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Hybrid Metaheuristic Optimization for Time Series Forecasting: Integrating Grey Wolf and Greylag Goose Strategies

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ABSTRACT

Time series forecasting is crucial in agricultural markets, where accurate predictions can enhance stakeholder decision-making. Traditional statistical models such as ARIMA often struggle with capturing complex patterns, necessitating the integration of metaheuristic optimization techniques to improve predictive performance. This study introduces a novel hybrid optimizer, the Grey Wolf-Greylag Goose Optimizer (GGGWO), which combines the strengths of the Grey Wolf Optimizer (GWO) and the Greylag Goose Optimizer (GGO) to enhance the forecasting accuracy of ARIMA models. The proposed GGGWO-ARIMA model is evaluated on a dataset of daily potato prices across multiple Indian cities and is compared against ARIMA, WOA-ARIMA, PSO-ARIMA, GWO-ARIMA, and GGO-ARIMA. Experimental results demonstrate that GGGWO achieves the lowest MSE (0.0027), RMSE (0.0184), and MAE (0.0116) while attaining the highest R-squared (0.9648) and Willmott Index (0.9565), outperforming all baseline models. These findings highlight the efficacy of hybridizing GWO and GGO, offering a robust optimization framework for improving time series forecasting in agricultural price prediction. This can aid policymakers, farmers, and market analysts make data-driven decisions.

Keywords: Metaheuristic Optimization ▪ Time Series Forecasting ▪ Grey Wolf Optimizer (GWO) ▪ Greylag Goose Optimizer (GGO) ▪ Hybrid ARIMA Model

1. INTRODUCTION

Time series forecasting is essential across nearly all domains, such as finance, healthcare, energy, and agriculture. Accurate forecasting aids stakeholders in decision-making, resource optimization, and preventing potential risks. Price forecasting is vital in agriculture because it directly influences farmers, traders, policymakers, and consumers [1, 2]. Furthermore, better predicting the price volatility of commodities, including potatoes, provides market participants with a more reliable forecast, leading to improved economic stability through planning and reduced uncertainty. However, agricultural price forecasting is challenging due to the influence of multiple dynamic factors, such as seasonal variations, supply chain disruptions, climate conditions, and policy changes [3, 4].

Time series forecasting has been extensively carried out using traditional statistical models, with the Autoregressive Integrated Moving Average (ARIMA) model being widely utilized. ARIMA can capture linear dependencies observed in the data and has been extensively applied in econometric and financial forecasting [5, 6]. Nevertheless, it has several limitations when modeling non-stationary and highly volatile data. Since agricultural commodity prices often exhibit nonlinear behaviors influenced by numerous external factors, no statistical model can deliver optimal predictive performance

[7].

Metaheuristic optimization algorithms have recently gained significant attention for improving forecasting models. Inspired by natural and biological processes, these optimization algorithms efficiently solve complex problem spaces. Metaheuristic techniques balance exploration (global search) and exploitation (local search), making them naturally suited for parameter optimization in forecasting models [8, 9]. The Grey Wolf Optimizer (GWO) and the Greylag Goose Optimizer (GGO) are among the most promising metaheuristic algorithms. GWO is inspired by the hunting behavior of grey wolves, which gives it strong exploitation characteristics. In contrast, GGO is modeled after the migratory behavior of greylag geese, which allows for efficient global exploration [10].

This study is motivated by developing an improved forecasting framework to capture agricultural commodity price dynamics. This study integrates GWO and GGO to leverage the complementary advantages of these two algorithms, thereby enhancing forecasting accuracy and model efficiency [11].

Forecasting agricultural commodity prices presents unique challenges due to the inherent stochastic nature of market behavior. Unlike financial assets, which are influenced by investor sentiment and economic indicators, agricultural commodity prices are determined by climatic conditions, transportation logistics, demand fluctuations, and government policies [12, 13]. Seasonal trends and irregular price movements make developing accurate forecasting models particularly difficult.

ARIMA is a traditional statistical model that predicts future values based on past values and linear relationships. While effective for stationary and well-structured time series data, it struggles to adapt to abrupt changes and complex nonlinear relationships [14]. Recently, hybrid approaches that merge traditional models with intelligent optimization techniques have shown promise in addressing these challenges. Optimization algorithms enhance forecasting models by fine-tuning parameters, reducing prediction errors and improving model robustness.

Several optimization techniques, such as the Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO), have enhanced ARIMA-based forecasting. These methods improve predictive performance to a certain extent but are constrained by challenges such as premature convergence and limited adaptability in highly dynamic datasets [15].

Grey Wolf Optimizer (GWO) and Greylag Goose Optimizer (GGO) present adaptive search strategies that draw inspiration from nature. GWO, based on the social hierarchy and cooperative hunting behavior of grey wolves, has strong exploitation capabilities, ensuring rapid convergence to near-optimal solutions. On the other hand, GGO, which mimics the flight and leadership switching behavior of greylag geese, provides enhanced exploration abilities, allowing the model to escape local optima. This study aims to develop a hybrid optimization framework that efficiently balances exploration and exploitation by integrating these two algorithms.

Several key objectives drive this research to address the challenges outlined above. First, it aims to investigate the limitations of conventional ARIMA models in agricultural price forecasting, identifying areas where they struggle with nonlinear dependencies and market volatility. Second, it seeks to develop a hybrid Grey Wolf-Greylag Goose Optimizer (GGGWO) that effectively integrates the strengths of GWO and GGO to enhance parameter tuning efficiency. Third, the study applies the proposed GGGWO-ARIMA model to forecasting daily potato prices across various Indian cities, demonstrating its applicability to real-world agricultural datasets. Fourth, it conducts a comparative analysis of the proposed hybrid model against baseline approaches, including ARIMA, WOA-ARIMA, PSO-ARIMA, GWO-ARIMA, and GGO-ARIMA, to assess improvements in predictive accuracy and robustness. Finally, the research evaluates the broader impact of the hybrid optimization approach on forecasting accuracy, model stability, and computational efficiency, highlighting its potential to enhance decision-making in agricultural markets.

This study presents a novel hybrid optimization framework, the Grey Wolf-Greylag Goose Optimizer (GGGWO), to enhance time series forecasting accuracy. The main contributions of this research are as follows:

- **Development of a Hybrid Metaheuristic Optimizer:** The integration of the Grey Wolf Optimizer (GWO) and the Greylag Goose Optimizer (GGO) introduces a synergistic balance between exploitation and exploration, improving the parameter tuning process for ARIMA-based forecasting models.
- **Application to Agricultural Price Forecasting:** The proposed GGGWO-ARIMA model is applied to predict daily potato prices across multiple Indian cities, addressing the challenges of price volatility and nonlinearity in agricultural markets.
- **Comparative Analysis with Existing Models:** The performance of the GGGWO-ARIMA model is rigorously evaluated against conventional ARIMA and metaheuristic-enhanced ARIMA models, including WOA-ARIMA, PSO-ARIMA, GWO-ARIMA, and GGO-ARIMA.
- **Performance Improvement and Robustness:** Experimental results demonstrate that GGGWO-ARIMA achieves superior predictive accuracy, as evidenced by lower Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), while attaining higher R-squared and Willmott Index scores.
- **Computational Efficiency:** Despite being a hybrid model, GGGWO maintains a competitive computational cost, making it suitable for real-world forecasting applications.

