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Hybrid GA–SVR and BAT–SVR Models for Short-Term Silver Price Forecasting with Uncertainty Quantification

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Abstract: Accurate forecasting of silver prices is essential for investors, policymakers, and industrial stakeholders due to the metal's dual role as both an investment asset and an industrial input. Silver price dynamics are characterized by strong nonlinearity, volatility, and regime changes, which limit the effectiveness of traditional linear time-series models. This study proposes a hybrid machine-learning framework for short-term silver price forecasting based on Support Vector Regression (SVR) and two metaheuristic optimization techniques: Genetic Algorithm (GA) and Bat Algorithm (BAT). Daily silver prices (XAG/USD) from 1 February 2025 to 1 February 2026 are used, and a lag-based supervised learning structure is adopted. Model performance is evaluated using a realistic one-month backtesting design and multiple criteria, including mean squared error (MSE), root mean squared error (RMSE), Akaike information criterion (AIC), and Bayesian information criterion (BIC). Empirical results demonstrate that both optimized models significantly outperform the baseline SVR, with GA-SVR achieving the highest predictive accuracy and the best balance between goodness-of-fit and model complexity. Forecast uncertainty is assessed through bootstrap-based 95% confidence intervals, while residual diagnostics using the Augmented Dickey–Fuller test confirm the adequacy of the selected model. The findings highlight the effectiveness of hybrid SVR–metaheuristic approaches for modeling nonlinear silver price dynamics and provide a reliable, uncertainty-aware forecasting framework for short-term decision-making.

Keywords: Silver price forecasting; Support Vector Regression; Genetic Algorithm; Bat Algorithm; Forecast uncertainty.

نماذج هجينة قائمة على GA-SVR و BAT-SVR للتنبؤ قصير الأجل بأسعار الفضة مع قياس عدم اليقين

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المستخلص: يُعد التنبؤ الدقيق بأسعار الفضة أمرًا بالغ الأهمية للمستثمرين وصنّاع القرار والقطاعات الصناعية، نظرًا للدور المزدوج الذي تؤديه الفضة كأصل استثماري ومدخل صناعي. وتتسم أسعار الفضة بدرجة عالية من اللاخطية والتقلب والتغيرات الهيكلية، مما يحد من كفاءة النماذج الخطية التقليدية في التنبؤ قصير الأجل. تهدف هذه الدراسة إلى تطوير إطار تنبؤي هجين يعتمد على الانحدار باستخدام متجهات الدعم (SVR) مع خوارزميتين تحسينيتين مستوحيتين من الطبيعة، هما الخوارزمية الجينية (GA) وخوارزمية الخفاش (BAT)، لتحسين اختيار المعلمات وتعزيز الدقة التنبؤية. تم استخدام البيانات اليومية لأسعار الفضة (XAG/USD) للفترة من ١ فبراير ٢٠٢٥ إلى ١ فبراير ٢٠٢٦، مع بناء نموذج إشرافي قائم على الإبطاءات الزمنية. جرى تقييم الأداء باستخدام تصميم اختبار خلفي واقعي لمدة شهر واحد، وبالاعتماد على مقاييس متعددة تشمل متوسط مربع الخطأ (MSE)، والجذر التربيعي لمتوسط مربع الخطأ (RMSE)، ومعياري أكايك وبايزي للمعلومات (AIC وBIC). أظهرت النتائج تفوقًا واضحًا للنماذج المُحسّنة مقارنةً بـSVR التقليدي، حيث حقق نموذج GA-SVR أعلى دقة وأفضل توازن بين جودة الملاءمة وتعقيد النموذج. كما تم تقدير عدم اليقين باستخدام فواصل ثقة ٩٥٪ بأسلوب الإقلاع (Bootstrap)، وأكد اختبار ديكي–فولر المعزز استقرارية المتبقيات. تؤكد النتائج فاعلية النماذج الهجينة في التنبؤ قصير الأجل بأسعار الفضة في بيئات سوقية متقلبة.

