Prediction of Fuzzy Sunspot Time Series By Using RBFANN

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Abstract

We are present in this paper a new modified method of prediction of Sunspot time series after Fuzzify the data by using Fuzzy C-means clustering method (FCM). Our method consist of forecasting as first phase and prediction as a second phase. The accuracy of the results that we obtained is measured by M.S.E and we got a good results.

Keywords: First order fuzzy time series, FCM, FLRs, Fuzzy vector, RBFANN, Forecasting, Prediction.

1.Introduction

The prediction plays a major role in planning for a future and construct a useful strategy formulation. This can be realized by accurate and realistic analysis of information and data that represent the past and present behavior of a phenomenon under consideration in order to predict a future behavior of it. Many time series models in linear and nonlinear forms was proposed for this purpose, complexity in some time series models increases the uncertainty about information's for this reason Zadeh in 1965 introduced a concept of fuzzy set and fuzzy logic [1]. The classical time series methods cannot deal the linguistic terms represented by fuzzy sets. Fuzzy time series (FTS) proposed by song and Chissom in 1993[2] by considering the trend and variations of time series as a fuzzy logic relations(FLRs) between fuzzy sets such that each observation of time series $x(t)$ represented by a fuzzy set A_i and a fuzzy time series is a sequence of fuzzy sets related historically by a linguistic relation since 1993 a large number of researchers developed a several methods to improve fuzzy time series Forecasting, starting with Chen's work in 1993[3]. These developments deal with steps of time series forecasting listed as:

1-The partition of universe of discourse.

2-The definition of fuzzy sets (membership functions).

3-Fuzzification of historical data.

4-Defuzzification and obtain a forecasted output.

Song and Chissom [2], [4], [5] and Chen [6], [7] partitioned the universe of discourse into equal length intervals, while Egriglu and Aladag in 2010,2011 in [8], [9] proposed an optimal interval length in high order fuzzy time series. In recent years many optimization methods proposed in fuzzification stage Cheng et. al. [10] and Li et. al. [11] in 2008 used a fuzzy c-mean clustering method to partition and fuzzification time series data into fuzzy sets (Clusters). The inner-relation of fuzzy time series is determined in stage of determination of fuzzy relation. Because this stage leads to finding a suitable model, it is considered one of the most important stages, so the contribution of this stage will be great in getting the best implementation. Song and Chissom [2], [4], [5] used fuzzy logic relation matrix in this stage. The first study that used feed forward artificial neural network(FFANN) in define the fuzzy relations proposed by Huarng and Yu [12] in 2006. and, Aladag et al. [13] developed the method of [12] and proposed a high order fuzzy time series forecasting model. For more accuracy in forecasting Yu and Huarng [14] used a membership values of each fuzzy set to determine the fuzzy relations in order to avoid a lack of information that caused by considering the index number of fuzzy sets or the centroid of fuzzy sets. In this study, using fuzzy c-means (FCM) clustering technique in fuzzification observations $x(t)$ of classical time series. We use the first order fuzzy time series to define the fuzzy relations by RBFANN where used all membership values in this stage and in defuzzification stage.

2. preliminaries

2-1. fuzzy time series

Definition 1 [1]: Let U can be defined as the universe of discourse where can denoted by $U = \{x_1, x_2, \dots, x_n\}$. A fuzzy set A_i in the universe of discourse U can be write as: $A_i = \mu_{A_i}(x_1)/x_1 + \mu_{A_i}(x_2)/x_2 + \cdots + \mu_{A_i}(x_n)/x_n$

Where the membership function of the fuzzy set A_i Symbolizes as μ_{A_i} which is also defined in the universe of discourse U, such that $\mu_{A_i}: U \to [0\,.1]$ and x_k is a number of fuzzy set A_i , $\mu_{A_i}(x_k)$ $.(k = 1,2, \dots, n)$ is the membership degree of x_k to A_i . μ_{A_i} $\in$ [0,1] and its range. It is important to note that neither the slash or the plus sign represent any type of algebraic operation. The slash links the elements of the support with their values of membership in A_i whereas the plus sign indicates that the listed pairs of elements and membership values collectively form the definition of A_i .