These contributions highlight the efficacy of combining nature-inspired metaheuristic techniques for optimizing time series forecasting models, particularly in agricultural market predictions.

The remainder of this chapter is structured as follows. Section 2 provides a comprehensive literature review on metaheuristic optimization in time series forecasting. Section 3 describes the proposed GGGWO-ARIMA model, detailing the mathematical formulations, optimization framework, and experimental setup. Section 4 presents the Hybrid Grey Wolf-Greylag Goose Optimizer (GGGWO), explaining its mechanism and the advantages of integrating GWO and GGO. Section 5 discusses the experimental findings, including a comparative performance evaluation of GGGWO-ARIMA against baseline models. Finally, Section 6 concludes the study by summarizing key findings, discussing limitations, and outlining potential future research directions.

2. LITERATURE REVIEW

Recent research has focused on applying optimization algorithms in various forecasting and predictive modeling tasks. Several studies have explored optimization strategies combined with machine learning and deep learning approaches to enhance prediction accuracy in energy consumption forecasting, wireless network traffic prediction, hydrological modeling, stock market forecasting, and wind speed prediction.

Energy forecasting is crucial for maintaining grid stability and efficient energy management. A novel hybrid forecasting system integrating Seasonal AutoRegressive Integrated Moving Average (SARIMA) with Least Squares Support Vector Regression (LSSVR), optimized by the Jellyfish Search (JS) algorithm, has been developed to predict energy consumption with high accuracy and lower input requirements [16]. Similarly, an AI-driven deep learning framework optimized with an improved Sine Cosine Algorithm (SCA) was proposed to handle energy forecasting tasks effectively, demonstrating superior mean square error rates across various energy generation datasets [17].

Wireless network traffic forecasting presents challenges due to its nonlinear patterns. A hybrid optimization approach combining the Fitness Grey Wolf and Dipper Throated Optimization algorithms has been proposed to optimize hyperparameters in Long Short-Term Memory (LSTM) models, achieving superior accuracy compared to conventional optimization approaches [18]. In addition, a revised enhanced extreme Grey Wolf Optimizer (REEGWO) was used to optimize CNN and BiLSTM models, significantly improving prediction accuracy in traffic flow [19].

Another application domain of optimization is hydrological forecasting. To improve streamflow forecasting accuracy, Equilibrium Optimization (EO), Henry Gases Solubility Optimization (HGSO), and Nuclear Reaction Optimization (NRO) metaheuristic algorithms were integrated with a Multi-Layer Perceptron (MLP) model. Among these, NRO exhibited the best performance in capturing streamflow patterns with the lowest prediction errors [20]. Likewise, a study comparing autoregressive (AR) models optimized using PSO, GA, and DE demonstrated that ARMA models outperformed other approaches in forecasting seasonal streamflow data for Brazilian hydroelectric plants [21].

Artificial Neural Networks (ANN) have been integrated with feature selection using Genetic Algorithms (GA) and metaheuristic algorithms such as Social Spider Optimization (SSO) and Bat Algorithm (BA) to enhance stock market predictions. These methods have outperformed traditional time-series models such as ARMA and ARIMA in predicting major stock indices [22].

A Wolf-Inspired Optimized Support Vector Regression (WIO-SVR) model was proposed to optimize the hyperparameters of the Support Vector Regression (SVR) model using the Grey Wolf Optimizer (GWO) for building energy consumption forecasting. This model significantly improved predictive accuracy compared to baseline machine learning models such as Random Forests (RF) and Decision Trees [23].

Wind speed forecasting plays a crucial role in ensuring power system stability. A novel weighted ensemble model optimized using Adaptive Dynamic Grey Wolf–Dipper Throated Optimization (ADGWDTO) was developed to improve wind speed prediction accuracy. This model successfully outperformed state-of-the-art wind forecasting algorithms [24]. Furthermore, a deep learning-based energy load prediction model using LSTM was developed and tuned using a metaheuristic optimization approach, demonstrating that parameter tuning can significantly improve forecasting accuracy [25].

Integrating optimization algorithms with machine learning and deep learning techniques has yielded promising results across various forecasting applications. Hybrid models, metaheuristic optimization strategies, and deep learning frameworks have significantly improved predictive accuracy for energy forecasting, traffic prediction, hydrological modeling, stock market analysis, and wind speed prediction. Future research should focus on further improving optimization algorithms and exploring hybrid approaches to enhance forecasting performance across multiple domains.

3. METHODOLOGY

3.1 Dataset Description

The dataset utilized in this study consists of daily pricing data for potatoes across multiple cities in India [26]. This dataset is instrumental in evaluating the effectiveness of the proposed Grey Wolf-Greylag Goose Optimizer (GGGWO) for time series forecasting, as it presents real-world agricultural price fluctuations influenced by various market dynamics.

The dataset contains the following key attributes:

- **Date**: This column records the specific date for which the price of potatoes was reported. Time-series forecasting models rely on this chronological order to analyze trends and patterns.
- **Centre_Name**: This column represents the district or city where the price data was collected. Since the dataset includes multiple locations, it allows for a broader understanding of regional price variations.
- **Commodity_Name**: Although present in the dataset, this column is implicit and can be ignored, as all entries contain the same value (potatoes). The dataset was initially extracted from a more extensive database containing multiple commodity prices.
- **Price**: This column indicates the recorded price of potatoes on a given date in a specific district. This is the target variable for forecasting models, and its historical fluctuations form the basis for predictive analysis.

Given its structured nature, this dataset provides a well-defined framework for applying time series forecasting techniques. Including multiple districts allows for potential generalization across different regions, making the study more applicable to real-world agricultural markets. The dataset also presents challenges commonly found in commodity price forecasting, such as seasonality, sudden market fluctuations, and external economic influences. Consequently, it is a suitable benchmark for evaluating the performance of traditional and hybrid metaheuristic-optimized forecasting models.

3.2 Data Preprocessing

Effective data preprocessing is crucial for ensuring the accuracy and robustness of forecasting models. Since real-world datasets often contain inconsistencies, missing values, and varying scales of numerical values, appropriate preprocessing techniques are applied to improve the dataset's quality before model implementation. This section outlines the preprocessing steps undertaken in this study, focusing on handling missing values and normalization techniques.

