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Comparison of Vector Error Correction Model Prediction and Multiresponse Fourier Series, Case Study: Open Unemployment Rate in Indones IA

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ABSTRACT

Unemployment is someone who has been classified in the active labour force is looking for work at a certain wage level, but not getting the job they want. According to the *International Monetary Fund* (IMF) 2023, Indonesia is ranked second highest in Southeast Asia, ranked 16th in Asia and ranked 58th in the world with a percentage of 5.45%. The data used in this study is semester data (February and August) regarding the number of open unemployment according to the highest education completed in Indonesia taken from the website of the Central Statistics Agency (BPS) starting from 2000 to 2022. This study using comparison of multi response Fourier series regression with trigonometry method using Gamma and *the Vector Error Correction Model* (VECM). The result of this study is Fourier series regression method of the cos function with gamma is the best model in predicting because this method has smaller MAPE value compared to VECM method. The MAPE of Fourier Series method is 0.01%, in other hand the MAPE of VECM method is 18.90% which can be categorized as prediction results with the Fourier Series method are very accurate. The results of prediction are expected to be used as reference for government to making ideal future plan to minimalize the rate of open unemployment in Indonesia.

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A. INTRODUCTION

Indonesia as a developing country has complex problem which requires an appropriate policy to minimize its impact towards economic rate of growth. Unemployment is defined as someone who are classified in the workforce and actively looking for a job at certain wage level, however don't get the job they want (Muslim, 2014). Based on data from the Central Statistics Agency (BPS) 2023, the unemployment rate in Indonesia reached 7.86 million people. A high unemployment rate can affect economic stability, social walfare, and a country's growth potential.

The high unemployment reflects the imbalance between the availability of jobs and the existing workforce. With the number of labor force in Indonesia increasing every year, accurate predictions of unemployment are crucial for the government in formulating the right policies to overcome this problem. Efforts made by the government to reduce open unemployment in Indonesia, such as pre-employment cards issued in 2020 in the form of training or incentives for people who are working (Pratiwi, 2022). However, the program does not seem to be optimal in reducing open unemployment, it is proven that according to the International Monetary Fund

(IMF) 2023, Indonesia is ranked second highest in Southeast Asia, ranked 16th in Asia and ranked 59th in the world with a percentage of 5.45% (Annur, 2023).

The unemployment program is part of the global problem included in Sustainable Development Goals (SDGs) no.8, namely reduce the unemployment rate, but also to improve the quality of life of workers and create fair opportunities for all levels of society, including vulnerable groups such as young people and women. Therefore, it is necessary to find a method to predict the open unemployment rate for future years as an anticipatory step and reference in reducing the open unemployment rate. A more realistic method to overcome this is to use the multi-response Fourier series regression method and the Vector Error Correction Model (VECM).

In economic analysis, various statistical methods have been developed to predict the dynamics of the Unemployment Rate. Among these methods, the Vector Error Correction Model (VECM) and the multi-response Fourier series emerged as two techniques capable of handling complex economic data. VECM is able to overcome short-term and long-term problems in the relationship between variables, while multi-response Fourier series is able to capture periodic patterns from data, which often arise in socio-economic phenomena such as unemployment.

The VAR model was first introduced by C.A. Sims as a development of Granger's thinking (S.Tsay, 2014). Granger states that if two variables such as x and y have a causal relationship, where x affects y and vice versa, then the past information of x can predict the value of y and vice versa (Febrianti, 2021). The VAR method uses Ordinary Least Square (OLS) estimation by minimizing the number of squares of errors (Y Nalita, 2021). If in the results of the analysis there is a cointegration in the variable, it must use the VECM method which is a form of VAR designed for nonstationary data that is known to have a cointegration relationship (Yong Lee, 2022). In addition to the VECM method, the Fourier series structure method first introduced by Biodeau (1992) is also used which combines the Fourier series and linear functions in a data trend. Then, Biederman et al. and Dette et al. develops the Fourier series in non-parametric regression using complete trigonometric base (Adrianingsih et al., 2020). The corresponding data pattern of the Fourier series is a repetitive or periodic data pattern, meaning the repetition of each response variable data for a different predictor variable data (Intaniah Ratna Nur Wisisono, 2018).

