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Hybrid Interval Forecasting Model for Iraqi Stock Prices Based on Optimized v-Support Vector Regression

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Abstract:
Stock price forecasting poses significant challenges due to non-stationarity, nonlinearity, and noise in financial markets, particularly for the Iraqi stock exchange. This study proposes an enhanced interval-valued forecasting model for daily prices of the Al Mansour Pharmaceutical Industries (MPI) company (2020–2025) using v-support vector regression (VSVR) with hyperparameters optimized via the waterwheel plant algorithm (WWPOA). The WWPOA approach tunes key VSVR parameters through population-based exploration and exploitation phases inspired by WWPOA, outperforming grid search (GS-VSVR) and cross-validation (CV-VSVR). Forecasting performance is evaluated using four criteria, namely mean absolute error (MAE), root mean squared error (RMSE), direction accuracy (DA) and coefficient of determination R^2. The empirical results show that the proposed WWPOA-VSVR model achieves lower MAE and RMSE, along with higher DA and R^2, compared to GS-VSVR and CV-VSVR, indicating superior accuracy, robustness, and directional forecasting capability. On training data (637 days), WWPOA-VSVR achieves superior metrics for center and radius compared to baselines; testing results (308 days) confirm robustness. Further, Diebold-Mariano tests validate center-based WWPOA-VSVR superiority over radius-based at 95% confidence ($p - value < 0.05$). On the training set, the center-based WWPOA-VSVR achieves MAE of about 0.18, RMSE of about 0.28, DA around 0.63, and R^2 close to 0.93, while the radius-based model attains MAE near 0.19, RMSE around 0.29, DA about 0.61, and R^2 near 0.92. On the test set, center forecasts retain strong performance, with MAE around 0.20, RMSE about 0.30, DA near 0.60, and R^2 approximately 0.92, and radius forecasts achieve MAE close to 0.17, RMSE near 0.27, DA about 0.57, and R^2 around 0.88.

Keywords: Interval-valued time series; stock price forecasting; v-support vector regression; waterwheel plant algorithm; Hyperparameter tuning; Iraqi stock market.
Classification: 62J05, 65K05.

1 Introduction

Stock price forecasting has become a very important task in the field of finance that is expected to establish the future price or trend of stocks, to enable the investors and traders make a wise decision. It entails modeling the patterns and

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trends in the market by examining historical price data, market indicators and external factors [1–4]. The financial markets are characterized by a combination of the appropriate signals and random noise and it is hard to distinguish between the important and unimportant fluctuations [5, 6]. This noise will seriously affect the quality of forecasting as well as cause volatility on the prediction. The prices of stock tend to be non-stationary in that the statistical characteristics, such as the mean and the variance, of the price vary with time. In addition, the market forces are very non-linear because of the multifaceted interplay of economic, political and psychological forces and the non-linearity of these forces makes it very difficult to apply the traditional methods [6].

Stock price forecasting methods encompass a wide range of traditional statistical approaches as well as modern machine learning models. Statistical-based stock price forecasting has a long history and is not expected to disappear despite the emergence of machine learning and deep learning techniques. These conventional statistical methods mainly focus on time series models and rely on historical price patterns for prediction [7]. Statistical stock price forecasting focuses on the time series analysis, such as autoregressive integrated moving average (ARIMA), and volatility models, such as generalized autoregressive conditional heteroskedasticity (GARCH) [8]. These approaches are interpretable and effective when dealing with linear and stationary data. However, they become problematic when applied to complex nonlinear market dynamics. The advantages of statistical models are that they are easy to interpret, have a good theoretical basis and are effective when the data are linear and stationary [9].

Stock markets are, by definition, noisy and nonlinear. They are also impacted by a myriad of external factors. These characteristics restrain the predictability of purely statistical models, especially in long-term forecasting and during periods of market regime changes.[5]. Other assumptions made in the models include the stationarity which may be limiting in the real-world financial data.

Machine learning methods have significantly advanced stock price forecasting by addressing the limitations of traditional models. They provide better nonlinear pattern recognition and allow the integration of diverse data sources. As a result, these models have become fundamental tools for both practitioners and researchers seeking more accurate and adaptive stock price predictions [10, 11]. Machine learning algorithms like support vector regression (SVR) [12–15] and random forest (RF) algorithms are commonly used. Further, deep learning methods, especially recurrent neural networks (RNN) and long short-term memory (LSTM) networks, are highly popular for their ability to model sequential and temporal dependencies in stock price data [16–20]. Several researchers have investigated stock price forecasting using support vector regression and interval-valued approaches. For example, Wang et al. (2016) proposed an improved v-support vector regression model for stock price forecasting, while Xiong et al. (2014)employed multiple-output SVRcombined with metaheuristic optimization for interval-valued stock index prediction. Despite their promising performance, these methods still face significant challenges, including non-stationarity, strong nonlinearity, and high sensitivity to hyperparameter selection. In particular, conventional tuning methods often fail to identify globally optimal solutions, which limits forecasting accuracy in volatile markets. Motivated by these challenges, the present study introduces an optimized interval-valued VSVR framework based on the waterwheel plant optimization algorithm. Interval-valued data occur quite naturally in a number of situations where such data reflect uncertainty (as in confidence intervals), variability (minimum and maximum of daily temperature) etc. Interval-valued data have received various perspectives. The interval analysis field presupposes the observations and estimation of the real world being typically incomplete or imprecise and, therefore, do not reflect the actual data accurately. This field suggests that in the case of preciseness, data should be expressed in terms of intervals containing real quantities [21, 22].

