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Draw Curves of the Rainfall Intensity-Duration-Frequency by Using Multilayer Artificial Neural Network for Al-Najaf Al-Ashraf

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Abstract

Curves of the Rainfall Intensity-Duration-Frequency are one of the most important engineering hydrology topics useful in water resources designs. It's created in desert climate of Najaf catchment harnessing a new programming method of the rapid artificial neural network, which differ from the old network and do not require an important criterion in the conducting of the normalization adjustment executing in the old style in the same field. The ANN outputs, from its intensity in millimeter / hour (mm / hr) unit for various periods in minutes (min), is obtained for a different frequency of the unit of the year. Its results were verified and the differences between them and the actual results were highly acceptable. The relationship between intensity (mm / hr) and duration (min) was found because of its importance employing the inverse logarithm of the fifth scale standard by performing Matlab version 2018a. The relationship between the frequency (year) and the duration (min) was also extracted recruiting the logarithm of the level v criterion. It has been discovered that the available data corresponds to the Lognormal Type III distribution and from this it is possible to calculate the periods of return.

Key Words: Intensity-Duration-Frequency; Artificial Neural Network; Al-Najaf Al-Ashraf; Curves of Rainfall; Minimum Mean Squared Error

1. Introduction

The designer of the intensity-duration-frequency (IDF) curve is one of the most complex hydrological issues due to the numerous methods being in which they are extracted. These curves change to vary according to the changing area depending on surrounding weather conditions [1-2]. On the grounds that the Artificial Neural Network (ANN) is very successful in dealing with these complex hydrological problems because of their multiple privileges in solving these problems [3-4]. But the program has some drawbacks and slowness. The modifications are done to ANN programming made it easy to solve any problem of the IDF where it will appear later.

2. Study of Acar

Acar et al., 2008 [5] have stipulated that the use of normalization before the beginning of the program to convert the three variables intensity (I), duration (D) and frequency (F) to form between 0 and 1 due to the difference between variable units as a year, min and mm/hr whereas I have managed to write a program without conditional formatting to convert data though from the fact that there is a difference between the units in the light of the fact that I have directly added the data manipulation processes within the program programming without the port intervention in the program thus reducing hardship and distress in the implementation of the program.

3. Components of Artificial Neural Network

From the knowledge of the form of the network, we can build it with multiple attempts that require patience and calm. Our network consists of three subnets as displayed in Fig. 1, the first of which is the input Nos.1 and 4, the layers Nos.1 and 4, the output No.1, the second input of Nos.2 and 5, the layers Nos.2 and 5, the output No.2, the third of the inputs Nos.3 and 6, layers Nos.3 and 6, and outlet No. 3.

From Fig. 2 which the program shows exercising the View command, you see that the network layout characteristics of inputs Nos.1 and 4, layers Nos.1 and 4, and output No.1 are indicated by the number of input elements, stratums, and connectors that you have specified for the owning network.

You are seen that the elements attached to the first layer are 46 two-column elements. It is possible to say that all the elements of the input included here have two columns and the elements of the accompanying target from one column. It can be seen that the first layer contains 46 elements. The first Column is I and second is D, and the object is F. The fourth layer consist of 52 elements, 46 elements from the first layer, and six elements from input No.4. The output of No.1 ends with 52 elements with three columns I, D and F and so forth (Table 1).

