Article

Artificial Intelligence Modelling Framework for Financial Automated Advising in the Copper Market

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Abstract: Financial innovation by means of Fintech firms is one of the more disruptive business model innovations from the latest years. Specifically, in the financial advisor sector, worldwide assets under management of artificial intelligence (AI)-based investment firms, or robo-advisors, currently amount to US$975.5 B. Since 2008, robo-advisors have evolved from passive advising to active data-driven investment management, requiring AI models capable of predicting financial asset prices on time to switch positions. In this research, an artificial neural network modelling framework is specifically designed to be used as an active data-driven robo-advisor due to its ability to forecast with today's copper prices five days ahead of changes in prices using input data that can be fed automatically in the model. The model, tested using data of the two periods with a higher volatility of the returns of the recent history of copper prices (May 2006 to September 2008 and September 2008 to September 2010) showed that the method is capable of predicting in-sample and out-of-sample prices and consequently changes in prices with high levels of accuracy. Additionally, with a 24-day window of out-of-sample data, a trading simulation exercise was performed, consisting of staying long if the model predicts a rise in price or switching to a short position if the model predicts a decrease in price, and comparing the results with the passive strategies, buy and hold or sell and hold. The results obtained seem promising in terms of both statistical and trading metrics. Our contribution is twofold: 1) we propose a set of input variables based on financial theory that can be collected and fed automatically by the algorithm. 2) We generate predictions five days in advance that can be used to reposition the portfolio in active investment strategies.

Keywords: robo-advisor; financial innovation; fintech; commodity investment; copper investment; neural networks; artificial intelligence

1. Introduction

The financial innovation industry has substantially grown up in recent years due to the effort of companies to create and manage dynamic and competitive processes to reinvent their services [1]. Financial advising and wealth management companies using artificial intelligence (AI) transformed their business model [2], offering new services to main street investors with an innovative business model known as robo-advisors. The worldwide assets under management (AUM) of robo-advisory companies currently amount to US$975.5 B, with an expected growth at an annual rate (CAGR 2019–2022) of 31.4% [3].

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One of the key differences between traditional asset management advisory firms and robo-advisors is that robo-advisors provide added value recommendations in risky portfolios to individual investors by means of AI investment algorithms and the delivery of advice is web-based with little human intervention [4]. This innovation permits the reduction of fees and investment thresholds of financial advice, easing access for the companies to the long tail market [5] and providing benefit from the aggregation of many small investors instead of focusing only on the great fortunes. The robo-advisor industry has evolved in recent years [6] from robo-advisors 1.0: 'product or portfolio proposal'; robo-advisors 2.0: 'risk-based portfolio allocation'; robo-advisors 3.0: 'algorithm-based adjustments and rebalancing proposals'; to robo-advisors 4.0: 'fully automated, self-learning algorithms and automated asset shifts'. In terms of the efficient market hypothesis (EMH) [7], the passive investment strategy of robo-advisors 1.0 (invest and hold) accepts that markets are efficient and that there is no way to predict the future behavior of prices with the information at hand. However, in the copper market, there are some previous contributions that question the EMH [8,9] and, specifically in the London Metal Exchange (LME) [10]. One reason behind this inefficiency could be the financialisation of the commodity markets [11,12].

Artificial neural networks (ANNs) are amongst the most popular AI models to solve business problems [13]. The main advantage of the application of ANNs to predict financial prices is that ANNs can model complex non-linear relations between variables without any previous assumptions with respect to the distribution of the series in terms of linearity and normality. Among the most widely used ANNs to model variables with nonlinear dynamics (i.e., financial series), are the Elman neural networks, which include feedback connections, and the multilayer perceptron networks (MLP).

