Mineral Commodity Price Forecasting through Time-Series Modeling Techniques and Artificial Neural Networks: A Nickel Case Study

BRIAN ANDONAIRE VILLEGAS

Department of Mining and Materials Engineering

McGill University, Montreal, Quebec

July 2021

A thesis submitted to McGill University in partial fulfillment of the

requirements for the degree of **Masters of Science**

Abstract

The forecasting of mineral commodity prices, yet perhaps the most important factor to the decision-making process of mining companies, still remains an intricate task due to the different elements that drive such prices. To this date, several techniques have been developed with the aim of improving the forecasting accuracy; however, their architecture has also varied in terms of complexity.

This thesis explores the use of Artificial Neural Networks (ANNs) on the forecasting of mineral commodity prices. ANNs have proven to be quite helpful modeling the hidden patterns that many time-series forecasting methods, be they the Autoregressive Integrated Moving Average (ARIMA) and the Generalized Autoregressive Conditionally Heteroscedastic (GARCH) have failed to.

A case study was conducted not only to assess the accuracy of the ANNs on nickel price forecasting but also to determine how this model compares to the ARIMA and the GARCH techniques. This study reveals that, indeed, the forecasted values based on ANNs more accurately captures the real values than those obtained by the other two methods. The same study also shows that, although these three methods are somewhat good at estimating future price values, their accuracy works better for short terms, i.e., from a couple of months to up to two years (or any time unit of interest).

Résume

La prévision des prix des matières premières minérales, pourtant peut-être le facteur le plus important du processus décisionnel des sociétés minières, reste une tâche complexe en raison des différents éléments qui déterminent ces prix. A ce jour, plusieurs techniques ont été développées dans le but d'améliorer la précision des prévisions; cependant, leur architecture a également varié en termes de complexité.

Cette thèse explore l'utilisation des Artificial Neural Networks (ANNs) pour la prévision des prix des matières premières minérales. Les ANNs se sont révélés très utiles pour modéliser les modèles cachés que de nombreuses méthodes de prévision de séries chronologiques, qu'il s'agisse de la AutoRegressive Integrated Moving Average (ARIMA) et de Generalized Autoregressive Conditionally Heteroscedastic (GARCH), ont échoué.

Une étude de cas a été menée non seulement pour évaluer l'exactitude des ANNs sur la prévision du prix du nickel, mais aussi pour déterminer comment ce modèle se compare aux techniques de ARIMA et GARCH. Cette étude révèle que, en effet, les valeurs prévues basées sur les ANNs ressemblent plus exactement aux valeurs réelles que celles obtenues par les deux autres méthodes. La même étude montre également que, bien que ces trois méthodes soient assez bonnes pour estimer les valeurs de prix futures, leur précision fonctionne mieux à court terme, c'est-à-dire de quelques mois à deux ans (ou toute unité de temps d'intérêt).

Acknowledgements

I would like to thank my parents who have always given me their full support, especially as I embarked on this new chapter of my life in a new country.

To the Peruvian Institute of Mining Engineers (IIMP) who are the responsible for making this whole dream of studying in a cutting-edge country come true.

I would also like to thank Professor Kumral for his unstinting support over these two years not only as a supervisor but also as friend.

Content

List of Figures

List of Tables

List of Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller test
AIC	Akaike Information Criterion
ANNs	Artificial Neural Networks
AR	AutoRegressive
ARCH	AutoRegressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
CBOT	Chicago Board of Trade
CEI	Chemical Engineering Index
COMEX	Commodity Exchange, Inc.
CPI	Consumer Price Index
CT	Chaos Theory
ETF	Exchange Traded Funds
GARCH	Generalized Autoregressive Conditionally Heteroscedastic
GDP	Gross Domestic Product
LBMA	London Bullion Market Association
LCPI	Logarithmic CPI
LME	London Metal Exchange
LPPI	Logarithmic PPI
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
M&S	Marshall & Swift Index for industrial equipment
MUV	Manufactures Unit Value Index
NR	Nelson Refinery Construction Cost Index
NYMEX	New York Mercantile Exchange
PACF	Partial Autocorrelation Function
PPI	Producer Price Index
R^2	Coefficient of Determination
RMSE	Root Mean Squared Error
SS_E	Sum of Squares
SS_{yy}	Sum of Residuals
WPI	Wholesale Price Index

Chapter 1

Introduction

1.1. Problem statement

Mineral commodity prices are one of the most crucial parameters used in the economic evaluation of a mining project. They have a considerable impact on the company's revenues, heavily influencing the strategic decisions to be made by the company's board. Moreover, since mining companies, in the majority of cases, play almost no role in the determination of the mineral prices, i.e., they are price takers, their plans are deeply dependant on mineral commodity prices.

