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Stock Market Price Forecasting Using Metaheuristic Search Algorithms: A Comparative Analysis

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ABSTRACT Stock market forecasting is an essential factor in the daily operations of many companies and individuals. However, the complex and nonlinear nature of the stock market and the unpredictable variations in factors affecting stock prices present significant challenges in accurate forecasting. To address this, we employ four model-based metaheuristic search algorithms (MHs), namely the Crow Search Algorithm (CSA), Particle Swarm Optimizer (PSO), Gray Wolf Optimizer (GWO), and Dandelion Optimizer (DO), to estimate the parameters of stock market prices models. The data utilized in our experiments are extracted from the widely recognized stock index of Standard & Poor's 500 (S&P 500), that serves as a representative benchmark for the United States stock market. Our findings demonstrate that the CSA outperforms other MHs by providing the best combination of parameters for modeling stock market prices. The optimized parameters for the CSA model yielded Variance-Account-For (VAF) values of 97.846% in the training set and 93.483% in the testing set. This suggests that CSA offers promising capabilities for enhancing the accuracy and effectiveness of stock market forecasting models.

KEYWORDS Stock market forecasting; metaheuristic search algorithms; computational intelligence; crow search algorithm; particle swarm optimizer; gray wolf optimizer; dandelion optimizer.

I. INTRODUCTION

MANY companies and individuals make crucial financial decisions based on stock market forecasting, which affects their financial status. The forecasting process must be accurate and consider many factors, such as the country's economic environment, other major countries' stock prices, and worldwide events like wars, earthquakes, and more. This makes the process complex, challenging, and an attractive research topic.

Predicting financial markets is significantly more uncertain compared to predicting the weather. It is incredibly challenging even to explain past market performance clearly [1], [2]. Despite the turbulent events that occurred over 2020 and 2021, such as an ongoing pandemic, increasing unemployment, substantial deficit spending, heightened political divisions, resurging inflation, and geopolitical tensions with China and Russia, the U.S. stock market, as indicated by the Wilshire 5000 index, remarkably gained over 53 percent within the two years ending on December 31, 2021, including dividends. These outcomes defy expectations, making it apparent that if we struggle to comprehend and interpret the past, we should approach predicting the future of financial markets with humility and uncertainty.

Forecasting stock market prices is essential for companies who would like to sell their shares and for individuals who would like to invest in them. These transactions typically occur in the setting of a stock exchange, which is a venue where stocks and company shares are traded. According to [3], the largest worldwide stock exchange is the New York Stock Exchange, followed by the NASDAQ and the Shanghai Stock Exchange.

Shares of various companies can be combined to form a stock index, which serves as a benchmark for evaluating the overall financial performance of the market. Investors often rely on significant stock indices like the Dow Jones Industrial Average (DJIA), S&P 500, and the Nasdaq Composite as indicators of market trends [4].

Much research focuses on utilizing technical indicators in stock market price prediction. These indicators represent the performance of individual company shares, specific stock exchanges, or stock indices [5]. Technical indicators encompass a range of information such as prices of closing and opening, highest and lowest prices, adjacent close values, and average trading volume of shares. These indicators provide valuable insights for forecasting stock market prices.

A. GOAL AND ORGANIZATION

This paper explores applying four MH algorithm-based models for stock market forecasting, explicitly using data extracted from the S&P 500 stock index. The study compares the quality of these models using five evaluation metrics. The paper sections are presented as follows: Section II provides information on stock market forecasting and related work in the field. Section III: Describes the metaheuristic algorithms utilized in our research. Section IV: Discusses the specific requirements and details of the modeling process employed in this study. Section V: Presents the experimental results obtained from our developed models. The conclusions section concludes the paper, summarizing the findings and implications of the research. By following this organization, the paper aims to comprehensively explore utilizing metaheuristic algorithms for stock market forecasting using the S&P 500 index.

II. BACKGROUND AND RELATED WORK

Forecasting the stock index is complex due to the financial markets' complexity and dynamic nature. Several techniques and approaches have been used for stock market predictions. Historically, the Efficient Market Hypothesis (EMH) theory claim that predicting future stock market values is impossible as insufficient information drives the prediction process [6]. However, over the years, researchers have disagreed with the EMH theory and proposed many methods and techniques that can be used to forecast stock market prices [7].

