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Alternative techniques for forecasting mineral commodity prices

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ABSTRACT

Forecasting mineral commodity (MC) prices has been an important and difficult task traditionally addressed by econometric, stochastic-Gaussian and time series techniques. None of these techniques has proved suitable to represent the dynamic behavior and time related nature of MC markets. Chaos theory (CT) and machine learning (ML) techniques are able to represent the temporal relationships of variables and their evolution has been used separately to better understand and represent MC markets. CT can determine a system's dynamics in the form of time delay and embedding dimension. However, this information has often been solely used to describe the system's behavior and not for forecasting. Compared to traditional techniques, ML has better performance for forecasting MC prices, due to its capacity for finding patterns governing the system's dynamics. However, the rational nature of economic problems increases concerns regarding the use of hidden patterns for forecasting. Therefore, it is uncertain if variables selected and hidden patterns found by ML can represent the economic rationality. Despite their refined features for representing system dynamics, the separate use of either CT or ML does not provide the expected realistic accuracy. By itself, neither CT nor ML are able to identify the main variables affecting systems, recognize the relation and influence of variables though time, and discover hidden patterns governing systems evolution simultaneously. This paper discusses the necessity to adapt and combine CT and ML to obtain a more realistic representation of MC market behavior to forecast long-term price trends.

1. Introduction

Mineral commodities (MCs) have been fundamental for human development and exploited for more than 7000 years. Gold, copper, silver and iron ore are the oldest MCs being mainly used for construction, fabrication of domestic goods and also as a reservoir of value [1–7]. Mineral activities provide income to companies and investors, promoting investments and technological developments. Governments receive taxes and royalties from mineral exploitation and take advantage of technological developments through the improvement of workforce skills. Mining industry generates jobs, increases incomes and develops infrastructure [8–13]. The significance of this industry to economic, technological and social development is quite obvious [6]. Therefore, understanding the future behavior of MC prices is vital for all agents of the economy, so-called governments, companies and society.

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Econometric, qualitative, survey, stochastic and time series methods have been mainly used to forecast MC prices and trends [14]. Due to the close relation between the global economy and MC prices, econometric models are the oldest and the most intensively used methods [15,16]. However, historical data do not guarantee accurate predictions, as there is no certainty that past events will be repeated in the future at the same intervals and intensity. The common assumption of random behavior of MC markets has encouraged the use of stochastic-Gaussian models working within pre-established and well known boundaries for forecasting prices [17]. Nonetheless, each MC market has its own features regarding processing, trading, transportation and application that result in particular configurations. These differences have significant implications for pricing not only for a particular MC, but also for the complementary and substitute commodities. Therefore, there is ongoing debate as to whether MC prices do exhibit random behavior. Furthermore, despite the long-term balance asserted by microeconomic theory, prices and costs do not fluctuate randomly [18].

The random behavior of systems evolving through time has been questioned in nature and the stock market since 1963, then

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CT characterized the concept of sensitivity to initial conditions and self-similarity patterns of variables in dynamic systems [19–26]. CT and ML arose in the 1960s as alternative methods able to represent dynamic systems by describing the causal relation between variables. They have been used to represent and predict the behavior of complex dynamic systems in the fields of medicine, neuroscience, meteorology, stock markets and also in MC markets [17,21,27–33].

The temporal and learning properties of CT and ML techniques are appropriate for capturing MC markets behavior. CT enables an accurate determination of two important properties to reconstruct chaotic systems dynamic so-called embedding dimension and time delay. The embedding dimension corresponds to the number of variables governing the system. The time delay corresponds to the temporal influence of variables, meaning for how long changes of variables can affect the system [23,34–37]. ML can emulate human learning and find hidden patterns into large high dimensional data sets. Thus, ML has become one of the most powerful techniques to represent complex dynamic systems and for forecasting MC prices and trends. Despite their refined features to represent dynamic systems, neither CT nor ML can represent the properties of MC markets by themselves. They are unable to simultaneously detect the embedding dimension and the time delay, select the most significant variables affecting behavior and discover the patterns governing the system. However, a combination of CT and ML provides a better representation of MC markets and prices.

This paper investigates the main features of different MC markets, their dynamics and key features to enable better understanding of the principles behind the current techniques for forecasting MC prices. Several of these forecasting techniques are examined and their main advantages and drawbacks discussed. This paper further introduces two techniques to represent complex dynamic systems so-called CT and ML. Finally, the necessity and suitability to combining CT and ML to obtain a more realistic representation of MC markets to forecast long-term prices trends were discussed.

