Ensemble Method Based on Two Level ARIMAX-FFNN for Rainfall Forecasting in Indonesia

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Abstract: ***One of relatively new modern methods for time series forecasting is ensemble forecasting that employs averaging or stacking from the results of several methods. This paper focuses on the development of ensemble ARIMAX-FFNN-Hybrid for rainfall forecasting by using averaging and stacking method. Three data about dasarian rainfall in Indonesia, i.e. Karangsuko, Kalipare and Gondanglegi area, are used as case study. Root mean of squares errors and Symmetric mean absolute percentage errors in testing datasets are used for evaluating the forecast accuracy. The results of ensemble ARIMA-FFNN-Hybrid are compared to two classical statistical method, i.e. individual ARIMA and ARIMAX, and five modern statistical methods, namely individual FFNN, individual Hybrid ARIMAX-FFNN, ensemble ARIMAX, ensemble FFNN, and ensemble Hybrid. The results show that ensemble hybrid yields more accurate forecast in Karangsuko area than other methods, whereas in Gondanglegi and Kalipare area show that individual hybrid and FFNN, respectively, is the best method. Additionally, this conclusion in line with the results of M3 competition, i.e. modern methods or complex methods do not necessarily produce more accurate forecast than simpler one.***

Keywords: Ensemble, ARIMAX, FFNN, Hybrid.

1. Introduction

Indonesia is a country that have potential in agricultural. One of the main factors of agricultural production failure in Indonesia is climate, especially rainfall. The solution for this problem is to develop a forecasting method that produces reliable and high accurate prediction for all data in climatology. Until now, statistical models that were developed and used for rainfall forecasting in Indonesia not yet give satisfactory results. One of statistical models to increase the prediction accuracy is using combination of several methods, i.e. ensemble.

A time series under study is can generated from a linear or nonlinear underlying process or whether one particular method is more effective than the other in testing datasets forecasting. In this research, using not only linear (i.e. ARIMA and ARIMAX) and nonlinear model (i.e. FFNN) but also the combination of linear and nonlinear model, i.e. hybrid and ensemble.

The aim of this research is to develop new methods for forecasting that appropriate for the dasarian, average of ten days, rainfall data in Indonesia. There are four main forecasting methods that will be studied further, namely Autoregressive Integrated Moving Average (ARIMA) and ARIMAX, Feed Forward Neural Networks (FFNN), hybrid ARIMAX-FFNN and Ensemble method, i.e. ensemble ARIMAX, ensemble FFNN, ensemble hybrid, and ensemble ARIMAX-FFNN-Hybrid. There are two combination of ensemble, i.e. averaging and stacking. In this research, there are six ways for optimization in stacking, i.e. optimization in 1, 2, 3, 4, 5 latest years in training datasets and all training datasets. The results, an accurate rainfall forecast, could be used effectively for planning agricultural production.

In this paper, Root Mean of Squares Errors (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE) is used for evaluating the forecast accuracy in testing datasets. The data about dasarian rainfall in certain area in Indonesia, i.e. Karangsuko, Kalipare and Gondanglegi area, are used as case study. The results show that that ensemble hybrid yields more accurate forecast in Karangsuko area than other methods, whereas in Gondanglegi and Kalipare area shows that individual hybrid and FFNN, respectively, is the best method.

2. Time Series Forecasting

There are four forecasting methods that will be studied further in this section, namely Autoregressive Integrated Moving Average (ARIMA), ARIMA with exogenous variables (ARIMAX), Feed Forward Neural Networks (FFNN), and hybrid method.

2.1. ARIMA

ARIMA model belongs to a family of flexible linear time series models that can be used for modeling many different types of seasonal as well as non seasonal time series. The ARIMA model can be expressed as [1, 2]:

$$\phi_p(B)\ \Phi_P(B^S)\ (1-B)^d\ (1-B^S)^D\ y_t = \theta_0 + \theta_q(B)\ \Theta_Q(B^S)\ \varepsilon_t \qquad (1)$$

where:

p = order of autoregressive
d = order of differencing
q = order of moving average
S = the seasonal period
P = order of autoregressive in seasonal period
D = order of differencing in seasonal period
Q = order of moving average in seasonal period
$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$
$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_P B^{PS}$
$\Theta_Q(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}$

and B is the backshift operator, and ε_t is a sequence of white noise with zero mean and constant variance. There are 4 iterative steps for forecasting using ARIMA based on Box-

Jenkins procedure [3], namely identification, parameter estimation, diagnostic checking, and forecasting [1,2].

