Enhancing Accuracy in Stock Price Prediction: The Power of Optimization Algorithms

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ABSTRACT

The purpose of this research was to improve the accuracy of stock price prediction by implementing optimization algorithms on forecasting methods, in this case, the exponential smoothing method. This research implemented the Particle Swarm Optimization (PSO) and Bat Algorithm metaheuristic optimization algorithms to determine the single-exponential smoothing method's smoothing parameters. Before implementing the optimization algorithm, the way to determine the smoothing parameters was by trial-and-error method, which is considered less effective. Therefore, the novelty of this research is tuning the parameters of the exponential smoothing method using a comparison of two metaheuristic algorithms, namely the particle swarm optimization algorithm compared to the bat algorithm. The Single Exponential Smoothing method with PSO and Bat algorithms was proven to improve accuracy.The alpha parameter found by the PSO algorithm is 0.9346, and the bat algorithm is 0.936465. With a MAPE of 1.0311%, it was better than the MAPE generated in the Single Exponential smoothing method by trial and error of 1.0316%. This research contributes to providing insight that in a highly sensitive stock prediction situation, metaheuristic algorithms can be used to create more accurate and efficient prediction results.

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1. INTRODUCTION

The emergence of the COVID-19 pandemic in late 2019 has resulted in a global crisis of unparalleled magnitude. In addition to its profound implications for public health, this epidemic has permeated several aspects of our society, exerting influence on human welfare and generating reverberations within economic and environmental spheres. The epidemic has had a major impact on global capital markets, resulting in significant disruptions to investment operations [1]. The financial market, which plays a crucial role in facilitating investment and fostering economic growth, has seen significant volatility due to the disruptive effects caused by the pandemic [2]. The epidemic generated significant fluctuations in the global financial markets. Stocks, bonds, and other financial instruments were very volatile, making it impossible for investors to plan long-term investments [3]. In the Indonesian context, it is noteworthy to mention the presence of a distinctive stock index known as the LQ45. This index holds significance as it encompasses a selection of 700 stocks listed on Indonesia's Stock Exchange. The LQ45 index comprises a collection of 45 stocks meticulously chosen based on their strong liquidity, significant market capitalization, and sturdy management structure.

Some things that an investor needs to decide about long-term investment include studying data to predict the appropriate investment for the investor. Investors can better plan their investment strategies by predicting the direction of future stock price movements. Stock forecasting assists with risk management. Understanding probable stock value fluctuations allows investors to take steps to protect their portfolios, such as investment diversification or the use of derivative financial instruments to offset risks [4]. In Indonesia, stock indices are considered to have a high level of liquidity, so the stocks in them are easily traded on the stock market. The index is known as the LQ45 index. The LQ45 index plays a crucial role as a significant point of reference for investors, especially when there is significant volatility in daily stock prices. This highlights the need to make precise predictions about the movements of the LQ45 index [5].

The task of predicting stock prices has long been a significant difficulty, which has been approached using several approaches like exponential smoothing [6], KNN regression [7], and ARIMAc[5]. The science of forecasting is utilized in a wide range of fields, including business, economics, and resource management [8]. Exponential smoothing is a commonly utilized forecasting approach that incorporates previous data by assigning weights to each observation. This approach comprises various iterations, such as Single Exponential Smoothing for datasets that do not exhibit pronounced trends or seasonality, Holt's Linear Exponential Smoothing for forecasting that is sensitive to trends, and Holt-Winters Exponential Smoothing, which integrates both trends and seasonality. Moreover, using two exponential weights in Double Exponential Smoothing contributes to the augmentation of predictive capability [7, 8]. Nevertheless, it is important to note that these exponential smoothing approaches have distinct advantages and disadvantages. Therefore, it is crucial to exercise caution when choosing a specific method, considering the available data and the level of complexity associated with the forecasting problem. The pivotal smoothing parameter (α), which ranges from 0 to 1, is a crucial factor in determining the level of forecast accuracy [9]. However, the parameter selection process is not a simple task, as testing values within the range of 0.1 - 0.9 does not necessarily result in a minimal predicting error.

Despite being widely used, the exponential smoothing approach is subject to ongoing development [9]. It is worth noting that Single Exponential Smoothing (SES) has exhibited superior outcomes in comparison to alternative approaches like artificial neural networks (ANN) [10]. Therefore, this study explores the domain of parameter tuning optimization, utilizing a metaheuristic algorithm - a method specifically intended to address complex optimization problems where precise solutions are difficult to get. Previous research has examined parameter tweaking in the context of the Exponential Smoothing framework. This study utilizes the Genetic Algorithm to identify optimal parameter values, resulting in a notable decrease in forecasting mistakes [11]. This study adopts a unique and innovative approach.