Interval-valued stock price forecasting is an advanced method of predicting not only a single point estimate of what the stock prices will be in the future, but also a range or interval of what the stock prices will be within [40]. This approach is less biased as it captures the uncertainty and variability of stock price changes and gives a more complete information to make risk management and investment decision. The essence here is to model stock price data as intervals, or better described by lower and upper responses of price in a specified interval, and not as the values. This kind of interval data is a more realistic representation of the volatility and randomness inherent to markets in relation to point forecasts. This extra dimension assists investors and policymakers to know about possible price changes and the risks involved and it is especially helpful in a volatile or a very uncertain market [39].

v-support vector regression (VSVR) is a superior version of support vector regression (SVR) that aims at enhancing the trade-off between the complexity of the model and its predictive accuracy. It adds a parameter $v$that directly regulates the number of support vectors and the margin of the regression model and hence provide a more flexible control over the sparsity and generalization capacity of the model [25–27]. VSVR is particularly helpful in the stock price forecasting context since it has a solid theoretical basis and is capable of working with nonlinear and noisy financial data. It employs the idea of support vectors to guess the underlying functional relationship between input features and the target stock price. Through the use of kernel functions, VSVR has the ability to project input information into a feature space of upper dimension and segment the space by a linear regression analysis, effectively trying to pick up nonlinear trends that are internal to stock price fluctuations [29, 41].

Henrique, et al. [12] showed that support vector regression can outperform traditional statistical models on noisy, high-frequency stock data, yet their framework still relies on point forecasts and struggles with regime shifts and volatility clustering. Mahmoodi, et al. [13] and Kazem, et al. [30] combined SVR with metaheuristics such as genetic algorithms and chaos-based firefly optimization to improve hyperparameter selection, but they did not explicitly model interval-valued prices or quantify forecast uncertainty. For interval-valued financial series, Xiong, et al. [29], Wang, et al. [41], and Jiang Jiang, et al. [31] demonstrated that multiple-output SVR and deep interval networks can capture price ranges more realistically; however, they also reported persistent challenges related to non-stationarity, strong nonlinearity, and the high sensitivity of interval models to hyperparameter tuning in volatile markets.

The VSVR computational efficient is highly reliant on a number of hyperparameters and effects that either have direct or indirect effects upon the optimal solution. The main contribution of our study is to enhance interval-valued forecasting accuracy for Iraqi stock market prices by integrating VSVR with metaheuristic algorithms for hyperparameter optimization, addressing VSVR's sensitivity issues.

2 Interval-Valued Time Series Construction

Interval-valued time series (ITS) represent time-ordered sequences where each observation is not a single point but an interval $[L_t, U_t]$ with lower bound, L_t, and upper bound, U_t, where $L_t \leq U_t$. This approach captures uncertainty and variability within each time period like stock price ranges [31]. Instead of applying traditional preprocessing techniques such as differencing or log-transformation, the proposed framework addresses non-stationarity through interval-valued time series construction. Daily stock prices are represented by lower and upper bounds and subsequently decomposed into center and radius components. This representation inherently captures volatility, variability, and structural changes in Iraqi stock prices, thereby mitigating non-stationarity effects without enforcing strict stationarity assumptions. To ensure numerical stability during VSVR In stock price modeling, an interval-valued variable, z, is defined as $[z_t] = \left\{ \left[z_t^L, z_t^U \right]^T : z_t^L, z_t^U \in \mathbb{R}, z_t^L \leq z_t^U \right\}$, in which $z_t^L$and z_t^U are the lower and upper stock price at the time t, respectively.

The center (mid-point), z_t^C, and the radius (half- range), z_t^R, of an interval-valued variable, are, respectively, calculated as

$$z_t^C = \frac{z_t^L + z_t^U}{2} \tag{1}$$

$$z_t^R = \frac{z_t^U - z_t^L}{2} \tag{2}$$

The adequacy of this interval representation in describing market uncertainty was assessed through several analytical procedures. The statistical behavior of the center and radius series was examined in comparison with the original price dynamics, indicating that the center component effectively captures the underlying trend, while the radius reflects the volatility and intra-day variability. Furthermore, independent forecasting evaluations were performed for both components using MAE, RMSE, DA,and R^2, confirming the capability of the model to predict both price level and uncertainty. A Diebold–Mariano test was also conducted to compare center-based and radius-based forecasts, and the results revealed that the center-based representation provides statistically superior performance in modeling WSKB price dynamics. Consequently, the adopted construction relies solely on real market information without additional assumptions and offers a more comprehensive representation of uncertainty than conventional point-based approaches.

3 v-Support Vector Algorithm

SVM have been applied successfully in solving various classification problems. But, the SVM has been extended to deal with the nonlinear regression problems with the introduction of ε-insensitive loss function by Vapnik [32].

