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LAMPIRAN

Lampiran 1. Data Penjualan Ban Mobil PT. Mitra Muda Sejati pada tahun 2013-2018

No	Tahun	Bulan	Ban Mobil
1	2013	1	14112
2	2013	2	12794
3	2013	3	12644
4	2013	4	12847
5	2013	5	10266
6	2013	6	13456
7	2013	7	14600
8	2013	8	8587
9	2013	9	11680
10	2013	10	9854
11	2013	11	9382
12	2013	12	9311
13	2014	1	11466
14	2014	2	10245
15	2014	3	11454
16	2014	4	10977
17	2014	5	9486
18	2014	6	10811
19	2014	7	9160
20	2014	8	10623
21	2014	9	11891
22	2014	10	8993
23	2014	11	9306
24	2014	12	8992
25	2015	1	10164
26	2015	2	6257
27	2015	3	11555
28	2015	4	8621
29	2015	5	9002

No	Tahun	Bulan	Ban Mobil
30	2015	6	10174
31	2015	7	11817
32	2015	8	11847
33	2015	9	11111
34	2015	10	8816
35	2015	11	8655
36	2015	12	10690
37	2016	1	14270
38	2016	2	9623
39	2016	3	12511
40	2016	4	12110
41	2016	5	10772
42	2016	6	16457
43	2016	7	10060
44	2016	8	14995
45	2016	9	11830
46	2016	10	13295
47	2016	11	11977
48	2016	12	14738
49	2017	1	12227
50	2017	2	15634
51	2017	3	18197
52	2017	4	15242
53	2017	5	12452
54	2017	6	10690
55	2017	7	12470
56	2017	8	15154
57	2017	9	12602
58	2017	10	11771

Lampiran 1. Data Penjualan Ban Mobil PT. Mitra Muda Sejati pada tahun 2013-2018 (Lanjutan)

No	Tahun	Bulan	Ban Mobil
59	2017	11	12046
60	2017	12	13138
61	2018	1	12860
62	2018	2	15952
63	2018	3	13366
64	2018	4	14789
65	2018	5	15285
66	2018	6	11117
67	2018	7	15248
68	2018	8	12225
69	2018	9	11682
70	2018	10	9433
71	2018	11	10331
72	2018	12	12091

Lampiran 2. Karakteristik Penjualan Ban Mobil PT. Mitra Muda Sejati pada tahun 2013-2018

Descriptive Statistics: 2013, 2014, 2015, 2016, 2017, 2018

Variable	Mean	StDev	Minimum	Maximum
2013	11628	2065	8587	14600
2014	10284	1062	8992	11891
2015	9892	1675	6257	11847
2016	12720	2093	9623	16457
2017	13469	2134	10690	18197
2018	12865	2104	9433	15952

Lampiran 3. Plot ACF *Differencing* lag 1 Data *In Sample* Penjualan Ban Mobil PT. Mitra Muda Sejati

