Long-term Power Consumption Demand Prediction: a comparison of Energy associated and Bayesian modeling approach

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***Abstract*— This paper contributes with two different prediction approaches for long-term power consumption demand prediction using an artificial neural networks (ANN) short-term time series predictor filter. The techniques proposed here are non-linear stochastic models using the energy associated to series and Bayesian inference, implemented by ANN. The system has the advantage of requiring as input only the historical demand time series of power consumption and allows its extension to a forecast medium and long term 3-6-12-18 months forward. The paper predicts the power consumption in the area covered by the country during the period January 1980 - November 2013 in Argentina. Thus, the next 18 forecasted values are presented by the evolution of total monthly power consumption demand of the National Interconnected System of Argentina. The computational results of the prediction comparison are evaluated against the classical non-linear ANN predictor on high roughness short term chaotic time series that shows a better performance of Bayesian approach in long-short-term forecasting.**

Keywords*— *power consumption forecast; energy time series; neural networks; energy associated to series; Bayesian inference; Computational Intelligence.

I. INTRODUCTION

Electricity is one of the most important and used forms of energy and they are widely used for different kind of needs. Nowadays electricity is essential for economic development especially for the industrial sector. Decision makers around the world widely use energy demand forecasting as one of the most important policy tools. So this issue becomes a key energy source in each country and an important condition for economic development. Reliable forecast of energy consumption represents a starting point in policy development and improvement of production and distribution facilities in Argentina.

Electricity demand forecasting is a central and integral process for planning periodical operations and facility expansion in the electricity sector [1]. Demand pattern is almost very complex due to the deregulation of energy markets. Therefore, finding an appropriate forecasting model [2] [3] for a specific electricity network is not an easy task. Although many forecasting methods were developed [4], none can be generalized for all demand patterns. Different models for electric energy demand forecasting have been proposed in recent decades [5] [6] [7] [8], which play an important role in economic planning and safe operation of modern power systems [9].

These models can be divided into two categories: the first includes the traditional algorithms of load forecasting, including time series analysis, regression and gray models. In the second category includes latest algorithms for load forecasting such as neural networks and intelligent expert systems [10] [11] [12] [13]. This paper proposes alternatives for improving prediction in electricity demand [14].

Time series forecasting recently has a preponderant significance in order to know which will be the best the behavioral of a system in study such as the availability of estimated scenarios for water predictability [15], the rainfall forecast problem [16] [17] in some geographical points of Argentina, the energy demand purposes [18] [19] [20], the guidance of seedling growth [21], [22]. For general feed-forward neural networks [23] [24] [25] [26], the computational complexity [27] [28] [29] [30] of these solutions grows exponentially with the number of missing features [46]. In this paper we describe an approximation for the problem of short-term prediction that is applicable to a large class of learning algorithms [10] [11] [12] and [26] including ANN's. One major advantage of the proposed technique solution is that the complexity does not increase with an increasing number of inputs. The solutions can easily be generalized to the problem of uncertain (noisy) inputs, such as Bayesian inference [31] against other generalized approaches [17].

The problem of short time series forecasting [32] [33] [34] poses a difficulty to the analysis which depend on what methods of estimation and prediction fit better and efficient. Various techniques exist as a solution to this problem, employing statistical and artificial intelligence techniques [35] [36] [37] [38]. The techniques proposed here are non-linear stochastic auto-regressive moving average (NAR) models using the energy associated [23] to series and Bayesian approach [17], implemented by ANN. The power consumption forecasts obtained using the proposed methods are then compared with a well-known neural network based predictor for a case study of Argentina. The study analyses and compares the relative advantages and limitations of each time-series predictor technique [39] used for issuing short-term electrical consumption forecast. The structure of the filter is changed taking into account the energy of the short series calculated as the primitive of the original and Bayesian inference. The long-short term stochastic dependence of the time series is measured by the Hurst parameter, in which they are considered as a path of the fractional Brownian motion. A 20 percentage of the dataset is considered to give the prediction horizon and the validation data. Moreover, the next 15 time series forecasted values are presented by cumulative monthly historical electricity consumption and solutions of the Mackey-Glass (MG) and one-dimensional Henon equation.

The paper is organized as follows; Section 2 presents a will review two methods for evolving various parameters of ANNs to model the NN parameters and the optimum architecture/weights applied to electrical time series. Section 3 provides an overview of dataset uses and the methodology proposed. In Section 4, prediction results are carried out and highlighted the application to electrical load forecasting. Finally, Section 5 provides some discussions and concluding remarks.

