IDENTIFICATION AND APPLICABILITY OF TIME CYCLES IN THE INDIAN STOCK MARKET

by

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DEDICATION

THIS DISSERTATION IS DEDICATED TO ALL THE BELIEVERS OF PROFITS IN THE STOCK MARKET AND MY MENTOR, PROF. DAVID ANNAN FOR HIS CONTINUOUS GUIDANCE

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In the journey of my Doctoral course, I have been helped and supported by many people, especially my wife, Deepti, and daughters, who gave me time and space to pursue my interest in this subject.

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ABSTRACT

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ATUL GOSWAMI

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Dissertation Mentor: prof. David Annan

Time cycle patterns have been identified across asset classes in financial markets (Hurst, 1972), and this is an area of great interest. This study aimed at testing some of the methods; including Hurst's time cycle envelope and Dewey’s statistical data analytics, to explore the possibility of using the same in stock trading in Indian markets profitably. Considering the dynamic nature of stock markets and their dependencies on various factors, the study tested one of the selected methods for the dataset to support the hypothesis that time cycles are more of an academic subject than a tool to trade in stock markets.

The study used an exploratory study that follows the principles of quantitative research. The study analyzed the Fast Fourier Transform and Goertzel general algorithms to select the one with the least error in the detection of the dominant cycle in terms of buy and sell signals.

A composite cycle was constructed to analyze and track the Nifty50 index for the period between 01/05/2023 and July 31, 2023, which shows the principle of variation cycles arrive earlier or later than the standard time cycle in a trendy market with absolute return of 5.03 % annualized return by Nifty 50 index and does not show value of using time cycles as

indicator of choice while other traditional indicators like MACD are showing 209.30% annualized return in the same period.

This study's findings could be valuable to stock market traders who are trying to time the market based on time cycle software and indicators. This research will provide traders with a base on which they can further build additional indicators to be able to make better trading decisions and improve profitability.

KEYWORDS

Stocks, Time Cycle, Fourier Transform, FFT, Goertzel, DFT, Nifty, Indian Stock Market, Cycles, Indicators, Seasonality, Trend, Trading Strategy, MACD, TF-IDF, NN, Neural Network, Artificial Intelligence, Deep Learning

LIST OF ABBREVIATIONS

FFT- Fast Fourier Transform

DFT- Discrete Fourier Transform

FT- Fourier Transform

PSD- Power Spectral Density

CSV- Comma Separated Value

MACD - Moving Average Convergence Divergence

TF-IDF- Ensemble deep learning framework for stock market data prediction

NN- Neural Network

LSTM- long short-term memory

RNNs- recurrent neural networks

SIWOA-Self-Improved whale optimization algorithm

DBN - Deep Belief network

AR - Autoregression Model

ARMA - Autoregressive Moving Average Model

ARIMA -Autoregressive Integrated Moving Average Model

OLS - Ordinary Least Square

SMRF-TM - Stock Market Random Forest-Text Mining system

RF- Random Forest

SEBI - Securities & Exchange Board of India

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CHAPTER I: INTRODUCTION

1.1 Introduction

The stock market is a dynamic environment where prices fluctuate rapidly. The behavior of stock prices is influenced by various factors and understanding the patterns in the stock market has always been of great interest to investors, economists, and researchers (Biswas and Ghosh, 2021). One of the patterns that have been identified in the stock market is "time cycles," which refer to the recurring patterns in the stock market's behavior over time (Hurst 1972).

Cyclical activities and their impact on various aspects of life have been identified (Saumendra and Venugopal, 2012; Celis, 2015), including on stock markets and stock prices at an individual level. Various tools have been developed to identify time cycles in stock markets (Hurst, 1972; Dewey, 1955) using methods like the Time Cycle Envelope and Fast Fourier Transform (FFT).

This study focused on comparing two methods of identifying time cycles in stock markets first: The Fast Fourier Transform and the Goertzel method (Goertzel, 1958). After a comparison of these two methods, the study identified the one with the lowest error rate and implemented it on Indian stock Market data to track the viability of its usage on Indian stock market indexes. Learning from this study will help create a tool/ process to improve profitability in stock trading by using time cycles as the base.

1.2 Research Problem

Prices in stock markets fluctuate very frequently and are dependent on many factors, including macroeconomic and microeconomic factors (Agwu and Haydar, 2023; Connolly and Stivers, 2005; Pinjaman, 2015). Researchers have analyzed the possibility of predicting the impact of some of the factors on the stock market (Biswas and Ghosh, 2021).

Hurst (1972), Gann (2009), and Dewey (1955) have shown the existence of time cycles and methods of using them to trade in stock and commodity markets. Following Hurst's eight (8) principles of time cycles (Hurst,1970; Grafton, 2011), the axioms of a mathematical theory define his cyclic theory.

The eight Principles of Hurst's Cyclic Theory are:

- The Principle of Commonality: All equity (or forex or commodity) price movements have many elements in common (in other words similar classes of tradable instruments have price movements with much in common)
- The Principle of Cyclicality: Price movements consist of a combination of specific waves and therefore exhibit cyclic characteristics.
- The Principle of Summation: Price waves that combine to produce the price movement do so by a process of simple addition.
- The Principle of Harmonicity: The wavelengths of neighboring waves in the collection of cycles contributing to price movement are related by a small integer value.
- The Principle of Synchronicity: Waves in price movement are phased to cause simultaneous troughs wherever possible.
- The Principle of Proportionality: Waves in price movement have an amplitude that is proportional to their wavelength.
- The Principle of Nominality: A specific, nominal collection of harmonically related waves is common to all price movements.
- The Principle of Variation: In essence, these principles define a theory that describes the movement of a financial market as the combination of an infinite number of "cycles". These cycles are all harmonically related to one another

(their wavelengths are related by small integer values) and their troughs are synchronized where possible, as opposed to their peaks.

The principles define exactly how cycles combine to produce a resultant price movement with an allowance for some randomness and fundamental interaction.

The study uses the principle of “variation” to make the time cycle fall earlier or later than ideally it should. Considering the above two factors (lots of factors affecting stock market movement and cycles bottoms arriving early or late) and the lack of research and texts on the profitability of using time cycles as a profitable and practical trading tool.

Therefore, the study analyzes the viability of the usage of time cycles for profitable trading in the Indian Stock market and use one of the two methods of identifying cycles, Goertzel and/or Fast Fourier transform, after comparison and identifying the one with the least amount of error.

1.3 Purpose of Research

Professional traders invest lots of money in buying software and/or platform subscriptions that provide an edge in the trading business. This edge can be in the form of a new indicator, a strategy, or a combination of several indicators and methods, but results always help traders “time the trade”.

This study explores the possibility and viability of identifying and using time cycles in Indian stock markets as one of the indicators. The result of this study will help traders make informed decisions about whether they should use time cycle software/platforms as a stand-alone solution that can give them consistent profits for a long time or whether they need to combine other indicators and fine-tune their trade timing to minimize decision error.

In addition to this, the study also reviewed literature from other researchers in the field of predicting stock market prices using various techniques and has added the views and points as to why these studies do not instill confidence that can be used to trade profitably and with certainty.

1.4 Specific Aims

The aims of this study are as follows:

1. To identify methods with minimum error in identifying the dominant time cycle in the Indian stock market.
2. Testing Indian stock market data against two pointers for timing the trade for profitability.
    a. Identifying the bottom of the time cycle and aligning buying trades with it.
    b. Identifying the peak of the cycle to exit the long trade and trade in the reverse direction for profit.

1.5 Significance of the Study

Financial markets around the world have seen significant changes in the last couple of decades since investment horizons became global and local stock markets received new global factors infusing volatility in terms of investments, political influence, etc. (Biswas & Ghosh, 2021).

Traditional investment decisions revolve around current strength, quarterly results, and future forecasts (Akib et al., 2023), which is not enough anymore. Hence, an investment in the right company at the wrong time does not yield good returns. The Indian stock market Index Nifty50 (in Figure 1) achieved the 18600 level on October 18, 2021, took more than a year (November 2022) to reach the same level again, and finally broke out of this level, eight months further down, in July 2023. Hence, investors who invested at the October 2021 level did not get a yield return in almost 20 months. However, if an investor had waited until after October 2021, a high of 8 months until June 2022, they would have made/yielded almost a

20% return in 13 months. The strategy of finding the peaks and troughs in the market is what makes all the difference. Selecting a fundamentally good stock is only half the job; the second and more important half of the job is to time the trade.

Figure 1 Nifty return and profit opportunity in 20 months

Various tools have been developed (Hurst, 1972; Dewey, 1955) to take care of timing a trade. But are these tools and methods enough as a stand-alone solution, or do we need to use them as part of the solution, combined with other indicators?

This study will help mitigate the importance for traders so that they can combine the knowledge produced because of this study with other professional tools to time the trades, maximize their profits, and minimize the magnitude of their maximum drawdown.

The research could have valuable implications for various groups, including individual investors, financial advisors, market administrators, and policymakers. By examining patterns and biases in investment behavior, the study's findings could assist individual investors in adjusting their strategies to optimize their returns. Additionally, financial advisors may be able to enhance their services by using this information to better cater to their client's needs.

One of the practical benefits of this study may be that it informs individual investors and financial advisors about the behaviors of investors during the days of the week and times of the day. The study's findings indicate the days and times of day when individual investors are most likely to trade equities. Individual investors may find this material useful in making informed decisions before making investments.

This information can help financial advisers and individual investors make the best possible investment choices. They might be able to create investing plans that call for them to sell stocks on days and times when prices are often higher and to purchase equities on days and times when prices are usually lower.

1.6 Research Purpose and Question/Hypothesis

This research will address the following questions:

1. Can trading be done profitably by predicting the cycle's bottom?

2. Examine the cycle peak and trough detection on long and short profitability using time cycle principles.

Hypothesis:

Hp1. There is a statistical difference between using time cycles and the profitability of trading by predicting the bottom of market cycles.

Hp2. Individual investors should use different methods in the trading cycle to maximize gains in the stock market through the impact of cycle peak and trough detection on the profitability of long and short trades using time cycle principles.

Answers to the above questions will help investors and traders decide on the viability of using time cycles as indicators in the Indian stock market.

1.7 Summary and Conclusion

This chapter included a description of the background of the study, the research problem, and the gap in current research. It also included the purpose of the study, research questions and hypotheses, the theoretical foundation of the study, and the nature of the study, including independent and dependent variables. Finally, the study described the significance of the study in terms of advancing theory and practice and influencing positive social change.

The next chapter 2 includes descriptions of sources and theories in detail. The research also provides an exhaustive review of current literature, including a review and synthesis of studies related to the research questions.

CHAPTER II: LITERATURE REVIEW

2. Introduction

Hurst's theory (1972) of stock market time cycles has been studied for decades, and many studies have confirmed it. Fourier analysis is used to identify dominant frequencies and harmonics, which can affect stock prices and create patterns for peak and trough forecasting. Investors can understand stock buying and selling cycles and make better investment decisions.

Chauvet (2001) linked business cycles to stock market swings, Rusu and Dumitrescu (2014) found months-to-years-long Bucharest stock market cycles, and Khan and Arslan (2018) found months-to-years-long Pakistan stock market cycles. The Fourier transform revealed dominant frequencies and harmonics affecting prices, trading intensifies cycles, political/election cycles, climate cycles, quarterly result cycles, monthly fed interest rate announcement cycles, yearly government budget announcement cycles, and festival cycles drive business cycles. Hurst, Fourier, and Fisher (1972, 1988) transform methods will be used to identify NSE time cycles.

The study also looked at Granger causality and deep learning algorithms used in predicting stock prices and stated some implications on time and stock market cycles.

2.1.2 Preliminary Literature Review

This literature review shows that stock market time cycles have been studied for decades. Hurst (1972) first identified stock market cycles. Since then, many studies have confirmed Hurst's theory of stock market time cycles. Many factors such as politics, business, and climatic cycles can affect stock market time cycles, as reviewed. Some studies have linked these factors to stock market behavior, but others have not. Hence, the study uses Hurst's cycle envelope technical indicator to analyze time cycles in the Indian stock market.

Most studies use Fourier's (1988) analysis to identify dominant frequencies and harmonics, which can affect stock prices and create patterns for peak and trough forecasting. The review also stressed the importance of studying shorter time cycles and stock prices. The figure below indicates how the Fourier time domain cycle works and shifts signals.

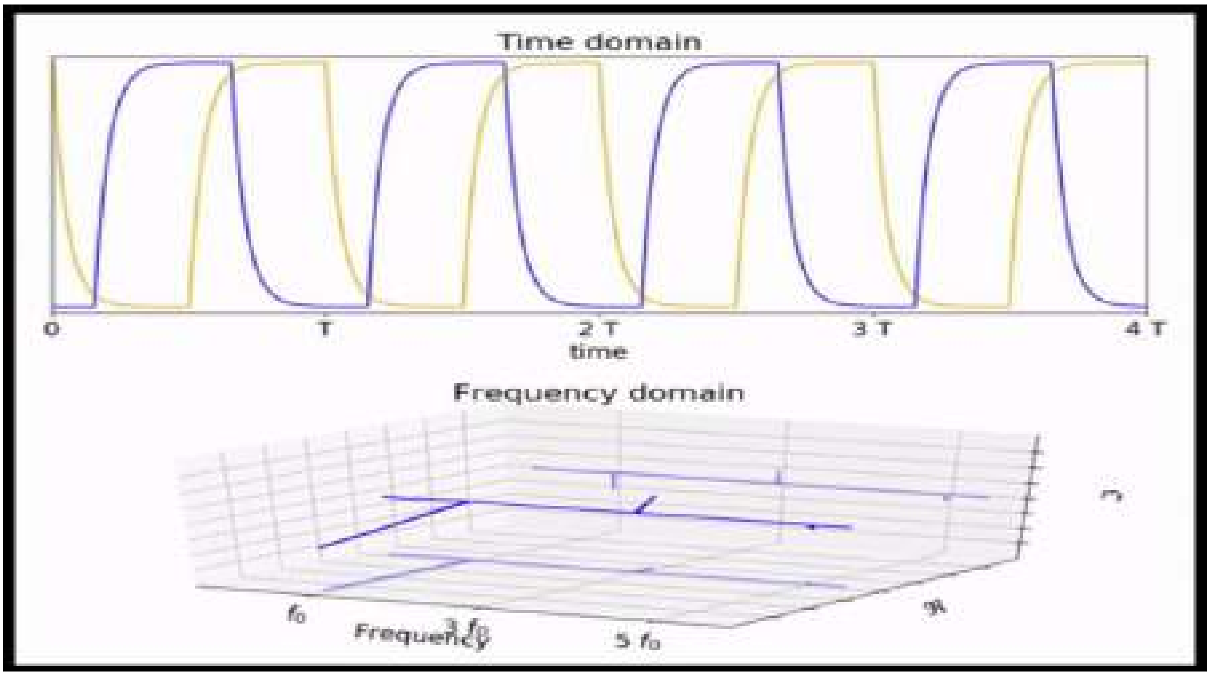


Figure 2 *Fourier Transform of a time-shifted signal. [Top] the original signal (yellow), is continuously time-shifted (blue). [Bottom] The resultant Fourier Transform of the time-shifted signal. Note how the higher-frequency components revolve in complex planes faster than the lower-frequency components.*

People's beliefs, attitudes, and intentions explain the theory of reasonable Action (TAR) behavior and these reasonable actions inform people, firms, and institutions about choices when it comes to investment platforms. Investors can understand stock buying and selling cycles. It can help investors understand stock market cycles and make better investment decisions. Hurst (1974) created long-term, intermediate, and short-term stock market time cycles.

Many studies, including Tim Ord's, have tested Hurst's theory (2007). The paper evaluates many criteria to create a Hurst-based technical signal for Indian stock market cycles. Evalita et al. (2020) found that stock market values drop in the first two years of the four-year presidential cycle and peak in the third and fourth. Chauvet (2001) linked business cycles to stock market swings.

Rusu and Dumitrescu (2014) found months-to-year-long Bucharest Stock Market cycles. According to Cycles predict stock prices, Khan and Arslan (2018) found months-to-years-long Pakistan stock market cycles. The Fourier transform revealed dominant frequencies and harmonics affecting prices and produced patterns that can predict future peaks and troughs.

When trading intensifies cycles. Ma 2017; Zhang 2020; Kim 2019; Choe 2015; Herath 2018, and Ranasinghe 2021), examined stock market cycles. Stock prices can be predicted from days to years in advance.

Cycle analysis using a time-cycle oscillator developed by Sherbini (2018) shows that volume can be used to predict stock market turning points early or late. in the study Sherbini used other technical indicators like Volume, moving averages, and momentum indicators like ADX. Using these indicators, entry and exit strategies were suggested. The study clearly shows that the usage of a time cycle oscillator may not be sufficient as a stand-alone technique to predict stock market trade timings. Ingram's mathematical approach combines Elliott waves with Hurst’s Time Cycle concept to predict price peaks and troughs, Kumar (2016).

Political/election cycles, climate cycles, quarterly result cycles, monthly fed interest rate announcement cycles, yearly government budget announcement cycles, and festival cycles drive business cycles. Festival studies show that businesses perform best around festivals, but forecasting future peaks and troughs is difficult due to their dynamic nature.

Hurst, Fourier, and Fisher (1988,1972) transform methods are used to identify NSE time cycles. It tests 2000–2022 data for forecasting accuracy, delay and variation frequency, and time cycle trading viability.

It is worth noting that the findings of cycle forecasting will be significant, considering that the overall market performance tends to be efficient in the long term. This suggests that investors cannot consistently outperform the market. As a result, the returns on each day of the week are expected to be similar to the returns on any other day (Sharif, 2019). However, numerous studies have indicated the existence of calendar anomalies in the market, suggesting that investors may have the opportunity to generate higher profits and outperform the market during specific periods.

According to research conducted by Afrilianto and Daryanto (2019), Anjun (2020), Hirshleifer et al., (2020), and Kumar (2016), stock market price changes can be predicted as returns are influenced by seasonality. However, it is important to note that calendar anomalies pose a significant challenge to the trading cycle.

Calendar anomalies have been observed to cause stock prices to vary depending on the day of the week, the month of the year, and even the time of day. These patterns in stock price behavior are not in line with predictable cycles. Karanovic and Karanovic (2018) suggest that astute investors can exploit these inconsistencies to generate significant profits in the stock market, capitalizing on the impact of these anomalies.

2.1. 3 Market Anomalies across trading Cycles

Financial market anomalies refer to stock price changes that cannot be explained by conventional financial theories, as mentioned by Afrilianto and Daryanto (2019). This term is used to describe behaviors or events that deviate from established theories, models, or hypotheses without a logical explanation for their occurrence.

According to Kahneman and Tversky (1979), anomalies typically exhibit consistent patterns and cannot be dismissed as random errors. In the context of financial markets, calendar anomalies pose a challenge to the Efficient Market Hypothesis (EMH) and random walk theories. When studied and brought to light, certain anomalies may vanish, while others continue to persist over time.

Numerous authors have conducted studies on the presence of financial anomalies in both developed and emerging markets. Similarly, there is a wealth of research demonstrating the existence of financial anomalies across various market sectors, such as foreign currency exchanges, derivatives, bitcoin, interest rates, and treasury bills. Calendar anomalies encompass a range of effects, including the January effect, day-of-the-week effect, Islamic calendar effect, turn-of-the-month effect, half-of-the-month effect, time-of-the-month effect, 4 month-of-the-year effect, holiday effect, and Halloween effect.

The January effect is a seasonal anomaly observed in the stock market, where higher mean returns are typically observed during the month of January compared to other months of the year (Patel, 2016). According to the random walk theory, successive one-period returns of a stock should be independent and follow a random path, suggesting that there should be no consistent variance in monthly stock returns over time. Therefore, the presence of the January effect in stock market returns is considered an anomaly. Wachtel (1942) examined the Dow Jones Industrial Average from 1927 to 1942 and noted frequent bullish tendencies from December to January.

Numerous studies have indeed demonstrated the presence of the January effect in various markets. One possible explanation for this effect is the window dressing hypothesis. According to Lakonishok and Smidt (1988), many investment managers sell their underperforming stocks in December to take advantage of tax rules and reduce their tax burdens. This selling pressure tends to depress stock prices in December. In January, these same managers often repurchase these stocks, leading to an increase in stock prices. This cycle of selling and subsequent buying back helps explain the higher returns observed in January (Caporale & Zakirova, 2017).

The turn-of-the-month effect anomaly refers to the phenomenon where average stock returns during the last and first three days of the month are higher compared to returns during the remaining days of the month. This anomaly has been observed in various equity markets by numerous researchers. Several explanations have been proposed to account for the turn-of-the-month effect, although no consensus has been reached regarding its exact causes.

Some researchers have linked it to the turn-of-the-year effect. Similar to the turn-of-the-year effect, investment managers dress up their portfolios at the end of each quarter per the window dressing hypothesis. Jebran and Chen (2017) indicated that the turn-of-the-month effect in the U.S. market is driven by the timing of dividend payments on equity and the interest payments on debt.

The month-of-the-year effect refers to changes in stock returns based on the specific month of the year. The January effect, as mentioned earlier, is one example of this phenomenon. Another example is the “Mark Twain effect”, which suggests that stock returns tend to be lower in October compared to other months (Caporale and Zakirova, 2017). Additionally, the half-of-the-month effect indicates that returns on equity during the first half of the month are typically higher than returns during the second half of the month.

The time-of-the-month effect is another anomaly that has been observed in various equity markets since its discovery. This phenomenon refers to the difference in returns on equity during each third of the month. Typically, the first third of the month exhibits the highest return, followed by the second third, while the last third of the month tends to have the lowest rate of return. Researchers have identified this anomaly in different markets worldwide.

The holiday effect refers to the observation that pre-holiday returns on equity tend to be higher compared to post-holiday returns. Seif et al., (2017) argued that this effect is a global phenomenon and is not specific to any particular country's capital market. It has been found that the pre-holiday rate of return is often significantly larger than the normal daily rate of return (Caporale and Zakirova, 2017)

The Halloween effect refers to the phenomenon where the rate of return on equity tends to be higher during the months from November to April compared to other periods. It has been observed that investors often sell their assets in May and then repurchase them in September (Caporale and Zakirova, 2017). Some investors may use this strategy in an attempt to achieve higher returns than the market average using business cycle forecasting.

2.1. 4 Business Cycle Forecasting

Chauvet (2001) linked business cycles to stock market swings. The study investigates the intricate interplay between stock market fluctuations and the business cycle. It can be inferred that fluctuations in the stock market are indicative of the positions adopted by market participants, which are influenced by their evaluations of the prevailing economic conditions.

This study examines the potential for predicting business cycle turning points by utilizing readily available financial indicators, taking into account the forward-looking behavior exhibited by stock market investors.

Nonlinear dynamic components at monthly frequency serve as representations of stock market swings and business cycles. The proposed model utilizes the business cycle factor to provide forecasts of business cycle turning points and further incorporates the stock market factor to anticipate these projected turns. The results suggest that the derived stock market component serves as a predictive measure for the status of the economic cycle, enabling real-time anticipation of turning events.

Even though the study's method is interesting, it may oversimplify the complex link between stock market swings and the business cycle. It assumes that there is a straight cause-and-effect relationship between the two, which means that people's opinions about the state of the economy are what moves the stock market. Still, the stock market is affected by several factors that go beyond economic principles. These include investor sentiment, changes in geopolitical events, and changes in monetary policy.

Also, it is possible that the study's claim that changes in the stock market can correctly predict turning points in the business cycle is overstated. Even though financial data and stock market behavior can give important clues about economic trends, it is important to remember that they are not foolproof predictors of how the business cycle will change in the future. Business cycles are hard to understand because they are affected by so many different economic factors. It is important to remember that making guesses based only on how the stock market moves can lead to wrong predictions.

Moreover, the suggested model's use of nonlinear dynamic elements to capture changes in the stock market and business cycles may add a certain amount of complexity, which could lead to overfitting or make it hard to understand. Incorporating nonlinear dynamics into economic modeling and forecasting can be very hard, so it's important to be careful.

When using the stock market as a forecast, the fact that possible feedback loops and endogeneity between the stock market factor and business cycle turning points are not taken into account could be a weakness. The effect of stock market movements on the economy is similar to the effect of the economy on the stock market. This makes for a complicated and possibly cyclical relationship that the model may not be able to fully describe as it creates market anomalies in stock prices.

Even though the study's results may suggest that the calculated stock market component could be used to predict the economic cycle, it is important to be careful when depending only on this method. A more thorough and all-encompassing look at the relationship between stock market instability and the business cycle, taking into account a wider range of economic data and possible factors that could change the results, would lead to a more accurate and stable understanding of the relationship.

2.2 The Co-movement and causality between the stock market cycle and business cycle

Si et al., (2019) in their study made an effort to establish how the stock market cycle and business cycle in China moved together and caused each other from 1992Q1 to 2018Q1. They used wavelet analysis to look for possible patterns that change over time and frequency. The findings show that when the economy is doing well, the stock market tends to lead the business cycle, but when the economy is doing badly, the business cycle tends to lead the stock market.

Also, when the business cycle comes before the stock market cycle, the two are always linked in a good way. When the business cycle comes before the stock market cycle, on the other hand, they tend to be linked in a bad way. They also found that the co-movement and causal relationship between the two cycles in China change a lot in time and frequency.
This suggests that the time- and frequency-variation features should not be ignored in future studies. This strengthens our argument that the Principle of Variation of the Time Cycle makes it difficult to adopt as a reliable method of predicting the stock market cycle's behavior.

Lastly, the relationship can be greatly affected by both internal interest rates and shocks from the outside, such as changes in interest rates or the business cycle in other major advanced countries. These results shed new light on research that only looks at one part of a relationship and doesn't look at how it changes over time or how often it happens.

A similar study was conducted by Sohn and Chung (2022) on Stock market cycle and Investment Strategies. This study looks at the performance of investment strategies that use an estimated stock market cycle based on a lead-lag link between the business cycle and the stock market cycle. This gives us empirical implications for risk management. The data runs from June 1953 to September 2022, and the probity model uses the detrended short rate, term spread, credit spread, and stock market volatility as major input variables to estimate the business cycle and stock market cycle.

Based on an estimate of the stock market cycle, two types of strategies are made, and their success is measured against a benchmark. Findings Two types of tactics can be used based on the stock market cycle: The first is to buy (or sell) stocks when the stock market is expected to grow (or shrink), and the second is to buy (or sell) stocks (or bonds) when the market is expected to grow (or shrink). Both in-sample and out-of-sample research show that tactics based on the stock market cycle do better than a simple "buy and hold" strategy.

The second strategy, which is in line with asset allocation, seems to be more profitable than the first one, based on data from outside the sample. Implications for Research or Originality The strategies looked at in this study are based on an estimated cycle of the stock market, which only depends on a few easy-to-find financial factors. This makes it easier to set up such a strategy. It means that investors can improve how well their investments do if they set their position on stocks or choose which asset class to buy based on the stock market cycle. This can be done by making a relatively simple trading strategy.

Certain aspects warrant a critical analysis to better understand the implications and limitations of the research. For example, the study spans from June 1953 to September 2022, which covers a significant time frame with diverse market conditions. However, the relevance of strategies developed using historical data to modern market dynamics might be questionable. Market structures, regulations, and economic conditions have evolved, potentially affecting the applicability of the findings to the present or future investment landscape.

The study suggests that the strategies outperform a simple "buy and hold" strategy. However, it does not address the potential influence of market efficiency, transaction costs, and slippage on the feasibility and profitability of executing the proposed strategies in real-world conditions. Investment decisions are often influenced by behavioral biases, sentiment, and emotional factors that may not be adequately captured by a model relying solely on financial indicators. The abstract does not discuss the potential impact of investor behavior on the strategies' performance.

While the study portrays the strategies as relatively simple, there is a lack of detail about how these strategies can be practically implemented. Real-world execution challenges, such as liquidity constraints, trading costs, and market access, are not addressed. While the study's findings appear promising and establish some correlation between Business cycles and Investment strategies, it does not explain or prove if stock market cycles can be used to predict stock price, although it explains the impact of business cycles and relevant strategies that can beat market returns. It also does not explain if these strategies are compared with other market indicators and how these strategies fare against them.

2.2.1 Intermarket Analysis: Oil, Gold, Dollar, Stock Market

Correlation between various asset classes has been researched by many researchers and is used to predict the direction and timing of movement. De Castro Aguado (2017) tried establishing relationships between different financial products/assets. Danielle et al., (2022) study the correlation between Oil, Gold, Dollar, and Stock Market to explore the possibility of predicting the interdependent movement of these asset classes and their timings.

The study looks at how oil, gold, the US dollar, and stock market prices all rely on each other. This is done to learn and predict economic cycles and help people decide how to spend their money. The study uses data from November 2011 to October 2022 to look at these assets. It does this by using regression and simultaneous equations. The results indicate that:

- The price of oil goes down when the price of stocks goes up.
- The price of oil goes up when gold and the US dollar go up.
- The stock market, the US dollar, and the price of oil all affect how much gold costs.
- The price of oil, gold, and stocks all hurt the US dollar.
- Oil, cash, stocks, and the US dollar are all linked around the world.

Intermarket research is a key part of allocating assets and predicting economic trends. Commodities, currencies, bonds, and stocks all give clues about how the economy will change in the future. There were problems with the way the study was done, such as missing data, time-consuming manual processes, and the possibility of errors because of the short time frame and other model limits. Even though the way markets work may change, it is still important to understand how they work to make good investments.

The study shows that the complicated links between oil, gold, the US dollar, and stock market prices can affect investment choices and help predict economic cycles, but there are many reasons to be skeptical.

First, using data from 2011–2022 only does not ensure that you can predict the market. Many things affect stock markets, and many of them can change quickly and out of the blue. Gold, oil, and the currency are not the only things that make the stock market hard to understand.

Changes in the government, new technologies, natural disasters, and even tweets from famous people can all affect the value of stocks. So, focusing only on these four asset types could make a hard trading situation too easy. The fact that the study admits to missing data and possible mistakes makes it hard to believe that it is correct. If data is missing or skewed, it could be risky to trade in real-time. Manual analysis tools like EViews and Microsoft Excel may not be fast enough or scalable enough for dealing that moves quickly. The same is true for regression and simultaneous equation models.

Markets often act in a way that makes no sense, and that no model can predict how they will act. These models might not take into account how traders think and act, which affects market trends today. And then business ties change over time. It is risky to try to time deals with fixed ties.

Lastly, the COVID-19 outbreak shows how unexpected outside forces can affect all types of assets in ways that could not have been predicted by looking at past data. When thinking about real-time stock market buying, it's important to know the risks and limits of the models. Even though it's important to understand how assets combine.

2.2. 2 Impact of Crowd Psychology on Stock Market Cycles

Xuan (2022), in her study about the relationship between crowd psychology and the stock market cycle in Vietnam, suggested that investing in the stock market is often influenced by crowd psychology, leading to similar actions when influenced by the crowd, which can be seen as cyclic in nature. A survey of 120 Vietnamese investors revealed that the majority of them choose stocks chosen by many other investors and easily react when the crowd reacts. The Vietnamese stock market goes through the same psychological cycles as other countries, with investors expected to be in a period of thrill or euphoria.

The herd effect is a common signal in Vietnamese investors, as they often choose stocks that many people choose even though they don't know the operating status of the company. The survey conducted by her for this study reveals that 67.1% of traders agree that they are influenced by the stock choices of people around them, with a quarter of investors choosing strongly to agree. Xuan concludes that Vietnamese investors are still affected by the herd effect, which affects their mood and behavior when choosing stocks and monitoring the actions of others. The current market is experiencing a rapid increase, with the Vietnam Index rising steeply with high trading volume. Investor psychology is in the stage of thrill or euphoria, indicating a hot growth situation. To make wise investment decisions, investors must be cautious and calm, avoiding crowd psychology and limiting the influence of the crowd.

While Xuan’s study sheds light on the influence of crowd psychology on investment decisions and the cyclic nature of stock market behavior in Vietnam, it raises some questions about its validity. To start with, the study's findings are based on a survey of 120 Vietnamese investors, which might not be representative of the entire investor population in Vietnam. It's important to recognize that individual behavior in the stock market can vary significantly, and conclusions drawn from a relatively small sample might not accurately reflect the broader investor landscape.

The study suggests a direct link between crowd psychology and investment decisions, it may oversimplify the complex factors that drive stock market behavior. Market movements are influenced by a multitude of variables, including economic indicators, company fundamentals, geopolitical events, and government policies. Crowd psychology is just one of many factors that contribute to market dynamics.

