UNP JOURNAL MANAGEMENT CENTER

math.ppj.unp.ac.id
p-ISSN 2716-0726
e–ISSN 2716-0734

Indexed

Comparison of Generalized Poisson Regression and Negative Binomial Regression Models in Handling Overdispersion in Downtime Cases

Celsy Aprotama[1], Fadhilah Fitri[1] and Yenni Kurniawati[1]

[1] Departement of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Negeri Padang

Article History
Received: Aug 12, 2025 | **Revised**: Sep 23, 2025 | **Accepted**: Sep 24, 2025 | **Published Online**: Oct 29, 2026

Subject Areas:
Statistic, Applied Statistics

Keywords:
Overdispersi, Generalized Poisson Regression, Negative Binomial Regression, Data Count, Downtime

Author for correspondence:
Celsy Aprotama
e-mail: celsyaprotamaaa@gmail.com

DOI:
https://doi.org/10.24036/rmj.v5i2.94

How to Cite:
Aprotama, C., Fitri, F., &Kurniawati, Y. (2026). Comparison of Generalized Poisson Regression and Negative Binomial Regression Models in Handling Overdispersion in Downtime Cases. *Rangkiang Mathematics Journal*, 5(2), 132-140.
https://doi.org/10.24036/rmj.v5i2.94

Abstract- Downtime in industrial machinery has a significant impact on efficiency and operational costs. To model the number of downtime events, Poisson regression is used, which has several assumptions, including that the response variable must be Poisson distributed, there is no linear relationship between predictor variables (multicollinearity), and the variance is equal to the mean (equidispersion). However, in practice, violations of these assumptions are often encountered, where the variance of the response variable exceeds its mean, known as overdispersion. This issue can be addressed using approaches such as Generalized Poisson Regression (GPR) and Negative Binomial Regression (NBR). In this study, a comparison of the GPR and NBR models will be conducted using secondary data from the cement manufacturing industry in Indonesia, consisting of downtime as the response variable and five predictors: duration of disruptions, number of mechanical and electrical disruptions, raw material availability, and production output. Assumption tests showed no multicollinearity and that the response distribution followed a Poisson distribution, but overdispersion was present. The results show that all predictor variables in the GPR and NBR models are significant except for the duration variable, which does not significantly affect the amount of downtime. The best model is determined based on the smallest Akaike Information Criterion. (AIC) and Root Mean Square Error (RMSE) values. The results show that GPR has an AIC of 148.3074 and an RMSE of 3.608414, while NBR has an AIC of 48.3083 and an RMSE of 3.608534. Based on these criteria, GPR was selected as the superior model.

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1. Introduction

Downtime in industrial machinery is a critical issue that directly impacts operational efficiency and production costs. Downtime is divided into two categories: planned downtime, which refers to scheduled downtime such as routine maintenance or overhauls, and unplanned downtime, which refers to unscheduled downtime caused by sudden breakdowns or disruptions (Rusdi et al., 2019). This study focuses on unplanned downtime, as these incidents are unpredictable and often the main cause of decreased machine productivity in the manufacturing sector.

To identify the factors that influence the number of downtime incidents, statistical modeling can be used to aid preventive and predictive decision-making in the field of machine maintenance (Andrzejczak et al., 2018). One approach that can be used is Poisson regression, which is used when the response variable is discrete and does not follow a normal distribution, but rather a Poisson distribution, while the predictor variables are either discrete or continuous (Guntur et al., 2022). The assumptions that must be made by Poisson regression include the mean value being equal to the variance value, or what is known as equidispersion (Safrida et al., 2013). However, problems are often found in the data, namely when the variance is greater than the expected value or overdispersion, causing the assumption of equidispersion in Poisson regression to not be fulfilled (Hilbe, 2014). Other models that can address the problem of overdispersion include Negative Binomial Regression (NBR) and Generalized Poisson Regression (GPR). NBR adds a dispersion parameter to accommodate higher variation, while GPR can handle both overdispersion and underdispersion and has greater flexibility with count data with many zeros (Famoye, 2007).

