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Estimation of Rainfall-Runoff Relationship Using Artificial Neural Network Models for Muskegon Basin

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***Abstract*— *In order to determine the use, protection and economic life of water resources; it is important to make estimations about rainfall-runoff values. However, it is quite complicated to estimate rainfall-runoff. For this reason, Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) methods, which are widely used today for complex hydrological problems, are preferred for the rainfall-runoff model. For model creation, the hydrological and seasonal data from the United States Muskegon basin are used. Estimation study was done with ANN and MLR methods using 1396 daily rainfall, temperature and rainfall data belonging to the region. According to the model results, it is seen that the ANN method has results with low error and high determination in the rainfall runoff model. ANN method can be used as an alternative way to classical methods in rainfall-runoff predictions.*

***Keywords*— Rainfall – runoff relation, Artificial neural networks, Multiple linear regression, Prediction.**

I. INTRODUCTION

Water is one of the most essential requirements for the survival of life. In the hydrological cycle, the only source that determines the localization of the water, the size of the water and the formation of fresh water on the earth is the rainfall. Therefore, the science of hydrology, which deals with the change and amount of water in the earth, uses the rainfall-runoff relationship, temporal and spatial change to determine this requirement. As a result of the analyzes; It is very important to find out the regional water demand, to protect the water resources, to use in the right projects and to have the most beneficial and economical decision.

Hydrological models can be used to estimate changes in hydrological sizes as a result of human effects on nature [1]. Due to the high number of parameters generated by the processing of hydrological data, it is recommended to use approximate methods instead of theoretical analysis.

It is difficult to obtain hydrological data by taking time dependent measurements in terrain conditions, both geographic and topographic, depending on many variables and planning under terrain conditions. Since it poses a major problem in terms of both economic and time, the methods suitable for hydrological laws and the models used in this study are needed.

The analysis is designed with the aid of mathematical and statistical models, made more accurate analysis and in the past has tried to estimate the parameters of the hydrological cycle since. In this hydrological cycle, the rainfall-runoff relationship has particular importance.

Artificial intelligence was applied to dam reservoir level, dam reservoir volume, evaporation and in many different disciplines-areas by many researchers [2-19]. ANN was used for modeling the suspended sediment in a number of works [20-22]. Uneş [23] predicted density flow plunging depth in dam reservoir using the ANN . Demirci et al [24] and Kaya et al [25] investigated that artificial neural network (ANN) approach to the daily forecasting of groundwater levels. Demirci et al [26] estimated the nearshore sandbar crest depth by using neural network (ANN).When the studies are examined, estimations can be made about the operation of watershed and water resources by using obtained hydrological and climatic data. As one of the artificial intelligence techniques, the ANN method is accepted as an alternative to classical methods in the definition and modeling of complex and nonlinear events in hydrology and water resources studies. Sharifi et al. [27] used linear method for rainfall-runoff modeling, support vector machines (SVM) fuzzy logic (ANFIS) and artificial neural networks (ANN). Nacar et al. [28], Haldizen Creek flow values in the East Black Sea Basin were estimated using Multivariate Adaptive Regression Curves and classical regression analysis. When the results of the method were examined, it was observed that the estimation values of Multivariate Adaptive Regression Curves method gave better results than classical regression analysis. Gemici et al. [29],

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estimated Kızılırmak river the amount of total flow by using multilayer artificial neural networks, radial-based artificial neural networks and adaptive network-based fuzzy inference system (ANFIS) models with the flow of each slice. In this study, they used the river base slope, the baseline roughness coefficient, the cross-section slice width, the water level passing through the slice and the river cross section width values as input data. Chakravarti et al. [30] examined the ANN model by using the rainfall-runoff data they obtained. According to the model results, they observed that the ANN model gave very good estimations. Tongal and Booij [31] have used their current meteorological data stream flow forecasts for artificial intelligence methods for flow simulation studies.

