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OPTIMIZATION OF OVERDISPERSION MODELING IN LOW BIRTH WEIGHT CASES IN CENTRAL SULAWESI USING CONWAY MAXWELL POISSON REGRESSION

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ABSTRACT

Low birth weight (LBW) is a condition of a baby weighing less than 2,500 grams where gestational age is not taken into account and the baby's weight is measured within 24 hours after birth. The level of infant development also plays an important role in determining the mortality rate and incidence rate of disease in infants with LBW. This study aims to find models and factors that influence LBW using *Conway Maxwell Poisson Regression* (CMPR). CMPR is an extension method of Poisson regression that has the advantage of overcoming violations of the equidispersion assumption, where data can experience overdispersion or underdispersion

Keywords : LBW, overdispersion, *Conway Maxwell Poisson Regression*

I. INTRODUCTION

Low Birth Weight (LBW) is a newborn baby whose weight is less than 2,500 grams without considering the mother's gestational age. Body weight is one of the most important health indicators in newborn babies, while LBW itself continues to be a major problem for public health (Usman, 2010). There are various problems related to LBW that require intensive care and attention to prevent complications that cause death in LBW babies. Apart from the role of health workers, the growth and development of LBW babies is further influenced by the involvement of the family, especially the mother and caregiver (Indasari, 2012).

Babies who experience low birth weight often experience disorders in various body systems, including the central nervous system, respiratory, blood, heart and blood vessels, body temperature regulation, digestive tract, and kidneys. In addition, the impact of LBW can also affect the cognitive development of children aged 6 to 8 years, with a difference in Intelligence Quotient (IQ) scores of around 10 points lower compared to children of the same age who have normal birth weight (Ministry of Health, 2015).

In 2021, there were 3,632,252 newborns. Of those babies, there are 111,719 affected by Low Birth Weight (LBW), which is about 2.5 percent of the total newborns. The case of low birth weight infants can be caused by various factors, including health and social factors. One way to find out is by modeling low birth weight based on the influencing factors (Ministry of Health, 2022).

The number of cases of infants suffering from low birth weight is one of the census data. (count). One of the simplest regression models for analyzing the relationship between response variables in count data and predictor variables in discrete, continuous, categorical, or mixed data is the Poisson regression model (Adiatma et al., 2021). The assumptions that must be met by the Poisson regression model include the presence of equidispersion, where the variance is equal to the mean. However, it is often encountered situations where the variance is greater than the mean, a condition known as overdispersion. Overdispersion in Poisson regression can lead to a significant increase in standard error and reduce the efficiency of parameter estimation, resulting in invalid outcomes that suggest the explanatory variables are likely to be influential, when in fact, these explanatory variables may not necessarily have an effect (Putra et al., 2013).

Conway Maxwell Poisson Regression is an extension of the Poisson regression model. The Conway Maxwell Poisson Regression model is based on the Conway Maxwell Poisson distribution. There are two parameters in the Conway Maxwell Poisson Regression model, which consist of the regression parameter and the dispersion parameter. The advantage of Conway Maxwell Poisson Regression is its ability to analyze various cases of overdispersion and underdispersion; this model has characteristics that make it methodologically interesting and useful in its applications (Afri, 2017).

Several previous studies were conducted by (Riyantie 2022) on Conway Maxwell Poisson regression modeling to address the violation of the equidispersion assumption in Poisson regression, using the case study of the number of people affected by Neonatal Tetanus in Indonesia in 2019. The research findings indicated that there are two factors that have a significant impact on the number of cases of Neonatal Tetanus in Indonesia in 2019. Thus, this study will use the Conway Maxwell Poisson Regression method to model and obtain the factors that influence cases of Low Birth Weight.

II. METHODS

2.1. Multicollinearity Test

The multicollinearity test aims to identify the presence of correlation between predictor variables in a regression model. In a regression model, it is important for the model to meet the assumption that there is no multicollinearity problem or no correlation between predictor variables. If multicollinearity is detected, it can produce a very high standard error value.

