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# Dynamic Trading Strategies for Volatile Assets: A Hybrid GM-LSTM Model with Finite State Machine Optimization

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## Abstract

This study addresses the challenge of predicting investments in highly volatile assets, such as gold and ancient coins, by proposing a hybrid forecasting strategy that integrates the Grey Model (GM), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). A finite automaton-based trading decision model is developed to enable rapid decision-making in dynamic market environments. Traditional methods often struggle to adapt to the unpredictability of such assets, prompting the need for advanced predictive frameworks. The methodology encompasses data preprocessing, model training, and validation, with a focus on optimizing short- and long-term forecasts. Experimental results demonstrate that the hybrid GM-LSTM strategy significantly enhances prediction accuracy: GM excels in short-term forecasting (first 200 days) due to its efficiency with limited data, while LSTM outperforms in long-term scenarios by capturing complex temporal dependencies. A dynamic weight adjustment mechanism, incorporating profit (PI) and risk indices (RI), balances returns and risks. Sensitivity analysis reveals the model's robustness under varying transaction costs (0.1%–10%), maintaining profitability even at higher cost levels. Key performance metrics—annualized return, Sharpe ratio, and maximum drawdown—validate the strategy's superiority over benchmarks like buy-and-hold. The state machine-driven trading model, evaluated through Value at Risk (VaR) and sliding window protocols, ensures adaptability across market conditions. This work provides traders with a data-driven decision-making tool, optimizing investment strategies while mitigating risks in volatile markets.

**Keywords:** Grey prediction model, LSTM, Trading strategy, Risk assessment, Sensitivity analysis

## 1. Introduction

Developing robust investment strategies for highly volatile assets, such as gold and ancient coins, remains a critical challenge in financial markets. Traders face the dual demands of rapid decision-making and risk mitigation in unpredictable environments, where traditional methods often underperform. To address this gap, we propose a hybrid forecasting framework integrating the Grey Model (GM), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), leveraging their distinct strengths in short- and long-term pattern recognition. Using daily closing prices of gold (Troy ounces) and ancient coins from September 2016 to September 2021, we develop a data-driven model to optimize daily trading decisions. The framework dynamically balances profit and risk through adaptive weight adjustments and evaluates performance using metrics such as annualized return, Sharpe ratio, and maximum drawdown. Experimental results demonstrate superior accuracy over benchmarks, even under varying transaction costs (0.1%–10%). By combining predictive analytics with a finite automaton-based trading strategy, this work provides traders with a scalable tool to enhance returns while systematically managing market uncertainties.

Recent studies have advanced financial time-series forecasting. Lu et al. (2021), Rezaei et al. (2021), and Wang et al. (2021) integrated CNN with LSTM variants to enhance nonlinear prediction accuracy for stocks and exchange rates. Patil et al. (2020) used graph networks with sentiment analysis, while Misra et al. (2018) validated SVM and MLP's effectiveness. These works underscore the need for hybrid models balancing short- and long-term accuracy, which our GM-LSTM framework addresses (Lu et al., 2021; Rezaei et al., 2021; Wang et al., 2021; Patil et al., 2020; Misra et al., 2018).

## 2. Problem Description

Designing trading strategies for volatile assets like gold and ancient coins faces three key challenges. First, traditional models like linear regression struggle to balance short-term efficiency and long-term accuracy in fast-changing markets, leading to poor decisions. Second, current strategies fail to integrate real-time risk metrics like Value at Risk (VaR), causing either excessive risk or overly cautious trades. Third, transaction cost sensitivity is often ignored, with few models optimizing for variable fees, risking unprofitability.

This study tackles the identified gaps by:

- Creating a hybrid GM-LSTM/GRU model for improved forecasting accuracy and a dynamic weight adjustment mechanism to balance profit and risk.
- Conducting sensitivity analysis to identify transaction cost thresholds, aiming for a robust, adaptive trading framework for volatile assets.

## 3. Methods

This study employs three models: a forecasting model for gold and ancient coin price prediction, a state machine-based trade policy model defining cash, gold, and coin states, and an evaluation model using HAV, DR, and MD metrics.