3.2.1 Handling Missing Values

Missing data is a common issue in time series forecasting and can significantly impact model performance if not addressed properly. In the given dataset, missing values may arise due to irregular reporting, data collection errors, or disruptions in the supply chain. To handle missing values effectively, the following strategies were employed:

- **Forward Fill (FF)**: If a price value is missing for a particular date in a specific district, the most recent previous value is propagated forward. This technique is proper when price trends exhibit gradual changes over time.
- **Backward Fill (BF)**: In cases where missing values appear at the beginning of a time series, the next available future value is carried backward.
- **Interpolation**: Linear Interpolation is applied when forward and backward filling methods are insufficient. This technique estimates missing values based on the trend observed in surrounding data points.
- **Removing Highly Incomplete Records**: If a particular district has excessive missing values that cannot be reasonably interpolated (e.g., over 30% missing data in a given time series), the district is excluded from the analysis to maintain data reliability.

By employing these techniques, the dataset is refined to ensure continuity and consistency, minimizing the impact of missing data on the forecasting models.

3.2.2 Normalization Techniques

Time series forecasting models, particularly those using optimization-based approaches, are sensitive to the scale of numerical values. Since the dataset contains raw price values that may vary significantly across different regions, normalization is applied to standardize the data and improve model convergence.

The following normalization techniques were considered:

- **Min-Max Scaling**: Each price value is scaled to a fixed range, typically between $[0,1]$, using the formula:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X' is the normalized price, X is the original price and $X_{\min}$ and $X_{\max}$ represent the minimum and maximum prices observed in the dataset, respectively. This method ensures that all values remain within a fixed interval, preventing dominance by large numerical values.

- **Z-Score Standardization**: In cases where the data exhibits a normal distribution, Z-score normalization is applied to transform the data into a distribution with zero mean and unit variance:

$$X' = \frac{X - \mu}{\sigma} \tag{2}$$

where μ represents the mean of the price values and σ denotes the standard deviation. This technique is particularly effective for datasets with varying levels of volatility across different districts.

- **Log Transformation**: To address the issue of skewed price distributions, logarithmic transformation is applied as follows:

$$X' = \log(1 + X) \tag{3}$$

Adding 1 ensures that zero-valued prices do not result in undefined logarithmic values. This transformation stabilizes variance and reduces the impact of extreme price fluctuations.

By implementing implementation techniques, the dataset I structures and optimizes the dataset models, ensuring effective operation with reduced bias and improved generalization. These steps enhance the overall efficiency of the proposed Grey Wolf-Greylag Goose Optimizer (GGGWO)-based forecast.

The bar chart in Figure 1 displays the average potato prices across different centers in India. This visualization highlights regional variations in pricing, which reflect economic, logistical, and climatic factors influencing agricultural markets. Such patterns emphasize the importance of accurate forecasting models like GGGWO-ARIMA.

The heatmap in Figure 2 presents the average potato prices by center and month, illustrating temporal and regional pricing patterns. Variations in price trends across months are evident, underscoring the necessity for dynamic forecasting models capable of accounting for seasonality and regional fluctuations, such as the proposed GGGWO-ARIMA model.

In Figure 3, the bar chart represents the average potato prices across different years, highlighting long-term price trends. The steady price increase over time reflects the impact of inflation, supply-demand dynamics, and policy changes. This trend reinforces the significance of accurate time series forecasting to assist stakeholders in market decision-making.

3.3 ARIMA Model for Time Series Forecasting

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used statistical method for time series forecasting, particularly for datasets exhibiting trends and sea-

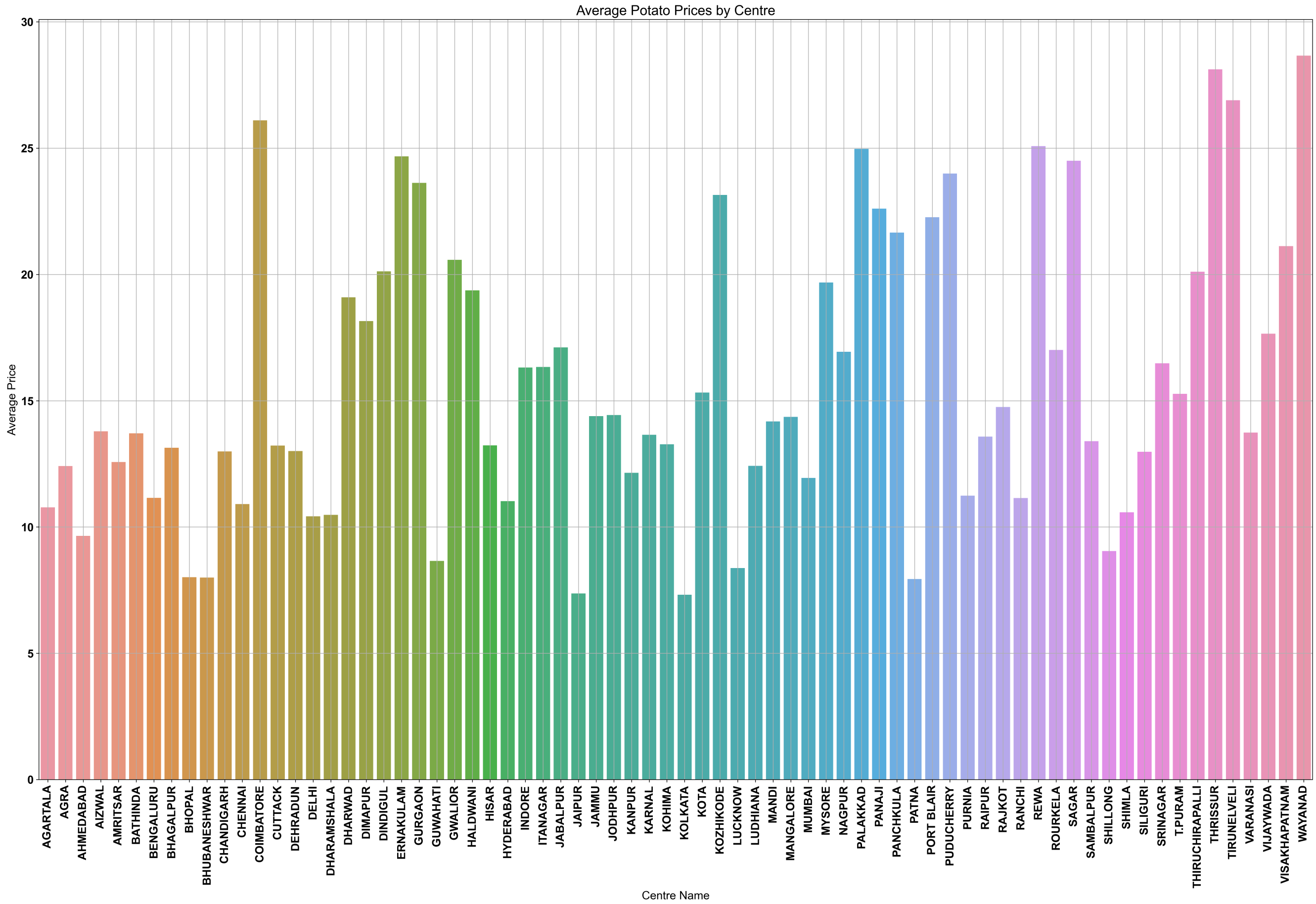

Figure 1. Bar chart showing average potato prices across different centers in India.

