LAMPIRAN

Lampiran 01. Data Jumlah Kunjungan Wisatawan Mancanegara ke Bali

Bulan	Tahun									
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Januari	288755	343663	452660	345191	451708	533392	2	0	329909	414937
Februari	333072	367024	447762	443805	436266	358929	12	1293	317005	454398
Maret	294737	354778	422757	484846	441707	166388	3	14617	366956	463804
April	309888	367370	474338	516143	476104	273	9	58315	410281	502870
Mei	287141	394443	486207	526281	483928	34	8	115553	439454	544492
Juni	357712	405686	503617	540462	549483	10	1	181545	478127	520792
Juli	381890	482201	591812	624337	604310	16	0	246442	541272	625569
Agustus	298638	437929	599827	572027	602457	12	0	276627	522063	613540
September	379397	442304	550238	555888	589984	8	0	291115	508297	591848
Oktober	366759	423140	462263	515859	565966	7	2	305152	458845	554892
November	262180	396150	358012	406679	492904	2	6	287025	397522	472714
Desember	363780	437946	307321	495641	544726	127	0	376361	478382	548685

Lampiran 02. Packages R-Studio yang Digunakan dalam Analisis Metode Kombinasi ARIMA-MLP

```
#packages
library(readxl)
library(forecast)
library(tseries)
library(MASS)
library(lmtest)
library(TSA)
library(nnfor)
library(ggplot2)
```

Lampiran 03. Hasil Analisis Deskriptif Data

```
> summary(data1)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
      3  273018  401607  345587  493591  625572
> |
```

Lampiran 04. Hasil Uji Stasioneritas dalam Varians

```
> # Box-Cox transformation
> u1 <- boxcox(lm(train_data ~ 1), lambda = seq(-2, 2, by = 0.1))  # Selang lambda dari -2 hingga 2
> #Mencari lambda terbaik
> lambda1 <- u1$x[which.max(u1$y)]
> print(paste("Lambda terbaik:", lambda1))
[1] "Lambda terbaik: 0.383838383838384"
> |
```

```
> #Transformasi data training
> if (lambda1 == 0) {
+   train_data_transformed <- log(train_data)
+ } else {
+   train_data_transformed <- (train_data^lambda1 - 1) / lambda1
+ }
> print(train_data_transformed)
            Jan        Feb        Mar        Apr        May        Jun        Jul        Aug
2015 322.342950 340.648422 324.910536 331.273174 321.644586 350.181533 359.150183 326.567662
2016 344.797534 353.678713 349.068048 353.807596 363.669012 367.641631 393.028846 378.671221
2017 383.543931 381.934763 373.545878 390.540016 394.287233 399.683207 425.389181 427.604832
2018 345.389606 380.626810 393.860427 403.494734 406.538090 410.735121 434.269230 419.839497
2019 383.232008 378.114827 379.930417 391.101199 393.572128 413.369779 428.836157 428.327887
2020 408.651267 350.641747 260.374079  19.924996   7.812815   4.367836   5.461259   4.761565
2021   2.226917   4.761565   2.577196   4.156855   3.934742   1.830265   1.366552   1.366552
2022   1.366552  38.188040 100.794196 173.247653 226.031303 269.323022 303.168835 317.034957
2023 339.393559 334.195837 353.653374 369.245701 379.180302 391.742474 410.972790 405.276303
            Sep        Oct        Nov        Dec
2015 358.241903 353.579951 310.521366 352.466681
2016 380.128788 373.676644 364.276619 378.676902
2017 413.589071 386.667994 350.295069 330.208870
2018 415.224274 403.408952 367.989222 397.225670
2019 424.881267 418.115775 396.376743 411.983808
2020   3.934742   3.699808   2.226917  14.270530
2021   1.366552   2.226917   3.449909   1.366552
2022 323.359785 329.305304 321.594301 357.130811
2023 401.114044 385.560669 364.763814 391.823188
```

Lampiran 05. Hasil Uji Stasioneritas dalam Rata-Rata

```
> #uji kestasioneran data dalam rata-rata
> #Plot ACF (Autocorrelation Function)
> nilai_acf <- acf(train_data_transformed, xlab = "Lag",
+                  ylab = "Autocorrelation", main = "Plot ACF", lag.max = 20)
> print(nilai_acf$acf)
, , 1

             [,1]
 [1,]  0.97632849
 [2,]  0.93699893
 [3,]  0.88669047
 [4,]  0.83116534
 [5,]  0.77662219
 [6,]  0.71799678
 [7,]  0.65899866
 [8,]  0.60013887
 [9,]  0.54348895
[10,]  0.48862835
[11,]  0.43574230
[12,]  0.38231434
[13,]  0.32504474
[14,]  0.26749891
[15,]  0.20791439
[16,]  0.14633671
[17,]  0.08674016
[18,]  0.02418095
[19,] -0.03759175
[20,] -0.09736278
```

