Comparative Analysis of Various Strategies Used in Algorithmic Trading

Análise Comparativa de Várias Estratégias Usadas em Negociação Algorítmica

Análisis comparativo de diversas estrategias utilizadas en el trading algorítmico

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Abstract

In the ever-growing era of technological advancements, the onset of machine learning and artificial intelligence has brought about a lot of scope in the financial market for the ones willing to undertake the risk. This research project deals with the analysis of various technical indicators which are used in designing Trade-Bots. Also, this research paper aims to assess demand in the Indian consumers regarding the use of algorithms being used for trading in the live market and their perception towards it. Major portion of this report includes creating and testing strategies using machine learning algorithms in python. Expected outcome of this research paper is to identify the best possible strategy for day trading by using the various technical indicators individually as well as in combination. Indian population is skeptical regarding the subject matter but it is evident from the performance of companies like RenTech (Renaissance Technologies) that use of algorithms has helped them gain immense profits, hence the scope of algorithmic trading is vast. Use of both these opportunities together opens up a vast sea of unexplored avenues, one of which is algorithmic trading and finding the best strategy is a never-ending process, this project aims at exploring the various strategies and their impact after back testing them with historical data. This study aims to help the individual investors as well as the investing institutions by exploring the potential of algorithmic trading and its future scope. The analysis provides evidence that SMA/EMA crossover trading strategy and Stochastic oscillator trading strategy are extremely good at predicting the movement of Reliance industries stock, and provide with more than approximately 15 times the initial investment.

Keywords: Algorithmic Trading, Technical Analysis, Intraday trading, vectorized back-testing.

Resumo

Na era cada vez maior de avanços tecnológicos, o início do aprendizado de máquina e da inteligência artificial trouxe muito escopo no mercado financeiro para aqueles dispostos a assumir o risco. Este projeto de pesquisa lida com a análise de vários indicadores técnicos que são usados no design de Trade-Bots. Além disso, este artigo de pesquisa visa avaliar a demanda dos consumidores indianos em relação ao uso de algoritmos usados para negociação no mercado ao vivo e sua percepção em relação a isso. A maior parte deste relatório inclui a criação e o teste de estratégias usando algoritmos de aprendizado de máquina em python. O resultado esperado deste artigo de pesquisa é identificar a melhor estratégia possível para day trading usando os vários indicadores técnicos individualmente, bem como em combinação. A população indiana é cética em relação ao assunto, mas é evidente pelo desempenho de empresas como a RenTech (Renaissance Technologies) que o uso de algoritmos os ajudou a obter lucros imensos, portanto, o escopo da negociação algorítmica é vasto. O uso de ambas as oportunidades juntas abre um vasto mar de avenidas inexploradas, uma das quais é a negociação algorítmica e encontrar a melhor estratégia é um processo sem fim, este projeto visa explorar as várias estratégias e seu impacto após testá-las com dados históricos. Este estudo visa ajudar os investidores individuais, bem como as instituições de investimento, explorando o potencial da negociação algorítmica e seu escopo futuro. A análise fornece evidências de que a estratégia

de negociação cruzada SMA/EMA e a estratégia de negociação do oscilador estocástico são extremamente boas em prever o movimento das ações da Reliance Industries e fornecem mais de aproximadamente 15 vezes o investimento inicial.

Palavras-chave: Negociação Algorítmica, Análise Técnica, Negociação Intraday, back-testing vetorizado.

Resumen
En la era de los avances tecnológicos, la llegada del aprendizaje automático y la inteligencia artificial ha abierto un amplio abanico de posibilidades en el mercado financiero para quienes estén dispuestos a asumir riesgos. Este proyecto de investigación aborda el análisis de diversos indicadores técnicos utilizados en el diseño de Trade-Bots. Además, este trabajo de investigación busca evaluar la demanda de los consumidores indios respecto al uso de algoritmos para operar en el mercado en vivo y su percepción al respecto. Gran parte de este informe incluye la creación y prueba de estrategias utilizando algoritmos de aprendizaje automático en Python. El resultado esperado de este trabajo de investigación es identificar la mejor estrategia posible para el day trading utilizando los diversos indicadores técnicos tanto individualmente como en combinación. Si bien la población india se muestra escéptica respecto al tema, el desempeño de empresas como RenTech (Renaissance Technologies) demuestra que el uso de algoritmos les ha permitido obtener enormes ganancias, lo que explica el amplio alcance del trading algorítmico. El uso conjunto de estas dos oportunidades abre un vasto mar de posibilidades inexploradas, una de las cuales es el trading algorítmico. Encontrar la mejor estrategia es un proceso continuo. Este proyecto busca explorar las diversas estrategias y su impacto tras realizar pruebas retrospectivas con datos históricos. Este estudio busca ayudar tanto a inversores individuales como a instituciones inversoras, explorando el potencial del trading algorítmico y su alcance futuro. El análisis demuestra que las estrategias de trading con cruce de media móvil simple (SMA)/media móvil exponencial (EMA) y con oscilador estocástico son extremadamente eficaces para predecir el movimiento de las acciones de Reliance Industries y permiten obtener aproximadamente 15 veces la inversión inicial.

Palabras clave: Trading algorítmico, análisis técnico, trading intradía, pruebas retrospectivas vectorizadas.

1. Introduction

In the ever-growing era of technological advancements, the onset of machine learning and artificial intelligence has brought about a lot of scope in the financial market for the ones willing to undertake the risk. Financial market in India is rising swiftly and is likely to appear as one of the bests in the global ground very soon. The possibility of the share market in India has expanded enormously over the previous few years, recognitions

to the unveiling of diversity of products and services. Share markets are, by nature, tremendously volatiles and hereafter the risk issue is an significant worry for the mediators. To lessen this risk, the idea of derivatives originates into the depiction. Derivatives are products whose price are resulting after one or more fundamental assets. These assets can be forex, equity, etc. The derivatives market in India is also increasing vastly with an augmented amount of market members using derivatives. The derivative market achieves a number of fiscal roles in an economy like they aid in channelizing risks from risk-averse individuals to risk concerned with people, they are supportive in the finding of upcoming as well as present prices, they benefit in increase risk-taking actions, aids in growing the bulk traded in markets since of contribution of risk averse persons in larger records & they aid the members surge their investments and funds in the lengthy track. Hedgers use futures or options to lessen or eradicate the risk related with the price of an asset. Risk-takers use futures and options agreements to become additional leverage in bookmaking on future activities in the price of an asset. They be able to upsurge together the possible improvements and possible fatalities by usage of derivatives in hypothetical scheme. Arbitrageurs are in specialized to take benefit of a inconsistency among prices in two diverse marketplaces.

Objectives of the Study

To understand various trading strategies formed through single or many technical indicators, which are Simple Moving Average Approach, Exponential Moving Average Approach, SMA/EMA crossover approach, Moving Average Convergence Divergence (MACD) approach, Relative Strength Index (RSI) approach, Stochastic Oscillator Strategy and Bollinger Bands Policy. To examine the presentation of overhead policies besides improve them for supreme effectiveness.

This paper is grounded on expressive investigation which is used to designate physiognomies of a populace or marvels presence is considered. It prepares for no response queries around how/when/why the features happened. The research is complete by back testing the approaches erected on procedural pointers explicitly Simple Moving Average (SMA), Exponential Moving Average (EMA), SMA/EMA crossover strategy, Moving

Average Convergence Divergence (MACD), Relative Strength Index (RSI), Stochastic Oscillator and Bollinger Bands.

