GWO Optimization with the Highest Sharpe Ratio

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***Abstract*—This article covers a hybrid robo-advisory platform that offers tailored financial advice by utilizing deep learning and the Grey Wolf Optimization (GWO) algorithm. Using Long Short-Term Memory (LSTM) networks, the system predicts 30-day stock prices. The Grey Wolf Optimization (GWO) method is used to maximize portfolio Sharpe Ratios according to investor risk profiles. Investor risk tolerance is categorized as low, medium, or high risk based on a systematic survey. Technical indicators and historical stock data are used to train the LSTM model. GWO then outperforms random and conventional optimization techniques by simulating the social hierarchy and hunting behaviors of grey wolves to optimize portfolio allocations. When evaluated using precise financial and machine learning criteria, the method shows good predictive performance and enhanced portfolio returns. For next-generation robo-advisors, this study highlights the potential of combining adaptive optimization with AI-driven forecasting. However, it also highlights the challenges of coordinating optimization results with subjective risk assessments.**

***Index Terms*—robo-advisor, deep learning, grey wolf optimization, portfolio management, LSTM**

I. INTRODUCTION

This study presents a hybrid robo-advisory model that combines investor risk profile determination, stock price prediction with LSTM, and portfolio optimization processes with the Grey Wolf Optimization (GWO) algorithm. The starting point of the model is a matrix-based risk analysis survey that provides results according to the investor's character, size, and risk perception with the investor risk analysis presented to users. As a result of this survey, various portfolio recommendations customized for three different risk levels are presented. LSTM is used in the model's prediction engine to predict future changes in stock prices. Based on these predictions, financial metrics such as the Sharpe Ratio are calculated and performance-sensitive portfolios are created. In order to ensure optimal performance of portfolios, GWO, a nature-based metaheuristic algorithm inspired by the hunting strategies of gray wolves, is used. Thanks to this method, the most optimal one is selected among millions of portfolio distribution samples. This study, which combines machine learning, behavioral risk analysis, and biologically inspired optimization, contributes to the development of flexible and data-driven new generation robo-advisor systems that support investment decisions in uncertain environments. The companies we use while conducting competitor analysis in the research phase are Betterment, Magnus AI and Jacobi. They apply machine learning for optimization while providing personal portfolio management services.

II. LITERATURE REVIEW

A. Robo-advisory and Wealth Management

Robo-advisory is a financial advisory methodology that leverages artificial intelligence (AI) and machine learning (ML) technologies to deliver personalized asset management services with minimal human intervention [19, 7]. This innovation has significantly enhanced efficiency, accessibility, and the level of personalization in financial services.

AI-powered robo-advisors utilize technologies such as ML algorithms and data analytics to automate complex financial tasks and optimize investment strategies. These platforms provide cost-effective wealth management and personalized portfolio recommendations aligned with individual risk tolerance and financial objectives [19, 21].

Wealth management traditionally involves setting financial goals, managing associated risks, and striving for returns. Robo-advisors perform these functions using algorithmic strategies without human advisors. Four primary categories of robo-advisors have been identified: autopilot, direct plan-based, goal-based, and full-service platforms [24].

According to PwC, robo-advisory services have experienced rapid growth in recent years, with firms such as Wealthfront and Betterment leading the U.S. market, while Nutmeg is prominent in the U.K. Betterment, noted as the first company to offer robo-advisory services.

Robo-advisory platforms target investors seeking personalized financial advice but who may lack the capital required by traditional advisory firms. These platforms employ advanced algorithms and intelligent software to improve investment performance, often surpassing human-managed alternatives due to their ability to process vast financial data sets efficiently [21].

The integration of finance and technology in robo-advisors has resulted in higher returns and democratized access to wealth management. They now play a critical role in risk profiling, portfolio construction, and ongoing investment management [8].

As robo-advisors become more sophisticated, recent research suggests they may eventually replace traditional financial advisors in certain contexts. Their potential to transform the financial advisory sector is substantial, particularly as demand for automated, low-cost, and reliable financial guidance continues to grow [8, 19].

B. Time Series Forecasting with ARIMA and LSTM Models

Models that can capture both complicated temporal dependencies and linear trends are necessary for financial time series forecasting. For a long time, stationary, linear time series have been modeled using conventional techniques such as ARIMA (AutoRegressive Integrated Moving Average). Although it struggles with the volatility and nonlinearities common in financial markets, ARIMA is nevertheless interpretable and useful for short-term projections [23].

