BAREKENG: Journal of Mathematics and Its Applications
March 2025 Volume 19 Issue 1 Page 0025–0034
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol19iss1pp0025-0034

MODEL SELECTION FOR B-SPLINE REGRESSION USING AKAIKE INFORMATION CRITERION (AIC) METHOD FOR IDR-USD EXCHANGE RATE PREDICTION

Indriani Wahyu Nur Pratiwi[1], Sri Utami Zuliana[2*]

[1,2]*Department of Mathematics, Faculty of Science and Technology, UIN Sunan Kalijaga Yogyakarta*
Jl. Laksda Adisucipto, Yogyakarta, 55281, Indonesia

*Corresponding author's e-mail: * **sri.zulianai@uin-suka.ac.id***

ABSTRACT

Article History:

Received: 1st January 2024
Revised: 24th September 2024
Accepted: 24th September 2024
Published: 13th January 2025

Keywords:

AIC;
B-Spline Regression;
Exchange Rate;
MAPE.

Exchange rate data is a collection of information about the exchange rate the foreign currency which collected by time. Autoregressive Integrated Moving Average (ARIMA) is a well-known time series analysis. Several assumptions that need to be checked before running the ARIMA model are stationarity, normality, and white noise. B-spline regression is a method of modeling time series data without considering assumptions. This research aims to create a forecasting model for Rupiah exchange rate against US Dollar using B-spline regression. The B-spline regression model was generated with a combination of degrees two to four and a maximum of four knots. After that, the optimal model is selected using the Akaike Information Criterion (AIC) score. The performance of the selected model is validated using Mean Absolute Percentage Error (MAPE) values. The optimal degree is 3 (quadratic) and the optimal number of knot points is two-knot points with an AIC value of 857.8322 and a MAPE value of 0.0148376. The best model is: $\hat{y} = 13526.08\, N_{-2,3}(x) + 14177.5\, N_{-1,3}(x) + 14145.24\, N_{0,3}(x) + 15698.26\, N_{1,3}(x) + 15156.4\, N_{2,3}(x)$.

How to cite this article:

I. W. N. Pratiwi and S. U. Zuliana, "MODEL SELECTION FOR B-SPLINE REGRESSION USING AKAIKE INFORMATION CRITERION (AIC) METHOD FOR IDR-USD EXCHANGE RATE PREDICTION", *BAREKENG: J. Math. & App.*, vol. 19, iss. 1, pp. 0025-0034, March, 2025.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article • Open Access

1. INTRODUCTION

ARIMA (Autoregressive Integrated Moving Average) model is a method of modeling time series data to draw relevant conclusions about economic activity. There are four types of time series data relationship patterns that can be considered for decision making: horizontal, trend, seasonal, and cyclical. ARIMA has been applied to financial data [1][2], one of which is the exchange rate of the Rupiah against the US Dollar data. Exchange rate data is time series data that can be predicted by taking into and account several assumptions that must be met. In the nonparametric approach, there are several methods for building models of time series data, namely kernel estimator [3] and spline regression [4]. The kernel estimator can be used to model data that does not have a fixed formula and is more flexible to use. However, spline regression can be used to analyze the behavior of different data at different time intervals [5]. Both have their advantages, but as an alternative to the nonparametric approach used, Spline regression is recommended to make the generated model more flexible.

A linear regression analysis, which is a continuous segmented truncated polynomial, can be used to adjust data more effectively [5]. Two common basis functions used in modeling time series data are the truncated basis function and the B-spline basis. However, the disadvantage of the truncated bases is that when the degree is high, the number of knots increases, resulting in a singular normal equation matrix. The use of the B-spline basis is an alternative solution that is also efficient in digital computation [6].

Many studies on the B-spline have been carried out such as comparative study of different B-spline approaches for functional data [7], and Bayesian quantile regression [8]. Some applications of B-spline regressions have been done, for example volatility modeling [9], stem taper and volume prediction [10], surface measurement [11], child mortality [12], and hydrologic frequency analysis [13]

Studies on exchange rate forecasting has been carried out using various methods and approaches. The exchange rate forecasting is taken using deep learning by Yilmaz and Arabaci [14], Chen, J. et.al. [15], and Maqsood, H. et.al [16]. B-spline regression is also applied for exchange rate prediction [17][18]. The exchange rate of the Rupiah against the US Dollar is a time series data that can be used to forecast the future. The stability of the US Dollar exchange rate against the Rupiah is important for investment practitioners who actively invest their capital, as if the exchange rate weakens, interest rates will rise and the stock price index will decrease, reducing the profits obtained [19]. Some studies about exchange rate IDR-USD have been done using different methods such as global ridge-regressions [20], Wavelet Fuzzy Model [21], ARIMA [22], and XGBoost [23].

