Sunspot behavior forecast using neural networks approaches

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***Abstract*—The study of solar activity is of great interest for the recognition of its influence on the earth. A great step in astronomy is the prediction of solar activity, allowing better preparation for study and recognition of future solar and terrestrial events. In our research we used Neural Networks models to predict sunspot numbers based on solar activity recorded between 1818 and 2019. Solar activity data were taken from the Solar Influences Data analysis Center (SIDC) website and Sunspot Index and Long-term Solar Observations (SILSO). Results show a high potential of this processing that become a competitive approach for the sunspots prediction.**

I. Introduction

The solar activity is a classical problem which has been demonstrated high importance due to the space exploration. Low-orbit satellites require shielding from solar wind and high-energy particles, space-manned flights demand magnetic field monitoring [1, 2]. Besides, radio communications, cable network and electric power on Earth also depend on the current solar activity [3].

The sun presents a cycle of 11.2 years, and after this period, its magnetic polarity is reversed: the north magnetic pole becomes the south pole, and vice versa [4]. Thus, a complete magnetic solar cycle lasts about 22 years, being known as Hale cycle [5] [6].

According to Hathaway (1998) [7], observations of sunspots and solar activity from the middle of XVII century showed that the number of sunspots and the area they cover grows rapidly from a minimum (close to zero) to the maximum (3 to 4 years after reaching the minimum). However, the maximum decreasing to the minimum is slow. This asymmetric growth and decreasing exhibit substantial variations from one cycle to another. Between years 1645 and 1715 was observed the longest solar minimum in history, the Maunder Minimum, when the cycles lasted 11 years. Due to this fact, the solar cycles have been numbered since 1755 and 24 cycles have been counted until the current year, 2019.

Currently, most benchmarks to measure solar activity are based on the number of sunspots present on the sun at any given time. Since 1981 the analysis of images provided by satellites and sun observatories have been done in an automated monitoring way by the Solar Influences Data analysis Center (SIDC) and website and Sunspot Index and Long-term Solar Observations (SILSO) [8]. SIDC is a world data center for the production, preservation and dissemination of the international sunspot number [9]. In this paper we consider the images recorded and disseminated by this center to forecast the number of sunspots for the next cycle (25).

The task of predict the exact behavior of models that can describe a natural system such the solar activity one is still unrealizable no matter how accurate is the model [2]. Usually predictions of the cycle is divided in two different classes: techniques for forecasting the ongoing cycle and methods for prediction of its future evolution [10]. The first class is widely explored considering all solar activity already recorded, where the SIDC predictions are used as a reference. There are three methods of predictions: the Standard Curves Hathaway-Wilson-Reichmann method (SC)[11], the McNish-Lincoln method (ML) [12] and and the combined method of Denkmayr-Cugnon (CM) [13].

These methods work on the ongoing solar activity cycle and cannot be used for the prediction of a future unknown sunspot evolution. They are purely formal and cannot assimilate in any form the results of numerical simulations in their forecast estimations. In order to solve this problem, the authors in [2] proposed a method for a monthly forecast of the total sunspot number time series, based on the combination of a dynamo model with an artificial neural network.

In our paper we propose an approach to deal with the prediction of the number of sunspots using artificial intelligence. For this purpose, we use machine learning techniques, and different neural network architectures are compared, analyzing 73565 days registered by SIDC. The main contribution of this work is an application of a recently developed neural network model which encompass the Radial Basis Network (RBF) and Extreme Learning Machine (ELM) together at the same architecture.

The rest of the work is organized as follow: Section II presents the background and the related investigations. Section

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III discusses the proposed approach to achieve the goal, while Section IV shows the experiments and the computational results. Section V presents the conclusions.

II. Background

In this section we describe the techniques applied to predict the behavior of sunspots using neural network models.

Sunspots are recurrent, meaning they appear and disappear in a matter of days or weeks. One way to analyze and try to find possible patterns is by using a large dataset, but the computational efforts and time to analyse these data are so expensive as the size of he dataset. For faster results, some computing and machine learning tools can be used, such as Radial Basis Function (RBF) and Extreme Learning Machine (ELM) networks.