Some previous studies that have been conducted related to the open unemployment rate based on the highest education completed are research conducted by Saputra (2019) in Pematangsiantar which in his research predicts the open unemployment rate based on the highest education completed with the Resilient Backpropagation method. The results of his research resulted in a prediction accuracy value of 75% with an MSE value in February of 0.00052083 and an MSE in August of 0.00105823 (Saputra et al., 2019). The other research conducted by Alan Prahutama (2013) examined the open unemployment rate in East Java using the Fourier series method. The results of his research resulted in a coefficient of determination value of 96.76% with an optimal K value of 12 (Prahutama, 2013). Then, the other research conducted by Rahmania (2024) examined the open unemployment rate in Kalimantan Island using the Fourier Series method. The result of her research resulted in a coefficient of determination value 74.22% and minimum GCV of 10.47% (Rahmania, 2024).

In reality, it can be observed that the pattern of open unemployment rates based on the highest education graduated, especially in the variables of junior high school, not yet graduated from elementary school, and has not finished school forms a fluctuating and repetitive time series pattern because it is periodic and cointegrated. Periodic means the state in which variables occur with a fixed or equal time interval. In addition, this study aims to examine if variables x and y have a relationship, where variable x affects y to predict y in the future. The final result of this study will be seen based on the comparison of the smallest Mean Absolute Percentage Error (MAPE) value between the two prediction methods (Wibowo et al., 2023). It is hoped that this research can be a reference for the government in predicting the open unemployment rate based on the highest education graduated, so that it can be a reference for more effective and efficient work programs for future years to anticipate.

B. METHODS

1. Data Source

The data used in this study is semester data (February and August) regarding the number of open unemployment according to the highest education completed in Indonesia taken from the website of the Central Statistics Agency (BPS) starting from 2000 to 2022.

2. Research Variables

The variables of this study use 2 types of variables, namely response variables and predictor variables. The response variable is the main variable of the data or influenced variables and the predictor variable is used to predicting the estimation of other variables based on the value or influencing variables. The research variables in Table 1 are presented as follows.

Table 1. Research Variables

Variable Type	Information
Predictor	Observation time (t)
Response	Elementary School (y_1)
	Junior High School (y_2)
	Not or Never Been to School (y_3)
	Not or Never Finished Elementary School (y_4)

3. Research Procedure

The research procedure in this study to analyze the data is described as follows:

a. Collecting the data of open unemployment rate based on the highest education graduated from the website of the Central Statistics Agency
b. Analyze descriptive statistics of data
c. Using the VECM method to predict the data (Hijri Juliansyah, 2022). (1) Stationary of data using ADF test; (2) Determine the optimal lag; (3) Analyze the cointegration test and causality test; and (4) Estimate the variance decomposition and VECM model.
d. Using the Fourier Series method to predict the data (M. Fariz Fadillah Mardianto E. F., 2019). (1) Using the Fourier Series method to predict the data; (2) Determine the

optimal parameter based on the minimum GCV Value; and (3) Estimate the Fourier Series method model based on the optimal parameter.

e. Choose the best model between the Fourier Series and VECM based on the smallest MAPE value.

4. Flow Chart

As for the Flowchart of this research method as shown in Figure 1.