2. Literature Review

Darrat et al., (2003) “Intraday trading volume and return volatility of the DJIA stocks”; Connection as well as the lead-slack connection between exchanging volume and return unpredictability all stocks involving the Dow Jones Industrial Average (DJIA) is examined in this paper. In any case, proof showing critical lead-slack relations between the two factors in countless DJIA stocks were found.

Chan et al., (2015) “Intraday Volatility in the Stock Index and Stock Index Futures Markets”; This paper clarifies the connection among returns A solid aftermarket reliance in the instability of the money and prospects returns. It was originated out that price progressions starting in either the securities exchange or the prospects market could foresee the forthcoming impulsiveness in the additional marketplace furthermore this connection perseveres in any event, during the periods where the reliance in returns themselves seems to debilitate. This study produces strong methodologies for controlling potential market gratings like offbeat exchanging the stock file. Satish et al., (2014) “Predicting Intraday Volume and Volume percentages”; This article examines late methods and results in areas of estimating intraday volume and intraday volume rates. By investigating ways of anticipating volume, the researchers look to work on the exhibition of exchanging calculations, large numbers of which rely on the volume that will exchange while the request is dynamic. Generally, calculations utilize verifiable midpoints to foresee volume over the lifetime of a request. The researchers show that working on the expectation of volume helps the exhibition of calculations.

Chaboud et al., (2014) had risen of the Machines: Algorithmic Trading in the distant Exchange Marketplace”; Researchers concentrate scheduled the consequence of algorithmic trading (AT) in the unfamiliar trade market utilizing quite a while series of high-recurrence information that recognize PC produced exchanging action. Brings about this study is steady with the view that AT works on instructive productivity by

accelerating value revelation, yet that it might likewise force higher unfriendly choice expenses on more slow dealers. Interestingly, the decrease in the autocorrelation of profits owes more to the algorithmic arrangement of liquidity. This study observes proof on the methodologies of algorithmic merchants being profoundly corresponded. This relationship, nonetheless, doesn't cause corruption in market quality, basically not by and large.

Curcio et al., (1998) “Do technical trading rules generate profits? Conclusions from the intra- day foreign exchange market”; This paper uses customized strategies identified and supplied by technical analysis on the intra-daily foreign exchange market. Authors provide us with evidence that, although some profits could be made by following these strategies in periods of trends, this is not the case on average. This result is further strengthened when it is incorporated with transaction costs. Eleuterio et al., (2019) “Programming language choices for Algo traders: The situation of duos trading”; owing to an upsurge in marketplace contributors, additional classy algorithms than those rummage-sale in the previous or currently obligatory to produce additional returns in duos trading tactics. Classy algorithms can reason an upsurge in intricacy which, in turn, upsurges computational runtime. Neely et al., (2003) “Intraday technical trading in the foreign exchange market”; This paper scrutinizes the out-of-sample presentation of intraday methodological transaction tactics designated by means of two procedures, a genomic database besides an augmented rectilinear predicting model. Once representative contract price in addition interchange periods remain booked into account, we discovery not at all indication of additional earnings to the interchange rubrics resulting with whichever procedure. Therefore, the consequences are dependable through marketplace efficacy. Though, the trading rules exposed particular strangely unchanging shapes in the statistics.

3. Methodology

3.1 Sampling: Decision Specimen, also mentioned as hypercritical specimen, is a non-probability sample method wherever the academic chooses components to be sampled created on his specific prevailing information, or his specialized finding. Now the Indian

stock market is examined and Trusted trades stock is nominated as it has achieved very well throughout the period frame under deliberation. Researcher uses Python3 and algorithms aimed at back-testing the policies constructed on practical pointers. Historical price data is regularly connected with the former presentation of a security or an asset. Forecaster's analysis historic return data once trying to forecast upcoming returns or to guess in what way a security might respond to a specific situation, such as drop in customer expenditure. Ancient returns can also be convenient once approximating wherever the future points of data may fall in terms of standard deviations. Calculating the past return is done by subtracting the most recent price from the oldest price and divide the outcome by the eldest values.

3.2 Data Source

Python module named y.finance which stands for Yahoo finance is used to download the historical prices directly from the website of National Stock Exchange. All securities have the standard intraday open, high, low and close prices. Trade volume is also provided with this data.

3.3 Tools of Analysis

Vectorized backtesting algorithms using Python 3.

3.4 Research Model

The process of analyzing the strategies which are built on technical indicators involves the use of Python and following modules/packages are required which are stated below with their description;

- Pandas: This python bundle offers debauched, supple, and communicative data structures premeditated to brand working with 'relational' or 'labeled' data together are easy and spontaneous. It objects toward be the important extraordinary level structure block for doing practical, data analysis in Python. Moreover, it has the wider goal of fetching the greatest influential besides supple open source data analysis/operation device obtainable in some language. It is previously well on his

way near this goal.

- NumPy: This package provides an array of arbitrary homogeneous items, fast mathematical operation over arrays, linear algebra, Fourier transforms and random number generation.
- SciPy: A scientific computing package for Python. SciPy inports all the functions from the NumPy namespace, and in addition provides sub-packages. Using any of these sub-packages requires an explicit import. For example ‘from scipy.optimize import brute’. Brute is an optimization algorithm which minimizes the function by taking the function and the set of values in which the function needs to be optimized.
- Matplotlib: An object-oriented intrigue collection. A technical interface is delivered by the companion pyplot module, which might be introduced unswervingly. This component is used to scheme tailored diagrams.
- Cufflinks: A productivity module that binds pandas and plotly to create interactive graphs in Python.
- yfinance: yfinance stands for Yahoo finance, this module is market data downloader. It is used to download real-time market data and also provides historical prices

Starting with data collection by using the ‘yfinance’ module historical prices of Reliance industries are downloaded for the period starting from 1st January, 2010 and ending on 31st March, 2022. Reliance industries is taken in this research as it has performed exceptionally during this time frame a simple buy and hold strategy during this period would’ve earned an investor a profit of 531% on investment. After downloading the data, it is processed and strategies built on individual technical indicators is compared to the cumulative returns of the simple buy and hold strategy. Strategies are defined using ‘pandas’ and ‘numpy’ modules and are visualized by the ‘matplotlib’ and ‘cufflinks’ modules. The result generated from strategies is used in vectorized strategy backtesting to get the returns and compare it with the returns from simple buy and hold strategy. This strategy is then built as a function using the object

oriente programming. ‘brute’ is then used to optimize the function to provide us with an array of parameters which provide the maximum returns during the time frame.

Further down is the raw data which is used for the investigation of dissimilar approaches. The data is from 4th January,2010 to 28th March, 2022. The dataset contains daily inaugural price, concluding price, maximum price on that day, lowermost price throughout the day and volume of trades.

