Available online at www.sciencedirect.com

ScienceDirect

Expert Systems with Applications 34 (2008) 665–672

Expert Systems with Applications

www.elsevier.com/locate/eswa

Predicting service request in support centers based on nonlinear dynamics, ARMA modeling and neural networks ☆

Emili Balaguer [a], Alberto Palomares [a], Emilio Soria [b,*], Jose David Martín-Guerrero [b]

[a] Tissat S.A., R&D Department, Av. Leonardo Da Vinci, 5. 46980 Paterna, Valencia, Spain

[b] G.P.D.S, Digital Signal Processing Group, Electronic Engineering Department, Escuela Técnica Superior de Ingeniería, Universitat de València, C/ Dr. Moliner 50, 46100 Burjassot, Valencia, Spain

Abstract

In this paper, we present the use of different mathematical models to forecast service requests in support centers (SCs). A successful prediction of service request can help in the efficient management of both human and technological resources that are used to solve these eventualities. A nonlinear analysis of the time series indicates the convenience of nonlinear modeling. Neural models based on the time delay neural network (TDNN) are benchmarked with classical models, such as auto-regressive moving average (ARMA) models. Models achieved high values for the correlation coefficient between the desired signal and that predicted by the models (values between 0.88 and 0.97 were obtained in the out-of-sample set). Results show the suitability of these approaches for the management of SCs.

Keywords: Time series analysis; Neural networks; Call centers

1. Introduction

Support centers (SCs) usually deal with all the requests reported by either external customers/citizens or internal users of an organization/company. Although telephone has been the traditional way to provide support in the call centers (CCs), nowadays the Internet provides new mechanisms of communication that overcome some of the limitations associated with telephone support, and it is widely used by SCs. The formal contract between the service provider and the service recipient is known as the service level agreement (SLA). SLA must define the quality measures or service level measurements (SLMs) that are used to evaluate the quality of the support service. SLA tends to contain clauses that economically incentive/penalize the SC depending on its degree of fulfillment according to SLMs. Although, SLMs is one of the most crucial and complex tasks in the management of SCs and is out of the scope of this study.

Different system performance and business parameters can be considered for SLMs: cumulative time-based parameters, service availability, number of affected users, metrics based on a particular business process, etc. These measurements must be automatically collected, maintained and analyzed in order to manage the service support process. HelpDesk consists of several software applications that allow to record, track and report all the information involved in a SC, including the SLA and SLM management. In general, the information than can be obtained from a HelpDesk is considerably wide: general information, purchases, complaints, etc. Operators usually answer many calls of different nature: sales, relational marketing, customer services, citizen services, technical support, and in general, any specialized activity related to business or public administration. Moreover, some contracts require a minimum fulfillment degree, and apply penalizations if this degree is not achieved.

There are several aspects that should be covered by a methodology which tries to help in the management of

☆ This work has been partially supported by the Spanish Ministry of Industry, Tourism and Commerce, with the project FIT-340001-2004-11.

* Corresponding author.
E-mail address: Emilio.soria@uv.es (E. Soria).

0957-4174/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2006.10.003

a certain SC. First, SCs are especially interested in managing the forthcoming events as good as possible. Second, operators are interested in searching optimal and fast solutions for the events they have to solve. Third, and as a general rule, it is preferable that problems are solved by operators at the first levels of the system hierarchy, otherwise, the participation of qualified technical personnel is required.

In this work, we analyze different eventualities managed by an official SC, called CETESI.[1] CETESI is part of a global project, which includes many other subprojects (Infoville, Infocentre, ...), and whose goal is to achieve a complete integration of Valencian Region within the Information Society.

Since there is much information that should be taken into account for improving the management of CETESI, the use of data mining (DM) techniques seems to be an appropriate choice to tackle the problem. In particular, time series analysis and prediction has been successfully used in a wide range of knowledge fields (Box & Jenkins, 1976; Makridakis, Wheelwrigth, & Hyndman, 1998; Brockwell & Davis, 2002). The aim of this work is to predict the number of forthcoming service requests as well as the time when they will occur in order to optimize the resources used to solve these events. Different classical models and advanced neural network models are tested in order to obtain a robust and reliable method to predict future events.

The remainder of the paper is outlined as follows. Section 2 presents the methods used in this work, Section 3 shows the obtained results, ending up the paper with the conclusions that can be extracted from this work in Section 4.

2. Methods

In this work, three different techniques are used for time series prediction:

1. Linear models: Auto-regressive moving average (ARMA) models (Box & Jenkins, 1976; Makridakis et al., 1998).
2. Time processing neural models, and in particular, the time delay neural network (TDNN) (Haykin, 1999).
3. Non-linear time series analysis (Kantz & Schreiber, 1999).