2.2. ARIMAX

ARIMAX model belong to ARIMA with exogenous variables. In this paper, exogenous variables are dummy variables for outlier case. There are four type of outlier [1], i.e. additive outlier (AO), innovational outlier (IO), level shift (LS), and temporary change (TC). Wei [1] proposed outlier detection using iterative procedure for two type of outlier, i.e. AO and IO. An observation is an AO if it have effect to observation in time-T, whereas an observation is an IO if it have effect to observation in time-$T, T+1, \ldots$. The ARIMAX model can be writing as

$$y_t = \sum_{j=1}^{k} \omega_j v_j(B)\, I_t^{(T)} + \frac{\theta(B)}{\phi(B)} a_t \qquad (2)$$

where:
$v_j(B) = 1$ if there is AO at $t = T_j$
$v_j(B) = \theta(B)/\phi(B)$ if there is IO at $t = T_j$
$v_j(B) = \frac{1}{(1-B)}$ if there is LS at $t = T_j$
$v_j(B) = \frac{1}{(1-\delta B)}$ if there is TC at $t = T_j$
$I_t^{(T)} = \begin{cases} 1, & t = T \\ 0, & t \neq T \end{cases}$

2.3. FFNN

Neural network was firstly introduced by McCulloch and Pitts [4]. The ideas of FFNN are design for neural architecture in brain of human. Multilayer perceptrons (MLP), also known as feed forward neural networks (FFNN), is probably the most commonly used NN architecture in engineering application.
In general, this model work by receiving a vector of inputs **X** and compute a response or output *Y*(**X**) by propagating **X** through the interconnected processing elements. The processing elements are arranged in layers and the data, **X**, flows from each layer to the successive one. Within each layer, the inputs to the layer are nonlinearly transformed by the processing elements and propagated to the next layer. Finally, at the output layer *Y*(**X**), which can be scalar or vector valued, is computed.
The response value $y_l(x_1, x_2, \ldots, x_m)$ of FFNN with one hidden layer is computed as

$$y_l(x_1, x_2, \ldots, x_m) = f\left(\sum_{k=1}^{p} w_{lk}\, z_k(z_{net.k})\right) + \varepsilon \qquad (3)$$

where :
$l = 1,2,\ldots,q$ (q is number of output unit)
$k = 1,2,\ldots,p$ (p is number of neuron in hidden layer)
$z_k(z_{net.k})$ is the activation function in hidden layer
$j = 1,2,\ldots,m$ (m is number of input unit)
w_{lk} is weighted from neuron at- k to output unit at- l
v_{kj} is weighted from input unit at- j to neuron unit at- k.
$f\left(\sum_{k=1}^{p} w_{lk}\, z_k(z_{net.k})\right)$ is the activation function in output unit

Figure 3.1 is an example of typical MLP with one hidden layer that known as FFNN with single hidden layer. In this example, FFNN contains three input units, i.e. X_1, X_2, X_3, four hidden units, and one output unit with linear activation function.

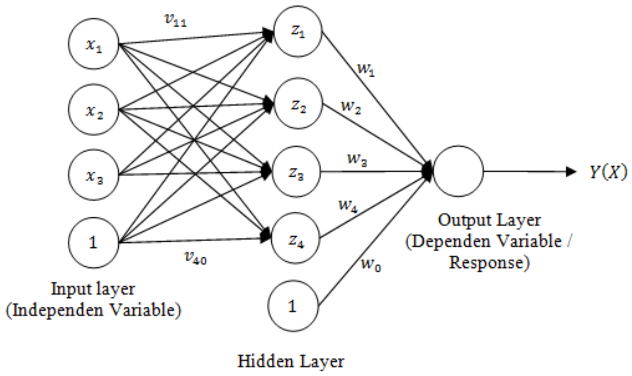


Figure 1. FFNN Architecture of A Single Hidden Layer with Three Input Units, Four Hidden Units, and One Output Unit

2.4. Hybrid

Hybrid method was firstly introduced by Zhang in 2003 [5]. The motivation of the hybrid model comes from, in practice, determine whether a time series under study is generated from a linear or nonlinear underlying process or whether one particular method is more efective than the other in testing datasets forecasting. In general, hybrid method can be compute using the formula below:

$$\mathrm{y_t} = \mathrm{L_t} + \mathrm{N_t} \qquad (4)$$

where $\mathrm{L_t}$ denotes the linear component and $\mathrm{N_t}$ denotes the nonlinear component.