Autocorrelation Function: dif_1

Lag	ACF	T	LBQ
1	-0.552910	-4.25	18.97
2	0.123483	0.75	19.93
3	-0.075079	-0.45	20.29
4	-0.020149	-0.12	20.32
5	0.035648	0.21	20.41
6	0.075274	0.45	20.79
7	-0.041829	-0.25	20.91
8	-0.109147	-0.65	21.75
9	0.184251	1.09	24.20
10	-0.106687	-0.62	25.03
11	-0.011687	-0.07	25.04
12	0.139804	0.80	26.54
13	-0.222426	-1.26	30.41
14	0.153129	0.85	32.29
15	0.065004	0.36	32.63
16	-0.160761	-0.88	34.79
17	0.055715	0.30	35.06
18	-0.041505	-0.22	35.21
19	0.100362	0.54	36.12
20	-0.100787	-0.54	37.05
21	0.190553	1.01	40.49
22	-0.242645	-1.27	46.22
23	0.044069	0.22	46.41
24	0.145348	0.74	48.59
25	-0.131930	-0.67	50.43
26	0.059868	0.30	50.82
27	-0.020654	-0.10	50.87
28	-0.041040	-0.21	51.06
29	-0.022401	-0.11	51.12
30	0.082538	0.41	51.97
31	0.007217	0.04	51.98
32	-0.099423	-0.50	53.29
33	0.161449	0.80	56.90
34	-0.262959	-1.29	66.86
35	0.226953	1.08	74.58
36	-0.064717	-0.30	75.24
37	-0.029050	-0.14	75.37
38	0.054170	0.25	75.88
39	-0.031931	-0.15	76.06
40	-0.063893	-0.30	76.83
41	0.058744	0.27	77.52
42	-0.008220	-0.04	77.54
43	-0.051932	-0.24	78.14
44	0.065925	0.31	79.19
45	0.007574	0.04	79.20
46	-0.025932	-0.12	79.39
47	0.012674	0.06	79.44
48	-0.063124	-0.29	80.74
49	0.054913	0.25	81.83
50	0.022302	0.10	82.02
51	-0.025783	-0.12	82.32
52	0.000529	0.00	82.32
53	0.002702	0.01	82.33
54	-0.001404	-0.01	82.33
55	0.001614	0.01	82.33
56	0.003239	0.01	82.34
57	-0.001351	-0.01	82.35
58	-0.003696	-0.02	82.40

Lampiran 4. Plot PACF *Differencing* lag 1 Data *In Sample* Penjualan Ban Mobil PT. Mitra Muda Sejati

Partial Autocorrelation Function: dif_1

Lag	PACF	T
1	-0.552910	-4.25
2	-0.262463	-2.02
3	-0.207286	-1.59
4	-0.227861	-1.75
5	-0.165741	-1.27
6	0.021028	0.16
7	0.062045	0.48
8	-0.136138	-1.05
9	0.081871	0.63
10	0.094237	0.72
11	-0.049133	-0.38
12	0.152767	1.17
13	-0.050714	-0.39
14	-0.010767	-0.08
15	0.199751	1.53
16	-0.007135	-0.05
17	-0.048505	-0.37
18	-0.117596	-0.90
19	0.051825	0.40
20	-0.055695	-0.43
21	0.089828	0.69
22	0.023040	0.18
23	-0.155282	-1.19
24	0.039522	0.30
25	0.048190	0.37
26	-0.076456	-0.59
27	-0.019834	-0.15
28	-0.006536	-0.05
29	-0.170999	-1.31
30	-0.146065	-1.12
31	0.093361	0.72
32	-0.025714	-0.20
33	0.021538	0.17
34	-0.142315	-1.09
35	-0.007155	-0.05
36	-0.021815	-0.17
37	0.070995	0.55
38	0.097893	0.75
39	-0.012339	-0.09
40	-0.110227	-0.85
41	0.000059	0.00
42	-0.104683	-0.80
43	-0.095569	-0.73
44	-0.005866	-0.05
45	-0.107891	-0.83
46	0.044008	0.34
47	0.048161	0.37
48	-0.058396	-0.45
49	0.085218	0.65
50	0.030732	0.24
51	-0.007806	-0.06
52	-0.039158	-0.30
53	0.140519	1.08
54	0.070297	0.54
55	-0.002651	-0.02
56	-0.069652	-0.54
57	-0.036786	-0.28
58	-0.022201	-0.17

Lampiran 5. *Syntax* R Uji *Dicky Fuller* Data *In Sample*

```
library(forcats)
library(car)
library(tseries)
library(xts)
data=read.csv("F:/kul/SKRIPSI HELEN/HELEN BENER/DATA PENJUALAN
BAN MOBIL.csv",header = TRUE)
banmobil=data[2:60,1]
plot.ts(banmobil)
adftest=adf.test(banmobil)
print(adftest)
```