Given a training dataset of n observations $\{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$, where $\mathbf{x}_i = (x_{i,1}, x_{i,2}, ..., x_{i,p}) \in \mathrm{R}^p$ represents a vector of the i^{th} feature, $y_i \in R$ for $i = 1, ..., n$ is the target variable, which is a quantitative variable, and ε-insensitive loss function, the SVR can be obtained through solving the following optimization problem

$$\begin{aligned} &\min_{\mathbf{w},b} \left\{ \tfrac{1}{2}\mathbf{w}^T\mathbf{w} + C\textstyle\sum_{i=1}^{n}\left(\zeta_i + \tilde{\zeta}_i\right)\right\} \\ &\text{S.T.} \quad \begin{cases} y_i - (\mathbf{w} \bullet \varphi(\mathbf{x}_i) + b) \le \varepsilon + \tilde{\zeta}_i \\ (\mathbf{w} \bullet \varphi(\mathbf{x}_i) + b) - y_i \le \varepsilon + \zeta_i \\ \zeta_i, \tilde{\zeta}_i \ge 0, \end{cases} \end{aligned} \tag{3}$$

where $C > 0$ is a penalized parameter that controls the tradeoff between the model complexity and training error, ζ_i and $\tilde{\zeta}_i$ are slack variables, $\varphi(\mathbf{x}_i)$ is a nonlinear mapping which is induced by a kernel function, $\mathbf{w}$ is the weight vector and $b$is bias.

Then, Eq.(3) can be solved by the Lagrangian multipliers after reformulated it into its dual problem as

$$\begin{aligned} &\min_{\tilde{\alpha},\alpha} \tfrac{1}{2} \textstyle\sum_{i,j=1}^{n}(\tilde{\alpha}_i - \alpha_i)(\tilde{\alpha}_j - \alpha_j)K(\mathbf{x}_i, \mathbf{x}_j) + \varepsilon \textstyle\sum_{i=1}^{n}(\tilde{\alpha}_i - \alpha_i) - \textstyle\sum_{i=1}^{n} y_i(\tilde{\alpha}_i - \alpha_i) \\ &\text{S.T.} \quad \begin{cases} \sum_{i=1}^{n}(\alpha_i - \tilde{\alpha}_i) = 0 \\ 0 \le \alpha_i, \tilde{\alpha}_i \le C, \end{cases} \end{aligned} \tag{4}$$

where $K(\mathbf{x}_i, \mathbf{x}_j)$stands for kernel mapping, and α_i, $\tilde{\alpha}_i$are Lagrangian multipliers. The regression hyperplane for the underlying regression problem is then given by

$$y_i = f(\mathbf{x}_i) = \sum_{\mathbf{x}_i = \mathrm{SV}} (\tilde{\alpha}_i + \alpha_i)\, K(\mathbf{x}_i, \mathbf{x}_j) + b\,, \tag{5}$$

where SV is the support vectors set.

The original problem in v-SVR leads to convex quadratic programming with inequality constraints as [21, 33–35, 37, 38, 41]

$$\min_{\mathbf{w},b}\left\{\tfrac{1}{2}\mathbf{w}^T\mathbf{w}+C\left[v\varepsilon+\tfrac{1}{n}\sum_{i=1}^{n}\left(\zeta_i+\tilde{\zeta}_i\right)\right]\right\}$$
$$\text{S.T.}\quad\begin{cases} y_i-(\mathbf{w}\bullet\varphi(\mathbf{x}_i)\,+b)\le\varepsilon+\tilde{\zeta}_i\\ (\mathbf{w}\bullet\varphi(\mathbf{x}_i)\,+b)-y_i\le\varepsilon+\zeta_i\\ \zeta_i,\tilde{\zeta}_i\ge 0,\ \varepsilon\ge 0,\end{cases}\tag{6}$$

Equation (4) can be solved by the Lagrangian multipliers after reformulated it into its dual problem as follows:

$$L(\mathbf{w},b,\varepsilon,\zeta,\tilde{\zeta})=\tfrac{1}{2}\mathbf{w}^T\mathbf{w}+C\left(\nu\varepsilon+\tfrac{1}{n}\sum_{i=1}^{n}(\zeta_i+\tilde{\zeta}_i)\right)-\sum_{i=1}^{n}\theta_i\zeta_i-\sum_{i=1}^{n}\tilde{\theta}_i\tilde{\zeta}_i-\gamma\varepsilon$$
$$+\sum_{i=1}^{n}\alpha_i(\mathbf{w}^T\varphi(\mathbf{x}_i)+b-y_i-\varepsilon-\zeta_i)+\sum_{i=1}^{n}\tilde{\alpha}_i(\mathbf{w}^T\varphi(\mathbf{x}_i)+b-y_i-\varepsilon-\tilde{\zeta}_i),\tag{7}$$

where α_i, $\tilde{\alpha}_i$, θ_i, $\tilde{\theta}_i,\gamma\ge 0$ are Lagrange multipliers. The solution of Eq. 7 can be achieved by partially differentiating with respect to ζ_i, $\mathbf{w}$, b, ε,and $\tilde{\zeta}_i$ as

$$\begin{cases}\frac{\partial L}{\partial\mathbf{w}}=\mathbf{w}+\sum_{i=1}^{n}\alpha_i x_i-\sum_{i=1}^{n}\tilde{\alpha}_i x_i=0\\ \frac{\partial L}{\partial b}=\sum_{i=1}^{n}\alpha_i-\sum_{i=1}^{n}\tilde{\alpha}_i=0\\ \frac{\partial L}{\partial\varepsilon}=\frac{C}{n}\sum_{i=1}^{n}\nu-\gamma-\sum_{i=1}^{n}(\alpha_i+\tilde{\alpha}_i)=0\\ \frac{\partial L}{\partial\zeta}=\sum_{i=1}^{n}\frac{C}{n}-\sum_{i=1}^{n}\alpha_i-\sum_{i=1}^{n}\theta_i=0\\ \frac{\partial L}{\partial\tilde{\zeta}}=\sum_{i=1}^{n}\frac{C}{n}-\sum_{i=1}^{n}\tilde{\alpha}_i-\sum_{i=1}^{n}\tilde{\theta}_i=0\end{cases}\Rightarrow\begin{cases}\mathbf{w}=\sum_{i=1}^{n}(\tilde{\alpha}_i-\alpha_i)x_i\\ \sum_{i=1}^{n}(\tilde{\alpha}_i-\alpha_i)=0\\ \sum_{i=1}^{n}(\tilde{\alpha}_i-\alpha_i)=C\nu-\gamma\le C\nu\\ \alpha_i=\frac{C}{n}-\theta_i\le\frac{C}{n}\\ \tilde{\alpha}_i=\frac{C}{n}-\tilde{\theta}_i\le\frac{C}{n}\end{cases}\tag{8}$$

