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A Study of Rain Station Network Distribution Using Artificial Neural Networks

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Abstract

Hydrological analysis is an important component in water resources management, especially for planning and controlling water infrastructure. This study evaluates the effectiveness of the rain station network in the Upper Ciliwung Watershed and identifies rain station with maximum accuracy in representing the study area conditions. Rainfall and discharge data were tested using statistical tests to ensure the absence of trends, stationary, persistence, and outliers. The evaluation of the rain station network density was conducted based on WMO guidelines, which determined the Upper Ciliwung Watershed met the criteria with a density of 37.981 km² per rain station. Analysis of rain station network distribution patterns using Artificial Neural Networks (ANN) was conducted with three data divisions (70-20-10, 60-25-15, 50-30-20) and tested at 100, 500, and 1000 epochs. The best results were obtained at 70-20-10 composition with 1000 epochs, showing the smallest relative error of 9.880% and NSE value of 0.983. The most effective rain station combinations are Gadog, Cilember, and Gunung Mas. This research provides recommendations in rain station network optimization to improve the accuracy of hydrological data.

Introduction

Water resources management requires accurate hydrological data to support the planning and control of water infrastructure. Rainfall as one of the main hydrological data has an important role in supporting various activities such as watershed management, flood mitigation, and irrigation planning. The quality of rainfall data is largely determined by the existence of a rain station network that is able to accurately represent hydrological conditions. However, challenges in the form of uneven distribution of rain station networks and non-optimal density often become obstacles in providing quality data.

The rain station is a post for observing and measuring rainfall. According to Arsyad (2017), rain is the main source that supplies water on the earth's surface, while rainfall characteristics vary depending on factors such as topography, distance from the sea, and wind direction (Seyhan et al., 1990). Comprehensive and real-time rainfall data is needed to accommodate the spatial and temporal representation of hydrological data (Anggraheni et al., 2018; Krajewski et al., 2021; Zhu et al., 2023; dos Reis et al., 2022). However, until now, there is no standardized guideline in Indonesia regarding the method of determining the density and distribution of the rain station network (Prawati, 2016; Gao et al., 2025; Pratama, 2023; Setiawan et al., 2018; Atmakusuma & Parikesit, 2018). The World Meteorological Organization (WMO) provides recommendation minimum densities of rain station networks, which is one automatic rain station per 250 km² for small islands and one manual station per

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25 km² (WMO, 2020). Higher network density can improve data accuracy, but on the other hand, it also results in more expensive operational costs (Prawati & Dermawan, 2018; Cavus et al., 2025; Hussein et al., 2022; Hu & Evans, 2004; Johansson, 2007). Therefore, an analytical approach is needed to determine the distribution and density of an efficient rain station network that still produces representative data.

The Upper Ciliwung River Watershed, which is a strategic water supply area for Bogor Regency, often faces high rates of disasters such as floods and landslides due to climate change, steep slopes, and land conversion. The flash flood in January 2021 in Gunung Mas area, Bogor, is an example of the impact of high rainfall and deforestation. To effectively predict floods, quality hydrological data is required. One way to obtain valid data is to conduct regular evaluations of existing rainfall stations and water stations. The representativeness of hydrological data is influenced by the density of rainfall stations, which includes the number and distribution pattern of rainfall stations in a watershed. The optimal number and distribution of rainfall stations will save costs and produce accurate data.

In this context, the Artificial Neural Network (ANN) method has been widely used in research to analyse complex data patterns and predictions in various fields. Hermawan (2006) mentioned that ANN is able to make decisions on data that has never been studied. Research by Fathoni et al. (2016) showed the success of ANN in evaluating the rain station network in the Kedungsoko watershed. Similarly, Aji et al (2018) utilized ANN to correlate the influence of topographic factors on rain station distribution patterns in the Kadalpang watershed, providing important insights in network optimization. Based on this description, this study aims to evaluate the density of the rain station network based on WMO standards, analyse the distribution pattern of the rain station network using the ANN method, and provide recommendations to improve the accuracy of hydrological data. With this approach, the research is expected to make a significant contribution to the provision of quality hydrological data to support efficient and sustainable water resources management.

Methods

The study site used as a research review is located in the Upper Ciliwung Watershed. The Upper Ciliwung Watershed has an area of 151,922 km^2 with a main river length of 22,75 km, and is located in the administrative area of Bogor Regency, West Java Province.

