Going Green through Specific Assets: A Neural Outlook

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Abstract

ETF typically mimic the underlying indices. We have investigated three chosen ETF namely GRID, LIT & QCLN from the green energy space. Green metals are the future, due to its need for low carbon technology so green metals like Nickle, Cobalt and Copper etc. are the ones that are very commonly and largely used hence the price of these are taken as one of the various variables. We've constructed feasible predictive analytics models with lower RMSE values for predicting ETF prices (GRID, LIT & QCLN) with the help of metals (Nickel, Copper, Cobalt, Zinc & Silver) having direct connection with green energy production. Thus, prediction of future prices of these Green ETFs could be carried out by these specific metal prices, while ensuring higher degree of predictability & robustness. Further we have deployed GMDH Neural Network algorithm for this prediction, which came out as quite effective. These models can therefore be used by industry and academia alike.

Keywords ***:** Green Finance, Sustainability, Green Energy, Green Metals, ETFs, Predictive modelling, GMDH, Neural Network*

***JEL Codes**: C45, C52, C53, Q02*

Introduction

Sustainable development is the future for all, clean source of energy has become inevitable and an necessity for industries and economies well-being. It is thereby the way to meet the requirement to start with the sustainable production and transmission of power in efficient and feasible manner. Production and transmission of power has seen a boom in transforming the whole way of working into a more reliable and resilient source hence clean and more efficient green metals is the way to go, every industry is now turning to these green metals. The bottleneck for the entire power supply chain is the storage and its replenishment done in an efficient way. To think about it sources of energy are limited, and it is getting exhausted are very high rate. Hence apart from effectively using it storing it is the biggest need. Therefore,

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the requirement of specific metals and semiconductors are booming. To understand better as to how the existing demand of these specific metals have an impact over the global trade index with a predictive model. The correlation between the green ETFs and the specific metals is seen.

Objective

To understand the demand of specific metals in contributing the sustainability of green energy and impact on global traded pricing. To find a relationship between the prices of the metals and global green ETF's. To understand which metals, have more impact and which metals have less impact with the help of GMDH.

Literature Review

In 2021, the renewable energy industry remained remarkably resilient. Rapid technology improvements and decreasing costs of renewable energy resources, along with the increased competitiveness of battery storage, have made renewables one of the most competitive energy sources in many areas. Despite suffering from supply chain constraints, increased shipping costs, and rising prices for key commodities, capacity installations remained at an all-time high. Being one of the fastest growing components of the energy industry and along with this increased demand for renewable energy there has been an increase in investing and financing activities.(Sadorsky, 2012). Metal demand development over time has increased by illustrating the impacts of different aspects of technological change using historical data. Providing a direct, quantitative comparison of relative change in global primary production for 4 metals over a period of time, capturing the range and variation of demand development for different metals within this period. The aspects of technological change contributing to this variation are investigated in more depth for these four different metals. Demand for these four metals has significantly increased over the years and will keep on increasing.

For four metals, demand in 2013 was about or more than usual of their demand in 1993. All of these metals had a total primary production of large production in 2013.(Langkau & Tercero Espinoza, 2018). Despite the obvious advantages of renewable energy, it presents important drawbacks, such as the discontinuity of generation, as most renewable energy resources depend on the climate, which is why their use requires complex design, planning and control optimization methods. Fortunately, the continuous advances in computer hardware and software are allowing researchers to deal with these optimization problems using computational resources, as can be seen in the large number of optimization methods that have been applied to the renewable and sustainable energy field. (Baños et al., 2011). The demand for green energy technologies—including solar panels, wind turbines, electric vehicles, and energy storage—continues to increase, so too does the demand for the minerals required to develop and deploy them. This growing demand should serve as an economic boon to those countries that are home to the principal reserves of strategic minerals for the transition, including cobalt, lithium, and rare earths.

The systematic risk of renewable energy companies is to either directly create a stable and predictable demand for renewable energy through direct government buying of renewable energy or indirectly via policies designed to spur consumer purchases of renewable energy. Renewable energy companies can expect to increase sales as more high income green minded individuals and governments become early adopters of renewable energy. Sales increases can also arise with government market pull policies like feed in tariffs, green rebates, green subsidies, and renewable energy portfolio standards. In addition to subsidizing energy efficiency initiatives and the greater use of renewable energy, governments can also tax fossil fuel usage. Fossil fuel consumption taxes and carbon taxes should help reduce the impact of oil price risk on the financing and investment activities of renewable energy companies (Sadorsky, 2012).

