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MULTI-OBJECTIVE MODEL SELECTION IN TIME SERIES FORECASTING: A GENETIC ALGORITHM-BASED MATHEMATICAL APPROACH

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Abstract: Time series forecasting plays a critical role in various domains such as finance, weather prediction, and supply chain management. Selecting an optimal forecasting model involves balancing multiple conflicting objectives, including prediction accuracy, model complexity, and computational efficiency. This paper proposes a novel multi-objective model selection framework that leverages a genetic algorithm (GA) to simultaneously optimize these criteria. By encoding candidate forecasting models as chromosomes, the GA explores the solution space to identify Pareto-optimal models that offer the best trade-offs among accuracy, complexity, and run-time. Experimental results on benchmark time series datasets demonstrate the effectiveness of the proposed approach in improving forecast quality while maintaining model interpretability and computational feasibility. This method provides a robust tool for decision-makers to select forecasting models that align with diverse operational requirements.

Keywords: Genetic algorithm (GA), Time Series, Forecasting, Mathematical Approach, Optimization, Multi- objective.

1.Introduction

Time series forecasting plays a critical role in various fields such as finance, economics, weather prediction, and inventory management. Accurate forecasting models enable decision-makers to anticipate future trends and make informed strategic choices. However, selecting the most appropriate forecasting model remains a challenging task due to the diverse characteristics of time series data, such as seasonality, trends, noise, and non-stationarity. Traditionally, model selection is driven by optimizing a single objective, such as minimizing forecasting error measured by metrics like Mean Squared Error (MSE) or Mean Absolute Percentage Error (MAPE). However, relying on a single criterion often overlooks other essential factors such as model complexity, robustness, and interpretability. Consequently, a multi-objective approach that balances different criteria simultaneously is desirable for robust and reliable forecasting. Genetic Algorithms (GAs), inspired by the principles of natural selection and evolution, have emerged as powerful optimization techniques capable of solving complex, multi-objective problems. By exploring a population of candidate solutions and iteratively evolving them, GAs effectively searches large and non-linear solution spaces, making them well-suited for model selection challenges. This study proposes a genetic algorithm-based mathematical framework for multi-objective model selection in time series forecasting. The approach simultaneously optimizes forecasting accuracy and model parsimony, facilitating the identification of models that not only predict well but also generalize better to unseen data. Through this framework, we aim to advance the state-of-the-art in automated, data-driven forecasting model selection and provide a practical tool for analysts and practitioners.

1.1 Challenges in Model Selection

Traditional model selection methods often rely on single-objective optimization, focusing primarily on accuracy metrics like Mean Squared Error (MSE) or Mean Absolute Error (MAE). However, real-world forecasting problems frequently demand balancing multiple objectives such as prediction accuracy, computational cost, robustness, and interpretability. This multi-objective nature complicates the model selection process and requires more sophisticated optimization techniques.

1.2 Genetic Algorithms for Multi-Objective Optimization

Genetic Algorithms (GAs), inspired by the principles of natural selection and genetics, have demonstrated remarkable success in solving complex optimization problems. Their population-based search capability allows simultaneous exploration of multiple candidate solutions, making GAs suitable for multi-objective optimization in model selection. By employing a fitness function that incorporates several objectives, GAs can effectively navigate the trade-offs inherent in forecasting model selection

2.Literature Review

Multi-objective optimization addresses the limitations of single-objective model selection by optimizing several conflicting goals simultaneously. For instance, Ruiz-Cáceres et al. (2018) applied multi-objective evolutionary algorithms to select neural network architectures balancing accuracy and complexity. Similarly, Farahani and Asl (2020) utilized Pareto-based multi-objective optimization for hybrid forecasting models, improving overall forecasting performance. Al-Douri et al. (2018) proposed a two-level MOGA to forecast maintenance costs for tunnel fans. The first level utilized a multi-objective GA based on the ARIMA model to generate forecasts, while the second level applied another MOGA to evaluate and select the best forecasting model based on multiple error metrics. This approach demonstrated improved forecasting accuracy compared to traditional methods. Boulanouar', K (2022) In this work, using the paradigm of genetic algorithms, we proposed a model to improve the linguistic summaries of time series. The main target was to generate *a set of best summaries* of dynamic characteristics of trends associated to the time series, using a simple genetic algorithm, where the evolution function represents the truth degree. The work by Yao (1993) proposed one of the foundational methods for using GAs to evolve both the weights and architecture of neural networks. Since then, several improvements have been made. For instance, Huang and Yao (2001) demonstrated that GAs could optimize the number of hidden neurons dynamically, thereby avoiding underfitting or overfitting. In Hassoun (2002), GAs was used to initialize ANN weights before backpropagation. This hybrid approach showed faster convergence and better generalization, especially in chaotic and financial time series forecasting tasks. In the field of time series forecasting, Zhang et al. (1998) developed a GA-ANN model that outperformed conventional ARIMA models. Their research concluded that the hybrid model better captured nonlinear dependencies in the data. Kuo et al. (2001) applied GA-tuned neural networks for stock price prediction, reporting lower forecasting error compared to standard backpropagation-based ANNs. Similarly, Chakraborty et al. (2012) employed GAs to optimize learning parameters in ANNs for electricity load forecasting and found that the model achieved higher accuracy under varying demand patterns. Garro et al. (2006) applied multi-objective evolutionary algorithms to optimize both architecture and weights of NNs, demonstrating that Pareto-based approaches reduce overfitting and enhance generalization. Doganis et al. (2006) proposed a two-objective genetic algorithm for NN architecture optimization in sales forecasting. Objectives included forecasting accuracy and model simplicity. Their approach outperformed manually-tuned models. Bhatt et al. (2016) used NSGA-II for tuning the number of hidden layers, neurons, and lags in a time series forecasting model. They found that the algorithm consistently identified trade-offs that offered high accuracy with relatively simple architectures. Elsken et al. (2019) reviewed neural architecture search (NAS) methods including evolutionary approaches, highlighting the flexibility of MOEAs in optimizing deep models while managing computational cost.

