A Genetic-Based Neuro-Fuzzy Approach for Prediction of Solar Activity

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ABSTRACT

This paper presents an application of the neuro-fuzzy modeling to analyze the time series of solar activity, as measured through the relative Wolf number. The neuro-fuzzy structure will be optimized based on the linear adapted genetic algorithm with controlling population size (LAGA-POP). First, the dimension of the time series characteristic attractor is obtained based on the smallest Regularity Criterion (*RC*) and the neuro-fuzzy modeling. Second, after describing the neuro-fuzzy structure and optimizing its parameters based on LAGA-POP, the performance of the present approach in forecasting yearly sunspot numbers is favorably compared to that of other published methods. Finally, the comparison predictions for the remaining part of the 22nd and the whole 23rd cycle of solar activity are presented.

Keywords: Neuro-fuzzy modeling, genetic algorithms, time series, prediction of Solar Activity

1. INTRODUCTION

Studying the features of the solar activity cycle is vital and of prime importance not only for its effect on the Climatologically parameters but for the practical needs as telecommunications, power lines, geophysical exploration, long range planning of satellite orbital trajectories and space missions planned by space organisms. During past decades, a wide variety of methods have been proposed in order to predict the amplitude to the onset of the next cycle for a few years ahead. The 23rd Solar cycle was achieved a great attention of several solar physicists to treat the problem of prediction. Numerous numerical techniques have been arduously developed to predict the amplitude and the phases of activity of solar cycles, before the sunspot cycle minimum. Among these suggested method: The method which depends on the even/odd behavior method[11, 14, 27, 16], mixed methods applied[26, 6, 7, and 15] and the Spectral technique[3]. The more reliable indicator to the activity is the precursor technique; especially the geomagnetic precursor which based on the records of geomagnetic storms[12, 19, and 10] published a summary of the scientific panel recruited by Space Environment Center (SCE) with support of NASA to assess prediction of cycle 23rd. A new suggested idea is depending on measurements of the spotless days. Recently a promising method depend on the time series analysis such as Neural Networks, Fuzzy neural networks and genetic algorithms have been applied by researchers such as[15]. Historical records of monthly means of sunspot numbers published in the NGDS (ftp://ftp.ngdc.noaa.gov/STP/) were used. Data are covering the period 1810-2003.

Fuzzy logic, neural networks and genetic algorithms are three popular artificial intelligence techniques that are widely used in many applications. Due to their distinct properties and advantages, they are currently being investigated and integrated to form new models used for predictions. Fuzzy systems are currently used in a number of industrial and scientific applications. Therefore, it is advantageous to have algorithms, which build and optimize systems automatically from data. The major powerful aspect of fuzzy systems is easy applicability of expert knowledge to the subject domain. However, in most cases this empirical information is not sufficiently accurate to build an optimal system. So, the Linear Adapted Genetic Algorithm with controlling POPulation size LAGA-POP[1] approach for optimizing the structure and automatic learning of internal parameters of a fuzzy system.

Different nonlinear methods were done to predict the maximum amplitude of solar 22nd, and 23rd cycles. Calvo[29] uses artificial neural networks (ANN) for prediction of solar activity. The sunspots data series, which is data counting dark patches on the sun and is related to the solar storms, shows an eleven-year cycle of solar maximum activity, and if accurately modeled, can forecast the severity of future activity. While solar activity is unavoidable, its impact can be

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lessened with appropriate forecasting and proactive action. In this work we use fuzzy model to forecast the solar activity, as measured by the relative wolf number. First, in section 1 we give an introduction about state of the art for prediction of the solar activity. Section 2 shows the structure of the fuzzy neural network. The embedding dimension of the solar dynamics attractor is introduced in section 3. Optimizing the neuro-fuzzy model based on LAGA-POP is discussed in section 4. The simulation results and conclusions are discussed in section 5, and section 6, respectively.

2. FUZZY NEURAL NETWORK (FNN)

The basic structure of a fuzzy neural network (FNN), introduced by[18] is shown in Fig. 1. This structure has been used by many authors such as[8, 23] and modified by[13, 2]. The original structure was optimized using a gradient search technique by Lin & Lee. In the following subsection we will describe this structure, showing the modification. Farag[23] optimized the structure parameters using a multiresolutional dynamic genetic algorithm (MRD-GA), which used floating representation for parameter coding. The following notation is used to describe the function of the nodes in each of the five layers.

net_i^L the net input value to the *i*th node in layer *L*.

