Buhlmann credibility model in predicting claim frequency that follows heterogeneous Weibull count distribution

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Abstract. In insurance, policyholder's claim experience is usually too limited to be given full credibility in predicting claim frequency, but policyholder's risk is usually a part of a large risk class which collective claim experience can provide information for credible statistical prediction. Credibility could be used to consider both information. By assuming that the policyholder's number of claims, given the policyholder's risk parameter, follows Weibull count distribution over its risk class, this paper explains Buhlmann credibility in predicting claim frequency. Weibull count distribution relaxes the equidispersion assumption of Poisson distribution. Thus, Weibull count distribution can handle non-equidispersed count data. This paper also shows that for a certain type of past claim frequency data, the use of Poisson assumption in Buhlmann credibility model could result in very low credibility factor which underrates the policyholder's experience.

1. Introduction

One approach to predict a policyholder's claim frequency in a certain period is by calculating the mean of that policyholder's claim frequency in previous policy periods. However, in most cases, policyholder's claim experience is too limited to be given full credibility in predicting claim frequency. Moreover, policyholder's risk is usually a part of a large risk class which collective claim experience can provide information for credible statistical prediction. One of the methods to take both informations into account is linear credibility theory first explained by Buhlmann in 1920 [2]. Credibility, in this paper, assigns weight to policyholder’s experience estimate and the collective experience estimate to predict policyholder’s claim frequency.

One of the distributions often used to model policyholder’s claim frequency is Poisson count model which has exponential interarrival times. However, Poisson count model is only valid if the data satisfy equidispersion assumption (the variance of the data equals its mean). Applying Poisson count model to the significantly overdispersed (the variance is more than its mean) or underdispersed (the variance is less than its mean) data could lead to misspecification of the distribution of the data [1]. Weibull distribution which is a generalization of exponential, is considered in this paper to develop a count model that can handle both overdispersion and underdispersion. Weibull interarrival times could handle overdispersed data when its shape parameter \( c \) is \( 0 < c < 1 \), and underdispersed data when \( c > 1 \), and is reduced as exponential when \( c = 1 \) [4]. The count model is called Weibull count model.

This paper explains Weibull count and heterogeneous Weibull count distribution. Heterogeneous Weibull count distribution could be used to fit the data distribution of a policyholder's past claim frequency in order to predict the next period claim frequency. By assuming that the policyholder’s number of claims, given the policyholder’s risk parameter, follows Weibull count distribution over its
risk class, this paper then explains an approach by Buhlmann credibility model in predicting claim frequency. Finally, we show that for a certain type of past claim frequency data, the use of Poisson assumption in Buhlmann credibility model could result in very low credibility factor which underrates the policyholder’s experience.

2. Weibull count model

Weibull count model is obtained by Taylor expansion and convolution method. The model is in recursive form, and by mathematical induction we obtain that the general form for $P(N(t) = n)$ is

$$ P(N(t) = n) = C_n(t) = \sum_{h=n}^{\infty} (-1)^{h+n} (\lambda t^r)^h \alpha_h^n, \quad n = 0, 1, 2, \ldots, \quad t > 0 \text{ and } \gamma, \lambda > 0 [4], $$

(1)

where

$$ \alpha_n^r = \begin{cases} \frac{1}{h+1}, & \text{for } n = 0, h = 0, 1, 2, \ldots \\ \frac{1}{h+1} \sum_{m=1}^{\infty} \frac{(-1)^{m+n} (\lambda t^r)^h \alpha_h^n}{\Gamma(h+1)}, & \text{for } n = 1, 2, \ldots, h = n+1, n+2, n+3, \ldots \end{cases} $$

The expectation of this model is given by

$$ E(N(t)) = \sum_{n=1}^{\infty} n C_n(t) = \sum_{n=1}^{\infty} \sum_{h=n}^{\infty} n^2 (-1)^{h+n} (\lambda t^r)^h \alpha_h^n, $$

and its variance is given by

$$ \text{Var}(N(t)) = E([N(t)]^2) - (E[N(t)])^2 = \sum_{n=1}^{\infty} \sum_{h=n}^{\infty} n^2 (-1)^{h+n} (\lambda t^r)^h \alpha_h^n, $$

and

$$ \frac{\sum_{n=1}^{\infty} \sum_{h=n}^{\infty} n! (-1)^{h+n} (\lambda t^r)^h \alpha_h^n}{(\gamma + 1)^{n+1}}. $$

[4].