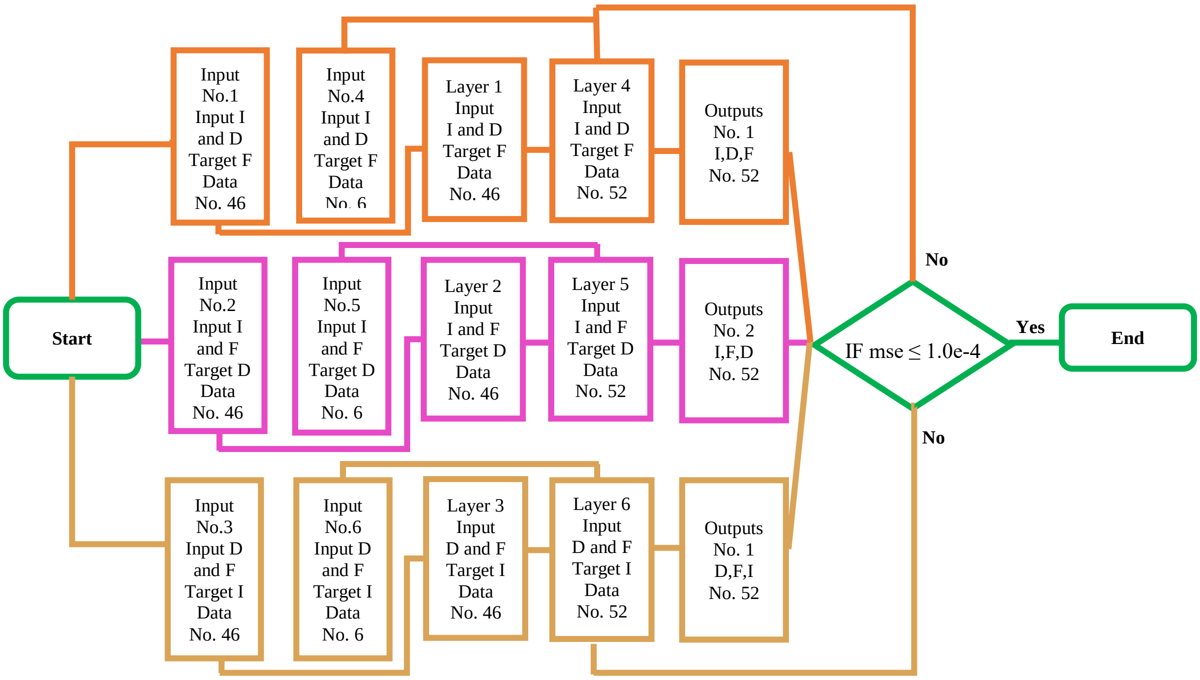

Fig. 1: Characteristics of the architecture of the ANN program on IDF

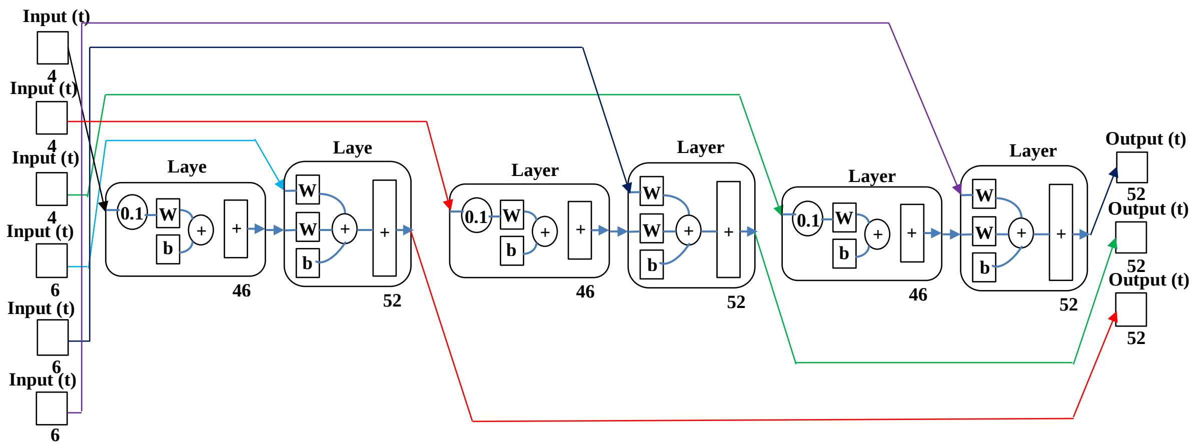

Fig. 2: View of my Neural Network

Table 1: Characterize the input data

Input Sections	Target Data	Input Data	Number of data
Input 1	F	I,D	46
Input 2	D	I,F	46
Input 3	I	D,F	46
Input 4	F	I,D	6
Input 5	D	I,F	6
Input 6	I	D,F	6

4. Discover the Intensity-Duration-Frequency (IDF) in the Artificial Neural Network (ANN)

The IDF is an appropriate problem that it needs to create a neural network of six numerical groups such as inserting data and six numeral sets as objectives or called targets within ANN, as indicated in Fig. 3. It is possible to accept the values in each of the three sub-networks regardless of the different units due to the placement of each layer in the Nguyen-Widrow layer initialization method (initnw) [6-11] This directive requires that the class you are configuring is a transport function of a restricted effective input range, the active input is the unlimited interval [-∞, ∞].

The use of mean absolute error (MAE) in the artificial neural network applied for the study was not emphasized. Chai and his group [12] also recommended that researchers not practice it for several reasons mentioned in his study , despite his frequent utilize in hydrology and precipitation studies in particular . They recommend executing root mean square error (Rmse or Rγ) (Eq.1) or mean square error (where mse is mentioned in Matlab while γ denotes it in this study) (Eq.2) , which is also employed in artificial neural networks and rejects arguments not to use it.

$$R\gamma = \sqrt{\frac{\sum_{i}^{N_{Data}}(\varphi_i - \widehat{\varphi_i})^2}{N_{Data}}} \quad (1)$$

$$\gamma = \frac{\sum_{i}^{N_{Data}}(\varphi_i - \widehat{\varphi_i})^2}{N_{Data}} \quad (2)$$

Where N_{Data} is number of data monitored, φ_i is the variable we get from artificial neural network outputs including both intensity or duration or frequency and $\widehat{\varphi_i}$ is the genuine spectacle variable.

The outputs must match the relevant target vectors with the $(mse\ or\ \gamma)$.

When training the IDF, Levenberg-Marquardt symbolized by Trainlm, was used to solve our problems in the IDF. Our goal of training is to get a continuation decrease in the value of γ. This situation continued in 242 attempts, until the value of γ began to increase then we were forced to stop the program as displayed in Fig. 4.