Lampiran 06. Hasil *Differencing* Data

```
> #Data belum stasioner dalam rata-rata sehingga dilakukan differencing
> train_data_transformed_diff <- diff(train_data_transformed)
> print(train_data_transformed_diff)
             Jan          Feb          Mar          Apr          May          Jun          Jul
2015               18.3054717  -15.7378858    6.3626381   -9.6285875   28.5369470    8.9686495
2016  -7.6691466    8.8811787   -4.6106649    4.7395482    9.8614159    3.9726193   25.3872145
2017   4.8670280   -1.6091670   -8.3888854   16.9941382    3.7472167    5.3959745   25.7059736
2018  15.1807360   35.2372038   13.2336170    9.6343075    3.0433558    4.1970307   23.5341095
2019 -13.9936619   -5.1171808    1.8155902   11.1707814    2.4709289   19.7976518   15.4663772
2020  -3.3325402  -58.0095202  -90.2676683 -240.4490825  -12.1121814   -3.4449795    1.0934231
2021 -12.0436132    2.5346485   -2.1843691    1.5796591   -0.2221136   -2.1044770   -0.4637127
2022   0.0000000   36.8214877   62.6061559   72.4534569   52.7836503   43.2917190   33.8458125
2023 -17.7372514   -5.1977224   19.4575373   15.5923267    9.9346008   12.5621724   19.2303162
             Aug          Sep          Oct          Nov          Dec
2015 -32.5825209   31.6742410   -4.6619521  -43.0585849   41.9453146
2016 -14.3576243    1.4575661   -6.4521436   -9.4000250   14.4002835
2017   2.2156514  -14.0157612  -26.9210767  -36.3729252  -20.0861990
2018 -14.4297336   -4.6152230  -11.8153223  -35.4197291   29.2364472
2019  -0.5082700   -3.4466201   -6.7654919  -21.7390316   15.6070646
2020  -0.6996932   -0.8268236   -0.2349340   -1.4728909   12.0436132
2021   0.0000000    0.0000000    0.8603648    1.2229921   -2.0833569
2022  13.8661227    6.3248276    5.9455190   -7.7110026   35.5365096
2023  -5.6964869   -4.1622598  -15.5533745  -20.7968549   27.0593743
```

Lampiran 07. Hasil ACF dan PACF Data yang Sudah Stasioner

```
> #Plot ACF (Autocorrelation Function)
> nilai_acf <- acf(train_data_diff, xlab = "Lag",
+                  ylab = "Autocorrelation", main = "Plot ACF", lag.max = 20)
> print(nilai_acf$acf)
, , 1

              [,1]
 [1,]  0.3924068673
 [2,]  0.2475309700
 [3,]  0.1061326783
 [4,] -0.0194902596
 [5,]  0.0796816333
 [6,]  0.0230209831
 [7,]  0.0192198281
 [8,] -0.0527937015
 [9,] -0.0318242424
[10,] -0.0171145946
[11,]  0.0061003644
[12,]  0.0661347003
[13,]  0.0407770732
[14,]  0.0422010326
[15,]  0.0526503616
[16,] -0.0404478009
[17,]  0.0826486664
[18,]  0.0061531575
[19,]  0.0005485185
[20,] -0.0095772340
```

```
> # Plot PACF (Partial Autocorrelation Function)
> nilai_pacf <- pacf(train_data_diff, xlab = "Lag",
+                    ylab = "Autocorrelation", main = "Plot PACF", lag.max = 20)
> print(nilai_pacf$acf)
, , 1

              [,1]
 [1,]  0.392406867
 [2,]  0.110574418
 [3,] -0.028300460
 [4,] -0.090508241
 [5,]  0.129426359
 [6,] -0.023303813
 [7,] -0.012907631
 [8,] -0.085122493
 [9,]  0.035742900
[10,]  0.002483832
[11,]  0.021682646
[12,]  0.051854706
[13,]  0.008485005
[14,]  0.004968719
[15,]  0.036128235
[16,] -0.090840600
[17,]  0.127425375
[18,] -0.056497298
[19,] -0.011082601
[20,] -0.027463587
```

Lampiran 08. Hasil Estimasi dan Signifikansi Parameter Model ARIMA

ARIMA (1,1,1)

```
> #Estimasi Parameter
> model1 <- Arima (train_data, order = c(1,1,1),method = 'ML')
> lmtest::coeftest(model1)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ar1  0.40936    0.29404  1.3922   0.1639
ma1 -0.17439    0.31516 -0.5533   0.5800

> summary(model1)
Series: train_data
ARIMA(1,1,1)

Coefficients:
         ar1      ma1
      0.4094  -0.1744
s.e.  0.2940   0.3152

sigma^2 = 2.707e+09:  log likelihood = -1312.83
AIC=2631.66   AICc=2631.89   BIC=2639.68

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE         ACF1
Training set 1421.744 51305.24 35577.57 1484.416 2324.827 0.2293984 -0.002649236
>
```