A. TIME SERIES ANALYSIS

The analysis of time series is a well-known approach for stock market prediction [8] wherein the future value is the output $y(k)$, which is generated based on the input previous values $y(k-n)$ considering the delay in time n as shown in Equation 1.

$$\begin{aligned} y(k) &= a_0 + \sum_{i=1}^{n} a_i y(k-i) \\ &= a_0 + a_1 y(k-1) + \cdots + a_n y(k-n) \end{aligned} \tag{1}$$

Techniques such as the Auto-Regressive (AR) model have been used in stock market forecasting [9] along with variations such as the Auto-Regressive Integrated Moving Average(ARIMA) [10] and the Auto-Regressive Moving Average (ARMA) [11]. The Exponential Smoothing Model (ESM) is another statistical technique that applies the smoothing function on time series [12]

B. MHS IN STOCK MARKET MODEL DEVELOPMENT

MHs provide many benefits in model development for various industry systems. They are robust and flexible, capable of finding reasonable solutions across various problem types without requiring problem-specific knowledge. MHs can search large spaces of solutions and effectively escape local optimal solutions. They are more likely to find the global optimal solution for the problem under study. MHs can effectively achieve a balance between two attributes: exploration and exploitation. Thus, they can explore complex search spaces while exploiting the details of the space.

Today, the stock market is so essential that it is considered a vital role and is a sign of the economic situation. The stock market has been an investment power for people with various motives and diverse experiences because they can secure extensive returns. Various software tools were utilized to understand better and predict stock price movement. In [13], the authors developed three models using fuzzy time series (FTS) combined with several MHs adopted to tune the fuzzy models: the cuckoo optimization algorithm (FTS-COA), (FTS-PSO), and the firefly algorithm (FTS-FOA). The models were compared, and the experimental results show that the FTS-COA model performed better than the other two models.

A novel hybrid algorithm, known as Fly Updated Whale Optimization Algorithm (FU-WOA), is the hybridization of WOA and Firefly Algorithm (FF) [14]. Another research effort to predict stock price indices using a trained ANN with MHs was presented in [15]. The author used social spider optimization (SSO) and bat algorithm (BA) to train ANN. Genetic Algorithms (GAs), a well-known evolutionary search algorithm, were used to pick the best features that enhance the prediction performance.

The research presented in [16] aims to present a novel method called Kernel-Based Ensemble Machines (KBEM) for time series forecasting. This method focuses on determining the most effective kernel characteristics and fine-tuning hyper-parameters. The optimization process employs a hybrid strategy that combines HHs with Local Weight Learning (LWL) to enhance the generation of ensemble layers. It was found that KBEM can be successfully used to determine the best hyper-parameter and kernel regularization for time-series prediction models.

Other evolutionary computation methods, such as genetic programming (GP), were also utilized for forecasting the stock market [17]. GP was used to develop a prediction model for the S&P 500 index. The experiments demonstrate numerous advantages of GP compared to many soft computing techniques for stock market problem-solving. These advantages include the ability to generate straightforward mathematical models and provide both the model structure and the values of the model parameters. A more advanced GP method called Multi-gene GP that can produce linear combinations of several non-linear models based on the input factors was also presented in [18] with promising results.

C. CHALLENGES

Stock market prediction models face several challenges that affect their accuracy and reliability. The drawbacks of existing stock market prediction algorithms can be summarized as follows:

1) Market Efficiency: Predictive models struggle to capture sudden market shifts, and events due to the efficient nature of the stock market [19].
2) Non-Stationarity: Stock market data exhibits changing statistical properties over time, which makes it challenging for traditional models to capture complex market dynamics [20].
3) Limited Predictive Power: Despite advancements, accurately forecasting stock prices consistently remains challenging due to many factors influencing stock market movements.
4) Data Quality and Availability: Inaccurate or incomplete historical data and difficulties obtaining high-quality, timely data pose challenges for predictive models.
5) Overfitting and Data Snooping: Overfitting and data snooping bias can lead to poor performance on unseen data and inflated performance estimates, respectively.
6) Changing Market Conditions: Models trained on historical data may become less effective or irrelevant when faced with new market conditions.
7) Lack of Causality: Models often rely on correlations and patterns without capturing underlying causal factors that drive stock market movements.
8) Market Manipulation and Noise: Factors like market manipulation, rumors, and noise trading can distort patterns and make predictions challenging.

