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COMPARISON OF FRUIT FLY OPTIMIZATION ALGORITHM (FOA) AND PARTICLE SWARM OPTIMIZATION (PSO) FOR SUPPORT VECTOR REGRESSION (SVR) IN UNITED TRACTORS STOCK PRICES FORECASTING

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ABSTRACT

Stock price forecasting is one of the analytical approaches used by capital market participants to identify future price movement patterns. This study evaluates the performance of the Support Vector Regression (SVR) model in predicting the stock price of United Tractors (UNTR) by optimizing the model's parameters using two metaheuristic algorithms. The selection of SVR is based on its ability to handle nonlinear regression problems through the use of the Radial Basis Function (RBF) kernel. The parameter optimization of SVR is carried out using the Fruit Fly Optimization Algorithm (FOA), an algorithm inspired by the olfactory and visual system of fruit flies in locating food sources. The advantage of FOA lies in its computational simplicity and fast convergence speed. This study also implements Particle Swarm Optimization (PSO) for comparison purposes. This algorithm adopts a collaborative mechanism among particles in the search space, inspired by the flocking behavior of birds. The stock price data used in this study, covering the period from January 2020 to December 2023, was obtained from Yahoo Finance (https://finance.yahoo.com). The results show that SVR-FOA yields a parameter combination of C = 1000, gamma = 0.9182, and epsilon = 0.9997, while SVR-PSO produces a different configuration, namely C = 1000, gamma = 0.0001, and epsilon = 1. Accuracy evaluation using Mean Absolute Percentage Error (MAPE) indicates that the SVR-PSO model achieves a MAPE of 2.3164%, suggesting a relatively low prediction error. SVR-FOA yields a MAPE of 5.8727%, which is still within the acceptable tolerance range for financial data. While this study focuses on a single stock and uses only historical closing prices, its results provide a strong baseline for applying SVR with metaheuristic optimization in financial forecasting. This research contributes by presenting a direct comparative analysis of FOA and PSO for SVR parameter tuning in an emerging market context, offering practical insights for investors and researchers seeking robust forecasting models.

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1. INTRODUCTION

Heavy equipment stocks represent one of the key sectors in the Indonesian capital market, exhibiting a strong correlation with real economic growth. The heavy equipment industry serves as a primary supporter of infrastructure development and mining activities across various regions in Indonesia. Investment in real-sector firms (e.g., heavy-equipment manufacturers) is highly cyclical and sensitive to government industrial policy, which can materially affect firms' investment decisions and stock prices [1]. Investors often monitor heavy equipment stocks as an indicator of the health of the national construction and mining sectors. As explained by Sudarmanto *et al.*, the Indonesian capital market plays a crucial role in financing the real sector, including infrastructure and heavy equipment, which reflects national economic growth dynamics [2].

PT United Tractors Tbk (UNTR) is the largest listed company in Indonesia's heavy equipment sector, with a market capitalization of IDR 112 trillion. UNTR's financial performance shows stable growth with consistently increasing net profits each year. UNTR stock is categorized as a blue-chip stock with high liquidity on the Indonesia Stock Exchange. The price movement of UNTR shares is often used as a benchmark to observe the overall trend of the heavy equipment sector. According to Wijoyo *et al.*, large companies categorized as blue-chip are highly attractive to investors due to their financial stability and strong fundamentals, making them common benchmarks in market analysis [3].

UNTR stock is selected as the object of this study due to its unique and complex characteristics, such as high volatility, sensitivity to macroeconomic factors, and the fluctuating dynamics of the heavy equipment industry. Its large daily trading volume and high liquidity make UNTR's historical data statistically representative for analysis. The volatility of UNTR stock tends to be higher than other similar issuers, creating an interesting challenge in building accurate prediction models. Fitriani *et al.* (2021) showed that financial ratios such as ROA, DER, cash ratio, and total asset turnover significantly influence stock prices in Indonesian firms listed on the IDX [4].

Due to the nonlinear and highly volatile nature of UNTR stock and its sensitivity to external factors such as market sentiment and news events, forecasting methods should incorporate nonlinear models and exogenous data [5]. Traditional methods such as ARIMA are often less effective due to their reliance on assumptions of stationarity and linearity. Support Vector Regression (SVR) offers a more robust solution through the use of kernel functions. The main advantage of SVR lies in its ability to handle non-linear relationships and prevent overfitting through structural risk minimization [6]. Rustam and Kintandani successfully implemented an SVR model optimized with Particle Swarm Optimization (PSO) for stock price prediction in Indonesia, showing significant accuracy improvements compared to traditional methods [7]. Such models are highly relevant when dealing with dynamic, non-linear capital market data like UNTR stock.

Grid Search, as a conventional optimization approach, exhibits fundamental limitations when applied to SVR [8]. This method performs an exhaustive evaluation of all parameter combinations within a defined range. Such a process is computationally intensive, especially in large multidimensional search spaces. Grid Search is also rigid as it does not dynamically consider inter-parameter relationships. Poorly designed search intervals increase the risk of suboptimal solutions—results that appear good within certain intervals but are not globally optimal [9].

