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Rainfall Monthly Prediction Based on Artificial Neural Network: A Case Study in Tenggarong Station, East Kalimantan - Indonesia

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Abstract

The accuracy of forecasting rainfall is very important due to the current world climate change. Afterwards, to get an accurate forecasting of rainfall, this paper applied an Artificial Neural Network (ANN) with the Backpropagation Neural Network (BPNN) algorithm. In this experiment, the rainfall data were tested using two-hidden layers of BPNN architectures with three different epochs which were [2-50-10-1, epoch 500]; [2-50-20-1, with epochs 1000 and 1500]. The mean square error (MSE) is employed to measure the performance of the classification task. The experimental results showed that the architecture [2-50-20-1, epoch 1000] produced a good result with the value of MSE was 0.00096341. Furthermore, BPNN algorithm has provided a good model to predict rainfall in Tenggarong, East Kalimantan - Indonesia.

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Keywords: ANN, BPNN, rainfall, MSE

1. Introduction

The rainfall forecast information is an essential requirement to support water resources management especially when it is related to climate change in tropical regions such as in Indonesia. Nowadays, climate change affects the

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pattern of rainfall. The impact of these effects includes extreme occurrence of flooding and droughts [1-3]. Furthermore, the prediction of rainfall with good and accurate method is indispensable in order to anticipate the impact [4-7].

Therefore, in order to produce efficient accurate results of forecasting rainfall and weather, a few methods have been developed. Among them, a statistical model has been widely used to make forecasts of rainfall. This model works by lowering the equation of the data itself (data driven) such as a simple method regression analysis (SRA), decomposition, exponential smoothing method (ES) and autoregressive integrated moving average (ARIMA). Several studies have indicated that they are still inaccurate methods to forecast rainfall and weather because weather data are non-linear [8, 9]. However, in some cases, rainfall prediction statistical method is also able to produce good and accurate predictions [10].

Along with the development of computing technology, many researchers are trying to make predictions using the ANN method in the field of hydrology. Abhishek, K. et al, have conducted research with ANN rainfall prediction in Udupi district of Karnataka, India. Another researchers also have predicted the data series of rainfall for 30 years (1977-2006) at the station of Nagpur, India. The results of this research has revealed that by using a backpropagatin neural network (BPNN), accurate prediction could be obtained [11, 12]. A combination of several ANN algorithms that was designed to predict monthly rainfall in the period of 1949 – 2011, from 24 stations Liuzhou, China, also showed accurate prediction results. The used research method was a hybrid between the ANN algorithm particle swarm optimization (PSO) and genetic algorithm (GA), called HPSOGA. The results of this research confirmed that the ANN has been very effective in making predictions of monthly rainfall in the city of Guangxi, the southwest of China [13].

Therefore, this paper will apply one of the ANN models, namely BPNN, in order to predict the rainfall which has a data type of non-linear in Tenggarong, East Kalimantan, Indonesia. The second part of this paper describes the architecture of BPNN models while time series predictor is discussed in the next part. Section 4 presents the analysis and discussion of the findings. Finally, conclusions are summarized in the last section.

2. Research Method and Process

2.1. The Artificial Neural Network

The ANN is an engineering concept of knowledge in the field of artificial intelligence designed by adopting the human nervous system. Wherein, the main processing of the human nervous system is composed of the brain nerve cells as the basic unit of information processing. In the concept of ANN, the basic unit of information processing are called neurons which serves process information in parallel and immediately. Furthermore, the process of training the ANN has many types and uses, including Perceptron, Backpropagation, Self-Organizing Map (SOM), and Delta [9, 10]. Therefore, this study proposes BPNN algorithm to predict rainfall data by studying and analyzing the patterns non-linear of the past data in order to obtain more accurate prediction results with minimum error. Furthermore, BPNN is briefly described.

