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LAMPIRAN

LAMPIRAN A – DATA SEKUNDER

Table 2
Sample data of engine performance data.

Fuel	Biodiesel %	Diesel %	ZnO %	Load (kg)	NO _x (PPM)	CO (PPM)	CO ₂ (PPM)	HC (PPM)	BP (kW)	BSFC (kg/kW.h)	BTE(%)
Pure Diesel	0	100	0	0	123	0.039	2.94	18.2	0.051	0.59	14.53
	0	100	0	3	277	0.042	1.67	30.1	0.508	0.35	24.49
	0	100	0	6	583	0.048	5.66	40	1.017	0.28	30.61
	0	100	0	9	1103	0.055	5.46	73	1.525	0.3	28.57
BDD	0	100	0	12	2580	0.059	6.62	85.2	2.033	0.33	25.97
	10	90	0	0	119	0.035	2.91	17.7	0.051	0.73	11.83
	10	90	0	3	268	0.039	1.60	28.70	0.508	0.45	19.18
	10	90	0	6	567	0.043	5.55	34	1.017	0.36	23.98
	10	90	0	9	1075	0.051	5.32	62	1.525	0.38	22.72
	10	90	0	12	2562	0.055	6.49	73.9	2.033	0.42	20.55
	20	80	0	0	115	0.033	2.76	16.1	0.051	0.63	13.80
	20	80	0	3	255	0.035	1.49	27.2	0.508	0.39	22.30
	20	80	0	6	551	0.042	5.41	32.08	1.017	0.31	28.05
	20	80	0	9	1021	0.05	5.18	57.7	1.525	0.33	26.35
	20	80	0	12	2487	0.052	6.31	71.3	2.033	0.36	24.15
	30	70	0	0	121	0.36	2.81	17.4	0.051	0.64	13.59
	30	70	0	3	273	0.042	1.54	28.9	0.508	0.4	21.74
	30	70	0	6	572	0.048	5.51	34.3	1.017	0.33	26.35
	30	70	0	9	1032	0.057	5.27	58	1.525	0.35	24.84
	30	70	0	12	2576	0.06	6.39	72.6	2.033	0.39	22.30
N ₂ BDD	10	90	2	0	111	0.029	2.71	15.2	0.051	0.63	13.74
	10	90	2	3	260	0.031	1.37	26.4	0.508	0.39	22.19
	10	90	2	6	558	0.037	5.34	31.8	1.017	0.32	27.04
	10	90	2	9	989	0.04	5.01	56.3	1.525	0.33	26.22
	10	90	2	12	2491	0.03	6.22	68.2	2.033	0.38	22.77
	20	80	2	0	103	0.026	2.21	14.4	0.051	0.6	14.53
	20	80	2	3	243	0.029	1.62	24.8	0.508	0.35	24.90
	20	80	2	6	538	0.038	5.18	29.7	1.017	0.29	30.06
	20	80	2	9	972	0.042	4.89	55.2	1.525	0.27	32.28
	20	80	2	12	2432	0.027	6.04	66.8	2.033	0.28	31.13
	30	70	2	0	107	0.027	2.36	14.9	0.051	0.62	14.20
	30	70	2	3	253	0.03	1.87	25.1	0.508	0.38	23.16
	30	70	2	6	549	0.037	5.26	30.2	1.017	0.26	33.85
	30	70	2	9	996	0.042	5.18	56	1.525	0.37	23.79
	30	70	2	12	2444	0.028	6.16	67.4	2.033	0.39	22.57
	N ₃ BDD	10	90	3	0	99	0.024	2.08	14.1	0.051	0.58
10		90	3	3	222	0.026	1.35	23.6	0.508	0.33	26.19
10		90	3	6	517	0.033	4.93	28.2	1.017	0.25	34.57
10		90	3	9	962	0.036	4.72	54.1	1.525	0.27	32.01
10		90	3	12	2412	0.024	5.81	65.6	2.033	0.274	31.55
20		80	3	0	94	0.023	1.87	13.2	0.051	0.56	15.55
20		80	3	3	212	0.025	1.26	22.1	0.508	0.32	27.21
20		80	3	6	501	0.03	4.79	26.5	1.017	0.24	36.28
20		80	3	9	954	0.032	4.66	52.3	1.525	0.26	33.49
20		80	3	12	2407	0.03	5.58	63.1	2.033	0.25	34.82
30		70	3	0	101	0.025	1.92	13.9	0.051	0.57	15.40
30		70	3	3	229	0.027	1.39	23.4	0.508	0.34	25.82
30		70	3	6	521	0.034	4.87	27.4	1.017	0.25	35.12
30		70	3	9	986	0.036	4.75	54.6	1.525	0.26	33.77
30		70	3	12	2431	0.032	5.71	65.9	2.033	0.27	32.52
N ₄ BDD		10	90	4	0	108	0.054	2.26	16.6	0.051	0.61
	10	90	4	3	235	0.057	1.47	26.2	0.508	0.38	22.69
	10	90	4	6	518	0.035	5.18	31.3	1.017	0.29	29.73
	10	90	4	9	1042	0.038	5.29	57.8	1.525	0.3	28.74
	10	90	4	12	2386	0.04	5.31	68.2	2.033	0.32	26.95
	20	80	4	0	102	0.051	2.17	16.1	0.051	0.6	14.48
	20	80	4	3	221	0.053	1.38	25.3	0.508	0.34	25.54
	20	80	4	6	502	0.039	5.01	30.5	1.017	0.26	33.40
	20	80	4	9	1031	0.042	5.12	56.4	1.525	0.27	32.17
	20	80	4	12	2354	0.041	5.20	67.7	2.033	0.28	31.02
	30	70	4	0	105	0.053	2.22	19.9	0.051	0.61	14.32
	30	70	4	3	238	0.055	1.45	31.9	0.508	0.37	23.62
	30	70	4	6	518	0.042	5.14	39.6	1.017	0.29	30.13
	30	70	4	9	1052	0.045	5.39	61.5	1.525	0.28	31.21
	30	70	4	12	2387	0.046	5.42	79.7	2.033	0.3	29.13