Deep learning models, on the other hand, particularly Long Short-Term Memory (LSTM) networks, are made to learn nonlinear patterns and long-range temporal correlations. By using memory cells and gating methods to regulate the flow of information across time steps, LSTM, a unique kind of Recurrent Neural Network (RNN), tackles problems such as disappearing gradients [3, 20]. Several research efforts have demonstrated that LSTM is well-suited to capturing the non-stationary and irregular behavior of stock prices due to these features [20].

In predicting the stock values of Apple, Google, and Tesla, Panchal et al. [20] discovered that LSTM performed noticeably better than ARIMA. Similarly, Chatterjee et al. [3] demonstrated how LSTM outperforms more straightforward econometric models.

However, Kobiela et al. [11] noted that ARIMA may perform better than LSTM, especially over larger prediction windows. A hybrid ensemble comprising LSTM and ARIMA was presented by Mochurad and Dereviannyi [18] in recognition of the complementing characteristics of both models. This ensemble showed stronger robustness across datasets and increased prediction accuracy compared to standalone LSTM.

These insights support our study's choice to use LSTM as the primary prediction model.

C. Modern Portfolio Theory

The seminal work *Portfolio Selection* by Harry Markowitz in 1952 introduced Modern Portfolio Theory (MPT) into investment science. Markowitz argued that the risk of an investment should be assessed by examining the entire portfolio, rather than individual assets. He proposed that variance can be used to measure risk, while covariance between assets can be leveraged to reduce it [13], [14].

The Markowitz model is built upon the "mean-variance" optimization approach, which aims to maximize returns for a given level of risk. The efficient frontier derived from this model represents optimal portfolios that provide the maximum expected return for each level of risk [5]. This methodology has been widely adopted.

Nonetheless, some critics argue that the model's assumption—that variance fully captures all aspects of risk—is an oversimplification [12].

Markowitz's contribution has had a profound and lasting impact on finance, forming the basis for more advanced models like the Sharpe Ratio and the Capital Asset Pricing Model (CAPM) [13], [5]. Beyond its academic significance, MPT remains foundational in many financial decision-making systems and continues to guide investors in achieving balanced risk-return portfolios through diversification.

D. Heuristic Algorithms in Portfolio Optimization

The Grey Wolf Optimizer (GWO) is a bio-inspired swarm intelligence algorithm modeled on the leadership hierarchy and hunting behavior of grey wolves. These heuristic methods excel in navigating complex, non-linear solution landscapes where traditional mathematical optimization approaches often face limitations [4].

Kamali [9] demonstrated that PSO not only produced lower portfolio variance but also converged faster than GA within a classical mean–variance optimization framework. In another study, Zhu et al. [25] applied PSO to a constrained portfolio optimization problem and reported superior performance in both accuracy and computational efficiency compared to benchmark algorithms.

More recently, GWO has gained recognition for its competitive performance. Arabi Zanjani, Aleemran, and Hasanzadeh [2] compared GWO, PSO, and a hybrid GWO–PSO approach across several portfolio optimization models, including mean–variance and Conditional Value at Risk (CVaR).

In summary, while PSO continues to be praised for its rapid convergence and high-quality solutions, GWO presents a modern and effective alternative, capable of achieving comparable outcomes in complex portfolio optimization problems.

III. Methodology

The six main steps include determining investor risk tolerance, developing a deep learning model for price prediction, calculating expected returns and Sharpe ratios, and applying Grey Wolf Optimization (GWO) for portfolio improvement.

A. Research Design

Our work follows a structured, data-driven quantitative research strategy aimed at creating an intelligent, personalized investment decision support system. The methodology draws from principles of quantitative finance, such as risk-adjusted returns and portfolio diversification, combined with deep learning (LSTM) for predictive modeling. This quantitative approach is particularly suitable for solving complex investment problems involving extensive numerical data by facilitating rigorous performance evaluation, prediction accuracy, and optimal allocation.

B. Data Collection Methods

We collected daily historical price data for 12 publicly traded companies using the Yahoo Finance `yfinance` API. The dataset spans January 2020 to May 2025 and includes Open, High, Low, Close, Adjusted Close, and Volume columns. Additionally, beta values were retrieved from Investing.com to classify companies into three risk tiers:

- **Low Risk** ($\beta < 1$): Coca-Cola Bottling, Johnson & Johnson, Microsoft, Procter & Gamble
- **Medium Risk** ($1 \leq \beta \leq 1.5$): Devon Energy, NVIDIA, Tesla, Uber

- **High Risk** ($\beta > 1.5$): Alnylam, Applovin, Nano X, Plug Power

To assess investor preferences, we designed a 10-question risk tolerance survey. Based on aggregate scores, participants were assigned to one of three groups: low, medium, or high risk tolerance.