الكلمات المفتاحية: التنبؤ بأسعار الفضة؛ الانحدار باستخدام متجهات الدعم؛ الخوارزمية الجينية؛ خوارزمية الخفاش؛ عدم اليقين التنبؤي.

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Introduction

Silver as an investment Silver, like other precious metals, may be used as an investment. Its price is influenced by a complex interplay of macro drivers - inflation expectations, credit risk spreads, currency translation effects, industrial demand, pure speculation and geopolitical noise. The price of silver has a large and highly nonlinear effect clustering-volatility, regime-dependence on More forcast based on linear time series models face serious problems. There is an importance in predicting silver prices to the investors, policy makers and industrialists. More recently, the complexity of global commodity markets has amplified the need for accurate and robust predictive models capable of capturing non-linear regime switching dynamics in volatile market environments. Economists have adopted classic econometric models such as the ARIMA (AutoRegressive Integrated Moving Average) and the GARCH (Generalized Autoregressive Conditional Heteroskedasticity), which they consider to be fundamentally proper, although they could possibly overlook these nonlinear/nonstationary patterns that are presented in most precious metal price series (Tsay 2010). To cope with these limitations, machine learning techniques have been widely used in predicting commodity prices. Among them, Support Vector Regression (SVR)—with a strong theoretical foundation in statistical learning theory and the property of balancing between model complexity and generalization—is especially attractive. The machine learning algorithm for example SVR model has been successfully applied to different financial prediction problems including commodity price, exchange rate and stock index predication (Hsu, Hsieh & Chen, 2016). By its kernel-based strategy, it is flexible for modeling complex non-linear relationships and without parametric assumption of the form of these relationships.

Nevertheless, SQ model has the disadvantages as follows: like traditional SVR [28], it is also sensitive to the choices of hyper-parameters which contain ρ :the regularization parameter: σ: the kernel width and tolerance of loss function. Choosing wrong parameter might run risk of bad prediction or over-modeling. Consequently, a few recent works have investigated the integration of SVR with intelligent optimization algorithms to assist in the automatic selection of proper settings for its parameters. In this respect, bio-inspired metaheuristic computational techniques are more efficient than gradient-based ones due to the fact that they are a kind of flexible and global trial input optimization search process (Boussaïd et al., 2013). Furthermore, hybrid prediction models integrating SVR with genetic or swarm intelligence algorithms have been proved effective in financial and economic domains. For example, optimized SVR models are observed to be more accurate and reliable in the presence of noisy and non-linear financial data (Kumar & Thenmozhi, 2021) compared with separate machine learning methods. This type of hybrid approaches are of particular interest for commodity market, where price dynamics are determined by heterogeneous agents interacting with one another and fast transmission of information.

In parallel, there has been increasing recognition of the importance of rigorous out-of-sample evaluation and uncertainty quantification in forecasting studies. Forecast accuracy metrics alone are often insufficient for assessing model adequacy, particularly in financial applications where risk assessment is critical. Information-theoretic criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) provide complementary insights by penalizing excessive model complexity (Burnham & Anderson, 2002). Moreover, residual diagnostics and statistical tests of stationarity play a crucial role in validating whether a model has adequately captured the underlying data-generating process (Enders, 2015). Motivated by these considerations, this study develops and evaluates a comparative forecasting framework for daily silver prices using SVR and two hybrid variants optimized via evolutionary computation techniques. By employing a recent and high-frequency dataset, implementing a realistic one-month-ahead forecasting design, and incorporating both accuracy and diagnostic measures, the study aims to provide a comprehensive assessment of hybrid machine learning approaches for precious metal price forecasting. The findings contribute to the growing literature on intelligent forecasting systems and offer practical insights for decision-makers operating in volatile commodity markets.

