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ANALYZING OPEN UNEMPLOYMENT RATE IN JAVA USING PENALIZED SPLINE NONPARAMETRIC REGRESSION

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ABSTRACT

Unemployment is one of the main problems faced by the Indonesian government. This phenomenon is the root of various existing social problems, such as poverty and crime, as well as social and cultural problems. In measuring the figures, the Central Statistics Agency (BPS) uses a primary indicator, the Open Unemployment Rate. Based on the publication of the BPS in 2021, Java Island has the highest open mountain levels in Indonesia. The problem needs to be studied more deeply to determine how much influence the factors that cause the high number are. Unfortunately, studies using a non-parametric approach to the Spline Penalized have never been carried out to view the open area on the island of Java. The purpose of this study is to model an open floor partition in Java using a non-parametric Penalized Spline approach. The study's results resulted in a Mean Square Error (MSE) value of 4.137 with a coefficient of determination of 44.58%, which the explanatory variables of 44.58% could develop.

Keywords: Nonparametric regression, Open unemployment rate, Penalized spline, Spline regression.

INTRODUCTION

Community welfare is one of the goals of the Indonesian government in improving national development (Sari & Budiantara, 2012). The government's efforts to improve people's welfare are contained in the National Medium-Term Development Plan 2020-2024 by strengthening economic resilience, increasing quality, and competitive human resources, and reducing unemployment. The problem of unemployment is one of the severe problems faced by the Indonesian government.

The Central Statistics Agency defines several things related to the concept of employment. A person can be unemployed if he does not have a job but is looking for work or preparing a business, feels it is impossible to get a job, or has been accepted for work but has not started work (BPS, 2021). In measuring the unemployment rate, BPS uses the primary indicator, the Open Unemployment Rate. The Open Unemployment Rate describes the percentage of the number of unemployed to the total labor force. The open unemployment rate in Indonesia in 2018-2020 tends to fluctuate, but there is a significant increase in 2020. In 2018 the open unemployment rate was 5.30 percent. In 2019 it decreased by 0.07 percent to 5.23 percent, and in 2020 there was an increase of 1.84 percent to 7.07 percent (BPS, 2021).

The phenomenon of unemployment is the root of various existing social problems, such as poverty and crime, as well as social and cultural problems (Ishak, 2018). Unemployment is a problem faced by almost all regions in Indonesia, including the island of Java. Java Island is the 13th largest island in the world, with a population of 151 million people (BPS, 2021). The open unemployment rate in the provinces on the island of Java varies from one to another. In 2020 three provinces occupy the largest open unemployment rate and are consistently above the national open unemployment rate, Banten Province at 10.64%, DKI Jakarta Province at 10.95%, and West Java Province at 10.46% (BPS, 2020).

One method that can be used to analyze a relationship between the explanatory variable and the response variable is regression analysis. There are three approaches in regression analysis, namely the parametric approach, nonparametric approach, and semiparametric approach. The parametric approach specifies that the relationship between the response variable and the explanatory variable must follow a specific distribution and the shape of the regression curve follows certain patterns, such as linear, quadratic, or cubic. The parametric approach has rigid and strict assumptions where these assumptions are often not met (Budiantara, 2011). When assumptions are not met in the parametric approach, the solution to the problem is to use anonparametric method to estimate the regression curve.

The nonparametric approach does not require assumptions regarding the shape of the regression curve between the response variables and the explanatory variables and has the advantage that in estimating the shape of the regression curve, it has high flexibility so that it can adjust to the data without the influence of the subjectivity of the researcher. Spline is a nonparametric regression method with high flexibility in estimating the regression curve because there is a knot point that indicates a pattern of behavior change in the data (Putra et al., 2015). Penalized spline is one method of estimating parameters in spline, which is the development of the B-Spline regression model (Eilers & Marx, 1996). Penalized spline regression is an estimation of parameters that have different segments on the polynomial pieces which are combined with knot points simultaneously.