ARIMA (1,1,0)

```
> model2<- Arima (train_data, order = c(1,1,0), method = 'ML')
> lmtest::coeftest(model2)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ar1 0.245604   0.094549  2.5976 0.009387 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> summary(model2)
Series: train_data
ARIMA(1,1,0)

Coefficients:
         ar1
      0.2456
s.e.  0.0945

sigma^2 = 2.688e+09:  log likelihood = -1312.96
AIC=2629.92   AICc=2630.03   BIC=2635.26

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 1498.562 51367.87 35616.53 591.2888 1469.785 0.2296495 -0.01201066
>
```

ARIMA (0,1,1)

```
> model3 <- Arima (train_data, order = c(0,1,1), method = 'ML')
> lmtest::coeftest(model3)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ma1 0.229423   0.096052  2.3885  0.01692 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> summary(model3)
Series: train_data
ARIMA(0,1,1)

Coefficients:
         ma1
      0.2294
s.e.  0.0961

sigma^2 = 2.706e+09:  log likelihood = -1313.3
AIC=2630.6   AICc=2630.72   BIC=2635.95

Training set error measures:
                   ME     RMSE      MAE      MPE    MAPE      MASE       ACF1
Training set 1584.284 51534.22 35958.84 -149.857 1832.95 0.2318567 0.01095373
>
```

ARIMA (0,1,2)

```
> model4 <- Arima (train_data, order = c(0,1,2), method = 'ML')
> lmtest::coeftest(model4)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ma1  0.20824    0.10099  2.0620  0.03921 *
ma2  0.10723    0.13726  0.7812  0.43466
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> summary(model4)
Series: train_data
ARIMA(0,1,2)

Coefficients:
         ma1     ma2
      0.2082  0.1072
s.e.  0.1010  0.1373

sigma^2 = 2.717e+09:  log likelihood = -1313.01
AIC=2632.02   AICc=2632.26   BIC=2640.04

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 1500.089 51393.46 35522.16 682.2229 2062.744 0.2290411 0.01526812
>
```

ARIMA (1,1,2)

```
> model5 <- Arima (train_data, order = c(1,1,2), method = 'ML')
> lmtest::coeftest(model5)

z test of coefficients:

     Estimate Std. Error z value Pr(>|z|)
ar1  0.283604   0.414905  0.6835   0.4943
ma1 -0.060613   0.401167 -0.1511   0.8799
ma2  0.069676   0.179821  0.3875   0.6984

> summary(model5)
Series: train_data
ARIMA(1,1,2)

Coefficients:
         ar1      ma1     ma2
      0.2836  -0.0606  0.0697
s.e.  0.4149   0.4012  0.1798

sigma^2 = 2.73e+09:  log likelihood = -1312.77
AIC=2633.54   AICc=2633.93   BIC=2644.23

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE     MASE        ACF1
Training set 1418.269 51273.14 35437.17 1465.567 2666.338 0.228493 0.004341181
```

ARIMA (2,1,1)

```
> model6 <- Arima (train_data, order = c(2,1,1), method = 'ML')
> lmtest::coeftest(model6)

z test of coefficients:

     Estimate Std. Error z value Pr(>|z|)
ar1  0.299697   0.667298  0.4491   0.6533
ar2  0.035827   0.191621  0.1870   0.8517
ma1 -0.068719   0.661669 -0.1039   0.9173

> summary(model6)
Series: train_data
ARIMA(2,1,1)

Coefficients:
         ar1     ar2      ma1
      0.2997  0.0358  -0.0687
s.e.  0.6673  0.1916   0.6617

sigma^2 = 2.733e+09:  log likelihood = -1312.82
AIC=2633.63   AICc=2634.03   BIC=2644.32

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE         ACF1
Training set 1418.684 51298.24 35536.55 1514.911 2347.784 0.2291338 0.0001868801
```

ARIMA (2,1,2)

```
> model7 <- Arima (train_data, order = c(2,1,2), method = 'ML')
> lmtest::coeftest(model7)

z test of coefficients:

    Estimate Std. Error z value  Pr(>|z|)
ar1  0.48681    0.74500  0.6534 0.5134795
ar2 -0.51661    0.33556 -1.5396 0.1236646
ma1 -0.28776    0.70327 -0.4092 0.6824087
ma2  0.60933    0.18306  3.3286 0.0008729 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(model7)
Series: train_data
ARIMA(2,1,2)

Coefficients:
         ar1      ar2      ma1     ma2
      0.4868  -0.5166  -0.2878  0.6093
s.e.  0.7450   0.3356   0.7033  0.1831

sigma^2 = 2.699e+09:  log likelihood = -1311.7
AIC=2633.41   AICc=2634   BIC=2646.77

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 1588.909 50738.37 35595.83 -663.9571 12027.35 0.2295161 0.02324052
```