4. Results

4.1 Data Analysis & Interpretation

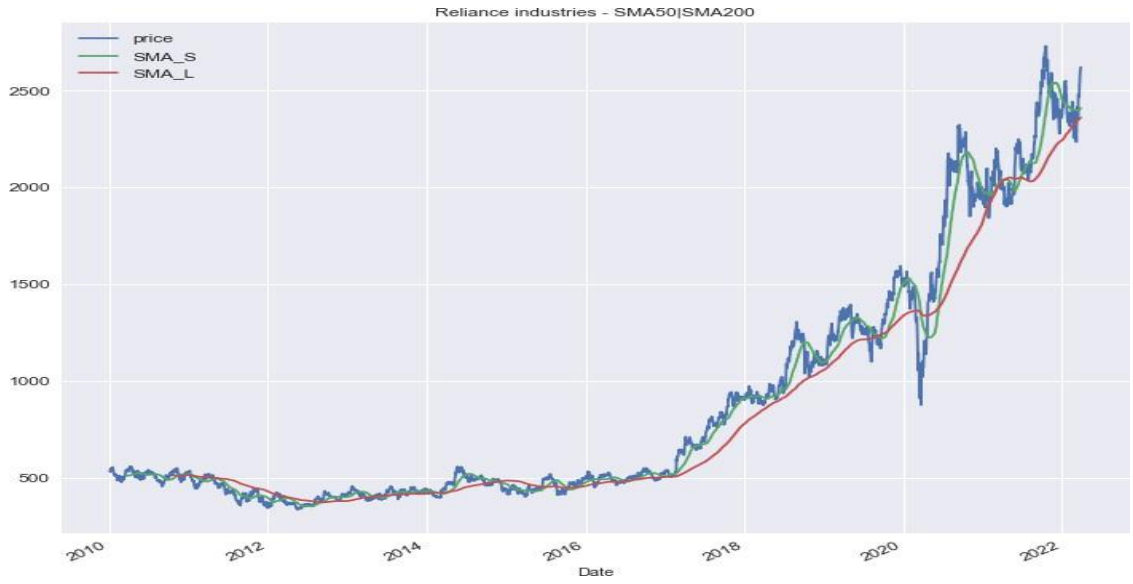
- Simple moving average is the rolling mean of short and long periods respectively as shown below.

```
df['SMA_S']=df.price.rolling(sma_s).mean()
df['SMA_L']=df.price.rolling(sma_l).mean()
```

```
df
```

Date	price	SMA_S	SMA_L
2010-01-04	532.700500	NaN	NaN
2010-01-05	530.323059	NaN	NaN
2010-01-06	538.891846	NaN	NaN
2010-01-07	547.832092	NaN	NaN
2010-01-08	546.395691	NaN	NaN
...	...	...	...
2022-03-22	2531.149902	2400.728013	2354.059003
2022-03-23	2539.199951	2402.792012	2355.706754
2022-03-24	2578.649902	2405.605010	2357.647503
2022-03-25	2595.850098	2408.411011	2359.489754
2022-03-28	2621.949951	2410.428008	2361.526503

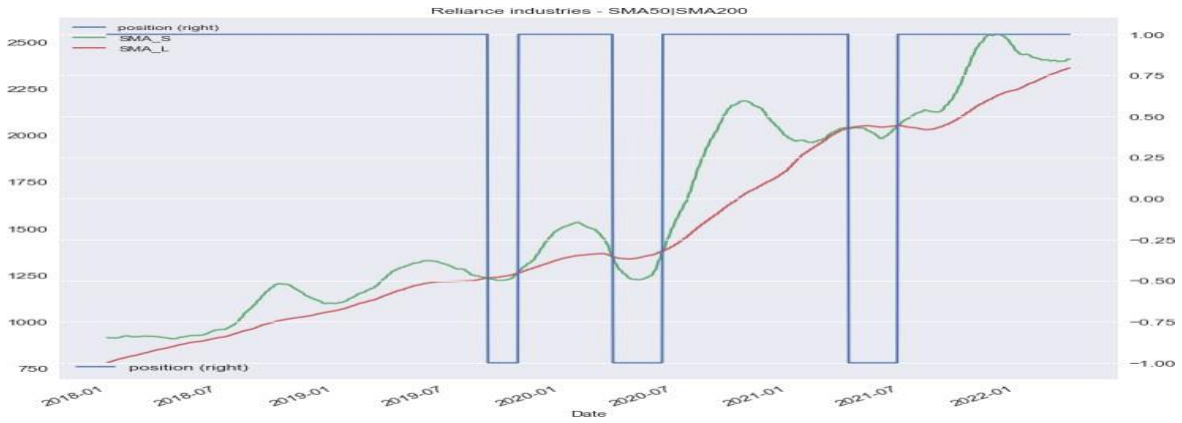
- Position is defined in the data set on the basis of strategy defined. SMAs are plotted afterwards.



- The positions taken by the algorithm on the basis of strategy defined is plotted below.

```
df['position']=np.where(df['SMA_S']>df['SMA_L'],1,-1)
df
```

Date	price	SMA_S	SMA_L	position
2010-10-19	517.296570	493.413931	512.372224	-1
2010-10-20	519.797852	494.023652	512.307711	-1
2010-10-21	535.746643	494.998412	512.334828	-1
2010-10-22	535.820923	496.080157	512.319474	-1
2010-10-25	540.055786	497.182211	512.280592	-1
...	...	...	...	...
2022-03-22	2531.149902	2400.728013	2354.059003	1
2022-03-23	2539.199951	2402.792012	2355.706754	1
2022-03-24	2578.649902	2405.605010	2357.647503	1
2022-03-25	2595.850098	2408.411011	2359.489754	1
2022-03-28	2621.949951	2410.428008	2361.526503	1



- An optimization algorithm is created using the function given below and the brute module helps in getting the best set of parameters for the SMA strategy. Array at the end denotes the best fit parameters.

```
def run_strategy(SMA):
    data=df.copy()
    data['returns']=np.log(data.price.div(data.price.shift(1)))
    data['sma_s']=data.price.rolling(int(SMA[0])).mean()
    data['sma_l']=data.price.rolling(int(SMA[1])).mean()
    data.dropna(inplace =True)

    data['position']=np.where(data['sma_s']>data['sma_l'],1,-1)
    data['strategy']=data.position.shift(1)*data['returns']

    return data[['returns','strategy']].sum().apply(np.exp)
```

```
brute(run_strategy_b,((10,50),(100,252)),finish=None)
```

```
array([ 10., 252.])
```

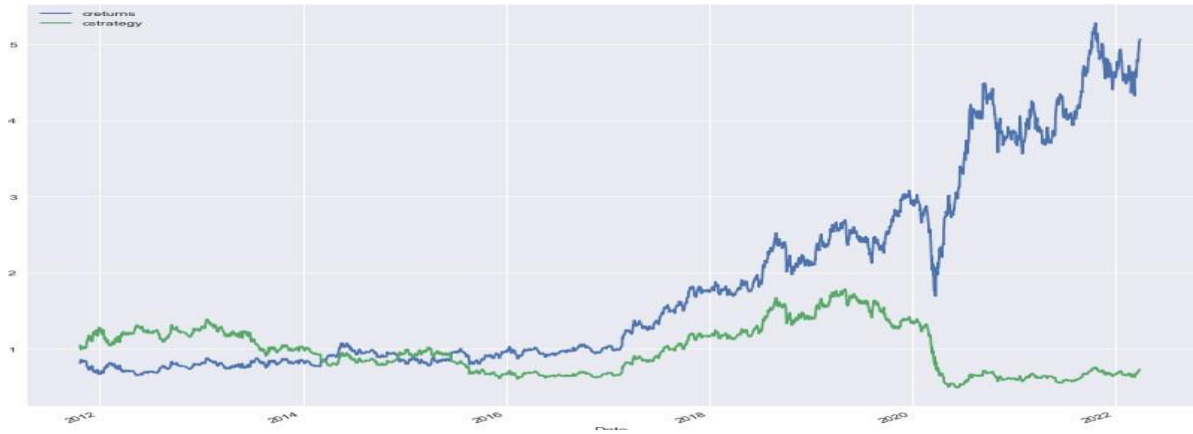
- Final performance is calculated by comparing the cumulative sum of strategy and returns.

