Hybrid ARMAX-ANN Model for Temperature Forecasting

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Abstract: Many researchers have been interested in improving known forecasting methods using several methods, including hybridizing time series models with one, two, or more models in order to obtain greater accuracy in predicting the data of the series to be predicted. Therefore, our research is an extension of the researchers who preceded us in order to provide forecasting methods that have an impact in the field in which they are used. Therefore, our study focused on the ARMAX model, as it is a model that combines time series models and a regression model, and it becomes more effective when it is hybridized with one of the artificial intelligence models (ANN) in order to improve forecasting results, which are considered important in decision-making and in all areas of life, including the average temperature in Basra Governorate. A comparison was made between the ARMAX models, the ANN model, and the ARMAX-ANN hybrid model in order to predict temperatures for the years (2024-2028), as it became clear that the hybrid model is better at forecasting using the MSE criterion.

1 INTRODUCTION

Researchers' pursuit of highly accurate forecasts is crucial, as it reduces risk and provides early warning to decision-makers regarding potential disruptions in the near future, enabling them to avoid them in various sectors. Although the ARIMAX model is excellent at predicting time series, these models may not provide highly accurate forecasts. This is because time series data contains two components: one linear and the other nonlinear. This means that ARIMAX models or neural networks alone may fail to model linear and nonlinear relationships. Therefore, we will use hybrid models, which are flexible and capable of handling different types of data. The forecasting process relies on a scientific and precise approach to predicting and obtaining future values. Therefore, this research aims to compare the ARIMAX model, the ANN model, and the hybrid model that combines them to determine which model is best for temperature forecasting. Based on the MAPE metric, it was found that the best forecasting model is the hybrid model.

2 PREVIOUS STUDIES

We will present some previous studies using the ARMAX model. Among these studies is the 2016 study by Muhammad & Fakhri, which aimed to achieve higher forecasting accuracy by using ARMAX models. They used a series of exogenous variables and a series of past errors, then used the best estimate method to predict the maximum temperature for the next 30 days [1]. Another study by Alkali & others in 2019 aimed to compare the ARIMA and ARIMAX models to predict residential property prices in Abuja, Nigeria, using quarterly data on average home sales prices from the first quarter of 2000 to the last quarter of 2017. The results showed that the ARMAX model outperformed ARIMA models in general [2]. Another study by Musa and others in 2021 aimed to study the impact of independent variables, such as rainfall, temperature, and humidity, on selected agricultural crops using the ARIMAX model and then predict them [3].

3 RESEARCH PROBLEM

The prediction process using some single models, such as the ARIMAX model or the ANN model, is considered insufficient, as the predictions do not provide high accuracy in most c Both linear and nonlinear relationships are present in this data. However, if the used series model is hybridized with an artificial intelligence (AI) prediction model, the hybrid model will perform better, and we will obtain more accurate predictions for the time series than the single models.

4 OBJECTIVE

To improve the ARMAX prediction model by using the hybridization method with an ANN model, one of the artificial intelligence methods, to predict average temperatures in Basra Governorate.

5 THEORETICAL ASPECT

5.1 The ARMA Model

It is called the Autoregressive Moving Averages (ARMA) model [3], and it is a special case of the Autoregressive Integrated Moving Means (ARIMA(p,d,q) model. When the series is stationary (d=0), it is written as ARMA(p,q), where p is the autoregressive order (AR) and q is the moving mean order (MA). The mathematical form of the ARMA model is: ases. Because the time series contains two parts, one linear and the other non-linear, they:

$$y_t = \delta + \sum_{i=1}^{p} \emptyset_i y_{t-i} + e_t - \sum_{j=1}^{q} \theta_j e_{t-j} \dots\dots(1)$$

5.2 ARMAX Model

The ARMAX (AutoRegressive Moving Average with eXogenous inputs) [4], [1] model is an extension of the ARMA model that incorporates external (exogenous) variables. In this model, the time series Y_t is expressed as a function of its past values, past error terms, and exogenous variables. The general form of the ARMAX model is given by:

$$y_t = \delta + \sum_{i=1}^{p} \emptyset_i y_{t-i} + e_t - \sum_{j=1}^{q} \theta_j e_{t-j} + \sum_{k=1}^{r} \pi_k X_{k,t-1} \dots\dots$$

- Yt: The value of the observed phenomenon at time t;
- δ: The constant;
- $\emptyset_i$: Autoregressive (AR) model parameters;
- θ j: Moving Average (MA) model parameters;
- π _k: The exogenous variable parameters;
- et: The random error.