Previous studies have compared the performance of GPR and NBR in handling overdispersion in count data. In general, the results show that the superiority of the two models depends on the characteristics of the data used. In a study using data on total cervical cancer cases in East Java, both models were found to be capable of handling overdispersion, but GPR provided more stable estimates for data with many zero values (Irawati & Purhadi, 2012). Another study on roof tile businesses in Bali found that GPR and NBR were equally effective, with no significant difference in performance (Keswari et al., 2014). Conversely, analysis of data on deaths due to dengue fever in South Sulawesi shows that NBR is superior based on the AIC value (Satriani, 2022).

In the case of data on the total poor population in Central Java, GPR showed a lower AIC value and was therefore considered better (Sihombing, 2023). Similar findings were also reported by Yadav et al. (2021), who reported that GPR had lower AIC and BIC values and smaller bias and MSE compared to NBR, even under conditions of high zero inflation (Yadav et al., 2021). In addition, the application of GPR to dengue fever data with high overdispersion levels also showed superior performance (Al Haris & Arum, 2022).

However, most studies comparing the performance of GPR and NBR models are still focused on health, population, or social issues. There are not many studies that apply both models to model industrial machine downtime specifically, especially in the manufacturing sector in Indonesia. Therefore, this article aims to compare the performance of GPR and NBR models in modeling the amount of downtime in grinding machine units in the cement industry.

The research method contains steps in obtaining results ranging from research instruments, instrument validation, data collection, data analysis. The authors are not allowed to describe the definition of those terms. The provision of the literature review articles is that the formulation of the problem must appear explicitly and the examining method should be written in this section. Especially for mathematical research, such as problem solving and not using certain methods, this section may be omitted. The order presented in the method section must be in accordance with the order in the research results section.

2. Methods

This study uses a quantitative method with an inferential approach to compare the performance of the Generalized Poisson Regression (GPR) and Negative Binomial Regression (NBR) models in modeling count data related to machine downtime in the manufacturing industry.

(a) Data and Variables

The data used is secondary data obtained from the internal recording system of one of Indonesia's national manufacturing industries. To maintain company confidentiality, the data has been anonymized, and the analysis unit used consists of 24 production system components in one year. Each unit reflects the frequency of downtime events observed in conjunction with five related independent as show in Table 1.

Table 1. Variables and Definitions

Variable Name	Variable Type	Description
Amount of downtime	Respon (Y)	Number of downtime incidents on machine components during the observation period
Duration	Prediktor (X_1)	Total downtime duration for each component (hours)
Mechanical	Prediktor (X_2)	Number of downtime incidents due to mechanical factors
Electrical	Prediktor (X_3)	Number of downtime incidents due to electrical factors
Raw materials	Prediktor (X_4)	Number of incidents due to raw material supply issues
Production output	Prediktor (X_5)	Total production output for that component (tons)

(b) Steps of Analysis

Rstudio software was used to analyze the data. The steps in this study were as follows:

1. Descriptive Data
   The condition of the data will be examined through descriptive analysis.

2. Assumption Testing
   Poisson regression has several assumptions that must be met, namely the response variable must follow a Poisson distribution, there must be no high linear correlation between predictor variables (multicollinearity), and the assumption of equidispersion must be met, which is the condition where the mean is equal to the variance. To test whether the response variable is Poisson-distributed, the Kolmogorov-Smirnov test can be used (Cahyandari, 2014). In this test, H_0 states that the response variable follows a Poisson distribution and H_1 states the opposite. The test statistic D is calculated based on the following equation (1):

   $$D = \max|F_s(y) - F_r(y)| \quad (1)$$

   If the value of D exceeds the Kolmogorov-Smirnov critical point, then H_0 is rejected.
   Meanwhile, to detect multicollinearity, one method used is to look at the Variance Inflation Factor (VIF) value. The VIF value for the jth predictor variable can be calculated using Equation (2).

   $$VIF_j = \frac{1}{(1-R_j^2)}, \text{ untuk j=1,2,...,p} \quad (2)$$

   When the VIF value exceeds 10, the assumption of non-multicollinearity is not met, or there is correlation among the predictor variables (Dobson & Barnett, 2008).