3. Heterogeneous Weibull count model

In Weibull count model, the value of lambda or the rate of event is assumed to be constant for every event. Otherwise, in heterogeneous Weibull count model, the rate of event varies across the population of units (heterogeneous). Let $\lambda_i$ be the value of $\Lambda_i$ that denotes the rate of event of unit $i$. $\Lambda_i$ is assumed to follow gamma distribution with shape parameter $r$ and rate $a$, and the pdf is
g\left(\lambda_i \mid r, a\right) = a^r (\lambda_i)^{r-1} e^{-a\lambda_i} / \Gamma(r)$. The unconditional probability that the number of events from unit $i$ up until time $t$ is $n$ is obtained by mixing.

$$ P(N(t) = n) = \int_0^n P[N(t) = n \mid \Lambda_i = \lambda_i] \cdot g(\lambda_i \mid r, a) d\lambda_i $$

Finally, the heterogeneous Weibull count model could be written as follows

$$ P(N(t) = n) = \sum_{h=n}^{\infty} \frac{(-1)^{h+1} (\lambda t^r)^h \alpha_h^n}{\Gamma(h+1)} \frac{\Gamma(r+h)}{\Gamma(r)a^h}, \quad \text{for } n = 0, 1, 2, \ldots, $$

where

$$ \alpha_n^r = \begin{cases} \frac{1}{h+1}, & \text{for } n = 0, h = 0, 1, 2, \ldots \\ \frac{1}{h+1} \sum_{m=1}^{\infty} \frac{(-1)^{m+n} (\lambda t^r)^h \alpha_h^n}{\Gamma(h+1)}, & \text{for } n = 1, 2, \ldots, h = n+1, n+2, n+3, \ldots \end{cases} $$

[4].

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The expectation of this model is given by
\[ E(N(t)) = \sum_{n=1}^{\infty} nC_n(t) = \sum_{n=1}^{\infty} \sum_{h=1}^{n} \frac{n(-1)^{h+n}(t^h)^h a_n^h \Gamma(r+h)}{\Gamma(ch+1) \Gamma(r)a^h} . \]
and its variance is given by
\[ \text{Var}(N(t)) = E\left(\left[N(t)\right]^2\right) - \left(E[N(t)]\right)^2 \]
\[ = \sum_{n=1}^{\infty} \sum_{h=1}^{n} \frac{n^2(-1)^{h+n}(t^h)^h a_n^h \Gamma(r+h)}{\Gamma(ch+1) \Gamma(r)a^h} - \left(\sum_{n=1}^{\infty} \sum_{h=1}^{n} \frac{n(-1)^{h+n}(t^h)^h a_n^h \Gamma(r+h)}{\Gamma(ch+1) \Gamma(r)a^h}\right)^2 \] [4].

4. Buhlmann credibility in predicting claim frequency that follows heterogeneous Weibull count distribution
In this section we will derive a Buhlmann credibility model with assumption that the policyholder’s number of events with unknown risk parameter follows Weibull count distribution. We derive this model the same way Buhlmann derived his credibility model in 1920 which is stated as follows.
\[ \alpha_0 + \sum_{j=1}^{n} \alpha_j X_j = Z\bar{X} + (1-Z)\mu, \]
where \( Z = \frac{n}{n+k} \), which is called the credibility factor, \( k = \frac{\nu}{\gamma} \), \( \bar{X} = \frac{1}{n} \sum_{j=1}^{n} X_j \), and \( \mu = E[\mu(\theta)] \).
\( \nu = E[\nu(\theta)] \), \( \gamma = Var[\mu(\theta)] \) [3]. \( \mu(\theta) \) is the hypothetical means or mean of individual risks in a certain risk class. \( \nu(\theta) \) is process variance or could also be described as the variability measure in policyholder’s risk experience.