5.3 Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) [5] are considered one of the most important and widely used methods of artificial intelligence. Their concept is derived from simulating the human brain's ability to recognize patterns and distinguish objects using computational models. This approach is based on a learning process inspired by the human brain, which relies on past experiences to improve performance in future tasks. The following Figure 1 illustrates a basic operating unit of a neural network.

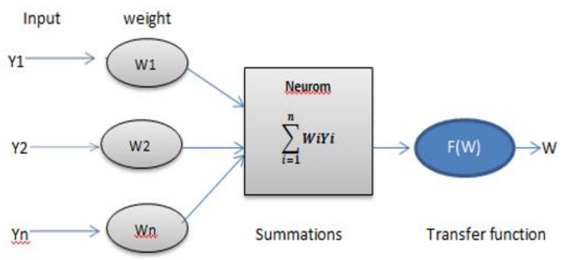

Figure 1: Model of an operating unit.

Each of the operating units contains one or more input paths through which information or data is transferred from the external world to the operating unit, which in turn performs a simple aggregation process. The information is then transformed after the aggregation process using an activation function known as a transfer function. It is then transferred as output through the output path. Mathematically, each artificial neuron will receive a few inputs (Y1, Y2,…, Yn), similar to the branches of neurons in humans. Each of these inputs is then multiplied by weights (W1, W2,…, Wn). These weights express the degree of importance of the inputs. The summed result ($\sum wiyi$) is then processed using the transfer function F(y) to obtain the final output.

5.4 Learning of the Neural Network

Learning of a neural network can be defined as the process by which a neural network can modify itself in response to inputs to produce the desired output [3], [6]. It can also be defined as the process of acquiring knowledge using input data. During the learning process, the connection weights are adjusted, and this process continues until the network's outputs approximate the actual outputs. The process of teaching or training the network involves discovering typical relationships present in the input data, using one of the following methods.

5.4.1 Supervised Learning

This method is one of the most widely used methods for training neural networks. The network compares the results obtained for external variables with the actual input variables for each input sample. Based on this, the network's weights are adjusted to reduce errors. This process is repeated several times until acceptable results are achieved.

5.4.2 Unsupervised Learning

This method is similar to supervised learning, but differs in that the samples used in the training process do not include any values of external variables. Instead, the training process consists of input data, which consists of several groups. The network is trained to detect the most important features not apparent in the groups. These features are then used to divide the input data into groups that are distinct from each other, but similar within each group.

This method is a combination of the two previous methods. It does not use the values of external variables in the training process, as in unsupervised training, but it does indicate the validity of the network's results, as in supervised training.

6 TYPES OF NEURAL NETWORK STRUCTURES

There are several types of neural network structures [6], [7], which we will briefly explain:

6.1 Single-Layer Feed-Forward Network

This network is the simplest type of artificial neural network structure and is considered one of the most common types. It is the basic model upon which other single-layer network structures are built. It is also the simplest type of feed-forward neural network, as information is transferred directly from the input layer to the output layer. The network is trained via supervised learning. Figure 1 above illustrates the structure of this network. The learning process in this network is carried out through the following steps:

Setting random initial values for the weights (W1, W2,…, Wn) as well as an initial value for the threshold value (θ) within the range [-0.5, 0.5].

This step is called the activation process. Each processing unit receives multiple input signals and calculates the weighted sum of these inputs using the following sum function:

$$Y = \sum_{i=1}^{n} \mathrm{WiYi} \ldots. \tag{3}$$

Where Y is the net weighted input to the neuron, Wi is the weights, Yi is the input value, and n represents the number of inputs to the neuron.

The output is calculated according to the following formula:

$$W(K) = STEP\left[\sum_{i=1}^{n} Wi(K)Yi\,(K) - \theta\right] \ldots \ldots \ldots \ldots (4)$$

The activation function is called the step function. There are many other activation functions, such as the sign function, the linear function, and the sigmoid function. The latter is the most commonly used because of its ease of differentiation and ease of calculating the slope.

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6.2 Multilayer Feedforward Network

This artificial multilayer network is used to solve many complex problems that cannot be solved by a single-layer network. It propagates input signals forward from one layer to the next, without going backward. However, its drawback is that it takes longer to complete. Figure 2 illustrates the network's operation:

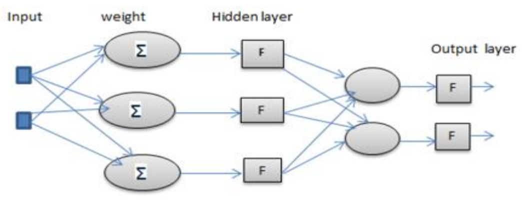

Figure 2: Multi-layer feed-forward network.