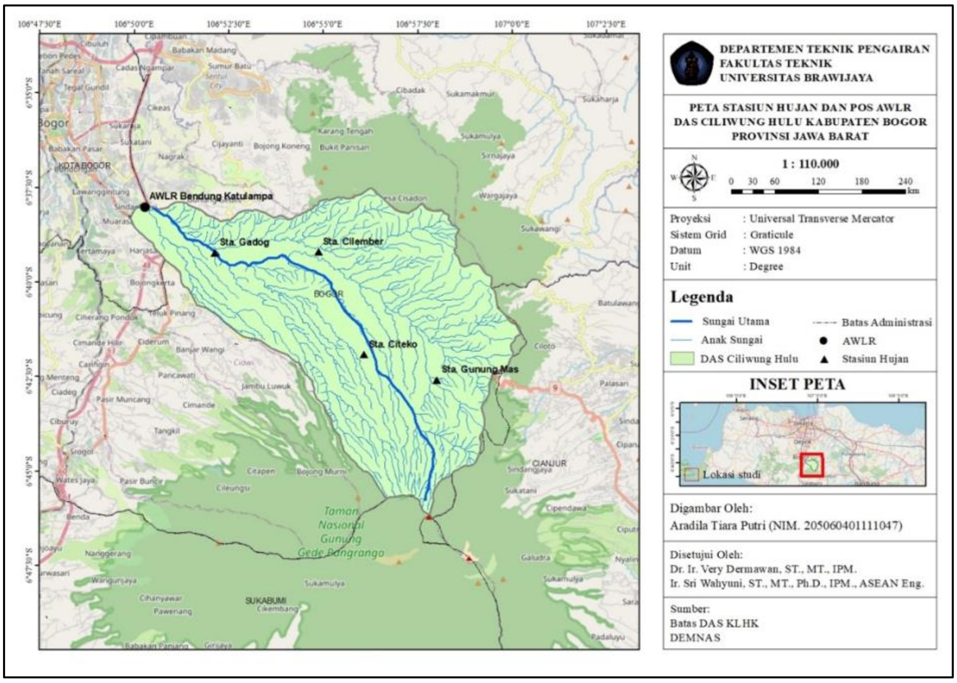

Figure 1.Map of the study area

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Geographically, the Upper Ciliwung Watershed is located between 6°35'0" LU - 6°47'30" LU and 106°47'30" BT - 107°2'30" BT. There are four rain station that influence the distribution of rain within the Upper Ciliwung Watershed, namely the Gunung Mas, Citeko, Gadog, and Cilember rain stations. If mapped, the rain station located within the Upper Ciliwung Watershed as shown in *Figure 1*.

Data and Data Collection Techniques

This study uses data in the form of rainfall, discharge data, topography, and coordinates of rainfall stations. Daily rainfall data from 2007-2022 came from, recorded by the Automatic Rainfall Recorder (ARR) of BBWS Ciliwung-Cisadane, for input to the artificial neural network analysis. Discharge data the Automatic Water Level Recorder (AWLR) of Katulampa Weir from 2007-2022 was used to validate the artificial neural network simulation results. Topographic data came from DEMNAS for spatial analysis of watershed map processing using ArcGIS software to map the Upper Ciliwung watershed. Coordinates of rain stations and AWLR posts were obtained from BBWS Ciliwung-Cisadane to complete the analysis.

Data Analysis

This study aims to analyze the distribution pattern of the rain station network using rain data as an independent variable and discharge data from the AWLR post as the dependent variable in the Upper Ciliwung River Watershed. The best alternative rain station network distribution is a combination of rain stations that produces artificial neural network discharge output predictions with the smallest relative error accuracy against AWLR discharge data. Before the artificial neural network analysis was carried out, the rainfall and discharge data were previously analysed for data quality including consistency tests, correlation tests, stationary tests, persistence test and inlier-outlier tests. The test was carried out using 16 years of data (2007 - 2022) from 4 rainfall stations and 1 AWLR station. The consistency test used for rainfall data is the Double Mass Curve method, while for discharge data the RAPS method was used. The rainfall data from the rain station posts that had been tested were then transformed into regional rainfall using the Thiessen Polygon method.

Neural Network Analysis

This study uses the Artificial Neural Network method with NeuroSolutions for Excel 7.1 student version software to analyse the distribution pattern of the rainfall station network in the Upper Ciliwung Watershed. NeuroSolutions for Excel is a Microsoft Excel add-in with very advanced features, suitable for both beginners and experts, with all operations can be performed directly from Excel. The learning method applied is the Backpropagation algorithm with a Multi-Layer Perceptron (MLP) network architecture. In this study analysis, the data is divided into four parts, namely training, cross validation, and testing. The following is the composition scenario of the division of training and testing data used is listed below: a) 50% *Trainning*, 30% *Cross Validation*, 20% *Testing*; b) 60% Trainning, 25% Cross Validation, 15% Testing; c) 70% *Trainning*, 20% *Cross Validation*, 10% *Testing*

The division of the number of iterations used for supervised network training was determined to be 100 Epochs, 500 Epochs and 1000 Epochs respectively. The optimal rain station network distribution was determined by identifying the combination producing the smallest relative error between predicted and actual AWLR discharge data.

Results and Discussion

Rainfall Data and Discharge Data Analysis

To ensure that the results of the discharge modeling using artificial neural networks can provide good accuracy results, the two main variables, namely rainfall data and discharge

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data, are first tested for their characteristics using statistical methods. This test aims to ensure data quality before further analysis. The results of statistical tests on rainfall data and discharge data in the 16 year data range (2007-2022) are shown in table 1.1. Several statistical tests were carried out, including the rainfall data consistency test using the double mass curve method, while the discharge data consistency test using the RAPS method, the absence of trend test, the stationary test, the persistence test, and the inlier-outlier test.

Table 1. Recapitulation of Rainfall Data Quality Test and Discharge Data

Rainfall stations and AWLR posts	Consistency Tests	Correlation Tests	Stationary Tests		Persistence Test	Inlier-Outlier Tests
			F Test	T Test		
Gadog Rain Station	Inconsistent (*fk* = 0,798)	No Trend	Stable variant	Stable average	No dependency	Data is not an outlier
Cilember Rain Station	Inconsistent (*fk* = 1,451)	No Trend	Stable variant	Stable average	No dependency	Outlier data
Gunung Mas Rain Station	Consistent	No Trend	Stable variant	Stable average	No dependency	Outlier data
Citeko Rain Station	Consistent	No Trend	Stable variant	Stable average	No dependency	Data is not an outlier
Awlr Katulampa Weir	(RAPS) Consistent	No Trend	Stable variant	Stable average	No dependency	Data is not an outlier

Source: Analysis results, 2024

The test results show that rainfall data from Cilember and Gunung Mas Rainfall Stations have several outlier data that deviate from their normal limits. However, the outliers are not too far from their normal data range. Therefore, in this study, outlier testing is ignored and the same data range is still used for further analysis.