A. Radial Basis Function

Radial Basis Function (RBF) is a linear neural network that learns from a training set, previously defined as known inputs and outputs. In this type of architecture, there is only one intermediate layer, where the activation functions are of high dimensionality [14].

RBF (Fig 1) can be used as a base function for nonlinear regression models (linear or nonlinear) and can also be used as an activation function of any multilayer network type [14], such as Multilayer Perceptron (MLP). The most used nonlinear function in a network is the Gaussian, where we have an approximation of centroids and length of each neuron, while in the output layer a linear activation function is used [15].

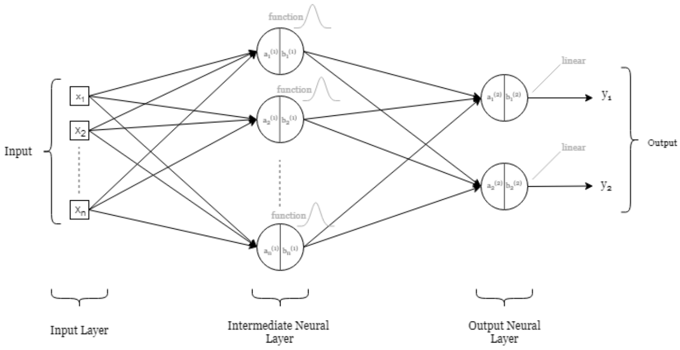

Fig. 1. Radial Basis Function Architecture

B. Extreme Learning Machine

Extreme learning machine (ELM) are feedforward neural networks and can be used for classification, regression, approximation [16, 17] and other applications [18, 19]. ELM dos not perform adjustments in the hidden layer, meaning that the synaptic weights in this layer are given at random [16]. Therefore, only weights in the output layer are tuned, characterizing a fast training method. Due to the randomness in ELM network model, it is classified as an unorganized machine [20, 21]. ELM has a similar architecture to MLP (Fig. 2), and the number of inputs and outputs vary according to the applications. Some authors say the ELM is a new learning process for MLP [22], and present ELMs with two or more hidden layers [23].

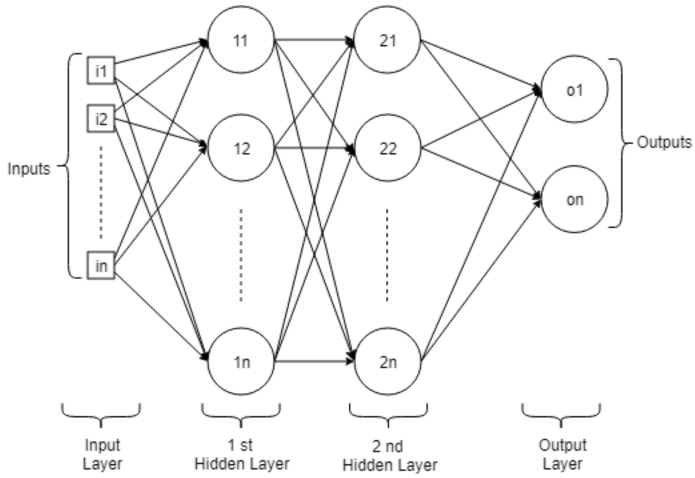

Fig. 2. Extreme learning machine with two hidden layers

III. Proposed Approach

This section presents the proposed approach to predict the number of sunspots using the data available at SIDC/SILSO. We apply machine learning techniques to find a pattern in order to estimate the number of sunspots.

The first step is to organize the available data into training, validating and testing sets, according to the inputs/outputs raw information, as shown in Figure 3.

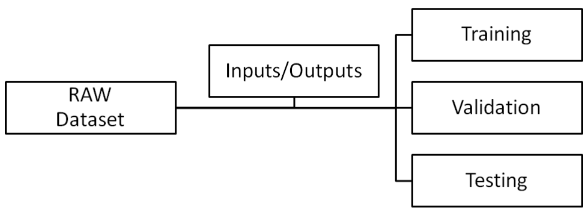

Fig. 3. Training, Validation and Testing sets

In this paper we consider the following for each set:

- Testing Set - 70 %
- Validating Set - 15%
- Testing Set - 15%

The training set considering the inputs and their respective outputs is submitted to a learning process (supervised) over a defined number of epochs to find the network weights minimizing the errors.