Addressing these challenges requires advancements in incorporating diverse data sources, improving feature engineering techniques, enhancing model interpretability, and employing robust validation procedures.

III. METAUHEURISTIC SEARCH ALGORITHMS

MHs are a class of optimization algorithms inspired by natural processes or collective behavior, and they aim to efficiently explore solution spaces and find high-quality solutions to complex problems. These algorithms do not guarantee an optimal solution but are designed to provide good approximations within a reasonable time. MHs algorithms, such as GAs, PSO, simulated annealing, ant colony optimization, and evolutionary algorithms, are widely used in computational intelligence. These algorithms draw inspiration from natural phenomena, such as evolution, genetics, swarm behavior, and optimization, to solve various modeling problems.

In this research, we employ four metaheuristic search algorithms to optimize the parameters of a stock index prediction model. These algorithms consist of CSA [21], GWO [22], PSO [23], and DO [24], which form part of the metaheuristic algorithm family. Among these algorithms, we focus on providing further insight into theCSA, which has demonstrated the best performance in our experiments.

A. CROW SEARCH ALGORITHM

The CSA is a bio-inspired MHs search algorithm evolved from the life behavior of crows [21], [25]. The CSA mimics the social behavior of crows, which exhibit a cooperative hunting strategy. The algorithm uses a population of solutions called crows to search the space of all possible solution and find the optimal among them. The algorithm follows a set of rules based on the behavior of crows, such as grouping, roosting, and scavenging, to perform the search. Here's a brief overview of the algorithm phases involved in the CSA:

1) Initialization
The evolutionary process starts by giving values to each tuning parameter of the CSA algorithm. These parameters include the awareness probability (AP), flight length (fl), flock size (N), and maximum number of iterations ($t_{\max}$). Subsequently, the initial population is randomly initialized with N crows within a d-dimension based on the number of parameters to be estimated. We also save each crow's position (i.e., values) in the memory.

$$\text{Crows} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1d} \\ x_{21} & x_{22} & \dots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \dots & x_{Nd} \end{bmatrix}$$

We initialized the memory of our crow population:

$$\text{Memory} = \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1d} \\ m_{21} & m_{22} & \dots & m_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ m_{N1} & m_{N2} & \dots & m_{Nd} \end{bmatrix}$$

2) Evaluation:
Applying the evaluation (i.e., objective) function, we assess the fitness of each crow (i.e., solution) by a given in Equation 2. Given that y and $\hat{y}$ are the actual and estimated stock index values, respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

3) Possible CSA states:
There are two states in which CSA can evolve.
State 1: Crow j is unaware that crow i is following it. Consequently, crow i will move towards the hiding place of crow j. The new position of crow i is obtained as follows:

$$x_{i,\mathrm{t}+1} = x_{i,\mathrm{t}} + r_i \cdot f_{li,\mathrm{t}} \cdot (m_{j,\mathrm{t}} - x_{i,\mathrm{t}}) \tag{3}$$

Where r_i is a random number with a uniform distribution between 0 and 1, and $fl_{i,\mathrm{t}}$ denotes the flight length of crow i at iteration t.
State 2: Crow j is aware that crow i is following it. To protect its cache from being stolen, crow j will deceive crow i by moving to a different position in the search

space. In summary, states 1 and 2 can be expressed as follows:

$$x_{i,\mathrm{t}+1} = \begin{cases} x_{i,\mathrm{t}} + r_i \cdot f_{l,i,\mathrm{t}} \cdot (m_{j,\mathrm{t}} - x_{i,\mathrm{t}}) & \text{if } r_j < \mathrm{AP}_{j,\mathrm{t}} \\ \text{a random position otherwise} & \end{cases} \tag{4}$$

Where r_j is a random number uniformly distributed between 0 and 1, and $\mathrm{AP}_{j,\mathrm{iter}}$ denotes the awareness probability of crow j at iteration iter.

