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Forecasting the COMEX copper spot price by means of neural networks and ARIMA models

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ABSTRACT

This paper examines the forecasting performance of ARIMA and two different kinds of artificial neural networks models (multilayer perceptron and Elman) using published data of copper spot prices from the New York Commodity Exchange, (COMEX). The empirical results obtained showed a better performance of both neural networks models over the ARIMA. The findings of this research are in line with some previous studies, which confirmed the superiority of neural networks over ARIMA models in relative research areas.

Introduction

Copper is one of the main metal commodities traded in the major physical futures trading exchanges: the London Metal Exchange (LME), the New York Commodity Exchange (COMEX), and the Shanghai Futures Exchange (SHFE). Prices on these exchanges reflect the balance between copper supply and demand at a worldwide level, although they may be strongly influenced by currency exchange rates and investment flows, factors that may cause volatile price fluctuations partially linked to changes in business cycle activity (Labys et al., 1998; Roberts, 2009).

Copper futures are financial tools that allow copper price mitigation opportunities, as copper prices are very sensitive to industries such as electrical wiring, construction and equipment manufacturing—all of them tending to follow economic cycles—as well as to producers—Codelco, Freeport-McMoRan Copper & Gold, Glencore Xstrata, BHP Billiton, Southern Copper Corporation, American Smelting and Refining Company, etc.—and even to countries like Chile and Zambia, whose economies are strongly dependent on copper production and subsequently on copper price evolution.

In these standardized markets, consumers, producers and investors use this asset each with their own purpose, generating an increasing demand on mathematical models to improve the prediction of price evolution using different methodologies: time series alone (Dooley and Lenihan, 2005) or combined with other methodologies such as wavelets (Kriechbaumer et al., 2014), model forecasting (Goss and Avsar, 2013), Fourier transformations (Khalifa et al., 2011), swarm optimization algorithm (Ma et al., 2013), multicommodity models (Cortazar and Eterovic, 2010), etc.

Through the purchase and sale of copper futures, consumers and producers are able to manage the price risk associated to their operations; consumers can secure a purchase price while producers can secure a selling price. Of course, investors can also take

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advantage of this market assuming the risk that the consumers and producers are trying to avoid.

Focusing on the COMEX (based on data availability), a part of the CME Group—one of the world's leading derivatives marketplaces—comprising among others the NYMEX (New York Mercantile Exchange), copper futures (HG symbol) are traded in contract sizes of 25,000 pounds and quoted in U.S. cents per pound; the contract basis is Grade 1 Electrolytic Copper Cathodes (full plate or cut) conforming to the specifications adopted by the American Society for Testing and Materials (CME Group, 2014).

In this market, where copper futures contracts are listed for the current month and the next 23 consecutive months according to the market contract specs, resulting a total of 24 different prices for the futures each trading day, the futures price at which parties agree to transact is determined using the spot price (price on the spot date, usually two bank days after the trading date), the money market rate—in order to include finance charges due to the delay of the payment—plus insurance and storage at any of the physical delivery places that CME Group has in the United States—which must be Licensed Warehouses—without any freight allowance.

This is the reason why spot prices, which indicate future price market expectations, and represent the underlying price of the future contracts, are the variables commonly used to study and analyze commodity price evolution or behavior.

Although the majority of the contracts are financially settled and never go to delivery, spot prices have direct relation with the place where delivery will occur. So, analyzing COMEX copper spot prices means analyzing copper prices in the United States. As CME Group is exploring to expand their copper futures business by opening new storage facilities in Chile—something completely opposite to the LME's policy of locating warehouses in consumption areas rather than in production areas (Thomas and Mason, 2013)—when this action takes place it will introduce the need to take new considerations into account when analyzing future COMEX copper spot prices.