6.3 Multi-Layer Feedback Network

This type of network differs from the previous multi-layer network in that it contains at least one feedback loop. Unlike the previous feed-forward network, the error between the network's output and the actual output is calculated. However, the error is also fed in the opposite direction, i.e., in the opposite direction of the inputs, to adjust the weights and reduce the error.

7 HYBRID MODEL

The hybrid model [8], [9] is formed by combining a linear model with another non-linear model to address shortcomings in the individual model, whether linear or non-linear. This reduces errors resulting from using an inappropriate model, and it is an effective means of improving future predictions.

7.1 Steps for Constructing the Hybrid Model

1) Assume that the time series (yt) is a combination of two parts: the first is the linear autocorrelation part (Lt) and the second is the non-linear part (Nt).
2) We first use the ARMAX model to predict temperature values, then subtract the predicted values from the actual values to obtain the residual, which is recorded as a nonlinear component.
3) The residual is fed into the ANN or artificial neural network (ANN) model for prediction.
4) We obtain the predicted values for the hybrid model as follows:

$$Y_t = \hat{L}_t + N_t \dots. \quad (5)$$

8 MEAN SQUARE ERROR

The mean square error (MSE) [1], [8] is used to measure the accuracy of estimation or forecasting and is defined as:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(\mathrm{Pi} - \mathrm{Ai})^2}{n}. \quad \dots \quad (6)$$

Where Ai denotes the actual (observed) value, Pi is the predicted (estimated) value, and n is the sample size.

9 PRACTICAL ASPECT

A practical analysis was conducted to predict temperatures in Basra Governorate by month using the ARMAX model, first relying on the AR and MA models, and the external variable, rainfall, for the years 1974-2023. Then, a neural network model was used, and the prediction was improved using the ARMAX-ANN mixed model, as follows:

Determining the rank of the ARMA(p, q) model: Before using the ARMAX model, it is necessary to know the stability of the time series of the two dependent variables, temperature and the external variable, rainfall. Using the unit root test, Table 1 was obtained:

Table 1: Unit root test for the dependent variable, average temperature in Basra (see Appendix, Table A1).

Null Hypothesis: Y has a unit root			
Exogenous: Constant			
Lag Length: 3 (Automatic - based on SIC, maxlag=19)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.64623	0.0058
Test critical values:	1% level	-3.440275	
	5% level	-2.865810	
	10% level	-2.569102	
*MacKinnon (1996) one-sided p-values.			

From Table 1, the Augmented Dickey-Fuller test statistic is less than the critical values at all significance levels, and the corresponding p-value (0.0058) is less than 0.05. Therefore, the null hypothesis of a unit root is rejected, indicating that the dependent variable (average temperature) is stationary at level.

Table 2: Unit root test for the external variable: average rainfall in Basra (see Appendix, Table A2).

Null Hypothesis: X has a unit root			
Exogenous: Constant			
Lag Length: 8 (Automatic - based on SIC, maxlag=19)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.682989	0.0046
Test critical values:	1% level	-3.440354	
	5% level	-2.865845	
	10% level	-2.569121	
*MacKinnon (1996) one-sided p-values.			

Similarly, the results in Table 2 show that the p-value (0.0046) is less than 0.05, leading to the rejection of the null hypothesis. Thus, the external variable (average rainfall) is also stationary at level.

The next step after stabilizing the variable at a difference of 0, is to determine the degree of both p and q in the ARMA model (Table 3):

By drawing the autocorrelation function and the partial autocorrelation function:

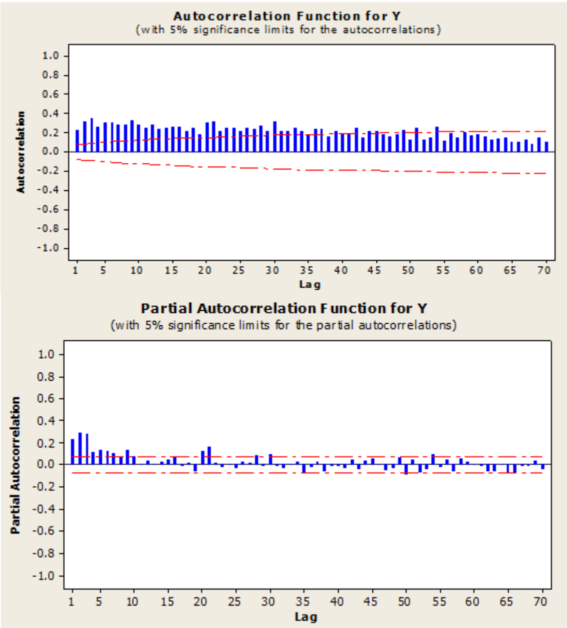

Figure 3: Autocorrelation and partial autocorrelation function of the dependent variable.