Robo-advising is a way of providing advisory services to the investor by using automatic tools to a great extent and by submitting recommendations to rebalance the positions taken by the investors. Most of the recommendations—either at the beginning or by a rebalancing—are addressed to exchange-traded funds (ETFs) [14,15]. Although prior research has contributed to the development of AI applications to financial market price prediction, it lacks contributions regarding the formal modelling of investment decisions based on the algorithms needed for the robo-advisor industry [16]. Most of the previous research proposes models that either require human intervention [17–21], use time periods that are too broad, i.e., monthly or quarterly [22–25], or propose a set of input variables not based in financial theory, that make the usability and repeatability of the model difficult with new data [26]. Our study is a first effort to address this research gap by putting forward an ANN modelling framework to predict copper prices using input variables grounded in financial theory as: prices of other commodities, economic variables, copper demand, day of the week effect, and big player expectations in the US over the counter (OTC) markets. The modelling framework is suitable for its application by the robo-advisory industry because of two specific features: 1) the collection of the input variables can be fully automated, and 2) the prediction is five days ahead and permits active data-driven recommendations to rebalance the positions of the portfolio.

To assess the forecasting ability of the proposed framework, we trained two sets of models for each one of the two periods with higher volatility of the recent copper prices: Period 1, from May 2006 to September 2008, in which the high levels of volatility were associated with the financialisation of the commodities markets; and period 2, from September 2008 to October 2010, a highly volatile period caused by the collapse of Lehman Brothers and the consequent turbulence in the financial markets. For each period, the best model had a MAPE of less than 3.1%, a correlation of predictions and a series of more than 97.7%. The accuracy of the models in the prediction of price changes in the 24 days out-of-sample dataset was 78.2% for period 1 and 65.2% for period 2. These predictions were benchmarked against buy/sell and hold trading strategies with promising results in terms of trading metrics.

To finish this section, we would like to state that the model we are proposing challenges the EMH, because it has some ability to forecast prices, and perhaps its implementation could contribute to improving the market efficiency, although this issue is not analyzed in this research.

The rest of the article is organized as follows: This introductory section continues with a review of the literature on robo-advisors, the copper financial market and specific applications of AI to forecast financial markets. Then we present the methodology and an analysis of the results. The final section concludes with a discussion of the findings, their implications and some limitations.

2. Literature Review

2.1. Robo-Advisors

In 2009, after the global financial crisis, investors shifted their preferences from expensive mutual funds to passive investing in ETFs, which provided better opportunities and lower fees to Main Street investors [27]. In recent years, big companies have regained market share in active stock-picking investments, by applying the technological tools to hand, restructuring their investment advising branches, and creating new business models. As Larry Fink, chief of BlackRock, explains: "The democratization of information has made it much harder for active management; we have to change the ecosystem—that means relying more on big data, artificial intelligence, factors and models within quant and traditional investment strategies" [27].

One of the keys to success of this innovative industry is that investors perceive human financial advice as expensive, prone to errors and biased by their own interest [28]. In contrast, investors perceive robo-advisors as less prone to errors, cheaper (flat fees typically vary from 0.25% to 0.50%), and less subject to conflict of interest because the fees do not depend on management or rebalancing of the positions. Other advantages perceived by investors are the multitude of automatic dynamic account balancing services, such as moving money out of the market, and keeping it in cash in a severe downturn, or tax-loss harvesting strategies consisting in offsetting the losses from a security with the gains of another.

To open an account in a robo-advisor company, the first step is to provide the necessary information in terms of age, risk tolerance, monthly income or amount to invest [15]. That data is collected by means of a questionnaire, and based on this information, the robo-advisor proposes different risk-adjusted investment plans depending on the age of the investors, marital status, number of children or other demographic or psychographic information. From a marketing perspective, this close relation with customers and the huge collection of data may become a further impulse towards marketing innovation [29] and also contribute to the customers' engagement, which is a key driver for electronic commerce and virtual communication [30].

However, this business model may have unknown risks that innovations may imply and cause severe negative externalities revealed only after substantial welfare losses [31]. In this vein, some authors [32] have warned of the risks derived from human–machine interactions in terms of human vulnerability, and about the risk that humans lose their knowledge and machines are the only entities retaining knowledge on financial markets when automation takes over a financial advisor's work.

Regarding the systemic risk of this innovative industry, robo-advisors are now considered investment advice services and there is not a specific regulation. In the EU context, MiFID II, which came into force at the beginning of 2018, does not mention robo-advisors; the same can be said for MiFIR. Nevertheless, there are some work groups discussing these issues, such as the Joint Committee of the European Supervisory Authorities [33] and other authorities, such as the European Banking Institute [34], who are proposing to follow the UK initiative and create a regulatory sandbox guided by an interplay between the supranational (EU) and national levels. This allows robo-advisor firms to test their automated services under official supervision. As a conclusion, although once again practice is going before regulation, robo-advisors are not considered a systemic risk.