For the risk-free rate, the US 10-Year Treasury yield (2% annually) was used. The equivalent daily risk-free rate was calculated as:

$$R_f = (1 + 0.02)^{\frac{1}{252}} - 1 \approx 0.000079$$

This was used in subsequent Sharpe Ratio calculations.

C. Algorithms or Models

The framework employs two key models: a forecasting model (LSTM) and an optimization model (GWO).

- **LSTM Forecasting Model**: A Recurrent Neural Network (RNN) architecture, Long Short-Term Memory (LSTM), was used to model sequential dependencies. We implemented a two-layer LSTM with 64 and 32 units to forecast stock prices 30 days ahead. Mean Squared Error (MSE) was used as the loss function.
- **Grey Wolf Optimizer (GWO)**: This meta-heuristic algorithm simulates the social hierarchy and hunting strategy of grey wolves. It was employed to optimize portfolio weights by maximizing the Sharpe Ratio.

D. Evaluation Criteria

We employed both machine learning and financial metrics to evaluate the performance of prediction and optimization stages.

a) LSTM Prediction Performance: To enhance LSTM accuracy, several technical indicators were added to the feature set alongside closing prices:

- **Relative Strength Index (RSI)**: Measures the strength and speed of price movements to detect potential reversals.
- **MACD and Signal Line**: Capture momentum through exponential moving averages.
- **Bollinger Bands**: Reflect market volatility via standard deviation bands.
- **20-Day Volume Moving Average**: Sheds light on underlying trends in trading activity.

Prediction performance was assessed using:

- **Mean Squared Error (MSE)** on the test set.
- A comparison chart visualizing forecasted versus actual closing prices over time.

b) Portfolio Performance Metrics: We used the following formulas to evaluate portfolio outcomes:

- **Daily Return**:
$$r_t = \frac{P_{t+1} - P_t}{P_{t+1}} \tag{1}$$
[6]
- **Expected Return**:
$$E(R_p) = \sum w_i \cdot \mu_i \tag{2}$$
[15]
- **Portfolio Risk (Standard Deviation)**:
$$\sigma_p = \sqrt{\mathbf{w}^T \Sigma \mathbf{w}} \tag{3}$$
[15]
- **Sharpe Ratio**:
$$\text{Sharpe} = \frac{E(R_p) - R_f}{\sigma_p} \tag{4}$$
[22]

These indicators provide a comprehensive view of the forecasting and optimization system's effectiveness.

E. Sources and Tools Used

The following tools and libraries were used in building and running the system:

- **Python**: Primary programming language
- **NumPy, Pandas**: Data manipulation
- **Matplotlib**: Visualization
- **Scikit-learn**: Scaling and preprocessing
- **TensorFlow/Keras**: Deep learning (LSTM)
- **Yahoo Finance API**: Financial data source
- **Custom Python Modules**: Risk profiling, optimization logic

All experiments were executed in Google Colab to ensure reproducibility and facilitate cloud-based data access.

F. Literature Integration

This methodology draws heavily from the original Grey Wolf Optimizer (GWO) proposed by Mirjalili et al. (2014), which models leadership dynamics and cooperative hunting behaviors to solve continuous optimization problems without relying on gradient information [17].

Further, Ahmadi et al. (2022) introduced an Advanced GWO (AGWO), which applies mirror boundary restrictions and sinusoidal modulation to improve convergence and reduce premature stagnation.

Although AGWO was not implemented in this study, its enhancements present promising directions for future research in portfolio optimization.

IV. RESULTS AND FINDINGS

A. LSTM Model Training Performance

The training performance graph (see Figure 1) illustrates the model's learning behavior over multiple epochs. Key observations from the graph include:

- **Loss Reduction Over Epochs:** The training loss steadily decreases, indicating effective error minimization on the training data.
- **Validation Curve Behavior:** Validation loss decreases in early epochs, confirming good generalization.
- **Model Convergence:** After around 60 epochs, both losses plateau, showing convergence.

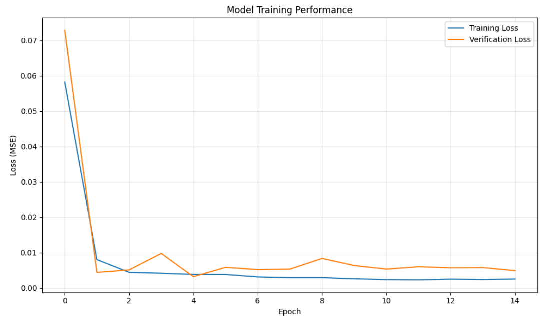

Fig. 1: Model training and validation loss (MSE) over epochs.