ARIMA (1,1,3)

```
> model8 <- Arima (train_data, order = c(1,1,3), method = 'ML')
> lmtest::coeftest(model8)

z test of coefficients:

    Estimate Std. Error z value  Pr(>|z|)
ar1 -0.52951    0.19225 -2.7543  0.005881 **
ma1  0.84274    0.18500  4.5555 5.227e-06 ***
ma2  0.30598    0.15147  2.0201  0.043370 *
ma3  0.27689    0.11163  2.4805  0.013120 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(model8)
Series: train_data
ARIMA(1,1,3)

Coefficients:
          ar1     ma1     ma2     ma3
      -0.5295  0.8427  0.3060  0.2769
s.e.   0.1922  0.1850  0.1515  0.1116

sigma^2 = 2.57e+09:  log likelihood = -1309.19
AIC=2628.38   AICc=2628.98   BIC=2641.75

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 1329.154 49507.82 34965.17 2829.847 9348.301 0.2254497 -0.02300014
```

ARIMA (0,1,3)

```
> model9 <- Arima (train_data, order = c(0,1,3), method = 'ML')
> lmtest::coeftest(model9)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ma1  0.32813    0.11293  2.9055 0.003667 **
ma2  0.09381    0.14554  0.6445 0.519220
ma3  0.20695    0.10659  1.9416 0.052185 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(model9)
Series: train_data
ARIMA(0,1,3)

Coefficients:
         ma1     ma2     ma3
      0.3281  0.0938  0.2069
s.e.  0.1129  0.1455  0.1066

sigma^2 = 2.658e+09:  log likelihood = -1311.43
AIC=2630.85   AICc=2631.24   BIC=2641.54

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 1284.544 50595.75 36171.66 2815.384 6298.452 0.2332289 -0.05067019
```

ARIMA (3,1,1)

```
> model10 <- Arima (train_data, order = c(3,1,1), method = 'ML')
> lmtest::coeftest(model10)

z test of coefficients:

    Estimate Std. Error z value  Pr(>|z|)
ar1 -0.55241    0.14346 -3.8507 0.0001178 ***
ar2  0.19385    0.11254  1.7225 0.0849746 .
ar3  0.18101    0.10143  1.7847 0.0743158 .
ma1  0.82339    0.11714  7.0289 2.082e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(model10)
Series: train_data
ARIMA(3,1,1)

Coefficients:
          ar1     ar2     ar3     ma1
      -0.5524  0.1939  0.1810  0.8234
s.e.   0.1435  0.1125  0.1014  0.1171

sigma^2 = 2.608e+09:  log likelihood = -1309.95
AIC=2629.91   AICc=2630.5   BIC=2643.27

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 1269.088 49877.02 35896.99 4489.951 10561.77 0.2314579 0.02203521
```

ARIMA (3,1,0)

```
> model11 <- Arima (train_data, order = c(3,1,0), method = 'ML')
> lmtest::coeftest(model11)

z test of coefficients:

    Estimate Std. Error z value Pr(>|z|)
ar1 0.229688   0.098269  2.3373  0.01942 *
ar2 0.043910   0.101681  0.4318  0.66586
ar3 0.030829   0.098580  0.3127  0.75448
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(model11)
Series: train_data
ARIMA(3,1,0)

Coefficients:
         ar1     ar2     ar3
      0.2297  0.0439  0.0308
s.e.  0.0983  0.1017  0.0986

sigma^2 = 2.73e+09:  log likelihood = -1312.77
AIC=2633.55   AICc=2633.94   BIC=2644.24

Training set error measures:
                   ME     RMSE      MAE      MPE    MAPE      MASE       ACF1
Training set 1374.852 51276.91 35683.18 2080.993 2924.14 0.2300793 0.00678261
```