2.2. Copper Financial Market

After the legislative modifications of the Commodities Exchange Act occurred in the United States at the beginning of 2000, commodities began to be considered as an asset class, and emerged as

a relevant investment for the investor's community [35]. In general, it can be said that commodity financialisation improves liquidity in the futures market and increases the correlation between the commodity futures market and the equity market [36]. In fact, the degree of correlation between commodities and stock markets represented by Standard & Poor's 500 (S&P 500) changed dramatically, for example, the correlation of 30% between S&P 500 and copper in 2001–2004 increased to 65% in 2005–2008.

However, commodities such as silver, gold, oil or copper are a special kind of asset because their prices in the financial markets are used worldwide to fix the price of the transactions between buyers and sellers of the physical commodity. They are therefore affected by the same factors that drive the movements in the financial markets, including fundamental ones like interest rates, exchange rates, GDP growth rates, other commodity prices, and industry or company specific risks.

In this research, we will focus on copper, one of the most actively traded assets in the industrial and financial markets. At present, Chile is the world's largest copper producer, Peru is second, and China is the third largest [37] (p. 53). On the demand side, China represents more than 49% of the total copper demand [38] (p. 48), estimated at 36 million metric tons [39] in 2019. Apart from the influence of the forces of supply and demand, copper prices are affected by investors' expectations represented by the speculative movements in the futures (i.e., London Metal Exchange) and OTC derivatives markets. To have an idea of the huge impact that OTC derivatives market expectations may have on copper prices, we compared the average weekly expected consumption for 2019 of 0.7 metric tons with the average weekly open interest in the first quarter of 2019 [40] in the US OTC markets of 3 million metric tons, and found that the OTC derivatives market is 4.4 times the size of the commercial market.

2.3. AI in Forecasting Financial Markets

The MLP and Elman networks, also known as deep learning networks, can be defined as a computational system that imitates the capabilities of biological systems using a large number of interconnected elements (for a detailed explanation of their architectures and error functions, see [41]). Their character, as a universal approximation of functions [42], allows the modelling of complex nonlinear relationships, extracting knowledge from a series of examples and then applying it to unknown situations. They are composed of a series of connected nodes, so that the acquired knowledge is stored in these connections. It consists of three layers: the input layer, hidden layer and output layer. The input layer receives the signals of the input variables and distributes them to the next layer, the hidden layer. The hidden layer, formed by one or more layers, is responsible for carrying out mathematical operations aimed at obtaining an exit. However, there is no defined rule to determine if the hidden layer must have one or more sublayers, and the number of neurons or intermediate functions, so the only method to configure the hidden layer is by trial and error [43]. However, there are several recommendations for its design, based on the number of available data [44] or the most desirable type of configuration [45]. There are additional conditions that must be met by the network for a correct specification, including avoiding overtraining [46]. Finally, the output layer is responsible for showing the result of operations performed in the hidden layer.

Dunis et al. [47] applied different ANN architectures, to forecast the euro/dollar exchange rate and they found that multilayer perceptron (MLP) outperforms simple trading strategies. Laboissiere et al. [17] used ANNs to predict the maximum and minimum daily stock prices of three Brazilian power distribution companies, but their model needed preliminary human analysis of data. Zahedi and Rounaghi [18] used ANNs to predict prices of the Tehran Stock Exchange using accounting variables, which hinder automate data collection. Weng et al. [26] used human processed 'disparate data sources' to predict the stock price of Apple one day ahead. De Oliveira et al. [19] used ANNs to predict the short-term direction of Petrobras, Brazil, combining it with technical, fundamental and time series analysis, which implies human intervention. Patel et al. [20], in line with this article, included economic factors affecting financial markets to compare different AI methods, but some variables were not suitable for automated data collection. Zhong and Enke [48] used ANNs and PCA

to predict S&P 500 Index ETF. Although they proposed a set of variables that can be fed into the model automatically, their prediction was only one day ahead.

