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Air Temperature Sensor Estimation on Automatic Weather Station Using ARIMA and MLP

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***Abstract*— Surface meteorological quantities are now measured by Automatic Weather Station (AWS). AWS Serang records weather parameters minutely in Banten Province of Indonesia. Air temperature sensor is one instrument of this system. This study aims to design an air temperature sensor estimator model using ARIMA and Artificial Neural Network (ANN) as solution for avoiding loss data. Air temperature sensor on AWS Serang data in August of 2022 period is segmented into training, validating and testing sections. Based on criterion calculation, ARIMA (1,1,5) is simulated. It obtains not more than 0.12 of RMSE, 0.052^{0}C of MAE, 0.193% of MAPE and 0.194% of SMAPE. Meanwhile, three different models of MLP ANN for air temperature estimator is also simulated. Input variables include air temperature, relative humidity and solar radiation intensity. Roy model has highest accuracy level for MLP ANN algorithm with 0.048 of RMSE, 0.026^{0}C for MAE, 5% of MAPE and 4.83% of SMAPE. Overall, ARIMA (1,1,5) is better than Roy MLP ANN model in estimating air temperature sensor data on AWS Serang. Nonetheless, both models are properly fulfilling WMO (World Meteorological Organization) accuracy requirements for air temperature measurement.**

***Index Terms*— air temperature sensor; ARIMA; Multi Layer Perceptron ANN**.

I. INTRODUCTION

Since 2013, Meteorology Climatology and Geophysics Agency of Indonesia has installed 367 Automatic Weather Stations (AWS). Automatic Weather Station is a digital meteorological measurement system. The measured parameters are consist of air temperature, relative humidity, air pressure, total daily rainfall, wind speed, wind direction and solar radiation intensity [1].

Air temperature has crucial roles on determining weather analysis and prediction. Air temperature is measured by outdoor thermometer inside a shield in the open air environment. Such shield covers the sensor material from solar direct radiation [2]. This parameter is measured by air temperature sensor of AWS minutely, hourly and daily. The sensor is installed inside an enclosure within relative humidity sensor 1,2 meters of height above ground.

Air temperature sensor of AWS is calibrated annually by field verification procedure. It is compared to reference portable AWS [3]. Nonetheless, the sensor has potential failure during operational time due to technical or non-technical factor. Sensor reparation or replacement needs certain time intervals, then it may causing loss data.

Air temperature sensor output can be estimated in order to minimize loss data. Smith et.al. (2007), have designed hourly temperature prediction system in Georgia using Artificial Neural Network (ANN) with air temperature, relative humidity, total rainfall and solar radiation intensity as model inputs [4]. Salcedo-Sanz et.al. (2016) forecast monthly temperature in New Zealand using Multi Layer Perceptron (MLP) with air temperature, Southern Oscillation Index (SOI), Indian Ocean Dipole (IOD) and Pacific Decadal Oscillation (PDO) as model inputs [5]. Then, Rahayu et.al. (2020) designed daily temperature estimation using Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) with air temperature, relative humidity, total rainfall and wind speed as model inputs [6].

Tran et.al. (2021) has reviewed air temperature prediction models based on various machine learning algorithms. Mostly, ANN-based model such as MLP often provide more accurate air temperature estimation results. However, air temperature estimation based on ANN has not been sufficiently compared to another soft computing approach for time series data. It is recommended that air temperature estimation using ANN model should be compared to Auto Regressive

Integral Moving Average (ARIMA) model for future works [7].

This study intends to propose an air temperature sensor estimation model using ARIMA and ANN. At final steps, both model results will be analyzed and compared to each other. Besides, this study also utilizes direct measurement from ground weather station for improving input qualities of previous described researches.

II. Data

This research uses AWS Serang data in August 2022 period. The parameter includes minutely air temperature, relative humidity, air pressure, wind speed and solar radiation intensity. Table I shows AWS Serang data.