In this study, Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) methods were used to obtain rainfall-runoff model estimation model. Data belongs to Muskegon River with station number 04121970. Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) methods were used to obtain rainfall runoff estimation model.

II. METHODOLOGY

2.1 Artificial Neural Networks (ANN)

Artificial neural networks (ANN); It is an artificial intelligence technique that takes the working structure of human brain as a model and simulates it in its own internal algorithm. This technique can be used in a wide range of fields ranging from civil engineering to mechanical engineering in financial analysis management from economics to medical science.

Figure 1 shows the three-layer and feed-forward ANN architecture. The data flow in this architecture is unidirectional. The data collected for the study will be included as an input in the ANN model and thus the analysis starts.

If the data in the input layer is called X_i, there is output value J_n, (n=1,2,3,…m) in output nodes up to X_i = (i=1,2,3,…k). These input values are multiplied by W_{ij} (J = 1,2,3,…h) in hidden layers and the output values are edited and used as input values of hidden layers. The information in the hidden layer is processed and transmitted to the output layer. In the output layer, the output value is determined and the results are produced and the process is completed.

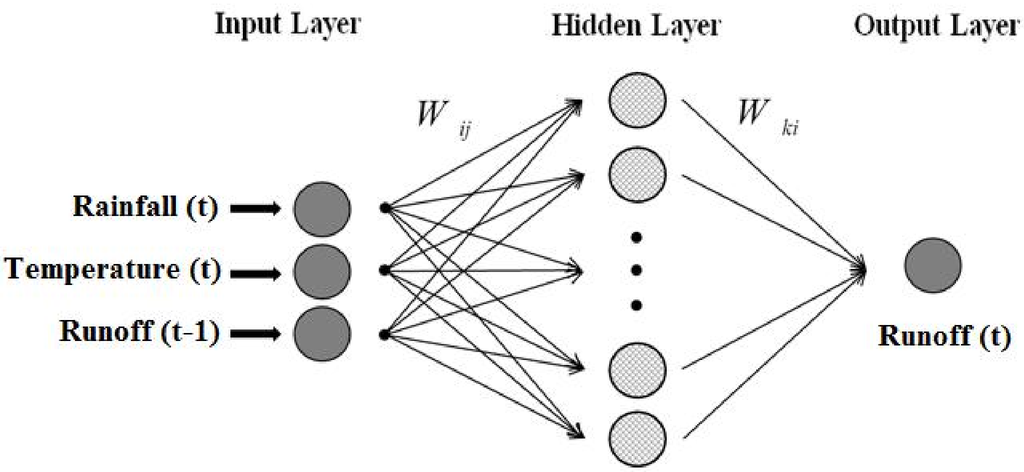

Fig.1: Network architecture used in ANN model

Because the interpretation of results as a model for education and to have a system that can be called with the name ANN. The model uses information from the analysis to interpret new events, such as the human brain, which is the most important difference between other models.

2.2 Multiple Linear Regression (MLR)

It is an analysis method to find the variance created by multiple dependent variables with a dependent variable. This regression model is shown in case of the dependent variable y with the independent variable x can be written as follows.

$$\left[y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \cdots + \varepsilon \right]$$

Here, β represents the regression coefficients, β_0 represents the breakpoint, and ε represents the error term.

III. STUDY AREA AND APPLICATION

3.1 Working Area

In this study, the Muskegon River, which meets the water demand of 6100 km^2 area of 348 km in Michigan, has been investigated. 1397 daily temperature, runoff and rainfall data were used. Data set is collected between the dates 14.08.2014 and 11.06.2018 by United States Geological Survey (USGS, [32]). In Figures 2 and 3, Muskegon river location and general views are given.