Next, we analyze the outstanding literature on modelling commodities prices with AI. Chiroma et al. [22] used an ANN model to predict natural gas prices based on quarterly price data of silver, gold, copper, soy, corn and wheat, a time frame not suitable for daily trading recommendations. Godarzi et al. [21] proposed an ANN model to predict oil price movements including both supply and demand side factors affecting oil markets, but some of their variables included human judgements as dummy variables representing political crisis. Kriechbaumer et al. [23] used a combination of wavelets and ARIMA to forecast the prices of different metals, including aluminum, copper, lead and zinc, but using a monthly time series, not suitable for daily trading. Zhao et al. [24] also including a monthly series, proposed an ANN model to predict crude oil prices, including, as independent variables, three categories: price series, stock and flow series, and macroeconomic and financial series, including industry indexes, stock prices, gold prices and the dollar index.

Specifically, on the copper market we found the following contributions. Buncic and Moretto [25] proposed a dynamic model of averaging and selection to predict the monthly copper returns, the model included demand variables, risk appetite variables as the TED spread or VIX, and other financial series. Sánchez Lasheras et al. [41] compared the ability of the MLP and Elman networks to forecast copper prices with an ARIMA model and found that both outperformed the ARIMA model. Liu et al. [49] proposed a decision tree learning model to predict future copper prices, using independent variables such as prices of crude oil, natural gas, gold, silver, lean hogs and coffee, the Dow Jones index, and past copper prices. Their model had a MAPE of 4%. More recent research compared MLP with different regression models and found that in terms of correlation, MLP performs better [50].

3. Methodology

3.1. Data

Outstanding previous research has applied machine-learning techniques with different training periods and different prediction time horizons to model the recent history of copper prices. The period from 2008 to 2011 was used by [49] to predict up to 2016. The training period from 2009 to 2015 was used to predict copper prices from 2016 to 2017 by [51]. The period from 2002 to 2014 was analyzed by [41]. Using more recent periods, [50] fitted an ANN for the period 2006 to 2018.

Acknowledging that the literature has successfully modelled the recent history of copper prices, and to challenge the predictive ability of the proposed framework, the criterion for selecting the training periods was to choose those with the highest volatility. Volatility, or standard deviation of price returns, is an indicator of the variability of the data and always negatively impacts the forecasting ability of the models. Furthermore, the level of difficulty increases when the period exhibits non-constant volatility and volatility clustering [52], in which large changes tend to follow large changes and small changes tend to follow small changes, as is the case for copper returns.

Figure 1 depicts the annualized five-day rolling window volatility of copper returns from 1999 to 2018. In blue is the first period (period 1) used in this research, from May 2006 to September 2008, with an average volatility of 32%. In red is the second period (period 2) used in this research with even greater volatility, an average of 42%, associated with the extreme events related to the collapse of Lehman Brothers in September 2008, and the resulting turmoil in the world financial markets up to 2010. The rest of the periods, in black, with an average volatility of 20%, can be considered as quieter in terms of the dynamics of copper prices.
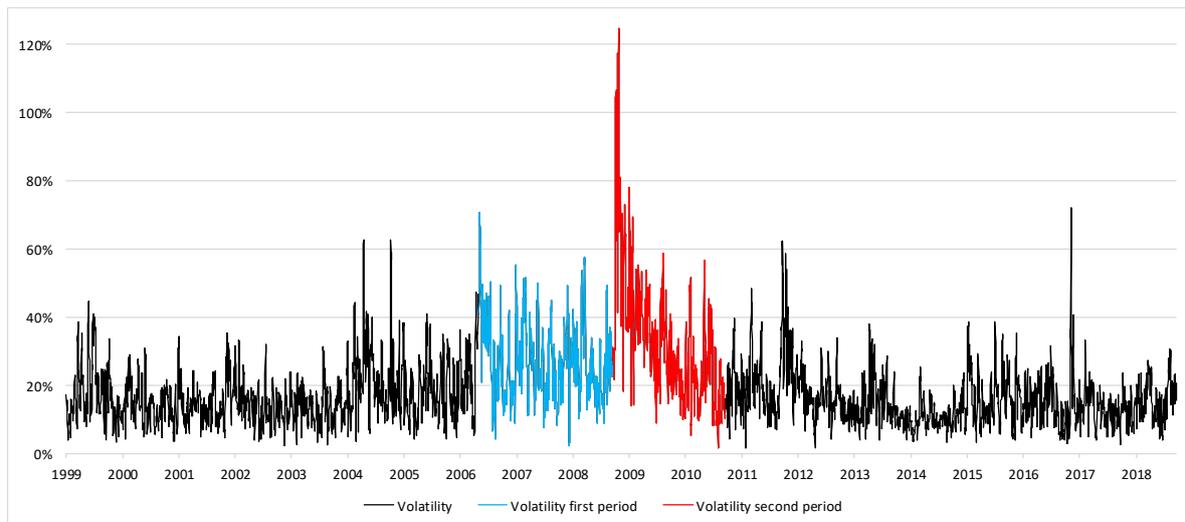
Figure 1. Five-day rolling window copper return annualized volatility from 1999 to 2018.

