ISSN 2303-4521
Periodicals of Engineering and Natural Sciences *Original Research*
Vol. 11, No. 3, May 20, 2023, pp.311-322

Estimation and prediction of temperature in Iraq using the multi-layered neural network model

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ABSTRACT

The forecasting using the multi-layered neural network model is one of the methods used recently in forecasting, especially in climate forecasts for certain regions, because of its accuracy in forecasting, which sometimes reaches levels close to the real collected data. In this research, the daily temperatures in the climate of Iraq were predicted, by taking data from the Iraqi Meteorological Authority by (228) observations, which represent the daily temperatures of Karbala Governorate in the year (2021), The results of the autocorrelation and partial autocorrelation showed that the daily temperature series of Karbala governorate is unstable, and this was confirmed by conducting the augmented Dickey Fuller test. The data was analyzed using the multi-layered neural network model in two stages, and it was later shown that the accuracy of estimation and prediction using the multi-layered neural network even if the time series is not stable, The results showed an indication of an rising increase in temperatures during the coming years. The researcher concluded that it is necessary to pay attention to the vegetation cover and to conduct many predictive studies of the climate using the multi-layered neural network.

Keywords: Temperature, Multi-Layered, Neural Network, Estimation, Prediction.

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1. Introduction

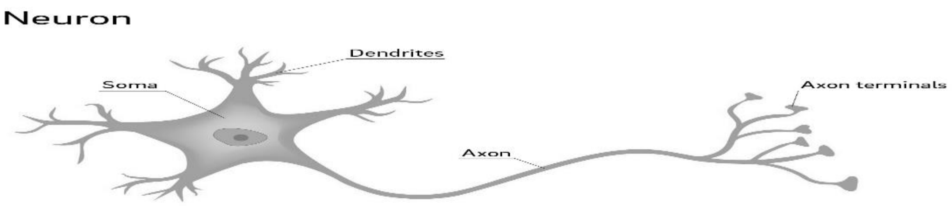
In many natural phenomena and in some areas of public life, we see that some phenomena change with the passage of time, and this change may occur on a regular basis, and some of them occur in certain seasons or in distant periods, or they change suddenly, which are sometimes called accidental changes. Iraq is distinguished as part of the Arab world by its location in the Middle East, which is an integral part of its airspace, due to the absence of climatic breaks of significant value between the parts of the Arab world, as our Arab homeland extends from the hot region south of the equator to the northern temperate region. This has resulted in a difference in temperature, winds, and rain, as it is affected by the western winds coming from the Atlantic Ocean and the Mediterranean Sea, which are moist and rainy, as well as the southeastern winds blowing from the Arabian Sea and the Arabian Gulf, which are accompanied by rain, as well as a cold, dry wind blowing from central Asia, as for the summer, local winds blow from the Arabian desert towards the north, and it is hot, dry, and dust-laden, like Al-Samum winds over Iraq. Likewise, mountains, plains, rivers and lakes all affect the climate in Iraq. These factors affected its climate, which is characterized by hot, dry summers and cold, fluctuating rains in winter, and those affected by these factors are humans. This series of changes can be measured temporally through data arranged within specific time periods that help us predict future values. This research aims to predict daily temperatures throughout Iraq using the multi-layered artificial neural network model.