  As shown below.

```
run_strategy((10,252))
```

```
returns     6.333960
strategy    1.225329
```

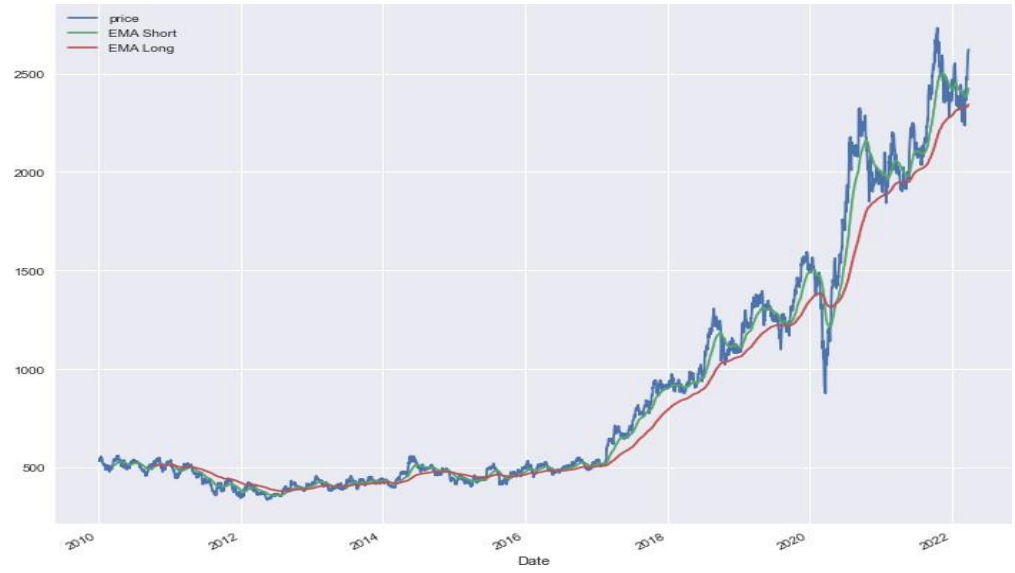
- Final performance is plotted comparing the returns and strategy returns.



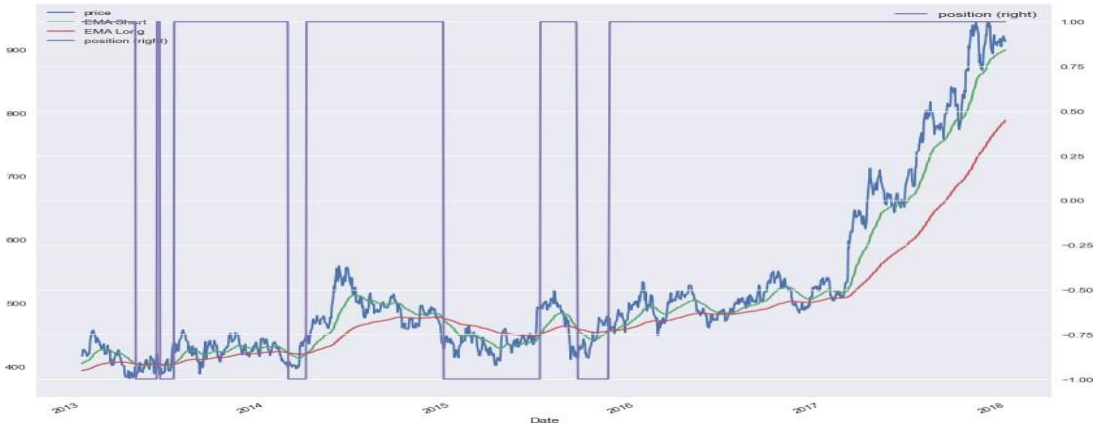
- It is evident from the above graph that when we back-tested our optimized SMA strategy it still did not perform on par with the simple buy and hold strategy. This shows the inherent nature of technical indicators as not all are suitable for all the securities.

4.2 Exponential Moving Average

Below is the plot of the variables present in the above table.



- Strategy is developed and the positions taken by the algorithm are plotted below.



- An optimization function is created using the below function and then the module brute is used to get the optimized results for the parameters by backtesting all possibilities, these values (array at the end) are then used to calculate final performance and plot the results.

```
def run_strategy(EMA):
    data=df.copy()
    data['returns']=np.log(data.price.div(data.price.shift(1)))
    data['ema_s']=data.price.ewm(span=EMA[0],min_periods=EMA[0]).mean()
    data['ema_l']=data.price.ewm(span=EMA[1],min_periods=EMA[1]).mean()
    data.dropna(inplace =True)

    data['position']=np.where(data['ema_s']>data['ema_l'],1,-1)
    data['strategy']=data.position.shift(1)*data['returns']

    return -data[['returns','strategy']].sum().apply(np.exp)[-1]
```

```
brute(run_strategy,((10,50,1),(50,252,1)),finish=None)
```

```
array([ 46., 175.])
```

- Below is the final performance of the optimized trading strategy, the performance is the strategy is recorded to be well below the standard returns.

```
run_strategy_b((46,175))
```

```
returns     5.979788
strategy    1.685819
```

- The performance of strategy is plotted below. This here explains the utter failure of SMA and EMA crossover strategies respectively in regard to Reliance industries stock.

Simple Moving Average/Exponential Moving Average Crossover Strategy

- Here the manipulations done on the data set for the previous two strategies

```
def run_strategy(SMA,EMA):
    data=df.copy()
    data['returns']=np.log(data.price.div(data.price.shift(1)))
    data['sma']=data.price.rolling(SMA).mean()
    data['ema']=data.price.ewm(span=EMA,min_periods=EMA).mean()
    data.dropna(inplace =True)

    data['position']=np.where(data['ema']>data['sma'],1,-1)
    data['strategy']=data.position.shift(1)*data['returns']

    return data[['returns','strategy']].sum().apply(np.exp)
```