The period from 2006 to 2008 has been extensively studied not only in the literature but also by the United Nations [53] to understand the reasons for the increase in volatility of commodities markets. One of the reasons found by [53] was financialisation and as a consequence, the effects of index-based investment in commodity futures causing a bubble-like increase of energy and non-ferrous metal prices. The same authors also estimated the price impact of index-based investment on energy and metal prices in the order of 3–10 per cent in 2006–2007 and 20–25 per cent in the first half of 2008. Which implies in the case of copper, that when the price was 402 USç/pound in April 2008, it would have been 333 USç/pound without index-based investment. Additionally, as explained by [54], from 2004 to 2008 the open interest in derivative markets grew significantly as passive, long-only commodity index investors sought commodities for incremental risk/return enhancement in large diversified portfolios. All these reasons make the period 2006 to 2008 especially interesting, because the high level of volatility was explained by reasons related to investors and financial market movements.

From a modelling point of view, the period from 2008 to 2010 is also extremely interesting because yearly volatility reached peaks of more than 120% and included clusters of volatility around 60% and 40% (Figure 1). The period also shows a sharp decrease of copper prices of 60%, from 313 USç/pound in September 2008 to 128 USç/pound in December 2008, and a progressive rise in prices up to 350 USç/pound in September 2010. Additionally, in this case, the turbulences were not only explained by financial market factors. Considering all these facts, it is expected that the predictive ability of the model for period 2 will be seriously affected.

In line with previous research on the prediction of copper prices [49], the first data set consisted of 601 daily closing prices of copper spot prices of the LME in USç/pound, ranging from 10 May 2006 to 22 September 2008. The second dataset included 529 daily observations from 22 September 2008 to 22 October 2010. In both cases, the last 24 observations were reserved as an out-of-sample prediction data set.

As inputs to our algorithms, we selected 25 different variables described in Table 1. All the input variables present a 5-day lag except the copper price itself, which includes 5, 6, 7 lags. The output variable copper price has no lag, meaning that we want to predict copper prices five days ahead. This fact is key in the design of the robo-advisor, as we can predict five days ahead with today's information and, this way, generate an algorithm to rebalance or maintain the long or short positions in our portfolio for the following days.

Table 1. Modelling framework. Input variables, and output variable.

Type of Variables	Input Variables	Output Variable
Commodities Markets	Brent oil price$_{(t-5)}$ West Texas oil price$_{(t-5)}$ Gold price$_{(t-5)}$ Silver price$_{(t-5)}$ Copper price$_{(t-5)}$ Copper price$_{(t-6)}$ Copper price$_{(t-7)}$ Copper price return$_{(t-5)}$ Copper return 5-day rolling window volatility$_{(t-5)}$ Tin price$_{(t-5)}$ Lead price$_{(t-5)}$ Zinc price$_{(t-5)}$ Aluminum price$_{(t-5)}$ Nickel price$_{(t-5)}$	Copper price$_{(t)}$
Fundamentals	S&P 500$_{(t-5)}$ Euro/US$ exchange rate$_{(t-5)}$	
Copper demand	Change in world copper inventory$_{(t-5)}$	
Day of the Week Effect	Day of the week$_{(t-5)}$	
Big Players	US OTC copper open interest$_{(t-5)}$ US OTC copper speculators long positions$_{(t-5)}$ US OTC copper speculators short positions$_{(t-5)}$ US OTC copper hedgers long positions$_{(t-5)}$ US OTC copper hedgers short positions$_{(t-5)}$ US OTC copper small speculators long positions$_{(t-5)}$ US OTC copper small speculators short positions$_{(t-5)}$	