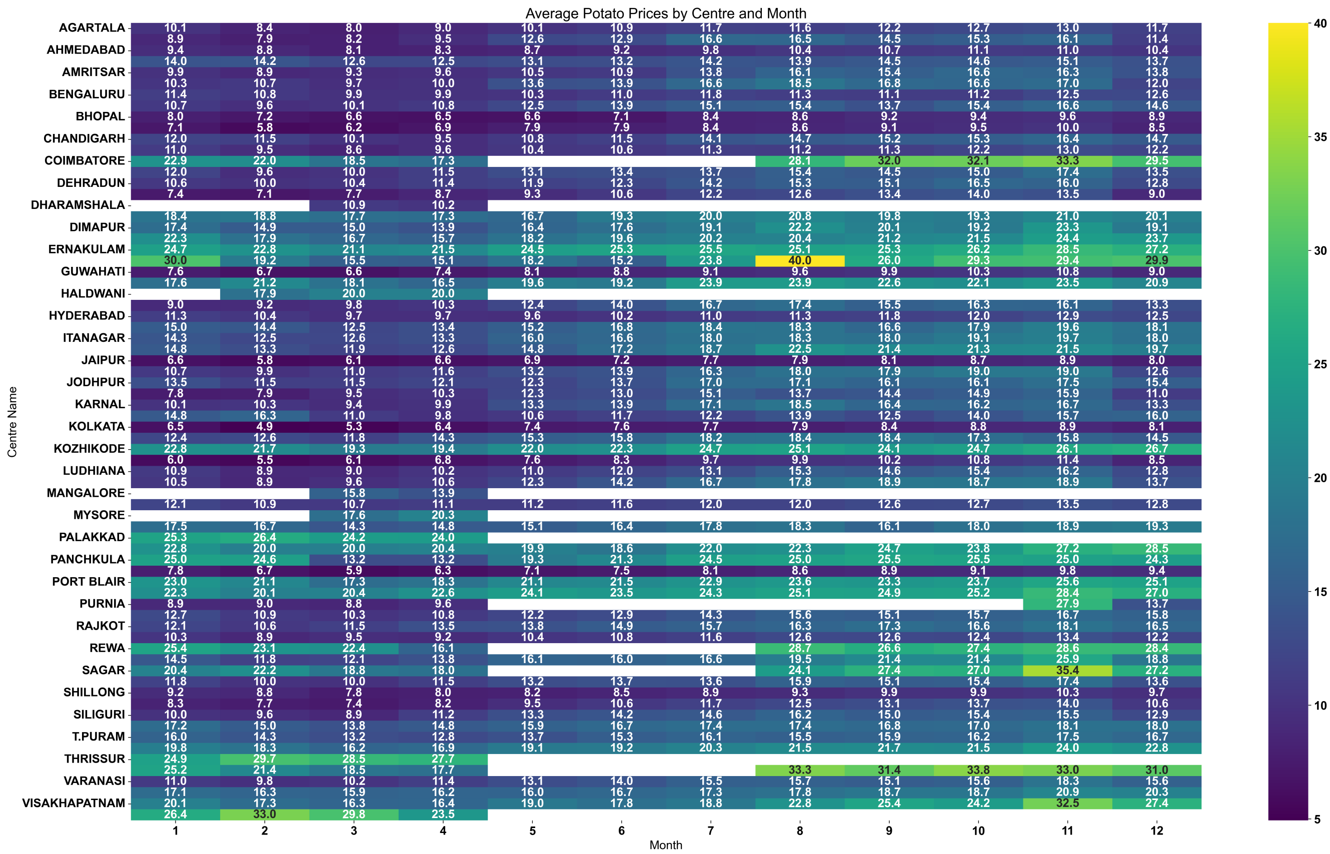

Figure 2. Heatmap of average potato prices by center and month.

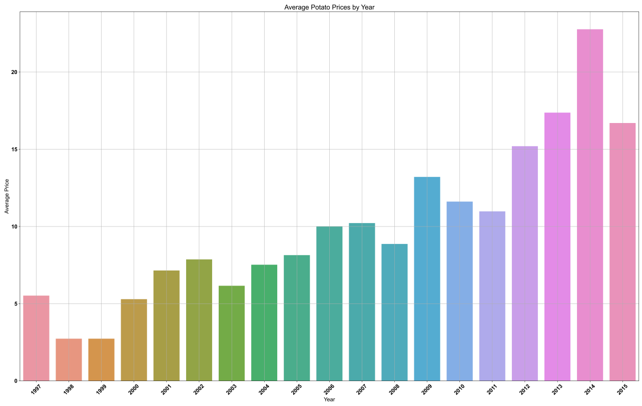

Figure 3. Bar chart showing average potato prices over the years.

sonality. ARIMA integrates three main components: autoregression (AR), differencing (I), and moving average (MA), which collectively help capture the underlying patterns in a time series.

3.3.1 Mathematical Formulation of ARIMA

An ARIMA(p,d,q) model is defined by three parameters:

- p: The number of lag observations included in the model (autoregressive component).
- d: The number of times the data must be differenced to achieve stationarity (integrated component).
- q: The size of the moving average window, which accounts for past forecast errors (moving average component).

The ARIMA model is mathematically expressed as:

$$\begin{aligned} Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} \\ + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots \\ + \theta_q \varepsilon_{t-q} + \varepsilon_t, \end{aligned} \tag{4}$$

where Y_t represents the time series value at time t, ϕ_i are the autoregressive coefficients, θ_i are the moving average coefficients, and ε_t is the error term.

To apply ARIMA effectively, the time series must be ensured. If the series is non-stationary, differencing operations are performed until stationarity is achieved. The order of differencing (d) is determined using the Augmented Dickey-Fuller (ADF) test.

3.3.2 Parameter Selection and Model Tuning

The effectiveness of ARIMA relies heavily on selecting the appropriate values for (p,d,q). Model selection is performed through:

- **Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)** plots to determine suitable values for p and q.
- **Akaike Information Criterion (AIC)** and **Bayesian Information Criterion (BIC)** to compare different model configurations and select the one with the lowest error metric.
- **Grid Search and Cross-Validation**, where multiple combinations of (p,d,q) are evaluated to find the optimal configuration.

Although ARIMA can capture linear relationships in time series, it struggles with complex nonlinear patterns, requiring additional enhancements to improve forecasting accuracy. This limitation motivates the integration of metaheuristic optimization techniques.

3.4 Metaheuristic Optimization of ARIMA

Metaheuristic optimization techniques enhance the performance of ARIMA's performance parameters for better predictive accuracy. Instead of relying on conventional manual tuning methods, metaheuristics explore a broader search space, leading to improved model robustness and generalization.