TABLE I. Raw Data of AWS Serang in August 2022

Date	Time (UTC)	T (^{0}C)	RH %	P (mb)	WS m/s	SR (W/m^2)
1/8	2:50	30.2	57	1005.1	2.1	571.3
1/8	2:51	30.2	57	1005.1	1.5	643.3
1/8	2:52	30.3	56	1005.0	2	746.1
…	…	…	…	…	…	…
17/8	8:53	23.5	91	1005.0	1.5	10.9
17/8	8:55	23.5	91	1005.0	1.2	7.6
17/8	8:56	23.5	91	1005.0	1.4	28.9
…	…	…	…	…	…	…
31/8	3:52	30.4	56	1005.1	2.3	513.5
31/8	3:53	30.5	52	1005.1	1.6	921.8
31/8	3:54	30.6	52	1005.1	1.7	1028.6

AWS Serang is located on Serang Meteorological Station at 6,1111^0 S and 106,1218^0 E with 25 meter in elevation. The air temperature sensor is a Vaisala active mode HMP155A. Sensor data is recorded by using Campbell Scientific CR3000 logger.

III. Methods

Air temperature sensor output estimation on AWS is designed based on ARIMA and MLP ANN models. ARIMA model only utilizes univariate temperature variable as input. While MLP ANN model utilizes multivariate variables as inputs. The multivariate variables are air temperature, relative humidity, air pressure, wind speed and solar radiation intensity.

Each model has its pros and cons. ARIMA is very effective and efficient for linear and stationary time series data. It also widely used for hydro-climatology parameters [8]. However, one parameter is often affected by other parameters in meteorology. ARIMA input is only consist of univariate variable. MLP is able to overcome such shortcomings of ARIMA weakness by using multivariate input variables. MLP also eases analysis for arbitrary nonlinear temperature data [7].

A. ARIMA Model

ARIMA model is combination of three statistical models: auto regression, integral and moving average. This model aims to analyze and to predict univariate variable in time series domain [8]. Mathematically, ARIMA model is stated as follows [9]:

$$W_t = \mu + \frac{\theta(B)}{\phi(B)} \tag{1}$$

$$(1-\mathrm{B})^{\mathrm{d}}\mathrm{Y}_{\mathrm{t}} = \mu + \frac{(1-\theta_1\mathrm{B}-\ldots-\theta_{\mathrm{p}}\mathrm{B}^{\mathrm{p}})}{(1-\phi_1\mathrm{B}-\ldots-\phi_{\mathrm{q}}\mathrm{B}^{\mathrm{q}})}\mathrm{a}_{\mathrm{t}} \tag{2}$$

Y_t as output variable, B as backshift operator, μ as mean value, θas auto regression operator, ϕas moving average operator, a_t as random errors. Value of p,d,q are ARIMA number models where p as auto regression number, d as differencing number and q as moving average number.

ARIMA model is arranged in some steps. These steps are consist of data identification, data preparation, data segmentation, model selection, and model evaluation [8]

1) Data Identification

First step of establishing ARIMA model is data stationary checking. Air temperature sensor data is plotted in time series domain. It is then plotted in auto correlation function graphic. Next, data stationary checking is held by Augmented Dicky-Fuller (ADF) Test, Phillip-Peron (PP) Test, Kowski-Phillips-Schmidt-Shin (KPSS) Test and Zivot-Andrews (ZA) Test [10].

2) Data Preparation

If air temperature sensor data is non-stationary, then it will be differenced. Differencing equation is stated as follow [10]:

$$X'_t = X_t - X_{t-1} \tag{3}$$

X_t is new input as result of subtraction of recent data to its previous data at t-1. Later, the differenced data will be identified again by data stationary checking methods. Data will be differenced more if it is still non-stationary.

3) Data Segmentation

After being prepared, air temperature sensor data is segmented into three parts: training data, validation data and testing data [11].