O_i^L the output value to the *i*th node in layer *L*.

w_{ij} the link that connects the output of the *j*th node in layer 3 with the input to the *i*th node in layer 4

The neuro-fuzzy model is consists of five layers, as follows:

Layer (1): Each node of this layer transmits the input values $\left(x_1, x_2, \cdots, x_m\right)$ to the next layer.

$$O_1^1 = x_1, \cdots, O_m^1 = x_m.$$

Layer (2): This layer is known as fuzzy layer, because each node has a fuzzy set. For a bell-shaped membership function, the activation input and output of this layer are:

$$net_i^2 = \begin{cases} O_1^1 & \text{for } i = 1, 2, \cdots, n_1 \\ O_2^2 & \text{for } i = n_1 + 1, \cdots, n_1 + n_2 \end{cases}$$

$$O_i^2 = \exp\left(-\left(\frac{\left(net_i^2 - c_i^2\right)}{\sigma_i^2}\right)^2\right) \quad \text{for } i = 1, \cdots, n_1 + n_2$$

where the parameters c and σ are the center and width of the bell-shaped function.

Layer (3): Rule layer

A T-norm operation is used to specify the precondition matching of the fuzzy rules. The output of the rule in this layer is determined by an AND-operation.

$$net_i^3 = \min\left(O_j^2, O_k^2\right), \quad i = n_2\left(j\text{-}1\right) + \left(k - n_1\right)$$

$$\text{for } j = 1, 2, \ \ldots, n_1; \ k = n_1 + 1, n_1 + 2, \ \ldots, \ n_1 + n_2.$$

$$O_i^3 = net_i^3 \ \ i = 1, \ 2, \ \ldots, \ n_1 \times n_2.$$

Layer (4): Rule weight layer

This node performs a fuzzy OR–operation to integrate the fired rules, which have the same consequent modified by rule weights. The output of this layer is represented by:

$$net_i^4 = \sum_{i=1}^{n_1 \times n_2} w_{ij} O_i^3$$

$$O_i^4 = \min\left(1, net_i^4\right), \quad \text{for } i = 1, 2, \ \ldots, \ n_3$$

The rule weight has *w* values either one or zero.

Layer (5): This layer computes the output of a fuzzy model based on the defuzzification method. The most widely used method is *center of area* defuzzification.

$$net_1^5 = \sum_{i=1}^{n_3} c_j^4 \sigma_j^4 O_j^4, \quad \text{then} \quad O_i^4 = \frac{net_1^5}{\sum_{i=1}^{n_3} c_j^4 \sigma_j^4}$$

where the *j*th link weight in this layer is $c_j^4 \sigma_j^4$.

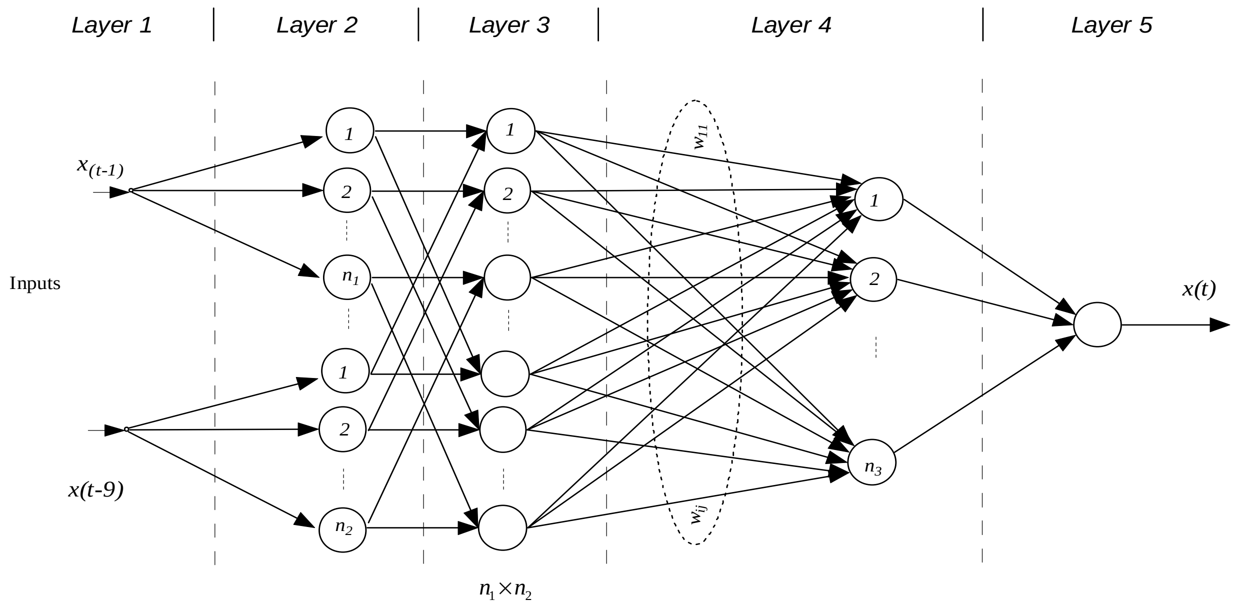

Figure 1 Basic structure of neuro-fuzzy topology [from Farag[23]].

