Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2021, 2021:73
https://doi.org/10.28919/cmbn/5652
ISSN: 2052-2541

MODELLING THE NUMBER OF HIV AND AIDS CASES IN EAST JAVA USING BIRESPONSE MULTIPREDICTOR NEGATIVE BINOMIAL REGRESSION BASED ON LOCAL LINEAR ESTIMATOR

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Abstract: A virus which attacks the CD4 lymphocytes of the immune system is called human immunodeficiency virus (HIV). If HIV is not addressed then the disease will develop into acquired immunodeficiency syndrome (AIDS). It means that HIV is the cause behind the AIDS infection. Indonesia has been classified into countries where HIV infection rates are high enough since 2006. East Java province was one of six other provinces in Indonesia entering endemic regions other than Jakarta, Papua, West Java, Riau and Bali. The our interest cases namely the number of HIV and AIDS cases in East Java, are two things that correlate with each other. They are categorized into discrete variables. Therefore, this study aims to model the our interest cases with both drug users and percentage of contraceptive users by using local linear Biresponse Multipredictor Negative Binomial (BMNB) regression model approach. By using maximum likelihood cross validation (MLCV) method, we obtain optimal

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Received March 6, 2021

bandwidth of first predictor variable (drug users) and second predictor variable (percentage of contraceptive users), i.e., 30 and 2.5, respectively. We get deviance values of 0.473 for local linear BMNB regression model approach and of 4.4822 for parametric regression model approach. It means that for modeling the our interest cases, the use of local linear BMNB regression model approach is better than the use of parametric regression model approach.

Keywords: HIV and AIDS; percentage of drug and contraceptive users; local linear BMNB regression model.

2010 AMS Subject Classification: 62G05, 62G08, 62J05, 62P10.

1. INTRODUCTION

The millennium development goals (MDGs) are global paradigm for development of 189 United Nations (UN) member states proclaimed in September 2000 in the Millennium Summit in New York. These MDGs generate 8 main objectives to be achieved in 2015. One of all is fighting against both virus of human immunodeficiency namely HIV and syndrome of acquired immunodeficiency namely AIDS [1]. The AIDS is a chronic disease which arises due to inclusion of an infection caused by a virus called HIV.

The HIV and AIDS problems have become a global health issue. In Indonesia, the HIV and AIDS have been registered by 433 (84.2 percent) in 514 districts/cities in 34 provinces since it was first discovered until June 2018 [2]. East Java Province was one among six other provinces entering endemic regions other than Jakarta, Papua, West Java, Riau and Bali. Up to December 2018, the number of cases reported in East Java were 920 for AIDS and 8885 for HIV where 193 (2.8 percent) of them died. It was actually much smaller than the numbers actually happened. The results of estimation until 2019 showed that the estimated number of HIV sufferers in East Java reached 63,581 people. In Addition, since September 2013, East Java province was set as HIV prevalence area that was concentrated along five provinces, i.e. Jakarta, Papua, Bali, Riau and West Java [3].

One cause of the increasing HIV and AIDS sufferers was the use of unsterile needles in drug addicts [4]. Using drugs injection associates with HIV and AIDS infections that affects global morbidity and mortality [5]. The use of contraception is a well-known determinant of indicators of HIV prevalence in the country that plays an important role in preventing the transmission of HIV [6]. Family planning for effective modern contraception is an important intervention for preventing unwanted pregnancies which also benefits from a private, family, and social [7]. Contraception is also the most cost-effective strategy for reducing the burden of HIV transmission from mother to child for women living with HIV who want to prevent pregnancy.