Deng et al. [11] studied modeling utilizing a seasonal exponential smoothing (SES) model and particle swarm optimization (PSO). The approach finds a set of smoothing parameters close to optimal. The proposed PSO-based SES model, which contains a non-trend component and an additional seasonal term, outperforms other models throughout most of the prediction horizon, suggesting that it might be a viable choice for estimating energy consumption. Thakkar et al. [12] shed light on the limitations of existing methods and propose potential avenues for future research to improve PSO-based predictions in the stock market. This article seeks to harmonize economic principles with computational intelligence. Additionally, it assesses the advantages of PSO in optimizing stock portfolios, predicting stock prices and trends, and exploring other relevant facets of the stock market while exploring the implications of employing PSO in these contexts. The study conducted by Bui et al. [13] unveiled the utilization of the Bat Algorithm (BA) metaheuristic to enhance the process of model selection for the Least Squares Support Vector Classification (LSSVC) by refining hyperparameters, including the regularization coefficient and kernel function parameters. Experimental findings demonstrate that BA effectively contributes to identifying the LSSVC model, yielding prediction accuracies surpassing 90%. Consequently, BA emerges as a potent optimization tool for parameter determination within a model.

Furthermore, our study follows previous scholarly investigations conducted by researchers [13, 14] who also focused on parameter optimization. The metaheuristic algorithm is a widely used optimization algorithm for complex problems [15]. The findings exhibited utilizing the metaheuristic algorithm can better anticipate forecasting results than conventional approaches [16]. Moreover, this research explores the utilization of Particle Swarm Optimization (PSO), a powerful tool in the optimization field. PSO is suitable for continuous data, such as financial time series data, as well as more dynamic and complicated optimizations, such as portfolio optimization. While some current literature has covered PSO-based stock prediction, it is critical to widen the horizons in the stock market with new studies that have used PSO [12]. Recent research findings highlight the effectiveness of Particle Swarm Optimization (PSO) in improving the accuracy of forecasting, specifically demonstrating its superiority over Genetic Algorithms (GA) when applied to optimize seasonal smoothing models [17, 18, 15]. Furthermore, the bat algorithm is examined as another noteworthy metaheuristic algorithm utilized for tackling intricate optimization difficulties [16, 19]. **This research differs from previous ones when it focuses on analyzing the optimization outcomes of PSO and Bat optimization algorithms in automatically identifying smoothing parameters** in the exponential smoothing approach. **This research aims** to provide insight into the importance of stock forecasting in the context of investment decisions. The main focus is to demonstrate that selecting methods to optimize stock forecasting is important in achieving forecasting accuracy and reliability. **This study's** findings can potentially improve risk management by offering more specific insights into selecting forecasting methodologies appropriate for investment characteristics and objectives.

2. RESEARCH METHOD

The research design step of this study begins with the collection of literature reviews and datasets. The implementation of the metaheuristic model is then followed by the assessment of the metaheuristic method on parameter adjustments.

2.1. Dataset

This study aims to explore the field of stock price forecasting using an innovative methodology. The basic methodology employed in this study is the widely recognized exponential smoothing technique, which is further enhanced by the strategic implementation of two advanced optimization algorithms: Particle Swarm Optimization (PSO) and the Bat Algorithm. The exploration of financial prediction is conducted within the context of a comprehensive and carefully curated dataset. To provide a comprehensive analysis of the LQ45 stock index, we utilize a dataset that encompasses the time period from 2020 to 2022, allowing for a very accurate examination of its dynamics. This extensive collection has a remarkable 735 data points, with each data point being diligently obtained from reliable financial platforms, such as `https://id.investing.com/indices/jakarta-lq45-historical-data`. This internet-based tool guarantees the preservation of data integrity and dependability, establishing a robust basis for our research endeavors.

By integrating this comprehensive dataset, we are able to capture the complex dynamics between market forces, investor sentiment, and economic fluctuations throughout the challenging era characterized by the COVID-19 epidemic. The dataset serves as the foundation upon which we apply our inventive methodology for predicting fluctuations in the LQ45 stock index. The combination of exponential smoothing, Particle Swarm Optimization (PSO), and the Bat Algorithm in this study elevates it to a groundbreaking investigation in the field of predictive analytics. The potential of exponential smoothing's historical data analysis is effectively utilized by integrating it with the collective intelligence of Particle Swarm Optimization (PSO) and the strategic principles inspired by echolocation found in the Bat Algorithm. The integration of these distinct techniques holds the potential to enhance forecasting precision, providing investors and financial professionals with valuable information to effectively navigate the intricate dynamics of the contemporary capital market. As we commence this endeavor, we extend an invitation for you to observe the amalgamation of finance, data science, and optimization approaches. This amalgamation possesses the potential to redefine the domain of stock price forecasting in a period characterized by exceptional problems and prospects.