Fruit Fly Optimization (FOA) is another promising alternative for SVR parameter optimization [10]. This algorithm adopts the efficient food-seeking behavior of fruit flies using their sense of smell and vision. FOA works by generating random solutions and refining them iteratively. FOA is known for its quick convergence to optimal solutions due to its direct refinement mechanism [9]. The algorithm is also relatively simple to implement. For non-stationary and noisy stock data, FOA has shown strong adaptability. The combination of computational efficiency and effective searching makes FOA a viable method for SVR parameter optimization.

The effectiveness of FOA in optimizing SVR in this study is consistent with previous findings, which developed an FOA-optimized SVR model to predict monthly electricity consumption [11]. The results showed that the FOA-SVR model had better predictive performance compared to other models, with lower RMSE and MAPE values. Guo conducted a similar study by proposing an FOA-optimized SVR model to predict the economic speed of marine vessels [12]. Their findings showed that the FOA-SVR model had higher prediction accuracy, with lower MSE and higher R^2 values.

Another promising optimization approach for enhancing SVR performance is Particle Swarm Optimization (PSO), which offers a different, more suitable method for SVR parameter tuning. This algorithm is inspired by the collaborative behavior of bird flocks in finding food. This mechanism allows more dynamic and adaptive exploration of the parameter space [13]. PSO can balance exploration (searching new areas) and exploitation (optimizing promising areas). It also demonstrates faster convergence to optimal solutions compared to Grid Search.

Dash *et al.* [14] developed a Fine-Tuned Support Vector Regression model for stock price prediction. The study confirmed that selecting optimal parameters significantly improves model accuracy while reducing memory and computational time. Particle Swarm Optimization (PSO) is more efficient in finding optimal parameters than Grid Search because it explores the parameter space more adaptively and is less prone to getting trapped in local optima.

The selection of an appropriate prediction method and model optimization strategy is key to addressing the complexity and volatility of the stock market. This study uses the closing price data of UNTR stock from 2020 to 2024 as the basis of analysis. The five-year period reflects various market conditions, ranging from the crisis during the pandemic to the economic recovery phase. Closing prices are chosen as they are often used as the primary indicator in technical analysis to forecast future price movements. In the context of operations management, closing price data serves as a key element in identifying performance efficiency and trends in the capital market [15].

2. RESEARCH METHODS

2.1 Data Sources and Research Variables

The type of data used in this study is secondary data obtained from the Yahoo Finance database. The data includes daily stock price information of PT United Tractors for the period from January 1, 2020, to December 31, 2024. The variable used in this study is the closing stock price of PT United Tractors. The dependent variable is the closing stock price of PT United Tractors, while the independent variables consist of lagged values of the closing price, representing the stock prices from previous periods.

2.2 Support Vector Regression (SVR)

The complexity of UNTR's price patterns cannot be adequately captured by traditional forecasting methods such as ARIMA. Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel offers a solution through its ability to perform nonlinear mapping. Given a training dataset $(x_i, y_i)_{i=1}^{n}$, where $\boldsymbol{x_i} \in \mathbb{R}^d$ represents the input data, $y_i \in \mathbb{R}$ is the corresponding output value, d denotes the dimensionality of the data sample, and n is the number of training samples. The SVR function mapping input to output is formulated as follows:

$$f(\boldsymbol{x}) = \boldsymbol{w}^T \varphi(\boldsymbol{x}) + b. \tag{1}$$

The optimization problem is defined in the form of Quadratic Programming as shown in equation [16]:

$$min \frac{1}{2} ||\boldsymbol{w}||^2, \tag{2}$$

subject to:

$$y_i - (\boldsymbol{w}^T \varphi(x_i) + b) \leq \varepsilon, \text{for } i = 1, 2, \dots, n, \tag{3}$$

$$(\boldsymbol{w}^T \varphi(x_i) + b) - y_i \geq \varepsilon, \text{for } i = 1, 2, \dots, n. \tag{4}$$

Eq. (2) assumes that all data points fall within the range $f(\boldsymbol{x}) \pm \varepsilon$. However, since some points may lie outside this margin, slack variables ξ_i dan ξ_i^* are introduced to handle infeasible constraints. The modified optimization problem is formulated as follows [17]:

$$\min(\boldsymbol{w}, \xi, \xi^*) = \frac{1}{2} ||\boldsymbol{w}||^2 + C \left(\sum_{i=1}^{n} (\xi_i + \xi_i^*) \right), \tag{5}$$

subject to:

$$y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x_i}) - b - \xi_i \leq \varepsilon, \text{for } i = 1, 2, \dots, n, \tag{6}$$

$$y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x_i}) + b - \xi_i^* \geq \varepsilon, \text{for } i = 1, 2, \dots, n, \tag{7}$$

$$\xi_i, \xi_i^* \geq 0. \tag{8}$$

The constant $C > 0$ determines the trade-off between the flatness of the function $f(x)$ and the upper bound on tolerated deviations exceeding ε [18]. Deviations greater than ε are penalized by a factor of C. The Lagrangian function can be used as an optimization solution as follows:

$$Q(\boldsymbol{w}, b, \xi, \xi^*, \alpha_i, \alpha_i^*, \eta_i, \eta_i^*) = L$$
$$= \frac{1}{2}\|\boldsymbol{w}\|^2 + C \cdot \left(\sum_{i=1}^{n} (\xi_i + \xi_i^*)\right) - \sum_{i=1}^{n} \alpha_i \left(\varepsilon + \xi_i - y_i + \boldsymbol{w}^T \varphi(\boldsymbol{x_i}) + b\right)$$
$$- \sum_{i=1}^{n} \alpha_i^* \left(\varepsilon + \xi_i^* - y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x_i}) - b\right) - \sum_{i=1}^{n} (\eta_i \xi_i + \eta_i^* \xi_i^*). \tag{9}$$

Here, $\alpha_i, \alpha_i^*, \eta_i, \eta_i^*$ are the Lagrange multipliers. The optimal solution is obtained by taking the partial derivatives of Q with respect to $\boldsymbol{w}, b, \xi, \xi^*$, resulting in:

$$\boldsymbol{w} = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) \varphi(\boldsymbol{x_i}). \tag{10}$$

Thus, the optimal hyperplane is expressed as:

$$f(\boldsymbol{x}) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) \varphi^T(\boldsymbol{x_i}) \varphi(\boldsymbol{x}) + b, \tag{11}$$

let $\beta_i = \alpha_i - \alpha_i^*$, then:

$$f(\boldsymbol{x}) = \sum_{i=1}^{n} \beta_i \varphi^T(\boldsymbol{x_i}) \varphi(\boldsymbol{x}) + b. \tag{12}$$

The optimal value b of can be determined using the Karush-Kuhn-Tucker (KKT) conditions as follows:

$$b = y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x_i}) - \varepsilon, \text{for } 0 < \alpha_i < C,$$
$$b = y_i - \boldsymbol{w}^T \varphi(\boldsymbol{x_i}) + \varepsilon, \text{for } 0 < \alpha_i^* < C. \tag{13}$$

Datasets that are not linearly separable can be addressed using the kernel method. The advantage of using a kernel function is its ability to map data to a higher-dimensional feature space. This study utilizes the Radial Basis Function (RBF) kernel, which is formulated as:

$$\boldsymbol{\varphi(x) = k(x_i, x_j) = exp\left(-\gamma \|x_j - x_i\|^2\right)}. \tag{14}$$

2.3 Fruit Fly Optimization

The performance of Support Vector Regression (SVR) heavily depends on the precision of the parameters C, epsilon, and gamma. This study compares two metaheuristic optimization approaches: Fruit Fly Optimization Algorithm (FOA) and Particle Swarm Optimization (PSO). According to [10], FOA is an algorithm inspired by the foraging behaviour of fruit flies. Fruit flies utilize both visual and olfactory senses, moving in swarms, spreading out, and seeking optimal solutions.

The steps of FOA begin by setting the main parameters, namely sizepop, maxgen, and the initial position of the fruit flies. Then, the position of each fly is randomly updated using the olfactory mechanism with the following formulas:

$$x_{i,j} = x_{0,j} + RV, \tag{15}$$

$$y_{i,j} = y_{0,j} + RV. \tag{16}$$

Next, the distance traveled by the fly from its initial position is calculated using the Euclidean formula:

$$Dist_{i,j} = \sqrt{x_{i,j}^2 + y_{i,j}^2}. \tag{17}$$

The smell concentration value is calculated as the inverse of the distance:

$$S_{i,j} = \frac{1}{Dist_{i,j} + \varepsilon}. \tag{18}$$

The smell concentration at each position is evaluated using an objective function (fitness function):

$$smell_{i,j} = FitnessFunction(S_{i,j}). \tag{19}$$

The fly with the best smell concentration is selected based on the applied method, and the best value is determined as follows:

$$[bestSmell, bestIndex] = \min(smell_{i,j}). \tag{20}$$

If a better value is found, the best position is updated using:

$$smellBest = bestSmell, \quad x_0 = x(bestIndex), \;\; y_0 = y(bestIndex). \tag{21}$$

This process continues iteratively until no further improvement is achieved or the maximum number of iterations is reached.

2.4 Particle Swarm Optimization

The iterative optimization process of FOA, which continues until a stopping criterion is met, provides a performance baseline to be compared with the Particle Swarm Optimization (PSO) approach. PSO is a swarm intelligence-based optimization algorithm developed by Eberhart and Kennedy in 1995, inspired by the flocking behavior of birds when searching for food. Each particle represents a potential solution and updates its position and velocity based on its personal best experience (pbest) and the global best of the swarm (gbest), using the following equations [19]:

$$v_{i,j}^{new} = wv_{i,j}^{old} + c_1 r_1 (pbest_{i,j} - x_{i,j}) + c_2 r_2 (gbest_{i,j} - x_{i,j}), \tag{22}$$

$$x_{i,j}^{new} = x_{i,j}^{old} + v_{i,j}^{new}, \tag{23}$$

where w denotes the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1 and r_2 are random values in the range [0,1].