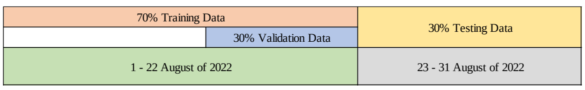


Fig. 1. First scenario of segmentation

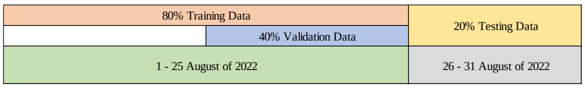


Fig. 2. Second scenario of segmentation

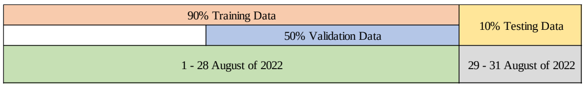


Fig. 3. Third scenario of segmentation

Figure 1 shows first scenario that divides data into 18.012 training data, 5.404 validation data which are overlapped to training data (13-22 August of 2022), and 7.719 testing data. Figure 2 shows second scenario that divides data into 20.585 training data, 8.234 validation data which are overlapped to training data (15-22 August of 2022), and 5.146 testing data. Figure 3 shows third scenario that divides data into 23.158 training data, 11.579 validation data which are overlapped to training data (14-28 August of 2022), and 2.573 testing data.

4) Model Selection

ARIMA model selection can be preceded by plotting auto correlation function (ACF) and partial auto correlation function (PACF) graph [12]. ACF is correlation between variable value in certain time with its value in whole previous times. PACF is partial correlation between variable value in certain time with its value in some of previous times. Equation (4) and (5) show ACF and PACF respectively [13].

$$\mathrm{ACF} = \mathrm{corr}(X_t, X_{t-k}) = \frac{\sum_{t=1}^{n-k}(X_t - \bar{X})(X_{t+k} - \bar{X})}{\sum_{t=1}^{n}(X_t - \bar{X})^2} \quad (4)$$

$$\mathrm{PACF} = \mathrm{corr}(X_t, X_{t-k} \mid X_{t-1}, X_{t-2}, \dots, X_{t-k+1}) \quad (5)$$

ACF plot is utilized in predetermining moving average number, while PACF plot is utilized in predetermining auto regression number [14]. Then, final selection will be assessed by using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) [15][16]. Equation (6) and (7) state AIC and BIC respectively.

$$\mathrm{AIC} = -2\ln(L) + 2k \quad (6)$$

$$\mathrm{BIC} = -2\ln(L) + k\ln(n) \quad (7)$$

L is maximum value of likelihood function, k is amount of model parameters, and n is amount of model data. Less value of AIC and BIC give better ARIMA model selection [17].

5) Model Evaluation

ARIMA model estimation accuracy is evaluated by obtaining coefficient determination (R-squared), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (SMAPE) [18]. Formulation of R-squared, RMSE, MAE, MAPE and SMAPE is respectively shown by equation (8), (9), (10), (11) and (12).

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\bar{Y} - Y_i)^2} \quad (8)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \quad (9)$$

$$\mathrm{MAE} = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i| \quad (10)$$

B. MLP ANN Model

ANN is one branch of artificial intelligence. ANN adopts human neural nervous system. Multi Layer Perceptron ANN (MLP ANN) is a type of ANN which is prominently applied for temperature forecasting [7]. It is formed by input, hidden and output layer. It processes input data through neural network operation with certain adaptive weighting. MLP ANN output is combination of activation function, input weighting, and bias. It is formulated as follow [19]:

$$Y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \quad (13)$$

Y is neuron output, x is input, w is weighting and b is bias. Equation (13) is called activation function. This research applies sigmoid, hyperbolic tangential and rectified linear unit function [20]. These functions are stated by equation (14), (15) and (16).

$$F_s = f(x) = \frac{1}{1 + e^{-x}} \quad (14)$$

$$F_t = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (15)$$

$$F_r = f(x) = \max(0, x) \quad (16)$$

Fs stands for sigmoid function, Ft stands for hyperbolic tangential function and Fr stands for rectified linear unit function [21]. MLP ANN model arrangement is consist of three main steps : data normalization, data selection, model training, validation and testing [22].