VIF value calculation can be done using the following formula:

$$VIF = \frac{1}{\left(1 - {r_{i,j}}^2\right)} \quad (2.1)$$

VIF : *Variance Inflation Factor*

$r_{i,j}$: Correlation coefficient between X_i and Y_j

Test criteria:

If the VIF value <10, it means that the regression model does not experience multicollinearity problems.

2.2. Poisson Distribution Test

The Poisson distribution has a condition where the average value and variance are equal or meet the assumption of a condition called equidispersion. According to Jannah (2018), to find out whether the observed data follows the Poisson distribution or not is by conducting a Kolmogorov-Smirnov test. The hypothesis in this test is as follows:

Hypothesis:

H_0:$F(X) = F_0(X)$(the sample comes from a population with a Poisson distribution)

H_1 : $F(X) \neq F_0(X)$ (the sample does not comes from a population with a Poisson distribution)

$\alpha = 0{,}05$

$D_{calculated} = Max|F_0(X) - F(X)|$

Test criteria:

The decision to reject H_0 if the D_calculated value>D_table or the p-value <α (0.05) means that the sample does not come from a population with a Poisson distribution.

2.3. Equidispersion

Equidispersion is a requirement that must be met in Poisson regression, where the mean value and variance value are the same. However, sometimes this assumption is violated in Poisson regression, for example if the variance value is greater or less than the mean value, it is called overdispersion and underdispersion. Overdispersion occurs when the variance of the response variable data exceeds its mean value, while underdispersion occurs when the variance is less than the mean value (Darnah, 2011).

$$\phi = \frac{nilai\ deviance}{df}$$

ϕ : Dispersi

df : *Degree of freedom*

If the value of ϕ>1, it means that an overdispersion condition occurs and if the value of ϕ<1, it means that an underdispersion condition occurs.

2.4. Conway Maxwell Poisson distribution

The Conway Maxwell Poisson distribution is a development of the Poisson distribution which was first introduced by Conway and Maxwell. Shmueli et al., (2010) stated that the Conway Maxwell Poisson distribution can overcome data that has overdispersion or underdispersion problems. The probability density function of the Conway Maxwell Poisson distribution is:

$$f(y;\mu,\phi) = \begin{cases} \dfrac{\mu^y}{(y!)^\phi}\dfrac{1}{Z(\mu;\phi)} ; & \mu > 0; \phi \geq 0 \\ 0 \quad ; & \text{lainnya} \end{cases}$$

2.5. Parameter estimation in the Conway Maxwell Poisson Regression

Parameter estimation in the Conway Maxwell Poisson Regression model uses the Maximum Likelihood Estimation (MLE) method. This approach is used in estimating the parameters of a model form whose probability function is known, with the following likelihood function form (Riyantie, 2020):

$$L(\beta,\phi;y_i) = \prod_{i=1}^{n}\left(f(y_i;\beta,\phi)\right)$$

$$L(\beta,\phi;y_i) = \prod_{i=1}^{n}\left[\frac{exp(x_i\beta)^{y_i} exp(x_i\beta)^{\frac{\phi-1}{2\phi}}(2\pi)^{\frac{\phi-1}{2}}\sqrt{\phi}}{(y_i!)^\phi\, exp\left(\phi\, exp\left(\frac{x_i\beta}{\phi}\right)\right)}\right]$$

Here is the Conway Maxwell Poisson Regression model:

$$\mu_i(x_{1i},x_{2i},\dots,x_{pi}) = exp\left(\frac{\beta_0+\beta_1x_{1i}+\beta_2x_{2i}+\cdots+\beta_px_{pi}}{\phi}\right) - \frac{\phi-1}{2\phi}$$

$$= exp\left(\frac{x_i\beta}{\phi}\right) - \frac{\phi-1}{2\phi}$$

2.6. Testing the Conway Maxwell Poisson Regression Model Parameters

2.6.1. Simultaneous Test

Simultaneous test aims to determine simultaneously or simultaneously the influence of predictor variables on response variables. The hypothesis in this test is as follows: Hypothesis: H_0: $\beta_1 = \beta_2 = \cdots = \beta_k = 0$ (predictor variables do not have a simultaneous effect on the response variable)

