Spatial Prediction of Monthly Precipitation in Sulaimani Governorate using Artificial Neural Network Models

Prof. Dr. Rafa H. AL-Suhaili
Prof., Civil Eng. Dept., College of Eng., University of Baghdad, Iraq
Email:rafaalsuhili@yahoo.com

Rizgar A. Karim
Asst. Lec., Dam and W. R. Eng. Dept., Faculty of Eng., University of Sulaimani, Iraq
Rizgar_Karim@yahoo.com

ABSTRACT:

ANN modeling is used here to predict missing monthly precipitation data in one station of the eight weather stations network in Sulaimani Governorate. Eight models were developed, one for each station as for prediction. The accuracy of prediction obtain is excellent with correlation coefficients between the predicted and the measured values of monthly precipitation ranged from (90% to 97.2%). The eight ANN models are found after many trials for each station and those with the highest correlation coefficient were selected. All the ANN models are found to have a hyperbolic tangent and identity activation functions for the hidden and output layers respectively, with learning rate of (0.4) and momentum term of (0.9), but with different data set sub-division into training, testing and holdout data sub-sets, and different number of hidden nodes in the hidden layer. It is found that it is not necessary that the nearest station to the station under prediction has the highest effect; this may be attributed to the high differences in elevation between the stations. It can also found that the variance is not necessary has effect on the correlation coefficient obtained.

Keywords: ANN models, monthly precipitation data, weather station networks, prediction, spatial distribution of precipitation.

الاستاذ الدكتور رافع هاشم السهيلي
أستاذ،قسم الهندسة المدنية ،كلية الهندسة
جامعة بغداد

رزكار أحمد كريم
مدرس مساعد ،قسم هندسة السدود والموارد المائية
كلية الهندسة ، جامعة السليمانية

الخلاصة:

تم استخدام تقنية نمذجة الشبكات العصبية الصناعية لتخمين بيانات الأمطار الشهرية في أحدى المحطات الهيدرولوجية المناخية من واقع ثمان محطات في شبكة المحطات المناخية في محافظة السليمانية. تم بناء ثمان نماذج من الشبكات العصبية لكل محطة نموذج. ثم للحصول على نماذج ذات دقة عالية لتخمين الأمطار الشهرية حيث تراوح معامل الارتباط بين الأمطار الشهرية المخمنة و تلك المقاسة من (٩٠% - ٩٧,٢%). كل نموذج تم ايجاده بعد محاولات عديدة لكل محطة و تم اختيار النموذج الذي يعطي أعلى معامل ارتباط. جميع النماذج للشبكات العصبية الصناعية وجدت ذات دالة تفعيل نوع (hyperbolic tangent) و (identity) للطبقة المخفية و طبقة المخرجات على التوالي، و بمعدل تعلم للشبكة (٠,٤) و معامل زخم (٠,٩) و لكن بمختلف أنواع تقسيم البيانات الى بيانات التدريب ، الاختبار و التخمين و مختلف الأعداد للعقد في الطبقة المخفية. كما وجد في تحليل التأثير القياسي بأنه ليس من الضروري أن تكون المحطة ذات المسافة الأقرب من المحطة تحت التخمين ذات أعلى تأثير على الأمطار الشهرية لتلك المحطة وذلك بسبب الفروقات العالية بين منسوب المحطات. كما وجد بأنه ليس من الضروري أن تكون المحطات ذات البيانات التي أعطت أعلى تباين أن تكون ذات أقل معامل الارتباط للقيم المخمنة مع تلك المقاسة.

1. INTRODUCTION:

Prediction of precipitation is essential in most of the hydrological studies and water resources systems design, construction and operation. Weather stations that cover a relatively large area are distributed spatially to reflect the aerial distribution of hydrological variables such as precipitation. When the number of weather stations is large; sometimes measurements in one or more of the stations are not available and need to be accurately predicted. Prediction of those missing values could be done by one of the available approximate method in hydrological science, such as arithmetic mean method, isohyetal method and thiessen method. However all of these methods are approximate. For more accurate prediction of the missing values in one or more locations of the weather station network, the ANN modeling is expected to produce these more accurate precipitation values.

Belayneh and Adamoski, 2012, had modeled the standard precipitation index in Awash River basin of Ethiopia using three data driven models. Their study compares the effectiveness of these three data driven models, artificial neural networks (ANNs), support vector regression (SVR), and wavelet neural network (WN). These models were compared using Root Mean Square Error RMSE, Mean Absolute Error MAE and Determination Coefficient R^2. The results indicate that the coupled wavelet neural network (WN) model had produced the best results; however the ANN model had also performed well.