ARIMA (3,1,2)

```
> model12 <- Arima(train_data, order = c(3,1,2),method = 'ML')
> lmtest::coeftest(model12)

z test of coefficients:

     Estimate Std. Error  z value  Pr(>|z|)
ar1 -1.357201   0.091687 -14.8025 < 2.2e-16 ***
ar2 -0.400204   0.156435  -2.5583 0.0105195 *
ar3  0.342246   0.092535   3.6986 0.0002168 ***
ma1  1.752429   0.069188  25.3285 < 2.2e-16 ***
ma2  0.999882   0.077190  12.9535 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

> summary(model12)
Series: train_data
ARIMA(3,1,2)

Coefficients:
          ar1      ar2     ar3     ma1     ma2
      -1.3572  -0.4002  0.3422  1.7524  0.9999
s.e.   0.0917   0.1564  0.0925  0.0692  0.0772

sigma^2 = 2.282e+09:  log likelihood = -1305.04
AIC=2622.08   AICc=2622.92   BIC=2638.12

Training set error measures:
                   ME     RMSE      MAE     MPE     MAPE      MASE        ACF1
Training set 1285.501 46428.73 34513.51 9582.27 49625.02 0.2225374 0.009311575
```

Lampiran 09. Hasil Uji Ljung Box Residual Model ARIMA

ARIMA (1,1,0)

```
> #Diagnosis checking model ARIMA
> #Uji Ljung-Box
> acf(rstandard(model2),plot=T)$acf[1:20]
 [1] -0.012010659  0.040854463  0.087612671 -0.214548806  0.101548790 -0.030971796  0.028450492
 [8] -0.142037885 -0.050877860  0.059253709 -0.106918343  0.264961495  0.020498702 -0.009454109
[15]  0.068639664 -0.097181057  0.124348334 -0.020365097  0.019308104 -0.071316696
> m2_LB_Test<-Box.test(model2$residuals, fitdf=1, type = "Ljung-Box", lag = 20)
> m2_LB_Test

	Box-Ljung test

data:  model2$residuals
X-squared = 25.642, df = 19, p-value = 0.1405
```

ARIMA (0,1,1)

```
> acf(rstandard(model3),plot=F)$acf[1:20]
 [1]  1.095373e-02  8.457175e-02  9.209760e-02 -2.064992e-01  1.031701e-01 -4.713256e-02
 [7]  2.723790e-02 -1.409551e-01 -5.579759e-02  6.289972e-02 -1.036100e-01  2.643785e-01
[13]  2.443307e-02 -3.055481e-05  7.542294e-02 -9.469238e-02  1.263518e-01 -2.735457e-02
[19]  1.770224e-02 -7.161380e-02
> m3_LB_Test<-Box.test(model3$residuals, fitdf=1, type = "Ljung-Box", lag = 20)
> m3_LB_Test

	Box-Ljung test

data:  model3$residuals
X-squared = 26.274, df = 19, p-value = 0.1227
```

ARIMA (1,1,3)

```
> acf(rstandard(model8),plot=F)$acf[1:20]
 [1] -0.02300014 -0.02842524 -0.05124404 -0.08841105  0.03501735  0.05350381 -0.01167209
 [8] -0.10783040 -0.06929142  0.04747510 -0.08647921  0.24653284  0.02641017 -0.01840148
[15]  0.01935650 -0.07514617  0.10490884  0.01505148  0.02382092 -0.08908718
> m8_LB_Test<-Box.test(model8$residuals, fitdf=1, type = "Ljung-Box", lag = 20)
> m8_LB_Test

	Box-Ljung test

data:  model8$residuals
X-squared = 16.019, df = 19, p-value = 0.656
```

ARIMA (3,1,2)

```
> acf(rstandard(model12),plot=F)$acf[1:20]
 [1]  0.009311575 -0.016753957  0.042004697 -0.129398040 -0.033568643  0.118410847 -0.053662656
 [8] -0.142446591  0.015387583 -0.057611734  0.018154383  0.164643125  0.090169824 -0.038860910
[15]  0.026140235 -0.021693607  0.023750622  0.084325426 -0.040689557 -0.069300139
> m12_LB_Test<-Box.test(model12$residuals, fitdf=1, type = "Ljung-Box", lag = 20)
> m12_LB_Test

	Box-Ljung test

data:  model12$residuals
X-squared = 13.729, df = 19, p-value = 0.7993
```

Lampiran 10. Hasil Uji Normalitas Residual Model ARIMA

ARIMA (1,1,0)

```
> #uji kolmogorov-Smirnov
> m2_ks_result<-ks.test(model2$residuals, "pnorm",
+                        mean=mean(model2$residuals),
+                        sd=sd(model2$residuals))
> m2_ks_result

	Asymptotic one-sample Kolmogorov-Smirnov test

data:  model2$residuals
D = 0.13427, p-value = 0.04073
alternative hypothesis: two-sided
```

ARIMA (0,1,1)

```
> m3_ks_result<-ks.test(model3$residuals, "pnorm",
+                        mean=mean(model3$residuals),
+                        sd=sd(model3$residuals))
> m3_ks_result

	Asymptotic one-sample Kolmogorov-Smirnov test

data:  model3$residuals
D = 0.14513, p-value = 0.02114
alternative hypothesis: two-sided
```