2.2. Forecasting Method of Single Exponential Smoothing

Formula (1) is used in the Single Exponential Smoothing method.

$$S_t = \alpha.D_t + (1 - \alpha).S_{t-1} \tag{1}$$

With, S_t is forecasting the next data, α is smoothing parameters, D_t is actual data, and S_{t-1} is current forecasting data. As one delves more into the core of SES, it becomes apparent that its allure stems from its inherent capacity for flexibility. By manipulating the value of α, it is possible to navigate the continuum between nimble reactivity to current input and the stability derived from past context. The SES generates predictions and formulates them with subtlety, effectively reflecting the fundamental aspects of market dynamics. Within this mathematical expression, we encounter the amalgamation of SESan enduring equation that encompasses the fundamental principles of predictive analysis, providing us with a discerning insight into forthcoming events through a skillful equilibrium of historical and contemporary data. This technology is utilized by both financial analysts and data scientists, offering significant insights into the continuously expanding realm of finance.

2.3. Performance Evaluation PSO for Single Exponential Smoothing Parameter Tuning

In our quest for precision and reliability in forecasting, it is imperative to evaluate the results with a discerning eye. To illuminate the effectiveness of our forecasting endeavors, we turn to a trio of indispensable metrics: the Mean Absolute Percentage Error (MAPE) [20], Root Mean Square Error (RMSE) [21], and the Normalized Root Mean Square Error (NRMSE) [22]. In this research, we shine a spotlight on MAPE, harnessing its insights to gauge the performance of our forecasting models. MAPE, often regarded as the gold standard for evaluating forecasting accuracy, assumes a pivotal role in our analysis. It operates as a touchstone, measuring the disparity between predicted and actual values in percentage terms. This crucial metric acts as our guiding star, illuminating the path to forecast refinement. The Formula (2) for MAPE, a guiding light, is stated as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} | \frac{D_{t+1} - S_{t+1}}{D_{t+1}} \times 100\% \tag{2}$$

The MAPE value, our compass in assessing forecasting accuracy, reveals itself as a percentage. This makes it universally interpretable and highly actionable. A smaller MAPE value heralds superior forecasting precision, akin to the sharpening of a finely honed tool. It signifies our ability to predict with acuity, aligning our forecasts ever closer to the true trajectory of financial markets.

In essence, MAPE encapsulates the essence of forecasting success. It empowers us to navigate the intricate terrain of financial predictions, making informed decisions and optimizing our strategies. As we scrutinize the MAPE values generated by our models, we hold steadfast to the principle that smaller MAPE values herald more accurate and reliable forecasts, enabling investors, analysts, and decision-makers to chart their course with confidence in an ever-evolving financial landscape.

The utilization of the Particle Swarm Optimization (PSO) method to refine the parameters of exponential smoothing can be likened to the meticulous coordination of a mathematically precise symphony. In this exposition, we offer a comprehensive insight into the complex coordination involved in the process of optimization. The PSO optimization algorithm proceeds, as seen in Figure 1.

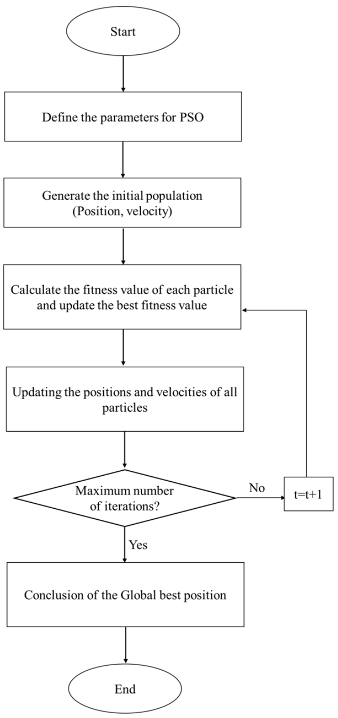

Figure 1. Flowchart of tuning parameter ES with PSO algorithm

This section aims to provide a clear definition of the parameters used in Particle Swarm Optimization (PSO). The commencement of the expedition entails a meticulous arrangement of Particle Swarm Optimization (PSO) parameters. The key parameters include the population size, which determines the quantity of particles within our swarm. A set of particles updates their relative positions iteratively, allowing the PSO algorithm to execute the search process more effectively. To find the best solution, each particle returns to its prior personal best (best) position and the global best (best) location in the swarm. The maximum iterations parameter establishes the time frame within which our optimization process operates, while the inertia weights regulate the particles' inclination to retain their present velocities. The acceleration coefficients, denoted as C1 and C2, are crucial in introducing dynamism to our swarm system, altering the particles' exploration to attain optimal solutions. Initialization of the PSO algorithm involves assigning an initial location and velocity to each individual particle in our swarm. The initial conditions provided serve as the basic foundation for our investigation into the solution space. For each working iteration t+1, the particle position and velocity are updated using the mathematical model shown in Formula (3) and (4).

