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On-Condition Maintenance for Wind Turbines

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Abstract — **This work presents a system to manage wind turbines maintenance through a predictive model. The system is based on specific maintenance software and hardware for data acquisition and also on algorithms for prediction based on time series. The maintenance software is called SMIT - (Terology Integrated Modular System). The acquisition system can be interconnected with professional, industrial and low cost acquisition systems. The communication channel is based on IP networks, using clock synchronization for data sampling. A time series prediction algorithm runs on low cost hardware, working as a monitoring trigger of the central system.**

Index Terms — **wind energy, renewable energy, equipment maintenance, time series prediction.**

I. INTRODUCTION

THE market of wind energy is growing in this century, mainly due to the trend of the oil scarcity, its high price in the international markets and the climatic alterations produced by pollution. The financial and energy crisis will also play an important role in future decisions on the energy production systems and wind generators. As mentioned, they can contribute for a better environment.

In this article it will be presented an integrated system for maintenance of wind energy production systems and a methodology to optimize the production cycles and, consequently, the reduction of other kinds of energy production.

The new methodologies will be later incorporated through new predictive maintenance modules in an integrated maintenance management system called SMIT (Terology Integrated Modular System) [9], [17], [14], [15].

The SMIT system includes the main modules of a traditional system, as well as a fault diagnosis, a non-periodic maintenance planning and a generic on-condition maintenance module, among other innovations. The new features will include, in the case of wind generators, on-line measures and the corresponding on-time treatment, using forecasting algorithms based on time-series and wireless technology to transmit the signals.

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II. AN INTEGRATED MAINTENANCE PRACTICE FOR RENEWABLE WIND SYSTEMS

A. The global system

The proposed system for integrated maintenance of wind systems is described on Fig. 1. The central system is based on a Linux server running apache web server and postgreSQL database [16]. The server incorporates the logic necessary to save the normal information adjacent to a maintenance system like: working orders; planned maintenance management (including on-condition maintenance); emission of reports, analyses and improvement of maintenance plans; spare parts; maintenance objects; suppliers (of equipment, parts and services); human resources management and tools management.

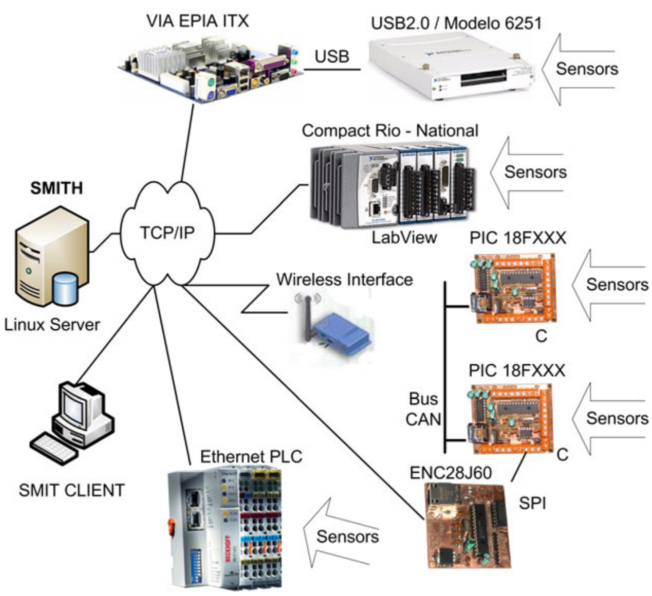

Fig. 1. An integrated system for maintenance of Wind systems

B. Important signals for wind maintenance systems

Figure 2 shows the most used wind generator by commercial companies. The important parts of wind generators are: the rotor blades; the main shaft; the gearbox; the secondary shaft and break system; the generator; the pitch control system of the rotor blades and the nacelle alignment system.

