MODELING OF TRIANGULAR UNIT HYDROGRAPHS USING AN ARTIFICIAL NEURAL NETWORK IN A TROPICAL RIVER BASIN

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ABSTRACT: Rainfall-runoff models are crucial for estimating floods in a river basin. Most watersheds in Indonesia have a data deficiency problem, especially in natural watersheds (ungauged river basins), which may affect the accuracy of design and planning of water resources. Most synthetic unit hydrograph methods are not in accordance with the characteristics of Indonesian watersheds, and adjustments should be made to obtain accurate results. This study aimed to develop a simple triangular unit hydrograph generated by using a neural network for different watersheds in Indonesia. The triangular unit hydrograph consists of the peak discharge, time to peak, and time base developed using a neural network with a learning process from the observed unit hydrograph, and the result will be compared to the Snyder-Alexeyev synthetic unit hydrograph after being adjusted to obtain accurate results in comparison to observed data. An artificial neural network (ANN) model was developed by inputting basin characteristics such as catchment area (A), river length (L), basin slope (S), shape factor (F), and runoff coefficient (C). The model will generate the output of a triangular synthetic unit hydrograph consisting of peak discharge (Qp), time to peak (Tp), and time base (Tb). A case study is discussed in tropical river basins mostly on Java Island, where flood events are frequent. The simulation result from applying an ANN using generalized reduced gradient neural network (GRGNN) methods is significantly in line with historical data. The ANN simulation shows more accurate results than the adjusted Snyder-Alexeyev unit hydrograph. The results indicated that the synthetic unit hydrograph generated by an ANN can be applied to an ungauged river basin.

Keywords: Observed Unit Hydrograph, Synthetic Unit Hydrograph, Triangular Unit Hydrograph, Neural Network

1 INTRODUCTION

1.1 General

The rainfall-runoff relationship is an essential component in the process of water resource evaluation and is considered a central problem in hydrology [7]. Furthermore, the rainfall-runoff relationship is used as a base component for evaluating water resources in a basin. Small basins (areas less than approximately 150 square kilometers or 58 square miles) function differently than large basins in terms of the relative importance of various phases of the runoff phenomenon. In small basins, the overland flow phase is predominant over the channel flow. Hence, the land use and intensity of rainfall play important roles in affecting peak discharge [13].

Hydraulic studies, including those needed by the implementation of hydraulic infrastructures, often require flood analysis. One of the most common methods applied for that purpose is the unit hydrograph (UH) method. When there are observed rainfall and runoff data, the UH can be derived by direct methods; otherwise synthetic hydrographs obtained by indirect methods can be applied [9]. Data availability is necessary for the design and planning of water resources; however, most Indonesian watersheds still have a data deficiency problem, especially in natural watersheds (ungauged river basins). Most synthetic unit hydrograph methods are still not in accordance with the characteristics of Indonesian watersheds, and an adjustment should be made to obtain an accurate result.

This study is aimed at developing a triangular unit hydrograph model that can be applied to the watershed in Indonesia. This study will analyze the correlation of the characteristics of the watershed with the triangular unit hydrograph by using an ANN model. The model is built by setting up both linear and nonlinear mathematical equations and neglecting physical processes; the important characteristic of this model is that the final result is similar to the actual condition [1].

The rainfall-runoff relation has been developed continuously by applying artificial intelligence as a black box model alternative called artificial neural network. By applying a black box model, it is not necessary to apply complex knowledge due to interrelated elements in a river basin, which are not explicitly represented in the relation of the elements and interaction processes of the rainfall-runoff model [5][6][10]. The two important parameters when predicting a flood hydrograph are the magnitude of the peak discharge and the time to peak discharge. The developed ANN models have been able to predict this information with great accuracy. This shows that ANNs can be very efficient in modeling an eventbased rainfall-runoff process for determining the peak discharge and time to the peak discharge very accurately [12].

An ANN model will be considered to develop a UH database by inputting basin characteristics such as catchment area (A), river length (L), basin slope (S), shape factor (F), and runoff coefficient (C), which generate the output of a triangular observed unit hydrograph by calculating the parameters of peak discharge (qp), time to peak (tp), and time base (tb), which are acquired from a learning process after calibration using an observed unit hydrograph in the ANN model. The study is aimed at developing a simple triangular unit hydrograph generated by using a neural network based on various land uses in a tropical river basin.