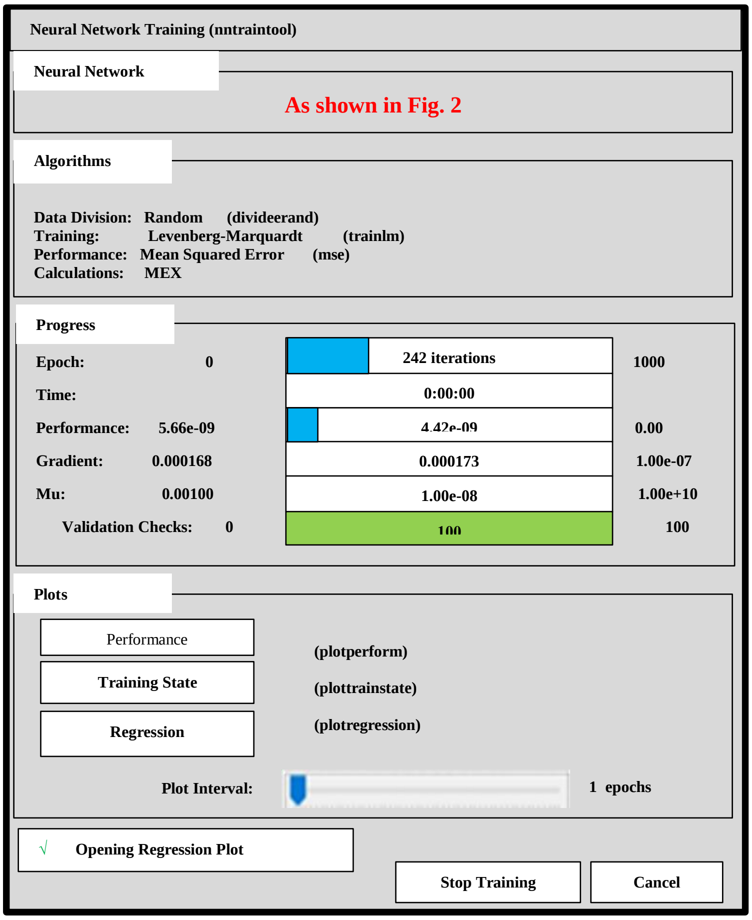

Fig. 3: Program execution interface

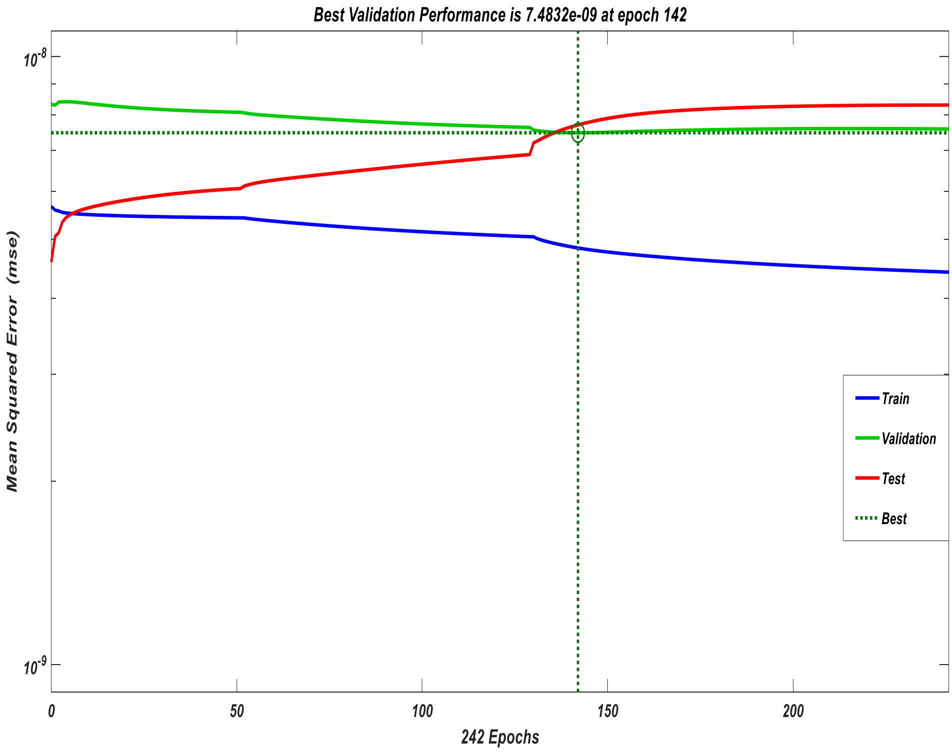

Fig. 4: Top Check execution

The implementation of the program can be verified veracity by finding the Gradient = 0.00017311, μ = 1.0e08 and Validation Checks = 100 at epoch 242 as appeared in Fig. 5.