LAMPIRAN B- NORMALISASI DATA TRAINING

Data	Biodiesel	Diesel	Zno	Load	Nox	CO	CO2	HC	BP	BSFC	BTE
50	1.00000000	0.00000000	0.75000000	1.00000000	0.94006436	0.24324324	0.83022388	0.73194444	1.00000000	0.06122449	0.84621677
46	1.00000000	0.00000000	0.75000000	0.00000000	0.00281577	0.05405405	0.12313433	0.00972222	0.00000000	0.67346939	0.14601227
13	0.66666670	0.33333330	0.00000000	0.50000000	0.18382945	0.51351351	0.77425373	0.26222222	0.48738650	0.14285714	0.66339468
12	0.66666670	0.33333330	0.00000000	0.25000000	0.06476267	0.32432432	0.04291045	0.19444444	0.23057520	0.30612245	0.42822086
10	0.33333330	0.66666670	0.00000000	1.00000000	0.99275945	0.86486486	0.97574627	0.84305556	1.00000000	0.36734694	0.35664622
59	0.66666670	0.33333330	1.00000000	0.75000000	0.37691070	0.51351351	0.72014925	0.60000000	0.74369320	0.06122449	0.83190184
61	1.00000000	0.00000000	1.00000000	0.00000000	0.00442478	0.81081081	0.17910448	0.09305556	0.00000000	0.75510204	0.10184049
29	0.66666670	0.33333330	0.50000000	0.75000000	0.35317780	0.51351351	0.67723881	0.58333333	0.74369320	0.06122449	0.83640082
51	0.33333330	0.66666670	1.00000000	0.00000000	0.00563154	0.83783784	0.18656716	0.04722222	0.00000000	0.75510204	0.09447853
4	0.00000000	1.00000000	0.00000000	0.75000000	0.40587289	0.86486486	0.78358209	0.83055556	0.74369320	0.12244898	0.68466258
48	1.00000000	0.00000000	0.75000000	0.50000000	0.17176187	0.29729730	0.67350746	0.19722222	0.48738650	0.02040816	0.95255624
49	1.00000000	0.00000000	0.75000000	0.75000000	0.35880933	0.35135135	0.65111940	0.57500000	0.74369320	0.04081633	0.89734151
3	0.00000000	1.00000000	0.00000000	0.50000000	0.19670153	0.67567568	0.82089552	0.37222222	0.48738650	0.08163265	0.76809816
32	1.00000000	0.00000000	0.50000000	0.25000000	0.06395817	0.18918919	0.11380597	0.16527778	0.23057520	0.28571429	0.46339468
26	0.66666670	0.33333330	0.50000000	0.00000000	0.00362027	0.08108108	0.17723881	0.01666667	0.00000000	0.73469388	0.11042945
54	0.33333330	0.66666670	1.00000000	0.75000000	0.38133548	0.40540541	0.75186567	0.61944444	0.74369320	0.12244898	0.69161554
64	1.00000000	0.00000000	1.00000000	0.75000000	0.38535801	0.59459459	0.77052239	0.67083333	0.74369320	0.08163265	0.79263804
40	0.33333330	0.66666670	0.75000000	1.00000000	0.93242156	0.02702703	0.84888060	0.72777778	1.00000000	0.06938776	0.80654397
17	1.00000000	0.00000000	0.00000000	0.25000000	0.07200322	0.51351351	0.05223881	0.21805556	0.23057520	0.32653061	0.40531697
62	1.00000000	0.00000000	1.00000000	0.25000000	0.05792438	0.86486486	0.03544776	0.25972222	0.23057520	0.26530612	0.48220859
35	1.00000000	0.00000000	0.50000000	1.00000000	0.94529364	0.13513514	0.91417910	0.75277778	1.00000000	0.30612245	0.43926380
33	1.00000000	0.00000000	0.50000000	0.50000000	0.18302494	0.37837838	0.74626866	0.23611111	0.48738650	0.04081633	0.90061350
5	0.00000000	1.00000000	0.00000000	1.00000000	1.00000000	0.97297297	1.00000000	1.00000000	1.00000000	0.18367347	0.57832311
41	0.66666670	0.33333330	0.75000000	0.00000000	0.00000000	0.00000000	0.11380597	0.00000000	0.00000000	0.65306122	0.15214724
25	0.33333330	0.66666670	0.50000000	1.00000000	0.96419952	0.18918919	0.92537313	0.76388889	1.00000000	0.28571429	0.44744376