1st: Literature Reviews

Recent research on silver and precious-metal price forecasting increasingly agrees that these markets exhibit strong nonlinearity, abrupt regime changes, and time-varying volatility, which limits the reliability of purely linear specifications especially for short-horizon decision support. Consequently, a growing stream of work adopts machine learning models that can better accommodate nonlinear input-output relationships and complex interactions among drivers. For example, a recent study forecasting silver prices using Extreme Gradient Boosting (XGBoost) reports that careful hyperparameter tuning is central to improving accuracy and stability in silver-price prediction tasks, underscoring the broader movement toward data-driven forecasting pipelines rather than fixed-parameter baselines. Within this modern toolkit, Support Vector Regression (SVR) remains a widely used benchmark because of its strong generalization properties and its effectiveness on noisy financial series. However, the literature consistently emphasizes that SVR performance is highly sensitive to its hyperparameters, motivating hybrid frameworks where an optimizer searches for the best (C,ξ, ϵ). A silver-specific contribution in this direction is the work of Yahya and Algamal (2025), who explicitly motivate SVR's sensitivity and propose metaheuristic tuning to improve daily silver forecasting, reporting meaningful gains over benchmarks. In the same optimization line, Taher, Mhamad, and Taha (2025) demonstrate that evolutionary optimization specifically genetic algorithms can substantially enhance SVR predictive performance in economic datasets, providing direct methodological support for GA-SVR designs used in financial prediction settings. Beyond evolutionary optimization, bat-inspired optimization mechanisms have recently been refined to improve convergence efficiency and robustness in nonstationary environments. In particular, an enhanced bat-algorithm study in Scientific Reports (2025) shows that algorithmic improvements to bat-based search can yield measurable forecasting gains when optimizing learning systems, and it benchmarks against SVR among other baselines reinforcing the practical relevance of bat-family optimizers for parameter tuning in predictive modeling. These findings collectively support the view that optimizer design matters: improved exploration-exploitation balance can translate into better tuned learning models and more stable forecasts under shifting regimes.

A parallel and increasingly influential thread in 2024–2026 concerns uncertainty-aware forecasting. Silver and other financial series are not only hard to predict accurately; they also require credible uncertainty estimates for risk-aware decisions. Recent silver-focused work using Gaussian Process Regression (GPR) highlights the value of probabilistic modeling and Bayesian-style calibration for commodity prices, illustrating that uncertainty-aware approaches can be competitive and interpretable for market participants. More generally, the financial forecasting literature is increasingly shifting from point forecasts to probabilistic outputs, as reflected in a 2025 review on probabilistic AI in finance that argues uncertainty quantification remains underutilized despite its importance for decision-making and regulation. Complementing this direction, recent probabilistic time-series models demonstrate how probabilistic forecasts can improve practical outcomes under uncertainty, supporting the inclusion of prediction intervals and reliability diagnostics in modern forecasting studies. Very recent work also explores foundation-style probabilistic forecasting with explicit uncertainty decomposition, indicating that uncertainty modeling is becoming a core research frontier rather than an optional add-on. Synthesis. Across 2023–2026, the literature supports three convergent conclusions: (i) silver-price forecasting benefits from nonlinear learners with tuned hyperparameters, (ii) hybrid SVR + metaheuristic optimization is a validated pathway for accuracy gains in economic/financial prediction contexts (including silver), and (iii) uncertainty quantification and diagnostic validation are increasingly expected components of credible forecasting systems.

2nd: Methodology

1- Data Source and Preprocessing

Daily silver prices denominated in U.S. dollars (XAG/USD) were collected from the Stooq financial database, which provides openly accessible and widely used historical market data. The sample period spans 1 February 2025 to 1 February 2026, yielding a continuous daily time series of closing prices. This period was selected to capture recent market dynamics while ensuring sufficient observations for training and evaluation.

Prior to modeling, the data were chronologically ordered and screened for missing values. The daily closing price was retained as the target variable, consistent with standard practice in commodity price forecasting (Asraa et al., 2018). To transform the univariate time series into a supervised learning structure, a lag-embedding approach was adopted. Specifically, each observation was represented by the previous (L = 10) daily prices, allowing nonlinear regression models to capture short-term temporal dependencies. Similar lag-based formulations have been successfully employed in economic and financial forecasting contexts (Aziz et al., 2023).

