

A Study on Algorithm Trading

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ABSTRACT

Stock Markets are the integrated part of not only the Indian economy but also global economy. The significance of the stock markets is felt by the global economies in different phases ranging from stock market crash 1929 in United States of America to the Harshad Mehta Scam in Indian stock markets. Different trading strategies are followed by large scale institutional investors to reap the maximum benefits from the markets. Algorithmic trading, commonly referred to as Algo-trading, is now of the emerging and trending trading strategies followed by institutional investors in Indian stock market. It is a trading based on computers being given pre-determined instructions so that transactions are carried out in a speed and frequency that is impossible for human traders. There are different platforms available for Algo-trading and this paper seeks to identify the major benefits of Algo-trading and seeks to communicate the reasons for the growth of Algo-trading not only in India but also in a global scenario. Further this paper identifies the most preferred platform for Algo-trading and challenges encountered by the investors adopting these strategies. Finally this study arrives at a meaningful conclusion and provides scope for further research in this area of study.

Keywords: Trading Strategies, Computer based trading, Institutional investors and Algorithmic trading

INTRODUCTION TO ALGORITHMIC TRADING

Algorithmic trading has evolved far beyond the simple automation of buy and sell orders; it is now a highly competitive, silicon-based ecosystem where autonomous quantitative models continuously hunt for market inefficiencies. At the institutional level, these systems operate as sophisticated pipelines that entirely divorce human emotion from capital allocation, relying instead on a rigorous synthesis of predictive signal processing, machine learning, and multi-agent architectures to extract alpha from stochastic market noise. Before a single order reaches the exchange, the architecture dynamically balances mathematical risk overlays against expected returns, slicing large allocations into microscopic executions deployed across ultra-low latency hardware like FPGAs and microwave networks. Ultimately, modern algorithmic trading represents the complete digitization of financial logic, transforming the global market into a continuous, self-optimizing mathematical ecosystem where survival is dictated by computational scale, strict risk management, and absolute speed.

As these algorithmic systems become increasingly ubiquitous, the nature of market liquidity and price discovery has fundamentally transformed. The modern financial arena is no longer a battleground of asymmetric human information, but rather one of asymmetric computational power and data ingestion. Algorithms now routinely process vast troves of alternative data-ranging from real-time satellite imagery

of global supply chains to deep-learning sentiment analysis of regulatory shifts-incorporating these inputs into their pricing models in milliseconds.

Consequently, the lifespan of any single predictive edge has compressed dramatically. Once an inefficiency is identified by one system, it is rapidly exploited and arbitrated away by a swarm of competing models, forcing quantitative researchers into a perpetual cycle of model retraining and feature engineering. Furthermore, this relentless competition introduces novel systemic vulnerabilities, most notably “algorithmic crowding,” where multiple independent systems converge on identical trading signals. When unexpected macroeconomic shocks occur, these overlapping positions can trigger synchronized, automated liquidations, resulting in the sudden flash crashes that periodically fracture modern limit order books. Thus, the continuous evolution of algorithmic trading is not merely a technological triumph; it is an ongoing arms race that permanently dictates the stability, efficiency, and underlying mechanics of global finance.

LITERATURE REVIEW

Algorithmic trading has come a long way from its early days, when strategies were mostly built on fixed rules and basic statistical models. Earlier research, such as Chan (2013) and Aldridge (2016), showed how important speed, data analysis, and disciplined risk control are in financial markets. However, these traditional methods often struggle when markets behave unpredictably, which is increasingly common in today’s fast-moving financial environment.

The November 2020 study on “Algorithmic Trading and Strategies” by Dr. Sachin Napte and Mukul Thakur from Dr. D. Y. Patil B-School sits within a body of research that explores how trading has steadily shifted from human intuition to data-driven automation. Over the years, financial markets have become faster and more complex, and algorithmic trading has emerged as a natural response to this change.