To represent commodities markets we included prices of oil, copper, copper return and volatility, and prices of other metals. Data on West Texas and Brent spot oil prices were downloaded from the webpage of the US Energy Information Administration [55]. We collected the LME spot prices of metals through the webpage of 'Comisión Chilena del Cobre' (Cochilco) [56].

In line with previous research in the forecasting of metal prices [25,49,57,58], to represent fundamentals of the economy we included two variables: 1) The S&P 500 index, with data from Yahoo Finance [59], as a representation of one major US stock index. 2) The Euro/USD exchange rate, obtained from the European Central Bank [60], because copper prices are fixed in US Dollars, and depreciation of the currency may imply increases in the commodity prices, and vice versa. The Euro/USD currency pair is one of the most traded in forex markets and has been previously used in the creation of models for metals [57,58].

We included the change in copper inventories in major exchanges [25] to represent the copper world demand by calculating the sum of the daily changes of inventories from the LME, New York Mercantile Exchange (COMEX) and the Shanghai Futures Exchange (SFE), also downloaded from Cochilco.

To include the 'day of the week effect', meaning more negative returns on Mondays, and more positive returns on Fridays, found in previous research in the copper markets [61–63], we created a dummy variable representing the day of the week; 1 for Mondays, 2 for Tuesdays, Wednesdays and Thursdays, and 3 for Fridays.

To represent the expectations of the big players in the OTC markets we used the Commitments of Traders (COT) reports provided by the US Commodity Futures Trading Commission [40], including open interest and positions of speculators and hedgers in the OTC derivatives markets.

To homogenize the data when a missing value appeared, we used the last price available to fill the gap. In regards to the return of copper prices, given the price level P_1, P_2, ..., P_t, we calculated the

rate of return at time *t* as $R_t = \log(P_t/P_{t-1})$. The volatility was calculated as a 5-day rolling window standard deviation of log returns. Because the COT reports provide weekly data, the same value was used for all the trading days of a given week.

3.2. Model

To find the best model for each period dataset, we trained almost 300 different ANNs combining different architectures (MLP or Elman), and internal structures of hidden layers. For each period, the four ANNs with lower (MAPE) and higher Pearson's correlation coefficient between the daily copper price series and the model prediction can be seen in Table 2.

Table 2. Summary of the best ANN models for each period. The first digit in the ANN is the number of input variables, the next three digits are the hidden layers structure, and the last digit is the number of output variables.

(a) Best Models Period 1			(b) Best Models Period 2		
ANN Type [Structure]	MAPE	Correlation	ANN type [Structure]	MAPE	Correlation
MLP [25 16 0 0 1]	1.78%	97.75%	MLP [25 8 1 0 1]	3.17%	98.82%
Elman [25 18 0 0 1]	1.82%	97.46%	MLP [25 6 6 0 1]	3.42%	98.71%
Elman [25 17 9 0 1]	2.12%	96.85%	MLP [25 6 1 0 1]	3.56%	98.51%
Elman [25 13 3 0 1]	2.57%	95.31%	MLP [25 19 2 2 1]	4.52%	97.87%