Definition 2 [8]: $let\ Y(t).(t = 0,1,2, \dots)$ be a subset of real numbers which is the universe of discourse by which fuzzy sets $f_i(t)$ are defined. If $F(t)$ is a collection of $f_i(t)$, then $F(t)$ is called the fuzzy time series defined on $Y(t)$.

Definition 3 [15]: Suppose $F(t-1) \to F(t)$ i.e. $F(t)$ is caused by $F(t-1)$ only, Then $F(t) = F(t-1) * R(t, t-1)$ is a relationship, where $R(t, t-1)$ is the fuzzy relationship between $F(t-1)$ and $F(t)$, and $F(t) = F(t-1) * R(t, t-1)$ is called the first order model of $F(t)$. where symbol " $*$ " is an operator.

Definition 4[15]: Let $F(t)$ be a fuzzy time series. If $F(t)$ is caused by $F(t-2).F(t-1) \dots F(t-n)$ then this fuzzy relationship is represented by $F(t-$

$n). \ldots . F(t-2). F(t-1) \rightarrow F(t)$and it is called the nth order fuzzy time series forecasting model.

2-2. Fuzzy C-means clustering(FCM) technique [15]

Bezdek was the first introduced The FCM clustering technique in 1981 [16]. This method based on a fuzzy logic concept that deals with the degree of membership and fuzzy partitioning that allow each point belonging to a certain cluster with a certain membership value, then each point may be belong to all cluster in the same time with a membership values in the interval [0,1] such that the sum of all membership values of a data point to these clusters equal to 1.

Let us assume that the data set is $X = \{x_1, x_2, x_3, \ldots, x_n\}$, where X is a finite subset of real number set. And let C be the number of desired clusters which is an integer,

$2 \le C \le n$, the FCM algorithm partition X into C fuzzy clusters such that the data in each cluster different as possible from another clusters. The partition of X can be represented by a membership matrix U_{c*n} and each entry of U denoted by $u_{ij} \in [0,1]$, $\forall i = 1,2, \ldots, C$. $\forall j = 1,2, \ldots, n$. The fuzzy clustering in this technique, is conducted by minimizing the least squared errors within clusters. Assume that u_{ij} be the membership values, v_i be the cluster center i, the number of variables be n , and the number of clusters be C. Then the objective function in fuzzy clustering which is tried to be minimized is

$$J_\beta(X.V.U) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{\beta}\, d^2(x_j . v_i) \quad (1)$$

where $d(x_j . v_i)$ is the distance between the data point x_j and the center v_i of cluster i , $\beta > 1$ is a constant called a fuzzy index or weighted exponent . the objective function J_β is minimized subject to the constrains

$$0 \le u_{ij} \le 1 \quad . \forall i = 1,2 \ldots \ldots c . \forall j = 1,2, \ldots n \quad (2a)$$

$$0 \le \sum_{j=1}^{n} u_{ij} \le n . \forall i = 1,2, \ldots . c \quad (2b)$$

$$\sum_{i=1}^{c} u_{ij} = 1 . \forall j = 1,2, \ldots . n \quad (2c)$$

In FCM clustering method, to minimize (1) with constrains (2), an iterative algorithm is used. The update of the values of v_i and u_{ij} are by using the formulas in each iteration, given in (3) and (4), respectively.

$$vi = \frac{\sum_{j=1}^{n} u_{ij}^{\beta} x_j}{\sum_{j=1}^{n} u_{ij}^{\beta}} \quad (3) . \quad u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d(x_j . v_i)}{d(x_j . v_k)}\right)^{2/\beta - 1}} \quad (4)$$

2-3. Radial basis function Artificial Neural Network(RBFANN).