2- Train–Test Design and Forecasting Strategy

The resulting dataset was divided into a training set and a hold-out test set, where the last 30 observations (approximately one month) were reserved for out-of-sample evaluation. This design allows the computation of forecast accuracy metrics using realized values while emulating a realistic one-month-ahead forecasting horizon.

All models were trained exclusively on historical information preceding the test window. Performance was evaluated using multiple criteria, including error-based and information-theoretic measures, in line with best practices in statistical learning and time-series forecasting (Hyndman & Athanasopoulos, 2021).

3- Support Vector Regression (SVR)

The main goal of *SVR* is to find a function that approximates the underlying relationship between input variables and continuous output values (Aziz, et al. 2023). This function should ideally fit the data within a specified margin of error, denoted by a threshold called ϵ (Taher et al., 2025). The regression function is generally represented as:

$$f(x) = [w, \phi(x)] + b \qquad (1)$$

where:

$\boldsymbol{w}$ is the weight vector that determines the importance of each feature.

ϕ(x) is a kernel function that maps the input features into a higher-dimensional space to facilitate the modeling of complex relationships.
b is the bias term that adjusts the function output.

A. Loss Function

SVR employs the ϵ-insensitive loss function, defined as:

$$L_\epsilon\left(y_i, f(x_i)\right) = \begin{cases} 0 & \text{if } |y_i - f(x_i)| \le \epsilon \\ |y_i - f(x_i)| - \epsilon & otherwise \end{cases} \quad (2)$$

This loss function allows for a margin of tolerance, meaning that small deviations within the ϵ margin are not penalized, which helps in focusing on more significant errors (Aziz, et al. 2023).

B. Optimization Problem in Support Vector Regression (*SVR*)

The core of Support Vector Regression (*SVR*) involves minimizing an objective function that balances the complexity of the model with the error allowed in the predictions (Taher et al., 2025). The optimization problem can be formulated as follows:
Objective Function
The goal is to minimize the following objective function:

$$min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i \quad (3)$$

Subject to the constraints:

$$y_i - f(x_i) \le \epsilon + \xi_i$$
$$f(x_i) - y_i \le \epsilon + \xi_i \qquad , \xi_i \ge 0$$

In this formulation, *C* is a regularization parameter that controls the trade-off between model complexity and error tolerance, while ξ_i are slack variables that account for deviations from the ϵ-insensitive margin.

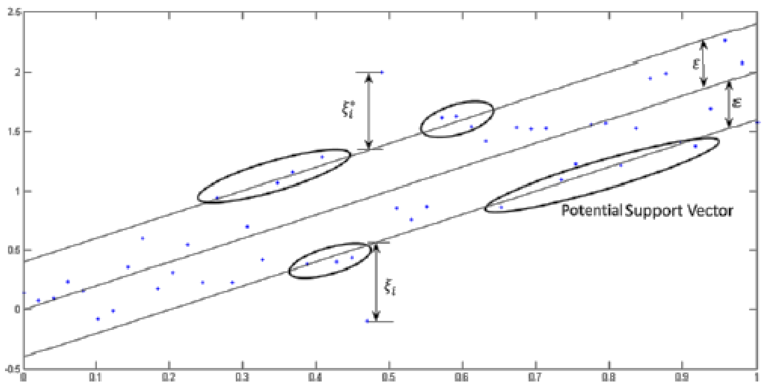

Figure (1): shows one dimension of SVR

C. Dual Formulation

The dual formulation of Support Vector Regression (SVR) is an important aspect of the methodology, allowing for more efficient optimization, especially in high-dimensional spaces. By converting the primal problem into its dual form, we can leverage the properties of Lagrange multipliers and kernel functions (Taher et al., 2025). To enhance computational efficiency, the optimization problem is converted into its dual form:

$$max_{\alpha,\beta} \sum_{i=1}^{n} (\alpha_i - \beta_i)\, y_i - \frac{1}{2} \sum\nolimits_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \beta_i)\left(\alpha_j - \beta_j\right) K\left(x_i - \beta x_j\right) \quad (4)$$

Subject to:

$$\textstyle\sum_{i=1}^{n} (\alpha_i - \beta_i) = 0 \qquad , 0 \le \alpha_i, \beta_i \le C$$

Here, $K(x_i, x_j)$ is a kernel function that computes the similarity between input vectors, facilitating non-linear regression.