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (P_{best_i}^t - x_i^t) + c_2 r_2 (g_{best_i}^t - x_i^t) \tag{3}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{4}$$

To find the best solution, each particle advances towards its previous and global best positions in the swarm. Assume a minimization problem, and the mathematical model for the particle's best position is shown in Formula (5) and (6).

$$P_{best_i}^t = x_i^* \mid f(x_i^*) = min_{k=1,2,\ldots,t}(\{f(x_i^k)\}) \text{ where } i \in 1, 2, \ldots, N, and \tag{5}$$

$$g_{best}^t = x_*^t \Big| f(x^t *) = min_{\substack{i=1,2,\ldots,N \\ k=1,2,\ldots,t}}(\{f(x_i^k)\}) \tag{6}$$

Where i is the index for the particle, t is the current iteration, f is the objective function (minimum or maximum), x denotes the position vector, and N is the number of particles in the swarm [23]. Determination of Fitness Value: the fundamental focus of our optimization endeavor lies in assessing the fitness value. To construct this fundamental indicator, we employ the exponential smoothing technique, utilizing the available stock data. The provided data undergoes a rigorous processing procedure utilizing the exponential smoothing algorithm, further refined by the PSO-tuned parameters. The MAPE formula represents the resulting fitness value, as it encapsulates the mean absolute percentage error. The objective at hand is both straightforward and significant: reducing this metric indicates the degree to which our forecasts correspond with actual empirical data. Updating Position and Velocity: The swarm undergoes dynamic alterations once equipped with fitness values. The particles collectively adjust their location and velocity values, driven by their pursuit of optimization. The aforementioned updates exemplify the intricate interplay between exploration and exploitation as particles traverse the solution space in pursuit of optimal parameter configurations.

The topic of discussion is iteration control. The dance persists in a cyclic pattern characterized by rhythmic iteration. If the maximum iteration count is not reached, the swarm continues its optimization process. This voyage entails modifying each particle's Personal Best (PBest) by considering the particle with the lowest fitness value. The Mean Absolute Percentage Error (MAPE) serves as the guiding principle that directs PBest toward its highest point. Concurrently, we discover the Global Best (GBest) value obtained from the most outstanding fitness value among all particles. The phenomenon entails a collective acknowledgment of the most exceptional individuals, resulting in an enhanced overall performance of the entire group. As the complex sequence of movements progresses, our Particle Swarm Optimization (PSO) algorithm iteratively improves the exponential smoothing parameters with a level of accuracy and grace that evokes the harmonious coordination of a meticulously rehearsed symphony. Every parameter modification can be seen as a musical note within the orchestration of optimization, progressively leading us toward the harmonious alignment of forecast precision. This endeavor, propelled by the utilization of data, mathematical principles, and a hint of swarm intelligence, ultimately enables individuals to navigate the complex landscape of stock price prediction with assurance and accuracy.

2.4. Performance Evaluation Bat Algorithm for Tuning Parameter of Single Exponential Smoothing

The process of optimizing exponential smoothing parameters by utilizing the Bat Algorithm can be described as the sequence of phases in Figure 2, where each step plays an important role in achieving a harmonious balance that improves the accuracy of predictions. The parameters used in the bat algorithm must be determined before. The first parameter is the population size, which determines the number of bats in the algorithm's swarm. Bat speed is governed by flying speed, but bat echolocation is impacted by frequency. The noise level shows the bats' exploration actions, whereas the emission ratio influences the strength of their ultrasonic emissions. The maximum iteration option sets a time restriction for our optimization search. The second phase in the procedure is initialization. This process involves identifying each bat's initial position, speed, frequency, noise level, and emission ratio. The previously described beginning circumstances are the foundation for the researcher's thorough exploration of the parameter space. The calculation process uses Formula (7), (8), and (9).

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{7}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x_*)f_i \tag{8}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{9}$$

where $\beta \in [0, 1]$ is a uniformly distributed random vector. Each bat is randomly allocated a frequency taken uniformly from $[f_{min}, f_{max}]$. During the exploitation step, we must modify the loudness Ai and pulse emission rate ri during iterations. Because the loudness normally falls once the bat discovers its food and the pulse emission rate increases, the loudness can be set between A_min and A_{max}. The Formula (10) and (11) are used to update the loudness and pulse emission rate.

$$A_i^{t+1} = \alpha.A_i^t \tag{10}$$

$$r_i^{t+1} = r_i^0[1 - exp(\gamma t)] \tag{11}$$

Where α and γ are constant. A_i^t will approach 0 and r_i^{t+1} will approach r_i^0 if t approaches infinity. As previously stated, whether a BA has global or local search capabilities is determined by its parameters; hence, adaptive parameters must be used to establish a balance between global and local search capabilities. The Formula (12) for the local search technique is given.

$$x_i(t+1) = x_* + \varepsilon\bar{A}(t) \tag{12}$$

Where ε is a random number with a value [-1, 1]. $\bar{A}(t)$ is the average loudness of bats [23]. The next step is the determination of Fitness Value. The central focus of our pursuit of optimization is on the fitness value, which serves as a metric for evaluating the proficiency of our forecasting model. The metric is constructed through the application of the exponential smoothing technique, whereby the available stock data is carefully analyzed and processed. The data is processed using the exponential smoothing algorithm, which incorporates the parameter configuration of the Bat Algorithm. The MAPE formula is utilized to incorporate the resulting fitness value, representing the mean absolute percentage error. We aim to reduce this number to achieve congruence between our forecasts and the actual market trends. This process can be depicted coherently through Figure 2.