After each training process the validation set is applied to verify whether the obtained network model presents satisfactory results, and also to analyze the network behavior when submitted to a new dataset. If this step is not performed our trained network will respond perfectly when analyzing the data we already have, but will lose performance when trying to predict outputs (guessing) based on new data.

Depending on the results, the network can be declared trained and ready to perform prediction over the testing set or go through a fine tuning and a new learning and validating cycle begins.

After the testing set has been submitted to the now trained network (inference), the expected and given outputs are compared and the mean square error is used as an indicative of performance. The learning and inferring process can be seen in Figure 5.

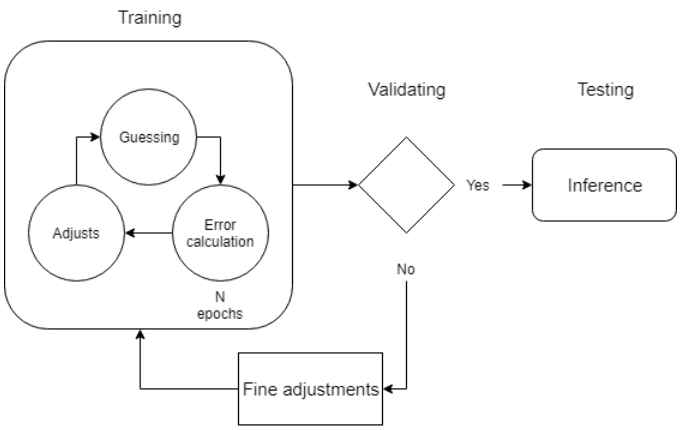

Fig. 4. Learning, Validation and Testing Process

In this paper we analyse three neural network architectures: ELM with one hidden layer, ELM with two hidden layer and ELM with RBF approach.

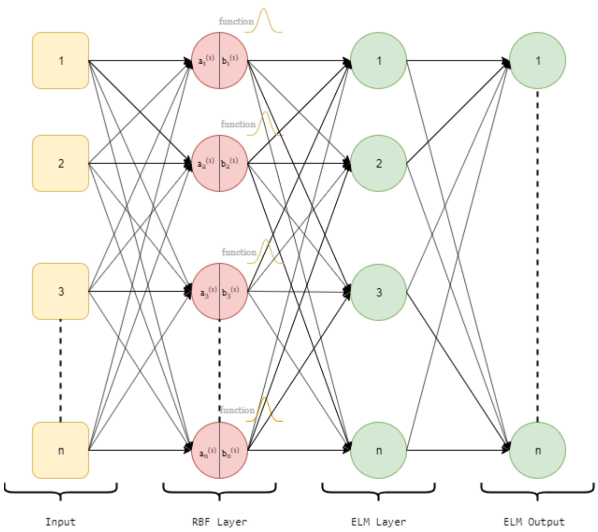

Fig. 5. Hybrid RBF+ELM

The ELM with RBF hybrid approach follows the schematic present on Figure 5. For this method, the RBF layer have been replaced by ELM Network. In summary, all data is processed by the RBF layer and then pass through ELM layers. The first one is a layer with a random number of neurons and the second one is the MoorePenrose pseudoinverse operations [24].

IV. Experiments and Results

In this paper we analyse a total of 73565 days, starting from January 1st. of 1818 until May 31st. of 2019. The csv data format contains year, month, day, date in fraction of year, daily total sunspot number, daily standard deviation of the input sunspot numbers from individual stations and the number of observations used to compute the daily value.

We investigate the Neural Network models prediction performance computing the mean square error (MSE) for all the days, which is given by the Equation 1:

$$MSE = \frac{1}{2nd}\sum_{i=0}^{nd}(R_{sv} - P_{sv})^2 \quad (1)$$

The variable nd represents the number of days, R_{sv} the real daily spots quantity value and P_{sv} the value of the predicted number of daily spots.

