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A New Technique for Solar Activity Forecasting using Recurrent Elman Networks

Salvatore Marra, and Francesco C. Morabito

***Abstract*—**In this paper we present an efficient approach for the prediction of two sunspot-related time series, namely the Yearly Sunspot Number and the *IR*5 Index, that are commonly used for monitoring solar activity. The method is based on exploiting partially recurrent Elman networks and it can be divided into three main steps: the first one consists in a "de-rectification" of the time series under study in order to obtain a new time series whose appearance, similar to a sum of sinusoids, can be modelled by our neural networks much better than the original dataset. After that, we normalize the de-rectified data so that they have zero mean and unity standard deviation and, finally, train an Elman network with only one input, a recurrent hidden layer and one output using a back-propagation algorithm with variable learning rate and momentum. The achieved results have shown the efficiency of this approach that, although very simple, can perform better than most of the existing solar activity forecasting methods.

***Keywords*—**Elman neural networks, sunspot, solar activity, time series prediction.

I. Introduction

SOLAR activity prediction is nowadays a topic of great interest in the scientific community because the emission of solar particles and electromagnetic radiations affects not only telecommunication systems, electric power transmission lines, space activities concerning operations of low-Earth orbiting satellites, but also long term climate variations, weather and other ionospheric parameters. Consequently, it is very important to know in advance the future behavior of solar activity, that is strongly related to the number of dark spots observed on the sun.

For this reason, the monthly and yearly sunspot numbers as well as the related time series are the most suitable indexes used to characterize the level of solar activity. In this work, we use data provided by the *Sunspot Index Data Center* of the *Federation of Astronomical and Geophysical Data Analysis Services* [1]. In the last years, a lot of studies have been made on the forecast of solar activity and in most cases the used predictors are based on learning machines, particularly Artificial Neural Networks (ANNs) [2], [3], [4], [5]. This is surely due to their well-known characteristics of adaptability and nonlinear universal mapping approximation. For example, we can cite the work presented in [2], that compares numerous neural architectures for the prediction of the *IR*5 Index, or the study in [5], that combines fossil and sunspot data to train a neural system to forecast the Yearly Sunspot Number. However, it is important to point out that interesting results have been also obtained using other prediction approaches [6].

This paper presents a forecasting methodology for sunspot-related time series exploiting partially recurrent Elman networks as predictor tools. Our choice has been addressed to this kind of neural model because it works well to process temporal patterns. We have developed an efficient data pre-processing phase consisting in two different steps before the training of the network, in order to convert the original time series into a new sequence that can be easily modeled by the chosen neural architectures, and to accelerate the learning phase. The combination of this approach with Elman networks has allowed to build a simple and very efficient prediction system for sunspot-related time series that performs better than most existing methods. Elman networks have been previously employed in literature to deal with the prediction of sunspot time series [2]. However, we train these models using a completely different method of presenting the training data to the network, with the advantage of obtaining better results using a much lower number of adjustable parameters.

The paper is organized as follows. The next Section describes the sunspot-related time series analyzed in this work. An overview on the neural structures used as forecasting tools is given in Section 3. In Section 4, the description of the proposed methodology is provided. Section 5 is dedicated to the experimental results obtained and Section 6, finally, gives the concluding remarks.

II. Sunspot Data

Solar activity is regularly monitored by many world observatories and research centers that are able to provide the relative number of dark spots observed on the sun day after day. These data are recorded to give the so-called sunspot related time series.