Data	Biodiesel	Diesel	Zno	Load	Nox	CO	CO2	HC	BP	BSFC	BTE
1	0.00000000	1.00000000	0.00000000	0.00000000	0.01166533	0.43243243	0.31343284	0.06944444	0.00000000	0.71428571	0.11042945
55	0.33333330	0.66666670	1.00000000	1.00000000	0.92196299	0.45945946	0.75559701	0.76388889	1.00000000	0.16326531	0.61840491
18	1.00000000	0.00000000	0.00000000	0.50000000	0.19227675	0.67567568	0.79291045	0.29305556	0.48738650	0.18367347	0.59386503
11	0.66666670	0.33333330	0.00000000	0.00000000	0.00844731	0.27027027	0.27985075	0.04027778	0.00000000	0.79591837	0.08057260
9	0.33333330	0.66666670	0.00000000	0.75000000	0.39460982	0.75675676	0.75746269	0.67777778	0.74369320	0.28571429	0.44539877
20	1.00000000	0.00000000	0.00000000	1.00000000	0.99839099	1.00000000	0.95708955	0.82500000	1.00000000	0.30612245	0.42822086
34	1.00000000	0.00000000	0.50000000	0.75000000	0.36283186	0.51351351	0.73134328	0.59444444	0.74369320	0.26530612	0.48916155
19	1.00000000	0.00000000	0.00000000	0.75000000	0.37731295	0.91891892	0.74813433	0.62222222	0.74369320	0.22448980	0.53210634
38	0.33333330	0.66666670	0.75000000	0.50000000	0.17015286	0.27027027	0.68470149	0.20833333	0.48738650	0.02040816	0.93006135
63	1.00000000	0.00000000	1.00000000	0.50000000	0.17055511	0.51351351	0.72388060	0.36666667	0.48738650	0.10204082	0.74846626
14	0.66666670	0.33333330	0.00000000	0.75000000	0.37288817	0.72972973	0.73134328	0.61805556	0.74369320	0.18367347	0.59386503
53	0.33333330	0.66666670	1.00000000	0.50000000	0.17055511	0.32432432	0.73134328	0.25138889	0.48738650	0.10204082	0.73210634
27	0.66666670	0.33333330	0.50000000	0.25000000	0.05993564	0.16216216	0.06716418	0.16111111	0.23057520	0.22448980	0.53456033
21	0.33333330	0.66666670	0.50000000	0.00000000	0.00683829	0.16216216	0.27052239	0.02777778	0.00000000	0.79591837	0.07811861
15	0.66666670	0.33333330	0.00000000	1.00000000	0.96259051	0.78378378	0.94216418	0.80694444	1.00000000	0.24489796	0.50388548
28	0.66666670	0.33333330	0.50000000	0.50000000	0.17860016	0.40540541	0.73134328	0.22916667	0.48738650	0.10204082	0.74560327
30	0.66666670	0.33333330	0.50000000	1.00000000	0.94046661	0.10810811	0.89179104	0.74444444	1.00000000	0.08163265	0.78936605
6	0.33333330	0.66666670	0.00000000	0.00000000	0.01005632	0.32432432	0.30783582	0.06250000	0.00000000	1.00000000	0.00000000
56	0.66666670	0.33333330	1.00000000	0.00000000	0.00321802	0.75675676	0.16977612	0.04027778	0.00000000	0.73469388	0.10838446
47	1.00000000	0.00000000	0.75000000	0.25000000	0.05430410	0.10810811	0.02425373	0.14166667	0.23057520	0.20408163	0.57218814
60	0.66666670	0.33333330	1.00000000	1.00000000	0.90909091	0.48648649	0.73507463	0.75694444	1.00000000	0.08163265	0.78486708



Lampiran C- SCRIPT PROGRAM RSTUDIO:

```
#membaca data excel
library(readxl)
data2 <- read_excel("ann04.xlsx")
#normalisasi
normalisasi<-function(x){(x-min(x))/(max(x)-min(x))}
skala2<-as.data.frame(lapply(data2[1:11],FUN = normalisasi))
data3<-skala2
#menampilkan all data
#data3
#pembagian data untuk training, validasi dan test
n1<- round(nrow(data3)*0.70)

#pengaturan banyaknya pengacakan
set.seed(30)
samp1=sample(1:nrow(data3),n1)
traininga20a = data3[samp1,]
#trainc5= data.frame(trainingc5)
#View(trainc5)
valtestdataa20a= data3[-samp1,]
#valtestdata

#pembagian sisa data training untuk data validasi dan data
testing (masing-masing 50%)
n2<- round(nrow(valtestdataa20a)*0.5)
samp2=sample(1:nrow(valtestdataa20a),n2)
validasia20a = valtestdataa20a[samp2,]
#validc5= data.frame(validasic5)
#View(validc5)
testinga20a= valtestdataa20a[-samp2,]
#testc5= data.frame(testingc5)
#View(testc5)

#buat rumus
feats <- names(data3[,1:4])
f <- paste(feats,collapse=' + ')
f <- paste('Nox+CO+CO2+HC+BP+BSFC+BTE~',f)
f <- as.formula(f);f

#memanggil fungsi neuralnet
library(neuralnet)
anna20a <- neuralnet(f,traininga20a,hidden=c(20),
threshold=0.001, stepmax=1e+10, algorithm = "rprop+",
act.fct = "logistic", err.fct= "sse",
linear.output=T)
#menampilkan error
anna20a$result.matrix[1,]
```

```

#ann15$result.matrix
#summary(ann15)
#menampilkan arsitektur ann
#plot (anna20a)

#prediksi hasil ann1 menggunakan data validasi
preda20a <- predict(anna20a, data3[,1:4])

#menampilkan hasil data validasi
akta20a<-data.frame(data3[,5:11])

#komparasi nox hasil pemodelan data train dengan data validasi
Nox<-data.frame(data2[,5])
predictednoxa20a=preda20a[,1] * abs(diff(range(Nox))) +
min(Nox)
actualnoxa20a=akta20a[,1] * abs(diff(range(Nox))) + min(Nox)
comparisonnoxa20a=data.frame(predictednoxa20a,actualnoxa20a)
View(comparisonnoxa20a)

#memanggil fungsi metrics
library(Metrics)
#prediksi NOX
#koefisien korelasi
cornoxa20a=cor(predictednoxa20a,actualnoxa20a)
#cornox
#koefisien determinasi
detnoxa20a=cornoxa20a^2
detnoxa20a
#error rmse
rmsenoxa20a=rmse(predictednoxa20a,actualnoxa20a)
rmsenoxa20a
#error mape
mapenoxa20a=mape(predictednoxa20a,actualnoxa20a)
mapenoxa20a

#komparasi CO hasil pemodelan data train dengan data validasi
CO<-data.frame(data2[,6])
predictedcoa20a=preda20a[,2] * abs(diff(range(CO))) + min(CO)
actualcoa20a=akta20a[,2] * abs(diff(range(CO))) + min(CO)
comparisoncoa20a=data.frame(predictedcoa20a,actualcoa20a)
View(comparisoncoa20a)

#prediksi CO
#koefisien korelasi
corcoa20a=cor(predictedcoa20a,actualcoa20a)
#corco
#koefisien determinasi
detcoa20a=corcoa20a^2