Figure 3 presents that the proposed model is ARMA (p, q). Therefore, several models were nominated, and it turned out that the best model is ARMA(1, 0) according to the MSE criterion:

Table 3: Comparison between ARMA models.

MSE	The Model
2.94	ARMA(1,0)
30.2	ARMA(0,1)
3.07	ARMA(2,0)
15.7	ARMA(0,2)
3.78	ARMA(1,2)
2.99	ARMA(2,1)
3.1	ARMA(2,2)

The results of ARMAX model estimation are presented in Figure 4.

From Figure 4, we note the significance of the estimated coefficients for the external variable, as well as the significance of the AR coefficient. The sign of the parameter for the variable coefficient is negative, which confirms the negative or inverse relationship between temperature and rainfall. Furthermore, the model explains approximately 96% of the changes in the temperature variable, which is a high percentage and confirms the model's predictive ability.

The forecasts for the years 2024-2028 are prepared monthly, as shown in Table 4 and Table 5. The result of ANN model estimation:

Dependent Variable: Y
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/01/25 Time: 02:31
Sample: 1970M01 2023M12
Included observations: 648
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	24.80536	3.552722	6.982072	0.0000
X	-0.007068	0.003121	-2.264740	0.0239
AR(1)	0.979614	0.008476	115.5721	0.0000
SIGMASQ	3.485951	0.126536	27.54916	0.0000

R-squared	0.959142	Mean dependent var	26.11034
Adjusted R-squared	0.958952	S.D. dependent var	9.243956
S.E. of regression	1.872860	Akaike info criterion	4.103917
Sum squared resid	2258.896	Schwarz criterion	4.131534
Log likelihood	-1325.669	Hannan-Quinn criter.	4.114631
F-statistic	5039.312	Durbin-Watson stat	2.684213
Prob(F-statistic)	0.000000		

Inverted AR Roots .98

Figure 4: ARMAX model estimation.

A neural network model was used to predict average temperatures. A feedback network with a hidden layer containing (30) nodes was used to build a model used for time series prediction. Data was fed into the artificial neural network, as shown in the Figure 5.

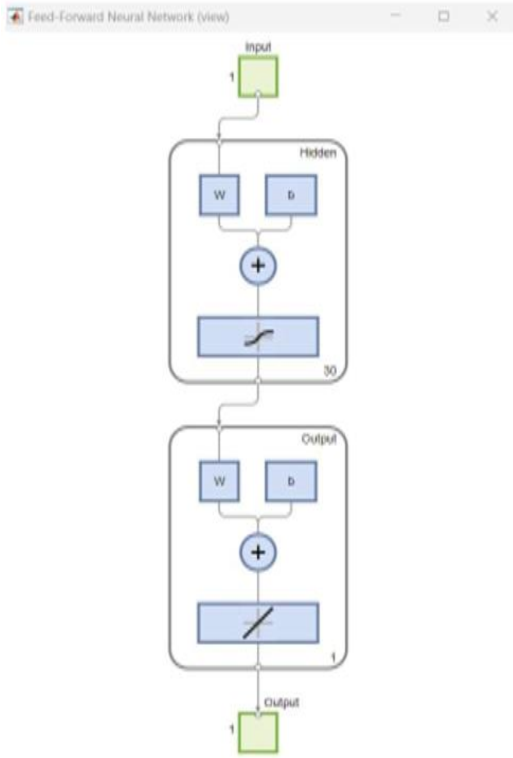

Figure 5: Artificial neural network architecture.

Through the Figure 5 and Figure 6, we notice that the input variables are linked to the hidden layer nodes, which number (30) nodes, and both of them are linked to the output node, and the strength of the relationship between the nodes, whether for input or output, is determined through the weight values (Wij), which are given initially in order for the network to be trained on them through the process of back-emission of the data.

Figure 6: Training results.

