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Order Imbalance Based Strategy in High Frequency Algorithmic Trading

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***Abstract* - Algorithmic trading, which is also called automated trading, uses a computer program that follows a defined set of instructions (an algorithm) to place a trade. Algorithmic trading can generate profits at a speed and frequency that is impossible for a human trader. Algo-trading renders markets more liquid and trading more systematic by ruling out the impact of human emotions on trading activities.**

***Index Terms* - Algorithmic trading, financial market, High frequency trading, Order imbalance-based strategy.**

I.INTRODUCTION

Trading is a crucial part of any economy. The common goal of every trader is to maximize profits. Algorithmic trading is a type of trading which uses a set of instructions known as algorithms to perform trades. Algo trading reduces the latency in performing trades and thus offers a higher efficiency. It also avoids human emotional interference. Thus, developing an algorithmic trading software which performs trades on a highly accurate strategy with almost no human interaction, offers a convenient trading system. Here for algorithmic trading, order imbalance strategy is used. As the name suggests, order imbalance is a well developed and tested strategy which uses analysis of the order book to conclude the current market trend. It relies upon the current and previous bid and ask prices from the order book to compare the prices and volumes to conclude a price momentum. The strategy gives a signal to enter a long position when the value is positive and a short position when the value comes to be negative; thus, signaling an upward or a downward trend respectively. Increase in the current bid price than the previous one implies an upward price momentum, whereas decrease in the current ask price than the previous implies a downward price momentum. The strategy thus offers a strong signal to choose the position to enter a trade.

II. LITERATURE SURVEY

This paper highlights the importance of rapidly developing High Frequency type of algorithmic trading. Further it illustrates the fundamental aspects and functions of "market maker" i.e. the control strategies available. Two of those are : Events Arbitrage: Here profit trading is done on the basis of market response to company events and performance. Statistical Arbitrage: A time series statistical analysis is used to predict and analyze stock prices and market volatility. The paper goes on to discuss methods and techniques to regulate the digital trading systems.[1]

Studies the statistical and economic performance of the statistical arbitrage strategy using Extreme Learning Machine (ELM) and Support Vector Regression (SVR) models, and their forecast combination through four linear combination models. Also evaluates the trading risk for the series described in this paper, using the Sharpe ratio as a risk measure. Hence presents evidence that financial performance for most cointegrated pairs can be improved by at least one linear combination technique.[2]

This paper explains about different HFAT strategies and how they vary. It discusses market makers strategy in detail which makes the trader enter from both sides of the trade, thereby increasing the liquidity of the equity. In addition, presents the results of simulation experiments to compare different kinds of market making strategies and shows that trading speed plays an important role in this strategy, especially when the number of HFTs increases.[3]

This paper focuses on explaining what algorithmic trading is, and that it is beneficial as digital machines are more efficient than humans. It discusses the actual structure of how an algorithm executes a trade, and its necessary parameters like trade signal generation, entry point, exit point etc. [4]

A comprehensive study is imparted here covering the order imbalance strategy for high frequency trading. This strategy depends upon the current as well as previous ask and bid prices and the volume of the equity traded to predict the future price of the equity, as well as execute the trades using them as a trigger. It also discusses the results of the strategy in the actual market, and on improvement for the same.[5]

III. SYSTEM ARCHITECTURE

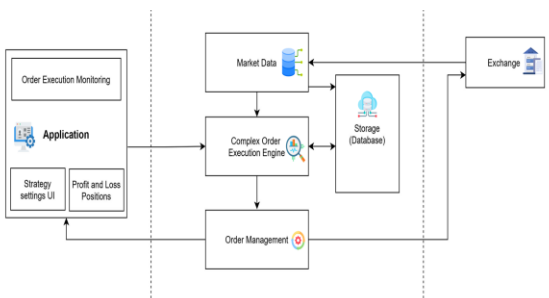

Fig. System Architecture

The user interacts with the UI to create a profile, log in to the system, set parameters and provide input to the algorithm. Based on the user input and the real-time market data coming from the Exchange API, the Complex Execution Engine executes the algorithm and makes trade decisions. Order Management keeps a record of trades made, updates the UI and sends data to the broker API, which further interacts with the stock exchange and executes the trades.