Luk et al., 2000, had used ANN modeling to model rainfall temporal and spatial distribution. Different lags and different numbers of spatial inputs were used to produce different ANNs models. These models were developed for the upper Parramatta River catchment located in western suburbs of Sydney, Australia. The normalized mean square error (NMSE) was chosen as the performance indicator. One important conclusion Obtained from this study is that the best performed network was lag-1 network with input from the eight nearest neighboring gauge stations.

Bustami et al., 2007, had used ANN models to predict missing readings of precipitation and water levels in the Bedup river catchment in the state of Sarawak, Malaysia. Back propagation ANN model was used for this purpose. The obtained accuracy of prediction of precipitation and water level in this basin are 96.4% and 85.3% respectively. Those results show that ANN is an effective tool in prediction of missing precipitation readings and water levels data.

El-Shafie et al., 2011, had developed a two rainfall prediction models for rainfall in Alexandria, Egypt. These models are ANN model and Multiple Linear Regression MLR model. The rainfall prediction was developed for annual and monthly basis. Comparison of results obtained by the two models was conducted using Root Mean Square Error RMSE, Mean Absolute Error MAE, Coefficient of Correlation R and BIAS. The Feed Forward Neural Network FFNN model has shown better results than the Multiple Linear Regression MLR model. The non-linear ANN mapping tool was found more suitable for rain prediction than the linear nature of MLR model. They concluded that more detailed studies are necessary due to uncertainties inherent in weather forecasting and efforts should be addressed to the problem of quantifying them in the ANN models.

Luk et al., 1999, had applied the ANN models to forecast spatial distribution of rainfall for urban catchment area. Three alternative types of ANN models were used with different multilayer feed forward neural networks. These models were found to provide reasonable prediction of spatial rainfall. They found also that all of the three types of networks had comparable performance.

Dozier, 2012, had investigated the influence of spatial variation in precipitation on artificial neural network rainfall – runoff modeling. An Elman-type recurrent ANN was trained to simulate observed stream flow for Fountain Creek at Pueblo, CO, using varying amount of spatial precipitation information. They found that spatial variability in precipitation data allows the ANN to achieve better performance.

There have been a number of reported studies that have used ANN to solve problems in hydrology. For example, **French et al., 1992**, used an ANN model to forecast rainfall for a catchment with artificial rainfall inputs, while **Hsu et al., 1995** applied an ANN to model the rainfall-runoff process. ANNs have found increasing use in diverse disciplines ranging over perhaps all branches of engineering and science **ASCE 2000a, b; Maria et al., 2005, cited in Hsu et al., 1995**. Such methods motivate the researchers to utilize in ANN modeling several applications. For example, **El-Shafie et al. 2010**,a reported an application of utilizing Adaptive Neuro-Fuzzy Inference System ANFIS for under water tracking Global Positioning System (GPS) sonobouy. In addition **El-Shafie et al., 2010b**, introduced the Radial Basis Function Neural Network (RBF-NN). ANN has also been used in water resources engineering over the last decade. These include flood forecasting **Garcia 2002**, Wright and **Dastorani, 2001**, rainfall-runoff modeling ,**Tokar and Johnson, 1999**, **Sobri Harun et al., 2002, Thurumalaiah and Deo, 2000, streamflow prediction ,Dolling and Varas 2001, Dastorani and Wright 2002, Wright et al., 2002**, water level prediction **Patrick and Collins, 2002**, **Huang et al., 2003.Ibrahim, 2012**, had used ANN models coupled with wavelet model to forecast the monthly municipal water consumption of Kirkuk city, Iraq and Madison city, USA, he observed that the use of such model had increased the correlation coefficient from that obtained using SARIMA model. **Saoud, 200**9, had used ANN model to model spatial water quality parameters in AL-Hammar marsh, Iraq. **Al-Suhaili and Ghafour, 2012**, had used ANN model to predict sodium adsorption ratio for Tigris river in Amara city.

In this research an attempt is made for using the ANN modeling to predict the monthly precipitation in one or more weather stations from the real measurements at the other stations. The case study adopted here is the monthly precipitation values in Sulaimani Governorate weather stations network. This network has eight weather stations distributed over an approximate area of (17023 km^2 or 6572.96 mil^2). **Table 1** shows the names, Latitude, Longitude and elevation of these stations. Figure 1 shows a Google map of the locations of these stations. **Table 2** shows the approximate distances between those stations. The available records of the monthly precipitation in these stations are for eight years 2004-2011, moderate of Agro-meteorological Center - General Directorate of Agricultural, Ministry of Agriculture, KRG. **Table 3** shows the descriptive statistics of these records.