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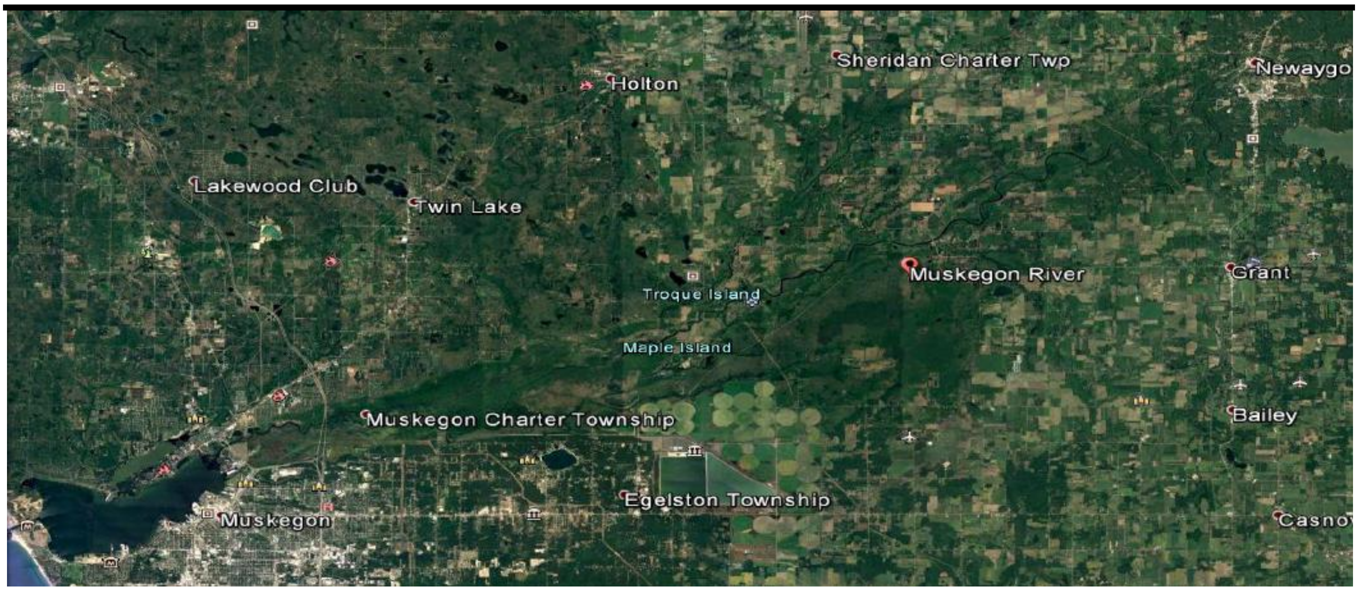

Fig.2: Positional view of the Muskegon river

Fig.3: General view of the Muskegon River

Figure 4, Figure 5 and Figure 6 shows the 1397 daily water temperature, rainfall and runoff change graphs respectively.