2 STUDY AREA

The study area for developing a unit hydrograph and applying the ANN has been chosen from several catchment areas on Java Island, as listed in Table 1. The catchment areas are the Leuwidaun, Dam Kamun and Cipeles basins located in the Cimanuk River Basin, as shown in Figure 1. The Gadang, Konto1, and Tawangrejeni basins are located in the Brantas River Basin, as shown in Figure 2.

Table 1 Study Area for Unit Hydrograph Analysis and Applying ANN

No	Catchment Area	River	Province
	Name	Basin	
1	Leuwidaun	Cimanuk	West Java
2	Dam Kamun	Cimanuk	West Java
3	Cipeles	Cimanuk	West Java
4	Gadang	Brantas	East Java
5	Konto 1	Brantas	East Java
6	Tawang Rejeni	Brantas	East Java



Fig. 1 The Area of Study for the Cimanuk River Basin

Hydrological attributes consist of rainfall and water level station plotted on the map to find the weighted area of rainfall station to produce the average rainfall area. Figure 3 shows the distribution of rainfall stations in the Cipeles Basin, with the weighted area of rainfall shown in Table 2.



Fig. 2 The Area of Study for the Brantas River Basin



Fig. 3 Hydrological Station Map of Cipeles Basin

Table 2 Weighted area for each rainfall station in Cipeles Basin

Station	sq (mi)	sq (km)	%
Sumedang	94.325	244.302	56.55%
Cijambu	33.260	86.143	19.94%
Darmaraja	20.300	52.576	12.17%
Dam	0.183	0.475	0.11%
Kamun			
Jatigede	18.732	48.515	11.23%
Tot	al	432.01	100%

3 METHODOLOGY

To develop the ANN model, the method has been illustrated in the flowchart shown in Figure 4. The method consists of two important phases. First is to develop the observed unit hydrograph and synthetic unit hydrograph, and the second is to develop a triangular UH model by the ANN approach.

- Develop observed UH and synthetic UH For developing an observed UH, it is necessary to select continuous rainfall from both rainfall and runoff data. The UH at a certain event is analyzed by using a synthetic approach (Snyder-Alexeyev method by inputting spatial data). The triangular hydrograph is taken to be developed from both observed and synthetic hydrographs.
- 2. Developing UH model by the ANN approach The modeling of an ANN is started by selecting the appropriate ANN method with the UH model approach, with layer optimizing being applied to the selected ANN. The last step of ANN modeling is to apply training and verification of the ANN result in the certain catchment area.



Fig. 4 Flow Chart of Artificial Neural Network Model

4 ANALYSIS

There are two sets of data acquired for the analysis, consisting of catchment area map and set of hourly rainfall and runoff data. The availability of hydrological data is shown in the table below, consisting of observed hourly rainfall and runoff data. The basic map for measuring the physical basin characteristics is processed from the spatial process of DEM as shown in Figure 3; this process was conducted for the entire study area basin. Average hourly rainfall area is generated by calculated weighted area for each rainfall station for each basin.

Table 3	Availability	of Hydro	logical Data
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Ν	Basin	Observ	AWLR	ARR Station
0	Name	ed Data	Station	
1	Leuwi-	2012-	Leuwi-	Bayongbong
	daun,	2014	daun	Cikajang
	Cimanuk			Leuwungtiis
2		2012-		Kamun
		2014		Jatigede

Dam		Ben-	Sukahaji
Kamun,		dung	Talaga
Cilutung		Kamun	Sadawangi
Warung	2012-	Cipeles	Sumedang
peuti,	2014	-	Cijambu
Cipeles			Darmawaja
			Jatigede
			Kamun
Gadang	2015-	Ga-	Jabung
Brantas	2016	dang	Ponco
			kusumo
			Sbr Brantas
			Pujon
			Tangkil
			Wagir
Konto 1	2015-	Konto1	Pujon
Brantas	2016		-
	Dam Kamun, Cilutung peuti, Cipeles Gadang Brantas Konto 1 Brantas	Dam Kamun, Cilutung Warung 2012- peuti, 2014 Cipeles Gadang 2015- Brantas 2016 Konto 1 2015- Brantas 2016	Dam Kamun, CilutungBen- dung KamunWarung peuti, Cipeles2012- 2014CipelesGadang Brantas2015- 2016Ga- dangKonto 1 Brantas2015- 2016Konto1 Brantas

4.1 Observed Unit Hydrograph

Data analysis was conducted in five different watersheds in Indonesia, with the characteristics of the watershed being obtained by analyzing spatial data (digital elevation model). An observed unit hydrograph is derived from hourly measured streamflow and rainfall data for each watershed.