The inertia weight controls the trade-off between exploration and exploitation. A higher w encourages global search, while a lower w emphasizes local search. It is dynamically updated using the following formula:

$$w = w_{max} - (w_{max} - w_{min}) \times \frac{iter}{iter_{max}}. \tag{24}$$

PSO iterates until the maximum number of iterations is reached or an optimal solution is found, allowing the algorithm to avoid local optima and achieve better performance across the search space.

2.5 Partial Autocorrelation Function (PACF)

PSO and FOA are optimization algorithms, whereas in time series data analysis, the relationship between data points can be analyzed using the Partial Autocorrelation Function (PACF). PACF is used to determine the input variables in a model by identifying lags that have a significant relationship with the current value. It measures the correlation between $\boldsymbol{Z_t}$ and $\boldsymbol{Z_{t+k}}$ while eliminating the linear effects of intermediate lags. The PACF can be computed using the following equation [20]:

$$\begin{aligned} \phi_{k+1,k+1} &= \frac{\rho_{k+1} \sum_{j=1}^{k} \phi_{kj} \; \rho_{k+1-j}}{1 - \sum_{j=1}^{k} \phi_{kj} \; \rho_j}, \\ \phi_{k+1,j} &= \phi_{kj} - \phi_{k+1,k+1} \phi_{k,k+1-j} \, , j = 1, \ldots, k. \end{aligned} \tag{25}$$

2.6 Forecasting

Forecasting is a calculation technique that uses data from previous times to estimate the likelihood that will occur in the future [21]. Forecasting is related to efforts to predict what will happen in the future, based on scientific methods (science and technology) and carried out mathematically. Forecasting is essential for planning budgets, sales, production, inventory, labor needs, and raw material requirements.

2.7 Mean Absolute Percentage Error (MAPE)

After identifying significant lags using the Partial Autocorrelation Function (PACF), the next step is to evaluate the model's performance to ensure the accuracy of the forecasting results. This evaluation is conducted using the Mean Absolute Percentage Error (MAPE), which measures the average percentage of absolute errors between the predicted and actual values [22]. MAPE can also be used to compare the accuracy of the same or different methods in two different series and measure the accuracy of the model's estimated values expressed in the absolute form of the mean percentage of error [23].

No forecasting model can achieve 100% accuracy. However, a good model should minimize error within an acceptable tolerance range. The MAPE is calculated using the following formula:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|F_t - A_t|}{A_t}. \tag{26}$$

The forecasting results are considered very good when the MAPE value is less than 10%. The following are the forecasting accuracy categories:

Table 1. MAPE Value Category

MAPE (%)	Interpretation
MAPE ≤ 10%	The ability of forecasting models is excellent
10% < MAPE ≤ 20%	Good forecasting model capabilities
20% < MAPE ≤ 50%	Decent forecasting model capabilities
MAPE > 50%	Poor forecasting model capabilities

2.8 Steps of Data Analysis

The data analysis stages in this study consist of several steps to forecast the stock price of PT United Tractors using Support Vector Regression (SVR) and SVR-PSO. The following are the data analysis steps carried out:

1. Preparing the daily closing stock price data of PT United Tractors for the period from January 1, 2020, to December 31, 2024, downloaded from Yahoo Finance.
2. Performing data pre-processing, including the determination of input variables.
3. Splitting the data into training and testing sets.
4. Selecting the Radial Basis Function (RBF) kernel as the optimal kernel and determining the initial parameters (C, epsilon, gamma) of the Support Vector Regression (SVR) to be optimized.
5. Optimizing SVR parameters using Fruit Fly Optimization (FOA) and Particle Swarm Optimization (PSO) by initializing FOA fruit flies and PSO particles.
6. Analyzing the comparison of Mean Absolute Percentage Error (MAPE) values from the SVR model optimized with FOA and PSO.
7. Forecasting the stock price of PT United Tractors on the testing data using the SVR model with parameters optimized by PSO.

3. RESULTS AND DISCUSSION

3.1 Exploratory Data Analysis (EDA)

Before building the predictive model, an Exploratory Data Analysis (EDA) was conducted to understand the behavior and characteristics of the stock price data. EDA helps in identifying trends, patterns, and potential anomalies in the dataset, which are important for selecting the appropriate modeling approach. One of the initial steps in EDA is visualizing the time series of the stock's closing price to observe its overall movement over time.

