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Optimized GARCH Neural Network Model for Forecasting Volatility and Trading Strategies for First Solar Stock in the Sustainable Energy Sector

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Abstract

This study presents an innovative approach for forecasting financial volatility by integrating the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with Neural Networks (NN). Financial volatility is a critical component in risk management and investment decision-making, as it provides insight into price fluctuations and market uncertainties. Data was collected from Yahoo Finance, specifically adjusted closing prices of First Solar stock, and underwent preprocessing to handle missing values and normalization. The GARCH model was first used to estimate historical volatility, and the resulting volatility data was fed into a neural network for further analysis and prediction. Incorporating key financial indicators such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and trading volume enhanced the feature set, improving model robustness. To further optimize the model, Bayesian Optimization was employed to fine-tune hyperparameters, ensuring improved accuracy in the volatility forecast. The model's forecasting performance was evaluated using standard metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), R-squared (R^2), and Standard Deviation (STD). The results demonstrate the model's superiority in forecasting short-term volatility compared to traditional methods, with the following performance metrics: MAE = 0.0262, MSE = 0.0015, RMSE = 0.0383, MAPE = 16.01%, R^2 = 94.21%, and STD = 0.1473. Additionally, based on the volatility forecasts, a trading strategy was developed that involves "Buy," "Sell," and "Hold" contributes to more informed and adaptive financial strategies in the face of volatile market conditions, while also supporting the broader shift towards sustainable and climate-resilient investments.

Keywords: Volatility Forecasting, GARCH Neural Networks, Financial Risk Management, Sustainable Energy, First Solar

Introduction.

In the increasingly complex context of climate change, the sustainable energy sector has become a top priority for nations. First Solar (FSLR), one of the leading companies in solar energy production, is significantly impacted by financial markets, renewable energy policies, raw material price fluctuations, and sustainable energy usage trends. This amplifies the demand for accurate stock volatility forecasting models to support effective investment decisions and risk management. The GARCH model is a widely used tool for modeling volatility, but it has limitations in handling nonlinear factors and long-term time dependencies. Therefore, combining GARCH with Neural Networks (NNs)—a powerful method for learning nonlinear data—promises improved forecasting accuracy. This study aims to achieve three main objectives: forecasting FSLR stock price volatility using the integrated GARCH-NN model, and building optimal trading strategies based on these forecasts. The study utilizes FSLR stock price data from Yahoo Finance. The performance of the model and trading strategies is evaluated using metrics such as MAE, MSE, RMSE, MAPE, R^2-Score, and STD. The study's findings are expected not only to assist investors in making effective trading decisions but also to provide valuable insights into the impact of climate change on financial markets in the sustainable energy sector.

1. Research Objectives

1.1 Developing a GARCH Model Combined with Artificial Neural Networks (ANN) to Forecast First Solar Stock Volatility

This objective focuses on constructing a hybrid forecasting model that integrates the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model with artificial neural networks (ANN). The aim is to predict the volatility of First Solar's stock, a key factor for investors in managing risks and making informed decisions in the stock market.

1.2 Optimizing Model Hyperparameters Using Bayesian Optimization to Improve Forecast Accuracy

This objective aims to enhance the forecasting performance of the developed model by fine-tuning its hyperparameters. Bayesian Optimization is used to identify the most optimal set of parameters that improve prediction accuracy, ensuring that the model produces more reliable

