International Journal on Science and Technology (IJSAT)
E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Proximal Policy Optimization (PPO)–Driven Reinforcement Learning Model for Automatic Stock Trading using the combination of Trend–Volume–Volatility Integration

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Abstract
The stock market trading is an area full of uncertainties as price changes happen very often, and the markets can be noisy; besides, market volatility can change too, which in turn causes unreliable signals when solely relying on a single technical indicator. This paper proposes the implementation of a strong and dependable multi-indicator trading system that combines the use of Simple Moving Average Crossover (SMAC) for identifying trends, Average Traded Volume (ATV) for validating participation of the market, and Bollinger Bands (BB) for confirmation of prices based on the volatility level. The SMAC indicator forms the backbone of the buy and sell signals, and the support of the trading activity represented by the ATV helps to reduce the risk of false breakouts. The use of Bollinger Bands helps to prevent trading activity during the extreme overbought or oversold market conditions and thus improves the market volatility-based timing of the entry and exit. Moreover, the proposed indicator framework can be further improved by a reinforcement learning agent based on Proximal Policy Optimization (PPO) that interacts with the historical market data in order to learn the best trading actions. The reinforcement learning model takes into account the trend direction, volume strength, volatility position and current portfolio status to make the decision of whether to buy, sell or hold. The historic stock market data-based experimental evaluation shows that the suggested SMAC–ATV–BB–PPO plan results in better trade accuracy, fewer false signals and best risk-adjusted returns in comparison with the conventional SMAC-based trading strategies.

Keywords: Reinforcement Learning, Proximal Policy Optimization, Stock Trading, Simple Moving Average Crossover, Average Traded Volume, Bollinger Bands.

1. Introduction

The financial markets are continually changing and unpredictable, where the price hikes and falls are affected by the traders' actions, market liquidity and volatility. The use of traditional rule-based trading strategies, which are dependent on just one technical indicator, mostly results in the inability to respond to the complex conditions of the market leading to the delayed signals, many false trades and unstable returns. Consequently, there has been an increasing interest in the so-called smart trading systems that ground their decisions on technical analysis and at the same time employ adaptive learning methods. The last few years have seen the rise of reinforcement learning (RL) as a major contributor to become a good trading strategy owing to its ability to represent the sequential decision-making process and to maximize the long-term rewards over the short ones. Through the continuous interaction with the market environment, the RL agents, as opposed to the supervised learning methods, acquire the most favorable trading policies. The methodology of reinforcement learning, being the best among all the trading systems when it comes to their design, was also supported by some studies (Kadia et al.., 2025). The survey studies indeed picture the deep RL models being excellently efficient in capturing the rapidly changing and nonlinear market behaviour (Adhikary et al., 2025). Nonetheless, the reinforcement learning methods based only on price signals are typically plagued with slow convergence, unstable learning, and poor interpretability. Creating a structured state representation by incorporating technical indicators (as recent studies suggest) might be of much help in solving these problems. Integrating technical indicators was found to have an effect of increasing the trading precision and stability by Rajraushan Kumar et al. (2026) and Patel et al. (2020). Hailing from these indicators, the Simple Moving Average Crossover (SMAC) has by far been the most popular in determining the market trend because of its simplicity, though it suffers from lagging and generating false signals in sideways or turbulent markets (Kadia et al., 2025)

To enhance the reliability of signals, Average Traded Volume (ATV) is habitually employed to ratify the participation of the market and the power of the trend. It has been proven that trading less through volume-validated methods and filtering through the movement of prices has been the most common way of conducting trading (Aditya Sharma et al., 2026; Dey et al., 2024; Karaila et al., 2024). Also, Bollinger Bands give a volatility-based mechanism to spot overbought and oversold conditions, which consequently improves the timing of the trade. Papers have shown that Bollinger Bands have a positive effect on trading when they are used as confirmation tools together with trend-following indicators (Kim and Enke, 2016; Kumar et al., 2020).

These results have pushed this research to the proposal of a hybrid trading system that includes Simple Moving Average Crossover (SMAC), Average Traded Volume (ATV), and Bollinger Bands under a Proximal Policy Optimization (PPO)–based reinforcement learning model. The method proposed that takes into account together the trend direction, liquidity strength, and the volatility conditions, intends to cut down on false signals, enhance the execution of trades, and reach automated stock trading with the best risk-adjusted performance.

2. Literature review

The fast development of algorithmic trading has greatly affected the modern financial market analysis and the reinforcement learning (RL) has become the main approach of intelligent trading systems. The classic trading methods that rely on fixed rules and single technical indicators often cannot adjust to the ever-changing market conditions, and therefore their performance becomes quite unstable. The recent studies noticeably advocate the coupling of technical indicators with reinforcement learning models to the extent of adaptability, interpretability, and risk-adjusted returns being improved. This section surveys the existing studies regarding the application of reinforcement learning in the financial markets, trend-following strategies, volume-based indicators, and volatility indicators such as Bollinger Bands, and hybrid indicator–RL frameworks.

2.1. Reinforcement Learning in Financial Markets

Reinforcement learning (RL) has established itself as a powerful tool for the resolution of sequential decision-making problems in challenging and uncertain areas like financial markets. Unlike supervised learning models that depend on labelled datasets, RL agents engage in the market environment through trial-and-error and learn the best trading strategies. Li et al. (2021) conducted a thorough survey of trading systems based on deep reinforcement learning and pointed out their capacity to capture nonlinear market behavior and temporal dependencies. Likewise, Kumar and Singh (2021) noted that policy-gradient and actor–critic methods promise more flexibility than traditional optimization techniques in algorithmic trading.

Following the path of the RL application's advancement in the financial market, Yu et al. (2022) went ahead and pointed out the key issues as feature selection, reward design, and risk management. Huang et al. (2023) showed that deep reinforcement learning models are superior to heuristic strategies in portfolio management provided that the models are equipped with informative state representations. Evidence from Xiong et al. (2023) affirmed that the addition of technical indicators to deep Q-learning frameworks greatly enhances the precision and stability of trading, thus, supporting the significance of structured inputs in RL-based systems.