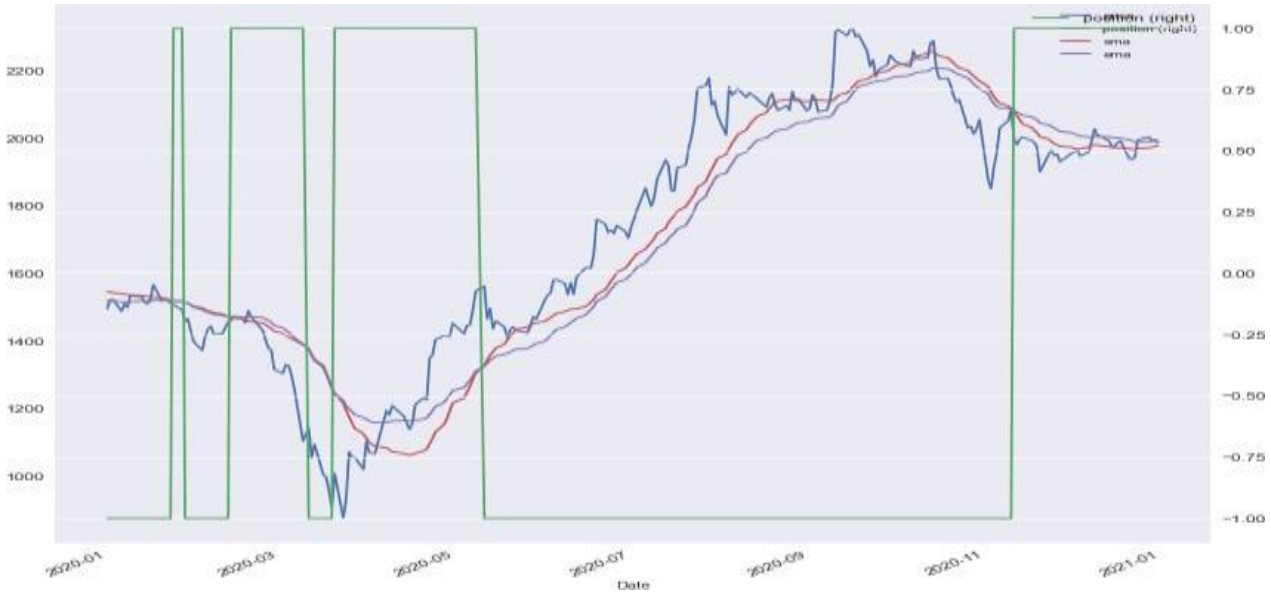
help to cut short the process. An optimization algorithm is created by using the below function.

- Optimization is automated with the help of brute module.

```
brute(run_strategy_optimization,((20,100,1),(20,100,1)),finish=None)
```

```
array([23., 33.])
```

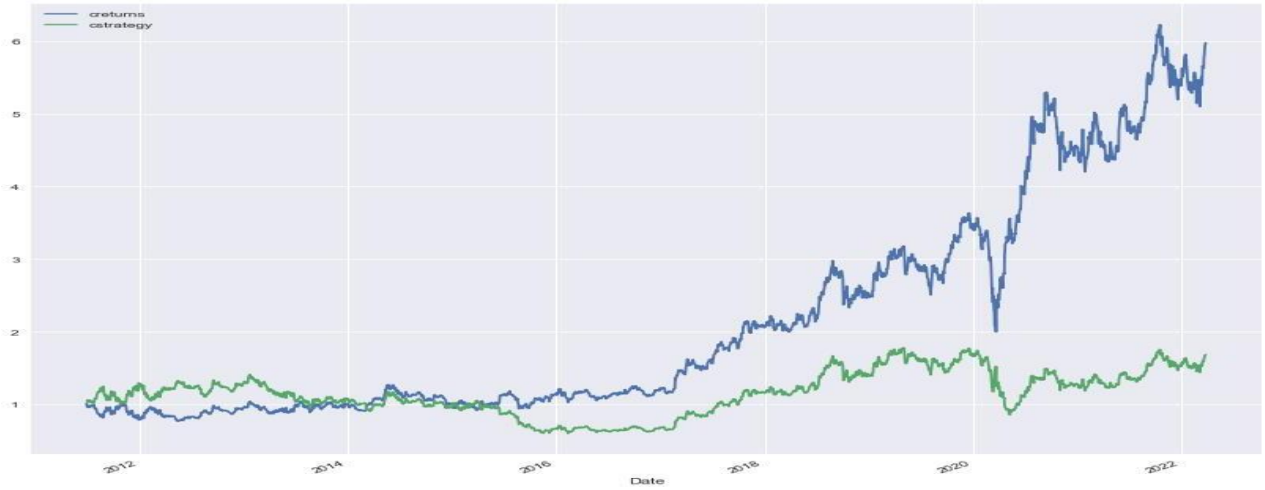
- Below is the plot of positions taken by the algorithm on the basis of optimized parameters.



- Final performance of the strategy is calculated and plotted as shown below.

```
run_strategy(23,33)
```

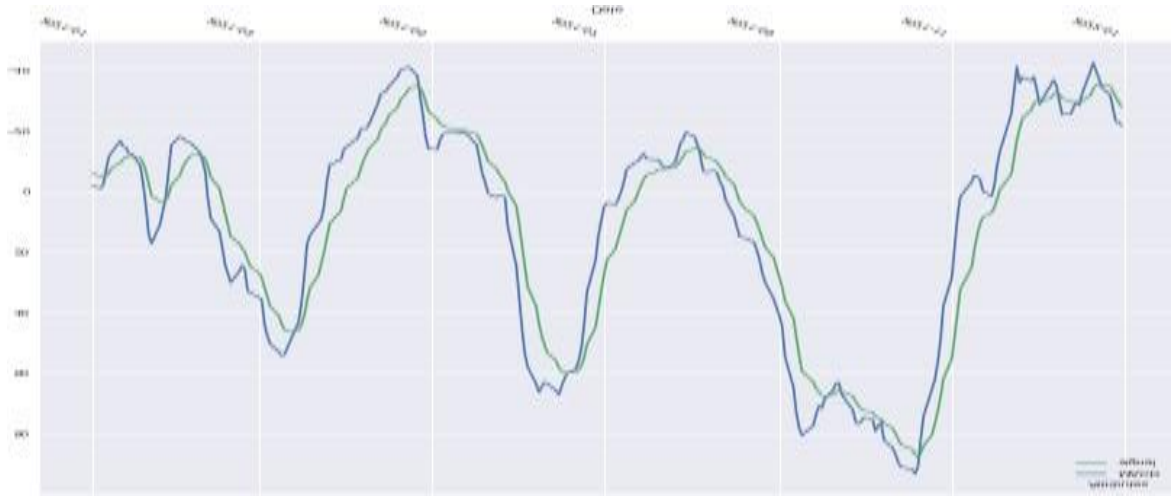
```
returns      5.305278
strategy    18.912151
```



- The performance of strategy has greatly outperformed the buy and hold strategy which is to be exact 1891% or 1361% better than the buy and hold strategy. This strategy is very well suited for the Reliance industries stock.

4.3 Moving Average Convergence Divergence (MACD) Strategy

MACD is calculated and plotted as shown below.



Optimization is done by creating the below function.