Fig. 5 Rainfall and Runoff Data at Cipeles Water Level Station

The detailed steps to derive the unit hydrograph from the observed data are described as follows:

- a. Several events selected for each watershed.
- b. Base flow specified for selected events to produce direct runoff (DRO).
- c. Unit hydrograph parameters (Qp, Tp, and Tb) specified by optimization and the ordinates of unit hydrograph calculated using the linear method.
- d. Direct runoff hydrograph from data yield by the discrete convolution equation from unit hydrograph and excess precipitation.

$$Q_n = \sum_{m=1}^{n \le m} P_m U_{n-m+1}$$
(1)

e. The optimization is done by minimizing the error between DRO observed data and the convolution of the unit hydrograph and excess rainfall. The constraint is to maintain the hydrograph value and error of peak discharge at less than 0.01. It is difficult to obtain exactly the same unit hydrograph from several events in one watershed because rainfall runoff is a complex process that involves several factors, both naturally and otherwise. Optimization is conducted to decide which unit hydrograph represents each watershed, by optimizing the total errors from each event to be minimized.



Fig. 6 Observed Unit Hydrograph of Cipeles Watershed

4.2 Synthetic Unit Hydrograph

Synthetic unit hydrograph methods are utilized to describe the entire unit hydrographs for a gauged watershed with one or two hydrograph parameters. These hydrograph parameters can be related to the characteristics of the watersheds and storms from which they are determined. Snyder Synthetic Unit Hydrograph (1938) from the Chow [5] method will be applied in this paper. The Synder-Alexeyev method is the best for Indonesian characteristics because it can be calibrated; other models such as Nakayasu, Limantara, Gama-1 and ITB models are not accurate unless calibrated with Indonesia basin characteristics [8].

Although Snyder-Alexeyev is the most appropriate method, some coefficients in the UH equation need to be modified in order to obtain a more accurate hydrograph. Based on previous analysis by Safarina [11], Ct and Cp have a significant effect on unit hydrograph calculation in the main basin compared to C_1 and C_2 . The adjusted method of Snyder-Alexeyev will be modified by finding a new range of coefficient Ct, Cp, n, and new coefficients C3. The adjusted parameters are shown in the equation below.

Time lag (t_o):

$$T_{lR} = \frac{c_1 c_t (L.Lc)^n}{5.5}$$
(2)

Specific discharge (qpR):

$$qpR = \frac{c_2 c_P T_P}{T_P}$$
(3)

$$\begin{array}{c} t_l & t_{lR} \\ \text{Time base (Tb):} \\ \end{array}$$

$$Tb = Ctb/q_{pR}$$
(4)
Rising curve:

$$Y = 10^{-a\frac{(1-x)^{c_1}}{x}}$$
(5)

Recession curve:

$$Y = 10^{-a \frac{(1-x)^{c^2}}{c^3}}$$
(6)

Coefficients C1 and C2 remain constant with the value obtained from the Snyder method. The new coefficient C3 is determined by optimizing the synthetic method with the observed hydrograph. This coefficient determines the recessing curve and maintains the hydrograph volume. After processing five watersheds with different characteristics, we obtained a new range of coefficients:

Table 4 Snyder's modified coefficient for 5 Basin

No	Snyder's Alexeyev coefficient	Original value	Modified value
1	C1	0.75	0.75
2	C2	2.75	2.75
3	C3	-	39.16-111.62
4	Ct	1.8 - 2.2	0.95 - 1.60
5	Ср	0.4 - 0.8	0.17 - 0.29
6	n	0.2 - 0.3	0.10 - 0.20
7	Ctb	5.56	5 - 5.56

The result of comparison between synthetic unit hydrograph and adjusted Snyder method calculation in Cipeles Basin is shown in Figure 7.



Fig. 7 Synthetic UH adjusted in Cipeles Watershed

4.3 Triangular Unit Hydrograph

There is some concern about the ability of the triangular shape unit hydrograph to be used in an operational setting. In general, it can be said that the triangular version will not cause or introduce noticeable differences in the simulation of a storm event, particularly when one is concerned with the peak flow.