Lampiran 6. *Output* R Uji *Dicky Fuller* Data *In Sample*

```
        Augmented Dickey-Fuller Test

data:  banmobil
Dickey-Fuller = -2.5951, Lag order = 3, p-value = 0.3344
alternative hypothesis: stationary
```

Lampiran 7. *Syntax* R Uji *Dicky Fuller* Data *In Sample* Setelah *differencing* 1

```
datadif_1=read.csv("F:/kul/SKRIPSI HELEN/HELEN BENER/DATA
PENJUALAN BAN MOBIL dif_1.csv",header = TRUE)
banmobildif_1=datadif_1[3:59,1]
plot.ts(banmobildif_1)
adftestdif_1=adf.test(banmobildif_1)
print(adftestdif_1)
```

Lampiran 8. *Output* Uji *Dicky Fuller* Data *In Sample* Setelah *differencing* 1

```
        Augmented Dickey-Fuller Test

data:  banmobildif_1
Dickey-Fuller = -6.017, Lag order = 3, p-value = 0.01
alternative hypothesis: stationary
```

Lampiran 9. *Syntax* SAS Model ARIMA (1,1,1)

```
data bm;
input y;
datalines;
14112
12794
12644
12847
 …
12602
11771
12046
13138
.
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;
/*ARIMA ([1,1,1])*/
proc arima data=bm;
identify var=y(1);
estimate p=1 q=1
noconstant method=ml
WHITENOISE=IGNOREMISS;
forecast out=ramalan lead=24;
run;
proc univariate data=ramalan normal;
var residual;
run;
```

Lampiran 10. *Output* SAS Model ARIMA (1,1,1)

```
                                   The SAS System
                                 The ARIMA Procedure

                             Maximum Likelihood Estimation

                                Standard                 Approx
            Parameter      Estimate         Error    t Value    Pr > |t|     Lag

            MA1,1           0.69641       0.12768       5.45      <.0001       1
            AR1,1          -0.14202       0.17162      -0.83      0.4079       1

                            Variance Estimate       3956195
                            Std Error Estimate     1989.019
                            AIC                    1066.529
                            SBC                    1070.684
                            Number of Residuals          59


                           Autocorrelation Check of Residuals

 To        Chi-             Pr >
   Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

    6        2.04      4    0.7290    -0.004     0.003    -0.078    -0.017     0.095     0.123
   12        4.62     10    0.9149    -0.008    -0.030     0.165    -0.014     0.020     0.082
   18        9.81     16    0.8763    -0.123     0.124     0.054    -0.167    -0.051     0.001
   24       17.38     22    0.7423     0.084    -0.010     0.051    -0.243    -0.031     0.090


                                Forecasts for variable y

                    Obs       Forecast    Std Error       95% Confidence Limits

                    61     12696.1759    1989.0186      8797.7710     16594.5807
                    62     12758.9244    2014.8134      8809.9627     16707.8860
                    63     12750.0127    2090.7109      8652.2946     16847.7308
                    64     12751.2784    2155.5162      8526.5442     16976.0125
                    65     12751.0986    2219.5637      8400.8338     17101.3635
                    66     12751.1241    2281.6568      8279.1590     17223.0893
                    67     12751.1205    2342.1261      8160.6378     17341.6033
                    68     12751.1210    2401.0699      8045.1104     17457.1317
                    69     12751.1210    2458.6015      7932.3506     17569.8913
                    70     12751.1210    2514.8172      7822.1699     17680.0720
                    71     12751.1210    2569.8034      7714.3989     17787.8431
                    72     12751.1210    2623.6375      7608.8860     17893.3559

                                 Tests for Normality

                     Test                  --Statistic---    -----p Value------

                     Shapiro-Wilk          W     0.975623    Pr < W      0.2819
                     Kolmogorov-Smirnov    D     0.097457    Pr > D     >0.1500
                     Cramer-von Mises      W-Sq  0.072738    Pr > W-Sq  >0.2500
                     Anderson-Darling      A-Sq  0.463183    Pr > A-Sq  >0.2500
```

