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Analisis Model Intervensi Fungsi Step untuk Peramalan Indeks Harga Konsumen di Provinsi Nusa Tenggara Barat

(*Analysis of Step Function Intervention Model for Consumer Price Index Forecasting in West Nusa Tenggara*)

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ABSTRACT

This study examines the application of a step-function intervention model to monthly Consumer Price Index (CPI) data for West Nusa Tenggara Province from January 2016 to December 2023. The original analysis used ARIMA modeling of the pre-intervention period, followed by identification and estimation of an intervention component. However, the CPI series uses different base years: 2012 = 100 for 2016–2019 and 2018 = 100 for 2020–2023. Accordingly, the apparent level shift at the start of 2020 cannot be attributed to COVID-19 without first harmonizing the data and reassessing the intervention date. Previously reported ARIMA and intervention parameters, as well as forecasts for 2024, must therefore be treated as preliminary. The study requires renewed model identification, diagnostic evaluation, and out-of-sample forecast assessment before substantive conclusions can be drawn.

Keywords: ARIMA; step-function intervention; consumer price index; base-year change; forecasting

ABSTRAK

Penelitian ini mengkaji penerapan model intervensi fungsi step pada data bulanan Indeks Harga Konsumen (IHK) Provinsi Nusa Tenggara Barat periode Januari 2016–Desember 2023. Analisis awal menggunakan ARIMA pada periode sebelum intervensi, dilanjutkan dengan identifikasi serta estimasi komponen intervensi. Akan tetapi, deret IHK tersebut memakai tahun dasar yang berbeda, yaitu 2012 = 100 untuk 2016–2019 dan 2018 = 100 untuk 2020–2023. Oleh karena itu, perubahan level indeks pada awal 2020 tidak dapat langsung diatribusikan kepada pandemi COVID-19 tanpa penyelarasan data dan peninjauan ulang waktu intervensi. Parameter ARIMA dan intervensi serta hasil peramalan tahun 2024 yang sebelumnya dilaporkan perlu diperlakukan sebagai hasil sementara. Identifikasi model, diagnostik residual, dan evaluasi akurasi peramalan di luar sampel harus dilakukan kembali sebelum ditarik kesimpulan substantif

Keywords: ARIMA; intervensi fungsi step; indeks harga konsumen; perubahan tahun dasar; peramalan

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1. Introduction

The Consumer Price Index (CPI) measures changes over time in the prices of a basket of goods and services purchased by consumers [1], [2]. Its month-to-month movements are used to calculate inflation and deflation. CPI is therefore relevant to monitoring consumer purchasing power and supporting economic policy. However, comparisons of index levels are meaningful only when the underlying base period, basket definition, and geographic coverage are consistent.

The published CPI for West Nusa Tenggara was 136.49 in December 2019 and 103.72 in January 2020 [11], [12]. These figures are not directly comparable because the official CPI base changed from 2012 = 100 (2016–2019) to 2018 = 100 (2020–2023) [11]. The value of 103.16 refers to April 2020 rather than January 2020 [13]. Consequently, the discontinuity between December 2019 and January 2020 must not be interpreted as deflation or as evidence of a COVID-19 effect. A pandemic-related intervention can be investigated only after a comparable series has been constructed and the event timing has been justified.

Intervention analysis is a time-series framework for examining changes associated with specified events while accounting for serial dependence [7]. A step input represents a persistent change beginning at a defined time, whereas a pulse input captures a one-period shock. Whether the CPI response is persistent, temporary, gradual, or absent should be investigated empirically rather than assumed. A methodological change in CPI compilation must also be distinguished from any economic intervention.

Previous studies have used ARIMA intervention models for consumer prices, inflation, and other economic series [1], [6], [8]–[10]. Nevertheless, a credible analysis requires a consistent CPI definition, an independently defensible event date, systematic model selection, and forecasting validation. In particular, a sharp plot discontinuity should not automatically be identified as the effect of the pandemic when an official base-year change occurs at the same point.