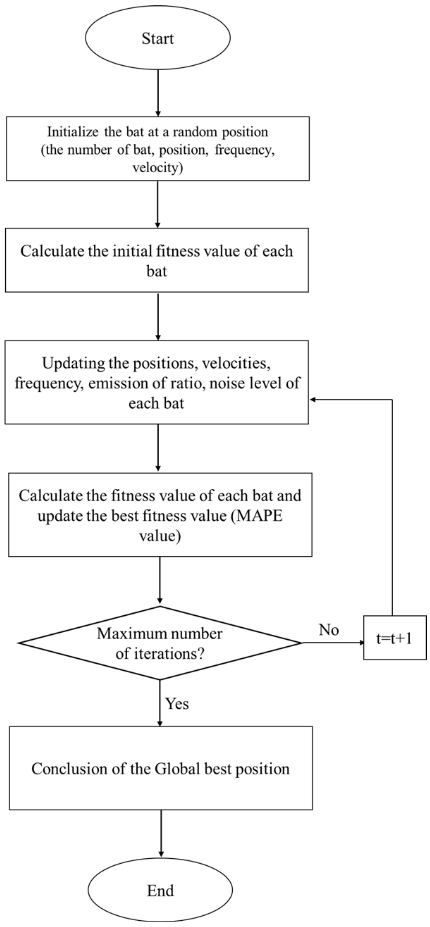

Figure 2. Flowchart of Tuning Parameter ES with Bat Algorithm

Revision of Position, Speed, Frequency, Noise Level, and Emission Ratio. Guided by fitness values, our virtual bats navigate around the algorithmic realm. Every individual bat adjusts its position, velocity, frequency, noise level, and emission ratio through a complex interaction of exploration and exploitation. These updates align with the objective of achieving optimal parameter configurations, ensuring that our forecasting model is synchronized with the market's rhythm. The topic of discussion is iteration control. The dance perpetuates itself through repetitive cycles, reflecting the enduring pursuit of optimization. Our virtual bats persist as long as the maximum iteration count is not reached. The fitness value is recalibrated during each repetition, and the bat with the lowest fitness value is identified. This bat is guided by the Mean Absolute Percentage Error (MAPE) and serves as a lighthouse. The bat in question has emerged as the primary holder of the most valuable position, symbolizing a significant advancement in the field of predictive accuracy.

In the course of this algorithmic symphony, the Bat Algorithm adeptly refines the parameters of exponential smoothing with meticulousness and elegance. Every parameter modification can be seen as a musical note within the optimization process, contributing to the overall composition and leading us towards achieving a harmonious resonance in forecast accuracy. This expedition, evocative of bats employing echolocation to travel through darkness, enables us to adeptly traverse the difficult terrain of stock price prediction with assurance and skill.

3. RESULT AND ANALYSIS

This study utilizes a comprehensive dataset of LQ45 daily stock data covering the period from January 1, 2020, to December 31, 2022. The dataset consists of 735 carefully collected data points, contributing to our analysis's pursuit of accuracy and precision. Researchers examine forecasting results using the pure exponential smoothing technique, the pure exponential smoothing method with PSO, and the exponential smoothing method with the bat algorithm in parameter adjustment.

3.1. Results

1. Single Exponential Smoothing without Tuning Parameter

As the researcher commences a data-driven endeavor, the preliminary investigation reveals a discernible pattern, visually shown in Figure 3, characterized by a wide range of horizontal dynamics. To capture this distinctive behavior, we refer to the well-established Single Exponential Smoothing approach [24]. This methodology offers the potential to uncover the nuanced patterns concealed inside the horizontal progression of the data, thereby aligning our predictions with the dominant tempo of the market.

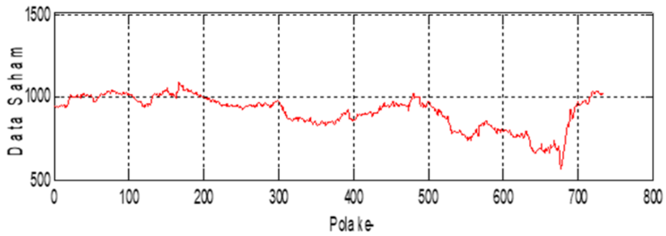

Figure 3. Actual data of LQ45 stocks

We aim to systematically identify the most effective parameter configuration through a rigorous and careful selection procedure. To make the model more flexible and adjust the level of trend and slope, the alpha value used is between 0.1 0.9 [23]. We explore a range of parameter values, spanning from 0.1 to 0.9, each corresponding to a distinct perspective through which we analyze the data. The evaluation criterion for these factors is determined by their capacity to provide the lowest MAPE (Mean Absolute Percentage Error) value, which serves as a reliable indicator of the accuracy of the forecasting process.