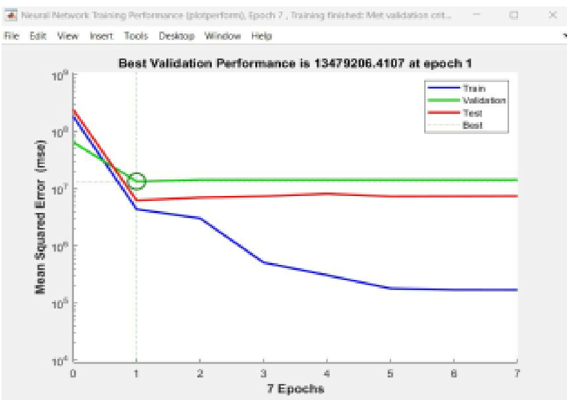

Figure 7: Best Validation Perform.

The data was divided into a training portion, which constitutes 60% of the original data, and a 20% portion for testing and validation of the robustness of the model outputted by the network. The learning parameter was set at 1% (alpha = 0.01). Figure 7 shows that the lowest error rate is achieved at iteration 107 during the neural network training process.

The Figure 7 shows that the slope value is equal to (0.0091) and will decrease as the number of training cycles for the network increases. As it decreases, the network learns more and more, thus decreasing the error rate (Mu = 0.001). The validation test is equal to (1) over (7) cycles. From the figure above, the errors generated by the neural network are normally distributed relative to the data that was trained and tested. This is a clear indication that the errors are acceptable, as they are normally distributed.

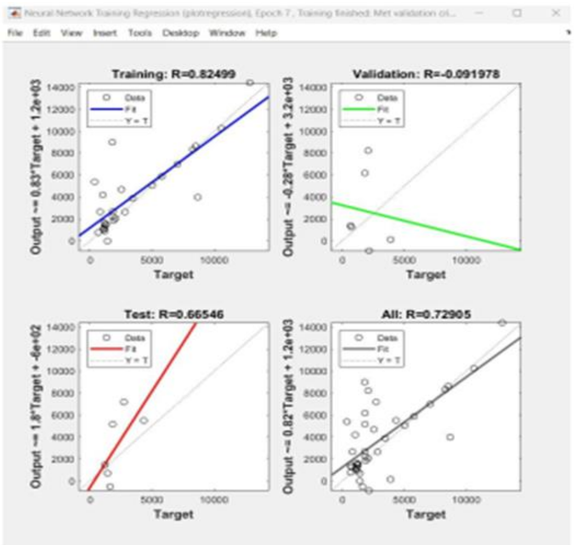

Figure 8: ANN Training regression (plot regression).

The Figure 8 shows that the training ratio was 0.82499 for the network sample, which consisted of 70% of the data. The testing ratio was 0.6654, which examines the samples, and the total ratio was 0.729.

The neural networks were predicted, and the mean square error was obtained with a value of 3.318782.

10 HYBRID MODEL

The errors generated by the ARMAX model were entered into the neural network, and the errors were obtained and combined with the predicted values of the ARMAX model to obtain the results of the hybrid model. The mean square error was calculated, and its value was 3.113275.

Table 4: Forecasting by using HYBRID MODEL for the years 2024-2028 by month.

Month of (2024)	Prediction value	Month of 2025	Prediction value	Month of2025	Prediction value	Month of 2025	Prediction value	Month of 2025	Prediction value
1	15.26213	1	17.30866	1	18.9109	1	20.1653	1	21.14737
2	15.45245	2	17.45766	2	19.02755	2	20.25663	2	21.21887
3	15.63892	3	17.60366	3	19.14185	3	20.34611	3	21.28893
4	15.82163	4	17.7467	4	19.25384	4	20.43379	4	21.35758
5	16.00065	5	17.88686	5	19.36357	5	20.5197	5	21.42483
6	16.17606	6	18.02418	6	19.47109	6	20.60387	6	21.49073
7	16.34793	7	18.15874	7	19.57643	7	20.68634	7	21.5553
8	16.51632	8	18.29058	8	19.67965	8	20.76715	8	21.61857
9	16.68132	9	18.41975	9	19.78078	9	20.84633	9	21.68055
10	16.84299	10	1854632	10	19.87987	10	20.92391	10	21.74129
11	17.00139	11	18.67034	11	19.97696	11	20.99992	11	21.8008
12	17.15659	12	18.79185	12	20.07209	12	21.0744	12	21.85911

Table 5: Forecasting by using ARMAX for the years 2024-2028 by month.