This study aims to assess the suitability of step-function intervention analysis for CPI dynamics in West Nusa Tenggara and to develop a forecasting procedure based on a comparable series. The essential analytical tasks are to harmonize or appropriately transform the historical CPI observations, specify and justify candidate intervention dates, compare intervention alternatives with ARIMA benchmarks, assess diagnostics, and evaluate predictive accuracy on observations not used for estimation.

2. Methods

This research adopts a time-series intervention framework combining an ARIMA error process with a prespecified intervention input. The intended setting is the official monthly CPI series for West Nusa Tenggara. The model-estimation and forecasting steps described below are conditional on first verifying comparability of the monthly observations across base-year revisions.

2.1 Data

The original dataset contains 96 monthly CPI observations from January 2016 through December 2023, obtained from Statistics Indonesia (BPS) for West Nusa Tenggara. The pre-2020 CPI covers 2016–2019 with base year 2012 = 100, whereas the 2020–2023 CPI uses 2018 = 100 [11]. BPS CPI for the province was based on the combined coverage of Mataram and Bima during this period [11]. The original study did not document a linking factor or a consistently rebased series.

Data comparability and intervention timing. Before estimating any single time-series model across January 2020, the author must obtain a consistent CPI series from official BPS-linked data or reconstruct a suitable comparable indicator with a documented procedure. One possible alternative is a correctly calculated monthly inflation series, provided that the underlying rates remain comparable under the base-year revision. The exact source, base, linking method, coverage, and treatment of transition months must be reported. The intervention should be dated using substantive policy/event evidence and tested for sensitivity to plausible alternative dates; it must not be chosen solely because a base-year discontinuity is visible in the plot.

2.2 Consumer Price Index (CPI)

The CPI is a price index, not itself a percentage inflation rate. As an illustrative fixed-basket index, CPI may be expressed by a Laspeyres-type weighted price ratio in Equation (1). The official BPS series, however, must be interpreted according to the base year, commodity basket, weights, and regional coverage applicable to each published period [11]. Monthly inflation is calculated from comparable consecutive index values as $100 \times (\mathrm{CPI_t}/\mathrm{CPI_{t-1}} - 1)$, when both observations use compatible definitions.

$$CPIt = \frac{\sum_{i=1}^{k} \frac{P_{ti}}{P_{(t-1)i}} P_{(t-1)i} Q_{0i}}{\sum_{i=1}^{k} P_{0i} Q_{0i}} \times 100 \tag{1}$$

where:

- P_{ti}= price of commodity $i$at time t
- P_{0i}= base period price of commodity i
- Q_{0i}= quantity of commodity $i$in the base period

2.3 Time Series Analysis

Time-series modeling begins with graphical exploration and checks of stationarity, trend, seasonality, structural breaks, and variance behavior. Differencing may address a stochastic trend, while transformation may stabilize the variance if supported by diagnostics. Stationarity should not be inferred from plots alone; suitable statistical tests (for example, ADF and KPSS) may be used alongside the ACF and PACF. The observations used for fitting, validation, and testing must be separated chronologically to prevent information leakage.

2.4 ARIMA Model Identification

The Box–Jenkins ARIMA approach characterizes serial dependence through autoregressive, differencing, and moving-average terms. Candidate specifications are identified using the transformed series, ACF/PACF diagnostics, and information criteria. The procedure used for the revised analysis should include the following stages:

1. Inspect the corrected series and document any changes in price-index definition or coverage.
2. Investigate trend, seasonality, variance changes, and stationarity using plots and appropriate tests.
3. Apply justified transformation and differencing; evaluate whether seasonal terms are needed.
4. Generate candidate ARIMA and, where justified, seasonal ARIMA models using ACF/PACF and information criteria.
5. Estimate parameters and examine their uncertainty, plausibility, and numerical stability.
6. Compare parsimonious models using AIC/AICc and BIC, without relying on individual coefficient p-values alone.
7. Examine residual autocorrelation using residual ACF and Ljung–Box tests at reported lags; assess residual distribution with suitable graphical checks.
8. Evaluate one-step-ahead or rolling-origin forecasts on an out-of-sample period using MAE, RMSE, and, where meaningful, sMAPE; report prediction intervals and compare against a naive/seasonal-naive benchmark.