The FNN works in the following manner[8,13]. In the forward regime the input values (crisp values, fuzzy sets) are first compared with all premises of the rules (input reference fuzzy sets). The outputs of the AND-neuron are then combined with rule-weight (preference between rules) to obtain the degree of rule activation. In the last layer these degrees are aggregated with the corresponding consequents of the rules (output reference fuzzy sets) according to the inference algorithm. The output of the FNN can be a fuzzy set or a crisp value (after defuzzification).

3. THE EMBEDDING DIMENSION OF THE SOLAR DYNAMICS ATTRACTOR

The problem of fuzzy system input selection is dealt with by methods proposed by[30,9]. First, we divide the data into two groups: A and B. We use the smallest regularity criterion, *RC*, for decisions when selecting inputs rather than the root mean square error (*RMSE*) used in the Jang method[9]. The regularity criterion (*RC*) is defined as follows:

$$RC = \left[\sum_{i=1}^{k_A} \left(y_i^A - y_i^{AB} \right)^2 \Big/ k_A + \sum_{i=1}^{k_B} \left(y_i^B - y_i^{BA} \right)^2 \Big/ k_B \right] \Big/ 2$$

Where y_i^{AB} is the model output for the group *A* input estimated by the model identified using the group B data, y_i^{BA} is the model output for the group *B* input estimated by the model identified using the group A data, y_i^A and y_i^B are the output data of groups A and B, and k_A and k_B are the amount of data in groups A and B.

In this section, the minimum numbers of variables required for reconstructing the solar dynamics are determined by selecting inputs for fuzzy model based on the smallest Regularity Criterion (*RC*). Applying the Sugeno method will reduce the complexity of the model[30]. For the candidates $x(t-1), x(t-2)..., x(t-n)$ as inputs to the system, which has one output, and the task is to select the appropriate inputs. Figure 2 shows the flow chart implementation of this approach as implemented in MATLAB. The following three steps provide an outline of the approach:

Step 1: There are *n* SISO fuzzy models (FM_1, FM_2,… and FM_n); each model has one input and one output. Find Regularity Criterion (*RC*) of each fuzzy model. Fix the model that has smallest *RC*, as shown in Fig. 1, assuming that FM_1 has the smallest RC_{FM_1}. Save the index of input $x(t-1)$ which leads to the smallest RC_{FM_1} of FM_1.

Step 2: Add the second input from the set of candidates to $x(t-1)$. This means that in this step there are three fuzzy models (FM_{12}, $FM_{1(n-1)}$, and FM_{1n}), each model has two inputs and one of them is $x(t-1)$. Then find *RC* for each model, and repeat step 1. The model that has the smallest *RC* gives us the set of inputs forwarded to the third step. In the example, model FM_{12} has the smallest $RC_{FM_{12}}$ as shown in Figure 2

Step 3: Now, two models with three inputs are considered. These inputs are $x(t-1), x(t-9)$ and $x(t-(n-1))$ for $FM_{12(n-1)}$, and $x(t-1), x(t-9)$ and $x(t-n)$ for FM_{12n}. Again, evaluate the smallest *RC* for $FM_{12\,(n-1)}$, and FM_{12n}. The model that has the smallest *RC* is selected, and the indices of the inputs are recommended. The last step is to compare all the smallest *RC* obtained in all steps, and choose the smallest *RC* from all steps, which will lead to the index of the appropriate and required inputs. In this example, these are $x(t-1)$, and $x(t-9)$, because their fuzzy model has the smallest *RC*, shown as in Figure 2.

We will assume that the solar dynamics is given by $x(t) = F(x(t-1))$, with *F* some unknown function. Calvo[29] suggested 12 unites in his neural networks as an input variables and single unit it the output one. To reduce the complexity structure of the fuzzy model by reducing the input variables to be only two variables based on fuzzy model and smallest regularity criterion using Sugeno and Yasukawa approach. Figure 3 shows a selection of two inputs from a set of twelve inputs using the Sugeno & Yasukawa approach[30] based on the LAGA-POP procedure for FNN model. The membership functions for the selected inputs $x(t-1)$ and $x(t-9)$ are three Gaussian fuzzy sets for each input variable. The training data set is the first half of the data represent the whole record (1700-1980) which represent (250 sample points), and the testing data set is the rest of the period (1980 – 2003), as shown in Figure 4.

4. OPTIMIZING THE FNN MODEL USING LAGA-POP

The main aspects of the LAGA-POP for optimizing the fuzzy model structure are discussed below. We will optimize structure parameters of the fuzzy model; such as fuzzy sets parameters, rule weights, and centroids of rule consequent. First, we have to define genetic algorithm parameters:

- Population size at the beginning of optimization = 750,
- Maximum number of generations = 150,
- P_c, and P_m follow the LAGA-POP approach.
- The number of bits for each parameter depends on the upper and lower values of the parameters considering the same bit resolution for all, and equals 10^4.
- Termination stop, $\eta = 10^{-4}$, or reach the maximum number of generations allowed.