The process of experimentation and refinement, as evidenced by our findings, eventually revealed an optimal parameter value of 0.9 that provided a minimal Mean Absolute Percentage Error (MAPE) value of 1.0316%. This accomplishment signifies a significant milestone in our pursuit of precision, shedding light on the trajectory toward enhanced forecasting approaches. The results for forecasting using the pure exponential smoothing method can be presented in Table 1.

Table 1. The Mape Value of Each Parameter

No	**(α) Parameter**	**MAPE (%)**
1	0.1	2.4988
2	0.2	1.707
3	0.3	1.4122
4	0.4	1.2577
5	0.5	1.167
6	0.6	1.1074
7	0.7	1.0661
8	0.8	1.0409
9	0.9	1.0316

However, achieving precision requires a significant time commitment. Determining the optimal parameter in computational analysis necessitates a deliberate approach, wherein each calculation is performed within a time frame ranging from 1.7 to 2 seconds. Given the requirement to investigate the range of values across nine repetitions, the cumulative computational duration amounts to a respectable 18 seconds. The allocation of time towards this endeavor demonstrates our unwavering commitment to achieving the highest standards of quality. It represents a very small cost in exchange for the significant and valuable knowledge and understanding it generates.

Fundamentally, this thorough exploration of data and computational processes proves our dedication to providing dependable and precise predictions. This statement exemplifies our steadfast commitment to seeking the most optimal tools and parameters, enabling investors and analysts to possess the requisite knowledge for effectively navigating the ever-changing landscape of the financial real.

2. Single Exponential Smoothing with PSO

By utilizing the Particle Swarm Optimization (PSO) algorithm, the laborious procedure of trial and error in selecting the value is rendered obsolete. The present study incorporates computational intelligence techniques to autonomously explore the parameter space, ultimately uncovering the parameter with exceptional precision. The result of tuning the alpha parameter using the PSO algorithm is shown in Figure 4. The optimal parameter is determined to be 0.9346, exhibiting a remarkably low mean absolute percentage error (MAPE) of 1.0311%.

The displayed history of the parameter's value reveals a fascinating convergence process. The convergence of the crucial parameter from the 9th iteration serves as evidence for the efficiency and usefulness of the PSO method. In the context of our research, we established a predetermined limit of 20 iterations, a deliberate decision aimed at striking a balance between computational resources and achieving optimal results in the optimization process. The PSO algorithm's swarm intelligence drives the quest for perfection, which occurs within a timeframe of 105 seconds. This investment yields significant benefits in terms of unmatched predicting accuracy.

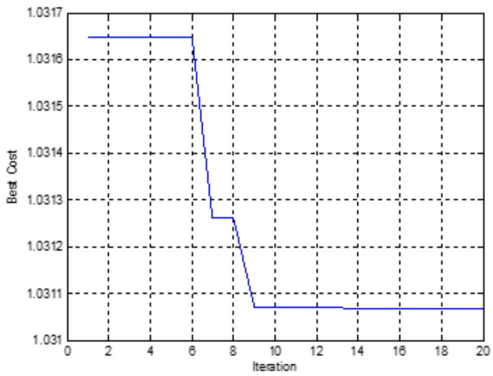

Figure 4. Iteration graph of SES method with PSO algorithm

By adopting this approach, our research surpasses the constraints associated with manual parameter selection, utilizing computational optimization to its fullest extent to determine the optimal α value. This accomplishment serves as a demonstration of our dedication to enhancing efficiency, accuracy, and originality in the field of stock price prediction. It equips decision-makers with the necessary resources to confidently traverse the complexities of financial markets. Figure 5 shows that with an α parameter of 0.9346, the MAPE obtained is minimal, pictorially showing that there is almost no difference between the factual and forecasting data.