Lampiran 11. *Syntax* SAS Model ARIMA (1,1,0)

```
data bm;
input y;
datalines;
14112
12794
12644
12847
 …
12602
11771
12046
13138
.
.
.
.
.
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.
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.
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.
.
;
/*ARIMA ([1,1,0])*/
proc arima data=bm;
identify var=y(1);
estimate p=1 q=0
noconstant method=ml
WHITENOISE=IGNOREMISS;
forecast out=ramalan lead=24;
run;
proc univariate data=ramalan normal;
var residual;
run;
proc print data=ramalan;
run;
```

Lampiran 12. *Output* SAS Model ARIMA (1,1,0)

```
                                   The SAS System
                                 The ARIMA Procedure
                             Maximum Likelihood Estimation

                                Standard                 Approx
              Parameter      Estimate         Error    t Value    Pr > |t|     Lag

              AR1,1          -0.54780       0.10898      -5.03      <.0001       1


                                 Variance Estimate       4658502
                                 Std Error Estimate     2158.356
                                 AIC                    1074.681
                                 SBC                    1076.759
                                 Number of Residuals          59


                              Autocorrelation Check of Residuals

 To        Chi-             Pr >
   Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

    6        8.24      5    0.1435    -0.153    -0.264    -0.056    -0.066     0.105     0.131
   12       12.54     11    0.3248    -0.099    -0.083     0.177    -0.075     0.001     0.079
   18       22.68     17    0.1598    -0.190     0.164     0.115    -0.205    -0.060     0.053
   24       34.78     23    0.0547     0.066     0.043     0.082    -0.271     0.012     0.190


                                  Forecasts for variable y

                    Obs       Forecast    Std Error       95% Confidence Limits

                     61     12539.8018    2158.3564      8309.5010     16770.1026
                     62     12867.4951    2368.7746      8224.7821     17510.2081
                     63     12687.9845    2871.8446      7059.2726     18316.6965
                     64     12786.3205    3139.6786      6632.6636     18939.9775
                     65     12732.4520    3463.9139      5943.3055     19521.5986
                     66     12761.9612    3720.1562      5470.5890     20053.3335
                     67     12745.7961    3980.2132      4944.7215     20546.8706
                     68     12754.6513    4213.6950      4495.9610     21013.3417
                     69     12749.8004    4440.3916      4046.7929     21452.8080
                     70     12752.4578    4653.1884      3632.3760     21872.5395
                     71     12751.0021    4858.1774      3229.1493     22272.8548
                     72     12751.7995    5054.0663      2846.0115     22657.5875


                                 Tests for Normality

                      Test                  --Statistic---    -----p Value------

                      Shapiro-Wilk          W      0.99063    Pr < W      0.9308
                      Kolmogorov-Smirnov    D     0.058595    Pr > D     >0.1500
                      Cramer-von Mises      W-Sq  0.027237    Pr > W-Sq  >0.2500
                      Anderson-Darling      A-Sq  0.188584    Pr > A-Sq  >0.2500
```

Lampiran 13. *Syntax* SAS Model ARIMA (0,1,1)

```
data bm;
input y;
datalines;
14112
12794
12644
12847
 …
12602
11771
12046
13138
.
.
.
.
.
.
.
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.
.
.
.
.
.
.
;
/*ARIMA ([0,1,1])*/
proc arima data=bm;
identify var=y(1);
estimate p=0 q=1
noconstant method=ml
WHITENOISE=IGNOREMISS;
forecast out=ramalan lead=24;
run;
proc univariate data=ramalan normal;
var residual;
run;
proc print data=ramalan;
run;
```