1) Data Normalization

Due to multivariate variables and quantities, input and output data should be normalized. Normalization aims to simplify correlation calculation [23]. All variables are transformed to be new contemporary variables based on their origin coordinates in range of 0-1. Data normalization is stated as follow [24]:

$$Z_{norm} = \frac{Z_i - \bar{Z}}{stdev(Z)} \quad (17)$$

Each variable is subtracted to its average and divided by its standard deviation. Data normalization result is then processed.

2) *Data Selection*

Input variables are adopted from recent air temperature forecasting ANN model [25]. It includes three previous delayed data for each variable [26]. Table II shows raw input variables.

TABLE II. RAW INPUT VARIABLES

Input	**Unit**	**Delay**
Air Temperature	^{0}C	(t-1),(t-2),(t-3)
Relative Humidity	% RH	(t-1),(t-2),(t-3)
Air Pressure	mbar	(t-1),(t-2),(t-3)
Wind Speed	m/s	(t-1),(t-2),(t-3)
Solar Radiation Intensity	W/m^2	(t-1),(t-2),(t-3)

Next, those variables are filtered by using Principal Component Analysis (PCA) algorithm. PCA is one of variability analysis method. It has purpose to reduce input dimension. PCA also determines the most significant input variable [27]. PCA runs based on matrix covariance calculation. After decomposing the eigen vectors, the biggest eigen values will be obtained from low dimensional subspace [28]. Eigen values correspond to variance of each input variable. It describes the input correlation strength to the output. Eigen vectors with biggest eigen value and largest variance will be detained as final input variables [29].

3) *Support Vector Regression Model*

Final input variables will be segmented in same scenarios as ARIMA model. It is also evaluated by using same accuracy parameters as ARIMA model, so that it will be fairly comparable.

IV. RESULT AND ANALYSIS

ARIMA and MLP model are tested based on comparison methods. The known actual tested value are compared simultaneously to the prediction results. Proportion of testing data has been explained in Figure 1, Figure 2 and Figure 3. Results of both models are checked by using five accuracy criteria: R-squared, RMSE, MAE, MAPE and SMAPE. R-squared shows correlation between actual and predicted value. RMSE and MAE evaluate the model based on same unit as air temperature in celsius degree. While MAPE and SMAPE assess the model in form of the error percentage.

A. *ARIMA Model Result*

Air temperature sensor data is plotted per minute. Figure 4 is an ACF graphic of air temperature original data in August of 2022 period. This figure shows a series of non-stationary data in variance, because its correlation value degradation moves down slowly from one lag to next lag.

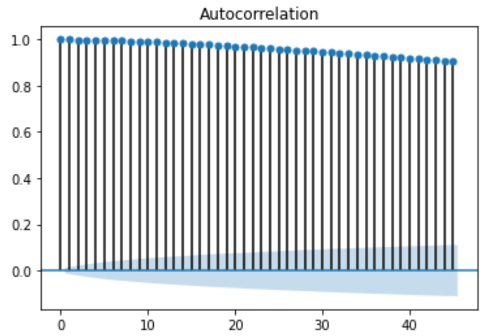


Fig. 4. ACF graphic of original air temperature sensor data

Next, air temperature sensor data is differenced once. Stationary characteristic of original data and differencing data are then tested. Table III shows stationary test result of both data.

TABLE III. STATIONARY DATA CHECKING

Test	**Original Data**		**Differenced Data**	
	p-value	**characteristic**	**p-value**	**characteristic**
ADF	0,000	weakly stationary	0,000	stationary
PP	0,000	weakly stationary	0,000	stationary
KPSS	0,117	weakly stationary	0,995	stationary
ZA	0,000	weakly stationary	0,000	stationary

The first order differenced data has became stationary data. Figure 5 shows ACF and PACF graphic of differenced data. ACF graphic describes significant correlation value degradation.