B. Technical Indicators Result

To support the deep learning-based predictions, we analyzed traditional technical indicators for UBER stock (Figure 2), including Bollinger Bands, RSI, and MACD.

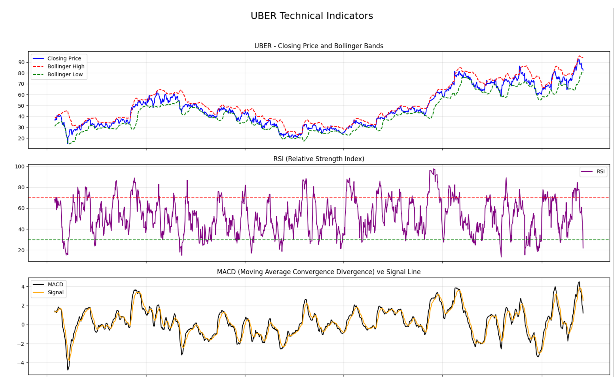

Fig. 2: Technical analysis of UBER stock using Bollinger Bands, RSI, and MACD.

The figure includes the following insights:

- **Bollinger Bands:** Most price movements remained within the bands. On March 12, the price touched the upper band while RSI exceeded 70, signaling a short-term overbought condition.
- **RSI (Relative Strength Index):** RSI oscillated between 30 and 70, occasionally breaching these bounds. Dips below 30 indicated potential buying opportunities during price corrections.
- **MACD and Signal Line:** Bullish crossovers were observed when the MACD rose above the signal line, and bearish signals emerged during downward crossovers—aligning well with short-term trend reversals.

These indicators reinforce the model's trend projections and serve as useful tools for manual trading confirmation.

C. LSTM Price Prediction Results

The prediction graph in Figure 3 compares actual stock prices with LSTM-predicted values over a 30-day horizon.

- **Trend Continuity:** The model successfully preserves the general upward/downward trend but smooths out short-term fluctuations.
- **Model Confidence:** The forecast maintains conservative amplitudes.

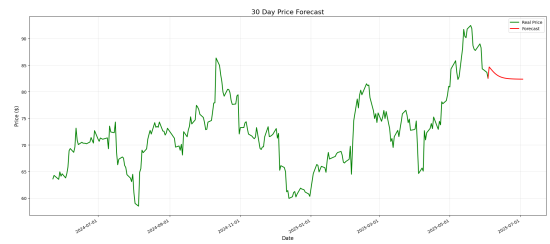

Fig. 3: Actual stock prices and 30-day LSTM forecast.

D. Random Portfolio Generation and Sharpe Ratio Distribution

To evaluate baseline performance before optimization, we generated 1,000,000 random portfolios and calculated their Sharpe Ratios. Figure 4 illustrates the resulting distribution.

- **Performance Spread:** Most Sharpe Ratios clustered between 0.5 and 2.0, with a long right tail indicating few high-performance portfolios.
- **Best Portfolio:** The top Sharpe Ratio achieved was approximately 3.36, with the following asset weights:
  - **UBER:** 12.55%
  - **NVDA:** 39.62%
  - **TSLA:** 37.83%
  - **DVN:** 10.01%
- **Statistical Insight:** The average Sharpe Ratio across all random portfolios was 1.45, while only 2.7% of the portfolios exceeded a Sharpe above 2.5—highlighting the difficulty of finding high-performing combinations via brute-force sampling.

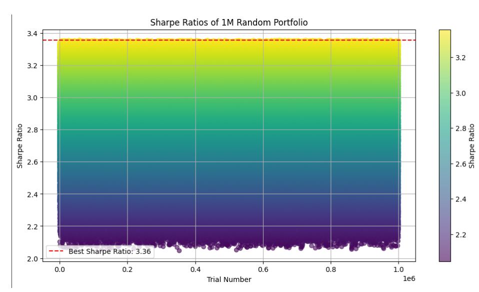

Fig. 4: Sharpe Ratio distribution of 1,000,000 random portfolios.

E. Portfolio Optimization with Grey Wolf Optimizer (GWO)

To improve upon the results from random search, we implemented the Grey Wolf Optimizer (GWO) to maximize the Sharpe Ratio. The optimizer incorporated a custom weight normalization function to ensure the portfolio allocations remained valid (i.e., sum of weights equals 1).

