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A novel hybrid forecasting framework based on the Archimedes optimization algorithm and least squares support vector machine for China's iron ore demand prediction

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Abstract. Making accurate demand forecasting of iron ore of China is essential for resource planning, strategic investment, and risk management. However, the complex and nonlinear nature of iron ore demand, driven by the interplay of domestic economic factors and international market forces, poses significant challenges to conventional forecasting methods. This study proposes a hybrid forecasting framework that integrates the Archimedes Optimization Algorithm (AOA) with the Least Squares Support Vector Machine (LSSVM) to predict China's annual iron ore demand. A comprehensive dataset spanning 2014 to 2025 is constructed, comprising ten explanatory variables that capture both macroeconomic conditions, including GDP, real estate investment, urbanization rate, industrial output, and steel apparent consumption, and international market factors, including steel net exports, iron ore prices, the Baltic Dry Index, and the USD exchange rate. The AOA is employed to automatically search for the optimal LSSVM hyperparameters, overcoming the limitations of manual grid-search approaches. Using the first eight years as the training set and the remaining four years for out-of-sample evaluation, the proposed model is benchmarked against the standard LSSVM without optimization. Empirical results demonstrate that the AOA-LSSVM model consistently outperforms the baseline across all evaluation metrics, reducing the mean absolute error by 7.05%, the root mean square error by 7.47%, and the mean absolute percentage error by 0.42 percentage points. These findings confirm the efficacy of AOA in enhancing LSSVM's generalization capability and underscore the value of integrating meta-heuristic optimization with machine learning for mineral resource demand forecasting. The proposed framework offers policymakers and industry practitioners a reliable tool for generating accurate demand projections to inform import strategies and resource security planning.

Keywords: iron ore demand forecasting, Archimedes Optimization Algorithm, Least Squares Support Vector Machine

1. Introduction

Iron ore is the lifeblood of the modern steel industry, serving as the primary feedstock for infrastructure, transportation, and urbanization. China, as the world's largest steel producer, consumes approximately half of the globally mined iron ore, with its imports accounting for over 70% of the global seaborne trade. This immense demand not only dictates the profitability of major multinational mining corporations but also exerts considerable influence over international commodity markets, shipping freight indices, and the macroeconomic stability of resource-exporting nations. Consequently, producing reliable forecasts of China's iron ore demand is a critical undertaking for governmental resource planning, corporate strategic investment, and risk management in commodity trading.

Nevertheless, forecasting China's iron ore demand has become increasingly challenging due to the commodity's evolving price-determination mechanism. Beyond traditional supply-demand fundamentals, iron ore prices and demand are now heavily influenced by financial factors, including ocean freight costs, exchange rate fluctuations, and speculative activities in futures markets. Moreover, China's ongoing economic restructuring—shifting from investment-led growth to innovation-driven development—has introduced structural breaks and non-linear dynamics into the consumption patterns of bulk commodities. The interdependencies among macroeconomic indicators, construction activities, industrial output, and international trade are highly complex, rendering conventional linear approaches inadequate for capturing the underlying data-generating process.

A substantial body of literature has addressed mineral demand forecasting using various methodologies. Classical econometric techniques, such as Autoregressive Integrated Moving Average (ARIMA) and cointegration analysis, offer interpretable results but generally assume linearity and stationarity, which are frequently violated in volatile commodity markets [1]. Grey system models, particularly GM(1, 1) and its rolling variants, have been widely applied for small-sample scenarios in iron ore import forecasting [2]. However, their mathematical simplicity often limits their capacity to accommodate exogenous shocks and multi-dimensional influencing factors. In recent years, machine learning paradigms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Extreme Learning Machines (ELM), have gained traction due to their superior non-linear mapping capabilities [3]. Among these, the Least Squares Support Vector Machine (LSSVM) stands out as a computationally efficient alternative to standard SVM, as it transforms the quadratic programming problem into a system of linear equations [4]. Despite its advantages, the predictive performance of LSSVM is highly sensitive to the selection of its regularization and kernel parameters. Traditional grid search or trial and error methods are not only computationally costly but also prone to local optima, undermining forecasting robustness.

