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A new Modern Technique used to Forecast the Rock Stratigraphy of Mountain Safeen in Iraqi Kurdistan

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Abstract
The geographical diversity of Safeen Mountain consists of rock units, topography, water resources, and types of soil. The rock units consist of limestone, goldstone, dolomite limestone, madly limestone, marl, siltstone, and conglomerates. Classify the soil type into sandy and clay soils. And that using the technique of neural fuzzy systems to forecast is considered one of the new techniques used in our current era and an alternative to the traditional statistical methods.
There is no difference in the results obtained using the technique of neural fuzzy systems and the proposed neural fuzzy systems, but only a difference in the time it takes to implement the algorithm. It is characterized by the accuracy of its final results through the speed of implementation, and this is a good indicator that enhances the quality of the method of proposed neural fuzzy systems. It is possible to rely on the proposed neural fuzzy systems for forecasting the layers of the earth in other regions.

1. Introduction
The topic of neural fuzzy systems is one of the most recent topics of our time. It is a terrible combination of two very important techniques, and the first to start integrating these two techniques were the researchers Brown and Harris in 1994. These two researchers proposed the Neuro-Fuzzy (NF), which is a non-linear dynamic model, and they showed that this system can distinguish empirical data as well as be discernible by giving us some insight into the nonlinear properties of a dynamical system. The main idea of fuzzy logic control is to build a model of a human control expert who is capable of controlling the plant without thinking in terms of a mathematical model. The control expert specifies his control actions in the form of linguistic rules. [Fabod and Khoshnoud, 2003; Zurada, 1994].
The quality of the fuzzy logic controller can have a significant impact on the controller's performance. Therefore, techniques for fine-tuning fuzzy logic controllers are necessary. [Zurada, 1994; HORMOZI, 2012].

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2. Theoretical Part

2.1 Neuro-Fuzzy Systems (NFS): The nerve of the mating between fuzzy logic and the neural networks used is the application of the neural fuzzy method, as this method uses a group of fuzzy systems and neural networks alike to solve any problem. This fusion between fuzzy groups and neural networks has one or two possibilities: either the model is neural fuzzy systems or the model is fuzzy neural systems, and the integration of these two technologies by classifying them into three main categories. [Fasile et al, 2001; Detlef and Rudolf, 1997]

Neural Fuzzy System: The neural fuzzy system uses neural networks as tools in the fuzzy model; in this method, the training data in the real system are available, and the fuzzy system includes membership functions and rules that are dependent on the training data. It can use a model of real data or a system. Adaptive Fuzzy Neural Network Inference Systems (ANFIS) are widely used in engineering applications. The training of algorithms can be defined as: [Nurnberger et al., 2001; Wei et al., 2023]

$$\{(x^1, y^1), \ldots, (x^k, y^k)\} \qquad (1)$$

Equation 1 contains a single input as well as a single output that trains the data, as follows:

Ri:If x is Ai then y = zi (2)

Where Ai is fuzzy membership functions and Zi is real numbers. The fuzzy membership function is known as the sigmoid function, as shown in equation
3. [Farbod and Khoshnoud, 2003;Ammar and Haidar,2013].

$$A_i(x) = \frac{1}{1 + e^{b_i(x - a_i)}} \qquad (3)$$

ai and bi are parameters of the membership function Ai. The fuzzy output can be processed through the center of gravity to reach the stage known as the stage of defuzzification, as indicated in the following faction:

$$O(x) = \frac{\sum_{i=1}^{n} A_i(x) z_i}{\sum_{i=1}^{n} A_i(x)} \qquad (4)$$

Where Zi represents the inputs, it is in real numbers. The training set can now be used to teach and train the required parameters for (ai,bi) and successive parameters Z. The model error can be written in the following equation:

$$E^k = E^k(a_i, b_i, z_i) = \frac{1}{2}(O^k(a_i, b_i, z_i) - Y^k)^2 \qquad (5)$$

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The algorithm parameter can be calculated based on the error function as follows [Fabod and Khoshnoud, 2003; Zurada, 1994].

$$Z_i(t+1) = Z_i(t) - \eta \frac{\partial E^k}{\partial z_i} = Z_i(t) - \eta (O^k - Y^k) \frac{A_i(x)}{\sum_{i=1}^{n} A_i(x)} \qquad (6)$$

Then

$$a_i(t+1) = a_i(t) - \eta \frac{\partial E^k}{\partial a_i} \qquad (7)$$

$$b_i(t+1) = b_i(t) - \eta \frac{\partial E^k}{\partial b_i} \qquad (8)$$

O, η are the learning ratios.