In this work we employ the *Yearly Sunspot Number*, showed in Fig. 1, that contains the yearly number of dark spots from 1700 to 2004, and the *IR*5 *Index*, a five-month

Manuscript received July 13, 2005.
S. Marra is with the Department of Informatics, Mathematics, Electronics and Transportation, University Mediterranea of Reggio Calabria, 89055 Italy (e-mail: salvomarra@ing.unirc.it).
F. C. Morabito is with the Department of Informatics, Mathematics, Electronics and Transportation, University Mediterranea of Reggio Calabria, 89055 Italy (Phone +39-0965-875224; fax: +39-0965-875220; e-mail: morabito@unirc.it).

running mean of the monthly sunspot number *MR*:

$$IR5_t = 1/5\ (MR_{t-3} + MR_{t-2} + MR_{t-1} + MR_t + MR_{t+1}) \qquad (1)$$

where $IR5_t$ is the index for month t and MR_t is the mean sunspot number of the same month. This time series is currently used, for example, by the French Telecom's research center, the *Centre National d'Ètudes des Télécommunications* (CNET), which regularly publishes and distributes reports about six-month ahead predictions of the *IR*5 Index to its users. The time series we take into account starts from January 1849 and ends in May 2004 (Fig. 2). Obviously, both the time series continue until now, but to make correct comparisons we have used the same set of values of other previous works.

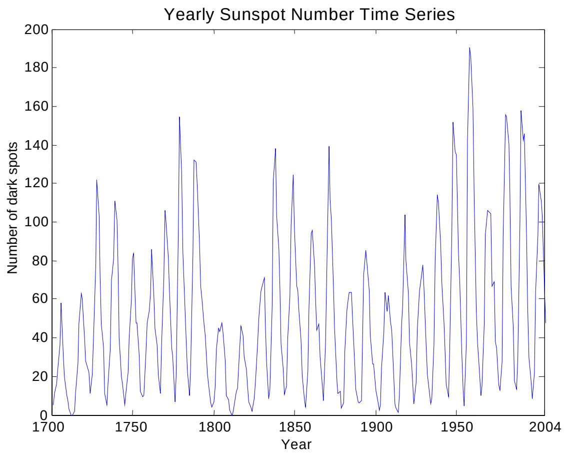

Fig. 1 The Yearly Sunspot Number

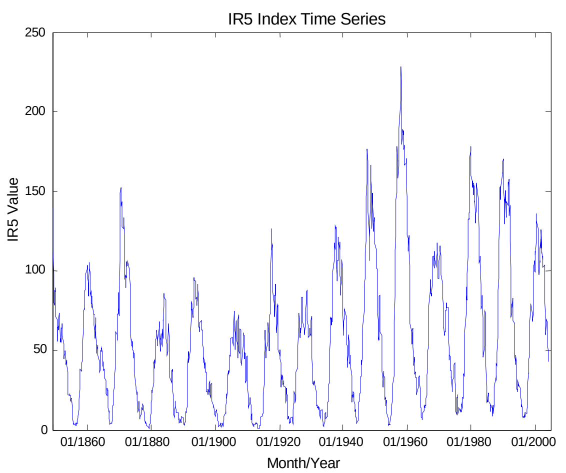

Fig. 2 The *IR*5 Index Time Series

III. Elman Neural Networks

The prediction of a time series consists, given a set of past observations (x_t, x_{t-1}, ..., x_{t-n}), in finding the future value x_{t+m}, with m >0. The forecast $\tilde{x}_{t+m}$ is computed on the past history as following:

$$\tilde{x}_{t+m} = f(x_t, x_{t-1}, \ldots, x_{t-n}). \qquad (2)$$

ANNs, that are well-known as universal function approximators, are today extensively employed to estimate the unknown function *f*. In order to process temporal patterns, an ANN must contain memory. If the neural model is a Multi Layer Perceptron (MLP), the simplest way to build memory into the network is to feed the network with a tapped delay line which stores past values of the input. The second way consists in using positive feedback, that is making the network recurrent.

In an Elman network [7], also known as partially recurrent neural network, positive feedback is exploited to build memory by adding recurrent connections as shown in Fig. 3. These structures are MLPs with the difference that the input layer is constituted by input neurons and *context units*, which store delayed hidden layer neurons values from the *previous* time step to present them to the network as additional inputs in the *current* time step. The outputs of the network are not fed back to the inputs. It is important to point out that each hidden neuron has a context unit, so an Elman network includes as many context units as hidden neurons. This means that, even if two Elman networks, with the same weights and biases, are given identical inputs at a given time step, the outputs can be different due to different feedback states. These architectures are usually called *partially recurrent neural networks* since the recurrent connections have weights fixed to 1, which are not modified during the training process. This results in the great advantage that standard back-propagation algorithms can be used to train this kind of models. The Elman networks we use in this work have only one hidden layer with hyperbolic tangent transfer function, and an output layer with linear activation function.