A data about our interest cases in the province of East Java were a count data. The HIV and AIDS cases are correlated to each other, so that the data was considered to have a high correlation. Model of our interest cases with drug users and the percentage of contraceptive users was performed and analyzed by regression analysis. Regression analysis is an analysis method for determining how responses and predictors variables relate functionally. Response variables in the regression analysis are to be able to continuous or discrete. For discrete response variable case, we can use Poisson regression model approach by assuming mean of response variable equals to its variance. It is called as equi-dispersion case. But, in fact, this assumption is often not met because the variance could be less than the mean that is called as under-dispersion case, and otherwise referred to as a case of over-dispersion. The use of negative binomial regression (NBR) model can be the solution to this over-dispersion [8]. The our interest cases are to be data distributed bivariate Poisson. However, some cases in the count data such as the our interest cases frequently shows over-dispersion condition. Therefore, in this study, the local linear BMNB regression model that contents two responses and two predictors is applied to analyze data of the our interest cases. As we know from many references, the analyzing data using regression model consists of parametric and nonparametric regression models approaches. In the model of parametric regression, its regression function type is known, and the relationship between dependent variable and independent variable follows a certain curve. While, nonparametric regression approach is used when the relationship between these variables does not follow a specific pattern but it is only assumed to be continuous and differentiable.

The regression models of parametric have been studied by several researchers. Some of them are [9–11]. Also, there are several researchers who have studied continuous response nonparametric regression in cases of biresponse and multiresponse, for examples researchers [12-22] used local linear, local polynomial, spline, and kernel estimators for real cases data using biresponse models, and researchers [23-33] used local linear, local polynomial, spline and kernel estimators for real cases data using multiresponse models. Whereas the nonparametric regressions of discrete responses have not been developed, such studies include the kernel estimator by [34]; spline estimator by [35]; kernel estimator by [36]; local linear estimator by [37]; and local polynomial estimator in Generalized Poisson regression model by [38].

Lately, many studies have developed modeling the our interest cases by using NBR model approach. Some of these studies are the use of biresponse NBR for modeling the our interest cases in Indonesia with one predictor namely the percentage of drug users by [39]; the use of local linear biresponse NBR for modeling the our interest cases in Indonesia with one predictor namely the percentage of drug users by [40]; the use of local linear biresponse NBR for modeling the our interest cases in East Java with one predictor namely the percentage of drug users by [41]. All researches mentioned above have not discussed the local linear NBR with more than one predictor variable. Therefore, in this study, we develop the local linear NBR into local linear biresponse multipredictor NBR called as local linear BMNB regression to model the our interest cases in East Java with two predictors namely percentage of drug users and percentage of contraceptive users.

2. PRELIMINARIES

In this section, we give short descriptions of biresponse NBR function, model of biresponse multipredictor nonparametric regression based on local linear, local likelihood estimator, data and analysis steps that would be used in this study.

2.1. Biresponse NBR Function

A negative binomial regression (NBR) that has correlated two response variables is called biresponse NBR. Let Y_{1i} and Y_{2i} for $i = 1,2,\dots,n$ are random variables that have

Poisson-Gamma mixture distribution. Joint probability function of the biresponse negative binomial is as follows [42]:

(1) $$f(y_1, y_2) = \frac{\Gamma\left(\frac{1}{\alpha} + y_1 + y_2\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(y_1+1)\Gamma(y_2+1)} \mu_1^{y_1} \mu_2^{y_2} \alpha^{-\frac{1}{\alpha}} \left(\frac{1}{\alpha} + y_1 + y_2\right)^{-\left(\frac{1}{\alpha}+y_1+y_2\right)}, y = 0,1,2,\cdots$$

where $(\alpha \geq 0)$ is the dispersion parameter.