2.2. Simple Moving Average Crossover Strategies

The Simple Moving Average (SMA) crossover strategy is still very much alive and one of the most popular methods in technical analysis mainly because it is simple and easy to understand. The trading signals are produced when the short-term and long-term moving averages intersect, which could mean that the trend is changing. One of the earliest studies done by Batten et al. (2014) confirmed the possibility of moving average–based strategies being effective in various equity markets. However, even though these strategies are very popular, they still have to deal with the drawbacks of lag times and the generation of false signals during turbulent or sideways trending market conditions.

Researches have been performed to find solutions to these problems by looking into adaptive and learning-based methods for moving average crossover strategies. Jha et al. (2025) concluded that the financial modelling accuracy is significantly improved by the use of a combination of optimisation techniques and machine learning, which raises the question of whether static SMA parameters are truly sufficient in the case of dynamic markets. In a similar vein, Kadia et al. (2025) have proved that SMA-based strategies could be more reliable in the case of integration with reinforcement learning and the use of confirmation indicators, thus confirming the continual relevance of SMA crossover in hybrid trading setups.

2.3. Volume's Effect on Technical Trading

The volume of trading is a very important element in confirming the price changes and judging the market involvement. The Average Traded Volume (ATV) is one of the major guides used for measuring the power and durability of trends. Bhattacharya et al. (2021) have shown that the application of volume data to hybrid machine learning models significantly improves stock price prediction precision. The results of the study imply that trading volumes accompanying price fluctuations are more trustworthy and less likely to be followed by false breakouts.

Kamble and Patil (2023) suggested a volume-weighted reinforcement learning approach for intraday trading and mentioned that it led to a decline in overtrading along with enhanced profitability. All these researches together bring forth the point that the use of volume-based confirmation, especially through ATV, is an essential factor in the process of filtering out the weaker or misleading signals and thus increasing the entire trading performance when combined with the trend-following strategies.

2.4.Volatility-Based Indicators: Bollinger Bands

Trading outcomes are seriously affected by market volatility since the fluctuations in prices may cause the entering and exiting of trades at undesired moments. Financial instruments that are based on volatility, such as Bollinger Bands, are most often employed for this purpose. These instruments are capable of changing their parameters according to the market conditions since the calculation of the upper and lower bands is based on a standard deviation around a moving average. Kim and Enke (2016) proved that volatility-aware trading systems come with the benefit of higher accuracy of decision-making in the futures market. The research pointed out that the testing of the Bollinger Band-based rules in identifying overbought and oversold conditions was successful.

Likewise, Kumar et al. (2020) found that the combination of the Bollinger Bands and machine learning models gives a better trend prediction accuracy. All these studies suggest that Bollinger Bands are very effective as confirmation tools and should not be used only as indicators, they fit nicely in the multi-strategy systems that rely on the information from trend, volume, and volatility interactions.

2.5. Hybrid Models: Combining Technical Indicators and Reinforcement Learning

Increased literature gradually supports hybrid trading frameworks that rely on the integration of various technical indicators in reinforcement learning environments. Wu and He (2023) showed that combining trend, volume, and volatility indicators in the RL-based trading systems not only enhances but also makes the trade drawdowns less. The works of Li et al. (2021) and Huang et al. (2023) indirectly supported this view when they asserted that the states enriched with indicators lead to quicker convergence and better risk-adjusted performance, which is the case in price-only RL models.

Particularly, policy-based methods have been the most successful ones because of their stability in continuous and stochastic environments. Proximal Policy Optimization (PPO), put forward by Schulman et al. (2017), has become a very powerful RL algorithm, thanks to its clipped objective function and stable policy updates. PPO's multifaceted nature has been one of the most important factors behind its extensive use in financial trading applications for executing trades optimally and risk managing effectively.

2.6. Research Gaps and Opportunities

However, in spite of notable progress, a number of voids still exist in current research. A lot of the trading systems based on reinforcement learning are associated with difficult-to-interpret deep learning models, which partially restrict their usage in practice. Furthermore, while the individual effects of SMA, volume, and volatility indicators have been investigated, the joint assimilation of these variables into a unified PPO-based reinforcement learning framework has received very little attention in the literature. Besides, most of the research has been concentrating on short-term performance and has been ignoring long-term stability and transaction costs.

The present study is a response to these gaps and proposes a hybrid trading framework that combines Simple Moving Average Crossover (SMAC), Average Traded Volume (ATV), and Bollinger Bands within a Proximal Policy Optimization (PPO)–based reinforcement learning model. The proposed method aims at enhancing trading reliability, interpretability, and risk-adjusted performance in the real stock market.

3. Methodology and model specifications

This research note outlines a sophisticated multi-indicator trading system that merges conventional technical indicators with a reinforcement learning model to raise the precision and trustworthiness of stock market trading decisions. The suggested method integrates Simple Moving Average Crossover (SMAC) for trend detection with Average Traded Volume (ATV) and Bollinger Bands for the confirmation and filtering of trading signals. A reinforcement learning agent based on Proximal Policy Optimization (PPO) is used to optimize trade execution by learning from past market behavior.

3.1. Data Acquisition

Data from the stock market comes from trusted and generally accepted financial sources. The data can be gathered from the Indian National Stock Exchange (NSE) and Bombay Stock Exchange (BSE), the American New York Stock Exchange (NYSE), and other world exchanges, among others. The information that makes up the dataset is Open, High, Low, Close, and Volume (OHLCV) price data that is necessary for computing technical indicators.

The historical data is what the reinforcement learning model was trained on and evaluated with, whereas the real-time data might be used for live signal generation. The study considers covering a five-year period of OHLCV data for selected large-cap stocks listed on NSE to ensure liquidity and stability.

3.2. Data Processing

The financial time-series data could be missing at times due to market holidays or temporary trading suspensions. To keep the data consistent, the forward-fill method is applied to missing values. The dataset is kept in chronological order to allow the temporal structure necessary for time-series learning and reinforcement learning processes to be preserved. Attributes that are not needed are deleted, and only the features that are necessary for the computation of indicators and the training of the model are kept.