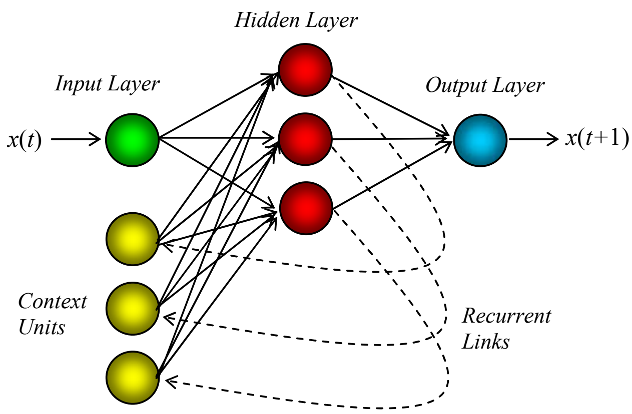

Fig. 3 Structure of an Elman network with one input and one output

IV. The Proposed Forecasting Methodology for Sunspot Time Series

In the last years ANNs have been widely used in time series prediction tasks and a lot of architectures, training algorithms and more and more efficient design procedures have been developed. The approach proposed in this work to predict sunspot-related time series is principally based on using Elman networks as forecasting tools, but it is characterized by a fine data pre-processing in order to prepare the most suitable training set for the network. Firstly, we use a more natural representation of the time series, achieved by "de-rectifying" the data so that the sign of the signal is switched at every cycle minimum, as shown in Fig. 4 for the Yearly Sunspot Number. In fact, as suggested by Wan [5], this is well motivated since the approximate 11 year solar cycle actually consists of a 22 year magnetic cycle that flips polarity every 11 years (see also [8]). In this way, the new time series appears more like a sum of sinusoids, whose oscillating character can be "learnt" much better than the original time series.

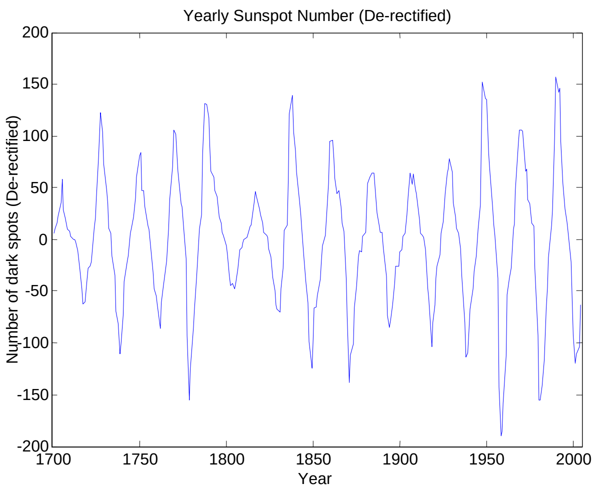

Fig. 4 De-rectification of the Yearly Sunspot Number

After that, we normalize data so that they have zero mean and unity standard deviation since, among the numerous methods of data normalization, this kind of approach has proved to match very well with the previous phase of de-rectification.

The used architectures present only one input neuron, a number of hidden units chosen by using trial and error procedures and one output unit. After the network design, we initialize the weights of the connections with the Nguyen-Widrow method [9]. Finally, the entire input sequence is presented to the network that is trained using a back-propagation algorithm with variable learning rate and momentum. In fact other algorithms, such as the Levenberg-Marquardt, tend to proceed so rapidly that they do not usually work well in an Elman network. After training, we test the prediction accuracy on the testing set. Obviously, it is necessary to normalize the testing data as previously done for the training set before to simulate the network. Fig. 5 shows a generic overview of the proposed approach.