Volatility in financial markets has always been a major topic of interest for both researchers and practitioners. GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models have become powerful tools for modeling and forecasting volatility. Palm (2005) provided a comprehensive overview of time-series volatility modeling using GARCH processes. The author pointed out that the Student-GARCH and GARCH-jump models can address the issue of excess kurtosis in volatility. Furthermore, the development of multivariate GARCH models and Factor-GARCH has enabled the representation of volatility in high-dimensional space. The Factor-GARCH model is particularly notable for its easy interpretability through economic theory and its flexibility in testing common factors. Gökbulut and Pekkaya (2014) applied asymmetric GARCH models such as CGARCH and TGARCH to forecast volatility in the Turkish financial market. The results showed that these models outperformed in capturing leptokurtosis, asymmetry, volatility clustering, and long memory in time series. Al-Najjar (2016) studied volatility characteristics in the Jordanian stock market using ARCH, GARCH, and EGARCH models. The study found that ARCH/GARCH models could adequately describe volatility clustering and leptokurtosis, while EGARCH did not support the existence of leverage effects. Awartani and Corradi (2005) conducted forecast comparisons between GARCH (1,1) and asymmetric GARCH models. The results indicated that asymmetric GARCH models were superior in short- and medium-term forecasts compared to GARCH (1,1). Pérez-Hernández et al. (2024) combined the GARCH model with artificial neural networks (ANN) and the EWMA method to optimize volatility forecasting. The results demonstrated that ANN and LSTM models excelled in stable periods, delivering better forecasting performance. Kartsonakis Mademlis and Dritsakis (2021) compared the hybrid GARCH-ANN model in the Italian stock market. The results showed that the EGARCH-ANN hybrid model provided the best forecasting performance while clearly reflecting the leverage effect. Muminov et al. (2023) used a Q-learning algorithm to combine blockchain data and Whale-Alert tweets for forecasting Bitcoin volatility. This model significantly improved accuracy and risk management. Kristjanpoller (2024) developed a new method combining GARCH with LSTM and distributed autoregressive models for forecasting financial volatility. This method provides detailed analysis for each time frame rather than relying on average values. The studies above show that GARCH models and their extended versions, particularly when combined with machine learning techniques like ANN, LSTM, or Q-learning, have significantly improved accuracy in forecasting market volatility. The combination of traditional models with modern technology will continue to be a promising research direction, especially in the context of increasing importance of non-structural factors in financial markets.

Research gap: Existing studies mainly focus on traditional financial markets or popular assets like Bitcoin. Research on stocks in the sustainable energy sector, particularly First Solar (FSLR), is still limited. The optimization of Garch models combined with Neural Networks often relies on popular optimization methods like Grid Search or Random Search.

3.1 Log returns and historical volatility

Log returns are calculated using the formula: $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$. Where: P_t is the adjusted closing price on day t. P_{t-1} is the adjusted closing price on day t−1. $\ln$ represents the Neperian logarithm function. This formula computes the daily percentage change in stock prices in natural logarithmic form, which helps eliminate the uneven percentage change effect across different price levels.

Historical Volatility is calculated as the standard deviation (std) of the log returns within a 21-day rolling window: $(Volatility_t)\ \sigma_t = std\left(r_{t-20},\ldots,r_t\right) = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t - \overline{r_t})^2}$. Where: std(...) represents the standard deviation of log return values within the 21-day rolling window. r_t represents the log return on day t. $\overline{r_t}$ is the average log return within the 21-day window. N is the number of observations (N=21). The rolling window covers 21 days (from day t−20 to day t), enabling the measurement of volatility over this period. This approach captures recent fluctuations in stock price returns, reflecting short-term risk. Historical volatility measures the degree of variation in log returns over a specified time window and serves as a critical indicator for assessing stock risk. The rolling window method calculates the standard deviation of the logarithmic returns, providing an updated measure of volatility as the window moves through time.

3.2 Data preparation for volatility forecasting

The dataset, sourced from Yahoo Finance using Adjusted Close (Adj Close) prices, undergoes preprocessing to remove missing values and normalize data for consistency. Volatility is calculated from historical Adj Close prices and visualized to identify trends and fluctuations. The data is split into 80% for training and 20% for testing, including indicators such as Volatility_Historical, Volume, RSI, and MACD. Volatility serves as the target variable for forecasting. The study utilizes the entire historical dataset of First Solar (FSLR) stock from November 6, 2006, to December 27, 2024, incorporating Adj Close prices, trading volume, and technical indicators. The dataset is divided into 80% training and 20% testing subsets to train and optimize the GARCH-NN model, capturing complex financial patterns to enhance volatility forecasting accuracy. The model further supports trading strategies such as "Buy," "Sell," and "Hold."