To infer the "health" of a wind system some signals are acquired like: active and reactive power; wind velocity; rotor blade velocity; shaft velocity and vibration signals on the

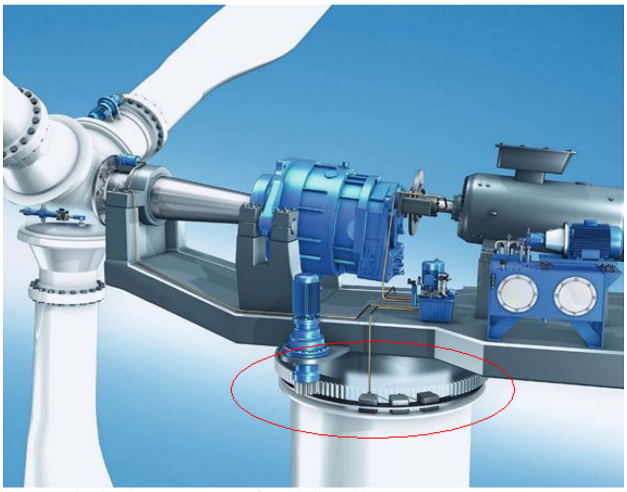

Fig. 2. Principal components of a wind turbine

gearbox and generator; and the state of the pitch control.

The signature of the wind generator is then compared with the power curve, using Support Vector Machine classifier. In this article only the process using time series will be described. Time series algorithms are used to predict problems in the generator and gearbox with help of Fast Fourier transform and they will be used to "track" the amplitude of spectral signals of the vibration on some range frequency values.

III. Time Series Analysis to predict wind generators maintenance

Time series analysis accompanies and "tries" to understand the evolution of data received through time. The important issues to measure are: trend; seasonality; cyclicality; and error or random components. In the science field, time series analysis are welcome on the economics to maximize profit, but also to predict important aspect of humans like ambient catastrophes, minimizing human dramas, predicting industrial production to adjust the production to the esteem levels of search, and many others.

Many techniques have been presented throughout the times, catalogued in three great methodologies: use of statistical methods; use of adequate models to the process in question or use of artificial intelligence methodologies [18], [19]. Although the innumerable methods, more or less elaborated, all them present forecasting errors, being one of the imperatives to minimize definitive metric adjacent to the measure of these errors.

A. Time Series Theory

If time series [1], [2], [3], [4], [5], [6], [7], [8] forecasting can be accomplished by normal function, the series is called deterministic, otherwise, if forecasting is only possible by statistical methods the time series is called stochastic. The respective stochastic process can be represented by $Y = \{y(t,\theta); t \in T, \theta \in \Omega\}$, where T represents the time space and Ω represents the space of a probabilistic event. A stochastic temporal process is stationary if is invariant to a time shift, i.e., $y(t,\theta) = y(t+\Delta t,\theta), \forall \Delta t \in T$.

For each observation, a stochastic time series will apply, represented by $y[k], k = 1,2,3,...$ where k represents a variable evenly spaced in time where $t = \Delta t_s \cdot k$. Our problem then, is how to forecast the values for $\hat{y}[k+m], m > 0$ (we will use notation $\hat{y}$ for prediction and in some cases, for better readability, $y_k = y[k]$).

$$\hat{y}[k+1] = f\left(y[k-i]\right), i = 0,..., k-1 \tag{1}$$

The quality of forecasting will be measured by error indicators: MSE – Mean Square Error and TIC-Theil Inequality Coefficient

$$MSE = \frac{1}{h}\sum_{i=k-h}^{k-1}\left(y[i+1] - \hat{y}[i]\right)^2 \tag{2}$$

$$TIC = \frac{\sqrt{\frac{1}{h}\sum_{i=k-h}^{k-1}\left(y[i+1] - \hat{y}[i]\right)^2}}{\sqrt{\frac{1}{h}\sum_{i=k-h}^{k-1} y[i+1]^2} + \sqrt{\frac{1}{h}\sum_{i=k-h}^{k-1}\hat{y}[i]^2}} \tag{3}$$

Moving Average Algorithm

Moving Average [20] (results will be labeled with *MAS*) takes the forecast as a weighted average of data in a window of fixed width, where $\sum_{i=0}^{N-1} W[i] = 1$.

$$\begin{cases} \hat{y}[k] = \dfrac{\sum_{i=0}^{N-1} y[k-i] \cdot W[i]}{\sum_{i=0}^{N-1} W[i]} \\ \hat{y}[k+m] = \hat{y}[k] + m \cdot \left(y[k] - \hat{y}[k-1]\right) \end{cases} \tag{4}$$

Exponential Smoothing Algorithm

Exponential smoothing (results will be labeled with *ES*) uses two values to predict the next forecast value, where $\hat{y}[1] = y[1]$

$$\begin{cases} \hat{y}[k] = \alpha \cdot y[k] + (1-\alpha) \cdot \hat{y}[k-1] \\ \hat{y}[k+m] = \hat{y}[k] + m \cdot \alpha \cdot \left(y[k] - \hat{y}[k-1]\right) \end{cases}, \text{ where } \alpha \in [0,1] \tag{5}$$

The value for α can be obtained minimizing the MSE, conducting to a non-linear optimization problem, usually solved by the Levenberg-Marquardt algorithm.