The study also highlights the prevalence of the herd effect among Vietnamese investors, it's essential to consider that not all investors blindly follow the crowd. Many investors conduct thorough research and analysis before making investment decisions. The study may not adequately differentiate between individuals who succumb to crowd influence and those who make informed choices.

The study acknowledges the impact of crowd psychology, it might overlook other behavioral biases that can influence investment decisions. Confirmation bias, loss aversion, and overconfidence are just a few examples of cognitive biases that can affect investor behavior independently of crowd influence.

The study assumes that crowd psychology always leads to suboptimal decisions. However, efficient market theory suggests that stock prices reflect all available information, including crowd sentiment. In such a scenario, the influence of crowd psychology might be already incorporated into stock prices, reducing its predictive power.

Finally, we think, that while Yen Xuan's study highlights the influence of crowd psychology on stock market behavior in Vietnam, it's important to approach the findings with a critical perspective. The relationship between crowd psychology and investment decisions is complex and might not be the sole driver of market cycles. Max pain theory (Upstox, 2023) suggests that market options expire where there is maximum pain for option buyers, that is retail investors and traders. This theory completely opposes the idea of crowd behavior causing any kind of cyclic change in the stock market.

2.2.3 Impact Mapping of Presidential Election Cycle in US Stock Markets

Wong and McAleer (2009) conducted interesting research on the correlation between stock market cycles and US Presidential elections. From January 1965 to December 2003, US stock prices followed a trend that matched the four-year cycle of presidential elections. Stock prices usually went down for the first two years of a President's term, reaching their lowest point in the second year. After that, they went up, reaching their highest point in the third or fourth year. This trend was especially clear when Republicans were in charge, which suggests that the Republican Party may have changed policies to help them get re-elected. Interestingly, times when the stock market went up often happened when Democrats were in charge. This cyclical pattern, called the Presidential Election Cycle, could be an outlier in the US stock market and give buyers important information.

The study talks about how Presidential elections affect stock prices. During election years, the stock market often does better because lawmakers put in place good business policies. The paper uses spectral analysis to show that the 4-year Presidential Election Cycle is present in the US stock market. It also talks about what this means and how investors might gain from it.

In the end, the study says that political actions by the government can have a big effect on both the performance of the economy as a whole and how people act in the economy. Especially during election times, the current government may change economic strategies to reach certain goals, which in turn affects the stock market.

First of all, one of the foundational principles of scientific research is that correlation does not mean causation. Just because the US presidential cycle correlates with the stock market movements doesn’t mean that this cycle has a direct impact on stock markets. There might be other intervening or latent variables affecting both.

Secondly, there are a lot of things that can affect the stock market, such as economic indicators, company earnings, geopolitical events, interest rates, and investor sentiment. It would be too simple to say that changes in the stock market are caused by a single to a single Presidential Election Cycle.

Another important perspective is that Sudden, random events, often called "black swan" events, can have a big effect on the financial markets. These can be anything from geopolitical problems to pandemics, and they can be much bigger than the effects of cycles. These events can be man-made or natural, and the impact of the same can’t be ignored irrespective of the timing of an election.

Finally, we would like to draw readers' attention to the fact that Different Markets React Differently: The study doesn't say if the trend seen affects all stock markets around the world or just a few. Different countries' stock markets can respond differently depending on their economies, politics, stage of social and political stability, and other unique factors.

When we consider the Indian stock market, which is the subject of this research, the basic fact is that presidential elections don't draw any attention from industry and have little or no impact on the stock market. Instead, we have a 5-year Prime Minister election cycle, which in terms of length of a cycle is different from the US presidential cycle which is 4 years long.

Year of PM Election	The first two years of a new government	Nifty 50	election result	% change in the index
1991	1991	575	Congress Won	19.10
	1992	1270		1208
1996	1996	899.1	BJP Won	-2.13
	1997	1079.40		20.05
1998	1998	884.25	BJP Won	-18.10
	1999	1480.45		67.42
2004	2004	2080.50	Congress Won	10.68
	2005	2836.50		36.36
2009	2009	5201.05	Congress Won	75.75
	2010	6134.50		17.93
2014	2014	8282.70	BJP Won	31.38
	2015	7946.35		-4.06
2019	2019	12168.45	BJP Won	12.04
	2020	13981.75		14.91

Table 1 - Stock Market Results during the first two years of a new government

When we compare the data of Indian elections, table 1, and its impact on the Indian Stock Market, it is completely different from the US stock market and its correlation with the US Presidential election because the Indian stock market has gone down multiple times in the first year of election like in 1996, and 1998. Another point in comparison is that many times governments did not last for the whole 5 years like in 1989, 1996, and 1998, which disrupted the 5-year election cycle. This clearly shows that the result of Wong & McAleer's (2009) study cannot be generalized across countries and cannot be used as the sole factor to decide on the timing of stock market trades.

2.2.4 Deep learning and stock market predictions

Deep learning, a subset of machine learning, is increasingly being employed to predict stock market prices. By leveraging neural networks, especially recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, deep learning models can process vast amounts of financial data, recognize intricate patterns, and make predictions based on past trends. These models can also incorporate diverse data sources, from historical price data to news sentiment, providing a multi-faceted approach to stock market forecasting. The depth and complexity of these networks allow for capturing nonlinear relationships in the data, offering potentially more accurate and sophisticated market predictions.

B L & B R (2021) conducted a study using Deep Learning methods for the prediction of stock prices.

The study goes into detail about how hard it is to guess stock prices. Traditional methods, which mostly rely on historical data or textual information, often fall short because stock markets are very volatile and are affected by many things, such as investor sentiment, government changes, and the way the economy works. To solve this problem, the study suggests a new way to look at stock data and news opinions together.

In the suggested method, moving average convergence divergence (MACD), relative strength index (RSI), and moving average (MA) is taken from stock data and used to find features. At the same time, news data goes through a long process to figure out how people feel. This routine includes pre-processing for keyword extraction and emotion categorization, using WordNet for keyword extraction, extracting features based on hole entropy, and categorizing sentiments using a deep neural network (NN). This neural network is taught with a self-improved whale optimization algorithm (SIWOA), which is an interesting choice. At the end of this process, an optimized deep belief network (DBN) is used to predict stock prices by mixing features from stock data with emotions from news. With the new SIWOA, the DBN's weights are set smartly.

This new method was tested on datasets from two different companies, Reliance Communications, and Relaxo Footwear, to see how well it worked. The results were impressively good. Most of the tests showed that the new framework was better than traditional algorithms, which shows that it could be a very useful tool for making stock market predictions.

A similar study was conducted by Ingle & Deshmukh (2021) using an ensemble deep learning framework This study used TF-IDF to look at news stories about many Bombay Stock Exchange companies from the internet. Using this data and other stock market indicators, an ensemble deep learning system estimates what the value of a stock will be the next day.

Indian individuals who spend their money trade intraday, swing, and positionally. For trading to be successful, you need to be able to predict how the market will act based on past data. The financial news can tell you a lot about a company's price. The budget, demonetization, and natural events can all have a big effect on stock prices. The fact that AR, ARMA, and ARIMA forecasting models can only use data from a single company shows how unpredictable stock markets are.

Learning a lot, deep learning models, which are made up of artificial neural networks with many layers, are known for being able to guess hard target functions by looking at a lot of data. By making features, these algorithms can find nonlinear data connections. Hierarchical data models use features from lower levels to figure out features from higher levels. Financial forecasting works well with deep learning because hierarchical processing can handle both controlled and unsupervised learning.

Early tests show that the deep learning architecture matches stock closing prices with 85% accuracy. The results of regression GBM were the same. Because the stock market is so unpredictable, it is almost impossible to make accurate predictions about it. Because of their TF-IDF, ITC Company had the lowest forecast error. The study says that future research should look at how data changes throughout the day and find better ways to extract features.

Both research papers offer promising approaches to predicting the stock market, which uses both stock data and the mood of the news, which is an interesting point of view. But when you look at it more closely, there are some possible problems and limits that might make you doubt its general effectiveness.

First, even though the impressive results shown on specific datasets show its promise, it raises the question of how generalizable this method is to a wider range of stocks or different market conditions. The problems that come with sentiment research make these worries even worse. It's not easy to figure out how people feel about the news, which often has mixed feelings, humor, or complicated language. If these feelings are misread, using them to make stock estimates could lead to big mistakes. And then, the weightage of emotions and feelings is different for different stocks, the same news for two different stocks may trigger two different intensity emotions. We never react to the same or similar news with the same intensity of emotions. With time, intensity starts fading away.

Also, the study only used data from two companies, which seems like a small amount of data to use for a study. For a thorough test of how well the method works, it would be important to include a wide range of companies from different industries. In the same way, it is good that the suggested method is better than traditional classifiers, but a comparison with more recent or ensemble techniques might show a different picture, possibly pointing out even better ways to predict.

Also, the way stock markets change over time adds another layer of difficulty. These markets are always changing, and the things that affect them can change over time. This change makes one wonder if the planned model can be changed. Will it stand the test of time and not need to be retrained all the time? And if it is true that frequent adjustments are needed, would the model still work in fast-paced, real-time trading?

Lastly, one cannot ignore the many outside forces that are at play. Even though news sentiment is certainly important, unexpected events or insider trading can also have a big effect on stock prices, and this often doesn't show up in the news right away. If the model relies too much on how people feel about the news, it could miss these important signs. The paper's new way of looking at things gives us a new way to look at stock market forecasts. But it's important to think about its possible flaws before recommending it as a safe way to predict everything.

2.2.5 Artificial Intelligence (AI) and Stock Market Forecasting

Studies have been conducted to explore the feasibility of AI techniques in improving the efficiency of high-frequency trading by forecasting very short-term price movements. Mousavi (2020) in his research used AI to create a system that can predict how the stock price will move thereby improving the efficiency of high-frequency trades.

Mousavi (2020) used an AI-based High-Frequency Trading Filter (HFTF). The first filtering phase finds the optimal features for high-frequency financial time-series data. How often and how these features change determines this. This involves using company correlations, stock market technical indicators, ARIMA, and Fourier models to identify features.

Filtering is implemented in the second stage of modeling. This filter is termed "Stage 2 Modelling Filter." The topic has two sections. The first layer predicts stock market movements using Stage 1 characteristics. Second is Deep Reinforcing Layer 2 learning agents provide trading signals and select whether to buy, sell, or hold.

This study used FTSEUK 100 stocks. The given data covers February–September 2018. Preliminary analysis preceded preparation. This featured seasonality trends, non-stationarity testing, and correlation matrices. The result of the study was that based on time-series data, Long Short-Term Memory Networks (LSTM) predicted stock price changes better than other networks.

The AI-HFTF predicted stock price changes with a maximum of 100% accuracy and a minimum of 0.82% accuracy and attained a better profit of 7.24% average with a fast execution time of .024 seconds maximum to .016 seconds minimum. The study demonstrated that the designed filter balances efficiency (speed) and performance (correctness, profitability).

Though this study explores the possibility of improving the efficiency of trading when we consider the following points, it raises some questions about its use in the real environment for trading. First of all, the Efficient Market Hypothesis (EMH) states that stock prices reflect all known information. If EMH is right, no analysis, including AI, can consistently beat the market since price fluctuations are random and hard to foresee.

Secondly, Economic data, political events, and natural disasters can affect stock markets, but the model may not. Stock trading requires quick market reactions, which the AI-HFTF may not be able to do and then the study uses short-term data. A model based on data from only a few months may not reflect market cycles that last years. The approach was only tested on a few high-frequency trading organizations; thus, it may not work for other industries.

Finally, In high-frequency trading, milliseconds matter. As noted, the model's execution time may be too slow for high-frequency trading, as competitors are continually seeking to improve execution times. When we consider the implementation of this model in the Indian Stock market, where the regulator has introduced the “Speed Bump” feature to regulate the speed of trading, it seems impractical to take advantage of high-frequency trading. Complex models require expensive computing power. These strategies may cost more than they earn for small to medium-sized trading enterprises. Moreover, high-frequency trading’s time frame of consideration is in milli and microseconds which doesn’t show any cyclicality of the price change.

2.3 Economic Cycles

Many authors make an effort to analyze the research done at the broader level and one in particular, Korotayev and Tsirel (2010). The study here found patterns called Kondratieff waves in the global GDP from 1870 to 2007. These patterns repeat roughly every 52-53 years. To see how solid these findings are, the researchers used a new method. They found there's a 4-5% chance these Kondratieff waves are significant in the global GDP.

Additionally, they found other patterns. There's a 2-3% chance of seeing Juglar cycles, which happen every 7-9 years, and “Kitchin cycles”, which happen every 3-4 years, in the global GDP. So, this study also backs up the idea that these cycles exist. However, they found something else interesting. What some people think is the Kuznets swing might just be a part of the Kondratieff wave. as one of its harmonics.

Now, about the current global economic situation: one way to see it, based on this study, is that the world might be in a temporary economic dip and might bounce back even stronger. But, another viewpoint, using the same study, is that this might be the start of a decline phase of the 5th Kondratieff wave.

Lastly, looking at the global GDP before 1870, the study couldn't find these waves. But they did find them in the Western world's GDP. This could mean that before 1870, the world wasn't as connected economically. Only after 1870 did the world become connected enough for these waves to show up globally.

Another study done in this domain we analyzed was Narkus (2012) on “Analysis of Long-Cycle Theory”. This study analyzed Kondratieff and Schumpeter's Long-waves, which are observed in developed capitalist countries like the U.S., U.K., France, and Germany. The analysis uses economic and historical data to determine that the economy grows in a sinusoidal form, with an average length of 54 years. The cycle is influenced by wars, which are divided into Peak wars and Trough wars. These wars help growth projections reach turning points, affecting the fluctuations. Schumpeter's contribution to the Long-cycles theory is the idea that innovations to the economy appear in clusters, with the first cycle influenced by steam engine invention, the second by locomotive usage, the third by electricity, the fourth by oil system and cars, and the fifth by IT technologies.

The theory of long cycles has evolved into a large aggregate cyclical-economic growth system, combining war theory, transport system development, population living and medical conditions, innovations, and monetary system changes. While some scholars argue that the Long-cycles system is an idealized historical overview, the main result shows that cycles repeat every half-century, repeating economic and social upswing and downswing phases.

When we look at the first study and its conclusion the cycles were not seen in the data before 1870 and seemed to be present after that due to the growing magnitude of globalization. To us, it seems like a curve-fitting exercise, as this theory was coined by Nikolai Dmytriyevich Kondratieff in 1935, and by then could not have enough data to give a hypothesis of a 52-year plus cycle in play.

2.3.1 Random Forest (RF) Algorithm

The Random Forest (RF) algorithm is a way for group learning that is used for tasks like classification, regression, and more. Breiman (2001) developed the first RF algorithm and suggested that the main idea behind the RF algorithm is to make a final result by combining the predictions from several decision trees. Each of these decision trees is taught on a random subset of the data and features, hence the name "forest." The final prediction is then made by adding up the results from all of these trees. This is often done by voting for classification or by taking the average for regression. When used on the stock market, the Random Forest algorithm can be used to predict stock prices, and stock moves (up, down, or no change), or to find outliers that could be signs of fraud or manipulation.

Elagamy et al., (2018) conducted a study using an RF algorithm on Dubai stock market data. This study makes important contributions to the field of using text mining to analyze the stock market. It focuses on using text mining on financial news to find important stock market indicators. This is different from earlier efforts, which relied heavily on numbers. Text mining, the Random Forest algorithm, and the expectation-maximization algorithm are all used in this work. This combined method helps predict unusual changes in the stock market and improves the way trade systems work.

The study experiments show that Random Forest does a better job of classifying financial news articles than other classifiers. Tree classifiers, like Random Forest, are especially good at finding hidden information and important connections between the features pulled from the text. Tree classifiers still work better than other types of classifiers when they are used on bigger datasets. Also, when compared to unigrams, classification results are better when bigrams are used as features.

Also, the study unveiled the Stock Market Random Forest-Text Mining system (SMRF-TM), which uses natural language processing in a semi-supervised way. The Random Forest algorithm was used to improve how features and news pieces were put into five different groups. Also, the expectation-maximization algorithm put these into three more semantic categories: economic, social, and political. This increased the number of groups from three to eight. This newly expanded classification in SMRF-TM makes it better at classifying both features and articles, which proves one of the research's main theories. Lastly, using the expectation-maximization clustering method makes it easier to understand why Random Forest chose to classify features and articles the way it did.

For the qualitative validation, the importance of domain expert opinion is highlighted in the limitation section of this study. And the word “Opinion” is subjective and may change from expert to expert which means reliance on the outcome cannot be standardized. Furthermore, the usage of selected words by news/media houses will denote different degrees of seriousness from country to country. So, the same words used in one country will have a different impact on stock prices than in other countries.

When we review the Random Forest Algorithm itself, even though the new way of using Random Forest (RF) to predict the stock market is interesting, it also raises some worries. Stock markets are inherently complicated and are affected by a wide range of unpredictable factors, such as global events, political shifts, investor sentiment, and changes in economic policy. Because of this, it might not be possible to make accurate predictions about them based only on past data, which is what RF uses as its main input. Another weakness of this model is that it depends on how the features are chosen. If the right factors aren't chosen or if irrelevant ones are used, the forecasts can be off.

Also, financial data is often noisy and doesn't stay the same, and while RF has some protection against overfitting, it's not perfect. The saying "past performance doesn't show what will happen in the future" is especially true for stock markets, which makes it risky to rely too much on historical data. Because the model is an ensemble, it may be hard to respond quickly in a market that changes quickly.

Also, unlike standard models like the Capital Asset Pricing Model, RF does not have a financial theory at its core. This could make its results harder to understand in terms of how markets work.

Lastly, Patel et al. (2015) say that stock markets are random, which means that any model, including RF, may be limited in how well it can predict the future. So, even though RF gives stock predictions a new, data-driven perspective, it's important to use it wisely, along with other analytical tools and within a larger financial framework.

2.3.2 Granger Causality

The Granger causality test is a statistical hypothesis test for determining whether one time series helps forecast another. As per the Granger causality, a signal X Granger causes a signal Y when the combination of past values of Y and X has a more significant impact on the value of Y than the past value of Y (Granger, 1969).

Due to its computational simplicity, Granger causality has been a popular method for the causal analysis of time series data for decades. As a result, studies such as Rao (2019); Kumar (2019); Samadder and Bhunia (2018); Kishor and Singh (2017); and Srivastava and

Sharma (2016) preferred Granger causality to examine the effect of foreign stock markets on the Indian stock market.

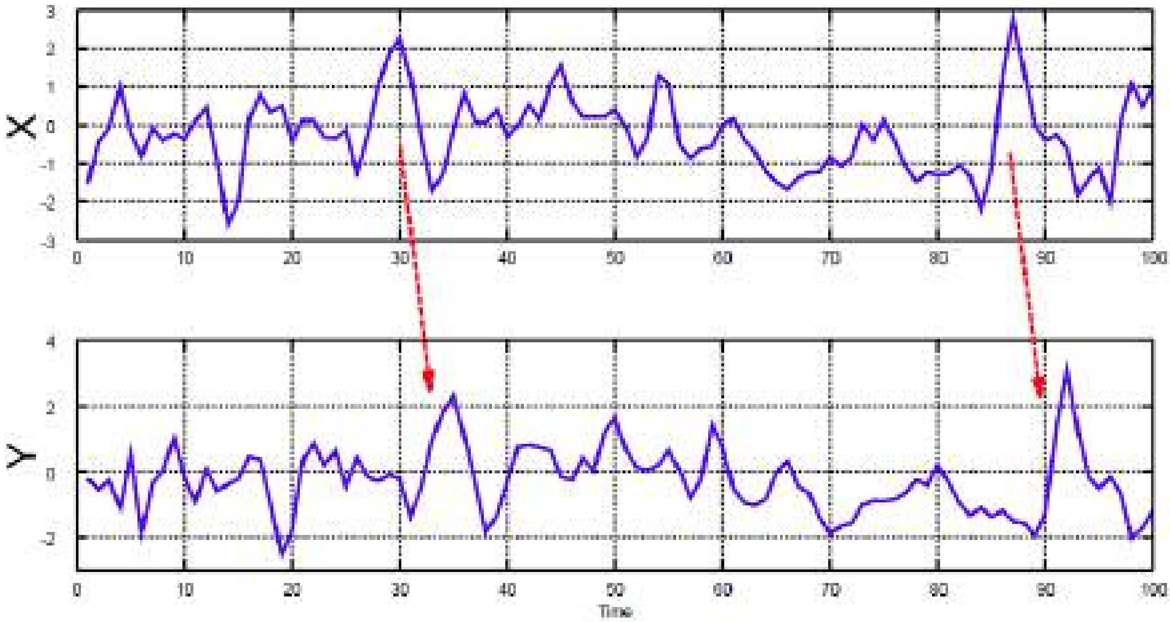


Figure 3 Granger causality visualization Source: (Observer, 2014)

Despite being so popular, Granger causality needs to be revised, such as: 1) Granger causality cannot be applied to non-stationary data. 2) Granger causality assumes linearity in the dataset for causality detection. 3) Granger causality still needs to provide more insight to understand the relationship between the variables.

As mentioned above, one of the limitations of Granger causality detection methods is that they need to work better with non-linear datasets. Text data is an example of non-linear data. This study also analyzed the impact of economic articles (text data) on the Indian stock market. Therefore, Granger causality was not the best choice for causality detection for this research. As a result, this research considered alternative approaches that showed all the strengths of Granger causality minus its limitations.

2.3.3 Summary

This chapter has examined the empirical studies that have analyzed the impact of time cycles on the Indian stock market and its applicability to the trading stock market. There are significant studies that analyzed the impact of the variables on the specific sector (such as information technology (IT)) of the Indian stock market.

Furthermore, the existing studies have employed the Granger causality test and this study employed different tools such as Hurst timing and trading to mitigate the time cycle.

Again, this study examines the Fourier transform method of dominant frequencies and harmonies affecting stock prices (Sherbrim, 2018), and explains the impact of market anomalies and its impact through the year and the relationships between crowd psychology and the stock market cycle.

However, further research still needs to consider ensemble model (incorporating statistical, machine learning, and deep-learning-based methods) methodologies for analyzing the impact, which is not limited by Granger's causality constraints and is more robust and convincing.

Additionally, using multiple causality detection techniques would enhance the credibility of the findings of this study.

2.3.3 Summary

For decades, several investigations have confirmed Hurst's stock market time cycle theory. Fourier research identifies prominent frequencies and harmonics that affect stock prices and form peak-trough forecasting patterns. This review emphasizes investigating shorter time cycles and market prices.

Theories of reasonable action (TAR) describe beliefs, attitudes, and intentions. Understand stock buying and selling cycles to make smarter investments. Hurst's cycle envelope technical indicator analyses Indian stock market time cycles. The study uses J.M. Hurst, Fourier, and Fisher Transform to find NSE time cycles.

Business cycle forecasting is another interest. Chauvet (2001) linked business cycles to stock market oscillations, and this study examines the intricate relationship between the two. The proposed model estimates business cycle turning points using the business cycle factor and the stock market factor. The results imply that the derived stock market component can predict economic cycle status in real-time. The study's method may oversimplify the complex relationship between stock market volatility and the business cycle. It presupposes a direct cause-and-effect relationship, yet investor sentiment, geopolitical events, and monetary policy affect the stock market beyond economic principles.

Incorporating nonlinear dynamics into economic modeling and forecasting is difficult, and stock market forecasts must be rigorous. A more complete and accurate understanding of the relationship between stock market instability and the business cycle would include a larger range of economic data and potential factors that could affect the results.

Si et al., (2019) examined the stock market-business cycle co-movement and causation in China from 1992Q1 to 2018Q1. Wavelet analysis identified time- and frequency-changing patterns. The data demonstrated that when the economy is good, the stock market leads the business cycle, and when the business cycle comes first, they are always linked positively. The link between the two cycles can be considerably altered by internal interest rates and external shocks like interest rate changes or business cycles in other industrialized countries.

Sohn and Chung (2022) examined investing strategies utilizing an estimated stock market cycle based on a lead-lag link between the business cycle and the stock market cycle. The study indicated that stock market cycle strategies outperform "buy and hold" strategies. The asset allocation-based second method is more profitable than the first, according to outside statistics.

The study's implications and limitations are unclear due to the period and different market situations. Market structures, rules, and economic conditions have changed, which may impact the conclusions' application to current or future investment landscapes. The analysis implies that the techniques beat a "buy and hold" approach, but it doesn't address how market efficiency, transaction costs, and slippage may affect their practicality and profitability in real life.

Intermarket analysis helps allocate assets and predict economic trends. Commodities, currencies, bonds, and stocks predict economic change. The study's methodology, including missing data, time-consuming manual processes, and model restrictions, makes it impossible to predict the stock market cycle.

The complicated links between oil, gold, the US dollar, and stock market prices affect investment decisions and economic cycles, according to the study. It is vital to doubt the study's validity. The 2011-2021 data is unreliable since government changes, new technologies, natural disasters, and celebrity tweets can alter stock market value. Missing data and probable errors make market prediction challenging, according to the study.

Xuan's study on crowd psychology and stock market cycles in Vietnam reveals that crowd psychology influences stock market investing, leading to comparable actions. A poll of 120 Vietnamese investors found that most choose securities chosen by others and react quickly to crowds. Vietnamese investors generally choose stocks that many others do, even if they don't know the company's functioning situation.

The study acknowledges crowd psychology but may ignore other behavioral biases that affect investing decisions. Cognitive biases including confirmation bias, loss aversion, and overconfidence can alter investor behavior without crowd influence. The study believes crowd psychology always leads to sub-optimal outcomes, whereas efficient market theory says stock prices reflect all available information, including crowd opinion.

In conclusion, crowd psychology affects stock market behavior in Vietnam, but the findings must be interpreted critically. Crowd psychology and investing decisions may not drive market cycles alone. From January 1965 through December 2003, Wong and McAleer discovered that stock prices followed a four-year cycle before the US presidential elections.

This pattern was most noticeable in a President's first two years, with the lowest point in the second. This pattern was particularly noticeable under Republicans, suggesting they adjusted policies to help them win re-election. The study also noted that favorable corporate practices during elections can boost stock market success.

The study accepts that correlation does not imply causality and that the US presidential cycle does not directly affect stock prices. Economic statistics, company earnings, geopolitical events, interest rates, and investor attitudes can also affect the stock market. Random events like "black swan" can affect financial markets regardless of election timing. The study does not suggest that the pattern seen affects all stock markets internationally because economies, politics, and social and political stability vary by country. Presidential elections in India have little impact on the stock market and lack industry attention. The Indian stock market has had multiple downturns in the first year of elections and government shutdowns, proving that the Wong and McAleer study cannot be applied to other nations or used to time stock markets.

Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are being utilized in deep learning to anticipate stock market prices. These algorithms can analyze massive financial data, identify complex patterns, and anticipate future trends. They can use previous price data and news sentiment to forecast stocks.

A deep learning study by B L & B R (2021) suggested combining stock data with news commentary to anticipate stock markets. The suggested method finds features using MACD, RSI, and MA, while news data is processed for a lengthy time to understand how people feel. The neural network is taught with a self-improved whale optimization algorithm (SIWOA), and an optimized deep belief network (DBN) predicts market values using stock data and news emotions. Both stock data and news opinion studies predicted stock market prices well. There are concerns about this method's applicability to more equities or market circumstances. Misreading conflicting sensations and emotions from news can make sentiment research difficult. The method must be tested by many companies from different industries. Comparing the proposed method to more modern or ensemble methods may yield improved predictions. Additionally, stock market changes over time make it difficult to assess if the planned model can be adjusted.

The research investigates if AI can foresee short-term price changes to improve high-frequency trading efficiency. Mousavi (2020) created an AI-based High Frequency Trading Filter (HFTF) to predict stock price fluctuations with 100% to 0.82% accuracy. The filter balances speed and accuracy/profitability. However, the research doubts its application in real situations like the Efficient Market Hypothesis (EMH), economic data, political events, natural disasters, and short-term data. The model's execution time may be too slow for high-frequency trading, as competitors strive to improve it. The Indian stock market, which uses "Speed Bump" to restrict trading speed, may not be ideal for high-frequency trading. The model's millisecond time frame eliminates price cyclicality.

In another study, Korotayev and Tsirel (2010) identified Kondratieff waves in global GDP from 1870 to 2007. They identified a 4-5% possibility these waves affect world GDP. The study also discovered that the Kuznets swing may represent a harmonic of the Kondratieff wave. The global economic condition may be a transitory dip or the start of the 5th Kondratieff wave's fall.

Narkus (2012) examined Kondratieff and Schumpeter's long-cycle theory, which integrates war theory, transport system development, population living and medical conditions, innovations, and monetary system changes. The major finding is that economic and social upswings and downswings reoccur every half-century. The next chapter introduces the research methodology of the study. It includes the description of the research design rationale including the study variables. It provides a detailed description of the methodology and the data used in the study. This chapter also explains the data sorting and organizing procedures used in this study. Further, it includes threats to the validity and ethical procedures used in the study.

The next chapter deals with the study methodology, research philosophy and research approach and how data was collected and analyzed.

CHAPTER III: METHODOLOGY

3.1 Introduction

This chapter the research methodology adopted for this research. This study is an exploratory study that follows the principles of quantitative research. The secondary data will be used in this study to meet the objective of the study. The first part of the study analyzes “Fourier transform” and “Goertzel general algorithms” to select the one with the least error concerning standard detected dominant cycles.

The second part of this study will analyze the data extracted from secondary sources using the selected method and collect data points in terms of buy and sell signals.

In conclusion, this research will prove its core hypothesis that the success rate of timing trades using time cycle indicators is very low.

3.2 Research Philosophy

Research philosophy refers to the beliefs that underpin how data should be collected, analyzed, and applied to a specific phenomenon (Kirongo et al., 2020; Kumar 2021). This study applies quantitative research to analyze the identification of the time cycle in the Indian Stock Market and its applicability for trading. Quantitative research is the process of collecting and analyzing numerical data.

Kumar (2021) posits that quantitative studies emphasize finding patterns, predicting, and testing causal relationships to generalize results to the wider population (Daniel, 2016). Moreover, this study hypothesizes that identifying the bottom of the time cycle should align with buying trades. Hence, there is a statistical difference between using time cycles and the profitability of trading by predicting the bottom of market cycles.

Moreover, individual investors should use different methods in the trading cycle to maximize gains in the stock market through the impact of cycle peak and trough detection on the profitability of long and short trades using time cycle principles.

It is critical to collect data from reliable sources to study the transformed relationship between variables' time cycles. Hence, the study has collected data from trustworthy secondary resources and compared it with different perspectives to create a reliable time cycle for the stock market.

3.3 Research Approach

The present study involved using the quantitative methodology. Chelaa (2017) described quantitative research as the study method that involves collecting and analyzing data using statistics. The quantitative method was the best approach to answer the research questions as it requires numerical data and generalizing results to a larger population.

Accordingly, this methodology was consistent with the purpose of this study, which was to identify time cycles in the stock market and its application to trading. Quantitative methods usually build upon existing theories, and results can be predictive, explanatory, or confirming (Williams, 2007).

The quantitative method is normally used to answer questions related to relationships between variables, either to establish or validate relationships. The quantitative research process normally consists of developing a problem statement and corresponding hypothesis. It is followed by an exhaustive literature review and data analysis.

Using the deductive research approach and testing the cycle envelope theory by Hurst (1972) and selected methods of identifying time cycles and testing the data set to explore the possibility of using these methods for profitable trading in the Indian stock market. The result of the study will help us drive hypotheses around the subject. For this study, secondary data will be used for the Indian stock market and algorithms for testing.

3.4 Research Strategy

A research strategy is about positioning and structuring a researcher's effort to achieve the research goals. This study uses an experimental research strategy as it provides researchers with the opportunity to find relations between variables if there are any (Creswell 2018). The study will collect Indian stock market data from secondary data providers. Lastly, the study uses statistical tools to identify dominant time cycles in the data set.

3.5 Research Population and Sampling Method

Population selection is imperative in a quantitative study, and it must be associated with research questions. Several factors determine the efficacy of the research design, including the quality of the data and the selected population. The purpose of this study was to test time cycles in the Indian stock market. The study used publicly available secondary data from the Indian National Stock Market (NSE) during the period from January 2012 to December 2022. The NSE is the largest stock exchange in India, with a market capitalization of its listed companies at over USD 3.27 trillion.