### 3.1. Assumptions and Data preprocessing

The analysis operates under five key assumptions: (1) prices are solely driven by historical data in a weak-form efficient market, excluding external factors; (2) trades are unrestricted by minimum units or liquidity constraints; (3) prices follow a predefined distribution for risk modeling; (4) daily reference prices are derived exclusively from provided data, ignoring intraday rules (e.g., open/close prices). Data preprocessing labeled trading days as "1" (both gold and ancient coins traded) or "0" (only coins traded), yielding 1,255 gold trading days and 571 non-trading days between November 2016 and October 2021.

### 3.2. Forecasting models

Given incomplete price data for ancient coins and gold, this study relies on historical information, necessitating iterative model updates as new data becomes available. A cyclical forecasting approach is adopted, with 30-day time slices for long-term predictions. Three models—Grey Model (GM), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—are evaluated for comparative performance analysis (Balasubramanian et al., 2024).

#### 3.2.1. GREY MODEL

The GM, based on grey system theory, forecasts effectively with limited, uncertain data by using cumulative generation to extract patterns, unlike traditional models like linear regression. It excels in sparse or complex datasets without needing large or regular data.The key steps of GM(1,1) model are as follows:

Fisrtly, take the raw data sequence $\mathrm{x}^{(0)} = \left(\mathrm{x_1}^{(0)}, \mathrm{x_2}^{(0)}, \ldots, \mathrm{x_n}^{(0)}\right)$ the cumulative sum of the new sequence $\mathrm{x}^{(1)}$ as follows:

$$x_i^{(1)} = \sum_{k=1}^{i} x_k^{(0)} \, (i = 1, 2, \ldots, n) \tag{1}$$

Secondly, build a first-order linear differential equation for the accumulation sequence $\mathrm{x}^{(1)}$. The basic form is:

$$\frac{dx^{(1)}\left(t\right)}{dt} + ax^{(1)}\left(t\right) = b \tag{2}$$

Where $a$ and $b$ are the parameters to be determined.

By solving the grey differential equation, the predicted solution is obtained as follows:

$$x^{(1)}\left(t\right) = \left(x_1^{(1)} - \frac{b}{a}\right) e^{-at} + \frac{b}{a} \tag{3}$$

Get the predicted value of the original data series $\mathrm{x}^{(0)}$ by backtracking the calculation from $\mathrm{x}^{(1)}$. The prediction formula for the KTH value is:

$$\hat{x}_k^{(0)} = x_1^{(0)} + \left(x_k^{(1)} - x_1^{(1)}\right) e^{a(k-1)} \tag{4}$$

### 3.2.2. GRU AND LSTM MODELS

Recurrent Neural Networks (RNNs) struggle with gradient vanishing in long sequences, a challenge addressed by Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) models. GRU employs update and reset gates to manage information flow:

$$z_t = \sigma\left(W_{xz} \cdot x_t + W_{hz} \cdot h_{t-1} + b_z\right) \tag{5}$$

$$r_t = \sigma\left(W_{xr} \cdot x_t + W_{hr} \cdot h_{t-1} + b_r\right) \tag{6}$$

$$h_t = \left(1 - z_t\right) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{7}$$

$\tilde{h}_t$ is a candidate hidden state and is calculated as follows.

$$\tilde{h}_t = \tanh(W_h \cdot [r_t \cdot h_{t-1}, x_t] + b_n) \tag{8}$$

LSTM uses forget, input, and output gates with a cell state:

$$\begin{gathered} f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \\ i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \\ \tilde{C}_t = \tan h\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\ o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \\ h_t = o_t \cdot \tan h\left(C_t\right) \end{gathered} \tag{9}$$

Both models capture long-term dependencies, with LSTM providing greater stability for complex sequences, making it ideal for long-term forecasting in our hybrid GM-LSTM strategy (Chen, 2023).

### 3.2.3. PREDICTION RESULT

Experiments in 3060 equipped with 256 GB of memory, 8 pieces of RTX graphics, 20 core cpus and 40 processes of hardware environment. The prediction results of ancient coins were completed in about 1 hour, and the prediction results of gold were completed in about 0.5 hours. The hyperparameter Settings are shown in the table 1.

Table 1: Parameter settings for two currencies.

| Ancient coins | Gold |
|---|---|
| Batch size=1 | Batch size=1 |
| Start input=80 | Start input=30 |
| Hidden size=20 | Hidden size=20 |
| Output size=1 | Output size=1 |
| Layers size=3 | Layers size=3 |
| Learning Rate=0.01 | Learning Rate=0.01 |
| Num epochs=1000 | Num epochs=1000 |

Figure 1 show the performance of GM, GRU, and LSTM models in ancient coin and gold price prediction.