2.2. The Backpropagation Neural Network

One of the ANN algorithms called BPNN is a supervised learning method. The BPNN was first introduced by Paul Werbos in 1974, then popularized by Rumelhart and McCelland in 1986. In general, the BPNN works by forwarding the output layer to the input layer in changing the weights [14-16]. Furthermore, ANN works like humans in which learning is performed through examples and exercises in each layer of ANN. The layer in BPNN consists of three parts, namely input layer, hidden layer and output layer, **Fig. 1.**

In general, the steps to build the BPNN algorithm for the prediction of rainfall data were adopted from previous research (Haviluddin & Alfred. R.) which is outlined [16]:

1. Data Normalization and separation; secondary data rainfall of the year 1986 - 2008 will be normalized using an asymptotic function called *sigmoid* function in order to get the value of rainfall data in smaller intervals which are [0.1 0.8] using the following equation,

$$x' = \frac{0.8(x - \alpha)}{b - \alpha} + 0.1$$

where; α is the minimum value, b is the maximum value, x is the data to be normalized, and x' 'is the data that have been transformed. Then, after the data have been normalized, from (1986 to 2003) will be used as the training data, and from (2004 to 2008) will be used as the test data.

2. BPNN design; to determine the amount of data input, hidden, and output layers and parameters to be used.
3. Testing and prediction; the test is aimed to determine the level of accuracy BPNN in predicting rainfall data in the future using statistical method.

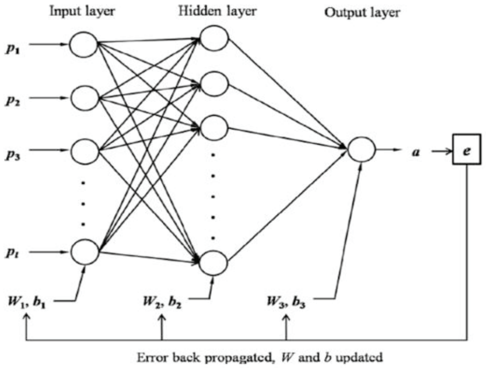


Fig. 1. A typical structure of BPNN architecture [17]

3. Experimental

3.1. Determining training samples and test samples

To get accurate prediction results in the coming year using the BPNN, rainfall data have been divided into two parts, namely the training and testing data. In this experiment, the rainfall data from 1986-2008 (276 samples data series) which have been taken from the station in Tenggarong, East Kalimantan, Indonesia, were used **Table 1** and **Fig. 2**. The data normalization process, which had been carried out, was then divided into training data; 216 (75%) or 1986-2003, and testing data; 60 (25%) or 2004-2008. The data had been governed by the rules of the neural network which consisted of two neurons P = [p(t-2),p(t-1)], and the output neuron was one, p'(t), **Table 2**. Then, the architecture of BPNN would comprise *two-hidden-layer*. The activation functions used from input to hidden layers were *tansig* and *logsig*, and *purelin* that were used for the hidden layers to the output, with Levenberg-Marquardt algorithm (*trainlm*). Furthermore, MSE was used to measure the degree of accuracy of prediction.

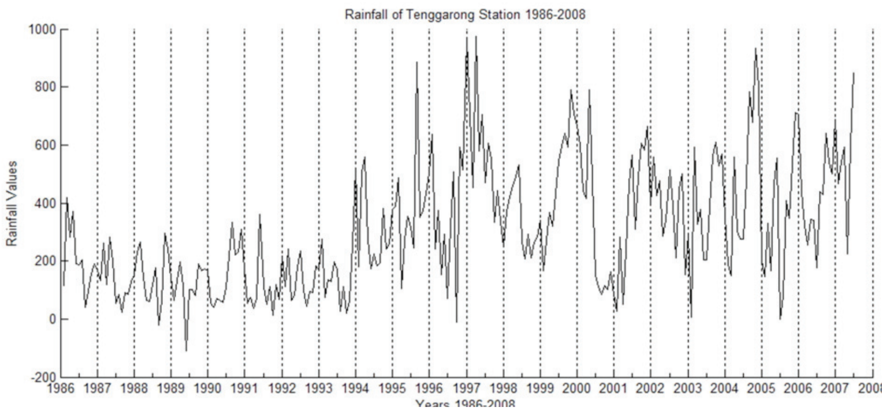


Fig. 2. Plot of real rainfall data of Tenggarong station 1986-2008

Table 1. Real of rainfall data 1986-2008.