The Artificial neural networks (ANNs) are mathematical models that mimic biological neural network. It's called ANNs because it is a network of interconnected elements, these elements inspired from studies of biological nervous systems [13]. These elements process information using a connectionist approach to computation, and these elements are called "neurons", "processing elements" or "units"[17]. There are various types of ANNs one of them is called feed forward artificial neural networks (FFANNs), In FFANN there is no feedback connections. Radial basis function artificial neural network(RBFANN) is a kind of FFANNs. In our approach, we used RBFANN to construct the fuzzy relations between the historical data which is represents by a vector of membership values of each observation to all clusters and we use the first order fuzzy time series in this approach. The performance of RBFANN are improved depend on, Network architecture and learning algorithm. we will summarize these elements that uses in our approach as follows: A network architecture: RBFANN consists of three layers feed forward showed in figure(1). input layer, hidden layer, and output layer. Each layer consists of neurons, these neurons are linked each other by weighted and in the same layer there is no linked among the neurons. We use the same number of neurons in all layers which is the same number of clusters that uses in FCM technique. The hidden layer using radial basis activation functions (i.e. it has radial symmetry with respect to a center). generally, using Gaussian function. That has the expression

$$\emptyset(\vec{x}.\vec{c}.r) = exp\left(\frac{-\|\vec{x}-\vec{c}\|^2}{r^2}\right) \ldots . (5)$$

where $\| \ \|$ is the Euclidean distance, $\vec{c}.\vec{x}.r$ are inputs, centers, and width of Gaussian function. The output layer neurons using linear combinations of hidden layer outputs with associated weights

$$y_k(\Phi.w) = \sum_{i=1}^{m} \emptyset_i\,(\vec{x}.\vec{c}.r) w_{ik} \quad (6)$$

Where k=1,2,…,m. m is the number of neurons, w_{ik} is associated weights of each k Gaussian. The learning algorithm of RBFANN is equivalent to finding the values of all weights such that the desired output is generated by corresponding inputs. These algorithms can learn from examples and can generalize what is learn. So the learning plays the important role in performance of RBFANN. The centers are estimated by the K-mean clustering [17]. We use the same width for each Gaussian function and we calculate by the form

$$r = \frac{d_{max}}{\sqrt{m}} \quad (7)$$

where is the maximum distance between any 2 centers that determined by K-mean clustering. Then the Gaussian activation function for each neuron i becomes $\emptyset_i(\vec{x}.\vec{c}.r) = exp\left(\frac{-m\|\vec{x}-\vec{c}\|^2}{d_{max}^2}\right) \quad (8)$

To calculating the weights w_{ik} between the hidden layer and output layer we use singular value decomposition(SVD)[18], [19] to directly optimized the weights.