Lampiran 14. *Output* SAS Model ARIMA (0,1,1)

```
                                The SAS System
                              The ARIMA Procedure
                          Maximum Likelihood Estimation

                        Standard                Approx
          Parameter      Estimate         Error    t Value    Pr > |t|     Lag

          MA1,1           0.75247       0.08929       8.43      <.0001       1


                        Variance Estimate       3940335
                        Std Error Estimate     1985.028
                        AIC                    1065.281
                        SBC                    1067.359
                        Number of Residuals          59


                       Autocorrelation Check of Residuals

To        Chi-             Pr >
   Lag      Square     DF     ChiSq    --------------------Autocorrelations--------------------

    6        2.63      5    0.7562    -0.092     0.066    -0.047     0.006     0.097     0.125
   12        5.80     11    0.8863     0.001    -0.033     0.177    -0.021     0.023     0.100
   18       11.00     17    0.8566    -0.135     0.128     0.054    -0.160    -0.028    -0.014
   24       18.79     23    0.7135     0.079    -0.038     0.073    -0.243    -0.025     0.087

                              Forecasts for variable y

                Obs       Forecast    Std Error       95% Confidence Limits

                61     12847.1422    1985.0277      8956.5594     16737.7251
                62     12847.1422    2044.9364      8839.1405     16855.1439
                63     12847.1422    2103.1393      8725.0650     16969.2194
                64     12847.1422    2159.7742      8614.0626     17080.2219
                65     12847.1422    2214.9615      8505.8975     17188.3870
                66     12847.1422    2268.8068      8400.3626     17293.9218
                67     12847.1422    2321.4035      8297.2750     17397.0094
                68     12847.1422    2372.8346      8196.4719     17497.8126
                69     12847.1422    2423.1743      8097.8078     17596.4766
                70     12847.1422    2472.4894      8001.1521     17693.1323
                71     12847.1422    2520.8398      7906.3869     17787.8975
                72     12847.1422    2568.2802      7813.4055     17880.8790

                              Tests for Normality

                 Test                  --Statistic---    -----p Value------



                 Shapiro-Wilk          W     0.980037    Pr < W      0.4416
                 Kolmogorov-Smirnov    D     0.089053    Pr > D     >0.1500
                 Cramer-von Mises      W-Sq  0.077038    Pr > W-Sq   0.2283
                 Anderson-Darling      A-Sq  0.445037    Pr > A-Sq  >0.2500
```

Lampiran 15. Uji Linieritas

```
library(readxl)

library(neuralnet)

library(forecast)

library(lmtest)

library(tseries)

library(DataCombine)


data_resi <- read.csv("F:/kul/SKRIPSI HELEN/HELEN BENER/data resi helen.csv")

data_resi <- data.frame(data_resi)

y1t=as.ts(data_resi[,2])

y2t=as.ts(data_resi[,3])

training=as.ts(y1t[1:59])

testing=as.ts(y1t[60:71])

linear=as.ts(y2t[1:60])

terasvirta.test(linear,type="F")
```

Lampiran 16. *Output* Uji Linieritas

```
        Teraesvirta Neural Network Test

data:  linear
F = 0.025709, df1 = 2, df2 = 57, p-value = 0.9746
```

