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Indonesian Crude Oil Price (ICP) Prediction Using Support Vector Regression Algorithm

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Abstract

Indonesian crude oil prices (ICP) experience fluctuating movements, influenced by several factors and other conditions that make ICP prices difficult to predict. ICP price prediction can be done with the Support Vector Regression (SVR) method. The information utilized originates from the Ministry of Energy and Mineral Resources' official website, specifically focusing on crude oil pricing data for six primary types of crude oil: SLC, Attaka, Duri, Belida, Banyu and SC. The data applied covers the time frame from January 2018 to August 2023. The forecast of the ICP relies on the date Brent variable and the Alpha factor through the use of support vector regression (SVR. In the case of a linear kernel, the parameters (epsilon) and C (cost) are determined using the Grid Search algorithm. In the Dated-Brent variable, the best parameter value is obtained with the value of C = 100 and ε = 1 while for the Alpha variable, the best parameter value for the SLC crude oil type is C= 0.01 and ε = 0.01, SC value C = 10 and ε = 1, Banyu value C = 100 and ε = 0.1, Banyu value C = 100 and ε = 0.1, Belida value C = 0.01 and ε = 0.1, Attaka value C = 0.1 and ε = 0.01 and Duri value C = 1 and ε = 1. The Alpha value of the main crude oil type is the Duri crude oil type with the lowest RMSE value of 0.9651. The MAPE value for SC crude oil type = 19.55% and Duri = 19.46% is in the good category. The R^2 value for Banyu crude oil = 0.60610, SC = 0.42717 and Duri = 0.50421 is in the good category and the MAPE value for Dated-Brent of 49.73% is included in the fair category.

Keywords: *ICP; prediction; SVR; RMSE;,MAPE*

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1. Introduction

Indonesia is one of the world's largest crude oil importers to meet the crude oil deficit for national needs. According to the Organization of Petroleum Exporting Countries (OPEC), Indonesia is one of the largest crude oil exporters in the Asia-Pacific region, ranking second, while in the world it ranks 26th [1].

There are more than 50 types of crude oil in Indonesia, but there exist six primary types of crude oil recognized as Indonesia's main crude oil, namely SLC, Attaka, Duri, Belida, Senipah Condensate, and Banyu Urip. Additional crude oils in Indonesia include Anoa, Arjuna, Arun Condensate, Bekapai, Belanak, Bentayan, Bontang Return Condensate (BRC), Bula, Bunyu, Camar, Cepu, Cinta, Geragai/Makmur, Geragai Condensate/Makmur Condensate, Handil Mix, Jambi, Jatibarang, Jene/Pendopo, Kaji/Matra, Kerapu [2].

Accurate predictions of crude oil prices are crucial, as crude oil prices have a significant impact on the global economy [3], [4]. Determining the price of crude oil in Indonesia is crucial as it has a substantial impact on the economy, ensuring smooth functioning of the country's economic activities [5], [6].

The movement of crude oil prices in Indonesia is dynamic, requiring stakeholders to prepare strategic measures to address issues caused by oil price fluctuations and prevent significant losses [7]. The prediction of the price of crude oil can help the government make decisions [8]. Forecasting is the art and science of predicting future events, which can be done by analyzing past data and using mathematical models to project future trends [9]. Industry, government and society can benefit from these price predictions [10].

Studies have been conducted using prediction algorithms, such as predicting stock, inventory, visitors, air quality, and others. Various algorithms

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exist for prediction, and one example is the support vector regression (SVR) algorithm [11]. The SVR algorithm is a concept derived from the principles of support vector machine (SVM) theory, specifically designed for regression cases. SVR is used to forecast crude oil prices, with MAPE accuracy criteria and the coefficient of determination (R Square/R^2) [12]. The conceptual framework of the SVR algorithm can generate reliable forecast values due to its ability to address the overfitting issue. Overfitting is the behavior of data when testing or training data produce almost perfect prediction accuracy.

The SVR method has been extensively used in previous research, with notable instances including a study by Rizky Amalia Putri et al. (2020) that used support vector regression (SVR) to estimate the coal index. The analysis revealed the smallest RMSE value when using a polynomial kernel with a sigma parameter of 0.100 and a C value of 1, resulting in an RMSE value of 0.619 [13].