Substituting Eq. (6) into Eq. (5), the Lagrange function can be rewritten as follows:

$$L=-\frac{1}{2}\sum_{i,j=1}^{n}(\tilde{\alpha}_i-\alpha_i)(\tilde{\alpha}_j-\alpha_j)K(\mathbf{x}_i,\mathbf{x}_j)+\sum_{i=1}^{n}(\tilde{\alpha}_i-\alpha_i)\,y_i,\tag{9}$$

Based on the Karush–Kuhn–Tucker (KKT) conditions, the optimization problem in Eq. (9) can be solved by working with its dual form [25, 26]. After obtaining the optimal solution from the dual problem, the final decision function of the v-SVR model can be written as:

$$y_i=f(\mathbf{x}_i)=\sum_{i=1}^{n}(\tilde{\alpha}_i+\alpha_i)\,K(\mathbf{x}_i,\mathbf{x}_j)+b\,.\tag{10}$$

4 The Proposed Improving

4.1 Exploitation Mechanism of WWPOA

The Waterwheel Plant Optimization Algorithm (WWPOA) adopts a population-based search strategy with explicitly separated exploration and exploitation phases, which distinguishes it from conventional metaheuristics such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). In PSO, solution updates are governed by velocity terms toward personal and global best positions, whereas GA relies on selection, crossover, and mutation operators. In contrast, WWPOAperforms exploration through wide-range stochastic position updates that enhance global search capability and reduce the risk of premature convergence. Exploitation is achieved by directing candidate solutions toward the best-so-far position using localized adaptive movements, with an additional mutation mechanism to escape stagnation. This structured exploration–exploitation balance makes WWPOAparticularly suitable for $v - Support$ vector regression (VSVR)hyperparameter tuning, as the VSVR parameter space is highly nonlinear and sensitive to small variations. ConsequentlyWWPOAenables efficient identification of near-optimal hyperparameter configurations, leading to improved prediction accuracy and generalization performance. In SVR, several important settings, known as hyperparameters, must be chosen before the model can work properly. These include the penalty parameter, the ε-insensitive loss, and the kernel parameter are selected. However, there is no exact mathematical method to determine the optimal values of these hyperparameters.[39]. Because of this, choosing suitable hyperparameters is a major part of SVR research [39–44]. Many studies have tried different ways to improve SVR performance by selecting better hyperparameters, and several nature-inspired optimization algorithms have been used for this purpose [30, 38, 42, 45–51, 53]. However, most of these methods focus only on tuning hyperparameters and do not perform feature selection at the same time.

The methods which are applicable to calculating the value of the hyper parameters include randomized search (RS), Bayesian optimization (BO), cross-validation (CV) and grid search (GS). These methods evaluate different combinations of hyperparameters and select the one that yields the best performance according to a predefined criterion. However, these methods are computationally expensive. Moreover, they often fail to exhaustively explore all possible hyperparameter combinations [54].

Therefore, more efficient and superior means of hyperparameters optimization of v-SVR should be obtained. In the past several years, there has been a wide application of metaheuristic optimization algorithms to the problem of hyperparameter tuning [55].

Over the last few years, scientists proposed a variety of new nature-based algorithms to enhance and develop the scope of exploration and utilization of the existing algorithms. One of the most popular algorithms of its new algorithms is a waterwheel plant algorithm (WWPOA) because it is very high-performin.

The current section outlines the mechanisms needed in the establishment of a WWPOA and then further demonstrates mechanisms in updating the geographic coordinates of the waterwheel during exploration and exploitation by use of a measurable model of the actual migratory behavior of the waterwheel [56]. Unlike conventional metaheuristic algorithms such as Particle Swarm Optimization(PSO) and Genetic Algorithms (GA)the Waterwheel Plant Optimization Algorithm (WWPOA) employs an explicit and adaptive separation between exploration and exploitation phases. Its population update mechanism allows wide stochastic movements during early iterations to explore the search space effectively, followed by controlled local search around the best solutions to ensure stable convergence. This design reduces premature convergence and enhances robustness against local optima. WWPOA is particularly well suited for tuning VSVRhyperparameters due to the nonlinear, multimodal, and noise-sensitive nature of the optimization landscape in interval-valued stock price forecasting, enabling superior generalization performance compared with grid search and cross-validation approaches.

Each waterwheel will represent specific values of the problem variables at any given stage, hence offering discrete representation of a candidate solution, which in mathematical terms can be viewed as a vector. It also implies that the total set of waterwheels, that is the WWPOA population, is best illustrated as a Eq. (11). When the algorithm is started, the initial state of each of the waterwheels in the population is set randomly through a random-sampling operation defined in Eq. (12).

