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ESTIMATING MEAN ARTERIAL PRESSURE AFFECTED BY STRESS SCORES USING SPLINE NONPARAMETRIC REGRESSION MODEL APPROACH

NUR CHAMIDAH^{1,4,*}, BUDI LESTARI^{2,4}, ARDION MASSAID³, TOHA SAIFUDIN^{1,4}

¹Department of Mathematics, Faculty of Science and Technology, Airlangga University, Surabaya, Indonesia

²Department of Mathematics, Fac. Math. and Natural Sci., The University of Jember, Jember, Indonesia

³Student of Statistics Study Program, Fac. Sci. and Tech., Airlangga University, Surabaya, Indonesia

⁴Research Group of Statistical Modelling in Life Science, Fac. Sci. & Tech., Airlangga University, Indonesia

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Abstract: An average arterial blood pressure needed for blood circulation to the brain is called as mean arterial pressure (MAP). Blood circulation to the brain supplies food and oxygen to the brain for nutrition and brain activity. If the MAP is too low, it can cause diseases such as tachycardi heart rate and hypotension. In contrast, if MAP is too high, it can cause brain blood vessel rupture and hypertension. Stress is believed to has a relationship with hypertension. This is thought to be through sympathetic nerve activity which can increase blood pressure intermittently. Also, stress can stimulate kidneys to release adrenaline hormone and stimulate the heart to beat faster and stronger, so that blood pressure will increase. An increase in stress scores can be followed by an increase in MAP as well. In this study, we are interested to investigate the aftermath of changes in the stress scores on MAP by using spline nonparametric regression model approach which can accommodate changes in data patterns, and then

*Corresponding author

E-mail address: nur-c@fst.unair.ac.id

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compare it with the parametric regression model approach. The results showed that based on the mean square error values, the nonparametric regression model approach based on spline estimator is better than the parametric regression model approach. The estimated model that we got can be used to predict and interpret the values of MAP affected by stress scores as an effort to prevent hypertension.

Keywords: mean arterial pressure; stress score; spline estimator; parametric and nonparametric regressions.

2010 AMS Subject Classification: 62G05, 62G08, 62P10, 65D07.

1. INTRODUCTION

The term MAP is a term in the medical field to express the average arterial blood pressure as long as a single heartbeat cycle obtained from systolic and diastolic blood pressures measurements. According to Pocock and Richards [1] MAP is the weighted average time for pressure of artery throughout the heart cycle, which is calculated as diastolic pressure plus one third of the pulse pressure. Vital organs perfusion requires maintenance at least 60 mmHg of MAP. If the MAP falls below 60 mmHg for a long time, manifestations of end organs for example infarction and ischemia can occur. Further, blood will not be able to penetrate brain tissue if MAP drops significantly, and consequently it will occur loss of consciousness and nerve death quickly [2]. The human body has several protective mechanisms to ensure adequate perfusion levels and regulate MAP which are maintained for the functioning of all organs.

The results of MAP measurements are determined by blood pressure measurements. Although in good condition though, the results of blood pressure measurements do not show constant results at all times. The blood pressure measurement results always change at any time. The inconstant results of blood pressure measurements are influenced by various factors, namely age, sex, stress, race, medication, arterial elasticity, cardiac output, peripheral vascular pressure, blood volume, and blood viscosity [2].

Besides these internal factors there are factors outside the body that can affect blood pressures of humans, namely psychological factors where one of them is stress. Stress that occurs

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in the community will trigger an increase in blood pressures with a mechanism that triggers an increase in adrenaline levels. Stress will stimulate the sympathetic nerves such that it will increase blood pressures and increase cardiac output. Stress will increase if the resistance of peripheral blood vessels and cardiac output increases, which stimulates sympathetic nerves. So that stress will occur several reactions on the human body which include increasing muscle tension, increasing heart rate and increasing blood pressures. This reaction is raised when the human body reacts quickly and it can trigger the occurrence of diseases including hypertension [2]. Next, because of the influence of stress on the value of MAP, it needs to model its authorship. Until now there has been no research on the effect of stress levels represented by stress scores on the value of MAP.