$H_1: \ \beta_j \neq 0, j = 1,2, \dots, p + r$ (there is at least one predictor variable that has a simultaneous influence on the response variable)

Taraf signifikan $\alpha = 0,05$

Statistik uji:

$$G = -2 \ln \left(\frac{L(\hat{\omega})}{L(\hat{\Omega})}\right) = 2\left(\ln\left(L(\hat{\Omega}) - L(\hat{\omega})\right)\right)$$

dimana:

$L(\hat{\omega})$: Maximum likelihood value for a simple model without involving predictor variables

$L(\hat{\Omega})$: The maximum likelihood value for the full model involving predictor variables

Test criteria:

The decision to reject H_0 if $G > x^2_{\alpha,n-k-1}$ or the p-value <α (0.05) which means that there is at least one predictor variable that has a simultaneous influence on the response variable.

2.6.2. Parsial Test

Partial test is used in testing model parameters with the aim of assessing the influence produced by the predictor variable on the response variable individually. The Wald test functions as a test statistic in a partial test. The hypothesis in this test is as follows:

Hipotesis:

$H_0: \ \beta_j = 0$ (predictor variables have no influence on the response variable)

$H_1: \ \beta_j \neq 0, \ j = 1,2,\dots,p$ (predictor variables have influence on the response variable)

Taraf signifikan $\alpha = 0,05$

Statistik Uji :

$$W = \frac{\hat{\beta}_j}{se(\hat{\beta}_j)}$$

$\hat{\beta}_j$: Estimated values for parameters$\hat{\beta}_j$

$se(\hat{\beta}_j)$: standard error estimate $\hat{\beta}_j$

2.7. Data

The data used in this research is secondary data regarding the number of stunted toddlers and the factors influencing low birth weight cases. This study utilizes secondary data obtained from the Indonesian Health Profile in 2022. The variables that will be used in this research are the response variable (Y) and the predictor variable (X), presented in the Table 1.

Table 1 : Types of Research Variables

Variable	Variable Name	Unit	Operational Definition
Y	Low Birth Weight Babies	Person	Babies born weighing less than 2500 grams.

X_1	Coverage of Healthcare Services for Pregnant Women K1	Percent (%)	The percentage of pregnant women who have received their first antenatal care from medical personnel.
X_2	Coverage of Healthcare Services for Pregnant Women K4	Percent (%)	The percentage of pregnant women who have received antenatal care services according to the standards, at least four times as recommended in each trimester.
X_3	Administration of Iron Supplements to Pregnant Women	Person	The number of pregnant women receiving Iron Supplement Tablets should be at least 90 tablets.
X_4	Pregnant Women who are HIV Positive	Person	The number of pregnant women infected with HIV is at high risk of transmitting the virus to the unborn baby.
X_5	Coverage of Pregnant Women with Chronic Energy Deficiency Receiving Supplementary Food	Percent (%)	The percentage of pregnant women who receive Supplementary Food Provision to increase their nutritional intake.
X_6	Pregnant Woman with Reactive HBsAg	Person	The number of pregnant women who infected with HBsAg (Hepatitis B Surface Antigen)

Data analysis in this study uses the Conway Maxwell Poisson Regression method, assisted by RStudio software. There are several stages of data analysis used in this study, namely:

1. Collecting data.
2. Calculating descriptive statistics.
3. Conducting multicollinearity testing by examining the Variance Inflation Factor (VIF) values.
4. Determining the Poisson regression model.
5. Performing Poisson distribution testing using the Kolmogorov-Smirnov test.
6. Conducting the equidispersion assumption test by checking the dispersion values to determine whether the data is experiencing overdispersion or underdispersion.
7. Determining the Conway-Maxwell-Poisson Regression model.
8. Conducting parameter significance testing. The purpose of parameter significance testing is to evaluate the significance of variables using simultaneous tests (likelihood ratio test) and partial tests (Wald test).
9. Conclusion.