Fuzzy Neural Systems: Is a method of modeling the traditional neural network, in that fuzzy neural networks retain their basic properties and architecture? In fuzzy neural networks, the critical neuron, which is a neuron, can become a fuzzy cell compared to the normal neuron, and this is a signal to activate the lower layer. It includes the inputs system, outputs, and membership functions, with the requirement that the rules associated with them exist. The goal of integrating these two techniques is to create a separate fuzzy model, which can be presented in a form based dependent on the input and output information, as this set of information taken from the input and output can be used as training data for the selected standard neural network., outputs, and membership functions, with the requirement that the rules associated with them exist. The available rules for fuzziness can be formulated as follows:

Ri: if x is Ai then y is Bi, i=1,…,k,…,n

Ai and Bi: are fuzzy groups, to define the following equations of membership from the mathematical form. [Fussel et al., 1997; Rakic, 2010].

$$x_j = a_1 + \frac{j-1}{N-1}(a_2 - a_1) \qquad (9)$$

$$y_k = b_1 + \frac{k-1}{M-1}(b_2 - b_1) \qquad (10)$$

Whereas $1 \le j \le N$ and $1 \le k \le M$ that's $N \ge 2, \quad M \ge 2$ can be chosen based on the amount of data that is derived from the functions membership.

c. Fuzzy-Neural Hybrid Systems: This system included integrating fuzzy techniques with neural networks to obtain hybrid systems. Efforts to integrate these two technologies are noted through the main role played by both fuzzy techniques and

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neural networks in the hybrid system, as they do their own work in serving the various functions in the hybrid system. It can develop the architecture of the adaptive fuzzy inference network, which is the backbone of this research on integrating these two technologies, by integrating the fuzzy inference system within the framework of the neural adaptive networks. And what is represented in neural networks, particularly in their architecture, is a system that is very easy to train or learn on traditional neural networks. [Ajith Abraham, 2003; Jang, 1993; Pabhakaran et al, 2019].

2.2 The Fuzzy-Neuro System: The union of neural networks and fuzzy models in a unified framework is necessary in order to generate numerical and symbolic information about any process using a machine language as the base and then extract the useful features from integrating them. Especially when there is little knowledge of the process.is based on two types of fuzzy models:

This system Mamdani Model [Mamdani, 1995]

Takagi Sugeno Model [Takagi and Sugeno, 1985]

Mamdani's model was used in this research because it was integrated with neural networks in 1996 to work on learning algorithms. The inputs and outputs are linguistically fuzzy groups, and the model's main purpose is to provide the most linguistic description of the process under consideration. This is a model that can be represented by the following layers: [Ayoubi, 1995; Wang Z., et al, 2022].

First level: Input Layer: Each node in this layer must represent a single input variable. Only the input values are sent directly to the next layer from this layer. This layer's interconnection is a single unit. So, in this layer, the input is a fuzzy group that can be defined as the membership functions with center mi and spread σi as shown below: [Ajith Abraham, 2003].

$$\mu_{A_i}(x) = \exp\left[-\left(\frac{(x-m_i)^2}{\sigma_i}\right)\right] \qquad (11)$$

Secerned level: Fuzzification Layer: The algorithm is the one that will decide the initial number and the type of membership operating in it so that they are assigned to both the variable and the final forms of the (NFS) model that will be nice forms during the learning of the network. We conclude from the foregoing that the second layer includes the cells of the neural base and that the strength of each base is given by the following equation:

$$\alpha = \min([\mu_{A_1}(x), \mu_{A_2}(x), ..., \mu_{A_n}(x)]) \qquad (12)$$

Third level: Rule Antecedent Layer: Any node in this layer represents the previous segment and typically follows the operator standard used in this node. The output of

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the third layer represents the starting power of the third layer to the fourth layer, which in turn is a fuzzy base.

Level Four: Rule Consequent Layer: In this layer, each node has two main tasks: First, merge the rule's precedence with the preceding layer. Second, estimating the degree to which the linguistic output explains the relationship, for example, (high level, medium level, low level, etc.) The number of nodes in this layer equals the number of grammars.