3. Ensemble Forecasting

Basically, ensemble forecasting is a forecasting technique that combines several outputs of forecasting methods. Recently, ensemble method becomes one of popular forecasting methods, especially for climate prediction [6]. Recent studies have shown that combining several models can improve the robustness and reliability, such as ensemble [7, 8, 9, 10, 11].

There are two major steps for construction of an ensemble. The first step is to make membership of ensemble and the second step is to find the appropriate combination of outputs from the ensemble members to produce the unique ensemble output. Figure 2 illustrates the two steps for construction of an ensemble. [12]

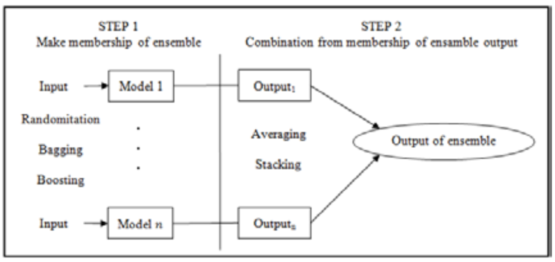


Figure 2. Steps for Construction of An Ensemble

Various approaches have been proposed to generate ensemble members, and generally can be classify into two kinds. First is creating several forecasting methods, while keeping the training data unchanged. For example, using randomization [9]. The second is altering the training data set, such as using re sampling [12].

Zaier et al. [10] showed that there were two methods usually be used for combining the difference outputs from membership ensemble, i.e. averaging and stacking.

3.1. Averaging

By using the averaging method, the output of the ensemble is obtained by computing the mean of the output from membership of ensemble. Suppose that N is the number of members in an ensemble, the combination function is:

$$y_t = \frac{1}{N}\sum_{k=1}^{N} \hat{z}_{k,t} + e_t \qquad (5)$$

where $\hat{z}_{k,t}$ is output from model k for observation t. The implementation of the averaging approach is easy, and it has been shown to be an effective approach to improve the performance of the univariate forecasting model like Neural Network [13].

3.2. Stacking

Stacking or stacked generalization is a general method of using the combination of the output from several models in order to achieve a greater predictive accuracy. The final output of the ensemble can be calculated using:

$$y_t = \sum_{k=1}^{N} C_k\, \hat{z}_{k,t} + e_t \qquad (6)$$

where $\hat{z}_{k,t}$ is output from model k for observation t and the coefficients C_k are estimated in order to construct the final output of the ensemble by minimizing the function G. The function G expressed as:

$$G = \sum_{t=1}^{n}\left[z_t - \sum_{k=1}^{N} C_k\, \hat{z}_{k,t}\right]^2 \qquad (7)$$

with using constrain $\sum_{k=1}^{N} C_k = 1$ and $0 \le C_k \le 1$. Breiman [12] suggested minimizing the function G that can give better generalization the model.

4. Fitting Ensemble for Rainfall forecasting

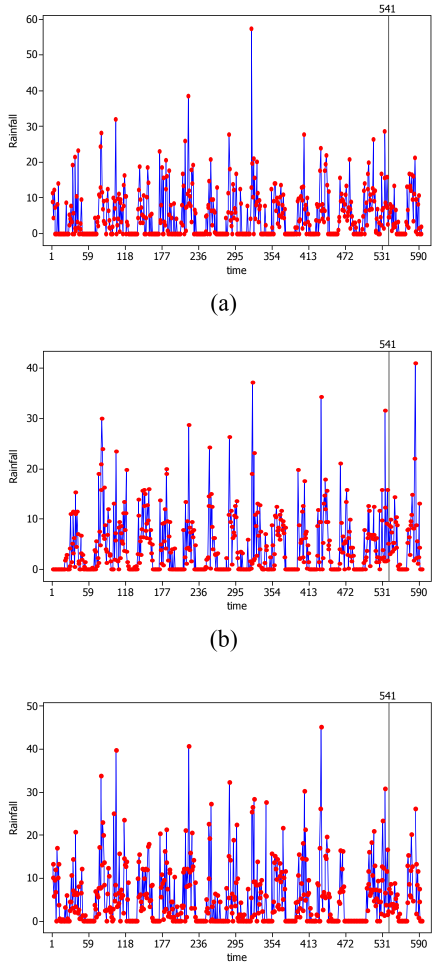
Climate data about dasarian rainfall from January 1996 – June 2012 at three certain area in Indonesia, i.e. Karangsuko, Kalipare and Gondanglegi, are used as case study. Data are divided in two parts, i.e. training and testing datasets. Rainfalls from January 2011 until June 2012 are used as testing datasets. Statistic descriptive about three dasarian rainfalls are shown in Table 1 and Time series plot for each datasets are shown in Figure 3.