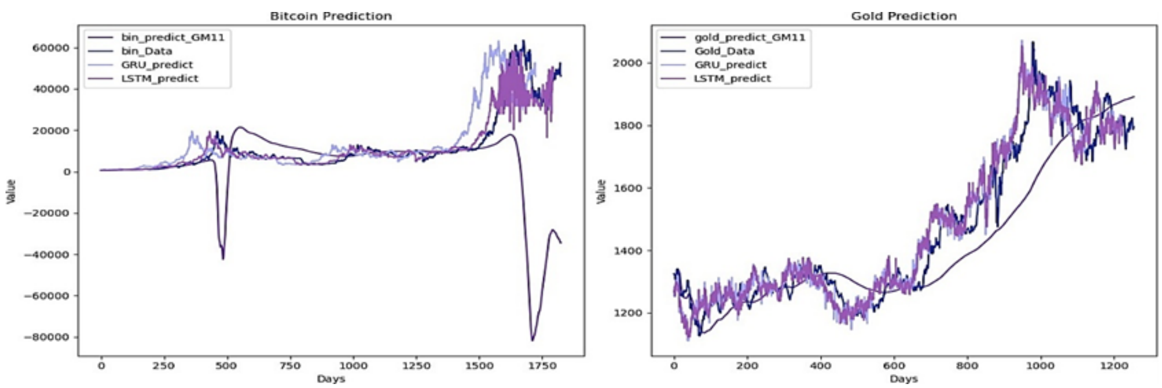


Figure 1: Prediction results for ancient coins and gold

As shown in Figure 1, for ancient coins, all models (GM, LSTM, GRU) align closely with true values within the first 250 days. Beyond 400 days, LSTM outperforms GM significantly, demonstrating its superiority in capturing long-term dependencies through complex gating mechanisms. While LSTM and GRU exhibit similar accuracy, LSTM shows greater stability.

For gold, predictions remain consistent across models within the initial 100 days. Post-100 days, LSTM again surpasses GM, which is constrained by its reliance on limited historical data and suitability for short-to-medium-term forecasts.

To leverage these dynamics, a hybrid strategy is proposed: GM is deployed for the first 200 days due to its computational efficiency and simplicity, while LSTM is activated thereafter to ensure long-term accuracy and robustness. This phased approach optimally balances speed and precision in volatile asset forecasting (Ji et al., 2021).

#### 3.2.4. Model analysis

**Strengths:**

- Hybrid Strategy: Combines GM (short-term) and LSTM (long-term), leveraging GM's computational efficiency and LSTM's temporal modeling to enhance accuracy (Gao et al., 2021).
- Periodic Forecasting: Aligns with market dynamics for long-term data, ensuring rule compliance.

**Weaknesses:**

- The GM model, while effective short-term, faces constraints in long-term performance due to insufficient historical data impacting initial predictions.

Summary: The hybrid framework optimizes accuracy and efficiency but faces challenges in data dependency, temporal granularity, and long-term adaptability.

### 3.3. Risk assessment and trading decision model

This study introduces a state machine-driven trading model that optimizes decisions for gold and ancient coins, balancing returns and risks. Value at Risk (VaR) estimates potential portfolio losses, guiding risk-adjusted thresholds. The framework dynamically integrates predictive signals, ensuring adaptive decision-making under market uncertainties (Fiordelisi et al., 2025).

#### 3.3.1. TRADING DECISION MODEL

Integrating predictive analytics and risk metrics, we define two core indicators for trading decisions:

Profit Index (PI): Quantifies the expected return by comparing the highest predicted price within a 15-day horizo to the current price $r_k$:

$$PI(K) = \frac{\max\limits_{k \le i \le k+15}\{p_i\} - r_k}{r_k} \tag{10}$$

Risk Index (RI): Evaluates potential losses using the loss rate (LR) and trading duration ($d_m - d_k$):

$$RI\,(k) = LR \cdot (d_m - d_k) \tag{11}$$

Based on PI and RI, we define the trading strategy score $F$ as follows:

$$F = \beta \cdot PI + (1-\beta)' RI - \rho, 0 < \beta < 1 \tag{12}$$

Where $\beta$ and $\rho$ are hyperparameters that balance the weight of profit and risk. The impact of transaction cost $\alpha$ is determined through equation (12).