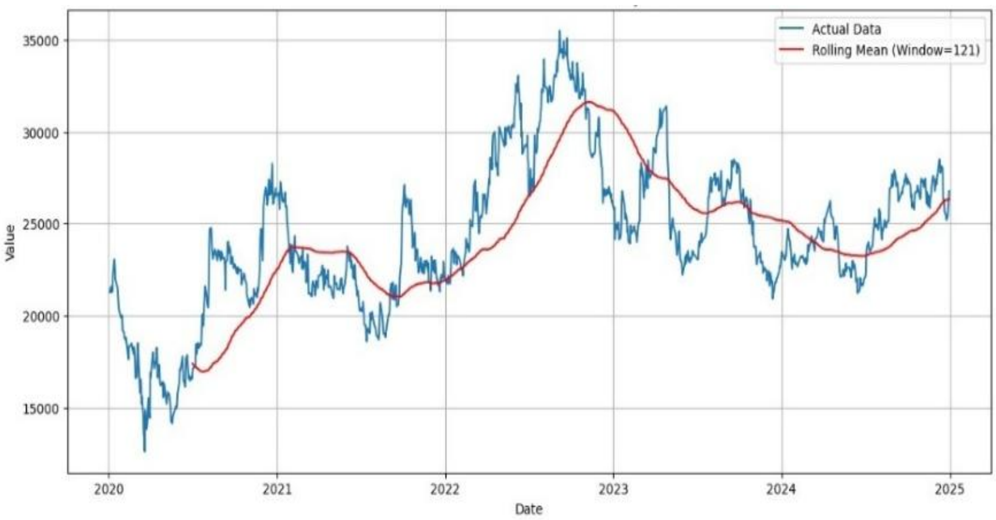

Figure 1. UNTR Stock Price Time Series Plot
(Source: Author's calculation using Jupyter Notebook)

Based on Fig. 1, it can be seen that the closing stock price of United Tractors experienced considerable fluctuations. In early 2020, the closing price tended to remain stable, but it began to decline significantly in mid-2020, most likely due to the impact of the COVID-19 pandemic. The closing price showed signs of recovery and an upward trend by mid-2021.

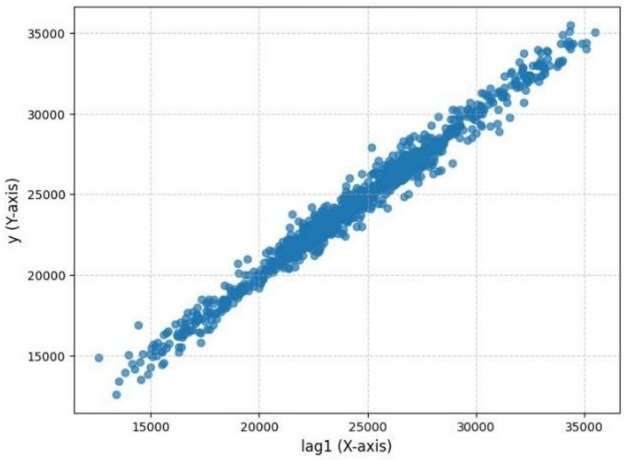

Figure 2. The Relationship Between Stock Prices and Previous Stock Prices
(Source: Author's calculation using Jupyter Notebook)

To understand the relationship between the current closing price (y) and the previous closing price (lag 1), a scatter plot analysis was conducted. The graph shows a strong positive correlation, as indicated by the pattern of data points that tend to form a straight line with a positive slope.

3.2 Data Pre-processing

In this study, the pre-processing stage focuses on the determination of input variables using the Partial Autocorrelation Function (PACF) plot. The PACF plot helps identify significant lags as predictor variables by analyzing the direct correlation between current and past observations.

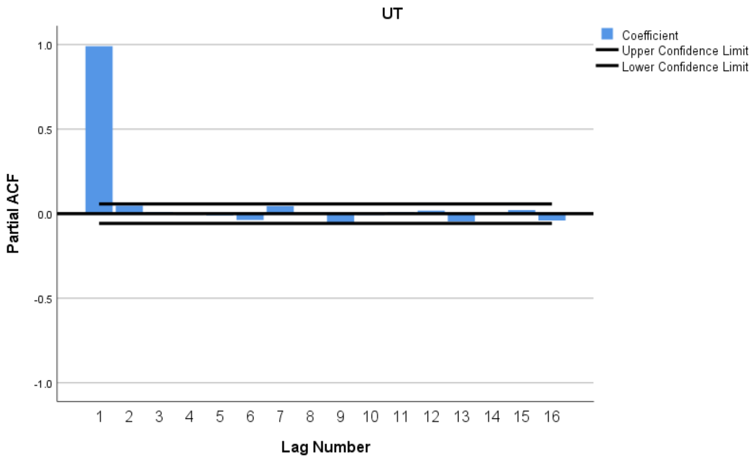

Figure 3. PACF Plot of United Tractors (UNTR) Stock
(Source: Author's calculation using Jupyter Notebook)

Based on Fig. 3, it is shown that only lag 1 has a vertical bar that exceeds the significance threshold. This indicates that only lag 1 has a significant partial correlation with the current value. In this study, it means that the current stock price (Y_t) is significantly influenced by the stock price from one previous period (Y_{t-1}). Therefore, based on the PACF plot, the selected input variable x is Y_{t-1}.