II. Review of Proposed neural networks algorithms

The main issue when forecasting a time series is how to retrieve the maximum of information from the available data [52]. In this work the coefficients of the ANNs filter are adjusted on-line in the learning process, by considering the two methods proposed: energy associated to series and Bayesian approach as a new entrance to the neural networks. In both cases, the criterion followed modifies at each pass of the time series the number of patterns, the number of iterations and the length of the tapped-delay line according to the long-short term stochastic behavior of the series, respectively.

A. Energy associated to series approach

The assumption of the method is the following [23]: the area resulting of integrating the time series data is obtained by considering each value of time series its derivate;

$$\int_{t_k}^{t_{k+1}} y_t dt \cong y_t \left(t_{k+1} - t_k \right) \quad (3)$$

where y_t is the original time series value. The approximation area is assumed to be its periodical primitive:

$$I_{t_n} = \int_{t_n}^{t_{n+p}} y_t dt = Y_t \Big|_{t_n}^{t_{n+p}}, n = 1,2,...N. \quad (4)$$

During the learning process, those primitives are calculated as a new input to the ANN. The predictor filter attempts to make the area of the forecasted times series equal to the primitive real area predicted. The real area is used in two instances; the first one from the real time series an area is obtained. The H parameter associated of this series is called HA. On the second one, the time series data is forecasted by algorithm, so the H parameter from this time series is called HS. After the training process is completed, both sequences - $\{\{I_n\}, \{I_e\}\}$ and $\{\int\{y_n, y_e\}\}$, in accordance with the hypothesis that they should have the same H parameter.

B. Bayesian approach for tuning the neural networks

A model is most often recognized as Bayesian when a probability distribution is used to describe uncertainty regarding the unknown parameters and when Bayes Theorem is applied [40]. A full Bayesian analysis can lead to the optimal choice among a set of alternative inferences, taking into account all sources of uncertainty in the problem and the consequences of every possible selection. When a rainfall series is being analyzed, it is important to make use of the simplest possible models. Specifically, the number of unknown parameters must be kept at a minimum. For forecasting problems, Bayesian analysis generates point and interval forecasts by combining all the information and sources of uncertainty into a predictive distribution for the future values [53]. It does so with a function that measures the loss to the forecaster that will result from a particular choice of forecasts.

The gamma distribution is chosen for this purpose [31]. When a Bayesian analysis is conducted, inferences about the unknown parameters are derived from the posterior distribution. This is a probability model which describes the knowledge gained after observing a set of data. The application of the regression problem [54] involving the correspond neural network function $y(x,w)$ and the data set consisting of N pairs, input vector lx and targets t_n (n=1,….,N).

Assuming Gaussian noise on the target, the likelihood function takes the form:

$$P(D/w,M) = \left(\frac{\beta}{2\pi}\right)^{N/2} \exp\left\{\frac{-\beta}{2}\sum_{n=1}^{N}\left\|y(x_n;w)-t_n\right\|^2\right\}, \quad (3)$$

$$P(w) = \left(2\pi w^2\right)^{-N/2} \exp\left(\frac{|w|^2}{2w^2}\right), \quad (3)$$

assuming that the expected scale of the weights is given by w set by hand. This was carried out considering that the network function f(xn+1,w) is approximately linear with respect to *w* in the vicinity of this mode, in fact, the predictive distribution for yn+1 will be another multivariate Gaussian.

III. Data and Methodology

The performance of the proposed approaches is given for predicting the long-short term chaotic time series that have appeared in the literature. The normalized symmetric mean-absolute percentage square error (SMAPE) is used as a performance index for measuring the quality of prediction of the time series.

A time series can be actually regarded as an integration of stochastic (or random) and deterministic components [40] [41] [42] [43]. Once the stochastic (noise) component is appropriately eliminated, the deterministic component can then be easily modeled. Rainfall is an end product of a number of complex atmospheric processes which vary both in space and time.

The standard non-parametric approaches presented in this work are based on stochastic techniques that assume non-linear relationship among data that reproduce the power consumption demand series only in statistical sense.

A. Power Comsunption demand series

The case study considered herein is referred to the evolution of total power monthly consumption demand series [44] from the National Interconnected System over the period January 1980 - September 2013 of Argentina shown in Fig.1.