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix} = \begin{bmatrix} P_{1,1} & \cdots & P_{1,j} & \cdots & P_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ P_{i,1} & \cdots & P_{i,j} & \cdots & P_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ P_{N,1} & \cdots & P_{N,j} & \cdots & P_{N,m} \end{bmatrix} \tag{11}$$

$$p_{i,j} = Lb_j + r_{i,j} \times (Ub_j - Lb_j)\,,\ i = 1, 2, ..., N,\ j = 1, 2, ..., m \tag{12}$$

Now suppose that the total number of waterwheels is $N$and $m$the number of variables. When $r_{i,j}$is a random number within [0, 1] and Lb_j, $Ub_j$are the lower and upper limits of the $j-th$variable,P determines the population matrix of locations of waterwheels. $P_i$is the $i-th$waterwheel (a candidate solution), and $P_{i,j}$ is the $j-th$variable.

The objective functions of each of the waterwheels are uniquely identifiable because each waterwheel or decision maker implements a particular optimization strategy. The elements of the vectorial components forming this objective function are best summarized in Eq. (13) [57].

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix} \tag{13}$$

In the optimization literature, $F$is a vector filled with all the objective function values, and $F_i$is the expectation of the $i-th$waterwheel. Within the context of this framework, the objective functions are the main criteria in order to choose the best solution so that the maximum value of F is the best member (i.e., the best candidate solution) and the minimum value of F is the worst member (the worst candidate solution). The optimum at any point in the search space will be temporary since the waterwheels will move randomly at each iteration.

The waterwheel species are highly sensitive to smell, which helps to identify the source of pests very accurately. Under the consideration of the WWPOA model, this olfactory-mediated predation is modeled by simulating the initial phase of population update process. WWPOA improves its exploratory ability of searching the best areas and avoiding the local maximum by integrating a representation of the prey-oriented behavior of waterwheels. As a result, the closeness of the waterwheel to the pest is clearly modelled and this leads to significant changes in the position of the waterwheel in the search space. A new candidate position is then obtained using the following formula along with the simulation of the water wheel approach to the insect. In the event that the value of the objective function increases when the waterwheel is moved to this location, then the previous location is substituted by the new location that has been calculated.

$$\vec{W} = \vec{r}_1 \times \left(\vec{P}(t) + 2K\right) \tag{14}$$

$$\vec{P}(t+1) = \vec{P}(t) + \vec{W} \times (2K + \vec{r}_2) \tag{15}$$

Should the iterative optimization not continue to improve the waterwheel position after three consecutive iterations, instead the following equation is used to adjust the position of the waterwheel:

$$\vec{P}(t+1) = Gaussian(\mu P, \sigma) + \vec{r}_1 (\frac{\vec{P}(t) + 2K}{\vec{W}}) \tag{16}$$

Suppose $\vec{r}_1$and $\vec{r}_2$are independent random variables which are restricted to the intervals [0, 2] and [0, 1] respectively. Moreover, consider a random variable Kthat is distributed as an exponential distribution with the parameter lambda on the range [0, 1] and a three-dimensional vector $\vec{W}$that represents the radius of the circular area in which the waterwheel plant will be searching its favorable environments.

An insect is placed into a waterwheel and then moved into a feeding tube. Such waterwheel activity simulation is used to support the second stage population update of the WWPOA algorithm. Transporting the insect to a tube matching a minor change in the position of the waterwheel in the search space, WWPOA increases its exploitation capability in the local search, and solutions converge faster to those already found. When designing the WWPOA, the developers simulate this by simply picking a new location randomly with each waterwheel in the population and labeling this a great place to eat insects. The relevant equations reveal that a waterwheel is moved to this new location only in case the value of the target function at the suggested location is higher than the one at the original location.

$$\vec{W} = \vec{r}_3 \times \left(K\vec{P}_{best}(t) + r_3\vec{P}(t)\right) \tag{17}$$

$$\vec{P}(t+1) = \vec{P}(t) + K\vec{W} \tag{18}$$

Let $\vec{r}_3$be a random variable with values falling under the interval [0, 2]. The best solution seen so far can be represented by $\vec{P}_{best}$whereas at iteration$t$, the current solution can be represented by $\vec{P}(t)$. As in the exploration phase, when the solution fails to improve after three iterations, then a mutation is applied to make sure that the algorithm does not fall into local minima.

$$P(t+1) = (r1 + K)\sin\left(\frac{F}{C}\theta\right) \tag{19}$$

When $F$and $C$are random variables with the interval of [-5, 5] and when Kdiminishes exponentially in accordance with the formula:

$$K = \left(1 + \frac{2 \times t^2}{T_{\max}} + F\right) \tag{20}$$

In order to optimize the hyperparameters of VSVR with the improvement proposition of WWPOA, the position vector X of every member is established as a dimension D vector that signifies the position of the coati on the WWPOA. As a result, the vectors X would be associated with a particular configuration of the RF, and the hyperparameters of the VSVR are represented by the dimensions of X. Thus, three locations that each coati in the swarm will be searching will be located. Consequently, our proposed improving is as:

Step 1: The number of waterwheels, $N_{waterwheel}$, is set to 30 and the maximum number of iterations is T= 500.

Step 2: The positions of each waterwheel are randomly specified. The three positions represent the hypermeters are randomly generated from uniform distribution as $C \sim U(0,6)$, $\sigma \sim U(0,8)$, and $v \sim U(0,1)$.