V. Experimental Results

The proposed methodology has been applied to predict the previously introduced sunspot-related time series. Since the temporal patterns under study are often used to test the quality of a prediction method, we can compare our approach with numerous results found in literature. According to the common practice, the accuracy of the prediction is evaluated in terms of the Normalized Mean Squared Error (NMSE), also called by some authors the Average Relative Variance (ARV):

$$\mathrm{NMSE} = \frac{1}{\sigma^2 N}\sum_{i=1}^{N}(x_i - \tilde{x}_i)^2 \qquad (3)$$

where:
x_i = actual value of the i^{th} point of the series of length N;
$\tilde{x}_i$ = predicted value;
σ^2 = variance of the true time series in the prediction interval N.

A. Yearly Sunspot Number

The first time series we take into account is the Yearly Sunspot Number. Usually, data from 1700 to 1920 are used for the training phase, and the performance of the model is evaluated on two or three testing set: from 1921 to 1955 (Test1), from 1956 to 1979 (Test2), and from 1980 to 1994 (Test3). After few experiments, we have found optimal performance using an Elman network with only 2 neurons in the hidden layer, for a total number of parameters of 11. Table I summarizes the prediction accuracy on the single-step prediction task and shows several comparisons with many

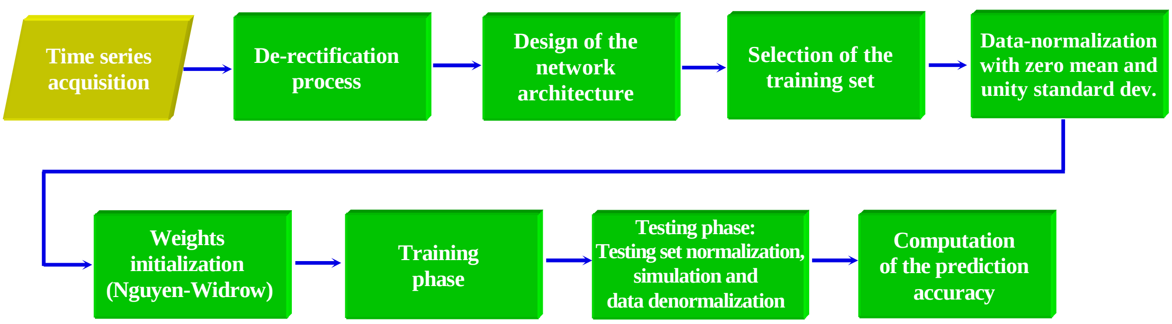

Fig. 5 Generic overview of the proposed method

previous works on this time series. For each design method we give the number of free variables used and the lowest NMSE (see [10] and [11] for the comparison results). From the results in Table I it is possible to observe that our approach outperforms simple Auto-Regressive models (AR), feed-forward MLPs such as the Weight Elimination Feed Forward Network (WNet) [12], fully recurrent neural networks as the Dynamical Recurrent Neural Network (DRNN) [13], the Soft Weight Sharing Network (SSNet) [14], the Scale Neural Network (ScaleNet) presented in [15], the Committee Prediction method of Wan [7], the recurrent networks trained with the Back Propagation Through Time algorithm (BPTT) and one of its variant, the Constructive BPTT developed in [11]. Only the Violation Guided Back Propagation technique (VGBP) [10], based on a recurrent Finite Impulse Response (FIR) network, is more accurate than our method on the first two tests. To our knowledge, the prediction result obtained on Test3 is better than that of any other existing approach. Fig. 6 graphically illustrates the achieved results. As regards the multi-step prediction task, it is known that one can train a network to directly forecast the desired prediction horizon as well as using the iterated method, that is exploiting the values predicted in the previous time steps as inputs for subsequent predictions. Analyzing both the approaches we have observed that, in this case and for this kind of neural architecture, the direct method is the best for this time series.