4- Genetic Algorithm–Optimized SVR (GA-SVR)

To enhance predictive performance, a Genetic Algorithm (GA) was employed to optimize the SVR hyperparameters. Genetic Algorithms are population-based meta-heuristic optimization techniques inspired by natural evolution and have demonstrated strong performance in complex, non-convex optimization problems (Holland, 1992). In this study, each chromosome encodes a candidate triplet (C, ξ, ϵ). The fitness function was defined as the mean squared error (MSE) computed on a validation subset extracted from the training data. Through iterative processes of selection, crossover, mutation, and elitism, the GA searches the hyperparameter space to identify configurations that minimize forecast error. The effectiveness of GA-based SVR optimization has been documented in both cross-sectional and time-series applications (Taher et al., 2025; Mirjalili et al., 2020).

5- BAT Algorithm–Optimized SVR (BAT-SVR)

In parallel, a BAT Algorithm (BAT) was implemented to optimize the SVR hyperparameters. The BAT algorithm is inspired by the echolocation behavior of microbats and balances global exploration and local exploitation through adaptive frequency, loudness, and pulse emission rates (Yang, 2010). Each bat represents a candidate SVR hyperparameter vector, and its movement through the search space is guided by both velocity updates and stochastic local searches around the current best solution. BAT-SVR hybrid frameworks have shown strong robustness and convergence properties in financial and economic forecasting problems, including interest rate and agricultural time-series data (Taher et al., 2025).

6- Performance Evaluation Metrics

To test the accuracy and performance of the proposed model, some statistical tests and measurements, including mean square error, root of mean square error, Akaike information criteria, and Bayesian information criteria (Salih et al., 2024; Ahmed, 2021).

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_i - \hat{y}_i)^2 \qquad (5)$$

where:

- n is the number of observations.
- y_i is the actual value.
- $\hat{y}_i$ is the predicted value.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_i - \hat{y}_i)^2} \qquad (6)$$

$$\text{AIC} = 2\,k - 2\ln(\mathscr{L}) \qquad (7)$$

$$\text{BIC} = k\,.\,\ln(n) - 2\ln(\mathscr{L}) \qquad (8)$$

Where:

- n: is the number of observations.
- $\mathscr{L}$: is the log-likelihood.
- k: is the number of explanatory variables in the model.

In conclusion, the lower MSE, RMSE, AIC, and BIC indicate a better fit of the model to the data, as it suggests that the predictions are closer to the actual values.

7- Forecast Uncertainty and Residual Diagnostics

To quantify forecast uncertainty, 95% confidence intervals for the 30-day forecasts were constructed using a bootstrap resampling of in-sample residuals (Asraa, et al. 2018). This nonparametric approach avoids restrictive distributional assumptions and is widely used in nonlinear forecasting models (Efron & Tibshirani, 1994). Finally, the Augmented Dickey–Fuller (ADF) test was applied to the residuals of the best-performing model to assess stationarity (Rasul, et al. 2025). Residual stationarity indicates that the model has adequately captured the systematic structure in the data, leaving only white-noise disturbances (Enders, 2015).

8- Methodological Framework (Pseudocode)

Input:

```
Daily silver prices y_t, t = 1,...,T
Lag length L
Forecast horizon H = 30
```

Step 1: Data Preparation

```
- Sort y_t by date
- Construct lagged dataset:
   X_t = [y_{t-1}, y_{t-2}, ..., y_{t-L}]
   Target = y_t
```

Step 2: Train–Test Split

```
- Training set: t = 1,...,T-H
- Test set: t = T-H+1,...,T
```

Step 3: Baseline SVR

```
- Initialize SVR with RBF kernel
- Train on training set
- Generate forecasts for test set
```

Step 4: GA-SVR Optimization

```
- Initialize population of SVR hyperparameters
- For each generation:
   * Evaluate fitness (validation MSE)
   * Apply selection, crossover, mutation
   * Update best solution
- Train SVR using optimal GA parameters
- Forecast test set
```