It is important to add that also the specific demand for a metal for a technology (i.e. demand by product or service unit) has a high impact on the relative change in demand. The example of lithium-ion batteries, which had a stronger impact on the cobalt than on the lithium market, partly due to the higher specific demand for cobalt for LiCoO2-based batteries. It is also important to remember that a metal, which is not significantly increasing in demand due to an emerging technology, can nonetheless be essential for this technology. A good example for this relation is copper, which is important for all electric and electronic technologies, though this is not directly visible in its continually, moderately increasing demand. The effects of efficiency increases, substitution and recycling become evident when examining changes in demand for Cu, Ag, Ni and Zn, all of which showed growth to less than 200% of their 1993 levels by 2013. (Langkau & Tercero Espinoza, 2018)

Research Methodology

This paper proposes a predictive method for the price movement of the green energy market. For the prediction of price movements, the proposed technique is GMDH, i.e., Group Method of Data Handling. The first section presents the metals data used, and then the structure of GMDH. Predictions of green sustainable energy ETF's prices are done with GMDH using the prices of metals as independent variables.

Data Collection and Preparation

The data downloaded includes the weekly closing prices of 5 metals(Nickel, Copper, Silver, Zinc and Cobalt) and 3 Green Energy ETF's(GRID, LIT, QCLN) from 22nd June 2012 to 10th June 2022. The data has been extracted from Bloomberg Terminal and Yahoo Finance). The log returns for the same has been calculated and used for predictive analysis.

Group Method for Data Handling

In this new-age world of innovation, various prediction models are available to make a prediction. GMDH is one among them. GMDH is a self-organizing strategy that produces a progressively more comprehensive approach based on its efficacy for a variety of multi-input, single-output data pairs (Xi,yi) (i = 1,2,…,M). The focus of our study involves five green energy metal prices as inputs and prices of green energy ETF'S as outputs. Basically, multiple inputs and single output. This is exactly why GMDH is considered for this study.

GMDH was introduced by Ivakhnenko as a multivariate analysis approach for complicated systems modeling and recognition. GMDH can be utilized to avoid the complexity of obtaining former information with the algebraic approach of the progression. Thus, GMDH can be utilized to demonstrate complicated systems without having particular information of the systems.

A GMDH model with multiple inputs and one output is a subset of components of the base function

$$Y(x_1, \dots, x_n) = a_0 + \sum_{i=1}^{m} a_i f_i \tag{1}$$

where fi are elementary functions dependent on different sets of inputs, ai are coefficients and m is the number of the base function components.

In order to find the best solution, GMDH algorithms consider various component subsets of the base function called partial models. Coefficients of these models are estimated by least squares method. GMDH algorithms gradually increase the number of partial model components and find a model structure with optimal complexity indicated by the minimum value of an external criterion. This process is called self-organization of models.

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As the first base function used in GMDH, was the gradually complicated Kolmogorov–Gabor polynomial

$$Y(x_1, \dots, x_n) = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots \quad (2)$$

Usually more simple partial models with up to second degree functions are used. The inductive algorithms are also known as polynomial neural networks. Jürgen Schmidhuber cites GMDH as one of the first deep learning methods, remarking that it was used to train eight-layer neural nets as early as 1971. For modeling using GMDH, only the selection criterion and maximum model complexity are pre-selected. Then, the design process begins from the first layer and goes on. The number of layers and neurons in hidden layers, model structure are determined automatically. All possible combinations of allowable inputs (all possible neurons) can be considered. Then polynomial coefficients are determined using one of the available minimizing methods such as singular value decomposition (with training data). Then, neurons that have better external criterion value (for testing data) are kept, and others are removed. If the external criterion for layer's best neuron reaches minimum or surpasses the stopping criterion, network design is completed and the polynomial expression of the best neuron of the last layer is introduced as the mathematical prediction function; if not, the next layer will be generated, and this process goes on.

Outcome from the Work

Confidence level is 95% is taken while carrying out the predictive analysis.