```

```

detcoa20a
#error rmse
rmsecoa20a=rmse(predictedcoa20a,actualcoa20a)
rmsecoa20a
#error mape
mapecoa20a=mape(predictedcoa20a,actualcoa20a)
mapecoa20a

#komparasi CO2 hasil pemodelan data train dengan data validasi
CO2<-data.frame(data2[,7])
predictedco2a20a=preda20a[,3] * abs(diff(range(CO2))) +
min(CO2)
actualco2a20a=akta20a[,3] * abs(diff(range(CO2))) + min(CO2)
comparisonco2a20a=data.frame(predictedco2a20a,actualco2a20a)
View(comparisonco2a20a)

#prediksi CO2
#koefisien korelasi
corco2a20a=cor(predictedco2a20a,actualco2a20a)
#corco20a
#koefisien determinasi
detco2a20a=corco2a20a^2
detco2a20a
#error rmse
rmseco2a20a=rmse(predictedco2a20a,actualco2a20a)
rmseco2a20a
#error mape
mapeco2a20a=mape(predictedco2a20a,actualco2a20a)
mapeco2a20a

#komparasi HC hasil pemodelan data train dengan data validasi
HC<-data.frame(data2[,8])
predictedhca20a=preda20a[,4] * abs(diff(range(HC))) + min(HC)
actualhca20a=akta20a[,4] * abs(diff(range(HC))) + min(HC)
comparisonhca20a=data.frame(predictedhca20a,actualhca20a)
View(comparisonhca20a)

#prediksi HC
#koefisien korelasi
corhca20a=cor(predictedhca20a,actualhca20a)
#corhc
#koefisien determinasi
dethca20a=corhca20a^2
dethca20a
#error rmse
rmsehca20a=rmse(predictedhca20a,actualhca20a)
rmsehca20a
#error mape

```

```
mapehca20a=mape(predictedhca20a,actualhca20a)
mapehca20a
```

```
#komparasi BP hasil pemodelan data train dengan data validasi
BP<-data.frame(data2[,9])
predictedbpa20a=preda20a[,5] * abs(diff(range(BP))) + min(BP)
actualbpa20a=akta20a[,5] * abs(diff(range(BP))) + min(BP)
comparisonbpa20a=data.frame(predictedbpa20a,actualbpa20a)
View(comparisonbpa20a)
```

```
#prediksi BP
#koefisien korelasi
corbpa20a=cor(predictedbpa20a,actualbpa20a)
#corbp
#koefisien determinasi
detbpa20a=corbpa20a^2
detbpa20a
#error rmse
rmsebpa20a=rmse(predictedbpa20a,actualbpa20a)
rmsebpa20a
#error mape cara 1
mapebpa20a=mape(predictedbpa20a,actualbpa20a)
mapebpa20a
```

```
#error mape cara 2
#mapebp151 = mean(abs((actualbp15-predictedbp15)
# /actualbp15))
#mapebp151
```

```
#komparasi BSFC hasil pemodelan data train dengan data validasi
BSFC<-data.frame(data2[,10])
predictedbsfca20a=preda20a[,6] * abs(diff(range(BSFC))) +
min(BSFC)
actualbsfca20a=akta20a[,6] * abs(diff(range(BSFC))) + min(BSFC)
comparisonbsfca20a=data.frame(predictedbsfca20a,actualbsfca20a)
View(comparisonbsfca20a)
```

```
#prediksi BSFC
#koefisien korelasi
corbsfca20a=cor(predictedbsfca20a,actualbsfca20a)
#corbsfc
#koefisien determinasi
detbsfca20a=corbsfca20a^2
detbsfca20a
#error rmse
rmsebsfca20a=rmse(predictedbsfca20a,actualbsfca20a)
rmsebsfca20a
#error mape
```

```
mapebsfca20a=mape(predictedbsfca20a,actualbsfca20a)
mapebsfca20a
```

```
#komparasi BTE hasil pemodelan data train dengan data validasi
BTE<-data.frame(data2[,11])
predictedbtea20a=preda20a[,7] * abs(diff(range(BTE))) +
min(BTE)
actualbtea20a=akta20a[,7] * abs(diff(range(BTE))) + min(BTE)
comparisonbtea20a=data.frame(predictedbtea20a,actualbtea20a)
View(comparisonbtea20a)
```

```
#prediksi BTE
#koefisien korelasi
corbtea20a=cor(predictedbtea20a,actualbtea20a)
#corbte
#koefisien determinasi
detbtea20a=corbtea20a^2
detbtea20a
#error rmse
rmsebtea20a=rmse(predictedbtea20a,actualbtea20a)
rmsebtea20a
#error mape
mapebtea20a=mape(predictedbtea20a,actualbtea20a)
mapebtea20a
```