Regardless of this dependence on mineral commodity price forecasts and the different techniques that have tried to address this issue, mineral price forecasting remains challenging due to the increased volatility in commodity markets. Globalization increased the sensitivities to economic, commercial, natural and political events at every point of the world. The markets of many commodities are international. A great deal of effort has been dedicated to developing and improving the forecasting methods used for the estimation of future mineral prices.

The main two drivers of mineral commodity prices are supply and demand. In fact, many conventional forecasting methods take advantage of historical supply and demand values and, through the use of mathematical techniques, attempt to obtain estimates of mineral prices in the short and long term (Espí Rodríguez and De La Torre, 2013).

The forecasting approach used by mining companies and stockbroker analysts are based on time-series techniques. These methods may be classified as:

a. Simple methods such as exponential smoothing and moving average (MA). In fact, exponential smoothing and MA are smoothing techniques rather than forecasting.

b. More sophisticated techniques such as the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA).

In addition to these techniques, simulation-based approaches (e.g., geometric Brownian motion and mean reverting techniques) and various machine learning techniques are also used for forecasting purposes.

Time series-based methods assume that past behaviour of a commodity price will continue into the future; however, their main pitfall is that all follow linear models, constraining the future values to be linear functions of past observations (Kriechbaumer et al., 2014). This issue poses a serious problem given that real-time series exhibit a mixture of linear and non-linear patterns.

In order to better model the patterns real-world time series show, several techniques have been proposed, some of which have proven to be more accurate than others at predicting future values. Two of the most widely used non-linear methods are the AutoRegressive Conditional Heteroskedasticity (ARCH) and the Generalized Autoregressive Conditionally Heteroscedastic (GARCH). Theoretically, when the behaviour of the series over time is the only factor taken into account, both generally represent an improvement from the conventional and still widely used ARMA and ARIMA models. Nonetheless, they are no without any drawbacks, as expected from any forecasting technique.

Researchers in the matter of price forecasting have shown that, even when ARIMA and GARCH are the go-to methods for mining companies and traders due to their simplicity, they tend to fall short to machine learning techniques such as Artificial Neural Networks (ANNs) (Chen et al., 2003).

ANNs have shown to more accurately model real-world time series, providing more accurate forecasts (Kristjanpoller and Minutolo, 2015). However, growing research on the factors that affect the capability of forecasting methods, even the most sophisticated one, has yielded interesting results as to what could possibly make one forecasting technique more accurate than the other at predicting future values (Dooley and Lenihan, 2005). This phenomenon will be discussed in later chapters.

In order to properly grasp the accuracy and usefulness of such forecasting methods, a case study needs to be conducted. The selection of the mineral commodity boasted different metals; however, given its critical nature as a raw material and its importance not only as a macroeconomic indicator but also for the industrial sector, *nickel* was chosen.

1.2. Research objectives

- Examine the appropriateness of the most common linear time-series method, i.e., the ARIMA technique.
- Determine the efficiency of the most common non-linear model for the data's volatility: The GARCH model. To that end, a hybrid ARIMA-GARCH model will be used, as it is not possible to forecast the mean values of the data using only the GARCH model.
- Investigate the performance of machine learning method, using ANNs on the forecast of mineral commodity prices. It will be verified the flexibility and non-linear capability of neural networks over the traditional linear and non-linear time-series model.
- Benchmark the outcomes of different methods.