The following variables are used to represent the metals throughout:

δ - Copper; β - Silver; γ - Nickel; σ - Zinc

Figure 1.0 Predicting relationship between GRID and the relevant metals (training: testing is 70:30)

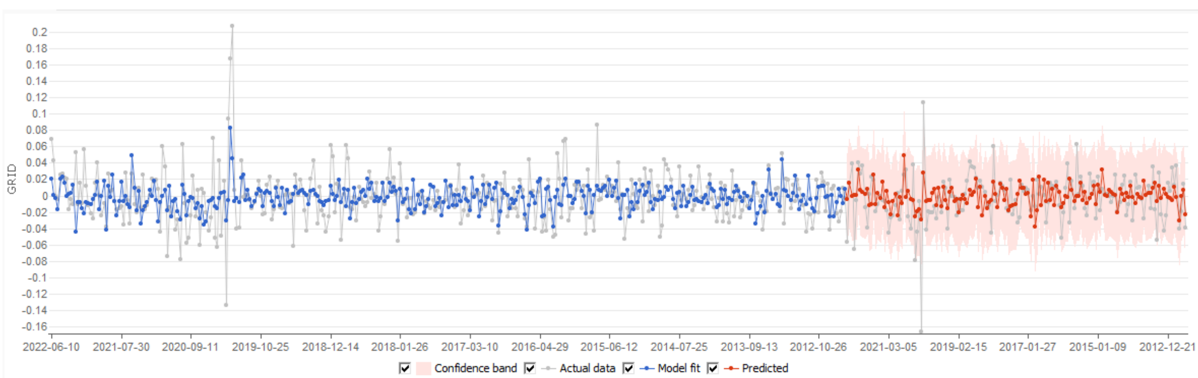

Figure 1.1 Residual visualization between GRID and the relevant metals

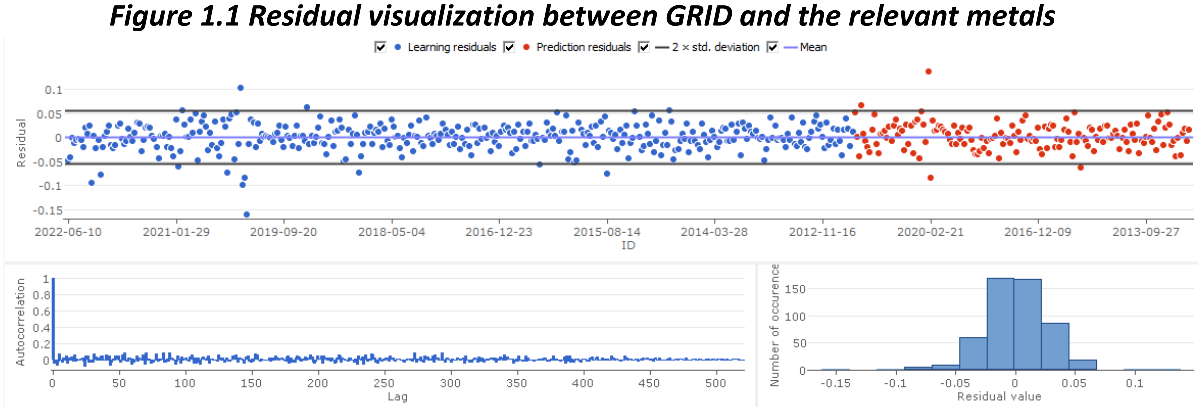

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Figure 1.2 Robustness measures between GRID and the relevant metals

Postprocessed results	Model fit	Predictions
Number of observations	365	156
Max. negative error	-0.196566	-0.131317
Max. positive error	0.158242	0.124104
Mean absolute error (MAE)	0.0282483	0.0301037
Root mean square error (RMSE)	0.0392976	0.0385423
Residual sum	1.06391E-14	0.7287
Standard deviation of residuals	0.0392976	0.0382582
Coefficient of determination (R²)	0.162067	0.0746996
Correlation	0.402575	0.304382

Equation 1

$$Y_1 = 0.000845 + 0.869532N57 + 0.59615N123$$
$$N123 = -0.001609 + 0.457647\beta - 0.033158\sqrt[3]{\beta}$$
$$N57 = -0.0014 + 0.4441\delta + 0.008656\sqrt[3]{\gamma}$$

Figure 2.0 Predicting relationship between LIT and the relevant metals (training: testing is 70:30)