There are two primary methods of collecting samples: probabilistic and non-probabilistic sampling. Almost all researchers evaluating calendar anomalies during the past 50 years have used non-probabilistic purposive sampling. Accordingly, the purposive sample data used for this study included all transactions on the NSE from 2012 to 2022. Using archived data as the sample for this study was appropriate because it was suited to answer the research questions by evaluating the historical relationship between variables.

Researchers create a sampling strategy to ensure their sample represents the population (McCombes, 2021). The research will collect daily time-series data from January 2012 to December 2022 for the Indian Stock Market using a non-random sampling technique.

3.6 Time Horizons

The research timeframe for this study will be from May 1, 2023, until July 31, 2023, but to generate enough time cycle signals, data will be collected from the period starting from January 1, 2012, through December 31, 2021. Daily time frame data of 10 years will help us plot a time cycle that will then project for 3 months in the future and stock market movement will be tracked in real-time daily to prove our hypotheses.

3.7 Data Collection

The methods used to collect data to make better decisions are referred to as data collection procedures (Bhandari, 2021). There are two types of data collection procedures: one is primary data collection, and the other is secondary data collection. The primary data is collected from first-hand experience and has not been used in the past (Sherif, 2018). Usually, the primary data is collected for a specific research purpose through interviews or questionnaires. Hence, it is highly accurate. Whereas the secondary data has been captured by someone other than the user. The secondary data is readily available through government reports, business journals, the internet, etc. These secondary data sources are less expensive and time-consuming than primary data.

Therefore, this study gathered information from secondary open data sources quickly. Data was procured from an authorized secondary data vendor for the Indian stock market (NSE) for the last 10 years and continuing.

3.8 Data Analysis

Data analysis involves inspecting, cleansing, transforming, and modeling data. Through this process, raw data are converted into useful information for decision-making. There are many approaches and techniques in data analysis that are used in different business and research settings. This section includes approaches and techniques in data analysis used in this study. I also describe software used for data analysis.

Furthermore, I explain the data cleansing and screening procedures that were used in the study. Statistical Package for the Social Science (SPSS) software was the primary tool used for data analysis in this study. The software can compute various descriptive statistics as well as create a comparative study to assess relationships between independent and dependent variables.

The present study involved using various statistical techniques, such as descriptive statistics, ANOVA, and a post hoc test to evaluate the influence of the individual investor behavior on the Monday effect for the U.S. stock market. The ANOVA test was used in this study to evaluate the influence of the independent variable on the dependent variables. A post hoc test was used when the ANOVA found statistically significant differences in the means of the dependent variables. It was used to identify sources of differences in the means of the dependent variables.

Following the data collection, this study will pass the data through the selected algorithms mentioned above to detect the dominant cycle length. The dominant cycle length was used to plot a time series chart with harmonics of the dominant cycle and their combined impact on the stock price. The same will be projected three months into the future, and daily movement of stock/index prices will be tracked against the ideal signal from the time cycle.

3.9. Reliability and Validity

The validity of the study defines the extent to which the concept is measured in the quantitative study (SÜRÜCÜ & MASLAKÇI, 2020). When conducting research, it is critical to consider the validity and reliability of data collection tools and methodology. Furthermore, there are three types of validity: content, construct, and criterion. Content validity examines whether the instrument measures all the variables it was designed to measure. Thus, as mentioned in the data source section, this research gathered foreign stock market data, currency exchange rate data, and economic articles from trusted sources.

The second type of validity examines how well the research has translated the construct into concrete and measurable characteristics (Taherdoost, 2018). Thus, this study used a spacy library to convert trading cycles into concise and measurable time cycles.

Criterion validity is the final measure of validity. The criterion for validity assesses how well different instruments measure the same variable (Taherdoost, 2018). As a result, the study used standard Fast Fourier Transform, Discrete Fourier Transform, Goertzel, and Goertzel Generalized Algorithms. All these algorithms are documented as program code with explanations as to how they are being used with various parameters.

Validity:

Reliability refers to the consistency of a measure. It ensures that the study will achieve the same results consistently by using the same method under the same circumstances (Heale and Twycross, 2015). This study was based on historical data from secondary sources such as the Indian Stock Market (NSE), The Financial Times, and Money Control. These data sources are well-known and trustworthy.

Furthermore, the research has been conducted using those mentioned statistical deep-learning methods using rerunnable Python codes on a Jupyter notebook, which produced consistent results for the same data with the same settings. As a result, the deterministic nature of this study makes it more reliable.

Hence the study was conducted on the Indian stock market Index Nifty 50. It is important to note that the length of the cycle varies from country to country as the number of trading days varies depending upon the standard trading days plus other holidays and special trading sessions. Countries like India have different numbers of holidays, some falling on trading days and some on weekends, and this number changes every year, as most of the holidays do not have fixed calendar dates.

It is worth noting that the same study will be valid in other countries only if the number of trading days is adjusted as per the country of choice taking into account the threat to validity.

Threat to Validity of Research:

Research findings are useful when results are true for similar individuals or subjects outside the study. The concept of validity applies to all types of research.
Additionally, it refers to the accuracy of measurements used in the research. In this regard, the researcher must choose the right instruments to evaluate relationships between independent and dependent variables.

There are three kinds of threats to validity in research: external validity, internal validity, and construct validity. Archived secondary data from the NSE was used for the study. Consequently, there was no direct or indirect interaction between me and the subjects during the data collection process. This method of using secondary archived data minimized common threats to validity.

External Validity

External validity refers to issues with the study design. It involves the validity of applying conclusions from a study outside the context of that study. It also involves measuring the generalizability of empirical findings to the general population. External validity is essential in most scientific research.

The dataset I used for the study was a large, archived dataset from the NSE. Individual investor trading data used in this study were accurate because they were electronically gathered by the NSE. The NSE is the largest stock exchange in the world with a market capitalization of its listed companies of over USD 3.27 trillion. The NSE compiled the dataset using transaction records of purchases and sales in their centralized stock market. Because the dataset was exceptionally large and represented individual investors' trading data from most of the U.S., the results of this study can be generalized to the whole population.

Internal Validity:

Internal validity refers to issues with subject selection. Internal validity measures the accuracy of conclusions drawn within the context of a particular study. It is needed to ensure that the observed results truly represent the behavior of the population and are not a result of methodological errors (Brewer, 2000).

The study used SPSS software as the primary tool for data analysis in the present study. This software is widely used for statistical analysis by educational institutions and businesses worldwide. I also used publicly available secondary data from the NYSE. The use of secondary data from a reputable source and the widely used SPSS software minimized any threat to internal validity in this study.

Construct Validity:

Construct validity measures the appropriateness of inferences made based on observations or measurements. It evaluates whether a test measures the intended construct (Peter, 1981). Construct validity in research is necessary to ascertain the overall validity of the test.

The tests used in this research such as descriptive statistics, ANOVA, and a post hoc test have been used in the past by several researchers in evaluating the calendar effect. Past successful use of the tests for similar studies and their acceptance by the scientific community minimized any threat to construct validity in this study.

Ethical Procedures:

Farrimond (2012) defined ethical research as studies following the current practices of ethical norms, codes, and regulations generally accepted by the scientific community. Accordingly, researchers must use methodologies that demonstrate the trustworthiness and credibility of their study. Walden University has instituted several processes and procedures to ensure that researchers follow strict ethical procedures. Like most universities, the Swiss School of Business Management (SSBM) has an IRB. IRB ensures that the Swiss School of Business Management research complies with all federal regulations and the university’s internal ethical standards.

Researchers have to go through an Institutional Review Board ethics review and approval process before they can start data collection or have dataset access.

The NSE electronically gathered the data used in this study from January 2010 to December 2022. Consequently, the data is nearly 12 years old from the start time collection data from NSE, and there was no direct or indirect interaction between me, as the researcher, and the subjects or the data collection process. This process minimized any ethical procedure violation.

3.10 Research Design Limitation

The reference point of this study is using the method of visually identifying the dominant cycle in the stock market data. While conducting research, a researcher is expected to think critically not only about the benefits of the research but also about its limitations. The research's limitations are potential flaws beyond the researcher's control (Ross & Bibler Zaidi, 2019). As a result, the study identified some potential flaws. The first uncertainty is the researcher's use of time cycles as an operationalized measure of the stock market as there are variations between different time zones of countries. However, while the research ensured accurate time series were used to represent an article, a few named entities were overlooked. Which could have given the economic articles a better representation.

The other potential area for improvement of that study might be the duration of data collection. Since the study has collected data from 1-Jan-2010 to 31-Dec 2022, it also results for the COVID period and may not be generalizable.

3.11 Summary

The chapter outlined the methodology, research design, and sample size, using the standard method of identifying dominant time cycles in the data and using it as a reference to identify error rate by comparing it with FFT and Goertzel generalized algorithms.

The purpose of this study was to test the theory of time cycles and its applicability in the Indian Stock Market. After evaluating the three methodologies, I selected the quantitative methodology for this study. It was the best method to answer research questions requiring numerical data and to apply the results to a larger population.

Additionally, this method was consistent with the purpose of this study. The study used publicly available secondary data from the NYSE and used SPSS software as the primary tool for data analysis. The next chapter explores the results from the findings in the data analysis.

CHAPTER IV:

Results

4.1 Introduction

This chapter presents the study's findings on the identification of the time cycle in Indian stock markets and its applicability to trading in NSE. The chapter begins by discussing the results of basic analysis methods such as the Fourier transform, the fast Fourier transform to signal the analysis of time, and the Goertzel algorithm as a digital signal processing algorithm that can be used to efficiently calculate the Discrete Fourier Transform (DFT) of a signal at a specific frequency.

Although these techniques shed light on the interrelationship of the variables, they did not prove causation. Therefore, the Goertzel generalized algorithm is a variation of the original Goertzel algorithm that can be used to detect multiple dominant cycles in a signal rather than just a single frequency. The chapter also includes a detailed analysis of the results of the time series in the data domain for the results and summarizes all the findings.

4.1. 2 Fourier Transform

The Fourier transform is a mathematical technique that can be used to analyze and decompose complex signals into a series of simple sine and cosine waves. In the context of the stock market. The Fourier transform can be used to decompose the price data of a stock into a series of simple periodic waves, which in turn identify the dominant cycles or frequencies that are present in the stock price data.

These dominant cycles can provide insight into the underlying patterns and trends that are driving the stock market. To use the Fourier, transform to analyze stock market data, we first need to convert the data from its original time domain into the frequency domain. This is done by applying the Fourier transform to the stock price data.

Once the Fourier transform has been applied, we can examine the resulting frequency spectrum to identify the dominant cycles or frequencies that are present in the data. We can then use this information to make predictions about future stock price movements.

It is imperative to state that the Fourier transform is a mathematical technique that is widely used in various fields for the analysis of signals and data. Here are some common applications of the Fourier transform that is used across various fields of work:

Signal Processing: The Fourier transform is used to analyze and manipulate signals in areas such as audio processing, image processing, and communications. It allows the decomposition of a signal into its frequency components, making it useful for tasks like filtering, compression, and modulation.

Spectral Analysis: In fields like physics, engineering, and astronomy, the Fourier transform is used to analyze the frequency content of signals. This is particularly useful in studying phenomena such as vibrations, electromagnetic waves, and astronomical signals.

Data Compression: The Fourier transform is used in data compression algorithms such as JPEG for image compression and MP3 for audio compression. By representing signals in the frequency domain, redundant information can be removed more efficiently.

Differential Equations: In mathematics, the Fourier transform is used to solve partial differential equations by transforming them into simpler algebraic equations in the frequency domain.

Quantum Mechanics: In quantum mechanics, the Fourier transform is used to describe wave functions and the behavior of particles in terms of their momentum and position.

Medical Imaging: Techniques like MRI and CT scans use the Fourier transform for image reconstruction and analysis, allowing for detailed visualization of internal structures.

Optical Imaging: In optics, the Fourier transform is used to analyze diffraction patterns and to design optical systems such as lenses and filters.

Data Analysis: In data science and statistics, the Fourier transform is used for analyzing time-series data, identifying periodic patterns, and extracting features from complex datasets.

These are just a few examples of the wide-ranging applications of the Fourier transform across different disciplines. Its versatility makes it a fundamental tool for understanding and processing various types of signals and data. Hence, this study uses the Fourier Transform to perform the same signal analysis of time.

4.1. 3 Fast Fourier Transform

The Fast Fourier Transform (FFT) is a more efficient version of the Fourier Transform (FT) (1982) that can perform the same signal analysis in a fraction of the time. The Fourier Transform considers a continuous signal as an input, while the FFT considers a discrete signal as an input and calculates the Discrete Fourier Transform (DFT) (Chaudhary, 2021), which is used for spectral analysis applications.

The main advantage of FFT over FT is its computational efficiency. The FT requires O(N^2) operations to compute the frequency spectrum of a signal with N samples, whereas the FFT algorithm can compute the same result with only O(NlogN) operations (Duhamel & Vetterli, 1990). This means that FFT is much faster than FT for large data sets, which makes it the preferred choice for practical applications.

Another advantage of FFT is its ability to handle non-uniformly sampled data. The FT assumes that the input signal is evenly sampled, but in practice, this is not always the case. FFT can handle unevenly spaced samples by using an interpolation method called resampling.

FFT is also more numerically stable than FT, meaning that it is less sensitive to rounding errors and other sources of numerical instability. This makes FFT a more reliable and accurate method for computing frequency spectra.

Hence, the FFT is a faster, more efficient, and more numerically stable version of the Fourier Transform, which makes it the preferred choice for signal analysis in practical applications.

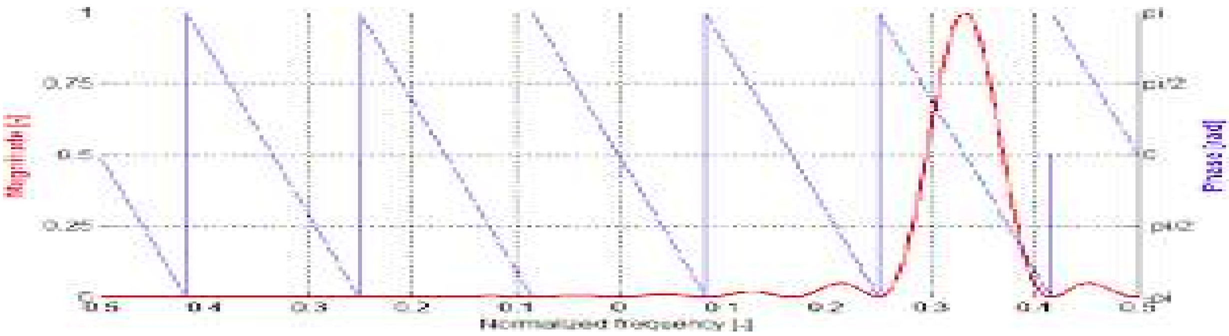
According to Sysel and Rajmic (2012), the Fourier Transform and its fast version work well with data with integer values and round off the non-integer number to its nearest value, which causes leakage in the restaurant coefficient. This study tries to determine the magnitude of this leakage and its impact on time cycles. The Goertzel generalized algorithm is one such method to stop this leakage, as it accepts non-integer values to generate coefficients to determine the phase and amplitude of the cycle.

In the recent past, Duhamel and Vetterli, (1987), stated that efforts have been made to reduce the arithmetic and structural complexity of the Fourier transform by introducing the discrete Hartley Transform, which has shown a reduction in the arithmetic side but increased structural complexity. Many improvements have been proposed in both FT and DHT recently (Duhamel and Vetterli, 1987). This study focused on FFT and the Goertzel generalized algorithm.

4.1. 4 Goertzel Algorithm

The Goertzel algorithm is a digital signal processing algorithm that can be used to efficiently calculate the Discrete Fourier Transform (DFT) of a signal at a specific frequency. The DFT is a mathematical technique that is used to convert a time-domain signal into its frequency-domain representation.

Figure 4. DFSP power signaling post



In the context of detecting dominant cycles in stock market data, the Goertzel algorithm can be used to calculate the power spectral density (PSD) of the signal at a specific frequency. The PSD is a measure of the power of a signal at different frequencies and can be used to identify dominant cycles in the data.

Here's how the Goertzel algorithm works:

1. Choose the frequency of interest (i.e., the frequency at which we plan to calculate the PSD).

2. Calculate the filter coefficients for the Goertzel filter at the chosen frequency. The filter coefficients can be pre-calculated and stored in a lookup table to save computation time.

3. Process the input signal sample by sample using the Goertzel filter. At each time step, the filter output is calculated using the current input sample, the previous filter output, and the filter coefficients.

4. After processing all the samples in the input signal, calculate the PSD at the chosen frequency using the filter output.

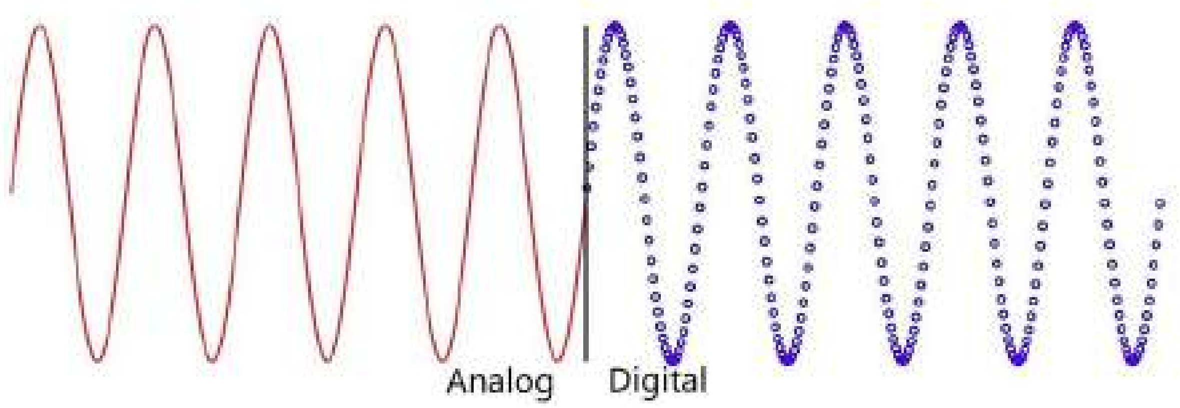
By repeating this process for different frequencies, we can create a PSD plot that shows the power of the signal at different frequencies. The dominant cycles in the data will correspond to the peaks in the PSD plot.

In the context of stock market data, the dominant cycles may correspond to seasonal trends, economic cycles, or other patterns that are present in the data. By identifying these dominant cycles, traders and analysts can gain insights into the underlying factors that are driving the market and make more informed investment decisions.

4.2 Generalized Goertzel Algorithm

The Goertzel generalized algorithm (GGA) is a variation of the original Goertzel algorithm that can be used to detect multiple dominant cycles in a signal rather than just a single frequency. This can be useful in stock market data analysis when there are multiple dominant cycles present in the data.

Figure 5 Analog and discrete signal



Differences between an analogic signal (red) and its discrete counterpart (blue). Continuous Fourier Transform (CFT), was originally proposed in 1822 by Jean-Baptiste Joseph Fourier, the father of modern engineering.

How the Goertzel generalized algorithm works:

1. Choose the frequencies of interest (i.e., the frequencies at which we plan to calculate the PSD).

2. Calculate the filter coefficients for each frequency using the Goertzel filter. The filter coefficients can be pre-calculated and stored in a lookup table to save computation time.

3. Process the input signal sample by sample using the Goertzel filter for each frequency. At each time step, the filter output is calculated using the current input sample, the previous filter output, and the filter coefficients for the current frequency.

4. After processing all the samples in the input signal, calculate the PSD for each frequency using the filter output.

5. Identify the dominant cycles by finding the frequencies with the highest PSD values. These frequencies correspond to the dominant cycles in the data.

By repeating this process for multiple frequencies, we identified all the dominant cycles present in the data. This approach is more flexible than the original Goertzel algorithm, which can only detect a single frequency, and can be useful in situations where there are multiple dominant cycles present in the signal.

In stock market data analysis, identifying the dominant cycles can help traders and analysts make more informed investment decisions. For example, if a dominant cycle is identified that corresponds to a seasonal trend in the market, traders may adjust their investment strategies accordingly.

4.2.1 Difference between FFT and GGA

Both the FFT and generalized Goertzel algorithms can be used for detecting dominant cycles in stock market data. However, there are some differences between the two approaches.

The Fast Fourier Transform (FFT) is a well-known algorithm for calculating the Discrete Fourier Transform (DFT) of a signal. The DFT is a mathematical technique that can be used to convert a time-domain signal into its frequency-domain representation.

The FFT is a fast algorithm for computing the DFT that can efficiently handle large datasets. In the context of detecting dominant cycles in stock market data, the FFT can be used to calculate the power spectral density (PSD) of the signal at multiple frequencies. The PSD is a measure of the power of a signal at different frequencies and can be used to identify dominant cycles in the data. By examining the peaks in the PSD plot, analysts can identify the dominant cycles in the data.

On the other hand, the Goertzel algorithm is a digital signal processing algorithm that can be used to calculate the DFT of a signal at a specific frequency. The Goertzel algorithm is a simpler algorithm than the FFT and is often used when we only need to calculate the DFT at a few specific frequencies.

The generalized Goertzel algorithm, as mentioned earlier, is a variation of the Goertzel algorithm that can be used to detect multiple dominant cycles in a signal rather than just a single frequency. It involves calculating the filter coefficients for each frequency of interest and then processing the input signal sample by sample using the Goertzel filter for each frequency. By repeating this process for multiple frequencies, the dominant cycles in the data can be identified.

One of the main differences between FFT and the generalized Goertzel algorithm is that FFT can be used to calculate the PSD at multiple frequencies simultaneously, while the generalized Goertzel algorithm needs to be applied to each frequency of interest separately. However, the generalized Goertzel algorithm is more flexible in that it can be used to detect multiple dominant cycles in the data, while FFT can only identify a few dominant frequencies at most.

In summary, both the FFT and generalized Goertzel algorithms can be used for detecting dominant cycles in stock market data, but they have some differences in terms of their flexibility and computational efficiency. The choice between these two methods will depend on the specific requirements of the analysis and the characteristics of the dataset.

4.2.2 FFT in the Financial Data Domain

Fourier transforms work in the frequency domain, and economic data of any kind works in the time domain, where data points are spread across uniform time units like every minute, every hour, every day, every week, and so on. For this study, we consider time series for DAILY Indian stock market data, and we will need to convert the time series data into frequency series data for the Fourier transform to work on and to give us a spectrum plot that will give us the amplitude and the coefficient of the Fourier transformation. This Fourier transform coefficient will help us plot various cycles present in the data with the correct phase and amplitude.

4.2.3 Seasonality, Trend, and Noise

Time series data is any dataset that measures a variable over time (Korstanje, 2022). Korstanje, beautifully described the effect of trend and noise in identifying the correct or close-to-correct seasonality in the data. If we consider stock market data, we see an uptrend in the last 10 years, but in between, we have many big events like COVID, which brought down worldwide financial markets by around 35% (Jabeen et al., 2022), and the Russia and Ukraine War, which impacted markets by almost 9% (Izzeldin et al., 2023). In market terms, they are called corrections or secondary trends. In terms of seasonality and cycles, these incidents work as noise and disrupt normal market cycles (Horta et al., 2022).

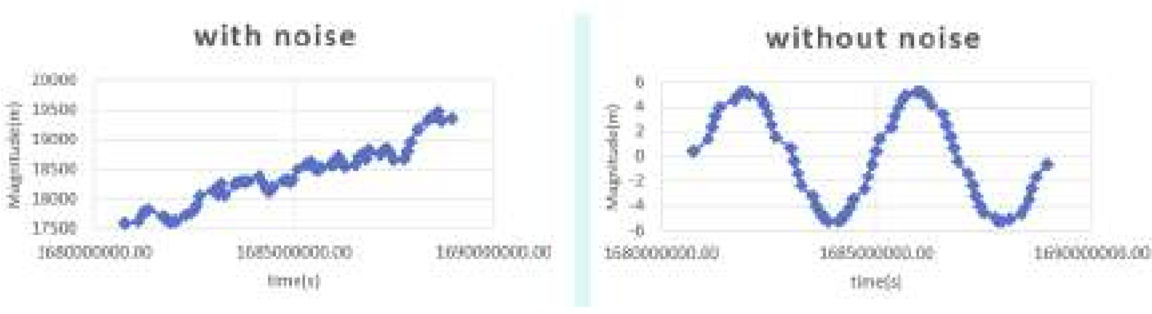


Figure 6 - FFT plot of the data, with and without noise

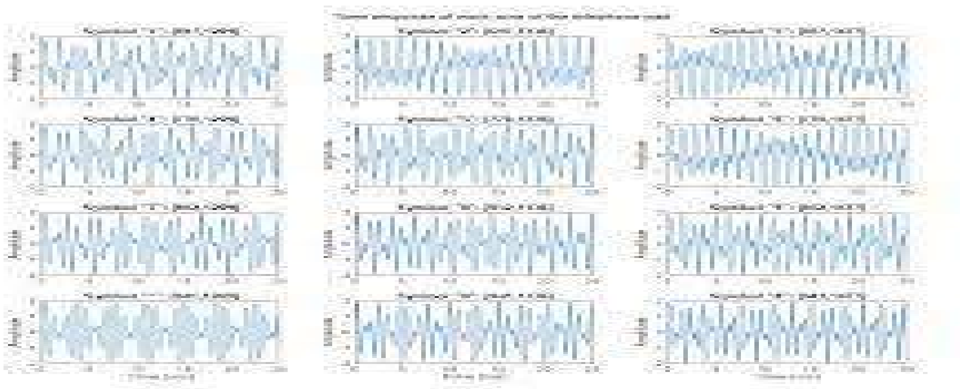
The FFT algorithm with noise reduction is used to identify and plot the dominant cycles.

4.2.4 The Discrete Fourier Transform

The data in question is not continuous in nature but measured at discrete intervals (daily data). The version of the Fourier transform used in time series data conversion is the Discrete

Fourier Transform (DFT). DFT accepts the series of variable values over time and gives us the signal strength for each frequency, which is known as the Fourier coefficient (Korstanje, 2022). A faster version of the DFT is the Fast Fourier Transform (FFT).

Figure 7- DFT frequencies



A DFT signal consists of the sum of two sinusoids – or tones – with frequencies taken from two mutually exclusive groups. These frequencies were chosen to prevent any harmonics from being incorrectly detected by the receiver as some other DFT frequency.

4.3 FFT Application on Indian Stock Market Data

Applying the FFT to the time series data of the Indian stock market gives us the strength of the frequency of the cycle. To apply the Fast Fourier Transform (FFT) to Indian Stock Market data, the study needs to obtain the stock market data first. Once we have the data, we can use FFT to analyze the frequency components of the time series data and identify any periodic patterns or dominant frequencies.

The Python code used for this purpose is as follows:

```
—----------------------------------------------------------------------------------------------------------------------
Import matplotlib.pyplot as plt
Import numpy as np
From scipy.fftpack import fft, ifft
Import pandas as pd

From Google. colab import files #######import data files as csv exl file by clicking on the button
“Choose file”
```

```
Upload = file.upload()
Saving stockdata1.csv to stockdata1 (1).csv
Import io
df = pd.read_csv(io.BytesIO(upload['stockdata1.csv']))

t=df.time
x=df.close
print(len(x))
x=np.array(x)
t=np.array(t)
plt.plot(t,x)
X=fft(x)
N = len(x)
n= np.arrange(N)
T= N/len(x)
Freq = n/T

plt.figure(figsize = 25, 6))
plt.subplot(131)
plt.stem(freq, np.abs(X), ‘b’ \
markerfmt= “ “, basefmt=”-b”)
plt.zlabel(‘Freq’)
plt.ylabel(‘FFT Amplitude’)
plt.ylim(0,0,2e6)
plt.subplot(132)
plt.stem(freq, np.abs(X), ‘b’, \
markerfmt=” “, basefmt=”-b”)
plt.xlabel(‘FFT Amplitude’)
plt.legend([‘left hand side frequencies’])
plt.xlim(0, 40)
plt.ylim(0,0.2e6)
plt.subplot(133)
plt.stem(freq, np.abs(X), ‘b’, \
markerfmt= “ “, basefmt=” -b”)
plt.xlabel(‘Freq’)
plt.ylabel(‘FFT Amplitude ‘)
plt.legend([‘right hand side frequencies’])
plt.xlim(260, 300)
```

```
plt.ylim(0,0.2e6).
```
—---

This code imports the required libraries:'matplotlib.pyplot' for visualization, 'numpy' for mathematical operations,'scipy.fftpack' for FFT functions, and 'pandas' for data manipulation. The code is being executed within a Google Colab environment. It imports the 'files' module from the 'google.colab' package to allow file uploads. The submitted file is stored in the 'upload' variable.

The uploaded CSV file named 'stockdata1.csv' is then read using the 'pd.read_csv()' function from the 'pandas' library. This code reads the attached CSV file into the 'df' Data Frame. The 'time' and 'close' columns are then retrieved from the DataFrame and assigned to the variables 't' and 'x', respectively. The extent of the 'close' data (the number of data points) is then printed. Next, 'x' and 't' are converted into NumPy arrays. Lastly, it plots 'x' against 't' using Matplotlib's 'plt.plot()' function.

The code then applies the Fourier Transform to the 'x' data using the 'fft()' function from the SciPy 'fftpack' module and stores the result in the variable 'X'. In addition, it computes the number of data points 'N', creates an array of integers from 0 to N-1 using 'np.arange()', and computes the time period 'T' based on the length of 'x'. Finally, the frequency array 'freq' is calculated by dividing 'n' by 'T'.

It creates a figure with three subplots of varying dimensions (25, 6) once completed. It plots the stem plot of 'freq' (frequency array) against the absolute values of 'X' (FFT amplitude) in the first subplot ('plt.subplot(131)') using 'plt.stem()'. It sets the y-label to 'FFT Amplitude', the x-label to 'Freq', and the y-axis limits to 0 to 2e6.

The second subplot ('plt.subplot(132)') is similar to the first, but it changes the x-label to 'FFT Amplitude', adds an annotation, and sets the x-axis limits from 0 to 40 and the y-axis limits from 0 to 0.2e6.

The third subplot ('plt.subplot(133)') is similar to the first, but it sets the x-label to 'Freq', the y-label to 'FFT Amplitude', adds a legend to the plot, and adjusts the x-axis limits from 260 to 300 and the y-axis limits from 0 to 0.2e6.

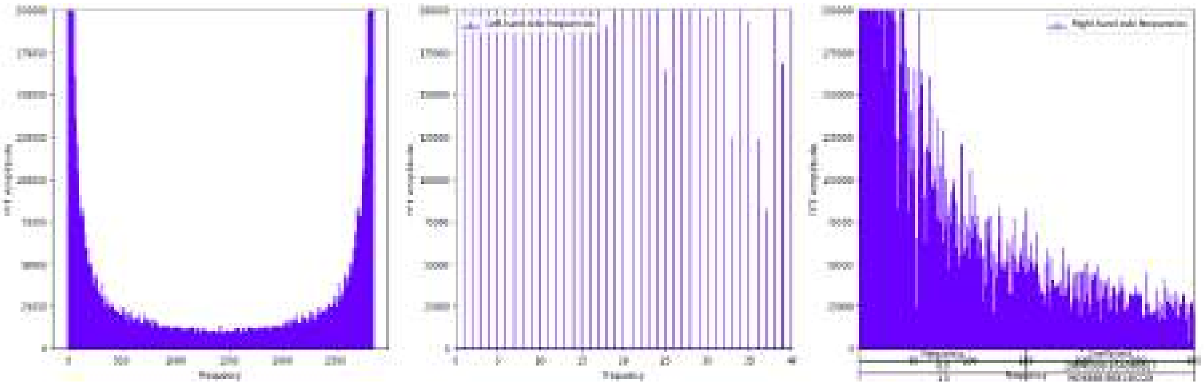


Figure 8 - FFT Frequency map of Nifty50 data

The above plot gives us right-side and left-side frequencies and amplitudes. Focusing on the current data and associated cycles, when reviewed on the right-side frequency plot, gives us the FFT spectrum plot.

4.3.1 Goertzel Generalized Algorithm Application to Indian Stock Market Data

The Goertzel algorithm is a digital signal processing technique that can be used to detect the presence of a particular frequency in a signal. It's often used for detecting specific tones in DTMF signaling and other applications.