   Interpretation of the obtained model.

III. RESULTS AND DISSCUSSION

3.1. Multicollinearity test

In regression analysis, it is important to perform a multicollinearity test to determine whether there is a correlation between the predictor variables. To evaluate the correlation between predictor variables, the necessary step is to examine the VIF values listed in Table 2.

Table 2 : Variance Inflation Factor (VIF) Value

Variable	VIF
X_1	1,11
X_2	1,23
X_3	3,83
X_4	3,06
X_5	1,06
X_6	3,99

Based on Table 2, it can be seen that the VIF values of all predictor variables are less than 10, which means that no multicollinearity issues were found in the data, or there is no correlation between each predictor variable. Therefore, the assumption of non-multicollinearity among the predictor variables has been met.

3.2. Distribusi Poisson Test

To determine whether the data being studied follows a Poisson distribution or not, a Kolmogorov-Smirnov test was conducted. The hypotheses used and the results of the analysis with the Kolmogorov-Smirnov test are presented in the Table 3.

Table 3 : Kolmogorov-Smirnov Test

p-value	Decision	Information
0.3265	Accepted H_0	Poisson Distribution Sample

Based on Table 3, it can be concluded that the *p-value* for the *Kolmogorov-Smirnov* test result is 0.3265, which means the *p-value* (0.3265) > α (0.05), so we H_0. Thus, it means that the sample comes from a population that is distributed according to a Poisson distribution.

3.3. *Equidispersion* Assumption Test

In the case of Poisson regression, there is often a violation of the equidispersion assumption , to find out whether the case is overdispersion or underdispersion can be detected by calculating the estimated dispersion value. The following are the results of the dispersion estimate listed in Table 4.

Table 4 : Estimated Dispersion Values

Deviance	df	Dispersion Estimation (ϕ)
18436.33	27	682,8271

Table 4, it can be seen that the estimated dispersion value obtained from the deviance value divided by the degrees of freedom is 682.8271 where the estimated dispersion value is more than 1, this means that the data is overdispersed, which indicates that the response variable has a greater variance value than its average value. To handle violations of these assumptions, one alternative is to use the Conway Maxwell Poisson Regression model.

3.4. Conway Maxwell Poisson Regression Model

Conway Maxwell Poisson Regression model is a form of statistical model that is implemented in analyzing the relationship between variables that experience overdispersion in the data. Parameter estimation results $\hat{\beta}$ and $\hat{\phi}$ using the Newton Raphson approach with R Studio software . To obtain the CMP model, first find the estimated value of the parameter β listed in Table 5.

Table 5 : Conway Maxwell Poisson Regression Parameter Estimation Values

Parameters	Estimate
β_0	2.452×10^3
β_1	-7.638×10^0
β_2	-1.361×10^1
β_3	$1{,}438 \times 10^{-2}$
β_4	-9.671×10^0
β_5	-2.721×10^0
β_6	2.086×10^0

Based on Table 5, it can be seen that the Conway Maxwell Poisson Regression model formed is as follows

$$\hat{\mu} = exp\left(\frac{x_i\beta}{\phi}\right) - \frac{\phi - 1}{2\phi}$$

$$= exp\left(\frac{2452 - 7{,}638x_1 - 13{,}61x_2 + 0{,}014x_3 - 9{,}671x_4 - 2{,}721x_5 + 2{,}086x_6}{682{,}8271}\right) - \frac{(682{,}8271 - 1)}{2(682{,}8271)}$$

$$\hat{\mu} = exp(3{,}59095 - 0{,}011186x_1 - 0{,}019932x_2 + 0{,}000020503x_3 - 0{,}0141632x_4 - 0{,}003985x_5 + 0{,}003055x_6) - 0{,}499268$$

3.5. Parameter Testing of the *Conway Maxwell Poisson Regression* Model

3.5.1. Simultaneous Test

Simultaneous testing is conducted with the aim of identifying the influence of predictor variables on response variables simultaneously or simultaneously. To conduct this test, a ratio likelihood test method is required, the results of which are listed in Table 6.

