ISSN 1112-9867

Available online athttp://www.jfas.info

MATHEMATICAL MODEL FOR DISSOLVED OXYGEN PREDICTION IN CIRATA RESERVOIR, WEST JAVA BY USING ARTIFICIAL NEURAL NETWORK

S. Supian¹, K. T. B. Achmad², I. Riyadhi³, Subiyanto⁴, G. Adiana⁵, A. F. Ireana Yusra⁵ and M. Mamat^{6,*}

¹Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, 45363 Bandung, Indonesia

²Faculty of Animal Husbandry, Universitas Padjadjaran, 45363 Bandung, Indonesia

³Master Program on Environmental Studies, Universitas Padjadjaran, 40132 Bandung,

Indonesia

⁴Department of Marine Science, Faculty of Fishery and Marine Science, Universitas Padjadjaran, 45363 Bandung, Indonesia

⁵East Coast Environmental Research Institute (ESERI), Universiti Sultan Zainal Abidin, 21300 Kuala Terengganu, Malaysia

⁶Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, 21300 Kuala Terengganu, Malaysia

Published online: 15 January 2018

ABSTRACT

Cirata reservoir is one of the reservoirs which suffer eutrophication with an indication of rapid growth of water hyacinth and mass fish deaths as a result of lack of oxygen. This paper presents the implementation and performance of mathematical model to predict the concentration of dissolved oxygen in Cirata Reservoir, West Java by using Artificial Neural Network (ANN).

Author Correspondence, e-mail: must@unisza.edu.my

doi: http://dx.doi.org/10.4314/jfas.v10i1s.5

The simulation program was created using Visual Studio 2012 C# software with ANN model implemented in it. Prediction process was carried out by training process followed by a testing process using weights that have been obtained from training process. ANN model for predicting dissolved oxygen in Cirata reservoir shows the best performance with correlation coefficient value of 77.44%, Root Mean Square Error (RMSE) = 0.12 and Willmott's Index of Agreement (WIA) = 0.72.

Keywords: reservoir eutrophication; artificial neural network; mathematical model; simulation; validation.

1. INTRODUCTION

Cirata reservoir is in eutrophication condition because of the huge amount of nitrogen and phosphorus. This condition can be seen from the rapid growth of water hyacinth and mass fish deaths because the oxygen inside the water is in lack condition [11]. Mass fish deaths financially impact the producer (floating net cage owner) because they lose a lot of fish and their remaining fish are cheap valued. In January 2014, total financial loss because of mass fish deaths in Jatiluhur and Cirata reservoir estimated about 3.6 billion IDR. This phenomenon also impacts the consumers, which are mostly from Jakarta, West Java, and Central Java will lose one of their protein sources [2, 15].

Eutrophication is a big problem for many people, so the government must solve it for the common good. One method that can be used to help solve it is by making a model that can represent the eutrophication phenomenon in Cirata reservoir. The best model for this problem is prediction model because it can help decision-making process by using historical data.

ANN (Artificial Neural Network) model is an alternative prediction model that can be used to predict eutrophication problem [12]. By using this model, the government will know phenomenon prediction that will happen (e.g. mass fish deaths) and anticipates it. Some research about eutrophication problem using ANN model are the research done by [8] using ANN model to predict 4 eutrophication indicators (total phosphor, Secchi disk, dissolved oxygen and chlorophyll-a) in Te-Chi reservoir, China. These models have a performance with a correlation coefficient between prediction results and observation results above 70%.

Another research was done by [5] using ANN model to predict 4 eutrophication indicators (total nitrogen, Secchi disk, dissolved oxygen and chlorophyll-a) at Fuxian Lake, China. These models have a performance with RMSE less than 0.2 and correlation coefficient above 70%.

The explanation above shows that ANN model has a good performance in predicting eutrophication problem. But, ANN model implementation from those researchers is limited to predict this time (t), not for the future/next time period (t+1). This study will discuss ANN [16-19] model implementation for predicting dissolved oxygen at next time period (t+1) with consideration of previous location (l-1).