To address the parameter optimization bottleneck, meta-heuristic algorithms have been increasingly integrated with LSSVM. The Archimedes Optimization Algorithm (AOA), recently proposed by [5], is a population-based optimizer inspired by the physical laws of buoyancy and acceleration. It has demonstrated superior global search capability, rapid convergence, and high stability compared to conventional algorithms such as Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) across various benchmark functions and engineering applications. While AOA has been tentatively applied to logistics demand forecasting, its potential for mineral resource demand prediction, particularly in the context of China's iron ore market, remains unexplored.

Forecast the iron ore demand is important as it is critical for China's economy. In this study, a demand forecasting model of China's annual iron ore demand is proposed. In order to predict the iron ore demand accurately, a comprehensive predictor set that integrates both domestic economic drivers is constructed. This study considers GDP, real estate investment, infrastructure investment, urbanization rate, industrial output, and steel apparent consumption, and international market factors, namely steel net exports, iron ore spot prices, the Baltic Dry Index (BDI), and the USD exchange rate. Using a panel of annual data from 2014 to 2025, this study emploies the first eight years as the training set and the remaining three years as the hold-out test set. To mitigate multicollinearity and isolate the most salient factors, a Grey Relational Analysis (GRA) is first applied. Subsequently, the AOA is deployed to iteratively search for the optimal hyperparameter pair (γ, σ) of the LSSVM model that minimizes training error. The optimized model is then validated against the test set and benchmarked against the standard LSSVM without optimization.

The remainder of this paper is structured as follows. Section 2 reviews the related literature on iron ore demand forecasting and intelligent optimization. Section 3 elaborates on the theoretical foundations of LSSVM, AOA, and the proposed hybrid methodology. Section 4 describes the data sources, variable definitions, experimental design and the results. Section 5 concludes with policy implications and directions for future research.

2. Literature review

The study of iron ore demand forecasting and market dynamics has attracted considerable scholarly attention, driven by the commodity's strategic importance to the global economy and, in particular, to China's industrial development. The literature relevant to this paper can be broadly classified into three streams. The first is studies examining the structural characteristics and evolutionary patterns of the global iron ore market. The second is empirical investigations into the determinants of iron ore demand and price. The third is methodological contributions to demand forecasting, encompassing both traditional econometric techniques and modern machine learning approaches.

A substantial body of literature has documented the dramatic transformation of the global iron ore supply demand landscape over the past half-century. Song et al. [6] conducted a comprehensive analysis of the temporal and spatial evolution of global iron ore production, consumption, and trade from 1971 to 2017, revealing that the centre of gravity of both production and consumption has shifted decisively from Europe to Asia and Oceania. Wu et al. [7] adopt a system analysis perspective, mapping China's iron flow through material flow analysis to present a comprehensive picture of the iron ore supply chain from mining to end-use. Their analysis identifies four key factors shaping iron ore development and concludes that the central challenge for China is securing overseas iron ore resources at a reasonable price. Tamvakis [8] provides an in-depth theoretical and empirical analysis of the iron ore trade, emphasising the non-competitive industrial structure that characterises the market. The empirical results from a partial adjustment model applied to major iron ore importers reveal substantial differences in the behaviour of Far East and West European importers, with Japan and South Korea demonstrating considerably greater flexibility in adjusting their import allocation than their European counterparts. The study also highlights the pivotal role of long-term contracts in the evolution of the market, particularly in the context of Japan's procurement strategy since the 1960s. Hurst [9] examines the competitiveness of the supply side response to China's unprecedented demand shock. This literature finds the sharp price increases are attributed to the scale and pace of China's demand growth, combined with natural constraints on supply expansion due to long lead times in mine development and the underestimation of Chinese demand by producers. The study also notes that the transition to a spot pricing system and the emergence of new supply from Africa and elsewhere are likely to exert downward pressure on prices in the long run.