In this study, the algorithm used in selecting the optimal number of knot points is a full-search algorithm. The selection of this algorithm is based on research conducted by Ruppert (2002), where the full-search algorithm is the algorithm that has the best performance for all cases tested. The criteria used to select the optimal smoothing parameter is the Generalized Cross Validation (GCV) method. The GCV method was chosen because it has asymptotic optimal properties, is invariant to the transformation, and in its calculation the population variance does not need to be known (Wahba, 1990).

RESEARCH METHOD

Data

This study uses a quantitative method, namely penalized spline nonparametric regression. In this study, the data used are secondary data obtained from BPS publication data and publication data from the Ministry of Education and Culture. The data to be analyzed in this study consisted of 119 district/city observations located on the island of Java. The variables that will be used are the open unemployment rate (Y), the dependency ratio (X_1), the GDP growth rate (X_2), the senior high school gross enrollment (X_3), the percentage of the poor (X_4), the human development index (X_5), and population growth rate (X_6).

Methods

The steps in analyzing the data in this study are:

1. Exploring data on each explanatoryvariable to determine the characteristics of districts/cities in Java.
2. Perform data visualization by making a scatterplot of response variables with explanatory variables.
3. Determine the polynomial order, the number of knot points, and the optimal smoothing parameters based on the minimum GCV criteria for each explanatory variable.

The smoothing parameter is used to control the balance between the natural smoothness of the function and the adjustment of the function to the data. In obtaining the optimal smoothing parameter value, the Generalized Cross Validation method will be used, which is defined as follows (Eubank, 1999):

$$GCV=\frac{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - f_j\left(x_{ji}\right)\right)^2}{\left(\frac{1}{n} \quad \mathbf{T} \quad {}^{-1} \quad \mathbf{T}\right)^2} \qquad (1)$$

The number of knot points is selected using a full-search algorithm. The knot point in the penalized spline regression lies in the sample quantile value of the unique explanatoryvariable $\{x_i\}_{i=1}^n$ where the k-th knot is the j-th quantile of the value unique explanatory variable where $j=\frac{j}{1+K}$. In the full-search knot algorithm, 1,2,3,… up to a certain number of knots have been tested with the provisions $K<n_{unique}-p-1$ where p is the order of polynomials and n_{unique} is the number of unique (single) values of the explanatory variable $\{x_i\}_{i=1}^n$.

4. Building a penalized spline nonparametric regression model.

The penalized spline consists of polynomial pieces with different segments joined together to form a knot $t_1,t_2,\ldots,t_k$. The nonparametric regression function of the penalized spline with order p and knot points $t_1,t_2,\ldots,t_k$ for n observations is expressed in the equation as follows (Ruppert et al., 2003):

$$f_j(x_{ji})=\beta_{j0}+\beta_{j1}x_{ji}+\ldots+\beta_{jp}x_{ji}^{p_j}+\sum_{k_j=1}^{K_j}\beta_{j(p_j+t_j)}(x_{ji}-t_{jk_j})_+^{p_j}$$

(2)

5. Estimating the nonparametric penalized spline regression parameters.

The estimator in penalized spline regression is obtained by minimizing the number of penalty squares, which consists of two functions: the sum of the squares of the error and the function of the measure of natural smoothness. The function of the sum of the squares of errors can be written in the following equation (Ruppert et al., 2003):

$$S_j=\frac{1}{n}\sum_{i=1}^{n}(y_i-f_j(x_{ji}))^2+\lambda_j\sum_{h=1}^{k_j}\beta_{j(p_j+h)}^2\quad,\lambda\geq 0$$

(3)

In obtaining the estimation of the penalized spline regression parameter, the function of the sum of the penalized squares will be minimized using the least squares method so that the following equation is obtained:

$$S_j=\frac{1}{n}(\mathbf{Y}^T\mathbf{Y}-2\boldsymbol{\beta}_j^T\mathbf{X}_j^T\mathbf{Y}+\boldsymbol{\beta}_j^T\mathbf{X}_j^T\mathbf{X}_j\boldsymbol{\beta}_j)+\lambda_j\boldsymbol{\beta}_j^T\mathbf{D}_j\boldsymbol{\beta}_j$$