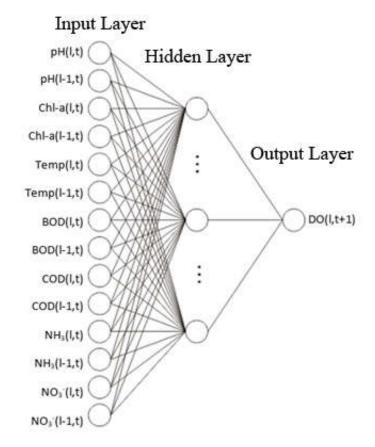
2. METHODOLOGY

This study uses secondary data from BPWC (*Badan Pengelola Waduk Cirata*) and PPSDAL (*Pusat Penelitian Sumber Daya Alam dan Lingkungan*) Universitas Padjadjaran. There are 40 sets of data from 2004-2014 in the quarterly time period. Table 1 shows water quality parameters used in this study.

Table 1. Parameters	
Parameter	Unit
pH (acidity)	-
Chl-a (Chlorophyll-a)	μg/L
Temp (temperature)	°C
BOD (Biological Oxygen Demand)	mg/L
COD (Chemical Oxygen Demand)	mg/L
NH ₃ (ammonia)	mg/L
NO ₃ ⁻ (nitrate)	mg/L
DO (Dissolved Oxygen)	mg/L

Table 1. Parameters

ANN model for dissolved oxygen prediction in this study made based on research from [5] which consider time factor and previous location, and in [6] which consider NO_3^- parameter as an important nutrient source causing eutrophication. COD as a result of anaerobic decomposition of detritus that reactive to oxygen also included in the model [4-6]. ANN



model for dissolved oxygen prediction scheme can be seen in Fig. 1.

Fig.1. ANN model for dissolved oxygen prediction scheme

where l = location being calculated, l-1 = previous location and t = time period being calculated

t + 1 = upcoming time period.

Assumptions used in this study are:

- 1. Pollutants in the reservoir are well mixed from the bottom to the surface.
- 2. Pollutants from floating net cage included in water quality parameters.
- 3. Hydrodynamic in the reservoir is constant.
- 4. Uncalculated parameters are considered not significant.

There are 9 sampling locations in Cirata reservoir as shown in Fig. 2. Because of this study use water quality data inside the reservoir, so that the data used is the data from location 2-7. Data testing that will be done in this study can be seen in Table 2.

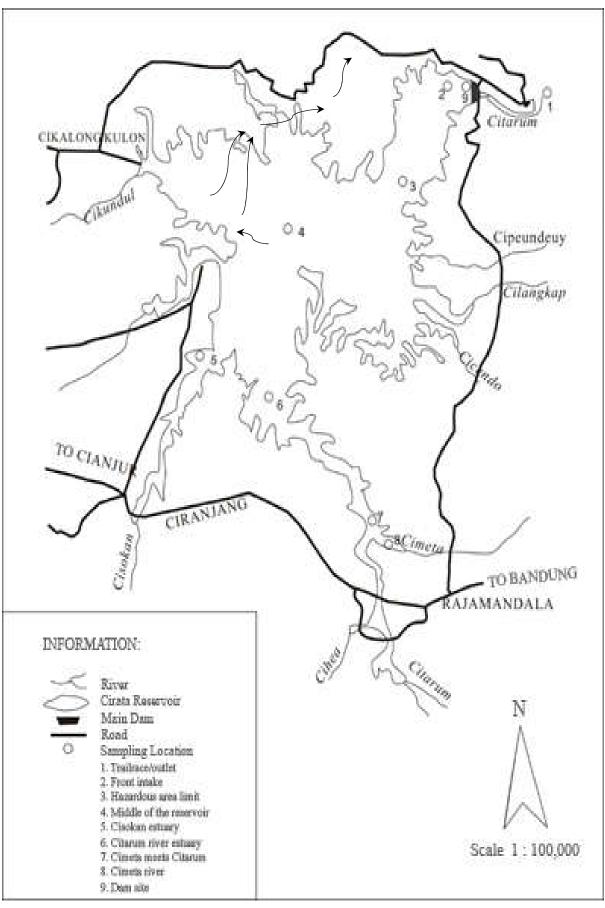


Fig.2. Sampling location map [1]

