**Introduction**

The report aims to provide an examination of the Nickel Industries Ltd (ASX: NIC) stock performance utilizing basic time-series models.

historical data to identify trends, patterns, and potential future developments.

The stock market is a dynamic and complex system, influenced by a multitude of factors, including fundamental and macroeconomic indicators, company-specific events, market sentiments, and global events. Analyzing the performance of a company's stock requires an in-depth understanding of the company's operations and financials, as well as broader market conditions and industry trends.

In this report, we will employ a range of analytical tools and techniques to provide a detailed analysis of the company's stock performance. Our approach includes statistical analysis, time-series modeling, and econometric methods, in addition to technical analysis and market-based metrics.

By offering a thorough and rigorous analysis of the company's stock, our report aims to facilitate evidence-based investment decision-making among investors and stakeholders. Furthermore, it seeks to contribute to the scientific literature on stock market analysis, highlighting the importance of employing sophisticated analytical tools and techniques to make informed investment decisions in dynamic and complex market environments.

**Nickel Industries Description**

Nickel Industries Ltd (ASX: NIC) is an Australian-based mining and exploration company that focuses on the production of nickel pig iron and other nickel products. The company operates in Indonesia and has a portfolio of assets that includes several large-scale nickel mines and processing facilities.

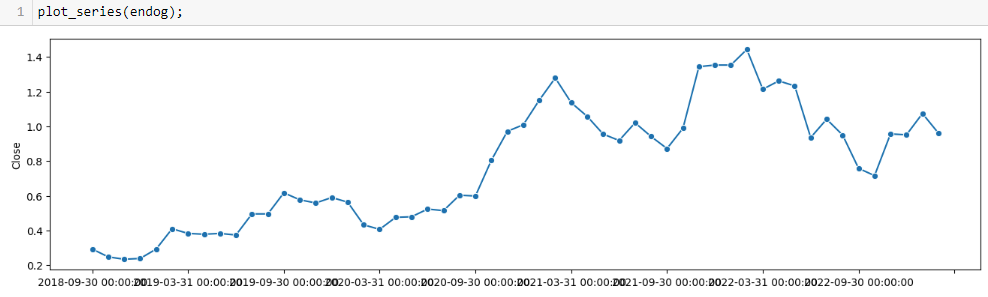
Nickel Industries Ltd's flagship asset is the Hengjaya nickel mine, which is located in the Morowali Regency of Central Sulawesi in Indonesia. The mine is operated by PT Hengjaya Mineralindo, which is a joint venture between Nickel Industries Ltd and China's Tsingshan Group. The mine produces nickel pig iron, which is a key component in the production of stainless steel.

Nickel Industries Ltd also has a 60% interest in the Ranger Nickel Project, which is a large-scale nickel laterite deposit located in Indonesia's Sulawesi province. The company has plans to develop the project into a major nickel operation.

In addition to its mining operations, Nickel Industries Ltd is also involved in exploration activities in Indonesia, with a focus on discovering and developing new nickel resources.

Nickel Industries Ltd is committed to operating in an environmentally and socially responsible manner, and has implemented policies and programs to minimize its impact on the environment and to support the local communities in which it operates. The company is well-positioned to benefit from the strong demand for nickel products, particularly in the growing stainless steel industry.

Graph of NIC Price:



**STL DECOMPOSITION**

STL decomposition is a time-series decomposition method that involves separating a time-series into three components: trend, seasonal, and residual.

Given a time-series data vector y with length n, STL decomposition seeks to decompose it into three components:

y = T + S + R

STL decomposition is a time-series decomposition method that involves separating a time-series into three components: trend, seasonal, and residual.

The trend component is the long-term pattern in the time-series, representing the overall direction of the data over a longer period of time. The trend component can be estimated using a moving average of the data, which smooths out the short-term fluctuations and highlights the long-term pattern.

The seasonal component represents the periodic fluctuations in the data that occur on a regular basis, such as daily, weekly, or monthly patterns. The seasonal component is estimated by averaging out the data over a certain seasonality period, typically using a moving average or a seasonal filter.

The residual component represents the remaining variation in the data that cannot be attributed to the trend or seasonal patterns. The residual component can be obtained by subtracting the estimated trend and seasonal components from the original time-series data.

The STL decomposition process involves iteratively smoothing the data to obtain the trend and seasonal components, while also updating the residual component. The smoothing parameters used in the decomposition process are determined by minimizing the sum of the squared residuals between the original data and the estimated trend, seasonal, and residual components.

STL decomposition is a powerful technique for identifying trends, seasonal patterns, and irregularities in time-series data, and has been widely used in various fields such as finance, economics, and climate research.

**STL DECOMPOSITION WITH MATH**

Sure, here are the mathematical formulas for STL decomposition:

Given a time-series data vector y with length n, STL decomposition seeks to decompose it into three components:

y = T + S + R

where T is the trend component, S is the seasonal component, and R is the remainder (residual) component.