It is possible to continuously update α value (results will be labeled with *ESMSE*) and introducing an estimation of α with an implicit error, considering that the old forecasting values are independent of α; equation (6) represents the update. However, we will use the mean of equation (6) with the equation (6) substituting $\hat{y}[i-1]=y[i-1]$ (MSE minimization).

$$\alpha=\frac{\sum_{i=n}^{k}\left(y[i+1]-\hat{y}[i-1]\right)\cdot\left(y[i]-\hat{y}[i-1]\right)}{\sum_{i=n}^{k}\left(y[i]-\hat{y}[i-1]\right)^2},n\geq 2 \quad (6)$$

Adaptive Response Rate Single Exponential Smoothing

This is a variant of exponential smoothing that continuously updates the smoothing parameter (results will be labeled with *ARRSES*). This method allows changes in a trend (normally at start, β=0.5 and α=0.5).

$$\begin{cases}\hat{y}[k]=\alpha_k\cdot y[k]+(1-\alpha_k)\cdot\hat{y}[k-1]\\ e_k=y[k]-\hat{y}[k-1]\\ E[k]=\beta\cdot e_k+(1-\beta)\cdot E[k-1]\\ M[k]=\beta\cdot|e_k|+(1-\beta)\cdot M[k-1]\\ \alpha_{k+1}=\left|\frac{E[k]}{M[k]}\right|\\ \hat{y}[k+m]=\hat{y}[k]+m\cdot e_k\end{cases} \quad (7)$$

Exponential Smoothing Algorithm – Holt-Winters forecast

Exponential smoothing described by equation (5) can be improved to handle better trends and seasonality (results will be labeled with *HWSas* with seasonality and *HW* without) of period *n* where $\alpha,\beta,\gamma\in[0,1]$, as described on equation (8).

$$\begin{cases}\hat{y}[k]=\alpha\cdot\left(y[k]+s[k-n]\right)+(1-\alpha)\cdot\left(\hat{y}[k-1]+b[k-1]\right)\\ b[k]=\beta\cdot\left(\hat{y}[k]-\hat{y}[k-1]\right)+(1-\beta)\cdot b[k-1]\\ s[k]=\gamma\cdot\left(y[k]-\hat{y}[k]\right)+(1-\gamma)\cdot s[k-n]\\ \hat{y}[k+m]=\hat{y}[k]+m\cdot b[k]+s[k+m-n]\end{cases} \quad (8)$$

The initial setup is very important and depends on the length *n* of the period of seasonality.

AR, MA, ARMA and ARIMA models, Box-Jenkins

To introduce these models let consider the Lag operator denoted L as $Ly[k]=y[k-1]$, with properties $L^2y_k=y_{k-2}$, $L^0y_k=y_k$ and $L^{-2}y_k=y_{k+2}$. This operator can also be used in polynomials $a(L)=a_0+a_1\cdot L+...+a_p\cdot L^p$, and applied to time series $a_p(L)\cdot y_k=a_0\cdot y_k+a_1\cdot y_{k-1}+...+a_p\cdot y_{k-p}$. In this case $a_p(L)$ have order *p*.

Considering $wn[k]$ as a white noise process with mean $E\{wn[k]\}=1$, $E\{wn[k_1]\cdot wn[k_2]\}=0$ and $E\{wn^2[k]\}=0$, then a ARMA (Auto-Regressive Moving Average) model - known as ARMA(p,q) (results will be labeled with *ARMA*) – is described by the following equation:

$$a_p(L)\cdot y[k]=b_q(L).wn[k] \quad (9)$$

A times series follows an ARIMA(p,d,q) process if and only if its derivative of order *d* follows an ARMA(p,q) (Auto-Regressive Integrated Moving Average, the I for integrated means when a time series needs to be differenced to be stationary):

$$a_p(L)\cdot\nabla^d y[k]=b_q(L).wn[k] \quad (10)$$

Setting p=0, d=0, equation (10) stands for a MA process, setting d=0, q=0 equation (10) stands for an AR process.