The optimization includes all parameters of the fuzzy rule structure, such as parameters of input reference fuzzy sets, rule weights, and output singletons. The block diagram for the LAGA-POP optimization process is shown in Figure 4.

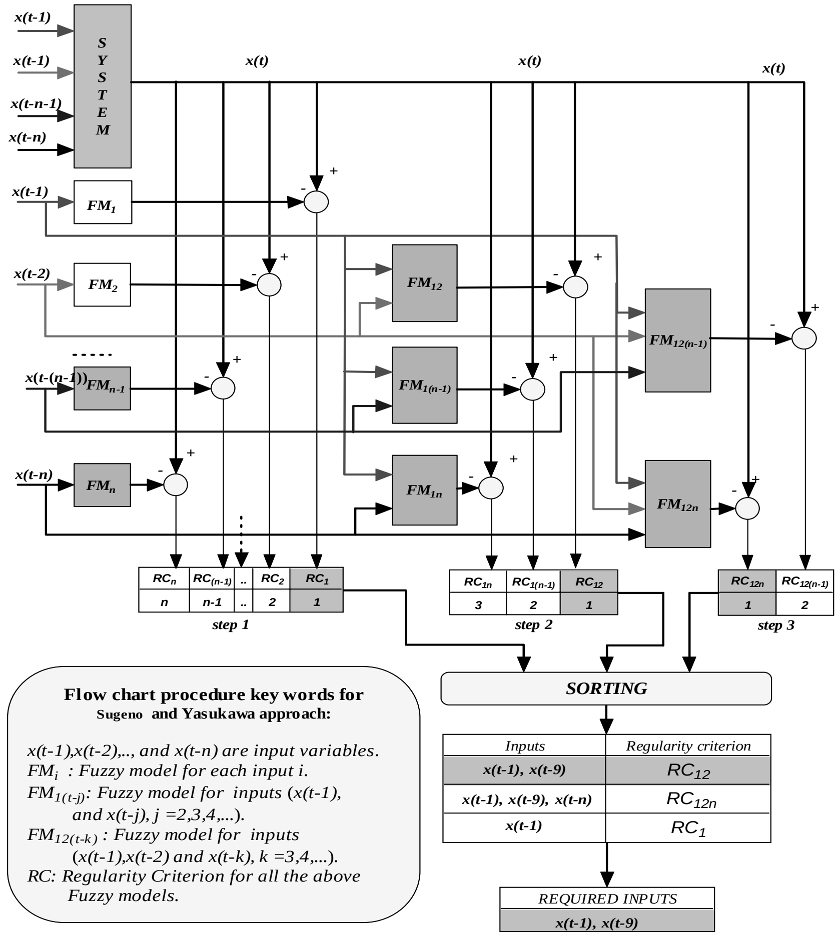

Figure 2 Flow chart implementation for the Sugeno and Yasukawa approach.

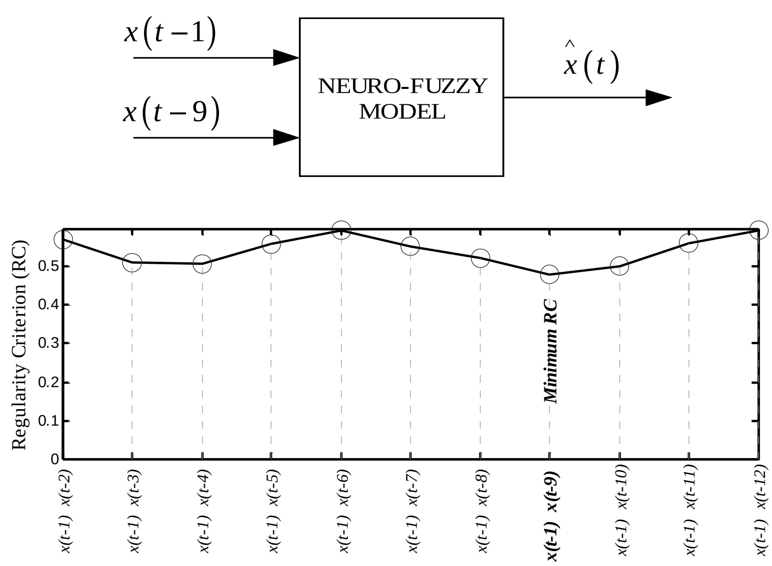

Figure 3 Input selection of the fuzzy model based on the smallest regularity criterion.