Step 5: BAT-SVR Optimization

```
- Initialize bat population
- For each iteration:
   * Update frequency, velocity, position
   * Perform local random walk
   * Accept new solutions based on fitness
- Train SVR using optimal BAT parameters
- Forecast test set
```

Step 6: Model Evaluation

```
- Compute MSE, RMSE, AIC, BIC for all models
- Compare results in tabular and graphical form
```

Step 7: Uncertainty Quantification

```
- Bootstrap in-sample residuals
- Construct 95% confidence intervals
```

Step 8: Residual Diagnostics

- Apply ADF test on model residuals

Output:

Forecasts, confidence intervals, evaluation metrics, optimized hyperparameters, diagnostic statistics

3rd: Results and Discussions

The GA-SVR model achieves the lowest validation MSE by selecting a large regularization parameter C, a small kernel width ξ and a moderate ϵ, indicating a strong fit with controlled smoothness. In comparison, BAT-SVR adopts a smaller C and tighter ϵ, leading to a more conservative model with slightly higher error. Overall, the results show that GA-based optimization identifies a more effective hyperparameter configuration than the Bat Algorithm for this dataset.

Table (1): Optimal hyperparameters of GA-SVR and BAT-SVR Models

Model	C	ξ	ϵ	Validation MSE
GA-SVR	993.242	0.0001896	0.0316747	2.97996
BAT-SVR	77.9692	0.0004375	0.009796	6.05857

The backtest results in table 2 clearly demonstrate the superiority of the optimized SVR variants over the baseline SVR. The standard SVR exhibits substantially larger forecast errors, as reflected by its high MSE and RMSE values, indicating limited ability to capture the nonlinear dynamics of silver prices in the test window. In contrast, GA-SVR achieves the lowest MSE (46.22) and RMSE (6.80), representing a dramatic improvement in predictive accuracy and confirming the effectiveness of genetic algorithm–based hyperparameter optimization. BAT-SVR also yields considerable error reduction relative to the baseline SVR, although its performance remains inferior to GA-SVR. Furthermore, the information criteria (AIC and BIC) consistently favor GA-SVR, suggesting that it provides the best trade-off between goodness-of-fit and model complexity among the competing models. Collectively, these findings indicate that metaheuristic optimization substantially enhances SVR forecasting performance, with GA-SVR emerging as the most reliable model for short-term silver price prediction in the examined period.

Table (2): Backtest performance metrics for SVR, GA-SVR, and BAT-SVR

Model	MSE	RMSE	AIC	BIC
SVR	1651.98	40.6446	228.2919	232.4955
GA-SVR	46.2198	6.7985	121.0022	125.2058
BAT-SVR	82.1689	9.0647	138.2633	142.4669

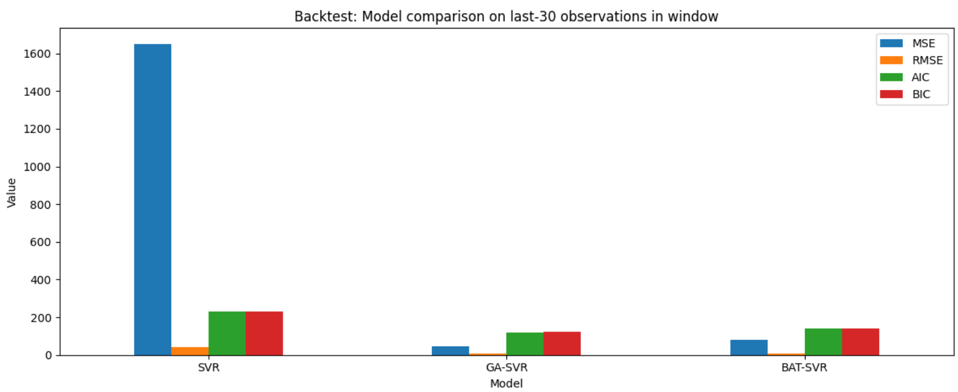

Figure (2): Backtest performance comparison and actual vs. predicted silver prices for testing dataset