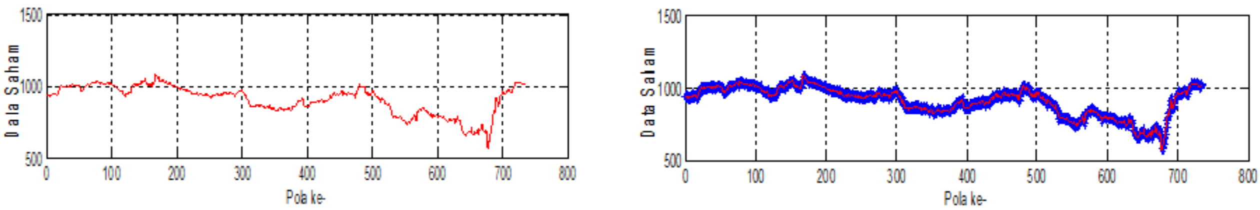

Figure 5. Comparison Graph of Actual Data and Forecasting Data using PSO Algorithm

3. Single Exponential Smoothing with Bat Algorithm

In the context of our persistent endeavor for accuracy, we examine not just one but two formidable algorithms to discover the best α parameter value. Specifically, we introduce the Bat Algorithm as our collaborator in this computational goal. In the context of this scholarly investigation, the Bat Algorithm emerges as a noteworthy subject, unveiling an α parameter of notable precision, specifically 0.93465, alongside a Mean Absolute Percentage Error (MAPE) of a tiny 1.0311%.

As we navigate along this algorithmic trajectory, carefully adjusted to adhere to the criteria set by the Particle Swarm Optimization (PSO) algorithm, the Bat Algorithm demonstrates its merit as a formidable competitor. The Bat Algorithm, like the PSO algorithm, adheres to the specified 20 iterations, allowing for a thorough examination of parameter space while also assuring computing efficiency. The allocation of time, precisely 117 seconds, serves as evidence of our dedication to meticulousness and the capacity to make significant comparisons between the two algorithms.

In this collaborative investigation, our research surpasses limitations by utilizing the combined capabilities of both the Particle Swarm Optimization (PSO) and the Bat Algorithm. Our study aims to present not only a single but rather two excellent values for the parameter. The wide range of choices available provides decision-makers with diverse tools, enabling them to gain detailed insights into the complex practice of predicting stock prices. This statement highlights our dedication to assuring the strength and scientific validity of our research, guaranteeing that our results are precise and thorough, shedding light on several approaches to achieving accuracy and quality in financial analysis. Figure 6 shows that by tuning the parameter using the bat algorithm, the α obtained is 0.9345, and the MAPE obtained is very small at 1.0311%. The figure shows that there is almost no difference between factual data and forecasting data.

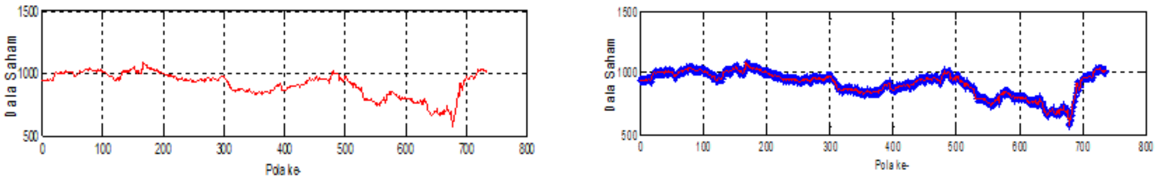

Figure 6. Comparison Graph of Actual Data and Forecasting Data using Bat Algorithm

3.2. Discussion

The domain of LQ45 stock forecasting, employing the Single Exponential Smoothing technique, reveals a pattern of notable precision, reaching an astonishing level of 1.0366%. However, it is important to acknowledge that the current success is accompanied by the recognition that the conventional approach of selecting the α value by trial and error is inadequate in consistently producing dependable outcomes for predicting LQ45 stocks. Hence, the present investigation embarks on a scholarly trajectory, employing the esteemed Particle Swarm Optimization (PSO) and Bat algorithms as pivotal tools in the pursuit of unraveling this complex enigma.

Table 2 serves as evidence of the progressive refinement in precision inside our research. The description clearly shows the PSO and Bat algorithms working together to get the ideal α parameter value in the Single Exponential Smoothing approach.

Table 2. The Performance Comparison of PSO Algorithm and Bat Algorithm

Method	alpha	MAPE	Computational Speed (second)
SES without optimization	0.9	1.0316%	18
SES-PSO	0.9346	1.0311%	105
SES-Bat	0.93465	1.0311%	117

Interestingly, a perceptive observer can identify a modest yet significant improvement in precision, amounting to a marginal gain of 0.0005%. Although seemingly tiny, this development represents a substantial advancement in the dependability of our predictions. The gradual increase in accuracy leads to more precise forecasts, providing investors and analysts with a competitive advantage to make well-informed choices within the unpredictable realm of finance. **This research also supports** the finding that PSO [11] and Bat Algorithm [25] can improve stock forecasting results.

However, it is imperative to recognize the trade-off involved in adopting these optimization algorithms, namely the limited time resource. Determining the appropriate parameter in computational analysis while yielding valuable insights requires a significant time commitment. Undoubtedly, achieving precision necessitates the virtue of patience, as optimization algorithms engage in a process of thoughtful contemplation, meticulous calculation, and continuous refinement. Nevertheless, within this temporal investment, we uncover the crucial point of our investigation - a fragile equilibrium between precision and computational efficacy.