Materials and methods

The present research used as its main source of data the copper spot closing prices from the COMEX from 2nd January 2002 to 16th January 2014. All the models employed in this paper were trained and validated using the free statistical software R version 3.0.1 (R Core Team, 2013) and with the help of the libraries *forecast* (Hyndman et al., 2013), *AMORE* (Castejon Limas et al., 2010) and *RSNNS* (Bergmeir and Benitez, 2012).

The ARIMA model

As is well-known, ARIMA models are nowadays the most generally used class of models for forecasting time series that can be stationarized by transformations such as differencing and logging (Mills and Markellos, 2008). The acronym ARIMA stands for auto-regressive integrated moving average. The lags of the differenced series appearing in the forecasting equation are called autoregressive terms, while lags of the forecast errors are called moving average terms. In general, any time series that needs to be differenced to be made stationary is said to be an integrated version of a stationary series (Bernardo Sánchez et al., 2013).

A nonseasonal ARIMA model (Mills and Markellos, 2008; Bernardo Sánchez et al., 2013) is classified as an ARIMA (p, d, q) model where p is the number of autoregressive terms, d is the number of non-seasonal differences and q is the number of lagged forecast errors in the prediction equation.

The generalized form of ARIMA can be described as follows (Ong et al., 2005):

$$\varnothing(B)\cdot\Phi(B^S)\cdot(1-B)^d\cdot(1-B)^D\cdot Y_t=\theta(B)\cdot\Theta(B^S)\cdot Z_t \quad (1)$$

where:

B is the backward shift operator,
d non-seasonal order of differences,
D seasonal order of differences,
$\varnothing$, Φ, θ, Θ polynomials in B and B^S.

Identifying the appropriate model for the stochastic component describing a time-series repetitive involves three steps, commonly known as the Box–Jenkins Approach (Box and Jenkins, 1970). First, based on preliminary information, a model is tentatively identified. Then, based on the tentative model, the corresponding model parameters are estimated. Finally, using the estimated coefficients, the goodness of fit of the model is estimated. As is clear from what has been said, the initial identification or simply specification is a very important element in the process of model building. However, combining the different orders p, d and q there is a huge number of possible models for any number of longitudinally-recorded data. Therefore, these stages are repeated until a suitable model for the given data set has been identified. In the present research, and in order to speed up the model identification process, a variation of the Hyndman and Khandakar algorithm has been used (Hyndman and Khandakar, 2008). This algorithm combines unit root tests and minimization of Akaike's Information Criterion (AIC) (Sugiura, 1978) and Maximum Likelihood Estimation (MLE) (Aldrich, 1997) to obtain the ARIMA models.

The multilayer perceptron neural network model

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. The MLP is a modification of the standard linear perceptron (Sánchez Lasheras et al., 2010). The MLP architecture is characterized as having its neurons grouped into layers of different levels. Each of the layers is formed by a set of neurons and three different kinds of layers are distinguished: the input layer, hidden layer and output layer. Fig. 1 shows a scheme of a MLP neural network with one hidden layer. Nowadays, multilayer perceptrons using a backpropagation algorithm are the standard algorithm for any supervised-learning pattern recognition process and the subject of ongoing research in computational

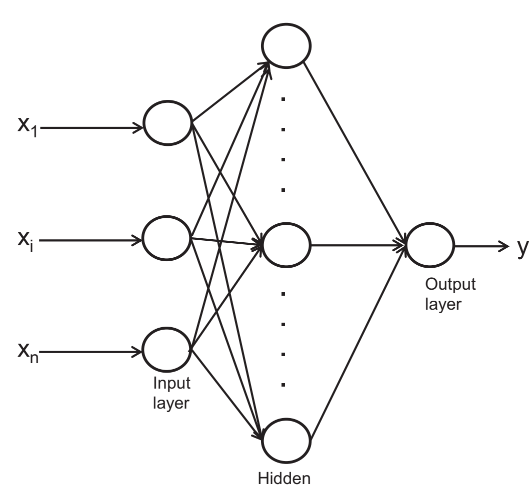

Fig. 1. Topology of feed forward multi-layer perceptron back-propagation ANN.