In the proposed $WWPOA - VSVR$ framework, the Waterwheel Plant Optimization Algorithm (WWPOA) was employed to optimize the key hyperparameters of the v-Support Vector Regression ($VSVR$) model. Specifically, the regularization parameter C , the kernel width parameter σ (corresponding to the RBF kernel), and the v-parameter ν which controls the proportion of support vectors and the size of the insensitive zone, were tuned. The search ranges of the hyperparameters were defined as $C \in (0,6)$, $\sigma \in (0,8)$, and $v \in (0,1)$ .Based on minimizing the prediction error as the fitness function, WWPOA identified the optimal combination of these parameters that yielded the best-performing model. The final optimized values of the hyperparameters are reported in the experimental results section.

Step 3: The fitness function is defined as

$$\text{fitness} = \min\,(\text{prediction error}). \tag{21}$$

Step 4: The positions of the waterwheel are updated using Eq. (16).

Step 5: Steps 3 and 4 are repeated until a T is reached.

5 Prediction Evaluation Criteria

To measure the forecasting performance of the proposed approach, four evaluation criteria, namely, mean absolute error (MAE), root mean squared error (RMSE), direction accuracy (DA), and coefficient of determination (R^2), are selected in this study to verify the prediction accuracy of the proposed model [58, 59]. Their mathematical expressions are listed in Table 1.

Table 1: Prediction evaluation criteria

Evaluation criterion	Mathematical formula		Decision
MAE	$\frac{1}{n}\sum_{t=1}^{n}\lvert z_t - \hat{z}_t\rvert$		Lower value is better
RMSE	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(z_t - \hat{z}_t)^2}$		Lower value is better
DA	$\frac{1}{n}\sum_{t=1}^{n} q_t, \quad q_t$ $\begin{cases} 1, & \text{if } (z_{t+1} - z_t)(\hat{z}_{t+1} - \hat{z}_t) \geq 0 \\ 0, & \text{otherwise} \end{cases}$	=	Higher value is better
R^2	$1 - \frac{\sum_{t=1}^{n}(z_t - \hat{z}_t)^2}{\sum_{t=1}^{n}(z_t - \bar{z})^2}$		Larger value near to 1 is better

6 Experimental Setting

6.1 Data Description

In this study, the daily Iraqi stock prices of the Al Mansour Pharmaceutical Industries (MPI) company from January 15, 2020, to October 14, 2025, were utilized as sample data for the experiment (https://www.investing.com), as depicted in Figure 1. The training data set was composed of 637 daily prices from January 15, 2020, to December 31, 2023 and the remaining 308 daily prices from January 3, 2024, to October 14, 2025was reserved for the test set. In Figure 1, both the lower and the upper daily stock prices are depicted.

6.2 Optimized VSVR Hyperparameters Using WWPOA

In the proposed WWPOA – VSVRframework, the Waterwheel Plant Optimization Algorithm (WWPOA)was employed to tune the key hyperparameters of the v – SupportVector Regression (VSVR)model. Specifically, the penalty parameter (C), the RBF kernel parameter (σ, equivalently γ)and the ν (nu) parameter were optimized. The $\varepsilon-$insensitive loss parameter (ε)was kept fixed and

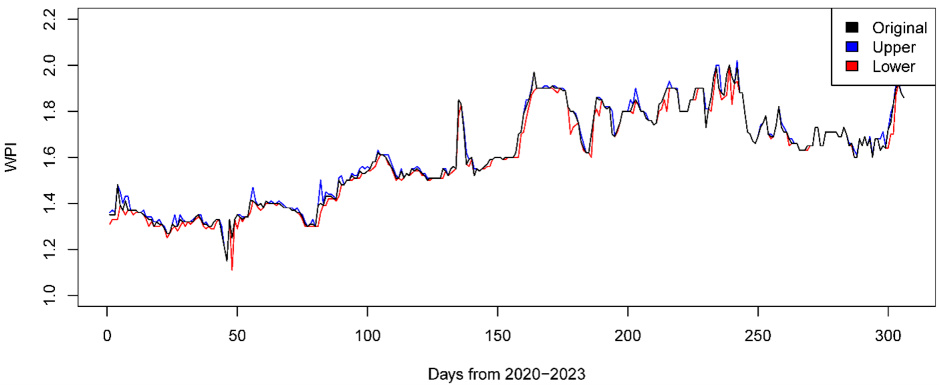

Figure 1: The daily stock price for the training data set of the MPI

was not included in the optimization process. The search ranges were defined as C $\in$ [0, 6], σ $\in$ [0, 8], and υ $\in$ [0, 1], as specified in Section 4 (Step 2).The optimized hyperparameter configuration obtained by WWPOA was used for all reported training and testing experiments.