- **Fuzzy model representation**

This section discusses how the fuzzy model is formulated using the LAGA-POP approach, where all the parameters of the fuzzy model are represented in a chromosome. The chromosome representation determines the GA structure. With the population size (*pop_size*), we encode the parameters of each fuzzy model in a chromosome, as a sequence of elements describing the input fuzzy sets in the rule antecedents followed by the parameters of weights and the rule consequents. Where the intervals of acceptable values for each fuzzy set shape forming parameter ($\Delta c = [c_{min}, c_{max}]$, and $\Delta\sigma = [\sigma_{min}, \sigma_{max}]$ for Gaussian) are determined based on 2nd order fuzzy sets for all fuzzy sets, as explained in chapter 4. Gaussian shape is chosen in order to show, how the parameters of fuzzy sets are formulated and coded in the chromosomes. The acceptable constraints for rule weights are between [0, 1], and for centroids they are the minimum and maximum values of the output.

- **Coding of fuzzy model parameters**

For the MISO system, *two* inputs $x(t-1)$, $x(t-9)$ and one output $x(t)$. After selecting appropriate inputs, each of the input fuzzy variables is classified into $(A_1,...A_{n_1})$, $(A_1,...A_{n_2})$, …, and $(A_1,...A_{n_m})$ reference fuzzy sets, respectively, where n_1, n_2, … n_m are number of fuzzy sets for inputs $(x_1, x_2,..., x_m)$, respectively. Each reference fuzzy set is described by Gaussian membership function[1]. The Gaussian membership function is specified by two parameters: center c and spread σ, resulting in ($2\sum_{i=1}^{m} n_i$) parameters in the corresponding layer. Using the Wang-Mendel technique[24] for generating rules from given data[25], the fuzzy model has k rules, which represent $\prod_{i=1}^{m} n_i$ theoretically possible rules. These rules represent the optimal generated rules due to the improvements to the Sugeno, and Jang approaches in the previous section. This means we have k rule weights w, and k centroids represented by singletons b. Thus a total of ($2\sum_{i=1}^{m} n_i + 2k$) parameters ($2\sum_{i=1}^{m} n_i + k_{\text{weights}} + k_{\text{centroids}}$) need to be optimized using LAGA-POP. The coded parameters of the fuzzy model are arranged as shown in Table 1 to form the chromosome of the population.

Table 1: Coded parameters of the fuzzy model.

Chromosome	Sub-chromosome of inputs		Sub-chromosome of rule weights	Sub-chromosome of rule consequents
	$x(t-1)$	$x(t-9)$	$w_1, \ldots\ldots, w_k$	$b_1, \ldots\ldots\ldots, b_k$
Parameters $2(\sum_{i=1}^{m} n_i + \prod_{i=1}^{m} n_i)$	$c_1, \sigma_1, \ldots, c_{n1}, \sigma_{n1}$ $2\times n_1$	$c_1, \sigma_1, \ldots, c_{nm}, \sigma_{nm}$ $2\times n_m$	$w_1, \ldots\ldots, w_k$ $k = \prod_{i=1}^{m} n_i$	$b_1, \ldots\ldots\ldots, b_k$ $k = \prod_{i=1}^{m} n_i$

- **Selection function**

The selection strategy decides how to select individuals to be parents for new '*Children*'. The selection usually applies some selection pressure by favoring individuals with better fitness. After procreation, the suitable population consists for example of L chromosomes, which are all initially randomized. Each chromosome has been evaluated and associated with fitness, the current population undergoes the reproduction process to create the next population, and the "roulette wheel" selection scheme is used to determine the member of the new population. The chance on the roulette-wheel is adaptive, and is given as $P_l / \sum P_l$, where $P_l = \frac{1}{J_l}$, $l \in \{1,..., L\}$, and J_l is the performance of the fuzzy model encoded in chromosome measured in terms of the normalized *Mean Square Error* (*MSE*), or J.

$$J = \frac{1}{N}\sum_{i=1}^{N}\left(x(t)_i - \hat{x}(t)_i \right)^2$$

where N is the number of point samples, $x(t)$ is the true output and $\hat{x}(t)$ is the model output.

- **Crossover and mutation operators**

The mating pool is formed, and crossover is applied and followed by a mutation operation following the LAGA approach. Finally, after these three operations, the overall fitness of the population is improved. The procedure is repeated until the termination condition is reached. The termination condition is the maximum allowable number of generations, or a certain value of (*MSE*) required to be reached.

- **Termination condition**

The procedure is repeated until the termination condition is reached. The termination condition is the maximum allowable number of generations, or a certain value of (*MSE*) required to be reached. Or a relative precision error of $\left(f^*(g)-f^*(g-1)\right)/f^*(g)<\eta$ is reached, where f^* is the maximum fitness value, and η is the allowed error.