(4)

where $\boldsymbol{\lambda}_j$ is a smoothing parameter of the j-th explanatory variable and $\mathbf{D}_j$ is a diagonal matrix defined as $\mathbf{D}_j=\text{diag}(\mathbf{0}_{(p+1)\times(p+1)},\mathbf{1}_{k\times k})$ which can be written as follows (Yao & Lee, 2008):

$$\mathbf{D}_j=\begin{pmatrix}\mathbf{0} & \vdots & \mathbf{0}\\ \cdots & \cdots & \cdots\\ \mathbf{0} & \vdots & \mathbf{1}\end{pmatrix}\quad(5)$$

To obtain the estimator value $\hat{\boldsymbol{\beta}}$, the equation S_j will be derivative to $\boldsymbol{\beta}_j$ to get the minimum value and the folloeing equation is obtained:

$$\hat{\boldsymbol{\beta}}_j=(\mathbf{X}_j^T\mathbf{X}_j+n\lambda_j\mathbf{D}_j)^{-1}\mathbf{X}_j^T\mathbf{Y}\quad(6)$$

6. Seeing the fit of the model obtained by the determination coefficient (R^2). Theformula for the coefficient determination is as follows:

$$R^2=\frac{SSR}{SST}=\frac{\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}\quad(7)$$

7. Test the significance of the parameters simultaneously (F-test) or partially (T-test)

a. Simultanous testing of parameter significance can be performed using F-test, with the following hypothesis (Kurniasari et al., 2019):

$H_0:\beta_1=\beta_2=\beta_3=\ldots=\beta_k=0$

H_1: minimal terdapat satu $\beta_k\neq 0$

The test statistics used are as follows:

$$F_{hitung}=\frac{MS_{regresi}}{MS_{error}}=\frac{\frac{\sum_{i=1}^{n}(\hat{y}_i-\bar{y})^2}{k}}{\frac{(y_i-\hat{y}_i)^2}{n-k-1}}$$

Reject H_0 if p-value<α, where k the number of regression coefficients and n is the number of observations.

b. Partial testing is used to see how much each explanatory variable can effect the response variable, using t-test with the following hypothesis:

H_0: $\beta_k=0$

H_1: $\beta_k\neq 0$

The test statistics used are as follows:

$$t=\frac{\hat{\beta}_k}{SE(\hat{\beta}_k)}$$

Reject H_0 if p-value<α, where k the looking at the value of the coefficient of determination (R^2) of the regression model and looking at the plot of the percentage value of the open unemployment rate observed with the percentage value of the estimated open unemployment rate.

number of regression coefficients and n is the number of observations

8. Interpretation of penalized splinenonparametric regression modeling results

RESULT AND DISCUSSION

Result

1. Data Exploration

Goodness of Fit the regression model to the data can be known through the value of

Data exploration in this study was carried out by descriptive analysis, which aims to describe the characteristics of the data in general. The results of the descriptive analysis for each variable are presented in Table 1.

Table 1. Descriptive Statistics of Research Variables

Variable	Min	Max	Mean	Std. Deviation
Y	2.16	14.29	7.22	2.74
X_1	35.24	57.50	45.52	4.44
X_2	-12.86	4.33	-2.97	3.01

X_3	56.07	125.43	91.70	14.22
X$	2.29	22.78	9.93	4.15
X_5	62.7	86.61	72.71	5.34
X&	-0.39	3.59	0.97	0.56

Based on Table 1, the highest unemployment rate (Y) is 14.29% in Bogor Regency and the lowest is 2.16% in Gunungkidul Regency. The highestdependency ratio (X_1) is in Garut Regency andthe lowest is in Tangerang Regency. The highest GRDP growth rate (X_2) is in Sidoarjo Regency and the lowest is in Lamongan Regency. The gross enrollment rate for SMA/SMK has the highest standard deviation among other variables, which indicates that thesenior high school gross enrollment in districts/cities in Java is very diverse. Sidoarjo Regency has the highest senior high school gross enrollment and the lowest is in BangkalanRegency. The highest percentage of poor people (X_4) is in Sampang Regency and the lowest is in South Tangerang City. The area with the highest human development index (X_5)is Yogyakarta City and the lowest is Sampang Regency. The highest population growth rate (X_6) is Bekasi Regency and Yogyakarta City's lowest. The population growth rate has the smallest standard deviation, indicating that the population growth rate is evenly distributed in every district/city on the island of Java.