3. Modeling using Poisson Regression
   This model is part of the Generalized Linear Model (GLM) that links the expected value of the response variable $\mu_i = E(Y_i)$ with a linear combination of predictor variables through a logarithmic link function (Agresti, 2015). The Poisson regression model can be generally written as equation (3) below:

$$ln\ \mu_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} \quad (3)$$

or in exponential form in equation (4):

$$\mu_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi}) \quad (4)$$

Overdispersion often occurs when the variance value is greater than the mean value, thereby violating the assumption of equidispersion (Hilbe, 2007). To detect overdispersion, the Pearson Chi-Square test statistic can be used. The hypotheses used for this test are H_0: ϕ or data with overdispersion and H_1 for data without overdispersion. The Pearson Chi-Square test statistic is expressed in equation (5).

$$\sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{\hat{\sigma}_i^2} \sim X^2_{(n-1)} \quad (5)$$

The response variable is said to be overdispersed if the Pearson chi-square test statistic divided by the degrees of freedom as in equation (6) yields a value greater than one.

$$\phi = \frac{X^2_{(n-k)}}{n-k} \quad (6)$$

4. Modeling using Generalized Poisson Regression

GPR is designed as an extension of Poisson regression to handle overdispersion and underdispersion in count data, where the variance can be greater or smaller than the mean value. This model adds a dispersion parameter θ such that when θ = 0, GPR reduces to pure Poisson regression. If $\theta > 0$or $\theta < 0$ the model can flexibly capture overdispersion or underdispersion (Irawati & Purhadi, 2012). The general log-likelihood function for GPR is shown in the following equation (7):

$$\ln L(\beta, \theta) = \sum_{i=0}^{n} \begin{Bmatrix} y_i\left(X_i^T\beta\right) - y_i ln\left(1 + \theta\ exp\left(X_i^T\beta\right)\right) + (y_i - 1)\ln(1 + \theta y_i) \\ -\ln(y_i!) - \exp\left(X_i^T\beta\right)(1 + \theta y_i)\left(1 + \theta\ exp\left(X_i^T\beta\right)\right)^{-1} \end{Bmatrix} \quad (7)$$

The parameters β and θ are estimated using the Maximum Likelihood Estimation (MLE) method with numerical algorithms such as Newton–Raphson to solve the system of derivative equations from the log likelihood. In model testing, the significance of parameter β is tested simultaneously using the likelihood ratio test, as well as tested partially with z-statistics based on standard error estimates (Hastie & Pregibon, 2017).

5. Modeling using Negative Binomial Regression

NBR is one of the models in GLM used to model count data when overdispersion occurs, i.e., when the data variance is greater than the mean value. The NBR model is an alternative to Poisson Regression, which assumes equidispersion, while NBR accommodates overdispersion by adding the dispersion parameter α so that the variance follows the form in equation (8):

$$Var(y_i) = \mu_i + \alpha\mu_i^2 \quad (8)$$

When α = 0 the NBR model becomes identical to the Poisson model (Hilbe, 2007). The NBR model is written in the form of a Generalized Linear Model (GLM) with a logarithmic link function in equation (9):

$$ln(\mu_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} \quad (9)$$

The log likelihood function for negative binomial can be expressed in equation (10) (Serwaa Omari-Baah, 2018):

$$\ln L(\theta, \beta) = \sum_{i=1}^{n} \begin{Bmatrix} \left(\sum_{i=0}^{y_i - 1} \ln(y_i + \theta^{-1})\right)\left(X_i^T\beta\right) - \ln(y_i!) - (y_i + \theta^{-1})\ x \\ ln\left(1 + \theta\ exp\left(X_i^T\beta\right)\right) + y_i ln\theta + y_i X_i^T\beta \end{Bmatrix} \quad (10)$$

where $\mu_i = \exp\left(X_i^T\beta\right)$ is a linear combination of predictors and θ is the dispersion parameter.

6. Compare the best models from the GPR and NBR results using the AIC and RMSE values.

In selecting the best model, several measures can be used, including the Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE), where the best model has the smallest AIC and RMSE values. AIC can be defined as the following equation (11):

$$AIC = -2 \ln L\left((y|\hat{\mu}) + 2p\right) \quad (11)$$

here $\ln L\left((y|\hat{\mu}) + 2p\right)$ = is the ln of the model involving all predictor variables.

3. Results and Discussion

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(a) Data and Variables

Descriptive statistics of the data are presented in Table 2.