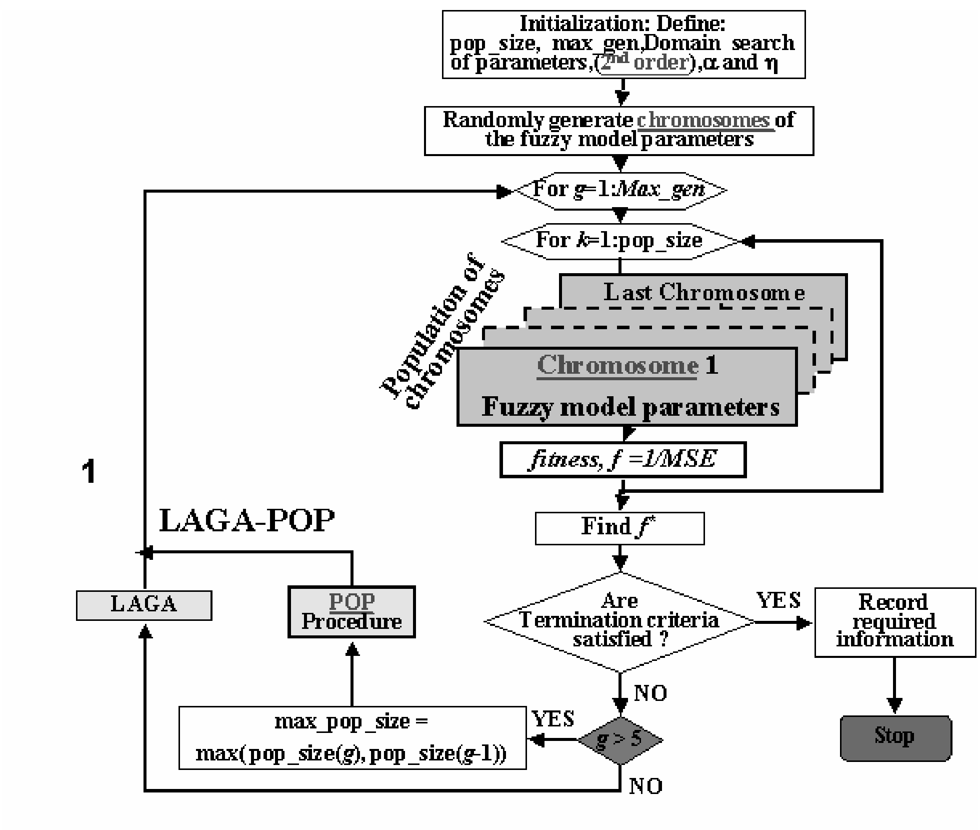

Figure 4 Block diagram for the LAGA-POP optimization process

5. SIMULATION RESULTS

After describing the neuro-fuzzy model and selecting its input variables based on the smallest regularity criterion and FNN model using Sugeno and Yasukawa approach, then optimizing the neuro-fuzzy model parameters using LAGAPOP approach. We will present here the results obtained using this method to predict the annual mean sunspot number. The generated fuzzy rules follow the Wang-Mendel technique, with the maximum number of rules equal to 8. The chromosome length of the model parameters is 592 bits.

After finishing the optimization process with 150 generations, the (*RMSE*) decreases to reach 0.456, as shown in Fig. 5. The population size is reduced from 750 at the beginning of the optimization to 218 at the end of the process, due to the LAGA-POP approach. Figure 5 shows the decreases in the population size with the generations of the whole optimization process. Figure 5 shows the effectiveness of LAGA-POP for optimizing the model parameters and reducing the computation time, together with better performance.