3.3. Calculation of Simple Moving Average Crossover (SMAC)

Trend identification is done primarily through the use of Simple Moving Average (SMA). By averaging the closing prices over a set period, the SMA filters out short-term price changes and shows the true direction of the market.

$$SMA(t,n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \qquad 1$$

where Pt is the closing price at time t, and n is the window length.

Two SMA values are computed:

- Short-term SMA
- Long-term SMA
-

Trading signals are generated as:

- **Golden Cross (Buy Signal):** Short-term SMA crosses above long-term SMA
- **Death Cross (Sell Signal):** Short-term SMA crosses below long-term SMA

As much as SMAC might help in identifying a prevailing sentiment, this signal might not always work on the sideways market or the penny-volume situation.

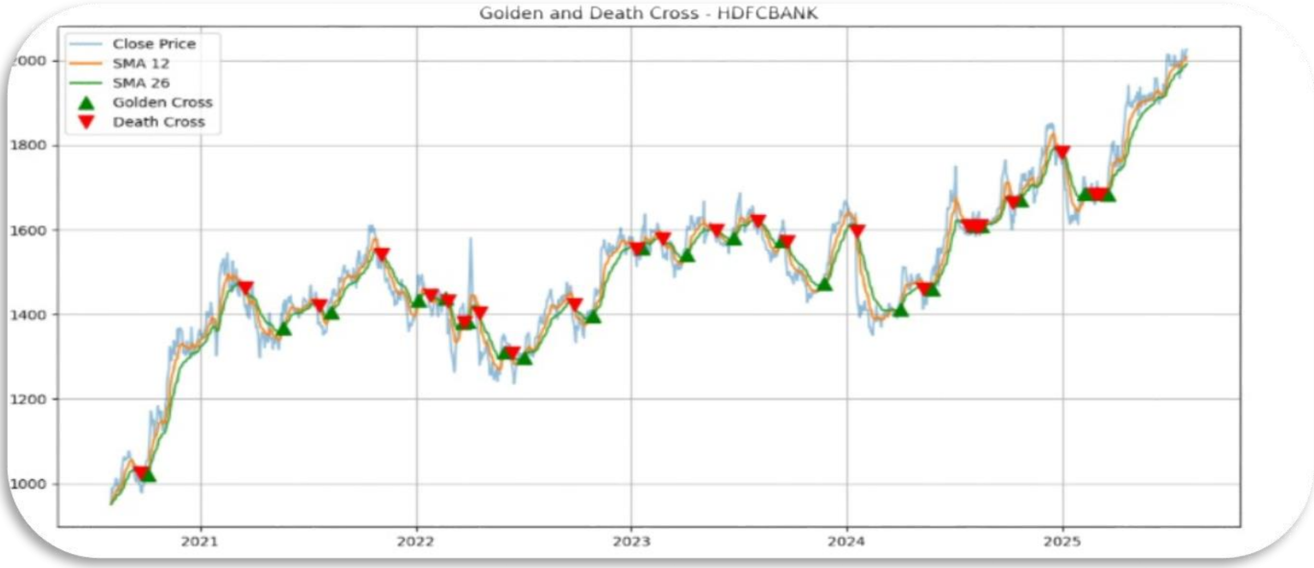

Figure 1: 12 Days and 26 Days SMA Crossover of HDFC Bank (1st June,2020 – 31st May,2025)

Figure 1 shows the 12-day and 26-day moving averages and their crossovers for the last 5 years. The 12-day SMA is denoted by the orange color and the 26-day SMA is depicted by the green color. A golden crossover happens when the orange line goes up and crosses the green line and is a buy signal represented by the green triangle, while the opposite with the red triangle stands for the death crossover or sell signal which takes place when the orange line goes down and crosses the green line from above to below.

3.4. Average Traded Volume (ATV) Confirmation

In order to fortify the signals generated by SMAC, the Average Traded Volume (ATV) is utilized as a volume confirmation indicator. ATV indicates the average shares exchanged during a certain period and indicates the extent of market involvement.

$$ATV_t = \frac{1}{m}\sum_{i=0}^{m-1} V_{t-i} \qquad 2$$

where Vt represents trading volume at time t.

A SMAC signal is considered valid only if:

$$V_i > ATV_t \qquad 3$$

A SMAC signal gets the status of a valid signal if and only if the current trading volume goes beyond the average volume traded, so that the price changes are backed up by the market participation which is enough. This scenario acts as a filter for weak signals and also lowers the number of false breakouts that are caused by low liquidity.

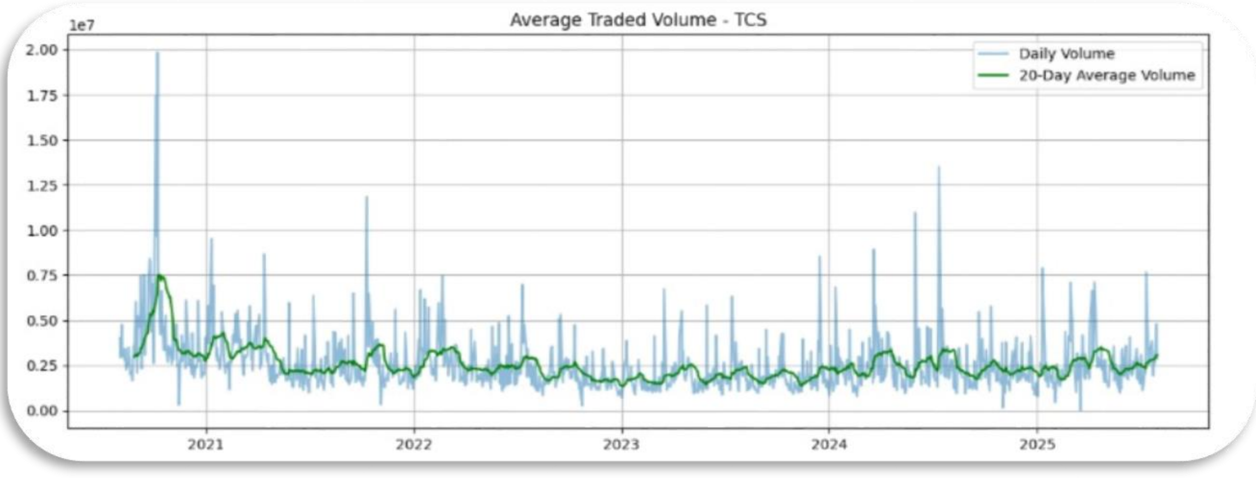

Figure 2: Average Traded Volume 20 Days MA (1st June,2020 – 31st May,2025)