2.1. ARMA modeling

ARMA models of order (n,m) can be viewed as linear filters from the point of view of digital signal processing. The time structure of these filters is the following models (Box & Jenkins, 1976; Makridakis et al., 1998):

$$y(k) = a_1 \cdot y(k-1) + \cdots + a_n \cdot y(k-n) + e(k) + b_1 \cdot e(k-1) \cdot + b_{m-1} \cdot e(k-m+1) + C \tag{1}$$

where $y(k)$ is the variable to be predicted using previous samples of the time series, $e(i)$ is a sequence of i.i.d.[2] terms which have zero mean, and C is a constant. As it can be observed from (1), ARMA modelling is made up of two parts:

- Those terms involving coefficients $\{a_i\}(i = 1, \ldots n)$ carry out a linear relationship between the value predicted by the model at time k and the past values of the time series; this part is known as auto-regressive (AR).
- Those terms involving coefficients b_i carry out a linear relationship between the value predicted by the model at time k and a Gaussian distribution of i.i.d. samples. This part is known as moving average (MA), and can be considered as the autoregressive structure of the residues (errors committed in the time series prediction).

Several steps must be followed in order to obtain the coefficients that appear in (1) (Makridakis et al., 1998):

(a) *Series stationarity*. ARMA modeling can only be used correctly if the time series is *wide sense stationary* (WSS). Exponential decreasing of autocorrelation function across lags is a strong indication of time series stationarity (Makridakis et al., 1998). Therefore, the first step is based on transformations of the time series in order to achieve the desired effect in the autocorrelation. Usually, a differentiation if the time series is sufficient. If the differentiation is carried out between consecutive values, it is called *simple differentiation*. Otherwise, if the differentiation is carried out between periods of the time series, it is known as *seasonal differentiation (or integration)*.
(b) *Identification*. The order of both the AR and the MA part must be estimated. Autocorrelation and partial autocorrelation computation is used to obtain these orders.
(c) *Optimization*. The model coefficients are calculated using a training group by means of the autocorrelation computed in the previous step.
(d) *Selection*. The most suitable models are chosen. These models should offer adequate predictions. In order to evaluate models, data are split into two groups: training and validation. The training group is used to build the model (as it was mentioned in the previous item), and the validation group to evaluate it. Moreover, the model should have a few number of parameters (as few as possible). Akaike information criterion (AIC) based on information theory is used

[1] CETESI is the acronym of "*Centro de Telecomunicaciones y Sistemas de Información de la Generalitat Valenciana* (Center of Telecommunications and Information Services of Generalitat Valenciana)". Generalitat Valenciana is the name of the autonomous government of the Valencian Region (Spain).

[2] Independent and identically distributed.

to achieve a trade-off between both requirements (an adequate prediction and a few number of parameters) (Weigend & Gershenfeld, 1996).

(e) *Residues.* Autocorrelation and partial autocorrelation of the residues are calculated to test whether they are statistically relevant. Ideally, residues should be i.i.d.

ARMA processing has shown to be the most effective tool to model a wide range of time series (Makridakis et al., 1998). However, these models do not work properly when there are elements of the time series that show a nonlinear behavior. In this case, other models, such as time processing neural networks, must be applied.

2.2. Neural networks

A neural network is a mathematical model formed by elementary processing units, the so-called neurons. Neurons are defined by the following parts, as shown in Fig. 1 (Haykin, 1999):

- Connections known as synaptic weights, which determine the neuron behavior. These connections may be either excitatory or inhibitory.
- A sum function which carries out a weighted sum of the neuron inputs.
- A nonlinear function, known as activation function.
- A bias (threshold).

Neurons can be arranged in different architectures. The most widely used is the so-called multilayer perceptron (MLP), shown in Fig. 2. In an MLP, neurons are arranged in fully-connected layers, and the values of the synaptic weights are usually obtained by means of the backpropagation algorithm (Haykin, 1999). There are numerous modifications of the MLP that are used in time series prediction. In this work, we used the TDNN, a neural network that includes a time memory in the input layer by means of time delays (Haykin, 1999). There are also other approaches, such as FIR, IIR, Elman and Jordan neural networks, but they are not considered in this study due to the excellent results provided by the simpler TDNN. The evaluation of the model is carried out using a data set different from that used to build the model. Likewise, the number of parameters of the model should be low in order to guarantee generalized results with unknown data sets (Vapnik, 1999). Therefore, neural networks used in this study are chosen by analyzing both the results achieved and the number of parameters (weights) involved.