Lampiran 17. *Syntax Hybrid* ARIMA-ANN

```
data_resi <- read.csv("F:/kul/SKRIPSI HELEN/HELEN BENER/data resi helen new.csv")

data_resi <- data.frame(data_resi)

y1t=as.ts(data_resi[,2])

y2t=as.ts(data_resi[,3])

training=as.ts(y1t[1:59])

testing=as.ts(y1t[60:70])

linear=as.ts(y2t[1:60])

terasvirta.test(linear,type="F")


#DIFFERENCING SEASONAL ORDER FOR YTRAIN

Wtrain=diff(training,lag=1)

par(mfrow=c(1,1))

plot(Wtrain)

#ORDER IDENTIFICATION USING ACF AND PACF FROM STATIONARY DATA

tick=c(1,12,24,36)

par(mfrow=c(1,1),mar=c(2.8,3,1.2,0.4))    #the number of picture and its margin

par(mgp=c(1.7,0.5,0))                     #the distance between labels and axis

#PACF
```

```
pacf(training,lag.max=40,axes=F,ylim=c(-1,1))

box()

axis(side=1,at=tick,label=tick,lwd=0.5,las=0,cex.axis=0.8)

#abline(v=tick,lty="dotted", lwd=2, col="pink")

axis(side=2,lwd=0.5,las=2,cex=0.5,cex.axis=0.8)


#PREPROCESSING STANDARDIZED#

mean.Yt = mean(training)

sd.Yt   = sd(training)

Yt_std <- scale(y1t)

Yt_std1 <- as.data.frame(scale(y1t))

lag=c(1)                          #sesuai lag yg keluar di PACF

data1=slide(Yt_std1, Var = 'V1', slideBy = -lag)

colnames(data1)=c("et1","et2")

mlag=max(lag)+1

mtes=length(training)+1

data=data1[mlag:length(training),]

datatest=data1[mtes:length(y1t),]

head(data)
```

```
#MEMBENTUK MODEL NEURAL NETWORK#

neuron=c(1:2)                    #neuron yang akan digunakan

n_fore=12                        #forecast berapa periode kedepan

seed=c(1,3,3,1,5,2,2)                #berdasarkan percobaan beberapa set.seed yang
berbeda

best.model_NN=list

fits.model_NN=matrix(0,nrow(data),length(neuron))

fore.model_NN=matrix(0,n_fore,length(neuron))



allvars=colnames(data)

predictorvarss=allvars[!allvars%in%"et1"]

predictorvarss=paste(predictorvarss,collapse = "+")

form=as.formula(paste("et1~",predictorvarss,collapse="+"))

for (k in seq_along(neuron))

{

  set.seed(1)

  best.model_NN=neuralnet(formula=form,data=data,hidden=neuron[k],
algorithm = "rprop+",

                        act.fct="tanh",linear.output=TRUE,likelihood=TRUE)

  best.model_NN[[k]]=best.model_NN

fits.model_NN[,k]=(as.ts(unlist(best.model_NN[[k]]$net.result)))*sd.Yt+mean.Yt
#hasil ramalan data training
```

```
#ARSITEKTUR NEURAL NETWORK#
  win.graph()
  plot(best.model_NN[[k]])
  #FORECAST k-STEP AHEAD#
  Ytest=c(data[,1],rep(0,n_fore))
  for(i in (nrow(data)+1):(nrow(data)+n_fore))
  {
    Xtest=datatest[,2:ncol(datatest)]
    Ytest[i]=compute(best.model_NN[[k]],Xtest)$net.result[i-nrow(data)]
  }
  fore.model_NN[,k]=Ytest[(nrow(data)+1):(nrow(data)+n_fore)]*sd.Yt+mean.Yt
#hasil ramalan data testing
}
fore.model_NN[,k]


#MEMBERI NAMA KOLOM UNTUK MATRIKS HASIL FORECAST#
colnames(fore.model_NN)=c("Neuron 1","Neuron 2")
#MENGHITUNG TINGKAT KESALAHAN PERAMALAN#
akurasi=matrix(0,length(neuron),6)
colnames(akurasi)=c("RMSE_training","MAE_training","MAPE_training",
                    "RMSE_testing","MAE_testing","MAPE_testing")
rownames(akurasi)=c("Neuron 1","Neuron 2")
baris=length(training)-max(lag)
```

```
for (i in 1:length(neuron))
{
  akurasi[i,1]=accuracy(fits.model_NN[,i],training[1:baris])[1,2]
  akurasi[i,2]=accuracy(fits.model_NN[,i],training[1:baris])[1,3]