1.3. Original contributions

As discussed in Section 1.1, the main shortcoming of the conventional time-series methods is their linearity assumption behind their models (smoothing techniques, ARIMA). To overcome this particular issue, different models, those based on pure non-linear time series and those based on machine learning techniques, are explored. In fact, machine learning methods such as ANNs have proven to effectively identify the hidden non-linear patterns that the pure non-linear time series models failed to do (Lorente-Leyva et al., 2019), outperforming the conventional time-series forecasting techniques. This research aims to demonstrate the pros and cons of the time-series forecasting techniques and extend more advanced ANNs technique. All techniques to be investigated will be tested through a case study.

1.4.Social and economic impacts

The forecast of mineral commodity prices has a great positive impact on all the stakeholders (i.e., mining corporates, governments, and local communities) of the mining industry. More precisely, the outcome of this research will most likely be beneficial to:

- *Tax makers*, by providing a broader understanding of the future behavior of the mineral commodity prices (Takatoshi and Rose, 2011). Thus, governments can set the most efficient yet reasonable tax rate to maximize benefit for society. Likewise, local communities would have a much clearer idea of the financial/social perks mining project operating in the nearby area would bring so the process to grant social license to operate would be less cumbersome and social risks could be reduced. Finally, mining corporates will have more reliable information on the profitability and sustainability of the operations,

- *Policymakers,* by effectively monitoring mineral prices, which are one of the major factors affecting policy goals (Rudenno, 2012). Consequently, as part of the mining policy, an ideal type of tax regime can be defined so as to balance between the benefit of society and sustainability of mining corporates. That is, the predicted price values can help governments to adopt regulatory actions that ensure a fair taxation system in all the possible price scenarios, allowing neither corruption nor exaggerated demand by the communities when prices rise. Furthermore, the satisfactory forecast of mineral prices facilitates the delineation of governmental mining policies so as to guarantee sufficient future mineral supplies (Radetzki and Wårell, 2016).
- *Investors*, by facilitating their decision-making process regarding their investments. In fact, every mining project is subject to numerous risks associated with the mineral commodity markets, and, therefore, a better and improved prediction of the commodities' prices can lead to better evaluation and optimization of investment opportunities in mining projects.
- *Corporations*, by reducing the level of uncertainty linked to the mineral commodity price. By doing so, the corporations will be able to make an informed decision regarding major strategic decisions: mine portfolio management, the construction of a new mine, or expansion of production (Radetzki and Wårell, 2016). Furthermore, mining companies will also be better equipped to elaborate on a more representative contingency plan that addresses the possible changes in the market conditions.

A more realistic forecast of the mineral commodity price can also provide a greater understanding of the financial value of a mining company (Schaeffer, 2008). That is, since the mineral commodity price is one of the main drivers in the mineral reserves calculation, which, in turn, are the principal parameter that underpins the liquidity of a mining company, a more accurate price forecasting can help a mining company understand its financial status in the short and long run.

- *Mine planners,* by helping them set more realistic and accurate capacities, developing cut-off grade strategy, and adjusting the corresponding mining method sequence (Rudenno, 2012). Consequently, mine planners are able to better adjust their mine plans, reflected as changes in the production sequencing, the life of mine, the mineral reserves, etc. so as to maximize the mine's profits in both the short, medium, and long term.

1.5. Outline

Chapter 1 states the research problem and identifies both the original contributions to the field and the research's social and economic impacts.

Chapter 2 reviews key statistical concepts and describes the existing methodologies and research in the mineral commodity price forecasting field.

Chapter 3 explains the methodology and the way it is organized,

Chapter 4 analyzes the conventional linear time-series method used in the mining industry: The ARIMA technique,

Chapter 5 examines the currently used non-linear time-series method, GARCH, as well as its joint performance ARIMA-GARCH on the mineral commodity price forecasting.

Chapter 6 evaluates the use of the machine learning technique ANNs in the mineral price forecasting.

Chapter 7 summarizes the key findings/findings of this research and outlines the future work.

Chapter 2

Literature Review

2.1. Commodity markets

The economic sectors can be categorized into the primary, secondary, and tertiary sectors. In this regard, only the primary sector includes raw materials, i.e., metals, agriculture, fishery, and forestry. The outcomes of primary sectors are generally called commodities, which are typically traded in *commodity exchanges* (Radetzki and Wårell, 2016).