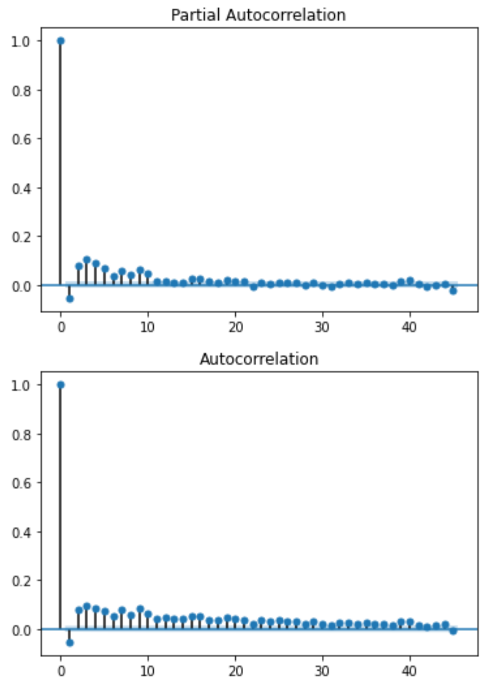


Fig. 5. PACF and ACF graphic of first differenced data

ACF graphic shows that fifth lag correlation is still significant, so moving average order is in range of 1-5. While PACF graphic shows that third lag partial correlation is significant, so auto regression order is in range of 1-3. These order estimations are then confirmed by calculating AIC and BIC values. Table IV describes AIC and BIC values for each ARIMA model simulation with d=1.

TABLE IV. AIC AND BIC VALUE FOR ARIMA MODEL

ARIMA Model	AIC	BIC
ARIMA (1,1,1)	-43,668.452	-43,643.985
ARIMA (1,1,2)	-44,173.694	-44,141.072
ARIMA (1,1,3)	-44,172.481	-44,131.704
ARIMA (1,1,4)	-44,177.763	-44,128.831
ARIMA (1,1,5)	-44,177.929	-44,120.841
ARIMA (2,1,1)	-44,155.510	-44,122.888
ARIMA (2,1,2)	-44,172.415	-44,131.638
ARIMA (2,1,3)	-44,172.704	-44,123.772
ARIMA (2,1,4)	-44,174.778	-44,117.691
ARIMA (2,1,5)	-44,174.467	-44,109.223
ARIMA (3,1,1)	-44,176.266	-44,135.489
ARIMA (3,1,2)	-44,175.169	-44,126.236
ARIMA (3,1,3)	-44,173.561	-44,116.473
ARIMA (3,1,4)	-44,171.465	-44,106.221
ARIMA (3,1,5)	-44,170.620	-44,097.221

Based on Table IV, ARIMA (1,1,5) has the smallest AIC value, and relatively smaller BIC value than the others. ARIMA (1,1,5) is then chosen as air temperature sensor data estimator model. ARIMA (1,1,5) equation for air temperature sensor estimator is stated as follow.

$$Y_t = 1{,}141 + 1{,}9575Y_{t-1} + 1{,}0470e_{t-1} - 0{,}1413e_{t-2} - 0{,}0194e_{t-3} + 0{,}0112e_{t-4} + 0{,}008e_{t-5} \quad (18)$$

ARIMA (1,1,5) model is trained, validated and tested based on three segmentation scenarios. Table V shows evaluation results of the model.

TABLE V. ARIMA (1,1,5) ACCURACY EVALUATION

Scenario	R^2	RMSE	MAE (^{0}C)	MAPE (%)	SMAPE (%)
1	0,998	0,119	0,052	0,193	0,194
2	0,998	0,105	0,048	0,181	0,181
3	0,998	0,114	0,047	0,172	0,172

Determination coefficient of ARIMA (1,1,5) is close to 1, so the estimator model is strongly correlated to the actual value. RMSE, MAE, MAPE and SMAPE values are very small, so the model is precisely accurate. An increase on training data percentage can increase the model's accuracy level.

