variable and use the following approach for approximating its value. We find the share of poles, denoted q_t, in the training dataset with $0.95 \geq \delta_i \geq 0.5$ at $t = 20$. This age is chosen because, based on Fig. 2, the number of poles $t \leq 20$ years that have been replaced due to internal degradation is assumed to be negligible. Further, we use the inverse survival functions of the Weibull distribution, denoted $S^{-1}(\cdot)$, to find an approximation of a that corresponds with q_t, i.e., $a = S^{-1}(\cdot)t - \delta_{i,min}\frac{D_0}{2}$. With $q_{t=20} = 0.0027$ we get $S^{-1}(q_t; s_W, \lambda_W) \approx 7.60$, which gives: $a = 7.60 \cdot 20 - 0.5 \cdot \frac{250}{2} \approx 89.54$. The value of $D_0 = 250$ is used as this is the median pole diameter in the dataset.

4.2.3 Formulating the observed degradation rate

Eq. (11) can be rewritten as:

$$r = \frac{d_t^* + a}{t}. \tag{15}$$

Further, when formulating a probability distribution for the observed degradation rate, one must consider that some poles have degradation rates so low that the degradation is not observable at the time of inspection. Thus, there is a censoring of poles with a degradation rate below the censoring threshold, e.g., $r_t < c_t$. The censoring threshold for internal degradation at time t is: $c_t = \left(a + 0.5\frac{D_0}{2}\right)/t$.

Moreover, some poles have a degradation rate so high that they have been replaced before the inspection. As we do not have data on the number of poles that have been replaced, poles with a degradation rate over the threshold $r_t > \tau_t$ are considered truncated. The truncation threshold at time t is: $\tau_t = \left(a + 0.95\frac{D_0}{2}\right)/t$. Thus, a probability distribution for the observed degradation rate, $r_{obs,t}$, can be expressed as:

$$h(r_{obs,t})\begin{cases} 0 & for \quad r_t < c_t \\ \frac{F(c_t)}{F(\tau_t)} & for \quad r_t = c_t \\ \frac{f(r_t)}{F(\tau_t)} & for \quad c_t < r_t \le \tau_t \\ 0 & for \quad r_t > \tau_t \end{cases}, \qquad (16)$$

where $f(\cdot)$ is the PDF and F(·) is the cumulative density function (CDF) of the Weibull distributed degradation rate. Fig. 4 shows a scatter plot of the observed degradation rate.

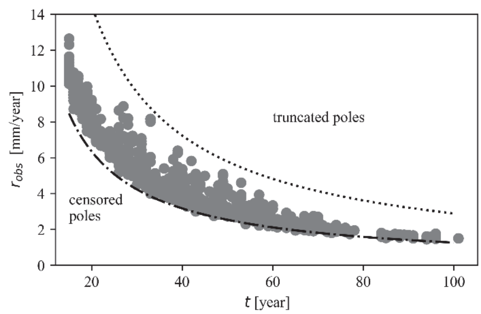

Fig. 4. Illustration of the observed degradation rate, r_{obs}. The dash-dot line illustrated the censoring threshold for a pole with $D_0 = 150$mm, and the dotted line illustrated the truncation threshold for a pole with $D_0 = 400$mm. Because the poles have a range of D_0 values, the dots representing censored r_{obs}-values are not aligned with the dashed line.

4.2.4 Updated model for the degradation rate

After iterating through several alternatives using a Bayesian workflow (Gelman et al. 2020), we propose the following updated model for the internal degradation rate:

We assume $r \sim Weibull(s, \lambda)$. The shape parameter is assumed to be gamma distributed. i.e., $s = ga(\alpha, \theta)$, with mean value: $\theta\alpha = s_W$ and standard deviation: $\theta\sqrt{\alpha} = 0.05$. Further, we adjust the scale parameter λ to account for the differences in climate and land types for the individual poles:

$$\lambda = \beta_\lambda \lambda_W + \beta_a k_a + \beta_{agri}\,\mathbf{1}_{\{s=agri\}} + \beta_{forest}\,\mathbf{1}_{\{s=forest\}}, \qquad (17)$$

where the parameter β_λ is used to adjust the size of the prior scale parameter, λ_W, and parameters β_a, β_{agri} and β_{forest} are used to adjust for the effect of the alternative climate parameter, k_a, poles placed in agricultural land, and poles located in forest, respectively. All the β-parameters are assumed to have normally distributed priors. Prior parameters used in the analysis are shown in Table 6. Due to the large number of censored and truncated datapoints in the training dataset, the use of non-informative priors leads to nonsensical outputs. We have thus ended up with relatively narrow priors that we believe represent a reasonable tradeoff between building on the established Timberlife model and learning from the inspection data.

Table 6. Priors used in the analysis

Parameters	Internal degradation	External degradation creosote	CCA
s_W	0.84	0.84	0.84
λ_W	0.91	0.041	0.088
a	89.54	11.43	19.4
$\theta\sqrt{\alpha}$	0.05	0.025	0.025
β_λ	N(1,0.25)	N(1,0.1)	N(1,0.25)
β_a	N(1,0.25)	N(0,0.1)	N(1,0.25)
β_{agri}	N(0,0.25)	N(0,0.1)	NA
β_{forest}	N(0,0.25)	N(0,0.1)	N(0,0.25)
β_{built}	NA	NA	N(0,0.25)

4.3 Updated models for external degradation

The development of updated models for external degradation has been done in a similar way as for the internal degradation model, with the following exceptions:

- Poles with $\delta_e > 0.15$ have been truncated from the datasets, resulting in $n = 5462$ for the CCA-treated poles and $n = 8505$ for the Creosote-treated poles.
- Only two of the geographical locations contained CCA-treated poles. Thus, 80% of the total number of CCA-treated poles were assigned to the training dataset, and the remaining 20% were reserved for the test dataset.
- The censoring threshold is set at $c_t = \frac{a+2}{t}$, as poles with a degradation dept smaller than 2 mm is believed not to have been registered. The truncation threshold is set at: $\tau_t = \left(a + 0.15\frac{D_0}{2}\right)$.
- The mean degradation rate for treated sapwood was found using $\bar{r}_{sap,tr} = \frac{k_{w,sap,un}k_a}{1+45C}$ (Wang et al. 2008).
- Agricultural land and Built-up area were used as explanatory variables for the model for external degradation in CCA-treated poles.

5. Results

The posterior distribution for r was computed using the No-U-Turn sampler (Hoffman and Gelman 2014) as implemented in version 5.23 of the PyMC Python library (Patil et al. 2010). The inferred parameters for the updated model are presented in Table 7. Fig. 5 shows comparisons between the number of degraded poles uncovered by inspections in the test datasets and the number of degraded poles predicted by the stochastic Timberlife model as presented in Ch. 7 of (Wang et al. 2008), the models proposed in (Anastasiades et al. 2024), and the updated model proposed in this paper.

Table 7. Parameters for the updated model.

Param.	Mean	Std.	HDI 3%	HDI 97%
	Internal degradation, creosote-treated poles			
β_λ	0.575	0.174	0.262	0.913
β_a	0.536	0.177	0.193	0.855
β_{agri}	0.228	0.144	-0.036	0.504
β_{forest}	-0.303	0.123	-0.547	-0.089
s	0.598	0.027	0.548	0.649
	External degradation, creosote-treated poles			
β_λ	0.867	0.096	0.688	1.048
β_a	0.024	0.007	0.011	0.037
β_{agri}	-0.006	0.006	-0.017	0.004
β_{forest}	-0.019	0.005	-0.028	-0.008
s	0.811	0.022	0.770	0.852
	External degradation, CCA-treated poles			
β_λ	-0.127	0.211	-0.524	0.259
β_a	0.152	0.023	0.108	0.191
β_{built}	0.038	0.016	0.008	0.066
β_{forest}	-0.030	0.011	-0.050	-0.009
s	0.863	0.025	0.818	0.911