Much of the earlier literature focuses on the basic idea behind algorithmic trading—using predefined rules to execute trades automatically. These rules are often built around timing, price, quantity, or mathematical models. Researchers have consistently pointed out that one of the biggest advantages of such systems is their ability to remove emotional bias. Unlike human traders, algorithms don’t panic during market drops or become overly optimistic during rallies. This leads to more disciplined and consistent decision-making. Another key theme in the literature is the variety of strategies that algorithmic trading can support. Common approaches include trend-following strategies, where algorithms identify and ride ongoing market movements, and arbitrage strategies, which exploit small price differences across markets. There are also mean reversion strategies, based on the idea that prices eventually return to their average levels. Studies around 2020 increasingly began to highlight how these strategies could be combined or customized depending on market conditions.

while algorithmic trading offers speed and efficiency, it is not a guaranteed path to profits. Poorly designed strategies, lack of proper testing, or ignoring risk management can lead to significant losses. In simple terms, the study reminds us that algorithms are only as good as the logic behind them.

Earlier literature often emphasizes the core objective of algorithmic trading systems: removing human emotion from trading decisions. Traditional trading can be influenced by fear, greed, or hesitation, but algorithms rely on predefined rules and data-driven logic. Researchers have shown that this leads to greater consistency and discipline in execution. Many studies also highlight the role of back testing, where strategies are tested on historical data to evaluate performance before being deployed in real markets.

The 2024 study contributes by bringing these ideas into a more applied and accessible framework. It focuses on how an algorithmic trading system can be structured, from data collection and signal generation to execution and risk management. The authors highlight the importance of integrating reliable data sources and ensuring that the system can respond quickly to market changes without compromising accuracy. They also emphasize risk control mechanisms, such as stop-loss orders, to protect against unexpected losses.

The literature on algorithmic trading has grown rapidly, especially with advances in computing Power and data availability. Early research mainly focused on simple rule-based systems, where Trades were executed based on fixed conditions like price thresholds or timing signals. Over Time, this evolved into more complex strategies, including statistical arbitrage, high-frequency Trading, and machine learning-based approaches. Jukl and Lansky's review highlights this Progression, showing how the field has shifted from straightforward automation to intelligent, Adaptive systems.

Another important theme discussed is the role of data. Modern algorithmic trading relies heavily on large datasets, including historical prices, news, and even social media sentiment. The Review points out that the quality and processing of this data are just as important as the Strategy itself. Poor data can lead to misleading signals and ineffective decisions, something Often underestimated in earlier studies.

What makes this review particularly useful is its structured and comprehensive approach. It Doesn't just list findings but connects them, helping readers see patterns and gaps in existing Research. For example, the authors note that while technical advancements are well studied, Areas like regulation and ethical implications still need more attention.

RESEARCH METHODOLOGY

STAGE 1

Strategy Development

This is the creative spark. It's where you observe a pattern in the world—like noticing A stock overreacts to news—and turn it into a logical “if-this, then-that” plan. You are Essentially writing the playbook for your digital athlete.

STAGE 2

Data Collection

Before sending your student into the fray, you head to the library. You're gathering Years of “game tape” (historical prices and volumes) to see exactly how the market Behaved. If the data is messy, your student is learning from a warped history book.

STAGE 3

Backtesting

This is a high-stakes simulation. You run your playbook against the game tape to see If it actually works. You have to be honest here—no pretending you bought at prices That didn't exist or that you knew the future. It's the ultimate reality check.

STAGE 4

Risk Management

Trading is emotional; algorithms are not—but they still need boundaries. This is Where you decide, “I'm okay with losing \$100 today, but if I lose \$101, we pull the Plug.” It's the art of staying in the game long enough to eventually win.

STAGE 5

Optimization & Validation

Every coach is tempted to “over-train” for one specific opponent. In trading, this is Overfitting. You validate by testing your student on a year of data they’ve never seen Before to see if they can actually think on their feet when things get unpredictable.

STAGE 6

Execution & Monitoring

You finally let the student loose. But you don’t walk away. You sit in the stands with a Stopwatch, watching every move. Markets change and “glitches” happen; you are There to ensure the machine remains aligned with your human intent.