3.4.1 Role of Metaheuristics in ARIMA Optimization

The primary role of metaheuristic algorithms in ARIMA optimization is to find the best combination of (p,d,q) values that minimize forecasting errors. This is achieved by defining an objective function, typically based on minimizing error metrics such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE), and leveraging optimization techniques to search for the best parameter set.

Given the vast number of potential (p,d,q) combinations, metaheuristic algorithms efficiently navigate the search space, balancing exploration (global search) and exploitation (local refinement) to achieve optimal model configurations.

3.4.2 Common Metaheuristic Algorithms for ARIMA Optimization

Several metaheuristic algorithms have been applied to ARIMA optimization, including:

- **Whale Optimization Algorithm (WOA)**: Inspired by the bubble-net hunting behavior of whales, WOA effectively optimizes ARIMA parameters by iteratively adjusting search agents.
- **Particle Swarm Optimization (PSO)**: Simulates the swarm intelligence of birds and fish, adjusting ARIMA parameters based on the best-known solutions within the population.
- **Grey Wolf Optimizer (GWO)**: Based on grey wolves' leadership and hunting strategies, GWO improves ARIMA by dynamically adjusting search behavior to avoid local optima.
- **Greylag Goose Optimizer (GGO)**: Mimics the cooperative flight patterns of geese, utilizing a balance between exploration and exploitation to refine ARIMA's parameter selection.

3.4.3 Proposed Hybrid Optimization Approach

While standalone metaheuristic methods enhance ARIMA's performance, each algorithm has strengths and limitations. The Grey Wolf Optimizer (GWO) excels at exploitation and efficiently refines solutions, whereas the Greylag Goose Optimizer (GGO) is highly effective at exploration and prevents premature convergence.

Table 1. Parameter settings for optimization algorithms.

Optimizer	Population Size	Maximum Iterations
ARIMA (Baseline)	-	-
WOA-ARIMA	30	500
PSO-ARIMA	30	500
GWO-ARIMA	30	500
GGO-ARIMA	30	500
GGGWO-ARIMA	**30**	**500**

This study integrates GWO and GGO into a unified optimization approach, the Grey Wolf-Greylag Goose Optimizer (GGGWO). This hybrid model aims to leverage:

- **The strong local search capability of GWO** enables rapid convergence to optimal ARIMA parameters.
- **The superior global exploration ability of GGO**, preventing stagnation and improving diversity in parameter search.

By integrating GWO and GGO, the proposed hybrid optimizer balances search efficiency and parameter tuning accuracy, ultimately enhancing ARIMA's forecasting performance. The subsequent sections of this study evaluate the effectiveness of GGGWO in optimizing ARIMA and compare its forecasting accuracy with existing optimization techniques.

3.5 Experimental Setup

3.5.1 Parameter Settings for Each Optimizer

The hyperparameters for the optimization algorithms were carefully tuned to balance exploration and exploitation. The configurations used for each optimizer are provided below:

Additionally, for GGGWO, the balance between exploration and exploitation was dynamically adjusted using:

- **Adaptive Exploration Rate:** Starting at 70% exploration and 30% exploitation, shifting to 30% exploration and 70% exploitation by the end of iterations.
- **GGO Leadership Rotation Frequency:** Every 20 iterations to prevent stagnation.
- **GWO Convergence Factor (γ):** Linearly decreased from 2 to 0.

3.5.2 Evaluation Metrics

To assess the forecasting accuracy of the models, a set of stagnation metrics include:

Mean Squared Error (MSE) Measures the average squared difference between actual and predicted values:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(Y_{\text{actual},i} - Y_{\text{predicted},i})^2. \tag{5}$$

Root Mean Squared Error (RMSE) The square root of MSE, providing an interpretable measure in the same unit as the target variable:

$$\text{RMSE} = \sqrt{\text{MSE}}. \tag{6}$$

Mean Absolute Error (MAE) Represents the average absolute difference between actual and predicted values:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|Y_{\text{actual},i} - Y_{\text{predicted},i}|. \tag{7}$$

Mean Bias Error (MBE) Measures systematic errors in prediction by capturing the average bias:

$$\text{MBE} = \frac{1}{N}\sum_{i=1}^{N}(Y_{\text{predicted},i} - Y_{\text{actual},i}). \tag{8}$$

Correlation Coefficient (r) Indicates the strength of the linear relationship between actual and predicted values:

$$r = \frac{\sum(Y_{\text{actual},i} - \bar{Y}_{\text{actual}})(Y_{\text{predicted},i} - \bar{Y}_{\text{predicted}})}{\sqrt{\sum(Y_{\text{actual},i} - \bar{Y}_{\text{actual}})^2 \sum(Y_{\text{predicted},i} - \bar{Y}_{\text{predicted}})^2}}. \tag{9}$$

R-Squared (R^2) Measures the proportion of variance in the dependent variable that is predictable from the independent variable:

$$R^2 = 1 - \frac{\sum(Y_{\text{actual},i} - Y_{\text{predicted},i})^2}{\sum(Y_{\text{actual},i} - \bar{Y}_{\text{actual}})^2}. \tag{10}$$

Relative Root Mean Squared Error (RRMSE) A normalized version of RMSE expressed as a percentage:

$$\text{RRMSE} = \frac{\text{RMSE}}{\bar{Y}_{\text{actual}}} \times 100. \tag{11}$$

Nash-Sutcliffe Efficiency (NSE) A widely used metric in hydrological forecasting, NSE measures how well a model predicts relative to the mean of observations:

$$\text{NSE} = 1 - \frac{\sum(Y_{\text{actual},i} - Y_{\text{predicted},i})^2}{\sum(Y_{\text{actual},i} - \bar{Y}_{\text{actual}})^2}. \tag{12}$$

Willmott Index (WI) A measure of agreement between predicted and actual values:

$$\text{WI} = 1 - \frac{\sum(Y_{\text{actual},i} - Y_{\text{predicted},i})^2}{\sum\left(|Y_{\text{predicted},i} - \bar{Y}_{\text{actual}}| + |Y_{\text{actual},i} - \bar{Y}_{\text{actual}}|\right)^2}. \tag{13}$$

Fitted Time (Execution Time) The computational efficiency of the models is evaluated using Fitted Time, which records the total execution time required for each forecasting model.

3.5.3 Reproducibility and Experimental Validity

To ensure the validity and reproducibility of the experimental results, the following practices were adopted:

- **Multiple Runs:** Each experiment was conducted over 30 independent runs, and the average performance was reported.

- **Statistical Significance Tests:** The results were validated using Wilcoxon signed-rank tests to compare the performance of GGGWO-ARIMA against other models.
- **Cross-Validation:** A rolling window validation approach was used to assess the robustness of forecasting models.

This section has outlined the framework, including parameter settings and evaluation metrics. The following sections will present the cognitive performance of GGGWO-ARIMA and other forecasting models.