2.5 Intervention Analysis

An intervention model adds an event-response component to the ARIMA noise process. In the present application, a substantive pandemic-related event date must be distinguished from the January 2020 CPI base-year revision. The analysis should consider alternative input shapes

(step and pulse) and plausible onset dates, and compare them using transparent criteria rather than presuming a permanent pandemic effect.

Following the intervention-model framework of Wei [7], the series can be represented as the sum of a systematic intervention response and an ARIMA error process:

$$Z_t = f(I_t) + N_t \tag{2}$$

where:

- Z_t= response variable at time t
- $f(I_t)$= intervention response function
- N_t= pre-intervention data following an ARIMA process

The intervention response function is expressed as:

$$f(I)_t = \frac{\omega_s(B)}{\delta_r(B)} B^b I_t \tag{3}$$

where:

- $\omega_s(B)$= operator of order s
- $\delta_r(B)$= operator of order r
- b, s, r= constants representing the intervention effect

In the conventional transfer-function notation $\omega_s(B)B^b/\delta_r(B)$, b is the delay, s is the polynomial order in the numerator, and r is the polynomial order in the denominator. In particular, s does not by itself represent the number of months for which an intervention persists. All orders and coefficient estimates must be stated consistently with the fitted equation and supported by diagnostic evidence.

A step input $S_t^{(T)}$ takes the value 0 before an intervention date T and 1 at and after T. The long-run behavior of the series depends jointly on the input type and the estimated transfer function; the existence of a persistent pandemic-induced shift must be tested rather than taken for granted.

$$S_t^{(T)} = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \tag{4}$$

where T is the justified onset date for the event or policy under investigation.

For one intervention event, the response may be expressed by the following step-function transfer model. Its coefficient values should be estimated on a verified and comparable series:

$$Y_t = \sum_{j=1}^{k} \frac{\omega_{s_j}(B)B^{b_j}}{\delta_{r_j}(B)} S_t^{(T)} + N_t \tag{5}$$

2.6 Research Procedure

The revised, reproducible research procedure should comprise the following stages:

1. Verify data sources, base-year changes, regional coverage, and any necessary linking/transformation.
2. Select an intervention date from independent event evidence and define pre-/post-event periods.
3. Fit and compare parsimonious ARIMA and, if indicated, seasonal ARIMA benchmark models.
4. Inspect counterfactual prediction errors or intervention residual patterns without treating re-basing jumps as intervention effects.

5. Specify and compare plausible transfer-function orders (b, s, r) and alternative step/pulse inputs.
6. Estimate intervention-model parameters and evaluate coefficient uncertainty and numerical stability.
7. Check residual dependence, distribution, and variance; compare competing model specifications.
8. Perform chronological out-of-sample evaluation, report forecast errors and intervals, and benchmark against ARIMA without intervention.
9. A nonsignificant residual autocorrelation test indicates that dependence was not detected at the tested lags; it does not prove independence. Similarly, a residual-normality test alone does not demonstrate forecasting accuracy or structural validity. The model should be retained only if the data are comparable, diagnostics are acceptable, and forecasts perform competitively on held-out observations.

3. Results and Discussion

The following plots, fitted values, coefficient tables, and 2024 forecasts reproduce the exploratory analysis in the original manuscript. They are retained for traceability, not as validated final results. Because the original CPI series crosses a change of base year in January 2020, the model must be re-estimated on comparable data before these outputs can support substantive conclusions.