Year	January	February	March	April	May	June	July	August	Sept.	Oct.	Nov.	Dic.
	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh	Consum. in MWh
1980	3.909	4.032	4.169	4.089	4.154	4.511	4.679	4.327	4.162	3.941	3.942	4.442
1981	4.325	4.452	4.553	4.495	4.510	5.048	4.879	4.590	4.655	4.368	4.393	4.602
1982	4.485	4.615	4.808	4.569	4.416	4.911	4.820	4.698	4.553	4.485	4.575	4.728
1983	4.564	4.567	4.720	4.632	5.098	5.301	5.166	5.135	4.876	4.726	4.780	4.982
1984	4.886	4.653	4.931	4.957	5.272	5.919	5.720	5.503	5.183	4.943	4.928	5.071
1985	5.338	5.311	5.624	5.536	5.694	5.976	6.046	6.024	5.900	5.475	5.715	5.725
1986	5.731	5.768	5.753	6.034	6.342	6.251	6.501	6.691	6.590	6.095	6.072	6.257
1987	6.442	6.329	6.577	6.548	7.543	7.585	7.481	7.842	7.190	6.879	7.217	7.291
1988	7.176	6.821	7.471	7.232	7.785	7.783	7.949	7.463	6.996	6.705	7.129	7.020
1989	7.098	7.174	6.974	6.991	7.155	7.041	7.495	6.442	6.401	6.241	6.408	6.548
1990	6.645	6.388	6.375	6.345	6.975	7.190	7.049	6.898	6.892	6.645	6.700	6.664
1991	6.610	6.594	7.111	6.952	7.295	7.723	7.886	7.892	7.409	7.301	7.331	7.147
1992	7.353	7.573	7.974	7.810	8.411	8.715	9.035	8.799	8.386	8.080	7.565	7.757
1993	8.065	7.906	8.749	8.317	9.105	9.126	9.325	9.158	9.056	8.481	8.540	8.759
1994	8.660	8.774	9.274	9.037	9.263	9.842	10.104	9.547	9.531	9.081	9.394	9.820
1995	9.386	9.253	9.890	9.550	9.563	10.190	10.213	10.117	9.317	9.659	9.614	10.058
1996	9.805	10.186	10.479	10.193	10.426	11.243	11.081	10.423	10.181	10.487	10.830	10.842
1997	10.721	10.899	10.971	11.399	11.366	11.776	11.656	11.661	10.959	11.066	11.161	11.526
1998	11.393	11.361	12.220	11.399	11.821	12.269	12.033	12.085	11.684	11.990	11.766	12.034
1999	11.382	12.259	12.650	11.734	12.112	12.545	12.730	12.503	11.862	12.154	12.470	12.640
2000	12.788	12.808	12.709	12.347	12.641	13.211	13.754	12.781	12.969	12.412	12.621	13.224
2001	13.501	14.061	13.780	12.866	12.968	13.639	13.794	13.030	12.642	12.365	12.595	12.626
2002	12.296	13.481	13.481	12.209	12.444	13.428	13.405	12.908	12.392	12.394	12.828	12.939
2003	13.774	13.900	13.721	12.670	13.218	13.567	14.359	14.331	13.570	13.384	13.461	14.185
2004	14.350	14.207	14.655	14.732	14.257	14.512	14.789	14.848	13.611	13.569	14.708	15.032
2005	15.129	15.253	15.211	14.552	14.900	15.699	15.792	15.648	15.485	14.799	16.143	15.657
2006	15.831	16.753	15.723	15.212	16.224	16.406	16.777	16.686	16.448	16.649	16.579	16.689
2006	15.831	16.753	16.335	15.898	16.876	17.037	17.395	17.309	17.097	17.252	17.237	17.323
2007	17.073	17.654	17.400	17.881	18.279	18.345	17.743	17.669	16.590	16.745	17.291	17.786
2008	17.885	17.930	17.697	17.129	18.670	19.126	18.389	18.071	17.615	16.652	18.441	17.571
2009	17.351	18.596	17.218	16.963	17.780	18.948	19.566	17.862	17.895	18.023	17.426	18.422
2010	19.370	19.332	18.408	16.937	18.228	18.770	20.396	20.743	19.346	17.211	18.353	20.209
2011	20.531	20.171	20.913	18.309	18.765	21.024	21.403	21.564	18.648	17.565	19.508	20.513
2012	21.309	21.949	20.095	18.264	18.472	20.978	20.912	19.995	18.626	17.834	20.991	20.921
2013	21.982	22.169	19.523	18.443	20.035	21.270	22.552	21.773	21.711	19.484	20.436	

Fig. 1. Total power monthly consumption demand series from the National Interconnected System of Argentina.