B. *MLP Model Result*

MLP ANN input and output data are normalized. Figure 6 is variance ratio percentage graphic as PCA result. This figure states that only seven input variables are significant to be injected into the model.

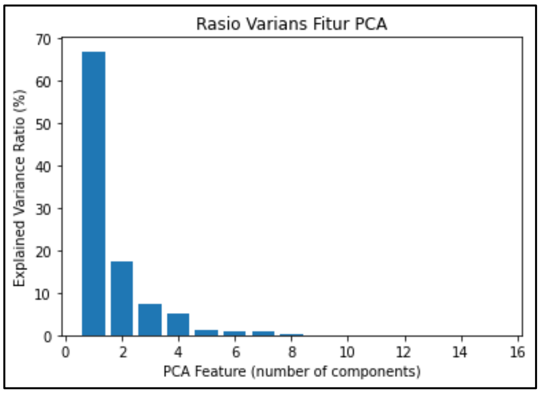


Fig. 6. Variance ratio percentage of PCA result

Table VI shows seven significant inputs for the MLP ANN model. These inputs has bigger eigen values than the rests. Such inputs are then detained. Significant inputs are dominated by the lagged air temperature data. Relative humidity is also strongly related to air temperature measurement dynamics, so it is significant too. However, lagged solar radiation intensity mainly influences all weather parameter measurement.

TABLE VI. SIGNIFICANT INPUT PARAMETERS

Significant Inputs	Eigen Value	Variance Ratio (%)
Air temperature (t-2)	0,30319	66,91
Air temperature (t-1)	0,30317	17,39
Air temperature (t-3)	0,30304	7,31
Relative humidity (t-1)	0,29850	4,95
Relative humidity (t-2)	0,29841	1,32
Relative humidity (t-3)	0,29815	0,90
Solar radiation intensity (t-3)	0,25150	0,84

MLP ANN model is adopted from previous existing air temperature forecasting model. Singh et.al. (2019), Roy (2020) and Lee et.al. (2020) have designed MLP ANN model with same inputs in Table VI partially [22], [31] and [32]. These three models are simulated for detained significant inputs. Table VII describes those models in detail.

TABLE VII. MLP ANN MODEL DETAIL

Model Version	Layer	Neuron	Activation Function
Singh et.al. (2019)	5	Layer 1 : 16 Layer 2 : 32 Layer 3 : 16 Layer 4 : 5 Layer 5 : 1	Layer 1 : relu Layer 2 : relu Layer 3 : relu Layer 4 : relu Layer 5 : linear
Roy (2020)	3	Layer 1 : 16 Layer 2 : 16 Layer 3 : 1	Layer 1 : relu Layer 2 : relu Layer 3 : linear
Lee et.al. (2020)	6	Layer 1 : 16 Layer 2 : 16	Layer 1 : tanh Layer 2 : tanh

		Layer 3 : 16 Layer 4 : 16 Layer 5 : 16 Layer 6 : 1	Layer 3 : tanh Layer 4 : sigmoid Layer 5 : sigmoid Layer 6 : linear

MLP ANN model is adopted from previous existing air temperature forecasting model. The models are trained and validated by using Adam optimizer with 32 batches and 100 epochs [25]. Figure 7 shows loss level against epochs for Singh et.al. model. Loss level is mean squared error for each epoch. Training and validating loss decrease fast at even less than 20 epochs. It proves that the increasing epochs should minimize losses until certain level. Loss value will be stagnant after reaching an effective total epochs.