Years	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
Jan	114	132	232	259	101	217	49	113	275	181	387	636
Feb	420	262	267	297	80	334	113	242	76	507	486	240
Mar	283	119	142	242	191	221	121	63	135	560	106	373
…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…
Nov	191	130	319	267	56	360	68	182	259	260	431	509
Dec	166	149	0	101	108	112	217	169	521	377	503	187
Years	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	
Jan	0	469	268	545	154	567	513	203	275	1078	439	
Feb	0	607	208	595	112	311	389	387	482	407	430	
Mar	0	551	291	639	86	490	211	563	783	347	642	
…	…	…	…	…	…	…	…	…	…	…	…	
…	…	…	…	…	…	…	…	…	…	…	…	
…	…	…	…	…	…	…	…	…	…	…	…	
Nov	578	489	321	789	239	286	377	302	467	340	598	
Dec	705	531	434	479	469	341	204	274	556	178	851	

Table 2. Rainfall data after normalization.

Group		Input neurons P = [p (t-2),p(t-1)]		Target neurons	Group		Input neurons P = [p (t-2),p(t-1)]		Target neurons
		t-2	t-1	t			t-2	t-1	t
Training Group	1	0.106	0.390	0.262	Testing Group	209	0.539	0.616	0.363
	2	0.390	0.262	0.343		210	0.616	0.363	0.519
	3	0.262	0.343	0.178		211	0.363	0.519	0.396
		…	…	…			…	…	…
		…	…	…			…	…	…
	206	0.288	0.455	0.562		274	0.206	0.554	0.790
	207	0.455	0.562	0.539		275	0.554	0.790	0.106
	208	0.562	0.539	0.616		276	0.790	0.106	0.390

3.2. Flow of BPNN for Prediction

The steps in the BPNN algorithm used in order to predict rainfall data are as follows:
Step 0: Initiation of all the weights;
Step 1: If the termination condition is not fulfilled, do step 2-8;
Step 2: For each pair of training data, do step 3-8

Phase 1: **Feed-forward propagation**

Step 3: Each unit receives input signals and transmitted to the hidden unit above.
Step 4: Calculate all the output in the hidden layer units z_j (j = 1,2,…,p)

$$z\_net_j = v_{jo} + \sum_{i=1}^{n} \mathrm{x_i}\, v_{kj};\ z_j = f(z\_net_j) = \frac{1}{1 + e^{-z\_net_j}}$$

Step 5: Calculate all the network output in unit output y_k (k = 1,2,…,m)

$$y\_net_k = w_{ko} + \sum_{j=1}^{p} z_j w_{kj};\ y_k = f(y\_net_k) = \frac{1}{1+e^{-y\_net_k}}$$

Phase 2: **Back-forward**

Step 6: Calculate factor δ output unit based on unit output error y_k (k = 1,2,…,m)

$$\delta_k = (t_k - y_k)f'(y\text{-}net_k) = (t_k - y_k)y_k(1-y_k)$$

t_k = output target; δ = output unit that will be used in the layer underneath the weight change

Calculate weight change w_{kj}, with the learning rate α ($\delta w_{ji} = \alpha\delta_k z_j$, k = 1,2,…,m; j = 0,1,…,p)

Step 7: Calculate factor δ unit hidden layer based on the error in each hidden layer unit z_j (j = 1,2,…,p)

$$\delta\_net_j = \sum_{k=1}^{m} \delta_k w_{kj}$$

Factor δ hidden layer unit [$\delta j = \delta\_net_j\, f'(z\_net_j) = \delta\_net_j\, z_j\,(1-z_j)$]

Calculate weight change rate v_{ji} [$\delta v_{ji} = \alpha\delta_k z_j$, k = 1,2,…,p; j = 0,1,…,n]

Phase 3: **Weight modification**

Step 8: Calculate the weight of all the changes that led to the output unit

$$wk_{j(new)} = wk_{j(old)} + \delta_{wji};\ (k = 1,2,\ldots,p;\ j = 0,1,\ldots,n)$$

Weight changes that led to the hidden layer units

$$[v_{kj(new)} = v_{kj(old)} + \delta_{vji};\ (j = 1,2,\ldots,p;\ w = 0,1,\ldots,n)]$$