Trading volumes for the last five years as indicated by the date and a 20-day moving average line of the same are shown in Figure 3. The rising of the line indicates that the volume is increasing and the traders are getting attracted to the stock. There is a chance that the prices will fluctuate a lot (upward or downward) in the very near future. The direction of the price movement (upward or downward) is indicated by the SMA and MFI whereas the movement of the average line is downward which means that the traders are losing interest in the stock. There is a high chance of price movement being sideways. A threshold medium was used to support this claim. Only the buy signals from the SMA were acted upon when the ATVMF was above its 20-day mean, indicating a positive money inflow; the sell signals were confirmed when the ATVMF fell below the mean.

3.5. Volatility-Based Indicators: Bollinger Bands

One of the purposes of Bollinger Bands is to add market volatility to the trading decision-making process. The bands consist of the middle band (which is the simple moving average) and two outer bands calculated based on the standard deviation.

$$Upper\ Band = SMA + k\sigma \quad (4)$$
$$Lower\ Band = SMA - k\sigma \quad (5)$$

where σ represents price volatility and k is typically set to 2.
The Bollinger Bands identify when stocks are becoming overbought or oversold.

- Prices near the **lower band** during an upward trend support buy decisions
- Prices near the **upper band** during a downward trend support sell decisions

This volatility-based filter restricts trading during extreme price situations, thus enhancing the timing of entry and exit into a market.

Figure 3: Bollinger Band–based volatility analysis of TCS stock price showing upper and lower bands along with buy and sell signals.

3.6. Reinforcement Learning Using PPO

An agent trained through reinforcement learning with Proximal Policy Optimization (PPO) is utilized to improve trade execution. The PPO presents a policy-gradient algorithm that is popular due to its reliability in learning and its regulation of policy changes.

- **State Space:** SMAC signal, ATV confirmation, Bollinger Band position, and position status
- **Action Space:** Buy, Sell, Hold
- **Reward Function:** Net profit adjusted for transaction costs and penalties for incorrect trades

The PPO objective function is given by:

$$L^{PPO}(\theta) = E[\min(r_t(\theta)A_t, clip(r_t(\theta), 1{-}\in, 1{+}\in)A_t] \quad 6$$

where rt(θ) is the probability ratio, At is the advantage function, and ϵ is the clipping parameter.