2. ANN MODEL DEVELOPMENT

As mentioned above the ANN modeling is used to predict the monthly precipitation in any of the eight stations in Sulaimani Governorate as output variable using the monthly precipitations at the other stations for the same month as input variables.

ANN modeling techniques are well known by now and proved its capability to model different engineering problems. This modeling technique can represent the non-liner relationship among the input and output variables. It consists of a grouped neurons or nodes in layers. The input layer neuron represents the input variables, while the output layer nodes represent the output variables. In between these two layers there exist hidden layers with a certain number of hidden nodes. The nodes between the layers were interconnected by weights. The input layer nodes receives the input values and transmit it’s liner weighted combination with a bias term to the hidden nodes, where it is processed with a suitable activation function to produce an output from each node in the hidden layer. These outputs will combine using weights between the hidden layer and the output layer which is received by the output layer nodes, and processed by an activation function to produce outputs. The process explained above is called feed-foreword.

In ANN modeling the set of data require is of the input variables and corresponding output variables. In order to find weights of the model the network should be trained using a partial set of the data, hence the original data set is to be divided to training, testing and hold out sub-sets. The training process is performed by using the training sub-set and assuming weights. The input data is subject to a feed-foreword process to produce output data using the assumed initial weights. These output are compared with the real output and errors are estimated. These errors are used to adjust weights using certain algorithm such as back propagation (BP). **Fig. 2** shows three-layer ANN architecture.

The ANN modeling is applied for each of the eight weather station monthly precipitation prediction in Sulaimani Governorate, using SPSS (version 19) software. For each model many trials are adopted for the division of the data set into training, testing and holdout data subset. Also many trials are adopted for the selection of the number of the hidden nodes in the hidden layer. The trial that exhibits the highest correlation coefficient between the predicted and the measured monthly precipitation is selected. Table 4 shows the final results of the selected ANN models for the eight weather stations at Sulaimani Governorate. For all these ANN models the selected activation functions for the hidden and the output layers are hyperbolic tangent and the identity functions respectively with a learning rate of 0.4 and a momentum factor of 0.9.

The selected models shown in table 4 above are used to predict the monthly prediction values and compare them with the real measured values. **Fig. 3** shows these comparisons which indicate the capability of the models to predict the monthly precipitation values with excellent accuracy, the correlation coefficients shown in **Table 4** indicates this high accuracy of prediction ranging from (90% to 97.2%).

Fig.4 shows the normalized importance analysis of each variable (input variables) on the output variable. Comparing **Fig. 4** results with the distances between the weather stations shown in **Table 2** indicates that it is not necessary that the nearest station has the highest effect on the station under prediction. This may be attributed to the fact that the difference in elevation between these stations is high as shown in **Table 1**. **Table 5** shows the normalized importance analysis in descending order with the distance and elevation of each related stations.

3. CONCLUSIONS:

The following conclusions could be deduced from this research.

- The ANN model can provide a good prediction models for predicting the monthly precipitation values for eight weather stations in the Sulaimani Governorate with correlation coefficient ranged (0.9 to 0.972).
- Comparing **Tables 3** and **4**, it is found that it is not necessary that the data set of the highest variance produce the lowest prediction correlation coefficient.
- The network can utilized the hyperbolic tangent and identity activation functions for the hidden and output layers respectively, with learning rate of 0.4 and momentum term 0.9, to produce good prediction results but with different data sub-set division, and different number of hidden nodes in the hidden layer.
- The normalized importance analysis indicates that it is not necessary that the nearest station has the highest importance on the value of precipitation of the station under prediction. This may be attributed to the effect of the high different in elevations of the stations.
- The equations developed can be used to predict any missing precipitation value in any of the eight stations with good accuracy.

4. REFERENCES:

Al-Suhaili R. H. and Ghafour Z. J., 2012, *Artificial Neural Network Model to Predict Sodium Adsorption Ratio for Tigirs River in Amara*, Accepted for publishing, Journal of Engineering, Collage of Engineering, University of Baghdad.

Belayneh A. M., Adamowski J. F., 2012, *Standard Precipitation Index Drought Forecasting using Neural Networks, Wavelet Neural Networks and Support Vector Regression* Hindawi Publishing Corporation, Journal of Applied Computational Intelligence and Soft Computing.

Bustami, R., Bessaih, N., Bong, C., Suhaili, S., 2006, *Artificial Neural Network for Precipitation and Water Level Predictions of Bedup River* IAENG International /journal of Computer Science, 34:2, IJCS_34_2_10.