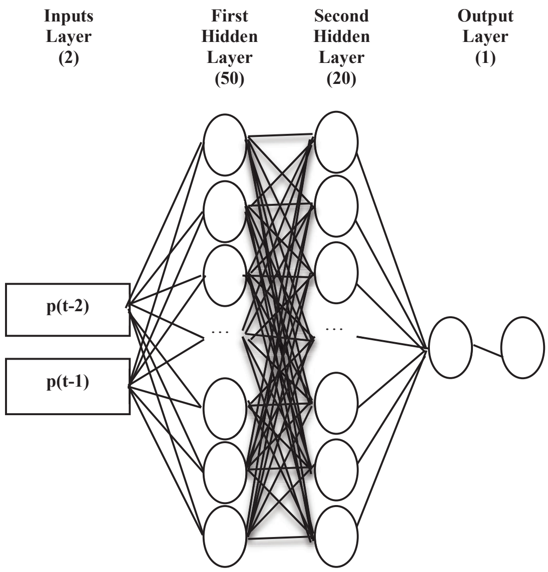


Fig. 3. A typical of BPNN by using 2-50-20-1 architecture

In this study, the input layers were evaluated based on a predefined function: P = [*p(t-2),p(t-1)*], and the output layer was one (*t*), where the values for *t-2*, *t-1*, and *t* were taken from **Table 2**. In order to demonstrate, the hidden layers were used two layers with first layer 50 and second layers 10 and 20. The architecture of BPNN as shown in **Fig. 3**.

4. Results and Discussions

This section describes the test results of rainfall data using the BPNN based on two different architectures. The first architecture 2-50-10-1 in which the first number indicates the number of neurons in the input layer, the second and the third one represent the neurons in the hidden layers, and the last number represents the neurons in the output layer. Then, epoch and learning rate have been set to 500 and 0.1. To compare the predicted output with the desired output, MSE was predefined as shown in **Table 3** and **Table 4**. The first BPNNN architecture that produced MSE was 0.00098998. Then, the second architecture of 2-50-20-1 was used in two different epochs of 1000 and 1500, with learning rate of 0.1. It has resulted in each MSE of 0.00096341 and 0.00099613. **Fig. 4** shows the best model used the BPNN architecture 2-50-2-1 with epoch 1000 and learning rate 0.1, **4.(a)** shows that the plot results of predicting, **4.(b)** shows the best regression results obtained was 0.9877, and **4.(c)** shows that the best performance of training obtained was 0.00096341. This means that the rainfall data training results had a good prediction accuracy by using the equation Y = 0.97*Target+0.009.

In this experiment, the duration of the iteration time was also investigated. The Iteration time training has met the best performance, even though not reaching predetermined times for each architecture. In the first architecture, the faster iteration has been achieved in 18 seconds and reached the epoch 107. Meanwhile, the second architecture, the iteration time was 22 seconds and reached the epoch 57. However, the third architecture has demonstrated longer iteration time with 45 seconds and reached the epoch 128, but the performance of results was good. On the other hand, the performances obtained in the first and second architecture were still not good. This means, the accuracy of determining the BPNN architecture also affects the performance of the duration of the iterations.

In this experiment, the best assessment of BPNN models was defined in which MSE < 0.05. Thus, the results of the third test architecture has gained a good value that was similar value of learning rate and the value of different epochs. Epochs also affect the performance of BPNN; thus epochs with values of 500 and 1500 have poor value because they were below a predetermined value. This means that the model BPNN architecture of 2-50-20-1 with epoch 1000 and learning rate 0.1 is an excellent model to predict rainfall data in the future, **Fig. 5**.

Table 3. Results of training.

