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Short-term time series algebraic forecasting with mixed smoothing

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ABSTRACT

Short-term time series algebraic prediction technique with mixed smoothing is presented in this paper. Evolutionary algorithms are employed for the identification of a near-optimal algebraic skeleton from the available data. Direct algebraic predictions are conciliated by internal errors of interpolation and external differences from the moving average. Computational experiments with real world time series are used to demonstrate the effectiveness of the proposed forecasting algorithm.

1. Introduction

Time series prediction is a challenging problem in many fields of science, engineering and finance. Time series forecasting techniques could be conditionally classified into long-term time series forecasting techniques and short-term time series forecasting techniques. In general, the object of all time series forecasting techniques is to build a model of the process and then use this model to extrapolate past behavior into future. Unfortunately, the applicability of techniques for building the model of a long time series for a short time series is often impossible simply due to the fact that the amount of available data for training, validation and testing is simply too small. On the other hand, one step-forward future horizon is often a sufficient requirement for a short-term time series predictor.

Smoothing methods can be successfully involved in short-term forecasting techniques. The use of general exponential smoothing to develop an adaptive short-term forecasting system based on the observed values of integrated hourly demand is explored in [1]. Short-term load forecasting with exponentially weighted methods is proposed in [2].

Applications of neural network techniques to short-term time series forecasting are widely used [3]. Artificial neural network (ANN) and Markov chain (MC) are used to develop a new ANN-MC model for forecasting wind speed in very short-term time scale [4]. A novel hybrid approach, combining adaptive-network-based fuzzy inference system, wavelet transform and particle swarm optimization for short-term electricity prices forecasting in a competitive market on the electricity market of mainland Spain, is presented in [5]. A similar day-based wavelet neural network method to forecast tomorrow's load is proposed in [6]. Another short-term load forecasting based on a semi-parametric additive model is presented in [7]. An adaptive neuro-fuzzy inference system to forecasting a very short-term wind time series is presented in [8]. The radial basis function ANN with a nonlinear time-varying evolution particle swarm optimization (PSO) algorithm is used to forecast one-day ahead and five-days ahead of a practical power system in [9]. PSO algorithms are employed to adjust supervised training of adaptive ANN in short-term hourly load forecasting in [10]. An adaptive two-stage hybrid network with self-organized map (SOM) and support vector machine (SVM) is used for short-term load forecasting in [11].

Artificial neural networks (ANNs) can be combined with other time series forecasting methods like autoregressive integrated moving average (ARIMA) models to take advantage of the unique strength of ARIMA and ANN models in linear and nonlinear modeling [12]. One day ahead forecasting techniques for energy demand and price prediction that combine wavelet transform (WT) with fixed and adaptive machine learning/time series models (multi-layer perceptron (MLP), radial basis functions, linear regression, or GARCH) are proposed in [13]. A hybrid methodology that combines both autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) models for predicting short-term electricity prices is proposed in [14]. Short-term electricity prices hybrid forecast model that detaches high volatility and daily seasonality for electricity price based on empirical mode decomposition, seasonal adjustment and ARIMA

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is developed in [15]. The comparison of the predictions of nonlinear models (artificial neural networks) with linear models (of the ARMA type) to forecast the short-term demand for electricity is presented in [16]. A robust two-step methodology for accurate wind speed forecasting based on Bayesian combination algorithm and three neural network models is proposed in [17]. A time series model of forecasting very short-term wind speed that integrates the concepts of structural breaks and Bayesian inferences, which allows prior information about the wind speeds to be incorporated into the model and boosts forecasting performance, is presented in [18].

Short-term time series forecasting techniques are successfully applied to predict weather conditions, especially wind speed. The promising results in electricity market while predicting next days electricity load demand or price implicate that short-term time series techniques can be successfully employed also in the financial market (where financial time series can be characterized by having the long-memory effect, thick tails and volatility persistence). A support vector machine (SVM) based Markov-switching multifractal (MSM) approach which exploits iterative MSM model to forecast volatility and SVM to model the innovations is proposed as a promising alternative to financial short-term volatility prediction [19]. A hybrid ANFIS based forecasting model using linear model and moving average technical index to forecast TAIEX stock is proposed in [20]. A hybrid method that combines multiple kernel learning (MKL) and a genetic algorithm (GA) to forecast short-term foreign exchange rates is presented in [21]. A three-stage nonlinear ensemble model, where three different types of neural-network based models are optimized by improved particle swarm optimization (IPSO) and generated by support vector machines (SVM) neural network, is used for a day-ahead stock e-exchange prices forecasting [22].

In spite of numerous amount of forecasting models and techniques, there cannot be a universal model that will predict everything well for all problems and there will probably not be a single best forecasting method for all situations. The combination of several prediction methods into a hybrid model could extend the limits of its applicability and could capture the patterns which are difficult to apprehend by using isolated traditional models [23]. Nevertheless, even hybrid models cannot be considered as being universal.

The main objective of this paper is to propose an algebraic short-term time series predictor with mixed smoothing which extends the functionality of algebraic predictors with external [24] and internal smoothing [25]. This paper is organized as follows. An overview of algebraic predictors with external and internal smoothing is presented in Section 2. The structure of algebraic predictor with mixed smoothing is discussed in detail in Section 3. The role of evolutionary algorithms in algebraic forecasting with mixed smoothing is presented in Section 4. Computational experiments are discussed in Section 6; concluding remarks are given in the last section.