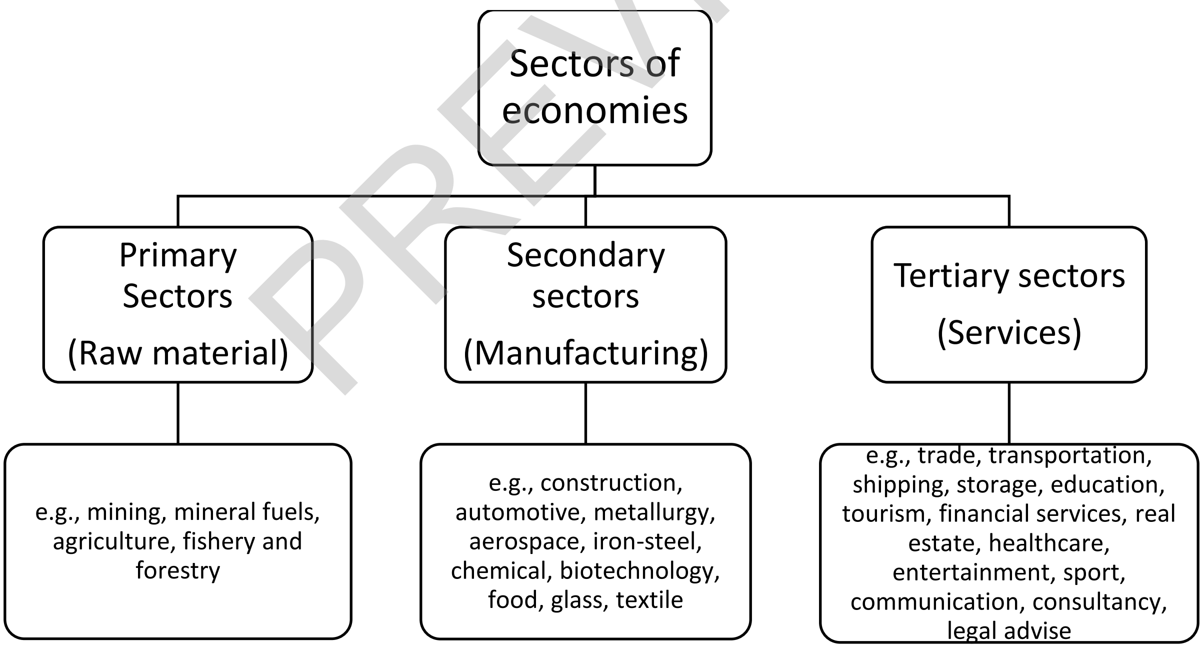

Figure 2.1 - Sectors of economies

(Source: "A Handbook of Primary Commodities in the Global Economy", Chapter 5, Radetzki et al., 2016)

A commodity exchange (also called commodity market) is the market where primary sector products are traded (Rudenno, 2012). Examples of such commodity exchanges are the London Bullion Market (LBMA), London Metal Exchange (LME), the CME Group (Chicago Board of Trade), the New York Mercantile Exchange (NYMEX), and Commodity Exchange, Inc. (COMEX) merged). These exchanges require high product standards (both quality and quantity) so as to guarantee a successful commodity trading between both parties (buyer and seller) (Priolon, 2018). The prices of the commodities are set on a daily basis on the exchanges and companies can buy or sell through the so-called brokers.

These commodity markets are usually driven by two fundamental economic factors: supply and demand (Radetzki and Wårell, 2016). These two elements determine the price that suppliers are inclined to take, and buyers are willing to pay. As a result, any major disruption or changes in both elements would shift the commodity prices.

In many of the commodity exchanges, different commodities are traded; the main tradable commodities can be found in Table 2.1.

Table 2.1 : Tradable commodities

Group	**Examples**
Precious Metals	Gold, Silver, Platinum
Base Metals	Copper, Lead, Molybdenum Nickel, Aluminum
Agro-Based Commodities	Wheat, Corn, Cotton, Oils, Oilseeds
Soft Commodities	Coffee, Cocoa, Sugar
Live-Stock	Live Cattle, Pork Bellies
Energy	Crude Oil, Natural Gas, Gasoline

(Source: "A Handbook of Primary Commodities in the Global Economy", Chapter 5, Radetzki et al., 2016)

There are different types of markets at which these commodities are traded, such as spot or physical markets, futures markets, auction markets, and commodity markets. Also, given that mining corporates are listed in stock markets, stock markets and commodity price dynamics are closely intertwined (Radetzki and Wårell, 2016).