2.3. Nonlinear dynamics

Dynamic systems analyze temporal evolution of either systems of continuous differential equations or discrete maps defined in a phase space, in which each axis represents a dynamic variable of the system (Wiggins, 2003). Last years, this analysis has been applied to stochastic experimental data. In this work, we try to determine which kind of time series we are dealing with. There are several possibilities:

(a) *Multiperiodical*: values are repeated following a certain combination of frequencies. In this case, it is not necessary to carry out an analysis based on non-

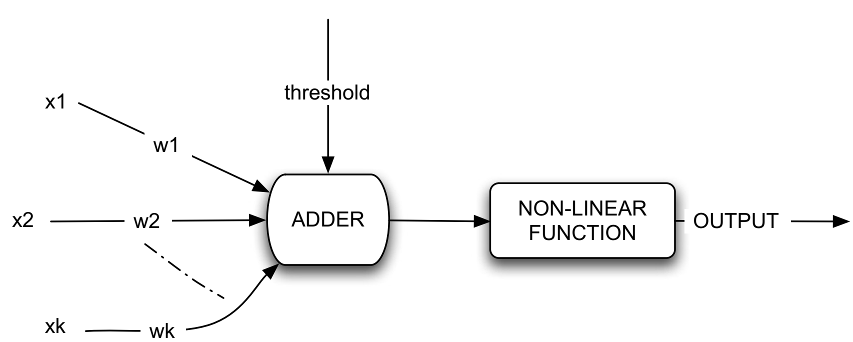

Fig. 1. Schematic of a neuron.

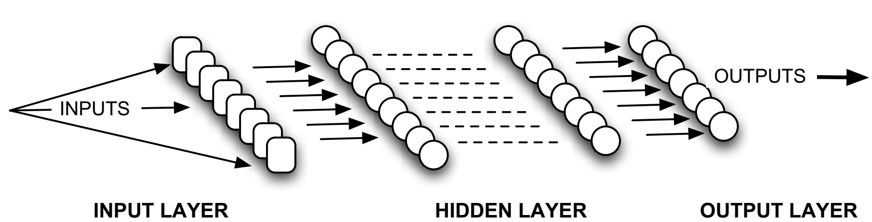

Fig. 2. Schematic of a Multilayer Perceptron.

linear dynamic systems. Either Fourier's analysis or correlation analysis is sufficient to describe time series.

(b) *Chaotic*: values do not follow a periodical evolution. Fourier's analysis and correlation analysis do not show any periodically repeated behavior. The evolution of the system can be rather fast, and the phase space shows a strange attractor (Kantz & Schreiber, 1999). Time series of this kind are strongly nonlinear and Fourier theory does not provide the necessary tools to analyze the time series.

The main problem to overcome is the likely presence of noise in the time series. This is because this noise may cause both Fourier's and autocorrelation analyses to show a wrong information since these mathematical tools cannot distinguish whether the nonperiodical part of the time series is caused by unpredictable noise or by the chaotic behavior of the time series. Nonlinear time series analysis can distinguish between the two possibilities. If there is noise but nonlinearities do not appear, ARMA models provide the best possible modeling, since the nonlinear part of the time series is purely stochastic, and therefore, unpredictable. However, if nonlinearities do appear, it is possible to improve ARMA predictions by using other models, such as neural networks.

In order to analyze system dynamics, the first step to do consists of embedding the time series in a suitable phase space. The criterion used in this work is based on considering that each axis of the phase space represents a delay of the time series. This way, the autocorrelation between axes shows its lowest value (Kantz & Schreiber, 1999). A two dimensional embedding is proposed; once the series attractor is obtained, the following parameters should be determined:

Correlation dimension (D_2). It is the attractor dimension is easiest to compute. A fractal dimension shows a "strange" attractor, and leads to a nonlinear behavior. The value of D_2 gives an idea about the suitable dimension of the phase space necessary to embed the series (typically, $\geqslant 2 \cdot D_2 + 1$) (Takens, 1981), although this criterion assumes the series to be deterministic and can be "relaxed" empirically. In order to calculate this parameter, and also the other chaos indicators, it is necessary to calculate the correlation sum (Kantz & Schreiber, 1999):

$$C(\varepsilon) = \frac{2}{(N - n_{\text{sec}}) \cdot (N - n_{\text{sec}} - 1)} \cdot \sum_{i=1}^{N} \sum_{j=i+n_{\text{sec}}}^{N} \theta(\varepsilon - \|\vec{X}_i - \vec{X}_j\|) \tag{2}$$