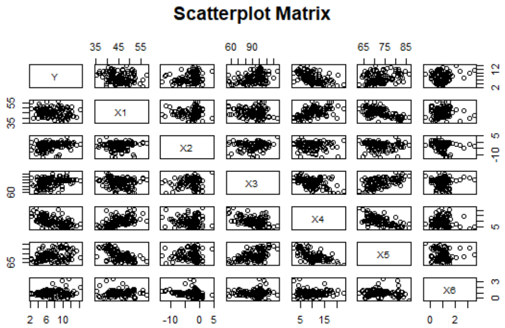

Figure 1. Scatterplot Matrix Between Variables

Based on Figure 1, it can see that the relationship between all explanatory variables and the response variables has an irregular random distribution pattern, so it is assumed that all explanatory variables are suitable for modeling using nonparametric methods.

2. Determining the Order of the Polynomial, Smoothing Parameters, and Optimal Number of Knot Points

Before modeling using penalizedspline nonparametric regression, selecting the order of polynomials, smoothing parameters, and the optimal number of knot points based on the minimum GCV criteria is necessary.

Table 2. Optimal Parameters of Each Explanatory Variable

Variable	Orde	Number of Knot	λ	GCV	Knot
X_1	1	1	0.475	7.193	45.59
X_2	2	2	0.161	7.224	-3.6; -1.35
X_3	1	2	0.906	6.389	87.22; 99.96
X$	1	1	1.039	5.786	9.945
X_5	1	1	1.179	6.998	71.845
X&	1	1	0	6.846	0.94

Table 2 shows that the X_2 variable has a polynomial order of quadratic form, and the other variables are linear. It can be seen that each explanatory variable has a variety of knots with varying values of the smoothing parameter "λ". Furthermore, the optimal value of the polynomial order, the number of knot points, and the smoothing parameter "λ" obtained will be used to create a penalized spline nonparametric regression model.

3. Estimation Parameter of Penalized

The next step is to estimate the additive nonparametric regression coefficient using a back-fitting algorithm. This back-fitting algorithm obtains an additive nonparametric regression coefficient when obtaining a convergent value of the sum of the squares of the residuals. The additive nonparametric regression model for the variable of the open unemployment rate in Java, as described in Table 4 is as follows:

$$\hat{Y}=-26,750-0,050X_1+0,068(X_1-45,59)_+ +10,171+1,127X_2+0,077X^2-0,241(X+3,6)^2$$

Spline Nonparametric Regression	$+0,236(X_2+1,35)^2_+ +5,269+0,016X_3$ $+0,091(X_3-87,22)_+ -0,138(X_3-99,96)_+$

$+10{,}215-0{,}306X_4+0{,}028(X_4-9{,}945)_+$
$+19{,}018-0{,}168X_5+0{,}164(X_5-71{,}845)_+$
$+7{,}406-0{,}580X_6+1{,}813(X_6-0{,}94)_+$

Based on the additive nonparametric regression estimation results, a plot can be made between the percentage value of the open unemployment rate from the modeling results and the percentage value of the open unemployment rate from the observation data. This is done to see the level of flexibility of the resulting model in following the distribution pattern of the observation data.