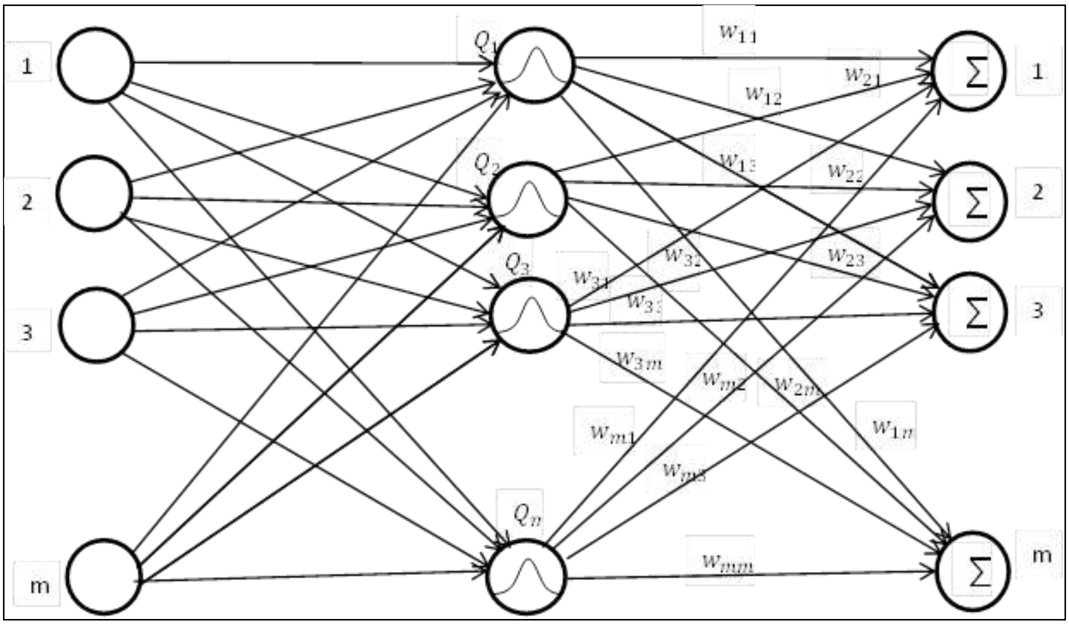

Figure (1) The Architecture of RBFNN of Proposed Method

3. The proposed method

In our proposed prediction model was build depending on methodology sort of rather about the other method, because in our proposed method we established prediction model according to fuzzy time series approaches and RBFANN. Thus, we providing a new idea for prediction model. this prediction model is nonlinear because the model is build depend on fuzzy time series and RBFANN where those are nonlinear models and are better used to handle nonlinear problems. More methods builds forecasting models based on fuzzy time series and there are articles using FFANN to improve the forecasting such as [12,13] Where the use of ANN in the stage of establishing the fuzzy relations. In our approach fuzzy time series forecasting was implying in the training phase where the action of forecasting in the range of available data. While prediction step given a new data out of available data. The two main important stages by RBFANN in our proposed method are training the network by learning it to establish the fuzzy relations from the training data and establishing the fuzzy relations by simulating the trained RBFANN. The problem of prediction consists of the prediction of future values based on past and/ or present values. In our proposed method, we build the prediction model based on iterative algorithm, in each iteration we produce a one-step prediction value represents the value of next year(time). Formally.

$$x(t+1) = f\big(x(t).x(t-1) \dots \dots x(t-n)\big) \qquad (9a)$$

$$x(t+2) = f\Big(x(t+1).x(t).x(t-1) \dots x\big(t-(n+1)\big)\Big) \quad (9b)$$

Generally

$$x(t+d) = f(x(t-(d-1)).x(t-(d-2)) \dots x(t-(d-(n-(d-1))))) \quad (9c)$$

where $x(t)$ is the observation of time series in time t, n is elapsed time, d is the maximum number of iterations which is the number of prediction steps, f represents the function of proposed prediction model. the proposed algorithm that using in each iteration given below by steps.

step1. Fuzzify the values of time series by FCM clustering technique. By applied this technique we get a matrix $U_{c\times n}$ and a vector $V_{c\times 1}$ of centers. each column $k.(k = 1 \dots n)$ in $U_{c\times n}$ contain c values which represents the membership degrees of observation $x(t-k)$ in all fuzzy sets where the sum of all membership degrees is equal 1 and we called each column by fuzzy vector of corresponding observation. Each raw i of the matrix$U_{c\times n}$ represents the fuzzy set $A_i.(i = 1.2 \dots c)$. finally, ordered fuzzy sets A_i are obtained depending on the ascending ordered centers, which are denoted by $v_i.(i = 1.2..c)$.

step2. Determining training samples and train RBFANN from it. The architecture and the training algorithm of RBFANN are given in subsection **(2-3)**. We select the input and target data from $U_{c\times n}$ to training the network to established the fuzzy relations. Since in first order fuzzy time series there are fuzzy relation between each two consecutive observations and Since in $U_{c\times n}$ each column represent the fuzzify vector to corresponding observation, hence the fuzzy relation between each two consecutive observations is constructing by RBFANN based on corresponding fuzzy vectors. Therefore, the inputs data of the network are the fuzzy vectors from 1 into $n-1$,and the targets data(desired outputs) of the network are the fuzzy vectors from 2 into n . training RBFANN from this inputs and targets data to determine the centers, width and find the values of weights. Finally, test the trained network by the same inputs data without the targets, the generated output of the network as fairly as the targets data.