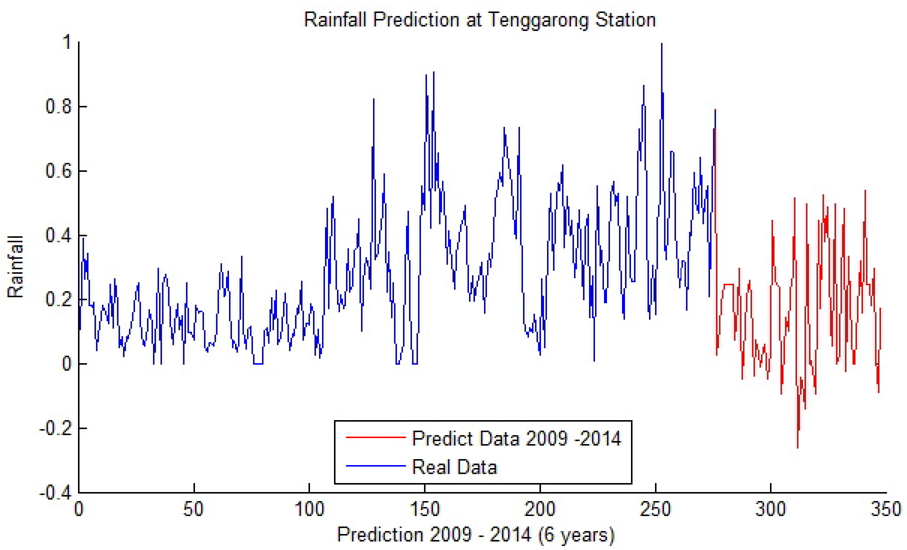
Model	Architectures	Epochs	MSE Training	MSE Testing
1	2-50-10-1	500	0.00098998	1.74433447
2	**2-50-20-1**	**1.000**	**0.00096341**	**0.70100104**
3	2-50-20-1	1.500	0.00099613	14.67280666

Table 4. Errors of Epochs of Testing Data.

Real	Epochs			Real	Epochs		
	500	1000	1500		500	1000	1500
0.143	0.2925	0.4323	0.1937	0.327	-0.5572	0.1493	-2.3759
0.104	0.5308	0.4850	0.4034	0.176	1.5047	-0.2460	-0.0282
0.080	0.8728	0.8726	0.0244	0.137	-0.3872	-0.0113	0.4126
0.108	-0.3587	-1.2480	-0.6389	0.520	-0.1555	-0.0130	-0.1398
0.094	-1.6781	1.2566	-0.1025	0.280	-2.0879	-1.8304	-2.0696
0.150	-0.1717	-1.5428	-0.0030	0.255	-0.2791	1.0997	-3.9786
0.080	0.0593	0.1434	0.1970	0.255	-0.1678	-1.8606	-3.4103
0.024	-0.2232	-0.3861	1.4735	0.447	-0.2412	-0.2492	-1.6702
0.262	1.1744	-0.2270	-0.4060	0.727	-0.4653	-0.5044	0.3662
0.048	0.1623	0.0155	0.3745	0.629	-0.4506	-0.0013	0.8815
0.222	0.2195	0.0884	0.5041	0.865	-2.4885	-1.5392	-0.2284
0.435	-1.7824	-0.5311	-4.2696	0.742	-2.0478	-0.6638	-3.8724
0.526	-0.6498	-0.4991	-4.8100	0.185	1.4723	-0.1672	-2.5315
0.288	1.2147	0.3246	-3.9105	0.136	-1.6795	-0.3401	-3.1516
0.455	-2.1171	-1.1714	-3.6711	0.306	-1.9442	-0.0515	-3.9297
0.562	-0.6795	-0.6105	-4.8467	0.153	2.1422	0.0470	-2.2693