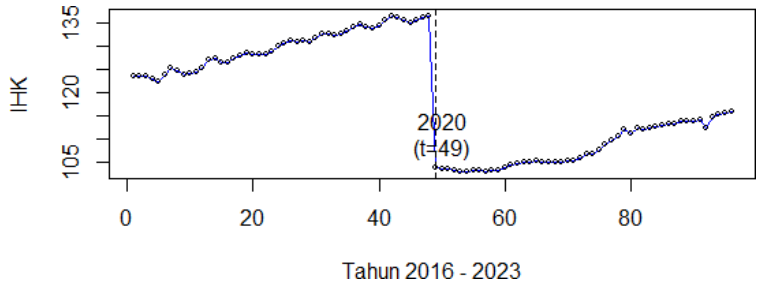

Figure 1 Plot of CPI Data for 2016-2023

Figure 1 displays a sharp apparent level change at the boundary between December 2019 (observation 48) and January 2020 (observation 49). This boundary coincides with the transition from CPI base year 2012 = 100 to 2018 = 100 [11]. It therefore cannot be used on its own to infer pandemic-related deflation. The 2016–2019 and 2020–2023 segments must first be made comparable. Only then can a substantive intervention date and its possible impact be examined.

In the original exploratory analysis, the first 48 observations were used for the ARIMA fit. That division reflects the date of the base-year change, not a verified pandemic intervention. After data harmonization, the proposed intervention date, pre-intervention estimation period, and forecast horizon must be selected and justified anew. Figure 2 depicts the pre-2020 index segment.

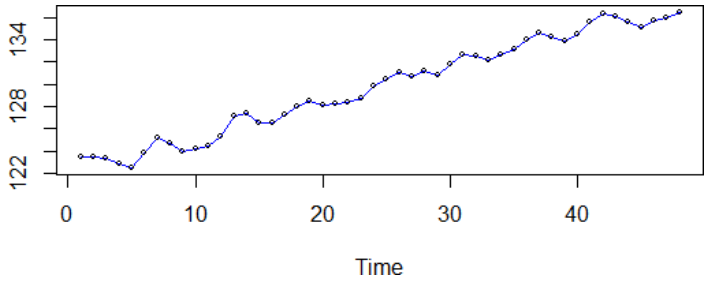

Figure 2 Pre-intervention Data Plot

Figure 2 suggests an upward trend in the pre-2020 index levels; the original manuscript applied Box–Cox transformation and differencing. However, the transformation parameter, stationarity test statistics, and differencing rationale were not reported. These must be documented and the stationarity assessment repeated before ARIMA orders can be finalized.

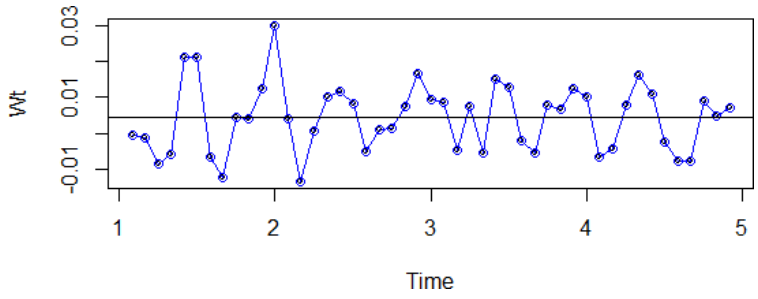

Figure 3 Plot Data After Differencing

. Figure 3 shows the transformed/differenced series from the original analysis. A visually fluctuating series is not sufficient evidence of stationarity; the transformation details and statistical diagnostics should be provided. The original manuscript compared ARIMA(2,1,2) with drift and ARIMA (2,1,1) with drift. Their previously reported information criteria appear in Table 1, but these values should be regenerated after confirming the preprocessing pipeline and the comparability of the target variable.