Understanding the factors that drive iron ore demand and price is a central concern in the literature. Niu [10] employs principal component regression analysis to forecast China's iron ore demand, selecting eight economic indicators, including GDP, industrial output, fixed asset investment, and urbanisation rate, as basic influencing factors. Long and Ye [11] provide a forecast of China's steel and iron ore demand based on an analysis of steel consumption patterns in industrialised countries. Feliks et al. [12] develop an artificial neural network model for short-term iron ore demand prediction, incorporating not only historical demand data but also production deviations and the CRU Steel Price Index.

The literature on iron ore demand forecasting encompasses a wide range of methodological approaches, from traditional statistical techniques to advanced machine learning algorithms. Classical time series methods have been extensively applied to iron ore demand forecasting. But recent advances in machine learning and meta-heuristic optimization have opened new avenues for improving forecasting accuracy. Yan and Chen [13] propose a prediction model for iron ore demand that couples phase-space reconstruction from chaos theory with neural networks. The phase-space reconstruction technique, based on Takens' theorem, extracts the underlying dynamics of the time series by embedding it in a higher-dimensional space, with the embedding dimension and time lag determined by the Cao method and autocorrelation function, respectively. The reconstructed data are then used to train a neural network, achieving an average relative error of 1.21% in empirical tests. This approach demonstrates the potential of combining chaos theory with machine learning to enhance the modelling of non-linear demand patterns.

Lundmark [14] applies a trade gravity model to analyse global bilateral iron ore trade flows using panel data from 1980 to 2016. The gravity model specification, which incorporates country fixed effects to account for multilateral resistance terms, yields results consistent with theoretical predictions which states trade increases with the economic size of trading partners and decreases with geographical distance. The estimated distance elasticity of −0.32 is substantially smaller than the meta-average of −1.1 reported by Head and Mayer [14], reflecting the predominantly seaborne nature of iron ore transport. The study projects that global iron ore trade value will continue to increase at approximately 5% per annum until 2035, driven by expected economic growth in both exporting and importing countries.

Our study contributes to the literature by present a forecasting method which optimising LSSVM parameters for iron ore demand forecasting using recently developed meta-heuristic algorithms AOA. The successful application of AOA to logistics demand forecasting by Xiao et al. [15] suggests its potential for logistics demand prediction. It contributes to the iron ore demand forecasting. Existing studies often focus on a narrow set of influencing factors, typically either domestic economic indicators or international market variables, rather than integrating both comprehensively. The annual nature of iron ore demand data, combined with the relatively small sample size typical of such studies, poses challenges for machine learning approaches that generally require large training datasets. This is a challenge that has not been adequately addressed in the literature. This study aims to address these problems by proposing an AOA-LSSVM hybrid forecasting framework for China's annual iron ore demand. This study constructs a comprehensive predictor set that integrates both domestic economic drivers, including GDP, real estate investment, urbanisation rate, industrial output, and steel apparent consumption, and international market factors, namely steel net exports, iron ore spot prices, the Baltic Dry Index (BDI), and the USD exchange rate. The AOA algorithm is employed to automatically search for the optimal LSSVM hyperparameters, overcoming the limitations of manual or grid-search approaches. By benchmarking the proposed model against the standard LSSVM without optimization, this study aims to quantify the marginal gains achievable through intelligent parameter tuning and to provide empirical evidence on the effectiveness of the AOA-LSSVM framework for iron ore demand forecasting.

3. Model

This section presents the theoretical foundations of the proposed hybrid forecasting framework. This study first establishes the mathematical formulation of the LSSVM regression model, followed by a description of the AOA for parameter optimization, and finally detail the integrated AOA-LSSVM forecasting procedure.