where N is the quantity of data, ε is the radium of the reticulum in which the phase space is divided, and $\vec{X}_i$ is the representative vector of a point in the phase space. For instance, in the two-dimensional case, $\vec{X}_i = [x(i)x(i-1)]$, where $x(i)$ is the value of the time series at instant i. Function θ is the so-called Heaviside function (step function which equals 1 for positive arguments, and 0 for negative arguments). Factor n_{sec} is the time chosen to avoid an excessive autocorrelation among the different vectors which made up the attractor, because it might distort the value of D_2. This sum gives information about the ratio of points of the phase space that are closest to ε, i.e., it gives information about the population density of the space (Kantz & Schreiber, 1999).

Nonlinearity test. A non parametric statistical test must be computed to check whether the origin of the nonlinearity of the time series is (Kantz & Schreiber, 1999). The null hypothesis considers that the time series is produced by an ARMA process with Gaussian inputs. An infinite number of artificial data sets with the same magnitude spectrum but different phase spectrum can be produced (Kantz & Schreiber, 1999). These "surrogate" data sets are time series with the same length and statistical moments that the original one, but produced by a linear ARMA process with normal inputs. Then, the characteristic parameter (D_2) of the nonlinear dynamics of the series is calculated. This nonlinear test consists of determining whether all the correlation dimensions of the artificial series are lower (or higher) than D_2. If they are lower, it can be rejected that the series was not generated by a linear process. In this work, we produced 20 artificial data sets, having a 95% bilateral confidence level (Kantz & Schreiber, 1999).

3. Results

In this section, we show the results achieved in the analysis of the events managed by CETESI during years 2003 and 2004. Three different kinds of events are analyzed, namely:

(a) Calls received at the CC. They represent 48.9% of the total registered events.
(b) Automatically generated calls (AGC): 40.6%.
(c) Requests from web forms (WF): 7%.

Events are usually related to projects focused on critic public services for citizens and public administration. The most interesting projects are shown in Table 1. They are also the oldest projects with many records and well-known characteristics.

According to CETESI criteria, a useful model must provide robust 6-hours ahead predictions. Therefore, this was the sample period used by our prediction models. Statistical analyses were carried out using SPSS®, whereas models (ARMA, TDNN and nonlinear analysis) are implemented in a Matlab® environment.

The methodology presented below was followed in all the projects. Therefore, it is shown only the detailed analysis related to the most relevant project in authors' opinion (Health Care System Card). The same methodology was

Table 1
Most important projects analyzed in this work

Project name	Percentage of the total	Majority kind of events
RED *(Network)*	18.4	AGC (64.2%)
INFOCENTRE *(Infocenter)*	16.1	AGC (52.0%)
LEGAL *(Legal)*	11.8	CC (79.1%)
TARJETA SANITARIA *(Health Care System Card)*	11.1	CC (87.4%)
MAIL *(E-Mail)*	6.7	CC (96.1%)
112 *(Emergency phone number)*	6.5	AGC (65.0%)
INFOVILLE XXI *(Citizen web portal)*	4.4	AGC (91.5%)

The English translation or description of the project names appears in italics. It is shown which percentage of the total number of events are related to each project (2nd column), and which is the majority kind of events in each case (3rd column).

also applied to the other projects with similar results and conclusions.

3.1. Descriptive analysis

The most important statistical parameters related to this project were obtained, as shown in Table 2. A first conclusion is that the number of outliers is rather scarce. Moreover, as the values of skewness and kurtosis indicate a behavior close to normality, we can consider as outliers those values beyond 3.5 standard deviations from the mean, with a 99.9% of confidence. Using this criterion, we found two outliers, which has been replaced by the maximum value of the remaining series (93 events/6 h).

Fig. 3 shows the weekly values of the mean and standard deviation in years 2003 and 2004. The homogeneity than can be observed is considered as an empirical indicator of the time series stationarity (Makridakis et al., 1998).

ANOVA shows that there are not significant differences in the means of the series ($F = 0.39$ with significance equal to 1.000). However, standard deviations did vary significantly, as it is shown by the Levene Test (3.0 in 2003 and 5.1 in 2004 with significance equal to 0.000). A decrease in the standard deviation is observed around week 34, due to summer holidays. Therefore, modeling was carried out in two ranges: before and after summer holidays.