Based on the equation (1), the random variables Y_1 and Y_2 have the expectation, variance and correlation as follows:

(2) $$E(Y_r) = \mu_r \ , \ = 1,2 \ ; \quad Var(Y_r) = \mu_r(1 + \alpha\mu_r) \ , \ r = 1,2 \quad \text{and}$$

$$Corr(Y_1, Y_2) = \sqrt{\frac{\alpha^2 \mu_1 \mu_2}{(1+\alpha\mu_1)(1+\alpha\mu_2)}} \quad \text{, respectively.}$$

Suppose given pairs of data $(\underset{\sim}{x}_i, y_{1i}, y_{2i})$, where $\underset{\sim}{x}_i = (x_{1i}, x_{2i}, \cdots, x_{pi})^T$, and y_{1i} and y_{2i} are discrete type of response variable with *n* sized random sample assumed to have biresponse negative binomial distribution. The biresponse NBR function is given as follows:

(3) $$f(y_{1i}, y_{2i} \mid \underset{\sim}{x}_i) = \frac{\Gamma\left(\frac{1}{\alpha} + y_{1i} + y_{2i}\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma(y_{1i}+1)\Gamma(y_{2i}+1)} [\mu_1(\underset{\sim}{x}_i)]^{y_{1i}} [\mu_2(\underset{\sim}{x}_i)]^{y_{2i}} \alpha^{-\frac{1}{\alpha}} \left(\frac{1}{\alpha} + y_{1i} + y_{2i}\right)^{-\left(\frac{1}{\alpha}+y_{1i}+y_{2i}\right)}$$

where $\mu_{1i} = \exp\left(\underset{\sim}{x}_i^T \underset{\sim}{\beta}_1\right)$ and $\mu_{2i} = \exp\left(\underset{\sim}{x}_i^T \underset{\sim}{\beta}_2\right)$.

2.2. Model of Biresponse Multipredictor Nonparametric Regression Based on Local Linear

Regression model of nonparametric is a statistical model where the shape of its regression function is uncertain or no prior knowledge about regression function collected to draw how the response and predictor variables associate functionally.

Relationship between response variable y and predictor variable x can be expressed in the following model:

(4) $$y_i = g(x_i) + \varepsilon_i \ , \quad i = 1,2, \dots, n$$

for a regression function $g(x_i)$ that will be estimated and it is assumed to be smooth. This assumption guarantees more flexible in estimating the regression function.

As an extension of equation (4) is BMNB regression model that given as follows:

(5) $$y_{ri} = g_r(x_i) + \varepsilon_{ri} \ , \quad i = 1,2,\cdots,n \ \text{ and } \ r = 1,2$$

for an unknown smooth regression function $g_r(x_i)$. Thus, for x_i the vicinity x_0, can be approximated locally by Taylor expansion with a degree polynomial of one as follows:

$$g_1(x_i) \approx g_1(x_0) + g_1^{(1)}(x_0)(x_i - x_0)^1 + \frac{g_1^{(2)}(x_0)(x_i - x_0)^2}{2!} + \cdots + \frac{g_1^{(d_1)}(x_0)(x_i - x_0)^{d_1}}{d_1!}$$

$$g_2(x_i) \approx g_2(x_0) + g_2^{(1)}(x_0)(x_i - x_0)^1 + \frac{g_2^{(2)}(x_0)(x_i - x_0)^2}{2!} + \cdots + \frac{g_2^{(d_1)}(x_0)(x_i - x_0)^{d_1}}{d_1!}$$

or in generally we can write it as follows:

(6) $$g_r(x_i) \approx \beta_{r0}(x_0) + \beta_{r1}(x_0)(x_i - x_0)^1 + \beta_{r2}(x_0)(x_i - x_0)^2 + \cdots + \beta_{rd_r}(x_0)(x_i - x_0)^{d_r}; \ r = 1 \ , \ 2$$

where

$$\beta_{rv}(x_0) = \frac{g_r^{(v)}(x_0)}{v!} \ ; \quad v = 0,1,2,\cdots,d.$$

Next, estimator for parameter $\underset{\sim}{\beta}$ is $\underset{\sim}{\hat{\beta}}$, that can be obtained by taking a sample pairs (x_i, y_i) of n samples and using the weighted least squares (WLS) method by means of minimizing the following equation:

(7) $$\sum_{i=1}^{n} \left\{ y_i - \left[\beta_0(x_0) + \beta_1(x_0)(x_i - x_0) \right] \right\}^2 K_h(x_i - x_0) \ ; \ i = 1,2,\cdots,n$$

for a kernel function $K_h(\cdot)$ with bandwidth h that is defined as follows [43]:

(8) $$K_h(u) = \frac{1}{h} K\left(\frac{\mu}{h}\right) \ ; \quad -\infty < u < \infty \ , \quad h > 0 \quad .$$

The Kernel function has a role as the weight of the data around x_0 .