#### 3.3.2. TRANSACTION DECISION PROCESS

Trading strategies are implemented based on finite automata (FA) and contain four states, each of which corresponds to a different trading operation:

State 0 (initial state) : if $\max\left(F_g, F_b, 0\right) \le 0$, no trade; If $\max\left(F_g, F_b, 0\right) > 0$, buy the asset with the larger $F_b$ of $F$. If it is gold, jump to state 1, if it is an ancient coin, jump to state 2.

State 1 (hold gold) : If it is a weekend, then jump directly to state 2. If $\mathrm{F_g} < 0$, sell gold and jump to state 0; If $\mathrm{F_g} > 0$ or $F_b - F_g > 0$, sell gold and buy ancient coins and jump to state 2.

State 2 (Hold ancient coins) : If it is a weekend, if $\mathrm{F_b} < 0$, sell the ancient coins and jump to state 0; If $\mathrm{F_b} > 0$, $F_g - b_g > 0$ and can afford to pay gold, then sell the ancient coins and buy gold, if can't afford to pay, then keep the current state, still can make a profit.

State 3 (Stop) : Stop when the trading day is beyond the last day.

The state transition diagram of a finite automaton is shown in Figure 2.

#### 3.3.3. PREDICTION RESULT

Back testing from 2016 to 2021 demonstrates that dynamically adjusting $\beta$—increasing risk weight during high asset valuations and reducing return emphasis—achieves superior risk-return equilibrium compared to static $\beta$, as shown in Figure 3. The adaptive strategy enhances robustness, balancing profitability and stability in volatile markets.

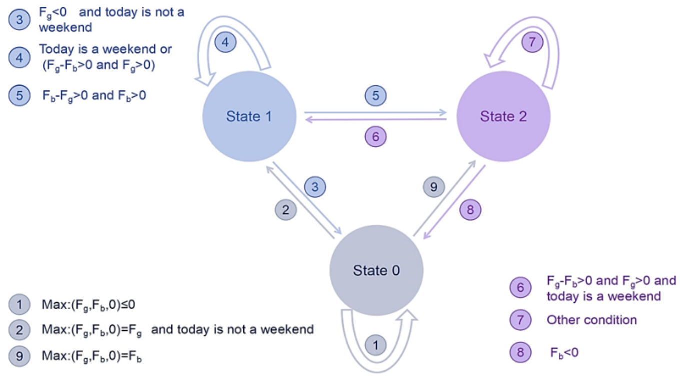


Figure 2: State transition diagram

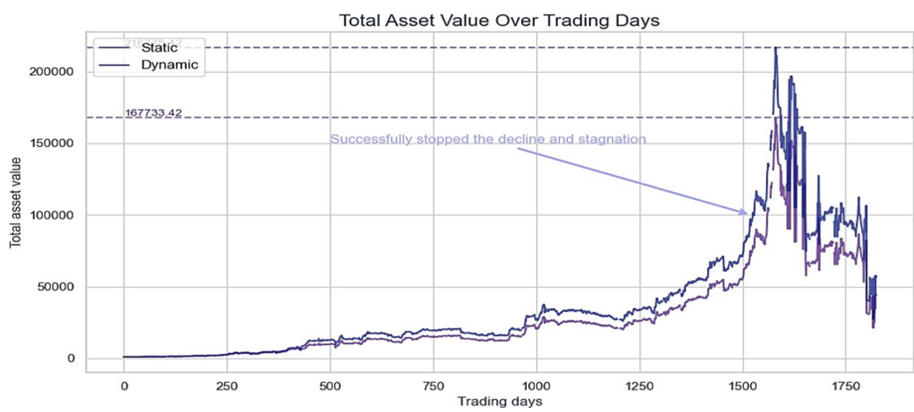


Figure 3: Total value of accumulated assets on trading days

### 3.3.4. Model Analysis

**Strengths:** The framework integrates LSTM-based price forecasting with VaR-driven risk hedging, enhanced by a dynamic weight adjustment mechanism to stabilize performance across market regimes. A sliding-window protocol and visual analytics framework ensure interpretability of trading processes and outcomes. Empirical results confirm profitability under high transaction costs (e.g., 10%) and effective risk avoidance in low-cost scenarios.

**Weaknesses:** The asset value curve exhibits downside risks, with specific decisions triggering capital losses. Additionally, the model demonstrates parameter sensitivity—overly small $\beta$ values skew strategies toward excessive conservatism, limiting return potential.