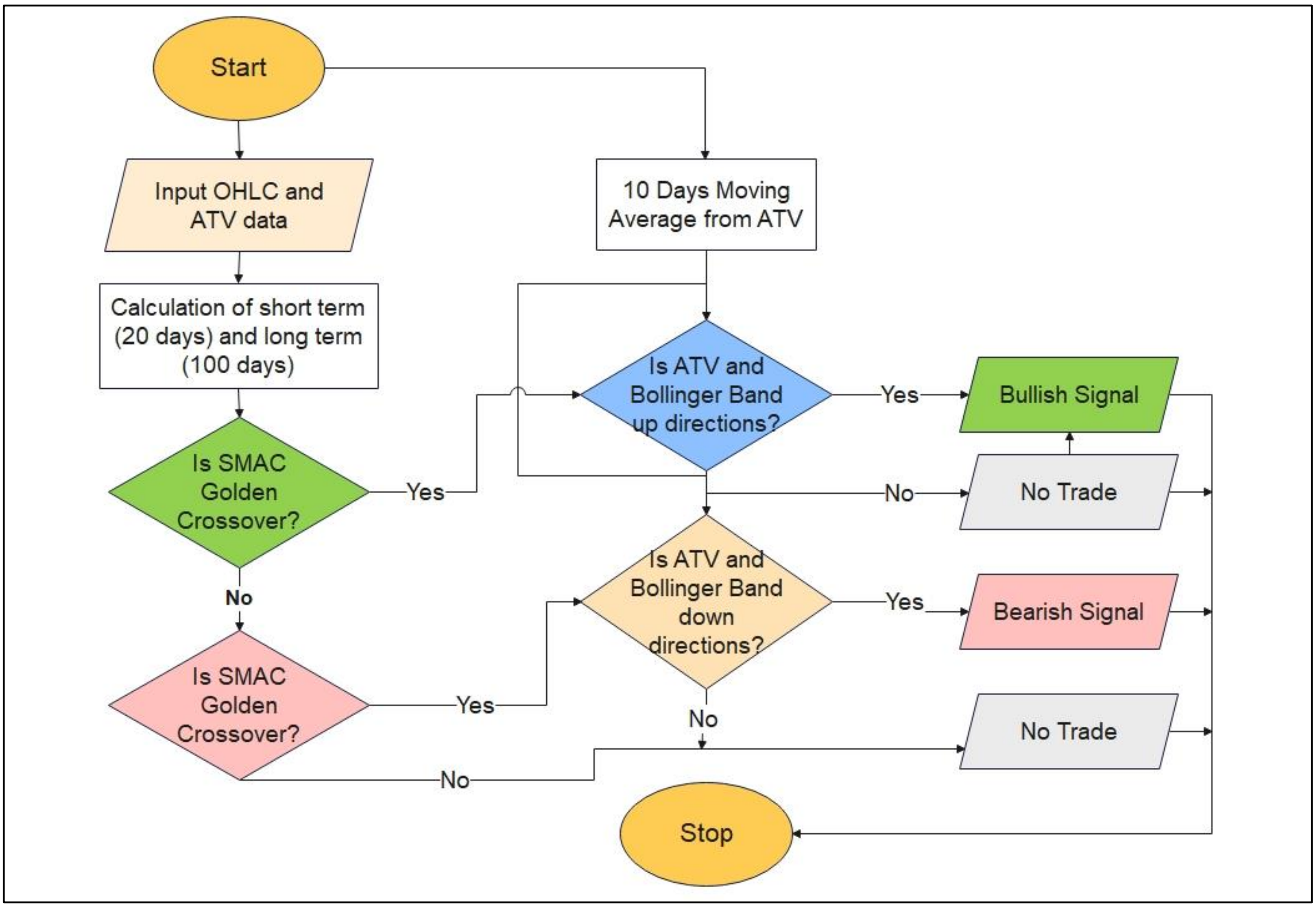

Figure 4: Flowchart of the proposed SMAC–ATV–Bollinger Band trading strategy

3.7. Summary of Methodology

The research work presents a hybrid trading methodology that improves the accuracy and reliability of stock trading decisions by using the combination of traditional technical analysis and modern reinforcement learning techniques. Among the employed technical indicators, SMAC is the main one for trend detection, use of ATV for price movement confirmation through market participation, and the application of Bollinger Bands for validation based on volatility to avoid extreme market conditions. The PPO-driven reinforcement learner not only selects the best trade among historical data and risk management but also acts by learning through the historical data. The whole proposed framework is able to amplify the trend, volume, and volatility signals altogether in an adaptive learning environment, thus, making a dependable and effective automated trading system.

4. Empirical Result

The suggested trading framework goes through an extensive back testing process based on historical stock market data that evaluates its performance and robustness. The performance analysis entails a comparison of several SMAC-based trading strategies through key performance metrics such as Return on Investment (ROI), average profit/loss, trade accuracy, Sharpe ratio, and Sortino ratio. Trade accuracy is defined as the ratio of profitable trades to the total number of executed trades, while the Sharpe and Sortino ratios indicate risk-adjusted performance.

The experimental evaluation is carried out on ten large-cap stocks listed on the Nifty 50 index—Reliance Industries, HDFC Bank, TCS, Infosys, ITC, ICICI Bank, Sun Pharma, Hindustan Unilever, Power Grid, and Asian Paints. Back testing is done with 5-minute, hourly, and daily price data across various trading horizons to ensure that the trading strategies are robust. Thus, the three-time frames correspond to short-term, medium-term, and long-term trading scenarios respectively.

4.1. Short-Term Performance (5-Minute Time Frame)

The monthly evaluation of the strategy's performance based on 5-minute price data shows that the SMAC-only strategy performs poorly due to the high number of trades it generates. Despite the fact that more trades are made, there are also lots of false signals, overtrading, and increased transaction costs, which limit the profitability of trading and make it riskier.

The use of Average Traded Volume (ATV) as a confirmation tool has a very positive impact on the strategy's performance. ATV only accepts SMAC signals during times when market participation is high, which leads to a significant drop in the number of losing trades and, thus, an increase in the overall trade precision. Moreover, the addition of Bollinger Bands to the strategy has a further positive impact on its performance because they are able to sharply reduce the number of trades by cutting out trading that happens during the periods of extreme volatility. In this way, Bollinger Bands make sure that the trades are not caught near the price levels where buying is already too expensive and selling is too cheap, which in turn means that the trade entry is close to the optimal one and the risk of losing due to short-term fluctuations is minimized. Thus, the combined SMAC–ATV–Bollinger Band strategy not only surpasses the SMAC-only method in terms of total profits earned but also in terms of trade accuracy.

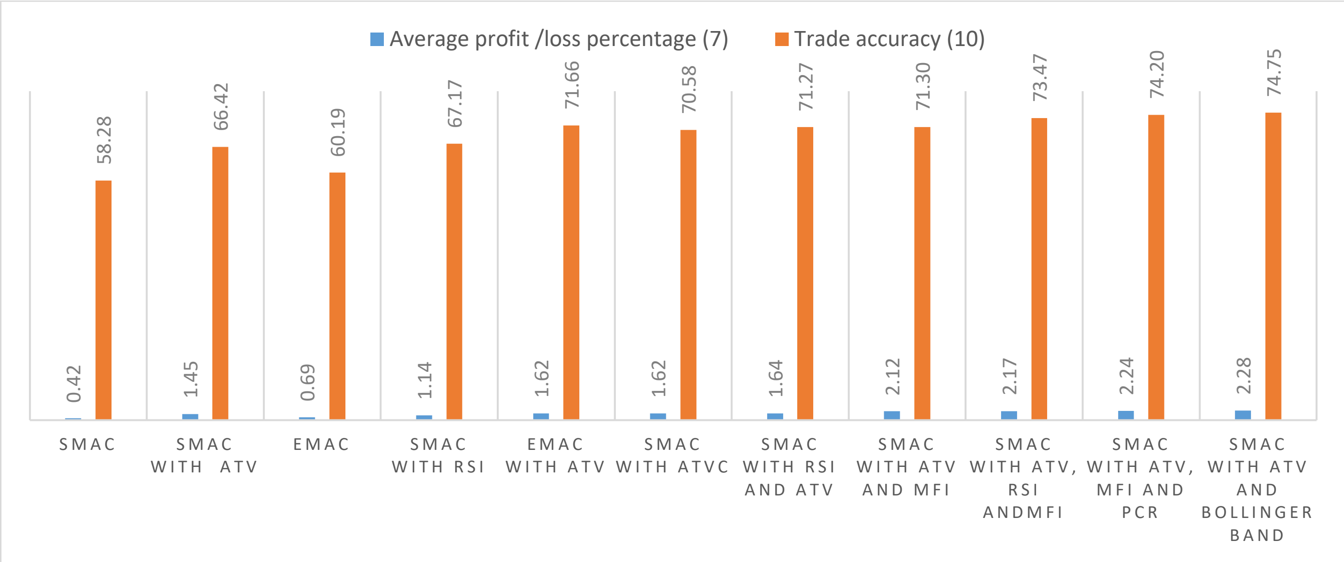

Figure 5: Cumulative profit and Trade accuracy are compared in 10 strategies in 1 month 5-min time frame