Furthermore, to analyze a function which presents the relationship between dependent variables and independent variables we can use analysis of regression. In analysis of regression, there are two models approach which can be used to analyze data. They are parametric regression model and nonparametric regression model. In nonparametric regression model there are some estimators to estimate regression function, for example, local polynomial estimator ([3], [4]), local linear estimator [5–10], and spline and kernel estimators [11–24]. Changes in stress levels are followed by changes in MAP values. Stress levels at different levels cannot be confused with the MAP value so it needs to be estimated locally by using spline estimator, especially least square spline estimator, of nonparametric regression model. Spline estimators provide high flexibility to accommodate behavior changes of data locally because in the spline there are points called as knots that show several behavior changes at sub-intervals. Therefore, in this study, we investigate the aftermath of changes in the stress scores on MAP by using spline estimator of nonparametric regression model approach, and then compare its results with parametric regression model approach to select the best estimated model of MAP affected by stress scores.

2. PRELIMINARIES

In this section, we provide brief overview of materials and methods we used, i.e., spline estimator in nonparametric regression, generalized cross validation, data and steps of analysis.

2.1. Spline Estimator in Nonparametric Regression

Polynomial pieces play an important role in approximation and statistical theory. Polynomial pieces are flexible and effective in handling the local properties of a function or data ([5-6], [8-9], [13], [16–18]). One important type of polynomial piece is spline polynomial. Spline used as approach to analyse data firstly was introduced by Whittaker in 1923, while the spline used as approach to take solution of an optimization problem was developed by Reinch in 1967 ([25-26]).

Spline is one of the estimators of nonparametric regression. Spline estimator has good ability to estimate functions of data that have different behavior in different sub-intervals. These functions that have different behavior in every sub-intervals are connected to each other by points called knots to form a spline ([13],[17–18]). In general, the function $g(x)$ in spline space that has order p with knots K_1, K_2, \dots, K_m is any function that can be expressed as the following equation [14],[16–17], [22]:

$$(1) \quad g(x) = \sum_{j=0}^p \beta_j x^j + \sum_{j=1}^m \beta_{j+p} (x - K_j)_+^p$$

$$\text{where } (x - K_{j-p})_+^p = \begin{cases} (x - K_{j-p})^p, & x \geq K_{j-p} \\ 0 & , x < K_{j-p} \end{cases}$$

Next, if given $\lambda = (K_1, K_2, \dots, K_m)$ is smoothing parameter represented by knots K_1, K_2, \dots, K_m and $\beta_j, j = 0, 1, 2, \dots, p$ are the parameters of the model given in (1) and p is the order of spline, then estimation of parameter $\beta_j, j = 0, 1, 2, \dots, p$ can be obtained by using least square method ([14], [16-17]). In this step gives estimated parameters as follows:

$$(2) \quad \hat{\boldsymbol{\beta}} = (\mathbf{X}_\lambda^T \mathbf{X}_\lambda)^{-1} \mathbf{X}_\lambda^T \mathbf{y}$$

Based on equation (2), we get estimation of function $g(x)$ in equation (1) which is expressed as:

$$(3) \quad \hat{g}_\lambda(x) = \mathbf{H}(\lambda) \mathbf{y}$$

where $H(\lambda) = X_\lambda(X_\lambda^T X_\lambda)^{-1} X_\lambda^T$. Furthermore, $\hat{g}_\lambda(x)$ given in (3) is called as least square spline estimator.

2.2. GCV (Generalized Cross Validation)

In nonparametric regression one of the criteria that is used to determine the optimal knots is GCV. We can determine the best estimated MAP model by using GCV criterion that is minimum value of GCV. The GCV function which is used in nonparametric regression based on spline (i.e., least square spline) estimator is as follows [14],[25-26]:

$$(4) \quad GCV(\lambda) = \frac{MSE(\lambda)}{(n^{-1}tr[I-H(\lambda)])^2}$$

$$(5) \quad MSE(\lambda) = n^{-1} \sum_{i=1}^n (y_i - \hat{g}(x_i))^2.$$

Minimum value of GCV function given in equation (4) is used as a criterion for get optimal knots.