To obtain the trend component T, we first apply a moving average smoothing function with window size m (an odd integer) to the original data vector y, denoted as yhat:

yhat[j] = (1/m) \* sum(y[i]) for i in [j - (m-1)/2, ..., j + (m-1)/2]

We then apply a low-pass filter to further smooth out the yhat vector, denoted as T:

T[j] = w[j] \* (yhat[j] - mhat[j])

where w is a weight vector that assigns larger weights to recent observations, and mhat is a moving average of yhat with window size s (another odd integer).

To obtain the seasonal component S, we first remove the trend component T from the original data vector y, denoted as y - T. We then calculate the seasonal component S by applying a seasonal smoothing function with window size L (an even integer) to the deseasonalized data:

y[t] - T[t] = S[t] + R[t]

S[j] = (1/L) \* sum(y[t] - T[t]) for t in {j - L/2, ..., j + L/2 - 1}

where the sum is taken over all observations in a given season, and j denotes the current season.

To obtain the remainder component R, we simply subtract the trend and seasonal components from the original data:

R[j] = y[j] - T[j] - S[j]

STL decomposition iteratively updates the trend, seasonal, and remainder components until convergence is achieved. The smoothing parameters m, s, and L, as well as the weight vector w, are typically chosen using cross-validation methods.

**ETS MODEL WITH MATH**

ETS (Error, Trend, Seasonality) is a family of time-series models that can be used to forecast future values based on historical data. The ETS models are widely used in various fields such as finance, economics, and operations research.

The basic idea behind ETS models is to decompose a time-series into three components: Error (E), Trend (T), and Seasonality (S). The error component represents the random fluctuations or noise in the data that cannot be explained by the trend or seasonality. The trend component represents the long-term direction or pattern in the data, and the seasonality component represents the periodic fluctuations in the data.

The simplest ETS model is the ETS(A,N,N) model, which assumes that the time-series has an additive error component, no trend, and no seasonality. The model can be written as:

y\_t = e\_t

where y\_t is the observed value at time t, and e\_t is the error term at time t.

The next step is to add a trend component to the model. The ETS(A,A,N) model assumes that the time-series has an additive error component, an additive trend, and no seasonality. The model can be written as:

y\_t = l\_{t-1} + b\_{t-1} + e\_t

where l\_{t-1} is the level at time t-1, b\_{t-1} is the slope at time t-1, and e\_t is the error term at time t.

The final step is to add a seasonal component to the model. The ETS(A,A,A) model assumes that the time-series has an additive error component, an additive trend, and an additive seasonal component. The model can be written as:

y\_t = l\_{t-1} + b\_{t-1} + s\_{t-m} + e\_t

where s\_{t-m} is the seasonal component at time t-m (m is the seasonal period), and e\_t is the error term at time t.

The parameters of the ETS models can be estimated using maximum likelihood estimation or state space methods. Once the parameters are estimated, the models can be used to forecast future values of the time-series.

In summary, ETS models are a flexible and powerful family of time-series models that can be used to capture the various components of a time-series, including error, trend, and seasonality. The models can be customized to fit different types of time-series data and can be used for forecasting future values.

**ETS MAN**

The ETS (MAN) model is a type of exponential smoothing model used for time series forecasting. It stands for Error-Trend-Seasonality (Multiplicative) model with Additive Trend, which includes additive trend and multiplicative error, trend, and seasonality components.

The math equation for the ETS (MAN) model is as follows:

Level equation: L\_t = α(Y\_t / S\_{t-m}) + (1-α)(L\_{t-1} + T\_{t-1}) Trend equation: T\_t = β(L\_t - L\_{t-1}) + (1-β)T\_{t-1} Seasonal equation: S\_t = γ(Y\_t / L\_t) + (1-γ)S\_{t-m}

where:

L\_t = level component at time t T\_t = trend component at time t S\_t = seasonal component at time t Y\_t = actual value of the time series at time t m = the number of seasons in a year α = smoothing parameter for level component β = smoothing parameter for trend component γ = smoothing parameter for seasonal component

The forecast for the next time period (t+1) is then given by:

Ŷ\_{t+1} = (L\_t + T\_t) × S\_{t+1-m}

Note that the ETS (MAN) model is just one of many variations of the ETS model, and different variations may have different equations.

**ETS AAA**

The ETS (AAA) model is another type of exponential smoothing model used for time series forecasting. It stands for Error-Trend-Seasonality (Additive-Additive-Additive) model, which includes additive error, trend, and seasonality components.

The math equation for the ETS (AAA) model is as follows:

Level equation: L\_t = α(Y\_t - S\_{t-m}) + (1-α)(L\_{t-1} + T\_{t-1}) Trend equation: T\_t = β(L\_t - L\_{t-1}) + (1-β)T\_{t-1} Seasonal equation: S\_t = γ(Y\_t - L\_{t-1} - T\_{t-1}) + (1-γ)S\_{t-m}

where:

L\_t = level component at time t T\_t = trend component at time t S\_t = seasonal component at time t Y\_t = actual value of the time series at time t m = the number of seasons in a year α = smoothing parameter for level component β = smoothing parameter for trend component γ = smoothing parameter for seasonal component

The forecast for the next time period (t+1) is then given by:

Ŷ\_{t+1} = L\_t + T\_t + S\_{t+1-m}

Note that the ETS (AAA) model is just one of many variations of the ETS model, and different variations may have different equations.