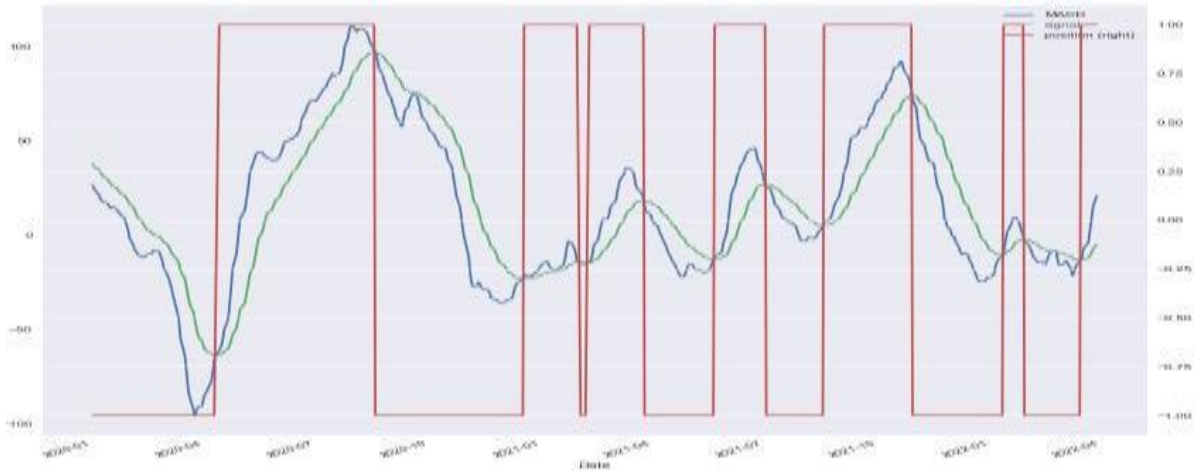
```
def run_strategy_op(x):
    data=df.copy()
    data['returns']=np.log(data.Close.div(data.Close.shift(1)))
    data['ema_s']=data.Close.ewm(span=x[0],min_periods=x[0]).mean()
    data['ema_l']=data.Close.ewm(span=x[1],min_periods=x[1]).mean()
    data['MACD']=data['ema_s']-data['ema_l']
    data['signal']=data.MACD.ewm(span=x[2],min_periods=x[2]).mean()
    data.dropna(inplace =True)

    data['position']=np.where(data['MACD']-data['signal']>0,1,-1)
    data['strategy']=data.position.shift(1)*data['returns']

    return -data[['returns','strategy']].sum().apply(np.exp)[-1]
```

Brute module is used to automate the back-testing of strategy and optimize the parameters.

```
brute(run_strategy_op,((10,50,1),(10,50,1),(10,50,1)),finish=None)
```

```
array([25., 43., 28.])
```

Positions taken by the algorithm on the basis of MACD oscillator crossover strategy is plotted below for the period of 1st January, 2020 to 31st March, 2022.



Performance of the strategy is computed as shown below. The strategy here performs almost similar to the buy and hold strategy returns.

```
run_strategy(25,43,28)
```

```
returns     4.882275
strategy    5.347958
```

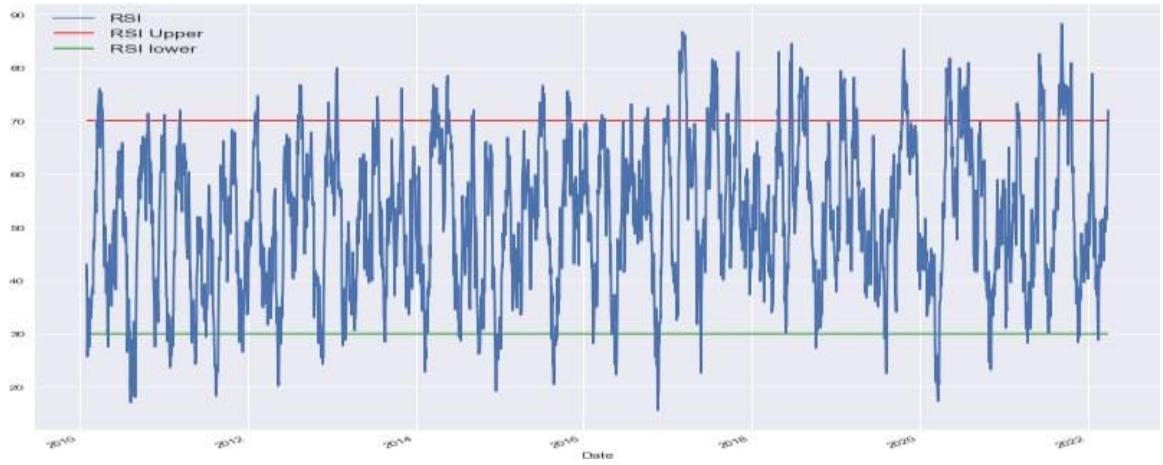
Final performance of MACD oscillator strategy is plotted below.

Here the strategy has performed on the similar level, which is evident in the above graph.

Hence this strategy is not well suited for the Reliance industries stock.

4.4 Relative Strength Index (RSI) strategy

- Using the above strategy, the function (shown below) is created to be used in optimization algorithm.
- This function is altered in order to return the dataset created and plot the RSI graph over the total period.

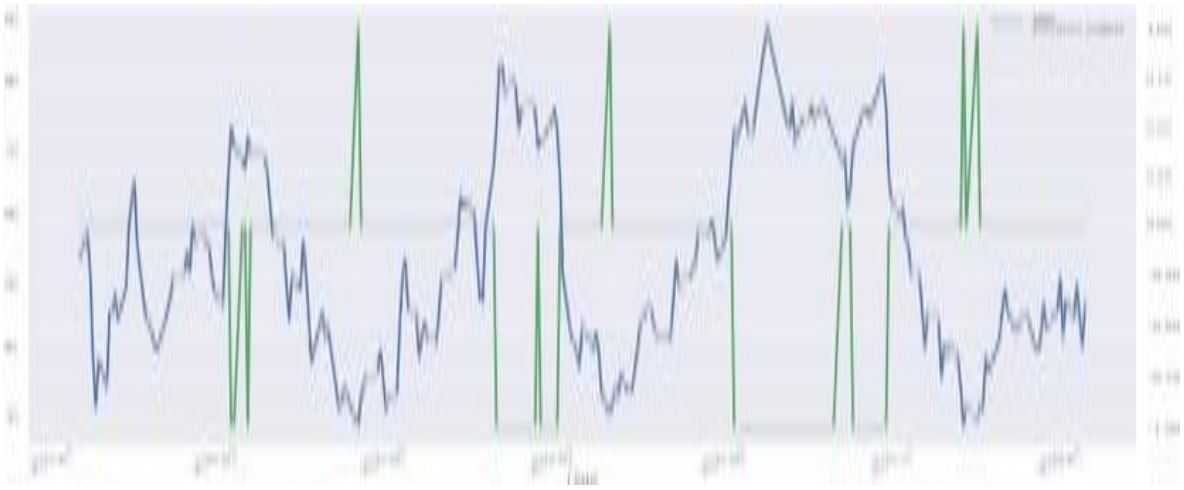


Function is altered again and used in the brute module to get the optimized values of parameters through back-testing. The upper band level is 78, followed by lower band level of 42. The RSI period is 19 days.

```
brute(run_strategy_op,((70,85,1),(20,50,1),(15,25,1)))
```