6.3 Experimental Results

The performance of our proposed algorithm, the WWPOA-VSVR, in relation to the forecasting is examined by conducting comprehensive comparison tests based on the grid search strategy (GS-VSVR), and the cross-validation approach with ten folds (CV-VSVR). We consider the forecasts as one of the various approaches of the interval valued stock price as per the Eq.(1) and Eq. (2). Table 2 to Table 5 contain the forecasting performances of the GS-VSVR, CV-VSVR and WWPOA-VSVR model in terms of evaluation criteria. For the testing dataset comprising 308 observations, the forecasting performance of the proposed WWPOA-VSVR model was quantitatively evaluated and compared against GS-VSVR and CV-VSVR using four standard metrics: MAE, RMSE, DA, and R^2, as reported in Tables 2-5. For the center-based interval forecasts, WWPOA-VSVR achieving an MAE of 0.203, RMSE of 0.304, DA of 0.601, and R^2 of 0.915. outperforming CV-VSVR and GS-VSVR Which exhibit notably larger errors and lower DA and R^2 values on the same testing set. Similarly, for the radius-based interval forecasts, WWPOA-VSVR also provides superior performance, recording lower MAE and RMSE together with higher DA and, R^2 Compared to both CV-VSVR and GS-VSVR. These results demonstrate the clear advantage of the proposed WWPOA-VSVR model over the benchmark methods on unseen data and facilitate a direct and fair comparison across all models. It should be emphasized that the objective of this comparative analysis is to assess interval-valued forecasting performance within a unified modeling framework. Accordingly, the proposed WWPOA-VSVR is evaluated exclusively against GS-VSVR and CV-VSVR, which adopt the same interval-based structure and differ only in their hyperparameter optimization strategies. Conventional point-forecasting models, such as LSTM, as well as alternative interval forecasting approaches, including quantile regression, are not considered in this study due to their fundamentally different modeling assumptions and evaluation paradigms. A comprehensive comparison with such models is therefore left for future research. In contrast, the competing methods yielded significantly inferior results. For instance, CV-VSVR recorded an MAE=3.146 , RMSE=3.562, DA=0.388, and R^2= 0.584. while CV-VSVR presented the weakest performance with an $\text{MAE} = 3.379$, $\text{RMSE} = 3.525$, $\text{DA} = 0.304$, and $R^2 = 0.550$ Even for radius-based forecasts, the proposed $\text{WWPOA} - \text{VSVR}$consistently outperformed these methods, highlighting its robustness and accuracy. Although the training R^2 values are high(> 0.95) , their sensitivity to the relatively short training period of 637 days was carefully examined. the dataset was divided chronologically into a training set 637 days and an independent hold-out testing set 308 days ensuring that no future information leaked into training process. The high consistency between training and testing performance (above 0.90 for the center-based model and above 0.88 for the radius-based model) indicates that the model does not suffer from severe overfitting. Moreover, the inherent regularization mechanism of v-SVR with jointly optimized parameters$C$, the υ, and the kernel parameters using the WWPAO algorithm. This optimization balances model complexity and empirical risk, preventing overly complex solutions that fit noise rather than signal. Furthermore, comparative results with GS-VSVR and CV-VSVR further demonstrate that the proposed WWPOA-VSVR generalizes better, particularly on unseen data, indicating that the high training R^2 is not merely an artifact of the limited sample size In terms of relative improvement, WWPOA-VSVR showed substantial reductions in forecasting errors compared to GS-VSVR and CV-VSVR. Based on Table 2, the reduction in terms of WWPOA-VSVR compared to GS-VSVR, CV-VSVR is 13.89%, 93.87% and 15.18%, and 90.18%, respectively. The same applies to the testing data (Table 3) as the respective criteria reduced by 8.91% and 94.89%, 23.25% and 92.88%, compared GS-VSVR These results indicate that meta-heuristic algorithms such as WWPOA are highly effective for prediction, even without additional data preprocessing, whereas classical methods like GS-VSVR and CV-VSVR may suffer due to arbitrary hyperparameter selection. Finally, regarding hyperparameter estimation CV-VSVR and GS-VSVR comparing highlights the importance of systematic optimization. The WWPOA algorithm ensures that the most appropriate parameters are selected, further contributing to the superior performance of WWPOA-VSVR.

Tables 4 and 5 extend the center-based analysis to radius-based interval-valued time. WWPOA-VSVR delivers the best training performance across all metrics. It has the lowest prediction errors MAE and RMSE, indicating more accurate radius forecasts. Further, WWPOA-VSVR has highest DA 0.605 and means it is better at capturing ups and downs in the radius component. Additionally, it has the

Table 2: The prediction results of the used methods for the training set based on center interval-valued method

	CV-VSVR	GS-VSVR	WWPOA-VSVR
MAE	0.205	2.389	0.182
RMSE	0.32	2.445	0.277
DA	0.571	0.355	0.628
R^2	0.799	0.595	0.928

highest R^2 of 0.922 shows it explains about 92.2% of the variance in the radius data. Moreover, CV-VSVR is competitive but clearly inferior to WWPOA-VSVR, indicates cross-validation tuning is effective but does not reach the global optimum like WWPOA.

In Figures 2 and 3, it can be seen that the forecast of the model WWPOA-VSVR outcome is basically the same as the actual price of WPI stock price per day and this is showing that the quality of the model is of high nature when it comes to forecasting the prices. Moreover, the prediction ability of WWPOA-VSVR is highly enhanced by training and testing costs. This is mixed with comparatively smooth time series of the WWPOA-VSVR. Consequently, the WWPOA-VSVR model forecasts daily WPI stock price e with high quality. Furthermore, the WPI stock price prediction based on CV-VSVR are a bit accurate than the WWPOA-VSVR. Conversely, the WPI stock price forecast of GS-VSVR is ineffective in their forecasts in the long run.