	14510 2	· Data testing	
Test	Location being Calculated	Previous Location	Season
1	Location 2	Location 3	All season
2	Location 3	Location 4	All season
3	Location 4	Location 5	All season
4	Location 4	Location 6	All season
5	Location 6	Location 7	All season
6	Location 2	Location 3	Rainy season
7	Location 3	Location 4	Rainy season
8	Location 4	Location 5	Rainy season
9	Location 4	Location 6	Rainy season
10	Location 6	Location 7	Rainy season
11	Location 2	Location 3	Dry season
12	Location 3	Location 4	Dry season
13	Location 4	Location 5	Dry season
14	Location 4	Location 6	Dry season
15	Location 6	Location 7	Dry season

 Table 2. Data testing

Verification is an error checking process of the simulation program that has been made and validation is a determining process of the model in representing the system studied [7]. In this study, the validation process will be done with some standard error, i.e.:

• The correlation coefficient (r) to determine the correlation degree between predicted results and observation results [10].

$$r = \frac{n \sum x_i y_i - (\sum x_i) (\sum y_i)}{\sqrt{\left\{n \sum x_i^2 - (\sum x_i)^2\right\} \left\{n \sum y_i^2 - (\sum y_i)^2\right\}}}$$
(1)

• Root Mean Squared Error (RMSE) to determine the standard deviation between predicted results and observation results [13].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (a_i - t_i)^2}$$
(2)

• Willmott's Index of Agreement (WIA) as a standard measure to determine the error degree of the model. WIA value is in the interval [0, 1]. A good model is the model with WIA value approaching to 1 [14].

$$WIA = d = 1 - \frac{\sum_{i=1}^{n} (P_{i-}O_{i})^{2}}{\sum_{i=1}^{n} (|P_{i} - \overline{O}| + |O_{i} - \overline{O}|)^{2}}$$
(3)

where n = total data, $x_i = a_i = P_i =$ the predicted result at the time period I, $y_i = t_i = O_i =$ observation result at the time period I and $\overline{O} = \overline{t} =$ observation result average.

3. RESULTS AND DISCUSSION

In the validation process for all season (test 1-5), total data used are 40 sets divided into 30 sets for training process and the rest 10 sets for the testing process. In the validation process for the rainy season (test 6-10) and dry season (test 11-15), total data used are 20 sets divided into 15 sets for training process and the rest 5 sets for the testing process. Total training and testing conducted are 30 times. ANN architecture is using sigmoid alpha value = 2, 4 hidden neurons, learning rate = 0.1 and maximum iteration = 10000.

				Training				
Test	1	2	3	4	5	6	7	8
R	79.95	94.66	97.22	94.84	92.31	99.3	97.14	99.07
RMSE	0.08	0.05	0.04	0.05	0.08	0.02	0.04	0.02
WIA	0.87	0.97	0.99	0.97	0.96	1	0.99	1
Test	9	10	11	12	13	14	15	
R	96.23	99.57	99.57	97.97	95.44	98.83	96.69	
RMSE	0.04	0.02	0.01	0.03	0.05	0.03	0.04	
WIA	0.98	1	1	0.99	0.98	0.99	0.98	
				Testing				
Test	1	2	3	4	5	6	7	8
R	-8.83	-22.92	-42.49	-24.6	77.44	-97.98	14.19	8.42