Hypothesis :

H_0 : $\beta_j = 0$, $j = 1,2, \dots, p$ (predictor variables do not have simultaneous influence on the response variable)

H_1 : $\beta_j \neq 0$, $j = 1,2, \dots, p$ (at least there is one predictor variable that has a simultaneous influence on the response variable

Table 6 : Results of Likelihood Ratio Test

Conway Maxwell Poisson Regression Criteria	Value
$\ln L(\hat{\Omega})$	−9110
$\ln L(\hat{\omega})$	−69257

Based on Table 6, we obtain:

$G = -2 \ln\left(\frac{L(\hat{\omega})}{L(\hat{\Omega})}\right)$

$= 2\left(\ln L(\hat{\Omega}) - \ln L(\hat{\omega})\right)$

$= 2(-9110 - (-69257))$

$= 120293$

Based on the results of the likelihood ratio test, a value of $G = 120293$ was obtained, while the value of $\chi^2_{0,05;34-6-1} = 40.1133$ means the value of $G > \chi^2_{0,05;34-6-1}$ and for p-value $= 2.2 \times 10^{-16} < \alpha$ (0.05) then reject H_0. With a significance level of (0.05), it can be concluded that there is at least one predictor variable that has a simultaneous influence on the response variable.

3.5.2. *Partial Test*

The partial test aims to analyze the influence of each predictor variable individually on the response variable. The test performed is the *Wald test* which can be seen as follows:

Hypothesis:

H_0 : $\beta_j = 0$, $j = 1,2, \dots, p$ (the predictor variable has no influence on the response variable)

H_1 : $\beta_j \neq 0$, $j = 1,2, \dots, p$(the predictor variable has an influence on the response variable)

$W_0 = \left(\frac{\hat{\beta}_0}{se(\hat{\beta}_0)}\right)^2 = \left(\frac{2452}{38,21}\right)^2 = 4118,01$

$W_1 = \left(\frac{\hat{\beta}_1}{se(\hat{\beta}_1)}\right)^2 = \left(\frac{-7,638}{0,1465}\right)^2 = 2718,22$

$W_2 = \left(\frac{\hat{\beta}_2}{se(\hat{\beta}_2)}\right)^2 = \left(\frac{-13,61}{0,3191}\right)^2 = 1819,125$

$W_3 = \left(\frac{\hat{\beta}_3}{se(\hat{\beta}_3)}\right)^2 = \left(\frac{0,014}{0,000212}\right)^2 = 4360,98$

$W_4 = \left(\frac{\hat{\beta}_4}{se(\hat{\beta}_4)}\right)^2 = \left(\frac{-9,671}{0,08543}\right)^2 = 12815,099$

$W_5 = \left(\frac{\hat{\beta}_5}{se(\hat{\beta}_5)}\right)^2 = \left(\frac{-2,721}{0,07636}\right)^2 = 1269,771$

$W_6 = \left(\frac{\hat{\beta}_6}{se(\hat{\beta}_6)}\right)^2 = \left(\frac{2,086}{0,01535}\right)^2 = 18467,66$

Thus, the results obtained are listed in Table 7.