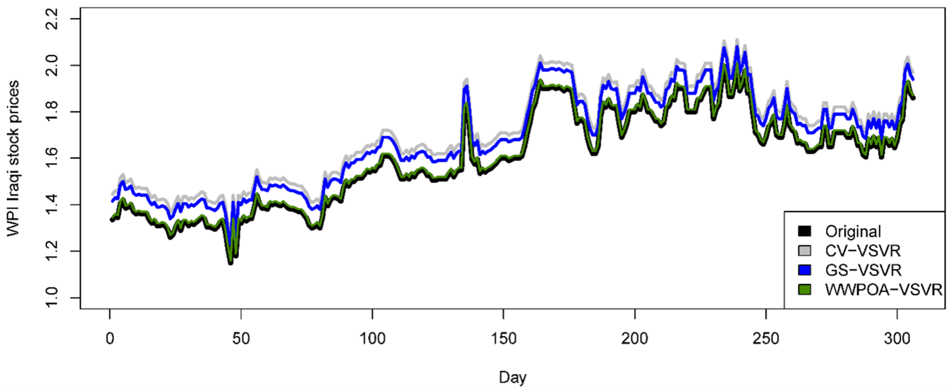

Figure 2: Prediction results in training dataset based on center interval-valued method

Among the center and the radius interval-valued methods, the center interval-valued method was the best option for predicting WPI Iraqi stock prices, achieving the lowest MAE and RMSE for both training and testing dataset with a highest DA and R^2. To further highlight the forecast performance of the center and the radius interval-valued methods, the Diebold Mariano (DM) test [60] as a statistical test is

Table 3: The prediction results of the used methods for the testing set based on center interval-valued method

	CV-VSVR	GS-VSVR	WWPOA-VSVR
MAE	0.22	3.416	0.203
RMSE	0.382	3.562	0.304
DA	0.557	0.338	0.601
R^2	0.768	0.584	0.915

Table 4: The prediction results of the used methods for the training set based on radius interval-valued method

	CV-VSVR	GS-VSVR	WWPOA-VSVR
MAE	0.216	2.404	0.193
RMSE	0.331	2.456	0.288
DA	0.548	0.332	0.605
R^2	0.901	0.571	0.922

Table 5: The prediction results of the used methods for the testing set based on radius interval-valued method

	CV-VSVR	GS-VSVR	WWPOA-VSVR
MAE	0.188	3.379	0.169
RMSE	0.348	3.525	0.266
DA	0.526	0.304	0.567
R^2	0.734	0.55	0.881

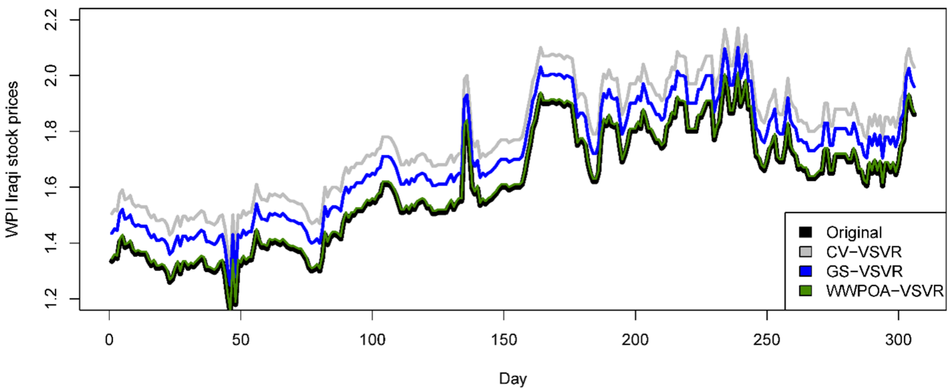

Figure 3: Prediction results in training dataset based on radius interval-valued method

performed to check their performances. The outcomes of the DM test for the training and testing datasets' forecasted future WPI Iraqi stock prices are shown in Table 6. The WWPOA-VSVR using center interval-valued is superior to the forecasted values provided by the WWPOA-VSVR using radius interval-valued at least at a 95% confidence level for WPI Iraqi stock prices prediction, according to the DM test, which indicates that when the WWPOA-VSVR using center interval-valued is treated as the target approach, the p-values are less than the significance level of 5%. At least a 95% confidence level.

Table 6: DM test results of for the WWPOA-VSVR

	center interval-valued	WWPOA-VSVR (train)	WWPOA-VSVR (test)
radius interval-valued	WWPOA-VSVR (train)	3.025 $(p-value = 0.0311)$	
	WWPOA-VSVR (test)		3.187 $(p-value = 0.0358)$

7 Conclusion

The proposed interval-valued forecasting framework using VSVR with WWPOA-based hyperparameter optimization provides a highly effective tool for modeling noisy, nonlinear dynamics in the Iraqi stock market. By constructing center and radius interval series from daily WPI prices and jointly optimizing key VSVR hyperparameters, the model achieves markedly lower errors and higher explanatory power than conventional GS and CV strategies in both training and testing stages. The empirical results demonstrate that the WWPOA–VSVR configuration consistently yields the smallest MAE and RMSE and the highest DA and R^2 for both center- and radius-based forecasts, confirming its strong generalization ability. Moreover, Diebold–Mariano tests indicate that center-based interval modeling is statistically superior to radius-based modeling at the 5% significance level, underscoring the practicality of center intervals for capturing price dynamics in this context. These findings highlight the promise of nature-inspired metaheuristics for hyperparameter tuning in advanced regression models and suggest that WWPOA-VSVR can serve as a robust decision-support tool for risk-aware investors and policymakers in emerging markets. Future research may extend this work by incorporating additional financial and macroeconomic predictors, testing other interval construction schemes, and comparing WWPOA–VSVR with recent deep learning–based interval forecasting approaches on broader market datasets.

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