2. Biological neural cell and artificial neural cell

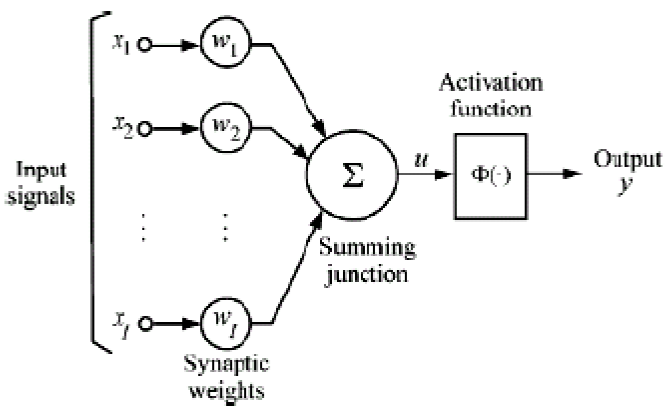
The human brain consists of a huge and complex number of neurons with complex internal connections, forming a large network of nerves (Neurons), which share characteristics with each other with other cells of the body, but it is unique in its ability to receive and process the transmission of the electrochemical signal along the nerve, which forms the link system of the brain. A nerve contains three parts: the cell body, the dendrites, and the axon. Dendrites extend from the cell body to other nerves to form a neural network. The synapse represents a passage or gateway to connect the dendritic branch coming from another nerve, as it is the connection points at which the sensory organ or receptor receives electrical signals and downloads information with the same time and speed. The inputs reach the cell body, some of them excite and stimulate the cell, while others inhibit and discourage it. The ganglion (nerve) works to integrate or accumulate signals in the cell body, and when it exceeds the required level (Threshold) for the cell, it will be inhibited and passed to the other cell along the axon, the dendritic branch modifies (changes) the amplitude of the signal transmitted through it, and this modification changes with time, as in the learning process of the artificial neural network [1, 2]. As for the artificial nerve cell, it was designed to simulate the basic characteristics of the biological nerve cell, where the input connections are represented by lines corresponding to the dendritic branches, which in turn represent the output of another nerve, When the signal represented by the vector X (input) comes from a specific correlation, it is multiplied by a number called the Weight of Connection, and the set of weights is represented by the vector W, which corresponds to the width of the biological dendritic branching, and the weighted signals or inputs are collected in the collection box that corresponds to the body of the neuron to determine the level of effect (Activation) for it to produce the output signal representing the input of other cells associated with it, and thus all the algebraically weighted inputs are combined to produce the achieved output called by the term (Net) calculated by the following formula [3]:

$$Net = \underline{WX} \qquad \dots (1)$$

Since: X: the input vector that includes the input group, which is W $x_1, x_2, \dots, x_n$. W: The weights vector containing the set of weights $w_1, w_2, \dots, w_n$. thus forming the artificial nerve (Artificial Neuron). Figure 1 (a) shows the components of a biological neuron and their analogues in an artificial neuron as in Figure 1 (b) [2].



(a) Components of a biological neuron



(b) Components of an artificial neuron

Figure 1. (a) Components of a biological neuron. (b) Components of an artificial neuron

Artificial neural networks have been called by several names, all of which are based on the idea of simulating the neural network in living organisms. They have been called the Biological Computer, Electronic Brain, Neuromorphic System, Connection Models, and Parallel Distribution. Processing Models [1,4].

Net is entered and processed in an activation function to produce the output of the neuron Output, as:
Output=R(Net)
Where R is the activation function and it may be linear or nonlinear.

3. Activation function

It is known as the Transfer Function because it converts the inputs through its interaction with the weights from one formula to another, and it is linear and non-linear, and the commonly used functions are:

Log-Sigmoid function
The function is most used at the nodes of the hidden layer of the network whose inputs have real values between (-∞, ∞) and its outputs for each node between (0, 1) and its mathematical formula is:

$$f(x) = (1 + \exp(-x))^{-1} \ldots (2)$$

And its derivative :

$$f'(x) = f(x)(1 - f(x)) \ldots (2)$$

They are linear and non-linear, and the commonly used functions are:

Hyperbolic tangent function
And is written as follows

$$f(x) = \tan h(x) \frac{1-\exp(-2x))}{1+\exp(-2x))} \ldots (3)$$

And its derivative :

$$f'^{(x)} = sech^2(x) = 1 - tanh^2(x)\left(1 - f^2(x)\right) \ldots (4)$$

This function is used at the output layer in the prediction case and is written in the following form:
Output=R(Net) …(5)

4. Multi-layer Artificial Network

These networks consist of one or more layers of hidden layers, and these (Hidden Nodes), which in turn contain a number of hidden nodes (Layer)) Networks consist of three levels:
It represents the first level in the network and contains a number of nodes that represent the number of explanatory variables (inputs) and receives the information to be processed. We would like to point out that when the input units are explanatory variables, the neural networks model will be similar to the multiple nonlinear regression model, and when the input units represent the offsets of the dependent variable, the nonlinear autoregression [5].
It represents the second level of the network, and this level may be one hidden layer or several layers, which in turn contain a number of hidden nodes, and each node has a weight that connects it with the previous level (inputs) and a weight that connects it with the subsequent level (outputs level) in which information is processed.
It represents the last level in the neural network, which is the outputs of the network, where the processing results are output to the external medium.