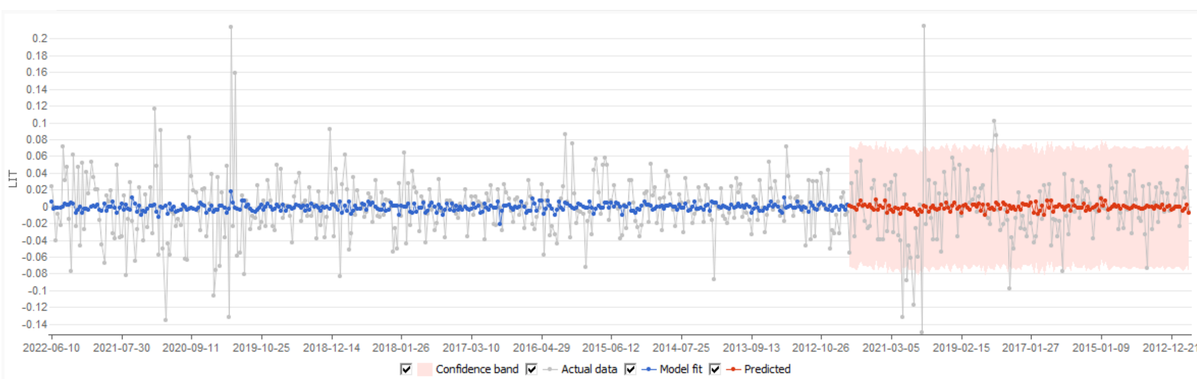

Figure 2.1 Residual visualisation between LIT and the relevant metals

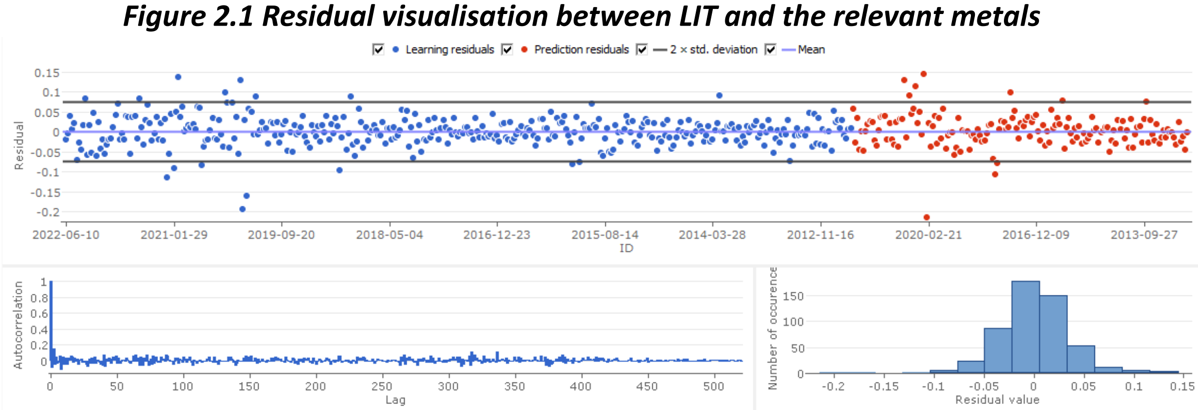

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Figure 2.2 Robustness measures between LIT and the relevant metals

Postprocessed results	Model fit	Predictions
Number of observations	365	156
Max. negative error	-0.194966	-0.214198
Max. positive error	0.135907	0.143942
Mean absolute error (MAE)	0.0260822	0.0283277
Root mean square error (RMSE)	0.0358907	0.0402247
Residual sum	3.6967E-15	0.407881
Standard deviation of residuals	0.0358907	0.0401396
Coefficient of determination (R^2)	0.0128333	0.00893467
Correlation	0.113284	0.117556

Equation 2

$$Y_2 = -0.000969 + \delta 0.19542 - \sigma 0.0729917$$

Figure 3.0 Predicting relationship between QCLN and the relevant metals (training: testing is 70:30)