The leaning process in applied in three different neural networks with the same features. The Tables I, II and III presents the best and worst MSE for the testing process considering different number of neuron.

TABLE I
MSE for ELM+RBF

Number of ELM neurons	Best	Worst
500	0.0213	0.0245
1000	0.0109	0.0127
1500	0.0096	0.0103
2000	0.0078	0.0084

Table II presents the MSE for the Radial Basis Function network with Extreme Learning Machine. It is clear that increasing the number of ELM neurons the MSE decreases, but the computational time increases.

TABLE II
MSE for ELM with 1 Layer

Number of neurons	Best	Worst
500	0.0134	0.0137
1000	0.0129	0.0129
1500	0.0126	0.0126
2000	0.0123	0.0124

Table III shows the MSE for the ELM structured with only one hidden layer. Differently of the results on Table I, the MSE does not decrease while the number of neurons increase - the data amplitude is 0.0014, highest minus lowest.

The same phenomenon observed in Table II occurs in Table III, meaning that the variation of the number of neurons does not affect the MSE.

In general, for the three approaches, the hybrid proposal ELM with RBF achieved the smallest errors with 2000 neurons in the hidden layer.

V. Conclusions

This work investigated neural networks models to predict the behavior of sunspots on the solar surface. Our experiments

TABLE III
MSE FOR ELM WITH 2 LAYERS

Number of neurons Layer 1	Layer 2	Best	Worst
500	500	0.0449	0.0464
1000	500	0.0464	0.0469
1500	500	0.0462	0.0465
2000	500	0.0453	0.0460
500	1000	0.0446	0.0457
1000	1000	0.0454	0.0466
1500	1000	0.0457	0.0476
2000	1000	0.0459	0.0464
500	1500	0.0451	0.0454
1000	1500	0.0453	0.0457
1500	1500	0.0453	0.0458
2000	1500	0.0456	0.0475
500	2000	0.0445	0.0459
1000	2000	0.0457	0.0463
1500	2000	0.0457	0.0471
2000	2000	0.0454	0.0465

addressed images from 73565 days registered by the Solar Influences Data analysis Center (SIDC) and Sunspot Index and Long-term Solar Observations (SILSO).

We analyzed three different neural networks: Extreme Learning Machines, Radial Basis Function Networks and a hybrid proposal using both mode. In the case study we addressed the same features and we measured the performance according to the mean square error (MSE). The results showed that the hybrid model could overcome the others.

Besides, we extended our analysis comparing ELM + RBF with a related paper to evaluate the prediction accuracy. The results showed that our method provide competitive performance.

In the future we expect to investigate more techniques to identify other relevant sun features to be predicted and classified, improving the research in this area.

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REFERENCES

[1] R. Schwenn, A. Dal Lago, E. Huttunen, and W. D. Gonzalez, "The association of coronal mass ejections with their effects near the earth," in *Annales Geophysicae*, vol. 23, no. 3, 2005, pp. 1033–1059.

[2] N. Safiullin, S. Porshnev, and N. Kleeorin, "Monthly sunspot numbers forecast with artificial neural network combined with dynamo model: comparison with modern methods," in *2018 Ural Symposium on Biomedical Engineering, Radioelectronics and Information Technology (USBEREIT)*. IEEE, 2018, pp. 199–202.

[3] D. H. Hathaway, "The solar cycle," *Living reviews in solar physics*, vol. 12, no. 1, p. 4, 2015.

[4] R. G. Giovanelli, "The relations between eruptions and sunspots." *The Astrophysical Journal*, vol. 89, p. 555, 1939.

[5] A. Gkana and L. Zachilas, "Sunspot numbers: data analysis, predictions and economic impacts." *Journal of Engineering Science & Technology Review*, vol. 8, no. 1, 2015.

[6] A. Gkana, "Complex population dynamics and economic repercussions: Predator-prey interactions, infectious disease transmission and solar magnetic activity," Ph.D. dissertation, University of Thessaly, 2018.