**ETS AAA WITH DAMPED TREND**

The ETS (AAA) model with damped trend is a variation of the ETS (AAA) model, which includes a damping parameter that reduces the impact of the trend component over time. The math equation for the ETS (AAA) model with damped trend is as follows:

Level equation: L\_t = α(Y\_t - S\_{t-m}) + (1-α)(L\_{t-1} + φT\_{t-1}) Trend equation: T\_t = β(L\_t - L\_{t-1}) + (1-β)φT\_{t-1} Seasonal equation: S\_t = γ(Y\_t - L\_{t-1} - φT\_{t-1}) + (1-γ)S\_{t-m}

where:

L\_t = level component at time t T\_t = trend component at time t S\_t = seasonal component at time t Y\_t = actual value of the time series at time t m = the number of seasons in a year α = smoothing parameter for level component β = smoothing parameter for trend component γ = smoothing parameter for seasonal component φ = damping parameter, which should be between 0 and 1

The forecast for the next time period (t+1) is then given by:

Ŷ\_{t+1} = L\_t + φT\_t + S\_{t+1-m}

Note that the damping parameter φ determines how quickly the trend component approaches a constant value over time. When φ is close to 0, the trend component is allowed to vary widely over time, while when φ is close to 1, the trend component approaches a constant value quickly.

**ARIMA**

ARIMA (AutoRegressive Integrated Moving Average) is a popular family of time-series models that can be used to forecast future values based on historical data. ARIMA models are widely used in various fields such as finance, economics, and engineering.

ARIMA models consist of three components: Autoregressive (AR), Integrated (I), and Moving Average (MA). The AR component captures the linear dependence of the time-series on its past values. The MA component captures the linear dependence of the time-series on its past error terms (i.e., residuals). The I component captures the non-stationarity of the time-series by differencing it to make it stationary.

The basic idea behind the ARIMA model is to model the differences between the values of the time-series instead of modeling the original values. This is achieved by applying differencing operations to the time-series. Specifically, the differencing operator Δ is defined as:

Δy\_t = y\_t - y\_{t-1}

The first-order differenced series Δy\_t is stationary if the original series y\_t has a unit root, which means that the series is non-stationary. The unit root test is often used to determine whether differencing is necessary.

The ARIMA model is denoted by ARIMA(p,d,q), where p is the order of the AR component, d is the order of differencing, and q is the order of the MA component. The AR component can be written as:

AR(p): y\_t = c + Σ\_{i=1}^{p} φ\_i y\_{t-i} + e\_t

where c is a constant, φ\_i is the coefficient of the i-th lagged value of the time-series, and e\_t is the error term at time t.

The MA component can be written as:

MA(q): y\_t = c + Σ\_{j=1}^{q} θ\_j e\_{t-j} + e\_t

where θ\_j is the coefficient of the j-th lagged error term, and e\_t is the error term at time t.

The order of differencing d is determined by the number of times that the series needs to be differenced to make it stationary. If the series is already stationary, then d=0.

The parameters of the ARIMA model can be estimated using maximum likelihood estimation or other statistical methods. Once the parameters are estimated, the model can be used to forecast future values of the time-series.

In summary, ARIMA models are a flexible and widely used family of time-series models that can capture the linear dependence of a time-series on its past values and error terms, as well as the non-stationarity of the time-series. The models can be customized to fit different types of time-series data and can be used for forecasting future values.

ARMA

An ARMA(p,q) model is a combination of an autoregressive (AR) model of order p and a moving average (MA) model of order q. The general equation for an ARMA(p,q) model is:

y\_t = c + φ\_1 y\_{t-1} + φ\_2 y\_{t-2} + ... + φ\_p y\_{t-p} + ε\_t + θ\_1 ε\_{t-1} + θ\_2 ε\_{t-2} + ... + θ\_q ε\_{t-q}

where:

* y\_t is the time series variable of interest at time t
* c is a constant term
* ε\_t is a random error term at time t
* φ\_1, φ\_2, ..., φ\_p are the autoregressive coefficients for lags 1 to p
* θ\_1, θ\_2, ..., θ\_q are the moving average coefficients for lags 1 to q

This equation can be written more compactly using the lag operator L, defined as L^k y\_t = y\_{t-k}. The ARMA(p,q) equation can then be written as:

(1 - φ\_1 L - φ\_2 L^2 - ... - φ\_p L^p) y\_t = c + (1 + θ\_1 L + θ\_2 L^2 + ... + θ\_q L^q) ε\_t

or

φ(L) y\_t = c + θ(L) ε\_t

where φ(L) and θ(L) are polynomials in the lag operator L, with degrees p and q, respectively.