4) Generate new population:
Let's consider $crow_i$, which aims to produce a new position. During this process, $crow_i$ randomly selects another crow from the flock, called $crow_j$. By following $crow_j$, $crow_i$ intends to uncover the hidden food sources stored in its memory, denoted as m_j. Suppose the randomly generated number r_j is greater than or equal to the awareness probability $AP_{j,t}$.
In that case, the new position of crow i is determined using Equation 5.

$$m_{i,\mathrm{t}+1} = \begin{cases} x^{i,\mathrm{t}+1} & \text{if} f(x^{i,\mathrm{t}+1}) \\ & \text{is better than} f(m^{i,\mathrm{t}}) \\ m^{i,\mathrm{t}} & \text{otherwise} \end{cases} \tag{5}$$

where r_j is a random number with a uniform distribution between 0 and 1 and $AP_{j,t}$ denotes the awareness probability of crow j at iteration t. This procedure is repeated for all the crows in the flock.

5) Check termination criterion
Steps 3-6 are iteratively performed until the maximum number of iterations, t_{max}, is reached. Once the termination criterion is met, the solution to the optimization problem is determined by reporting the best position from memory, considering its corresponding objective function value.

Figure 1 depicts a graphical diagram illustrating the concept of flight length in the CSA. The flight length parameter is a crucial setting in CSA, influencing the algorithm's search capability. The graph shows the relationship between the fl and the algorithm's search behavior. A smaller value of fl corresponds to a local search, where the algorithm focuses on exploring the neighborhood around its current position, denoted as x_t^i.

The CSA can achieve a balance between exploration, which involves random exploration and global search, and exploitation, which focuses on a local search around roosts [21]. By emulating the collective intelligence and behavior of crows, this algorithm aims to converge toward the optimal solution.

IV. MODELING PROCESS

In the system modeling process, the process refers to the steps involved in creating a mathematical or computational model that represents a system, phenomenon, or relationship within a given dataset (See Figure 4). The modeling process can be presented with several key steps:

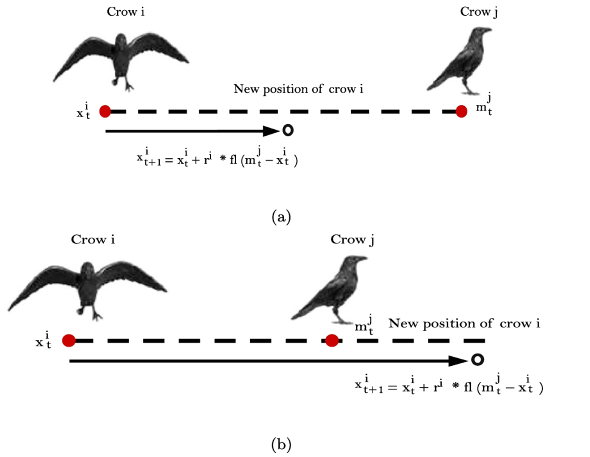

Figure 1. Flight length of Case 1 (a) *fl* <1 and (b) *fl* >1 inspired from [21]

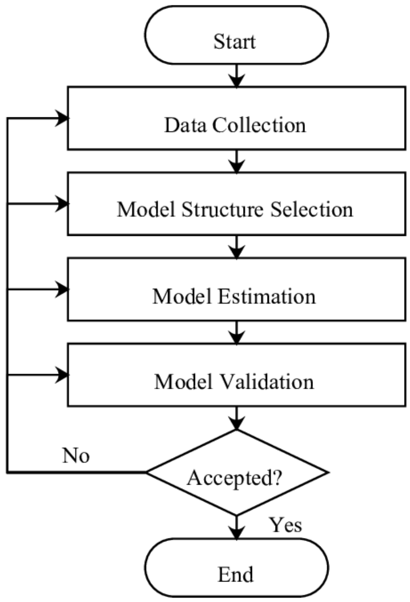

Figure 2. Modeling Process steps

1) **Data collection:** This step involves gathering pertinent data required for training and evaluating the prediction model. Ensuring the collected data is accurate, complete, and representative of the problem domain is crucial. This study utilized the Yahoo dataset available at [26]. The dataset consists of weekly data from April 29, 2013, to April 24, 2023. The model inputs comprise the opening, high, and low prices, while the closing price is the output variable. The dataset consists of 518 measurements, of which 388 were utilized for training the model, while the remaining 129 measurements were employed to test the model's performance.
2) **Model Structure Selection:** Choose an appropriate modeling technique or algorithm that suits the problem. Consider factors such as the type of problem, available data, assumptions, complexity, interpretability, and