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step3. Construct fuzzy relation that represents the prediction of fuzzy vector of observation $x(t+1)$ by simulate the trained network by giving it the targets data above as inputs data to obtain the outputs represents the fuzzy vectors of the observations from $x(t-(n-1))$ to $x(t+1)$.

step4. Defuzzification of forecasting fuzzy vectors. After obtained the generated outputs of RBFANN in step2 which represents the forecasted membership degrees of observations $x(t-(n-1)$ to $x(t)$ that represented by fuzzy vectors. It should be here noted that the sum of forecasted membership degrees of fuzzy vectors may not be equal to 1, hence in equation (10) given below we divide each forecasted membership degree on the sum of the degrees of memberships of the fuzzy vector, so forecasted membership degrees are used in Equation (10) to transformed it into weights. And finally, the defuzzified forecast of the observation at atime t is calculated by equation (11).

$$w_{it} = \frac{\hat{\mu}_{A_i}(x(t))}{\sum_{i=1}^{c} \hat{\mu}_{A_i}(x(t))} \qquad (10)$$

$$\hat{x}(t) = \sum_{i=1}^{c} w_{it}\, v_i \qquad (11)$$

Where $\hat{\mu}_{A_i}(x(t))$ is forecasting membership degree of observation $x(t)$ belonging to A_i , v_i is the ordered center of fuzzy set A_i that belonging to $V_{c\times 1}$ $(i = 1.2 \ldots .c)$.

Step5. Defuzzification of prediction fuzzy vector. The predicted fuzzy vector is the final fuzzy vector obtained from outputs generated in step3 which contain the predicted membership degrees of observation $x(t+1)$ in all fuzzy sets. We using the equations (10), (11) to defuzzify predicted membership degrees observation $x(t+1)$.

Step6. Performance evaluation of forecasting and prediction. We choose mean square error(MSE) to measure the accuracy of forecasting where:

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(x(t) - \hat{x}(t))^2 \qquad (12)$$

Where T number of forecasted observations, $x(t)$ *and* $\hat{x}(t)$represents the actual and forecasted observations at time t, respectively. And we choose the absolute error to measure the accuracy of prediction model in each iteration in d where the equation is:

$$ABSE = |x(t+p) - \hat{x}(t+p)| \;\; for\ all\ p = 1,2,\ldots,d \qquad (13)$$

where $x(t+p)$ *and* $\hat{x}(t+p)$ represents the actual and predicted observations at time $t+p$, $(p = 1.2 \ldots d)$. our proposed approach has some important advantages which can summarized as:

1) using FCM clustering to determine the membership values by a more systematic method and eliminate the problems of partition universe of discourse.

2) fuzzify each data in a fuzzy vector that contain all membership values of this data in all fuzzy set instead of fuzzify the data in fuzzy set that has the maximum membership value of this data. This advantage is more desired because it doesn't loss the effective of membership values.

3) using all membership values in all steps of prediction models. Therefore, information loss is avoided and an increase in the explanation power of the model is provided. So it is clearly expected that the proposed approach has highly accuracy.

4. The applications

In this section, we will present the results of our proposed method. All code are written in MATLAB version(9.0),(R2016a),under Windows 7, Core i5,(intel) CPU 2.40 GHz, RAM 4.00 GB, the proposed method was applied to data of yearly mean total sunspot number from year 1960 into year 2003 that shown in table(1), we get the data from http://sidc.be/silso .