Table 1: Statistic descriptive

Area	*N-Missing*	*Mean*	*Standart deviation*	*Mini-mum*	*Maxi-mum*
Karangsuko	0	4,997	6,715	0	57,600
Kalipare	0	4,389	5,988	0	41,000
Gondanglegi	3	5,320	7,044	0	45,364

Table 1 show that the largest of maximum is rainfall in Karangsuko area. Gondanglegi area is areas which have the largest mean and standard deviation. Gondanglegi areas have three missing data at February 2012. Figure 3 shows that there are several outliers in three areas. Time series plot show that there is trend in seasonal.

In this paper, five methods are used to rainfall forecasting, i.e. ensemble forecasting (ensemble ARIMAX, ensemble FFNN, ensemble Hybrid, and ensemble ARIMAX-FFNN-Hybrid), and individual methods (ARIMA, ARIMAX, hybrid ARIMAX-FFNN). Root Mean of Square Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE) are used for evaluating the forecast accuracy in testing datasets.



(a)

(b)

(c)

Figure 3. Time Series Plot of Karangsuko (a), Kalipare (b), and Gondanglegi (c) area.

There are four steps for forecasting using ARIMA based on Box-Jenkins procedure, namely identification, parameter estimation, diagnostic checking (a white noise and normal distribution of residuals), and forecasting [1,2]. Identification step based on autocorrelation function (ACF) and partial autocorrelation function (PACF) yield three order of tentative ARIMA models for Karangsuko's rainfall, i.e. ARIMA$(1,0,0)(0,1,1)^{36}$, ARIMA$(0,0,1)(0,1,1)^{36}$, dan ARIMA$(0,0,[1,36])(0,1,0)^{36}$. The three ARIMA model for Karangsuko's rainfall have significant of parameter and white noise of residual, but not normal distribution of residual. It is because there are several outliers. ARIMAX is one of the solutions for it case.

There are 89 outlier in ARIMA$(1,0,0)(0,1,1)^{36}$ model, called ARIMAX$(1,0,0)(0,1,1)^{36}$. The estimation of it model with 89 outlier show that it model have significant parameter. But it model don't have white noise of residual. ACF of residual at lag 5, 8, and 48 are large. It is caused the residual of ARIMAX (1, 0, 0) (0, 1, 1)^{36} not a white noise process. This problem show that ARIMA (1, 0, 0) (0,1,1)^{36} is not actual model for outlier detection. So we use lag 5, 8, and 48 in orde of AR and MA, i.e. ARIMAX([1,5,8,48],0,0)(0,1,1)^{36} and ARIMAX(1,0,[5,8,48])(0,1,1)^{36}. Those models have significant of parameters but not white noise of residuals. ACF for each lag are less than $2/\sqrt{504}$ so we can called the residual of two models ARIMAX is white noise process. ARIMAX([1,5,8,48],0,0)(0,1,1)^{36} and ARIMAX(1,0,[5,8,48])(0,1,1)^{36} don't have normal distribution of residual. It is caused by there are many accurate prediction (leptocurtic of histogram) and there are many outlier. The histogram of residual from ARIMAX([1,5,8,48],0,0)(0,1,1)^{36} model showed in Figure 4. So we assume that it have normal distribution of residual.

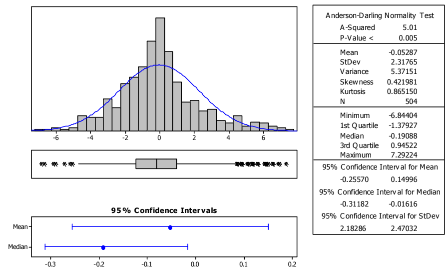


Figure 4. Histogram of residual from ARIMAX ([1,5,8,48],0,0)(0,1,1)^{36}

Using the same procedure, from ARIMA (0,0,1)(0,1,1)^{36} and ARIMA(0,0,[1,36])(0,1,0)^{36}, there are three ARIMAX model, i.e. ARIMAX([4],0,[1,3]) (0,1,1)^{36} with 88 outlier, ARIMAX(0,0,[1,4])(0,1,1)^{36} with 88 outlier, and ARIMAX ([3,4],0,1)(0,1,1)^{36} with 86 outlier.