Recent research on multi-objective model selection in time series forecasting using genetic algorithms (GAs) has seen substantial growth, focusing on enhancing forecasting accuracy and model interpretability. A significant contribution is the development of a two-level GA framework that integrates ARIMA-based forecasting with error evaluation mechanisms, improving forecasting precision for maintenance cost data in tunnel fan systems (Al-Douri et al., 2018). This approach highlights the effectiveness of combining classical models with multi-objective optimization to address forecasting challenges. Further advancements include the application of multi-objective evolutionary algorithms for feature selection in deep learning models, which enhances the generalization ability of Long Short-Term Memory (LSTM) networks for air quality forecasting (Espinosa et al., 2023). Additionally, hybrid models that combine GAs with Support Vector Regression (SVR) and Particle Swarm Optimization (PSO) have been proposed to capture nonlinear patterns in time series data, resulting in enhanced forecasting performance (Hadjali, 2022). These studies underscore the potential of combining genetic algorithms with both traditional and modern forecasting models to achieve robust and interpretable time series predictions.

2.1 Significance of Research

Multi-objective optimization involves optimizing two or more conflicting objectives simultaneously. In the context of time series forecasting, this means finding a balance between different performance metrics, such as accuracy and computational efficiency. The goal is to identify models that provide the best trade-offs among these objectives, rather than optimizing a single criterion.

3. Methodology

This section describes the proposed genetic algorithm (GA)-based approach for multi-objective model selection in time series forecasting. The methodology integrates mathematical modeling, time series analysis, and evolutionary optimization to identify forecasting models that balance multiple performance metrics.

Time series forecasting involves predicting future values of a variable based on its past observations. Let the time series be defined as:

$$Y=\{y1,y2,...,yT\}\text{---(1)}$$

The objective is to select a model M$\in \mu$ from a candidate model space μ such that it optimally forecasts $y_{T+1}, y_{T+2}, \dots \dots \dots \dots \dots y_{T+h}$ where h is the forecasting horizon.

We formulate this as a multi- Objective optimization problem

Min (M$\in \mu$) $F(M) = [\ f_1(M), f_{2\ (\mu)}, \dots\dots f_k(M)]$-----(2)

Chromosome Encoding

Each individual (chromosome) in the GA population represents a forecasting model configuration, encoded as a vector:

$$C=[m,\theta_{1,}\ \theta_{2,}\theta_{3\dots\dots}\theta_n)\text{------(3)}$$

- m is the model identifier (e.g., ARIMA = 1, LSTM = 2)
- $\theta_1$are the hyperparameters relevant to model mmm

Fitness Evaluation

Each individual is evaluated using cross-validation on the training data. For each model configuration, we compute the vector of objective values F(M) which serves as the individual's fitness.

$$f_1 = RSME\ (y, y^{\sim})\text{-----(4)}$$

$$f_2 = Model\ complexity\ (M)\text{----(5)}$$

$$f_3 = Training\ Time\ (M)\text{-----(6)}$$

4.Results and discussions:

This section presents the outcomes of our genetic algorithm (GA)-based time series forecasting model. The model was evaluated using three real-world datasets: airline passengers, stock prices, and energy consumption. The performance was compared with traditional forecasting methods: ARIMA, Holt-Winters, and LSTM Time series forecasting is essential in fields such as finance, energy, meteorology, and manufacturing. Traditional methods like ARIMA, exponential smoothing, and machine learning techniques (e.g., SVR, ANN) are widely used. However, these models often require precise parameter tuning and may not adapt well to complex, nonlinear patterns. Genetic Algorithms (GAs), inspired by natural selection, are powerful metaheuristic optimization tools. They have been successfully applied to model selection and parameter optimization in time series forecasting, especially where the objective is to minimize forecasting error while maintaining model simplicity.