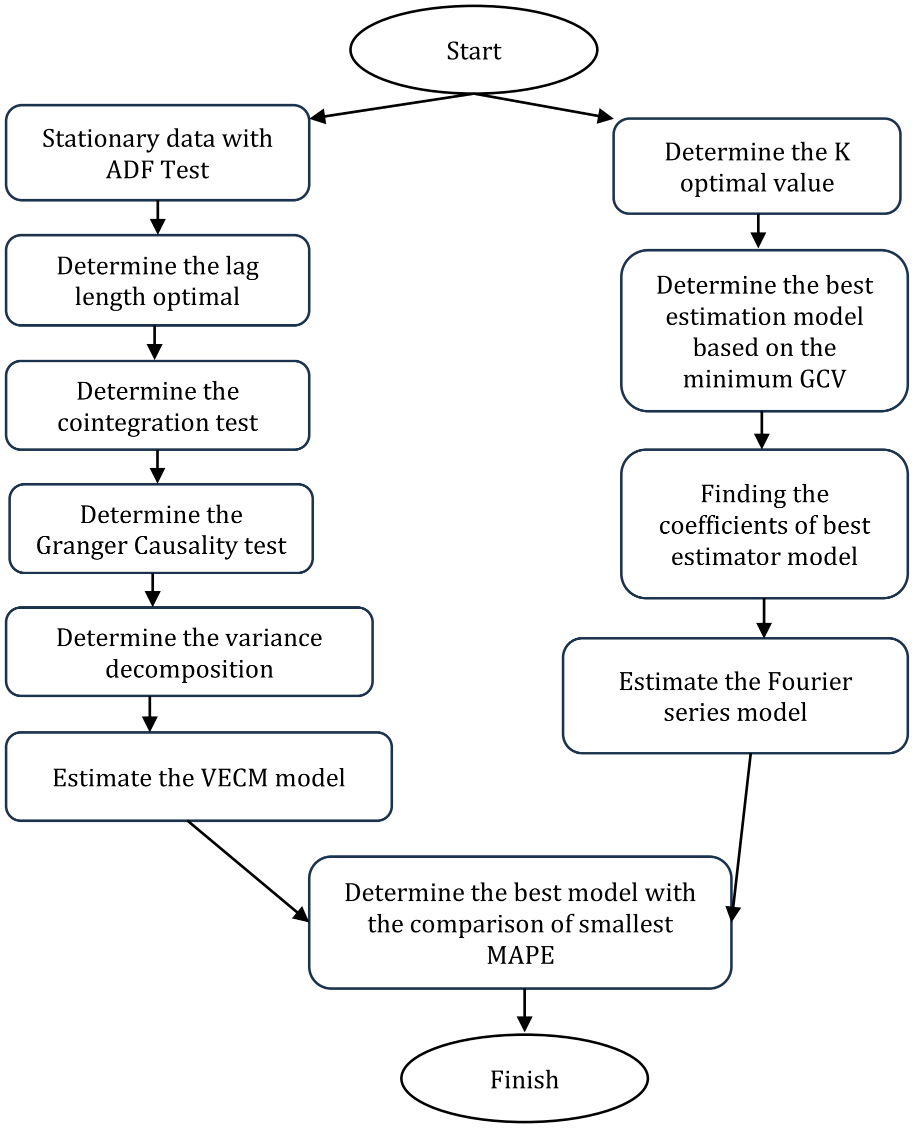

Figure 1. Flowchart of this research method

C. RESULT AND DISCUSSION

1. Descriptive Statistic

Before conducting further research, a descriptive statistical analysis will be carried out first on every semester of unemployment rate based on the highest-level education completed in Indonesia. The result of descriptive analysis on this research are presented in Table 2.

Table 2. Statistics Descriptive

Variable	Mean	Minimum	Median	Maximum
Elementary School	115808	17066	90741	352518
Junior High School	506071	192232	520316	737610
Not or Never Been to School	1620202	865778	1402858	2753558
Not or Never Finished Elementary School	1831962	1137195	1693203	3151231

2. Predictions Analysis Using VECM Method

The first step in conducting a VECM method is to identify the stationarity of the data. The method that can be used in the identification of stationarity is the ADF test (Eva Maulia, 2017) whose results are presented in Table 3.