5. Artificial neural network architecture

The architecture (structure) of an artificial neural network means the arrangement of nodes in levels or layers and the form of interconnection within or between levels (layers) or in between. It is one of the most important characteristics of a neural network on the basis of which the network is described. Networks are classified according to the number of their levels (layers) into two main categories. They are single-level or layer networks that do not have a hidden layer, and multi-level or layers networks, which have one or more hidden levels (layers). They are also two types: Feed Forward Network and Feed Backward Network networks. In general, the architecture of a typical artificial neural network consists of three levels (layers):
1- Input level (layer): It is the first level in the neural network. It contains a number of nodes representing the number of independent variables (inputs).
2- The hidden level (layer): it is the middle level that lies between the first level (input) and the last level (output), as it follows the first level.

3 - Output Level (layer): It is the last level in the artificial neural network that represents the output of the neural network.
Each of the above three levels consists of:
a. Nodes: These are the neural connections between the levels (layers) of a neural network.
b. Level: The set of nodes or cells that receive input and have output.
c. Weights: The weights indicate the strength of the neural connection between the levels (layers) of the neural network. Each node (cell) has a weight that connects it with the previous level, and a weight that connects it with the next level. The initial values of the weights at the beginning of network training are random numerical values that are generated from statistical distributions [6, 7].
There are three layers of weights in a neural network:
1- Weights layer of Input and Hidden levels.
2- Weights layer between hidden levels (Hidden Weights)
3- Weights layer of output and Hidden levels.
Figure (2-7) is a diagram illustrating the architecture of a typical artificial neural network.

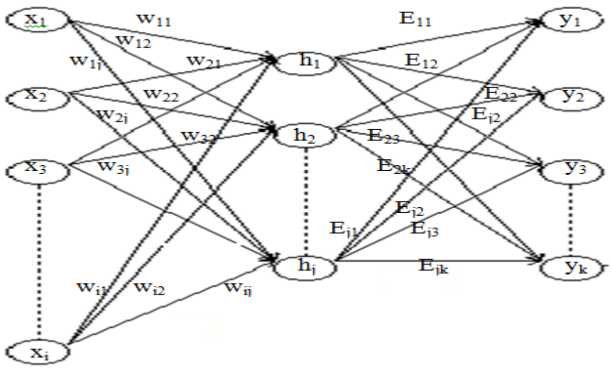


Figure 4: The architecture of the artificial neural network

6. Learning and training (information process in neural network)

There are two types of artificial neural networks: (Fixed N Nets) which do not change their weights when training or learning, and (Adaptive N Nets), which have the ability to change their weights. Information processing in neural networks means the passage of data in adaptive neural networks in two basic stages, namely the Learning or Training step and the Doing or Recall Step.

Learning is generally defined as a relatively permanent and continuous change in behavior that occurs through experimentation and testing. Learning in neural networks is a given application of (input-output) operations through a set of examples, Learning is an urgent necessity when there is a lack of understanding of the relationship between input and output so that it is difficult to describe. During this stage, new information (data) is produced in the network as a result of changing the weight of the network [2]. The process of training the artificial neural network on the given application begins with entering data into the network, so it learns the characteristics and advantages of this data, which are represented in the form of (Vectors). Each vector consists of two parts, the first part represents the set of independent variables, for example (input), while the second part represents the values of the criteria (dependent variables) (the desired output), the two parts together form the vector that prepares the input to the network, and each of the input nodes represents one of the values of the first part of the vector (the independent variables). The vector is entered into the network in the form of a matrix, the network is trained on the data, that is, its weights change according to specific laws and in a sequential manner. Thus, the weights gradually approach the ideal values that give the best estimate of the standard values, which represent the required output of the network [6]. Accordingly, training in adaptive artificial neural networks (adaptation of system parameters) has two basic methods: supervised training and unsupervised training [8].

1- Supervised Training (by trainer or instructor):

It is guided training and usually used in Feed Forward Networks which requires a pair of Input and Target Output, which represent the training pair, the neural network is trained on a number of these pairs and compares the output of the applied input vector with the expected output vector, and the difference between them represents the (Training Error) returned through the network so that the weights change according to the algorithm in the direction of reducing the error. All vectors of the training set are applied, the weights are changed, and the error is calculated until the input training set reaches the (Minimum Training Error) using one of the common methods for reducing the error, which is the asymptotic least squares (LMS), and as a result we get the optimal weights that can be adopted in the prediction of new data that have not undergone training or learning, and this is the goal of training the artificial neural network [9].