B. Chaotic time series

The benchmark chosen are called MG17 with τ=17 and MG30 τ=30 in the forecasting. Here one of the proposed algorithms to predict values of time series are taken from the solution of the MG equation [46], which is explained by the time delay differential equation defined as:

$$\dot{y}(t) = \frac{\alpha y(t-\tau)}{1 + y^{c}(t-\tau)} - \beta y(t) \qquad (1)$$

Equation (1) is solved by a standard fourth order Runge-Kutta integration step, and the series to forecast is formed by sampling values with a given time interval.

The algorithm uses wavelet method to estimate the H parameter in the time series to have an idea of roughness of a signal [48] [49]. Such series are considered as a trace of an fBm depending on the so-called Hurst parameter 0<H<1.

Furthermore, by setting the parameter β between 0.1 and 1.9 the stochastic dependence of the deterministic time series obtained varies according to its roughness. [47].

In order to compare the results of the proposed technique with the results published in the literature, the second set of times series is chosen from the Henon equation [50] according to [51], where the constants are taken to be A = 1.3, B = 0.22, x(0) = 0 and x(1) = 0. The benchmark is called HEN. The first 65 data points are used for training and the remaining 15 points are kept for validation data.

IV. PREDICTION RESULTS

The simulation results in different order approximations and time periods are presented in the following Table 1. The performance of the comparison is measured by the Symmetric Mean Absolute Percent Error (SMAPE) proposed in the most of metric evaluation, defined by,

$$SMAPE_S = \frac{1}{n}\sum_{t=1}^{n}\frac{|X_t - F_t|}{(X_t + F_t)/2}\cdot 100 \qquad (9)$$

where t is the observation time, n is the size of the test set, **s** is each time series, X_t and F_t are the actual and the forecasted time series values at time t respectively. The *SMAPE* of each series s calculates the symmetric absolute error in percent between the actual X_t and its corresponding forecast value F_t, across all observations t of the test set of size n for each time series **s**. where t is the observation time, n is the size of the test set, s is each time series, Xt and Ft are the actual and the forecasted time series values at time t respectively. The SMAPE of each series s calculates the symmetric absolute error in percent between the actual Xt and its corresponding forecast value Ft, across all observations t of the test set of size n for each time series s.

In each figure are detailed the testing and computing data, where the testing are labeled "Validation data" and had not been used in the computation of the predictor filter.

The assessments of the obtained results by comparing the performance of the predictor filter shows a significance improvement measured by SMAPE index toward Bayesian approach over the energy associated and NAR neural networks approach, all based on ANN.

Although the difference between filters resides only in the model, the coefficients that each filter has, each ones performs different behaviors. It can be noted that even the training points are too short for the learning process [44], the behavior of the proposed filter reach the expectation for short-term time series prediction [26]. The POWER series presents more roughness than MG and HEN solutions, so the Bayesian approach applied to the parameter of the ANN demonstrate a level improvement, in which the adequate prior distribution model chosen demonstrate it can be used for tuning the parameters and outputs of the predictor filter [36].

TABLE I. RESULTS OBTAINED BY THE PROPOSED APPROACHES

Series No.	Filter	H	Real Mean	SMAPE
POWER	Energy	1.68	20.42	0.689
POWER	Bayesian	0.71	20.42	0.026
POWER	Neural	0.71	20.42	0.689
MG17	Energy	2.92	2.80	184.56
MG17	Bayesian	1.78	1.72	7e-06
MG17	Neural	1.78	1.76	1.20
HEN	Energy	0.346	0.349	0.19
HEN	Bayesian	0.469	0.474	6.5e-15
HEN	Neural	0.469	0.559	13.41

The Monte Carlo method was used to forecast the next 15 values from each MG, HEN, and 18 values for POWER time series. Such outcomes are shown from Fig. 2 to Fig. 4.