Before deriving the Buhlmann credibility model using Weibull count assumption, we first recall the Buhlmann credibility model if the assumption used is that the individual number of events, conditional on the policyholder’s risk parameter, follows Poisson distribution. Suppose the number of claims of a policyholder in year \( j \) with unknown risk parameter \( \theta \), \( X_j|\theta \) are assumed to be independently and identically Poisson distributed for \( j = 1, \ldots, n \). We also assume that the risk parameter follows gamma distribution with shape parameter \( r \) and rate \( a \). Then,
\[ \mu(\theta) = E[X_j|\Theta = \theta] = \theta \] and \( \nu(\theta) = Var[X_j|\Theta = \theta] = 0. \]
Thus,
\[ \mu = E[\mu(\Theta)] = E[\Theta] = ra, \quad \nu = E[\nu(\Theta)] = E[\Theta] = ra \] and \( \gamma = Var[\mu(\Theta)] = Var[\Theta] = ra^2. \)
Then we could obtain \( k \)
\[ k = \frac{\nu}{\gamma} = \frac{ra}{ra^2} = \frac{1}{a} \]
and the credibility factor \( Z \)
\[ Z = \frac{n}{n+k} = \frac{n}{n + \frac{1}{a}} = \frac{na}{na+1}. \]
Thus, the credibility model is
\[ Z\bar{X} + (1-Z)\mu = \frac{na}{na+1} \bar{X} + \frac{1}{na+1} ra \] [3].

Finally, we derive the Buhlmann credibility model assuming that the number of events of a policyholder, conditional on the policyholder’s risk parameter, follows Weibull count distribution. The policyholder’s risk parameter in this paper is denoted by \( \lambda_i \). We assume that the value \( \lambda_i \) varies and represents heterogeneity among the individuals. We also assume that its random variable \( \Lambda_i \) follows gamma distribution.
Assumption 4.1
1. $N_j | \lambda_i$ are independent and follow Weibull count distribution for $j = 1, \ldots, w$ with
$E[N_j | \lambda_i] = \mu(\lambda_i)$ and $\text{Var}[N_j | \lambda_i] = \sigma^2(\lambda_i)$ where $\mu(\lambda_i)$ and $\sigma^2(\lambda_i)$ are the hypothetical mean and process variance which are respectively the mean and variance of the Weibull count model.
2. $\lambda_i$ is the value of $\Lambda_i$ where $\Lambda_i$ follows gamma distribution with shape parameter $r$ and rate $a$.

By double expectation theorem, $E[N_{(i+1)}] = (N_{1, \ldots, N_{w}})^T$ and $N_{(i+1)}$ is independent of $(N_j, j = 1, 2, \ldots, w)$. It is also assumed that $(N_j | \Lambda_i)$ are independent for $j = 1, \ldots, w, w+1$ [2]. Thus, the linear estimator for predictive random variable $N_{(i+1)}$ is [2]

$$\mu_{i+1}(\Lambda_j) = \alpha_0 + \sum_{k=1}^m \alpha_{i+k} N_{i+k}$$

(2)

where the value of $\alpha_0, \alpha_{i1}, \ldots, \alpha_{mw}$ which we will notate by $\alpha_{0j}, \alpha_{i1}, \ldots, \alpha_{mw}$ would be chosen by minimizing the expected quadratic error $Q = E\left[\left(\mu_{i+1}(\Lambda_j) - \alpha_0 - \sum_{k=1}^m \alpha_{i+k} N_{i+k}\right)^2\right]$. To do so, we differentiate $Q$ with respect to $\alpha_0$ and $\alpha_{i1}, \ldots, \alpha_{mw}$ and set the equations equal to zero which result in (3) for $j = 0$ and (4) for $j > 0$.

$$E\left[\mu_{i+1}(\Lambda_j)\right] = \alpha_0 + \sum_{k=1}^m \alpha_{i+k} E[N_{i+k}]$$