In addition, the SVR method has been applied to forecast COVID-19 cases in India, achieving a 97% accuracy in predicting death and recovery, and an 87% accuracy in predicting new daily cases [14]. Research to predict crude oil prices conducted by Krislianti (2023) concluded that based on the results of the analysis, it is known that the accuracy value of the prediction of testing data using the SVR method produces a MAPE value of 3.618%, which means that SVR is a good method because it produces a small error value [15].

Research by Rezzy Eko Caraka (2017) explains that when forecasting crude palm oil prices using precision measures using MAPE and R2, it can be concluded that the model evaluation shows good validity and precision of the model that has been performed with an R^2 training value of 98.71738% and an R^2 test of 83.45659% [16]. Approaches to predicting oil prices using opening and closing market prices can also be done with ARIMA, SVR, and linear regression models. The best model is selected for the prediction of the oil price using the value of R2 against training and testing with the justification that the model is not over-fitting [17]. In modeling, calculate the deviation of oil production parameters using linear regression, segmented linear regression, polynomial regression, and SVR models [18].

This research is a methodology for building predictive models using a machine learning approach. On the basis of the research results that have been found above, the focus of the research conducted is to predict crude oil prices. As a comparison, the main focus of the research carried out is to use the variables of the alpha and dated Brent values to determine ICP predictions with the date Brent formula plus-minus (±) Alpha using the SVR method.

The Indonesian Crude Oil Price (ICP) formula is stated in the Decree of the Minister of Energy and Mineral Resources Number 1907 K/12/MEM/2018 on the Determination of the Indonesian Crude Oil Price Formula. In the decree issued by the Minister of Energy and Mineral Resources for the 2017/2018 period, the main crude oil price formula is calculated based on the publication Dated Brent ± Alpha publication. Dated Brent is determined by computing the average publication throughout the present month.

Meanwhile, the calculation of Alpha involves taking into account the average publication either for the ongoing month or the average publication over two months, which are the current month and the preceding month. This is done considering the compatibility of crude oil quality and / or trends in international crude oil prices and/or national energy security [19].

The purpose of this research is to apply the Support Vector Regression method to find a better crude oil price prediction model. The accuracy of the prediction in the study was carried out with Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (R Square/R^2). The urgency of this research is carried out in the hope of being able to predict ICP prices with a better model. The prediction of future crude oil prices in Indonesia is based on historical crude oil prices data from the preceding period, using available time series data. Prediction of crude oil prices is expected to provide solutions to the Indonesian people to predict and prepare for the impact of fluctuations in crude oil prices in Indonesia [20].

2. Research Methods

2.1 Research Stages

This research was completed in stages as shown in Figure 1. Based on Figure 1, the research stages can be described as follows: Literature study, namely to identify problems related to the Prediction of ICP; Collecting of data extracted from the Ministry of Energy and Mineral Resources' published website; Pre-processing plays a crucial role in the design of predictive models.

Data preprocessing is divided into several stages, namely data cleaning, data transformation, and data reduction; Data processing using SVR, conducting SVR analysis to produce modeling; Testing is the determination of the best model by testing (evaluation); Analyze the predictions results using the best model generated in the SVR analysis; The conclusion is drawn by making interpretations and conclusions based on the data processing results.

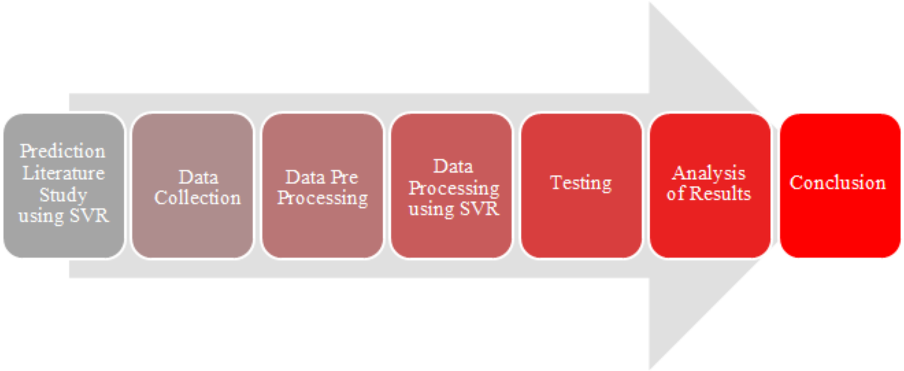

Figure 1. Research Stages

2.2 *SVR Concept*

Forecasting is thinking about a quantity, such as the demand for one or more products in a future period. Forecasting is generally used to predict something likely to happen, such as demand conditions, amount of rainfall, economic conditions, etc. Ozcan (2005) says that forecasting makes it possible to anticipate the future and conform to the plans made. Good forecasting is the basis for short-, medium-, and long-term planning [21], and generally all aspects of the system are important to include as system success factors. Forecasting aims to obtain estimates that can minimize prediction error and can be tested [22].