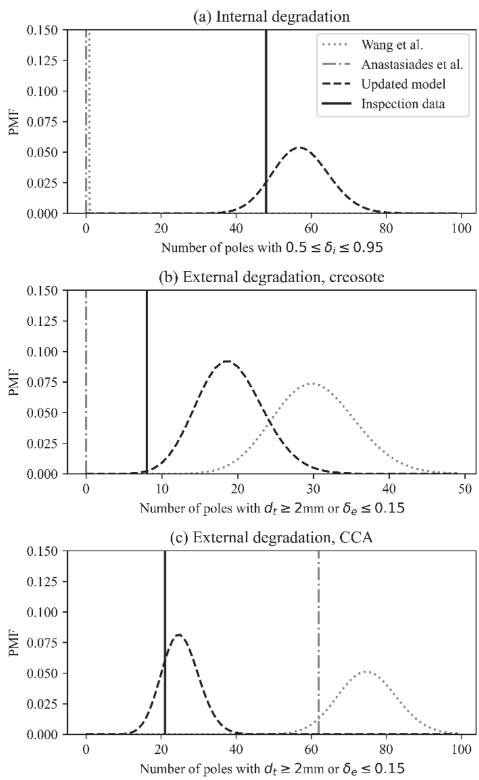

Fig. 5. Comparison between the number of degraded poles identified through inspections and the predicted number of degraded poles based on the stochastic Timberlife model as presented in (Wang et al. 2008), the model proposed in (Anastasiades et al. 2024) and the updated model proposed in this paper.

The Probability Mass Functions (PMFs) for the number of degraded poles have been found by calculating the Poisson binomial distribution based on the probability of the individual poles in the test dataset to have a share of degradation, δ, or degradation depth, d_t, as stated on the y-axis on the individual plots in Fig. 5. The probability of degradation according to the original Timberlife-model (Wang et al. 2008) has been estimated based on Monte Carlo sampling with 10 000 iterations. As only a deterministic model is presented in (Anastasiades et al. 2024), the predictions from this approach are shown as a line in Fig. 5.

In all three plots in Fig. 5, the updated model proposed in this paper is closest to the actual number of degraded poles found in the inspection data. As the oldest pole in the test dataset for internal degradation (Fig. 5 (a)) is 64 years old, none of the poles in the test dataset is, in accordance with Eq. (7), predicted to be degraded. For external degradation, the original Timberlife model (Wang et al. 2008) overestimates both the number of degraded creosote- and CCA-treated poles, see (Fig. 5 (b)) and (Fig. 5 (c)) respectively.

6. Concluding Remarks

The degradation of wooden utility poles at the ground level is a major concern for power grid companies. This is due to the large number of poles in the power grid, large variability in wood degradation, the potential for severe consequences from pole failures, and the difficulty of assessing the actual condition of the geographically dispersed wooden poles. Thus, models that improve inspection and renewal policies for wooden poles can yield considerable cost savings. The Timberlife model has been widely used to predict the degradation of wooden structures. However, comparison with inspection data collected from utility poles made of Scotch pine located in the south-eastern part of Norway shows that the original Timberlife model, as presented in (Wang et al. 2008), and the updated Timberlife model proposed by Anastasiades et al. (2024), considerably underestimates the degradation rate at the ground level for creosote-treated poles. Moreover, the updated Timberlife model proposed in (Anastasiades et al. 2024) considerably overestimates the degradation rate at ground level for CCA-treated poles.

This has motivated the development of updated models for the degradation of creosote- and CCA-treated Scotch pine utility poles in ground contact. These models are presented in Ch. 4 of this paper and Fig. 5 shows that predictions from our updated models are closer to the actual number of degrade poles than those from the previously proposed Timberlife models.

However, our proposed model has potential for improvement in several areas. For instance, the approach for determining the intercept, a, for the latent degradation depth, d_t^*, is rather ad hoc and may lead to errors in the predicted degradation rate. Another weakness is that the model assumes the degradation rate is uniform across the pole's cross-section, which may lead the number of poles predicted to have $\delta_i > 2/3$ to be too high in the updated model. The method used to account for climate also has room for improvement.

We aim to address these weaknesses in further studies by collecting a larger dataset of utility pole inspection data.

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