The ARIMA methodology includes analyzing data for model identification, model estimation and model validation. The main problem with ARIMA models resides on model identification suitable for the actual data. Some author use genetic programming [7], others [8] use ANN for ARIMA model tuning.

Support Vector Machines Regression - SVR

Support Vector Regression [12], [13] (results will be labeled with *SVR+Kernel*) performs a non linear mapping between the user space and the feature space and then performs a normal linear regression.

Given a dataset $\{(x_1,y_1),...,(x_k,y_k)\}\subset\chi\times\Re$, where X is de input space, in ε-SVR the goal is to find a function f(x) with a deviation of ε.

In the linear case

$$f(x)=\langle w,x\rangle+b, w\in\chi, b\in\Re, \quad (11)$$

where $\langle .,.\rangle$ is a dot product. Using Euclidian norm, the optimization problem can be written as:

$$\begin{array}{l}\min_{\vec{w}}\left\{\frac{1}{2}\langle w,w\rangle=\frac{1}{2}\|\vec{w}\|^2\right.\\ subject\quad\begin{cases}y_i-\langle w,x_i\rangle-b\leq\varepsilon\\ \langle w,x_i\rangle+b-y_i\leq\varepsilon\end{cases}\end{array} \quad (12)$$

The main idea is always the same: to minimize error, individualizing the hyper plane that maximizes the margin, keeping in mind that part of the error is tolerated [21].

The loss function can be quadratic, Laplace, Huber or ε-sensitive (Fig. 3). The first one corresponds to the least square error criterion. Second is less sensible to outlier's points. Huber's function is used when the underlying distribution of the data is unknown, and the last one is an adaptation of the function of Huber introduced by Vapnik. More details can be seen in [21],[22],[23].

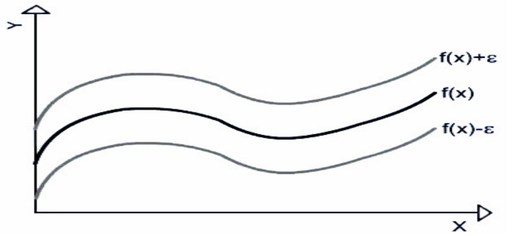

Fig. 3. Representation in $\Re^2$ of the loss function indicating the error tolerance; in this case the ε-sensitive

B. Using Time Series Analysis for Predicting future damage on wind turbines

Several works in the past and in the present are under progress in this field as can be seen on [10], [11].

First, not forgetting the central goal of this work:

"… to forecast the temporal instant where we will have one probable damage. With this information launch an working order in the SMIT maintenance software, to opportunely the causes that in the future will give damages are corrected in the present …".

The answer to this question stipulates, at first hand, the continuity of key variables that must be observed, and provides instant information to the "state of health" of equipment.

By analogy with human life, and removing rare exceptions, no person instantly passes from a state of good health to a state of death (except, accidents). There are lots of medical examinations that allow foresee any serious illness.

Even in extreme cases such as exposure to pathogens harmful to human life, for example, viruses, chemical weapons or, in a case of death by drowning, probably a monitoring system in some measurable variable of the human body could predict what would happen. In the case of drowning, monitoring the amount of oxygen allowed by the pulmonary system, amount of water absorbed or heart rhythm would predict the death before this happens.

What is intended to emphasize, it is to indicate that there is a high expectable probability of the monitored systems to keep some continuity on the variables monitored, that are, mathematically speaking, most probable that they are functions without discontinuities. Similarly, it is also foreseeable that if a determined functionality of equipment begins to enter in a deterioration state, some measurable variable of the equipment departs from nominal values, entering into a rise or fall continuously.

The speech related to the previous paragraph supposedly and mostly of time is true, however, incorporating the result of the maintenance intervention (with/without substitution of damaged components), it is intuitive, after the cause of the anomaly is corrected, and evidently the monitored signals will enter again inside of the tolerable range values. This behavior, studied by the time series level, indicate the existence of a seasonal period which will be necessarily directly related to the mean time between failures. Other likely hypothesis is the existence of a discontinuity at the parameter measured, between the moments between pre-maintenance and post-maintenance.

To overcome this problem, if the Mean Time Between Failures (MTBF) is known, then a normal algorithm can be used (rather then trying to estimate the seasonal length), otherwise, after a maintenance intervention, the time series will be initialized again. This last procedure will overcome the problem of measuring accurately the seasonal period and, in practice, will remove it. Another feature of the algorithm is the necessity, for each signal: to indicate the intervals of tolerance, in particular; acknowledgment interval and the critical interval. When the time series provides an output out of these bauds, the SMIT software launches a warning to the operator.