The prediction results must contain a degree of uncertainty called error. The error element is not the only cause of deviations in the prediction results, but the failure of a prediction model to identify additional factors. Data series also affect the amount of deviation in prediction. Various evaluation techniques can be used to assess the accuracy and predictability of a model, such as using the average squared difference between predicted and observed values, commonly known as the original mean square error [23]. The formula for RMSE is shown in Formula 1.

$$\text{RMSE} = \sqrt{\sum \frac{(Y' - Y)^2}{n}} \quad (1)$$

Y' is the predicted value, Y is the actual value, and n is the amount of data.

Mean Absolute Percent Error (MAPE) is a statistical measure assessing the precision of predictions in forecasting techniques. MAPE provides insight into the extent of forecast errors relative to the actual values in the series. A lower percentage error value in MAPE indicates higher precision in forecasting results [24], [25]. The MAPE formula can be seen in Formula 2.

$$\text{MAPE} = \frac{\sum_{t=1}^{n} \left| \left(\frac{A_t - F_t}{A_t} \right) 100 \right|}{n} \quad (2)$$

At is the actual demand for t, Ft is the forecasting result for t, and n is the amount of forecasting data. MAPE is computed by determining the error or absolute error in each period, dividing it by the actual observation value in that period, and then calculating the average of the absolute percentage error.

The coefficient of determination (R2) test is performed to assess and forecast the extent or significance of the collective contribution of independent variables to the dependent variable. The square value of R ranges from 0 to 1, with the stipulation that a value closer to one is preferable. For example, if the square R is 0.6, it means that 60% of the variance in the dependent variable can be accounted for by the independent variable. The remaining 40% cannot be explained by the independent variable and can be attributed to variables outside it (error component). A small square value of R indicates a large error component [26].

The Support Vector Machine (SVM) was developed by Boser, Guyon, and Vapnik, and was first introduced in 1992 at the Annual Workshop on Computational Learning Theory. SVR is an application of SVM that is used for regression cases where the output is a real or a continuous number. SVR is a method that can overcome overfitting, so it will produce good performance [27].

In general, SVR constructs a hyperplane or a set of hyperplanes in a high- or finite-dimensional space that can be used for classification, regression, or other tasks. The basic goal of the SVR algorithm is to find the best-fit decision line. In SVR, the best-fit line is the hyperplane that has the maximum number of points.

Unlike other regression models that try to minimize the error between the actual value and the predicted value, SVR tries to fit the best line within a threshold value. SVR works to find the best value within a certain margin called epsilon. SVR works to find the best value within a certain margin called epsilon. The concept of SVR can be seen in Figure 2.

A hyperplane serves as a boundary between two data classes in a dimension higher than the original dimension. In SVR, the hyperplane is characterized as a line utilized to predict the target value, which is continuous. The data points on either side of the hyperplane that are closest to the hyperplane are called the support vector.

A kernel is a set of mathematical functions that take data as input and convert them into the necessary format. Kernel functions are typically used to identify a hyperplane within a higher-dimensional space. Commonly used kernels in SVR include the sigmoid kernel, polynomial kernel, Gaussian kernel, among others.

Boundary lines consist of two lines drawn around the hyperplane at a specific distance (epsilon). They are commonly employed to establish a margin between data points.