Fundamentally, our endeavor encompasses a dedication to advancement. The transition from dependence on conventional techniques to leveraging the computing capabilities of optimization algorithms represents a transformative process. This statement acknowledges and appreciates the persistent pursuit of achieving high standards in stock forecasting. It emphasizes the value placed on making gradual improvements in accuracy, even if it requires investing additional time, as these advancements contribute to a better-informed and empowered financial environment. This is in line with research conducted by Liantoni [25], which shows that forecasting accuracy using exponential smoothing can support decision-making when trading stocks.

Although our research has yielded helpful insights, it is crucial to accept certain limits. The measurement of the time required for a computer to do a specific task. The potential delay in computing time inherent to optimization algorithms could potentially hinder their practical implementation in situations where rapid processing is of the utmost importance. Future research endeavors should aim to achieve a harmonious equilibrium between precision and expediency to advance the field.

Our research primarily investigated the Particle Swarm Optimization (PSO) and Bat Algorithm. Additional investigation could extend this inquiry to include a broader array of optimization techniques, potentially revealing swifter and more precise methodologies. The concept of data dynamics refers to the changing nature and behavior of data over time. The primary goal of our study was to analyze a particular dataset within the framework of the Single Exponential Smoothing technique. Future studies may investigate the performance of optimization algorithms across a wide range of datasets and forecasting approaches.

Fundamentally, our exploration has shown a potentially fruitful avenue for improving forecasting accuracy. However, it also elicits inquiries and ambitions for future undertakings. By acknowledging these constraints and adopting innovative methodologies, we may persistently progress in the field of stock price prediction, thereby equipping investors and analysts with the necessary resources to succeed in an ever-changing financial environment.

4. CONCLUSION

The novelty of this research is the parameter tweaking of the exponential smoothing approach utilizing the particle swarm optimization metaheuristic algorithm and the bat algorithm. Our research has discovered a crucial finding in the field of stock price forecasting using the Single Exponential Smoothing method. It has been observed that optimization algorithms greatly improve the accuracy of selecting the α parameter, as opposed to the conventional trial-and-error methods. The careful utilization of particle swarm optimization (PSO) and the bat algorithm has shed light on the trajectory towards enhanced predictive capabilities, characterized by gradual improvements in precision, albeit accompanied by a rise in computational resources required. Nevertheless, our expedition does not reach its termination at this point; rather, it serves as a gateway to further investigations. Upon careful analysis of our data, it becomes apparent that the pursuit of an optimization technique that may achieve faster convergence in optimizing the α parameter is of utmost importance. Although PSO and the Bat Algorithm have proven effective in improving accuracy, the extended computation times still provide a constraint that requires attention. Many earlier studies have examined the exponential smoothing technique using traditional parameter selection. However, this study's findings demonstrate that tweaking exponential smoothing parameters with PSO and Bat algorithms can result in significant performance gains. The study's focus on achieving precision through optimizing algorithms presents numerous potential directions for future research. Efficiency-driven algorithms refer to computational procedures that prioritize optimizing resource use and execution time. These algorithms are designed to minimize computational complexity and maximize efficiency to achieve the result. Future research can focus on exploring new optimization algorithms specifically developed to accelerate the process of selecting the parameter while ensuring that accuracy is not compromised. The endeavor to enhance efficiency in computational finance has the capacity to profoundly transform the field.

This research provides implications in the form of positive insights into the world of stocks and finance. Such insights about prediction need to be gained to make investment decision-making more accurate. In making these predictions, it is necessary to use methods that can increase accuracy. This study proves that using computational methods will make forecasting results more accurate than manual results. PSO and Bat algorithm can improve forecasting results marked by the minimum MAPE value achieved. In terms of time efficiency, the trial-and-error method makes the forecasting process inefficient, so optimizing algorithms can improve results and certainly be more time efficient. Although this work contributes significantly to understanding PSO and Bat parameter tweaking in exponential smoothing, some limitations must be addressed. This study is confined to the scope of a specific dataset; hence, the findings' generalizability may be subject to further investigation in future research. Researchers can employ hybrid techniques to integrate the advantageous aspects of many optimization algorithms, so attaining a harmonious equilibrium between accuracy and computational efficiency. The integration of several methodologies has the potential to unveil novel opportunities in the field of forecasting. One important aspect of the field of forecasting is real-time forecasting. Real-time decision-making is a crucial aspect of the banking industry's success. Future research might prioritize the enhancement of optimization algorithms to achieve efficient parameter optimization for real-time stock price forecasting, specifically addressing the evolving requirements of investors in a dynamic market environment.

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6. DECLARATIONS

AUTHOR CONTIBUTION

Vivi Aida Fitria, the first author, was the data collector and analyzed the data. Lilis Widayanti, the second author, reviewed and analyzed the literature.

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COMPETING INTEREST

Further research can be directed towards creating an optimization model that can automatically determine the best parameters in the field of forecasting.

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