In both periods, the MLP net structure outperformed the others, with MAPE smaller than the 4% obtained by [49], and correlations with the original series were in the order of 98%, almost 9% higher than the correlation of 89% of the MLP proposed by [41]. The adjustment between the selected models for each period and the copper prices is depicted in Figure 2.
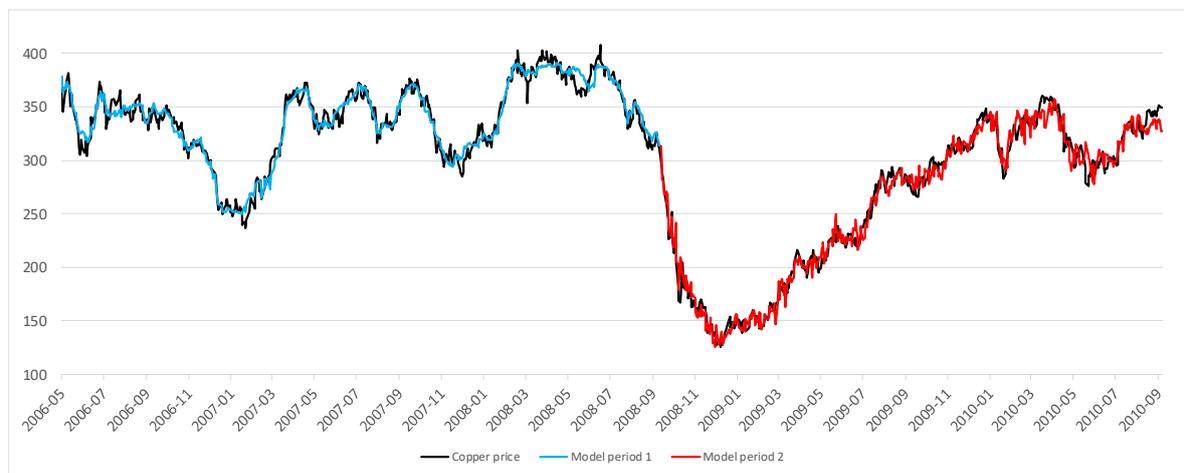

Figure 2. Comparison between the model outputs and the copper prices.

To assess the predictive ability of the model to forecast changes in prices, we first calculated difference in copper and predicted prices and applied the following rule: if the price goes up, the change is recorded as 'up', and if it goes down, the change is recorded to 'down'. With this data we created the confusion matrix with the R library Caret [64] for the training and out-of-sample sets (Table 3). The confusion matrix measures the proportion of times that the model predicts a price movement and the market moves in that direction, for example, in the training set (Table 3a) the model correctly predicts a down movement in 185 days, and fails in 91 days, in which predicts an up movement and the market goes down. Accuracy is the number of total correct predictions divided by total predictions. The level of accuracy of the model for the training set of period 1 is 66.7%, and 53.4% for the model

of period 2 (Table 3a,c). The accuracy for the out-of-sample sets increases to 78.2% and 65.2% for the models of periods 1 and 2, respectively (Table 3b,d).

Table 3. Confusion matrices of the models for the two periods: (a,c) training sets, (b,d) out-of-sample sets. Positive class down.

(a) Training Set Model Period 1			(b) Out-of-sample Set Model Period 1		
Model			Model		
Market	Predicts down	Predicts up	Market	Predicts down	Predicts up
Actual down	185	91	Actual down	14	2
Actual up	101	199	Actual up	3	4
Accuracy:	66.70%		Accuracy:	78.26%	
(c) Training Set Model Period 2			(d) Out-of-sample Set Model Period 2		
Model			Model		
Market	Predicts down	Predicts up	Market	Predicts down	Predicts up
Actual down	134	118	Actual down	6	3
Actual up	117	136	Actual up	5	9
Accuracy:	53.47%		Accuracy:	65.22%	

To further test the ability of the model to be used as a robo-advisor, a simulation exercise during the 24 days of the out-of-sample predictions was performed, consisting of staying long if the model forecasts an up movement and short if the model forecasts a down movement. That strategy is compared to the result with the two basic passive strategies [65], buy and hold, and sell and hold, during the 24-day out-of-sample window. The model for period 1 outperformed both strategies (Table 4a) with a cumulative return of 29.1%, compared to 16.9% for the sell and hold strategy and −16.9% for the buy and hold strategy (no rebalancing fees were included because of the flat fee nature, of most robo-advisors). The 8.9% cumulative return of the model for period 2 (Table 4b) was slightly below the 10% obtained with the best passive strategy, buy and hold.

Table 4. Mean return, standard deviation and Sharpe ratios of the different strategies for each period for the out-of-sample set.