Changes in exchange rates greatly affect the investment activity and future profits of the investor. Therefore, an investor must be able to predict the exchange rate in order to estimate future profits. Based on the above description, the author discusses the selection of the best B-Spline regression model using the Akaike Information Criterion (AIC) method for time series data. The Akaike Information Criterion (AIC) optimization is used to determine the optimal degree and number of knot points for B-spline regression. This study uses AIC optimization with a combination of degree 2 to 4 and the number of knot points 1 to 4 knots. After obtaining the optimal combination of degree and knot points, the estimated parameters of the B-Spline regression model will be formed. A parameter significance test is conducted to determine the significance of the model parameters, and the Mean Percentage Absolute Error (MAPE) value is used to test the feasibility of the model.

Exchange rate policy has an important role in economic performance. Governments should make a policy about exchange rate. The forecast of exchange rate will give a big description about the change in economic. This research proposes B-spline regression to forecast the volatility of exchange rate.

2. RESEARCH METHODS

2.1 Regression Analysis

Regression analysis is a statistical analysis that can be used to analyze and model the relationship between predictor variables and response variables, where predictor variables can be described with (x) and response variables can be described with (y). A simple linear regression equation can be defined in Equation (1).

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, i = 1, 2, 3, \ldots, n \tag{1}$$

The estimation of the linear regression **Equation (1)** is:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i \tag{2}$$

The coefficients $\hat{\beta}_0$ and $\hat{\beta}_1$ can be calculated using a distribution approach by maximizing the maximum likelihood function assuming ε_i is independent and normally distributed $NIDN(0, \sigma^2)$. The maximum likelihood function can be defined as follows:

$$L = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n e^{-\frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i\right)^2} \tag{3}$$

or it can be calculated by minimizing the sum of the least squares. The sum of least squares can be defined as follows:

$$\sigma^2 = \frac{\sum_{i=1}^{n}\left(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i\right)^2}{n} \tag{4}$$

There are two ways to estimate the regression function, namely by using parametric and nonparametric approaches.

2.2 Parametric Regressions

Parametric regressions are statistical methods used to determine the linear or nonlinear relationship between the predictor variable (x) and the response variable (y) whose form of the regression function is known. In addition, the process of making conclusions are based on bound assumptions that must be met. If all assumptions can be met, then parametric models can be used. However, if there are assumptions that are not met, then the application of parametric models can be misleading. This can be overcome using a nonparametric approach.

2.3 Nonparametric Regressions

Nonparametric regression models can be constructed by selecting the appropriate function space in which the regression function $f(x_i)$ is assumed to be included. The selection of this function space is motivated by the smoothing owned by the regression function resulting in higher flexibility. The function is said to be smooth if the curve does not change rapidly. The general equation of nonparametric regression is written in **Equation (5)**.

$$y_i = f(x_i) + \varepsilon_i, i = 1,2, \dots, n \tag{5}$$

The function $f(x_i)$ can be estimated using spline regressions.

2.4 Spline Regressions

Spline regression has a commonly used function base, namely the truncated function base and the B-Spline function base **[5]**. The basis of truncated functions has the disadvantage that when the order is high, the number of knots increases and the location of knots too close will create a matrix that has almost no inverse (singular), thus making the equation not easy to solve. The B-Spline nonparametric regression approach can be an alternative solution to solve problems in almost singular normal matrix equations.

2.5 B-Spline Regression

B-Spline regression was first introduced by D. Boor. At that time, B-Spline regression was known as the D. Boor algorithm. However, over time the term changed to B-Spline regression introduced by Isaac Jacob Schoenberg in 1946 **[24]**. B-Spline regression is a polynomial that has the property of continuous pieces (segments) so that it can explain the characteristics of data functions.

The nonparametric regression equation model (**Equation (5)**) if approximated with a basis B-Spline of degree j with m knots can then be defined as the following **Equation (6) [5]**.

$$y_i = \sum_{u}^{j+m} \beta_u, N_{u,j}(x) + \varepsilon \tag{6}$$

where $N_{u,j}$ is the basis of the B-Spline function of degree j and β_u is the B-Spline regression parameter.