In order to increase the verification, Fig. 6 exhibits the decrease in the γ value of the objectives for training, testing and verify the veracity. The coefficient of determination was found to R=1.0. This condition is very excellent.

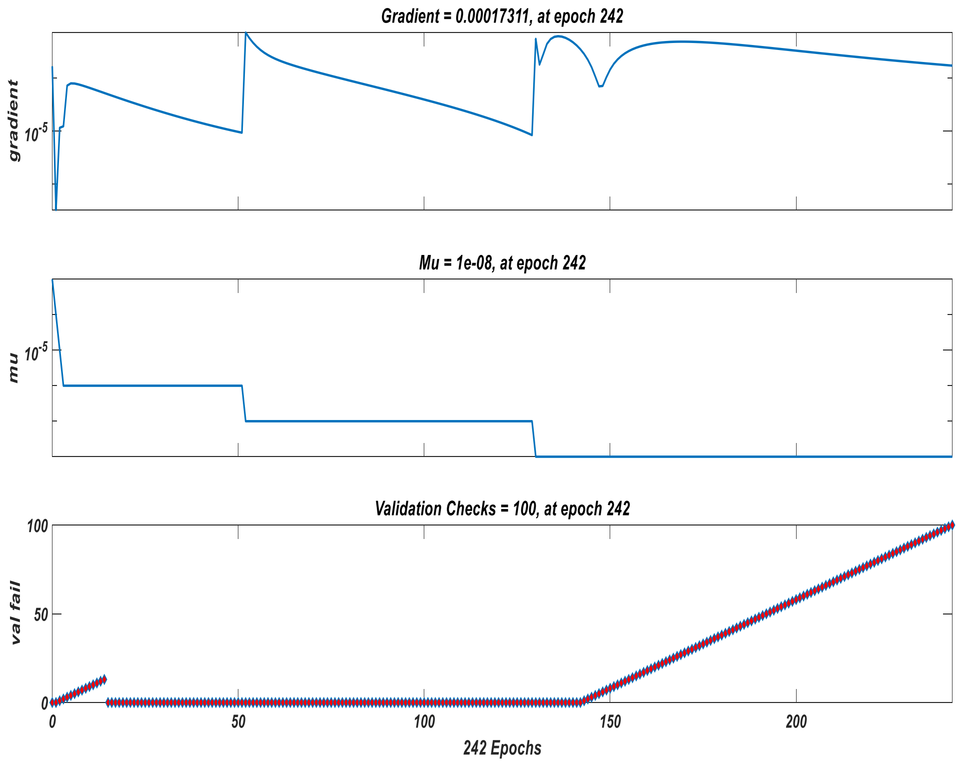

Fig. 5: Values of Gradient, Mu and Validation Checks at epoch 242

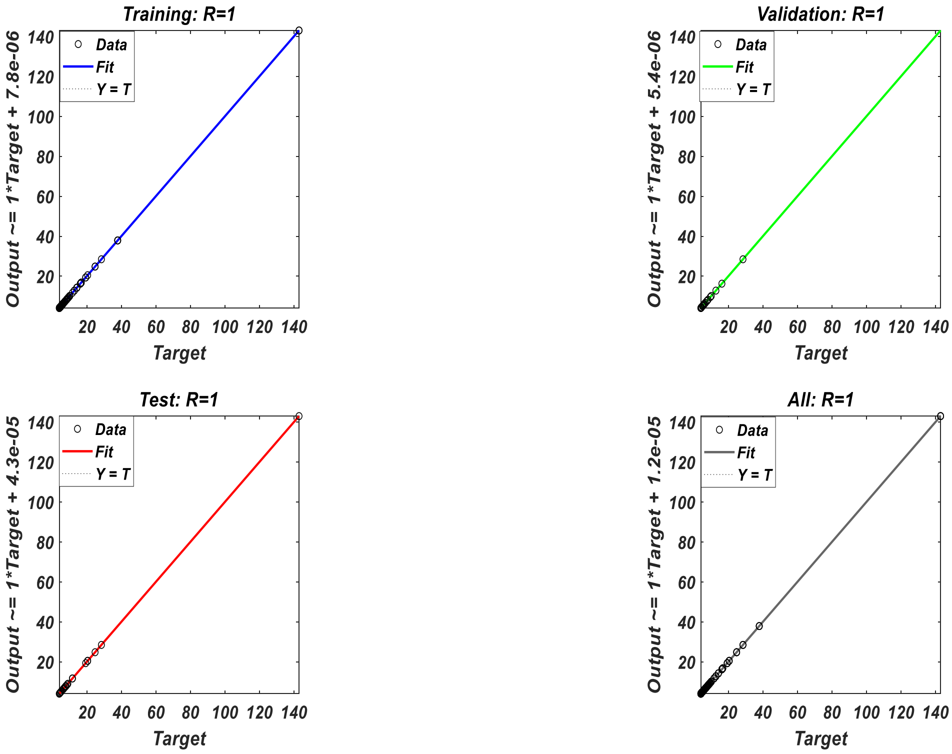

Fig. 6: Coefficient of determination R for training, testing, validation and all

5. City of Al-Najaf Al-Ashraf

Najaf is located in the southwestern part of Iraq, far from the capital Baghdad 161 km, with an area of 28,822 km^2 between longitudes 43.0oE-44.4 oE along with latitudes 32.0^{o}N-30.0^{o}N latitudes as given in Fig. 7. Its data onto raindrops for the maximum precipitation during the period 1966-2018 [13-14]. There is also a significant difference in the amount of cloudburst per year as they fluctuate significantly