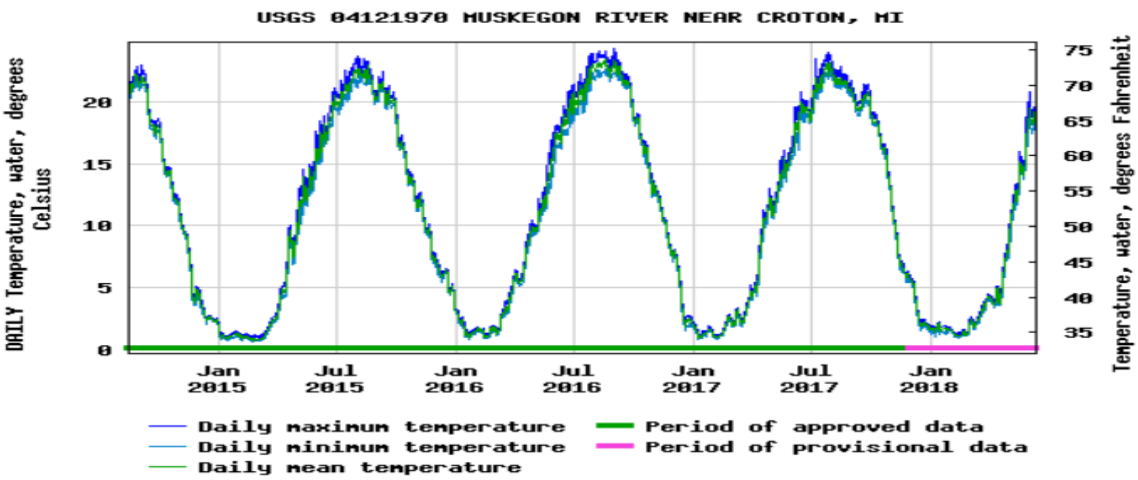

Fig.4: Amount of Daily Water Temperature (°C/°F) [32]

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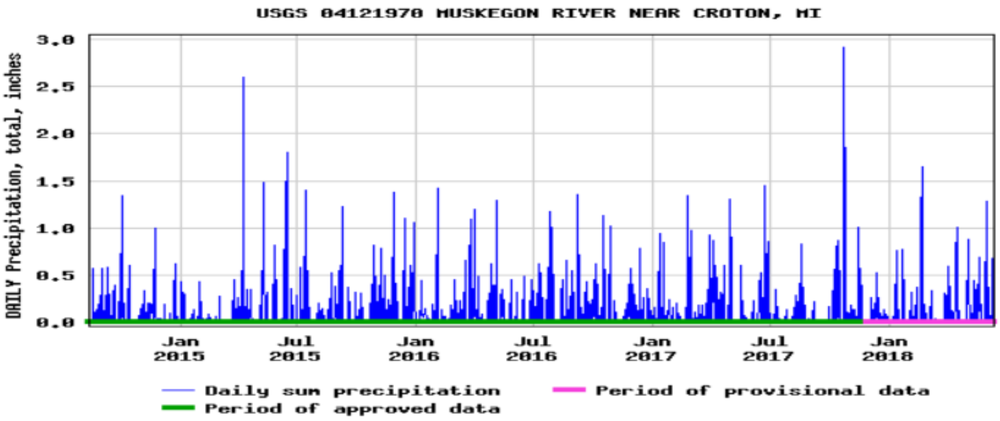

Fig.5: Daily rainfall (inches) [32]

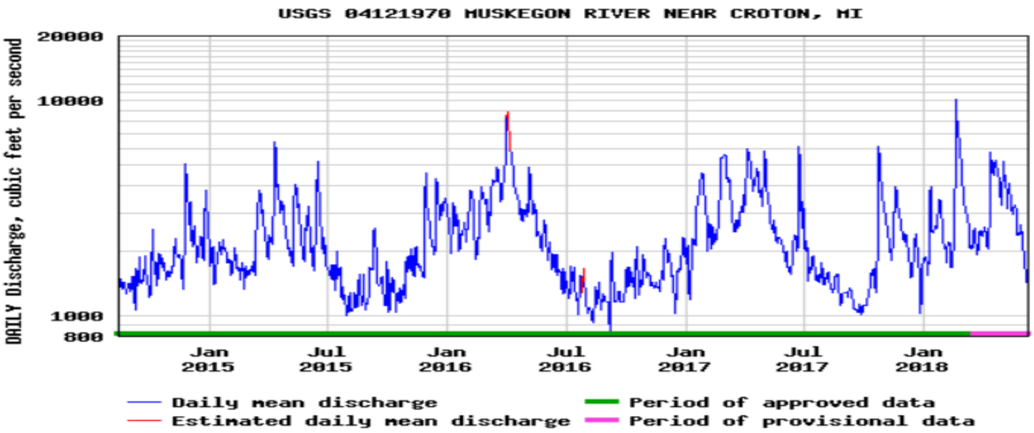

Fig.6: Daily Runoff Amount (ft^3/s) [32]

3.2 Application

In this study, the results of ANN1, ANN2, MLR1 and MLR2 were compared according to the following statistical criteria. Daily water temperature, rainfall and runoff time series and runoff (3 input 1 output) modeling was performed for the model ANN1 and MLR1. In addition, in the model ANN2 and MLR2, runoff modeling was performed with water temperature, rainfall, rainfall time series and runoff time series (4 inputs 1 output).