2. Mineral commodities

Mineral Commodities (MCs) are non-renewable resources classified as energy, metallic and non-metallic. Energy commodities refer to fluid and solid fossil fuels used for power generation. This group encompasses oil, gas, coal and uranium. Non-metallic commodities are defined as those minerals that do not contain recoverable metals. The group includes (among others) phosphate rocks, potash, salts, clays, sands, boron, and crushed and broken stones such as limestone and granite. Metallic commodities are defined as solid materials containing an appropriate composition of metal ores to be extracted and used as a metal precursor or as a direct raw material for manufacturing. They are categorized as either ferrous, light, precious or base metals [14,38,39]. However, this grouping can vary according to ultimate uses, market configuration and trading peculiarities (e.g. silver). MCs are traded worldwide in diverse futures and spot exchange markets (EXM). Table 1 provides the main markets for mineral commodities. The New York Mercantile Exchange (NYMEX) and the London Metal Exchange (LME) are the most important markets.

As with any other product traded in the markets, MC prices are fundamentally determined by supply and demand. Supply is driven by production costs and technology that reflect the competitiveness of the business. Demand is on the other hand driven by income and customer preferences that reflect the strength of the economy [9,10,12]. Economic, technological, political and psychological factors are the main variables affecting the balance between supply and demand in MC markets; therefore, their prices.

Table 1
Main exchange markets for mineral commodities (Adapted from [14,16,30,40–44]).

Market	Mineral commodities
London Metal Exchange (LME)	Aluminum, Aluminum alloy (NASAAC), copper, lead, nickel, silver, zinc, North American Special.
New York Mercantile Exchange (NYMEX)	Coal, natural gas, palladium, platinum, WTI
Shanghai Metal Exchange (SHME)	Aluminum, copper, lead, nickel, tin, zinc
Commodity Exchange of New York (COMEX)	Copper, gold, silver
Tokyo Commodity Exchange (TOCOM)	Aluminum, gold, silver, palladium, platinum
Chicago Board of Trade (CBOT)	Gold, silver
Kuala Lumpur Tin Exchange	Tin
Intercontinental Exchange (ICE)	Brent, coal, natural gas
European Energy Exchange (EEX)	Brent, coal, natural gas
Multi Commodity Exchange (MCX)	Coal, natural gas

The relationship between economic development and mineral industries is obvious. Increasing demand for goods and services has been historically driven by the economic expansion of developing countries. As a result, MC production grows to meet this increasing demand. Pei and Tilton claimed that in the short-term, the demand for MCs has elastic behavior to the Gross Domestic Product (GDP) and inelastic to the income [45]. Technological advances have reduced the adverse economic effects of mineral depletion. Development of more efficient and low cost technologies for mining and processing has increased ore reserves and mineral recovery performance [10,46]. Governments have an important influence on MC markets by introducing trading policies and market regulations generally when MC prices rise. Periods with high prices have encouraged the emergence of economically nationalist governments adopting regulations aimed at increased taxes and royalties [9,13,47]. Governments have gone further, manipulating not only taxation, but also the base for prices and company revenues [48]. Therefore, it human psychology must also be taken into account when considering systems exhibiting dynamic equilibrium through time, such as technological developments and economic growth [49], having significant impact on MC prices. In the past, Smith also claimed that market expectations are generated by the preferences of customers driven by psychological states [12]. In the risk premium theory, Keynes restated the significance of expectation of markets stating that under "normal" supply conditions, expected prices exceed current prices [50,51]. Human beings are complex systems fluctuating between disordered phases and complex stages of order. Influenced by the fluctuating environment and their own genetic inheritance, humans acquire experience over time. Experience can change their attitude which has a crucial influence for the decision-making process, especially during critical situations [52].

The evolution of MC prices and supply levels can provide important clues to understand the effects of economic, political, technological and psychological factors on MC markets. Fig. 1 shows the evolution of copper prices and production between 1850 and 2015, which also includes important geopolitical and economic events occurred in this period. The graph emphasizes the strong temporal relation between copper prices and economic, financial and technological factors.

3. Background of forecasting of mineral commodity prices

The analysis of market data provides important guidelines for choosing the most suitable model to predict prices [30,53]. Qualitative, trend exploration, linear, econometric, stochastic and time