- The physical market (or the spot market) is a market where commodities are exchanged. That is, the seller supplies the amount of the commodity requested by the buyer, who takes delivery of it. In these markets, the transactional price is also called the spot price. Although, in reality, only a relatively small percentage of the commodity is actually delivered, since transactions are mainly made through future contracts, some exchanges do have storage facilities/warehouses (Rudenno, 2012).
- Auction markets: Sellers introduce the lowest price willing to accept and buyers bid the highest price willing to pay.
- Future markets, as opposed to the stop markets, are the markets where the buyer and seller of the mineral commodity "settle in advance" to a certain amount of the commodity at an agreed-upon price to be delivered at the pre-defined time in the future. Since the price has already been pre-defined and agreed upon by both parties, futures markets can provide a tool for estimating mineral commodity prices. One example of future markets is the NYMEX.
- Commodity markets, as per its name suggests, is the market at which primary sector products are traded.

In general, the exchanges discussed above can serve a number of purposes. One of those is the establishment of competitive and representative commodity prices. In fact, as competitive markets, these exchanges define the commodity prices by weighing in the transactions made by both buyers and sellers (Takatoshi and Rose, 2011). Consequently, these commodity prices can be taken as benchmarks by outside buyers who wish to purchase commodities at entities outside the exchanges. Furthermore, these prices set by the exchanges can come in handy to not only perform an economic valuation of investment portfolios, but also establish commodity indices as well as exchange traded funds (ETF) (Jones et al., 2019). In addition to the benefits mentioned above, these commodity exchanges can also serve as delivery locations.

An example of commodity markets is the LME, which is one of the world trading centers for mineral commodities, especially non-ferrous metals such as copper and nickel[1], where future buyers and sellers of metal futures and options meet. These commodities can be traded in different forms: an agreed-upon quantity of a metal is bought/sold on a pre-defined date, at a fixed price agreed today, or via an option, in which futures contract are sold/bought at a price (also known as the strike price) agreed today (The London Metal Exchange, 2019). This exchange also offers prospective clients a tool to manage the risks against metal price movements through hedging. That is, by allowing its clients to hedge their commodity prices, the LME helps mine operators to reduce the potential losses that might incur as a result of falling.

This exchange also provides prospective sellers and buyers with a physical market of last resort, via the worldwide network of LME-approved warehouses (The London Metal Exchange, 2019). In fact, LME has approximately 700 warehousing facilities, serving as a spot market with more than 500 brands of metal products listed. That way, through the LME, consumers are able to purchase mineral commodities in times of extreme shortage, whereas producers are also able to sell their metals in times of oversupply, granted that they both meet the criteria set by the exchange.

[1]. The LME is the major world trading center for copper and lead.

Other exchanges of significant relevance are those that belong to the CME, a merger of the NYMEX, and the COMEX. The NYMEX is an exchange where futures and options are traded. The metals it trades are copper, gold, zinc, and silver. This exchange has set, as any other exchange, a set of rules governing the adequate trading, yet its rules are not as strict as those of the LME. In fact, the NYMEX trade is vastly confined to the American market and, taking advantage of the preference the American producers have to deal directly with the buyers.

LBM is the market at which gold and silver are traded. This trading, which is usually conducted by buyers and sellers directly, is overseen by the Bank of England and is represented by the LBMA. Since all transactions are conducted between both parties to maintain confidentiality, all risks exist only between the two counterparts. In this exchange, the members of the LBM, along with the Bank of England, act as gatekeepers to the market and certify the bullion traded and delivered meets the LBMA standards. Table 2.2 shows the metals and the exchanges they are traded at.