In this study, 350 of the 1397 daily temperature and rainfall-runoff data were used for testing, while the remaining 1047 were used for training. In the modeling, R^2 (R Square Calculation), MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) were calculated and the results were interpreted by two evaluations.

The determination coefficient (R^2) measures the strength of the linear correlation between the x and y binary values. The fact that the linear relationship is 1 indicates that the result is very close. In this case, the interpretation of the closest value to 1 is the most reasonable and appropriate. The mean absolute error (MAE) measures the accuracy by continuously calculating the mean size of the errors in the estimation without taking into account the aspects of the variables. The root of mean squared errors (RMSE) measures the error average magnitude. MAE and RMSE are used to diagnose the possibility of errors. MAE and RMSE can go from zero to infinite. Lower values mean more useful.

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}\left|Q_{\mathrm{meauserement}} - Q_{\mathrm{estimate}}\right| \qquad Q: \mathrm{runoff}, m^3/s$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_{\mathrm{measurement}} - Q_{\mathrm{estimate}}\right)^2} \qquad Q: \mathrm{runoff}, m^3/s$$

$$R^2 = \left[\frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{\left(n\left(\sum x^2\right) - (\sum x)^2\right)}\sqrt{\left(n\left(\sum y^2\right) - (\sum y)^2\right)}}\right]$$

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Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and determination coefficient (R^2) statistics are calculated for comparison of methods used. ANN results and MLR results are given in Table 1.

Table.1: Statistical results of the models

	MLR1	**MLR2**	**ANN1**	**ANN2**
INPUTS	T, P, Q_{t-1}	T, P, P_{t-1}, Q_{t-1}	T, P, Q_{t-1}	T, P, P_{t-1}, Q_{t-1}
MAE	5.38	**5.02**	5.16	**3.28**
RMSE	11.53	**9.56**	9.45	**7.12**
R^2	0.90	**0.93**	0.94	**0.97**

The most appropriate result among the models where data is used, as shown in Table 1, gave ANN2 model analysis. Distribution and scatter graphs of ANN1, ANN2 and MLR1, MLR2 models are shown in Figure 7-10 below, respectively.

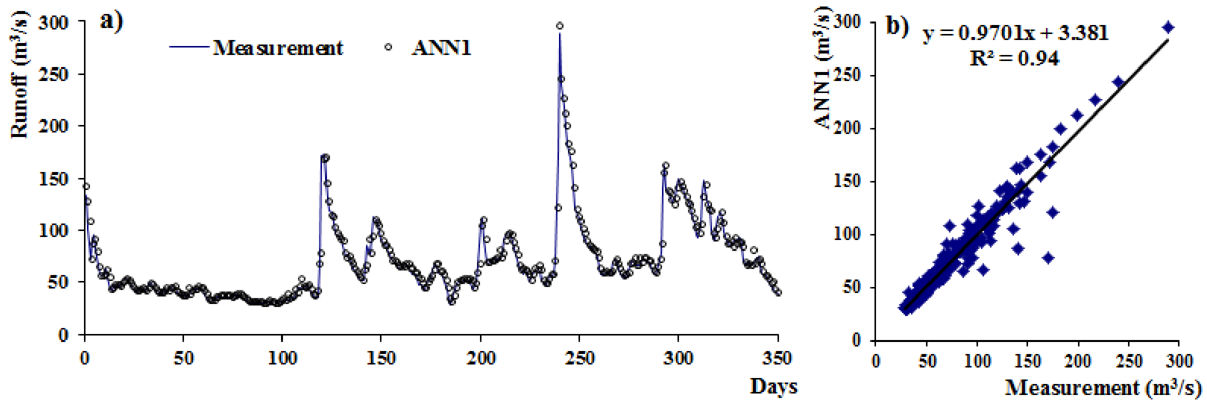

Fig.7: ANN1 model charts for Muskegon River test data
***a)** distribution chart **b)** scatter chart*