Dastorani, M. T., and Wright, N. G., 2002, *Artificial Neural Network Based Real-Time River Flow Prediction*, in the Proceedings of Hydroinformatics.

Dolling, O. R., and Varas, E. A., 2002, *Artificial Neural Networks for Streamflow Prediction*, Journal of Hydraulic Research. 40(5), pp. 547-554.

Dozier, A., 2012, *Influence of Spatial Variation In Precipitation on Artificial Neural Network Rainfall-Runoff Model*.

El-Shafie A, Abdalla O., Noureldin A., Aini H. 2010 a. *Performance Evaluation of a Nonlinear Error Model for Underwater Range Computation Utilizing GPS Sonobuoys*, Neural Computer Application, 19(5): 272-283.

El-Shafie A, Abdelazim T, Noureldin A., 2010b, *Neural Network Modeling of Time-Dependent Creep Deformations In Masonry Structures*, Neural Computer Application, 19(4): 583-594.

El-Shafie, A. H., El-Shafie, A., El Mazoghi, H. G., Shehata, A., Taha, M. R., (2011), *Artificial Neural Network Technique for Rainfall Forecasting Applied To Alexandria, Egypt*, International Journal of the Physical Sciences Vol. 6(6), 1306-1316.

French, M., Krajewski, W., and Cuykendall, R. R.,1992, *Rainfall Forecasting in Space and Time Using a Neural Network*, Journal of Hydrology, 137, p1-31.

Hsu, K. L., Gupta, V. and Soroshian, S., 1995, *Artificial Neural Network Modeling of the Rainfall-Runoff process*, Water Resources Research, Vol.31, No. 10, p 2517-2530.

Huang, W., Murray, C., Kraus, N., and Rosati, J., 2003, *Development of A Regional Artificial Neural Network Prediction for Coastal Water Level Prediction*, Ocean Engineering vol. 30, pp. 2275-2295.

Ibrahim H. M., 2012, *Forecasting Models for Municipal Water Demand*, Ph.D. Dissertation, Collage of Engineering, University of Sulaimani.

Luk, K. C., Ball, J. E., Sharma, A., 2000, *A Study of Optimal Model Lag and Spatial Inputs to Artificial Neural Network for Rainfall Forecasting*, Journal of hydrology 227: 56-65.

Luk, K. C., Ball, J. E., Sharma, A., 2001, *An Application of Artificial Neural Networks for Rainfall Forecasting*, Mathematical and Computer Modeling 33(2001) 683-693.

Patrick, A. R., Collins, W.G., Tissot, P.E., Drikitis A., Stearns, J., Michaud, P.R., and Cox, D.T., (\2002)\, *use of the NCEP Mesoeta Data in a Water Level Predicting Artificial Neural Network*, in the Proceedings of 19th Conf. on weather Analysis and Forecasting/15th Conf. on Numerical Weather Prediction.

Saoud A. A., 2009, *Water Quality Simulation by Artificial Neural Network Technique for South Al-Hammar Marsh, Iraq*, M. Sc. Thises

Sobri, H., Hashim, M. K., and Irwan, A. N., 2002, *Rainfall-Runoff Modeling using Artificial neural Network*, Proceedings of 2nd World Engineering Congress. Kuching.

Thirumalaiah, K., and Deo, M. C., 2000, *Hydrological Forecasting using Artificial Neural Network*, Journal of Hydrologic Engineering, 5(2), pp. 180-189.

Tokar, A.S., and Johnson, P.A., 1999, *Rainfall-Runoff Modeling using Artificial Neural Networks*, Journal of Hydrologic Engineering, 4(3), pp. 223-239.

Wright, N. G., and Dastorani, M. T., 2001, *Effects o River Basin Classification on Artificial Neural Networks Based Ungauged Catchment Flood prediction*, Proceedings of the International Symposium on Environmental Hydraulics, Phoenix.

Sulaimani Governorate Weather Station Records ,2004–2011. *Agro-Metrological Center – General Directorate of Agricultural, Ministry of Agriculture, KRG; Iraq.*

Table 1. Names, latitude, longitude and elevation of selected weather stations.