in the amount of rainfall from year after year. Its climate can be considered a desert owing to the fact that no raindrops throughout the year. The average annual temperature here are 23.6 °C and the annual rainstorm are 100 mms. Rainfall starts in October through the end of May .

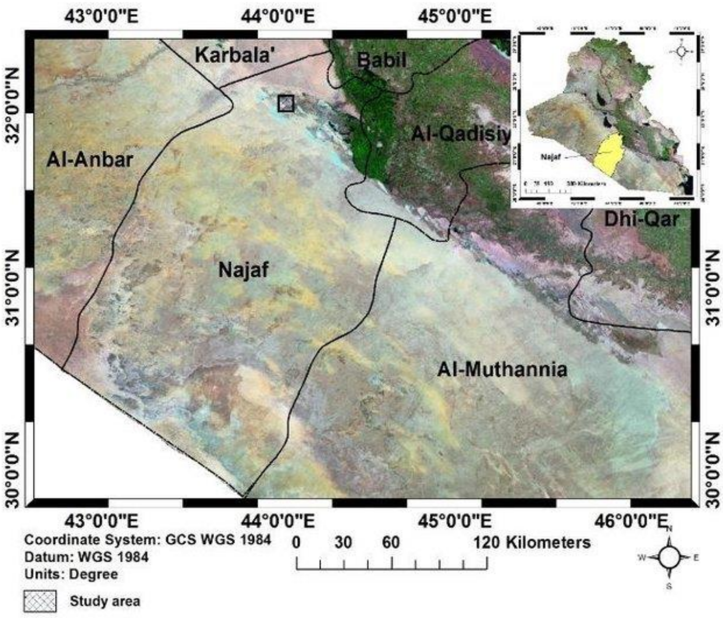

Fig. 7: Basin of Al-Najaf Al-Ashraf

6. Computations and valuations of the IDF curve

After analyzing the historical data onto the rainfall IDF of the basin of Al-Najaf Al-Ashraf it was found that the compatibility of the Graphical fitting is better than the rest of the other methods, depending on the rate of γ painted in Fig. 8.

After obtaining the results of the IDF from a software application for the new technique and drawing the IDF curve in the same old drawing paper, it was found to be very identical and was drawn in two linear and logarithmic sheets, as offered in Fig. 9 and 10.