3.3 Garch neural networks model (Garch-NN)

The GARCH-NN model combines the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework with Artificial Neural Networks (ANN) to enhance the accuracy of financial volatility forecasting.

nonlinear changes in market volatility. The estimated parameters are used to calculate the conditional variance σ_t^2, which is then utilized to predict future volatility.

Integrating a neural network into the GARCH model enhances predictive performance by capturing complex and nonlinear patterns in financial data, surpassing the capabilities of traditional GARCH models.

3.4 Bayesian optimization (BO) algorithm

Bayesian optimization is employed to optimize the hyperparameters of the GARCH-NN model, including the number of hidden layers, learning rate, and other critical parameters. The objective function in Bayesian Optimization evaluates model performance for each set of hyperparameters and updates a probabilistic surrogate model (e.g., Gaussian Process) to predict the next promising set of parameters. This iterative process efficiently explores the hyperparameter space, balancing exploitation (testing parameters known to perform well) and exploration (trying new parameter sets). As a result, Bayesian Optimization identifies the optimal hyperparameters, enhancing the predictive accuracy and robustness of the GARCH-NN model.

3.5 Comprehensive Evaluation of the GARCH-NN model

The GARCH-NN model is trained with hyperparameters optimized using Bayesian Optimization and evaluated on the test set using MAE, MSE, RMSE, MAPE, R^2 Score, and STD metrics. Forecast results are compared with actual values through visual charts, highlighting the model's accuracy and deviations. The 21-day volatility forecast supports trading strategies such as "Buy," "Sell," and "Hold" based on volatility trends. The model demonstrates effectiveness in capturing complex nonlinear relationships and improving forecasting performance compared to traditional Garch, Tarch and Geometric Brownian Motion models.

3.6 Research Instrument

The system utilized for this research is based on Google Colab, a cloud-based platform that provides the computational power of GPU (T4) for deep learning model training and data analysis. The system incorporates a range of Python libraries such as yfinance for financial data retrieval, ta for technical analysis indicators (RSI, MACD), scikit-learn for data preprocessing and model evaluation, arch for volatility modeling, and TensorFlow for building and training machine learning models. The optimization of hyperparameters is achieved through the Bayesian Optimization method using the bayes_opt library.

First Solar (FSLR) is listed on NASDAQ and is a leading global solar panel manufacturer. Its supply chain involves multiple countries, including China, Vietnam, and the US. China plays a significant role in the global solar supply chain, especially in producing solar modules, photovoltaic cells, and wafers. First Solar has partnered with Saigon VRG in Vietnam to distribute solar technologies in Southeast Asia. While the Philippines' specific involvement

First Solar (FSLR) from Yahoo Finance, spanning from 2006 to 2024, is used. The adjusted close ('Adj Close') and trading volume columns are selected, with missing values removed. Then, a correlation matrix is calculated between the data columns, and historical volatility is computed using log returns and a 21-day rolling window. A plot of historical volatility over time is generated.

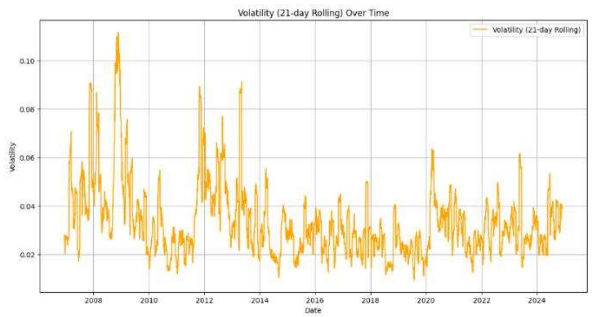

Figure 1. Historical Volatility of FSLR Stock Prices

The logarithmic returns and historical volatility of First Solar stock are calculated using a 21-day rolling window. Data is normalized with Min Max Scaler to enhance model stability. RSI and MACD indicators are included for trend analysis. The feature set (X) and target (Y) are created, with historical volatility as the target for prediction. PCA is applied to reduce data dimensions, simplifying the machine learning model without losing key information. The data is split into training and testing sets. Linear Regression forecasts volatility, evaluated by Mean Squared Error (MSE). The regression coefficients and the importance of PCA components are also assessed to optimize model performance.