SN	Name of weather station	Latitude	Longitude	Elevation (amsl)
1	Sulaimani	35° 33′ 20.56″ N	45° 27′ 11.61″ E	879.65 m
2	Dukan	35° 57′07.15 ″ N	44° 57′ 29.48″ E	514.5 m
3	Darbandikhan	35° 06′ 27.75″ N	45° 41′ 03.10″ E	512 m
4	Penjwin	35° 37′ 03.71″ N	45° 57′ 13.12″ E	1282.60 m
5	Chwarta	35° 43′ 00.89″ N	45° 34′ 12.35″ E	1153 m
6	Halabjah	35° 10′ 57.95″ N	45° 58′ 48.25″ E	686.4 m
7	Bazian	35° 36′ 00.03″ N	45° 08′ 13.13″ E	819.3 m
8	Chamchamal	35° 31′ 58.88″ N	44° 50′ 02.66″ E	708.96 m

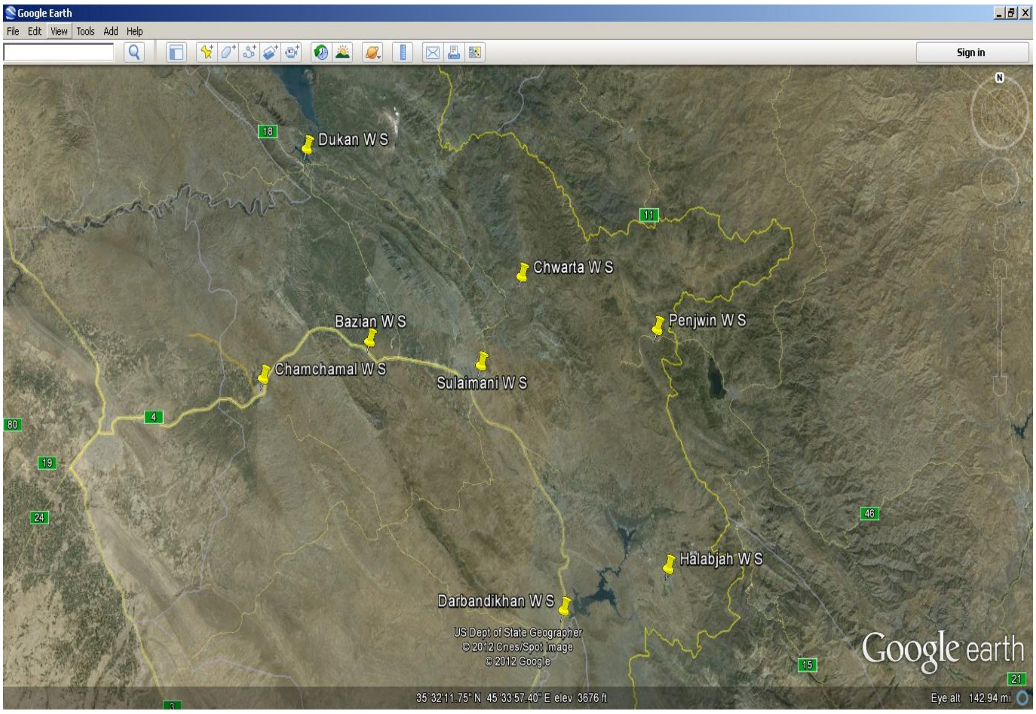


Figure 1. Google map of the locations of the selected weather stations at Sulaimani governorate.

Table 2. Approximate distances between selected weather stations of Sulaimani governorate in (km)

Name of Weather Station	Sulaimani	Dukan	Darbandikhan	Penjwin	Chwarta	Halabjah	Bazian	Chamchamal
Sulaimani	0	62.76	54.00	45.88	20.85	63.36	29.17	56.10
Dukan	62.76	0	114.73	97.10	61.20	125.85	42.00	47.90
Darbandikhan	54.00	114.73	0	61.40	68.68	28.36	73.98	90.57
Penjwin	45.88	97.10	61.40	0	36.53	48.22	74.15	102.12
Chwarta	20.85	61.20	68.68	36.53	0	69.73	41.30	69.90
Halabjah	63.36	125.85	28.36	48.22	69.73	0	89.50	111.05
Bazian	29.17	42.00	73.98	74.15	41.30	89.50	0	28.41
Chamchamal	56.10	47.90	90.57	102.12	69.90	111.05	28.41	0

Table 3. Descriptive statistics of the available monthly precipitation records of the weather stations network in Sulaimani governorate, 2004-2011.