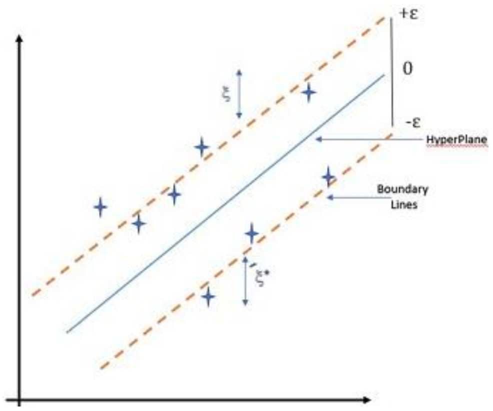

Figure 2. Support Vector Regression (SVR) Concept

The SVR model parameter training process uses a quadratic optimization problem formulation where there is a single optimum solution. Therefore, the SVR model is expected to avoid the problem of overfitting the model [28]. The SVR aims to identify a function, denoted f (x), that acts as a regression hyperplane that fits all input data by minimizing the error (ε) as much as possible. Assuming there are l training datasets, (X_i, Y_i), i = 1,2,…,l where X_i represents the input vector is shown in Formula 3.

$$x = \{x_1, x_2, \dots, x_n\} \subseteq \Re^n \quad (3)$$

scalar output $y=\{y_i,\dots,y_l\}\subseteq \Re$), l is the number of training data. With the SVR method, the regression function is obtained in Formula 4.

$$f(x) = w^T\varphi(x) + b \quad (4)$$

w is the l-dimensional weight vector, φ(x) is the function that maps x to a space with l dimensions, b is the bias.

2.3 *SVR Analysis to Generate Modeling*

The stages of data analysis with the SVR analysis can be described in Figure 3.

ICP Data: The data source used in this study is the price data of the primary varieties of crude oil comprising six types, which are SLC, Attaka, Duri, Banyu, Belida, and SC. The amount of data observed and used as data in this study is from the period January 2018 to August 2023.

Training Data and Testing Data: The data are split into two sets: training data and testing data. Training data constitute 70% of the total data, while testing data constitute 30% of the total dataset.

Modeling based on SVR analysis: SVR is an implementation of the SVM method in the case of regression. The objective of SVR is to identify a function acting as a hyperplane (separating line) in the form of a regression function, with the aim of accommodating all input data with minimal error.

Selecting the best parameters using the grid search time series cross-validation algorithm. Perform SVR analysis with the best parameters, the -insensitive loss function, and the linear kernel function. Perform data prediction using the SVR model with the best parameters, -insensitive loss function and linear kernel function.

Evaluation: Testing the Model using RMSE, MAPE, R^2.

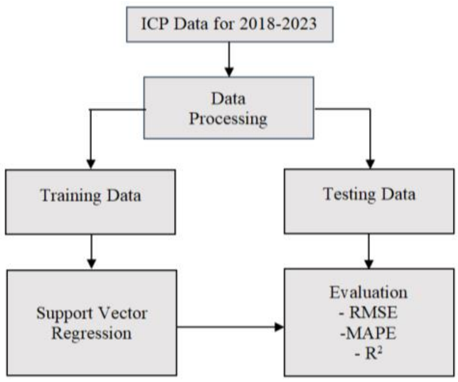

Figure 3. Stages of SVR Analysis

3. Results and Discussions

3.1 *Data Processing*

Data come from the Ministry of Energy and Mineral Resources of the Republic of Indonesia Ministerial Decree on the Indonesian Crude Oil Price for the period January 2018 to August 2023. For this investigation, the data used consist of the primary types of crude oil, which are SLC, Attaka, Duri, Belida, Banyu, and Senipah Condensate (SC). The data used are Alpha values of 6 major crude oil types and Dated Brent values. The following Dated Brent values show a description of the data used.

```
[ 69.18  65.19  65.9   71.8   76.93  74.33  74.35  72.62  78.85  81.15
  64.74  57.39  59.46  64.03  66.12  71.26  71.12  64.1   64.04  59.
  62.77  59.72  63.02  67.02  63.5   31.83  18.55  28.98  40.07  43.35
  44.82  40.81  40.15  42.66  49.86  54.84  62.22  65.63  64.7   68.75
  73.04  75.03  70.81  74.58  83.66  81.44  74.1   87.22  98.19 118.81
 104.39 113.25 123.7  112.7   99.99  89.87  93.33  91.67  81.12  82.78
  82.49  78.56  84.94  75.55  74.7   80.05  86.22]
```

Table 1 displays the Alpha values for the main types of crude oil. The data will then be divided into training data and testing data.