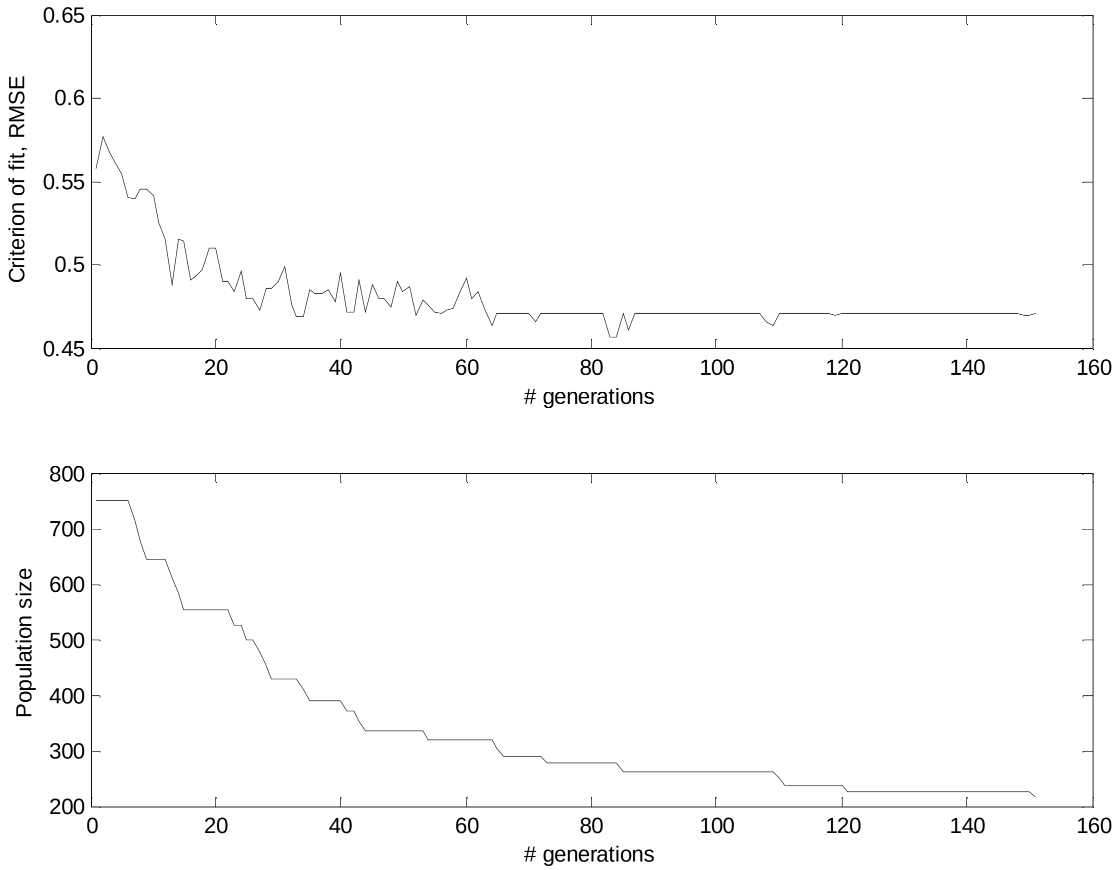

Figure 5 The effectiveness of reducing the population size, together with better performance due to LAGA-POP approach.

After validating the neuro-fuzzy model capabilities, in the rest of this section, we present our predictions for the rest of the 22^{nd} cycle and the complete of 23^{rd} cycle. Figure 6 shows the prediction of the optimized neuro-fuzzy model will be determined as in Figure 6. Figure 6 shows that the fuzzy model has a good match with the observed data after optimizing the parameters using LAGA-POP with *RMSE* = 0.456. Fig. 7 shows the prediction error between the observed and outputs of our model for the whole data. The maximum amplitude of the sunspot number of 23^{rd} cycle is predicted 132 as shown in Figure 6.

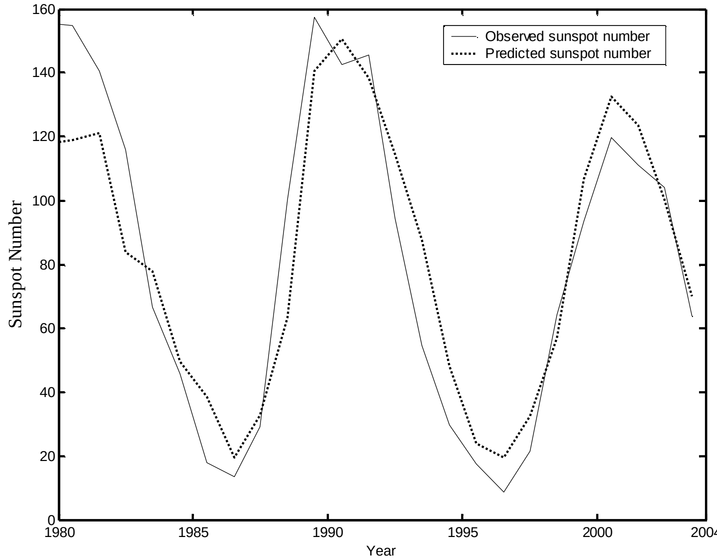

Figure 6 Comparison of between observed sunspots numbers (solid line) and the predictions using FNN model (dashed line)