Table 3. ANN model for dissolved oxygen prediction validation results

RMSE	0.16	0.34	0.3	0.24	0.12	0.18	0.19	0.21
WIA	0.3	0.43	0.26	0.4	0.72	0	0.52	0.42
Test	9	10	11	12	13	14	15	
R	-11.46	-85.2	41.71	-45.87	34.32	-15.69	-33.42	
RMSE	0.24	0.22	0.21	0.21	0.12	0.22	0.28	
WIA	0.46	0.04	0.5	0.06	0.42	0.36	0.35	

Data in Table 3 shows that for the overall training results, test 11 was the best with the biggest correlation coefficient, the smallest RMSE value, and the greatest WIA value. Therefore, it can be concluded that ANN model has the best performance in recognizing dissolved oxygen data pattern with a correlation coefficient of 99.57%, RMSE = 0.01 and WIA = 1.

Based on the overall testing results, the 5th test is the best with a good correlation coefficient, good RMSE value and the greatest WIA value. Therefore, it can be concluded that ANN model has the best performance with a correlation coefficient of 77.44%, RMSE = 0.12 and WIA = 0.72. Training and testing results using simulation program of the 5th test can be seen in Fig. 4 and 5.

	Testing			
Mod	lel Settings			Sigmoid Alpha 2 Hidden Neuron 4
		DO 5		
0	Predict Phosphate			Learning Rate 0,1 Max. Iteration 10000
0	Predict Tranparency			Start Stop
0	Predict Chlorophyll-a			Training Info
	Predict Dissolved Oxy	rgen		Total Sample : 30 r 92,31%
	in the second			Iteration RMSE 0,08
Trainir	ng File G:\TESIS M	I.IL\DATA FIX\do5tra	ainin Open	10000 WIA 0.96
	pH (l.t)	pH (I-1,t)	Chl-a (I,t) ^	
×.	0.688715953	0,714669261	0,023937981	ANN Model for Dissolved Oxygen Prediction (Training)
	0,389105058	0,482490272	0,000655252	Observation — Prediction
	0,338521401	0,354085603	0,00167217	
	0,221789883	0,221789883	0,00167217	0,9
	0,377431907	0,455252918	0,028711961	0.8
	0,468287938	0.494163424	0,000765879	0.7
	0,55381323	0,607003891	0,001182858	
	0,254202335	0,39688716	0,001182858	0.6 0.6
	0,254202335	0,299610895	0,019164	
	0.403501946	0,455252918	0,000544625	
	0,544747082	0,649805447	0.002161481	
	0,592723735	0,710116732	0,002161481	
	0,610894942	0,591439689	0,038259922 🗸	
			>	
<				
	ivity Analysis			

Fig.4. Training result of the 5th test

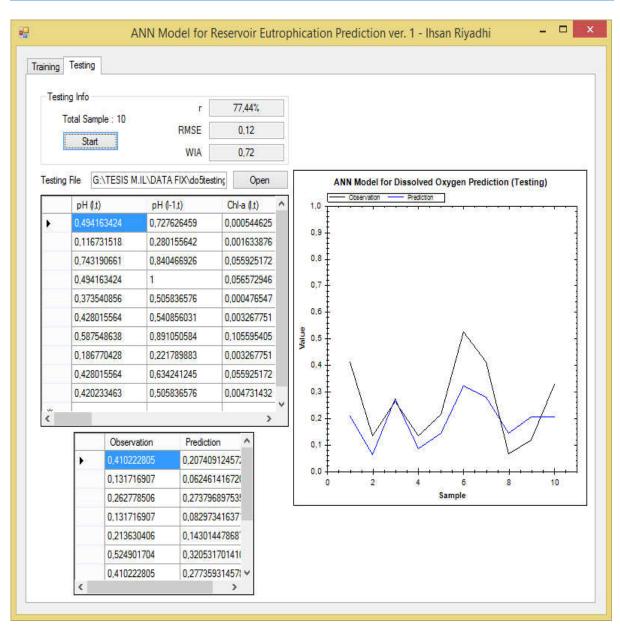


Fig.5. Testing result of the 5th test

To determine sensitivity level of each input to output in the model which has been obtained from training process, a sensitivity analysis must be. Sensitivity analysis in this study is done by adding each input value by 5%. Change occurs on output is calculated as a parameter sensitivity level [5]. Sensitivity analysis results can be seen in Table 4.