Based on equation (8) with n observations dan p predictor variables, the multivariate kernel function can be written as follows [44]:

(9) $$K_{\mathbf{h}}\left(x_j - X_{ij}\right) = \prod_{j=1}^{p} \frac{1}{h_j} K\left(\frac{x_j - X_{ij}}{h_j}\right)$$

where $\mathbf{h} = \left(h_1, h_2, \cdots, h_p\right)$.

Bandwidth h is a constant and as a positive valued smoothing parameter that is used to control the balance between the smoothness of curves and compatible use of the data. If the value of the bandwidth is too small, it will lead to rough estimates obtained curve and a large variance, whereas if we choose a large bandwidth, the estimated value gives smoother curve, but it provides great consequence biased value. Therefore, we need an optimal bandwidth value. One method for selecting the optimal bandwidth that is used in regression model of nonparametric with discrete response variable is maximum likelihood cross validation (MLCV) method. If $\hat{g}_{-i}(x)$ is an estimate of the regression function at point x_i without including the i^{th} observation, then MLCV is a function of the bandwidth h as given in the following equation [45]:

(10) $$MLCV_h = \sum_{i=1}^{n} \ln f(y_i, \hat{g}_{-i}(x)).$$

The optimal value of bandwidth is determined based on MLCV in equation (10) that has the largest value.

2.3. Local Likelihood Estimator

The local likelihood estimator in regression model of nonparametric was introduced by Tibshirani & Hastie in 1987 [45]. This estimator is to be scatterplot smoothing technique that is extended from a likelihood function of linear model.

The method used to estimate the regression function $g(x_i)$ at the point x_0 is the local weighted maximum likelihood method, so that the form of the likelihood function at point x_0 which depends on the degree of polynomial d and bandwidth h can be written as follows:

(11) $$L\left(\underset{\sim}{\beta}, \alpha, x_0\right) = \prod_{i=1}^{n} g\left(y_i \mid x_i\right)^{K_h(x_i - x_0)}$$

Whereas the form of the local likelihood function for the case of the multipredictor variable as an extension of equation (11) can be written in the following equation:

$$L\left(\underset{\sim}{\beta},\alpha,x_{0j}\right)=\prod_{i=1}^{n}\left\{g\left(y_i\mid x_i\right)^{\prod_{j=1}^{p}K_{hj}\left(x_{ij}-x_{0j}\right)}\right\} \tag{12}$$

Because of value $l\left(\underset{\sim}{\beta},\alpha,x_0\right)$ will have the same results of $\ln\left\{L\left(\underset{\sim}{\beta},\alpha,x_0\right)\right\}$ then the equation (12) can be written into the following equation:

$$\ln\left\{L\left(\underset{\sim}{\beta},\alpha,x_{0j}\right)\right\}=\ell\left(\underset{\sim}{\beta},\alpha,x_{0j}\right)=\ln\left\{\prod_{i=1}^{n}\left\{g\left(y_i\mid x_i\right)^{\prod_{j=1}^{p}K_{hj}\left(x_{ij}-x_{0j}\right)}\right\}\right\} \tag{13}$$

Local maximum likelihood estimator $\hat{\underset{\sim}{\beta}}$ is obtained by maximizing equation (12) with respect to $\underset{\sim}{\beta}$, that is by differentiating equation (13) with respect to $\underset{\sim}{\beta}$ and then its result is equalized to zero.