Table 3. ADF Test Results

Variable	Original data	1^{st} differencing	2^{nd} differencing
Elementary School	0.1506	0.8657	0.000
Junior High School	0.6696	0.0003	0.000
Not or Never Been to School	0.1636	0.0000	0.000
Not or Never Finished Elementary School	0.1190	0.2790	0.000

Based on the Table 3, the p-value of the original data on all variables is more than α (0.05) so it can be decided to fail to reject which means that the data on all variables are not stationary. Therefore, 1^{st} differencing was carried out and there are 2 variables are less than α (0.05) so it can be decided to reject H_0 which means that the data on that 2 variables stationary but the other 2 variables are more than α (0.05) so it can be decided to fail to reject which means that the data on that 2 variables are not stationary. Then, 2^{nd} differencing was carried out on and the p-value on all variables is less than α (0.05) so it can be decided to reject H_0 which means that the data on all variable stationary. After the data has been stationary, the next is step is to determine the optimal lag length based on the minimum criteria values are shown in Table 4.

Table 4. Optimal Lag Test Results

Lag	FPE	AIC	SC	HQ
0	4.24e+15	107.2029	107.3789	107.2643
1	4.20e+40	104.8831	105.7628*	105.1901
2	2.83e+40	104.4521	106.0365	105.0048*
3	2.56e+40*	104.2601*	106.5474	105.0584

Based on the results, for the criteria FPE and AIC, the optimal lag order with the minimum value for the model is 3. The SC and HQ criteria indicates the other lags as the optimal value, but the models based on this specification proved no to viable. So, it means the only model with a maximum of 3 lags can be considered as the limited number of observations (T Kusuma, 2022).

After the optimal lag has been found, the next step is to investigate whether there is a long-term relationship between the four variables using Johansen Cointegration Test. This test applies the Maximum Likelihood procedures of the VAR model to determine the number of co-integrating vector (Yannick Fanchette, 2023). The results of cointegration test are shown in Table 5.

Table 5. Cointegration Test Results

Hypothesized No. of CE(s)	Eigenvalue	Test Trace	0.05 Critical Value	P-value
None	0.676061	66.58960	47.85613	0.0004
At most 1	0.360328	26.01045	29.79707	0.1284
At most 2	0.209107	9.925677	15.49471	0.2865
At most 3	0.040287	1.480349	3.841466	0.2237

Based on the table, the p-value of Johansen Cointegration Test is less than α (0.05) so it can be decided to reject H_0 which means that the variables in the data are cointegrated. This means there are stable and there is long-term relationship between the variables. On the premise, of the existence of cointegration relationships, VECM modeling can be further conducted. In order to detect the causal relationship for each variable, both in the long run and short run, an error correction model can be used if a cointegration relationships exist among the variables. This test using chi-square statistic and probability values constructed under the null hypothesis of non-causality show that there is causal relationship between those variables (Oana Popovici, 2016). The Granger Causality Test that are shown in the Table 6 as follows.

Table 6. Granger Causality Test

Dependent variable: Elementary School				**Dependent Variable: Junior High School**			
Excluded	**Chi-Sq**	**Df**	**P-value**	**Excluded**	**Chi-Sq**	**Df**	**P-value**
Junior High School	6.6561	2	0.0359	Elementary School	1.1807	2	0.5541
Not or Never Been to School	0.7448	2	0.6891	Not or Never Been to School	9.4530	2	0.0089
Not or Never Finished Elementary School	3.3061	2	0.1915	Not or Never Finished Elementary School	1.7512	2	0.4166
All	12.899	6	0.0447	All	13.787	6	0.0321
Dependent variable: Not or Never Been to School				Dependent variable: Not or Never Finished Elementary School			
Excluded	Chi-Sq	Df	P-value	Excluded	Chi-Sq	Df	P-value
Elementary School	4.7643	2	0.0923	Elementary School	5.6651	2	0.0589
Junior High School	8.4661	2	0.0145	Junior High School	10.184	2	0.0061
Not or Never Finished Elementary School	0.0864	2	0.9577	Not or Never Been to School	0.6582	2	0.7195
All	19.714	6	0.0031	All	12.014	6	0.0616