IV. Experimental Results for Forecasting Maintenance Based on Time Series Analysis

In this section results for the algorithms presented on section III-B will be presented.

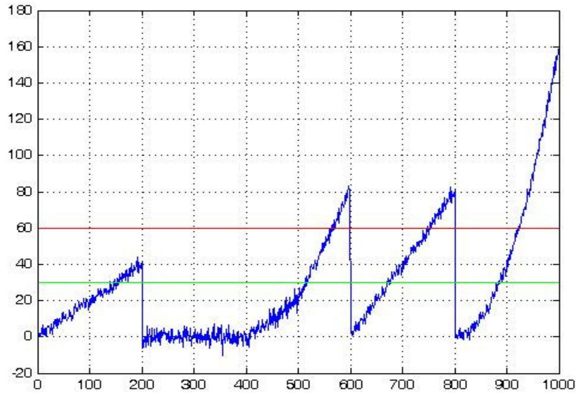

Fig. 4. Typical time series for maintenance parameters to track

Figure 4 shows the first typical time series to track divided for better understanding in 10 different types of situation that

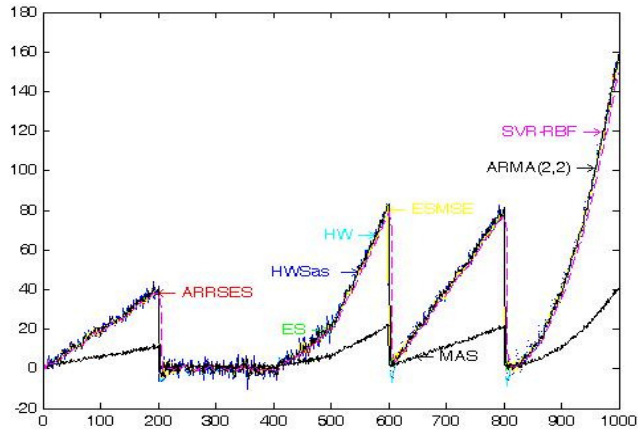

Fig. 5. Methods results, where smoothing moving average prediction, will not work, and is normal experimental result as expected (MAS signal).

could occur. From 0-200 we have a situation of accentuate trend, from 200-400 a normal operation, from 400-600

TABLE I
PREDICTION OF 1 STEP AHEAD

	MSE	*TIC*	*ME*	*STD*	*MAE*
ARRSE	28.362	0.0627	0.3995	5.3132	2.7672
ES	26.057	0.0601	0.3145	5.0974	2.6602
HW	26.225	0.0600	**0.1665**	5.1209	2.6537
HWSAS	29.464	0.0636	0.1880	5.4275	3.0439
ESMSE	**24.039**	**0.0575**	0.2464	**4.8992**	**2.6514**
MAS-2	1029	0.5976	21.096	24.190	21.857
ARMA(2,2)	42.470	0.0762	-0.1165	6.5191	2.7513
SVR-RBF	84.286	0.1099	1.1043	9.1187	4.2527
SVR-LIN	57.268	0.0880	-0.1571	7.5697	2.9946

TABLE II
PREDICTION OF 10 STEP AHEAD

	MSE	*TIC*	*ME*	*STD*	*MAE*
ARRSE	718.64	0.2893	-1.0357	26.801	10.929
ES	532.52	0.2537	-1.2953	23.051	11.572
HW	**40.268**	**0.0759**	**-0.6918**	6.3111	**2.9670**
HWSAS	56.319	0.0895	-0.7201	7.4737	4.3308
ESMSE	766.09	0.2961	-1.3597	27.659	13.638
MAS-2	232320	0.8564	-335.12	346.62	337.93
ARMA(2,2)	44.743	0.0784	-2.9514	**6.0057**	4.1333
SVR-RBF	84.687	0.1162	0.9923	9.1535	4.1557
SVR-LIN	155.15	0.1444	-2.4963	12.209	5.8031

accentuate trend with different slopes, from 600-800 a high slope trend and finally from 800-1000 a quadratic trend.