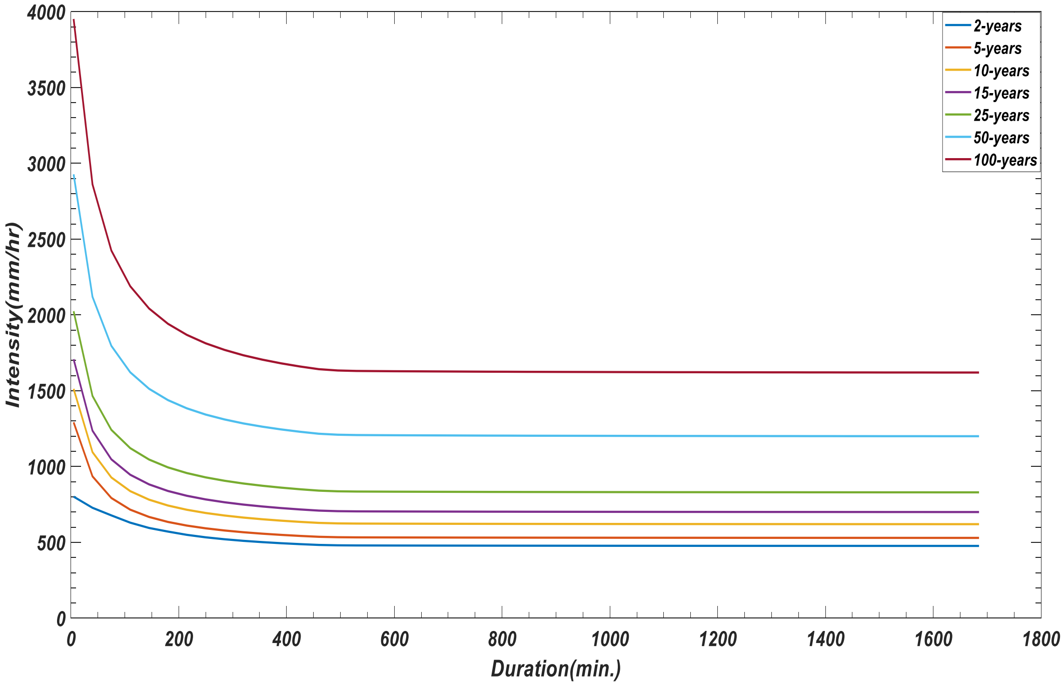

Fig. 8: Curves of rainfall IDF of the basin of Al-Najaf Al-Ashraf

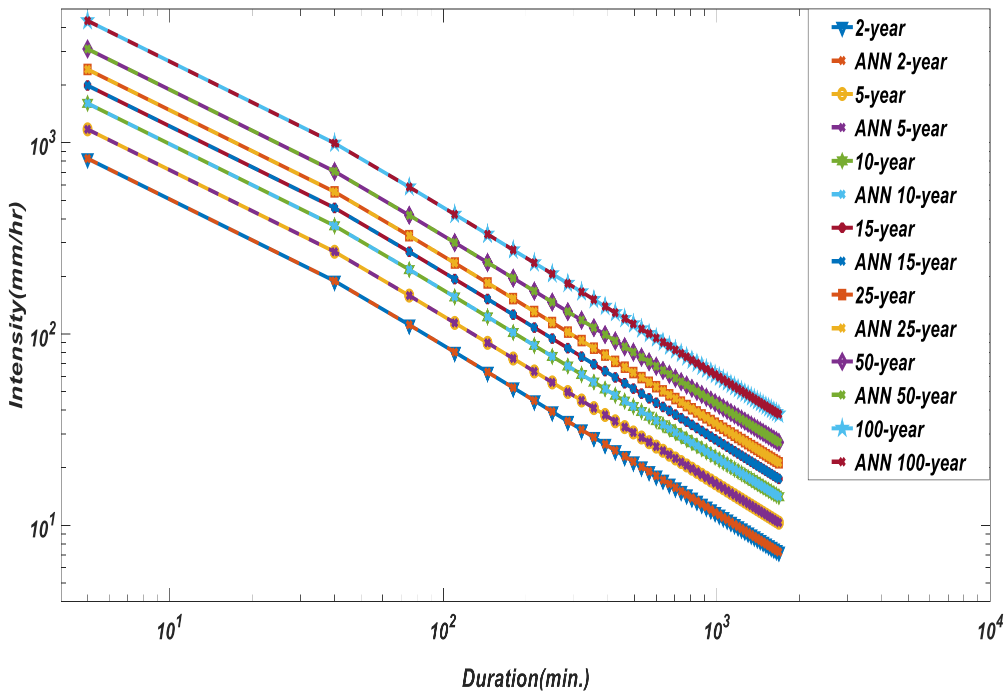

Fig. 9: Rainfall curves in the IDF through the graphical installation and ANN of the Al-Najaf Al-Ashraf basin of a Logarithmic paper

The results obtained from ANN are written specifically from outputs 1, 2, and 3 are then verified for a set of six data for only three types.

1) Supposing that the knowledge of intensity is needed as long as the duration and frequency are already clear as mentioned in Table 2.

2) In case that the duration is required if the intensity and frequency are known as presented in Table 3.

3) Assuming that frequency is extracted on condition that both duration and intensity are defined as exhibited in Table 4.

Table 2: Precipitation intensity of ANN output 1

Duration (min)	Frequency (year)	Intensity (mm/hr)	Actual intensity (mm/hr)
75	**5**	775.921	772.864
180	**10**	894.541	896.801
390	**15**	901.471	899.367
600	**25**	1019.006	1020.911
915	**50**	1248.089	1246.142
1230	**100**	1576.154	1571.381

Table 3: Rainfall duration of ann output 2

Intensity (mm/hr)	Frequency (year)	Duration (min)	Actual duration (min)
300	**2**	1813.28	1816.12
750	**10**	437.47	441.57
1000	**15**	219.01	221.06
1250	**25**	203.68	207.54
1500	**50**	352.39	349.78
2000	**100**	334.08	331.98

Table 4: Precipitation frequency of ANN output 3

Duration (min)	Intensity (mm/hr)	Frequency (year)	Actual frequency (year)
75	**750**	5	4.67
180	**1000**	15	14.02
390	**1250**	32	33.07
600	**1750**	95	94.84
915	**2500**	279	278.01
1230	**3500**	735	734.76

7. The Relationship between Intensity and Duration

The relationship between intensity (mm / hr) and duration (min) was established due to its importance utilizing the inverse logarithm of the fifth rank Eq. 3 through the use of Matlab version 2018a [15-19].

$$I = \beta_0 + \frac{\beta_1}{lnD} + \frac{\beta_2}{lnD^2} + \frac{\beta_3}{lnD^3} + \frac{\beta_4}{lnD^4} + \frac{\beta_5}{lnD^5} \quad (3)$$

Where $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ *and* β_5 in Eq.3 represent the constants that can be obtained from Table 5. A Standard Error of The Estimate = 2.89308e-05 with coefficient of multiple determination R^2 = 1.0. The inverse relation between intensity and duration is evident.