2- Unsupervised Training:

This type of training does not use the external parameter and relies only on locational information. This type of training is referred to as self-organizing networks, i.e. self-organizing the data that is provided to the network. In this training, the neural network has some information during the training, that is, it has only inputs, and it does not know what the correct answer will be, and it does not know what the desired output is, that is, there is no (Desired Output) for the network to compare with the results. This training was discovered by researcher (Cohen et al.), In which the training set consists of an input vector and a training algorithm to change the weights of the network to produce a fixed output vector, the input is applied to produce the specified output [30].

The work stage (retrieval) is the second stage for processing the information (data) of the artificial neural network, and in it the given input is applied with the weights resulting from the first stage (the training stage) and in one step we get the desired output (Desired Output). The work phase (retrieval) is a feed forward only, where the neurons are connected with the layers, which leads to the flow of data in one direction only, that is, each neuron receives information only from the neurons in the previous layer, The input for each neuron represents the weighted output of the neurons in the previous layer. Figure 5 shows the structure of the feed-forward neural network.

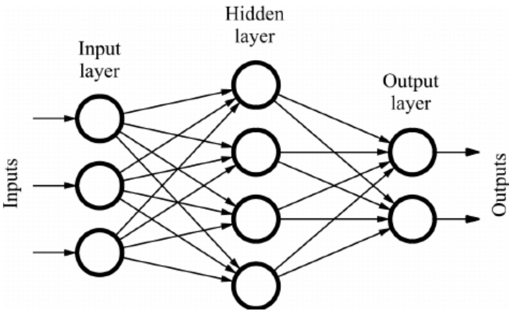


Figure 5. The structure of the feed-forward neural network

7. Results and discussion

The data for the research was obtained from the Iraqi Meteorological Authority, which represents the daily temperatures recorded in Karbala Governorate for the year (2021), which included (228) observations, according to what is available from them. Data fairness was tested according to the goodness of fit test. For the purpose of obtaining the estimated values of the temperature series in Karbala Governorate, using the original series of data consisting of (228) observations that suffer from instability, and which were tested according to the following:

First, we draw a data series that represents the daily temperatures recorded in Karbala Governorate to identify the behavior of the series and its characteristics. Figure 6 represents the drawing of the series.

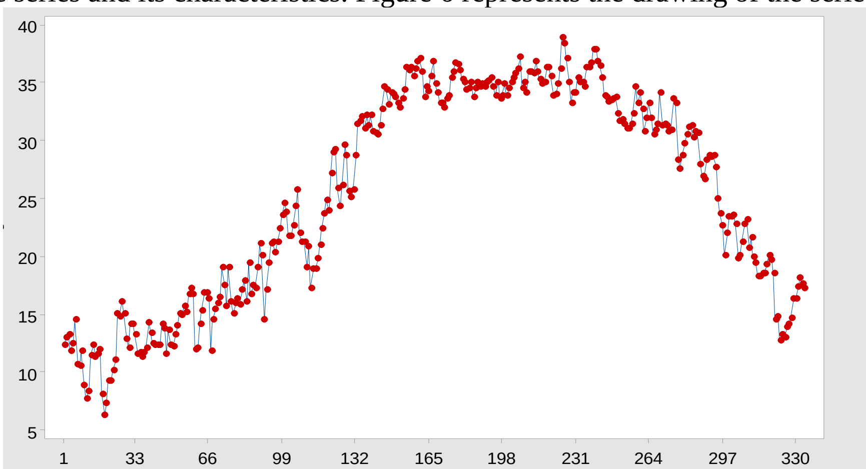


Figure 6. The series of daily temperatures in Karbala Governorate

Through Figure 6, we notice that the vertical axis represents the daily temperature values, and the horizontal axis represents the days, and we notice the instability of the time series as it expresses the general trend with time, in addition to the presence of fluctuations represented in concavities and protrusions, these fluctuations are repeated regularly at a similar pace every day with its difference, which increases from one day to another, and these changes indicate to us that there is a general trend movement and a seasonal movement and that the chain is unstable. For more accuracy, we draw the Auto Correlation Function and the Partial Auto Correlation function, as in Figure 7:

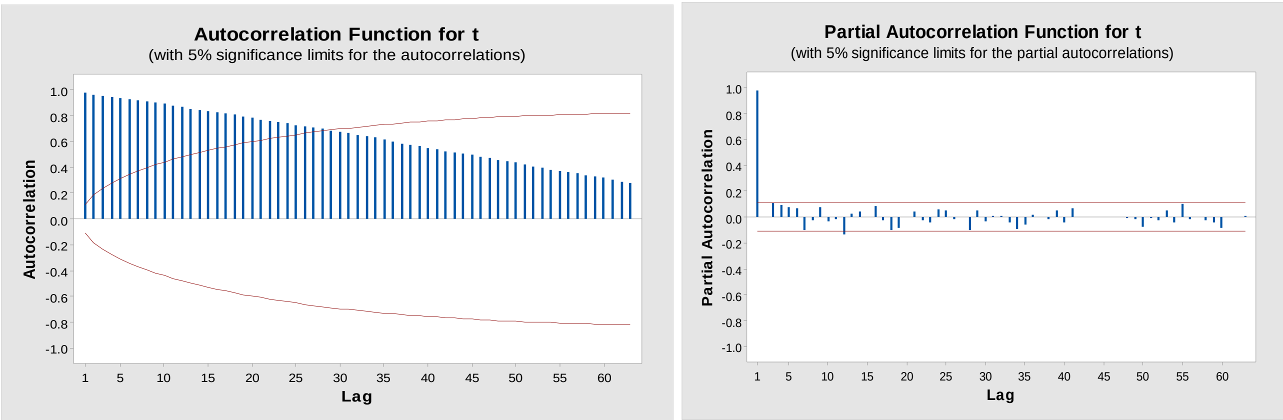


Figure 7. Graph of the autocorrelation function ACF and partial autocorrelation PACF for temperatures in Karbala Governorate

We note from Figure 7 that many of the autocorrelation function ACF coefficients are outside the limits of confidence at the level of 95%, as well as some partial autocorrelation coefficients, and this is an indication of the instability of the chain. Table 8 shows the values of the Auto Correlation Function and the Partial Autocorrelation Function Auto correlation function for the temperature series in Karbala Governorate.

Table 8. The values of the ACF and PACF functions of temperature in Karbala Governorate

Lag	**ACF**	**PACF**
1	0.881911	**0.881911**
2	0.866252	**-0.09686**
3	0.853511	**0.010255**
4	0.843956	**-0.00828**
5	0.836531	**-0.02368**
6	0.830531	**-0.03578**
7	0.820071	**-0.19923**
8	0.808912	**-0.12382**
9	0.800044	**-0.02058**
10	0.794012	**-0.13245**
11	0.782842	**-0.11781**
12	0.769674	**-0.23399**
13	0.757251	**-0.07571**
14	0.746802	**-0.06136**
15	0.737568	**-0.10602**
16	0.731243	**-0.01385**
17	0.723633	**-0.12672**
18	0.711227	**-0.19885**
19	0.695978	**-0.18255**
20	0.683042	**-0.09199**

Lag	ACF	PACF
21	0.672508	**-0.05547**
22	0.66232	**-0.12793**
23	0.650717	**-0.14416**
24	0.640088	**-0.03795**
25	0.630877	**-0.04937**
26	0.621507	**-0.11971**
27	0.612825	**-0.10721**
28	0.600141	**-0.20371**
29	0.587283	**-0.05278**
30	0.574249	**-0.13513**
31	0.563495	**-0.08984**
32	0.553989	**-0.08884**
33	0.543969	**-0.13844**
34	0.530229	**-0.1901**
35	0.514622	**-0.15585**
36	0.500282	**-0.08457**
37	0.486422	**-0.10817**
38	0.474179	**-0.11283**
39	0.462877	**-0.05249**
40	0.449453	**-0.13858**
41	0.437731	**-0.03578**
42	0.42749	**-0.10272**
43	0.417926	**-0.10079**
44	0.406837	**-0.10732**
45	0.39454	**-0.10774**
46	0.381371	**-0.10191**
47	0.369271	**-0.10347**
48	0.358509	**-0.10929**
49	0.348068	**-0.11943**
50	0.335634	**-0.17264**
51	0.321658	**-0.11183**
52	0.3073	**-0.12488**
53	0.295534	**-0.04761**
54	0.283664	**-0.14185**
55	0.274562	**-0.00171**
56	0.264468	**-0.11809**
57	0.253313	**-0.10727**
58	0.242162	**-0.12582**
59	0.231041	**-0.14058**
60	0.217659	**-0.18256**
61	0.203765	**-0.10735**
62	0.190289	**-0.09721**