Summarizing, there are four modeling periods (two per year) in which the time series showed a quasi-steady behavior with regard to mean and standard deviation. Moreover, CETESI ruled out weeks 1, 48 and 49 of year 2003, and also weeks 1 and 6 of year 2004 (a 4.7% of the total quan-

Table 2
Statistical parameters of the events related to the project "Health Care System Card"

Year	Maximum	Mean	Standard deviation	Percentile 5	Percentile 50	Percentile 95	Skewness	Kurtosis
2003	93	21	25	0	13	56	1.04	−0.18
2004	93	24	21	0	9	65	1.04	−0.18

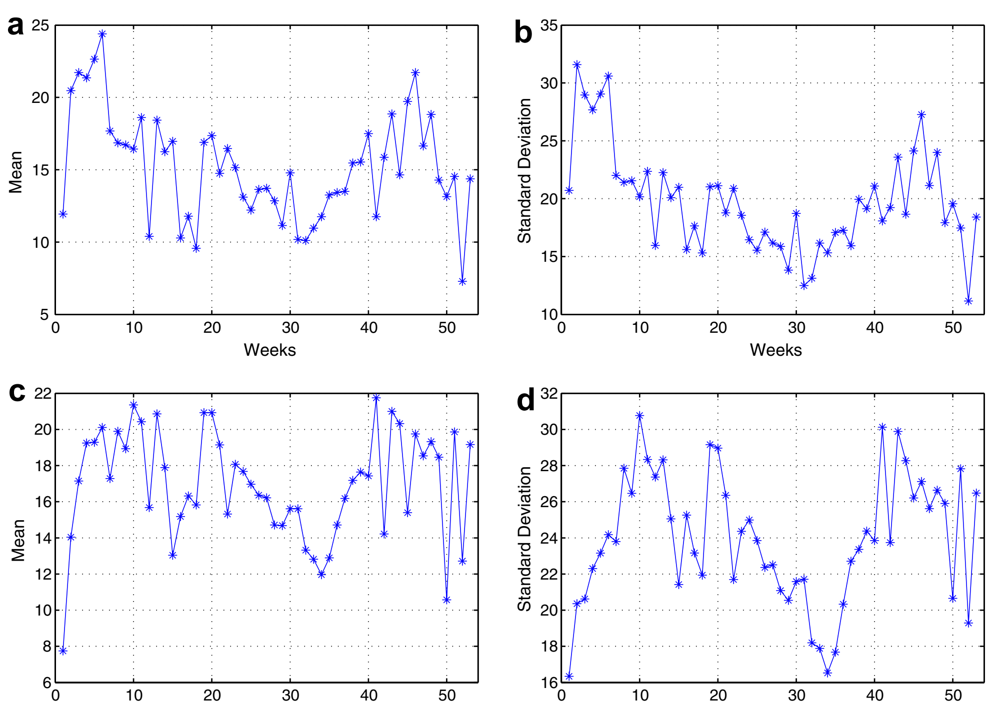

Fig. 3. Representation of the weekly values of mean and standard deviation for the project "Health Care System Card". (a) Mean-year 2003; (b) standard deviation-year 2003; (c) mean-year 2004; (d) Standard deviation-year 2004.

tity of data) because there were some problems in the management of events.

A daily analysis of statistical parameters showed no significant differences. Moreover, since no events were recorded on weekends, weekends were not taken into account in the analysis.

Once the series stationarity was analyzed, the likely periodical structure was studied. Daily periodicity was analyzed by means of both total and partial autocorrelations (Fig. 4). The daily period (each four samples) was much more relevant than the weekly period (each 20 samples). A four-order differentiation was proposed in order to eliminate this periodicity.

3.2. Linear models

Once the time series has been differentiated, ARIMA modeling is carried out. After the daily differentiation, Total Autocorrelation (TAC) and Partial Autocorrelation (PAC) show that it is not necessary any other differentiation, being a possible candidate either the model ARMA(0, 1) or ARMA(1, 0), where the indicated model is seasonal (a for samples daily period). This is because it was observed a fast decrease of TAC (and PAC in the second model) after the first delay and multiples of four delays (Box & Jenkins, 1976). Algorithm stopping criterion is given by the sum of least-squares (if the change between consecutive iterations is lower than 0.001%). Using this threshold, all the models used in this study achieve convergence in 3–10 iterations. The best ARMA structure, according to AIC (Box & Jenkins, 1976; Makridakis et al., 1998) was an ARMA(0, 1). Table 3 also shows predictions obtained by the winner model. Correlation coefficients between the desired signal and the model output in the validation groups were very appropriate in the first

Table 3
Results obtained with an ARMA(0, 1) model in the project "Health Care System Card it should be pointed out that the gap between weeks 26 and 37 corresponds to summer period