  akurasi[i,3]=accuracy(fits.model_NN[,i],training[1:baris])[1,5]
  akurasi[i,4]=accuracy(fore.model_NN[,i],datatest[,1])[1,2]
  akurasi[i,5]=accuracy(fore.model_NN[,i],datatest[,1])[1,3]
  akurasi[i,6]=accuracy(fore.model_NN[,i],datatest[,1])[1,5]
}
akurasi



#MEMBUAT PLOT PERBANDINGAN DATA AKTUAL DAN RAMALAN SEMUA NEURON#
a=min(min(fits.model_NN),min(training[1:baris]))      #batas bawah plot data training
b=max(max(fits.model_NN),max(training[1:baris]))   #batas atas plot data training
c=min(min(fore.model_NN),min(testing))    #batas bawah plot data testing
d=max(max(fore.model_NN),max(testing))    #batas atas plot data testing
#colors()                                #warna yang tersedia di R
par(mfrow=c(1,2),mar=c(2.3,2.7,1.2,0.4))  #banyaknya gambar dan ukuran margin
```

```
par(mgp=c(1.3,0.5,0))                    #jarak judul label ke axis

warna=c("red2","blue2","pink2","green3","grey88","yellow2","skyblue")



#PLOT DATA TRAINING#

plot(as.ts(training[1:baris]),ylab="Yt",xlab="t",lwd=2,axes=F,ylim=c(a*1.1,b*1.1
))

box()

title("Data training",line=0.3,cex.main=0.9)

axis(side=2,lwd=0.5,cex.axis=0.8,las=2)

axis(side=1,lwd=0.5,cex.axis=0.8,las=0,at=c(1,seq(35,400,35)))

for (i in 1:length(neuron))

{lines(as.ts(fits.model_NN[,i]),col=warna[i],lwd=2)}

#PLOT DATA TESTING#

plot(as.ts(testing),ylab="Yt",xlab="t",lwd=2,ylim=c(c*1.1,d*1.2),cex.lab=0.8,axe
s=F)

box()

title("Data testing",line=0.3,cex.main=0.9)

axis(side=2,lwd=0.5,cex.axis=0.8,las=2)

axis(side=1,lwd=0.5,cex.axis=0.8,las=0,at=c(1:24),labels=c(145:168))

for (i in 1:length(neuron))

{lines(as.ts(fore.model_NN[,i]),col=warna[i],lwd=2)}
```

```
#MEMBERI NAMA LEGEND#
legend("topright",c("Data aktual","Neuron 1"),
      col=c("black",warna),
      lwd=2,cex=0.7)
#MEMBUAT PLOT PERBANDINGAN DATA AKTUAL DAN RAMALAN#
a=min(min(fits.model_NN),min(training[1:baris]))       #batas bawah plot data training
b=max(max(fits.model_NN),max(training[1:baris]))   #batas atas plot data training
c=min(min(fore.model_NN),min(testing))    #batas bawah plot data testing
d=max(max(fore.model_NN),max(testing))    #batas atas plot data testing

#colors()                                #warna yang tersedia di R
par(mfrow=c(2,1),mar=c(2.3,2.7,1.2,0.4))  #banyaknya gambar dan ukuran margin
par(mgp=c(1.3,0.5,0))                   #jarak judul label ke axis

#PLOT DATA TRAINING#
plot(as.ts(training[1:baris]),ylab="Yt",xlab="t",lwd=2,axes=F,ylim=c(a*1.1,b*1.5
))
box()
title("Data training neuron 1",line=0.3,cex.main=0.9)
```

```
axis(side=2,lwd=0.5,cex.axis=0.8,las=2)

axis(side=1,lwd=0.5,cex.axis=0.8,las=0,at=c(1,seq(50,699,50)))

lines(as.ts(fits.model_NN[,1]),col="red2",lwd=2)

legend("topleft",c("Data aktual","Data ramalan"),

      col=c("black","red2"),lwd=2,cex=0.7)

#PLOT DATA TESTING#

plot(as.ts(testing),ylab="Yt",xlab="t",lwd=2,ylim=c(c*1.1,d*1.5),cex.lab=0.8,axe
s=F)

box()

title("Data testing neuron 1",line=0.3,cex.main=0.9)

axis(side=2,lwd=0.5,cex.axis=0.8,las=2)

axis(side=1,lwd=0.5,cex.axis=0.8,las=0,at=c(1:30),labels=c(700:729))

lines(as.ts(fore.model_NN[,1]),col="red2",lwd=2)

legend("topleft",c("Data aktual","Data ramalan"),

      col=c("black","red2"),lwd=2,cex=0.7)
```