2.4. Data Source and Analysis Steps

The data that was used for this research is a secondary data of the our interest cases in East Java with percentage of both drug users and contraceptive users recorded in 2016 by the Department of Health of East Java province. The analysis steps in modeling the data of the our interest cases using local linear BMNB regression approach are: (a). testing the correlation between response variables, (b). providing paired data $\left(x_{1i},x_{2i}y_{1i},y_{2i}\right)$, $i=1,2,...,n$ and estimating the parameters of BMNB regression model [42] by using method of weighted maximum likelihood in term of local linear, and (c). using Newton & Raphson method, if the step (b) is not success or fail.

3. Main Results

Two response variables, namely the our interest cases, resulted in correlation coefficient of 74.7 percent. It brings to the proof that there is high enough correlation between HIV cases and AIDS cases. Therefore, we can use local linear BMNB regression approach to model the our interest cases.

Next, plots between two responses and two predictors variables created by using open source software R (OSS-R) is given in Figure 1, where based on the Figure 1 it can be assumed that the drug users and percentage of contraceptive users variables have a pattern of relationship that spreads to the our interest cases or we can claim that it does not follow a particular pattern, so the appropriate approach for modelling our interest cases is local linear MNB regression model approach.

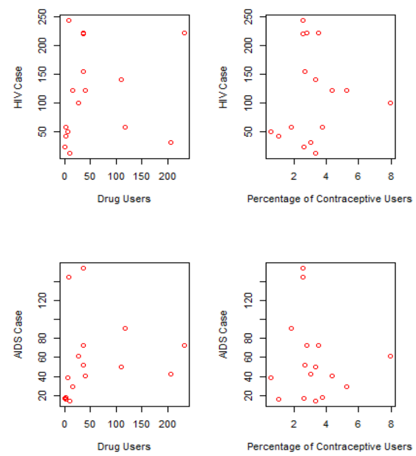

Figure 1. Scatter Plot Between Two Responses and Two Predictors Variables

Furthermore, we also get optimal values of bandwidth and MLCV values for drug users and percentage of contraceptive users which are given in Table 1.

Table 1. Optimal Bandwidth and MLCV Values.

Drug Users		Percentage Of Contraceptive Users	
Bandwidth (h_1)	MLCV1	Bandwidth (h_2)	MLCV2
29.5	-9.847012	1.5	24.19275
30.0	-8.109649	2.0	33.01677
30.5	-8.184970	2.5	46.48032
31.0	-8.351439	3.0	33.11915
31.5	-8.546227	3.5	17.67778
32.0	-11.20330	4.0	18.56345

Hence, the values in Table 1 can be described by plots as given in Figure 2.

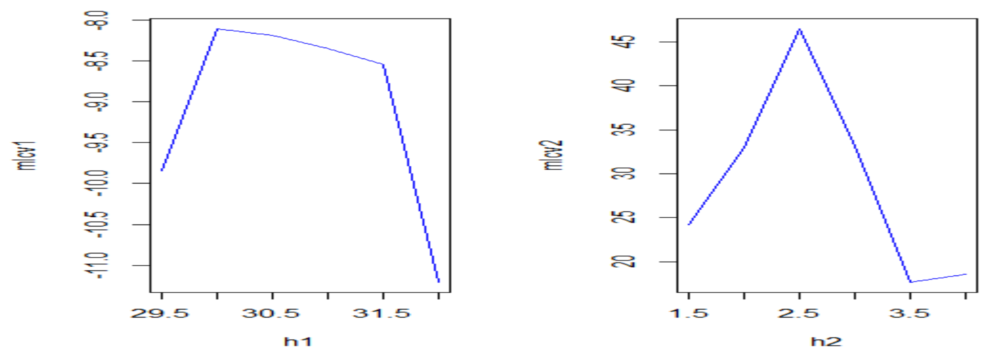

Figure 2. Plots of MLCV versus Bandwidth for Drug and Contraceptive Users.