Table (1). The yearly mean total sunspot number

NO.	years	Actual	NO.	Years	actual	NO.	Years	Actual
1	1960	159	16	1975	22.5	31	1990	191.8
2	1961	76.4	17	1976	18.4	32	1991	203.3
3	1962	53.4	18	1977	39.3	33	1992	133
4	1963	39.9	19	1978	131	34	1993	76.1
5	1964	15	20	1979	220.1	35	1994	44.9
6	1965	22	21	1980	218.9	36	1995	25.1
7	1966	66.8	22	1981	198.9	37	1996	11.6
8	1967	132.9	23	1982	162.4	38	1997	28.9
9	1968	150	24	1983	91	39	1998	88.3
10	1969	149.4	25	1984	60.5	40	1999	136.3
11	1970	148	26	1985	20.6	41	2000	173.9
12	1971	94.4	27	1986	14.8	42	2001	170.4
13	1972	97.6	28	1987	33.9	43	2002	163.6
14	1973	54.1	29	1988	123	44	2003	99.3
15	1974	49.2	30	1989	211.1			

In our applied, we using the proposed method to get the prediction for four steps. We show that the application of proposed method in 1-step prediction and finally we get the final results of the 4 steps. At first we using FCM to fuzzify the training data from 1960.5 into 1999.5 to 10 fuzzy sets (clusters) where the ordered fuzzy sets $Ai.(i = 1.2..c)$ are obtained according to the ascending ordered centers, which are denoted by
$vi.(i = 1.2..c)$ are given in table (2) and table (3), respectively.

Table (2). ordered centers of fuzzy sets

V1	V2	V3	V4	V5
19.6942	44.83788	69.85173	92.65083	131.686
V6	V7	V8	V9	V10
149.0148	160.6651	192.2157	202.5257	218.4963

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Table (3) Fuzzification data (1960-2000) by FCM method