[7] D. H. Hathaway, "The solar dynamo," *NASA Technical Report NASA-TM-111102, NAS 1.15:111102*, 1994.

[8] S. Couvidat, J. Schou, J. T. Hoeksema, R. S. Bogart, R. I. Bush, T. L. Duvall, Y. Liu, A. A. Norton, and P. H. Scherrer, "Observables processing for the helioseismic and magnetic imager instrument on the solar dynamics observatory," *Solar Physics*, vol. 291, no. 7, pp. 1887–1938, 2016.

[9] F. Clette, D. Berghmans, P. Vanlommel, R. A. Van der Linden, A. Koeckelenbergh, and L. Wauters, "From the wolf number to the international sunspot index: 25 years of sidc," *Advances in Space Research*, vol. 40, no. 7, pp. 919–928, 2007.

[10] D. H. Hathaway, "The solar cycle," *Living Reviews in Solar Physics*, vol. 7, no. 1, p. 1, Mar 2010. [Online]. Available: https://doi.org/10.12942/lrsp-2010-1

[11] D. H. Hathaway, R. M. Wilson, and E. J. Reichmann, "The shape of the sunspot cycle," *Solar Physics*, vol. 151, no. 1, pp. 177–190, 1994.

[12] A. McNish and J. Lincoln, "Prediction of sunspot numbers," *Eos, Transactions American Geophysical Union*, vol. 30, no. 5, pp. 673–685, 1949.

[13] K. Denkmayr and P. Cugnon, "About sunspot number medium-term predictions," in *Solar-Terrestrial Prediction Workshop V, edited by: Heckman, G., Maruboshi, K., Shea, MA, Smart, DF, and Thompson, R., Hiraiso Solar Terrestrial Research Center, Japan*, vol. 103, 1997.

[14] S. S. Haykin *et al.*, *Neural networks and learning machines*. New York: Prentice Hall,, 2009.

[15] J. T. Belotti, L. N. A. Lazzarin, F. L. Usberti, and H. Siqueira, "Seasonal streamflow series forecasting using recurrent neural networks," in *2018 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*. IEEE, Nov. 2018.

[16] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: theory and applications," *Neurocomputing*, vol. 70, no. 1-3, pp. 489–501, 2006.

[17] G.-B. Huang, D. H. Wang, and Y. Lan, "Extreme learning machines: a survey," *International journal of machine learning and cybernetics*, vol. 2, no. 2, pp. 107–122, 2011.

[18] H. Siqueira, L. Boccato, R. Attux, and C. Lyra, "Unorganized machines for seasonal streamflow series forecasting," *International journal of neural systems*, vol. 24, no. 03, p. 1430009, 2014.

[19] H. Siqueira, L. Boccato, I. Luna, R. Attux, and C. Lyra, "Performance analysis of unorganized machines in streamflow forecasting of brazilian plants," *Applied Soft Computing*, vol. 68, pp. 494–506, 2018.

[20] H. Siqueira, L. Boccato, R. Attux, and C. Lyra, "Echo state networks and extreme learning machines: A comparative study on seasonal streamflow series prediction," in *International Conference on Neural Information Processing*. Springer, 2012, pp. 491–500.

[21] L. Boccato, E. S. Soares, M. M. L. P. Fernandes, D. C. Soriano, and R. Attux, "Unorganized machines: from turings ideas to modern connectionist approaches," in *Natural Computing for Simulation and Knowledge Discovery*. IGI Global, 2014, pp. 221–236.

[22] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 2, pp. 513–529, 2011.

[23] B. Qu, B. Lang, J. Liang, A. Qin, and O. Crisalle, "Two-hidden-layer extreme learning machine for regression and classification," *Neurocomputing*, vol. 175, pp. 826 – 834, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S092523121501663X

[24] Y. de Souza Tadano, H. V. Siqueira, T. A. Alves, and M. H. de Nobrega Marinho, "Forecasting particulate matter concentrations: Use of unorganized machines," *International Journal of Advanced Engineering Research and Science*, vol. 4, no. 4.