(3)

$$E\left[\mu_{i+1}(\Lambda_j) N_j\right] = \alpha_0 E[N_j] + \sum_{k=1}^m \alpha_{i+k} E[N_j N_{i+k}]$$

(4)

By double expectation theorem, $E\left[\mu_{i+1}(\Lambda_j)\right]$ and $E\left[\mu_{i+1}(\Lambda_j) N_j\right]$ could be stated respectively as (5) and (6).

$$E\left[\mu_{i+1}(\Lambda_j)\right] = E\left[E\left[N_{(i+1)} | \Lambda_j\right]\right] = E\left[N_{(i+1)}\right]$$

(5)

$$E\left[\mu_{i+1}(\Lambda_j) N_j\right] = E\left[E\left[\mu_{i+1}(\Lambda_j) N_j | \Lambda_j\right]\right] = E\left[E\left[N_{(i+1)} | \Lambda_j\right] E[N_j | \Lambda_j]\right]$$

$$= E\left[E\left[N_{(i+1)} N_j | \Lambda_j\right]\right] = E\left[N_j N_{(i+1)}\right]$$

(6)

Thus, (3) and (4) becomes

$$E\left[N_{(i+1)}\right] = \alpha_0 + \sum_{k=1}^m \alpha_{i+k} E[N_{i+k}]$$

(7)

$$E\left[N_j N_{(i+1)}\right] = \alpha_0 E[N_j] + \sum_{k=1}^m \alpha_{i+k} E[N_j N_{i+k}]$$

(8)

By (7) and (8), we obtained

$$\text{Cov}(N_j, N_{(i+1)}) = \sum_{k=1}^m \alpha_{i+k} \text{Cov}(N_j, N_{i+k})$$

(9)

Note that we will predict the number of claims of policyholder $i$ in period $w+1$ given the information of that policyholder in periods $j = 1, 2, \ldots, w$ which means $t = 1$ period or 1 year. Thus,
because the number of claims of a policyholder conditional on $\Lambda_i$ is assumed to follow Weibull count distribution, the hypothetical means is

$$\mu(\chi_i) = \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \chi_i,$$

and the process variance is

$$\sigma^2(\chi_i) = \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n^2(-1)^{h+n} \alpha_h \chi_i - \left( \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \chi_i \right)^2.$$

$N_j | \Lambda_i$ are independent for $j = 1, 2, ..., w$ so it is obtained that

$$E[N_j | \Lambda_i] = \mu(\chi_i) = \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \chi_i,$$

and

$$\text{Var}[N_j | \Lambda_i] = \sigma^2(\chi_i) = \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n^2(-1)^{h+n} \alpha_h \chi_i - \left( \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \chi_i \right)^2.$$

Thus, for a policyholder $i$, we define $\mu_0$ as the mean of hypothetical means

$$\mu_0 = E[\mu(\Lambda_i)] = E\left[ \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Lambda_i \right]$$

$$= \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Gamma(ch+h) \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Gamma(ch+h)$$

$$= \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Gamma(r+h) \Gamma(r) a_h,$$

which turns out to be the mean of heterogeneous Weibull count model, $\sigma^2$ as mean of the process variance

$$\sigma^2 = E[\sigma^2(\Lambda_i)] = E\left[ \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n^2(-1)^{h+n} \alpha_h \chi_i - \left( \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \chi_i \right)^2 \right]$$

$$= \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Gamma(r+h) \Gamma(r) a_h - E\left[ \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Lambda_i \right]^2,$$

and $\tau^2$ as the variance of the hypothetical means

$$\tau^2 = \text{Var}[\mu(\Lambda_i)] = \text{Var}\left[ \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \alpha_h \Lambda_i \right].$$

By (10), (11), and (12), the mean and variance of $N_{ij}$ and the covariance between $N_{ij}$ and $N_{ik}$ could be obtained.