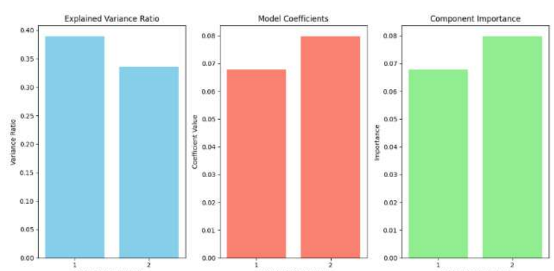

Figure 2. Principal Component Analysis (PCA)

The results provide key insights into the volatility forecasting model. The Explained Variance Ratio (0.389 and 0.336) indicates that the two principal components explain 72.5% of the variance, showing successful dimensionality reduction. The Mean Squared Error (MSE) optimized to minimize the model's loss function (MSE). The garch_nn_objective function, built with TensorFlow's Keras API, trains on historical data (X_train, Y_train) and evaluates on test data. Bayesian Optimization explores parameter configurations across iterations to find the best combination, improving prediction accuracy and preventing overfitting using early stopping. This approach enhances forecasting performance in financial risk management and asset allocation.

Table 1. Optimal Hyperparameters for the GARCH-NN Model

Hyperparameters	Optimal Value
1. Activation	0.5924: Sigmoid
2. dropout_rate	0.0232
3. early_stopping	0.6075
4. learning_rate	0.0171
5. n_hidden_layers	1.2602
6. n_lag	9.5400
7. n_neurons_per_layer	96.9069

Source: Author

The optimal results from Bayesian Optimization for the GARCH-NN model show significant improvements in forecasting performance. The activation parameter near 0.59 indicates the use of a Sigmoid function, which enhances the model's ability to learn nonlinear relationships in the data. A low dropout rate of 0.0232 ensures that most important features are retained, which is crucial in financial contexts to avoid missing key input relationships. Early stopping, with a rate of 60-70%, prevents overfitting by halting training when no significant improvement is observed, enhancing generalization. The small learning rate of 0.0171 allows for steady learning, minimizing the risk of overlooking important factors and maintaining model stability. Using a single hidden layer with about 97 neurons helps reduce model complexity while ensuring effective feature learning, avoiding overfitting. The 9lag parameter indicates that the model uses 9 historical values to predict future ones, suitable for financial problems that depend on past data. In summary, these optimal parameters lead to a GARCH-NN model with accurate, stable predictions, avoiding overfitting, and improving performance in volatile financial tasks.

After cleaning and transforming the parameters, they will initialize the optimal GARCH-NN model. The optimal parameters, including hidden layers, neurons per layer, dropout rate, and learning rate, will be applied for accurate forecasting. The model will be trained on X_train, Y_train for 50 epochs, with early stopping to avoid overfitting.

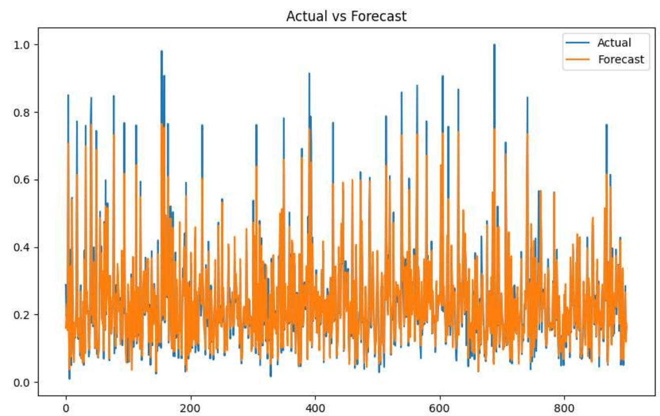

Figure 3. Actual vs Forecasted Volatility

The model evaluation results demonstrate impressive forecasting performance. MAE: 0.0263 indicates a very low average deviation between actual and predicted values, reflecting high accuracy. MSE: 0.0015 suggests minimal large errors, with predictions closely aligning with actual values. RMSE: 0.0382 quantifies prediction error compared to actual data, and its small value indicates precise forecasting. MAPE: 16.01% is considered acceptable in financial applications. The R^2 Score: 0.9422 confirms the model's ability to explain most of the variance in the data, while STD: 0.1474 indicates forecast stability with low standard deviation. These results highlight the GARCH-NN model's effectiveness in time series forecasting tasks, particularly in financial applications, where accuracy and reliability are crucial.