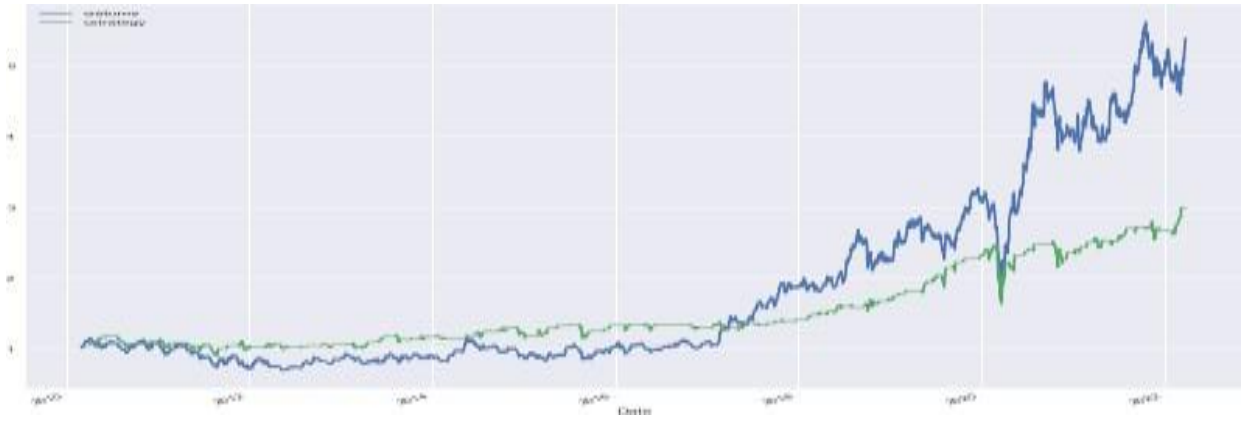
```
array([78., 42., 19.])
```

Based on the strategy, positions taken up by the algorithm is plotted below for the period of 1st January, 2021 to 31st January, 2022.



Final performance based on the value of parameters is computed and plotted as shown below.

```
run_strategy(78,42,19)

returns     5.059842
strategy    2.864305
```



- This strategy has greatly underperformed which indicates it is not fit for the underlying asset which is Reliance industries stock.

- Dataset used for calculating the stochastic oscillator uses opening, closing, highest and closing prices.

Attributes	Close	High	Low	Open
Date				
2010-01-04	532.700500	540.427307	506.127411	540.427307
2010-01-05	530.323059	569.551208	527.697937	569.551208
2010-01-06	538.891846	542.111328	530.298279	534.879883
2010-01-07	547.832092	552.265076	533.938782	538.891846
2010-01-08	546.395691	551.670715	542.854309	548.797974
...	...	...	...	...
2022-03-22	2531.149902	2534.949951	2453.600098	2460.100098
2022-03-23	2539.199951	2564.850098	2523.000000	2523.000000
2022-03-24	2578.649902	2584.149902	2510.000000	2510.000000
2022-03-25	2595.850098	2616.000000	2577.000000	2582.500000
2022-03-28	2621.949951	2629.750000	2586.500000	2610.000000

- In order to calculate the value of stochastic oscillator we use following calculations.

```
period = 14
```

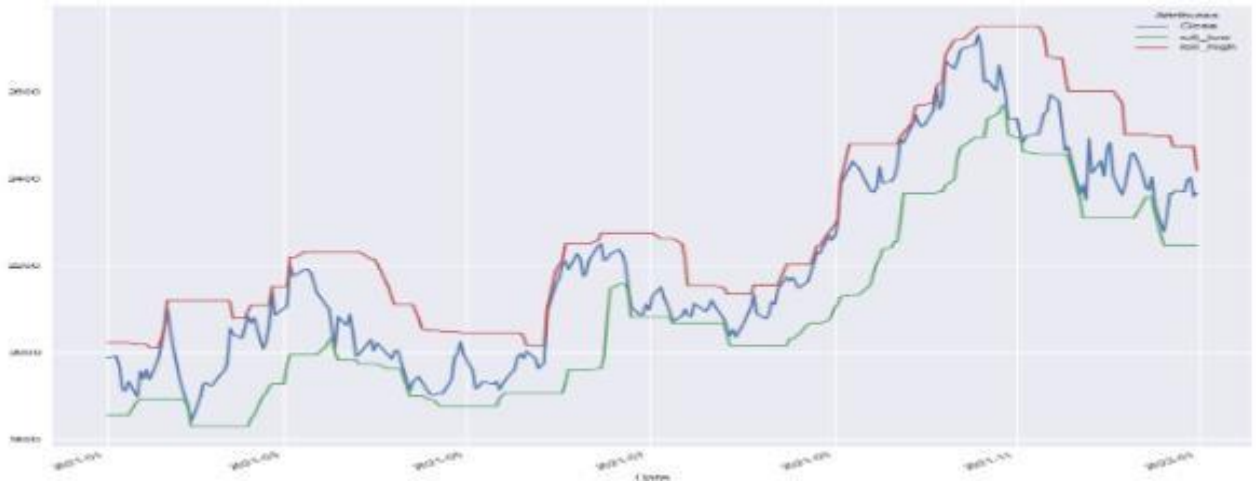
```
re['roll_low']=re.Low.rolling(period).min()
re['roll_high']=re.High.rolling(period).max()
```

```
## calculate %K
re['k']=(re.Close - re.roll_low)/(re.roll_high-re.roll_low)*100
```

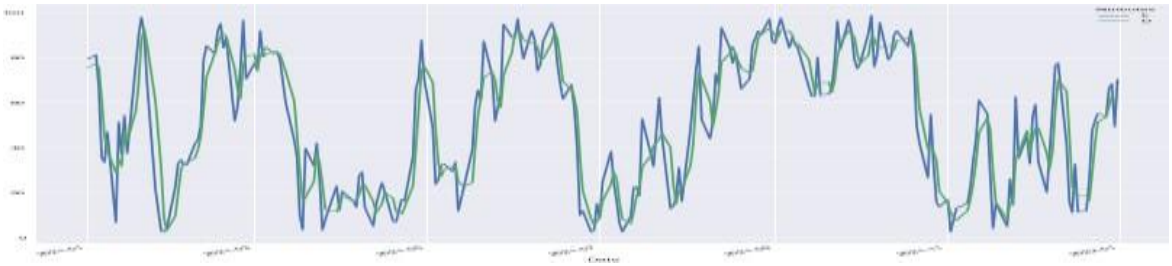
```
## %D is the moving average of %K
window=3
```

```
re['D']=re.k.rolling(window).mean()
```

- Values calculated above are plotted for visualization.

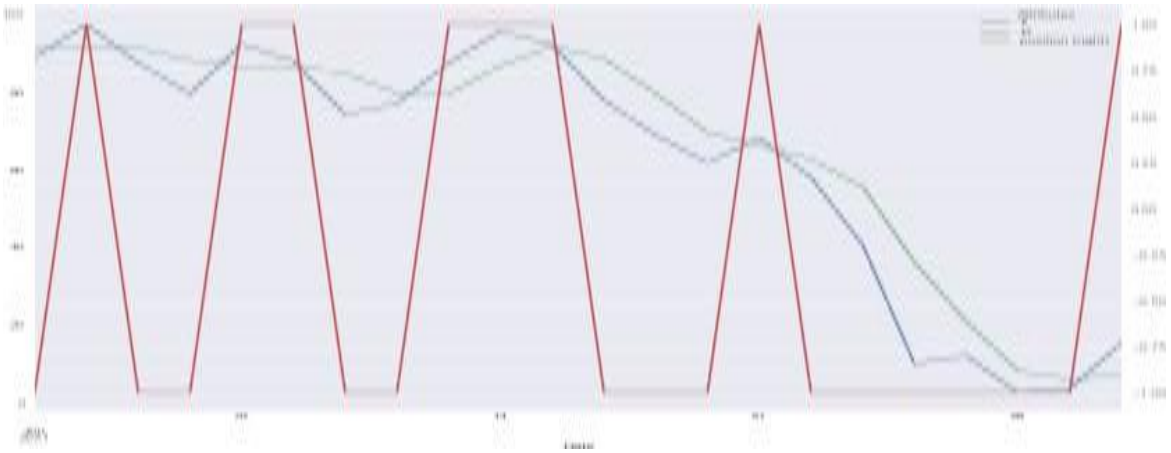


Stochastic oscillator is plotted as shown below.