Level Five Defuzzification Layer: There are node-specific operations in this layer. The nodes operate a set of rules that are involved and incorporated in order to regulate the use of the arithmetic function; the application of Blur dissipation is in layers (third, fourth, and fifth); and the output (y) cannot be calculated without the weight (w) value, as shown in equation 13. [Heesche, 1995].

$$y = \frac{\sum_k M_k \sum_j (w_{kj}.\alpha_j)}{\sum_k A_k \sum_j (w_{kj}.\alpha_j)} \qquad (13)$$

Where Mk and Ak are functions membership. wkj=1 Partial connection or 0 The rules in the NFS model used for Mamdani's fuzzy model can be written in the following form:

R1: If x1 is A1 and x2 is B1 …. Then y is C1
R2: If x1 is A2 and x2 is B2 …. Then y is C2
Rn: If x1 is An and x2 is Bn …. Then y is Cn

Wherex1,x2: represent inputs, and C1, C2,…,Cn: represent outputs. A large number of training parameters usually need to be defined in the perfect network. In other words, the number of bases is a very perfect number. The EA, or tendency, of the algorithms that should be used for training determines the precise form and location of membership functions. [Liu et al, 2005].

3. Description of Experiment Site: The experimental site chosen for this research is Safeen Mountain, located in Erbil Governorate. Choosing a section for this mountain is characterized as consisting of two parts, the lower part in the west and the upper part in the east, and the rock units consist of limestone and goldstone, which is denoted by the symbol (A), which corresponds to the number 1, and Marley limestone, which is symbolized by the symbol (B). Which corresponds to 0, and the clay stone is red and gray, which is symbolized by the symbol (C), corresponding to the number -1 in the upper part, and it consists of sandstone and dolomite limestone. The difference between A and B is equal to one and the difference between B and A is also equal to one. The error value must be greater than the allowable value the network is trained for with an error value of 0.15. Only the bottom part was taken.

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The sample of this research is 650 observations; it includes 260 input elements and one hidden layer consisting of 26 hidden nodes, as well as one output layer consisting of one node. The bias coefficient value has also been increased on both the hidden layer and the output layer (600), an element of the forecast.

3.1 Neural Fuzzy Systems of Experiment Site: The basic idea of neural fuzzy systems is to work on fragmenting the largest permissible error and representing it with conditional rules, like the fuzzy model's rules, in order to gauge the program's progress toward the least permissible error, which is represented by the desired error that is symbolized by the symbol (Eoptimal). The initial conditional rule is that upon arrival of all elements chosen, the maximum error rate is equal to (0.15), which is typically obtained at a very high speed. To satisfy the condition of conformance, the maximum allowed error's percentage is changed to one that is smaller than it, and so on, until we reach the optimal, and after experimenting with a number of fuzzy method conditional rules. For each rule and stage, the percentage reduction in the greatest permissible error was calculated by subtracting (0.15) from the maximum allowable error for the stage before attaining optimal.

The following formula can demonstrate the fundamental conditional rule:

$$R_i : If \;\; \mathrm{E_{cal}} \le E_{\max} \quad \text{then} \;\; \mathrm{E_{max}} = E_{\max} * 0.85$$

Where: Ecal is the percentage error of each step. Emax denotes the maximum allowed error. optimal: The researcher's estimated percentage of the maximum desired error. If the desired error is equal to 0.06, the maximum error that can occur at the beginning of the program is 0.15, which indicates that Emax is equal to 0.15. As a result, the following will be how the conditional rules for the earlier data are constructed:

$$R_1 : If \;\; \mathrm{E_{cal}} \le 0.15 \qquad \text{then} \;\; \mathrm{E_{max}} = 0.15 * 0.85 = 0.1275$$

$$R_2 : If \;\; \mathrm{E_{cal}} \le 0.1275 \qquad \text{then} \;\; \mathrm{E_{max}} = 0.10837$$

$$R_3 : If \;\; \mathrm{E_{cal}} \le 0.10837 \qquad \text{then} \;\; \mathrm{E_{max}} = 0.092118$$

$$R_4 : If \;\; \mathrm{E_{cal}} \le 0.092118 \qquad \text{then} \;\; \mathrm{E_{max}} = 0.0783$$

$$R_5 : If \;\; \mathrm{E_{cal}} \le 0.0783 \qquad \text{then} \;\; \mathrm{E_{max}} = 0.0665$$

$$R_6 : If \;\; \mathrm{E_{cal}} \le 0.0665 \qquad \text{then} \;\; \mathrm{E_{max}} = 0.056$$

$$R_7 : If \;\; \mathrm{E_{cal}} \le Eoptimal \quad \text{then Done}$$

The number of bases differs depending on the percentage of the maximum error that is allowed; more than the percentage of the maximum needed error, more bases are required until it is reached. The forecasting algorithm employs the Appendix1 neural

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fuzzy networks technique. And when put into practice, it improved the time it took for the final findings to arrive, as seen in Table 1.