Table 1 AIC and BIC Values of ARIMA Models

ARIMA Model	AIC	BIC
(2,1,2) *With drift*	-326.7616	-315.6607
(2,1,1) *With drift*	-322.7744	-313.5236

Based on Table 1, the ARIMA $(2, 1, 2)$with drift model has smaller AIC and BIC values than the ARIMA $(2, 1, 1)$with drift model. Therefore, the ARIMA $(2, 1, 2)$with drift model was selected as the best model for forecasting the pre-intervention data. In general, the ARIMA $(2, 1, 2)$model can be interpreted as an ARMA $(2, 2)$model after the differencing process. To derive the ARMA $(2, 2)$form from the ARIMA $(2, 1, 2)$model, the differencing operator $(1 - B)^d$must be transformed back into its original form so that the model can be expressed in terms of the original variable Z_t, resulting in the following equation:

$$Z_t = (1 + \phi_1)Z_{t-1} - (\phi_1 - \phi_2)Z_{t-2} + \phi_2 Z_{t-3} + \mu + \alpha_t - \theta_1\alpha_{t-1} - \theta_2\alpha_{t-2}$$

thus,

$$Z_t = (1 + 0.9425)Z_{t-1} - (0.9425 - (-0.9745))Z_{t-2} + (-0.9745)Z_{t-3} + 0.0043 + \alpha_t - (-1.0118)\alpha_{t-1} - 0.7876\alpha_{t-2}$$

Thus, an ARIMA (2,1,2) model with drift was obtained for the pre-intervention data, namely:

$$Z_t = 1.9425Z_{t-1} - 1.917Z_{t-2} + 0.9745Z_{t-3} + 0.0043 + \alpha_t + 1.0118\alpha_{t-1} - 0.7876\alpha_{t-2}$$

The ARIMA (2,1,2) with drift model refers to an ARIMA model with order p = 2, d = 1, and q=2 that is influenced by a drift or shift of 0.0043. ARIMA models with drift are often used because they can capture long-term changes in data patterns that may not be visible using ARIMA models without drift. After determining the best ARIMA model, forecasting can be performed. Pre-intervention CPI data forecasting was performed using the best ARIMA model obtained, namely

ARIMA (2,1,2) with drift. The following is a plot of pre-intervention CPI data with the results of forecasting using the ARIMA (2,1,2) with drift model.

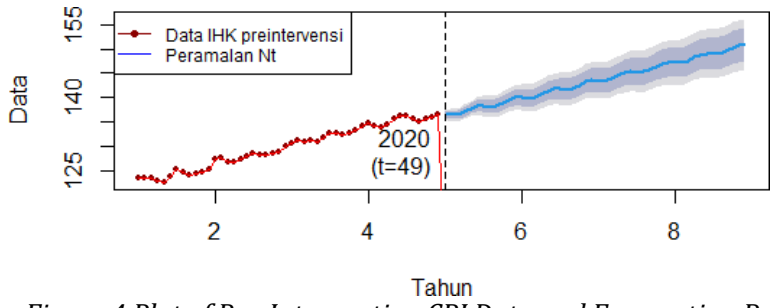

Figure 4 Plot of Pre-Intervention CPI Data and Forecasting Results

Based on the results of the pre-intervention CPI data forecast plot, where the red line represents the CPI data before the intervention and the blue line represents the forecast results using the ARIMA (2,1,2) with drift model, the forecast plot shows that the CPI data should have increased. However, due to the influence on the data, the CPI data experienced deflation, which led to the intervention. Unexpected changes in the CPI can affect investment values and make it difficult for the government and entrepreneurs to plan economic policies and business strategies. Therefore, we need to model the CPI data for NTB Province to anticipate inflation and deflation. Because CPI data experiences extreme fluctuations and the effects are felt for a long time, the appropriate method for analyzing CPI data for NTB Province is step function intervention.

The next step is to determine the step function intervention model for the data during and after the intervention, by first determining the order of intervention, which is done by identifying the residual plot. The residual plot can help in understanding the impact of the intervention, as well as helping to evaluate the suitability of the model used to analyze the intervention data. The following is the residual plot obtained.