4. HYBRID GREY WOLF-GREYLAG GOOSE OPTIMIZER (GGGWO)

4.1 Greylag Goose Optimization (GGO) Overview

The Greylag Goose Optimization (GGO) is a recently developed swarm-based metaheuristic algorithm inspired by the dynamic behavior of greylag geese during migration [27]. Geese fly in a V-shaped formation to reduce air resistance, conserve energy, and optimize flight paths. GGO integrates these adaptive and cooperative mechanisms into its optimization process.

The key mechanisms in GGO include:

1. **Dynamic Grouping:** The population is divided into two dynamically adjusting groups: the exploration and exploitation groups. The exploration group searches for new promising regions, while the exploitation group refines the best-known solutions.
2. **Leadership Rotation:** The leader of the V-formation is periodically rotated among the members to prevent stagnation in suboptimal solutions.
3. **Search Space Adaptation:** The algorithm mimics the geese's ability to balance between long-distance migration (global search) and short-distance re-adjustments (local search).

Mathematically, GGO updates the positions of geese using the following equation:

$$X_{\text{new}} = \omega_1 \cdot X_{\text{random}} + \omega_2 \cdot (X_{\text{best}} - X_{\text{current}}), \tag{14}$$

where:

- X_{random} is a randomly selected solution, promoting exploration.
- X_{best} represents the best-known solution so far, enhancing exploitation.
- ω_1 and ω_2 are adaptive weights that regulate the balance between exploration and exploitation.

GGO's dynamic search process enables it to escape local minima effectively, making it a suitable algorithm for complex optimization problems.

The Grey Wolf Optimizer (GWO) is another population-based optimization algorithm inspired by the leadership hierarchy and cooperative hunting strategies of grey wolves [28]. Wolves hunt in packs, following a structured hierarchy where the best solutions guide the movement of the rest of the population.

The key components of GWO include:

1. **Hierarchical Leadership:** The population consists of four categories:
   - Alpha (α): The best solution that leads the search.
   - Beta (β): The second-best solution, guiding the search.
   - Delta (δ): The third-best solution, supporting α and β.
   - Omega (ω): The rest of the population follows the top three.
2. **Encircling and Attacking Prey:** Wolves encircle the optimal solution and gradually move toward it using:

   $$X(t+1) = X_{\text{best}} - A \cdot |C \cdot X_{\text{best}} - X_{\text{current}}|, \tag{15}$$

   where:
   - $A = 2a \cdot r_1 - a$, where a decreases from 2 to 0 over iterations.
   - $C = 2 \cdot r_2$, where r_1 and r_2 are random numbers in $[0,1]$.
3. **Exploration and Exploitation:** Initially, GWO emphasizes exploration (global search), but as iterations progress, it shifts towards exploitation (local refinement).

GWO is computationally efficient and works well for constrained optimization problems, but it can suffer from. However, due to its rigid leadership structure, literature convergence is due to a rigid leadership structure.

4.2 Motivation for Hybridization

While both GGO and GWO are powerful optimizers, each has inherent limitations:

- GWO excels at exploitation but struggles with maintaining search diversity.
- GGO is strong in exploration, dynamically adjusting search strategies, but may lack fine-tuning capabilities in local search.

By hybridizing GWO and GGO, we introduce an adaptive mechanism that:

- Enhances global search efficiency through GGO's dynamic grouping.
- Strengthens local search through GWO's hierarchical encircling behavior.
- Balances between exploration and exploitation, reducing the risk of premature convergence.

4.3 Mathematical Formulation of GGGWO

The Hybrid Grey Wolf-Greylag Goose Optimizer (GGGWO) integrates the leadership-based search of GWO with the adaptive exploration mechanism of GGO.

4.3.1 Population Initialization

Each search agent is randomly initialized within the search space:

$$X_i = X_{\min} + r(X_{\max} - X_{\min}), \tag{16}$$

where r is a uniformly distributed random number in $[0,1]$.

4.3.2 Dynamic Grouping Mechanism

At each iteration, the population is dynamically divided into:

$$N_{\text{exploration}} = N - N_{\text{exploitation}}, \tag{17}$$

$$N_{\text{exploitation}} = N \times \frac{t}{T}, \tag{18}$$

where t is the current iteration, and T is the maximum number of iterations. Early iterations emphasize exploration, while later iterations prioritize exploitation.

4.3.3 GGGWO Position Update

The final position update equation combines both GGO's adaptive exploration and GWO's local refinement:

Exploration Phase (Global Search via GGO):

$$X(t+1) = \omega_1 X_{\text{random}} + \omega_2 (X_{\text{best}} - X(t)), \tag{19}$$

where X_{random} is a randomly selected solution, and X_{best} is the best-known solution.

Exploitation Phase (Local Search via GWO):

$$X(t+1) = \frac{X_\alpha + X_\beta + X_\delta}{3} + \gamma(X_{\text{best}} - X(t)), \tag{20}$$

where γ is a convergence coefficient controlling step size.

4.4 Optimization Process for ARIMA Parameter Selection

GGGWO is used to fine-tune the (p,d,q) parameters of the ARIMA model:

1. Define the fitness function using Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N} (Y_{\text{actual}} - Y_{\text{predicted}})^2. \tag{21}$$

2. Initialize the search population with potential ARIMA configurations.
3. Use GGGWO's hybrid search strategy to refine parameters iteratively.
4. Select the best (p,d,q) values that minimize MSE.

The Hybrid Grey Wolf-Greylag Goose Optimizer (GGGWO) effectively integrates GWO's leadership-based hunting and GGO's migratory-inspired exploration, making it a powerful hybrid optimizer for complex forecasting and optimization tasks.

5. RESULTS AND DISCUSSION

5.1 Performance Comparison of Models

The proposed Grey Wolf-Greylag Goose Optimizer (GGGWO) was rigorously evaluated against five benchmark models: ARIMA, WOA-ARIMA, PSO-ARIMA, GWO-ARIMA, and GGO-ARIMA. The comparative performance results are summarized in Table 2, which highlights the effectiveness of the proposed hybrid model across multiple statistical evaluation metrics, including MSE, RMSE, MAE, MBE, Correlation Coefficient (r), R^2, RRMSE, Nash-Sutcliffe Efficiency (NSE), Willmott Index (WI), and Fitted Time.

The results reveal that the proposed GGGWO model significantly outperformed the baseline models across all evaluation metrics. Specifically, GGGWO achieved the lowest values for error-based metrics such as MSE (0.00273), RMSE (0.01847), MAE (0.01159), and MBE (0.00490). Additionally, it exhibited the highest R^2 (0.96478), correlation coefficient ($r = 0.95633$), and the Willmott Index (WI = 0.95648), indicating its superior ability to capture the underlying dynamics of the dataset.

The Q-Q plots in Figure 4 visualize the distribution of each metric across the evaluated models against a standard distribution. The plots illustrate how the residuals align with theoretical expectations, emphasizing the consistency and accuracy of the GGGWO model. Metrics such as MSE, RMSE, and RRMSE show tight alignment, indicating the robustness of the proposed hybrid optimization approach.