LAMPIRAN D – HASIL RUN PROGRAM ANN

error	1.273407e-01
reached.threshold	9.881815e-04
steps	2.175400e+05
Intercept.to.1layhid1	1.116954e+00
Biodiesel.to.1layhid1	-9.720008e-01
Diesel.to.1layhid1	-1.413272e+00
ZnO.to.1layhid1	-1.392019e+00
Load.to.1layhid1	-2.473435e+00
Intercept.to.1layhid2	-2.464780e+00
Biodiesel.to.1layhid2	-2.408573e+00
Diesel.to.1layhid2	-2.715380e+00
ZnO.to.1layhid2	-3.678010e-02
Load.to.1layhid2	1.849275e+01
Intercept.to.1layhid3	2.785510e+00
Biodiesel.to.1layhid3	1.301492e+00
Diesel.to.1layhid3	1.181098e+00
ZnO.to.1layhid3	-8.902134e+00
Load.to.1layhid3	-4.975302e-01
Intercept.to.1layhid4	4.383509e+00
Biodiesel.to.1layhid4	2.766944e+00
Diesel.to.1layhid4	2.171856e+00
ZnO.to.1layhid4	4.363802e+00
Load.to.1layhid4	-8.928446e+00
Intercept.to.1layhid5	1.872659e-01
Biodiesel.to.1layhid5	8.325474e-01
Diesel.to.1layhid5	-5.343770e-01
ZnO.to.1layhid5	-3.031334e+00
Load.to.1layhid5	8.243264e-01
Intercept.to.1layhid6	5.781662e-01
Biodiesel.to.1layhid6	-1.367735e+00
Diesel.to.1layhid6	-2.898113e-01
ZnO.to.1layhid6	2.727165e+00
Load.to.1layhid6	3.071227e+00
Intercept.to.1layhid7	-4.427267e-01
Biodiesel.to.1layhid7	2.255993e-01
Diesel.to.1layhid7	-3.382650e-01
ZnO.to.1layhid7	-9.512645e-01
Load.to.1layhid7	7.790546e+00
Intercept.to.1layhid8	-1.934843e+00
Biodiesel.to.1layhid8	-4.377072e-01
Diesel.to.1layhid8	-2.124363e+03
ZnO.to.1layhid8	1.109062e-01
Load.to.1layhid8	4.314281e-01
Intercept.to.1layhid9	2.292834e+00
Biodiesel.to.1layhid9	-5.105454e-02
Diesel.to.1layhid9	-2.848497e-01
ZnO.to.1layhid9	1.549948e-01
Load.to.1layhid9	-2.651883e+00
Intercept.to.1layhid10	-8.123203e-01