Month of 2024	Prediction value	Month of 2025	Prediction value	Month of 2026	Prediction value	Month of 2027	Prediction value	Month of 2028	Prediction value
1	15.2853	1	17.4627	1	19.1849	1	20.55937	1	21.66145
2	15.4955	2	17.6217	2	19.3116	2	20.6607	2	21.74295
3	15.6932	3	17.7777	3	19.4359	3	20.76019	3	21.82301
4	15.8857	4	17.9307	4	19.5579	4	20.85786	4	21.90165
5	16.0747	5	18.0809	5	19.6776	5	20.95377	5	21.97891
6	16.2601	6	18.2282	6	19.7951	6	21.04794	6	22.05481
7	16.4420	7	18.3728	7	19.9105	7	21.14042	7	22.12937
8	16.6204	8	18.5146	8	20.0237	8	21.23123	8	22.20264
9	16.7954	9	18.6538	9	20.1348	9	21.3204	9	22.27463
10	16.9671	10	18.7904	10	20.2439	10	21.40798	10	22.34536
11	17.1355	11	18.9244	11	20.3510	11	21.49399	11	22.41487
12	17.3007	12	19.0559	12	20.4561	12	21.57847	12	21.89218

We note that using the hybrid model led to a reduction in the mean square error value. Therefore, it was used to predict the years 2024-2028 by month, and the following results were obtained in Table 5.

11 CONCLUSIONS

The results of the unit root test are presented in Table 1. The findings indicate that the ARMA(1,0) model is the most appropriate among the considered ARMA models. Furthermore, the neural network model demonstrates superior forecasting performance compared to the ARMA model, as evidenced by the mean square error (MSE) criterion. In addition, the ARMA–ANN hybrid model further improves forecasting accuracy, as reflected by a reduction in MSE values. Based on the forecasting results, an increase in temperatures in the coming years in Basrah Governorate is observed. These results highlight the importance of employing hybrid models in forecasting applications. Moreover, it is noted that predictive efficiency in time series analysis decreases when the data contain nonlinear components.

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APPENDIX

Table A1: Average temperature in Basra.