Name of Weather Station	Mean	Standard Deviation	Skewness	Kurtosis	Maximum	Minimum
Sulaimani	76	60.212	1.256	2.161	276	0
Dukan	70.2	63.280	1.411	2.450	299	0
Darbandikhan	74.4	63.982	1.068	0.456	247	0.3
Penjwin	126	98.565	1.450	3.935	534	0
Chwarta	88.3	72.284	1.084	1.497	334	0.7
Halabjah	81	64.718	1.204	2.720	342	0
Bazian	71.5	68.227	1.475	2.555	323	0
Chamchamal	51.2	58.033	1.957	5.174	301	0

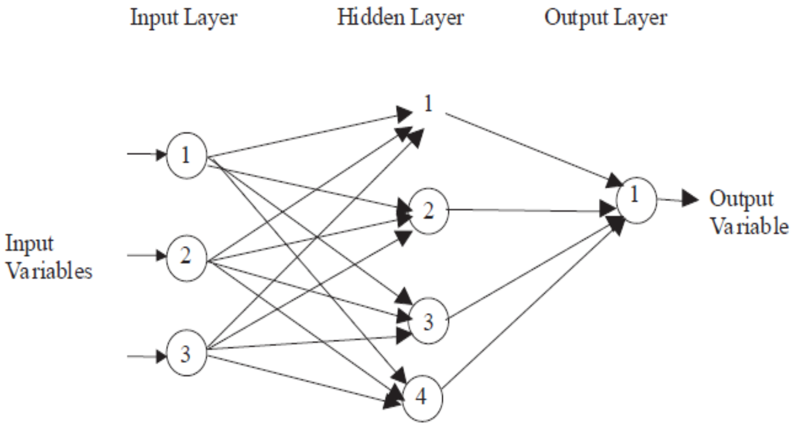
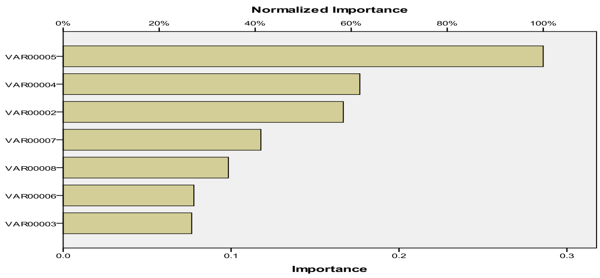


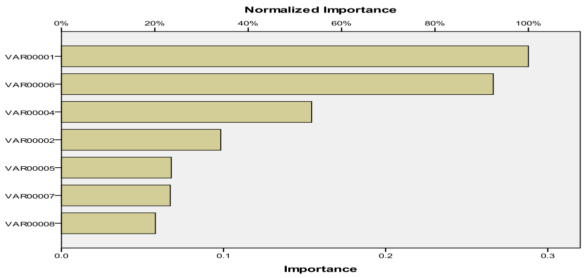
Figure 2. A 3-layer ANN architecture used for Monthly precipitation prediction.

Table 4. ANN Models for different weather stations at Sulaimani governorate.

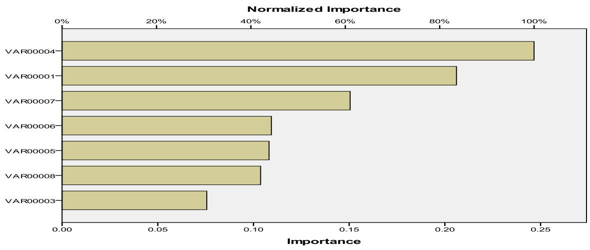
Weather Station under Prediction	Training	Testing	Holdout	No. of Hidden Nodes	Learning Rate	Momentum Factor	Correlation Coefficient
Sulaimani	44	14	6	6	0.4	0.9	97.2%
Dukan	50	12	2	6	0.4	0.9	94.3%
Darbandikhan	49	13	2	8	0.4	0.9	90%
Penjwin	52	11	1	3	0.4	0.9	96.9%
Chwarta	56	6	2	8	0.4	0.9	95.1%
Halabjah	49	5	10	10	0.4	0.9	96.0%
Bazian	46	10	8	3	0.4	0.9	95.0%
Chamchamal	52	6	6	3	0.4	0.9	94.9%



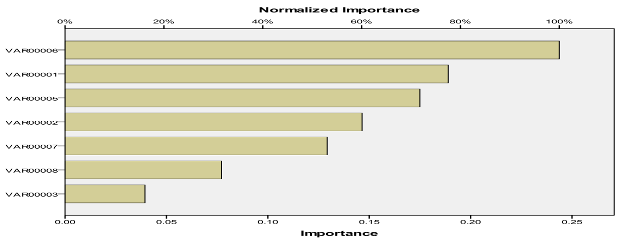
(a)



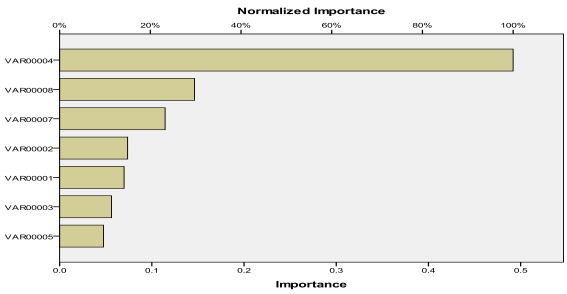
(b)