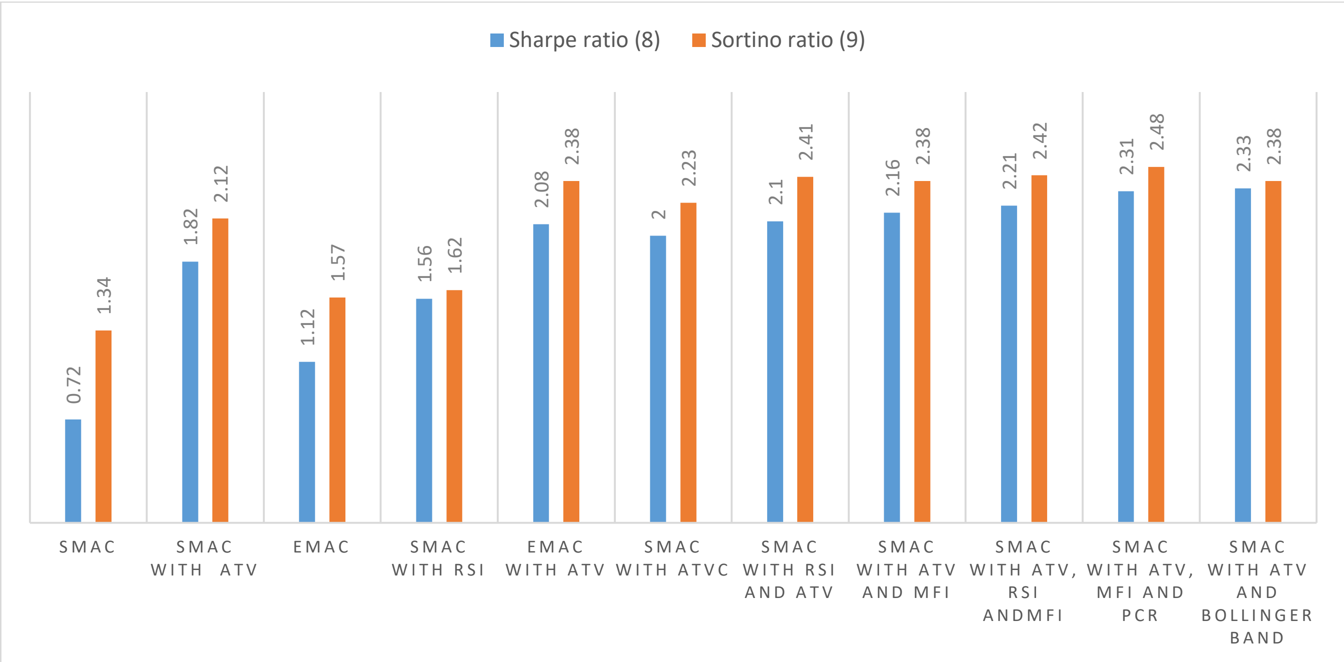

Figure 6: Sharpe ratio and Sortino ratio are compared in 10 strategies over 1 month 5-min time frame

4.2. Medium-Term Performance (Hourly Time Frame)

The medium-term evaluation that makes use of hourly price data for one year period once again emphasizes the effectiveness of multi-indicator confirmation. The SMAC-only strategy is still suffering in range-bound and low-volume market situations by generating a lot of false signals and unstable returns. The introduction of ATV, on the other hand, lessens the problem of overtrading by filtering trades to only very active market periods.

Introducing Bollinger Bands means you are using volatility to validate entry and exit and this is already another level of decision making. Trading during high volatility is avoided hence this helps to stabilize trade execution. The cooperation of this indicator trio with the PPO-based RL agent leads to a tremendous increase in execution efficiency. The PPO agent gets trained for the optimal buy, sell, and hold actions according to the historical results which yields higher trade accuracy, smoother profit curves, and better risk-adjusted returns as seen in the rising Sharpe and Sortino ratios.

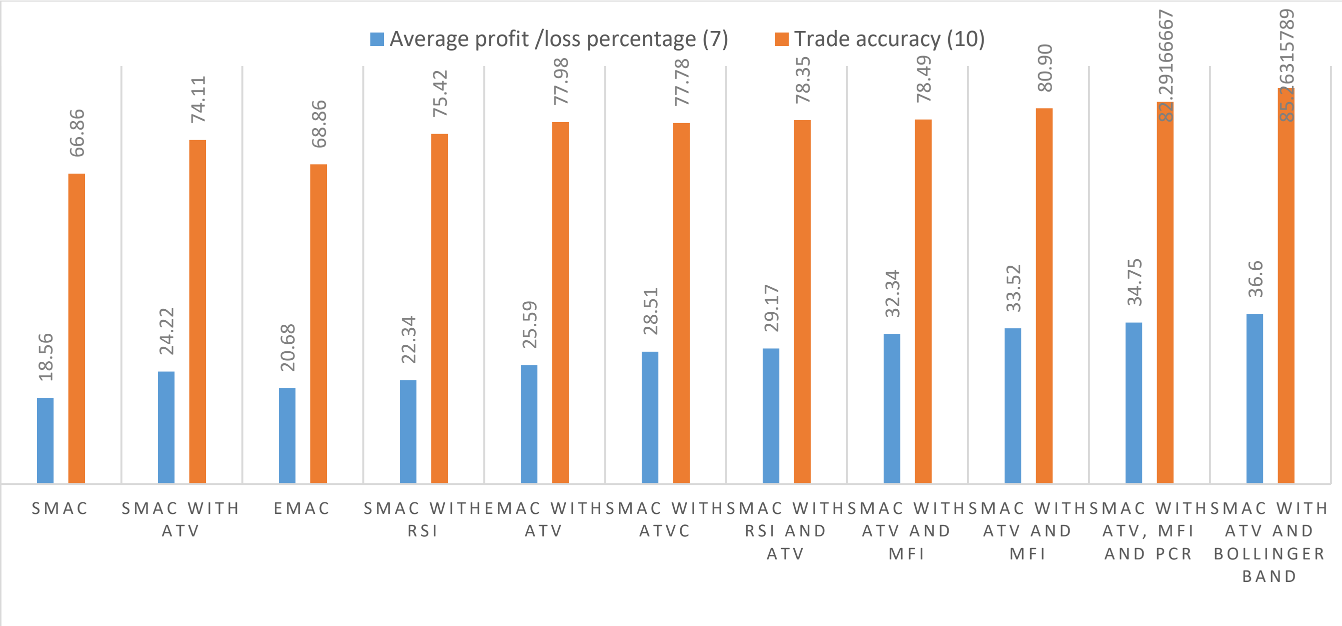

Figure 7: Cumulative profit and Trade accuracy are compared in 10 strategies in 1-year's hourly time frame