Results will be described for 1 and 10 steps ahead for algorithms described on section III. The normal situation will be 200-600 where we have described the normal time life of

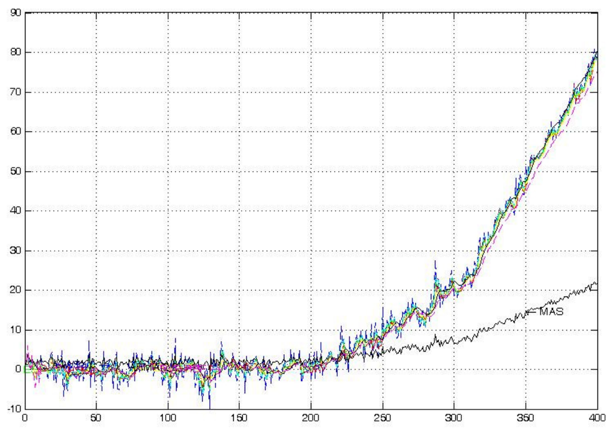

Fig. 6. Prediction only for time 200-600 of Fig. 5

equipment followed by its end of life stage. Green and Red lines show limits (Fig. 4), indicating acknowledge and critical intervals.

Table I, II, III, IV and figures 5 and 6 show the results for the tested methods.

From these preliminary tests, the Holt Winter algorithm without seasonality gets a better performance when predicting

TABLE III
PREDICTION OF 1 STEP AHEAD (TIME 200-600)

	MSE	*TIC*	*ME*	*STD*	*MAE*
ARRSE	10.072	0.0601	0.5281	3.1333	2.5372
ES	10.510	0.0612	0.3779	3.2239	2.5530
HW	10.501	0.0609	0.1940	3.2387	2.5427
HWSAS	10.567	0.0611	0.2045	3.2483	2.5509
ESMSE	9.8944	0.0598	0.6197	3.0878	2.4857
MAS-2	371.69	0.5555	9.1922	9.1922	11.834
ARMA(2,2)	**9.0579**	**0.0566**	0.3849	**2.9887**	**2.3602**
SVR-RBF	12.821	0.0694	1.2580	3.3565	2.8791
SVR-LIN	10.355	0.0602	**0.0971**	3.2205	2.5538

TABLE IV
PREDICTION OF 10 STEP AHEAD (TIME 200-600)

	MSE	*TIC*	*ME*	*STD*	*MAE*
ARRSE	133.37	0.2147	-1.3967	11.479	7.7911
ES	213.76	0.2626	-1.5506	14.557	11.488
HW	**4.9649**	**0.0446**	**-0.8799**	**2.0498**	**1.7598**
HWSAS	5.7404	0.0480	-0.8823	2.2304	1.8841
ESMSE	40.486	0.1228	-1.3147	6.2336	4.7259
MAS-2	85751	0.8588	-174.42	235.52	179.19
ARMA(2,2)	14.927	0.0761	-1.1757	3.6850	3.0207
SVR-RBF	12.363	0.0755	1.1625	3.3226	2.8044
SVR-LIN	22.037	0.0921	-1.6377	4.4051	3.7564

10 steps ahead. SVR-RBF seems to be a stable solution to be studied more deeply, because under these tests only 10 points were used for the training. However, further improvements should be done on SVR while in training, during the time to stabilize.

The tests were done with the presence of white noise of mean 3 and 2.

For each algorithm the parameters were ARRSE(0.5,0.2); ES(0.5); HW(0.5,0.2); HWSAS(0.5,0.2, 0.2,20); ESMSE(0.5,0); MAS(2); ARMA(2,2); SVR-RBF(30,10) and SVR-LIN(30,10);

V. CONCLUSION

The algorithms proposed are used for forecasting problems in wind turbine systems, and the results are promising. Next future work will pursue the goal to automate the choice of the model used depending on the signal/situation. Another important issue is to accommodate the results for non periodic sampled time series. This is an important goal, because most of the cases, the data will be sampled with different period over time.

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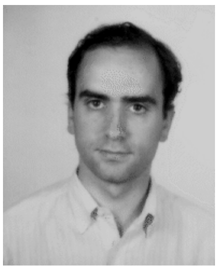

Inácio Fonseca was born in Coimbra, Portugal, in 1971. He received the B.S. degree in electrical engineering from Coimbra University, Portugal, in 1994, and the M.Sc. degree in 1998 from the University of Coimbra. Presently, he is PhD student at Oporto University.
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