To apply the Goertzel algorithm to Indian Stock Market data, we would need to define the specific frequency or frequencies that we are interested in detecting within the stock market data. Once we have identified the target frequency or frequencies, we can use the Goertzel algorithm to detect the presence of these frequencies in the data.

The code for the result created from the GGA function is as follows:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from google.colab import files
upload = files.upload()

df = pd.read_csv(io.BytesIO(upload['stockdata1.csv']))
```

```
t = df.time
x = df.close
print(len(x))
x = np.array(x)
t = np.array(t)
plt.plot(t, x)

def goertzel(x, k):
    N = len(x)
    omega = 2 * np.pi * k / N
    sine = np.exp(1j * omega)
    coeff = 2 * np.cos(omega)
    s_prev = 0
    s_prev2 = 0

    for n in range(N):
        s = x[n] + coeff * s_prev - s_prev2
        s_prev2 = s_prev
        s_prev = s

    power = np.abs(s_prev2**2 + s_prev**2 - coeff * s_prev * s_prev2)
    return power

N = len(x)
freq = np.arange(N) / N
powers = [goertzel(x, k) for k in range(N)]
plt.figure(figsize=(25, 6))
plt.subplot(131)
plt.stem(freq, powers, 'b', markerfmt=" ", basefmt="-b")
plt.ylabel('Goertzel Power')
plt.xlabel('Freq')
plt.subplot(132)
plt.stem(freq, powers, 'b', markerfmt=" ", basefmt="-b")
plt.xlabel('Goertzel Power')
plt.legend(['left hand side frequencies'])
plt.xlim(0, 40)
```

```
plt.subplot(133)
plt.stem(freq, powers, 'b', markerfmt=" ", basefmt="-b")
plt.xlabel('Freq')
plt.ylabel('Goertzel Power')
plt.legend(['right hand side frequencies'])
plt.xlim(260, 300)
plt.show()
```

The above code uploads the stock market data file, reads the data into a data frame, and plots the original complex-valued signal. The code assumes that the DataFrame has columns named 'time' and 'close', and it converts the 'close' data into a NumPy array.

This code defines the `Goertzel function, which implements the Generalized Goertzel Algorithm. It takes the input signal `x` and a frequency index `k` as input. Inside the function, it initializes variables and constants required for the algorithm, such as the number of data points `N`, the angular frequency `omega`, the complex exponential `sine`, and the coefficient `coeff`. It then iterates over the input signal using a loop and calculates the intermediate values `s`, `s_prev`, and `s_prev2` at each iteration. Finally, it calculates the power at the specified frequency index using the Goertzel formula and returns the result.

The code also calculates the number of data points `N` and creates an array `freq` containing the corresponding frequencies for each index. Then, it iterates over each frequency index using list comprehension and calculates the power at each frequency using the `Goertzel () ` function. The resulting powers are stored in the `powers` list.

It then creates a figure with three subplots of dimensions (25, 6). In each subplot, it plots the stem plot of the frequencies against the corresponding powers using `plt.stem()`. The stem plot visualizes the power of each frequency component. It sets the y-label as 'Goertzel Power', and the x-label as 'Freq', and adds legends for the plots. It also sets the x-axis and y-axis limits to focus on specific frequency ranges.

Overall, this code allows us to upload and read complex-valued data, perform the Generalized Goertzel Algorithm to calculate the powers at different frequency components and visualize the results using stem plots.

4.3.2 Error Rate of FFT and GGA Application

The Goertzel generalized algorithm detects dominant cycles more effectively as it can work on non-integer coefficients, which shows the existence of error if FFT is used for the same, and this error can have a significant impact on the timing of buy/sell decisions in the stock market.

The following steps are taken to calculate the error rate between both algorithms:

1. Obtain actual cycle lengths using FFT and Goertzel Generalized algorithms. These cycle lengths work like a point of reference for error rate calculation.
2. Using FFT and Goertzel Generalized algorithm to detect dominant cycles.
3. Compare the detected cycle lengths with reference to the original dominant cycles and calculate the absolute difference or error between the detected cycle lengths and actual cycle lengths.
4. Divide the number of incorrect detections by the total number of detections, and multiplying it by 100 gives us an error rate in percentage.

Error Rate = (Number of Incorrect Detections / Total Number of Detections) * 100

A lower error rate indicates better accuracy and performance. It's crucial to keep in mind that several variables, including data noise, sampling rate, windowing, and parameter selection for the algorithms, can affect cycle length detection accuracy (Sudheer Kumar et al., 2023) Therefore, the FFT algorithm with noise reduction is used to identify and plot the dominant cycles.

4.3.3 FFT application to stock market data with and without noise reduction

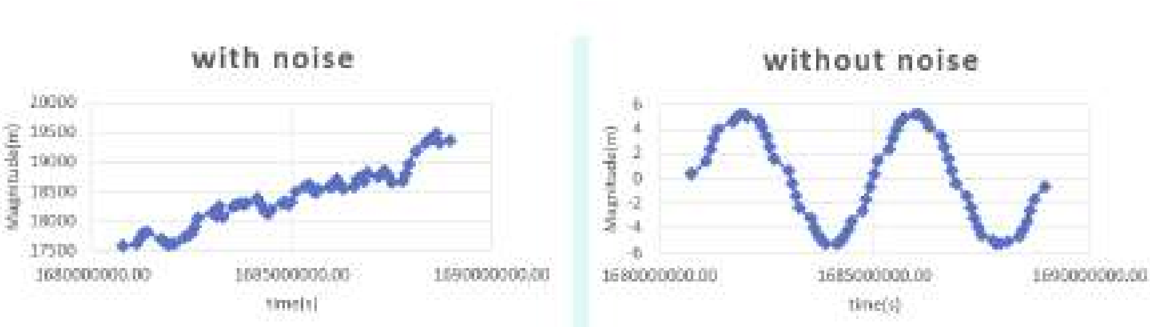


Figure 9- FFT plot of the data, with and without noise

The following algorithm calculates the error rate between FFT and the Goertzel generalized algorithm over stock market data.

```
import pandas as pd
import numpy as np
from scipy.fft import fft
from scipy.signal import Goertzel

# Step 1: Upload stock market data file
data_file = 'stock_data.csv'  # Replace with file path or name

# Read the CSV file into a pandas DataFrame
df = pd.read_csv(data_file)

close_prices = df['Close']

# Step 2: Define actual or estimated cycle lengths
actual_cycle_lengths = [5, 10, 15, 20]  # Replace with actual or estimated cycle lengths

# Step 3: Apply FFT algorithm
fft_result = fft(close_prices)
fft_cycle_lengths = np.abs(fft_result).argmax(axis=0) + 1

# Step 4: Apply Goertzel generalized algorithm
goertzel_cycle_lengths = []
for cycle_length in actual_cycle_lengths:
    _, _, _, max_val = Goertzel(close_prices, cycle_length)
    goertzel_cycle_lengths.append(cycle_length)

# Step 5: Compute error rate
```

```
total_cycles = len(actual_cycle_lengths)
incorrect_detections = sum(a != b for a, b in zip(fft_cycle_lengths, goertzel_cycle_lengths))
error_rate = (incorrect_detections / total_cycles) * 100

# Step 6: Print error rate
print("Error rate: {:.2f}%".format(error_rate))
```

4.3.4 Original Cycle Length

By visually identifying periods and measuring the space between two consecutive cycle bottoms in bar or candlestick charts, it has been possible to determine the original cycle lengths using the Hurst (1972) method.

Trading days are equal to 0.7 times calendar days, or 70% of the calendar days (*Trading Day*, 2023), so two major adjacent bottoms give us trading days, which is 70% of calendar days or the complete cycle length.

Below is the candlestick chart of the Nifty index for the last 12 months, with multiple cycles seen in play as follows:

1. Cycle 1: 13/14 trading days or 19/20 calendar days
2. Cycle 2: Appearing twice in 36 trading days, or 52 calendar days.
3. Cycle 3: The Longest cycle of 98/100 trading days or 141 calendar Days.

Figure 9 - Cycle lengths using the Hurst method of detection

4.3.5 FFT Code for detection of cycle lengths

The following code detects dominant cycle lengths close to the original cycles using FFT. The result of the same can be seen in the table given below.

—--

```
import pandas as pd
import numpy as np
from google.colab import files
from scipy.fft import fft, fftfreq

# Step 1: Upload stock market data file
uploaded = files.upload()

# Read the CSV file into a pandas DataFrame
import io
df = pd.read_csv(io.BytesIO(uploaded['stockdata.csv']))
close_prices = df['close'].values  # Convert to numpy array

# Step 2: Define the original cycle lengths
original_cycle_lengths = [19, 52, 141]

# Step 3: Implement cycle length detection
def detect_cycle_length(data, cycle_lengths):
    freqs = fftfreq(len(data), d=1)  # Frequencies of the DFT
```

```
    magnitudes = np.abs(fft(data))  # Magnitudes of the DFT

    detected_lengths = {}
    for cycle_length in cycle_lengths:
        # Find the frequency index corresponding to the specified cycle length
        idx = np.abs(freqs - 1 / cycle_length).argmin()
        detected_lengths[cycle_length] = 1 / freqs[idx]

    return detected_lengths

# Step 4: Detect cycles of specified lengths
cycles_detected = detect_cycle_length(close_prices, original_cycle_lengths)

# Print the detected cycle lengths
for cycle_length, detected_length in cycles_detected.items():
    print(f"Original Cycle Length: {cycle_length}, Detected Cycle Length:
{detected_length:.2f}, Difference: {abs(detected_length - cycle_length):.2f}")
```

—---

4.3.6 GA Detection Code of Cycle Lengths.

This code provides a generalized Goertzel algorithm implementation and a function to detect cycle lengths based on a given signal, target frequency, and sample rate. The goertzel_algorithm (GA) function calculates the magnitude of the frequency component at a specific index k, and the detect_cycle_length function uses the Goertzel algorithm to detect the cycle length of a signal at a specified target frequency and sample rate. The following code detects dominant cycle lengths close to the original cycles using the Goertzel generalized algorithm.

The result of the same can be seen in the table given below:

—---

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from google.colab import files

# Step 1: Upload stock market data file
```

```
uploaded = files.upload()

# Read the CSV file into a pandas DataFrame
import io
df = pd.read_csv(io.BytesIO(uploaded['stockdata.csv']))
close_prices = df['close'].values  # Convert to numpy array

# Step 2: Define the original cycle lengths
original_cycle_lengths = [19, 52, 141]

# Step 3: Implement Goertzel Generalized Algorithm
def goertzel_algorithm(data, cycle_length):

    # ...

# Step 4: Detect cycles of specified lengths
cycles_detected = {}
tolerance = 0.1  # Adjust this tolerance to control how close the detected cycles should be to
the original lengths

for cycle_length in original_cycle_lengths:
    closest_length = None
    closest_difference = None

    for magnitude in np.linspace(0.01, 2.0, num=200):
        detected_length = cycle_length / magnitude
        difference = abs(detected_length - cycle_length)

        if (
            difference > 0  # Ensure the detected length is not exactly the same as the original
length
            and difference <= cycle_length * tolerance
            and (closest_difference is None or difference < closest_difference)
        ):
            closest_length = detected_length
            closest_difference = difference

    if closest_length is not None:
        cycles_detected[cycle_length] = (closest_length, closest_difference)

# Step 5: Print the detected cycles closest to the original cycle lengths but not the same
for cycle_length, (closest_length, closest_difference) in cycles_detected.items():
    print(f"Original Cycle Length: {cycle_length}, Detected Cycle Length:
{closest_length:.2f}, Difference: {closest_difference:.2f}")
```

```
# Plot the stock data
plt.figure(figsize=(10, 6))
plt.plot(close_prices)
plt.title("Stock Market Data")
plt.xlabel("Time")
plt.ylabel("Close Prices")
plt.grid(True)
plt.show()
```

Original detected cycle length	FFT cycle length	Error in FFT detection	Goertzel, generalized Algo detected cycle	Error in GG detection
19	18.99	.05%	18.81	1%
52	51.80	.38%	51.49	.98%
141	142.45	1.02%	139.60	.99%
Average Error		.48%		.99%

Table 3 - Error Rate Detection between Algorithms

4.4 Composite Cycles

Composite cycles are created by adding the amplitude of the individual cycles across time. We created a composite cycle of the three originally identified cycles of lengths 19, 52, and 141. The sine waves for each cycle length are then plotted using 'np.sin(2 * np.pi * t / cycle_length)`, where `t` is the time points array, and `cycle_length` is the cycle length for the corresponding sine wave.

The resulting plot will show three sine waves with cycle lengths of 19, 52, and 141. Each sine wave will complete one full period within the range of 0 to 2*pi on the x-axis. The amplitudes of the sine waves will vary based on the cycle lengths, with shorter cycle lengths resulting in higher frequencies and larger amplitudes. Here `np.linspace` is used to create a set of time points `t`.

—---

```
import numpy as np
import matplotlib.pyplot as plt

# Define the cycle lengths
cycle_lengths = [19, 52, 141]

# Create time points for plotting with x-axis in the step of 0.01
num_periods = 7  # Increase this value to show more future cycles
num_points_per_period = 100
t = np.arange(num_periods * num_points_per_period) * (2 * np.pi / num_points_per_period)

# Plot the individual cycles and the composite cycle
plt.figure(figsize=(12, 6))

# Plot individual cycles
for cycle_length in cycle_lengths:
    sine_wave = np.sin(2 * np.pi * t / cycle_length)
    plt.plot(t, sine_wave, label=f'Individual Cycle: {cycle_length}')

# Calculate and plot the composite cycle by adding individual cycles
composite_cycle = np.zeros_like(t)
for cycle_length in cycle_lengths:
    composite_cycle += np.sin(2 * np.pi * t / cycle_length)

# Normalize the composite cycle to keep the amplitude consistent with individual cycles
composite_cycle /= len(cycle_lengths)

# Plot the composite cycle
plt.plot(t, composite_cycle, label='Composite Cycle', color='black', linewidth=2)
plt.xlabel('Time')
plt.ylabel('Amplitude')
plt.title('Individual Cycles and Composite Cycle (Including Future Cycles)')
plt.legend()
plt.grid(True)
plt.show()
# Save the plot as a PNG image
plt.savefig('three_cycles.png', dpi=300, bbox_inches='tight')
```

—---

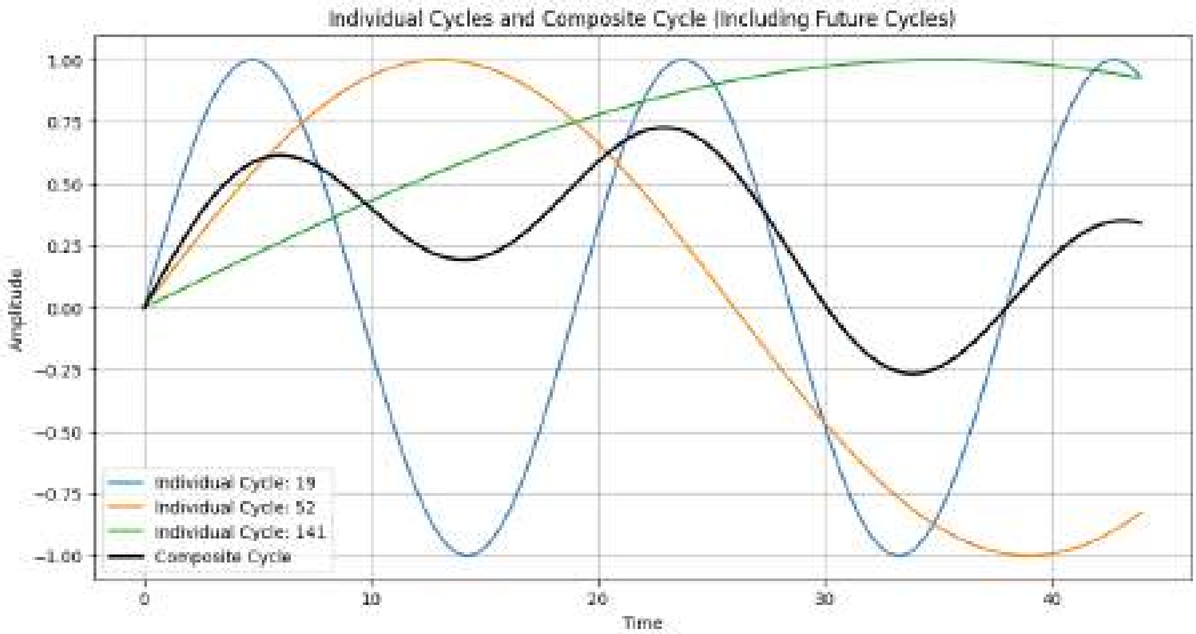


Figure 10 - Individual Cycles and the composite cycle plot

Below is the plot of three composite waves made out of the three methods, Original, FFT, and Gortzel Generalized Algorithm.

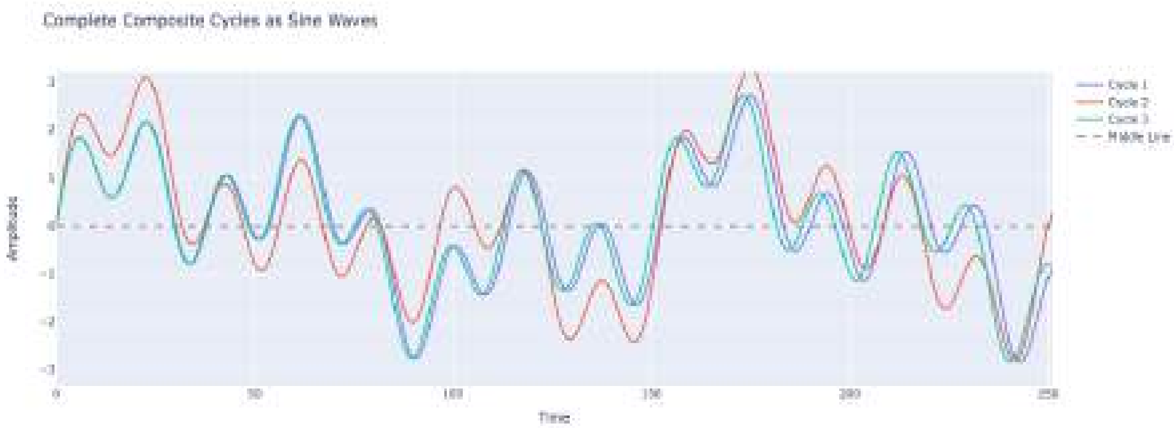


Figure 11 - Composite Cycles plot indicating error between cycle lengths

An error rate of 0.48% with FFT denotes a delay/pre-arrival of one plus day. If we consider the error rate of the Goertzel generalized algorithm at 0.99%, it translates into the pre-arrival or left translation (Crystal, 2020.) of peaks and troughs by two plus days.

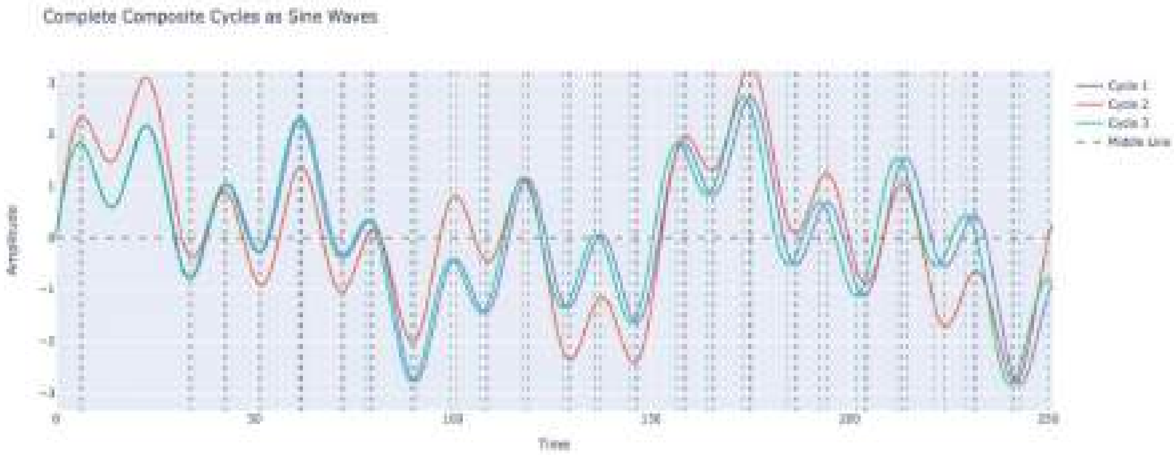


Figure 12 - Peaks and Troughs difference for 3 cycles

4.4.1 Impact of Left and Right Translations Cycles

Following the principle of variation (Hurst, 1972), the significance and impact of the error rate can be noticed in the decision-making process.

Left Translation: Left translation indicates the early bottom of a cycle, and it impacts the profitability of the trade. If we take the error rate of Goertzel's generalized algorithm, and wait for the cycle to bottom, even though the cycle bottom came early, we end up buying the stock or index a couple of days later. A couple of days delay in a minimum of 19 days and a maximum of 141 days cycle will result in reduced profit as there are still many days for it to attain the next peak.

Right Translation: The right translation indicates the late bottoming of the cycle. This means the trough of the current cycle is delayed by a couple of days, and this becomes a big risk if decisions are taken on that basis. If we buy considering the standard cycle length a couple of days early and then it goes down further for the next couple of days, our trade is already at a loss, which will take some time to recover.

According to Crystal (2020), a fixed cycle without translation starts appearing after 3 iterations and stays for six to twelve iterations before it starts shifting or starts showing translation. This stable cycle length of 6-12 iterations is only described in the text. We are not able to find any other reference for the number of iterations for fixed-length cycles. Considering these non-fixed cycle lengths, which can shift after any number of iterations from 6th to 12th, trading decisions cannot be taken.

In this study, we will be tracking the Nifty 50 index movement for three months and seeing if the composite cycle of the standard cycles correctly identifies the peaks and troughs.

Composite cycle for the Indian stock market:

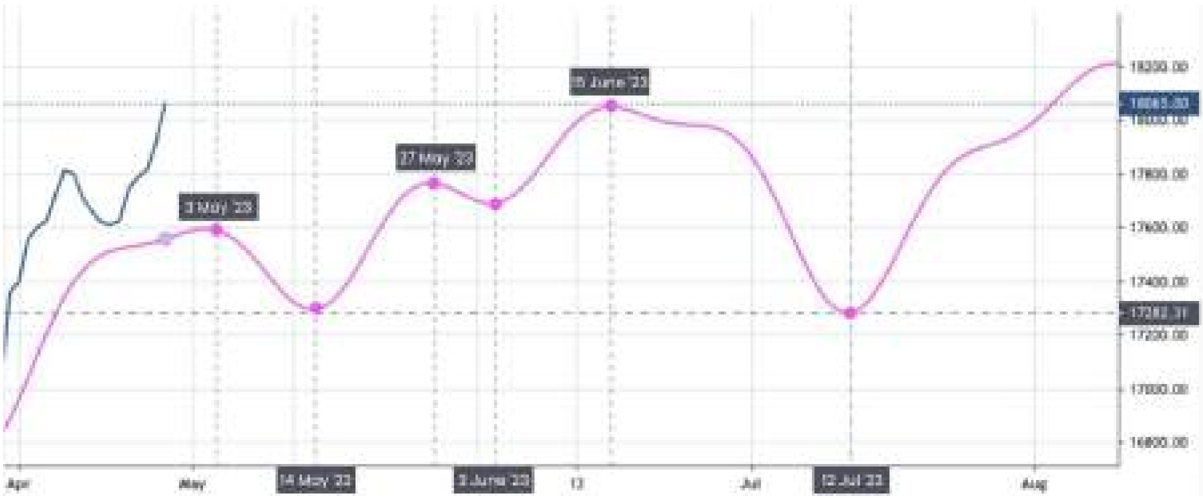


Figure 13 - Composite Cycle plot on Nifty Index data

Peaks and troughs shown in the figure above for the period between May 1, 2023, and July 31, 2023, will be used to track returns in the Nifty 50 index by taking buy and sell positions.

Peak	03/05/2023	27/05/2023	15/06/2023	
Trough	01/05/2013	15/05/2023	03/06/2023	12/07/2023

Table 4 - Peaks & Troughs during the selected period

4.4.2 Results

Following the dates from Table 4, buy and sell trades are placed as given below:

1. Buy one lot of Nifty on the date showing the trough of the composite cycle, and exit the short position, if there is any.
2. Exit the buy trade on the date of the peak from Table 1. At the same time, enter a short trade.

Table 5- shows the Buy / Sell trades following the rules given above with net profit from each trade.

Date of trade	Trade Type	Entry Level	Exit level	Net profit(INR)
01/05/2023	Buy	18124.8	18147.65	1142.5
03/05/2023	Sell	18092	18314	-11100
15/05/2023	Buy	18339	18499	8000
27/05/2023	Sell	18619	18534	4250
03/06/2023	Buy	18612	18755	7150
15/06/2023	Sell	18774	19439	-33250
12/07/2023	Buy	19497.45	20000	25127.5
Total Profit / Loss				1320

Table 5 Trade execution sheet following Peaks and Troughs

The above table shows that 5 out of 7 trades are profitable following the composite cycle of the Nifty50 Index.

It is worthy of note to state that using the FFT and various algorithms to drive various data from the Indian Stock market produces the following results from Together Investment Club in the Nifty 90 Indian Stock market. Some of the names of the profit and lost results of the time series generated are from HDFC Bank, Tata Motors, SBI, Tata Steel, and Baja Finance, to mention just a few as indicated in the figure below:

TradingViewStrategies-Consolidated

TOGETHER INVESTING CLUB

	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpOpenStrategy	47.51%	184.19%	136.68%	6.69%	1767.84%	1343	559	784	1.346
Bollinger Band strategy	-4.41 %	19.97 %	24.38 %	6.12 %	4642.11 %	149	84	64	0.819
Channel breakout strategy	8.7 %	55.76 %	47.09 %	3.27 %	6344.47 %	883	376	507	1.185
Consecutive up down strategy	11.47 %	36.56 %	26.16 %	4.38 %	6234.71 %	586	235	351	1.322
Inside bar strategy	-3.68 %	29.39 %	33.07 %	7.79 %	1595.73 %	264	105	158	0.889
Keltners channels strategy	5.65 %	23.32 %	17.47 %	5.67 %	4257.5 %	120	40	77	1.335
MACD strategy	4.11 %	44.19 %	40.08 %	2.5 %	4294.3 %	585	226	359	1.102
Momentum strategy	12.65 %	45.08 %	32.42 %	4.24 %	8557.21 %	518	197	321	1.39
Moving avg 2 line cross strategy	2.18 %	39.01 %	36.85 %	5.69 %	4422.4 %	427	174	253	1.059
Moving avg cross	12.58 %	59.05 %	47.68 %	3.83 %	6068.29 %	1231	455	776	1.265
Outside bar strategy	-3.81 %	29.61 %	33.42 %	9.67 %	1713.35 %	288	144	144	0.883
Parabolic SAR strategy	12.33 %	55.16 %	42.83 %	3.32 %	8575.66 %	697	304	393	1.288
Pivot extension strategy	-1.51 %	53.37 %	54.88 %	6.15 %	8033.3 %	1036	491	536	0.973
Pivot reversal strategy	9 %	38.69 %	28.69 %	4.29 %	8035.3 %	342	139	203	1.303
Price channel strategy	10.91 %	31.64 %	20.73 %	2.22 %	5138.3 %	228	99	129	1.529
Rob booker	6.13 %	14.72 %	8.58 %	1.64 %	4488.16 %	104	52	52	1.715
RSI strategy	-1.36 %	12.51 %	13.87 %	0.71 %	5530.8 %	63	37	26	0.902
Stochastic slow strategy	-5.68 %	18.11 %	23.79 %	6.61 %	4843.3 %	204	124	80	0.761
Supertrend strategy	54.79 %	171.62 %	116.84 %	10.36 %	9557.21 %	288	123	165	1.469
Technical ratings strategy	14.29 %	31.76 %	17.46 %	2.19 %	8033.3 %	113	48	65	1.819
Volty expan close strategy	32.7 %	87.91 %	55.2 %	1.58 %	8070.01 %	1751	833	918	1.582

HDFCBANK

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpOpenStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	0.19 %	[illegible]	[illegible]	0.77 %	[illegible]	116	65	58	1.111
Channel breakout strategy	-0.87 %	5.38 %	4.45 %	1.14 %	[illegible]	682	208	471	0.805
Consecutive up down strategy	[illegible]	0.42 %	0.37 %	[illegible]	[illegible]	239	113	123	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	398	199	201	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	29	14	15	1.479
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	471	168	298	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	427	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	299	[illegible]	144	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	274	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	175	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	79	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	14	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	128	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

The rest of the results generated are attached in Appendix A.

4.4.3 Summary

In summary, Hurst's (1974) method of detection is used to determine the original cycle lengths using various algorithms. The FFT algorithm detects dominant cycle lengths close to the original cycles, while the Goertzel generalized algorithm detects cycles of specified lengths. The error rate detection between these algorithms ranges from 0.48% with FFT to .99%. Goertzel generalized algorithm. The error rate translates into the pre-arrival or left translation of peaks and troughs by up to two-plus days.

The principle of variation (Hurst, 1972) highlights the significance of the error rate in the decision-making process. Left translation indicates the early bottom of a cycle, impacting the profitability of the trade. If the error rate of Goertzel's generalized algorithm is taken, buying the stock or index a couple of days late can result in reduced profit as there are still many days for it to attain the next peak. The right translation indicates the late bottoming of the cycle, causing a delay in the current cycle's trough, which becomes a big risk if decisions are taken based on this.

Crystal (2020) suggests that a fixed cycle without translation starts appearing after 3 iterations and stays for six to twelve iterations before shifting or starting to show translation. This stable cycle length of 6-12 iterations is only described in the text and considering non-fixed cycle lengths from 6th to 12th can make trading decisions difficult.

This study aimed to track the Nifty 50 index movement for three months and determine if the composite cycle of standard cycles correctly identifies peaks and troughs. The peak and troughs for the period between May 1, 2023, and July 31, 2023, are used to track returns in the Nifty 50 index by taking buy and sell positions. The trade execution sheet following peaks and troughs shows that 5 out of 7 trades are profitable following the composite cycle.

The next chapter will discuss the response to research questions.

CHAPTER V: DISCUSSION

5.1 Discussion of Research Questions

Data analyzed using trade results in the tables above from the results indicates that the percentage of profitable trades is 71.42% which shows confidence in the method used to predict the time of the trade. On the other hand, if we calculate the return on investment from these trades in 3 months times, that comes out to be 1.257% on an absolute basis and 5.029 % on an annualized basis, which is less than the risk-free return of 7% in India. The Nifty 50 index itself gave a return of 10.34% in three months, which is 41.38% on an annualized basis.

Even though there is net profit shown as a result of following peaks and troughs of the composite cycle, it is not economically viable to use it as it is not able to beat risk-free return and is significantly below the Index return itself.

5.1.2 Trade Direction of Trends

Kirkpatrick et al. (2016) described types of trends in their book “Technical Analysis”. According to them, primary trends stay in effect from months to years, and in between corrections occur in the form of secondary trends.

Rhea (1932) in his book “The Dow Theory” formulated three hypotheses, one of which is “The primary trend is inviolate”. In the context of the Dow Theory, the statement "The primary trend is inviolate" means that the primary trend of the market, whether it's an upward or downward trend, is considered to be unbreakable or unchangeable.

This hypothesis suggests that the primary trend of the market will continue in the same direction until there is a clear and decisive indication of a reversal. It emphasizes the importance of identifying and following the primary trend in market analysis and investment decision-making.

In this context when we consider the Indian Stock Market, it seems to be on an uptrend as its primary trend for almost 9 years now, as can be seen in the figure given below.

Figure 14 - Indian Stock Market Index from 2014 till 2023

Considering the Uptrend as the primary trend in the India Stock Market for over 9 years, if we decide to take only long trades based on troughs identified by the composite cycles, the result looks more favorable. It comes out to be 39.45% on an absolute basis for 3 months and 157.79% on an annualized basis. This result beats the risk-free return and even the market index return.

5.1.3 Time Cycle Vs Other Indicator

Taking it further from the above section, the study compares the result of Time Cycles with another technical indicator with Only Long Trades at the troughs and the MACD crossover. MACD stands for "Moving Average Convergence Divergence." It is a popular technical analysis indicator used by traders and analysts to identify trends and potential trend reversals in financial markets, particularly in stock trading. The MACD indicator is based on the comparison of two moving averages of an asset's price.