2.3. Data and Steps of Analysis.

In this study, we use primary data of MAP and stress scores that were recorded from the results of interviews with 39 respondents by using questionnaires at Cardiac Polyclinic of Hajj Hospital in Surabaya which was conducted from April 2019 to May 2019. The variables used to build model in this study consists of dependent or response variable and independent or predictor variable. The response variable (y) is mean arterial pressure (MAP), while the predictor variable used is the stress scores (x).

The steps to build MAP model and interpret the estimated model of MAP which is influenced by stress scores based on least square spline of nonparametric regression are: (a). Inputting paired data for response variable (y), i.e., mean arterial pressure (MAP), and predictor variable (x), i.e., stress score; (b). Determining the optimal values of the number of knots and their knots, and order of spline by considering minimum value of GCV in equation (4); (c). Estimating parameters of model by using equation (2); (d). Determining estimation of MAP model using equation (3); (e). Determining MSE as goodness of fit criterion using equation (5); (f). Plotting the observed and the estimated of mean arterial pressure (MAP) versus stress scores; and (g). Interpreting the estimated model of mean arterial pressure (MAP) affected by stress scores.

3. MAIN RESULTS

For estimating the mean arterial pressure (MAP) affected by stress scores, we need to provide a scatter plot to find out whether there exist behavior change of data or no. Result of this step is given in Fig. 1.

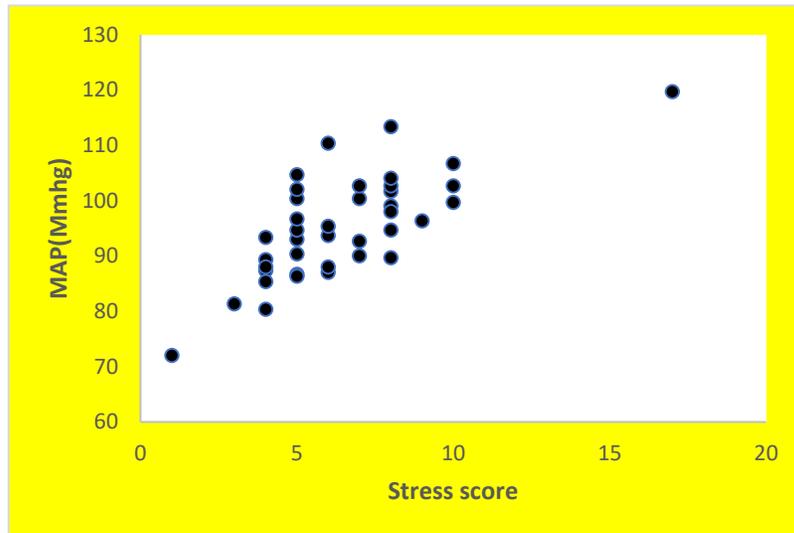


Figure 1. Scatter Plot of MAP versus Stress Scores

Figure 1 shows that plot of data does not form a specific pattern which indicates to the parametric regression patterns, i.e., linear form, cubic form, etc., and there is a behavior change of MAP data pattern on stress scores, so that using least square spline estimator of nonparametric regression model is very suitable for estimating the model of MAP. It is because in the form of fragments of function segments are combined by knots. The knots in this study were obtained by using the quantile method, and results of this method are given in Table 1.

Table 1. Estimation results on number of knot points, knot points, order of spline, and minimum values of GCV.