	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970
A1	0.000137686	0.010626	0.045471	0.054046	0.960178	0.985112	0.004022	0.000114	5.64E-05	8.81E-06	6.18E-05
A2	0.000205014	0.0343	0.704666	0.904966	0.023765	0.010042	0.018502	0.000188	8.66E-05	1.35E-05	9.56E-05
A3	0.000336203	0.796835	0.190863	0.024596	0.007032	0.002287	0.95823	0.000367	0.000149	2.34E-05	0.000167
A4	0.000606955	0.129381	0.033531	0.00793	0.003509	0.001049	0.013354	0.000901	0.000291	4.60E-05	0.000332
A5	0.003581421	0.011179	0.008429	0.002619	0.001554	0.000435	0.00212	0.990003	0.002857	0.000472	0.003823
A6	0.026798481	0.00648	0.005651	0.001853	0.001178	0.000325	0.00132	0.005619	0.987047	0.998105	0.98811
A7	0.963747221	0.004812	0.00449	0.001513	0.000997	0.000272	0.001013	0.001893	0.008424	0.001167	0.006343
A8	0.00242181	0.002547	0.002681	0.000951	0.000674	0.000181	0.000567	0.000415	0.000538	8.08E-05	0.00052
A9	0.001410383	0.002148	0.002323	0.000834	0.000602	0.000161	0.000484	0.000301	0.000347	5.25E-05	0.000342
A10	0.000754826	0.001692	0.001895	0.000692	0.000511	0.000136	0.000388	0.000199	0.000204	3.10E-05	0.000205
	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	
A1	0.000541949	0.00371	0.047714	0.020141	0.977351	0.996223	0.070291	3.79E-05	6.32E-05	4.10E-06	
A2	0.00123131	0.008089	0.658398	0.921496	0.01542	0.002387	0.881014	6.32E-05	8.26E-05	5.37E-06	
A3	0.005019095	0.029245	0.227642	0.041113	0.003432	0.00063	0.028947	0.000125	0.000112	7.33E-06	
A4	0.988558001	0.919295	0.038005	0.009287	0.001564	0.000303	0.009493	0.000319	0.000156	1.02E-05	
A5	0.002175588	0.019381	0.009383	0.002577	0.000645	0.00013	0.003166	0.997197	0.000325	2.14E-05	
A6	0.001014021	0.008518	0.00627	0.00176	0.000481	9.78E-05	0.002245	0.001446	0.000502	3.33E-05	
A7	0.000688807	0.005662	0.004974	0.001411	0.000403	8.24E-05	0.001834	0.000533	0.000718	4.80E-05	
A8	0.000316118	0.002515	0.002961	0.000857	0.000267	5.52E-05	0.001155	0.000125	0.003263	0.000229	
A9	0.000258708	0.002045	0.002564	0.000746	0.000237	4.92E-05	0.001014	9.17E-05	0.008215	0.000607	
A10	0.000196403	0.001541	0.00209	0.000612	0.0002	4.17E-05	0.000841	6.13E-05	0.986563	0.999035	
	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	
A1	0.00030353	0.000144	0.00053	0.034024	0.99788	0.957277	0.336546	0.005321	0.000765	5.82E-06	
A2	0.00041069	0.000212	0.001264	0.230957	0.001394	0.025413	0.567687	0.009295	0.001014	7.99E-06	
A3	0.000585331	0.000342	0.006024	0.647809	0.000338	0.007566	0.052546	0.020102	0.001405	1.16E-05	
A4	0.000863485	0.000602	0.988554	0.054808	0.000158	0.003783	0.019676	0.06165	0.001998	1.75E-05	
A5	0.002157675	0.003105	0.001627	0.01118	6.63E-05	0.001678	0.007103	0.752644	0.004444	4.77E-05	
A6	0.003917075	0.01635	0.0008	0.007231	4.96E-05	0.001273	0.005125	0.083904	0.007271	9.42E-05	
A7	0.006667844	0.9732	0.000555	0.005647	4.17E-05	0.001078	0.004226	0.040026	0.011018	0.000178	
A8	0.218171428	0.003295	0.000263	0.003266	2.78E-05	0.000728	0.00271	0.011853	0.078588	0.997896	
A9	0.74153917	0.001819	0.000217	0.002809	2.47E-05	0.000651	0.002389	0.008979	0.381201	0.001499	
A10	0.025383771	0.000931	0.000166	0.00227	2.09E-05	0.000553	0.001993	0.006227	0.512298	0.000242	
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	
A1	1.76E-05	0.000133	0.009997	6.07E-06	0.905119	0.905074	0.698258	0.00368	0.001302	0.288235	
A2	2.37E-05	0.00022	0.032545	0.999984	0.067893	0.053674	0.232958	0.00917	0.002116	0.108079	
A3	3.34E-05	0.000428	0.814704	6.20E-06	0.013207	0.017475	0.035285	0.050897	0.00401	0.034609	
A4	4.86E-05	0.001048	0.116113	1.69E-06	0.005796	0.009026	0.01456	0.915089	0.009293	0.126685	
A5	0.00011596	0.988216	0.010294	5.12E-07	0.002328	0.004112	0.005601	0.009203	0.831621	0.197947	
A6	0.000201809	0.006653	0.005983	3.56E-07	0.001723	0.00314	0.004102	0.004699	0.109515	-0.02803	
A7	0.00032717	0.00223	0.004448	2.88E-07	0.001439	0.002669	0.003408	0.003308	0.029823	-0.00705	
A8	0.004840501	0.000487	0.002359	1.78E-07	0.000947	0.001818	0.002219	0.001604	0.005663	0.07928	
A9	0.991815972	0.000353	0.00199	1.55E-07	0.00084	0.001627	0.001963	0.001328	0.004037	0.116876	
A10	0.002575293	0.000233	0.001569	1.28E-07	0.000707	0.001385	0.001646	0.001022	0.002621	0.083372	

Second, in table (4) we obtain the results of the defuzzify on the output of training data which hat get the forecasting data and evaluate the performance of the network.