The full meaning of MACD can be broken down as follows:

Moving Average: This refers to the calculation of the average price of an asset over a specific period of time. The moving average is used to smooth out short-term fluctuations and highlight longer-term price trends.

Convergence: This part of the indicator refers to the moving averages coming closer together, indicating a potential change in the trend.

Divergence: This part of the indicator refers to the moving averages moving further apart, indicating a potential strengthening of the current trend.

The MACD indicator is typically represented as a line on a chart, and it is used to generate buy and sell signals based on the crossovers and divergences of the moving averages.

In summary, the MACD indicator is a tool used to identify changes in momentum and potential trend reversals in financial markets.

Hence, the results look as follows:

MACD Crossover (Buy Signal) occurred on 2nd May 2023 and crossed under (Sell Signal) on 17th May 2023, and the next Buy signal occurred on 30th June 2023. This resulted in a total profit of Rs. 54,940, 52.32% absolute in 3 months and 209.30% on an annualized basis. This shows huge improvement if used as the preferred method of getting buy/ sell signals and trading only in the direction of the Primary Trend.

Figure 15 - Indian Stock Market Index and Buy/Sell Signal using MACD

Thanekar and Shaikh (2020) conducted a similar study to compare returns from five strategies which were combinations of more than one indicator structured to produce positive trading profits. The same indicator can produce different results for different stocks/indices or financial instruments.

One such example is given below in Table 4. Considering the different results for different financial instruments, it is not realistic to announce one indicator like Time Cycles giving consistent results across the board.

Indicators	Stock/Index Name	Profitability -12 months
SuperTrend	Nifty50	43.29
SuperTrend	SBIN	40.85
Supertrend	TataMotors	41.44
Supertrend	BajajFinance	45.83
Supertred	HDFCBank	31.39

Table 5 - Supertrend profitability indicator across 5 instruments

5.1.4 Variation Principle

Hurst (1974) in his book "Profit Magic of Stock Transaction Timing" outlined the principles of Cycle theory, and one of the principles discussed is the Principle of "Variation". The Principle of Variation suggests that financial markets will not obey theoretical perfection, which means the cycle bottom may come earlier or later than its standard length.

Crystal (2020) in the Chartered Market Technician (CMT) Level 1 Curriculum suggests that it is very common to have early or late troughs in financial markets. Another suggestion in his text is that harmonics of a cycle can disappear and reappear, which raises a very valid question Cycles can be trusted to predict trade timings, as disappearance and reappearance of cycle harmonics cannot be predicted, so cannot be taken into consideration in the calculation of a cycle length.

This gives rise to two scenarios:

1. Use a composite cycle for peak and trough detection. In this scenario, if one of the components of this composite cycle simply disappears without notice, the resultant cycle will be different from what was thought of earlier. Then the composite cycle is not valid anymore.
2. The second scenario is using just one dominant cycle of maximum strength to avoid the chances of the disappearance of one of its harmonics. This scenario becomes invalid as every dominant cycle's peak and trough timing changes due to the impact of other harmonics and if we ignore their significance, it can result in losses for traders. This can be seen in Table 5 which shows the timing of trades and profit/ loss based on the timing of the most dominant cycle of length of 19 days.

Date of trade	Trade Type	Entry Level	Exit level	Net profit(INR)

06/05/2023	Sell	18126	18314	-9400
03/05/2023	Buy	18339	18285.4	-2680
26/05/2023	Sell	18268.9	18534	-13255
03/06/2023	Buy	18612	18601	-550
13/06/2023	Sell	18631	18856	-11250
22/06/2023	Buy	18853	19189	16800
02/07/2023	Sell	19246.5	19439	-9625
12/07/2023	Buy	19497.45	19800	15127
Total Profit / Loss				-14833

Table 8 - Trading Records following the dominant cycle only

Following just one dominant cycle, we have 75% of the trade-in loss with a net loss of Rs. 14833, which is a 14.13% loss on the capital used for trade in one lot of the Nifty 50 index.

5.2 Efficient Market Hypothesis (EMH)

Phama (1970) in his noble price-winning paper "Efficient Market Hypothesis" suggested that financial markets are informationally efficient, meaning that stock prices at any given time fully reflect all available information. As a result, it's deemed impossible for investors to consistently outperform the market through expert stock selection or market timing.

In essence, according to EMH, stocks always trade at their fair value, making it futile for investors to seek undervalued stocks or predict future market movements for profit. This theory suggests that, in the long run, individual investors cannot expect returns greater than those from a broad market index. The weak form of the efficient market hypothesis claims that stock prices encompass all known public information, but not private, undisclosed information.

Ullah and Asghar (2023) conducted a study to test EMH using ten years of data from 2012-2020, from the Financial Times Stock Exchange Group-100 index. Analysis was carried out using the Ordinary Least Square (OLS) regression via SPSS software. The results indicated that the beta coefficient's value was not equal to 0 for all lag values from t-1 to t-10. This means that past stock performances could predict future prices, contradicting the efficient market hypothesis. Consequently, it suggests investors might outperform the market by examining past market trends since these trends can foresee future performance.

A point of discussion here is that the efficient market hypothesis (EMH) says that all known information is already reflected in stock prices. This means that regularly outperforming the market is a hard thing to do. It therefore shows that stock prices can be predicted based on past trends, which could make several points.

First, there is the chance of bias from data snooping. If we try enough patterns, we will find some that seem important just by chance. Also, the fact that the study used data from the past 10 years for a certain measure could lead to overfitting. In this case, the model seems to be correct for the group, but it may not be able to predict what will happen in the future.

Another worry comes from things like government changes or natural disasters that can't be predicted by looking at stock data from the past. Also, prices change. If a pattern or trading technique becomes widely known, more traders may start to use it, which could make it less effective. It's also important to think about the costs of doing business. Costs like commissions or bid-ask spreads can make it hard to make money from exploiting trends that have been found.

The random walk theory is another important part of financial theory. It says that stock prices move in ways that are hard to predict, which means that trends seen in the past might not be repeated in the future. Lastly, people's behavior isn't always predictable, and psychological factors can affect investment choices. This makes it even harder to predict stock prices based only on historical data. In light of these arguments, the idea that stock trends in the past can accurately predict how stocks will do in the future becomes very hard to defend.

5.2.1 Seasonality

Seasonality in the stock market refers to the predictable patterns that stocks or certain areas follow at certain times of the year. This happens because of things like taxes, holidays, fiscal reporting dates, and other cyclical events that change how investors act. For example, Rozeff & Kinney (1976) coined the term the "January Effect" which says that stocks tend to go up more in January.

This is usually because people spend their year-end bonuses or the stocks, they sold for tax reasons in December bounce back. "Sell in May and Go Away" is another popular saying. It comes from the fact that stock returns are usually lower from May to October, which makes some investors change their portfolios. Some holidays, like Thanksgiving and Christmas, also seem to bring people together.

Quarterly earnings reports are put out by many companies. Stock and sector moves can be predicted based on how closely these reports match what the market was expecting. During the summer, when many investors are on vacation, there is often a time called the "Summer Doldrums," which is marked by lower trading volumes and less volatility. But it's important to remember that even though these patterns have happened in the past, they don't promise what will happen in the future. As more people notice these trends and investors try to make money off of them, they may become less easy to predict.

In their study, Rozeff & Kinney (1976) posit that the monthly rates of return on the New York Stock Exchange from 1904 to 1974 show signs of seasonality. Except for 1929–1940, there are statistically significant changes between the average returns for each month.

This is mostly due to the high returns in January. Measures of dispersion do not show any clear seasonal trends, and the characteristic exponent seems to be the same from month to month. We also look at what the observed seasonality might mean for the capital asset pricing model and other areas of study.

Similar studies have been done to identify the seasonality of stocks, another one is Xagoraris (2023) in which he is exploring of possibility of rejecting EMH theory by offering the possibility of trading stocks based on seasonality. This study suggests that Calendar events affect institutional investors, like tax-offsetting, window dressing, and earnings calls, which are seasonal. Seasonality will control the financial markets for the next few years.

Many individual investors are constantly entering the market and using technical trading, which means using past data, and inefficiencies like the January effect will be used to make money because individuals are not affected by tax offset or other institutional investor strategies. and because the market is less liquid, small purchasers can impact the market with significant trade in small-capitalization stocks. Giving individual purchasers a chance to get rich is crucial because a more diversified market is more efficient. People need to understand about money to make healthy financial decisions.

Though the effect of seasonality cannot be denied in the stock market, its usefulness as a tool for trading is questionable. Even though the idea that stock prices change with the seasons is interesting, it is not a solid basis for making investment or trading choices. Often, the way these seasonal trends show up depends on the specific periods that are looked at. What is obvious in one decade might be less noticeable in another. Due to things like the rise of algorithmic trading and the fact that the world is becoming more linked, financial markets are always changing. This can change or even completely wipe out seasonal patterns that have been seen in the past. as can be seen in Figure 10, which shows the seasonality pattern of Ultratech Cement stock for the period Jan 2012 till Dec. 2022 on the National Stock

Exchange. It can be seen that in the month of February, Ultratech Cement fell on average by 7.6%, but when we look at the performance of the same stock in February, as can be seen in Figure 11, it has given a return of 4.94% positive return. So, can we rely on seasonality for stock trading?

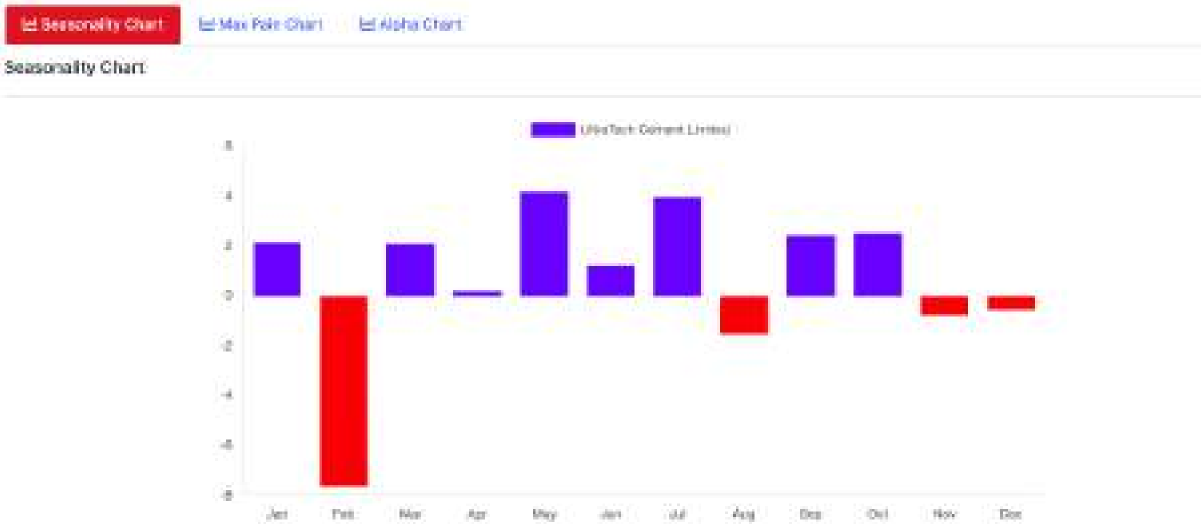


Figure 16 Seasonality Chart for Ultratech Cement.

Figure 17- Return of Ultratech Cement in February 2023

As these patterns become more popular in academic and investment groups, their potential to make money decreases. This is because too many investors acting on the same insight can cancel out its benefit. This is made even harder by the fact that the things that caused seasonality in the first place can change, like tax rules or how people act around the holidays. Also, unexpected events like business changes or geopolitical disasters can override seasonal patterns, making them useless tools for predicting the future.

Lastly, an investor might not pay attention to more important, fundamental information about a business or the economy as a whole if they focus too much on calendar anomalies. In conclusion, seasonality can tell us interesting things about the past, but because it changes and is often unpredictable, it can't be used as a safe anchor for investment plans.

5.2.2 Fundamental Analysis and Brokerage House Predictions

Fundamental Analysis involves evaluating a company's financial statements, understanding the overall health of the economy, industry trends, and other qualitative and quantitative factors. It helps to calculate the intrinsic value of the stock of a company. Investors using this method believe that they can find stock values that the market hasn't yet recognized.

Fundamental analysis is the most widely used technique by brokerage houses and fund houses, as they like to buy low and sell at high, or buy at high and sell at higher. So, it becomes very important for these fund managers to understand the fundamental strength of the stock they are interested in.

Fundamental analysis primarily focuses on evaluating a company's intrinsic value by examining:

A. Its financial statements
B. management quality
C. product lineup
D. competitive position
E. industry trends
F. Various ratios
G. and some more

When we review the main factors, some of which are given above, that are responsible for calculating intrinsic value, we realize that all this is public information and mostly published by the company itself, and audited by authorized auditors.

Furthermore, when a pre-defined and accepted method of calculation is applied to the same publicly available data, the simple assumption is that the result should be the same even if any number of researchers try it. This means all the brokerage firms or fund houses must be able to arrive at the same number as intrinsic value for the same stock and its future price target. For instance, a research website, such as “trendlyn.com”, publishes future target prices of various stocks (Tata Motors for this example), the result shown, as can be seen in the figure below, is a range of target prices suggested by various brokers or fund houses.

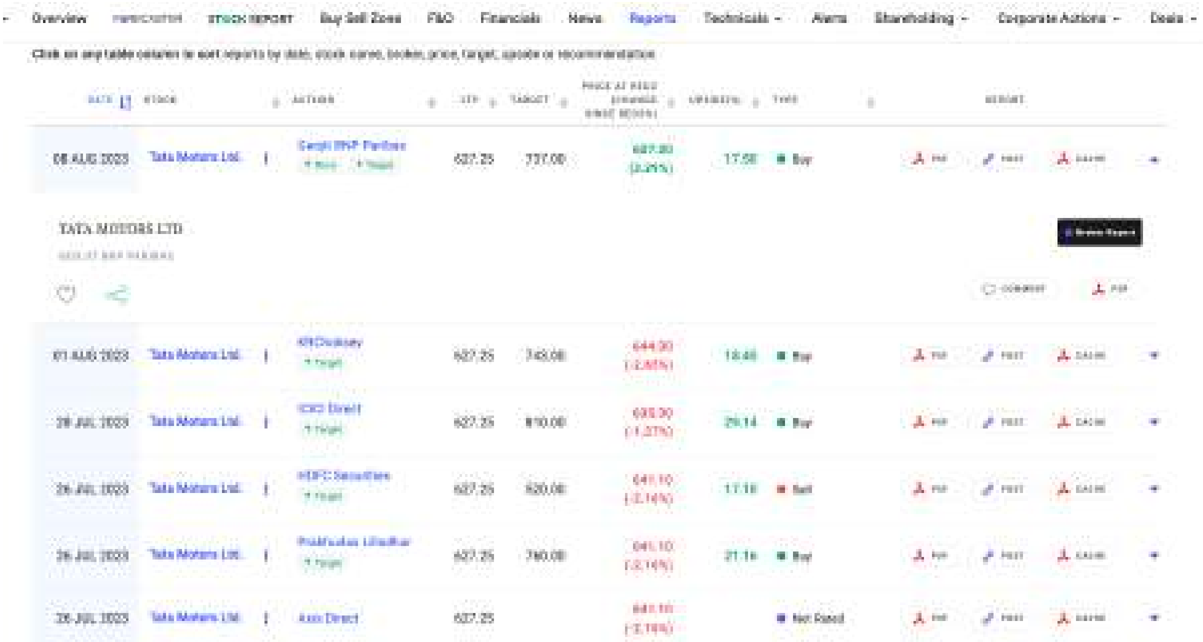


Figure 18 - Tata Motors target given by various brokerage houses.

Now the question arises that if brokerage firms and fund houses, with sufficient research resources, and publicly available information are not able to agree on the future price of a stock, then is it possible to even use this technique as the basis for stock trading or investing?

5.2.3 Effect of Future and Options Trading on Stock Price

The fundamental idea behind future and options trading is to be able to predict future trends of financial instruments and hedge our positions to minimize the risk. Later it evolved as a tool for speculators and has become a method to trade for profit even if you don’t have any position to hedge.

Shenbagaraman, (2003) conducted an interesting study in this domain to explore the possibility of any impact of Future and Options introduction on stock volatility. The study examined how volatility behaves before and after the introduction of futures trading. Before futures were introduced, market information had a lasting impact on volatility: if there was a sudden change in volatility today due to new market information, that effect would carry over to subsequent days.

However, after futures trading began, this continued effect disappeared. Now, any abrupt changes in volatility today don't impact the next day's volatility or any future volatility. This could mean that the market is becoming more efficient, as it quickly absorbs and reflects new information in prices.

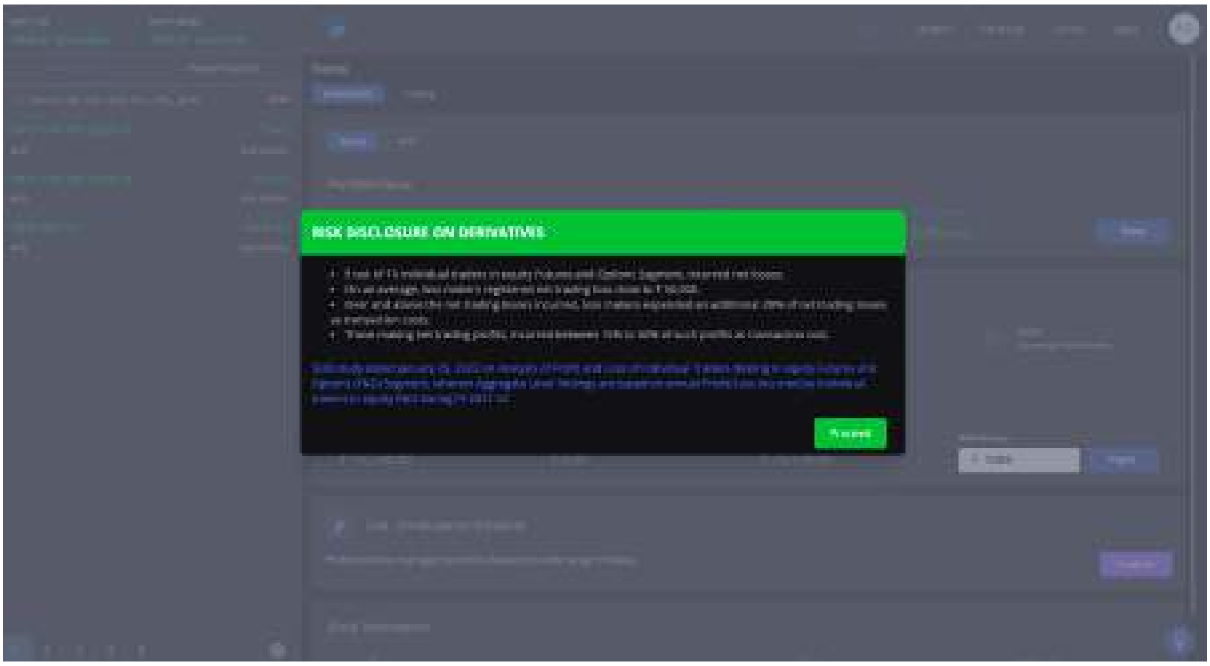
This is a significant piece of work which showed through this study that absorption of any new information in the stock market has become much quicker after the introduction of future and options trading and has made markets much more efficient, in which stock has all the current information priced in, hence predicting the future price of the stock is extremely unlikely.

5.3 Who is Winning?

Considering all the above, the interesting question that comes to mind is if the majority of traders are making profits or the majority of them are in losses, and is this happening continuously or randomly sometimes we win and sometimes we lose.

There was a significant change in the number of active traders after COVID-19, almost across the globe. Numbers went multifold to understand the seriousness of the fact that more and more people are getting involved in speculative trades.

Indian regulator Securities & Exchange Board of India (SEBI) conducted a study on the profitability of traders in Future and Options trades and the result was an eye opener and worrisome that SEBI made it mandatory for all the broking firms to show a warning message on the login screen itself (Figure 5.6) and asked traders to accept that message as accepting the risk of trading in future and options.



SEBI| study -Analysis of Profit and Loss of Individual Traders Dealing in Equity F&O Segment (2023) conducted study on 42.5 Lac traders, which is an increase from 7.1 lac traders only in 2019, which shows number of traders went up between 2019 to 2022 almost 6 times. According to the study:

1. 89% of individual traders incurred losses in equity Futures and Options trades.
2. Excluding outliers, only 6% of the individual traders made a profit with an average of Rs3400, which if considered trading expenses, will also fall into net losses.

3. The remaining 5% were in actual profits of over Rs. 1.9 Lacs during this period.

The study does not offer any data regarding the strategy or methods used by the traders in question. So, it is not reasonable to conclude that the 5% profitable traders know and implement tools or strategies to make a profit and can do it continuously. But it clearly shows a concern after seeing 89% of them losing money in trades, that as a policy and rule all the brokers must now show this as a warning and only after traders understand and accept this risk, they should be allowed to trade.

Points to be considered from the above-mentioned study are:

1. All the traders making losses- 89%, were not using the same strategy for trades. There is no mention in the study, but our assumption here is 89% of around 42.5 Lac overall Future and Options Traders, that is 3782500 traders must have tried every strategy they could find or developed to beat the market returns, but the return shows that they lost money, even though market touched lifetime highs.
2. The remaining 11% remained in profit, it is not mentioned in the study what did they to be in profit, but there is a chance these profitable traders used many of the strategies used by loss-making traders but maybe the entry and exit points made all the difference. The point here is that it is not clear if these profitable traders could repeat success.

The study concludes this by saying that the seriousness of the matter and the action taken by SEBI shows that the majority is not able to preserve their capital, let alone beat the market, even after trying all tools, methods, and strategies.

Furthermore, the researcher reviewed the success ratio of all the top strategies listed as per technical analysis on tradingview.com and tried running the same against the top 50 stocks Indian stock markets that are constituents of the Nifty 50 index. The result shows that except for one strategy for just one specific stock, all other strategy produces substandard results when compared to the “Buy & Hold” strategy for the same parameters and triggers. The results of this exercise are listed in Appendix A.

This part of the study shows that buy & hold strategies have generated over a thousand percent in many stocks in the last 10 years, though active trading is producing rarely over a hundred percent in the last 10 years cumulatively. If this is the case, the question arises if there is any point in predicting stock market moves and/or prices when we can simply buy and just hold for greater profits.

5.4 Summary

The Hurst Hypothesis is a concept that is often associated with time series analysis and the study of long-range dependence in time series data.

The Hurst Exponent is a measure of the long-term memory of a time series. It is used to quantify the degree of persistence or anti-persistence in a time series, which is related to the concept of long-range dependence. The Hurst Exponent is named after the hydrologist Harold Edwin Hurst, who first introduced it in the 1950s.

The Hurst Hypothesis, also known as the Hurst Phenomenon, is a theory that suggests that certain time series data exhibit long-term memory and self-similarity, meaning that patterns observed in the data at one scale are similar to patterns observed at other scales. This hypothesis has been applied to various fields, including hydrology, finance, and other areas where the analysis of time series data is important.

In the context of time series analysis, the correlation of the Hurst Hypothesis with time series results can be seen in the following ways:

Identification of Long-Range Dependence: The Hurst Hypothesis provides a framework for identifying and quantifying long-range dependence in time series data. This is important for understanding the persistence of trends and patterns in the data over different time scales.

Financial Time Series Analysis: In finance, the Hurst Exponent has been used to analyze the behavior of financial time series data, such as stock prices and market returns. It has been applied to assess the degree of predictability and persistence in financial markets in India.

Modeling and Forecasting: The presence of long-range dependence, as indicated by the Hurst Exponent, can influence the modeling and forecasting of time series data. It can impact the choice of statistical models and techniques used to analyze and predict future values of the time series.

Overall, the correlation of the Hurst Hypothesis with time series results lies in its role in identifying and characterizing long-range dependence in time series data, which has implications for understanding and modeling complex patterns and behaviors observed in various fields.

CHAPTER VI: SUMMARY, IMPLICATIONS AND RECOMMENDATIONS

6.1 Summary

In summary, the use of 'Time Cycles' for predicting trade timings is not economically viable due to its structural flaw following the principle of Variations. Even a single dominant cycle is not an economically viable option as a trading tool, as the result shows net loss in our study.

When compared to other technical indicators like MACD, it gives inferior results. The maturity of time cycle indicator tools is also questionable when compared to other technical indicators as Time cycles have been the subject of research by many, but their practical usage is very limited and is not proven.

Crystal (2020) also suggests that every cycle shifts after six to twelve interactions and impacts the amplitude of the cycle, which is also caused by some big new item, which makes the shortest-term cycle the dominant one and changes the character of the composite cycle. The Principle of Variation suggests that financial markets will not obey theoretical perfection, and the cycle bottom may come earlier or later than its standard length.

This raises questions about the reliability of Cycle theory in predicting trade timings, as the disappearance and reappearance of cycle harmonics cannot be predicted. Two scenarios are proposed: using a composite cycle for peak and trough detection or using just one dominant cycle of maximum strength to avoid the chances of disappearance of one of its harmonics.

Phama's "Efficient Market Hypothesis" (1970) posits that financial markets are informationally efficient, meaning stock prices reflect all available information. This makes it impossible for investors to consistently outperform the market through expert stock selection or market timing.

However, a study by Ullah and Ashgar (2023) tested EMH using ten years of data from the Financial Times Stock Exchange Group-100 index. The results showed that past stock performances could predict future prices, contradicting the EMH hypothesis.

Seasonality in the stock market refers to predictable patterns that stocks follow at specific times of the year due to factors like taxes, holidays, fiscal reporting dates, and other cyclical events. The term "January Effect" suggests that stocks tend to go up more in January due to people spending their year-end bonuses or selling stocks they sold for tax reasons in December. Other popular sayings include "Sell in May and Go Away" and quarterly earnings reports.

Furthermore, Xagoraris (2023) explored the possibility of rejecting the EMH theory by offering the possibility of trading stocks based on seasonality. Calendar events affect institutional investors, such as tax-offsetting, window dressing, and earnings calls, which are seasonal. Seasonality will control the financial markets for the next few years.

However, as many individual investors enter the market and use technical trading, inefficiencies like the January effect may be used to make money. Small purchasers can impact the market with significant trades in small-capitalization stocks, making a more diversified market more efficient. Understanding money is crucial for making healthy financial decisions.

Moreover, seasonality in the stock market is an interesting concept, but its usefulness as a trading tool is questionable. Seasonal trends can vary depending on the specific time periods studied, and due to algorithmic trading and global connectivity, financial markets are constantly changing. Seasonal patterns can be overridden by factors like tax rules, holiday behavior, business changes, or geopolitical disasters, making them unreliable for predicting the future.

Fundamental analysis is a technique used by brokerage houses and fund houses to evaluate a company's intrinsic value, which includes financial statements, management quality, product lineup, competitive position, industry trends, and various ratios. However, this method assumes that all brokers or fund houses can agree on the same number of intrinsic values and future price targets for the same stock.

The effect of future and options trading on stock prices is also questionable. Futures trading aims to predict future trends of financial instruments and hedge positions to minimize risk. A study by Shenbagaraman (2003) found that market information had a lasting impact on volatility before futures trading began, but this effect disappeared after futures trading began. This suggests that the market becomes more efficient, as it quickly absorbs and reflects new information in prices.

In conclusion, Time cycle indicators have shown results that can give confidence in predicting stock prices and cannot be used as a stand-alone method for trading profitably. Seasonality can provide interesting insights about the past but cannot serve as a reliable anchor for investment or trading plans. Future and options trading, while useful, may not always accurately predict future stock prices due to the rapid absorption of new information in the market.

6.1.2 Implications of Study Hypothesis

The Hurst Hypothesis and the concept of long-range dependence have several implications for practitioners in various fields, particularly those involved in time series analysis, financial modeling, and other disciplines that deal with complex data patterns. Some of the key implications include:

Forecasting and Predictive Modeling: Understanding long-range dependence, as indicated by the Hurst Exponent, can influence the approach to forecasting and predictive modeling. Practitioners can use this understanding to develop more robust models that account for persistent trends and patterns in the data.

Risk Management: In finance and investment, the presence of long-range dependence can have implications for risk management. It can influence the assessment of market volatility, the modeling of asset returns, and the development of risk management strategies that account for persistent trends in financial time series data.

Time Series Analysis: Practitioners involved in time series analysis can benefit from the Hurst Hypothesis by gaining insights into the degree of persistence or anti-persistence in the data. This understanding can inform the selection of appropriate statistical models and techniques for analyzing time series data.

Infrastructure Planning: In fields such as hydrology, environmental science, and engineering, the Hurst Hypothesis has implications for infrastructure planning and management. It can inform the assessment of long-term trends in natural processes and the design of infrastructure that accounts for long-range dependence on environmental data.

Signal Processing and Telecommunications: The concept of long-range dependence has implications for signal processing and telecommunications, where the analysis of complex data patterns is crucial. Practitioners in these fields can benefit from understanding how long-range dependence affects signal transmission, network performance, and data processing.

Algorithmic Trading: In finance, the Hurst Exponent and the Hurst Hypothesis have implications for algorithmic trading strategies. Practitioners can use insights from long-range dependence to develop trading algorithms that account for persistent trends in financial markets.

Overall, the implications of the Hurst Hypothesis for practitioners are broad and diverse, spanning fields such as finance, engineering, environmental science, and telecommunications. Understanding long-range dependence can lead to more informed decision-making, improved modeling techniques, and better management of complex systems and processes.

6.1.3 Implications for Social Change and Investors

Time series analysis has significant implications for the stock market and individual investors, influencing investment decisions, risk management, and the development of trading strategies. Some of the key implications include:

Trend Analysis: Time series analysis allows investors to identify and analyze trends in stock prices and market movements over time. This helps investors understand the historical behavior of stocks and indices, which can inform investment decisions and portfolio management.

Volatility Modeling: Time series analysis provides tools for modeling and forecasting stock price volatility. Understanding volatility patterns is crucial for risk management and the assessment of potential price movements.

Seasonality and Cyclical Patterns: Time series analysis can reveal seasonal and cyclical patterns in stock prices, helping investors anticipate market behavior during specific times of the year or economic cycles.

Forecasting and Predictive Modeling: Investors use time series analysis to forecast future stock prices and market trends, aiding in the development of investment strategies and trading decisions.

Risk Management: Time series analysis is essential for risk management in the stock market. It allows investors to assess the risk associated with different stocks, portfolios, or investment strategies, leading to informed risk management decisions.

Algorithmic Trading: Time series analysis is utilized in the development of algorithmic trading strategies, including high-frequency trading algorithms that use historical price data to make rapid trading decisions.

Technical Analysis: Individual investors often use technical analysis techniques, which rely on time series data, to make investment decisions based on chart patterns, moving averages, and other price-related indicators.

Market Sentiment Analysis: Time series data can be used to analyze market sentiment and investor behavior, providing insights into the psychology of market participants and potential market trends.

Portfolio Optimization: Time series analysis helps investors optimize their portfolios by assessing the historical performance of different asset classes, sectors, or individual stocks.

Overall, time series analysis plays a crucial role in shaping the investment landscape for both institutional and individual investors. It provides valuable insights into market behavior, risk factors, and the development of investment strategies, ultimately influencing investment decisions and portfolio management.

6.2 Recommendations

This study focused on the Indian stock market Index with limited cycles to create a composite cycle. Since the parameters used in this study are limited, we recommend future research focus on bringing down the parameters list to the very minimum where results are positive for all kinds of financial services instruments ranging from stocks, crypto, commodities, and currency and then build on it to expand the scope and arrive at conclusion and/ or methods to make its usage practical for traders.

The government regulatory bodies will be able to see that around 90% of the retail traders are losing money in future and option trades, then a serious discussion is required to ascertain if Future and options trading be allowed for retail traders and investors. The same report reporting the remaining 10%'s success in generating profits also doesn't tell us anything about if some tested and tried strategies and/or methods were used to generate that profit or was by chance, and in that case, even these 10% profitable traders lose their meaning.

6.2.1 Recommendation for Future Research

For future research in time series analysis, several areas present exciting opportunities for exploration and advancement. Some recommendations for future research in time series analysis include:

Deep Learning and Time Series Forecasting: Investigating the application of deep learning techniques, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, for improved time series forecasting and predictive modeling.

Nonlinear Time Series Analysis: Exploring advanced methods for analyzing nonlinear time series data, including chaos theory, fractal analysis, and other nonlinear dynamics approaches to capture complex patterns and behaviors in time series.