12.6	21.4	25.3	30.1	33.4	33.9	32.4	29.7	26.3	20.1	16.6	12.9
12.6	19.7	25	31.3	33.5	33.6	31.6	31.5	23.4	19.4	14.6	12.7
10.1	18.3	26.6	30.8	34.7	33.1	33.5	27.9	24.5	18.2	12.1	10.3
12.9	17.4	27.3	31.9	35.2	34.1	32	30.4	24.8	18.9	16.8	10.8
12.4	20.3	25.7	31.5	33.6	33.9	33.2	30.2	23.5	19.3	13.2	10.5
12.1	18.9	24.1	32.7	33.7	34.9	33.4	30.5	24.9	18.5	13.9	11
15.5	19.4	27	30.7	33.2	33.2	33.2	28.8	24	16.6	13.2	12.2
15	18.2	24.6	32	34.7	34.5	33.7	31.3	24.6	20.9	16.9	10.1
15.9	15.6	26.5	30.7	32	35	32	29.9	25.2	19.9	16	13.4
13.2	20.3	27.3	32.8	34.3	34.3	34.1	30.1	26	19.5	17.3	14
13.7	20.7	26.5	31.7	34.9	37.4	35.3	30.8	26.3	20.2	13.8	12.1
11.4	16.3	26.9	34.3	34.1	36.1	34.8	31.8	26.2	17.2	11.9	12.3
14.7	21.5	25.1	31.7	35.2	36.8	34.8	31.8	23.7	17.2	13.5	10.1
12.1	20.1	25.8	32.6	33.6	37.4	34.2	30.2	26.5	20.4	15.6	12.7
13.7	20.7	25.9	32.8	37.4	35.5	34.7	32.4	25.6	18.4	13.7	14.2
12.2	17.9	29.6	34.9	37.7	37.9	34.2	31.8	25.6	19	15.1	12.7
14.9	19.6	26.9	33.4	37	37.5	35.3	34.1	25.4	18.7	17.3	12.6
13.3	18.2	27.9	32.8	35.4	36.6	34.4	30.7	24.5	18.6	14.4	11.3
12.9	20.2	27.6	32.7	37.1	38.2	34.2	31.7	26.7	18.9	11.3	9.2
15.5	20.9	28.1	32.5	35.9	38.4	35.9	33.3	25.7	19.5	14.4	10.9
14.4	21	26.6	32.3	35.6	36.6	35.5	29.8	26.7	18.9	13.4	11.9
13	19.3	26.4	33.9	36.7	36.1	35.7	30.7	24.7	15.8	12.7	9.5
16	19.2	28.7	33.7	37.9	38	35.8	30.8	25	19.4	13	11
11.6	21.2	28.4	34.4	36.4	37.3	36.3	32.7	28.1	20.4	15.6	15.4
13.1	19.5	27.3	33.3	37.6	37.5	36.8	32.8	25.4	20.1	16	13.7
17.5	20.3	27.3	34.2	39.3	39.9	38.2	34.2	24.9	20	16.5	13.6
13.6	20.4	28.6	34.3	36	37.8	37.6	33	24.3	17.4	13.3	14.2
16.8	22.1	27.9	35.1	39.8	38.5	38.5	33.2	26.6	18.9	15	11.7
13.9	19.8	29.7	34.7	38.9	38.3	37.9	33.7	27.1	19.3	16	14.3
14.1	18.7	27.3	33.7	39.8	40.2	37	34.2	29.8	19.7	14.4	12.5
16.9	19.4	28.8	34.9	39	38.7	36.6	33.5	29.2	22.2	16	12.5
14.3	19.8	30	34.6	37.8	39.6	36.9	33.7	25.8	21.8	15.4	12.3
14.7	20	33	34.6	38	39.7	37.8	33.8	25.8	22.2	15.3	12.5
11.5	20.8	28.9	34.1	37.2	38.8	37	33.9	26.1	19.9	16	12.4
15.9	18.8	28.1	33.5	37.8	38.8	36.4	32.9	26.9	20.4	17.3	12.6
10.4	18.8	29.5	32.4	39.2	38.1	37.7	33.9	26.6	21.3	15.3	13.1
13.6	20.3	29.4	34.4	38.8	38.2	37	34.3	25.9	19.2	14.7	12.3
13.7	19.4	27.8	35.1	38.6	38.4	37.1	33.3	26.3	20.2	14.2	9.4
15.9	20	29	33.8	37.7	37.8	37.6	33.8	25.4	19.9	16.9	11.4
15	20.4	29.9	35.6	39.7	39.3	38.3	33.3	27.7	22.3	18	15.5
12.4	17.9	29.9	34.7	39.8	39.2	36.7	33.8	26.6	19.5	14.7	13.1
15.4	21.9	29.6	34.6	39.1	40.4	38.1	34.9	26.6	18.6	14.3	12.6
16	22	30	35	38	39.7	36.7	34.8	26.6	21.2	17.4	13.5
16.3	19.4	29	35.4	38.5	38.7	37.1	34.9	26.3	21.1	17.3	13.7
12.9	20.5	31.1	36.1	40.4	40.2	37.8	34.3	27.2	21.3	17	14.1
14	19.1	28.5	34.9	40	40.3	38.3	34.2	27.3	22	17.3	13.1
15.6	20.8	29.5	36.3	40.3	41.2	38.4	34.6	28.1	21	13.5	13.5
16.2	19.8	29.9	37.5	39.3	40.1	38.8	33.3	26.4	24.2	18.3	14.5
16	20	30	38	42	40	39.6	34.4	25.5	19.2	16.1	14.5
15.1	20.2	30.6	36.5	39	39.1	39.6	34.4	25.5	19.2	16.1	14.5
14.8	21.7	27.9	36.5	38.3	41.2	38.2	33.5	25	20	16.3	14.1
15.6	21.5	29.8	35.2	41.2	41	38.2	35.8	28.9	21.8	17.7	14.3
16.9	22.3	30.9	35.6	39.8	39.8	38.9	32.7	28.5	20.1	17.4	12.9
17.5	21.4	30.7	37.3	40.5	41.1	38.3	33.1	27.2	21.6	15.5	12.7

Table A2: Rainfall in Basra.