Table 2. Descriptive statistics of the data

Variable	Minimum	Maximum	Mean	Standard Deviation
Y	0	43	21.12	28
X_1	0	241.18	81.24	1125.42
X_2	0	32	9.87	12.25
X_3	0	10.25	2.5	5.75
X_4	0	21	6.54	10.25
X_5	0	79641	43913	57542

Based on the results of the descriptive analysis, the total downtime ranged from 0 to 43 incidents per month with an average of 21.12 and a standard deviation of 28, indicating significant fluctuations between components. The variables of downtime duration, mechanical and electrical disturbances, raw material availability, and production output also showed a similar pattern, with standard deviation values exceeding the average values.

(b) Assumption Test

To test whether the response variable follows a Poisson distribution, the Kolmogorov-Smirnov test was conducted using RStudio software, yielding a p-value of 0.09517. If $\alpha = 0.05$ then p-value > α, so there is insufficient evidence to reject H_0. This means the response variable satisfies the assumption of a Poisson distribution. The results of the multicollinearity test are shown in Table 3.

Table 3. IF Values of Predictor Variables

Variable	VIF
X_1	9.710473
X_2	2.676390
X_3	5.198404
X_4	3.714136
X_5	1.843740

The results in Table 3 show that the predictor variables as a whole have VIF values less than 10, indicating no multicollinearity among the five predictor variables. Therefore, all predictor variables are suitable for inclusion in the model.

(c) Poisson Regression Modeling

Parameter estimation using Poisson regression modeling is shown in Table 4.

Table 4. Parameter Estimation Results of the Poisson Regression Model

Parameter	Estimate	Standard Error	z-value	p-value
β_0	1.368	1.869e-01	7.321	2.47e-13
β_1	-0.00216	2.121e-03	-1.018	0.308508
β_2	0.0484	8.629e-03	5.612	2.00e-08
β_3	0.07011	1.937e-02	3.620	0.000294
β_4	0.0601	1.477e-02	4.070	4.70e-05
β_5	0.00000985	3.233e-06	3.048	0.002306

Modeling using the Poisson regression method yields parameter estimates as shown in Table 4. Based on these results, the model using equation (4) is formulated as:

$$\mu_i = \exp(1.368 - 0.00216x_1 + 0.0484x_2 + 0.07011x_3 + 0.0601x_4 + 0.00000985x_5$$

Based on the results of the negative binomial regression modeling, it was found that the Mechanical, Electrical, Raw Material Availability, and Production Output variables significantly. influence the monthly downtime when $\alpha = 0.05$ while Total Duration of Disruptions does not significantly influence it. Each additional case of mechanical disruption increases the amount of downtime by approximately 5%, electrical disruptions by 7.3%, and raw material availability issues by 6.2%. Additionally, an increase in production output has a positive effect, albeit very small, where each additional ton of production output increases the amount of downtime by 0.000985%. Thus, the model indicates that the type of disruption cause and production volume are important factors influencing the frequency of machine downtime. To use this model, the assumption of equidispersion must be tested using the Pearson chi-square test. The test results show that the value of ϕ is 1.2097, so $\phi > 1$ indicates that there is overdispersion. This can cause the standard error in the Poisson regression model to be underestimated. Therefore, further modeling was performed using GPR and NBR.

(d) Modeling using Generalized Poisson Regression

Table 5. Estimated parameters of the GPR Model

Parameter	Estimate	Standard Error	z-value	p-value
$\boldsymbol{\beta_0}$	1.368	1.869e-01	7.321	2.47e-13
$\boldsymbol{\beta_1}$	-0.00216	2.121e-03	-1.018	0.308491
$\boldsymbol{\beta_2}$	0.0484	8.629e-03	5.612	2.00e-08
$\boldsymbol{\beta_3}$	0.07011	1.937e-02	3.620	0.000294
$\boldsymbol{\beta_4}$	0.0601	1.477e-02	4.070	4.70e-05
$\boldsymbol{\beta_5}$	0.00000985	3.233e-06	3.048	0.002306

Modeling using the GPR method produces parameter estimates as shown in Table 5. Based on these results, the model using equation (4) is formulated as:

$$\mu_i = \exp(1.368 - 0.00216x_1 + 0.0484x_2 + 0.07011x_3 + 0.0601x_4 + 0.00000985x_5$$

In the GPR model, the AIC value obtained was 148.3074.