In water resource design and planning, Qp, Tp, and Tb are the important parameters of unit hydrograph. Therefore, the synthetic unit hydrograph that has been adjusted with observed unit hydrograph is simplified into triangular unit hydrograph by maintaining its volume as the same.



Fig. 8 Triangular UH in Cipeles Basin

4.4 Discrepancy Ratio

In this research, synthetic methods are validated against the observation unit hydrograph by using the comparison parameters. Comparison parameters consist of the error shape of hydrograph (E) and discrepancy ratio (d) of the peak discharge, peak time and time base. The discrepancy ratios of hydrograph unit parameters are:

Basin	dTb	dTp	dQp
Leuwidaun	0.981	1.000	1.000
Dam Kamun	0.938	0.999	1.000
Cipeles	0.965	1.000	1.000
Gadang	0.949	1.000	1.000
Konto 1	0.844	0.996	1.000
Tawangrejeni	0.995	1.000	1.000

Table 5 Discrepancy Ratio

4.5 Result and Discussion

Due to the numerous parameters and the high complexity of parameter interaction, the optimization of model parameters is mostly applied by the method of trial-and-error. To overcome these difficulties, artificial neural networks (ANNs) have been proposed [14]. An ANN is a flexible mathematical structure that is capable of identifying complex nonlinear relationships between input and output datasets [2].

In recent years, ANNs as black box models have been optimally used to model nonlinear input-output relationships in complex hydrological processes, potentially becoming a promising decision-making tool in hydrology [6].

In this study, the GRGNN (generalized reduced gradient neural network) method is applied for the training process of neural networks to learn the characteristics of observed UH in the form of triangular UH with peak discharge (qp), time to peak

(tp) and time base (tb) parameters. The learned GRGNN architecture is then used to generate a synthetic UH using the morphological characteristics of an adjacent watershed as the input: catchment area (A); river length (L); river slope (S); shape factor (F); and runoff coefficient (C). The generated UHs are then verified with observed triangular UH.

The limitation of GRGNN is that they are usually accurate within only a limited range; extrapolation might not be possible, so the catchment area, river length, slope, shape factor, and runoff coefficient should be in a proper range. The training process is applied to five different watersheds in the upper Cimanuk and upper Brantas basins.

The five characteristics of ANN inputs have been normalized and were applied to the database for reducing redundancy and forming a better correlation with each other. The input data and normalization of learning input data are stated in Tables 6-7.



Fig. 9 Architecture of ANN Network

4.5.1 Testing

The model accuracy shown in the graphics consists of two lines of historical hydrographs, with a simulated hydrograph and discrepancy ratio of each basin. The comparison of the simulated hydrographs by using ANN with the GRGNN approach is significantly in line with historical hydrographs, showing the optimal iteration with minimal error being found.



Fig. 10 Testing ANN in Cipeles Basin

No			Input Node				Output Node	e
	A (km ²)	F	L (km)	S	С	Qp (m ³ /s)	Tp (hour)	Tb (hour)
1	449.5	1.43	31.8	0.0201	0.2	12.11	3.15	20.62
2	623.6	2.56	56.72	0.0248	0.4	23.01	2.35	15.06
3	432.01	3.32	47.242	0.0268	0.33	12.57	2.27	19.10
4	701.11	1.43	37.77	0.0362	0.46	22.30	2.31	17.47
5	10.68	3.11	2.95	0.1115	0.6	0.82	1.22	7.27

Table 6 Input Data and Output ANN

Table 7 Normalized Learning Data

No			Input Node			(Output Node	e
	A (km^2)	F	L (km)	S	С	Qp (m ³ /s)	Tp (hour)	Tb (hour)
1	0.64	0.00	0.54	0.00	0.00	0.51	1.00	1.00
2	0.89	0.60	1.00	0.05	0.50	1.00	0.58	0.58
3	0.61	1.00	0.82	0.07	0.33	0.53	0.54	0.89
4	1.00	0.00	0.65	0.18	0.65	0.97	0.56	0.76
5	0.00	0.89	0.00	1.00	1.00	0.00	0.00	0.00

Table 8 Discrepancy Ration Cipeles Basin

	Historical	GRGNN	Discrepancy
	Data	Model	Ratio
Qp (m ³ /s)	12.567	12.568	1.000
Tp (hour)	2.273	2.272	1.000
Tb (hour)	19.099	19.101	1.000
Vol (m ³)	432010	432085	1.000