B-Spline basis function of degree j with m knots have $2j + m$ augmented knots. The additional $2j$ points are $v_{-(j-1)} < \cdots < v_{-1} < v_0 < \cdots < v_{(j+m)}$ with $v_{-(j-1)} = \cdots = v_0 = a$ and $v_{m+1} = \cdots = v_{m+j} = b$. Generally, the value of a is obtained from the smallest value of x and the value of b is obtained from the largest value of x [25]. A set of real valued function $N_{u,j}$ (for $j = 0,1,\cdots,n$, n is the degree of the B-spline basis) with m knot points is recursively defined as the following **Equation (7)**:

$$N_{u,j(x)} = \frac{x - v_u}{v_{u+j-1} - v_u} N_{u,j-1(x)} + \frac{v_{u+j} + x}{v_{u+j} - v_{u+1}} N_{u+1,j-1(x)} \tag{7}$$

with $u = -(j-1), \ldots, m$, and

$$N_{u,2}(x) = \begin{cases} 1, x \in v_u, v_{u+1} \\ 0, \quad \text{others} \end{cases}$$

2.6 Parameter Significance Test

Parameter significance testing is carried out to see whether the predictor variables (x) simultaneously have a significant effect on the response variable (y). Parameter significance testing can be carried out using simultaneous testing or F-test. F-test formula is:

$$F = \frac{SSR/((j+m)-1)}{SSE/(n-(j+m))}$$

with $SSR = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$; $SSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$; $j =$ B-spline order; $m =$ number of knots; $n =$ number of observations.

2.7 Akaike Information Criterion (AIC)

The best model in this study is chosen by AIC because AIC will test the model fits performance without over-fitting it. A goodness-of-fit is increasing the score of AIC, but the over-fitting is decreasing the score of AIC. The AIC scores are compared among some models and the best model is chosen with the lowest AIC score. It means the model has the optimal performance to fit the data set without over-fitting it.

There are two formulas for calculating the AIC value [26][27] . If the amount of data is large, the AIC value can be obtained using the Maximum Likelihood function written in the following formula:

$$\text{AIC} = -2\log(L) + 2p$$

Where $\boldsymbol{L}$ is the maximum likelihood used to find the coefficient of the $\boldsymbol{\beta}$ by deriving the likelihood function against the parameter and $\boldsymbol{p}$ is the number of parameters to be calculated. As for the sum of the smallest squares can use the formula:

$$\text{AIC} = \text{n}\log(\sigma^2) + 2p$$

2.8 Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is a matrix that defines the measure of accuracy of a forecasting method. When the performance of forecasting methods needs to be compared across different time series, accuracy measures such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) are inappropriate. This is because there is often such a large variation in the scale of observations between series that a few series with large values can dominate the comparison [28]. Under these conditions, unit-free measures need to be used and the average absolute percentage of land loss (MAPE) is probably the most widely used measure for this type. MAPE is defined below for forecasts made for periods 1 to n of a series [29].

$$\text{MAPE} = \sum_{i=1}^{n} \frac{\left|\frac{y_i - \hat{y}_i}{y_i}\right|}{n} \times 100\%$$

There are four levels of MAPE value criteria, namely if the MAPE value is less than 10%, then the model has very good predictive ability. If the value is between 10% and 20%, then the model has good predictive ability. If the value is between 20% and 50%, then the model has a fairly good predictive ability, and if the MAPE value is more than 50%, then the model has poor predictive ability [30].

2.9 USD to IDR Forecast

Governments maintain control over exchange rate changes for countries that adopt a fixed exchange rate system. Foreign exchange demand can be influencing by payment for imports of goods and services and capital outflow. On the other hand, foreign exchange supply can be influencing by receiving of exports of goods and services; and capital inflow [31]. Although there are some differences on how exchange rate indicates economic crises between developing countries and developed countries, but exchange rate control is the common leading indicator of crises. For developing countries, exchange rate is a dominant indicator of crises. Government needs exchange rate forecast in order to make some policies. The exchange rate forecast is one of tools to mapping current and expected economic conditions [32].