computational requirements. In this study, we adopted the polynomial model given in Equation 6.

$$y = a_0 + a_1 y(k-1) + a_2 y(k-2) + a_3 y(k-3) \quad (6)$$

where y is the closing stock price, $y(k-1), y(k-2)$ and $y(k-3)$ are the open, high and low stock price.

3) **Model Estimation:** We adopted several MHs search algorithms to estimate the proposed model parameters. They include CSA, PSO, GWO, and DO.
4) **Model Validation:** To evaluate the performance of the implemented models, we used five metrics: VAF, Manhattan distance (MD), Euclidian distance (ED), and Mean Magnitude of Relative Error (MMRE).
   The following equations show the formula to calculate each metric where $\hat{y}$ is the predicted stock market value, y is the actual stock market value, and n is the number of points considered in our experiment during the testing phase.

$$VAF = [1 - \frac{var(y - \hat{y})}{var(y)}] \times 100\% \quad (7)$$

$$ED = \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (8)$$

$$MD = (\sum_{i=1}^{n} |y_i - \hat{y}_i|) \quad (9)$$

$$MMRE = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \quad (10)$$

5) **Model Acceptance:** Model acceptance refers to the process of evaluating and determining the suitability of the model according to Equations 7, 8, 9 and 10.

V. EXPERIMENTAL RESULTS

To develop our MHs models, we utilized MATLAB programming language to produce our results. Each of the CSA, PSO, GWO, and DO models were adapted to find the optimal parameters of the proposed model. In Figure 3, different models' predicted closing stock prices are compared with the actual values during the training phase on the left and the testing phase on the right. This allows for assessing how well each model performs in predicting stock prices.

Convergence curves are commonly used to evaluate and compare optimization algorithms. These curves track the progress of the algorithms by storing the best solutions obtained at each loop iteration. By plotting these curves, we can visually analyze an algorithm's performance concerning the model's ability to locate the global optimum solution within a given number of iterations. The curves provide a graphical representation of the algorithm's convergence behavior, allowing us to observe the progress and assess the algorithm's effectiveness in finding the desired solution.

Figure 4 shows the convergence curves for CSA, PSO, GWO, and DO algorithms based on the MSE criteria given in Equation 2. The convergence analysis provides valuable insights into the proposed algorithms' exploitation and exploration processes and allows for performance comparisons between the adopted metaheuristic search algorithms.

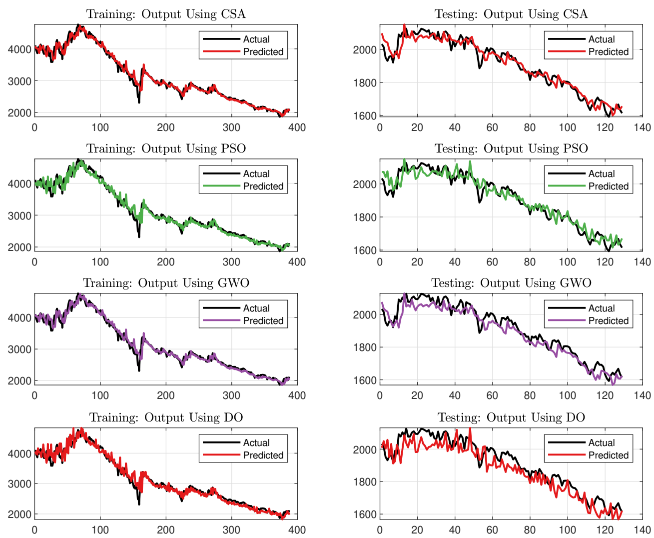

Figure 3. Actual and Predicted Stock price values based on estimated model parameters obtained using various metaheuristic search algorithms.