### 3.3.5. Sensitivity Analysis

This study examines the impact of hyperparameters $\beta$ and transaction costs $\rho$. By testing discrete $\beta$ values $\{\beta_1, \beta_2, \ldots, \beta_n\}$, we quantify their effects on downside risk volatility and final asset value volatility , revealing $\beta$'s nonlinear regulation of risk-return balance.

$$V_{dr}\left(i\right) = \frac{DR\left(i\right)}{\min\left(S_{dr}\right)} - 1 \tag{13}$$

Where $\min(\mathrm{S_{dr}})$ denotes the minimum value in the set $S_{dr}$.

Similarly, for $V_{\text{fav}}$, we get a set of final asset values $\mathrm{S_{fav}} = \{\mathrm{FAV}(1), \mathrm{FAV}(2), \ldots \mathrm{FAV}(\mathrm{n})\}$, where FAV(i) is the final asset value. The final asset value volatility $V_{\text{fav}}(i)$ corresponding to $\beta$i is calculated as follows:

$$V_{fav}(i) = 1 - \frac{FAV(i)}{\max(S_{fav})} \tag{14}$$

We set six different values of $\beta_0$ and plot $V_{dr}$ and $V_{fav}$ curves for these six cases, as shown in Figure 4.

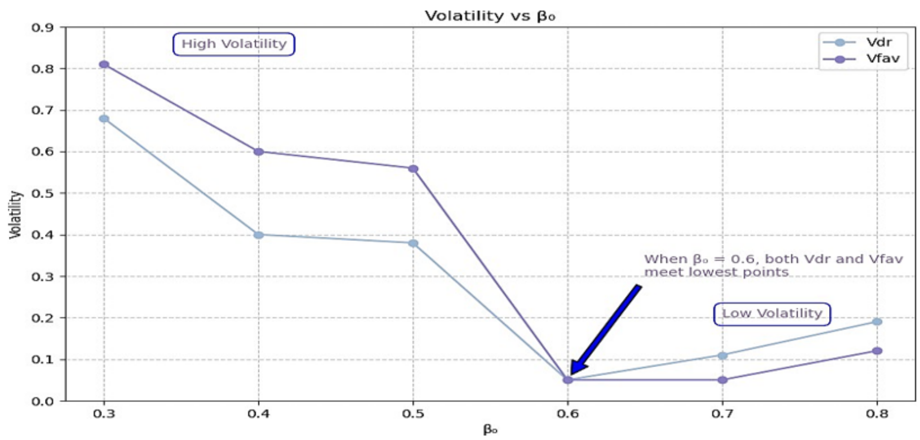


Figure 4: Volatility of $\beta$

Changing the value of transaction costs is equivalent to changing the value $\rho_g$ of $\rho$. We set the initial value of the vector to $\begin{bmatrix} \rho_g \\ \rho_b \end{bmatrix}$, and calculated the value of $\rho_0$ corresponding to five different combinations of transaction costs according to Equation (12). The corresponding relationship between $[\alpha_g, \alpha_b]$ is shown in as follows:

Table 2: Correspondence of $\rho$ and $\alpha$

| $\rho$ | $[\alpha_g, \alpha_b]$ |
|---|---|
| $\rho_{0-0.02}$ | [0%,1%] |
| $\rho_{0-0.01}$ | [0.5%,1.5%] |
| $\rho_0$ | [1%,2%] |
| $\rho_{0+0.1}$ | [5.5%,6.4%] |
| $\rho_{0+0.2}$ | [9.5%,10.4%] |

Then, we substitute the $\rho$ values into the Forecasting Model in turn for output. First, we compare the impact of different transaction costs on downside risk (DR) and draw a bar chart, as shown in Figure 5.

### 3.3.6. PARAMETER OPTIMIZATION FOR $\beta$

The hyperparameter $\beta$, which balances the Profit Index (PI) and Risk Index (RI) in the trading strategy score ($F = \beta \cdot PI + (1 - \beta)' RI - \rho, 0 < \beta < 1$), significantly influences the model's