0.539	-2.2723	-0.3419	-4.8234	0.433	-3.9843	-0.1894	-3.6040
0.616	-0.7499	0.2745	-4.9005	0.516	-1.6138	-0.6533	-3.6835
0.363	-2.4693	1.1118	-4.6472	1.000	-2.2648	-0.7671	-4.6219
0.519	-0.4430	-1.8911	-4.8031	0.377	-1.2542	-0.4197	-2.9921
0.396	0.3578	-0.5505	-4.6807	0.321	2.3012	-0.0689	-3.0867
0.442	0.2318	-1.0068	-4.7271	0.494	0.2891	-0.2320	-4.6118
0.265	0.8641	-0.5944	-4.5499	0.659	-0.9804	-0.4187	-4.8709
0.316	-1.3159	-0.3334	-4.6009	0.655	-0.2505	-0.5091	-4.9397
0.476	-2.2508	-0.2075	-4.7604	0.406	-0.0176	-0.6661	-4.6907
0.361	-1.9142	0.1259	-4.0362	0.299	0.1319	-0.2218	-4.5833
0.196	0.0037	0.1456	-3.9108	0.237	0.8967	-0.3984	-4.5206
0.418	0.0491	0.0452	-4.7030	0.318	-1.7970	-0.1021	-4.5092
0.463	0.1623	0.3375	-4.7475	0.315	-1.6865	-0.0366	-3.9422
0.141	0.5337	1.6425	-4.4256	0.165	-1.1048	-0.0095	-3.6035
0.272	0.4223	-1.3188	-4.5564	0.407	-1.5280	-0.0224	-4.6921
0.006	-0.5911	-0.2305	-3.1743	0.399	-0.5316	0.0332	-4.6832
0.549	-2.2526	-0.5145	-4.8173	0.595	-0.0916	-0.0177	-4.8799
0.303	-1.8107	-0.2148	-4.5879	0.504	-0.4101	0.2407	-4.7882
0.350	-2.0840	-0.1856	-4.6309	0.466	-0.1820	0.2280	-4.7504
0.189	-1.6177	-0.1941	-3.8117	0.638	-0.3406	0.5434	-4.9224
0.188	-0.7880	-0.7929	-2.2587	0.434	-0.0769	1.7107	-4.7184
0.359	-1.9038	-0.3749	-4.6386	0.502	0.1658	-2.3305	-4.7860
0.522	-2.2622	-0.3483	-4.8068	0.551	0.7761	0.7939	-4.8358
0.566	-0.4146	0.6569	-4.8493	0.206	-2.3482	1.9039	-4.4910
0.490	-0.0032	0.3228	-4.7744	0.554	-0.7451	-1.6187	-4.8389
0.529	0.4752	-0.2021	-3.8931	0.790	0.8877	-2.6168	-5.0695

(a)



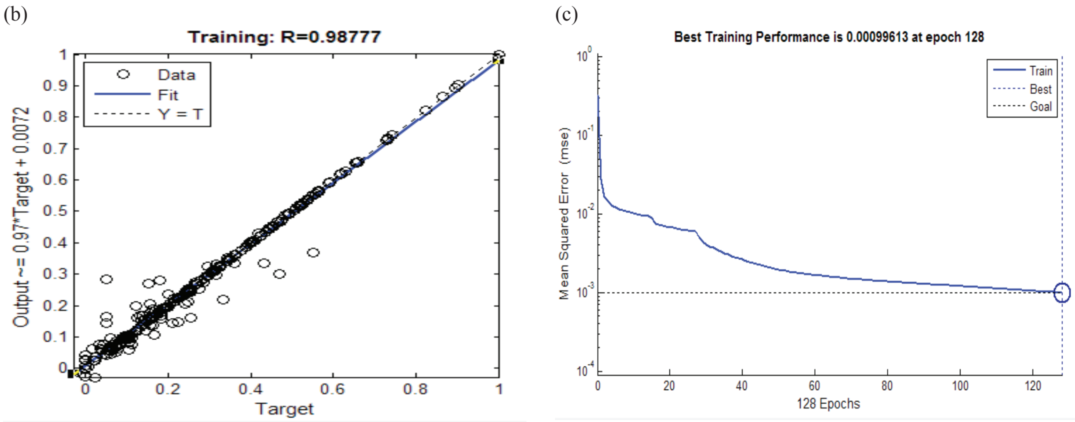


Fig. 4. (a) Plot result of prediction, (b) Regression, and (c) Performance

Table 5, the 2009-2014 predicted results have revealed that there would be heavy rainfall in September 2009, July 2010, August 2011, September 2012, March 2013 and June-July 2014 respectively with 566, 670, 450, 87, 634 and 65. However, the highest rainfall prediction results would occur in July 2010 of 0.775. Meanwhile, the average rainfall was high in 2009, 2010, 2011, 2012, 2013 and 2014 respectively with 258, 299, 125, 26, 179 and 33. It can be said there would often rain around Tenggarong area in 2009, **Fig. 5**. These test results are in accordance with the nature of the rainfall in the Mahakam river basin which has an equatorial type of two peak rainy seasons in April and November the detail plot prediction of each year as shown in **Fig 6**.

Table 5. Rainfall prediction value 2009-2014.