Table 1: the change in the Learning Rate and time required to Forecast.

Learning Rate	Time (Hours)	No. of Deviation Value
0.1	0:0:49:330	7
0.2	0:0:35:240	6
0.3	0:0:30:300	7
0.4	0:0:27:400	5
0.5	0:0:23:130	4
0.6	0:0:24:436	8
0.7	0:0:20:241	1*
0.8	0:0:25:271	7
0.9	0:0:72:620	4

Reference: Prepared by the researcher based on the program's outputs
***: less time minimum number of deviation value.**

Table 1 shows that the best learning ratio for the shortest amount of time is equal to 0.7 at a time of (0:0:20:241) at the percentage of the maximum allowable error. For selecting the optimal learning ratio, as it is always equal to 0.7, this is proof that the method of neural fuzzy systems was chosen for the development process in order to speed up the program's work while retaining the accuracy of the findings. We are currently working to lower the percentage of the maximum error down to the required error of 0.001 when choosing the optimal learning rate of 0.7, as shown in Table 2.

Table 2: the constant Value of the Learning Ratio with a Change in the error to get the actual Forecast

Learning Rate	Error	Time (Hours)	No. of Deviation Value
0.7	0.1	0:0:39:451	5
0.7	0.3	0:0:25:135	7
0.7	0.06	0:0:15:230	Zero
0.7	0.15	0:2:25:360	Zero
0.7	0.075	0:5:28:230	Zero
0.7	0.005	0:3:1:341	Zero
0.7	0.001	0:15:34:231	Zero

Reference: Prepared by the researcher based on the program's outputs

This result does not differ from Table 1 to determine the maximum permissible error percentage, as it is always equal to ($\eta = 0.7$). Table 2 shows that the best forecast values were obtained when the intended error ratio was at its maximum, which was equal to 0.06, and when the forecasting time was (0:0:15:230). This result demonstrates the preference for applying the fuzzy systems model method to anxiety.

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Appendix 2 has its forecast values at the neural fuzzy systems method's optimal learning ratio of 0.7.

3.2 Analysis of Neural Fuzzy Systems Idea: the analysis of this method is the behavior of the error curve at each learning rate that serves as a focal point of the network's operation. It can be started by determining the rate of the largest permissible error percentage when choosing the learning rate. If we carefully examined each case, the program's performance would be dependent on a set of learning rates that were carefully chosen based on scientific considerations and learning in which the rate of regression of the largest permissible error percentage to the desired ideal case is as fast as possible.

i. Analysis of The Maximum Permissible Error's Curve: The curves for the maximum permissible error change with time as shown in the figures, starting with the initial value of the learning rate equal to 0.1 and ending with the last learning percentage equal to 0.9 at the percentage of the maximum allowable error equal to 0.2 as follows:

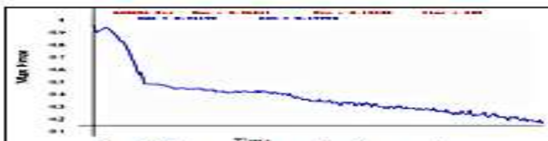

Fig.1: the maximum ratio of error at the curve allowable Neta=0.1

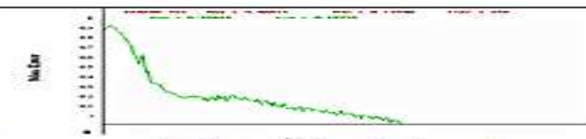

Fig.2: the maximum ratio of error at the curve allowable Neta=0.2

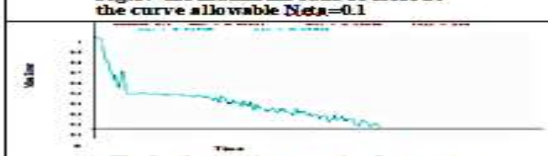

Fig.3: the maximum ratio of error at the curve allowable Neta=0.3

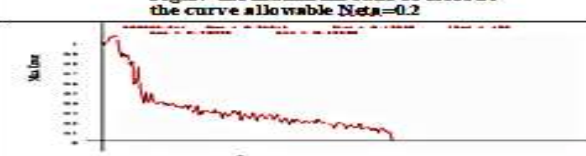

Fig. 4: the maximum ratio of error at the curve allowable Neta=0.4

Fig.5: the maximum ratio of error at the curve allowable Neta=0.5

Fig.6: the maximum ratio of error at the curve allowable Neta=0.6

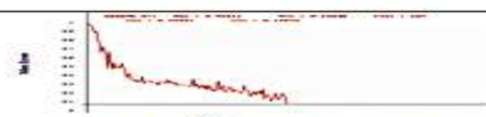

Fig.7: the maximum ratio of error at the curve allowable Neta=0.7

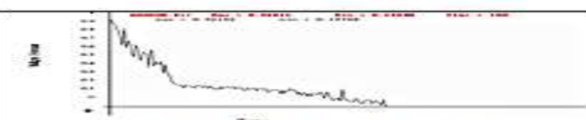

Fig. 8: the maximum ratio of error at the curve allowable Neta=0.8

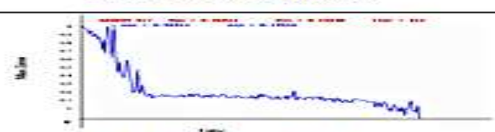

Fig.9: the maximum ratio of error at the curve allowable Neta=0.9

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Fig. 2 shows that the best error curve at the initial stage of the program's operation was at the value of Neta equal to 0.2, which has the greatest fluidity and is free from fluctuation. This is because the program was able to slope the curve from the percentage of the greatest error that was allowed to 0.5 with a time of approximately 7 seconds, in contrast to the other curves and at the values of the other selected Neta learning ratios, where its beginning was marked by great fluctuation. This is because it takes time for it to arrive at an inaccuracy of 0.5. The best error curve at the value of Neta is equal to 0.4 and is confined between the two values of the percentage of the maximum error possible between the two values (0.3, -0.5) in terms of the difference of this part with the rest of the parts for the same selected period and for the values of the learning ratios chosen in all training. This is because it has a clear flow and a slope towards zero faster than the rest of the curves.

ii. Building the Rules of the Proposed Neural Fuzzy Systems Model: The conditional rules were developed to be used as inputs to forecast the following values based on the values of the learning ratios that were previously chosen from the forms of the largest permitted error curves:

R1: If Ecal > 0.5 then Neta = 0.2
R2: If 0.3<Ecal < 0.5 then Neta = 0.4
R3: If 0.1<Ecal < 0.3 then Neta = 0.5
R4: If 0.05<Ecal < 0.1 then Neta = 0.4
R5: If 0<Ecal < 0.05 then Neta = 0.2

iii. Forecasting Algorithm by using the Proposed of Neural Fuzzy Systems:

Depending on the rules that were built in the previous stage, the algorithm of the method of fuzzy neural networks was developed by adding these rules that will be freed from the previous restriction in choosing the learning rate if it works to speed up the work of the programs.

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Table 3: Forecasting Values by using the Proposed Neural Fuzzy Systems Method

Id	Element Symbol	Forecast Value	The actual Value of Series	The Element Series Forecast
600	0	1.901	A	A
601	2	0.123	C	C
602	2	0.431	C	C
603	0	0.513	A	A
604	1	1.134	B	B
605	0	1.834	A	A
606	1	1.689	B	B
607	1	1.821	B	B
608	1	1.819	B	B
609	1	1.614	B	B
610	2	1.213	C	C
611	2	1.531	C	C
612	2	1.101	C	C
613	2	1.667	C	C
614	2	1.817	C	C
615	2	1.821	C	C
616	1	1.829	B	B
617	0	1.99	A	A
618	0	1.898	A	A
619	0	1.186	A	A
620	2	1.879	C	C
621	2	1.628	C	C
622	2	1.561	C	C
623	1	1.341	B	B
624	1	0.761	B	B
625	1	0.541	B	B
626	1	0.761	B	B
627	1	0.761	B	B
628	1	1.451	B	B
629	1	1.091	B	B
630	1	1.234	B	B
631	2	1.001	C	C
632	2	1.87	C	C
633	0	0.521	A	A
634	2	1.643	C	C
635	1	1.684	B	B
636	2	1.697	C	C
637	2	1.801	C	C
638	0	0.821	A	A
639	1	1.829	B	B
640	1	1.806	B	B
641	1	1.831	B	B
642	1	1.845	B	B
643	1	1.891	B	B
644	0	0.781	A	A
645	1	1.821	B	B
646	1	1.845	B	B
647	1	1.857	B	B
648	1	1.889	B	B
649	1	1.621	B	B