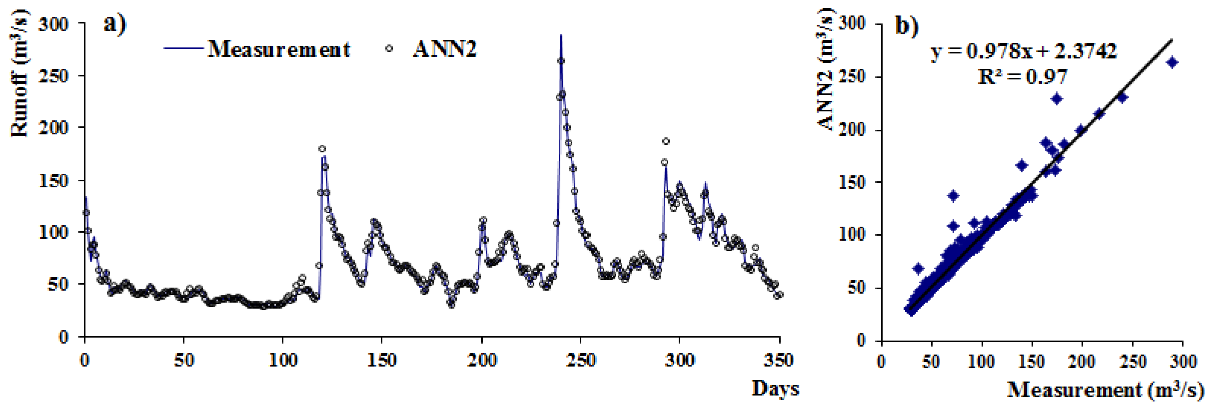

Fig.8: ANN2 model charts for Muskegon River test data
***a)** distribution chart **b)** scatter chart*

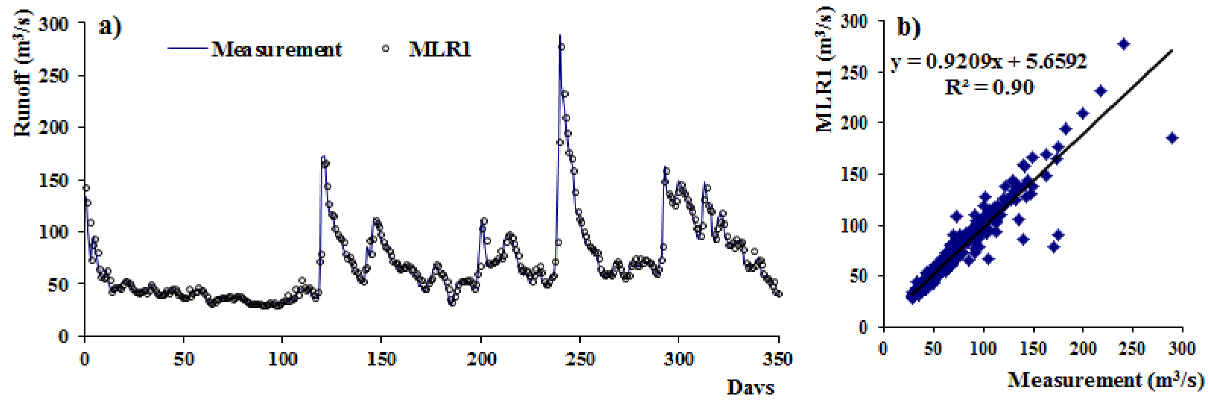

Fig.9: MLR1 model charts for Muskegon River test data
***a)** distribution chart **b)** scatter chart*