ARIMA (1,1,3)

```
> m8_ks_result<-ks.test(model8$residuals, "pnorm",
+                        mean=mean(model8$residuals),
+                        sd=sd(model8$residuals))
> m8_ks_result

	Asymptotic one-sample Kolmogorov-Smirnov test

data:  model8$residuals
D = 0.1084, p-value = 0.1579
alternative hypothesis: two-sided
```

ARIMA (3,1,2)

```
> m13_ks_result<-ks.test(model13$residuals, "pnorm",
+                        mean=mean(model13$residuals),
+                        sd=sd(model13$residuals))
> m13_ks_result

	Asymptotic one-sample Kolmogorov-Smirnov test

data:  model13$residuals
D = 0.078094, p-value = 0.5254
alternative hypothesis: two-sided
```

Lampiran 11. Hasil Nilai AIC Model ARIMA

ARIMA (1,1,3)

```
> summary(model8)
Series: train_data
ARIMA(1,1,3)

Coefficients:
          ar1     ma1     ma2     ma3
      -0.5295  0.8427  0.3060  0.2769
s.e.   0.1922  0.1850  0.1515  0.1116

sigma^2 = 2.57e+09:  log likelihood = -1309.19
AIC=2628.38   AICc=2628.98   BIC=2641.75
```

```
> #Pemilihan model terbaik menggunakan nilai AIC
> AIC(model8)
[1] 2628.383
```

ARIMA (3,1,2)

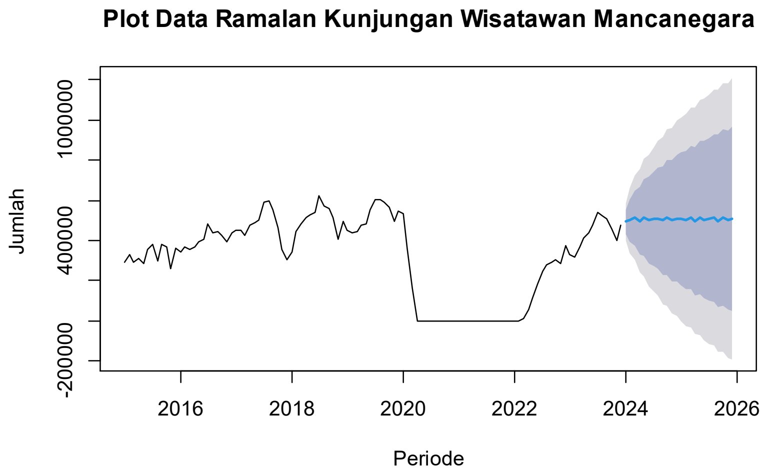
```
> summary(model12)
Series: train_data
ARIMA(3,1,2)

Coefficients:
          ar1      ar2     ar3     ma1     ma2
      -1.3572  -0.4002  0.3422  1.7524  0.9999
s.e.   0.0917   0.1564  0.0925  0.0692  0.0772

sigma^2 = 2.282e+09:  log likelihood = -1305.04
AIC=2622.08   AICc=2622.92   BIC=2638.12
```

```
> AIC(model12)
[1] 2622.083
```

Lampiran 12. Hasil Peramalan Menggunakan Model ARIMA (3,1,2)

```
> ramalan<-forecast(model12, h=24)
> ramalan
         Point Forecast     Lo 80    Hi 80       Lo 95     Hi 95
Jan 2024       493064.5 431305.13 554823.9  398611.678  587517.4
Feb 2024       498993.6 393738.08 604249.2  338019.157  659968.1
Mar 2024       512745.8 374683.80 650807.9  301598.177  723893.5
Apr 2024       496732.5 328855.45 664609.5  239986.714  753478.3
May 2024       514991.4 322818.54 707164.2  221088.387  808894.3
Jun 2024       501325.6 286885.30 715766.0  173367.448  829283.8
Jul 2024       507085.0 272198.05 741972.0  147856.409  866313.6
Aug 2024       510986.5 258144.74 763828.2  124298.411  897674.5
Sep 2024       498709.4 227921.45 769497.4   84574.945  912843.9
Oct 2024       515781.6 229297.49 802265.7   77641.967  953921.2
Nov 2024       498859.8 196707.58 801012.1   36757.842  960961.8
Dec 2024       510792.0 194013.70 827570.2   26321.418  995262.5
Jan 2025       507212.7 176730.21 837695.1    1783.363 1012642.0
Feb 2025       501503.8 157163.05 845844.5  -25119.934 1028127.5
Mar 2025       514768.1 157995.29 871540.8  -30868.811 1060404.9
Apr 2025       497825.5 128216.84 867434.2  -67442.165 1063093.2
May 2025       513557.7 132079.53 895035.9  -69862.821 1096978.2
Jun 2025       503526.1 110421.15 896631.0  -97676.025 1104728.1
Jul 2025       505046.4 100341.67 909751.2 -113896.079 1123988.9
Aug 2025       512382.0  97014.37 927749.6 -122867.956 1147631.9
Sep 2025       498384.4  71885.52 924883.3 -153889.357 1150658.2
Oct 2025       514966.5  78262.85 951670.2 -152914.114 1182847.2
Nov 2025       500573.7  53524.45 947622.9 -183129.126 1184276.5
Dec 2025       508680.8  51538.05 965823.6 -190458.736 1207820.4
```