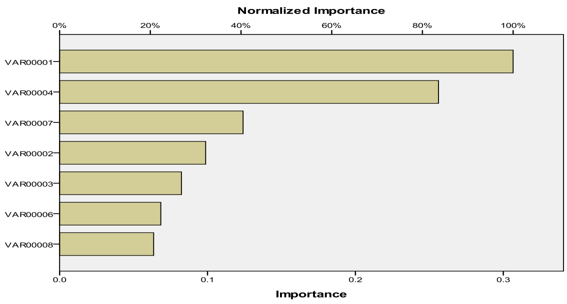
(c)



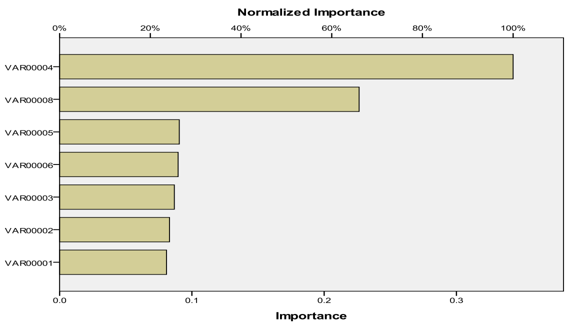
(d)



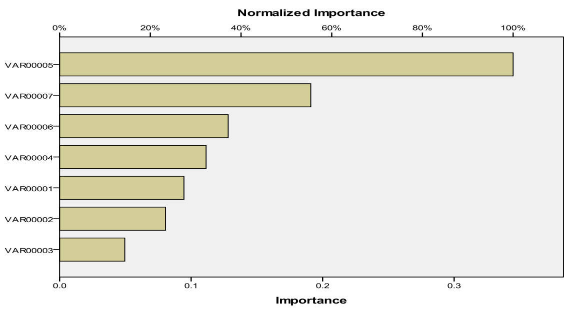
(e)



(f)



(g)



(h)

Figure 3. Normalized importance analysis for weather stations in Sulaimani governorate. a) Sulaimani, b) Dukan, c) Darbandikhan, d) Penjwin, e) Chwarta, f) Halabjah, g) Bazian, h) Chamchamal.

Figure 4. Continued (var0001:Sulaimani, var0002:Dukan,var0003Darbandikan,var0004: Penjwin,var0005:Chwarta,var0006:Halabjah,var0007:Bazian:var0008:Chamchamal).

Table 5. Normalized importance analysis in descending order with the distance and elevation of each related stations.

Model Prediction Station	Independent Importance Station	Chwarta	Penjwin	Dukan	Bazian	Chamchamal	Halabjah	Darbandikhan
Sulaimani Weather Station	Importance in descending order	100%	61.8%	58.4%	41.2%	34.4%	27.2%	26.8
	Distance from Sulaimani Station(km)	20.85	45.88	62.36	29.17	56.10	63.36	54.00
	Elevation difference from Sulaimani station	273.35	402.95	-365.15	-60.35	-170.70	-193.25	-367.65

Model Prediction Station	Independent Importance Station	Penjwin	Sulaimani	Bazian	Halabjah	Chwarta	Chamchamal	Darbandikhan
Dukan Weather Station	Importance in descending order	100%	83.6%	61%	44.3%	43.9%	42.1%	30.7%
	Distance from Dukan Station (km)	97.10	62.76	42.00	125.85	61.20	47.90	114.73
	Elevation difference from Dukan station	768.1	365.15	304.8	171.9	638.5	194.46	-2.50

Model Prediction Station	Independent Importance Station	Sulaimani	Halabjah	Penjwin	Dukan	Chwarta	Bazian	Chamchamal
Darbandikhan Weather Station	Importance in descending order	100%	92.5%	53.6%	34.1%	23.5%	23.3%	20.1%
	Distance from Darbandikhan Station(km)	54.00	28.36	61.40	114.73	68.68	73.98	90.57
	Elevation difference from Darbandikhan station	367.65	174.4	770.6	2.5	641	307.3	196.96

Model Prediction Station	Independent Importance Station	Halabjah	Sulaimani	Chwarta	Dukan	Bazian	Chamchamal	Darbandikhan
Penjwin Weather Station	Importance in descending order	100%	77.5%	71.8%	60.1%	53%	31.6%	16.2%
	Distance from Penjwin Station (km)	48.22	45.88	36.53	97.10	74.15	102.12	61.40
	Elevation difference from Penjwin station	-596.2	-402.95	-129.6	-768.1	-463.3	-573.64	-770.6

Table 5. Continued.