We notice from Table 9 that most of the values of the autocorrelation and partial autocorrelation functions are slow after the first shift, meaning that ||ACF |>|1.96⁄√n| و |PACF |>|1.96⁄√n|

And to make sure of the instability of the temperature series in Karbala governorate, we resort to the augmented Dickey-Fuller test. Table 10 shows the test results.

Table 10. The results of the extended temperature series Dickey-Fuller test

Test	Statistic	Table Statistic	Sig
Augmented Dickey – Fuller	-1.643455	-2.16676	0.21304

The test results in Table 10 show that the absolute value of the test statistic is less than the tabular value of the augmented Dickey-Fuller test at a significant level (0.05). This calls us not to reject the null hypothesis and to reject the alternative hypothesis that refers to the stability of the time series, meaning that the series is unstable. The data was analyzed using the multi-layered neural network model, which was done in two stages, the first is preparing the data, which is the process of converting the data into the standard format (Normalized), as well as defining the inputs of the neural network, as for the second stage, it is the process of dividing the data, as the data was divided in a ratio of (8:2) into two groups, the training group, including the validation group, consisting of (259) observations with a rate of (76.1%), and the second group is the test data (Testing set) consisting of (70) observations with a rate of (23.9%). After the data was prepared to be entered into the network, the network was designed, which consisted of three main phases: the training phase, the verification phase, and the testing phase, as follows:

First: the training phase: the multi-layered neural network was formed and trained and values were given as close as possible to the temperature data by entering and processing the training data and choosing the number (30000) as the number of training sessions with an error rate of (0.0000001). It was found that the best architecture for estimating the observations is by choosing five nodes for the input layer and using two layers two hidden ones, the first contained six nodes, and the second included two nodes and one output node.

Second: Verification phase: The network was selected by entering the audit data, as this data is compared with the trained data obtained in the training phase to obtain a match with the target data, and thus the network is verified to have been well trained.

Third: The testing phase: After completing the training and verification process, the test data and the ideal weights stored in the network are now entered and processed, and a test is made for the efficiency of the trained neural network and its ability to give acceptable estimated values. Thus, the required outputs were obtained from the artificial neural network. Figure 8 shows the architecture of the artificial neural network.

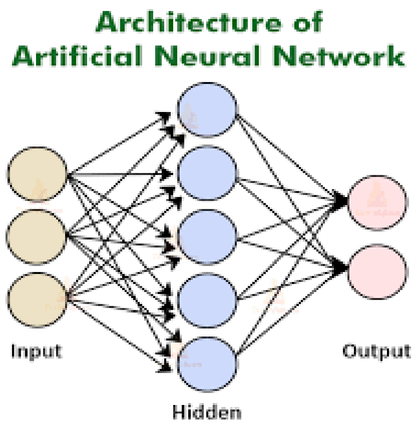


Figure 8. The architecture of the artificial neural network

Table 10 and Figure 8 show the estimated values of the daily temperature series in Karbala governorate using the artificial neural network, which is consistent with the original values of the series, and this indicates the accuracy and good efficiency of the estimated model.