IV. ALGORITHM STRATEGY

For a successful trading algorithm, it is important to identify the trend. Order imbalance is one such strategy that can help us identify the current trend of equity in a live market.

Order Imbalance Strategy

$$OI_t = \delta V_t^B - \delta V_t^A$$

where

$$\delta V_t^B = \begin{cases} 0, & P_t^B < P_{t-1}^B \\ V_t^B - V_{t-1}^B, & P_t^B = P_{t-1}^B \\ V_t^B, & P_t^B > P_{t-1}^B \end{cases}, \qquad \delta V_t^A = \begin{cases} V_t^A, & P_t^A < P_{t-1}^A \\ V_t^A - V_{t-1}^A, & P_t^A = P_{t-1}^A \\ 0, & P_t^A > P_{t-1}^A \end{cases}$$

Fig. Order Imbalance Strategy

Where V B t and V A t are the bid and ask volumes at time t respectively and P B t and P A t are the best bid and ask prices at time t respectively

If there is a decrease in the current bid price than the previous bid price, it is implied that the trader might have cancelled their buy limit order or that an order got filled at that price P B t-1 The intent of the trader cannot be ascertained as we do not have a briefer order book, so δVBt is set to 0. If there is no change in the current bid price than the previous, the difference between the volumes is used to represent incremental buying pressure. If there is an increase in the current bid price than the previous bid price, it is clear that the trader's intent is to buy at a higher price. Hence, it can be interpreted as an upward price momentum. Using the ask prices analogously, downward price momentum can be interpreted.

Order imbalance only forms a part of the algorithm. The complete steps for the algorithm are as follows: Upon receiving the real time data from the stock exchange, the data is processed based on order imbalance. This detects the momentum of the market and the system takes a decision to go long or short by plotting a graph of VOI against Price change for the previous values, we can apply linear regression to predict the future price of the equity. This gives the system a virtual final point for exit of trade, assuming no trend reversal in between The system continuously checks the market data using the same order imbalance strategy to keep monitoring the trend and if there is a trend reversal, exiting the trade. This process continues on a loop, thus placing a high number of orders by the end.

V. ALGORITHMIC ANALYSIS

The algorithm can be considered to have three parts, namely:

A. Trend Identification - Entry
B. Price prediction - Virtual Exit
C. Trend monitoring - Exit

The final time complexity can be calculated by calculating the time complexities of each part separately.

A. Trend Identification - The list of market orders received is iterated to conclude the trend direction. Thus, its time complexity comes to be *O(n)*.

B. Linear Regression Assuming the data matrix to be of size (n x k), the run time of linear regression comes to be $O(k^2 * (n+k))$.

C. Trend monitoring This is the same as the first step and has the same time complexity, that is $O(n)$.
Thus, the total time complexity of the algorithm is:
$= O(n) + O(k^2 (n+k)) + O(n)$
$= O(2n + k^2 (n+k))$

VI. CONCLUSION

Irrespective of the stock market conditions and current behavior, taking these algorithmic trading strategies into consideration we can perform profitable trades with very less to no human interaction based on a pre-studied strategic algorithm. Algorithmic trading not only provides Security, Cost-effectiveness, and Speed but is also a revolutionary technology for the future financial markets. The Order Imbalance Strategy discussed here is well tested and can be used to predict the momentum of the equity and the direction of price change successfully.

Industries and real-time applications can be listed as following for algorithmic trading:
i. Institutional investors like banks, credit unions
ii. Insurance companies, investment advisors
iii. Mutual funds companies
iv. FinTech Platforms use algo trading and AI to provide clients with curated portfolios.

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