In Figure 5, the radar plot compares model performance metrics, including error-based and agreement-based measures. The GGGWO model outperforms all baseline models across most metrics, particularly in MSE, RMSE, and RRMSE. Its compact shape near the ideal region highlights its balanced and efficient performance.

The heatmap in Figure 6 visualizes the performance metrics of each model, emphasizing the contrast between error-based (MSE, RMSE, MAE, MBE) and agreement-based (R, R^2, NSE, WI) measures. The GGGWO model exhibits superior performance with lower error values (shown in lighter shades) and higher agreement metrics (darker shades), demonstrating its robustness and efficiency.

The parallel coordinates plot in Figure 7 provides a visual comparison of model performance across multiple metrics, including MSE, RMSE, MAE, MBE, R, R^2, RRMSE, NSE, and WI. Each line represents a model, allowing for simultaneous analysis of performance trends. The GGGWO model demonstrates superior performance, with lower error-based metrics (MSE, RMSE, MAE) and higher agreement-based metrics (R, R^2, WI).

5.2 Error Analysis

The detailed error analysis highlights the improvements achieved by the GGGWO model:

- **MSE and RMSE:** GGGWO achieved an MSE of 0.00273, which represents an 89.42% reduction compared to the baseline ARIMA model (MSE = 0.02576). Similarly, its RMSE (0.01847) is significantly lower than that of ARIMA (0.16049) and other optimized models, including GWO-ARIMA (0.03914) and GGO-ARIMA (0.03591). This highlights GGGWO's ability to minimize large prediction errors.
- **MAE and MBE:** The MAE (0.01159) and MBE (0.00490) of GGGWO indicate minimal deviation

Table 2. Performance comparison of forecasting models.

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI	Fitted Time
ARIMA	0.02576	0.16049	0.07700	0.01878	0.59112	0.64942	41.6634	0.48224	0.73117	0.00572
WOA-ARIMA	0.02178	0.14757	0.09262	0.03914	0.62316	0.68833	38.3107	0.50826	0.77648	0.00985
PSO-ARIMA	0.00819	0.05548	0.03482	0.01471	0.75644	0.77654	35.5660	0.63166	0.89988	0.01036
GWO-ARIMA	0.00578	0.03914	0.02457	0.01038	0.80965	0.83246	28.8723	0.65506	0.92328	0.01099
GGO-ARIMA	0.00530	0.03591	0.02254	0.00952	0.91777	0.92279	23.3498	0.77448	0.93372	0.01099
GGGWO	**0.00273**	**0.01847**	**0.01159**	**0.00490**	**0.95633**	**0.96478**	**18.8548**	**0.88448**	**0.95648**	**0.01099**

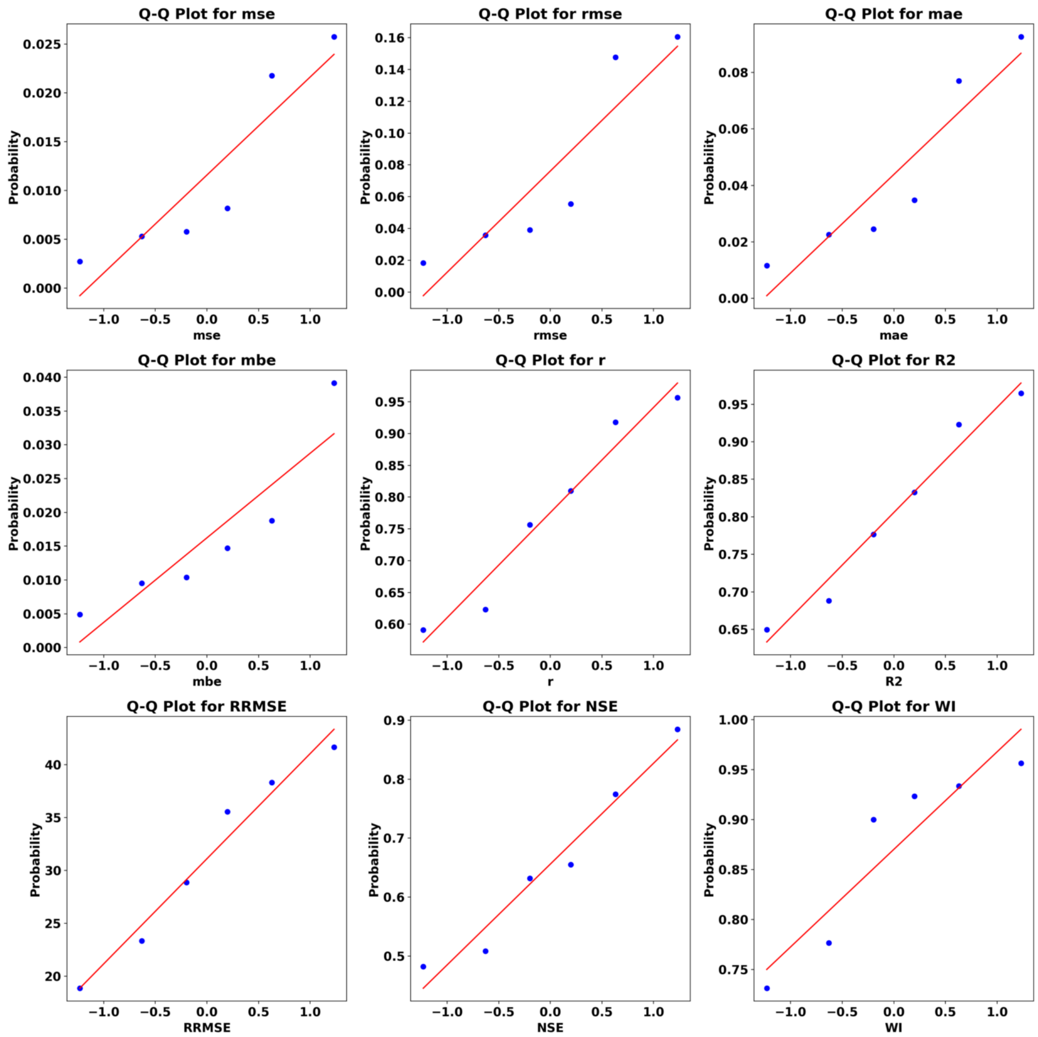

Figure 4. Q-Q Plots illustrating the distribution of statistical metrics for model evaluation.

and bias in predictions, compared to ARIMA's MAE (0.07700) and MBE (0.01878). These values confirm that the hybrid model produces highly accurate and unbiased predictions.

- **Correlation Coefficient (r):** GGGWO achieved the highest correlation coefficient ($r = 0.95633$), which reflects its strong linear relationship between actual and predicted values. This represents a significant improvement over ARIMA ($r = 0.59112$), WOA-ARIMA ($r = 0.62316$), and even standalone GGO-ARIMA ($r = 0.91777$).
- **RRMSE:** The RRMSE value of 18.85% achieved by GGGWO is the lowest among all models, demonstrating its ability to normalize prediction errors relative to the actual values. This highlights its robustness across different regions and data distributions.
- **NSE and WI:** GGGWO achieved the highest NSE (0.88448) and WI (0.95648), surpassing all baseline models. The high NSE score reflects its ability to predict data that is close to observed, while the WI score indicates strong agreement between predicted and actual values.