From Figure 2, we get that the optimal value of bandwidth for drug users (h_1) equals to 30.0 with maximum MLCV value of -8.109649, and the second optimal bandwidth value (h_2) is 2.5 with maximum MLCV value of 46.48032. Furthermore, the estimated models have different coefficients depending on the location. For example, the estimated models that obtained in Jombang regency as follows:

(14) $$\hat{\mu}_1 = \exp\left(5.406 + 0.011(x_1 - 36) - 0.080\left(x_2 - 9.08\right)\right),\ 6 < x_1 < 66;\ 6.58 < x_2 < 11.58$$

(15) $$\hat{\mu}_2 = \exp\left(3.451 + 0.006(x_1 - 36) - 0.135\left(x_2 - 9.08\right)\right),\ 6 < x_1 < 66;\ 6.58 < x_2 < 11.58$$

The estimated model in (14) shows that every addition by 10 of drug users, it will result in an increase in the amount cases of HIV 1.116 times than the previous cases, and every one percent increment of contraceptive users, it will result in an increase in the amount cases of HIV 0.923 times than the previous cases. Next, the estimated model in (15) shows that every addition by 10 of drug users, it will result in an increase in the amount cases of AIDS 1.062 times than the previous cases, and every one percent increment of contraceptive users, it will result in an increase in the amount cases of AIDS 0.874 times than the previous cases. As a result, in East Java province, increasing drug users will rise the amount of the our interest cases, and an increasing percentage of contraceptive users will be able to reduce the increasing amount cases of HIV and AIDS.

Estimated models in equation (14) and (15) were used to predict the our interest cases that occur in certain district/city of East Java province based on drug users and percentage of contraceptive users. As an example, Jombang regency in 2016 had the drug users of 36 and percentage of contraceptive users of 9.08 with 220 HIV cases and 14 AIDS cases. In 2017, drug users in Jombang regency was 46 and percentage of contraceptive users was 10.08%. Thus, in 2017 in Jombang regency, the predicted values were 231 cases for HIV and 30 cases for AIDS. Thus, it can be concluded that HIV cases in Jombang regency changed from 220 cases to 231 cases or the number of HIV cases in 2017 had changed by 1.05 times from those cases in 2016, and AIDS cases in Jombang regency changed from 14 cases to 30 cases or the amount of AIDS case in 2017 has changed by 2.14 times from those cases in 2016.

Goodness of fit testing result for estimated model using local linear BMNB regression approach for the our interest cases with the amount of both drug users and percentage of contraceptive users as predictor variables can be determined from the deviance value, that equals to 0.473. This deviance value is less than 37.652 namely value of Chi-square distribution. Hence, the estimated model that we obtained using our proposed approach is suitable. Next, as a comparison, we also use the regression model of parametric approach to estimate the our interest cases. In this process, we obtained the estimation of models as follows:

$$\hat{\mu}_1 = \exp\left(4.476 + 0.0014x_1 + 0.0532x_2\right) \tag{16}$$

$$\hat{\mu}_2 = \exp\left(4.068 + 0.0015x_1 - 0.0351x_2\right) \tag{17}$$

Also, the deviance value of 4.4822 is obtained by means of the estimated model.

Plots of estimated response variables based on equations (14) and (15) and observations are shown in Figure 3, where the red dots are values of observation, the line in blue is the parametric estimation results, and the line in green is the nonparametric estimation results.