Validation period (Training Period)	Correlation Coefficient (validation)
Weeks 23–26; 2003 (Weeks 2–22; 2003)	0.91 ± 0.01 (0.88 ± 0.01)
Weeks 49–52; 2003 (Weeks 37–48; 2003)	0.78 ± 0.01 (0.91 ± 0.01)
Weeks 23–26; 2004 (Weeks 2–22; 2004)	0.97 ± 0.01 (0.93 ± 0.01)
Weeks 49–52; 2004 (Weeks 37–48; 2004)	0.81 ± 0.01 (0.81 ± 0.01)

Parentheses indicate the training period while the validation period is indicated without parentheses.

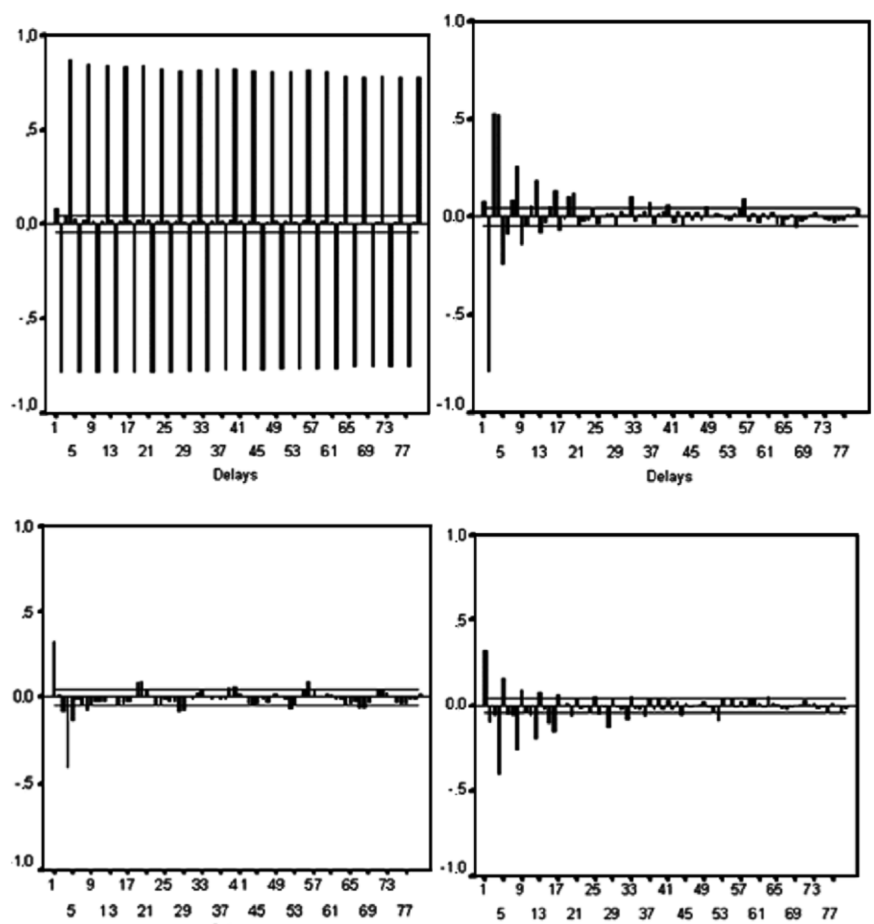

Fig. 4. Total autocorrelation (TAC) (top-left figure) and partial autocorrelation (PAC) (top-right figure) of the time series "Health Care System Card". The same information, but after carrying out daily differentiation, is shown in bottom figures.

months of years 2003 and 2004 (values of 0.91 and 0.97, respectively). Validation groups had a length of four weeks in both years 2003 and 2004.

Fig. 5 shows the autocorrelation analysis of the residues. There are not clear tendencies, being the residues quite close to white noise. Therefore, the identification carried out by ARMA model was correct.

Summarizing, the predictor showed an excellent behavior for the first weeks of the year and moderate for the last weeks.