Years / Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Min	Max	Mean
2009	97	489	318	210	210	210	210	210	566	336	192	48	48	566	258
2010	535	167	178	373	70	109	670	105	637	595	69	79	69	670	299
2011	53	226	138	170	22	35	69	450	90	134	109	4	4	450	125
2012	12	2	1	27	14	15	12	10	87	45	47	42	1	87	26
2013	361	9	634	72	2	6	149	280	2	61	568	4	2	634	179
2014	9	40	17	25	29	65	65	30	65	4	3	40	3	65	33

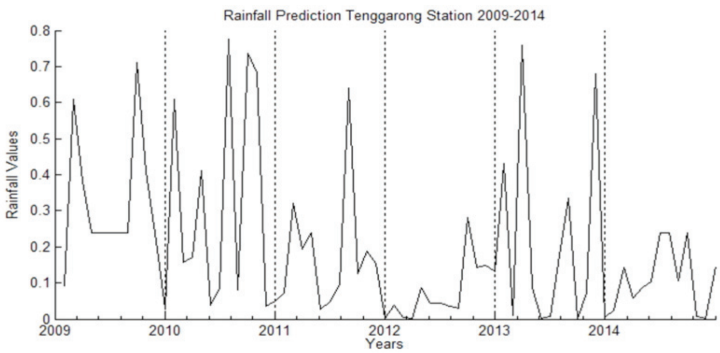


Fig. 5. Plot result of prediction with [2-5-20-1], epoch 1.000

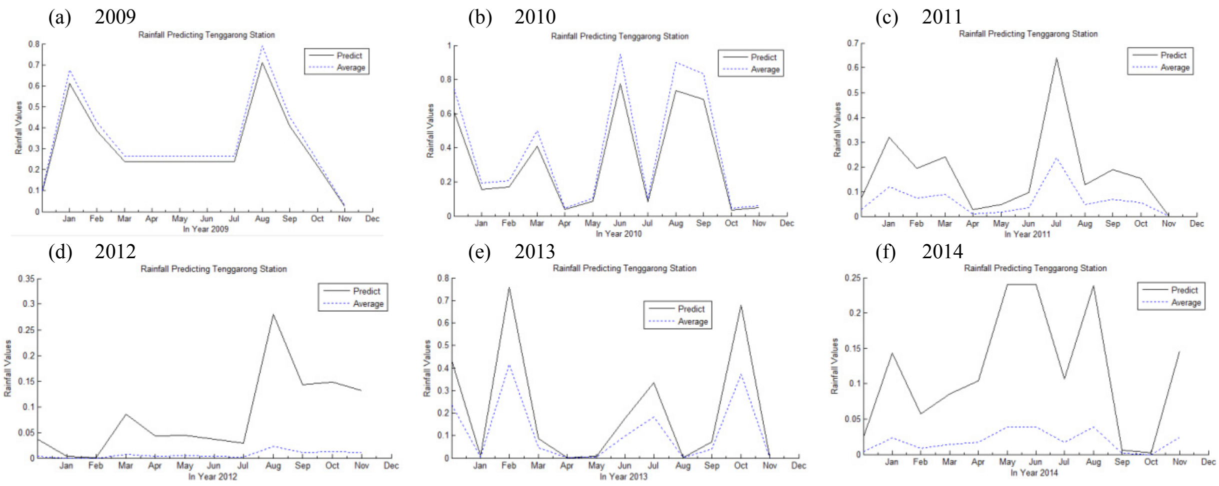


Fig. 6. Plot result of prediction of each year's 2009-2014

5. Conclusion

In this paper, a BPNN algorithm has been used to model and predict rainfall in Tenggarong, East Kalimantan - Indonesia. After testing the three architectures with different epochs; 500, 1000 and 1500, then the best MSE value obtained was 0.00096341, with 2-50-20-1 architecture and epochs 1000, the results of this study have showed that BPNN models can be used as a predictive algorithm that provides a good predictive accuracy. The prediction results have demonstrated the suitability of the area Tenggarong that has an equatorial type of two peak rainy seasons in April and November . Future work is suggested to include a comparison of a few ANN methods and the optimization process in order to obtain more accurate prediction results.

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