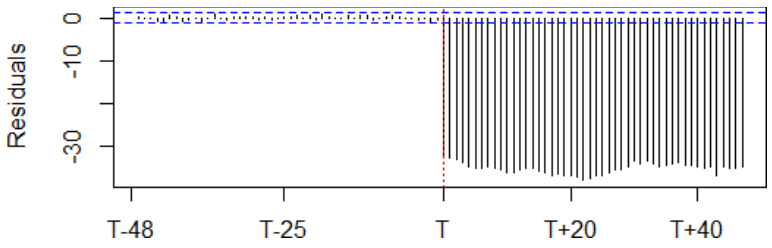

Figure 5 Plot Residual Intervensi

The residual plot is utilized to identify the intervention orders (b, s, r). The parameter $b$represents the time when the intervention effect first appears, while $s$indicates the duration of the intervention effect after $b$periods. Meanwhile, the parameter $r$describes the pattern of the residuals returning to zero following the intervention period. Based on the residual plot shown in Figure 5, the intervention effect occurs immediately, resulting in an order of $b = 0$. The intervention effect persists throughout the observed post-intervention period, leading to an order of $s = 48$, which indicates that the intervention has a substantial and long-term impact on the data. In addition, the value $r = 0$suggests that no additional lag or new residual pattern appears after the intervention period, since the residuals after $T + 48$remain relatively stable without further fluctuations. Therefore, the identified step function intervention model is characterized by the orders $b = 0$, $s = 48$, and $r = 0$. After determining these intervention orders, the next stage is parameter estimation for the intervention model.

Intervention parameter estimation refers to the measurement of how much a change affects outcomes. This estimation is conducted once the intervention response is detected by examining the residual response patterns during and after the intervention period. The results of the intervention parameter estimation are presented below.

Table 2 Coefficients

	ar_1	ar_2	ma_1	ma_2	$T49 - AR_1$	$T49 - MA_1$
	0.4218	−0.1823	0.4431	0.005	−0.2812	13.2346
$s.e$	3.4211	0.3355	3.4651	2.569	0.0780	0.7431

Based on table 2, which shows the results of the intervention parameter estimation, the intervention parameters ω_0 and ω_1 were obtained, where $T49 - AR_1$ is the intervention parameter (ω_0) and $T49 - MA_1$ is the intervention parameter (ω_1), after performing parameter estimation. Next, a parameter significance test is performed to determine whether the estimated parameters are significant in explaining changes in data patterns due to intervention or not. The results of the intervention parameter significance test can be seen in Table 3 below.

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Table 3 Z test of coefficients

	Estimate	Std.Error	Z value	Pr(> |z|)
ar_1	0.4218	3.4211	0.1233	0.9018812
ar_2	−0.1823	0.3355	−0.5433	0.5869008
ma_1	0.4431	3.4651	0.1279	0.8982495
ma_2	0.0051	2.5694	0.0020	0.9984301
$T49 - AR_1$	−0.2812	0.0780	−3.6032	0.0003143
$T49 - MA_1$	13.2346	0.7431	17.8088	$2.2e - 16$

Parameter significance tests were conducted to ensure that the estimated parameters were significant and that the model used was appropriate. The results of the parameter significance tests in Table 2.3 show that the parameters ω_0 and

ω_1 are significant, because the p-values for ω_0 and ω_1 are < 0.05. Based on Table 2.3, the values obtained are $\omega_0 = -0.2811850$ and $\omega_1 = 13.2346271$.

Thus, the intervention model for the NTB Province CPI data is obtained as follows:

$$Y_t = -0.281S_t^{(49)} - 13.234S_{t-1}^{(49)} + 1.9425Z_{t-1} - 1.917Z_{t-2} + 0.9745Z_{t-3} + 0.0043 + \alpha_t + 1.0118\alpha_{t-1} - 0.7876\alpha_{t-2}$$

According to [1] a model is suitable for use if it produces residuals that satisfy the assumptions of white noise (residual independence) and residual normality. If the p-value exceeds the significance level (0.05), then the assumptions are satisfied. To test residual independence or white noise, the Ljung-Box test is used, and to test residual normality, the Kolmogorov-Smirnov test is used.