TABLE I
COMPARISON BETWEEN DESIGN METHODS FOR THE SINGLE STEP PREDICTION OF THE YEARLY SUNSPOT NUMBER

Training Set	Design Method	Para.	NMSE Test1 (1921-1955)	Test2 (1956-1979)	Test3 (1980-1994)
1700-1920 (220 points)	AR (12)	14	0.427	0.966	0.238
	WNet	113	0.086	0.350	0.219
	SSNet	N/A	0.077	N/A	N/A
	DRNN	30	0.091	0.273	N/A
	COMM	N/A	0.065	0.240	0.148
	ScaleNET	N/A	0.057	0.130	N/A
	RNN+BPTT	155	0.084	0.300	N/A
	RNN+CBPTT	15	0.092	0.251	N/A
	VGBP	11	0.033	0.052	0.033
	Proposed	**11**	**0.043**	**0.080**	**0.028**

Also in this prediction task, the networks have only 2 hidden neurons. Table II summarizes the mean results obtained until a prediction horizon of 6. In order to make a comparison with the most recent results published in literature about a medium-term horizon prediction of the Yearly Sunspot Number, we have computed the NMSEs on the cumulated test set involving Test1 and Test2. In all the multi-step predictions, the Elman networks designed and trained using the proposed approach present the best performance, as one can see also from Fig. 7, that illustrates a graph showing a comparison between the presented forecasting methodology and three Recurrent Neural Networks (RNNs) trained with the BPTT algorithm, the CBPTT and the Exploratory BPTT (EBPTT) [11].

TABLE II
NMSES OBTAINED BY VARIOUS METHODS FOR MULTI STEP PREDICTION OF THE YEARLY SUNSPOT NUMBER

Steps Ahead	Design Methods: Proposed	RNN+EBPTT	RNN+CBPTT	RNN+BPTT
2	**0.153**	0.53	0.69	0.88
3	**0.238**	0.79	0.99	1.14
4	**0.231**	0.80	1.17	1.22
5	**0.239**	0.88	0.99	1.01
6	**0.288**	0.84	1.01	1.02

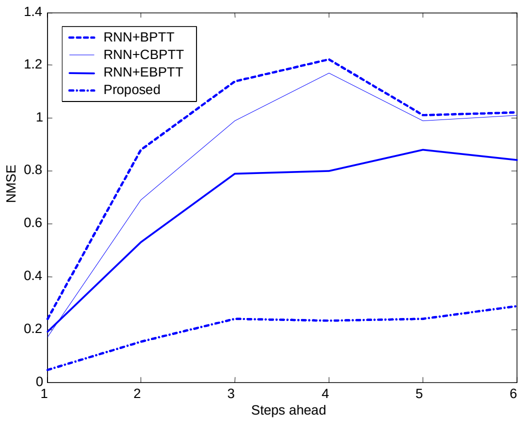

Fig. 7 NMSEs obtained by various methods on the cumulated test set (1921-1979) versus the prediction horizon