3.1. LSSVM model

The Least Squares Support Vector Machine, belongs to the family of kernel-based learning methods [16]. Its key distinction from the standard SVM lies in the manner in which the learning problem is formulated: whereas the conventional SVM seeks to solve a quadratic programming problem with inequality constraints, LSSVM adopts equality constraints in conjunction with a least-squares loss function. This reformulation substantially reduces the computational burden, as the solution is obtained by solving a system of linear equations rather than a more demanding quadratic programme.

Consider a collection of training observations $\{(u_i, z_i)\}_{i=1}^{m}$, where each $u_i \in R^n$ denotes an input feature vector and $z_i \in R$ is the associated scalar output. The LSSVM constructs a regression function of the form (Equation (1)):

$$z(u) = v^{\top}\varphi(u) + c \tag{1}$$

In this expression, $\varphi(\cdot) : R^n \to R^{n_h}$ represents a nonlinear feature mapping that projects the input data into a higher-dimensional space, v is the weight vector defined in that feature space, and c is a scalar bias term. The feature mapping is typically not explicitly defined; rather, it is accessed indirectly through the use of kernel functions, as will be discussed shortly.

The optimization problem that LSSVM seeks to solve balances two competing objectives: achieving a simple model (characterised by a small weight vector norm) and obtaining a close fit to the training data. This trade off is expressed through the minimisation problem in Equations (2) and (3).

$$J(v, \delta) = \tfrac{1}{2} v^{\top} v + \tfrac{1}{2\lambda} \textstyle\sum_{i=1}^{m} \delta_i^2 \tag{2}$$

subject to the set of equality constraints:

$$z_i = v^{\top}\varphi(u_i) + c + \delta_i, \quad i = 1, 2, \ldots, m \tag{3}$$

Here, $\lambda > 0$ is the regularisation parameter that determines the relative importance assigned to model complexity versus empirical error. The terms δ_i are the residuals between the predicted and actual outputs for each training instance.

A distinctive feature of the LSSVM formulation is the use of equality rather than inequality constraints. This seemingly minor modification has profound implications for the solution procedure. Instead of solving a constrained quadratic programme—which is what the standard SVM requires—the LSSVM problem can be converted into a linear system by means of the Lagrangian method.

To proceed, this method introduces the Lagrange multipliers $\beta_i \in R$ for each constraint, yielding the Lagrangian function (Equation (4)):

$$L(v, c, \delta, \beta) = J(v, \delta) - \textstyle\sum_{i=1}^{m} \beta_i [v^{\top}\varphi(u_i) + c + \delta_i - z_i] \tag{4}$$

The stationarity conditions of this Lagrangian—obtained by taking derivatives with respect to v, c, δ_i, and β_i—give rise to a set of coupled linear equations. Upon eliminating the primal variables v and δ_i, these conditions condense into the matrix system in Equation (5).

$$\begin{bmatrix} 0 & 1_m^\top \\ 1_m & \Theta + \lambda^{-1} I \end{bmatrix} \begin{bmatrix} c \\ \beta \end{bmatrix} = \begin{bmatrix} 0 \\ z \end{bmatrix} \tag{5}$$

In this system, $z = [z_1, \ldots, z_m]^\top$ denotes the vector of target values, 1_m is an m-dimensional column vector of ones, $\beta = [\beta_1, \ldots, \beta_m]^\top$ collects the Lagrange multipliers, and Θ is the $m \times m$ kernel matrix whose entries are given by $\Theta_{ij} = \varphi(u_i)^\top \varphi(u_j)$.

The key advantage of this formulation is that the unknowns c and β are obtained by solving a linear system of dimension $m + 1$, which is computationally straightforward and can be accomplished efficiently even for moderately sized datasets.

Once the system is solved, the regression function for any new input u takes the form (Equation (6)):

$$z(u) = \sum_{i=1}^{m} \beta_i K(u, u_i) + c \tag{6}$$

where the kernel function $K(\cdot, \cdot)$ computes the inner product in the feature space without requiring explicit knowledge of the mapping φ. This is the well-known kernel trick, which enables LSSVM to capture nonlinear relationships while maintaining computational tractability.