Average Regional Rainfall

The regional rainfall estimation utilizes the Thiessen Polygon method, assuming each station has a distinct area of influence, as illustrated in Figure 1.2. The method yields a Thiessen Polygon area of 151.92 km², with the area of influence results presented in Table 1.2.

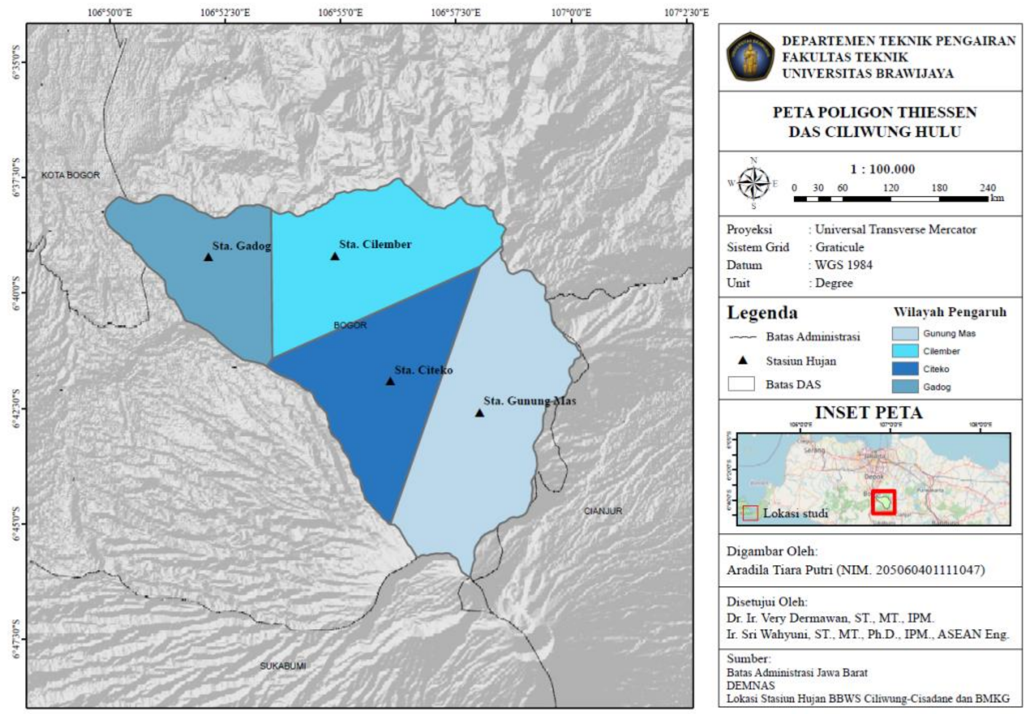

Figure 2. Thiessen Polygon Existing Rainfall Station in the Upper Ciliwung Watershed

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Table 2. Area of Influence of 4 Rainfall Stations in the Upper Ciliwung Watershed

No.	Rainfall Stations	Area of Influence (km^2)	Area Percentage (%)	Thiessen Coefficient
1	Gadog	27,017	17,783	0,178
2	Cilember	39,161	25,777	0,258
3	Gunung Mas	35,344	23,265	0,233
4	Citeko	50,400	33,175	0,332
	quantity	151,922	100,000	1,000

Source: Analysis results, 2024

WMO Rainfall Station Network Density Analysis Method

The Upper Ciliwung River Watershed, covering an area of 151.922 km², is situated in a region that exhibits inherent natural characteristics amidst rapid urbanization, thereby qualifying it as a small island region. Consistent with guidelines established by the World Meteorological Organization (WMO), small island regions necessitate a minimum rainfall station density of 1 station per 250 km². This requirement is specifically tailored for automatic recording stations, as delineated in Table 1.3.

Table 3. Minimum Rainfall Station Density Requirements per km^2

Physiograpihic unit	Precipitation		Evaporation	Streamflow	Sediments	Water quality
	Non-recording	Recording				
Coastal	900	9.000	50.000	2.750	18.300	55.000
Mountains	250	2.500	50.000	1.000	6.700	20.000
Interior plains	575	5.750	5.000	1.875	12.500	37.500
Hilly/undulating	575	5.750	50.000	1.875	12.500	47.500
Small islands	**25**	**250**	**50.000**	**300**	**2.000**	**6.000**
Urban areas	-	10 – 20	-	-	-	-
Polar/arid	10.000	100.000	100.000	20.000	200.000	200.000

Source: *Guide to Hydrological Practices*, WMO 2020

The calculation results show that the average density of existing rainfall stations in the Upper Ciliwung Watershed is 37.981 km2 per station. This value is then compared with the rainfall station density requirements set by WMO, in the Guide to Hydrological Practices (2020). Based on Table 1.3, it can be concluded that the density of rainfall stations in the Upper Ciliwung Watershed still meets the standards set by WMO.

Rain Station Combination Planning

Rain station network combination planning aims to optimize the selection of the number of rainfall stations that can provide high accuracy using the Artificial Neural Network method. This combination planning is carried out by reducing the number of rainfall stations one by one using the combination formula without considering the order and without repetition. With this approach, a total of 15 combinations are obtained.