3.2 *Data Processing with SVR*

In SVR analysis, the initial stage that must be performed for prediction using the SVR method is to determine the value of the parameter. The parameters used in the linear kernel are ε (Epsilon) and C (Cost) generated using the Grid Search algorithm combined with the time series cross-validation method on training data and validation data using the Python program. The C and epsilon values used are:

```
C_arr = [0.1,1,10,100,1000]
eps_arr = [1,0.1,0.01,0.001,0.0001,0.00001]
```

Table 1. Alpha Value

Year	Month	SLC	Attaka	Duri	Banyu	Belida	SC
2018	1	-3.35	-1.00	-5.80	4.17	-0.88	-0.46
2018	2	-2.88	-1,13	-5.26	4.17	-1.14	-1.12
2018	3	-3.05	-1.91	-5.64	4.17	-1.46	-1.89
2018	4	-3.41	-2.06	-5.94	4.17	-1.49	-2.37
2018	5	-3.78	-2.15	-6.10	4.17	-1.50	-2.04
….	….	…	…	…	…	…	…
2023	4	-3.31	-4.40	3.74	4.42	-4.38	-10.05
2023	5	-2.24	-4.76	2.80	4.58	2.80	-10.61
2023	6	-1.43	-4.22	3.64	4.82	-4.16	-13.39
2023	7	-1.03	-3.52	3.58	5.75	-3.73	-13.61
2023	8	0.28	-2.16	3.56	6.94	-2.07	-12.71

Table 2 shows the values obtained from the combination of C and epsilon values.

Table 2. Result Value of Combination of Cost and Epsilon Value

	C	Epsilon	Correlation
12	10.0	1.00000	0.730760
0	0.1	1.00000	0.730760
18	100.0	1.00000	0.730760
6	1.0	1.00000	0.730760
24	1000.0	1.00000	0.680334
8	1.0	0.01000	0.516308
9	1.0	0.00100	0.516308
10	1.0	0.00010	0.516308
11	1.0	0.00001	0.516308
28	1000.0	0.00010	0.516308
27	1000.0	0.00100	0.516308
26	1000.0	0.01000	0.516308
29	1000.0	0.00001	0.516308
2	0.1	0.01000	0.516308
3	0.1	0.00100	0.516308
4	0.1	0.00010	0.516308

Based on the results of finding the best hyperplane parameters using the Grid Search Algorithm, the best hyperplane parameters were obtained for the Dated-Brent value and the Alpha value of the six main types of crude oil. The best hyperplane parameters can be seen in Tables 3 and 4.

Table 3. Best Hyperplane Parameters for Dated-Brent Values

	C	Epsilon
Dated-Brent	100	1

Table 4. Best Hyperplane Parameters for Alpha Value

Type of Crude Oil	C	Epsilon
SLC	0.01	0.01
SC	10	1
Banyu	100	0.1
Belida	0.01	0.1
Attaka	0.1	0.01
Duri	1	1

3.3 *Performance Evaluation*

The parameters that have been obtained using the Grid Search algorithm are then continued by mapping the training data and test data and evaluated using RMSE, MAPE and R^2. The MAPE prediction accuracy scale is shown in Table 5.

Table 5. MAPE Value Range

Range of MAPE	Meaning
< 10%	Forecasting model ability is very good
10-20%	Forecasting model ability is good
20-50%	Forecasting model ability is fair
>50%	Forecasting model ability is poor

The results obtained can be seen in Tables 6 and 7.

Table 6. Calculation Results of RMSE, R^2 and MAPE for Date-Brent Value

Dated-Brent Value	RMSE	R^2	MAPE	MAPE Value Description
SLC, SC,	8.605	0.6077	49.73	Forecasting

Duri, Belida, Banyu and SC	model ability fair

Evaluation of the prediction results can be seen in the form of modelling, namely the comparison graph of Actual and Predicted values for crude oil SLC, Attaka, SC, Banyu, Duri, Belida oil types and Dated-Brent values in Figures 4 to 10.