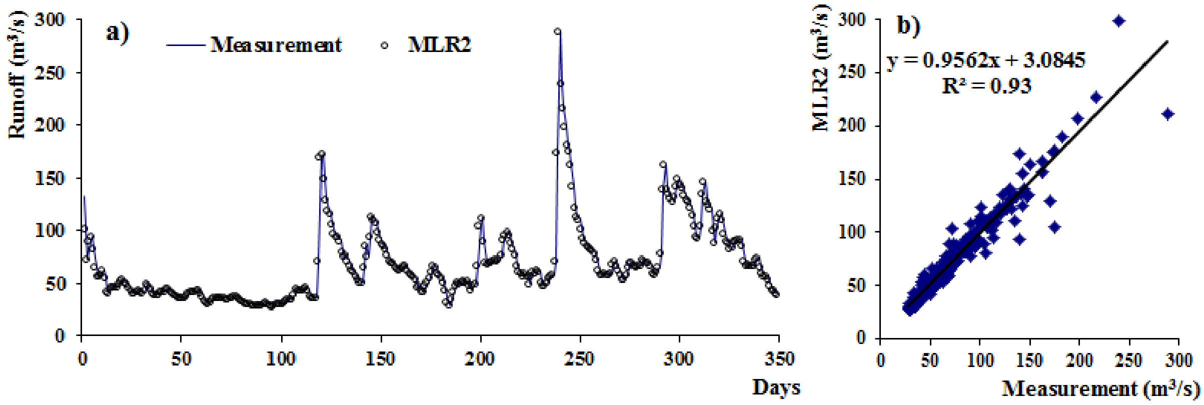

Fig.10: MLR2 model charts for Muskegon River test data
***a)** distribution chart **b)** scatter chart*

According to Table 1 and distribution-scatter charts, it is observed that all models have good results for the test data. When the table is analyzed, we can express the good results with the high coefficient of determination (R^2) and the lowest error amount (RMSE, MAE). Accordingly, the best estimation and low error rate of the ANN2 model and the highest number of determinations (R^2 = 0.97) and the lowest RMSE (7.12 m^3/s) and MAE (3.28 m^3/s) error is seen. In addition, when the MLR were evaluated in itself, MLR2 model has the number of determinations (R^2 = 0.93) and RMSE (9.56 m^3/s) and MAE (5.02 m^3/s) error. As a result of this study, the relationship between rainfall-runoff modeling ANN which is one of the artificial intelligence methods can be presented as an alternative to traditional MLR method.

IV. CONCLUSION

In this study, Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) methods were used to obtain the rainfall-runoff estimation model of the Muskegon River. Water temperature, rainfall, runoff time series and runoff) modeling was performed for the model ANN1 and MLR1. In addition, in the model ANN2 and MLR2, runoff modeling was performed with water temperature, rainfall, rainfall time series and runoff time series (4 inputs 1 output). ANN model results are compared with the measured runoff quantity and the results of the MLR method.

It has been observed that the MLR method gives quite accurate results in the solution of the problem. However, comparison of ANN model and MLR method shows that, ANN has better estimation performance for rainfall-runoff relation.

As a result, the low amount of error (MAE, RMSE) ratios and high determination (R^2) provided the desired performance in both methods. However, it has been observed that the ANN model gave better results than the MLR model. The reason for the high correlation of the MLR method is that the relationship between rainfall and runoff is linear. ANN models provide good results in both linear and nonlinear situations. However, the ANN model generally gives better results in non-linear situations.

Artificial Neural Networks have been found to be a model that can be applied in the estimation of the runoff occurring with rainfall, in the studies which water planning is required and in determining the water level changes. As a final result, it is understood that ANN can be used for hydrological modelling which is necessary for water resources management and planning future requirements.

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