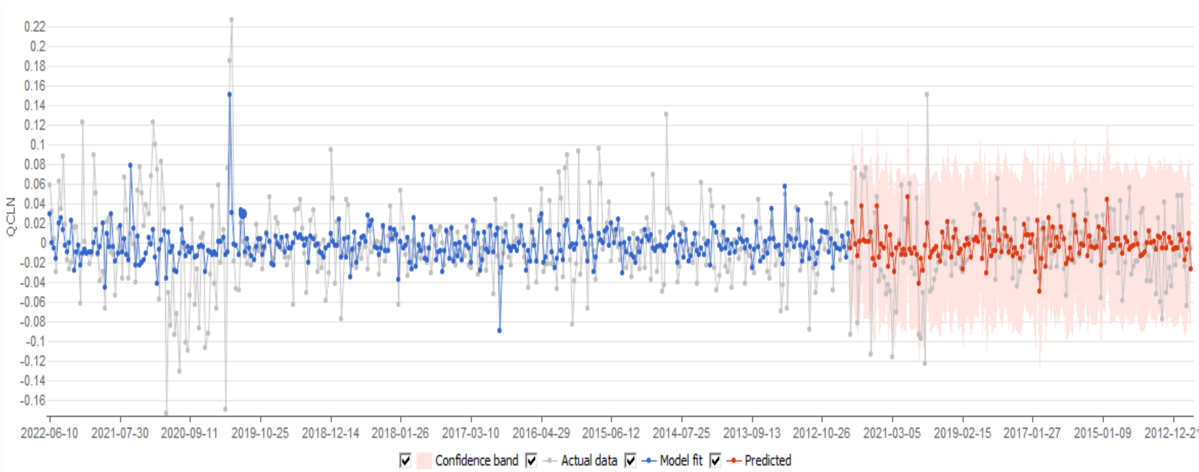

Figure 3.1 Residual visualization between QCLN and the relevant metals

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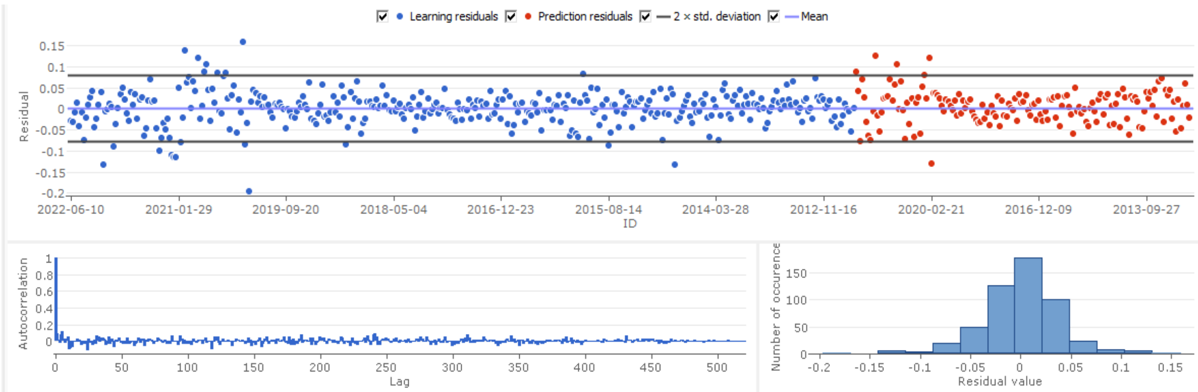

Figure 3.2 Robustness measures between QCLN and the relevant metals

Postprocessed results	Model fit	Predictions
Number of observations	365	156
Max. negative error	-0.196566	-0.131317
Max. positive error	0.158242	0.124104
Mean absolute error (MAE)	0.0282483	0.0301037
Root mean square error (RMSE)	0.0392976	0.0385423
Residual sum	1.06391E-14	0.7287
Standard deviation of residuals	0.0392976	0.0382582
Coefficient of determination (R^2)	0.162067	0.0746996
Correlation	0.402575	0.304382

Equation 3

$$〖Y = -0.002977 + 0.571\,\delta + 4.2\,\delta\,\beta 3\_〗$$

Interpretation

The focus of the work is to establish a relation between the prices of metals and ETF’s so that a predictive model can be generated using the same. We observe that all of the outcomes show a high correlation between the prices of green ETF’s and the associated relevant metals. If we look at the residual visualization, we can notice a close to normal distribution which implies that the model is linear in nature. Values related in the predicted data model shows a variety of the results. Residual visualization, predicting relationship between QCLN and the relevant metals and others are in the sync with the data provided and the predicted. In the robustness model for the QCLN, LIT, GRID and their respective relevant metals we can see that Model fit and the Predicted value are with the data provided. Lower values of RMSE relates better fit of predictive model which are evident in the above results. The correlation co-efficient for GRID and QCLN are relatively stronger than LIT. This implies that the price of metals have more impact on GRID and QCLN than LIT.

Conclusion

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The purpose of this paper is to predict using Predictive Modelling and to establish a relationship between LIT, GRID, QCLN and the relevant metals. For modelling, GMDH was used for the analysis approach. The outcome of this approach has shown us the prediction shown above. Progress in production technologies leading to higher efficiency can sustain metal demand on a constant value even when applications are growing above average Moreover, high metal prices can be a powerful incentive for efforts concerning efficiency, recycling and substitution to mitigate demand increases, Although the success of efforts geared towards substitution, recycling and increased efficiency is to a certain extent determined by intrinsic technological factors and cannot be simply transferred from one metal to another, it appears reasonable that incentives in these areas are conducive to securing metal supplies as well as to reducing ecological impacts connected with mining in the future.

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