Based on the results, if p-value is less than the significant level, then it indicates the need to accept the null hypothesis. Therefore, it can be found that there are four relationships at a significance level of 5%: (a) SLTP Granger causes SD (P-value = 0.0359); (b) Tidak/Belum Pernah sekolah Granger causes SLTP (P-value = 0.0089); (c) SLTP Granger causes Tidak/Belum Pernah Sekolah (P-value = 0.0145); and (d) SLTP Granger causes Tidak/Belum Tamat SD (P-value = 0.0061). After analyze the Granger Causality Test, the next step is to regressed measure the contribution of each type of shocks to the forecast variance called variance decomposition. It also can be applied to analyze the influence of each variable's update on other variables, which shows relative effects (Fatimah Kari, 2014). The result of variance decomposition can be shown in the Table 7 as follows.

Table 7. Variance Decomposition Results

Variance Decomposition of Elementary School					
Period	**S.E.**	**Elementary School**	**Junior High School**	**Not or Never Been to School**	**Not or Never Finished Elementary School**
1	234362.1	100.0000	0.000000	0.000000	0.000000
2	308839.9	92.31124	1.746049	2.502358	3.440349
3	377810	90.57830	4.183431	2.557231	2.681042
4	452220.6	85.10142	3.368652	9.654268	1.875662
5	517990.4	85.02451	3.371578	10.03192	1.571995
6	575673.4	81.77778	2.797887	14.05057	1.373756
7	623904.9	81.35444	2.420128	14.90662	1.318809
8	662128.6	79.63022	2.174778	16.96249	1.232518
9	689762.4	79.19664	2.051594	17.53766	1.214102
10	709658.3	78.21271	2.125970	18.49054	1.170781
Variance Decomposition of Junior High School					
Period	**S.E.**	**Elementary School**	**Junior High School**	**Not or Never Been to School**	**Not or Never Finished Elementary School**
1	194061.1	42.36767	57.63233	0.000000	0.000000
2	261179.8	48.01341	50.86785	1.066385	3.440349
3	344483.5	52.84719	36.48508	9.301084	2.681042
4	423538.4	59.25592	26.87259	12.62450	1.875662
5	491062.3	61.26313	20.95743	16.38990	1.571995
6	548927.8	62.86122	16.95002	18.73709	1.373756
7	593971.0	63.45398	14.47825	20.63336	1.318809
8	626559.6	63.77776	13.05862	21.73803	1.232518
9	648946.6	63.67028	12.35830	22.57347	1.214102
10	662703.5	63.52033	12.13781	22.97146	1.170781
Variance Decomposition of Not or Never Been to School					
Period	**S.E.**	**Elementary School**	**Junior High School**	**Not or Never Been to School**	**Not or Never Finished Elementary School**
1	55360.38	2.184318	17.31979	80.49589	0.000000
2	59278.73	6.060958	23.43159	70.48081	0.026638
3	70252.08	7.862765	32.54122	59.02104	0.574969
4	74346.66	8.052041	34.91577	56.49508	0.537111
5	81941.26	16.16044	36.05022	46.50814	1.281195
6	88750.83	19.89385	32.49670	46.34469	1.264756
7	95978.68	27.74311	29.56097	41.03995	1.655981
8	102695.9	30.74758	25.99585	41.64297	1.614601
9	108058.1	35.15611	23.62220	39.47045	1.751244