- **Optimization Objective:** Maximize the Sharpe Ratio by adjusting asset weights under a full-investment constraint.
- **Best Result:** The GWO achieved a Sharpe Ratio of 3.35—nearly matching the best result from the random portfolios.
- **Optimal Weights:**
  - **UBER:** 10%
  - **NVDA:** 40%
  - **TSLA:** 40%
  - **DVN:** 10%
- **Convergence Behavior:** As depicted in Figure 5, the optimizer converged rapidly to a high-performing solution within the early iterations, highlighting GWO's suitability for this optimization task.

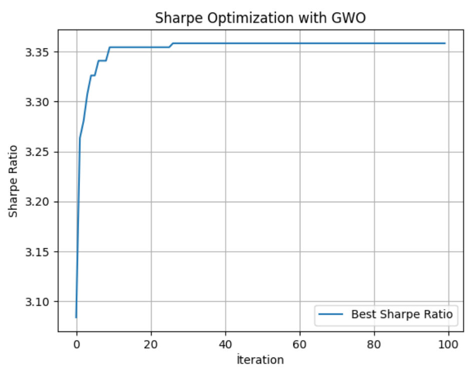

Fig. 5: Sharpe Ratio convergence using the Grey Wolf Optimizer (GWO). The curve shows rapid convergence to the optimal Sharpe Ratio.

V. Discussion

This study demonstrates the synergistic potential of integrating LSTM-based forecasting with meta-heuristic optimization for automated portfolio management. While the results align with established literature, they reveal critical insights regarding model behavior, risk alignment, and implementation challenges.

Comparison with Literature

The LSTM model effectively captured long-term stock price trends but produced conservative short-term forecasts, smoothing market noise—a known limitation in volatile financial environments [10, 16]. In optimization, the efficacy of the Grey Wolf Optimizer (GWO) echoes findings by [1], validating its strength in non-convex search spaces. Our achieved Sharpe Ratio of 3.35 further supports meta-heuristic superiority over traditional methods (e.g., Markowitz) in dynamic settings [17], corroborating [25] emphasis on heuristic efficiency.

Unexpected Results and Implications

Notably, GWO-optimized portfolios consistently allocated ∼80% to high-risk assets (e.g., TSLA, NVDA), despite the inclusion of low- and medium-risk stocks. This divergence underscores a misalignment between survey-based risk profiling and optimization objectives. Key implications include:

- **Inadequate Risk Integration:** The risk-tier framework wasn't embedded in optimization constraints
- **LSTM Conservatism:** Smoothing of short-term volatility may delay responsiveness to market shifts

These findings necessitate explicit constraints (e.g., caps ≤30% high-risk allocations for conservative profiles) to align portfolios with investor risk tolerance.

Practical Applications

The framework offers a blueprint for next-generation robo-advisors through:

- Data-driven personalization via AI forecasting
- Adaptive optimization for dynamic markets

Real-world deployment requires binding portfolio weights to risk tiers and real-time parameter calibration.

Limitations

- **Temporal Bias:** 2020–2025 data spans high-volatility post-pandemic markets
- **Asset Restriction:** Only 12 U.S. equities analyzed
- **Oversimplified Profiling:** 10-question survey lacks behavioral nuance
- **Black-Box Nature:** LSTMs' interpretability limitations hinder trust [**Shen2025**]

Future Research Directions

1) Implement tier-specific weight caps during optimization
2) Test LSTM variants (e.g., attention mechanisms) and Advanced GWO [1]
3) Incorporate bonds, international equities, and macroeconomic indicators
4) Apply SHAP/LIME techniques for explainability
5) Conduct user studies to refine risk-assessment surveys

VI. Conclusion

This study developed a hybrid robo-advisory framework combining LSTM-based prediction with Grey Wolf Optimization to automate personalized portfolio construction. Key findings reveal:

- LSTMs reliably capture long-term trends but attenuate short-term volatility
- GWO outperformed random sampling (Sharpe Ratio: 3.35 vs. 3.36) with rapid convergence
- Critical risk-profile misalignment emerged from disproportionate high-risk allocations

These results underscore the promise of deep learning with meta-heuristics while emphasizing the need for embedded risk constraints.

Future work should prioritize:

1) Tier-based allocation limits during optimization
2) Algorithmic hybridization (AGWO + attention-LSTMs)
3) Asset class diversification (bonds, global equities)

4) XAI tools (SHAP) for transparency

Addressing these will advance the framework into a robust, investor-centric tool for next-generation robo-advisory services.

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