For the present study, this study adopts the Radial Basis Function (RBF) kernel, which is widely used in nonlinear regression contexts due to its flexibility and locality properties (Equation (7)):

$$K(u_i, u_j) = exp\left(-\frac{\|u_i - u_j\|^2}{2\rho^2}\right) \tag{7}$$

The parameter $\rho > 0$, known as the kernel bandwidth, controls the smoothness of the regression function. Together with the regularisation parameter λ, it constitutes the two hyperparameters that critically determine the generalisation performance of the LSSVM model. Their appropriate selection is therefore essential for obtaining reliable forecasts, and it is this selection problem that motivates the use of the optimization algorithm described in the following subsection.

3.2. Archimedes Optimization Algorithm

The Archimedes Optimization Algorithm (AOA) is a population-based meta-heuristic that draws inspiration from the physical principle governing the buoyant force experienced by objects submerged in fluids. In this algorithmic framework, each candidate solution to the optimization problem is conceptualized as an immersed object possessing three characteristic properties: density, volume, and acceleration. These properties evolve throughout the search process, guiding the population towards regions of the solution space that yield superior objective function values.

The algorithm operates through a structured iterative process. Initially, a population of objects is randomly distributed across the feasible search domain, with each object assigned initial values for its density, volume, and acceleration. The fitness of each object is evaluated against the objective function, and the object achieving the best performance is recorded as the current optimum. As iterations proceed, the algorithm transitions between two distinct behavioural modes, that is, exploration and exploitation, controlled by a transfer operator that declines exponentially from unity to zero over the course of the optimization run.

During the exploration phase, objects are considered to be in a state of collision, analogous to the random motion of particles in a fluid. The acceleration of each object is updated based on the properties of a randomly selected companion object, promoting widespread coverage of the search space. This mechanism facilitates the discovery of promising regions and prevents premature convergence to suboptimal solutions. In contrast, during the exploitation phase, objects are assumed to move in a coordinated manner, with accelerations calculated relative to the current best performing object. This refinement stage enables the algorithm to intensively probe the neighbourhood of the identified optimum, enhancing solution precision.

The acceleration values computed through either phase are subsequently normalized to a standardized range to maintain numerical stability. Position updates for each object are then performed according to the behavioural mode currently active, incorporating stochastic elements to preserve diversity. The algorithm alternates between these modes until the maximum number of iterations is reached, at which point the best-discovered solution is returned as the optimal parameter combination. This conceptual framework underpins the use of AOA for hyper-parameter tuning in the present study.

3.3. Proposed AOA-LSSVM hybrid framework

The proposed hybrid framework integrates AOA with LSSVM for automated hyperparameter optimization. The workflow consists of the following steps.

The first step is data preprocessing. The input features and target variables are normalised using min-max scaling to the range [0,1], to eliminate the influence of different units of measurement.

The second step is AOA parameter optimization. The AOA is employed to search for the optimal LSSVM hyperparameters (λ, ρ) that minimise the Root Mean Square error (RMSE) on the training set. Each object in AOA represents a candidate parameter combination (λ, ρ). The fitness function is defined as Equation (8):

$$fitness = RMSE_{train} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(z_i - \hat{z}_i)^2} \quad (8) \tag{8}$$

where z_i is the actual value and $\hat{z}_i$ is the predicted value.

The third step is LSSVM model training. Once the optimal (λ^*, ρ^*) are identified, the LSSVM model is trained on the full training set using these optimised parameters.

The fourth step is forecasting. The trained AOA-LSSVM model is applied to generate out-of-sample forecasts for the testing period.

The AOA-LSSVM framework addresses the critical limitation of manual or grid-search parameter selection by intelligently exploring the parameter space and converging to the global optimum. This enhances both the predictive accuracy and robustness of the LSSVM model for iron ore demand forecasting.