Table 4, Number of Rain Station Network Combinations

No	Number of rain stations (n)	Number of selected rainfall stations (r)	Combination formula	Combination (C)
1	4	4	C_4^4	1
2	4	3	C_3^4	4
3	4	2	C_2^4	6

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4	4	1	C_1^4	4
Amount				15

Source: Analysis Results, 2024

Results of Artificial Neural Network Testing for All Combinations

The design of data variables was carried out in 15 (fifteen) combination scenarios. Each design was carried out in 9 data training sessions, each of which was tested with 100 Epochs, 500 Epochs, and 1000 Epochs, and tested with three data division compositions. Data division for training and testing was carried out with three data division compositions as follows: 1) 50% Training, 30% Cross Validation, 20% Testing; 2) 60% Training, 25% Cross Validation, 15% Testing; 3) 70% Training, 20% Cross Validation, 10% Testing

Thus, there were 135 network training trials. The results of the combination of variables for each data training design in the artificial neural network can be seen in table 1.5.

Table 5. Recapitulation of Artificial Neural Network Data Training Results for Rain Station Combinations

Combination 1 Gadog Rainfall Station, Cilember Rainfall Station, Gunung Mas Rainfall Station, Citeko Rainfall Station							
Classification of Data (%)	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,006	0,075	0,008	19,341	0,942	Very Good
	500	0,022	0,050	0,010	14,661	0,960	Very Good
	1000	0,011	0,079	0,031	33,519	0,823	Very Good
60-25-15	100	0,019	0,046	0,008	13,108	0,967	Very Good
	500	0,022	0,048	0,009	13,812	0,961	Very Good
	1000	0,033	0,052	0,011	11,795	0,977	Very Good
70-20-10	100	0,029	0,012	0,005	16,466	0,961	Very Good
	500	0,028	0,010	0,005	15,203	0,962	Very Good
	1000	0,029	0,010	0,005	16,709	0,962	Very Good
Combination 2 Gadog Rainfall Station, Cilember Rainfall Station, Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,009	0,065	0,008	16,528	0,958	Very Good
	500	0,043	0,043	0,010	18,234	0,964	Very Good
	1000	0,041	0,060	0,013	16,902	0,969	Very Good
60-25-15	100	0,045	0,041	0,021	27,859	0,874	Very Good
	500	0,018	0,060	0,016	26,662	0,905	Very Good
	1000	0,024	0,038	0,008	15,931	0,957	Very Good
70-20-10	100	0,030	0,012	0,011	19,342	0,944	Very Good
	500	0,029	0,010	0,005	14,602	0,969	Very Good
	1000	**0,028**	**0,013**	**0,005**	**9,880**	**0,983**	**Very Good**
Combination 3 Gadog Rainfall Station, Cilember Rainfall Station, Citeko Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**

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		Train	Cross Validation	Testing			
50-30-20	100	0,006	0,072	0,018	31,045	0,883	Very Good
	500	0,060	0,043	0,022	32,328	0,883	Very Good
	1000	0,010	0,069	0,010	14,874	0,951	Very Good
60-25-15	100	0,014	0,049	0,016	30,706	0,878	Very Good
	500	0,032	0,043	0,015	21,648	0,923	Very Good
	1000	0,024	0,040	0,005	14,544	0,972	Very Good
70-20-10	100	0,030	0,010	0,006	18,377	0,962	Very Good
	500	0,028	0,016	0,010	16,845	0,946	Very Good
	1000	0,029	0,009	0,006	14,296	0,965	Very Good
Combination 4 Gadog Rainfall Station, Citeko Rainfall Station, Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,006	0,079	0,015	28,536	0,892	Very Good
	500	0,008	0,070	0,018	32,803	0,859	Very Good
	1000	0,015	0,073	0,014	15,574	0,948	Very Good
60-25-15	100	0,082	0,058	0,024	36,713	0,829	Very Good
	500	0,038	0,038	0,021	33,363	0,825	Very Good
	1000	0,031	0,038	0,007	13,709	0,965	Very Good
70-20-10	100	0,022	0,015	0,015	29,712	0,882	Very Good
	500	0,028	0,013	0,006	19,305	0,954	Very Good
	1000	0,030	0,011	0,006	16,771	0,961	Very Good
Combination 5 Cilember Rainfall Station, Citeko Rainfall Station, Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,006	0,073	0,008	16,230	0,952	Very Good
	500	0,006	0,078	0,011	20,203	0,930	Very Good
	1000	0,069	0,046	0,039	43,415	0,809	Very Good
60-25-15	100	0,019	0,054	0,073	15,242	0,953	Very Good
	500	0,033	0,039	0,006	15,917	0,968	Very Good
	1000	0,021	0,055	0,005	17,485	0,960	Very Good
70-20-10	100	0,027	0,012	0,005	15,404	0,960	Very Good
	500	0,028	0,011	0,004	16,296	0,960	Very Good
	1000	0,028	0,014	0,006	19,051	0,948	Very Good
Combination 6 Gadog Rainfall Station, Cilember Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,135	0,052	0,128	26,861	0,905	Very Good
	500	0,086	0,050	0,052	55,357	0,623	Very Good
	1000	0,004	0,083	0,022	36,743	0,855	Very Good
60-25-15	100	0,029	0,044	0,023	29,499	0,901	Very Good