High-Frequency Time Series Analysis: Research methods for analyzing high-frequency financial data, such as tick data and order book data, to understand market microstructure and develop advanced trading strategies.

Multivariate Time Series Analysis: Advancing techniques for analyzing multivariate time series data, which involves the simultaneous analysis of multiple time series to capture interdependencies and correlations across different variables.

Time Series Anomaly Detection: Developing novel approaches for detecting anomalies and irregularities in time series data, with applications in fraud detection, cybersecurity, and abnormal event detection.

Time Series Interpretability and Explainability: Investigating methods to enhance the interpretability and explainability of time series models, particularly in the context of machine learning and deep learning models for time series analysis.

Time Series Forecast Evaluation Metrics: Researching the development of robust evaluation metrics and statistical tests for assessing the accuracy and reliability of time series forecasting models, including measures of uncertainty and prediction intervals.

Long-Range Dependence and Hurst Exponent Applications: Further exploring the implications of long-range dependence in time series data, particularly in financial markets, hydrology, environmental science, and other fields where persistent trends are important.

Time Series Data Visualization: Advancing visualization techniques for time series data to facilitate the exploration, interpretation, and communication of complex temporal patterns and trends.

Time Series Applications in Healthcare and Biomedical Sciences: Investigating the use of time series analysis for medical signal processing, patient monitoring, disease prediction, and other healthcare applications.

These areas represent promising avenues for future research in time series analysis, with the potential to advance the field and contribute to a deeper understanding of complex temporal data patterns across various domains.

6.2.2 Recommendation for Action

Recommendations for action are as follows:

1. Future researchers should use cycle indicators as a base but not the main method to identify the trade timing. It is like knowing the monsoon arrives in India in the month of July every year but does not tell us which day it will rain.
2. Future researchers should use another indicator or combination of indicators to use this base and get a confirmation for the time of trade.

3. Combine these additional indicators with the base of the cycle indicator and build a complete tool that can be tested for future trades.
4. Future researchers should back test this combined indicator will not work due to the principle of variations cycle bottoms change, and the result will not be valid. It must only be tested for future trade prices before it is approved or rejected.

6.3 Limitations of the study

The biggest limitation of the study is its timing. This study considered the period that turned out to be the bullish period in the Indian stock market (though the study did not know it when we decided on three months for the study consideration).

In a trendy market, all indicators work. Ideally, the study should be conducted in a sideways market where the trend is not very strong as the real impact of the cycle can only be seen after detrending the data. In addition to this, we have some more points that show the limitations of this study:

1. Data Limitations: Sample Size and Period: The data period (2010 till 2022) we have chosen might be limited. Different time frames could offer different results, especially in stock markets where the nature of market cycles can change based on various external factors. Choice of the time period for analysis -1st May 2023 till 31st July 2023, may be a very limited time period, if we make it longer, the success rate of time cycle-based trading may be different.
2. Methodological Limitations
    a. Assumption of Linearity: Algorithms like FFT and DFT assume the system (in this case, the stock market) to be linear. Stock markets, however, can have non-linear dynamics influenced by a plethora of factors.

b. Spectral Leakage: This is a limitation inherent in FFT. If cycles in the stock market do not precisely align with the sampling points, it can result in inaccuracies in frequency estimates.

c. Resolution: The Goertzel algorithm is more focused and has higher resolution than FFT for specific frequencies. However, if there's a slight error in choosing these frequencies, it might not capture the real market cycles.

3. External Factors Not Considered: Stock markets are influenced by a myriad of factors, including political events, policy changes, natural disasters, and more. This study, by focusing on time cycles, might not account for such unpredictable events that can disrupt the identified cycles, or maybe that’s the point we are trying to highlight in this study that any kind of external event can disrupt the time cycles of any stock or stock index or economy.

4. Market Psychology: Human behavior, sentiments, and mass psychology play a significant role in stock market movements. These aspects can introduce a lot of variability in how cycles manifest and can deviate from mathematically predicted patterns.

5. Application Across Different Segments: The behavior of blue-chip stocks might differ from mid-cap or small-cap stocks. Our study doesn't segment its findings, the identified cycles might not apply universally to all market segments and may give different results if a particular segment of stock / financial instrument is analyzed.

6. Market Structure Changes: Over time, the structure and functioning of markets can change (e.g., the introduction of algorithmic trading, and change in regulations). This could affect the applicability of identified time cycles in the future. Algorithmic trading is considered to be contributing most of the trading volume currently across

stock exchanges, and if this continues then rule-based algo trading may start causing time cycles to be present in a more accurate way in the future.

6.4 Conclusion

While further work is required to study time cycles in the stock market, the scope of our study was limited to the identification of time cycles in the Indian stock market and their impact. In a trendy market, an absolute return of 5.03 % (less than the current risk-free return of 7%, and 41.38 5 annualized return by the Nifty 50 index in the same period) does not show us the value of using time cycles as an indicator of choice while other traditional indicators like MACD are showing 209.30% annualized return in the same period.

The study also discussed the future opportunity of exploring the possibility of combining cycle indicators with some other indicators to produce better results. But as a stand-alone solution, our recommendation is not to use a time cycle indicator for trading as it may end up producing substandard results for traders. Referring to the study conducted by SEBI in India on active traders between 2019 to 2022, we are trying to show that the majority of the traders (89% shown in the study) bear losses and that is a big number to ignore when considering if stock market trades can be timed.

Appendix A

Top 50 stocks active trading Vs Buy & Hold result.

HDFCBANK

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpOpenStrategy	[illegible]	[illegible]	[illegible]	19.27 %	[illegible]	1144	472	651	1.142
Bollinger Band strategy	0.19 %	[illegible]	[illegible]	[illegible]	[illegible]	116	65	50	1.111
Channel breakout strategy	-0.47 %	[illegible]	[illegible]	[illegible]	[illegible]	582	108	471	0.585
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	1.27 %	279	125	125	[illegible]
Inside bar strategy	-0.48 %	[illegible]	[illegible]	[illegible]	[illegible]	398	191	201	[illegible]
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	39	[illegible]	25	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	471	[illegible]	[illegible]	[illegible]
Momentum strategy	-0.73 %	[illegible]	[illegible]	[illegible]	[illegible]	427	137	286	[illegible]
Moving avg 2 line cross strategy	-0.47 %	[illegible]	[illegible]	[illegible]	[illegible]	360	132	224	[illegible]
Moving avg cross	-0.35 %	[illegible]	4.57 %	[illegible]	[illegible]	1189	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	299	153	144	[illegible]
Parabolic SAR strategy	-0.49 %	[illegible]	[illegible]	[illegible]	[illegible]	505	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	917	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	-0.63 %	[illegible]	[illegible]	[illegible]	[illegible]	234	99	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	179	55	[illegible]	[illegible]
Rob booker	-0.39 %	[illegible]	[illegible]	[illegible]	[illegible]	79	[illegible]	[illegible]	[illegible]
RSI strategy	-0.63 %	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	-0.59 %	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	60	39	[illegible]
Supertrend strategy	-1.53 %	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	40	60	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	128	[illegible]	89	[illegible]
Volty expan close strategy	-0.75 %	[illegible]	[illegible]	[illegible]	[illegible]	1344	432	[illegible]	[illegible]

ONGC

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpOpenStrategy	6.98 %	219.83 %	212.85 %	21.63 %	656.6 %	1108	449	642	1.033
Bollinger Band strategy	-0.21 %	0.61 %	0.83 %	0.31 %	1078.14 %	119	68	51	0.743
Channel breakout strategy	-0.39 %	1.59 %	1.98 %	0.45 %	660.11 %	669	220	448	0.801
Consecutive up down strategy	-0.38 %	1.31 %	1.68 %	0.45 %	660.94 %	409	151	256	0.783
Inside bar strategy	0.23 %	1.58 %	1.35 %	0.21 %	622.76 %	426	223	199	1.17
Keltners channels strategy	-0.04 %	0.36 %	0.4 %	0.16 %	1001.18 %	45	17	28	0.906
MACD strategy	-0.08 %	1.44 %	1.53 %	0.48 %	1278.52 %	433	152	279	0.945
Momentum strategy	-0.34 %	1.34 %	1.68 %	0.47 %	1008.02 %	427	126	300	0.798
Moving avg 2 line cross strategy	-0.03 %	1.31 %	1.34 %	0.19 %	1147.25 %	358	135	220	0.98
Moving avg cross	-0.05 %	2.08 %	2.13 %	0.29 %	759.17 %	1063	371	679	0.976
Outside bar strategy	-0.38 %	1.05 %	1.43 %	0.49 %	677.37 %	302	120	178	0.737
Parabolic SAR strategy	-0.43 %	1.47 %	1.9 %	0.56 %	670.23 %	487	167	318	0.774
Pivot extension strategy	-0.37 %	1.72 %	2.09 %	0.42 %	804.33 %	793	370	413	0.824
Pivot reversal strategy	-0.16 %	1.07 %	1.23 %	0.37 %	866.94 %	267	91	175	0.866
Price channel strategy	-0.12 %	0.83 %	0.96 %	0.33 %	987.74 %	175	67	107	0.871
Rob booker	0.24 %	0.52 %	0.28 %	0.08 %	484.98 %	76	37	39	1.85
RSI strategy	0 %	0.38 %	0.38 %	0.17 %	1012.6 %	37	24	13	1.008
Stochastic slow strategy	0.11 %	0.74 %	0.63 %	0.14 %	926.68 %	113	67	46	1.174
Supertrend strategy	-15.05 %	90.72 %	105.77 %	24.23 %	1042.65 %	144	53	90	0.858
Technical ratings strategy	7.5 %	42.59 %	35.09 %	7 %	779.7 %	114	34	80	1.214
Volty expan close strategy	-0.94 %	2.15 %	3.09 %	1.08 %	654.9 %	1274	427	839	0.696

AIRTEL

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpOpenStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	-0.22 %	1.2 %	[illegible]	[illegible]	[illegible]	103	62	41	[illegible]
Channel breakout strategy	-0.81 %	[illegible]	[illegible]	[illegible]	[illegible]	564	192	372	0.776
Consecutive up down strategy	-1.15 %	[illegible]	[illegible]	1.2 %	[illegible]	340	129	[illegible]	0.657
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	385	170	[illegible]	[illegible]
Keltners channels strategy	-0.66 %	[illegible]	[illegible]	[illegible]	[illegible]	35	11	24	0.555
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	137	347	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	121	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	299	118	179	1.058
Moving avg cross	-0.86 %	[illegible]	[illegible]	1.2 %	[illegible]	[illegible]	[illegible]	[illegible]	0.814
Outside bar strategy	[illegible]	1.47 %	[illegible]	[illegible]	[illegible]	[illegible]	136	149	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	1.42 %	[illegible]	[illegible]	157	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	689	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	-0.36 %	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	73	132	[illegible]
Price channel strategy	-0.26 %	[illegible]	[illegible]	[illegible]	[illegible]	151	54	97	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	64	27	36	[illegible]
RSI strategy	-0.26 %	[illegible]	[illegible]	[illegible]	[illegible]	25	12	13	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	101	64	38	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	109	36	73	1.271
Volty expan close strategy	-1.72 %	[illegible]	[illegible]	[illegible]	[illegible]	1106	[illegible]	728	[illegible]

BAJAJFINANCE

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	42.64 %	285.47 %	242.83 %	22.18 %	55773.79 %	1008	437	569	1.176
Bollinger Band strategy	-4.11 %	4.69 %	8.8 %	4.34 %	57962.93 %	120	65	53	0.533
Channel breakout strategy	3.67 %	15.44 %	11.77 %	1.21 %	55770.4 %	682	209	471	1.311
Consecutive up down strategy	-0.68 %	11.45 %	12.28 %	3.73 %	58325.47 %	442	174	259	0.973
Inside bar strategy	-2.03 %	9.86 %	11.89 %	4.11 %	88372.32 %	479	244	225	0.829
Keltner channels strategy	4.25 %	7.33 %	3.08 %	1.03 %	84611.54 %	51	16	35	2.378
MACD strategy	2.21 %	12.28 %	10.04 %	2.24 %	86230.44 %	514	189	306	1.22
Momentum strategy	-0.7 %	10.69 %	11.39 %	3.72 %	82144.6 %	384	120	262	0.94
Moving avg 2 line cross strategy	5.57 %	12.4 %	6.83 %	2.1 %	89766.34 %	383	164	212	1.816
Moving avg cross	2.66 %	16.38 %	13.73 %	2.03 %	89497.44 %	1242	476	666	1.298
Outside bar strategy	-0.26 %	8.45 %	8.71 %	4.08 %	84642.2 %	341	172	164	0.97
Parabolic SAR strategy	-2.59 %	13.22 %	15.81 %	4.89 %	55916.68 %	543	169	369	0.836
Pivot extension strategy	-1.15 %	12.68 %	13.84 %	4.11 %	57068.36 %	961	453	431	0.917
Pivot reversal strategy	6.47 %	11.86 %	5.38 %	1.06 %	58608.15 %	271	93	177	2.2
Price channel strategy	7.02 %	10.46 %	3.43 %	0.69 %	60063.56 %	185	67	126	3.046
Rob booker	2.46 %	3.69 %	1.21 %	0.58 %	60635.65 %	59	26	32	3.052
RSI strategy	3.52 %	7.13 %	3.62 %	1.68 %	63328.66 %	44	28	16	1.972
Stochastic slow strategy	-4.6 %	4.24 %	8.84 %	5.38 %	38801.4 %	115	69	45	0.48
Supertrend strategy	216.58 %	402.54 %	185.96 %	16.34 %	61775.03 %	134	63	70	2.164
Technical ratings strategy	55.6 %	92.73 %	47.13 %	6.59 %	55720.41 %	153	53	96	1.795
Volty expan close strategy	3.73 %	20.31 %	16.58 %	16.58 %	69911.81 %	1584	410	1138	1.226

BAJAJFINSERV

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	45.47 %	154.02 %	108.55 %	5.16 %	2447.03 %	551	250	295	1.419
Bollinger Band strategy	-16.73 %	7.72 %	24.45 %	17.44 %	3301.09 %	67	35	32	0.316
Channel breakout strategy	3.64 %	33.98 %	30.34 %	3.85 %	3232.25 %	404	136	266	1.12
Consecutive up down strategy	8.2 %	31.81 %	23.61 %	3.53 %	2736.65 %	252	102	150	1.347
Inside bar strategy	3.6 %	28.06 %	24.47 %	4.47 %	2406.63 %	263	135	128	1.147
Keltner channels strategy	6.33 %	9.51 %	3.17 %	0.89 %	3034.04 %	23	14	9	2.996
MACD strategy	3.15 %	30.86 %	27.7 %	5.5 %	3767.32 %	272	98	174	1.114
Momentum strategy	9.84 %	30.87 %	21.03 %	2.75 %	2687.24 %	241	83	156	1.466
Moving avg 2 line cross strategy	8.42 %	29.54 %	21.12 %	4.79 %	2686.98 %	201	75	126	1.399
Moving avg cross	7.78 %	39.71 %	31.93 %	4.08 %	2537.62 %	617	201	412	1.244
Outside bar strategy	6.62 %	23.91 %	17.29 %	3.24 %	2015.6 %	183	81	101	1.383
Parabolic SAR strategy	-2.26 %	30.17 %	32.43 %	7.62 %	2653.5 %	309	95	214	0.93
Pivot extension strategy	8.84 %	38.33 %	29.5 %	3.42 %	2616.77 %	491	230	220	1.3
Pivot reversal strategy	14.81 %	29.08 %	14.27 %	2.33 %	2626.79 %	151	62	89	2.036
Price channel strategy	19.34 %	26.38 %	7.04 %	1.03 %	3060.60 %	97	44	52	3.746
Rob booker	3.29 %	4.48 %	1.19 %	0.28 %	3291.07 %	31	15	15	3.751
RSI strategy	6.1 %	11.17 %	5.07 %	3.5 %	4265.16 %	21	12	9	2.202
Stochastic slow strategy	-11.12 %	9.87 %	20.99 %	13.72 %	3456.06 %	67	40	27	0.47
Supertrend strategy	65.24 %	150.15 %	84.91 %	17.20 %	2959.03 %	70	30	39	2.315
Technical ratings strategy	4.02 %	21.58 %	17.56 %	6.04 %	2608.25 %	55	18	37	1.229
Volty expan close strategy	7.47 %	44.65 %	37.18 %	3.59 %	2657.56 %	698	259	439	1.201

ITC

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	-28.28 %	163.28 %	191.55 %	33.28 %	2451.55 %	1362	496	833	0.852
Bollinger Band strategy	0.1 %	0.59 %	0.49 %	0.24 %	2544.54 %	132	83	48	1.209
Channel breakout strategy	-0.28 %	1.29 %	1.58 %	0.41 %	2452.73 %	778	251	520	0.82
Consecutive up down strategy	-0.06 %	1.01 %	1.07 %	0.36 %	2454.46 %	484	169	271	0.945
Inside bar strategy	-0.12 %	0.97 %	1.09 %	0.21 %	2463.38 %	564	210	281	0.887
Keltner channels strategy	-0.06 %	0.29 %	0.35 %	0.2 %	2565.34 %	53	20	33	0.838
MACD strategy	-0.18 %	1.05 %	1.23 %	0.39 %	2663.38 %	527	188	334	0.852
Momentum strategy	-0.63 %	0.82 %	1.44 %	0.63 %	2468.61 %	522	145	372	0.567
Moving avg 2 line cross strategy	-0.53 %	0.69 %	1.22 %	0.55 %	2667.91 %	418	147	266	0.566
Moving avg cross	-0.17 %	1.53 %	1.7 %	0.39 %	2366.89 %	1275	410	639	0.901
Outside bar strategy	0.09 %	0.82 %	0.74 %	0.14 %	2468.23 %	327	147	177	1.109
Parabolic SAR strategy	-0.51 %	1.11 %	1.62 %	0.56 %	2381.29 %	684	206	396	0.684
Pivot extension strategy	-0.18 %	1.39 %	1.57 %	0.34 %	2410.17 %	977	470	478	0.884
Pivot reversal strategy	-0.29 %	0.7 %	0.99 %	0.41 %	2582.9 %	341	110	230	0.71
Price channel strategy	-0.29 %	0.5 %	0.79 %	0.35 %	2565.41 %	221	66	153	0.628
Rob booker	-0.08 %	0.24 %	0.31 %	0.11 %	3725.15 %	91	27	64	0.757
RSI strategy	-0.03 %	0.26 %	0.29 %	0.1 %	2931.28 %	41	25	16	0.904
Stochastic slow strategy	0.09 %	0.56 %	0.49 %	0.1 %	2567.23 %	138	83	55	1.187
Supertrend strategy	-32.3 %	61.81 %	94.11 %	35.87 %	4016.7 %	169	56	111	0.657
Technical ratings strategy	-2.26 %	37.8 %	40.04 %	8.01 %	2390.87 %	199	90	109	0.944
Volty expan close strategy	-0.18 %	1.88 %	2.06 %	0.43 %	2461.44 %	1527	547	971	0.914

TITANS									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	176	[illegible]	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.02
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

INFOSYS									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	0.6 %	265.6 %	265.6 %	265 %	223112.5 %	1460	557	887	1.002
Bollinger Band strategy	−0.87 %	1.27 %	2.14 %	0.94 %	176470 %	122	70	51	0.582
Channel breakout strategy	−0.91 %	4.25 %	5.16 %	1.31 %	223112.5 %	752	238	511	0.824
Consecutive up down strategy	−0.19 %	3.55 %	3.73 %	0.38 %	243059.28 %	479	172	296	0.953
Inside bar strategy	−0.98 %	2.93 %	3.92 %	1.2 %	227862.5 %	459	226	222	0.811
Keltners channels strategy	−0.93 %	0.73 %	1.66 %	1.12 %	202533.13 %	54	15	39	0.438
MACD strategy	−0.63 %	3.42 %	4.04 %	0.75 %	187666.14 %	518	183	324	0.845
Momentum strategy	−0.07 %	3.43 %	3.51 %	0.65 %	202533.13 %	435	142	290	0.979
Moving avg 2 line cross strategy	0.6 %	3.49 %	2.89 %	0.55 %	214452.83 %	356	148	208	1.208
Moving avg cross	−1.1 %	4.55 %	5.65 %	1.23 %	227862.5 %	1100	306	783	0.805
Outside bar strategy	−0.72 %	2.4 %	3.12 %	1.02 %	243059.28 %	290	132	155	0.769
Parabolic SAR strategy	−0.94 %	3.94 %	4.88 %	1.17 %	227862.5 %	569	197	368	0.807
Pivot extension strategy	−0.27 %	4.7 %	4.97 %	0.98 %	227862.5 %	947	447	470	0.945
Pivot reversal strategy	−0.05 %	2.72 %	2.76 %	0.62 %	260428.31 %	285	100	185	0.983
Price channel strategy	0.38 %	2.45 %	2.07 %	0.41 %	227862.5 %	190	75	114	1.182
Rob booker	0.5 %	1.29 %	0.79 %	0.16 %	182270 %	87	40	46	1.637
RSI strategy	−0.1 %	0.61 %	0.72 %	0.29 %	214452.83 %	34	21	13	0.857
Stochastic slow strategy	0 %	2.2 %	2.19 %	0.65 %	214452.83 %	152	95	57	1.002
Supertrend strategy	65.01 %	261.4 %	196.39 %	19.84 %	227862.5 %	166	62	104	1.331
Technical ratings strategy	17.33 %	63.65 %	46.32 %	9.81 %	227862.5 %	143	52	90	1.374
Volty expan close strategy	−0.33 %	6.19 %	6.52 %	0.86 %	227862.5 %	1560	538	1015	0.95

TATA CONSUMERS									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	11	23	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

NESTLE

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	7.71 $	47.23 $	39.51 $	3.79 $	421.49 $	420	226	194	1.195
Bollinger Band strategy	6.6 $	19.91 $	13.11 $	3.69 $	384.32 $	64	41	21	1.519
Channel breakout strategy	-3.27 $	39.18 $	42.45 $	5.68 $	475.1 $	348	119	229	0.924
Consecutive up down strategy	1.68 $	29.9 $	28.22 $	4.09 $	423.91 $	215	83	130	1.059
Inside bar strategy	-4.78 $	30.91 $	35.69 $	8.54 $	421.21 $	291	140	151	0.87
Keltners channels strategy	-6.43 $	8.14 $	14.57 $	7.46 $	365.26 $	24	8	16	0.559
MACD strategy	3.99 $	32.51 $	28.52 $	4.31 $	395.13 $	231	96	135	1.14
Momentum strategy	-5.99 $	25.91 $	31.9 $	6.4 $	402.19 $	217	74	143	0.812
Moving avg 2 line cross strategy	-3.48 $	10.71 $	14.37 $	7.08 $	441.48 $	183	68	114	0.912
Moving avg cross	18.34 $	52.34 $	34 $	3.99 $	448.95 $	529	230	297	1.54
Outside bar strategy	-5.06 $	23.11 $	26.33 $	7.33 $	423.99 $	164	71	99	0.805
Parabolic SAR strategy	-5.44 $	36.11 $	38.07 $	4.89 $	423.43 $	261	100	161	0.937
Pivot extension strategy	7.72 $	47.23 $	39.52 $	3.79 $	422.49 $	420	226	194	1.195
Pivot reversal strategy	-5.77 $	20.91 $	26.69 $	6.27 $	463.43 $	141	46	95	0.784
Price channel strategy	-1.67 $	18.34 $	20.01 $	5.4 $	401.19 $	95	29	66	0.917
Rob booker	-2.19 $	5.24 $	7.43 $	3.63 $	328.97 $	37	10	27	0.668
RSI strategy	5.7 $	13.64 $	7.94 $	2.4 $	350.57 $	24	15	9	1.718
Stochastic slow strategy	2.13 $	18.23 $	16.13 $	5.41 $	341.2 $	73	47	25	1.133
Supertrend strategy	-6.72 $	21.43 $	28.14 $	16.32 $	366.83 $	63	18	45	0.761
Technical ratings strategy	0.1 $	4.8 $	4.7 $	1.19 $	408.97 $	33	12	20	1.022
Volty expan close strategy	-17.66 $	49.34 $	67.22 $	17.91 $	409.62 $	682	211	451	0.737

MARUTI

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	12.43 $	143.56 $	131.09 $	131.09 $	4440.03 $	883	331	507	1.095
Bollinger Band strategy	-4.53 $	7.7 $	18.6 $	9.72 $	4409.71 $	88	44	44	0.427
Channel breakout strategy	3.28 $	31.88 $	28.61 $	4.34 $	4799.95 $	566	209	357	1.106
Consecutive up down strategy	8.55 $	26.09 $	17.54 $	1.58 $	3970.03 $	399	128	364	1.488
Inside bar strategy	0.72 $	23.47 $	22.75 $	4.02 $	4482.1 $	355	146	159	1.032
Keltners channels strategy	2.87 $	10.26 $	7.39 $	3.79 $	3996.41 $	38	14	24	1.389
MACD strategy	-1 $	24.78 $	6.44	3.32 $	3409.1 $	337	126	211	0.961
Momentum strategy	4.98 $	20.07 $	20.09 $	4.18 $	4325.14 $	308	115	115	1.248
Moving avg 2 line cross strategy	2.11 $	23.48 $	20.75 $	2.94 $	3362.87 $	301	135	156	1.132
Moving avg cross	8.97 $	37.09 $	28.12 $	3.2 $	4404.34 $	787	297	489	1.319
Outside bar strategy	1.57 $	20.01 $	18.48 $	3.81 $	4584.99 $	233	113	118	1.071
Parabolic SAR strategy	0.55 $	29.2 $	28.65 $	3.74 $	4401.79 $	409	162	277	1.019
Pivot extension strategy	3.89 $	25.58 $	21.68 $	3.28 $	4404.66 $	680	324	309	1.123
Pivot reversal strategy	5.33 $	22.18 $	17.94 $	1.65 $	4320.17 $	216	81	135	1.301
Price channel strategy	6.84 $	19.12 $	12.28 $	2.46 $	3997.83 $	132	57	75	1.557
Rob booker	2.43 $	6.28 $	3.79 $	0.9 $	3332 $	53	27	26	1.651
RSI strategy	0.31 $	9.56 $	9.45 $	5.72 $	4499.35 $	40	26	14	1.032
Stochastic slow strategy	-8.93 $	11.45 $	19.63 $	10.49 $	3626.15 $	94	47	47	0.583
Supertrend strategy	53.66 $	131.33 $	77.66 $	9.34 $	3991.34 $	108	42	66	1.691
Technical ratings strategy	12.12 $	29.63 $	17.5 $	3.24 $	4462.97 $	69	28	41	1.693
Volty expan close strategy	8.03 $	45.62 $	37.6 $	4.27 $	4656.33 $	979	389	610	1.213

TATA CONSUMERS

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	6.78 $	118.5 $	111.79 $	18.31 $	443.43 $	628	261	366	1.004
Bollinger Band strategy	-0.69 $	0.77 $	3.82 $	0.36 $	471 $	37	58	29	0.937
Channel breakout strategy	-0.87 $	1.76 $	1.82 $	0.34 $	441.35 $	446	141	304	0.964
Consecutive up down strategy	0.33 $	1.32 $	1.1 $	0.24 $	486.15 $	259	101	148	1.172
Inside bar strategy	-0.11 $	1.34 $	1.45 $	0.31 $	443.42 $	246	113	133	0.927
Keltners channels strategy	0.26 $	0.08 $	0.02 $	0.2 $	495.2 $	34	11	23	1.116
MACD strategy	0.18 $	1.65 $	1.47 $	0.27 $	461.41 $	280	104	176	1.128
Momentum strategy	0.1 $	1.49 $	1.29 $	0.4 $	385.09 $	294	92	202	1.072
Moving avg 2 line cross strategy	0.26 $	1.31 $	1.17 $	0.33 $	454.69 $	232	85	147	1.121
Moving avg cross	0.27 $	2.19 $	1.92 $	0.17 $	468.53 $	675	237	438	1.139
Outside bar strategy	-0.37 $	1.06 $	1.43 $	0.54 $	424.41 $	201	82	119	0.738
Parabolic SAR strategy	0.05 $	1.75 $	1.71 $	0.34 $	493.21 $	343	125	218	1.027
Pivot extension strategy	-0.13 $	1.82 $	1.96 $	0.44 $	424.47 $	538	237	268	0.935
Pivot reversal strategy	0.01 $	1.27 $	1.26 $	0.23 $	475.77 $	181	73	108	1.006
Price channel strategy	0.26 $	1.1 $	0.84 $	0.18 $	463.42 $	122	45	77	1.319
Rob booker	0 $	0.3 $	0.29 $	0.09 $	164.84 $	46	19	27	1.006
RSI strategy	-0.48 $	0.08 $	0.77 $	0.37 $	391.43 $	38	14	19	0.37
Stochastic slow strategy	-0.23 $	0.72 $	0.95 $	0.44 $	407.79 $	86	50	36	0.759
Supertrend strategy	14.27 $	11.15 $	16.88 $	19.05 $	354.09 $	83	29	52	1.351
Technical ratings strategy	-0.53 $	19.95 $	10.53 $	0.32 $	493.41 $	91	27	64	0.974
Volty expan close strategy	-0.15 $	2.1 $	1.45 $	0.25 $	473.61 $	736	253	491	0.909

IOC									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	31.25 %	259.18 %	227.93 %	17.84 %	256.84 %	949	391	543	1.137
Bollinger Band strategy	−0.17 %	0.34 %	0.51 %	0.21 %	379.23 %	109	63	45	0.66
Channel breakout strategy	−0.13 %	1.07 %	1.2 %	0.27 %	241.77 %	634	217	415	0.892
Consecutive up down strategy	−0.04 %	0.89 %	0.93 %	0.22 %	247.7 %	393	155	232	0.958
Inside bar strategy	−0.08 %	0.79 %	0.87 %	0.22 %	249.17 %	412	193	219	0.903
Keltners channels strategy	0.06 %	0.3 %	0.25 %	0.07 %	496.61 %	45	21	24	1.199
MACD strategy	0.19 %	1.01 %	0.82 %	0.11 %	478.09 %	416	181	249	1.226
Momentum strategy	−0.08 %	0.8 %	0.88 %	0.22 %	309.78 %	421	133	288	0.911
Moving avg 2 line cross strategy	−0.07 %	0.78 %	0.84 %	0.22 %	356.63 %	348	129	219	0.922
Moving avg cross	0.18 %	1.35 %	1.17 %	0.16 %	249.17 %	1012	383	631	1.154
Outside bar strategy	−0.02 %	0.67 %	0.7 %	0.14 %	243.71 %	261	128	133	0.965
Parabolic SAR strategy	0.12 %	1.09 %	0.97 %	0.09 %	246.15 %	442	170	269	1.121
Pivot extension strategy	−0.02 %	1.2 %	1.22 %	0.14 %	249.88 %	804	371	393	0.988
Pivot reversal strategy	−0.02 %	0.76 %	0.78 %	0.2 %	317.58 %	283	90	191	0.969
Price channel strategy	−0.03 %	0.8 %	0.82 %	0.18 %	338.32 %	181	62	119	0.968
Rob booker	−0.02 %	0.18 %	0.2 %	0.07 %	397.68 %	69	25	44	0.898
RSI strategy	−0.16 %	−0.16 %	0.34 %	0.18 %	386.12 %	44	23	21	0.54
Stochastic slow strategy	0.04 %	0.51 %	0.47 %	0.09 %	319.59 %	121	79	42	1.077
Supertrend strategy	−21.12 %	98.14 %	119.26 %	7.67 %	397.49 %	1175	49	58	0.823
Technical ratings strategy	4.83 %	42.58 %	37.75 %	7.67 %	257.72 %	124	39	85	1.128
Volty expan close strategy	−0.37 %	1.39 %	1.77 %	0.43 %	254.42 %	1220	392	827	0.789