2.10 Research Model

Our approach to selecting the B-spline regression model consists of the following steps:

1. Analyze the time series data of the Rupiah exchange rate (IDR) against the US Dollar (USD) for the period January 2018 to January 2023.
2. Modify Rupiah (IDR) exchange rate data against the US Dollar (USD) into predictor variables and response variables, namely $(x_i, y_i) = Z_{i-1}, Z_i$ with $i = 2, 3, 4, \ldots, 61$.
3. Determine the approximate B-Spline regression model based on the degree and number of knots points desired.
4. Determine the optimal combination of degree and number of knot points based on the minimum AIC value with the R software.
5. Estimate the parameters of the best B-Spline regression model based on AIC criteria.
6. Test the significance of B-Spline regression model parameters.
7. Test the feasibility of the model based on the MAPE value.

3. RESULTS AND DISCUSSION

3.1 Data Description

This research uses exchange rate of the Rupiah (IDR) against the US Dollar (USD) data for the period January 2018 to January 2023 [33]. The data used is exchange rate of the Rupiah (IDR) against the US Dollar (USD) data for the period January 2018 to January 2023 obtained from Bank Indonesia through the official website of Bank Indonesia (Indonesia, 2022).

Figure 1 shows a graph of the fluctuating movement of the Rupiah exchange rate against the US Dollar (USD) over the last five years. The lowest exchange rate occurred in January 2018 at 13380.36, while the highest exchange rate occurred in May 2020 at 15867.43.

3.2 Selecting of the Optimal Degree and Number of Knot Points

An optimal B-Spline regression model can be formed through selecting the optimal degree and number of knots. This study uses the Akaike Information Criterion (AIC) method so that in sorting the optimal degree and the optimal number of knots. A minimum AIC value is used for the best estimate. The degree to be presented is degree 2 to degree 4 with the number of knot points 1 to 4 knots.

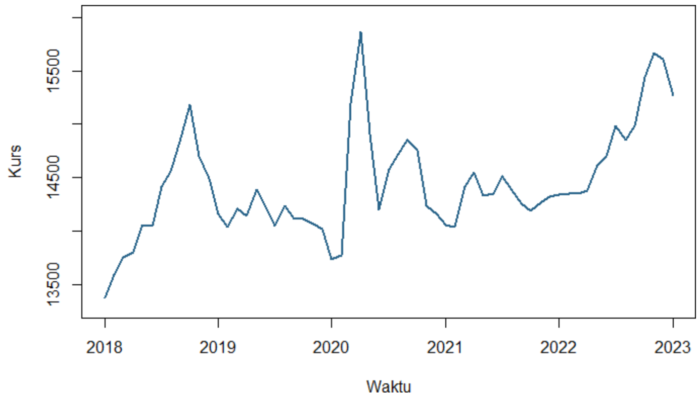

Figure 1. Plot of Rupiah (IDR) Exchange Rate Data against US Dollar (USD) for the January 2018 - January 2023 Period

3.3 B-Spline Model

To obtain the exact degree and the optimal number of knots, it is necessary to test the combination between the degree and the number of knots present. The test starts from a combination of degree 2 and 1 point knots, then degree 3 and 1 point knots, carried out up to degree 4 and 4 point knots. The results of the combination test can be presented in Table 1.

Table 1. The Optimal Number of Knots for Each Degree

Degree	Number of Knots	AIC
Linear	1	862.1868
	2	861.9001
	3	863.9001
	4	865.9001
Quadratic	**2**	**857.8322**
	3	859.8064
	4	861.8064
Cubic	3	860.1547
	4	862.1363

Table 1 shows the optimal combination of degree and number of knots when using the 3rd degree approach (Quadratic B-Spline) and the number of two knots (13907.92; 14837.43) with a minimum AIC value of 857.8322.

3.4 Estimating Parameter of B-Spline Model

After obtaining the optimal combination of order and number of knots, the next step is to carry out parameter estimation to determine the estimated parameters for the model. Based on previous calculations, the estimated parameter β is presented in Table 2.

Table 2. Parameter Estimation Using AIC Method

Parameter	Parameter Estimation
β_{11}	13526.08
β_{12}	14177.50
β_{13}	14145.24
β_{14}	15698.26
β_{15}	15156.40

Based on Table 2, the best B-Spline regression model parameter estimation equation can be written using the AIC method:

$$\hat{y} = 13526.08N_{-2,3}(x) + 14177.5N_{-1,3}(x) + 14145.24N_{0,3}(x) + 15698.26N_{1,3}(x) + 15156.4N_{2,3}(x)$$

Addition knots is defined as $v_{-(j-1)} = \cdots = v_0 = x_{\min}$ and $v_{m+1} = \cdots = v_{m+j} = x_{\max}$ in which $j = 3$ and $m = 5$. So, we obtain the knots:

$v_{-2} = \cdots = v_0 = 13380.36$, $v_1 = 13907.92$, $v_2 = 14837.43$ and $v_3 = \cdots = v_5 = 15867.43$

The interpretation of the B-Spline regression model is explained by considering the values of the B-Spline basis:

$$\hat{y} = 13526.08N_{-2,3}(x)$$

which

$$N_{-2,3}(x) = \begin{cases} \left(\dfrac{13907.92 - x}{527.56}\right)^2, & 13380.36 < x \leq 13907.92 \\ 0, & \text{others} \end{cases}$$

$$\hat{y} = 15156.4N_{2,3}(x)$$

which

$$N_{2,3}(x) = \begin{cases} \left(\dfrac{x - 14837.43}{1030}\right)^2, & 14837.43 < x \leq 15867.92 \\ 0, & \text{others} \end{cases}$$

When the Rupiah exchange rate against the US Dollar is at a minimum of Rp.13380.36, the exchange rate will increase by Rp.13500. In addition, when the Rupiah exchange rate against the US Dollar is at a maximum of Rp.15867.43, the exchange rate will increase by Rp.15157.

3.5 Parameter Significance Test

Based on the results of the parameter significance test using the F test or ANOVA test, it shows that the F_{count} value is 36.03387 and the F_{table} value is 2.769431. The H_0 hypothesis is rejected if F_{count} more than F_{table}. That is, the predictor variables (x) together have a significant effect on the response variable (y) or it can also be concluded that the parameters of the B-Spline model have been significant.

3.6 Model Feasibility Test

Figure 2 shows a comparison graph of the actual exchange rate value with the predicted exchange rate value of the B-Spline model and ARIMA model. It can be seen that the predicted value using the B-Spline model produces a smoother graph compared to the ARIMA model prediction graph, so it can be concluded that the best model can be used to forecast Rupiah Exchange Rate (IDR) data against American Dollar (USD) is a B-Spline regression model. To ensure this, it is necessary to test the feasibility of the B-Spline regression model using the Mean Percentage Error (MAPE) value. The ability of the model to explain the influence of variables is shown by a MAPE value of 0.01483769, meaning that the resulting B-spline regression model has a very good ability to determine indications of ups and downs in values the rate that will occur.

Table 3. MAPE Value Comparison

Research	MAPE Value
Zuliana (2012)	0.06190000
Septiarini (2016)	0.03450000
Islam, et.al (2016)	0.11643000
Qonita, et.al (2017)	1.25944200
Pratiwi & Zuliana (2024)	0.01483769

Based on the MAPE value criteria, this value shows that the B-Spline model's performance in forecasting is very good to be used to model the Rupiah Exchange Rate (IDR) data against the US Dollar (USD). The MAPE value criteria have a smaller value compared to several previous studies i.e. 0.0619 [20], 0.0345 [21], 1.259442 [22] and 0.11643 [23].

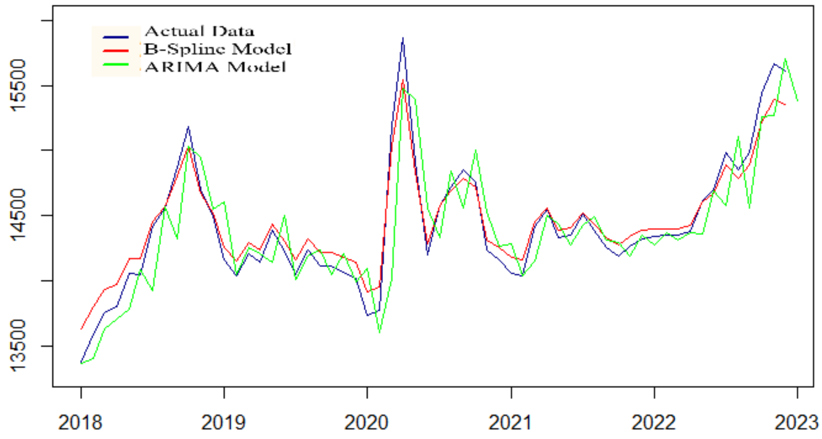

Figure 2. Comparison among Actual Data, B-Spline Model and ARIMA model

4. CONCLUSIONS

In this paper, we applied B-spline regression using AIC method for IDR-USD exchange rate prediction. We use degree from 2 to 4 with the number of knot points 1 to 4 knots. We got minimum AIC value, 857.8322 with the model the 3rd degree and the number of 2 knots (Quadratic B-Spline). The best B-Spline model on Rupiah (IDR) exchange rate data against the US Dollar (USD) is presented in the equation:

$$\hat{y} = 13526.08N_{-2,3}(x) + 14177.5N_{-1,3}(x) + 14145.24N_{0,3}(x) + 15698.26N_{1,3}(x) + 15156.4N_{2,3}(x)$$