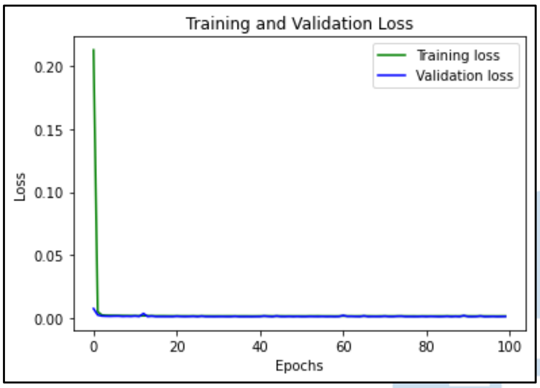


Fig. 7. Loss vs total epochs in Singh et.al. Model

Each model gives various timing process. Figure 8 shows training epochs duration for each model in three segmentation scenarios. Roy model has shortest timing process : 138.20 seconds for first scenario; 147.52 seconds for second scenario; and 161.69 seconds for third scenario. It is a fast computation process since it only has three layers of modelling.

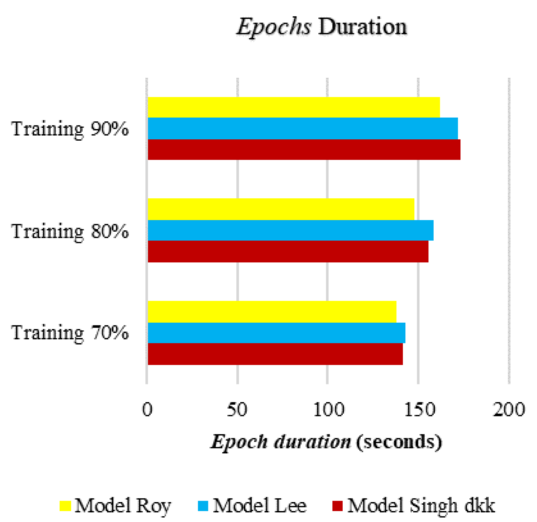


Fig. 8. Training epochs duration

Table VIII explains detailed training and validation loss for each model after 100 epochs. Singh et.al. and Roy model have same loss value due to similarity of activation function. Both are lesser than Lee et.al. model which is combined by sigmoid and tanh function.

TABLE VIII. MLP ANN MODEL DETAIL

Model Version	Scenario	Training Loss (MSE)	Validation Loss (MSE)
Singh et.al. (2019)	1	0,0015	0,0012
	2	0,0016	0,0012
	3	0,0013	0,0013
Roy (2020)	1	0,0018	0,0014
	2	0,0021	0,0014
	3	0,0018	0,0017
Lee et.al. (2020)	1	0,0015	0,0012
	2	0,0016	0,0012
	3	0,0013	0,0013

TABLE IX. MLP ANN MODEL DETAIL

Model	Scenario	R^2	RMSE	MAE (^{0}C)	MAPE (%)	SMAPE (%)
Singh et.al. (2019)	1	0,998	0,036	0,019	4,95	4,89
	2	0,998	0,038	0,022	5,30	5,09
	3	0,997	0,045	0,020	4,94	4,83
Lee et.al. (2020)	1	0,998	0,039	0,022	5,81	5,57
	2	0,998	0,041	0,023	5,32	5,04
	3	0,997	0,048	0,026	5,49	5,18
Roy (2020)	1	0,998	0,036	0,019	4,87	4,76
	2	0,998	0,038	0,020	5,00	4,83
	3	0,997	0,044	0,020	4,66	4,53

The models are then tested to estimate air temperature sensor data. Prediction result is evaluated against actual measurement value. Table IX shows model evaluation results.

All determination coefficients of MLP ANN model show strong correlation value. An increase of training data amount may decrease the correlation due to higher bias probability in small testing data amount.