10	112488.4	36.50414	21.82654	39.97204	1.697288
Variance Decomposition of Not or Never Finished Elementary School					
Period	**S.E.**	**Elementary School**	**Junior High School**	**Not or Never Been to School**	**Not or Never Finished Elementary School**
1	96202.77	12.11997	38.12840	9.352133	40.39949
2	102758.3	10.73307	43.24676	9.795833	36.22434
3	122508.2	8.317415	51.36466	10.03304	30.28489
4	129945.9	7.826369	49.22676	15.51716	27.42971
5	138127.5	11.50586	49.32273	13.74744	25.42397
6	144558.9	12.22955	45.94004	18.25378	23.57663
7	149816.2	15.93552	43.69376	17.79211	22.57850
8	154449.7	16.92230	41.12695	20.57148	21.37927
9	157215.3	18.85467	39.71411	20.55331	20.87791
10	159520.2	19.16721	38.70082	21.81551	20.31646

Based on the Table 7, the most dominant component from each variable in 10^{th} quarter is SD with the biggest variance is 78.21% than other variables. The shocks that happened in SD causing dominant change, rather than the shocks than happened in SLTP causing not so dominant change because quickly divided evenly to the other variable. The most difficult shock to absorb by other variables is, meanwhile the easiest shock to absorb by other variables is SLTP. That means the role of SLTP variable easily and quickly disappears. After all of the VECM analysis have been performed, then the last step is finding the VECM estimation. Based on the table, the result of VECM estimation model is as shown in Table 8.

Table 8. Estimation Model Results

	Elementary School	**Junior High School**	**Not or Never Been to School**	**Not or Never Finished Elementary School**
Elementary School (-1)	0.536378	0.113551	-0.117944	-0.124204
Elementary School (-2)	0.071809	0.114135	0.018913	-0.123022
Junior High School (-1)	0.721796	0.828350	0.130801	0.300747
Junior High School (-2)	-0.208529	0.027857	0.086024	0.080776
Not or Never Been to School (-1)	-0.428707	-0.600905	-0.053196	-0.176200
Not or Never Been to School (-2)	-0.466053	-1.898386	0.392178	0.269978
Not or Never Finished Elementary School (-1)	-0.93626	0.097737	-0.015823	-0.139420
Not or Never Finished Elementary School (-2)	-0.936826	0.680842	-0.040656	0.274971
C	-72360.37	-222334.4	-126877.9	128289.5
R-squared	0.881014	0.897167	0.731917	0.543492
AIC	25.99408	27.77490	27.78935	24.88889
SC	26.38592	28.16674	27.78935	25.28073

$$\begin{bmatrix}\Delta Y_1 t\\ \Delta Y_2 t\\ \Delta Y_3 t\\ \Delta Y_4 t\end{bmatrix}=\begin{bmatrix}-72360.37\\ -222334.4\\ -126877.9\\ 128289.5\end{bmatrix}+\begin{bmatrix}0.536378 & 0.113551 & -0.117944 & -0.124204\\ 0.721796 & 0.828350 & 0.130801 & 0.300747\\ -0.428707 & -0.600905 & -0.053196 & -0.176200\\ -0.93626 & 0.097737 & -0.015823 & -0.139420\end{bmatrix}\begin{bmatrix}\Delta Y_{1(t-1)}\\ \Delta Y_{2(t-1)}\\ \Delta Y_{3(t-1)}\\ \Delta Y_{4(t-1)}\end{bmatrix}$$

$$+\begin{bmatrix}0.071809 & 0.114135 & 0.018913 & -0.123022\\ -0.208529 & 0.027857 & 0.086024 & 0.080776\\ -0.466053 & -1.898386 & 0.392178 & 0.269978\\ -0.936826 & 0.680842 & -0.040656 & 0.274971\end{bmatrix}\begin{bmatrix}\Delta Y_{1(t-2)}\\ \Delta Y_{2(t-2}\\ \Delta Y_{3(t-2)}\\ \Delta Y_{4(t-2)}\end{bmatrix}$$

The data on Table 8 shows that the value of $R^2 > 0.5$ with AIC and SC criteria value are relatively small, which indicates the reasonability of the mode estimation (Zou, 2018).