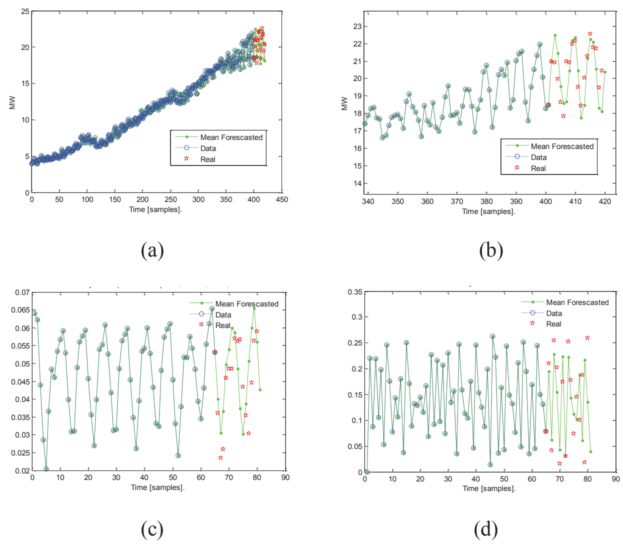

Fig. 2. Non-linear Autoregressive (NAR) Neural network predictor filter; a) POWER series, b) Horizon of POWER Series, c) MG17 series with τ =17, d) HEN one-dimensional series with a=1.3 and b=0.22.

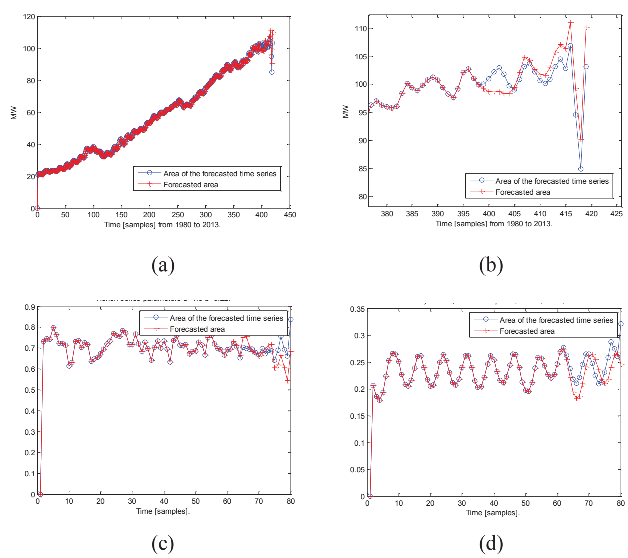

Fig. 3. Energy associated approach-based neural network predictor filter; a) POWER series, b) Horizon of POWER Series, c) MG17 series with τ =17, d) HEN one-dimensional series with a=1.3 and b=0.22.

Discusion & Conclusions

This paper reports the results of two different techniques, namely, energy associated to series and Bayesian inference approach for forecasting power consumption demand forecast. The main contribution resides only considering the associated Bayesian model of the ANN output to forecasts the next 18 months taking into account the power series provided as single input to the ANN. The discussion of this work is to extend this approach with correlation variable as new entries to the ANN obtained between those algorithms are compared with the well-known NAR ANN predictor for a case study of total monthly power consumption demand of the National Interconnected System of Argentina [44]. The study analyzed and compared the relative advantages and limitations of each time-series predictor filter technique, used for issuing long-short-term time series forecast. The structure of the filter is changed according the long-short term stochastic dependence method taking into account the energy of the short series calculated as the primitive of the original and Bayesian inference.

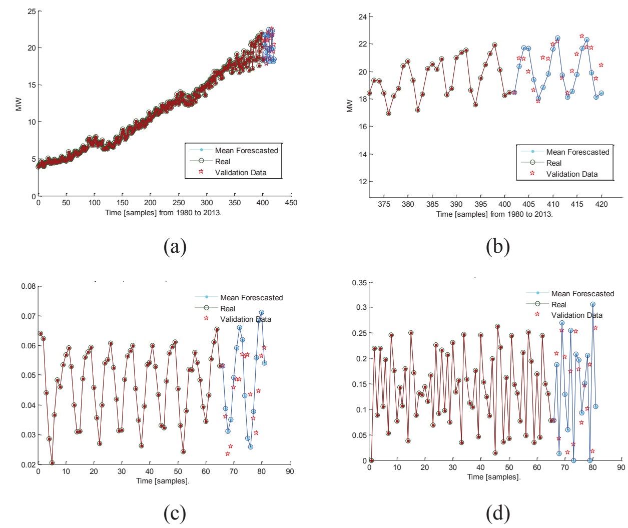

Fig. 4. Bayesian approach-based neural network predictor filter; POWER series, b) Horizon of POWER Series, c) MG17 series with τ =17, d) HEN one-dimensional series with a=1.3 and b=0.22.

Although the comparison was only performed on ANN-based filters, the experimental results shows that the Bayesian method can predict electrical load time series more effectively in terms of SMAPE indices when compared with other existing forecasting methods in the literature..

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