3.3. Neural networks

The results shown in previous subsections suggest the existence of nonlinearities that ARMA models could not manage. Therefore, a nonlinear structure, such as a TDNN (Haykin, 1999), was used for series modeling. The main characteristics of the TDNN used in this work were the following (Bishop, 1995):

(a) Weights were initialized following a Gaussian distribution of zero mean and unity variance.
(b) The used learning algorithm was a simple variant of the classical backpropagation, in which the learning rate and the momentum coefficient increased (decreased) depending on the error committed by the network (if the error decreased, then the learning rate and the momentum coefficient increased, and viceversa) (Haykin, 1999). Increase/decrease factors were taken equal to 1.1 and 0.6, respectively. The initial learning rate was varied between 0.01 and 0.1 and the initial momentum coefficient between 0.01 and 0.2.
(c) Only one hidden layer formed by a number of neurons between 1 and 4 was used. The number of delays in the input layer was set to 4 as suggested by autocorrelation analyses (Fig. 4).
(d) Cross-validation strategies were not used as stopping criterion due to the short length of the time series. Instead, overtraining was avoided by selecting that TDNN which improved the ARMA predictions using the smallest number of neurons, in order to maximize the generalization ability of such perceptron-like architecture (Vapnik, 1999; Haykin, 1999).

Table 4
Correlation coefficients obtained by TDNN and ARMA in the out-of-sample time series predictions (i.e., predictions during the validation period)

Validation period (Training period)	Correlation coefficient (validation)	
	TDNN	ARMA
Weeks 49–52; 2003 (Weeks 37–48; 2003)	0.88 ± 0.01	0.78 ± 0.01
Weeks 49–52; 2004 (Weeks 37–48; 2004)	0.90 ± 0.01	0.81 ± 0.01

Parentheses indicate the training period while the validation period is indicated without parentheses.

Table 4 shows correlation coefficients between the actual time series and the ARMA and TDNN out-of-sample predictions (i.e., using data not previously shown to the models). Models are obtained during the training period, and then evaluated during the corresponding validation period.

3.4. Nonlinear analysis

Since TDNN did increase prediction performance, it could be assumed the existence of nonlinearities in the analyzed time series. In order to reassert this claim, the nonlinear behavior of the time series between weeks 37 and 52 of years 2003 and 2004 was determined. First of all, time series should be embedded in the phase space. Since autocorrelation analyses indicated a strong single-periodic behavior (daily), it was expected a low dimensional attractor (Kantz & Schreiber, 1999). Therefore, we started using a two-dimensional phase space since it was expected that this dimension would be sufficient for a good embedding (Takens, 1981). The two axes were the actual and the previous values of the series, since the first minimum of the autocorrelation function corresponded to the first delay.

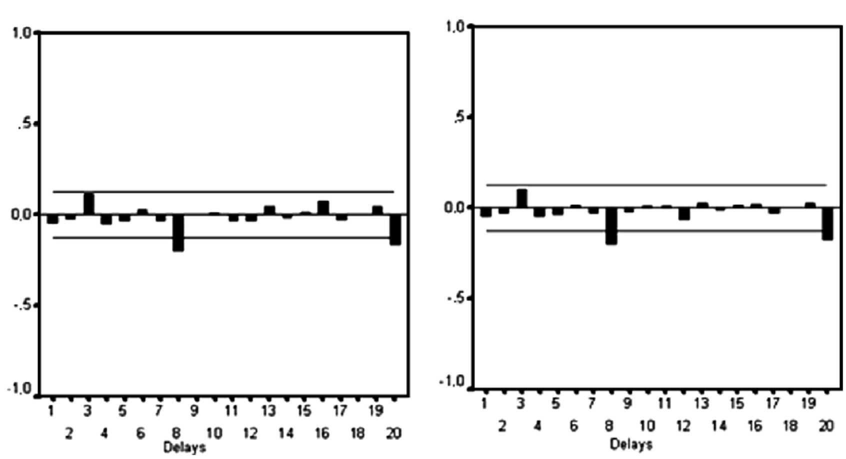

Fig. 5. TAC and PAC of the residues of the model ARMA (0, 1), after a seasonal four-order differentiation.

Table 5
Correlation coefficients obtained by TDNN and ARMA in the out-of-sample time series predictions (i.e., predictions in the validation period) in the projects 'Legal' and 'Mail'

Project name	Validation period (Training period)	Correlation coefficient in out-of-sample predictions (best model)
LEGAL	Weeks 23–26, 2003 (Weeks 2–22, 2003)	0.94 ± 0.01 (ARMA, TDNN)
	Weeks 49–52, 2003 (Weeks 37–48, 2003)	0.87 ± 0.01 (TDNN)
	Weeks 23–26, 2004 (Weeks 2–22, 2004)	0.93 ± 0.01 (ARMA, TDNN)
	Weeks 49–52, 2004 (Weeks 37–48, 2004)	0.86 ± 0.01 (ARMA, TDNN)
Mail	Weeks 23–26, 2003 (Weeks 2–22, 2003)	0.88 ± 0.01 (ARMA, TDNN)
	Weeks 49–52, 2003 (Weeks 37–48, 2003)	0.86 ± 0.01 (TDNN)
	Weeks 23–26, 2004 (Weeks 2–22, 2004)	0.91 ± 0.01 (ARMA, TDNN)
	Weeks 49–52, 2004 (Weeks 37–48, 2004)	0.75 ± 0.01 (ARMA, TDNN)

Parentheses in the second column indicate the training period while the validation period is indicated without parentheses. In the third column, the best model is enclosed in parentheses.