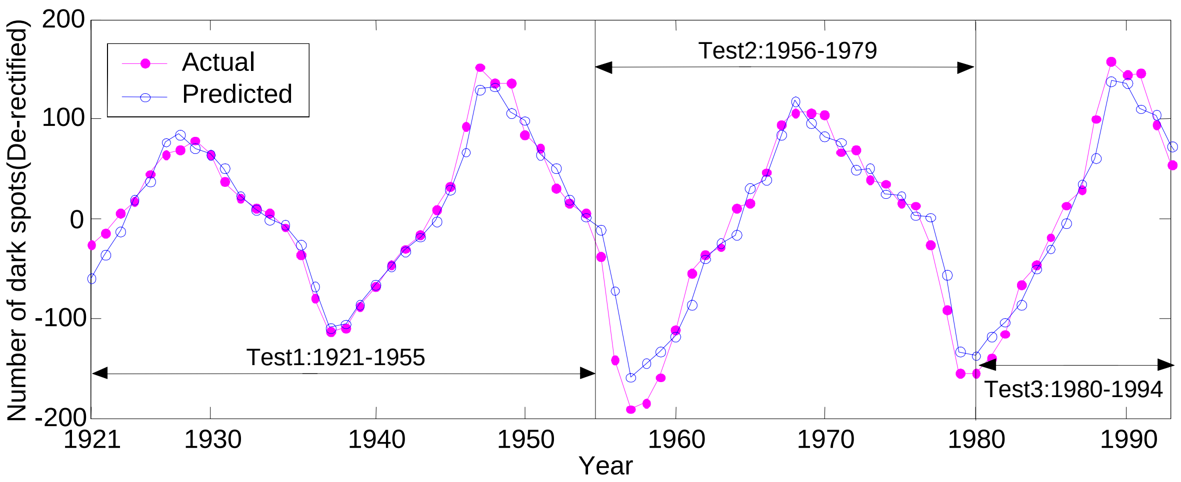

Fig. 6 Single-step prediction of the Yearly Sunspot Number

B. IR5 Index

The second dataset we consider in this work is the *IR*5 Index, used in several research centers in order to produce reports on monthly predictions of the solar activity. The CNET center, for example, constantly provides reports to its users about six-month ahead predictions of the *IR*5 Index. According to other previous works on this time series [2], [3], data from January 1849 to February 1972 (1478 points) are used for the training phase, whereas the samples from March 1972 to December 1991 (238 points) are employed to test the model. Since the time series continues until now, in order to give more results and for a further evaluation of the proposed methodology, we also use a test set ranging from March 1972 to May 2004 (387 points). We are interested in predicting the *IR*5 Index five or six months afterwards. To begin, we have "de-rectified" the time series as previously done for the Yearly Sunspot Number. After some attempts, we have obtained the results summarizes in Table III using an Elman network with 3 hidden units for a total number of 19 free parameters. As it can be see from the NMSEs summarized in Table III (see [3] for the comparison results), the proposed approach performs better than the simple heuristic used by the CNET prediction service, a simple MLP, Modular Architecture, Expert Mixture, and the Conditional Distribution Discrimination Tree (CDTT) presented in [6]. Fig 8 shows the 5-month ahead prediction achieved on the testing set from March 1972 to May 2004.

We wish to point out that, unlike reported in [6], we distinguish between the results found in literature on 5-month ahead predictions, as obtained by the CDTT in [6], and 6-month ahead predictions, as summarized in [3]. It is very interesting to observe that the accuracy of the predictions we obtain on the first testing set is very close to that achieved in the second (and much larger) testing set. This confirms the quality of the proposed forecasting methodology.

TABLE III
NMSEs FOR TWO MULTI STEP PREDICTIONS OF THE IR5 INDEX

Training Set	Testing Set	Design Methods	NMSE 5-month ahead	NMSE 6-month ahead
January 1849-February 1972	March 1972-December 1991	CNET heuristic	N/A	0.113
		Simple MLP	N/A	0.088
		Expert Mixture	N/A	0.076
		Modular Arch.	N/A	0.064
		CDDT	0.056	N/A
		Proposed	**0.045**	**0.055**
	March 1972-May 2004	**Proposed**	**0.047**	**0.059**

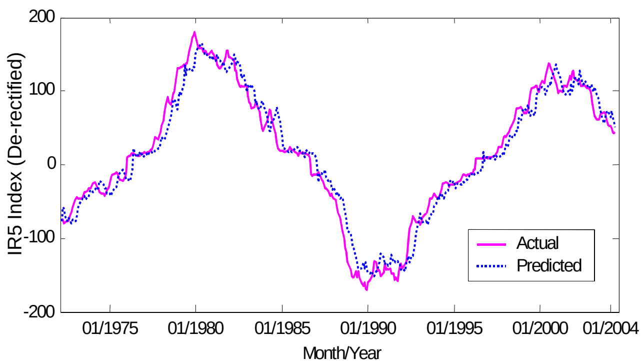

Fig. 8 5-month ahead prediction of the *IR*5 Index

VI. CONCLUSIONS

In this paper we have proposed a forecasting methodology based on using neural networks for sunspot-related time series. Among the numerous architectures proposed in these last years for time series prediction tasks, we have decided to exploit partially recurrent Elman networks for their simple and well-organized structure able to process temporal sequences. Moreover, an efficient data pre-processing phase to prepare the most suitable training set for the model have been developed. In fact the "de-rectification" process of this kind of data together with the normalization procedure with zero mean and unity standard deviation has proved to be an excellent coupling before the training of the network.