Table 7 : Wald Test Results

Parameter	Wald	Table χ^2	Decision
β_0	4118.01	3.841	Reject H_0
β_1	2718.22	3.841	Reject H_0
β_2	1819.125	3.841	Reject H_0
β_3	4360.98	3.841	Reject H_0
β_4	12815.099	3.841	Reject H_0
β_5	1269.771	3.841	Reject H_0
β_6	18467.66	3.841	Reject H_0

Based on Table 7, it can be observed with a significance level of 0.05, it can be concluded that there are 6 variables that have a significant influence on cases of low birth weight babies, coverage of healthcare services for pregnant women K1 (X_1), coverage of healthcare services for pregnant women K4 (X_2), administration of iron supplements to pregnant women (X_3), pregnant women who are hiv positive (X_4), coverage of pregnant women with chronic energy deficiency receiving supplementary food (X_5) and pregnant woman with reactive HBsAg (X_6).

3.6. Conway Maxwell Poisson Regression Model

After obtaining the results of the partial test, the *Conway Maxwell Poisson Regression model was obtained* with the parameters that influence the model, namely β_0, β_1, β_2, β_3, β_4, β_5 and β_6 as follows:

$$\hat{\mu} = exp(3{,}59095 - 0{,}011186x_1 - 0{,}019932x_2 + 0{,}000020503x_3 - 0{,}0141632x_4 - 0{,}003985x_5 + 0{,}003055x_6) - 0{,}499268$$

With a significant variable, namely coverage of healthcare services for pregnant women K1 (X_1), coverage of healthcare services for pregnant women K4 (X_2), administration of iron supplements to pregnant women (X_3), pregnant women who are hiv positive (X_4), coverage of pregnant women with chronic energy deficiency receiving supplementary food (X_5) and pregnant woman with reactive HBsAg (X_6)

Based on the model above, it can be concluded that:

1. Estimated values for parameters β_0 namely 3.59095 which means that the average number of low birth weight babies will remain at exp (3.59095) – 0.499268 = 35.76925 without being influenced by other variables.
2. Estimated values for parameters β_1 namely - 0.011186 which means that for every 1 percent increase in coverage of maternal health services K1, it will be inversely proportional to the average number of babies experiencing LBW of exp (- 0.011186) – 0.499268 = 0.489608.

3. Estimated values for parameters β_2 namely - 0.019932 which means that for every 1 percent increase in coverage of K2 maternal health services, it will be inversely proportional to the average number of babies experiencing LBW of exp(- 0.019932) – 0.499268 = 0.480997.
4. The estimated value for the parameter β_3 is 0.000020503, which means that for every 1 additional amount of iron tablets given to pregnant women, it will be proportional to the increase in the average number of babies experiencing LBW of exp(0.000020503) – 0.499268 = 0.500753.
5. Estimated values for parameters β_4 namely - 0.0141632 which means that for every additional 1 number of pregnant women who are HIV positive, it will be inversely proportional to the average number of babies who experience LBW of exp(- 0.0141632) – 0.499268 = 0.486669.
6. Estimated values for parameters β_5 namely - 0.003985 which means that for every 1 percent increase in coverage of pregnant women with chronic energy deficiency receiving PMT, it will be inversely proportional to the average number of babies experiencing LBW of exp(- 0.003985) – 0.499268 = 0.496755.
7. Estimated values for parameters β_6 namely 0.003055 which means that for every 1 additional number of HBsAg reactive pregnant women, it will be proportional to the increase in the average number of babies experiencing LBW of exp(0.003055) – 0.499268 = 0.503792.

IV. CONCLUSION

The Conway Maxwell Poisson Regression model with parameters that influence the model, namely β_0, β_1, β_2, β_3, β_4, β_5 and β_6 as follows:

$$\hat{\mu} = exp(3{,}59095 - 0{,}011186x_1 - 0{,}019932x_2 + 0{,}000020503x_3 - 0{,}0141632x_4 - 0{,}003985x_5 + 0{,}003055x_6) - 0{,}499268$$

With a significant variable, namely coverage of healthcare services for pregnant women K1 (X_1), coverage of healthcare services for pregnant women K4 (X_2), administration of iron supplements to pregnant women (X_3), pregnant women who are hiv positive (X_4), coverage of pregnant women with chronic energy deficiency receiving supplementary food (X_5) and pregnant woman with reactive HBsAg (X_6).

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