Test\Parameter	pH(l,t)	pH(l-1,t)	Chl-a(l,t)	Chl-a(l-1,t)	Temp(l,t)	Temp(l-1,t)	BOD(l,t)	BOD(l-1,t)
1	35.85	-3.81	1.15	-0.63	27.87	-19.82	-38.7	21.08
2	131.86	-172.04	-1.8	-1.32	-56.02	42.27	56.15	-71.39
3	<u>44.01</u>	<u>-62.83</u>	<u>6.98</u>	-2.71	-40.67	<u>33</u>	<u>-43.59</u>	<u>-1.3</u>

Table 4. Sensitivity analysis of ANN model for dissolved oxygen prediction

4	58.44	-134.32	-5.49	1.93	-22.96	77.53	38.32	-33.85
5	<u>0.15</u>	<u>-70.45</u>	<u>7.24</u>	<u>-2.91</u>	<u>9.31</u>	<u>5.12</u>	<u>-7.18</u>	<u>13.34</u>
6	73.49	1.6	3.89	-4.65	32.39	-9.25	-11.34	14.94
7	-15.87	-51.39	0.82	-16.32	2.62	102.93	51.5	-19.91
8	-149.94	115.27	-18.14	-0.8	-6.67	19.73	1.79	-3.92
9	-12.55	-57.18	-8.48	-1.45	8.16	42.12	0.84	0.81
10	<u>194.91</u>	<u>-172.17</u>	<u>16.25</u>	<u>0.06</u>	<u>54.57</u>	<u>14.45</u>	<u>-14.11</u>	<u>42.27</u>
11	<u>37.6</u>	<u>-2.78</u>	<u>1</u>	<u>1.47</u>	<u>124.16</u>	-82.09	<u>-33.79</u>	<u>17.38</u>
12	-21.83	-147.03	-1.9	1.06	-94.89	-59.37	36.55	-30.38
13	155.44	-276.13	3.3	-3.25	111.98	99.74	85.87	-15.52
14	182.95	-270.42	-1.69	0.76	15.52	142.62	104.19	-50.29
15	-128.67	-146.77	-0.6	-4.86	25.44	51.85	106.38	80.05
Test\Parameter	COD(l,t)	COD(l-1,t)	NH3(l,t)	NH3(l-1,t)	NO3(l,t)	NO3(l-1,t)		
1	65.87	-32.8	-1.54	4.63	5.83	1.9		
2	-55.12	98.27	26.75	-50.93	-17.49	1.21		
3	<u>140.58</u>	<u>-37.01</u>	<u>-17.65</u>	<u>23.7</u>	<u>-11.67</u>	<u>4.67</u>		
4	46.89	-67.53	-17.05	24.45	-11.81	30.1		
5	<u>58.7</u>	<u>-51.49</u>	<u>5.01</u>	<u>0.2</u>	<u>16.35</u>	<u>-21.03</u>		
6								
	6.39	-34.64	-13.93	3.15	-0.65	8.21		
7	6.39 -57.45	-34.64 -65.77	-13.93 13.98	3.15 20.1	-0.65 3.04	8.21 12.75		
7 8								
	-57.45	-65.77	13.98	20.1	3.04	12.75		
8	-57.45 -16.31	-65.77 -10.36	13.98 0.86	20.1 10.7	3.04 2.96	12.75 -17.51		
8 9	-57.45 -16.31 -24.37	-65.77 -10.36 -16.73	13.98 0.86 1.96	20.1 10.7 5.84	3.04 2.96 -0.18	12.75 -17.51 -7.28		
8 9 10	-57.45 -16.31 -24.37 <u>-51.25</u>	-65.77 -10.36 -16.73 <u>27.94</u>	13.98 0.86 1.96 <u>10.34</u>	20.1 10.7 5.84 <u>9.24</u>	3.04 2.96 -0.18 <u>-27.67</u>	12.75 -17.51 -7.28 <u>-0.91</u>		
8 9 10 11	-57.45 -16.31 -24.37 <u>-51.25</u> <u>43.06</u>	-65.77 -10.36 -16.73 <u>27.94</u> <u>20.1</u>	13.98 0.86 1.96 <u>10.34</u> <u>-0.35</u>	20.1 10.7 5.84 <u>9.24</u> <u>-1.5</u>	3.04 2.96 -0.18 <u>-27.67</u> <u>-15.6</u>	12.75 -17.51 -7.28 <u>-0.91</u> <u>-0.85</u>		
8 9 10 11 12	-57.45 -16.31 -24.37 <u>-51.25</u> <u>43.06</u> 65.85	-65.77 -10.36 -16.73 <u>27.94</u> <u>20.1</u> 119.05	13.98 0.86 1.96 <u>10.34</u> <u>-0.35</u> -0.84	20.1 10.7 5.84 <u>9.24</u> - <u>1.5</u> -3.75	3.04 2.96 -0.18 <u>-27.67</u> <u>-15.6</u> -8.6	12.75 -17.51 -7.28 <u>-0.91</u> <u>-0.85</u> 4.47		