In this paper, architecture of FFNN are one hidden layer, one until five neuron with tangent hyperbolic as activation function, and one output unit with identity as activation function. Based on ARIMA, ARIMAX [14], and PACF [15], there are six number of inputs that be used for FFNN at Karangsuko's rainfall data. The input of FFNN showed in Table 2.

Table 2: Inputs of FFNN in Karangsuko Area

Number of input	*Input (Lag)*	*Based on*
1	36	ARIMA(0,0,1)(0,1,1)^{36} ARIMA(0,0,[1,36])(0,1,0)^{36}
3	1, 36, 37	ARIMA(1,0,0)(0,1,1)^{36} ARIMAX(1,0,[5,8,48])(0,1,1)^{36} ARIMAX(1,0,[5,8,48])(0,1,1)^{36}
3	4, 36, 40	ARIMAX([4],0,[1,3])(0,1,1)^{36}
5	3, 4, 36, 39, 40	ARIMAX(0,0,[1,4])(0,1,1)^{36}
9	1, 5, 8, 36, 37, 41, 44, 48, 84	ARIMAX([1,5,8,48],0,0)(0,1,1)^{36}
32	1, 4, 8, 32, 34, 36, 37, 38, 40, 44, 47, 68, 70, 71, 72, 73, 74, 75, 83, 86, 97, 102, 107, 108, 110, 111, 122, 133, 135, 138, 144, 146	PACF

Hybrid ARIMAX-FFNN is method that applied linear model (i.e. ARIMA and ARIMAX) and nonlinear model (i.e. FFNN). There are eight model of ARIMA and ARIMAX for Karangsuko's rainfall, and use the same architecture of FFNN, we can build 40 model hybrid ARIMAX-FFNN.

In this paper, there are four tipe of ensemble, i.e. ensemble ARIMAX, ensemble FFNN, ensemble Hybrid, and ensemble ARIMAX-FFNN-Hybrid. Ensemble ARIMAX has ARIMA and ARIMAX as membership of ensemble. FFNN is used for membership of ensemble FFNN, and so on for ensemble hybrid and ensemble ARIMAX-FFNN-Hybrid. The combination for ensemble are averaging and stacking. In this paper, there are six way for optimization of ensemble using stacking as the combination, i.e. 1 until 5 years latest of training datasets and all training datasets.

The five method for Karangsuko's rainfall are used to forecast 1 until 3 dasarian, three and six month, 1 and 1,5 years forward. The best method for each forecast, based on the smallest RMSE in testing dataset, show in Table 3.

Table 3: The Best Model for Karangsuko's Rainfall Forecasting

Forecast	*RMSE*	*SMAPE*	*The best model*
1 dasarian	0.119	2.625	Ensemble ARIMAX-FFNN-Hybrid using stacking and optimize at 1 years latest
2 dasarian	0.377	6.880	ARIMA(1,0,0)(0,1,1)36
3 dasarian	0.492	34.521	Ensemble ARIMAX-FFNN-Hybrid using stacking and optimize at 2 years latest
3 months	2.155	41.576	Ensemble ARIMAX-FFNN-Hybrid using stacking and optimize at 2 years latest
6 months	3.036	46.629	Ensemble ARIMAX-FFNN-Hybrid using stacking and optimize at 3 years latest
1 year	3.474	71.247	Ensemble ARIMAX using averaging
1,5 years	4.533	89.533	Ensemble Hybrid using averaging

Table 3 shows that forecast accuracy of ensemble method is less than the membership ensemble, except for 3dasarian forecasting. The best method for 1, 5 years forecasting rainfall in Karangsuko area is ensemble hybrid using averaging. It have accurate prediction, because RMSE less than standard deviation in Karangsuko's rainfall.