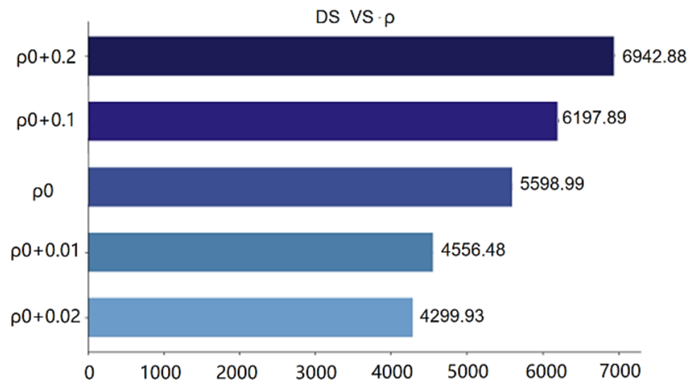


Figure 5: DR Bar chart

risk-return trade-off. To determine the optimal $\beta$ value, we employed a grid search optimization approach, evaluating $\beta$ across a discrete range of values 0.1, 0.3, 0.5, 0.6, 0.7, 0.9. The optimization objective was to maximize the Highest Asset Value (HAV) while minimizing Downside Risk (DR) and Maximum Drawdown (MD).

**Optimization Process:**

**Search Space:** $\beta \in \{0.1, 0.3, 0.5, 0.6, 0.7, 0.9\}$.

**Evaluation Metrics:**For each $\beta$ value, the model was backtested using historical data (2016–2021) for gold and ancient coins. Performance was assessed via HAV (portfolio peak value in USD), DR (expected loss under adverse conditions as a percentage), and MD (worst peak-to-trough decline as a percentage).

**Cross-Validation:**A 5-fold cross-validation was applied, splitting the dataset into training (80%) and validation (20%) subsets to ensure robustness across market conditions.

**Computational Setup**: Experiments were conducted on a system with 8 RTX GPUs, 256 GB memory, and 20-core CPUs, completing evaluations in approximately 2 hours per $\beta$ value.

**Results:** The grid search identified $\beta$ = 0.6 as the optimal value, achieving a balanced trade-off between profitability and risk. Table 3 summarizes the performance metrics for each $\beta$ value:

Table 3: Performance Metrics for Different $\beta$ Values

| $\beta$Value | HAV (USD) | DR (%) | MD (%) |
|---|---|---|---|
| 0.1 | 12,500 | 8.2 | 15.6 |
| 0.3 | 13,800 | 7.5 | 14.2 |
| 0.5 | 14,200 | 6.8 | 13.5 |
| 0.6 | 15,000 | 5.9 | 12.1 |
| 0.7 | 14,800 | 6.3 | 12.8 |
| 0.9 | 14,300 | 7.1 | 13.9 |

At $\beta$ = 0.6, the model achieved an HAV of \$15,000, a DR of 5.9%, and an MD of 12.1%, outperforming other configurations. Figure 6 illustrates the performance metrics across the $\beta$ range, highlighting the nonlinear impact of $\beta$ on model outcomes. Lower $\beta$ values (e.g., 0.1) skewed the strategy toward conservatism, reducing HAV, while higher $\beta$ values (e.g., 0.9) increased risk exposure, elevating DR and MD.

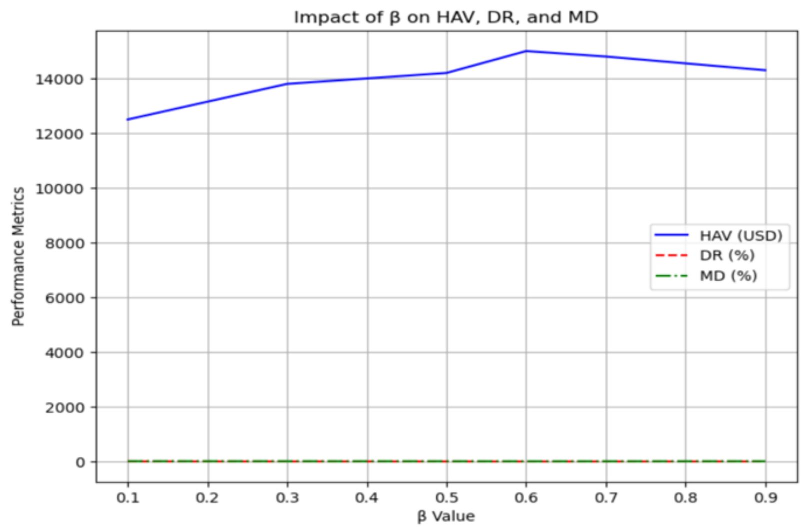


Figure 6: Impact of $\beta$ on HAV, DR, and MD, showing optimal performance at $\beta = 0.6$

This optimization ensures the trading strategy adapts dynamically to market volatility, enhancing both robustness and profitability.