Fig. 11 Testing ANN in Gadang Basin

Table 9 Discrepancy Ratio Gadang Basin

	Historical	GRGNN	Discrepancy
	Data	Model	Ratio
Qp (m ³ /s)	22.296	22.623	1.015
Tp (hour)	2.312	2.359	1.021
Tb (hour)	17.470	17.412	0.997
Vol (m ³)	701119	70949	1.011



Fig. 12 Testing ANN in Dam Kamun Basin

Table 10 Discrepancy Ratio Dam Kamun Basin

	Historical	GRGNN	Discrepancy
	Data	Model	Ratio
Qp (m ³ /s)	23.007	22.662	0.985
Tp (hour)	2.352	2.307	0.981
Tb (hour)	15.056	15.098	1.003
Vol (m ³)	623500	615877	0.988



Fig. 13 Testing ANN in Konto 1 Basin

	Historical	GRGNN	Discrepancy
	Data	Model	Ratio
Qp (m ³ /s)	0.816	0.816	1.000
Tp (hour)	1.224	1.225	1.001
Tb (hour)	7.268	7.268	1.000
Vol (m ³)	10672	10673	1.000

Table 11 Discrepancy Ratio of Konto 1



Fig. 14 Testing ANN in Leuwidaun Basin

Table 12 Discrepancy Ratio Leuwidaun

	Historical	GRGNN	Discrepancy
	Data	Model	Ratio
Qp (m ³ /s)	12.110	12.108	1.000
Tp (hour)	3.153	3.128	0.992
Tb (hour)	20.621	20.621	1.000
Vol (m ³)	449500	449424	1.000

4.5.2 Verification

Verification is executed by analyzing the unit hydrograph of the Tawangrejeni subwatershed (in the upper Brantas River) using artificial neural networks with the data input of catchment area, river length, and slope; besides, the selected key stream gauging station for hydrograph data is at the Tawangrejeni station.

The data and the simulation results from applying the ANN are shown in the table below, which shows the fitted line between historical data and simulated data by using the GRGNN approach in the following.



Fig. 15 Verification of ANN in Tawangrejeni Basin

Table 13 Input Data Verification Tawangrenjeni

А	F	L	S	С	Qp	Тр	Tb
384.07	2.51	38.73	0.0379	0.16	9.77	3.06	21.85

Table 14 Result of GRGNN Model Simulation

	Historical	GRGNN	Discrepancy
	Data	Model	Ratio
Qp (m ³ /s)	9.767	9.792	1.003
Tp (hour)	3.062	3.123	1.020
Tb (hour)	21.847	21.847	1.000
Vol (m ³)	384070	385081	1.003



Fig. 16 Comparison of Qp in Tawangrejeni Basin

Comparison of Tp observed and Tp model



Fig. 17 Comparison of Tp in Tawangrejeni Basin



Fig. 18 Comparison of Tb in Tawangrejeni Basin

5 CONCLUSION

The aim of this research is to develop a unit hydrograph database using an ANN model by inputting basin characteristics such as catchment area (A), river length (L), basin slope (S), shape factor (F), and runoff coefficient (C), which generate the output of a triangular synthetic unit hydrograph (Qp, Tp, and Tb). This case study evaluates a tropical river basin in Indonesia. The study area for developing unit hydrographs and applying the ANN has been taken from several catchment areas in Java.

According to flood discharge planning procedures issued by the Indonesian National Standardization (SNI), the Snyder-Alexeyev method is the most suitable for Indonesian watersheds. However, the results show that Snyder-Alexeyev unit hydrographs cannot be used directly without adjusting the coefficient based on the observation data.

From the analysis, the synthetic unit hydrograph generated from the GRGNN model presents the better result compared to the adjusted triangular Synder-Alexeyev hydrographs. The triangular UH generated by the GRGNN was successfully verified by watershed from the training results by incorporating the characteristics of the Tawangrejeni watershed and yielding peak discharge (qp), time to peak (tp) and time base (tb) data that accurately corresponded to the triangular observation UH.

The verification of the GRGNN simulation result in the Tawangranjeni basin has shown a fitted line between historical data and simulated data. The result confirms that the synthetic unit hydrograph generated by an ANN model can be applied to ungauged river basins in Indonesia. However, this research is based on a limited river basin database, and extensive training and testing are required for historical hourly rainfall and runoff data from more river basins, and thus, further analysis is necessary.

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