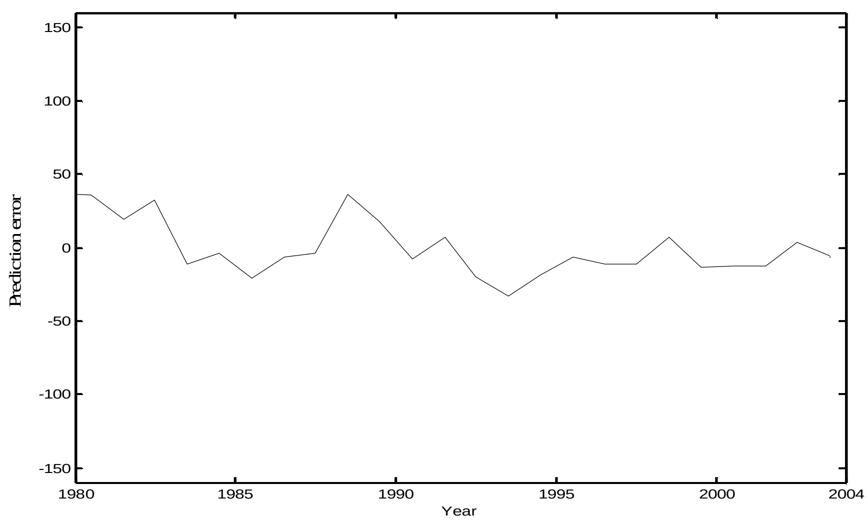

Figure 7 Prediction error between observed sunspot numbers and FNN model.

Figure 8 depicts the Gaussian type membership functions for each input variable before and after training, using LAGA-POP for two inputs problem with bit resolution of 10^4.

Table 2: Sample of the early predicted values of the maximum sunspot number of cycles 22 and 23 as a result of different numerical methods.

Cycle no.	Max. sunspot no.	Reference
22	165±35	Kane,1989
	148.3	Thompson,1993
	150	**Our model**

23	*208*	
	198.8±26.5	**Kopecky, 1991**
	181	Wilson, 1992
	138±30	Letfus, 1993
	>=164.9	**Schattenetal,1996**
	158	Thompson,1996
	160±30	Bounar,1997
	156	Joselyn et.al.,1997
	149.3±19.9	Khaled et.al.,1997
	158±18	Li, 1997
	168±15	Rajmal,1997
	144±29	Wilson et.al., 1998a
	160	Wilson et.al., 1998b
	154±21	Hanslmeier, 1999
	140±9	Hathaway et.al,1999
	133&122	Kane,1999
	110-122	Lantos,2000
	132	**Our model**

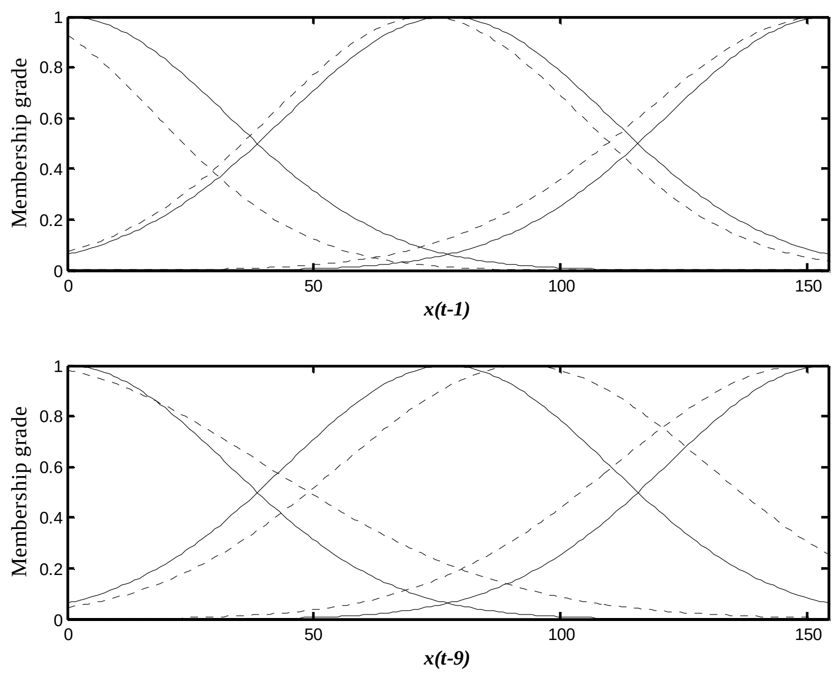

Figure 8 Membership functions in sunspot number prediction. Solid line: Normalized *MFs* before learning. Dashed line: Optimized *MFs* after learning.

6. CONCLUSIONS

We have used the neuro-fuzzy model to study the solar dynamics, as measured by the annual mean value of the Wolf number. First, we determined the embedding dimension of the time series attractor based on the smallest regularity criterion and FNN model. The complexity of the neuro-fuzzy model reduced due to reducing the input variables of the model. Optimization of the parameters of the neuro-fuzzy model was based on the LAGA-POP approach, which enhances the performance of the model and shortens the computation time of the learning process. The performance of the present approach in forecasting yearly sunspot numbers is favorably compared to that of other published methods. Finally, the comparison predictions for the remaining part of the 22^{nd} and the whole 23^{rd} cycle of are presented as in Table 2. From this study we conclude that the neuro-fuzzy model is a reliable tool for time series analysis. In particular the fuzzy model seems to be able to capture the intrinsic dynamics of solar activity.

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