12	11	10	9	8	7	6	5	4	3	2	1	السنوات
39.6	1.9	0	0	0	0	0	1.5	10.2	24.8	3	60.5	1970
40.6	2.9	1	1	1	1	1	2.5	11.2	25.8	4	61.5	1971
41.6	3.9	2	2	2	2	2	3.5	12.2	26.8	5	62.5	1972
42.6	4.9	3	3	3	3	3	4.5	13.2	27.8	6	63.5	1973
43.6	5.9	4	4	4	4	4	5.5	14.2	28.8	7	64.5	1974
44.6	6.9	5	5	5	5	5	6.5	15.2	29.8	8	65.5	1975
45.6	7.9	6	6	6	6	6	7.5	16.2	30.8	9	66.5	1976
46.6	8.9	7	7	7	7	7	8.5	17.2	31.8	10	67.5	1977
47.6	9.9	8	8	8	8	8	9.5	18.2	32.8	11	68.5	1978
48.6	10.9	9	9	9	9	9	10.5	19.2	33.8	12	69.5	1979
49.6	11.9	10	10	10	10	10	11.5	20.2	34.8	13	70.5	1980
50.6	12.9	11	11	11	11	11	12.5	21.2	35.8	14	71.5	1981
51.6	13.9	12	12	12	12	12	13.5	22.2	36.8	15	72.5	1982
52.6	14.9	13	13	13	13	13	14.5	23.2	37.8	16	73.5	1983
53.6	15.9	14	14	14	14	14	15.5	24.2	38.8	17	74.5	1984
54.6	16.9	15	15	15	15	15	16.5	25.2	39.8	18	75.5	1985
55.6	17.9	16	16	16	16	16	17.5	26.2	40.8	19	76.5	1986
56.6	18.9	17	17	17	17	17	18.5	27.2	41.8	20	77.5	1987
57.6	19.9	18	18	18	18	18	19.5	28.2	42.8	21	78.5	1988
58.6	20.9	19	19	19	19	19	20.5	29.2	43.8	22	79.5	1989
59.6	21.9	20	20	20	20	20	21.5	30.2	44.8	23	80.5	1990
60.6	22.9	21	21	21	21	21	22.5	31.2	45.8	24	81.5	1991
61.6	23.9	22	22	22	22	22	23.5	32.2	46.8	25	82.5	1992
62.6	24.9	23	23	23	23	23	24.5	33.2	47.8	26	83.5	1993
63.6	25.9	24	24	24	24	24	25.5	34.2	48.8	27	84.5	1994
64.6	26.9	25	25	25	25	25	26.5	35.2	49.8	28	85.5	1995
65.6	27.9	26	26	26	26	26	27.5	36.2	50.8	29	86.5	1996
66.6	28.9	27	27	27	27	27	28.5	37.2	51.8	30	87.5	1997
67.6	29.9	28	28	28	28	28	29.5	38.2	52.8	31	88.5	1998
68.6	30.9	29	29	29	29	29	30.5	39.2	53.8	32	89.5	1999
69.6	31.9	30	30	30	30	30	31.5	40.2	54.8	33	90.5	2000
70.6	32.9	31	31	31	31	31	32.5	41.2	55.8	34	91.5	2001
71.6	33.9	32	32	32	32	32	33.5	42.2	56.8	35	92.5	2002
72.6	34.9	33	33	33	33	33	34.5	43.2	57.8	36	93.5	2003
73.6	35.9	34	34	34	34	34	35.5	44.2	58.8	37	94.5	2004
74.6	36.9	35	35	35	35	35	36.5	45.2	59.8	38	95.5	2005
75.6	37.9	36	36	36	36	36	37.5	46.2	60.8	39	96.5	2006
76.6	38.9	37	37	37	37	37	38.5	47.2	61.8	40	97.5	2007
77.6	39.9	38	38	38	38	38	39.5	48.2	62.8	41	98.5	2008
78.6	40.9	39	39	39	39	39	40.5	49.2	63.8	42	99.5	2009
79.6	41.9	40	40	40	40	40	41.5	50.2	64.8	43	100.5	2010
80.6	42.9	41	41	41	41	41	42.5	51.2	65.8	44	101.5	2011
81.6	43.9	42	42	42	42	42	43.5	52.2	66.8	45	102.5	2012
82.6	44.9	43	43	43	43	43	44.5	53.2	67.8	46	103.5	2013
83.6	45.9	44	44	44	44	44	45.5	54.2	68.8	47	104.5	2014
84.6	46.9	45	45	45	45	45	46.5	55.2	69.8	48	105.5	2015
85.6	47.9	46	46	46	46	46	47.5	56.2	70.8	49	106.5	2016
86.6	48.9	47	47	47	47	47	48.5	57.2	71.8	50	107.5	2017
87.6	49.9	48	48	48	48	48	49.5	58.2	72.8	51	108.5	2018
88.6	50.9	49	49	49	49	49	50.5	59.2	73.8	52	109.5	2019
89.6	51.9	50	50	50	50	50	51.5	60.2	74.8	53	110.5	2020
90.6	52.9	51	51	51	51	51	52.5	61.2	75.8	54	111.5	2021
91.6	53.9	52	52	52	52	52	53.5	62.2	76.8	55	112.5	2022
92.6	54.9	53	53	53	53	53	54.5	63.2	77.8	56	113.5	2023