The relationship between frequency (year) and duration (min) harnessing the fifth order logarithm Eq. 4.

$$F = \beta_0 + \beta_1 lnD + \beta_2 lnD^2 + \beta_3 lnD^3 + \beta_4 lnD^4 + \beta_5 lnD^5 \quad (4)$$

Where $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ *and* β_5 in Eq. 4 represent the constants that can be obtained from Table 5. A Standard Error of The Estimate = 1.62356E-03 with coefficient of multiple determination R^2 = 0.99998. Relation of proportionality between frequency and duration is obvious.

The relationship between intensity and duration in the upper figure, as well as the relation between frequency versus duration in the middle shape and the two relations combined in the bottom shape and the three forms together are illustrated in Fig.10.

Table 5: Constants of Eq. 1 and Eq. 2

Variable	Values	
	Eq. 1	**Eq. 2**
$\boldsymbol{\beta_0}$	1.38740e+01	9.2456e-01
$\boldsymbol{\beta_1}$	-4.36709e+02	2.3541
$\boldsymbol{\beta_2}$	4.45890e+03	-1.4358
$\boldsymbol{\beta_3}$	-2.1854e+04	0.4712
$\boldsymbol{\beta_4}$	7.3547e+04	-4.3845e-02
$\boldsymbol{\beta_5}$	-9.2109e+04	2.6892e-03

8. Lognormal Type III distribution

Employing the advantages of frequency analysis to set the relationship of rainstorm intensity, tempest duration and frequency from obtainable precipitation data. A Lognormal Type III model is utilized to reckon precipitation intensity in periods of precipitation in addition to assorted periods of return to form the historical IDF curves of the Najaf basin. The relationship between the maximum precipitation intensity and the duration intervals are specified appointing a Lognormal Type III distribution is determined by the determination of the plotting position Eq.5, which is dependent on the ocular view as manifested in Fig.11. The return period can be determined based on the calculated probability of Eq. 5 of Fig.11.

$$P_{\text{Non-exceedance}} = \frac{\varepsilon_i - 0.0865}{N_{Data} - 0.0675} \quad (5)$$

$P_{\text{Non-exceedance}}$ be a symbol for Non-exceedance probabilities. The sample elements are arranged according to the amount of each item from the smallest to the largest worth. A sequence of each element is then given after the order in which ε_i is symbolized and N_{Data} denotes the number of sample elements. It is possible to know that the calculation of the return period after ($T_{\text{return period}}$) knowledge $P_{\text{Non-exceedance}}$ by applying Eq. 6.

$$T_{\text{return period}} = \frac{1}{1 - P_{\text{Non-exceedance}}} \quad (6)$$

9. Conclusion

Previously when appointing the old method all sub-methods utilized to establish the relationship between the IDF should be applied. The best method are chosen to depend on the lowest possible γ as shown in Figure 1. In addition to this takes a long time with effort. While the ANN method of the new adjustments is considered to be fast added to it's accurate in its results so arguably it's much better than the old methods clearly and strikingly. After applying the new adjusted ANN, the results were compared with the actual results and were satisfactorily accepted.