(e) Modeling using Negative Binomial Regression

Table 6. Estimated parameters of the NBR Model

Parameter	Estimate	Standard Error	z-value	p-value
$\boldsymbol{\beta_0}$	1.368	1.869e-01	7.321	2.47e-13
$\boldsymbol{\beta_1}$	-0.00216	2.121e-03	-1.018	0.308527
$\boldsymbol{\beta_2}$	0.0484	8.630e-03	5.612	2.00e-08
$\boldsymbol{\beta_3}$	0.07011	1.937e-02	3.620	0.000295
$\boldsymbol{\beta_4}$	0.0601	1.477e-02	4.070	4.71e-05
$\boldsymbol{\beta_5}$	0.00000985	3.233e-06	3.048	0.002306

Modeling using the NBR method produces parameter estimates as shown in Table 6. Based on these results, the model using equation (4) is formulated as:

$$\mu_i = \exp(1.368 - 0.00216x_1 + 0.0484x_2 + 0.07011x_3 + 0.0601x_4 + 0.00000985x_5$$

In the NBR model, the AIC value obtained is 148.3083.

(f) Comparing the best models from the GPR and NBR results using AIC and RMSE values

Table 7. Comparison of AIC and RMSE values along with significant parameter

Model	AIC	RMSE	Significant parameters
Generalized Poisson Regression	148.3074	3.608414	$\beta_0, \beta_2, \beta_3, \beta_4, \beta_5$

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Negative Binomial Regression	148.3083	3.608534	$\beta_0, \beta_2, \beta_3, \beta_4, \beta_5$

Table 7 shows that GPR has the smallest AIC and RMSE values, namely 148.3074 and 3.608414, when compared to the NBR model. The comparison between the two models is not significantly different; however, since the AIC and RMSE of the GPR model are the smallest, the Generalized Poisson Regression model is selected to model the number of downtime events.

(g) Discussion

Several previous studies have compared GPR and NBR in handling overdispersion in count data. Rahmadeni & Desmita (2016) found that GPR was superior to NBR for cases of filariasis in Riau based on significance tests and AIC–BIC values. In the study by Haryanto & Wibowo (2022) similar results were reported, although the difference in AIC between the two was not significant, and NBR had the smallest RMSE value (1.310). Keswari et al (2014) compared GPR and NBR and found that the AIC and BIC values of both models were nearly identical. Statistically, this indicates that both GPR and NBR are equally effective for analyzing the number of workers in the roof tile manufacturing industry in Br. Dukuh, Pejaten Village. In the study by Ibnas et al (2023) it was shown that for data on deaths due to dengue fever, NBR was better with the smallest AIC value of 66.50 and the significant factor being the ratio of health facilities.

Another study focused on the application of GPR as an alternative to Poisson when overdispersion occurs. Arisandi et al (2019) showed that GPR is effective in addressing overdispersion in dengue fever cases in Makassar with a minimum AIC of 254.976. Ramayanti et al (2022) found that the percentage of poor people significantly affects the number of dengue fever cases in Southeast Sulawesi, based on the Wald Chi-Square test. Wulandari & Melaniani (2015) also applied GPR to model maternal mortality rates in East Java, which showed variance greater than the average, making GPR the appropriate choice. Meanwhile, NBR is also widely used to address overdispersion. Fitri et al (2021) showed that NBR is the best method for modeling infant mortality data with the lowest AIC. Ferliana et al (2025) found that the percentage of vitamin A coverage has a significant negative effect on cases of child malnutrition in Southeast Sulawesi. Syafiqoh et al (2024) reported that NBR provided the lowest AIC and BIC values for tuberculosis cases in West Java, with the total number of nursing staff as a significant factor. Fatmala et al (2024) also confirmed that NBR is more effective than Poisson for HIV/AIDS case data in Lampung Province due to its lower AIC value.

4. Conclusion

The analysis of downtime data shows that the Poisson regression model is not suitable for use due to detected overdispersion with a value of $\phi > 1$. memTo address this condition, two alternative approaches were used: Generalized Poisson Regression (GPR) and Negative Binomial Regression (NBR). Parameter estimates indicate that all predictor variables in both models significantly influence downtime duration, except for the duration variable, which is not significant. Both models successfully address overdispersion, but GPR has lower AIC and RMSE values compared to NBR. Therefore, GPR was selected as the best model and was deemed superior in modeling count and overdispersed downtime data in the context of this manufacturing industry.

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