Note: the best performance per season, the best overall performance

From the previous discussion, the 5th test has the best performance. This good performance can't be separated from the model that has been obtained from training process. Based on data in Table 4, a sensitive parameter affecting dissolved oxygen decline for the next quarter at location 6 is pH at location 7 with sensitivity value of -70.45%, followed by COD at station 7 with sensitivity value of -51.49% and nitrate at station 7 with sensitivity value of -21.03%. Increased pH causing declined dissolved oxygen because it will increase phytoplankton population that requires oxygen for respiration process, so that the dissolved oxygen content decreased [4]. Increased COD causing declined dissolved oxygen because chemical compounds require oxygen in the process of decay, so the dissolved oxygen content decreased [3].

Increased nitrate cause declined dissolved oxygen because it will increase phytoplankton population too that require oxygen for respiration process so that the dissolved oxygen content decreased [4]. In addition, the decomposition process of dead phytoplankton both aerobic and anaerobic causing declined dissolved oxygen too [9]. Therefore, it can be concluded that low dissolved oxygen content in Cirata reservoir is caused by pH change (towards alkaline conditions), high COD which require oxygen in the decay process and high nitrate nutrients which increase phytoplankton population that requires oxygen for respiration and decomposition of dead phytoplankton.

4. CONCLUSION

The conclusions from this study are:

- ANN model for dissolved oxygen prediction can be implemented in a simulation program using Visual Studio 2012 C # with training process followed by a testing process using weights that have been obtained in training process.
- 2. ANN model for dissolved oxygen prediction has the best performance with a correlation coefficient of 77.44%, RMSE = 0.12 and WIA = 0.72.
- 3. The ANN model can help represent eutrophication phenomenon occurred in Cirata reservoir through sensitivity analysis.

Based on the results of this study, there are some suggestions, i.e.:

- 1. Collaborate software and hardware to create a real-time water quality surveillance system and automatically interpreted by the program.
- 2. Determine the long-term standard for water quality sampling to make sure data continuity and compatibility to a variety of models.

5. ACKNOWLEDGEMENTS

We would like to thank the financial support from Universitas Padjadjaran through the grant program of the Academic Leadership Grant (ALG) under the coordination of Prof. Dr. Sudradjat.