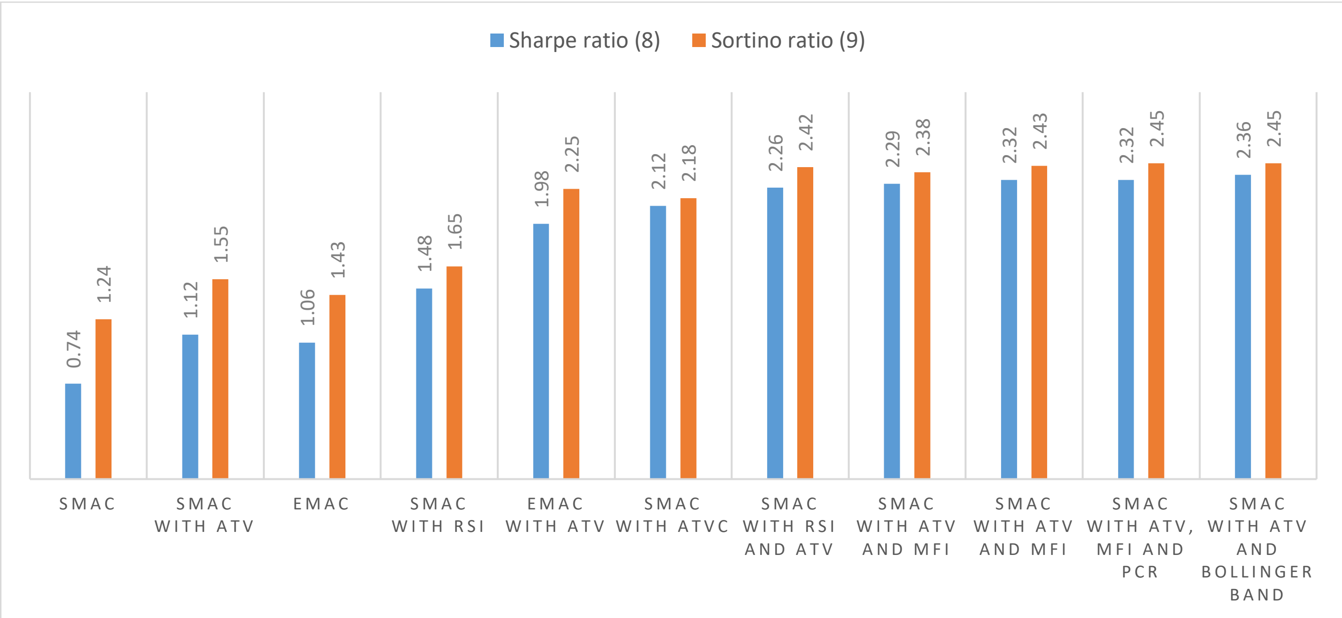

Figure 8: Sharpe ratio and Sortino ratio are compared in 10 strategies over 1-year hourly time frame

4.3. Long-Term Performance (Five-Year Period)

The analysis of long-term performance performed on a five-year basis provides proof of the proposed framework's strength and dependability. The SMAC-only strategy is subject to performance fluctuations owing to prolonged sideways markets and sudden volatility changes. The introduction of ATV guarantees that trend signals are backed by strong market participation thus efficiently filtering out weak breakouts.

Besides, the application of Bollinger Bands, which assist in the long-term volatility filtering and avoid trades in the case of extreme price movements, further enhances the performance. Bollinger Bands take up the role of a stabilizing mechanism by synchronizing trades with the price ranges that are statistically meaningful. The joint SMAC–ATV–Bollinger Band strategy, when implemented through the PPO-based reinforcement learning model, secures the highest cumulative returns, greater trade accuracy, and the most consistent risk-adjusted performance across all time horizons experimented with.

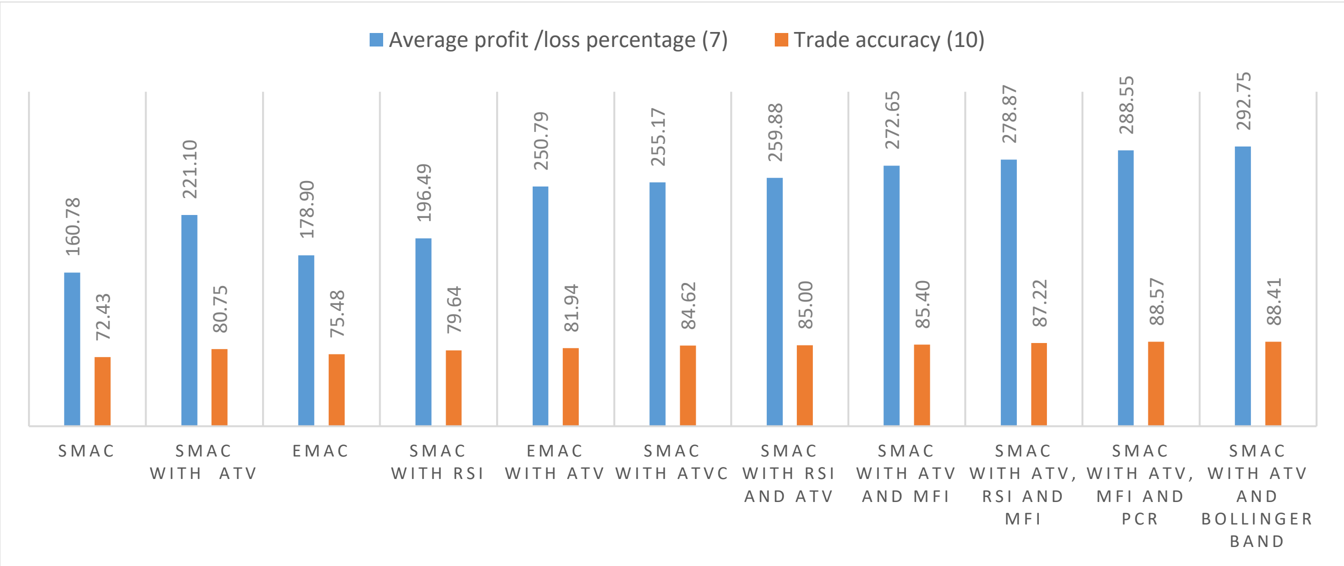

Figure 9: Cumulative profit and Trade accuracy are compared in 10 strategies in 5-years