In addition, the Nguyen-Widrow method has surely contributed to correctly initialize the set of weights and to speed up the learning phase. The results achieved on the predictions of the Yearly Sunspot Number are very good, especially on a medium-term horizon, and have been obtained using a neural architecture with a very small number of free parameters, which shows the efficiency of the proposed methodology. The same remarks can be said for the prediction of the *IR*5 Index, surely a task more difficult than the previous one, for which work in progress aims to further improve the prediction accuracy. In conclusion, we would like to point out the importance of forecasting sunspots remembering that *Skylab*, the space laboratory launched by the USA in the 1973, was brought to a premature demise in 1979 due to improperly forecasting increased atmospheric drag associated to a sunspot maximum.

REFERENCES

[1] Van der Linden, R. A. M. & the SIDC team. *Online catalogue of the sunspot index*. Available: http://sidc.oma.be/html/sunspot.html

[2] S. Bengio, F. Fessant, D. Collobert, "On the Prediction of Solar Activity using Different Neural Networks Models," *Annales Geophysicae*, vol. 14, pp.20-26, 1995.

[3] F. Fessant, S. Bengio, D. Collobert, "Use of Modular Architectures for Time Series Prediction," *Neural Processing Letters*, vol. 3, pp. 101-106, 1996.

[4] Lj. R., Cander, X. Lamming, "Neural Networks in Ionospheric Prediction and Short-Term Forecasting," *Proceedings of the IEEE Tenth International Conference on Antennas and Propagation*, vol. 2, pp. 14-17, 1997.

[5] E. A. Wan, "Combining Fossils and Sunspots: Committee Predictions," *Proceedings of the IEEE International Conference on Neural Networks*, vol. 4, pp. 2176-2180, 1997.

[6] M. G. Genet, A. Pétrowsky, "Sunspot Number Prediction by a Conditional Distribution Discrimination Tree," *Proceedings of the IEEE International Joint Conference on Neural Networks*, vol. 1, pp. 814-819, 2003.

[7] J. L. Elman, "Finding Structure in Time," *Cognitive Science*, vol. 14, pp. 179-221, 1990.

[8] R. Bracewell, "Spectral Analysis of the Elatina Series," *Solar Physics*, vol. 116, pp. 179-197, 1988.

[9] D. Nguyen, B. Widrow, "Improving the Learning Speed of Two Layer Neural Networks by Choosing Initial Values of the Adaptive Weights," *Proceedings of the International Joint Conference on Neural Networks*, vol. 3, pp. 21-26, 1990.

[10] B.W. Wah, M. L. Qian, M.L, "Time-series Predictions using Constrained Formulations for Neural-Network Training and Cross Validation," *Proceedings of the International Conference on Intelligent Information Processing, 16th IFIP World Computer Congres*s, pp. 220–226, 2000.

[11] R. Boné, M. Crucianu, "An Evaluation of Constructive Algorithms for Recurrent Networks on Multi-Step Ahead Prediction," *Proceedings of the International Conference on Neural Information Processing*, pp. 547-551, 2002.

[12] A. S. Weigend, B. A. Huberman, D. E. Rumelhart, "Predicting the Future: a Connectionist Approach," *International Journal of Neural Systems*, vol. 1, no. 3, pp. 193-209, 1990.

[13] A. Aussem, "Dynamical Recurrent Neural Networks Towards Prediction and Modeling of Dynamical Systems," *Neurocomputing,* vol. 28, pp. 207-232, 1999.

[14] S. Nowland, G. Hinton, "Simplifying Neural Networks by Soft Weight Sharing," *Neural Computation*, vol. 4, no. 4 pp. 473-493, 1992.

[15] A. B. Geva, "ScaleNet – Multiscale Neural-Network Architecture for Time Series Prediction," *IEEE Transactions on Neural Networks*, vol. 9, no. 5, pp. 1471-1482, 1998.