Number of Knot points	Knot Points	Order of Spline	Minimum Values of GCV
1	6	1	42.75
		2	43.71
2	5 ; 7.3	1	42.12
		2	46.2
3	5 ; 6 ; 8	1	44.44
		2	48.04

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Table 1 shows that the smallest GCV value is 42.12 and the number of knots is 2, i.e., 5 and 7.3 and order of spline is 1. Based on results given in Table 1, we obtain that by using spline estimator of nonparametric regression approach we get the estimated MAP model as follows:

$$(6) \quad \hat{y} = 64.22 + 5.99x - 4.52(x - 5)_+^1 + 0.75(x - 7.3)_+^1$$

Hence, based on equation (6) we get estimation of MAP model as the following equation:

$$(7) \quad \hat{y} = \begin{cases} 64.22 + 5.99x, & \text{for } x < 5 \\ 86.82 + 1.47x, & \text{for } 5 \leq x < 7.3 \\ 81.345 + 2.22x, & \text{for } x \geq 7.3 \end{cases}$$

The MSE value of estimated MAP model given in (7) is 33.92. Next, based on the estimated MAP model given in equation (7), we can provide plots of estimated MAP values and observation values of MAP versus stress scores as given in Figure 2.

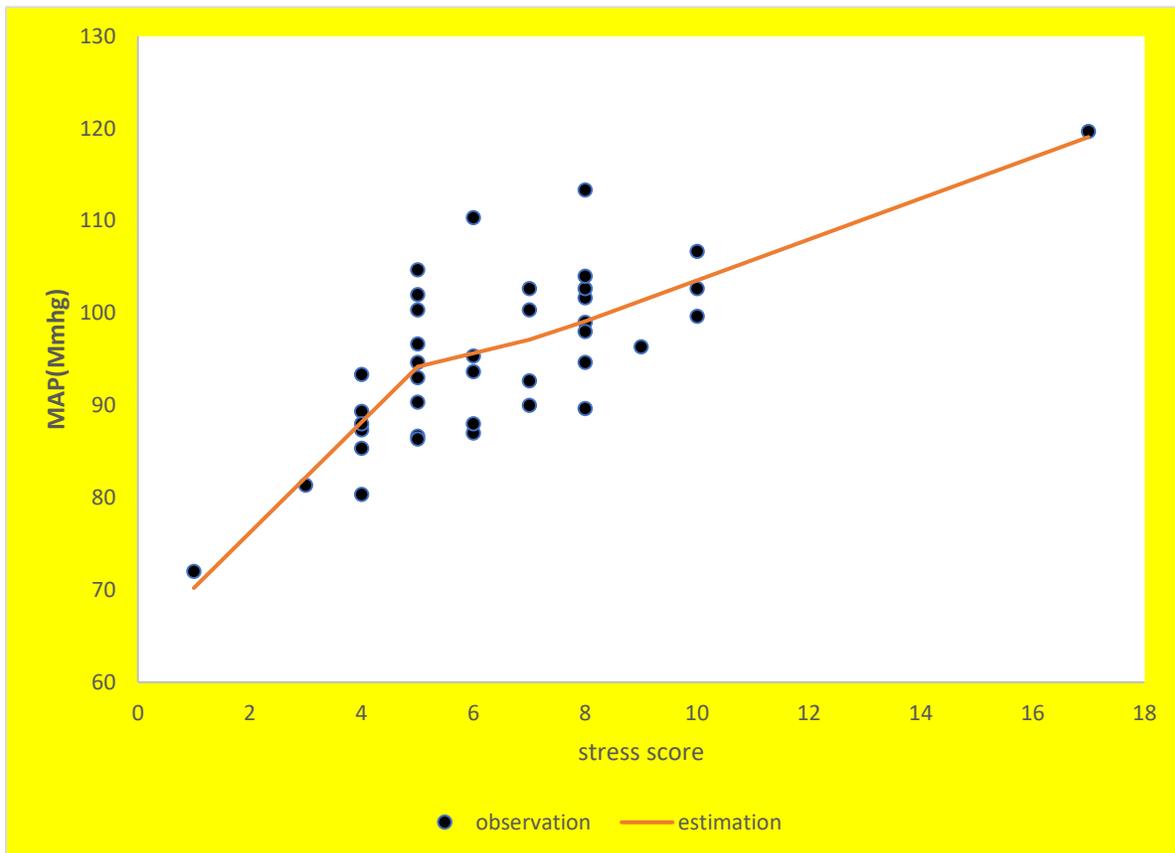


Figure 2. Plots of observation and estimated MAP on stress scores using nonparametric regression approach.