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	500	0,036	0,037	0,013	19,597	0,945	Very Good
	1000	0,034	0,039	0,023	37,602	0,834	Very Good
70-20-10	100	0,029	0,010	0,005	14,083	0,969	Very Good
	500	0,029	0,012	0,010	19,862	0,944	Very Good
	1000	0,026	0,012	0,009	19,510	0,936	Very Good
Combination 7 Gadog Rainfall Station, Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,003	0,077	0,017	31,849	0,876	Very Good
	500	0,020	0,054	0,007	10,857	0,981	Very Good
	1000	0,037	0,056	0,021	14,249	0,970	Very Good
60-25-15	100	0,063	0,037	0,010	21,882	0,918	Very Good
	500	0,025	0,046	0,003	12,749	0,974	Very Good
	1000	0,028	0,046	0,008	17,960	0,952	Very Good
70-20-10	100	0,028	0,014	0,010	21,612	0,940	Very Good
	500	0,028	0,013	0,007	16,720	0,952	Very Good
	1000	0,030	0,010	0,005	13,794	0,968	Very Good
Combination 8 Cilember Rainfall Station, Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,006	0,069	0,011	21,317	0,935	Very Good
	500	0,047	0,049	0,018	27,172	0,922	Very Good
	1000	0,011	0,069	0,007	11,248	0,973	Very Good
60-25-15	100	0,023	0,042	0,005	11,386	0,982	Very Good
	500	0,018	0,056	0,011	21,639	0,930	Very Good
	1000	0,021	0,041	0,009	19,617	0,938	Very Good
70-20-10	100	0,027	0,016	0,004	13,264	0,968	Very Good
	500	0,030	0,013	0,003	12,549	0,974	Very Good
	1000	0,028	0,016	0,003	9,941	0,975	Very Good
Combination 9 Gadog Rainfall Station, Citeko Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,057	0,059	0,042	45,910	0,616	Very Good
	500	0,020	0,045	0,006	13,906	0,978	Very Good
	1000	0,054	0,060	0,014	20,707	0,947	Very Good
60-25-15	100	0,037	0,035	0,007	21,226	0,930	Very Good
	500	0,019	0,047	0,010	19,216	0,945	Very Good
	1000	0,027	0,027	0,011	24,569	0,898	Very Good
70-20-10	100	0,027	0,012	0,010	24,485	0,926	Very Good
	500	0,025	0,010	0,011	24,431	0,920	Very Good
	1000	0,027	0,007	0,007	17,622	0,954	Very Good
Combination 10 Cilember Rainfall Station, Citeko Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**

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		Train	*Cross Validation*	*Testing*			
50-30-20	100	0,007	0,078	0,014	23,802	0,909	Very Good
	500	0,071	0,044	0,032	45,848	0,778	Very Good
	1000	0,037	0,050	0,018	22,132	0,943	Very Good
60-25-15	100	0,020	0,049	0,005	12,163	0,971	Very Good
	500	0,029	0,026	0,010	27,014	0,869	Very Good
	1000	0,028	0,038	0,014	22,879	0,926	Very Good
70-20-10	100	0,029	0,009	0,008	23,154	0,929	Very Good
	500	0,028	0,010	0,005	18,930	0,948	Very Good
	1000	0,029	0,009	0,003	15,276	0,968	Very Good
Combination 11 Citeko Rainfall Station, Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Ket.**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,047	0,049	0,014	19,240	0,954	Very Good
	500	0,040	0,058	0,013	18,425	0,962	Very Good
	1000	0,042	0,050	0,011	18,025	0,961	Very Good
60-25-15	100	0,047	0,056	0,013	19,171	0,944	Very Good
	500	0,054	0,053	0,014	22,292	0,937	Very Good
	1000	0,036	0,047	0,012	22,816	0,907	Very Good
70-20-10	100	0,032	0,013	0,005	17,132	0,948	Very Good
	500	0,033	0,015	0,014	30,317	0,878	Very Good
	1000	0,024	0,011	0,009	22,487	0,938	Very Good
Combination 12 Gadog Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,024	0,067	0,016	14,033	0,950	Very Good
	500	0,011	0,057	0,016	21,201	0,920	Very Good
	1000	0,009	0,060	0,014	21,637	0,932	Very Good
60-25-15	100	0,017	0,057	0,017	27,500	0,927	Very Good
	500	0,019	0,048	0,012	20,816	0,928	Very Good
	1000	0,038	0,048	0,009	14,829	0,975	Very Good
70-20-10	100	0,028	0,013	0,007	17,001	0,958	Very Good
	500	0,030	0,011	0,008	17,273	0,949	Very Good
	1000	0,023	0,012	0,011	23,553	0,909	Very Good
Combination 13 Cilember Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,032	0,070	0,065	21,807	0,888	Very Good
	500	0,018	0,061	0,016	18,543	0,958	Very Good
	1000	0,011	0,083	0,021	24,347	0,906	Very Good
60-25-15	100	0,023	0,055	0,006	14,941	0,870	Very Good
	500	0,022	0,060	0,006	11,674	0,968	Very Good
	1000	0,024	0,056	0,007	14,792	0,970	Very Good