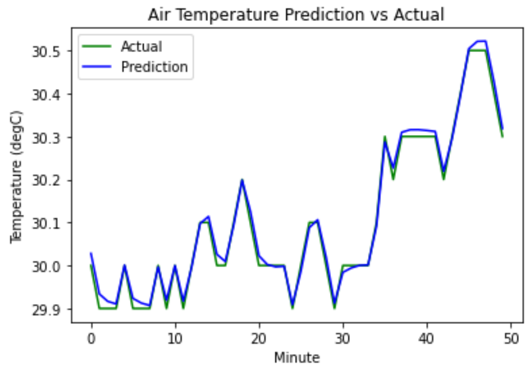
Singh et.al. and Roy MLP ANN model have relatively same RMSE and MAE values for each segmentation scenario. RMSE, MAE, MAPE and SMAPE of Singh et.al. and Roy model are lower than Lee et.al. model. It proves that relu activation function is more suitable than sigmoid or tanh for air temperature sensor estimator model on AWS Serang. Roy model has smallest MAPE and SMAPE value at all segmentation scenarios.

Therefore, Roy MLP ANN model has higher accuracy level than two other models. It indicates that an increase on layer or neuron amount of MLP ANN does not vouch the model accuracy. In addition, Roy model has fast computation time. It can be inferred that Roy model is quite effective and efficient for air temperature sensor data estimator on AWS Serang.

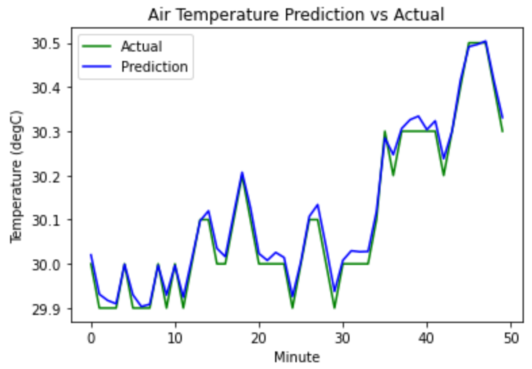
C. *ARIMA vs MLP*

Based on Table V and Table IX, ARIMA (1,1,5) has smaller MAPE and SMAPE values than MLP ANN model significantly. Meanwhile, it has bigger RMSE and MAE values than MLP ANN model. Nevertheless, MAPE and SMAPE values are more sensitive on explaining error parameters than RMSE and MSE, because both are proportionally compared against the actual values in percentage.

Figure 9 shows air temperature sensor output estimation plot of ARIMA (1,1,5) and Roy MLP ANN model in same certain periods. ARIMA (1,1,5) prediction plot is fitter than Roy MLP ANN model. Roy model has little ripples in stable air temperature condition.



(a)



(b)

Fig. 9. Comparison of (a) ARIMA(1,1,5) and (b) Roy MLP ANN prediction plot

However, MAE value of both models are still fulfilling WMO (World Meteorological Organization) accuracy requirements for air temperature measurement. Permitted maximum error in WMO No.8 document is below 0.2^0C. MAE value of both models are even less than 0.1^0C.

On the other aspect, ARIMA (1,1,5) needs lesser input variables than Roy MLP ANN model. Moreover, it has faster computation process and smaller memory capacities. By utilizing Python 3.6 programming, ARIMA (1,1,5) spends only 4 kilobytes, while MLP ANN model spends 7 kilobytes.

ARIMA (1,1,5) is potentially applied in AWS logger programming code or in server processing. New input can be maintained as new trained model routinely in order to enrich and improve air temperature estimation accuracy.

V. Conclusions

According to result analysis, it can be inferred that ARIMA and MLP ANN is able to estimate minutely air temperature sensor data on AWS Serang. ARIMA (1,1,5) has lowest AIC, so it is proper to estimate air temperature data with very small MAPE and SMAPE value. Roy model has better accuracy than Singh et.al. And Lee et.al. model as MLP ANN estimator for air temperature sensor data. Overall, ARIMA (1,1,5) is more accurate than Roy MLP ANN model. Besides, it also has simpler computation processing than MLP ANN model. Hybrid model of ARIMA and ANN is recommended for future works in order to improve air temperature estimator accuracy.

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