Model Prediction Station	Independent Importance Station	Sulaimani	Penjwin	Bazian	Dukan	Darbandikhan	Halabjah	Chamchamal
Chwarta Weather Station	Importance in descending order	100%	83.5%	40.5%	32.2%	26.9%	22.3%	20.7%
	Distance from Chwarta Station (km)	20.85	36.53	41.30	61.20	68.68	69.73	69.90
	Elevation difference from Chwarta station	-273.35	129.6	-333.7	-638.5	-641	-466.6	-444.04

Model Prediction Station	Independent Importance Station	Penjwin	Chamchamal	Bazian	Dukan	Sulaimani	Darbandikhan	Chwarta
Halabjah Weather Station	Importance in descending order	100%	29.7%	23.3%	15%	14.2%	11.4%	9.7%
	Distance from Halabjah Station (km)	48.22	111.05	89.50	125.85	63.36	28.36	69.73
	Elevation difference from Halabjah station	596.2	22.56	132.9	-171.9	193.25	-174.4	466.6

Model Prediction Station	Independent Importance Station	Penjwin	Chamchamal	Chwarta	Halabjah	Darbandikhan	Dukan	Sulaimani
Bazian Weather Station	Importance in descending order	100%	66%	26.4%	26.1%	25.3%	24.2%	23.6%
	Distance from Bazian Station (km)	74.15	28.41	41.30	89.50	73.98	42.00	29.17
	Elevation difference from Bazian station	463.3	-110.34	333.7	-132.9	-307.3	-304.8	60.35

Model Prediction Station	Independent Importance Station	Chwarta	Bazian	Halabjah	Penjwin	Sulaimani	Dukan	Darbandikhan
Chamchamal Weather Station	Importance in descending order	100%	55.4%	37.2%	32.3%	27.4%	23.4%	14.4%
	Distance from Chamchamal Station (km)	69.90	28.41	111.05	102.12	56.10	47.90	90.57
	Elevation difference from Chamchamal station	444.04	110.34	-22.56	573.64	170.69	-194.46	-196.96

Calculation steps for the prediction of monthly precipitation in Sulaimani governorate:

The following equations are those used for the prediction of the missed precipitation values at sulaimani station. Similar forms of equations are also available for the estimation of the missed precipitation for each of the other stations.

1. Find matrix $Zin_{(6x1)}$.

$$Zin_{(6x1)} = V_o bias_{(6x1)} + V^T_{(7x6)} * X_{(7x1)}$$

Where: $W_o bias_{(1x1)} = \begin{bmatrix} 0.837 \end{bmatrix}$, $X_{(7x1)} = \begin{bmatrix} Duk \\ Drb \\ Pnj \\ Chw \\ Hlb \\ Bzn \\ Chm \end{bmatrix}$

$$Vobias(6x1) = \begin{bmatrix} 1.107 \\ 0.311 \\ 1.037 \\ -0.729 \\ 0.098 \\ 0.428 \end{bmatrix}$$

$$V_{(7x6)} = \begin{bmatrix} 0.007 & -0.035 & -0.080 & 0.207 & 0.212 & 0.321 \\ -0.864 & -0.168 & -0.526 & 0.023 & -0.191 & -0.121 \\ -0.158 & 0.339 & -0.104 & 0.298 & -0.065 & -0.209 \\ 0.116 & -0.099 & 0.383 & 0.006 & -0.047 & -0.305 \\ 0.213 & 0.373 & 0.329 & -0.534 & 0.458 & -0.327 \\ -0.064 & -0.014 & 0.560 & -0.042 & -0.642 & 0.243 \\ 0.246 & -0.422 & 0.865 & 0.447 & -0.049 & 0.009 \end{bmatrix}$$

$$W_{(6x1)} = \begin{bmatrix} -1.242 \\ 0.745 \\ 0.851 \\ 1.074 \\ \\ \end{bmatrix}$$

0.035

0.105

2. Find $Z_{(6x1)} = \text{tansh}(Zin_{(6x1)})$
3. Find $yin_{(1x1)} = W_o bias_{(1x1)} + W^T_{(6x1)} * Z_{(6x1)}$
4. Find $y_{(1x1)} = yin_{(2x1)}$

$$= \begin{bmatrix} y_1 \end{bmatrix}$$

5. Find $Suly = y_1 * sd_{Suly} + Mean_{Suly}$