REFERENCES

[1] H. Yu, L. J. Ming, R. Sumei, and Z. Shuping, "A hybrid model for financial time series forecasting—integration of EWT, ARIMA with the improved ABC optimized ELM," *IEEE Access*, vol. 8, pp. 84501–84518, 2020, doi: 10.1109/ACCESS.2020.2987547.

[2] T. Li, J. Zhong, and Z. Huang, "Potential dependence of financial cycles between emerging and developed countries: Based on ARIMA-GARCH Copula model," . *Emerg. Mark. Financ. Trade, 56(6), 1237-1250.*, vol. 56, no. 6, pp. 1237–1250, 2020, doi: https://doi.org/10.1080/1540496X.2019.1611559.

[3] A. Altan and S. Karasu, "The effect of kernel values in support vector machine to forecasting performance of financial time series," *J. Cogn. Syst.*, vol. 4, no. 1, pp. 17–21, 2019.

[4] P. D'Urso, L. A. García-Escudero, L. De Giovanni, V. Vitale, and A. Mayo-Iscar, "Robust fuzzy clustering of time series based on B-splines," *Int. J. Approx. Reason.*, vol. 136, pp. 223–246, 2021, doi: https://doi.org/10.1016/j.ijar.2021.06.010.

[5] R. L. Eubank, *Nonparametric Regression and Spline Smoothing (2nd ed.)*. Marcel Dekker Inc., 1999.

[6] C. de Boor, *A practical guide to splines*. New York: Springer-verlag, 1978.

[7] A. M. Aguilera and M. C. Aguilera-Morillo, "Comparative study of different B-spline approaches for functional data," *Math. Comput. Model.*, vol. 58, no. 7–8, pp. 1568–1579, Oct. 2013, doi: 10.1016/j.mcm.2013.04.007.

[8] P. Das and S. Ghosal, "Bayesian quantile regression using random B-spline series prior," *Comput. Stat. Data Anal.*, vol. 109, pp. 121–143, 2017.

[9] S. Corlay, "B-spline techniques for volatility modeling," *J. Comput. Financ.*, vol. 19, pp. 97–135, 2016.

[10] E. Kublin, J. Breidenbach, and G. Kändler, "A flexible stem taper and volume prediction method based on mixed-effects B-spline regression," *Eur. J. For. Res.*, vol. 132, pp. 983–997, 2013.

[11] W. Lu *et al.*, "Uncertainty-guided intelligent sampling strategy for high-efficiency surface measurement via free-knot B-spline regression modelling," *Precis. Eng.*, vol. 56, pp. 38–52, 2019.

[12] L. Alkema and J. R. New, "Global estimation of child mortality using a Bayesian B-spline bias-reduction model," *Ann. Appl. Stat.*, pp. 2122–2149, 2014.

[13] B. Nasri, T. Bouezmarni, A. St-Hilaire, and T. B. Ouarda, "Non-stationary hydrologic frequency analysis using B-spline quantile regression," *J. Hydrol.*, vol. 554, pp. 532-544., 2017.

[14] F. M. Yilmaz and O. Arabaci, "Should deep learning models be in high demand, or should they simply be a very hot topic? A comprehensive study for exchange rate forecasting.," *Comput. Econ.*, vol. 57, no. 1, pp. 217–245, 2021.

[15] J. Chen, C. Zhao, K. Liu, J. Liang, H. Wu, and S. Xu, "Exchange rate forecasting based on deep learning and NSGA-II models.," *Comput. Intell. Neurosci.*, vol. 2021, pp. 1–13, 2021, doi: https://doi.org/10.1155/2023/1741886.

[16] H. Maqsood *et al.*, "A local and global event sentiment based efficient stock exchange forecasting using deep learning," *Int. J. Inf. Manage.*, vol. 50, pp. 432–451, 2020, doi: https://doi.org/10.1016/j.ijinfomgt.2019.07.011.