3. Prediction using Fourier Series

The first step to predicting using Fourier series is determine the oscillation parameter (k) optimal. The optimal K selected based on the minimum CGV value of the Fourier series function. The result of minimum GCV calculation for the data are presented in Table 9 as follows.

Table 9. K Optimal Results

Method	K optimal	GCV minimum	MSE	R²
Sin tanpa Gamma	1	0.0247	3.4664	0.7454
Cos tanpa Gamma	1	0.0237	3.3264	0.7422
Sin Cos tanpa Gamma	1	0.0179	3.1830	0.7347
Sin dengan Gamma	1	0.0225	2.9911	0.8962
Cos dengan Gamma	1	0.0216	2.8749	0.8932
Sin Cos dengan Gamma	1	0.0225	2.8394	0.8934

Based on the Table 9, the minimum GCV values is cos function with gamma. With an optimum k value of 1, the Fourier series function has 91.19% with low MSE 2.6021 which can be considered as fairly high model estimation (Mardianto et al., 2019). After decided the best Fourier series estimation is cos function with gamma, the next step is finding the estimation model. Based on the optimum k value of 1 and j = 1,2,3,4, multi response nonparametric regression model with a Fourier series approach is obtained using a cos base with gamma whose general form is presented in equation as follows (Mardianto et al., 2019).

$$\hat{y}_{ij} = \frac{\hat{a}_{oj}}{2} + \hat{\gamma}_j t_{i1} + \sum_{k=1}^{K} (\hat{a}_{kj} \cos kt_{i1} + \hat{\beta}_{kj} \sin kt_{i1})$$

Furthermore, Table will show the coefficients of the Fourier series estimator model on a cos basis with gamma parameter as shown in Table 10.

Table 10. Best Estimation Model Coefficients Results

J	$\frac{\hat{a}_{oj}}{2}$	$\hat{\gamma}_j$	$\hat{\alpha}_j$
1	47922.24	-13501.15	-18797.00
2	504838.3	-7982.537	-18109.20
3	1424488	-18990.75	-29669.40
4	1813734	-51265.67	-499.3544

Based on the best estimator model coefficients that have been analyzed, nonparametric model estimates can be formulated with the Fourier series estimator presented in equation as follows:

$$\begin{aligned}
\hat{y}_{i1} &= 47922.24 - 13501.15 \cos t_{i1} - 18797.00 \sin t_{i1} \\
\hat{y}_{i2} &= 504838.3 - 7982.537 \cos t_{i1} - 18109.20 \sin t_{i1} \\
\hat{y}_{i3} &= 1424488 - 18990.75 \cos t_{i1} - 29669.40 \sin t_{i1} \\
\hat{y}_{i4} &= 1813734 - 51265.67 \cos t_{i1} - 499.3544 \sin t_{i1}
\end{aligned}$$

4. Selection of The Best Method

After analyzing the data using Fourier series method and VECM, the next step is select the best method by comparing the smallest MAPE value. The comparison results of MAPE values in two methods is presents in Table 11 as follows.

Table 11. Comparison of the Best Method

Method	MAPE value
VECM	18.90%
Fourier series	0.01%

Based on the Table 11, the best model is the Fourier series with the basis of the cos function with gamma. When compared to the VECM model, this model has a very small MAPE, so it has higher level of accuracy than the VECM model. In other words, the performance of the Fourier series model is better than VECM model (Mardianto et al., 2021).

D. CONCLUSION AND SUGGESTION

In this study, the open unemployment rate based on the highest education graduated in Indonesia were selected simultaneously using the Fourier Series and VECM approaches simultaneously from 2000 – 2022. The results of the model test show that the Fourier Series method of the cos function with gamma is the best model in predicting because this method has smaller MAPE value compared to VECM method. The Fourier Series method is 0.01%, in other hand VECM method is 18.90% which can be categorized as prediction results with the multi response Fourier series regression method is very accurate. The results of prediction are expected to be used as reference for government to making ideal future plan to minimalize the rate of open unemployment in Indonesia.

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