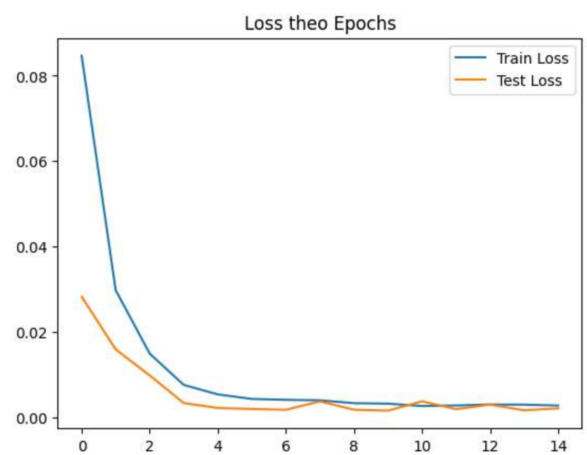

Figure 4. Convergence of Loss Function

Table 2. Forecast Results for Volatility Over the Next 21 Days

Day	Prediction	Strategies
2024-12-28	0.179441	Hold
2024-12-29	0.259876	Buy
2024-12-30	0.231030	Sell
2024-12-31	0.383106	Buy
2025-01-01	0.235559	Sell
2025-01-02	0.305263	Buy
2025-01-03	0.302149	Sell
2025-01-04	0.360524	Buy
2025-01-05	0.185329	Sell
2025-01-06	0.271912	Buy
2025-01-07	0.437810	Buy
2025-01-08	0.078678	Sell
2025-01-09	0.078679	Buy
2025-01-10	0.263947	Buy
2025-01-11	0.351221	Buy
2025-01-12	0.089821	Sell
2025-01-13	0.162510	Buy
2025-01-14	0.173480	Buy
2025-01-15	0.290843	Buy
2025-01-16	0.122933	Sell

Source: Author

The forecast of FSLR stock price volatility over the next 21 days reveals significant fluctuations, with the lowest volatility value recorded at 0.078678 on 2025-01-08 and the highest at 0.437810 on 2025-01-07. High-volatility days, such as 2024-12-31 and 2025-01-07, may reflect significant events or exogenous factors strongly impacting the market. Conversely, low-volatility days indicate relative market stability or cautious investor sentiment.