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Forecasting values of 0:0:15:230 were obtained without any deviation values when the algorithm was applied to forecasting using the neural fuzzy systems method developed by using the C++ program; this means that predicted values were obtained that exactly matched the neural fuzzy systems method as shown in Table 3.
In Table 4 shows the neural fuzzy system strategy and the neural fuzzy systems used for forecasting in this research, as well as the length of time needed to arrive at the results and the number of deviations:

Table 4: Compare the Neural Network for using Models

Mode	The best rate of Neta	Time	No. of Deviations
NF	0.7	0:0:20:241	Zero
NF Proposed	0.7	0:0:15:230	Zero

Reference: Prepared by the researcher based on the program's outputs

4 Conclusion Recommendations

4.1Conclusion: Neural fuzzy systems and the proposed neural fuzzy systems model were used in the application part of the forecast of rock stratigraphy of Mountain Safeen in Iraqi Kurdistan data, resulting in the following findings:
1. The results on the applied side show that the proposed neural fuzzy systems technology is the best modern forecasting method used in this research because it takes much less time than neural fuzzy systems and is distinguished by the accuracy of its final results due to the speed at which it extracts results. This is a good signal that, when compared to other systems, raises the quality of the neural fuzzy system approach without impacting the accuracy of the findings.
2. In Table 3, the forecasting algorithm shown by using the proposed neural fuzzy systems. Depending on the rules, forecasting values of 0:0:15:230 were obtained without any deviation values, which means that predicted values were obtained that exactly matched the neural fuzzy systems method.
3. The analysis of the Maximum Permissible Error's Curve is shown in Fig. 2. The best error curve at the value of Neta is equal to 0.4 and is confined between the two values of the percentage of the maximum error possible between the two values (0.3, -0.5) in terms of the difference of this part with the rest of the parts for the same selected period and for the values of the learning ratios chosen in all training. This is because it has a clear flow and a slope towards zero faster than the rest of the curves.
4. Only the difference in time between the results by using methods, the neural fuzzy systems technique, and the proposed neural fuzzy systems.
5. The technology of the proposed neural fuzzy systems is stopped automatically when reaching the final solution (optimal values).
4.2 Recommendations

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It can depend on the proposed neural fuzzy systems to forecast the layers of the earth in other regions.
The proposed neural fuzzy systems can be used and compared with other neural networks for forecasting.
It recommends conducting studies using intelligent computer methods to forecast multiple time series.

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Appendix 1 and Appendix 3:

https://docs.google.com/document/d/1ATGFq_kOxBhusuYSk06GhLq5gJEP4A_k/edit

Appendix 2: Forecasting Values by using the Neural Fuzzy Systems at learning ratio of 0.7

Id	Element Symbol	Forecast Value	The actual Value of Series	The Element Series Forecast
600	0	1.901	A	A
601	2	0.123	C	C
602	2	0.431	C	C
603	0	0.513	A	A
604	1	1.134	B	B
605	0	1.834	A	A
606	1	1.689	B	B
607	1	1.821	B	B
608	1	1.819	B	B
609	1	1.614	B	B
610	2	1.213	C	C
611	2	1.531	C	C
612	2	1.101	C	C
613	2	1.667	C	C
614	2	1.817	C	C
615	2	1.821	C	C
616	1	1.829	B	B
617	0	1.99	A	A
618	0	1.898	A	A
619	0	1.186	A	A
620	2	1.879	C	C
621	2	1.628	C	C
622	2	1.561	C	C
623	1	1.341	B	B
624	1	0.761	B	B
625	1	0.541	B	B
626	1	0.761	B	B
627	2	0.761	B	B
628	2	1.451	B	B
629	2	1.091	B	B
630	1	1.234	B	B
631	2	1.001	C	C
632	2	1.87	C	C
633	0	0.521	A	A
634	2	1.643	C	C
635	1	1.684	B	B
636	2	1.697	C	C
637	2	1.801	C	C
638	0	0.821	A	A

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639	1	1.829	B	B
640	1	1.806	B	B
641	1	1.831	B	B
642	1	1.845	B	B
643	1	1.891	B	B
644	0	0.781	A	A
645	1	1.821	B	B
646	1	1.845	B	B
647	1	1.857	B	B
648	1	1.889	B	B
649	1	1.621	B	B