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70-20-10	100	0,037	0,015	0,004	12,507	0,972	Very Good
	500	0,033	0,014	0,004	15,258	0,968	Very Good
	1000	0,035	0,015	0,003	10,675	0,977	Very Good
Combination 14 Gunung Mas Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,035	0,058	0,015	18,536	0,981	Very Good
	500	0,036	0,049	0,015	23,310	0,933	Very Good
	1000	0,018	0,054	0,007	12,114	0,981	Very Good
60-25-15	100	0,025	0,052	0,012	15,956	0,984	Very Good
	500	0,036	0,046	0,015	19,789	0,932	Very Good
	1000	0,024	0,040	0,011	17,076	0,942	Very Good
70-20-10	100	0,030	0,012	0,005	16,320	0,963	Very Good
	500	0,030	0,011	0,005	17,212	0,960	Very Good
	1000	0,029	0,014	0,006	18,169	0,946	Very Good
Combination 15 Citeko Rainfall Station							
Classification of Data	***Epoch***	**MSE**			**KR (%)**	**NSE**	**Performance Rating**
		Train	***Cross Validation***	***Testing***			
50-30-20	100	0,025	0,059	0,010	13,618	0,868	Very Good
	500	0,059	0,042	0,019	28,578	0,898	Very Good
	1000	0,106	0,042	0,039	36,638	0,755	Good
60-25-15	100	0,023	0,038	0,011	23,236	0,967	Very Good
	500	0,042	0,030	0,011	26,694	0,902	Very Good
	1000	0,043	0,027	0,009	25,028	0,914	Very Good
70-20-10	100	0,030	0,010	0,007	21,450	0,931	Very Good
	500	0,027	0,011	0,010	22,745	0,921	Very Good
	1000	0,029	0,011	0,006	20,079	0,943	Very Good

Source: Analysis results, 2024

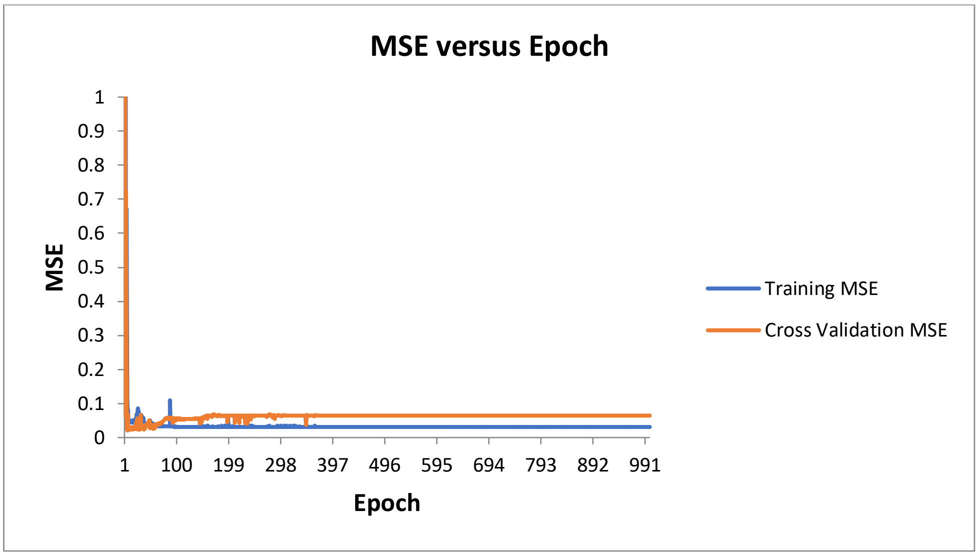

Figure 3. Relationship between MSE and Epoch for a combination of 2 70-20-10 data splits with 1000 epochs

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From all the tests that have been done, the best combination among the best is chosen. The combination is combination 2 consisting of Gadog Rain Station, Cilember Rain Station, and Gunung Mas Rain Station, with a data composition of 70-20-10; 1000 epochs obtained a relative error value of 9.880%, NSE 0.983 very good category (Moriasi, 2014), and the smallest MSE train, MSE cross validation.

Source: NeroSolutions Calculation Results, 2024

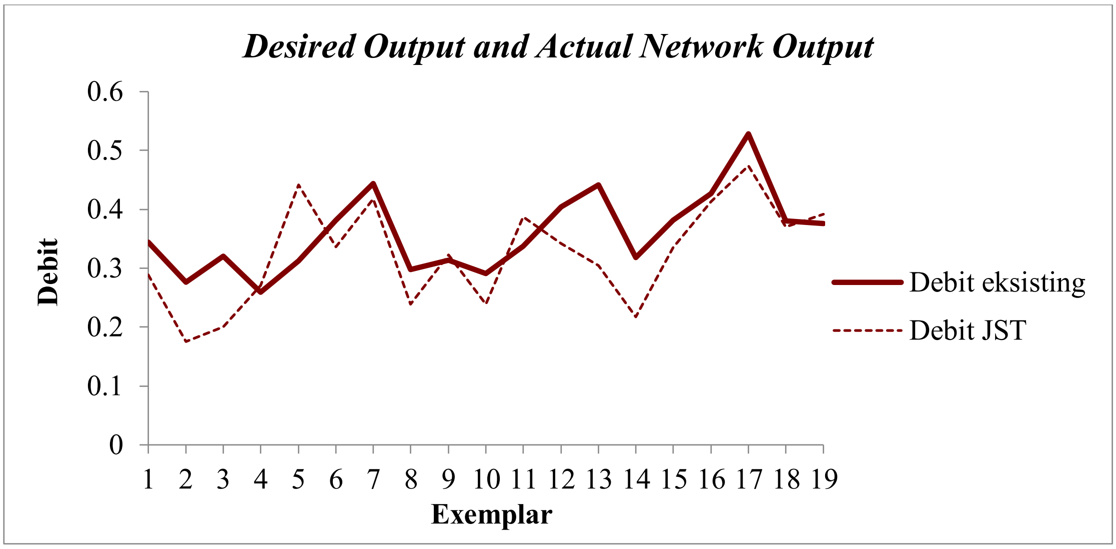

Figure 4. Comparison graph of JST forecast discharge results with existing discharge in combination 2, data composition 70-20-10 with 1000 epochs