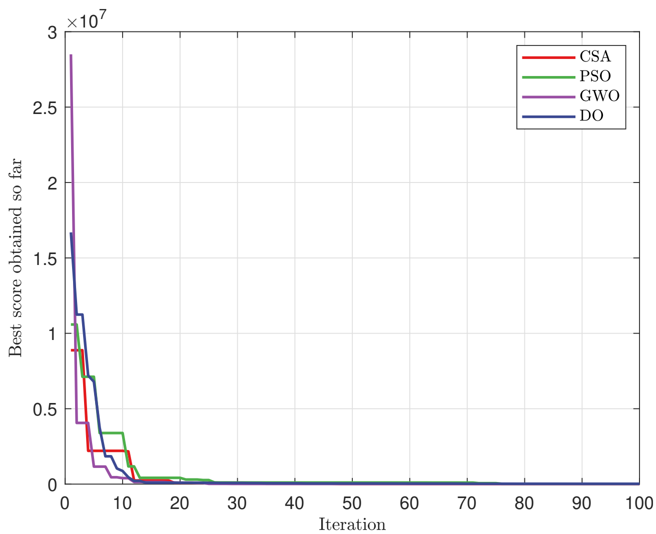

Figure 4. Convergence curves for the metaheuristic search algorithms.

In Table 1, the final computed parameter values for each model are presented. These values are crucial in understanding the configuration and settings of the models, which can significantly impact their performance and predictive accuracy.

The calculated evaluation criteria for each model in both the training and testing phases are shown in Table 2. The CSA demonstrates the highest VAF values for both the training and testing cases, indicating a strong ability to

Table 1. Computed model parameters for each algorithm

Alg.	a_0	a_1	a_2	a_3
CSA	43.4727505	0.5993983	1.30070461	-0.9537110
PSO	90.2595728	-0.6725605	2.66965436	-1.0904601
GWO	-20.436688	0.6510424	1.26590606	-0.9508272
DO	-15.0572184	-1.5640073	3.36028076	-0.8618371

explain the variance in the data. It also achieves relatively low MSE, ED, MD, and MMRE values, suggesting accurate predictions and good model performance.

Table 2. Calculated evaluation criteria for each algorithm at training and testing

Algorithm	VAF	MSE	ED	MD	MMRE
CSA Training	**97.846**	13649	2301.2	77.974	0.024499
CSA Testing	**93.483**	1587.8	452.58	30.623	0.016056
PSO Training	97.273	17354	2594.9	92.037	0.029062
PSO Testing	92.272	1889.4	493.7	34.93	0.018302
GWO Training	97.79	14032	2333.3	81.004	0.025794
GWO Testing	93.435	2284.7	542.89	38.413	0.019917
DO Training	96.353	23137	2996.2	108.3	0.034819
DO Testing	89.447	4197	735.8	54.507	0.028222

The PSO algorithm performs well regarding VAF, MSE, and MMRE but has slightly higher ED and MD values than the "CSA" algorithm. Similarly, the GWO algorithm achieves high VAF and relatively low values for MSE, ED, MD, and MMRE, indicating its effectiveness in the prediction task. However, the DO algorithm exhibits lower performance than the other algorithms, as it has lower VAF values and higher MSE, ED, MD, and MMRE values for training and testing cases.

VI. CONCLUSIONS

In conclusion, stock market forecasting is a critical task with significant implications for companies and individuals. The complex and nonlinear nature of the stock market and the unpredictable factors influencing stock prices pose considerable challenges to accurate forecasting. We employed four model-based MHs search algorithms to address these challenges: CSA, PSO, GWO, and DO. Our study utilized data extracted from the widely recognized S&P500 stock index, serving as a representative benchmark for the US stock market. Our findings highlight the superior performance of the CSA among the MHs search algorithms tested. With its best combination of parameters for modeling stock market prices, CSA showcases its potential to significantly enhance the accuracy and effectiveness of stock market forecasting. This research underscores the value of utilizing MHs search algorithms in stock market forecasting and emphasizes the promising capabilities of the CSA.

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