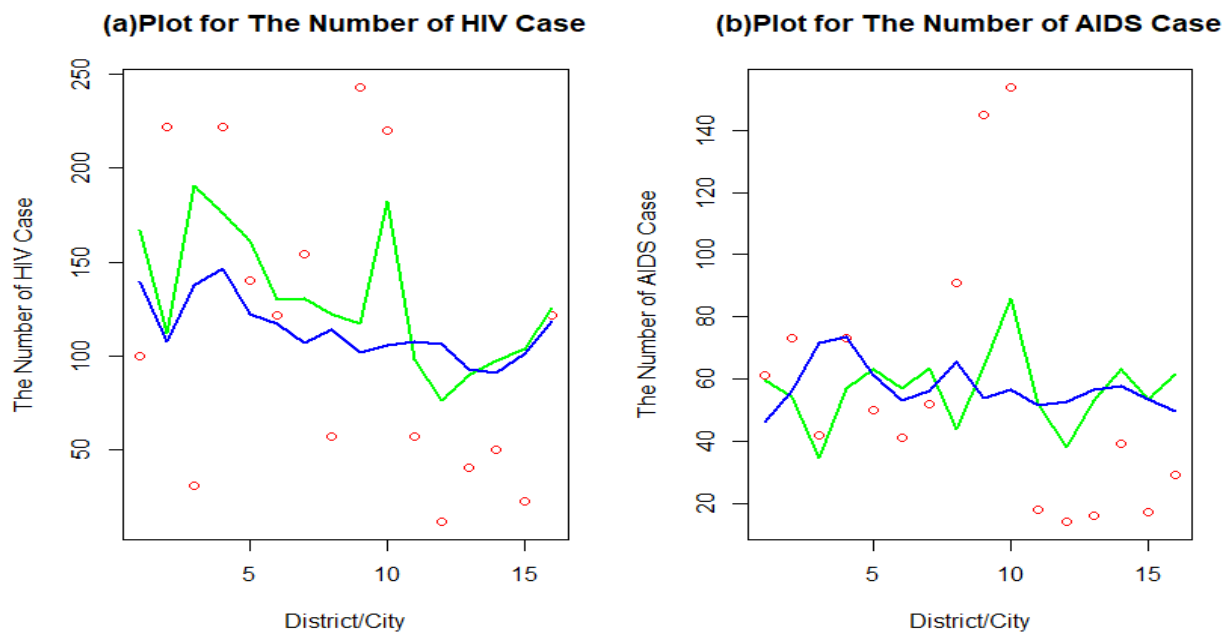

Figure 3. Plots of Observation and Estimation Results for Cases of HIV and AIDS.

Figure 3 shows that values of estimation using local linear BMNB nonparametric regression approach (represented by the green line) are closer to values of observation (represented by the red points) than values of estimation using parametric regression approach (represented by the blue line). Furthermore, if we compare values of deviance for testing the goodness of fit between local linear BMNB nonparametric regression approach and parametric regression approach then the deviance value of estimated model using local linear BMNB nonparametric regression approach equals to 0.473 that less than 4.4822 namely the deviance value of estimated model using parametric regression approach. Based on these results, it shows that the use of local linear BMNB regression approach for modeling the our interest cases is better than the use of BNR approach. Also, by adding percentage of contraceptive users as predictor variable into the previous model approach proposed by [46] namely biresponse NBR with only one predictor variable, we have the BMNB regression model with two predictor variables that can improve the goodness of fit significantly because our proposed model approach has deviance value of 0.473 that less than 2.632 namely the deviance value of the previous model approach proposed by [46].

4. CONCLUSIONS

Based on the values of deviance, for modeling the our interest cases the use of our proposed model approach namely the local linear BMNB regression model approach is better than the use of not only regression model of parametric approach but also the previous model approach proposed by [46]. Every additional number of both drug users and percentage of contraceptive users can increase the number of both HIV and AIDS cases. Therefore, we can use the our proposed model approach for predicting the number of HIV and AIDS cases which occurs in certain district/city in East Java based on the amount of drug users and percentage of contraceptive users.

ACKNOWLEDGMENTS

This research was funded through the Doctoral Dissertation Research Grant with a contract No. 823/UN3.14/PT/2020. Therefore, the authors thank to the Directorate of Research and Public Service, the Ministry of Education and Culture of the Republic of Indonesia.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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