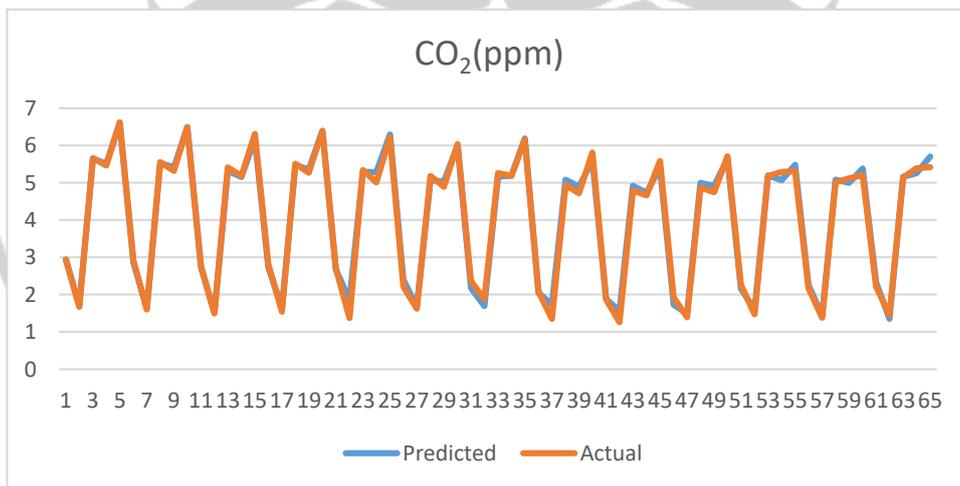
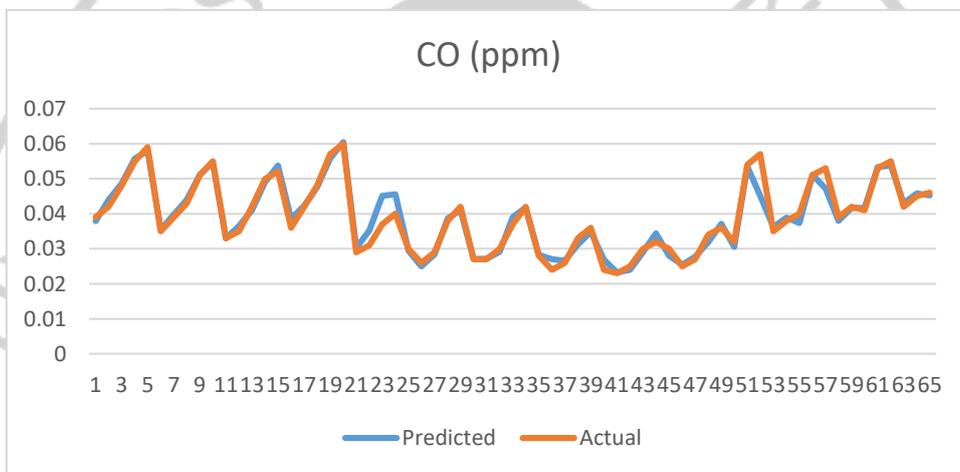
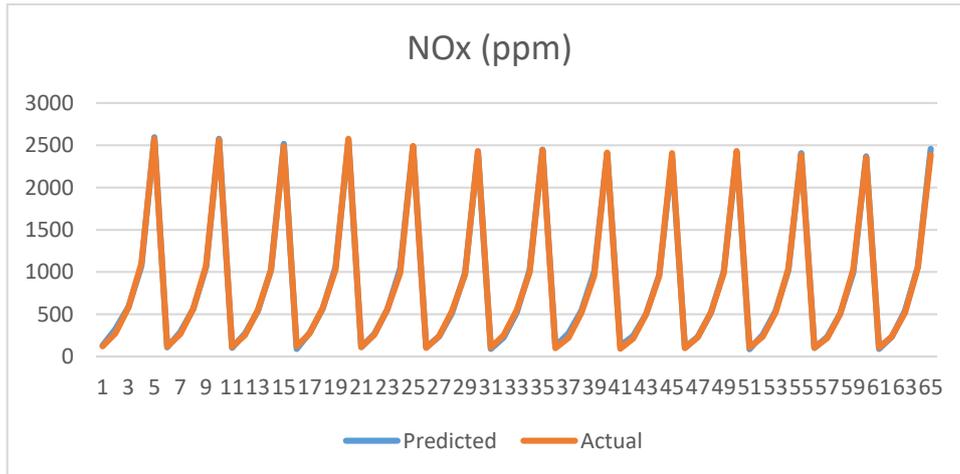
Biodiesel.to.1layhid10	-1.136634e+00
Diesel.to.1layhid10	-1.004391e+00
ZnO.to.1layhid10	4.810719e+00
Load.to.1layhid10	-7.428267e-01
Intercept.to.1layhid11	-5.194360e-01
Biodiesel.to.1layhid11	1.052621e+00
Diesel.to.1layhid11	9.130285e-01
ZnO.to.1layhid11	-1.266376e+00
Load.to.1layhid11	-1.406681e+00
Intercept.to.1layhid12	7.668106e+00
Biodiesel.to.1layhid12	-2.474762e-01
Diesel.to.1layhid12	-7.078210e-02
ZnO.to.1layhid12	6.959714e-01
Load.to.1layhid12	-7.544749e+00
Intercept.to.1layhid13	-1.518888e+00
Biodiesel.to.1layhid13	-2.623990e-01
Diesel.to.1layhid13	-2.825900e-01
ZnO.to.1layhid13	-1.130196e-01
Load.to.1layhid13	-5.595386e+00
Intercept.to.1layhid14	-2.366331e-01
Biodiesel.to.1layhid14	-6.636335e-01
Diesel.to.1layhid14	-1.520150e-01
ZnO.to.1layhid14	2.992347e+00
Load.to.1layhid14	-2.410920e+00
Intercept.to.1layhid15	-1.426907e+00
Biodiesel.to.1layhid15	-1.118424e+00
Diesel.to.1layhid15	-1.620082e+00
ZnO.to.1layhid15	3.781375e+00
Load.to.1layhid15	3.576164e+00
Intercept.to.NoX	1.184993e+00
1layhid1.to.NoX	6.293648e+00
1layhid2.to.NoX	4.288437e-01
1layhid3.to.NoX	1.984535e-01
1layhid4.to.NoX	-7.865619e-04
1layhid5.to.NoX	-1.915856e-01
1layhid6.to.NoX	1.790084e+00
1layhid7.to.NoX	-1.156181e+00
1layhid8.to.NoX	1.940075e-01
1layhid9.to.NoX	-1.277571e+00
1layhid10.to.NoX	2.768466e-01
1layhid11.to.NoX	-2.037948e+00
1layhid12.to.NoX	-1.276889e+00
1layhid13.to.NoX	-6.460578e+00
1layhid14.to.NoX	-2.101093e-01
1layhid15.to.NoX	1.266586e-03
Intercept.to.CO	8.980206e-01
1layhid1.to.CO	-4.060170e+00
1layhid2.to.CO	3.180898e-01
1layhid3.to.CO	4.937218e+00
1layhid4.to.CO	7.799018e-02
1layhid5.to.CO	-2.848406e+00