3.3 Support Vector Regression – Fruit Fly Optimization Analysis

The training data in SVR optimization using Fruit Fly Optimization (FOA) aims to optimize the SVR parameters, namely C (penalty), gamma (γ), and epsilon (ε). The detailed training steps are as follows:

1. Initialization of Fruit Fly Population
   The parameters initialized include the number of flies (N), set to 30. The parameter value ranges used are: C: 1–1000, gamma (γ): 0.0001–1, and epsilon (ε): 0.0001–1.
2. Fitness Function Evaluation
   The next step is to calculate the fitness function value for each fruit fly. The fitness function used is the Mean Absolute Percentage Error (MAPE).
3. Update Fruit Fly Positions
   The positions of the fruit flies are updated based on the food scent (best fitness value). This process involves moving the flies toward new positions.
4. New Fitness Evaluation
   After updating the position of each fly based on the smell concentration calculation, the next step is to evaluate the updated fitness value of each fly.

Table 2. Fruit Flies and MAPE Converging at a Certain Value

Fruit Fly	C	Gamma	Epsilon	MAPE
1	1000	0.9982	0.9665	7.6862%
2	1000	1	1	7.6862%
3	1000	1	1	7.6862%
⋮	⋮	⋮	⋮	⋮
15	850.9902	1	1	7.6862%
16	981.5142	0.8494	1	7.6862%
17	1	0.9354	0.9521	7.6862%
⋮	⋮	⋮	⋮	⋮
28	1000	0.9239	1	7.6862%
29	1000	1	1	7.6862%
30	1000	1	0.9938	7.6862%

This evaluation is carried out by calculating the Mean Absolute Percentage Error (MAPE) obtained from the SVR model predictions using the latest parameters discovered by each fly.

5. Update Best Fitness
   Based on the iteration results, the best global fitness value obtained is 5.8727%.

6. Iteration until Convergence
   The optimization process will terminate if the MAPE value has stabilized with a change of less than 0.0001%, and the model parameters (C, gamma, epsilon) show absolute changes below 0.0001 for 10 consecutive iterations. Alternatively, the process will also stop upon reaching the maximum limit of 100 iterations. In this case, the algorithm successfully achieved convergence after 24 iterations with a validation MAPE of 7.6862%. The optimal parameters obtained were precisely at the upper bound of the search range, namely C = 1000, gamma = 0.9182, and epsilon = 0.9997.

Model validation is conducted using testing data to evaluate the performance of the trained model. The resulting model for the testing process is as follows:

$$f(x) = \sum_{i=1}^{1.211} (\alpha_i - \alpha_i^*) exp(0{,}9182\|y_i - x_i\|^2).$$

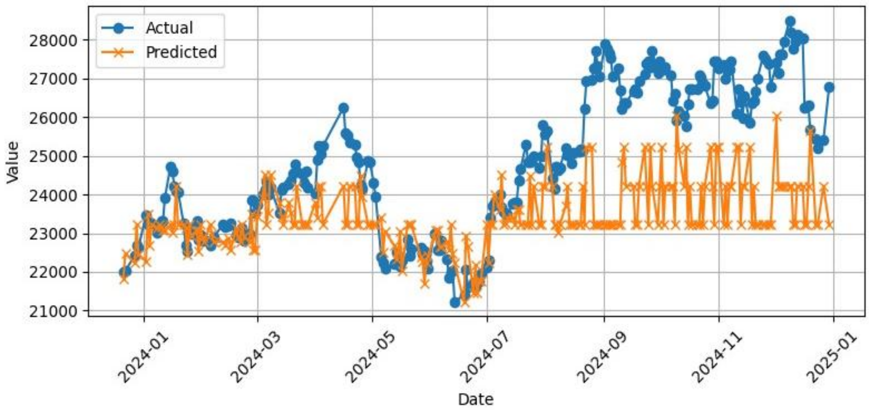

Figure 4. Comparison Plot of Actual and Predicted Values Using FOA
(Source: Author's calculation using Jupyter Notebook)

The comparison plot between actual and predicted values shows a pattern that closely aligns with the actual data, with a final MAPE value of 5.8727%.

Table 3. Comparison of Actual and Predicted Values Using FOA

Date	Actual Value	Predicted Value
December 21, 2023	22000	21824
December 22, 2023	22025	22474
December 27, 2023	22425	22224.75
December 28, 2023	22700	23224.75
December 29, 2023	22625	22449
January 2, 2024	23475	22276
January 3, 2024	23225	23499
January 4, 2024	23275	22701
⋮	⋮	⋮
December 23, 2024	25450	23224.75
December 24, 2024	25200	23224.75
December 27, 2024	25400	24224.75
December 30, 2024	26775	23224.75

The comparison table shown in Table 3 presents a comparative analysis between the predicted values and the actual values to evaluate the performance of the model.

3.4 Support Vector Regression – Particle Swarm Optimization Analysis

The training data process aims to obtain the optimal parameter values. The training stages in this study are as follows:

1. The PSO algorithm begins by initializing parameters and particles. Each particle contains three parameters, C, gamma, and epsilon, which are randomly initialized within a certain range. Additionally, the velocity of each particle is randomly initialized to determine the initial direction and magnitude of movement.
2. After initialization, the fitness value (MAPE) for each particle is calculated. This fitness value indicates the performance level of each particle.
3. In the initial iteration, each particle's best position (Px_best) and best fitness value (Pf_best) are initialized with the particle's current parameter and fitness values. The global best position (Gx_best) and global best fitness value (Gf_best) are also initialized based on the particle with the lowest MAPE.
4. In each iteration, particle velocities and positions are updated according to the PSO formula. The particle velocity evolves across iterations, reflecting the direction and magnitude of the particle's movement.
5. The PSO algorithm successfully identified the best particle position with the optimal parameters: C = 1000, gamma = 0.0001, and epsilon = 1. The validation MAPE for this position is 3.0235%.