Lampiran 13. Grafik Hasil Peramalan Menggunakan Model ARIMA (3,1,2)



Lampiran 14. Residual dari Model ARIMA (3,1,2)

```
> #Menghitung residual
> residual_arima <- residuals(model12)
> residual_arima
             Jan          Feb          Mar          Apr          May          Jun          Jul
2015    288.7578   38408.5367  -42483.3271   16619.3466  -21310.9530   72963.9709   -2924.2531
2016 -19544.7466   -1530.6972   -2167.4774   16657.6648    3969.3595   32820.5228   35422.6412
2017  41561.6603  -41360.3576   -7433.4500   61812.4640  -26776.2000   48196.0222   39338.4113
2018  91044.9306   51437.2866   27764.7224   14301.6595  -16549.5688   40549.9636   40740.0291
2019 -37686.4635  -22326.1892   12331.7092   50051.3552  -37224.0409  102389.1185   -7528.3040
2020   4858.2132 -188679.3934 -123881.1745  -89149.0541   34742.4606   25671.9875  -22195.1194
2021  21569.9082  -14718.0378    4353.4014    6854.9214  -16114.8087   21215.5929  -21022.9529
2022  20094.1530  -14969.5613   21206.3395   39509.7398   30891.6710   62728.4577   21695.8661
2023 -62807.0203   -3012.1052   50256.1497   36416.8595   -1193.1620   44124.8594   36000.9478
             Aug          Sep          Oct          Nov          Dec
2015 -69155.0896   72370.9252   -7116.1464 -108562.0650  115688.0334
2016 -37063.8897    2114.6012  -24373.4196    4410.2687   11359.1456
2017  14479.4541  -71062.2100  -69962.0698  -53090.0264  -47991.7335
2018 -46353.9172  -16712.8294  -36181.7981  -70911.5437   88343.4847
2019   8499.7611  -22601.7327  -28737.3458  -36844.2091   39560.8789
2020  13465.5119   -1685.5229  -10196.6185   19272.9509  -23296.8559
2021  15686.2746   -6633.3818   -3828.4315   13121.4625  -18999.5916
2022  24738.1176   -5917.0268    9360.5855  -14015.7172   79902.9369
2023 -34501.0405   -2984.3838  -57495.7507  -23449.5931   79910.3952
> plot(residual_arima)
```

Lampiran 15. Hasil Normalisasi Data Residual

t	$a_{t_{norm}}$	t	$a_{t_{norm}}$	t	$a_{t_{norm}}$	t	$a_{t_{norm}}$
1	0.08718	28	-0.39808	55	0.00257	82	0.00610
2	-0.36860	29	0.22831	56	-0.17792	83	-0.18182
3	0.16754	30	-0.09273	57	-0.08231	84	0.09091
4	-0.20407	31	-0.15401	58	-0.08986	85	-0.19309
5	0.30223	32	-0.38641	59	0.23380	86	0.07973
6	-0.34944	33	-0.05460	60	-0.19171	87	0.01129
7	-0.31245	34	0.00581	61	-0.80000	88	-0.09181
8	0.48319	35	-0.03928	62	0.18935	89	0.06312

9	-0.36322	36	0.47366	63	0.07420	90	-0.21595
10	-0.44732	37	-0.21050	64	0.41566	91	-0.04716
11	0.80000	38	-0.14947	65	-0.09355	92	-0.17621
12	-0.57671	39	-0.11037	66	-0.24213	93	-0.00030
13	0.01018	40	-0.17696	67	0.07776	94	-0.14833
14	-0.06125	41	0.15986	68	-0.11683	95	0.30087
15	0.01328	42	-0.05808	69	-0.09140	96	-0.60535
16	-0.10740	43	-0.39235	70	0.05405	97	0.17019
17	0.05168	44	0.05471	71	-0.22184	98	0.14519
18	-0.04884	45	-0.13337	72	0.11302	99	-0.11181
19	-0.33641	46	-0.19181	73	-0.19778	100	-0.20284
20	0.09123	47	0.55109	74	0.01423	101	0.11474
21	-0.16025	48	-0.54147	75	-0.04923	102	-0.08992
22	0.05142	49	0.00002	76	-0.14678	103	-0.32881
23	-0.03220	50	0.07392	77	0.08415	104	0.06189
24	0.05686	51	0.08565	78	-0.22057	105	-0.26757
25	-0.37638	52	-0.39305	79	0.08178	106	0.07158
26	0.07112	53	0.47587	80	-0.14429	107	0.33703
27	0.20638	54	-0.47976	81	-0.04807		