Table 4 Intervention Diagnostic Test

	$p-value$
Uji Ljung-Box	0.2152
uji Kolmogorov-Smirnov	0.4967

The results of the Ljung–Box test presented in Table 4 indicate that the intervention model produces a p-value of 0.2152, which is greater than 0.05. Therefore, the null hypothesis cannot be rejected, implying that the residuals satisfy the white noise assumption. Furthermore, the Kolmogorov–Smirnov test yields a p-value of 0.4967, which also exceeds 0.05, indicating that the residuals follow a normal distribution. Since the intervention model fulfills both the white noise and normality assumptions, the model is considered appropriate for forecasting purposes.

Forecasting with the intervention model is carried out when the model satisfies the assumptions of white noise and normality. Since these conditions are fulfilled, the model is appropriate for use, allowing forecasting to proceed. Therefore, the resulting intervention model is:

$$Y_t(-1) = -0.281S_t^{(49)} - 13.234S_{t-1}^{(49)} + (1.9425)Z_{t-1} - 1.917Z_{t-2} + 0.9745Z_{t-3} + 0.0043 + \alpha_t + 1.0118)\alpha_{t-1} - 0.7876\alpha_{t-2}$$

The following are the results of the NTB Province CPI forecast from January to August 2024 using the ARIMA (2,1,2) with drift model with intervention order $b = 0$, $s = 48$, and $r = 0$.

Table 5 Intervention Forecasting Results

No	Periode	Hasil Peramalan Intervensi
1	Januari 2024	116.0325
2	Februari 2024	116.1780
3	Maret 2024	116.5437
4	April 2024	117.0376
5	Mei 2024	117.4363
6	Juni 2024	117.6176
7	Juli 2024	117.6854
8	Agustus 2024	117.8597

Table 5 shows the results of CPI forecasting in NTB Province from January to August 2024. Based on the forecast results in table 2.5, there is an upward trend in the forecast values. The forecast value starts at 116.0325 in January and continues to increase to 117.8597 in August 2024. The analysis and forecast results of NTB Province CPI data are shown in figure 6.

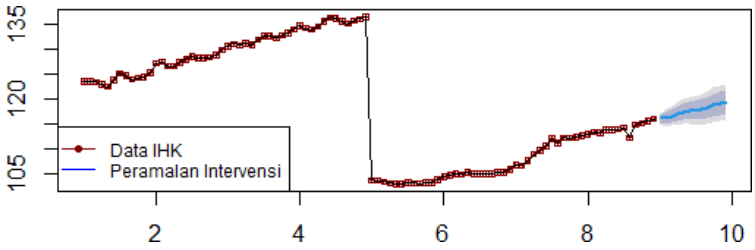

Figure 6 Plot CPI Data and Step Function Intervention Forecast Results

The plot of the forecast results using the intervention model in figure 3.6 shows that the forecast of the CPI value using the intervention model is expected to continue to increase. The intervention model predicts that the upward trend in the CPI will continue consistently. Figure 6 also shows that the forecast results are not much different from the CPI data. This means that the intervention model has successfully captured the pattern of change caused by the intervention.

4. Conclusions

From the findings of the study and analysis, it is possible to conclude that:

a. The intervention model formed on the NTB Province CPI data with the best ARIMA model for pre-intervention data (2,1,2) with drift and the best intervention model is an intervention model with order b = 0, s = 48, and r = 0, with the equation:

$$Y_t = -0.281S_t^{(49)} - 13.234S_{t-1}^{(49)} + 1.9425Z_{t-1} - 1.917Z_{t-2} + 0.9745Z_{t-3} + 0.0043 + \alpha_t + 1.0118\alpha_{t-1} - 0.7876\alpha_{t-2}$$

b. The results of CPI forecasting in NTB Province using the intervention model show a pattern of monthly increases in CPI values. The intervention model predicts that the upward trend in CPI will continue consistently. Figure 3.6 also shows that the forecast results are not much different from the CPI data. This means that the intervention model has successfully captured the pattern of change caused by the intervention.Ucapan Terima Kasih

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