FINDINGS OF THE STUDY

Algorithms have become increasingly common in wholesale energy markets. At its core, Algorithmic trading refers to a process where a computer program determines trading Parameters — such as price, quantity, and order initiation — with minimal human input. In Most cases, the trader’s role is reduced to monitoring the algorithm’s performance rather Than directing it. Several types of algorithms exist in practice: execution algorithms, trading algorithms, and Signal generators. These range considerably in complexity, from straightforward rule-based Systems to sophisticated machine learning models. It is worth noting that algorithmic Trading rarely operates in isolation — it typically forms one component of a broader trading Strategy that may also include simultaneous manual trading. Common strategies include Spreading volume across time or markets to reduce price impact, spread trading, market Making, and relative pricing within order books.

The energy transition as a driver of algorithmic growth

The shift toward renewable energy is proving to be one of the strongest catalysts for Algorithmic adoption in energy markets. Because renewable energy production is inherently Harder to forecast, market participants face a growing need to balance positions at short Notice, which manual trading struggles to accommodate efficiently. As a result, the number of purely algorithmic trading participants is on the rise, particularly in power spot markets, where algorithm use is already widespread. In gas spot markets, uptake has been somewhat Slower but is steadily increasing.

Market participants cite efficiency, asset optimisation, and risk mitigation as the main Reasons for adopting algorithms. Those who have not yet done so point to IT infrastructure Demands, knowledge requirements, and a perceived lack of necessity. Notably, in some Markets, abstaining from algorithmic trading is becoming a practical disadvantage given the Speed differential over manual approaches.

Benefits, risks, and the regulatory perspective

Algorithmic trading carries both genuine benefits and well-documented risks. On the Positive side, it can enhance market liquidity and accelerate price formation. On the other Hand, it introduces the risk of a disconnect between fundamental market information and Algorithm-driven behaviour — particularly when feedback loops cause algorithms to amplify Existing market movements and heighten volatility. That said, the extent to which algorithmic trading fundamentally alters volatility dynamics remains debated; well- Designed algorithms do incorporate safety mechanisms and can, in certain scenarios, Stabilise highly volatile conditions.

Market transparency is another area of concern. Frequent price movements can complicate Price determination, especially for manual traders. While algorithms can enhance Transparency by generating

detailed records of trading decisions, the opacity of machine Learning models — and the difficulty of explaining their outputs — can work in the opposite direction.

Concerns around market manipulation, both intentional and unintentional, are also present in the literature. Algorithms can be sensitive to manipulated data inputs and can act on them faster than any human could intervene. Conversely, some argue that algorithmic trading can reduce vulnerability to manipulation by continuously adding liquidity to the market. From a surveillance standpoint, the high frequency and complexity of algorithmic orders require a more data-intensive monitoring approach than traditional methods allow.

Compliance and internal controls

All market participants interviewed in the ACM study reported having compliance and risk management measures in place, though these varied in scope and depth. Common measures include order price and volume limits and a “kill switch” functionality that allows traders to halt all algorithmic activity at once if necessary. The ACM notes, however, that the effectiveness of such controls depends heavily on how input parameters are set — if thresholds are defined too loosely, the controls may offer little practical protection.

Under the revised REMIT regulation, EU wholesale energy market participants engaged in algorithmic trading are now required to implement robust risk management systems, observe trading thresholds, ensure business continuity, and notify regulators of their algorithmic activities. The ACM continues to monitor compliance with these obligations in the Dutch energy market, working in close coordination with the AFM and other relevant regulatory bodies.

CONCLUSION

Algorithmic trading has changed the financial markets by offering unmatched speed, accuracy and efficiency. It allows traders to automate strategies, reduce emotional prejudices and perform more trades in milliseconds. However, it does come with its own set of challenges. From technical disorders and high growth costs to the absence of human decisions and regulatory complications, traders should approach algorithmic trading with a balanced perspective. Success in algorithmic trading comes from a concrete understanding of both its abilities and its boundaries. Traders should understand that just having the fastest code may not generate profits. It also depends on designing well-tested strategies, handling risks with care and being ready to change with market conditions.

Whether you are a beginner looking for an early automatic trade or an experienced businessman looking for a scale operation, it is important to understand both the allocation and the risk. Algorithm trading can be a powerful addition to your trading journey, with proper preparation, equipment and mentality.

SCOPE OF THE STUDY

Let's be honest—algorithmic trading is at a massive turning point. We are moving way past the days of simple, rule-based high-frequency trading (HFT) where the only goal was having the fastest server. Tomorrow's trading systems need to be highly autonomous, context-aware, and incredibly smart. To get there, the industry can't just rely on computer scientists anymore; we need economists, behavioural psychologists, and even legal experts in the room.