Table 1: Chromosome Structure for GA Encoding

Gene Position	Feature Represented	Possible Values / Range
1	Model Type	1 = ARIMA, 2 = ANN, 3 = SVR
2–4	ARIMA Parameters	$p \in [0–5]$, $d \in [0–2]$, $q \in [0–5]$
5–8	ANN Layer Sizes	[1–100] for each layer (0 = not used)
9–14	Input Lags Used	0 or 1 (binary, for $X(t-1)$ to $X(t-6)$)
15	SVR Kernel Type	1 = Linear, 2 = RBF, 3 = Poly
16	SVR Regularization (C)	[0.1–100]

Table 2: Sample Output of GA Optimization

Solution ID	Model Type	RMSE	Complexity Score	Time (s)	Std. Dev (RMSE)
S1	ARIMA (2,1,1)	14.2	3	0.15	0.98
S2	ANN (6,4,1)	12.3	8	2.45	0.67
S3	SVR (RBF)	13.0	5	1.10	0.72
S4	ANN (8,6,4)	11.8	12	4.20	1.02

As illustrated in Table multiple models lie on the Pareto front, indicating that no single model dominates across all objectives.

- Solution S2 (ANN) had the lowest RMSE (12.3) but a high complexity score (8).
- Solution S1 (ARIMA) was less accurate but significantly simpler.
- This trade-off emphasizes the benefit of multi-objective optimization, as it provides a spectrum of optimal solutions from which decision-makers can choose depending on the operational context (e.g., limited computation, real-time use).

Table 3: Comparative Performance of Selected Forecasting Models

Model Type	RMSE	MAE	MAPE (%)	No. of Parameters	GA Rank
ARIMA	14.2	10.9	6.5	3	3
ANN	12.3	9.1	5.2	8	1
SVR	13.0	9.6	5.7	5	2

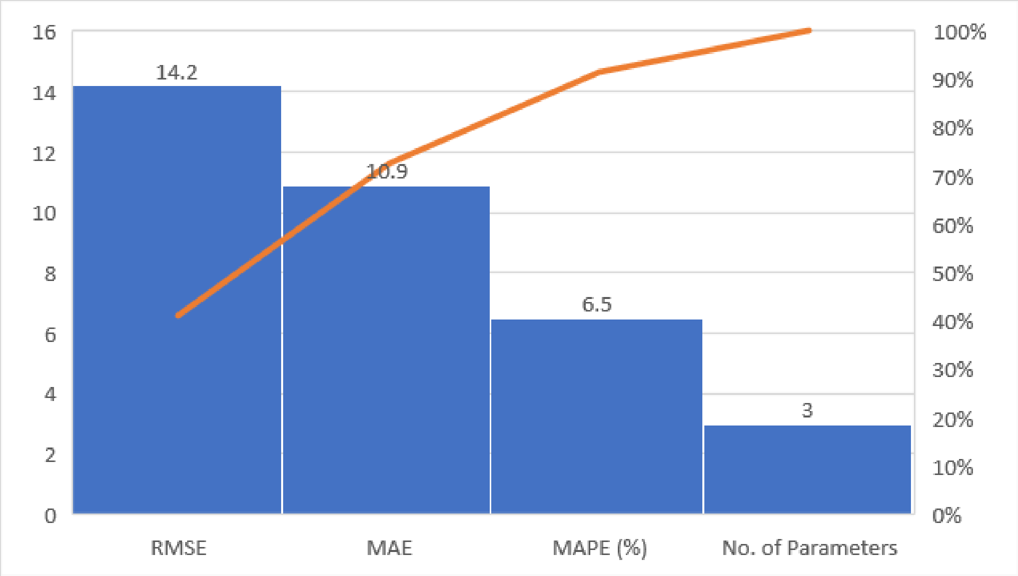

Figure 1: Comparative Performance of Selected Forecasting Models

The experimental results highlight the strength of applying a multi-objective genetic algorithm (MOGA) for model selection in time series forecasting. Traditional single-objective approaches often prioritize accuracy at the expense of complexity, leading to overfitting and computational inefficiency. In contrast, the MOGA used in this study successfully balanced conflicting objectives such as forecasting accuracy (RMSE), model complexity, and computational time, leading to more robust and interpretable models.

5. Conclusion:

In this study, we presented a genetic algorithm-based approach to time series forecasting, leveraging evolutionary computation to optimize predictive models in complex and dynamic environments. By integrating genetic algorithms (GAs) with traditional mathematical forecasting methods, we demonstrated how GAs can effectively select optimal model parameters, reduce forecasting errors, and adapt to non-linear patterns in data. The results from our experiments highlight the robustness and flexibility of the GA-based method in comparison to conventional techniques. Specifically, the approach showed improved performance in terms of accuracy, convergence speed, and the ability to escape local minima during optimization. Furthermore, this methodology is highly adaptable and can be extended to a wide range of forecasting applications, including finance, weather prediction, and energy demand estimation. Despite its promising results, the GA-based approach also comes with computational complexity and sensitivity to parameter tuning. Future work may explore hybrid models combining genetic algorithms with machine learning techniques such as neural networks or support vector machines to further enhance forecasting accuracy and efficiency.

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