Figure 3 presents a backtest comparison between the actual silver prices and the forecasts generated by the SVR, GA-SVR, and BAT-SVR models over the final 30 observations of the sample period. The GA-SVR model closely follows the actual price trajectory and successfully captures both the upward trend and short-term fluctuations, indicating strong predictive accuracy and adaptability. The BAT-SVR model tracks the general direction of the series but exhibits smoother responses and lags during periods of rapid price changes, leading to moderate deviations from observed values. In contrast, the baseline SVR consistently underestimates the price level and fails to adjust to the evolving market dynamics. Overall, the visual evidence reinforces the quantitative results, confirming that metaheuristic optimization particularly GA-based tuning—substantially improves SVR performance in short-term silver price forecasting.

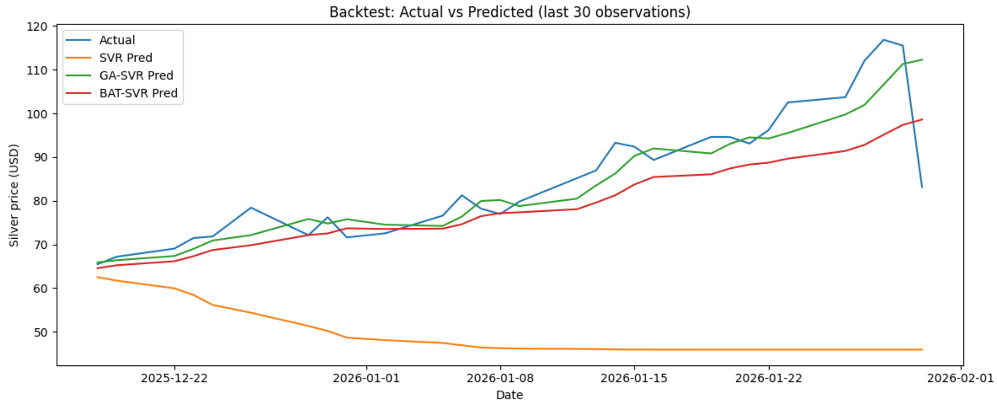

Figure (3): Backtest comparison of actual and predicted silver prices using SVR, GA-SVR, and BAT-SVR for testing dataset

The ADF test results indicate that the null hypothesis of a unit root is rejected at the 5% significance level, as evidenced by the p-value of 0.0353. This confirms that the GA-SVR backtest residuals are stationary, implying that the model has effectively captured the systematic structure of the silver price series. Consequently, the remaining residuals behave as white noise, supporting the adequacy and reliability of the GA-SVR model for short-term silver price forecasting.

Table (3): Augmented Dickey–Fuller (ADF) test results for GA-SVR backtest residuals

Statistic	Value
ADF Test Statistic	−2.9956
p-value	0.0353

The table below reports GA-SVR multi-step future forecasts for daily silver prices from 2 to 27 February 2026, along with 95% confidence intervals obtained via bootstrap simulation. The forecasts indicate a strong upward trajectory over the horizon, while the widening confidence bands reflect increasing uncertainty as the forecast horizon extends, which is typical in multi-step nonlinear time-series forecasting.

Table (4): GA-SVR future silver price forecasts with 95% confidence intervals

Date	GA-SVR Forecast	95% CI (Lower)	95% CI (Upper)
2/2/2026	110.1807	105.867	112.9412
2/3/2026	112.8212	108.128	115.4404
2/4/2026	116.6077	111.6036	119.5473
2/5/2026	119.7315	113.8788	122.4881
2/6/2026	124.2145	117.8571	127.4304
2/9/2026	126.7431	118.1553	130.2946
2/10/2026	130.488	121.2052	133.8504
2/11/2026	133.1665	123.419	137.0404
2/12/2026	136.2786	125.3799	139.8873
2/13/2026	138.2083	126.3231	142.0745
2/16/2026	143.5791	131.5662	147.6569