Six-hundred and forty vectors in the phase space were used to calculate D_2 with a security time equal to 5 in order to avoid an excessive autocorrelation between vectors; the radius of the reticulum was varied between $\sigma/20$ and $\sigma/2$, being σ the standard deviation of data. As it was expected, D_2 showed a value equal to [1.5, 1.6], i.e. according to Takens Theorem, our embedded space should be at least 3-dimensional (Takens, 1981; Kantz & Schreiber, 1999).

After that, twenty data sets were generated from the original series, thus obtaining values for D_2 between 1.79 and 1.86. Each of the D_2 surrogates values were higher than the original time series D_2 value (1.6), hence, the time series can be considered as significantly nonlinear with a confidence of 95%. Details of this nonlinearity test can be found in Kantz and Schreiber (1999).

Summarizing, time series of the project "Health Care System Card" showed a behavior which was mainly periodic, having nonlinear effects in the last months of years 2003 and 2004. Therefore, linear models offered a suitable prediction in the number of events 6 h ahead, but TDNN improved considerably prediction performance in the last months of both years. This improvement was due to the significantly-deterministic nonlinear behavior of the series, i.e. the origin of the nonlinearities was not only noise.

3.5. Other projects

The analyses shown in previous subsections were also carried out in all the projects shown in Table 1. Table 5 presents the most successful models in terms of the prediction accuracy in other two relevant CETESI projects, namely, '*Legal*' and '*Mail*'. Correlation coefficients between the targets and the model outputs were also very adequate in out-of-sample predictions, except in the case of the project *'Mail'* during the weeks 49–52 of 2004, in which the correlation coefficient was equal to 0.75. In both projects, deterministic nonlinear effects were only relevant during the weeks 49–52 in 2003, in which TDNN significantly improved the ARMA model predictions. In the rest of the projects shown in Table 1, it was possible to build accurate prediction models in several periods, but the standard of high accuracy required by CETESI (out-of-sample prediction coefficient >0.8) was not always achieved.

4. Conclusions

Time series related to the number of events in projects managed by CETESI have been analyzed in this study. Stochastic modeling and analysis has been used, as well as time processing neural networks and nonlinear time series analysis tools. The proposed approach allows to know whether time series show a deterministic behavior, and hence, it is possible to obtain a prediction model.

Results have shown the suitability of our approach in predicting the number of events 6 h ahead in the project "health care system card". This series is essentially linear, and therefore, ARMA modeling has offered robust predictions in many cases. However, there is a significant nonlinear effect in the last months of both years, being the prediction improved by the use of neural networks in these periods. Moreover, analysis of nonlinear parameters has proved this nonlinearity, and moreover, has guaranteed a prediction horizon that can be extended until one day ahead with an 88–97% prediction accuracy (correlation between out-of-sample observed data and model output). The proposed approach can be successfully applied to other CETESI projects, with 86–94% prediction accuracy in many of the year periods. We feel that this new method is a useful tool for management of Support Centers.

References

Bishop, M. (1995). *Neural networks for pattern recognition*. Clarendon Press.

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: forecasting and control*. Wiley.

Brockwell, P. J., & Davis, R. A. (2002). *Introduction to time series and forecasting*. Springer.

Haykin, S. (1999). *Neural netwoks: a comprehenshive foundation*. Prentice Hall.

Kantz, H., & Schreiber, T. (1999). *Nonlinear time series analysis*. Cambridge University Press.

Makridakis, S., Wheelwrigth, S. C., & Hyndman, R. J. (1998). *Forecasting: methods and applications*. Prentice Hall.

Takens, F. (1981). Detecting strange attractors in turbulence. *Springer lecture notes in mathematics, 898*, 366–381.

Vapnik, V. N. (1999). *The nature of statistical learning*. New York: Springer.

Weigend, A. S., & Gershenfeld, N. A. (1996). *Time series prediction: forecasting the future and understanding the past*. Addison-Wesley.

Wiggins, S. (2003). *Introduction to applied nonlinear dynamical systems and chaos*. New York: Springer.