2. Preliminaries

2.1. The rank of a sequence

An order n linear recurrence sequence (LRS) with constant coefficients reads

$$x_k = \alpha_{n-1}x_{k-1} + \alpha_{n-2}x_{k-2} + \cdots + \alpha_0 x_{k-n}; \quad k = 0, 1, \ldots; \tag{1}$$

where coefficients α_j, $j = 0, 1, \ldots, n-1$ are constants. The initial conditions x_k, $k = 0, 1, \ldots, n-1$ uniquely determine the evolution of this LRS [26,27]. The auxiliary polynomial to Eq. (1) reads

$$P(\rho) = \rho^n - \alpha_{n-1}\rho^{n-1} - \alpha_{n-2}\rho^{n-2} - \cdots - \alpha_0. \tag{2}$$

If the n roots $\rho_1, \rho_2, \ldots, \rho_n$ of Eq. (2) are all distinct then the LRS takes the form

$$x_j = \mu_1\rho_1^j + \mu_2\rho_2^j + \cdots + \mu_n\rho_n^j; \tag{3}$$

where the coefficients $\mu_1, \mu_2, \ldots, \mu_n$ are determined in order to fit the initial conditions of the recurrence. Note that all roots are real or complex conjugate if only LRS is real. If though some roots coincide, then the recurrence reads

$$x_j = \sum_{k=1}^{r}\sum_{l=0}^{n_k-1} \mu_{kl}\binom{j}{l}\rho_k^{j-l}; \tag{4}$$

where r is the number of distinct roots; n_k is the multiplicity index of the kth root; $n_1 + n_2 + \cdots + n_r = n$.

The algorithm for the reconstruction of the model of LRS from a sequence $(x_j)_{j=0}^{+\infty}$ is more complex if the order of RMS is not known beforehand. Hankel transform of $(x_j)_{j=0}^{+\infty}$ yields the sequence $(h_j)_{j=0}^{+\infty}$ where $h_j = \det H_j$ and $H_j = (x_{k+l-2})_{1\le k,l\le (j+1)}$ is a Hankel catalecticant matrix (the dimensions of H_j are $(j+1)\times(j+1)$). If there exists $n \ge 1$ such that $h_n \ne 0$ but $h_k = 0$ for all $k > n$, then $(x_j)_{j=0}^{+\infty}$ is LRS, its order is n and the auxiliary equation (2) now reads

$$\begin{vmatrix} x_0 & x_1 & \cdots & x_n \\ x_1 & x_2 & \cdots & x_{n+1} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n-1} & x_n & \cdots & x_{2n-1} \\ 1 & \rho & \cdots & \rho^n \end{vmatrix} = 0. \tag{5}$$

This linear system of algebraic equations has one and the only one solution because $h_n \ne 0$ [28].

The following example illustrates the identification of the algebraic model of a time series. Let us consider a sequence

$S = (2, 5, 14, 42, 130, 406, 1266, \ldots)$.

The proposed sequence is an order $n=3$ linear recurrence sequence because $h_k = 0$ for all $k > 3$. The auxiliary equation

$$\begin{vmatrix} 2 & 5 & 14 & 42 \\ 5 & 14 & 42 & 130 \\ 14 & 42 & 130 & 406 \\ 1 & \rho & \rho^2 & \rho^3 \end{vmatrix} = -2\rho^3 + 14\rho^2 - 32\rho + 24 = 0$$

yields roots $\rho_1 = \rho_2 = 2; \rho_3 = 3$. Then $n_1 = 2; n_2 = 1$ and (4) takes the following form: $x_n = \mu_{10}\rho_1^n + \mu_{11}n\rho_1^{n-1} + \mu_{20}\rho_2^n$. The linear algebraic system for identification of coefficients μ_{10}, μ_{11}, μ_{20} reads

$$\begin{bmatrix} 1 & 0 & 1 \\ \rho_1 & 1 & \rho_2 \\ \rho_1^2 & 2\rho_1 & \rho_2^2 \end{bmatrix}\begin{bmatrix} \mu_{10} \\ \mu_{11} \\ \mu_{20} \end{bmatrix} = \begin{bmatrix} 2 \\ 5 \\ 14 \end{bmatrix}.$$

Solutions are $\mu_{10} = 0$, $\mu_{11} = -1$, $\mu_{20} = 2$. Thus, finally, $x_n = 2\cdot 3^n - n\cdot 2^{n-1}$.

Corollary 1. *The order of a random sequence is infinite. The proof is straightforward. Assume that the order of a random sequence is finite. Then, according to Eq. (4), it is possible to reconstruct the algebraic model governing the evolution of this random sequence. Thus, the dynamics of the sequence is deterministic, what contradicts to the definition of a random sequence.*

Corollary 2. *Let the order of $(x_j)_{j=0}^{+\infty}$ is m and the order of a random sequence $(\varepsilon_j)_{j=0}^{+\infty}$ is infinite. Then the order of $(x_j+\varepsilon_j)_{j=0}^{+\infty}$ is infinite. The proof follows from Eq. (4).*

All real world time series are inevitably contaminated with an additive noise. Thus a straightforward application of algebraic LRS theory is impossible to real world time series. Special adaptive