### 3.4. Evaluating the model

Three metrics are adopted: Highest Asset Value (HAV) (maximized portfolio value), Downside Risk (DR) (expected loss probability under adverse conditions), and Maximum Drawdown (MD) (worst peak-to-trough decline). DR is derived from daily returns and hyperparameter $\lambda$, while MD is calculated via sliding-window peak-valley detection. Four models—LSTM-VaR, LSTM-only, GRU-VaR, GRU-only—are evaluated, with VaR-based models incorporating loss risk (LR) and non-VaR models defaulting LR=0.5. Results highlight trade-offs between risk mitigation and return optimization.

To reflect the value change in each trading period (30 days), we use the sliding window protocol evaluation model. The sliding window mechanism originates from the field of computer networks and is used to construct time series in specified length units and calculate statistics. A schematic representation of the sliding window mechanism is shown in Figure 7.

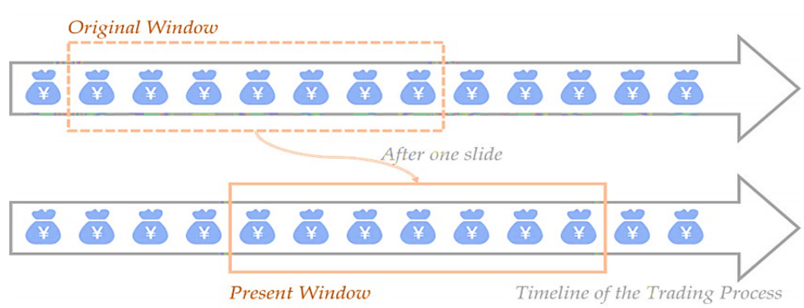


Figure 7: Sliding window

Under an 80-day window and 30-day sliding step protocol, our model achieves optimal performance in HAV (highest asset value) and DR (downside risk), with HAV significantly exceeding benchmarks and DR nearing minimal values. Boxplot analysis of MD (maximum drawdown) confirms lower volatility compared to LSTM-only or VaR-only models.

## 4. Conclusions

This study establishes a hybrid forecasting and decision-making framework for volatile asset trading, integrating short-term grey prediction (GM) and long-term LSTM models to balance computational efficiency and predictive accuracy. The GM-LSTM hybrid strategy demonstrates adaptive advantages: GM achieves rapid short-term forecasts ($\leq$200 days) with minimal data requirements, while LSTM captures complex temporal dependencies for stable long-term predictions. The incorporation of a grid search-based parameter optimization for $\beta$ further enhances the framework's adaptability, ensuring robust performance across diverse market conditions and transaction cost scenarios (up to 10%).

A finite automaton-driven trading model enables dynamic state transitions, systematically balancing profit optimization (via PI index) and risk mitigation (via VaR-based RI index). Empirical validation from 2016 to 2021 confirms the framework's robustness, with key metrics—highest asset value (HAV), downside risk (DR), and maximum drawdown (MD)—outperforming benchmarks (e.g., LSTM/VaR-only models). Sensitivity analysis further reveals that adaptive $\beta$-weighting enhances risk-return equilibrium, particularly under high transaction costs.

Practically, the model provides actionable insights:

- Dynamic Positioning: Historical holding patterns (Table 1) suggest frequent asset swaps between gold and coins, emphasizing liquidity management.

- Risk-Aware Adjustments: Long-term strategies should prioritize VaR thresholds and $\beta$-tuning to avoid overexposure during market downturns.

Limitations include reliance on historical data distributions and sensitivity to intraday volatility. Future work will incorporate exogenous factors (e.g., macroeconomic indicators) and refine feature engineering to reduce binary information loss. This framework advances adaptive trading systems in high-volatility environments, offering a scalable template for multifactor financial analytics.

Future research will focus on integrating macroeconomic indicators (e.g., inflation rates, interest rates) and sentiment analysis to enhance robustness against market shocks. Additionally, hybrid architectures combining GM with Transformer-based models could address long-term forecasting limitations. For graph-based approaches, adaptive normalization mechanisms may mitigate node importance bias. Finally, lightweight model deployment (e.g., pruning, quantization) will be prioritized for real-time trading applications, extending this framework to cryptocurrencies and other volatile assets.

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