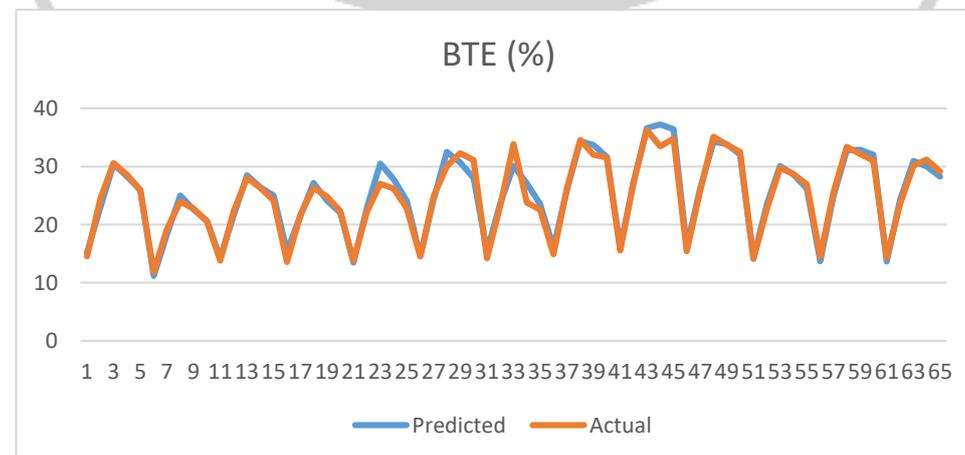
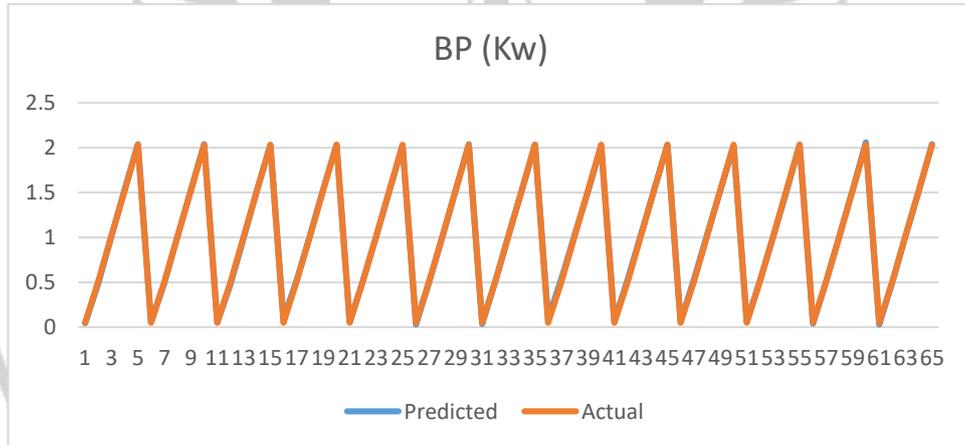
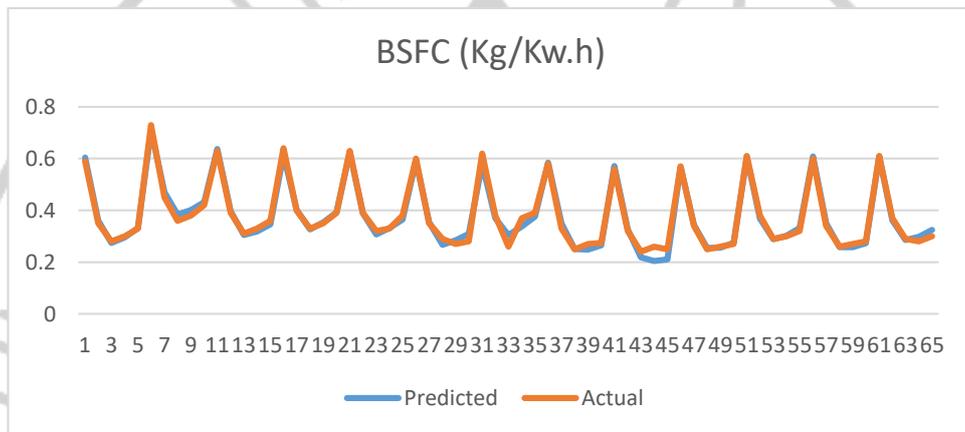
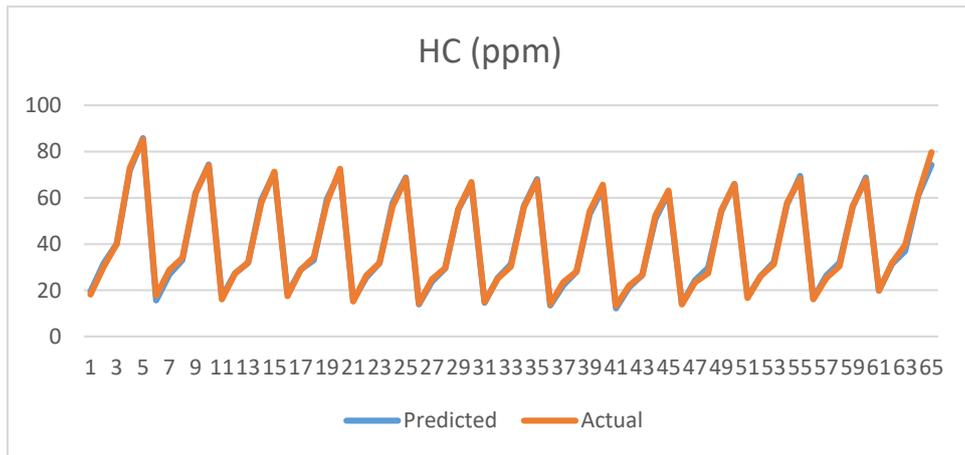
1layhid6.to.CO	-2.485619e+00
1layhid7.to.CO	-3.756451e+00
1layhid8.to.CO	1.272660e+00
1layhid9.to.CO	1.965597e+00
1layhid10.to.CO	4.002891e+00
1layhid11.to.CO	1.116279e+00
1layhid12.to.CO	3.899596e-01
1layhid13.to.CO	-9.372455e+00
1layhid14.to.CO	-3.856238e+00
1layhid15.to.CO	2.986810e+00
Intercept.to.CO2	6.034145e-01
1layhid1.to.CO2	3.164233e+00
1layhid2.to.CO2	1.705636e+00
1layhid3.to.CO2	1.036129e-01
1layhid4.to.CO2	-7.931110e-02
1layhid5.to.CO2	-2.351953e-01
1layhid6.to.CO2	5.510753e-01
1layhid7.to.CO2	-6.596016e-01
1layhid8.to.CO2	3.561503e-01
1layhid9.to.CO2	9.666436e-01
1layhid10.to.CO2	-7.266011e-01
1layhid11.to.CO2	-4.119754e+00
1layhid12.to.CO2	-5.958535e-01
1layhid13.to.CO2	4.473586e+00
1layhid14.to.CO2	7.782299e-03
1layhid15.to.CO2	-3.403394e-01
Intercept.to.HC	1.575348e+00
1layhid1.to.HC	-6.414637e-01
1layhid2.to.HC	-6.954059e-01
1layhid3.to.HC	5.464895e-01
1layhid4.to.HC	-2.466176e-01
1layhid5.to.HC	-3.014237e-02
1layhid6.to.HC	-1.420309e-01
1layhid7.to.HC	8.555556e-01
1layhid8.to.HC	6.502462e-01
1layhid9.to.HC	-8.732130e-01
1layhid10.to.HC	1.969889e-01
1layhid11.to.HC	-3.547545e+00
1layhid12.to.HC	8.219326e-01
1layhid13.to.HC	3.595614e+00
1layhid14.to.HC	-5.083274e-01
1layhid15.to.HC	-3.703837e-01
Intercept.to.BP	9.929227e-01
1layhid1.to.BP	-2.962606e-02
1layhid2.to.BP	-9.786271e-03
1layhid3.to.BP	4.529381e-02
1layhid4.to.BP	8.339779e-02
1layhid5.to.BP	3.387045e-01
1layhid6.to.BP	1.133605e-01
1layhid7.to.BP	3.084676e-01
1layhid8.to.BP	-1.313658e-02