	(a) Strategy Model Period 1			(b) Strategy Model Period 2		
	Buy & Hold	Sell & Hold	Robo-Advisor	Buy & Hold	Sell & Hold	Robo-Advisor
Cum. return	−16.97%	16.97%	29.18%	10.01%	−10.01%	8.91%
Mean return	−0.74%	0.74%	1.27%	0.44%	−0.44%	0.39%
Std. dev.	2.05%	2.05%	1.77%	1.22%	1.22%	1.23%
Sharpe ratio	−0.36	0.35	0.71	0.35	−0.36	0.31

Table 4 also shows the calculations of the average daily returns, daily standard deviations and Sharpe ratios [66] (using a US T. Bond risk-free rate of 3.69% for September 2008 and 2.56% for September 2010) for each one of the strategies and the two different periods. In the case of period 1, the robo-advisor is the one that performs better with a higher average return, lower standard deviation and higher Sharpe ratio of 0.71 as opposed to the values obtained for the buy and hold, and sell and hold of −0.36 and 0.35, respectively. The results of the model for period 2 are slightly worse with a lower mean return; 0.44% of the buy and hold strategy compared to 0.39% of the model, almost the same standard deviation, and a Sharpe ratio of 0.31 compared to 0.35 for the buy and hold strategy.

4. Discussion and Conclusions

In this study, an ANN modelling framework was designed to serve as a robo-advisor algorithm. The goal of the model is to forecast copper prices 5 days ahead with today's information. Using

data from the two periods from recent history with a higher volatility of the returns of copper prices (May 2006 to September 2008, and September 2008 to September 2010), the two models created using the framework outperformed previous research results in terms of correlation of the copper price prediction and the original series and MAPE. The proposed models present a predictive ability to forecast copper prices and consequently their changes in the out-of-sample 24-day window of 78.2% for period 1 and 65.2% for period 2. With the forecasted prices and applying a dynamic rebalance of positions, the cumulative return obtained for period 1 was 29.1% compared with 16.9% from the best passive strategy. The model for period 1 also performed better than the alternative passive strategies in terms of higher average return, lower standard deviation and higher Sharpe ratio. For period 2, the cumulative return of the rebalancing strategy was 8.9%, a little below the 10% of the best passive strategy. It also had a slightly lower mean return as well as Sharpe ratio; 0.31 compared with the 0.35 of the buy and hold strategy. Although the model for period 2 was trained with a series that included very extreme events, such as the collapse of Lehman Brothers, sharp decreases in prices, and very high volatility and volatility clusters, it can be considered that the proposed framework is robust and that it performed well in those circumstances in terms of out-of-sample forecasting ability and trading performance.

Our research contributes to the existing literature on predicting changes in copper prices with AI by considering input variables grounded on financial theory, including variables not used before, such as OTC market's expectations, which can be automatically collected by the algorithm and assures consistency and repeatability of the results. The proposed modelling framework also contributes to existing research because of its ability to predict copper prices five days in advance. This feature has managerial implications for the robo-advisory industry, fitting perfectly into their data-driven strategy because of the permits to automate all the data collection and recommendations in active portfolio management.

We are aware of some limitations of our study, which can be the basis for further research based on the proposed framework in this article. The effect of the predictive power of exchange rates and interest rates of commodity exporter countries has not been considered, although previous research found a substantial predictive power of exchange rates [67] and interest rates [68] of the commodity exporter countries on the price of the commodity itself. Moreover, the modelling framework could be tested in more recent periods with lower levels of volatility to assess the predictive ability of the proposed models. Because we have focused exclusively on a single commodity, to further improve the tools at hand for the robo-advisory industry, another possibility for future research is the application of the design of the present study to other heavily traded commodities in the financial markets, such as precious metals, other industrial metals, oil or agricultural products.

Finally, we should bear in mind that the implementation of this initiative in the robo-advisor industry is based on a flawed EMH, regardless of the form considered (weak, semi-strong and strong). Nevertheless, we suspect that if this modelling framework were used to a considerable extend by the industry, its forecasting ability would dampen. This hypothesis also opens new avenues for future research.

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