$$E[N_{ik}] = E\left[ E(N_{ik} | \Lambda_i) \right] = E[\mu(\Lambda_i)] = \mu_0$$

$$\text{Var}[N_{ik}] = E[\text{Var}(N_{ik} | \Lambda_i)] + \text{Var}[E(N_{ik} | \Lambda_i)] = E[\sigma^2(\Lambda_i)] + \text{Var}[\mu(\Lambda_i)] = \sigma^2 + \tau^2$$

$$\text{Cov}(N_{ij}, N_{ik}) = \begin{cases} \text{Var}[N_{ij}] = \sigma^2 + \tau^2, & \text{for } j = k \\ E[N_{ij}N_{ik}] - E[N_{ij}]E[N_{ik}] = E\left[ E(N_{ij} | \Lambda_i)E(N_{ik} | \Lambda_i) \right] - E[\mu(\Lambda_i)]^2 
= \text{Var}[\mu(\Lambda_i)] = \tau^2, & \text{for } k \neq j \end{cases}$$
Substituting (13), (14), and (15) to (7), we obtain that

\[
\bar{\alpha}_{i0} = 1 - \sum_{k=1}^{w} \bar{\alpha}_{ik}
\]  

(16)

and subtituting (13), (14), and (15) to (9), we obtain that

\[
\bar{\alpha}_{gi} = \frac{\tau^2}{\sigma^2} \left(1 - \sum_{k=1}^{w} \bar{\alpha}_{ik}\right).
\]  

(17)

By (16) and (17), we obtain

\[
\alpha_{i0} = \frac{\sigma^2}{\tau^2} \mu_0 + \sum_{k=1}^{w} \frac{1}{w+\sigma^2/\tau^2} N_{ik} \left(1 - \frac{w}{w+\sigma^2/\tau^2}\right) \mu_0 \frac{w}{w+\sigma^2/\tau^2} \sum_{k=1}^{w} \frac{1}{w} N_{ik}
\]  

(20)

Substituting (18) and (19) to (2), we have the Buhlmann credibility model stated in (20).

Finally, with an assumption that the number of claims of policyholder in year \(j\), given that the risk profile of policyholder is gamma distributed with shape \(r\) and rate \(\alpha\), follows Weibull count distribution, the Buhlmann credibility model to predict the number of claims of a policyholder \(i\) in a certain policy period could be stated as (21).

\[
\mu_{i=1}(\Lambda_i) = \bar{\alpha}_{i0} + \sum_{k=1}^{w} \bar{\alpha}_{ik} N_{ik} = \eta_i N_i + (1 - \eta_i) \mu_0,
\]  

(21)

where

\[
\eta_i = \frac{w}{w+\kappa},
\]  

which is called the credibility factor and denoted by \(Z\) in the original Buhlmann credibility model,

\[
\kappa = \frac{\sigma^2}{\tau^2}, \quad N_i = \sum_{k=1}^{w} \frac{1}{w} N_{ik}
\]  

and

\[
\mu_0 = \sum_{h=0}^{\infty} \sum_{h=0}^{\infty} n(-1)^{h+n} \left(\frac{r^h}{\Gamma(r+h)}\right) \frac{\alpha_h^n \Gamma(r+h)}{\Gamma(r) \alpha_h^{n}},
\]  

(22)

\[
\sigma^2 = \sum_{h=0}^{\infty} \sum_{h=0}^{\infty} \frac{n(-1)^{h+n} \left(\frac{r^h}{\Gamma(r+h)}\right) \alpha_h^n \Gamma(r+h)}{\Gamma(c+h+1)} \frac{\Gamma(r+h)}{\Gamma(r) \alpha_h^{n}} - \frac{\left(\sum_{h=0}^{\infty} \sum_{h=0}^{\infty} \frac{n(-1)^{h+n} \alpha_h^n \Lambda_h}{\Gamma(c+h+1)} \right)^2}{\sum_{h=0}^{\infty} \sum_{h=0}^{\infty} \frac{n(-1)^{h+n} \alpha_h^n \Lambda_h}{\Gamma(c+h+1)}}
\]  

(23)

\[
\tau^2 = \text{Var}\left(\sum_{h=0}^{\infty} \sum_{h=0}^{\infty} \frac{n(-1)^{h+n} \alpha_h^n \Lambda_h}{\Gamma(c+h+1)}\right)
\]  

(24)

\(\mu_0\) is the mean of hypothetical means and is analogous to \(\mu\) in the original Buhlmann credibility model. \(\sigma^2\) is the mean of the process variance and is analogous to \(\nu\), \(\tau^2\) is the variance of the
hypothetical means and is analogous to \( y \), and \( N_i \) is the average value of policyholder \( i \)'s claim experience which is denoted by \( \bar{X} \) in the original Buhlmann credibility model.