Table 4. Converged Particles and MAPE

Particle	C	Gamma	Epsilon	MAPE
1	1000	0.0001	1	3.0235%
2	1000	0.0001	1	3.0235%
3	1000	0.0001	1	3.0235%
⋮	⋮	⋮	⋮	⋮
15	1000	0.0001	1	3.0235%
16	1000	0.0001	1	3.0235%
17	1000	0.0001	1	3.0235%
⋮	⋮	⋮	⋮	⋮
28	1000	0.0001	1	3.0235%
29	1000	0.0001	1	3.0235%
30	1000	0.0001	1	3.0235%

The optimization process will stop when either of the two conditions is met: when the MAPE value shows a relative change of less than 0.0001% and the model parameters (C, gamma, epsilon) have absolute changes below 0.001 for 10 consecutive iterations, or when the maximum of 100 iterations is reached. Convergence was achieved at iteration 17, when the best MAPE value (3.0235%) was first found, and no significant improvement occurred in subsequent iterations.

6. After obtaining the optimal parameters, the next step is to evaluate the model's performance on the test data. With the best parameters (C = 1000, gamma = 0.0001, epsilon = 1), the MAPE on the test data is 2.3164%. The MAPE value on the test data (2.3164%) is lower than the MAPE on the validation data (3.0235%), indicating that the model optimized with PSO performs well on the test data.

Model validation was carried out using the test dataset to assess how well the trained model generalizes. The training process resulted in the most optimal model parameters, namely C = 1000, epsilon = 1, and gamma = 0.0001. The resulting model for the testing process is as follows:

$$f(x) = \sum_{i=1}^{1.211} (\alpha_i - \alpha_i^*) exp(0{,}0001\|y_i - x_i\|^2)$$

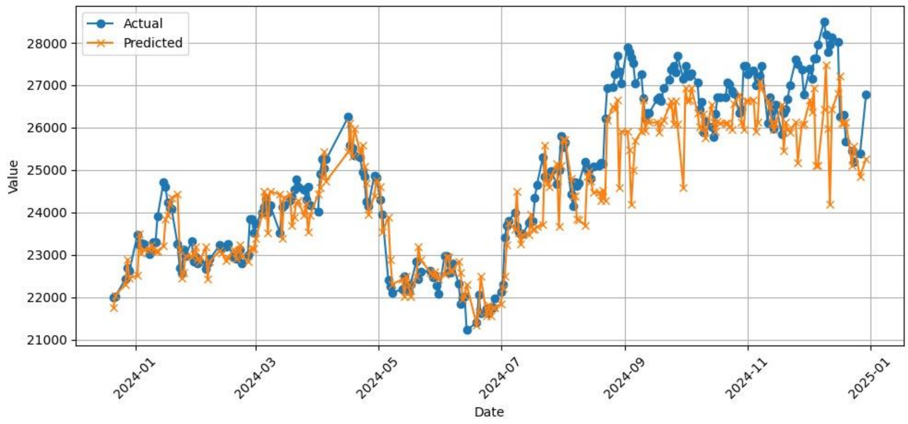

Figure 5. Comparison Plot of Actual vs Predicted Values (PSO)
(Source: Author's calculation using Jupyter Notebook)

Based on the evaluation of the SVR model, the prediction plot generated using PSO-optimized parameters follows the same pattern as the actual values. As shown in Fig. 5, the predicted data closely overlap with the actual data, indicating that the SVR model is capable of producing stock price predictions that are very close to the real stock prices.

As a further step in evaluating the performance of the SVR model optimized using Particle Swarm Optimization (PSO), the following table presents a comparison between actual and predicted values:

Table 5. Comparison of Actual and Predicted Values (PSO)

Date	Actual Value	Predicted Value
December 21, 2023	22000	21751
December 22, 2023	22025	22047.12
December 27, 2023	22425	22302.44
December 28, 2023	22700	22817
December 29, 2023	22625	22449
January 2, 2024	23475	22513.71
January 3, 2024	23225	23501
January 4, 2024	23275	23044.36
⋮	⋮	⋮
December 23, 2024	25675	26136.05
December 24, 2024	25450	25104.76
December 27, 2024	25200	25563.99
December 30, 2024	25400	24849.92
December 21, 2023	26775	25262.3

3.5 Stock Price Prediction

Based on the forecasting model evaluation, the PSO-optimized data yielded better results compared to the FOA optimization. The parameters obtained from the PSO optimization will be used to predict the daily stock price of United Tractors using the best-performing model. The forecasting is conducted to estimate the daily stock prices of United Tractors for the next 15 periods. As a result, the parameters obtained from the PSO optimization will be used to predict the daily stock price of United Tractors using the best-performing model identified during the evaluation process. The forecasting is conducted to estimate the daily stock prices of United Tractors for the next 15 periods, providing valuable insights for short-term investment or trading decisions.