Lampiran 18. *Output Forecasting Hybrid* ARIMA-ANN

```
> fore.model_NN[,k]
 [1] -47.82461 -47.82461 -47.82461 -47.82461 -47.82461 -47.82461
-47.82461 -47.82461 -47.82461 -47.82461
[10] -47.82461 -47.82461 -47.82461
```

Lampiran 19. *Output* Tingkat Kesalahan *Hybrid* ARIMA-ANN

```
> akurasi
         RMSE_training MAE_training MAPE_training RMSE_testing MAE_testing MAPE_testing
Neuron 1      2139.997     1664.579        101.0602            0           0            0
Neuron 2         0.000        0.000          0.00            0           0            0
```

Lampiran 20. Bukti Bimbingan Skripsi

Unipa Surabaya

PROGRAM STUDI STATISTIKA
FAKULTAS MATEMATIKA DAN ILMU PENGETAHUAN ALAM
UNIVERSITAS PGRI ADI BUANA SURABAYA

FORM F.SK05
BUKTI BIMBINGAN SKRIPSI

Nama Mahasiswa : Helen Eka Kurnia
NIM :162400008
Dosen Pembimbing : Artanti Indrasetianingsih, S.Si., M.Si.
Judul Skripsi : Peramalan Penjualan Ban Mobil Menggunakan Metode ARIMA Box Jenkins dan *Hybrid Autoregeressive Integrated Moving Average-Artificial Neural Network* (ARIMA-ANN) di PT. Mitra Muda Sejati

	Materi Pembimbingan Proposal	Tanda Tangan Dosen Pembimbing
1.	Sedalu di jelaskan gambar / tabel berapa jangan hanya seperti gambar / tabel berikut	
2.	Penulisan kurung model ARIMA belum tepat	
3.	Mencoba model yang lain, syntax SAS revisi	
4.	Jarak tabel dengan tulisan kurang renggang	
5.	Rumus ARIMA simbolnya belum tepat	
6.	Saran dirubah yang lebih dipahami	
7.	Diagram alir perlu diperbaiki	
8.	Kriteria SMAPE diganti MAPE	

Catatan: *) Coret yang tidak sesuai

Lembar ini digunakan untuk mendaftar Seminar dan Ujian Skripsi (bimbingan proposal minimal 8 kali)

BIODATA PENULIS

Penulis bernama Helen Eka Kurnia yang biasa dipanggil Helen lahir di Kediri pada tanggal 10 Maret 1998. Penulis merupakan anak pertama dari dua bersaudara dari pasangan Soliman dan Sarti, dari mereka saya merasakan cinta yang luar biasa. Penulis telah menempuh pendidikan formal di SDN Ploso III Surabaya, SMP Negeri 29 Surabaya, SMA Negeri 6 Surabaya dan melanjutkan ke jenjang perguruan tinggi di Program Studi Statistika UNIPA Surabaya sejak tahun 2016. Selama perkuliahan penulis aktif dalam beberapa organisasi antara lain Himpunan Mahasiswa Statistika Family (HIMASTAF), Senat Mahasiswa Fakultas Matematikan dan Ilmu Pengetahuan Alam (SEMA FMIPA) dan Ikatan Himpunan Mahasiswa Statistika Indonesia (IHMSI). Selain itu, penulis juga aktif mengikuti kepanitiaan di berbagai acara yang di adakan oleh organisasi-organisasi tersebut. Saat memasuki semester 6 perkuliahan, penulis bekerja di salah satu perusahaan distributor ban di PT. Sumber Jaya Ban Surabaya. Segala kritik dan saran akan diterima penulis untuk perbaikan kedepannya. Jika ada keperluan berdiskusi dengan penulis tentang skripsi ini dapat disampaikan melalui email heleneka20@gmail.com.