Table 7. RMSE, R^2 and MAPE Calculation Results for Alpha Value

Crude Oil Alpha Value	RMSE	R^2	MAPE	MAPE Value Description
SLC	1.9535	-0.00473	54.42	Forecasting model capability poor
SC	1.0307	0.42717	19.55	Forecasting model ability good
Banyu	1.5862	0.60610	47.73	Forecasting model ability fair
Belida	1.8588	-0.12972	58.66	Forecasting model ability poor
Attaka	1.8024	0.55311	49.91	Forecasting model ability fair
Duri	0.9651	0.50421	19.46	Forecasting model ability good

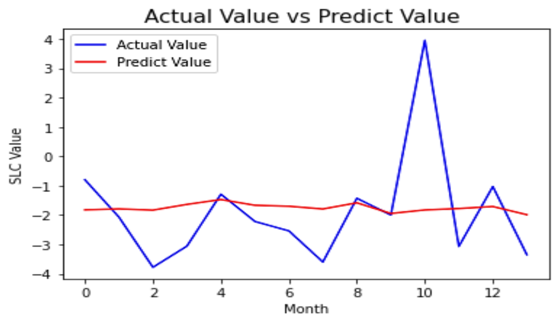

Figure 4. Comparison of Actual and Predicted Values for SLC Crude Oil Type

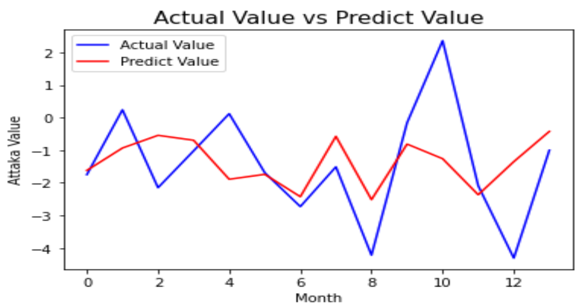

Figure 5. Comparison of Actual and Predicted Values for Crude Oil Attaka Type

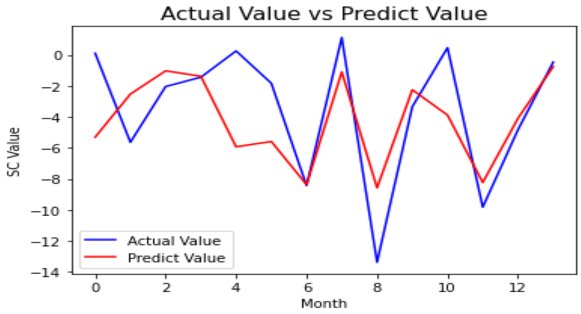

Figure 6. Comparison of Actual and Predicted Values for SC Crude Oil Type

Figure 7. Comparison of Actual and Predicted Values for Banyu Crude Oil Type

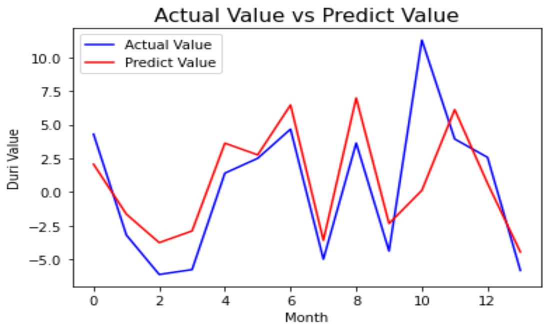

Figure 8. Comparison of Actual and Predicted Values for Duri Crude Oil

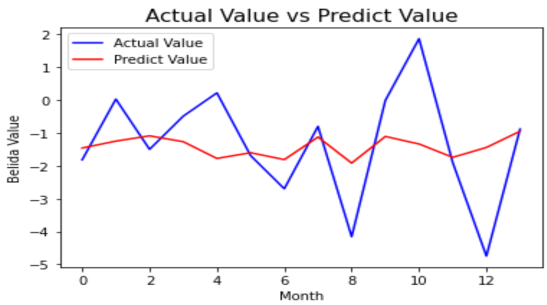

Figure 9. Comparison of Actual and Predicted Values for Belida Crude Oil

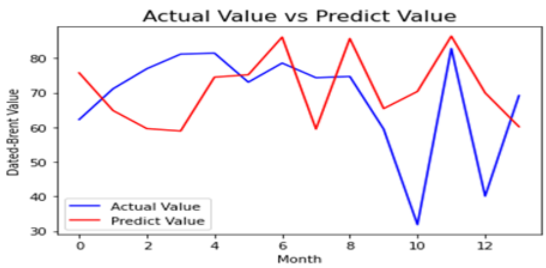

Figure 10. Comparison of Actual and Predicted Values for Dated-Brent values

3.4 ICP Prediction

The results of coding using the phyton programming language for the SVR analysis process can be used to predict the Alpha values of crude oil, including SLC, Attaka, Belida, Banyu, Duri and SC, and the Dated-Brent value. Figures 11 to 17 are the prediction results for the next 4 months (September to December 2023) marked with a green 'x' sign.