SBI LIFE									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	−1.36 %	23.4 %	24.76 %	3.63 %	79.51 %	199	87	110	0.944
Bollinger Band strategy	−0.42 %	0.46 %	0.88 %	1.63 %	81.42 %	19	9	10	0.511
Channel breakout strategy	−1.33 %	1.4 %	2.72 %	1.48 %	73.69 %	144	34	110	0.512
Consecutive up down strategy	−0.24 %	1.26 %	1.47 %	1.63 %	73.29 %	97	30	57	0.86
Inside bar strategy	0.48 %	1.65 %	1.17 %	1.29 %	73.27 %	87	46	41	1.41
Keltners channels strategy	0.09 %	0.29 %	0.2 %	1.2 %	89.45 %	5	3	2	1.43
MACD strategy	−1.03 %	1.04 %	2.07 %	1.03 %	77.54 %	93	22	71	0.501
Momentum strategy	−0.29 %	1.08 %	1.37 %	1.39 %	83.45 %	75	20	55	0.798
Moving avg 2 line cross strategy	−0.11 %	1.13 %	1.24 %	1.6 %	84.71 %	64	23	39	0.909
Moving avg cross	−0.93 %	1.65 %	2.38 %	1.61 %	77.29 %	216	63	153	0.776
Outside bar strategy	−0.25 %	1.02 %	1.27 %	1.69 %	79.29 %	53	24	28	0.8
Parabolic SAR strategy	−0.47 %	1.45 %	1.82 %	1.69 %	84.78 %	91	26	65	0.797
Pivot extension strategy	−0.27 %	1.65 %	1.82 %	1.57 %	83.57 %	157	67	85	0.850
Pivot reversal strategy	−0.74 %	0.8 %	1.54 %	1.74 %	83.44 %	63	13	50	0.518
Price channel strategy	−0.23 %	0.71 %	0.94 %	1.49 %	88.32 %	35	10	25	0.757
Rob booker	−0.13 %	0.33 %	0.47 %	1.23 %	69.8 %	19	5	14	0.716
RSI strategy	0.12 %	0.44 %	0.32 %	1.21 %	84.15 %	7	5	2	1.387
Stochastic slow strategy	0.17 %	0.75 %	0.58 %	1.26 %	87.74 %	21	12	9	1.286
Supertrend strategy	2.14 %	12.2 %	10.06 %	4.6 %	78.52 %	20	8	12	1.213
Technical ratings strategy	0.02 %	4.58 %	4.56 %	1.58 %	81.47 %	31	12	19	1.004
Volty expan close strategy	−0.31 %	2.12 %	2.44 %	1.6 %	75.69 %	232	77	155	0.872

COAL INDIA									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	21	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	215	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	18	10	8	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	25	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	22	64	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	400	[illegible]

EICHER MOTORS

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	-17.87 %	176.78 %	194.65 %	21.9 %	213896 %	933	412	490	0.908
Bollinger Band strategy	-0.22 %	4.17 %	4.39 %	1.07 %	222919.94 %	105	57	48	0.95
Channel breakout strategy	1.75 %	11.06 %	9.31 %	1.23 %	213752 %	626	196	429	1.187
Consecutive up down strategy	-0.62 %	8.47 %	9.09 %	2.1 %	222724.11 %	423	179	243	0.932
Inside bar strategy	-0.86 %	8.65 %	9.5 %	2.78 %	213472 %	474	226	237	0.91
Keltera channels strategy	-1.65 %	3.06 %	4.61 %	2.58 %	172128.69 %	50	17	33	0.622
MACD strategy	-0.87 %	8.23 %	9.09 %	1.82 %	213340 %	430	142	278	0.905
Momentum strategy	0.11 %	8.44 %	8.34 %	2.32 %	172148.04 %	381	120	259	1.013
Moving avg 2 line cross strategy	-0.34 %	8.23 %	8.57 %	1.11 %	266865 %	352	126	216	0.961
Moving avg cross	3.17 %	12.43 %	9.26 %	0.91 %	222394.94 %	866	365	500	1.343
Outside bar strategy	0.63 %	7.58 %	6.95 %	1.92 %	213612 %	321	156	157	1.09
Parabolic SAR strategy	-1.04 %	9.32 %	10.36 %	2.9 %	209815.18 %	481	152	329	0.9
Pivot extension strategy	1.05 %	11.71 %	10.65 %	1.56 %	223965.77 %	812	400	371	1.099
Pivot reversal strategy	0.25 %	7.44 %	7.19 %	1.45 %	185222.78 %	276	81	195	1.035
Price channel strategy	-0.45 %	6 %	6.45 %	2 %	266990 %	195	60	125	0.93
Rob booker	0.55 %	1.78 %	1.23 %	0.35 %	198736.64 %	63	21	42	1.444
RSI strategy	0.69 %	3.45 %	2.77 %	0.9 %	162675.59 %	48	30	18	1.248
Stochastic slow strategy	0.97 %	5.73 %	4.76 %	2.14 %	233342.08 %	117	72	45	1.203
Supertrend strategy	24.73 %	24.73 %	150.84 %	31.62 %	185005.51 %	142	49	92	1.159
Technical ratings strategy	47.63 %	89.97 %	42.34 %	6.07 %	223694.94 %	120	56	63	2.133
Volty expan close strategy	3.97 %	16.59 %	12.62 %	1.2 %	199705.62 %	1231	379	837	1.315

BAJAJ AUTO

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	-1.08 %	95.93 %	96.01 %	96.01 %	1110.27 %	603	239	421	1.046
Bollinger Band strategy	-0.22 %	3.47 %	4.09 %	1.71 %	1480.46 %	71	39	32	0.944
Channel breakout strategy	-0.85 %	11.86 %	14.1 %	1.96 %	959.71 %	408	165	243	0.942
Consecutive up down strategy	0.05 %	11.51 %	10.67 %	3.04 %	1347.36 %	248	103	145	1.079
Inside bar strategy	-2.61 %	9.23 %	11.89 %	3.79 %	1132.22 %	235	121	114	0.78
Keltera channels strategy	-5.53 %	1.87 %	7.39 %	6.51 %	1175.11 %	34	6	28	0.253
MACD strategy	3.8 %	14.1 %	11.4 %	4.37 %	1208 %	255	93	162	1.695
Momentum strategy	0.37 %	10.89 %	10.82 %	2.95 %	1211.31 %	242	87	155	1.036
Moving avg 2 line cross strategy	-0.18 %	9.1 %	10.09 %	4.06 %	1189.61 %	208	78	130	0.985
Moving avg cross	1.76 %	14.83 %	14.11 %	8.95 %	1109.27 %	950	272	480	1.197
Outside bar strategy	-4.25 %	7.31 %	11.75 %	4.85 %	1009.3 %	193	79	114	0.629
Parabolic SAR strategy	0.79 %	13.46 %	13.69 %	1.7 %	1215.24 %	315	115	199	1.053
Pivot extension strategy	1.18 %	15.47 %	14.39 %	2.39 %	1046.31 %	458	346	212	1.083
Pivot reversal strategy	-0.55 %	9.04 %	9.29 %	3.67 %	1111.78 %	157	57	100	0.943
Price channel strategy	1.63 %	7.94 %	6.32 %	2.52 %	1319.56 %	93	36	56	1.257
Rob booker	1.39 %	4.04 %	3.40 %	8.75 %	1040.47 %	48	13	35	1.524
RSI strategy	1.12 %	3.43 %	2.3 %	1.41 %	1270.78 %	28	22	6	3.506
Stochastic slow strategy	-3.09 %	5.23 %	8.51 %	3.68 %	1445.59 %	75	42	33	0.628
Superstrend strategy	11.64 %	61.35 %	49.71 %	12.56 %	1115.59 %	72	30	42	1.649
Technical ratings strategy	4.93 %	16.5 %	11.58 %	4.86 %	1095.38 %	76	22	54	1.425
Volty expan close strategy	-1.89 %	11 %	12.89 %	4.34 %	1187.35 %	727	337	464	0.862

BPCL

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	5.36 %	258.43 %	253.14 %	21.4 %	499.4 %	1139	459	694	1.021
Bollinger Band strategy	0.47 %	1.3 %	0.83 %	0.18 %	1009.29 %	138	93	47	1.56
Channel breakout strategy	-0.1 %	3.31 %	3.41 %	0.37 %	984.37 %	686	223	463	0.904
Consecutive up down strategy	0.5 %	3.03 %	3.00 %	0.47 %	954.34 %	387	162	225	1.303
Inside bar strategy	0.41 %	3.03 %	1.92 %	0.31 %	980.08 %	202	103	199	1.357
Keltera channels strategy	-0.16 %	0.33 %	0.47 %	0.33 %	1071.29 %	58	18	40	0.707
MACD strategy	0.5 %	3.13 %	1.63 %	0.16 %	1017.33 %	468	177	256	1.273
Momentum strategy	-0.16 %	1.95 %	2.1 %	0.23 %	991.32 %	448	149	299	0.923
Moving avg 2 line cross strategy	-0.23 %	1.75 %	1.98 %	0.4 %	1060.33 %	373	158	222	0.886
Moving avg cross	0.94 %	3.11 %	2.97 %	0.23 %	868.64 %	1003	363	685	1.046
Outside bar strategy	0.04 %	1.46 %	1.42 %	0.46 %	941.82 %	291	138	148	1.025
Parabolic SAR strategy	-0.49 %	2.16 %	2.65 %	0.38 %	901.16 %	512	193	315	0.815
Pivot extension strategy	-0.12 %	3.09 %	2.42 %	0.34 %	909.99 %	814	397	403	0.958
Pivot reversal strategy	-0.28 %	1.38 %	1.76 %	0.34 %	981.97 %	306	109	197	0.843
Price channel strategy	-0.38 %	1.19 %	1.57 %	0.42 %	1013.56 %	178	67	111	0.759
Rob booker	0.11 %	0.63 %	0.52 %	0.08 %	1160.42 %	98	36	58	1.208
RSI strategy	0.17 %	0.69 %	0.52 %	0.17 %	1115.31 %	48	34	14	1.333
Stochastic slow strategy	0.12 %	1.14 %	1.09 %	0.29 %	1041.89 %	128	85	40	1.129
Superstrend strategy	-16.34 %	96.17 %	115.21 %	29.55 %	964.34 %	141	54	87	0.858
Technical ratings strategy	-6.6 %	37.29 %	46.19 %	9.35 %	864.33 %	119	36	83	0.935
Volty expan close strategy	-0.37 %	3.46 %	3.83 %	0.78 %	929.1 %	1304	475	831	0.904

Dr. Reddys

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1121	493	627	1.053
Bollinger Band strategy	6.77 %	[illegible]	[illegible]	[illegible]	[illegible]	124	74	50	2.046
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	646	237	409	1.036
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	413	167	245	0.989
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	468	227	240	1.107
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	45	15	30	0.824
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	464	189	274	1.137
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	435	140	295	0.78
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	325	129	196	0.84
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1039	372	659	1.094
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	386	131	254	0.796
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	502	187	315	0.91
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	819	443	367	1.236
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	278	109	169	0.937
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	179	67	112	0.87
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	60	21	39	1.015
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	45	29	16	1.183
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	137	89	48	2.429
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	139	58	81	1.029
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	132	44	88	1.03
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1263	436	827	0.942

Power Grid

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	769	313	455	0.833
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	77	47	29	1.152
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	451	118	333	0.419
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	237	109	128	0.848
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	274	156	118	0.960
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	17	4	13	0.268
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	272	102	170	0.941
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	288	79	209	0.542
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	217	88	129	0.841
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	762	243	519	0.644
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	182	81	99	0.851
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	324	93	231	0.409
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	553	298	255	1.003
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	178	58	120	0.534
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	116	42	74	0.531
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	46	18	28	1.115
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	24	21	3	3.786
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	64	43	21	1.242
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	58	11	47	0.707
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	91	22	69	0.648
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	817	247	564	0.456

TATAMOTORS

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	43.86 %	396.47 %	352.61 %	11.28 %	2373.31 %	1527	644	881	1.124
Bollinger Band strategy	−0.96 %	1.16 %	2.12 %	0.96 %	2205.77 %	153	83	69	0.546
Channel breakout strategy	0.14 %	3.78 %	3.64 %	0.92 %	2338.05 %	869	320	547	1.038
Consecutive up down strategy	−0.01 %	3.02 %	3.03 %	0.41 %	2486.18 %	569	223	337	0.898
Inside bar strategy	0.24 %	2.84 %	2.6 %	0.36 %	2205.77 %	446	227	217	1.09
Keltners channels strategy	0.44 %	1.44 %	1 %	0.32 %	1926.84 %	80	33	47	1.442
MACD strategy	0.9 %	3.42 %	2.52 %	0.42 %	2266.77 %	522	220	294	1.357
Momentum strategy	0.64 %	3.12 %	2.49 %	0.52 %	2663.23 %	519	179	339	1.257
Moving avg 2 line cross strategy	0.7 %	3 %	2.3 %	0.51 %	2136.17 %	430	170	260	1.303
Moving avg cross	0.49 %	4.26 %	3.77 %	0.42 %	2447.37 %	1275	450	806	1.131
Outside bar strategy	−0.45 %	2.02 %	2.47 %	0.63 %	1774.14 %	293	135	157	0.817
Parabolic SAR strategy	0.18 %	3.57 %	3.39 %	0.31 %	2416.07 %	635	252	381	1.053
Pivot extension strategy	0.18 %	3.95 %	3.77 %	0.39 %	2416.07 %	1029	491	521	1.049
Pivot reversal strategy	0.65 %	2.65 %	2 %	0.30 %	2653.23 %	336	129	203	1.327
Price channel strategy	0.51 %	2.34 %	1.83 %	0.5 %	2331.94 %	226	82	144	1.276
Rob booker	0.01 %	0.78 %	0.77 %	0.26 %	1930.84 %	104	41	62	1.016
RSI strategy	−0.47 %	0.72 %	1.19 %	0.55 %	2526.03 %	51	28	23	0.606
Stochastic slow strategy	−0.84 %	1.27 %	2.11 %	0.32 %	2486.18 %	173	104	69	0.602
Supertrend strategy	127.28 %	409.50 %	282.67 %	15.69 %	2526.03 %	210	89	120	1.45
Technical ratings strategy	27.74 %	80.64 %	52.90 %	6.07 %	2526.03 %	151	53	98	1.525
Volty expan close strategy	0.79 %	5.29 %	4.5 %	0.57 %	2581.2 %	1662	672	981	1.177

SBI

Strategy name	[redacted]	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy-and-hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy		44.8 %	288.87 %	288.87 %	10.57 %	3011.4 %	1140	440	675	1.208
Bollinger Band strategy		-0.33 %	0.87 %	1.35 %	0.39 %	2511.11 %	121	121	50	0.719
Channel breakout strategy		0.42 %	2.85 %	2.43 %	0.43 %	3267.42 %	661	240	410	1.174
Consecutive up down strategy		-0.22 %	2.15 %	2.38 %	0.39 %	2889.13 %	400	150	150	0.905
Inside bar strategy		0.32 %	2.06 %	1.74 %	0.21 %	3222.72 %	361	174	181	1.183
Keltners channels strategy		-0.03 %	0.88 %	0.89 %	0.43 %	3513.93 %	73	29	29	0.916
MACD strategy		0.62 %	2.5 %	1.88 %	0.28 %	2523.03 %	417	166	248	1.331
Momentum strategy		0.29 %	2.27 %	1.98 %	0.18 %	3892.71 %	414	154	260	1.146
Moving avg 2 line cross strategy		-0.22 %	1.92 %	2.14 %	0.67 %	3014.27 %	334	124	206	0.898
Moving avg cross		0.29 %	3.01 %	2.73 %	0.21 %	2971.04 %	994	313	604	1.106
Outside bar strategy		-0.85 %	1.35 %	2.2 %	0.98 %	3479.73 %	205	107	100	0.588
Parabolic SAR strategy		-0.07 %	2.53 %	2.59 %	0.47 %	3044.05 %	531	186	344	0.974
Pivot extension strategy		0.61 %	3.02 %	2.41 %	0.16 %	2902 %	802	305	393	1.251
Pivot reversal strategy		0.51 %	1.96 %	1.45 %	0.18 %	3237.85 %	259	97	162	1.352
Price channel strategy		0.07 %	1.54 %	1.47 %	0.38 %	3370.87 %	197	73	124	1.046
Rob booker		0.1 %	0.53 %	0.43 %	0.12 %	3434.8 %	76	23	53	1.244
RSI strategy		-0.13 %	0.49 %	0.62 %	0.5 %	2471.98 %	44	27	16	0.798
Stochastic slow strategy		-0.29 %	1.08 %	1.37 %	0.39 %	3378.03 %	139	86	53	0.786
Supertrend strategy		40.35 %	168.59 %	128.24 %	16.54 %	3019.47 %	152	62	90	1.315
Technical ratings strategy		9.78 %	49.31 %	39.54 %	6.08 %	2942.31 %	138	44	94	1.247
Volty expan close strategy		1.31 %	4.29 %	2.97 %	0.24 %	2728.06 %	1240	498	736	1.442

TATASTEEL

Strategy name	[redacted]	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy		34.46 %	337.51 %	303.04 %	12.39 %	737.74 %	1267	552	606	1.114
Bollinger Band strategy		-1.20 %	2.7 %	3.98 %	1.49 %	794.00 %	133	71	62	0.679
Channel breakout strategy		0.95 %	7.77 %	6.82 %	1.19 %	818.98 %	745	297	448	1.138
Consecutive up down strategy		0.99 %	6.99 %	6.01 %	1.09 %	736.7 %	461	153	268	1.164
Inside bar strategy		0.69 %	5.43 %	4.74 %	0.83 %	799.09 %	353	179	176	1.147
Keltners channels strategy		1.69 %	3.38 %	1.69 %	0.58 %	799.44 %	76	33	43	2.016
MACD strategy		1.87 %	6.95 %	5.07 %	0.49 %	857.29 %	515	196	318	1.368
Momentum strategy		2.14 %	6.55 %	4.41 %	0.4 %	736.01 %	467	175	288	1.486
Moving avg 2 line cross strategy		3.05 %	6.36 %	3.31 %	0.33 %	757.97 %	375	177	193	1.921
Moving avg cross		1.23 %	8.86 %	7.63 %	0.58 %	732.59 %	1105	393	305	1.162
Outside bar strategy		0.64 %	4.93 %	4.28 %	0.6 %	700.98 %	288	131	148	1.15
Parabolic SAR strategy		-0.56 %	4.77 %	7.33 %	1.35 %	793.34 %	598	238	361	0.623
Pivot extension strategy		0.68 %	7.83 %	7.16 %	0.82 %	702.88 %	897	438	452	1.096
Pivot reversal strategy		1.2 %	5.42 %	4.22 %	0.48 %	746.94 %	298	116	188	1.283
Price channel strategy		1.55 %	4.60 %	3.11 %	0.51 %	789.07 %	197	83	114	1.497
Rob booker		0.01 %	1.34 %	1.33 %	0.58 %	830.29 %	86	28	58	1.007
RSI strategy		-1.85 %	1.26 %	2.91 %	1.77 %	727.01 %	54	28	26	0.432
Stochastic slow strategy		-0.8 %	2.83 %	3.62 %	0.98 %	801.93 %	173	97	76	0.78
Supertrend strategy		165.05 %	165.05 %	172.8 %	10.81 %	849.94 %	172	76	96	2.071
Technical ratings strategy		15.52 %	62.47 %	46.95 %	5.81 %	706.05 %	148	48	100	1.331
Volty expan close strategy		0.44 %	10.05 %	9.61 %	1.25 %	723.59 %	1488	625	856	1.046

RELIANCE

Strategy name	[redacted]	Net profit	Gross Profit	Gross Loss	Max Drawdown	BuyHold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy		11.48 %	258.34 %	234.41 %	33.54 %	[illegible]	1401	546	823	1.093
Bollinger Band strategy		-0.84 %	1.31 %	1.85 %	1.39 %	[illegible]	149	87	49	0.906
Channel breakout strategy		1.19 %	7.72 %	6.53 %	1.83 %	[illegible]	769	288	481	1.183
Consecutive up down strategy		-0.11 %	5.71 %	3.82 %	1.32 %	[illegible]	469	175	294	0.984
Inside bar strategy		-2.21 %	4.39 %	6.5 %	2.81 %	[illegible]	411	208	208	0.665
Kaltners channels strategy		0.29 %	1.31 %	1.24 %	0.71 %	[illegible]	77	26	51	1.128
MACD strategy		-0.13 %	4.21 %	4.36 %	1.44 %	[illegible]	512	196	313	0.98
Momentum strategy		1.41 %	4.61 %	5.2 %	0.68 %	[illegible]	513	173	341	1.273
Moving avg 2 line cross strategy		0.79 %	3.39 %	5.6 %	0.68 %	[illegible]	400	156	243	1.172
Moving avg cross		0.47 %	3.41 %	7.75 %	0.77 %	[illegible]	1,125	399	816	1.086
Outside bar strategy		-1.81 %	1.84 %	3.64 %	1.43 %	[illegible]	359	156	193	0.48
Parabolic SAR strategy		0.19 %	7.25 %	7.1 %	0.78 %	[illegible]	998	333	464	1.021
Pivot extension strategy		-0.18 %	7.49 %	7.67 %	1.19 %	[illegible]	908	477	448	0.977
Pivot reversal strategy		1.18 %	3.57 %	1.39 %	0.49 %	[illegible]	1,649	113	186	1.846
Price channel strategy		1.69 %	4.48 %	1.29 %	0.53 %	[illegible]	1,132	50	132	1.332
Rob booker		0.21 %	1.41 %	1.09 %	0.25 %	[illegible]	106	38	65	1.287
RSI strategy		-0.89 %	1.32 %	2.11 %	1.07 %	[illegible]	47	29	18	0.577
Stochastic slow strategy		-1.87 %	3.82 %	1.99 %	1.89 %	[illegible]	153	124	61	0.731
Supertrend strategy		7.89 %	180 %	231.11 %	14.07 %	[illegible]	198	77	121	1.065
Technical ratings strategy		8.13 %	55.89 %	46.96 %	11.12 %	[illegible]	174	54	122	1.173
Volty expan close strategy		1.9 %	11.25 %	9.84 %	0.55 %	[illegible]	1108	396	508	1.203

AXIS BANK

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	-2.27 %	138.52 %	140.78 %	10.65 %	794.88 %	827	323	499	0.984
Bollinger Band strategy	-0.44 %	1.4 %	1.84 %	0.68 %	790.88 %	86	55	30	0.76
Channel breakout strategy	-0.13 %	3.53 %	3.66 %	0.65 %	699.8 %	444	161	282	0.966
Consecutive up down strategy	-0.85 %	2.62 %	3.47 %	1.34 %	753.23 %	298	115	182	0.756
Inside bar strategy	0.43 %	2.5 %	2.06 %	0.38 %	718.72 %	204	100	101	1.205
Keltners channels strategy	0.75 %	1.42 %	0.67 %	0.25 %	560.14 %	34	15	19	2.117
MACD strategy	-0.65 %	2.7 %	3.35 %	0.94 %	645.84 %	324	105	219	0.806
Momentum strategy	-1.35 %	2.38 %	3.73 %	1.49 %	604.54 %	306	89	216	0.636
Moving avg 2 line cross strategy	-0.60 %	2.49 %	3.06 %	0.91 %	628.14 %	231	90	138	0.816
Moving avg cross	-0.02 %	3.99 %	4.01 %	0.55 %	663.03 %	673	227	443	0.996
Outside bar strategy	0.01 %	2.42 %	2.41 %	0.72 %	732.58 %	202	83	118	1.004
Parabolic SAR strategy	-0.53 %	3.18 %	3.71 %	0.88 %	731.71 %	362	126	223	0.856
Pivot extension strategy	0.11 %	3.76 %	3.65 %	0.32 %	614.95 %	531	246	275	0.973
Pivot reversal strategy	-0.11 %	2.24 %	2.34 %	0.41 %	664.28 %	173	61	112	0.954
Price channel strategy	0.06 %	1.78 %	1.72 %	0.45 %	688.86 %	108	44	65	1.036
Rob booker	0.23 %	0.89 %	0.67 %	0.14 %	566.15 %	54	19	33	1.338
RSI strategy	-0.88 %	0.32 %	1.2 %	0.88 %	617.05 %	19	7	12	0.266
Stochastic slow strategy	-0.2 %	1.6 %	1.8 %	0.6 %	693.41 %	87	58	29	0.891
Supertrend strategy	50.39 %	122.58 %	72.19 %	10.4 %	590.2 %	88	40	48	1.698
Technical ratings strategy	3.4 %	22.62 %	19.22 %	5.9 %	631.96 %	83	22	60	1.177
Volty expan close strategy	0.85 %	5.47 %	4.63 %	0.4 %	689.11 %	851	343	507	1.181

ICICIBANK

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	41.29 %	[illegible]	[illegible]	[illegible]	[illegible]	1228	487	711	1.149
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	117	71	71	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	449	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	442	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	373	[illegible]	171	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	475	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	139	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	344	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	364	[illegible]	147	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	176	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	114	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	79	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

KOTAKBANK

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	879	378	493	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	18	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	274	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.047
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	411	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	217	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.14
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	64	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	32	18	14	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	107	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1849	[illegible]	[illegible]	[illegible]

M&M

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

L&T

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

CIPLA

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	0.16 %	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

DLF

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDnStrategy	-9.48 %	181.9 %	191.37 %	21.84 %	-30.23 %	787	316	464	0.951
Bollinger Band strategy	0.11 %	1.61 %	1.49 %	0.29 %	-38.66 %	78	51	27	1.077
Channel breakout strategy	-0.18 %	3.66 %	3.84 %	0.61 %	-29.39 %	430	150	280	0.953
Consecutive up down strategy	-0.36 %	3.01 %	3.37 %	0.86 %	-38.03 %	292	95	196	0.893
Inside bar strategy	0.81 %	2.85 %	2.04 %	0.46 %	-36.07 %	227	111	116	1.447
Keltners channels strategy	0.81 %	1.61 %	0.7 %	0.47 %	-43.94 %	39	17	22	2.153
MACD strategy	0.17 %	3.14 %	2.97 %	0.44 %	-36.07 %	276	101	173	1.056
Momentum strategy	0.26 %	2.79 %	2.52 %	0.34 %	-36.76 %	245	93	152	1.104
Moving avg 2 line cross strategy	0.47 %	2.89 %	2.42 %	0.74 %	-27.97 %	211	87	123	1.193
Moving avg cross	0.72 %	4.35 %	3.63 %	0.4 %	-38.4 %	636	216	420	1.198
Outside bar strategy	-0.24 %	2.35 %	2.59 %	0.86 %	-32.42 %	163	76	87	0.909
Parabolic SAR strategy	0.34 %	3.53 %	3.19 %	0.27 %	-33.22 %	319	128	191	1.106
Pivot extension strategy	-0.61 %	3.5 %	4.11 %	0.76 %	-34.57 %	516	243	269	0.851
Pivot reversal strategy	0.59 %	2.57 %	1.98 %	0.54 %	-35.64 %	170	71	99	1.296
Price channel strategy	0.5 %	1.97 %	1.47 %	0.19 %	-28.29 %	113	48	65	1.342
Rob booker	0.36 %	1.19 %	0.83 %	0.2 %	-48 %	64	22	41	1.439
RSI strategy	-0.96 %	0.55 %	1.51 %	1.27 %	-36.28 %	28	14	14	0.363
Stochastic slow strategy	0 %	1.37 %	1.37 %	0.38%	-31.69 %	91	62	29	0.999
Supertrend strategy	14.7 %	115.58 %	100.88 %	18.34 %	-48.21 %	96	38	58	1.146
Technical ratings strategy	1.37 %	27.77 %	26.4 %	6.73 %	-39.37 %	80	35	45	1.052
Volty expan close strategy	0.66 %	5.16 %	4.5 %	0.48 %	-38.47 %	783	334	448	1.147

ADANI PORTS

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDnStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	1.03 %	[illegible]	74	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	421	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	241	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy	[illegible]	[illegible]	0.91 %	[illegible]	[illegible]	32	9	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	271	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	211	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	171	58	114	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.946
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	7	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.146
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	91	[illegible]	[illegible]	[illegible]
Volty expan close strategy	0.05 %	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

TECHMAHINDRA

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDnStrategy	72.54 %	222.4 %	149.86 %	6.55 %	1115.4 %	784	328	371	1.484
Bollinger Band strategy	-0.46 %	1.59 %	2.05 %	0.81 %	822.56 %	74	44	30	0.776
Channel breakout strategy	-1.01 %	4.36 %	5.37 %	1.37 %	1049.47 %	456	142	314	0.8
Consecutive up down strategy	-0.76 %	3.04 %	3.79 %	1.2 %	1071.56 %	288	97	179	0.802
Inside bar strategy	0.32 %	3.86 %	3.54 %	0.59 %	1005.36 %	274	134	140	1.09
Keltners channels strategy	0.55 %	1.3 %	0.75 %	0.21 %	810.34 %	30	12	18	1.734
MACD strategy	-0.82 %	3.41 %	4.23 %	1.23 %	530.58 %	302	96	206	0.806
Momentum strategy	0.26 %	3.69 %	3.42 %	0.52 %	1046.66 %	327	103	224	1.077
Moving avg 2 line cross strategy	1.4 %	3.62 %	2.22 %	0.3 %	458.72 %	214	103	110	1.631
Moving avg cross	-0.06 %	4.88 %	4.94 %	0.84 %	1079.83 %	714	236	477	0.988
Outside bar strategy	-0.16 %	2.8 %	2.74 %	0.46 %	1060.76 %	161	66	96	0.947
Parabolic SAR strategy	-0.63 %	3.86 %	4.5 %	1.17 %	1053.66 %	333	116	217	0.86
Pivot extension strategy	-1.63 %	3.68 %	5.31 %	2.11 %	1067.72 %	549	248	302	0.693
Pivot reversal strategy	0.42 %	3.14 %	2.72 %	0.42 %	1030.32 %	173	67	106	1.154
Price channel strategy	1.47 %	3.11 %	1.64 %	0.33 %	813.62 %	99	45	54	1.901
Rob booker	-0.02 %	0.88 %	0.9 %	0.29 %	312 %	55	26	30	0.973
RSI strategy	-1 %	0.49 %	1.49 %	1 %	851.87 %	26	13	13	0.308
Stochastic slow strategy	-1.28 %	1.51 %	2.79 %	1.51 %	1020.16 %	70	43	27	0.542
Supertrend strategy	110.97 %	208.88 %	97.92 %	9.92 %	858.63 %	83	36	47	2.133
Technical ratings strategy	26.82 %	46.61 %	19.79 %	4.05 %	1133.61 %	70	26	44	2.358
Volty expan close strategy	-0.68 %	5.51 %	6.19 %	0.97 %	1101.87 %	801	306	499	0.891

HCL TECHNOLOGIES

Strategy name	[redacted]	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

ASIAN PAINTS

Strategy name	[redacted]	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

ULTRATECH

Strategy name	[redacted]	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy		−9.17 %	119.49 %	128.66 %	21.14 %	2602.43 %	779	332	443	0.928
Bollinger Band strategy		−3.82 %	7.43 %	11.25 %	5.44 %	2629.7 %	80	46	34	0.66
Channel breakout strategy		−3.42 %	21.42 %	24.85 %	5.62 %	2703.44 %	540	180	336	0.862
Consecutive up down strategy		−0.9 %	17.1 %	18 %	3.61 %	2644.5 %	290	113	177	0.96
Inside bar strategy		−0.29 %	17.78 %	18.58 %	4.14 %	2651.58 %	343	172	175	0.984
Keltners channels strategy		−7.02 %	3.24 %	10.27 %	7.02 %	2387.61 %	40	13	27	0.316
MACD strategy		1.31 %	19.05 %	17.74 %	3.36 %	2445.56 %	350	137	213	1.074
Momentum strategy		2.9 %	16.85 %	14.05 %	2.23 %	2710.75 %	310	104	206	1.207
Moving avg 2 line cross strategy		2.88 %	15.94 %	13.06 %	1.96 %	2512.03 %	232	91	141	1.221
Moving avg cross		4.84 %	28.1 %	23.16 %	2.01 %	2688.68 %	776	281	495	1.213
Outside bar strategy		−3.88 %	14.1 %	18.08 %	4.2 %	2681.21 %	223	91	132	0.78
Parabolic SAR strategy		−8.29 %	18.79 %	27.09 %	6.92 %	2387.67 %	407	134	273	0.694
Pivot extension strategy		−2.22 %	22.41 %	24.64 %	4.55 %	2568.65 %	620	292	321	0.91
Pivot reversal strategy		−1.61 %	13.21 %	14.81 %	2.2 %	2754.88 %	213	77	136	0.88
Price channel strategy		0.27 %	11.54 %	11.28 %	2.09 %	2497.35 %	134	46	88	1.024
Rob booker		−0.26 %	4.89 %	5.15 %	1.35 %	2387.18 %	60	26	38	0.95
RSI strategy		0.78 %	4.86 %	4.08 %	2.74 %	2291.46 %	28	15	13	1.198
Stochastic slow strategy		3.33 %	12.86 %	9.53 %	2.13 %	2384.37 %	86	61	36	1.349
Supertrend strategy		73.93 %	132.69 %	58.77 %	4.42 %	2387.18 %	90	41	49	2.258
Technical ratings strategy		6.95 %	26.45 %	19.5 %	5.62 %	2681.4 %	101	28	73	1.328
Volty expan close strategy		−11.07 %	25.85 %	36.92 %	11.37 %	2725.5 %	924	268	656	0.7