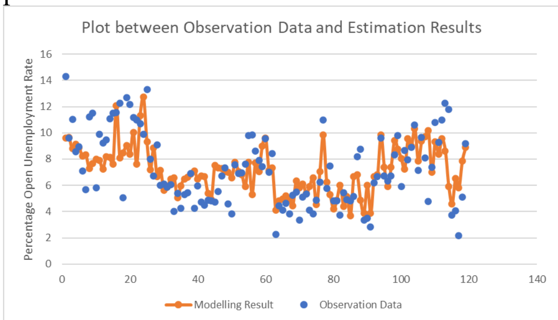

Figure 2. Plot between Observation Data and Open Unemployment Rate Estimator

Based on Figure 2, it can be seen that the modeling results using penalized spline nonparametric regression have good flexibility, it can be seen that the model is able to follow the pattern of data distribution on the percentage of open unemployment rates observed. The additive Mean Square Error (MSE) is 4.137 and the coefficient of determination is 0.4458. This shows that the explanatory variables used can explain the percentage of the open unemployment rate in Java of 44.58%, so it can be said that the model can explain 44.58 % of the open unemployment rate in Java. In contrast, the rest, 55.42% is explained by other factors not included in the model.

4. Testing of Parameter Significant

Simultanous Testing

Table 3 shows the results of the F test on the penalized spline nonparametric regression model.

Table 3. F-test Result

F-Statistic	p-value
3.9408	2.068×10^{-6}

Based on Table 3, the F-Statistic is 3.941 with a p-value of 2.068×10^(-6). With a significance level of 0.05, found that the p-value <α, then the decision taken was Reject H_0, meaning that the explanatory variables had a significant effect on the response variables.

Partial Testing

Table 4 shows the results of the t-test on the penalized spline nonparametric regression model.

Table 4. Coefficient Regression and Significance Parameter Testing Result

Variable	Coefficient	t-statistic	p-value
X_1 (AK)	-26.750	5.430	4.094×10-7*
	-0.050	3.405	0.001*
	0.068	2.158	0.033*
X_2 (LPP)	10.171	8.566	0.000*
	1.127	3.235	0.002*
	0.077	2.739	0.007*
	-0.241	2.540	0.013*
	0.236	2.021	0.046*
X_3 (APK)	5.269	1.244	0.217
	0.016	1.079	0.283
	0.091	1.923	0.057
	-0.138	2.212	0.029*
X_4 (PPM)	10.215	14.146	0.000*
	-0.306	4.295	4.118×10^{-5}*
	0.028	1.094	0.277
	19.018	0.688	0.493

X_5 (IPM)	-0.168	0.331	0.742

Variable	Coefficient	t-statistic	p-value
	0.164	1.334	0.185
X_6 (LP)	7.406	14.857	0.000*
	-0.580	3.224	0.002*
	1.813	4.543	1.580×10^{-5}*

*signfikan

Based on the criteria for a significance level of 0.05, the regression coefficient is said to reject H_0 if the p-value obtained is smaller than the 0.05 significance level. Based on this, 14 regression coefficients significantly affect the model. The variables that have a significant effect are the dependency ratio (X_1), the GDP growth rate (X_2), the senior high school Gross Enrollment (X_3), the percentage of the poor (X_4), and the population growth rate (X_6). One variable that is not significant in influencing the model is the Human Development Index (X_5) variable.

Discussion

The interpretation of the results of modeling the open unemployment rate with the variable dependency ratio (X_1) in Java when the variables X_2, X_3, X_4, X_5, dan X_6 are considered constant are as follows.

$$\hat{f}_1(X_1)=-26.750-0.050X_1+0.068(X_1-45.59)_+$$

$$\hat{f}_1(X_1)=\begin{cases}-26.750-0.050X_1, & X_1<45.59\\ -29.850+0.018X_1, & X_1\geq45.59\end{cases}$$

The results showed that the dependency ratio significantly affected the open unemployment rate. If the dependencyrate increases by one percent, the open unemployment rate will decrease by 0.050% for areas with a dependency rate of less than 45.59%, and the open unemployment rate will increase by 0.018% for areas with adependency rate of more than or equal to 45.59%. This study is in line with the research conducted by (Prasanti et al., 2015).