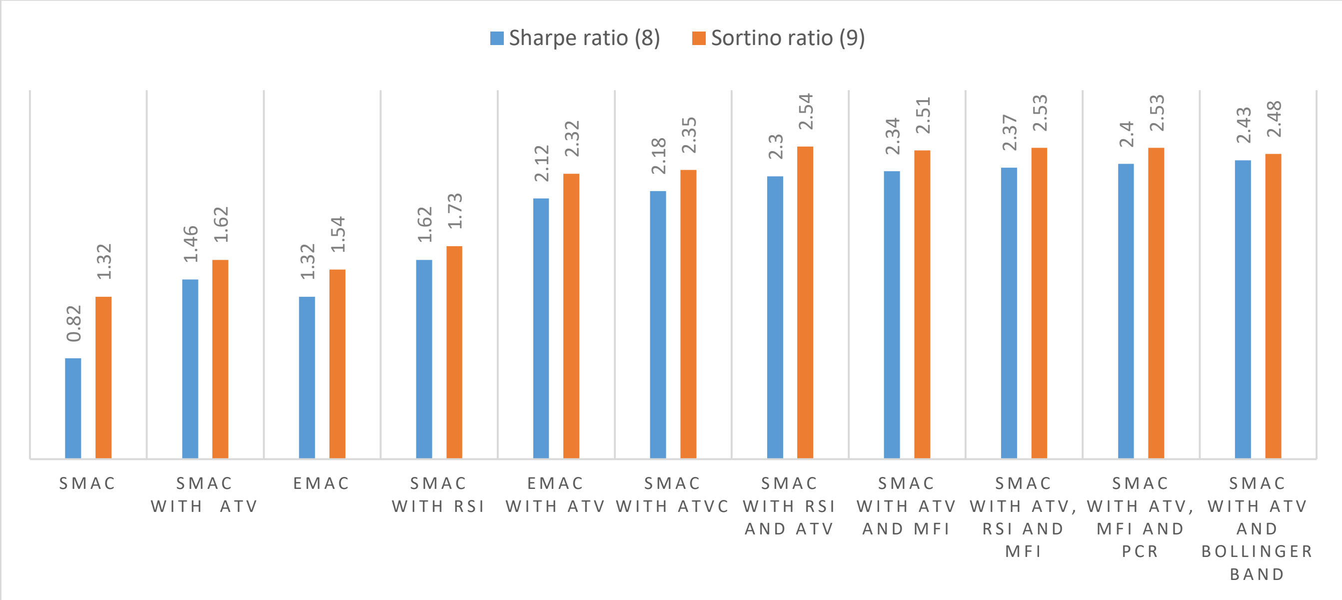

Figure 10: Sharpe ratio and Sortino ratio are compared in 10 strategies over 5-years

4.4 Overall Result Interpretation

The empirical results have shown that single-indicator strategies like SMAC are not capable of dealing with market noise and will frequently signal false trades. The use of ATV in conjunction with market trend detecting has strengthened the verification of the market's participation and at the same time the use of Bollinger Bands has made the trade to be more reliable by using a price filter based on volatility. The PPO methodology applied in the reinforcement learning model has improved trade execution further by determining the most favorable actions (buys, sells, holds) based on the performance of the market in the past.

In summary, the SMAC–ATV–Bollinger Band–PPO framework is significantly more profitable, accurately traded, and risk-adjusted returns than the traditional SMAC-based approaches. Such outcome shows that the merged trend, volume, and volatility data within an adaptive reinforcement learning environment are very powerful, thus making the proposed framework an excellent candidate for the automation of stock trading in real market scenarios.

5. Conclusion

In this research, a multi-indicator trading framework was suggested that was both powerful and flexible, combining the Simple Moving Average Crossover (SMAC), Average Traded Volume (ATV), and Bollinger Bands into a Proximal Policy Optimization (PPO)–based reinforcement learning environment. The main goal of the method proposed was to increase the precision and trustworthiness of trading by eliminating false signals which are often the result of the use of single technical indicators in isolation, especially during volatile and low-liquidity situations.

The new approach was confirmed through enormous back testing of Nifty 50 large-cap stocks over short-term, medium-term, and long-term trading horizons and showed its effectiveness. The outcomes illustrate that the old SMAC-only strategy, which could detect the general trend direction, had the main drawback of overtrading and unstable performance. The integration of ATV, to be sure, very much enhances the quality of the signals by letting only the trades during the times that are good for the market. Moreover, Bollinger Bands have come in handy and have made it even harder to lose money by means of filtering trades in the time of very high price divergences, thereby improving the timing of entry and exit, making the overall trade stable.

The PPO-based reinforcement learning agent's integration has, in turn, made the framework much more robust by executing trades through decision-making that is dependent on the situation. The agent, by observing the market through past interactions, learns to take optimal buy, sell, and hold actions while being mindful of transaction costs and risk levels, thus leading to better trade throughput and higher risk-adjusted returns that are evident through the Sharpe and Sortino ratios being higher.

All in all, the SMAC–ATV–Bollinger Band–PPO framework proposed achieves the combination of trend detection, volume confirmation, and volatility validation seamlessly in an adaptive learning model making it a trustworthy and indeed practical solution for automated stock trading. Future research might take this work forward by including more sentiment indicators, modelling transaction costs, and doing multi-asset portfolio optimization to improve the system's performance further.

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