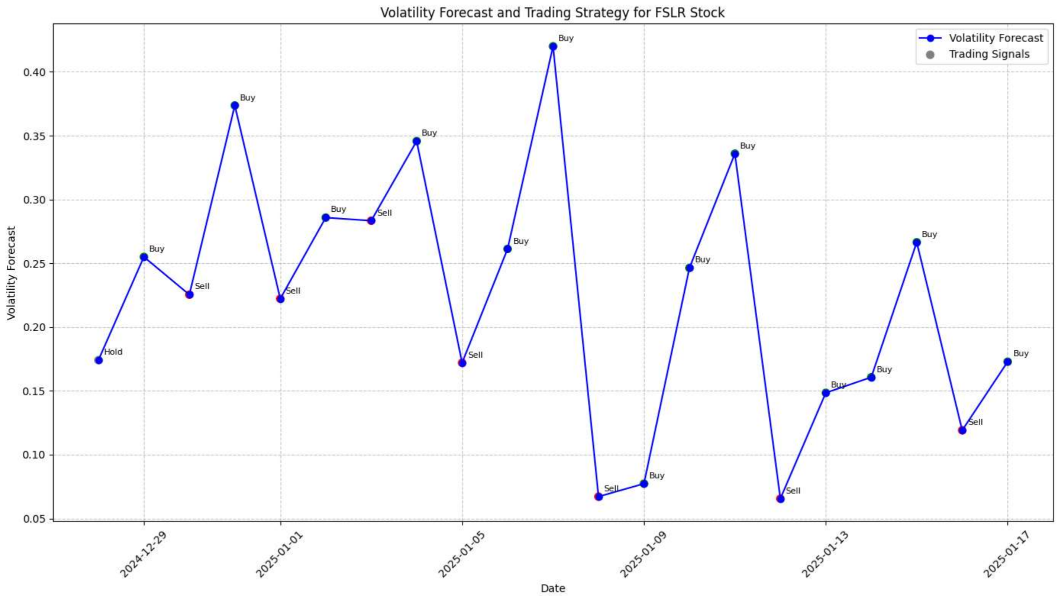

Figure 5 Volatility Prediction and Trading Strategies

The trading strategy is constructed based on these volatility trends. A "Buy" signal emerges during periods of increased volatility, reflecting potential profit expectations. Dates such as 2024-12-29, 2025-01-07, and 2025-01-11 present attractive investment opportunities. A "Sell" signal occurs when volatility decreases, helping investors mitigate potential risks, as observed on 2024-12-30, 2025-01-05, and 2025-01-12. A single "Hold" signal appears on 2024-12-28, indicating temporary market stability. The alternation between these signals demonstrates a flexible trading strategy, capable of adapting swiftly to short-term market shifts. Additionally, climate change and extreme weather events such as hurricanes and floods can significantly influence stock price volatility. Countries including the United States, Vietnam, China, and the Philippines are frequently impacted by these events, which disrupt supply chains and cause market uncertainty. The forecast results and the corresponding trading strategy offer a comprehensive perspective on FSLR stock volatility trends, assisting investors in making informed decisions, optimizing profits, and minimizing short-term risks.

Natural disasters, such as storms and climate change, can increase risks and cause "Buy" or "Sell" signals to change rapidly. Investors need flexible trading strategies to cope with uncertainty and market fluctuations. Overall, the quick changes caused by these factors not only impact the economy but also require investors to adjust their decisions to buy, sell, or hold in order to minimize risks and optimize profits.

Table 3. Comparison of GARCH-NN with Traditional Models

Metrics	Garch-NN	Garch	Tarch	GBMotion
MAE	0.0263	2.0545	1.2063	0.7301
MSE	0.0015	6.7621	1.8700	1.0214
RMSE	0.0383	2.6004	1.3675	1.0107
MAPE	16.01%	50.99%	4.8794	105.80%
R^2	94.22%	-165.46%	-67.10%	-0.18%
STD	0.1474	1.5960	1.0585	1.0105

Source: Author

The performance of different models in forecasting financial volatility. The GARCH-NN model outperforms others with MAE=0.0263, MSE=0.0015, RMSE=0.0383, MAPE=16.01%, STD=0.1474 and R^2=94.22%, demonstrating its accuracy and stability. In contrast, the GARCH model performs the worst, with MAE=2.0545, MSE=6.7621, and R^2_Score=-165.46%, indicating poor fit with the data. Other models like Tarch and GB-Motion show some improvement but still do not reach the performance level of GARCH-NN.

The GARCH-NN model performs well but has limitations. MAPE of 16.01% may be higher than desired in finance. To improve, parameter optimization is needed, learning from extreme fluctuations, and incorporating macroeconomic factors or market news to enhance accuracy and responsiveness.

Conclusion

The study developed a GARCH model combined with Artificial Neural Networks (ANN) to forecast the volatility of First Solar stock, aiming to provide accurate and stable predictions. Hyperparameter optimization using Bayesian Optimization improved forecast accuracy, with performance metrics such as MAE = 0.0263, MSE = 0.0015, RMSE = 0.0382, MAPE=16.01%, STD=0.1474 and R^2 = 94.22%, outperforming traditional methods.

The forecasting results indicate that the model can quickly respond to market volatility and support the development of flexible trading strategies that adjust to market changes. This is crucial for making effective short-term trading decisions, especially in the face of unpredictable volatility. The optimized GARCH-NN model can be adjusted to track trends in the renewable energy sector, helping investors identify long-term opportunities in the shift towards sustainable energy. For First Solar, a leader in the renewable energy industry, this model can support long-term investment strategies and contribute to the goal of mitigating the impacts of climate change.