The interpretation of the results of modeling the open unemployment rate with the GDP growth rate (X_2) in Java when the variables X_1, X_3, X_4, X_5, and X_6 are considered constant are as follows.

$$\hat{f}_2(X_2)=10.171+1.127X_2+0.077X^2_2-0.241(X_2+3.6)^2_+ +0.236(X_2+1.35)^2_+$$

$$10.171+1.127X_2+0.077X^2, \quad X^2<-3.6$$

The results show that the rate of population growth has a significant effect on the open unemployment rate. When the GRDP growth rate increases by one percent, the open unemployment rate will decrease by 0.164% in areas with GRDP growth rates ranging from -3.6% to less than -1.35%. The results of this study are in line with Tutupoho (2019). If the GRDP growth rate increases by one percent, the open unemployment rate will increase by 0.077% for areas with a GRDP growth rate of less than or equal to -3.6%, and the open unemployment rate will increase by 0.072% for areas with a GRDP growth rate greater than -1.35%. This finding is similar to the research conducted by Rahayu et al (2019).

The interpretation of the results of modeling the open unemployment rate with the senior high school gross enrollment (X_3) in Java when the variables X_1, X_2, X_4, X_5, and X_6 are considered constant are as follows.

$$\hat{f}_3(X_3)=5.269+0.016X_3+0.091(X_3-87.22)_+ -0.138(X_3-99.96)_+$$

$$\hat{f}_3(X_3)=\begin{cases}5.269+0.016X_3, & X_3<87.22\\ -2.668+0.107X_3, & 87.22\leq X_3<99.96\\ 11.126-0.031X_3, & X_3\leq99.96\end{cases}$$

The results showed that the senior high school gross enrollment significantly affected the open unemployment rate. If the senior high school gross enrollment gross enrollment increases by one percent, it will cause the open unemployment rate to fall by 0.031% for areas where the senior high school gross enrollment gross enrollment is less than or equal to 99.96%. This finding is in line with the research conducted by Tantri & Ratnasari (2016).

The interpretation of the results of modeling the open unemployment rate with the percentage of the poor (X_4) in Java when the variables X_1, X_2, X_3, X_5, and X_6 are considered constant are as follows.

$$f_2(X_2)=\begin{cases}7.048-0.608X_2-0{,}164X_2^2, & -3.6\leq X_2^2<-1.35\\ 7.478+0.029X_2+0.072X_2^2, & X_2^2\geq -1.35\end{cases}$$

$$f_4(X_4)=10.215-0.306X_4+0.028(X_4-9.945)_+$$

$$f_4(X_4)=\begin{cases}10.215-0.306X_4, & X_4<9.945\\ 9.937-0.278X_4, & X_4\geq 9.945\end{cases}$$

The results showed that the percentage of the poor had a significant effect on the open unemployment rate. When the area with the percentage of poor people is less than 9.945% and increases by one percent, the open unemployment rate decreases by 0.306%.

The interpretation of the results of modeling the open unemployment rate with the population growth rate (X_4) in Java when the variables X_1, X_2, X_3, X_5, and X_6 are considered constant are as follows.

$$\hat{f}_6(X_6)=7.406-0.580X_6+1.813(X_6-0.94)_+$$

$$\hat{f}_6(X_6)=\begin{cases} 7.406-0.580X_6, & X_6<0.94 \\ 5.702+1.233X_6, & X_6\geq 0.94 \end{cases}$$

If the area with a population growth rate of less than 0.94% and increases by one unit, the open unemployment rate will decrease by 0.580%. A region with a population growth rate greater than 0.94% and increases by one unit causes the open unemployment rate to increase by 1.233%.

CONCLUSION

The penalized spline additive nonparametric regression model is an appropriate method for the open unemployment rate in regencies/cities on the island of Java, with an additive Mean Square Error value of 4.137 and a coefficient of determination of 44.58%. Based on the results of the parameter significance test, five variables that significantly influence the open unemployment rate in Java are the dependency ratio (X_1), the GDP growth rate (X_2), the senior high school gross enrollment (X_3), the percentage of the poor (X_4), and the rate of population growth (X_6).

Suggestion

Suggestions that can convey in this study are to model the open unemployment rate using other nonparametric regression methods, such as smoothing splines, b-splines regression, kernel regression, and so on. In future research, the latest data can be used by adding other variables that are thought to influence the open unemployment rate in Java.

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