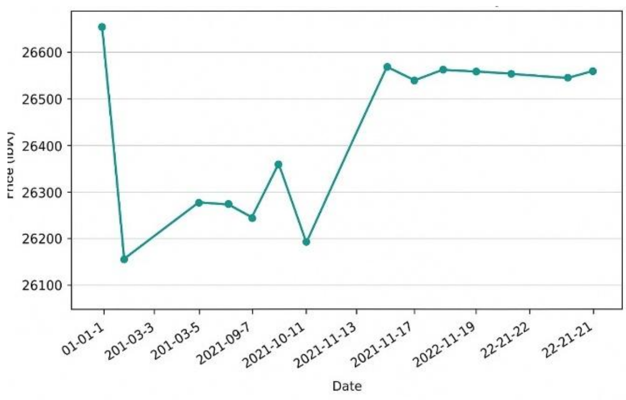

Figure 6. Stock Price Movement of United Tractors
(Source: Author's calculation using Jupyter Notebook)

Based on the forecasting results using the SVR-PSO method, the stock price movement of United Tractors (UNTR) in January 2025 shows an upward trend followed by stabilization from mid to late month. To clearly present the forecasted stock prices of United Tractors, the following table shows the projected stock prices for the next 15 days:

Table 6. United Tractors Stock Price Prediction

Date	United Tractors
2 January 2025	Rp. 26,642.59
3 January 2025	Rp. 26,049.37
6 January 2025	Rp. 26,214.76
7 January 2025	Rp. 26,220.28
8 January 2025	Rp. 26,193.46
9 January 2025	Rp. 26,339.03
10 January 2025	Rp. 26,145.24
13 January 2025	Rp. 26,557.78
14 January 2025	Rp. 26,523.89
15 January 2025	Rp. 26,549.01
16 January 2025	Rp. 26,545.71
17 January 2025	Rp. 26,551.47
20 January 2025	Rp. 26,540.51
21 January 2025	Rp. 26,557.53
22 January 2025	Rp. 26,524.64

The prediction results shown in Table 6 reinforce the initial observation that United Tractors' stock price is likely to experience slight volatility in the early days of January 2025, followed by a period of relative stability. The lowest predicted price occurs on January 3, 2025, at Rp. 26,049.37, indicating a short-term dip. However, starting from January 6, 2025, the price gradually stabilizes within a narrow range around Rp. 26,500, suggesting a consolidation phase. This pattern implies reduced market uncertainty and may reflect improved investor confidence or stable external economic conditions. These findings are consistent with previous studies suggesting that the SVR model, particularly when combined with optimization techniques like PSO, is effective for predicting financial time series with nonlinear and short-term patterns. The observed stability in mid to late January further supports the idea that SVR-PSO models perform well during periods of low volatility, making them a useful tool for investors seeking short-term predictions with minimized risk exposure.

4. CONCLUSION

Based on the analysis of stock price forecasting for United Tractors (UNTR) using Support Vector Regression (SVR) optimized by the Fruit Fly Optimization (FOA) and Particle Swarm Optimization (PSO) algorithms, several significant findings were obtained. The SVR-FOA model demonstrated a reasonably good accuracy level with a MAPE of 5.8727%. This model produced optimal parameters (C = 1000, gamma = 0.9182, epsilon = 0.9997) and was able to follow the general trend of stock price movements. The main advantage of FOA lies in its computational efficiency, marked by a rapid convergence at the 24th iteration, making it suitable for short-term forecasting. In contrast, the SVR model optimized using PSO showed superior predictive performance with a MAPE of 2.3163%. Besides producing more stable 15-day ahead price projections within the range of Rp. 25,262 to Rp. 26,556, this model also demonstrated high effectiveness in capturing nonlinear patterns in the time series data. The optimal parameters obtained (C = 1000, gamma = 0.0001, epsilon = 1) and convergence at the 16th iteration prove PSO's ability to deliver more precise prediction results. The forecasting accuracy difference of 3.5563% between PSO and FOA strengthens the evidence that PSO is numerically superior. Thus, PSO can be recommended as a more effective optimization method to improve the accuracy of stock price forecasting using SVR, especially in contexts requiring high-precision predictions. Although this study focuses on a single stock and uses closing price data as the primary variable, this may reduce its generalizability to other sectors or multi-factor models. Future studies may extend this approach to other sectors, incorporate macroeconomic variables or technical indicators, and explore alternative metaheuristic algorithms to further enhance generalizability and robustness.

Author Contributions

Belva Hadaya Wibowo: Conceptualization, Methodology, Formal Analysis, Writing-Original Draft, Software, Visualization, Validation. Iut Tri Utami: Formal Analysis, Visualization, Validation, Writing-Review and Editing. Masithoh Yessi Rochayani: Formal Analysis, Visualization, Validation, Writing-Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement, including grammar, spelling, and clarity. The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. All final text was reviewed and approved by the authors.

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