Similar with Karangsuko's rainfall, ARIMA, ARIMAX, FFNN, hybrid and ensemble models are also applied to Kalipare's and Gondanglegi's rainfall data. Based on ACF and PACF, the tentative ARIMA models for Kalipare's and Gondanglegi's rainfall are ARIMA$(2,0,0)(0,1,1)^{36}$ dan ARIMA$(1,0,1)(0,1,1)^{36}$, respectively. Based on ARIMA $(2,0,0)(0,1,1)^{36}$, ARIMAX model for Kalipare's rainfall are ARIMAX$([1,2,30],0,[6,8])(0,1,1)^{36}$ with 58 outlier and ARIMAX$(2,0,[6,8,30])(0,1,1)^{36}$ with 58 outlier. ARIMAX $(1,0,1)(0,1,1)^{36}$ with 114 outlier is ARIMAX model for Gondanglegi's rainfall forecasting.

Based on ARIMA, ARIMAX, and PACF, there are three number of input for FFNN in Kalipare area, i.e. 5 inputs ($y_{t-1}, y_{t-2}, y_{t-36}, y_{t-37}, y_{t-38}$), 7 inputs ($y_{t-1}, y_{t-2}, y_{t-30}, y_{t-36}, y_{t-37}, y_{t-38}, y_{t-66}$), and 22 inputs ($y_{t-1}, y_{t-2}, y_{t-5}, y_{t-33}, y_{t-36}, y_{t-37}, y_{t-38}, y_{t-41}, y_{t-47}, y_{t-65}, y_{t-67}, y_{t-69}, y_{t-72}, y_{t-73}, y_{t-77}, y_{t-83}, y_{t-101}, y_{t-103}, y_{t-108}, y_{t-109}, y_{t-116}, y_{t-137}$).

There are two number of inputs for FFNN in Gondanglegi area, i.e. 3 inputs ($y_{t-1}, y_{t-36}, y_{t-37}$) and 29 inputs ($y_{t-1}, y_{t-2}, y_{t-3}, y_{t-32}, y_{t-35}, y_{t-36}, y_{t-37}, y_{t-38}, y_{t-39}, y_{t-42}, y_{t-58}, y_{t-65}, y_{t-67}, y_{t-68}, y_{t-71}, y_{t-72}, y_{t-73}, y_{t-75}, y_{t-78}, y_{t-83}, y_{t-94}, y_{t-101}, y_{t-102}, y_{t-103}, y_{t-108}, y_{t-111}, y_{t-119}, y_{t-138}, y_{t-144}$).

The best method for each forecast, based on the smallest RMSE in testing dataset, for Kalipare area show in Table 4. And for Gondanglegi area show in Table 5.

Table 4: The Best Model for Kalipare's Rainfall Forecasting

Forecast	*RMSE*	*SMAPE*	*The best model*
1 dasarian	0.948	10.337	FFNN 7 inputs and 5 neurons
2 dasarian	2.281	40.942	FFNN 7 inputs and 4 neurons
3 dasarian	1.972	31.347	FFNN 7 inputs and 4 neurons
3 months	2.331	30.889	Ensemble FFNN using averaging
6 months	3.275	68.891	Ensemble ARIMAX-FFNN-Hybrid using stacking and optimize at 4 years latest
1 year	2.945	107.190	Ensemble Hybrid using averaging
1,5 years	6.200	101.941	FFNN 7 inputs and 4 neurons

Table 5: The Best Model for Gondanglegi's Rainfall Forecasting

Forecast	*RMSE*	*SMAPE*	*The best model*
1 dasarian	0.347	4.521	Hybrid ARIMA$(1,0,1)(0,1,1)^{36}$-FFNN 3inputs and 3 neurons
2 dasarian	0.531	10.380	Hybrid ARIMA$(1,0,1)(0,1,1)^{36}$-FFNN 3 inputs and 4 neurons
3 dasarian	0.473	8.201	Hybrid ARIMA$(1,0,1)(0,1,1)^{36}$-FFNN 3 inputs and 4 neurons
3 months	1.962	30.391	FFNN 29 inputs and 1 neuron
6 months	2.445	56.790	FFNN 29 inputs and 1 neuron
1 year	3.101	99.331	Ensemble ARIMAX-FFNN-Hybrid using averaging
1,5 years	4.710	74.576	Hybrid ARIMA$(1,0,1)(0,1,1)^{36}$-FFNN 3 inputs and 3 neurons

Table 4 shows that forecast accuracy of ensemble method is less than the membership ensemble for 3 month until 1 year forecasting. Whereas, FFNN with 7 inputs and 4 neurons is the best method for 1, 5 years forecasting rainfall in Kalipare area. RMSE of FFNN with 7 inputs and 4 neuron is similar to standard deviation in Kalipare datasets. It show that it model not too accurate for 1.5 years forecasting.