Source: NeroSolutions Calculation Results, 2024

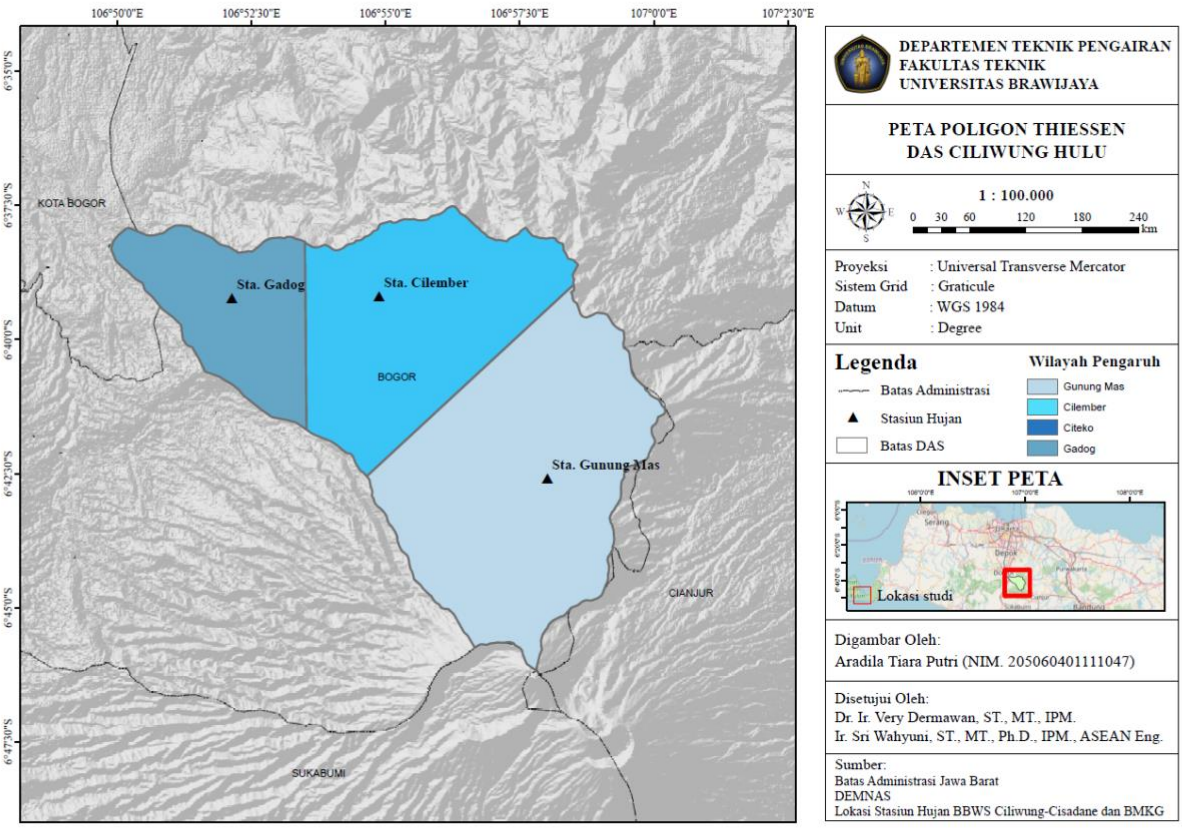

Figure 5. Thiessen Polygon Combination 2 Gadog Rainfall Station, Cilember Rainfall Station, Gunung Mas Rainfall Station

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The design of the network architecture drawing for combination 2 can be seen in the following figure:

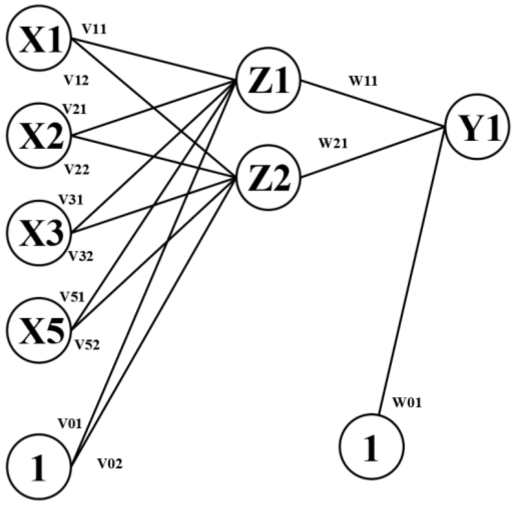

Figure 6. Multi-Layer Perceptron network architecture with four *inputs*

Source: Analysis results, 2024

Network architecture description:

X_1 = Monthly rainfall of Gadog Rainfall Station multiplied by the polygon correction factor Thiessen (mm)
X_2 = Monthly rainfall of Cilember Rainfall Station multiplied by the polygon correction factor
Thiessen (mm)
X_3 = Monthly rainfall of Gunung Mas Rainfall Station multiplied by the correction factor Thiessen polygon (mm)
$X_5 = X_1 + X_2 + X_3$ (mm)
Y_1 = Monthly discharge AWLR (m^3/second)

The model equation for combination 1 with *Multi-Layer Perceptron architecture, Backpropagation* algorithm , and hyperbolic tangent (tanh) activation function is as follows:

Computational equations in hidden layers

Input to neuron Z1:

$$z1_{in} = v_{01} + x1.v_{11} + x2.v_{21} + x3.v_{31} + x5.v_{51}$$

The output of neuron Z1 with tanh activation function:

$$z1 = tanh(z1_{in})$$

Input to neuron$z2$

$$z2_{in} = v_{02} + x1.v_{12} + x2.v_{22} + x3.v_{32} + x5.v_{52}$$

The output of neuron Z1 with tanh activation function:

$$z2 = tanh(z2_{in})$$

Computational equations in the output layer

Input to output neuron Y1:

$$y1_{in} = w_{01} + z1.w_{11} + z2.w_{21}$$

The output of neuron Y1 with tanh activation function:

$$y1 = tanh(y1_{in})$$

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The complete equation is:

Computation in *Hidden Layer* :

$$z1_{in} = v_{01} + x1.v_{11} + x2.v_{21} + x3.v_{31} + x5.v_{51}$$
$$z2_{in} = v_{02} + x1.v_{12} + x2.v_{22} + x3.v_{32} + x5.v_{52}$$
$$z1 \quad = tanh(z1_{in})$$
$$z2 \quad = tanh(z2_{in})$$

Computation in *Output Layer* :

$$y1_{in} = w_{01} + z1.w_{11} + z2.w_{21}$$
$$y1 \quad = tanh(y1_{in})$$

To update the weights $v$and $w$with backpropagation, it is necessary to compute the derivative of the error function with respect to the weights and update it in the negative direction *of the gradient* .

Backpropagation Steps :

***Feedforward* :** Calculate the network output for each *input* .

Calculate *error* :

$$E = \frac{1}{2}\sum(t_k - y_k)^2$$

Where $t_k$is the target *output* and $y_k$is the actual *output of the network.*

Propagate error backwards:

- Calculate the delta for *the output layer* :

$$\delta_{output} = (t_k - y_k).\ tanh'(y1_{in})$$

- Calculate the delta for *the hidden layer* :

$$\delta_{hidden,1} = \delta_{output} \cdot w_{11}.\ tanh'(z1_{in})$$
$$\delta_{hidden,2} = \delta_{output} \cdot w_{21}.\ tanh'(z2_{in})$$

Update weight:

- Update the weights from *the hidden layer* to *the output layer* :

$$w_{baru,11} = w_{lama,11} + \eta \cdot \delta_{output} \cdot z1$$
$$w_{baru,21} = w_{lama,21} + \eta \cdot \delta_{output} \cdot z2$$
$$w_{baru,01} = w_{lama,01} + \eta \cdot \delta_{output} \cdot 1$$

Update the weights from the input layer to the hidden layer:

$$v_{baru,ij} \ = v_{lama,ij} + \eta \cdot \delta_{hidden,j} \cdot x_i$$
$$v_{baru,0j} = v_{lama,0j} + \eta \cdot \delta_{hidden,j} \cdot 1$$

Information:

$\eta$is *the learning rate*

$tanh'(x) = 1 - tanh^2(x)$is the derivative of the tanh activation function.

The findings from this study underscore the importance of learner-centered technology in modern education. The high ratings across all evaluated areas—content quality, functionality, and usability—reflect a positive reception that goes beyond superficial engagement. These results suggest that the app effectively catered to the academic needs of its target users,

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offering structured yet flexible learning pathways that align with the dynamic routines of senior high school students. The consistency of responses implies a shared experience among users, one that points to the app's success in delivering accessible and meaningful content.

The intuitive design and ease of navigation appeared to significantly contribute to users' ability to interact with the application efficiently. With minimal friction in exploring its features, students were able to focus more on learning rather than struggling with technical barriers. This suggests that the application's user interface played a critical role in reducing cognitive overload and promoting self-directed exploration of lessons, assessments, and multimedia content. Such a design approach may foster digital confidence and autonomy, which are vital in nurturing independent learners. Moreover, the results revealed how the application supported a sense of continuity in learning despite potential classroom limitations. By integrating resources that mirror real-world scenarios and applying concepts relevant to the HUMSS strand, the app enabled users to contextualize their learning. This not only improved comprehension but also enhanced retention and application of knowledge. The app functioned not merely as a digital textbook but as a dynamic companion in the academic journey, supporting both revision and skill-building.

There is also a notable implication regarding motivation. The positive feedback may reflect an increased enthusiasm for engaging with academic materials through digital platforms. When students perceive learning tools as helpful and responsive to their preferences, their willingness to invest time and effort naturally increases. This reinforces the value of educational technologies that are not only informative but also interactive and appealing.

Conclusion

Based on the calculations and data analysis conducted, several conclusions can be drawn. The evaluation of the existing rain station network density in the Upper Ciliwung Watershed, in accordance with the World Meteorological Organization (WMO) standard from the Guide to Hydrological Practices (2020), indicates that the area falls under the small islands category with a standard density of 250 km^2 per station for automatic recording posts. With four rain stations and a density of 37.981 km^2 per station, the Upper Ciliwung Watershed exceeds the WMO standard. Furthermore, the distribution pattern analysis using the artificial neural network (ANN) method was conducted with 15 station combinations and three data division ratios (70-20-10, 60-25-15, 50-30-20) over 100, 500, and 1000 epochs. The results showed that the best performance for the 70-20-10 ratio was at 1000 epochs, achieving the lowest relative error of 9.880% and a Nash-Sutcliffe Efficiency (NSE) of 0.983, classified as excellent. Similarly, the 60-25-15 ratio performed best at 100 epochs with an NSE of 0.982, while the 50-30-20 ratio performed best at 500 epochs with an NSE of 0.981. Among all combinations, the best forecasting result was achieved with the 70-20-10 data division, yielding the lowest error and highest accuracy. The combination involving Gadog, Cilember, and Gunung Mas Rain Stations demonstrated the most reliable performance, with an NSE close to 1, indicating very high predictive accuracy of the model.

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