NTPC

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	1.42 %	105.38 %	103.96 %	12.94 %	114.56 %	802	317	478	1.014
Bollinger Band strategy	0.19 %	0.52 %	0.33 %	0.08 %	91.26 %	102	63	37	1.58
Channel breakout strategy	−0.47 %	0.91 %	1.38 %	0.57 %	109.5 %	518	151	358	0.657
Consecutive up down strategy	−0.03 %	0.85 %	0.88 %	0.23 %	106.57 %	282	111	168	0.961
Inside bar strategy	0.04 %	0.92 %	0.88 %	0.14 %	114.19 %	335	168	172	1.047
Keltners channels strategy	−0.33 %	0.13 %	0.46 %	0.37 %	88.18 %	44	11	33	0.283
MACD strategy	0.14 %	0.97 %	0.83 %	0.14 %	84.08 %	318	128	188	1.164
Momentum strategy	−0.13 %	0.74 %	0.86 %	0.23 %	106.13 %	326	115	211	0.854
Moving avg 2 line cross strategy	−0.08 %	0.72 %	0.8 %	0.26 %	100.4 %	261	110	148	0.904
Moving avg cross	−0.19 %	1.16 %	1.36 %	0.31 %	116.01 %	831	266	564	0.856
Outside bar strategy	−0.17 %	0.59 %	0.75 %	0.21 %	115.38 %	208	88	118	0.777
Parabolic SAR strategy	−0.48 %	0.86 %	1.33 %	0.53 %	185.77 %	362	138	224	0.641
Pivot extension strategy	0.16 %	1.27 %	1.11 %	0.12 %	114.08 %	628	328	282	1.148
Pivot reversal strategy	−0.28 %	0.58 %	0.86 %	0.38 %	120.19 %	207	78	131	0.671
Price channel strategy	−0.17 %	0.38 %	0.56 %	0.2 %	86.85 %	132	53	78	0.702
Rob booker	0.12 %	0.26 %	0.14 %	0.04 %	73.22 %	51	23	27	1.837
RSI strategy	0.25 %	0.43 %	0.18 %	0.13 %	97.17 %	36	28	8	2.34
Stochastic slow strategy	0.16 %	0.49 %	0.33 %	0.08 %	93.92 %	92	51	38	1.498
Supertrend strategy	−9.67 %	42.85 %	52.52 %	18.38 %	84.85 %	98	48	58	0.81
Technical ratings strategy	−0.67 %	15.15 %	15.82 %	6.7 %	116.51 %	68	28	62	0.958
Volty expan close strategy	−0.94 %	1.18 %	2.12 %	0.97 %	112.46 %	988	313	671	0.558

BIOCON

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	0.65 %	133.68 %	133.03 %	11.80 %	630.07 %	730	295	421	1.005
Bollinger Band strategy	0.33 %	0.8 %	0.47 %	0.11 %	689.60 %	102	68	34	1.697
Channel breakout strategy	−0.30 %	1.15 %	1.51 %	0.36 %	605.07 %	543	157	303	0.759
Consecutive up down strategy	−0.39 %	0.85 %	1.24 %	0.48 %	651.94 %	334	117	211	0.686
Inside bar strategy	−0.43 %	0.76 %	1.19 %	0.48 %	586.73 %	326	142	175	0.642
Keltners channels strategy	0.07 %	0.41 %	0.34 %	0.1 %	588.47 %	27	10	17	1.194
MACD strategy	−0.49 %	0.9 %	1.39 %	0.57 %	751.7 %	389	112	276	0.646
Momentum strategy	−0.13 %	0.93 %	1.07 %	0.25 %	864.52 %	352	100	250	0.875
Moving avg 2 line cross strategy	0.11 %	0.88 %	0.77 %	0.19 %	695.93 %	277	106	266	1.142
Moving avg cross	−0.4 %	1.33 %	1.73 %	0.42 %	642.16 %	855	259	592	0.767
Outside bar strategy	−0.4 %	0.62 %	1.02 %	0.43 %	642.16 %	237	92	143	0.607
Parabolic SAR strategy	−0.33 %	1.03 %	1.36 %	0.36 %	647.42 %	373	127	144	0.756
Pivot extension strategy	−0.22 %	1.25 %	1.47 %	0.31 %	631.99 %	880	327	342	0.853
Pivot reversal strategy	−0.43 %	0.64 %	1.07 %	0.44 %	687.81 %	227	66	161	0.598
Price channel strategy	−0.56 %	0.45 %	1.01 %	0.56 %	776.78 %	161	36	124	0.444
Rob booker	−0.06 %	0.32 %	0.38 %	0.14 %	775.80 %	75	23	52	0.851
RSI strategy	−0.27 %	0.17 %	0.44 %	0.33 %	776.66 %	24	11	13	0.38
Stochastic slow strategy	0.06 %	0.61 %	0.54 %	0.16 %	681.34 %	87	51	36	1.116
Supertrend strategy	−14.62 %	70.81 %	85.03 %	24.46 %	725.80 %	102	26	76	0.827
Technical ratings strategy	−2.05 %	26.6 %	28.65 %	6.06 %	586.17 %	112	24	88	0.928
Volty expan close strategy	−0.20 %	1.62 %	1.81 %	0.47 %	610.83 %	912	314	593	0.851

ASHOK LEYLAND

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	17.04 %	253.82 %	236.78 %	14.95 %	5785.09 %	859	371	438	1.072
Bollinger Band strategy	−0.14 %	0.21 %	0.36 %	0.18 %	7375.67 %	117	67	48	0.603
Channel breakout strategy	−0.09 %	0.63 %	0.73 %	0.13 %	5785.09 %	618	215	397	0.876
Consecutive up down strategy	−0.1 %	0.53 %	0.62 %	0.12 %	6188.29 %	401	172	267	0.841
Inside bar strategy	−0.03 %	0.54 %	0.57 %	0.21 %	6646.28 %	374	191	177	0.948
Keltners channels strategy	0.1 %	0.27 %	0.17 %	0.04 %	5779.49 %	53	20	33	1.601
MACD strategy	−0.08 %	0.56 %	0.63 %	0.11 %	6332.47 %	453	162	283	0.878
Momentum strategy	−0.16 %	0.48 %	0.65 %	0.19 %	6648.28 %	413	119	290	0.748
Moving avg 2 line cross strategy	−0.03 %	0.51 %	0.55 %	0.14 %	6188.29 %	356	134	215	0.94
Moving avg cross	0.08 %	0.83 %	0.74 %	0.05 %	6648.28 %	995	336	631	1.117
Outside bar strategy	−0.08 %	0.42 %	0.5 %	0.18 %	6046.91 %	280	116	159	0.834
Parabolic SAR strategy	−0.08 %	0.6 %	0.68 %	0.14 %	5785.09 %	401	176	301	0.904
Pivot extension strategy	−0.06 %	0.71 %	0.77 %	0.14 %	6046.91 %	815	374	403	0.92
Pivot reversal strategy	−0.08 %	0.45 %	0.51 %	0.08 %	6485.71 %	273	92	185	0.86
Price channel strategy	−0.08 %	0.36 %	0.41 %	0.15 %	5785.09 %	194	60	131	0.844
Rob booker	0.08 %	0.18 %	0.1 %	0.03 %	6485.71 %	60	27	37	1.523
RSI strategy	−0.28 %	0.03 %	0.31 %	0.28 %	6822.56 %	32	12	20	0.101
Stochastic slow strategy	−0.02 %	0.28 %	0.3 %	0.1 %	7375.67 %	117	76	39	0.918
Supertrend strategy	45.49 %	223.4 %	177.93 %	27 %	5783.09 %	144	54	90	1.256
Technical ratings strategy	13.05 %	56.33 %	43.28 %	7.3 %	5785.09 %	123	41	82	1.302
Volty expan close strategy	−0.12 %	0.93 %	1.06 %	0.20 %	6332.47 %	1226	398	806	0.885

WIPRO

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	17.86 %	201.92 %	214.03 %	41.86 %	55395.18 %	1192	459	697	1.057
Bollinger Band strategy	−0.22 %	0.97 %	1.19 %	0.54 %	52686.31 %	128	80	47	0.816
Channel breakout strategy	−0.07 %	2.35 %	2.42 %	0.88 %	55352.33 %	702	228	471	0.969
Consecutive up down strategy	0.54 %	2.08 %	1.54 %	0.21 %	52806.4 %	405	178	227	1.35
Inside bar strategy	0.32 %	1.99 %	1.66 %	0.24 %	44753.8 %	418	216	198	1.195
Keltner channels strategy	0.53 %	1.03 %	0.5 %	0.17 %	48518.47 %	55	20	34	2.059
MACD strategy	0.38 %	2.12 %	1.75 %	0.24 %	52959.04 %	488	180	308	1.216
Momentum strategy	0.27 %	1.98 %	1.72 %	0.4 %	58640.17 %	477	147	327	1.154
Moving avg 2 line cross strategy	0.68 %	2.02 %	1.35 %	0.15 %	55405.68 %	403	170	222	1.501
Moving avg cross	0.27 %	2.66 %	2.39 %	0.33 %	53890.88 %	1146	390	739	1.113
Outside bar strategy	−0.38 %	1.41 %	1.8 %	0.64 %	52940.88 %	341	148	187	0.782
Parabolic SAR strategy	0.08 %	2.26 %	2.18 %	0.73 %	52936.31 %	541	188	353	1.039
Pivot extension strategy	−0.92 %	1.95 %	2.87 %	0.86 %	55357.09 %	893	408	482	0.679
Pivot reversal strategy	0.49 %	1.72 %	1.27 %	0.3 %	58969.28 %	291	108	183	1.36
Price channel strategy	0.3 %	1.43 %	1.13 %	0.24 %	58150 %	234	98	137	1.269
Rob booker	−0.04 %	0.42 %	0.46 %	0.11 %	52836.31 %	87	34	52	0.923
RSI strategy	−0.09 %	0.44 %	0.53 %	0.18 %	43029.59 %	48	31	17	0.836
Stochastic slow strategy	−0.32 %	0.9 %	1.23 %	0.44 %	52705.4 %	138	77	59	0.737
Supertrend strategy	104.73 %	335.6 %	230.87 %	49.91 %	59491 %	173	69	101	1.454
Technical ratings strategy	25.63 %	78.67 %	53.04 %	12.22 %	52790.86 %	174	61	109	1.483
Volty expan close strategy	−0.14 %	3.14 %	3.28 %	0.84 %	52904.48 %	1433	1433	207	0.959

SUN PHARMA

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1808	888	907	0.94
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	136	89	47	1.200
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	708	305	403	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	435	182	253	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	409	238	347	1.08
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	40	12	29	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	413	167	218	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	309	112	206	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	347	138	206	1
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1113	258	858	1.08
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	331	143	186	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	404	171	333	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	844	418	408	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	273	105	167	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	156	42	113	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	75	31	88	1.112
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	36	23	13	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	122	78	44	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	132	46	83	0.94
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	129	47	82	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1258	896	811	[illegible]

SHREE CEMENT

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy&Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	27.98 %	192.36 %	164.38 %	7.9 %	100311.45 %	673	283	388	1.17
Bollinger Band strategy	−10.97 %	30.6 %	41.57 %	24.07 %	123200.4 %	103	49	54	0.736
Channel breakout strategy	−6.13 %	87.91 %	94.05 %	19.21 %	199614.83 %	648	198	449	0.935
Consecutive up down strategy	7.32 %	75.55 %	68.22 %	16.08 %	91386.39 %	369	174	195	1.107
Inside bar strategy	−2.99 %	66.83 %	69.82 %	16.45 %	100391.9 %	425	227	198	0.957
Keltner channels strategy	−30.98 %	14.61 %	45.59 %	36.73 %	140494.21 %	38	13	25	0.32
MACD strategy	6.2 %	74.67 %	68.47 %	13.28 %	133719.47 %	406	167	238	1.091
Momentum strategy	13.95 %	68.52 %	54.58 %	9.47 %	107897.9 %	341	124	216	1.256
Moving avg 2 line cross strategy	0.80 %	60.18 %	61.08 %	17.28 %	124412.72 %	313	130	181	0.985
Moving avg cross	46.24 %	123.98 %	77.74 %	4.4 %	108900.97 %	899	398	593	1.595
Outside bar strategy	27.2 %	73.49 %	46.29 %	6.87 %	111016.13 %	299	143	155	1.587
Parabolic SAR strategy	−37.29 %	72.84 %	110.13 %	39.04 %	110823.84 %	491	157	334	0.661
Pivot extension strategy	4.31 %	96.13 %	91.82 %	10.08 %	101258.59 %	704	389	363	1.047
Pivot reversal strategy	−16.57 %	49.96 %	66.53 %	22.27 %	115966.12 %	246	89	159	0.751
Price channel strategy	−16.57 %	37.8 %	64.38 %	20.44 %	124197.08 %	160	56	104	0.695
Rob booker	5.01 %	20.99 %	15.98 %	5.81 %	149208.71 %	61	23	37	1.319
RSI strategy	17.47 %	35.78 %	18.27 %	7.70 %	75273.89 %	35	21	14	2.074
Stochastic slow strategy	7.78 %	41.43 %	33.65 %	12.82 %	124436.10 %	99	53	46	1.231
Supertrend strategy	172.82 %	303.07 %	131.86 %	23.09 %	110758.24 %	101	45	56	2.313
Technical ratings strategy	31.2 %	56.88 %	25.68 %	6.98 %	110634.38 %	83	39	44	2.215
Volty expan close strategy	−33.81 %	110.74 %	144.55 %	50.9 %	101476.72 %	1210	346	859	0.766

JSWSTEEL

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDown Strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Keltners channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

HUL

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDown Strategy	−1.86 %	8.91 %	10.76 %	2.56 %	3626.82 %	1464	528	936	0.828
Bollinger Band strategy	0.08 %	2.99 %	2.91 %	1.13 %	3442.81 %	143	81	81	1.027
Channel breakout strategy	0.22 %	6.88 %	6.64 %	1.08 %	3588.32 %	772	268	500	1.039
Consecutive up down strategy	−0.47 %	5.51 %	5.98 %	1.57 %	3534.3 %	441	183	258	0.921
Inside bar strategy	−0.84 %	5.02 %	5.86 %	1.2 %	3569.05 %	462	224	236	0.857
Keltners channels strategy	−0.96 %	1.76 %	2.73 %	1.4 %	3179.04 %	60	17	43	0.646
MACD strategy	1.56 %	6.52 %	4.96 %	0.98 %	3050.01 %	524	181	337	1.316
Momentum strategy	0.26 %	5.35 %	5.09 %	0.8 %	3445.87 %	481	152	328	1.051
Moving avg 2 line cross strategy	0.45 %	4.94 %	4.49 %	0.64 %	3208.26 %	382	147	233	1.101
Moving avg cross	0.53 %	8.29 %	7.77 %	1.02 %	3544.57 %	1189	428	750	1.068
Outside bar strategy	−0.97 %	3.95 %	4.92 %	1.37 %	3574.13 %	307	136	168	0.802
Parabolic SAR strategy	−0.55 %	6.56 %	7.12 %	1.76 %	3589.05 %	602	204	398	0.922
Pivot extension strategy	−1.36 %	6.77 %	8.11 %	2.27 %	3562.81 %	909	418	481	0.834
Pivot reversal strategy	0.92 %	4.24 %	3.32 %	1.14 %	3538.84 %	310	109	200	1.278
Price channel strategy	−0.08 %	3.23 %	3.31 %	0.93 %	3444.57 %	211	74	137	0.975
Rob booker	−0.09 %	1.11 %	1.2 %	0.27 %	3080.3 %	87	33	53	0.924
RSI strategy	0.19 %	2.1 %	1.91 %	1.04 %	3514.21 %	45	32	13	1.098
Stochastic slow strategy	0.46 %	3.22 %	2.74 %	0.62 %	3369.46 %	144	86	57	1.176
Supertrend strategy	−24.83 %	70.58 %	95.42 %	29.13 %	3428.78 %	165	53	112	0.74
Technical ratings strategy	−10.47 %	25.68 %	36.26 %	13.64 %	3569.1 %	159	43	116	0.712
Volty expan close strategy	−1.86 %	9.04 %	10.79 %	2.56 %	3639.33 %	1466	530	937	0.829

INDUSIND BANK

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDown Strategy	36.16 %	267.68 %	231.52 %	16.1 %	3637.56 %	979	414	558	1.156
Bollinger Band strategy	0.01 %	3.06 %	3.04 %	0.86 %	3890.37 %	116	73	43	1.004
Channel breakout strategy	0.22 %	6.75 %	6.52 %	0.06 %	3712.71 %	644	205	430	1.035
Consecutive up down strategy	−1.52 %	4.73 %	6.26 %	2.09 %	2655.19 %	379	144	234	0.756
Inside bar strategy	−0.66 %	4.88 %	5.55 %	1.56 %	3653.78 %	356	165	191	0.88
Keltners channels strategy	0.66 %	2.83 %	2.17 %	0.76 %	3676.62 %	52	20	32	1.304
MACD strategy	0.14 %	5.92 %	5.78 %	1.14 %	3662.32 %	420	140	271	1.024
Momentum strategy	−0.15 %	5.38 %	5.53 %	0.84 %	2558.57 %	397	126	271	0.973
Moving avg 2 line cross strategy	0.67 %	6.26 %	4.68 %	0.86 %	3450.11 %	321	128	292	1.546
Moving avg cross	0.45 %	7.83 %	7.38 %	1.37 %	3168.7 %	959	326	620	1.061
Outside bar strategy	−1.12 %	4.07 %	5.19 %	1.85 %	3168.7 %	266	107	160	0.785
Parabolic SAR strategy	−0.03 %	6.04 %	6.07 %	1.42 %	3204.9 %	485	169	316	0.996
Pivot extension strategy	−2.17 %	5.72 %	7.89 %	2.46 %	3185.78 %	774	346	413	0.725
Pivot reversal strategy	0.62 %	4.71 %	4.1 %	0.76 %	3073.84 %	267	98	169	1.15
Price channel strategy	−0.04 %	3.84 %	3.87 %	1.18 %	3544.27 %	171	62	109	0.991
Rob booker	−0.48 %	0.52 %	1.01 %	0.57 %	4294.25 %	62	14	46	0.517
RSI strategy	−0.19 %	1.9 %	2.1 %	0.94 %	3677.93 %	47	35	12	0.907
Stochastic slow strategy	0.17 %	3.37 %	3.2 %	3.2 %	3968.88 %	107	74	33	1.054
Supertrend strategy	48.62 %	183.19 %	134.57 %	22.62 %	3646.82 %	125	49	76	1.361
Technical ratings strategy	14.38 %	54.69 %	40.61 %	6.85 %	2911.24 %	1156	400	754	1.116

HINDALCO									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	1.71 %	165.69 %	163.98 %	12.65 %	202.73 %	807	336	471	1.01
Bollinger Band strategy	−0.33 %	0.64 %	0.97 %	0.38 %	197.66 %	76	45	31	0.662
Channel breakout strategy	−0.17 %	1.9 %	2.07 %	0.34 %	225.56 %	410	158	250	0.916
Consecutive up down strategy	−0.08 %	1.41 %	1.51 %	0.22 %	203.26 %	255	99	153	0.939
Inside bar strategy	−0.3 %	1.31 %	1.61 %	0.34 %	204.16 %	234	118	116	0.812
Keltner channels strategy	0.25 %	0.81 %	0.56 %	0.22 %	166.17 %	32	11	21	1.443
MACD strategy	−0.1 %	1.62 %	1.72 %	0.27 %	156.13 %	285	105	180	0.942
Momentum strategy	0.13 %	1.46 %	1.33 %	0.16 %	216.18 %	260	94	166	1.097
Moving avg 2 line cross strategy	0.12 %	1.39 %	1.27 %	0.16 %	199.51 %	210	96	114	1.093
Moving avg cross	−0.45 %	2.04 %	2.49 %	0.47 %	213.14 %	648	198	445	0.82
Outside bar strategy	−0.07 %	1.08 %	1.16 %	0.36 %	200.46 %	155	64	90	0.937
Parabolic SAR strategy	−0.42 %	1.66 %	2.07 %	0.58 %	211.59 %	338	129	209	0.797
Pivot extension strategy	0.31 %	2.14 %	1.83 %	0.17 %	208.88 %	807	258	244	1.168
Pivot reversal strategy	0.13 %	1.27 %	1.13 %	0.25 %	211.84 %	190	93	95	1.119
Price channel strategy	0.13 %	0.97 %	0.84 %	0.17 %	190.45 %	108	44	64	1.157
Rob booker	−0.21 %	0.26 %	0.47 %	0.21 %	90.17 %	46	11	34	0.56
RSI strategy	−0.26 %	0.29 %	0.55 %	0.37 %	104.34 %	22	13	9	0.532
Stochastic slow strategy	−0.11 %	0.86 %	0.97 %	0.32 %	181.94 %	88	53	35	0.881
Supertrend strategy	20.7 %	99.91 %	79.22 %	11.65 %	167.2 %	90	34	56	1.261
Technical ratings strategy	8.29 %	28.97 %	20.67 %	5.32 %	208.76 %	70	22	48	1.401
Volty expan close strategy	0.29 %	2.8 %	2.50 %	0.26 %	209.41 %	822	327	497	1.083

BRITANNIA									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	17.05 %	154.69 %	137.64 %	12.66 %	3615.01 %	847	392	442	1.124
Bollinger Band strategy	−0.54 %	4.2 %	4.74 %	1.06 %	2846.04 %	110	65	45	0.887
Channel breakout strategy	−1.35 %	9.82 %	11.17 %	1.86 %	3924.33 %	682	192	488	0.879
Consecutive up down strategy	2.44 %	8.58 %	6.14 %	0.75 %	3468.2 %	381	175	206	1.397
Inside bar strategy	−0.74 %	7.29 %	8.03 %	1.04 %	3145.54 %	507	262	248	0.908
Keltner channels strategy	0.87 %	3.09 %	2.13 %	0.96 %	2973.66 %	28	12	16	1.454
MACD strategy	1.08 %	8.47 %	7.4 %	0.91 %	2518.28 %	433	182	225	1.146
Momentum strategy	1.99 %	7.61 %	5.62 %	0.64 %	3201.67 %	381	121	258	1.354
Moving avg 2 line cross strategy	3.46 %	7.64 %	4.25 %	0.76 %	2656.59 %	327	149	274	1.801
Moving avg cross	2.21 %	11.99 %	9.79 %	1.06 %	3581.33 %	1059	449	596	1.225
Outside bar strategy	1.16 %	6.52 %	5.36 %	1.72 %	2848.14 %	359	169	186	1.216
Parabolic SAR strategy	−2.19 %	8.58 %	10.79 %	3.41 %	3886.66 %	487	153	334	0.797
Pivot extension strategy	1.01 %	11.11 %	10.11 %	1.06 %	3577.38 %	809	412	372	808
Pivot reversal strategy	1.54 %	6.73 %	5.19 %	0.98 %	3336.7 %	291	87	204	1.298
Price channel strategy	1.93 %	6.71 %	4.78 %	0.92 %	2922.64 %	191	64	127	1.612
Rob booker	0.42 %	1.44 %	1.02 %	0.3 %	2642.58 %	56	23	33	1.413
RSI strategy	−1.52 %	1.44 %	2.86 %	2.5 %	3006.38 %	43	24	19	0.487
Stochastic slow strategy	−2.48 %	2.68 %	5.15 %	2.98 %	2317.96 %	107	64	43	0.517
Supertrend strategy	46.89 %	128.65 %	81.75 %	9.71 %	3219.35 %	107	42	65	1.573
Technical ratings strategy	9.75 %	39.64 %	29.8 %	2.9 %	3766 %	137	46	91	1.327
Volty expan close strategy	−4.63 %	13.53 %	17.96 %	6.05 %	3481.84 %	1281	293	988	0.622

DIVIS LAB									
Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	730	251	414	1.022
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	91	47	44	0.506
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	558	174	384	0.877
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	327	124	203	1.185
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	319	173	146	1.195
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	35	13	22	1.315
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	335	126	206	0.76
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	321	161	219	0.85
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	289	111	190	1.19
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	795	274	511	1.079
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	235	105	130	0.883
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	405	133	272	0.719
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	658	311	336	0.959
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	231	79	152	0.909
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	129	48	81	1.341
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	71	39	31	0.637
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	38	21	17	0.684
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	85	49	33	0.675
Supertrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	97	40	57	1.812
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	90	31	59	1.512
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	937	311	626	0.95

HERO MOTOCORP

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	−14.79 %	117.64 %	132.42 %	26.8 %	779.19 %	970	398	562	0.888
Bollinger Band strategy	−1.39 %	6.48 %	7.86 %	1.81 %	957.39 %	109	60	49	0.822
Channel breakout strategy	−1.83 %	17.5 %	19.33 %	3.69 %	782.12 %	584	211	372	0.906
Consecutive up down strategy	0.49 %	14.86 %	14.17 %	3.04 %	698.46 %	346	157	188	1.035
Inside bar strategy	3.98 %	16.81 %	12.82 %	1.39 %	766.19 %	373	188	192	1.311
Keltner channels strategy	−0.61 %	4.77 %	5.38 %	3.01 %	1018.11 %	33	14	19	0.887
MACD strategy	−1.9 %	15.39 %	17.29 %	3.46 %	976.35 %	403	138	266	0.89
Momentum strategy	−1.09 %	12.65 %	13.68 %	2.13 %	806.64 %	387	132	256	0.92
Moving avg 2 line cross strategy	−3.11 %	10.84 %	13.95 %	3.07 %	818.09 %	294	116	178	0.777
Moving avg cross	−0.6 %	21.08 %	21.69 %	2.51 %	748.85 %	827	321	506	0.972
Outside bar strategy	−0.15 %	12.06 %	12.21 %	2.41 %	604.39 %	284	113	147	0.988
Parabolic SAR strategy	−4.78 %	15.08 %	19.85 %	5.40 %	788.19 %	455	168	287	0.758
Pivot extension strategy	4.83 %	21.94 %	17.11 %	1.39 %	748.85 %	683	355	326	1.282
Pivot reversal strategy	−2.08 %	10.19 %	12.27 %	3.69 %	673.09 %	236	74	162	0.83
Price channel strategy	−5.4 %	6.94 %	12.34 %	6.34 %	673.9 %	167	49	119	0.562
Rob booker	−0.77 %	3.18 %	3.96 %	1.61 %	1001.8 %	70	19	56	0.804
RSI strategy	−0.57 %	3.65 %	4.22 %	2.09 %	896.65 %	31	16	15	0.865
Stochastic slow strategy	1.85 %	9.55 %	7.69 %	1.6 %	893.23 %	129	83	46	1.241
Superstrend strategy	−13.04 %	62.08 %	75.12 %	25.52 %	879.42 %	116	38	78	0.828
Technical ratings strategy	−2.35 %	21.27 %	23.61 %	6.36 %	746.03 %	126	33	93	0.901
Volty expan close strategy	−1.19 %	25.52 %	26.7 %	4.02 %	725.03 %	1886	395	691	0.956

Grasim

Strategy name	Net profit	Gross Profit	Gross Loss	Max Drawdown	Buy/Hold profit/Loss	Total Trades	Winning Trades	Losing Trades	Profit ratio
BarUpDownStrategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1103	454	639	1.145
Bollinger Band strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	117	64	52	0.566
Channel breakout strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	666	235	431	1.046
Consecutive up down strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	399	156	243	1.262
Inside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	443	228	215	1.211
Keltner channels strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	45	21	24	1.609
MACD strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	432	161	268	1.123
Momentum strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	421	149	272	1.216
Moving avg 2 line cross strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	328	137	191	1.683
Moving avg cross	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1813	342	641	1.331
Outside bar strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	330	138	192	1.038
Parabolic SAR strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	346	155	191	0.874
Pivot extension strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	609	310	299	1.068
Pivot reversal strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	241	102	137	1.194
Price channel strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	178	67	111	1.632
Rob booker	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	78	28	48	1.071
RSI strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	41	22	16	0.457
Stochastic slow strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	115	64	51	0.371
Superstrend strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	129	57	72	1.566
Technical ratings strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	118	35	78	1.572
Volty expan close strategy	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1147	429	716	1.095

Appendix B

STOCK	NET PROFIT	BUY&HOLD	Best Strategy
TATA MOTORS	127.00%	2526.00%	Supertrend Strategy
SBI	44.00%	3011.00%	barupand down
HDFC BANK	0.92%	29669.90%	Kelters channels strategy
HDFC	0.88%	10423.77 %	barupand down
TATA STEEL	34.46 %	737.74 %	BArupand down
ONGC	68.89%	656.60%	BArupand down
RELIANCE	21.88%	6963.60%	BArupand down
AXIS BANK	-2.27%	704.80%	BArupand down
AIRTEL	19.92%	4393.59%	Supertrend Strategy
ICICI BANK	43.55%	16916.55%	Supertrend Strategy
KOTAK BANK	61.62%	23053.99%	Supertrend Strategy
BAJAJ FINANCE	216.26%	61775.50%	Supertrend Strategy
BAJAJ FINSERV	85.24%	2959.23%	Supertrend Strategy
M&M	35.69%	310.80%	Supertrend Strategy
L&T	25.45%	2754.28%	BArupand down
ITC	0.90%	2567.00%	Stochastic STR
CIPLA	54.44%	1097.60%	BARupand down
DLF	14.70%	-40.70%	Supertrend Strategy
TITANS	30.91%	55045.27 %	Supertrend Strategy
ADANI PORTS	4.25%	241.07%	Supertrend Strategy
TECHMAHINDRA	72.14%	1115.40%	BARupand down
INFOSYS	61.10%	227862.5 %	Supertrend Strategy
HCL TECHNOLOGIES	26.47%	634.59%	Supertrend Strategy
ASIAN PAINT	7.70%	12256.02 %	Supertrend Strategy
ULTRATECH	1.31%	2445.96 %	MACD STRATEGY
NESTLE	18.36%	640.94 %	MOVING AVERAGE CROSS
NTPC	1.24%	114.56 %	BarUPndown STRATEGY
BIOCON	0.70%	966.47 %	KELTERS CHANNELS STRATEGY
TATA CONSUMERS	14.27%	854.69 %	Supertrend Strategy
ASHOK	45.48%	5785.08 %	Supertrend Strategy

LEYLAND			
IOC	31.25%	256.84 %	BarUPndown STRATEGY
WIPRO	104.50%	50491 %	Supertrend Strategy
SUN PHARMA	6.08%	10987.4 %	Technical Rating Strategy
MARUTI	53.66%	3981.24 %	Supertrend Strategy
SBI LIFE	2.14%	76.52 %	Supertrend Strategy
SHREE CEMENT	172.53%	110758.24 %	Supertrend Strategy
JSW STEEL	41.64 %	2607.36 %	Supertrend Strategy
COAL INDIA	0.28%	−49.56 %	Stochastic STR
HUL	1.56%	3090.01 %	MACD Strategy
INDUSIND BANK	267.88%	3637.55 %	BarUPndown Strategy
EICHER MOTORS	176.68%	213896 %	BarUPndown Strategy
HINDALCO INDS	20.70%	187.2 %	Supertrend Strategy
BRITANNIA	46.89%	3216.35 %	Supertrend Strategy
BAJAJ AUTO	32.64%	1115.59 %	Supertrend Strategy
DIVIS LAB	39.18%	5849.69 %	Supertrend Strategy
HERO MOTOCORP	4.83%	748.85 %	Pivot Eextension Strategy
BPCL	5.36%	889.6 %	BarUPndown Strategy
DR REDDY	9.25%	3211.71 %	BarUPndown Strategy
GRASIM	108.29%	5311.76 %	Supertrend Strategy
HDFCLIFE	0.07%	56.61 %	Price Channel Strategy
POWERGRID	0.18%	92.99 %	RSI Strategy
TCS	6.16%	2863.14 %	Technical Rating Strategy
UPL	0.52%	748.74 %	Volty Expan Close Strategy

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