5.3 Computational Efficiency

All optimization-enhanced models, including WOA-ARIMA, PSO-ARIMA, GWO-ARIMA, GGO-ARIMA, and GGGWO, demonstrated comparable fitted times, with GGGWO achieving 0.01099 seconds per iteration. Despite its hybrid structure, GGGWO maintained computational efficiency comparable

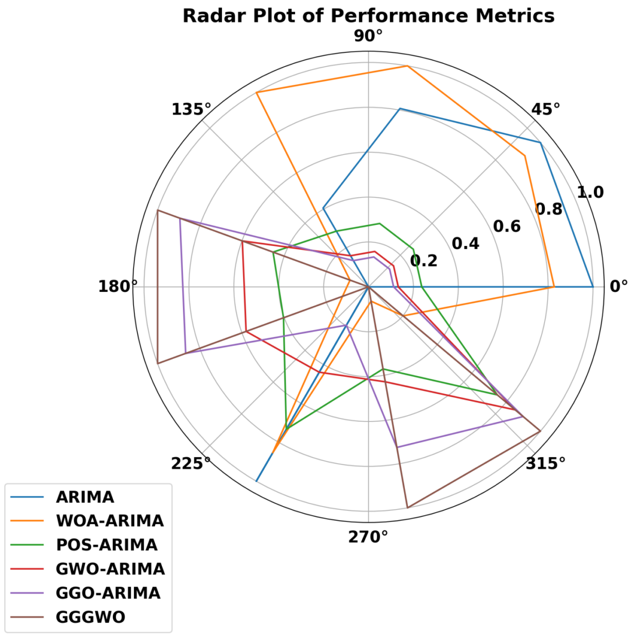

Figure 5. Radar Plot comparing the performance of forecasting models.

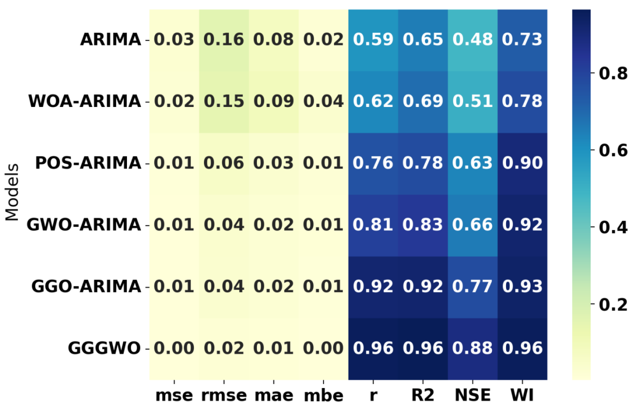

Figure 6. Heatmap showing performance metrics for all forecasting models.

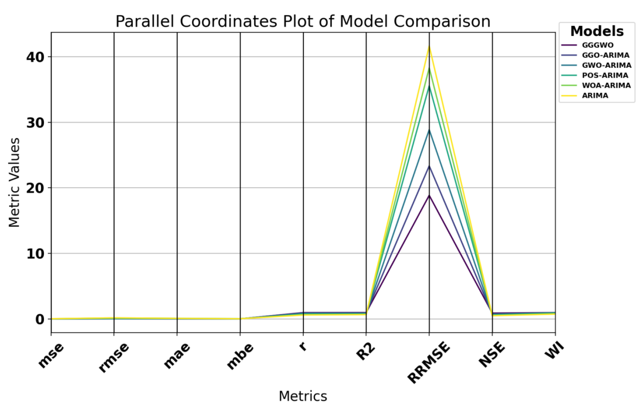

Figure 7. Parallel Coordinates Plot comparing model performance across various statistical metrics.

to standalone GWO and GGO optimizers. This efficiency underscores its practicality for real-world forecasting tasks, even in scenarios requiring large-scale data processing.

5.4 Discussion on Optimization Effectiveness

The superior performance of GGGWO can be attributed to its hybrid design, which combines the strengths of GWO and GGO:

- **Enhanced Exploration:** The adaptive grouping mechanism of GGO ensures that a significant portion of the population focuses on global search during early iterations, effectively avoiding premature convergence.
- **Refined Exploitation:** GWO's hierarchical leadership structure refines the search in later stages, ensuring convergence toward high-quality solutions.
- **Dynamic Transition:** GGGWO adapts to the search space by dynamically balancing exploration and exploitation, providing robust parameter tuning for ARIMA models.

The hybridization effectively addresses the weaknesses of standalone GWO and GGO models. GWO's tendency GGO's dynamic exploration mitigates GWO's tendency to stagnate in local optima of fGWO's intense local refinement compensates GGO's lack of fine-tuning capability GGGWO model achieved significant improvements in forecasting accuracy compared to baseline models, as demonstrated by its superior performance across all evaluation metrics. These results highlight the potential of hybrid optimization techniques for enhancing time series forecasting, particularly in complex datasets such as agricultural commodity prices. The computational efficiency and robustness of GGGWO further underscore its practical applicability in real-world scenarios.

6. CONCLUSION AND FUTURE WORK

This study proposed the Grey Wolf-Greylag Goose Optimizer (GGGWO), a novel hybrid metaheuristic optimization algorithm, and applied it to enhance ARIMA models for time series forecasting. The GGGWO-ARIMA model demonstrated superior performance compared to five baseline models—ARIMA, WOA-ARIMA, POS-ARIMA, GWO-ARIMA, and GGO-ARIMA—using a dataset of daily potato prices across Indian cities. The hybrid approach achieved the lowest error metrics, such as MSE (0.00273) and RMSE (0.01847), while attaining the highest R^2 (0.96478) and correlation coefficient ($r = 0.95633$), underscoring its robustness and accuracy. By leveraging GWO's leadership-based exploitation and GGO's dynamic exploration capabilities, the hybrid model effectively addressed limitations in standalone optimization methods. These findings highlight the potential of GGGWO-ARIMA for accurate price forecasting in agricultural markets, offering practical benefits for farmers, policymakers, and supply chain managers by enabling better planning and decision-making.

Future research can extend the application of GGGWO to other commodities, validate its scalability for large-scale datasets, and integrate it with deep learning models such as LSTMs or Transformers to improve forecasting of complex time series. Real-time forecasting capabilities could be explored to adapt GGGWO for dynamic Marto conditions and hybridization with other metaheuristics, such as Genetic Algoritgenetic algorithms, instead of performance gains. This work establishes a strong foundation for hybrid optimization in time series forecasting, with wide-ranging applications across agriculture, finance, and other sectors where accurate predictions are critical for strategic decisions.

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