Table 5 shows that hybrid model, as membership ensemble, is more accurate than ensemble methods for 1.5 years forecasting. Hybrid ARIMA $(1,0,1)(0,1,1)^{36}$-FFNN 3 inputs and 3 neurons is the best method for 1.5 years forecasting of Gondanglegi's rainfall. RMSE of it model is less than standard deviation of datasets in Gondanglegi area. It shows that hybrid method yield accurate prediction.

5. Concluding Remark

In this paper, we have proposed and applied an averaging and stacking method for ensemble ARIMAX, FFNN, Hybrid and ARIMAX-FFNN-Hybrid. Three empirical data were used to compare the forecasting accuracy between ARIMA, ARIMAX, FFNN, Hybrid and ensemble methods. In this paper, there are three conclusions. First, the results at Karangsuko areas showed that ensemble yields more accurate forecast in testing datasets than other methods, whereas the best method in Kalipare area is FFNN and the best method in Gondanglegi is hybrid method. Second, hybrid ARIMAX-FFNN method is not always producing more accurate than ARIMA or ARIMAX. The last conclusion is not always stacking using optimization, in 1 until 5 years latest in training datasets and all training datasets produce more accurate than averaging method. Additionally, the three conclusion in line with the results of M3 competition, i.e. complex methods do not necessarily produce more accurate forecast than simpler one [16].

References

[1] W.W.S. Wei, Time Series Analysis, Univariate and Multivariate Methods, 2nd ed., Pearson Education Inc., Pennsylvania, 2006.

[2] J.D. Cryer, and K.S. Chan, Time Series Analysis with Application in R, 2nd ed., Springer Science+Business Media, New York, 2008.

[3] G.E.P. Box, G.M. Jenkins, and G.C. Reinsel, Time Series Analysis, Forecasting and Control, 3rd ed., Prentice Hall, Englewood Cliffs, 1994.

[4] W.S. McCulloch and W. Pitts, "A Logical calculus of ideas immanent in nervous activity," Bulletin of Mathematical Biophysics, (15), pp. 115–133, 1943.

[5] G.P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," Neurocomputing, (50), pp. 159-175, 2003.

[6] M. Leutbecher and T.N. Palmer, "Ensemble forecasting," Journal of Computational Physics, (227), pp. 3515-3539, 2008.

[7] D.V. Sridha, R.C. Seagrave, and E.B. Bartlett, "Process modeling using stacked neural network," AIChE Journal, (42), pp. 2529-2539, 1996.

[8] J. Zhang, E.B. Martin, A.J. Morris, and C. Kiparissides, "Inferential estimation of polymer quality using stacked

neural networks," Computer Chemical Engineering, (21), pp. 1025-1030, 1997.
[9] C. Shu, and D.H. Burn, "Artificial neural network ensembles and their application in pooled flood frequency analysis," Water Resource Research, (40), pp. 9, 2004.
[10] I. Zaier, C. Shu, T.B.M.J. Ouarda, O. Seidou, and F. Chebana, "Estimation of ice thickness on lakes using artificial neural network ensembles," Journal of Hydrology, (383), pp. 330-340, 2010.
[11] A.J.C. Sharkey, "Combining Artificial Neural Nets: Ensemble and Modular Multi-Net Systems (Ed.), Springer-Verlag, New York, 1999.
[12] L. Breiman, "Stacked regression," Machine Learning, (24), pp. 49-64, 1996.
[13] C.M. Bishop, Neural Network for Pattern Recognition, Clarandon Press, Oxford, 1995.
[14] J. Faraway and C. Chatfield, "Time series forecasting with neural network: a comparative study using the airline data," Applied Statistics, (47), pp. 231–250, 1998.
[15] S.F. Crone and N. Kourentzes, "Input-variable Specification for Neural Network–an Analysis of Forecasting low and high Time Series Frequency," Proceeding of International Joint Conference on Neural Networks, Atlanta, Georgia, USA, June 14-19, 2009.
[16] S. Makridakis, and M. Hibon, "The M3-Competition: results, conclusions and implications," International Journal of Forecasting, 16, pp. 451-476, 2000.

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