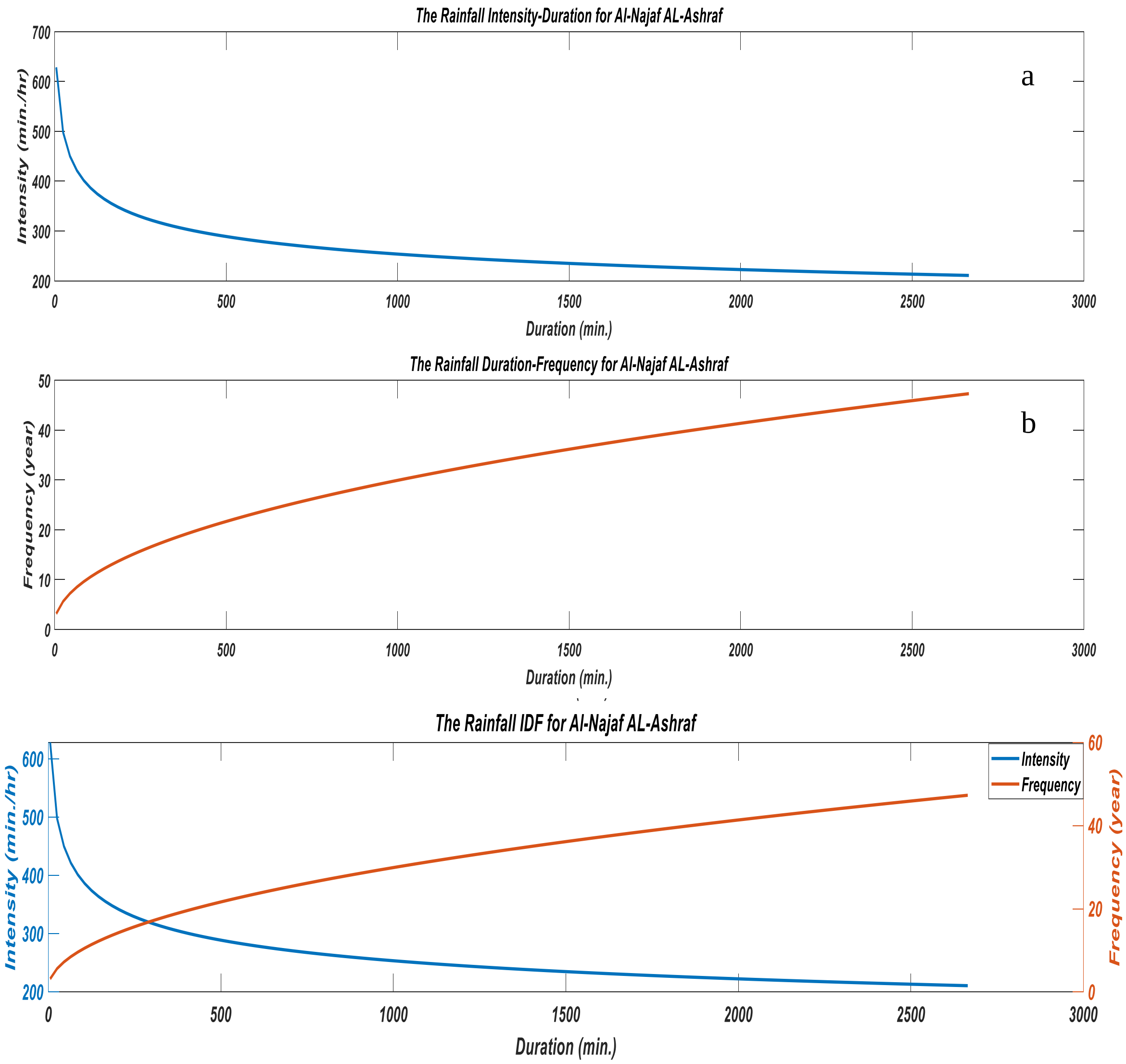

Fig. 10: Group representation between each two intensity, duration and frequency of the basin of Al-Najaf Al-Ashraf

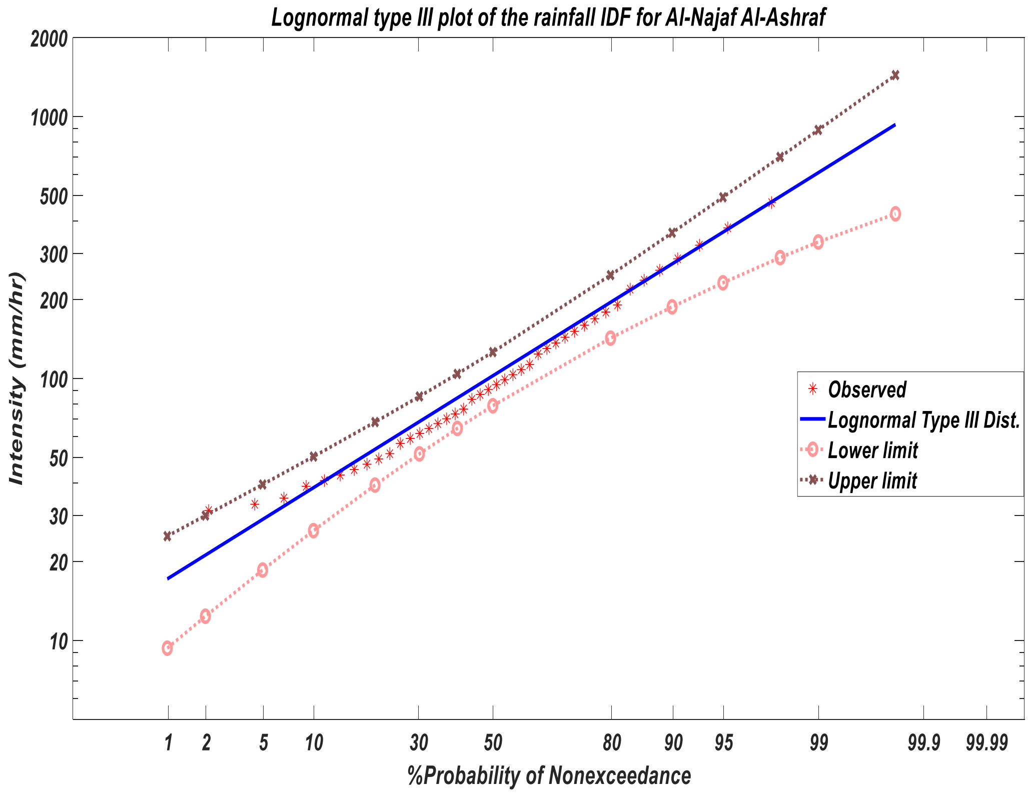

Fig. 11: Demonstrate the compatibility of rain intensity for the lognormal distribution of the third type

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