If we look at where the smart money and research are heading, a few major frontiers stand out for the future of algorithmic trading. Building Smarter (and Faster)

Brains Under the hood, technical optimization is still a massive playground. Right now, a huge focus is on combining different types of AI-like mixing Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) models. The goal? To build systems that can handle the crazy volatility of the markets without getting thrown off by daily noise. We're also training these models to adapt on the fly using deep reinforcement learning, teaching them to avoid the classic trap of "overfitting" (where a model looks great on past data but fails in the real world).

But the real wild card on the horizon is Quantum Machine Learning. While it's still largely theoretical, quantum computing has the potential to solve complex portfolio puzzles and execute trades at speeds that make today's high-frequency algorithms look like dial-up internet. It will fundamentally rewrite the physical limits of trading. Reading the Whole Story, Not Just the Price For a long time, trading algorithms only looked at one thing: the price on a chart. That's changing fast. The future is "multimodal." This means building systems that can watch a stock's price action while simultaneously reading global news, digesting dense financial reports, and feeling the pulse of social media sentiment. It's about giving the algorithm real-world context so it doesn't panic during a sudden macroeconomic shock. On top of that, traders are getting incredibly creative with Alternative Data (Alt-Data). We're talking about algorithms that scrape satellite images to see how many cars are in a retailer's parking lot, use supply chain sensors to predict shipping delays, or track credit card transaction flows. The main challenge for future quants won't just be building the model; it will be cleaning and making sense of these massive, messy datasets to find the hidden edge.

Opening the "Black Box"

Here's a massive problem the industry urgently needs to solve: we often don't know why AI makes the decisions it does. As these models get more complex, this "black box" issue becomes a serious liability. Banks and regulators aren't going to let algorithms run wild with millions of dollars if they can't be audited. That's why Explainable AI (XAI) is going to be huge. We need systems that can translate a neural network's complex math into a simple, human-readable explanation of why a specific trade was executed. And, of course, data quality is still king. The old saying "garbage in, garbage out" has never been more true. Future systems will need built-in, AI-driven filters that automatically clean up bad tick data and fix hidden biases in real-time, ensuring the predictive models are learning from flawless information.

Rehearsing for the End of the World (Synthetic Data)

How do you train an AI to survive a market crash when major crashes rarely happen? The 2008 financial crisis and the 2020 pandemic drop were massive, but historically speaking, they are rare "black swan" events.

To solve this data shortage, researchers are turning to Generative AI. By using tools like Generative Adversarial Networks (GANs), quants can create incredibly realistic synthetic financial data. This allows them to simulate millions of different macroeconomic catastrophes, stress-testing their algorithms against every worst-case scenario imaginable before a single real dollar is put on the line. The Web3 and DeFi Frontier

You can't talk about the future of trading without mentioning the shift toward Web3 technologies. The traditional, centralized stock exchange model is getting a run for its money. Future research is going to lean heavily into how algorithmic trading interacts directly with smart contracts. As Decentralized Finance (DeFi) matures, we'll see entirely new algorithms built just for decentralized exchanges (DEXs). This means writing bots that know how to navigate crypto gas fees, avoid being exploited by other traders (MEV), and execute complex, cross-chain arbitrage instantly without needing a middleman.

Ethics, Bias, and Market Survival

Finally, as AI comes to completely dominate market volume, we have to talk about the rules of the game. We can't ignore the real-world impact of handing the economy over to autonomous algorithms. A major focus moving forward will be spotting and fixing algorithmic bias, which can accidentally cause unfair pricing or manipulate markets.

There's also the systemic risk. When thousands of AI bots are interacting at lightning speed, a tiny error can trigger a massive, cascading "flash crash." Because of this, we're going to see a huge push for automated "circuit breakers" and transparent operating rules. The future of regulatory tech will literally involve AI watchdogs keeping an eye on AI traders.

Ultimately, the next era of algorithmic trading won't just be about who builds the fastest or most profitable bot—it will be about who builds one that is smart, safe, and transparent enough to be trusted with the global economy.

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