Table 2.2: Main metals and their principal exchanges

<table>
<tr><th colspan="2">Group</th><th>Exchanges</th></tr>
<tr><td rowspan="8">Base Metals</td><td>Copper</td><td>LME, COMEX</td></tr>
<tr><td>Lead</td><td>LME</td></tr>
<tr><td>Zinc</td><td>LME</td></tr>
<tr><td>Nickel</td><td>LME</td></tr>
<tr><td>Molybdenum</td><td>LME</td></tr>
<tr><td>Tin</td><td>LME</td></tr>
<tr><td>Steel</td><td>NYMEX</td></tr>
<tr><td>Aluminum</td><td>LME</td></tr>
<tr><td rowspan="2">Precious Metals</td><td>Gold</td><td>COMEX, LBMA</td></tr>
<tr><td>Silver</td><td>COMEX</td></tr>
</table>

2.2. Commodity price mechanisms

In order to understand the intricate economic drivers of the mineral commodity price, it is useful as a starting point to consider the basic economic theory of supply and demand.

Mineral reserves this period = Mineral reserves last period - New mineral consumption last period + Amount of mineral recycled last period + New mineral reserves discovered last period

Figure 2.2- Definition of mineral supply

Theoretically, the price of a mineral commodity settles at the equilibrium point of both the supply and demand curve. As a result, considering a competitive market, this settlement of the price would prevent suppliers and consumers from charging higher price and offering way less money than determined, respectively. In this regard, commodity markets do not behave any different than any competitive market (Priolon, 2018). What really sets commodities markets apart is the group of factors that influences their supply and demand (Zsidisin, 2011).

2.2.1. Supply-driven factors

Mineral commodities can be extracted as main products, co-products, or by-products. The way these commodities are extracted directly affects the mine's output and viability (Radetzki and Wårell, 2016).

Once processed and consumed, some metals can be recovered and recycled. Recycled materials make up what is called "secondary" production and are often referred to as "scrap." Scrap material is usually classified into two categories: new scrap, which is generated in the manufacturing of new goods, and old scrap, which derives from goods that have reached the end of their useful lives or have become obsolete. In this regard, according to Rudenno (2012), the flow of minerals supplied in a given period needs to consider the relationship between the depletion of a finite mineral stock, current mineral reserves, new mineral supply, recycled materials, and additions to stocks from new discoveries, technological change, or changes in prices.

Unexpected changes in the mineral commodity supply can be attributed to different factors including the opening or closure of mining operation(s), the significance of certain mining operation to the global production as stalled production in a highly production-contributive country due to a company's external or internal factor that can decline the overall world metal production of a certain commodity. In fact, disruptive events such as strikes, accidents in major mines, natural disasters such as floods and fires, failure of important machinery can be detrimental to mineral supply worldwide.

2.2.2 Demand-driven factors

The main driver for the demand of a commodity is associated with its industrial use. This use may change over time due to new technologies or the effects of substitutes or complementary products.

What determines the demand behavior for a mineral at any given point in time are the technological level, the quantity of consumers and their preferences, and the prices of both the commodities and any other substitute products (Takatoshi and Rose, 2011).

The competition between different producers is the determinant of the way goods are produced. In theory, the chosen method would be the one with the lowest cost at any time. That is, if at certain point in time a new method of production with a lower cost than the current one is found, this one will displace the old one.

When the supply of a given metal/mineral increases, the demand will also increase. Consequently, the price of the mineral commodity will rise until the overall production peaks what is wanted from buyers. Similarly, when there is an overproduction of a mineral commodity, buyers will take the lowest price (or last price quoted at an exchange) and this will continue until the excess of material is exhausted and the equilibrium is re-established. Production will decrease and because demand has stayed the same, eventually, the supply and demand situation will equalize, and the price will be back to normal. In a nutshell, the major factors influencing mineral demand include (Radetzki and Wårell, 2016):

- Incomes which are often represented by the Gross Domestic of a country.
- Industrial output
- The past behaviour of the commodity's price
- Prices of substitute and complement materials
- Technology improvements or new technology, which not only help reduce other industries' demand for a mineral commodity; but also affect the competitiveness of a mineral commodity in the market.
- Consumer preferences, which can vary depending on the consumer's income and economic scenario of a region/country.
- Government policies, regulations, activities

Supply, on the other hand, is mainly determined by the production of existing mines, recycling activity, mining production costs, among others.