Based on the estimated MAP model given in (7), we obtain that if the stress scores are less than 5, then for every increase of one unit of stress scores can increase the MAP by 5.99. Also, if the stress scores are more than or equal to 5 and less than 7.3, then for every increase of one unit of stress scores can increase the MAP by 1.47. Next, if the stress scores are more than and equals to 7.3, then for every increase of one unit of stress scores can increase the MAP by 2.22.

In the next step we estimate the MAP model by using linear model of parametric regression approach. In this step we get the following estimated MAP model:

$$(8) \quad \hat{y} = 78.8 + 2.58x$$

Based on the estimated MAP model given in (8), we state that globally for every increase of one unit of stress scores can increase the MAP by 2.58. Also, in this step we get the MSE value of the estimated model given in (8) that is 42. Hence, in Figure 3 we present plots of estimated MAP values and observation values of MAP versus stress scores.

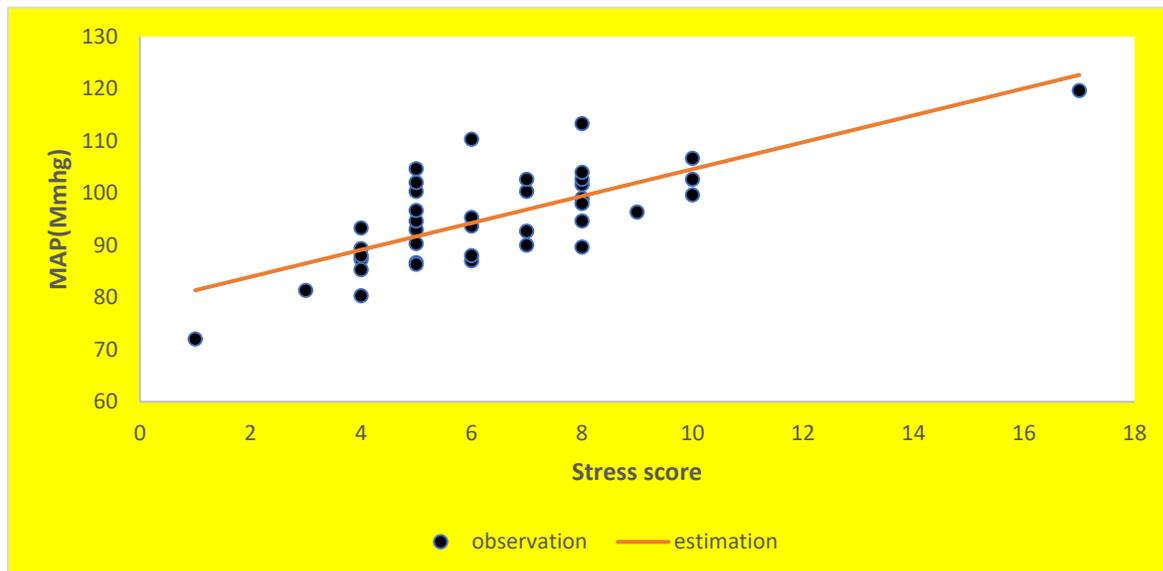


Figure 3. Plots of observation and estimated MAP versus stress scores using parametric regression approach.

From results that have been obtained both when using spline estimator of nonparametric regression approach or using linear parametric regression approach shows that estimation of MAP model by using spline nonparametric regression approach is better than that by using linear

parametric regression approach. The estimation results of the model using spline estimator of nonparametric regression approach are more able to show changes in behaviour of MAP on the sub-intervals of stress scores than those using linear parametric regression approach. Also, the MSE value of nonparametric regression approach is less than that of parametric regression approach. Therefore, for the purposes of predicting and interpreting MAP influenced by stress scores, we use estimated MAP model that obtained by using spline nonparametric regression approach which is better than that based on linear parametric regression approach.

4. CONCLUSIONS

The effects of stress scores on MAP have different patterns at some investigated sub-intervals of stress scores, so that for the purposes of predicting and interpreting MAP influenced by stress scores, in this case, the estimated MAP model based on spline nonparametric regression is more appropriate to use than that based on linear parametric regression.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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