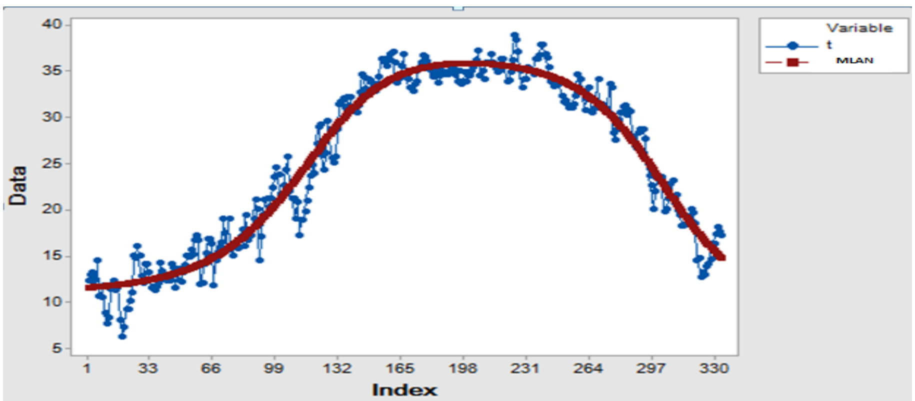


Figure 9. The estimated and real values of the temperature series in Karbala Governorate, estimated according to the multi-layered artificial neural network

From Figure 9, we note that the estimated values of temperatures are consistent with the original values of the series, which indicates the accuracy of the estimate by the method of multi-layer neural networks as for the predictive values of the temperature series in Karbala Governorate for the years (2020-2024).

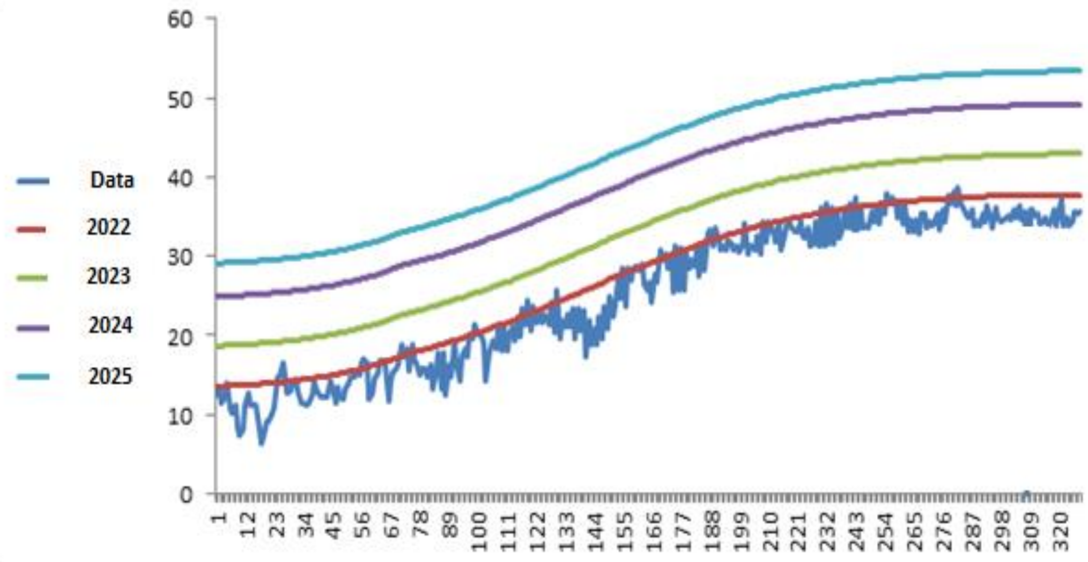


Figure 10. The real and predictive values of the temperature series in Karbala Governorate, estimated according to the multi-layered artificial neural network for the years (2022-2025).

From Figure 9, we note that the predictive values of the daily temperatures are increasing over the years. In the year (2025), the temperatures will reach the highest level in 2021. By the way, artificial intelligence can be used in all branches of computer and communication engineering [10-29].

8. Conclusions

From the results obtained, the following conclusions were reached:
1. Accuracy of estimation and prediction using a multi-layered neural network, even if the time series is unstable.
2. The estimated values of temperatures are consistent with the original values of the series, which indicates the accuracy of the estimation using the multi-layered neural network method.
3. The predictive values of the daily temperatures are increasing over the years. In the year (2025), the temperatures will reach the highest level from the year (2021).
4. The results of the research indicate an increasing rise in temperatures during the coming years.

From the conclusions reached, we recommend the following:
1. The need to take care of gardens and plant trees and flowers to reduce the phenomenon of desertification.
2. The need for maintenance of electric power systems, especially in the summer.
3. Conducting a study to predict the future values of other climate elements (rainfall, relative humidity, atmospheric pressure, etc.) using the multi-layered neural network method.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

No funding was received from any financial organization to conduct this research.

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