[17] G. Pompeu and J. L. Rossi, "Real/Dollar Exchange Rate Prediction Combining Machine Learning and Fundamental Models," 2022. doi: http://dx.doi.org/10.18235/0004491.

[18] E. J. Lee and J. H. Jhong, “Change Point Detection Using Penalized Multidegree Splines,” *Axioms*, vol. 10, no. 04, p. 331, 2021, doi: https://doi.org/10.3390/axioms10040331.

[19] L. A. Alvian and C. Azari, “Pengaruh Inflasi, Nilai Tukar Dan Tingkat Suku Bunga Terhadap Indeks Harga Saham Gabungan (Studi pada Bursa Efek Indonesia Periode 2015-2017),” *Apl. Adm. Media Anal. Masal. Adm.*, pp. 18–30, 2019.

[20] S. U. Zuliana, “Penerapan Global Ridge-Regression pada Peramalan Data Time Series Non Linear Studi Kasus: Pemodelan Nilai Tukar US Dolar terhadap Rupiah,” *Kaunia*, vol. 8, no. 2, pp. 107–117, 2012.

[21] T. W. Septiarini, “Application of wavelet fuzzy model to forecast the exchange rate IDR of USD. Application of Wavelet Fuzzy Model to Forecast the Exchange Rate IDR of USD,” *Int. J. Model. Optim.*, vol. 6, no. 1, pp. 66–70, 2016.

[22] A. Qonita, A. G. Pertiwi, and T. Widiyaningtyas, “Prediction of Rupiah against us Dollar by using ARIMA.,” in *4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, 2017, pp. 1–5.

[23] S. F. N. Islam, A. Sholahuddin, and A. S. Abdullah, “Extreme Gradient Boosting (XGBoost) Method in Making Forecasting Application and Analysis of USD Exchange Rates against Rupiah,” *J. Phys. Conf. Ser. IOP Publ.*, vol. 1722, no. 1, pp. 1–11, 2016, doi: 10.1088/1742-6596/1722/1/012016.

[24] T. Hastie, R. Tibshirani, and J. H. Friedman, *The Elements Of Statistical Learning: Data Mining, Inference, and Prediction, Volume 2.* Springer, 2009.

[25] I. N. Budiantara, F. Suryadi, B. W. Otok, and S. Guritno, “Pemodelan B-Spline dan Mars Pada Nilai Ujian Masuk Terhadap IPK Mahasiswa Jurusan Disain Komunikasi Visual Uk. Petra Surabaya,” *J. Tek. Ind.*, vol. 8, no. 1, pp. 1–13, 2006.

[26] K. P. Burnham and D. R. Anderson, “Multimodel Inference: Understanding AIC And BIC In Model selection.,” *Sociol. Methods Res.*, vol. 33, no. 2, pp. 261–304, 2004.

[27] H. Akaike, “A New Look at the Statistical Model Identification,” *IEEE Trans. Automat. Contr.*, vol. 19, no. 6, pp. 716–723, 1974, doi: 10.1109/TAC.1974.1100705.

[28] C. Chatfield, “Apples, Oranges and Mean Square Error,” *Int. J. Forecast.*, vol. 4, no. 4, pp. 515–518, 1988.

[29] P. Goodwin and R. Lawton, “On the Asymmetry Of The Symmetric MAPE,” *Int. J. Forecast.*, vol. 15, no. 4, pp. 405–408, 1999.

[30] P. C. Chang, Y. W. Wang, and C. H. Liu, “The Development of A Weighted Evolving Fuzzy Neural Network for Pcb Sales Forecasting,” *Expert Syst. Appl.*, vol. 32, no. 1, pp. 86–96, 2007.

[31] I. Simorangkir and Suseno, *Seri Kebanksentralan Bank Indonesia 12: Sistem dan Kebijakan Nilai Tukar*. Bank Indonesia, 2004.

[32] A. Abubakar, G. A. Utari, and P. Azwar, “Early Warning Indicators and Optimal Policies for Mitigating Economic Crises: Evidence from Meta-Analysis,” *Bull. Monet. Econ. Bank.*, vol. 23, no. 2, pp. 269–294, 2020, doi: https://doi.org/10.21098/bemp.v23i1.1421.

[33] Bank Indonesia, “Informasi Kurs,” *bi*, 2022. https://www.bi.go.id/id/statistik/informasi-kurs [access on 17th, December, 2022 12.47 WIB].