5. Testing and results
In this section we show the outcome of using Poisson assumption and Weibull count model assumption in Buhlmann credibility model for a type of past claim frequency data which could illustrate claim frequency data in fire insurance.

| Number of Claims | Number of Policies |
|------------------|-------------------|
|                  | Year              |
|                  | 1     | 2     | 3     | 4     | 5     | 6     |
| 0                | 1661  | 1650  | 1653  | 1677  | 1668  | 1682  |
| 1                | 573   | 584   | 581   | 557   | 566   | 552   |
| 2+               | 0     | 0     | 0     | 0     | 0     | 0     |

We will compare the credibility factors obtained when the individual number of events, conditional on the policyholder’s risk parameter, is assumed to follows Poisson distribution and when it is assumed to follows heterogeneous Weibull count distribution.

This table below shows the parameter estimates obtained when fitting the data with Weibull count model with parameters \( c \) and \( \lambda \), and Poisson model with parameters \( \mu \), where the lambda has gamma distribution with shape \( r \) and rate \( a \). The Weibull count parameter estimates are obtained by maximizing the likelihood function

\[
l(c,r,a) = \ln \prod_i P(N = n_i) = \sum_i \ln \frac{\Gamma(c+h)}{\Gamma(ch+1)} \left( \frac{r}{a} \right)^{n_i} \Gamma(h+1) \Gamma(r+h) \]

and the Poisson parameter estimates are obtained using \texttt{fitdist} command in \texttt{R} software.

| Parameters | Count models | Poisson |
|------------|--------------|---------|
| \( \hat{c} \) | 8        | -       |
| \( \hat{r} \) | 3        | 100.00000063 |
| \( \hat{a} \) | 10       | 344.0660989 |

We then obtain the structural parameters of the Buhlmann credibility model assuming the data follows the two count models. As for the Weibull count, we subtitute the value of \( c, r, \) and \( \lambda \) obtained to (22), (23), and (24) and obtain the estimate using \texttt{R} software. For the Poisson it is simply that \( \mu = \nu = \frac{r}{a} \) and \( y = \frac{r}{a^2} \). The results are shown below.

| Parameters of Buhlmann credibility model | Count models | Poisson |
|-----------------------------------------|--------------|---------|
| \( \hat{\mu}_0 \) | 0.2487129   | \( \hat{\mu} \) | 0.29064183 |
| \( \hat{\sigma}^2 \) | 0.17420341  | \( \hat{\nu} \) | 0.29064183 |
| \( \hat{\tau}^2 \) | 0.01434385  | \( \hat{y} \) | 8.447267281e-4 |
| \( k = \hat{\sigma}^2 / \hat{\tau}^2 \) | 12.4481537   | \( k = \hat{\nu} / \hat{y} \) | 344.0660989 |
The credibility factor for a policyholder using Poisson assumption would be $Z = 6/(6 + k) = 0.01713962026$. In that case, at least 39 years of claim experience of a policyholder is needed only to obtain credibility factor of 0.1. Otherwise, by relaxing the model to Weibull count, we obtain that the credibility factor for a policyholder is $\eta = 6/(6 + \kappa) = 0.3306729706$. The result obtained by using Weibull count assumption seems to be more fair.

6. Conclusion
We have shown that for a certain type of past claim frequency data, the use of Poisson assumption in Buhlmann credibility model could result in very low credibility factor. This could be considered underrating policyholder’s experience. On the other hand, Weibull count assumption results in more reasonable credibility factor.

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