Table (4) Actual and Forecasted data for years (1961-1999)

years	actual data	forecasted data	years	actual data	forecasted data
1961	76.4	73.89997197	1981	198.9	199.7473524
1962	53.4	53.00329151	1982	162.4	160.5017218
1963	39.9	45.46101502	1983	91	92.63163013
1964	15	21.69521993	1984	60.5	66.50374437
1965	22	20.35464738	1985	20.6	19.79088567
1966	66.8	70.01057929	1986	14.8	21.84769061
1967	132.9	131.814939	1987	33.9	41.39348019
1968	150	149.0748389	1988	123	131.1412426
1969	149.4	149.0216338	1989	211.1	208.0265083
1970	148	149.0275691	1990	191.8	192.219625
1971	94.4	92.71152969	1991	203.3	202.4674381
1972	97.6	93.61741752	1992	133	131.8392571
1973	54.1	54.39723433	1993	76.1	73.48338408
1974	49.2	46.72473444	1994	44.9	44.83815579
1975	22.5	20.6886728	1995	25.1	23.63060033
1976	18.4	19.87356581	1996	11.6	24.7079884
1977	39.3	45.44600467	1997	28.9	31.09078368
1978	131	131.7159088	1998	88.3	92.06670892
1979	220.1	218.1115247	1999	136.3	134.3638629
1980	218.9	218.4695631			
			MSE	15.441639	

Third, simulate RBFANN to obtain fuzzy relation between 1999 and 2000 where the membership values that resulting after simulate the network represent the prediction membership values of the observation for year 2000, we obtained the defuzzify value of this observation from table (5) and compare the result with the actual value.

Finally, we obtain taFble (5) to show the results of 4 steps of prediction by fuzzy time series and using RBFANN to define the fuzzy relations and using the absolute error to find the difference between real data and the prediction data.

Table (5) Four step prediction the results predictions based on fuzzy time series and RBFANN

NO. of prediction step	Years	actual data	prediction data	*ABSE*
1	2000	173.9	173.4531674	0.4468
2	2001	170.4	139.5207299	30.8793
3	2002	163.6	163.8041064	0.2041
4	2003	99.3	96.77794151	2.5221

The result of experiment proves that the prediction model has good prediction effect. From figure (2) we obtained the graph of actual data and predicted data from 2000 to 2003.

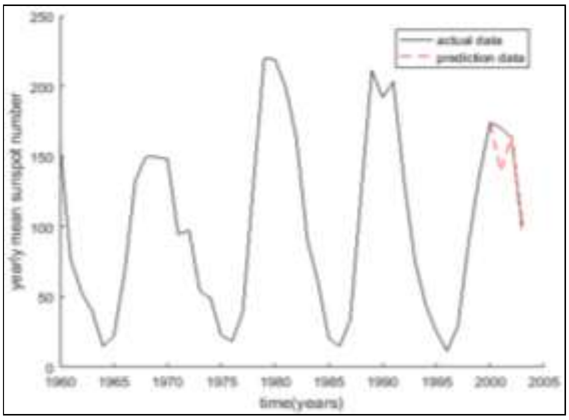

figure (2). The graph of actual data and predicted data

Conclusion

In this paper, we obtained a good results after fuzzify the original data entered into our network were processed using the FCM method. We conclude that the use of the fuzzy in this network gave a good results in addition to that the network was used in two stages, the stage of forecasting and prediction stage and both stages were a good results compared to the original data taken from the original data.

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استخدام شبكة (RBFNN) المضببة للتنبأ بالسلسلة الزمنية للبقع الشمسية

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الملخص

قدمنا في هذا البحث طريقة معدلة جديدة في التنبأ بالسلسلة الزمنية للبقع الشمسية بعد تضبيب البيانات الاصلية باستخدام طريقة العنقدة (FCM). تضمنت الطريقة المقترحة طورين اثنين: الاول هو عملية التكهن وعملية التنبأ تمثل الطور الثاني. تم اعتماد معيار قياس الخطأ (M.S.E) وقد تم الحصول على نتائج جيدة باستخدام الطريقة المقترحة.