l1ayhid9.to.BP	-1.361503e+00
l1ayhid10.to.BP	1.868746e-01
l1ayhid11.to.BP	-5.468299e-01
l1ayhid12.to.BP	-5.051815e-02
l1ayhid13.to.BP	5.391612e-01
l1ayhid14.to.BP	-7.321817e-03
l1ayhid15.to.BP	-4.349657e-02
Intercept.to.BSFC	-4.930336e-01
l1ayhid1.to.BSFC	-2.155584e+00
l1ayhid2.to.BSFC	-5.262077e-01
l1ayhid3.to.BSFC	1.420748e-01
l1ayhid4.to.BSFC	9.950043e-01
l1ayhid5.to.BSFC	3.086542e-01
l1ayhid6.to.BSFC	2.627494e-01
l1ayhid7.to.BSFC	1.278081e+00
l1ayhid8.to.BSFC	7.732871e-01
l1ayhid9.to.BSFC	-6.426675e-01
l1ayhid10.to.BSFC	-1.768353e+00
l1ayhid11.to.BSFC	-4.308039e-01
l1ayhid12.to.BSFC	-6.384061e-01
l1ayhid13.to.BSFC	1.092381e+01
l1ayhid14.to.BSFC	1.812461e+00
l1ayhid15.to.BSFC	1.279902e-01
Intercept.to.BTE	1.818395e+00
l1ayhid1.to.BTE	-1.270085e+00
l1ayhid2.to.BTE	7.251216e-01
l1ayhid3.to.BTE	1.302484e-01
l1ayhid4.to.BTE	-1.647880e+00
l1ayhid5.to.BTE	-7.556598e-01
l1ayhid6.to.BTE	-2.015049e+00
l1ayhid7.to.BTE	-9.932761e-01
l1ayhid8.to.BTE	-1.424612e+00
l1ayhid9.to.BTE	2.753346e+00
l1ayhid10.to.BTE	3.549783e+00
l1ayhid11.to.BTE	1.200327e+00
l1ayhid12.to.BTE	6.382572e-01
l1ayhid13.to.BTE	-6.769656e+00
l1ayhid14.to.BTE	-3.945693e+00
l1ayhid15.to.BTE	-1.503133e-01

SEMARANG

LAMPIRAN E – GRAFIK PREDIKSI VS AKTUAL





LAMPIRAN F – DATA PREDIKSI

Prediksi kinerja dan emisi mesin diesel bahan bakar B0 s.d B50 (Load 0%)

Bxx	Input		Output							
	BD	D	ZnO	Nox	CO	CO ₂	HC	BP	BSFC	BTE
0%	0	100	2	112.8	0.044	3.02	24.4	0.032	0.57	15.78
10%	10	90	2	122.4	0.041	2.96	22.5	0.033	0.61	13.66
20%	20	80	2	133.7	0.039	2.90	21.0	0.035	0.646	11.58
30%	30	70	2	144.5	0.037	2.86	19.7	0.037	0.679	9.73
40%	40	60	2	150.8	0.036	2.80	18.9	0.038	0.700	8.52
50%	50	50	2	147.8	0.035	2.72	18.4	0.039	0.702	8.40

Prediksi kinerja dan emisi mesin diesel bahan bakar B10 dengan variasi ZnO (Load 12%)

BD	Input		Output							
	D	ZnO	NOx	CO	CO ₂	HC	BP	BSFC	BTE	
10	90	0	2586.3	0.056	6.61	81.2	2.03	0.36	24.3	
10	90	2	2583.8	0.035	6.80	79.4	1.96	0.40	19.2	
10	90	3	2445.7	0.035	6.46	76.6	2.00	0.34	25.5	
10	90	4	2376.1	0.029	5.94	71.9	2.02	0.27	30.9	
10	90	5	2334.0	0.026	5.52	68.3	2.03	0.23	33.5	
10	90	6	2291.7	0.029	5.31	67.0	2.02	0.23	33.0	