6. REFERENCES

 BPWC, Perkembangan Jumlah KJA (1988-2013). Kab. Bandung Barat: Badan Pengelola Waduk Cirata, 2014

[2] Pos Kota News. Puluhan ton ikan di Cirata mati, peternak rugi besar. 2014, http://poskotanews.com/2014/01/27/puluhan-ton-ikan-di-cirata-mati-peternak-rugi-besar/

[3] Garno Y S. Beban pencemaran limbah perikanan budidaya dan eutrofikasi di perairanWaduk pada DAS Citarum. Jurnal Teknologi Lingkungan, 2002, 3(2):112-120

[4] Garno Y S. Kualitas air dan dinamika fitoplankton di perairan Pulau Harapan. Jurnal Hidrosfir Indonesia, 2008, 3(2):87-94

[5] Huo S, He Z, Su J, Xi B, Zhu C. Using artificial neural network models for eutrophication prediction. Procedia Environmental Sciences, 2013, 18:310-316

[6] Karul C, Soyupak S, Çilesiz A F, Akbay N, Germen E. Case studies on the use of neural networks in eutrophication modeling. Ecological Modelling, 2000, 134(2):145-152

[7] Kleijnen J P. Verification and validation of simulation models. European Journal of Operational Research, 1995, 82(1):145-162

[8] Kuo J T, Hsieh M H, Lung W S, She N. Using artificial neural network for reservoir eutrophication prediction. Ecological Modelling, 2007, 200(1):171-177

[9] Salmin, Oksigen terlarut (DO) dan kebutuhan oksigen biologi (BOD) sebagai salah satu indikator untuk menentukan kualitas perairan. Oseana, 2005, XXX(3):21-26

[10] N. Sudjana. Metode statistika. Bandung: Tarsito, 2005

[11] Tjahjo D W, Purnamaningtyas S E. Kajian kebiasaan makanan, luas relung, dan interaksi antar jenis ikan di Waduk Cirata, Jawa Barat. Jurnal Iktiologi Indonesia, 2008, 2(2):59-65

[12] Velten K. Mathematical modeling and simulation: Introduction for scientists and engineers. New Jersey: John Wiley and Sons, 2009

[13] Wang W, Xu Z, Weizhen Lu J. Three improved neural network models for air quality forecasting. Engineering Computations, 2003, 20(2):192-210

[14] Willmott C J, Robesonb S M, Matsuuraa K. Short communication: A refined index of model performance. International Journal of Climatology, 2012, 32(13):2088-2094

[15] Koran Jakarta. Air Waduk tercemar, ikan mati terkapar. 2014, http://koran-jakarta.com/?26219-air%20waduk%20tercemar,%20ikan%20mati%20terkapar

[16] Zabidi A, Yassin I M, Hassan H A, Ismail N, Hamzah M M, Rizman Z I, Abidin H Z. Detection of asphyxia in infants using deep learning convolutional neural network (CNN) trained on Mel frequency cepstrum coefficient (MFCC) features extracted from cry sounds. Journal of Fundamental and Applied Sciences, 2017, 9(3S):768-778

[17] Hashim F R, Daud N N, Ahmad K A, Adnan J, Rizman Z I. Prediction of rainfall based on weather parameter using artificial neural network. Journal of Fundamental and Applied Sciences, 2017, 9(3S):493-502

[18] Hashim F R, Adnan J, Ibrahim M M, Ishak M T, Din M F, Daud N G, Rizman Z I. Heart abnormality detection by using artificial neural network. Journal of Fundamental and Applied Sciences, 2017, 9(3S):1-10

[19] Mohd Yassin I, Jailani R, Ali M, Amin M S, Baharom R, Hassan A, Huzaifah A, Rizman Z I. Comparison between cascade forward and multi-layer perceptron neural networks for NARX functional electrical stimulation (FES)-based muscle model. International Journal on Advanced Science, Engineering and Information Technology, 2017, 7(1):215-221

How to cite this article:

Supian S, Achmad KTB, Riyadhi I, Subiyanto, Adiana G, Ireana Yusra AF, Mamat M.Mathematical model for dissolved oxygen prediction in cirata reservoir, west java by using artificial neural network. J. Fundam. Appl. Sci., 2018, *10(1S)*, *66-78*.