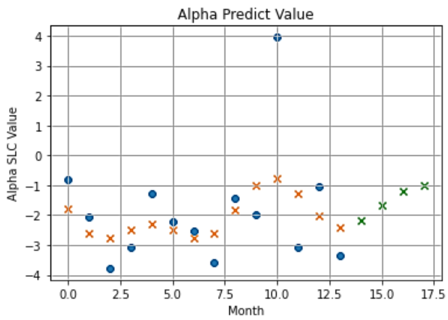

Figure 11. Predicted Alpha values of SLC Crude Oil

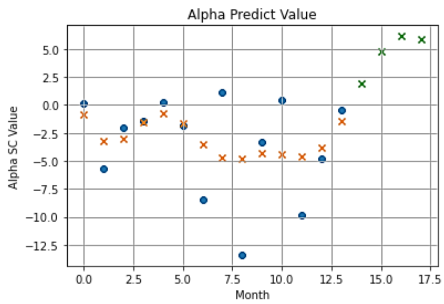

Figure 12. Predicted Alpha Values of SC Crude Oil

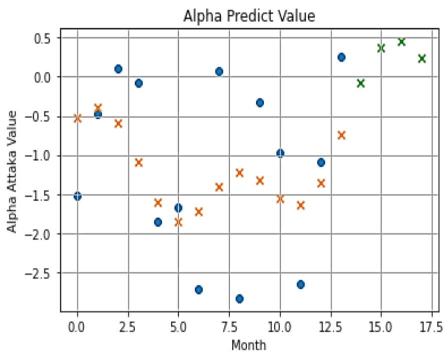

Figure 13. Predicted Alpha Values of Crude Oil Attaka

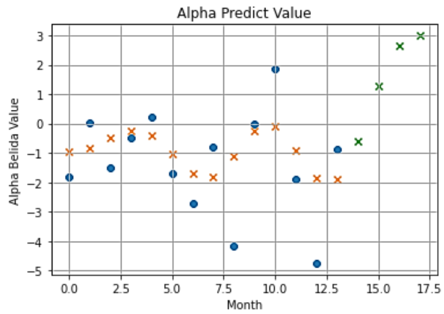

Figure 14. Predicted Alpha values of Belida Crude Oil

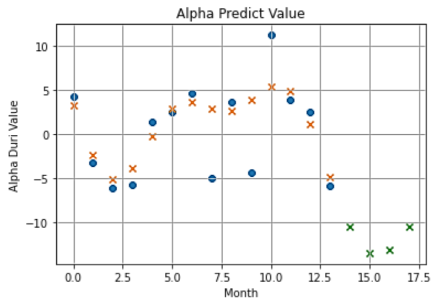

Figure 15. Predicted Alpha values of Duri Crude Oil

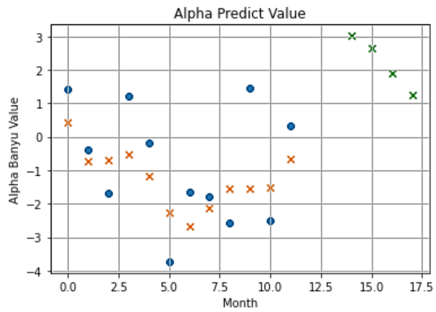

Figure 16. Predicted Alpha values of Banyu Crude Oil

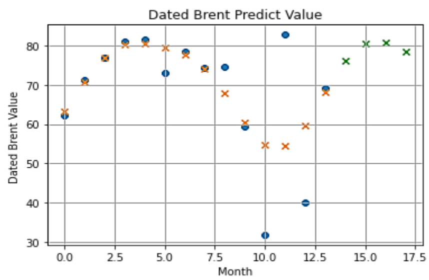

Figure 17. Predicted Dated-Brent Value

4. Conclusions

The Support Vector Regression method can predict Indonesian crude oil prices (ICP) well on a linear kernel. The results of tuning the hyperplane parameters using the Grid Search algorithm on the Linear Kernel produce the best C and epsilon values of each major crude oil. The lowest value of RMSE is 0.9651 for Duri crude oil, which is a good model result. MAPE values for SC and Duri crude oil types provide good modeling results.

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