2/17/2026	147.5626	134.483	151.3462
2/18/2026	151.8032	139.2692	155.8983
2/19/2026	155.9971	142.9	160.3005
2/20/2026	160.3857	145.9836	164.9411
2/23/2026	164.6274	149.6815	169.0245
2/24/2026	169.0415	153.6121	173.7149
2/25/2026	173.4109	158.0965	177.9241
2/26/2026	177.8943	162.2113	182.4885
2/27/2026	182.3554	166.5007	187.1852

The figure below illustrates the GA-SVR multi-step forecasts for daily silver prices over the future period from 2 February to 1 March 2026, together with the associated 95% confidence intervals derived from bootstrap simulation. The point forecasts indicate a pronounced upward trend, suggesting continued strengthening in silver prices over the forecast horizon. The shaded confidence band gradually widens as the forecast extends further into the future, reflecting the accumulation of uncertainty inherent in iterative multi-step forecasting. Overall, the figure demonstrates both the predictive signal captured by the GA-SVR model and the increasing forecast uncertainty over time, providing a transparent and risk-aware outlook for short-term silver price dynamics.

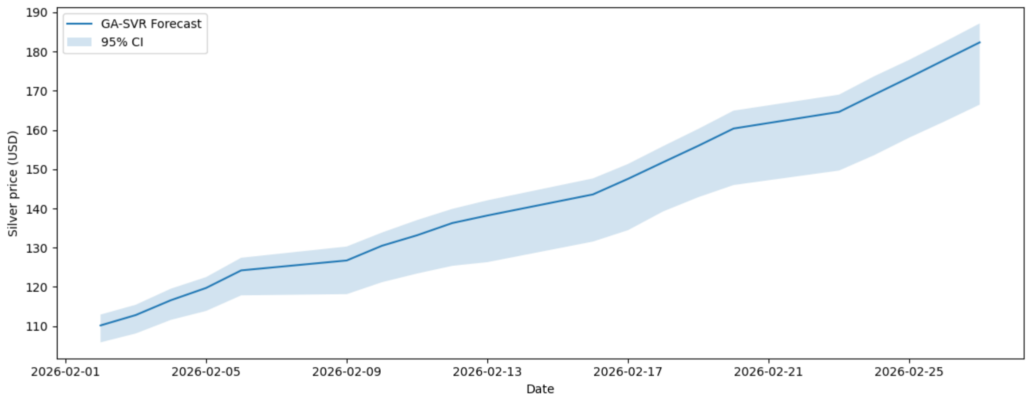

Figure (4): GA-SVR future silver price forecasts with 95% confidence intervals

4th: Conclusions

This study demonstrates that integrating Support Vector Regression with metaheuristic optimization techniques substantially improves short-term silver price forecasting accuracy. Both GA-SVR and BAT-SVR outperform the standard SVR model across all evaluation metrics, confirming the importance of optimal hyperparameter selection in nonlinear regression tasks. Among the competing approaches, GA-SVR consistently delivers the lowest forecast errors and information-criterion values, indicating superior generalization ability and a favorable trade-off between accuracy and model complexity. The bootstrap-based confidence intervals further provide valuable insight into forecast uncertainty, while residual stationarity confirmed by the ADF test supports the statistical adequacy of the proposed framework. Overall, the results validate GA-SVR as a robust and reliable tool for short-term silver price forecasting in volatile market conditions.

6th: Limitations

Despite its strong empirical performance, the study has several limitations. First, the analysis relies solely on historical silver prices and does not incorporate exogenous macroeconomic or financial variables that may influence price movements. Second, the forecasting framework is evaluated over a relatively short time horizon, which may limit its applicability to longer-term forecasting. Finally, the metaheuristic algorithms require careful tuning of their own control parameters, which may affect convergence speed and computational efficiency.

7th: Future Study

Future research may extend this framework by incorporating additional explanatory variables such as exchange rates, inflation indicators, or industrial demand measures. Hybridization with probabilistic or deep learning models could further enhance forecasting performance and uncertainty quantification. Moreover, applying the proposed approach to longer horizons and other precious metals would provide deeper insights into its generalizability and robustness across different commodity markets.

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