Lampiran 16. Pemodelan Model MLP (5-5-1)

```
> #Latih MLP dengan 20 kali pengulangan
> model_mlp_1 <- mlp(residual_arima, lags = 1:6, hd = 5)
> print(model_mlp_1)
MLP fit with 5 hidden nodes and 20 repetitions.
Series modelled in differences: D1.
Univariate lags: (1,2,3,4,5)
Forecast combined using the median operator.
MSE: 585374479.7867.
```

```
> # Ambil error dari result.matrix
> error_vals <- as.numeric(model_mlp_1$net$result.matrix["error", ])
> best_idx <- which.min(error_vals)
> cat("best repetition:", best_idx, "\nError:", error_vals[best_idx], "\n")
best repetition: 1
Error: 0.5272252
```

Lampiran 17. Hasil Peramalan Residual Menggunakan Model MLP (5-5-1)

Bulan	Tahun	Hasil Peramalan
Januari	2024	0,10992
Februari		-0,1049
Maret		-0,3115
April		0,08874

Bulan	Tahun	Hasil Peramalan
Mei		-0,2266
Juni		0,26331
Juli		-0,0011
Agustus		-0,6003
September		0,18602
Oktober		-0,1943
November		0,01621
Desember		0,36487
Januari	2025	-0,7707
Februari		0,35406
Maret		-0,088
April		0,02365
Mei		0,02886
Juni		0,10992
Juli		-0,1049
Agustus		-0,3115
September		0,08874
Oktober		-0,2266
November		0,26331
Desember		-0,0011

Lampiran 18. R-Code Hasil dan Grafik Peramalan Menggunakan Model Kombinasi ARIMA (3,1,2)-MLP (5-5-1)

```
> # Kombinasikan hasil peramalan ARIMA dengan residual MLP
> comb_forecast <- ts(ramalan$mean + ramalan2,
+                      start = start(ramalan$mean),
+                      frequency = frequency(ramalan$mean))
> # Tampilkan hasil peramalan kombinasi
> comb_forecast
          Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
2024 421710.1 439528.4 478160.1 484320.7 524526.4 543553.7 553423.0 601381.7
2025 598406.0 607764.7 479627.1 526614.5 506977.5 516536.1 628685.7 450134.2
          Sep      Oct      Nov      Dec
2024 577067.6 528154.0 549759.0 517873.2
2025 543944.9 552906.3 560045.8 511071.0
> # Visualisasi hasil kombinasi
> ts.plot(data1, col = "black", lty = 1,
+         main = " Plot Hasil Peramalan Kombinasi ARIMA-MLP",
+         ylab = "Kunjungan Wisatawan", xlab = "Periode")
> lines(comb_forecast, col = "blue", lwd = 2)
> lines(test_data, col = "red", lty = 2)
> legend("topleft", legend = c("Data Aktual", "Ramalan", "Data Testing"),
+        col = c("black", "blue", "red"), lty = c(1, 1, 1), lwd = 2)
```

RIWAYAT HIDUP

Ni Kadek Sariningsih lahir di Sekardadi pada tanggal 11 Juli 2003. Penulis lahir dari pasangan suami istri Bapak I Wayan Darma dan Ibu Ni Nyoman Teka. Penulis berkebangsaan Indonesia dan beragama Hindu. Kini penulis beralamat di Jalan Raya Sekardadi, Desa Sekardadi, Kecamatan Kintamani, Kabupaten Bangli, Provinsi Bali.

Penulis menyelesaikan pendidikan dasar di SD Negeri Sekardadi dan lulus pada tahun 2015. Kemudian penulis melanjutkan di SMP Negeri 1 Susut dan lulus pada tahun 2018. Pada tahun 2021, penulis lulus dari SMA Negeri 1 Susut Jurusan Matematika dan Ilmu Pengetahuan Alam dan melanjutkan ke Sarjana Jurusan Matematika di Universitas Pendidikan Ganesha. Pada semester akhir tahun 2025 penulis telah menyelesaikan Tugas Akhir yang berjudul "Peramalan Jumlah Kunjungan Wisatawan Mancanegara ke Bali Menggunakan Metode Kombinasi ARIMA-MLP". Selanjutnya, mulai tahun 2025 sampai dengan penulisan skripsi ini, penulis masih terdaftar sebagai mahasiswa Program S1 Matematika di Universitas Pendidikan Ganesha.