Function is created to aid in optimization of strategy to get most optimal values.

```
def run_strategy_op(x):
    data=df.copy()
    data['returns']=np.log(data.Close.div(data.Close.shift(1)))
    data['roll_low']=data.Low.rolling(int(x[0])).min()
    data['roll_high']=data.High.rolling(int(x[0])).max()
    data['k']=(data.Close - data.roll_low)/(data.roll_high-data.roll_low)*100
    data['D']=data.k.rolling(int(x[1])).mean()
    data.dropna(inplace=True)

    data['position']=np.where(data.k>data.D,1,-1)
    data['strategy']=data.position.shift(1)*data['returns']

    data['creturns']=data.returns.cumsum().apply(np.exp)
    data['cstrategy']=data.strategy.cumsum().apply(np.exp)

    return -data[['returns','strategy']].sum().apply(np.exp)[-1]
```



Positions taken by the algorithm based on the provided strategy are plotted below.

Final performance is computed as shown below.

```
run_strategy(31,4)
```

```
Attributes
returns      4.956793
strategy    17.641280
```

Final performance is visualized with the help of the following spot. The strategy developed by using the stochastic oscillator has performed extremely well, the returns received by this strategy are astounding 1764% which has significantly

outperformed the buy and hold strategy. This technical indicator is extremely adaptable to the Reliance industries stock.

4.5 Bollinger Bands Strategy

First step for creating Bollinger bands is creating a simple moving average of a defined period.

```
sma = 30
dev =2
```

```
df['sma']=df['price'].rolling(sma).mean()
```

This function is then used in optimization algorithm with the help of brute, the final performance of the strategy is also calculated and shown below.

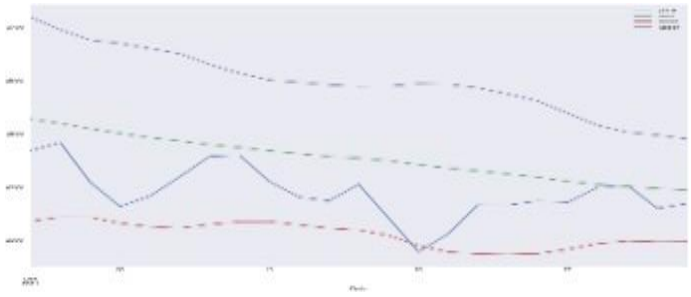
```
brute(run_strategy_op,((25,100,1),(1,5,1)))
```

```
array([95.,  1.])
```

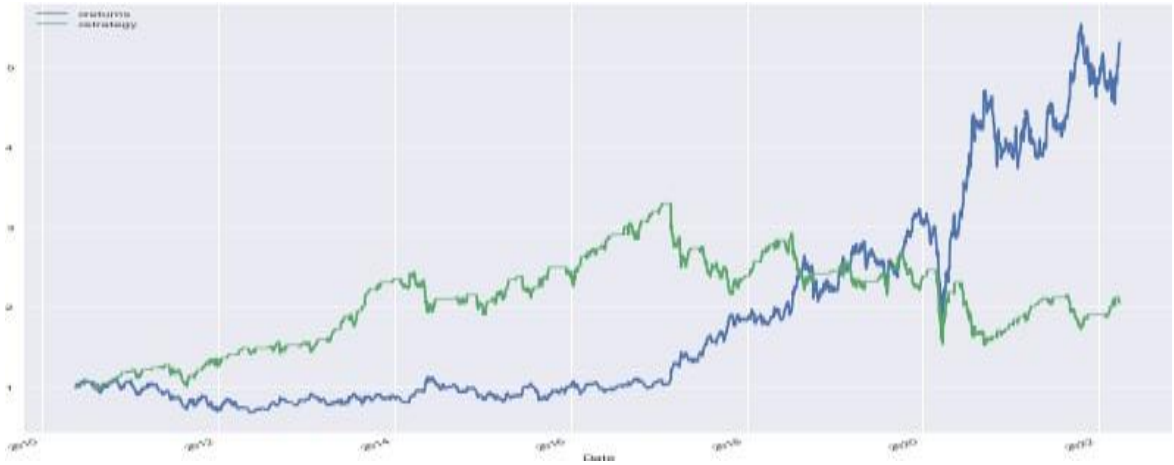
```
run_strategy(95,1)
```

```
returns     5.317269
strategy    2.049419
```

Bollinger bands for the month of December, 2021 is plotted below.



Final performance is plotted below.



The plan has significantly underperformed when in contrast to the buy and hold strategy.

This implies that this technical indicator is not suited for the Reliance industries stock.

5. Discussion

- Simple Moving Average Strategy: The strategy does not perform very well, the earnings are abundant inferior than the simple buy and hold stratagem returns.

- Exponential Moving Average Strategy: This strategy performs similar to SMA strategy.

  It is not well suited and fails to match the normal returns of the Reliance industries stock.

- SMA/EMA Crossover Strategy: This approach uses both simple and exponential moving means to produce buy/sell indications. After optimization this strategy has performed extremely well by providing with 18.91 times the initial investment during the time span under consideration.

- MACD Strategy: This strategy has not performed very well even after optimization; this indicates that this technical indicator is not successful in generating correct Conclusion

In this research paper it is observed that not all technical indicators are well suited to different securities, in the case of Reliance industries stock seven strategies were tested which were Simple moving average crossover approach, Exponential moving average verge approach, Simple and Exponential moving average crossover strategy, MACD oscillator strategy, RSI strategy, Stochastic oscillator strategy and Bollinger bands strategy (Ciana, 2011). Out of these Simple and Exponential moving average crossover strategy and Stochastic oscillator strategy have performed extremely well with a return of approximately 1800% and 1700% on the initial investment. This when compared to the returns of buy and hold strategy, which yielded approximately 500%, is almost more than twice. Considering that Reliance industries stock has performed very well during the time period of the study, if these trading strategies were used then an investor could get a considerable amount of profit during this time frame.

This performance of algorithmic trading is just a preview of the sheer power of the possibilities which arise when using them. As there were tailored strategies for Reliance industries stock, similarly we can create and optimize strategies for various securities as it is a well-known practice to diversify the portfolio in order to mitigate the risk such as Rawal (2015) and Bai et al. (2016). The vectorized backtesting allows us to build strategies which can be used in all asset classes be it stocks, forex trading, crypto trading, etc. Since these markets are highly volatile, therefore, there is a constant need to update the algorithm according to the vigorous marketplace circumstances in order to offer with the best conceivable optimizations.

6. Limitations of the study

- The data used in this paper is of only one security which is Reliance industries stock;
- Each strategy requires extensive coding and computation, which in-turn requires a lot of time;
- The study is limited to my knowledge of Python3 and its modules.

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