4. Numerical experiments

This section delineates the experimental design, data sources, model implementation, and empirical findings of the proposed AOA-LSSVM forecasting framework for China's iron ore demand. This study commences with a description of the dataset and variable definitions, followed by the experimental settings, and subsequently present a comparative analysis of the forecasting performance of the AOA-LSSVM model against the standard LSSVM model.

4.1. Data description

The dataset employed in this study spans the period from 2014 to 2025, comprising annual observations of China's iron ore demand and ten explanatory variables that encapsulate the principal economic, industrial, and market drivers of iron ore consumption. The dependent variable is China's annual iron ore demand, measured in ten thousand tonnes. Since official statistics on iron ore demand are not directly published, this study derives this variable using the internationally recognized empirical coefficient of 1.6—that is, iron ore demand is estimated as 1.6 times the annual pig iron production reported by the National Bureau of Statistics of China.

This approach is widely adopted in the literature and provides a reasonable approximation of actual ore consumption.

The explanatory variables are selected based on a comprehensive review of the literature on iron ore demand determinants and data availability. They encompass three broad categories. (1) macroeconomic conditions, including Gross Domestic Product (GDP, X_1) and urbanization rate (X_3); (2) industrial and construction activity, including real estate development investment (X_2), industrial output measured by the main business revenue of industrial enterprises above a designated size (X_4), and steel apparent consumption (X_5); and (3) international market factors, including steel net exports (X_6), iron ore price (X_7), the Baltic Dry Index (BDI, X_8), and the USD exchange rate (X_9). All variables are annual and expressed in their original units as reported by the respective sources.

The data are compiled from multiple authoritative sources to ensure reliability and consistency. The dependent variable (iron ore demand) is calculated from pig iron production data published by the National Bureau of Statistics of China. GDP, real estate investment, urbanization rate (computed as the ratio of urban population to total population), and industrial output are obtained from the China Statistical Annual. Steel apparent consumption and steel net exports are sourced from the World Steel Association, with data for China and Taiwan summed to maintain consistency with the definition of China's total demand. Iron ore price data are taken from the World Bank Commodity Price Data, specifically the annual average spot price of iron ore in US dollars per dry metric tonne unit. The BDI is obtained from Investing.com, using the closing price on the last trading day of each year as the annual reference value. The USD exchange rate (annual average) is sourced from the International Monetary Fund's exchange rate database.

Table 1 shows the observations of each variable from 2014-2025. Table 2 presents the descriptive statistics of all variables over the 2014-2025 period. It shows that China's iron ore demand exhibits considerable variation, ranging from approximately 110,626 to 142,236 ten thousand tonnes, reflecting the fluctuations in domestic steel production and macroeconomic conditions over the sample period. The explanatory variables also display substantial variability, with GDP increasing steadily from 655,783 billion yuan in 2014 to over 1.4 million billion yuan in 2025, while real estate investment peaked in 2021 and has since declined, capturing the recent structural adjustments in China's property sector.

Table 1. Observations from 2014-2015

Year	Iron ore demand (10,000 t)	GDP (billion yuan)	Real estate investment (billion yuan)	Urbanization rate	Industrial output (billion yuan)
2014	1,141,996.48	65,578.29	9,024.721	55.75%	233,197.4
2015	1,106,260.8	70,251.15	9,091.149	57.33%	234,968.9
2016	1,123,637.28	76,119.3	9,690.001	58.84%	245,406.4
2017	1,141,790.88	84,738.29	10,342.738	60.24%	275,119.3
2018	1,247,802.08	93,601.01	11,274.023	61.50%	301,089.3
2019	1,293,590.08	100,587.24	12,361.014	62.71%	311,011.2
2020	1,422,361.76	103,486.76	13,201.368	63.89%	311,231.2
2021	1,389,708.48	117,382.3	13,763.332	64.72%	369,903.7
2022	1,382,124.48	123,402.94	12,384.78	65.22%	388,651.6
2023	1,395,372.8	129,427.17	11,214.225	66.16%	392,183
2024	1,362,779.2	134,806.62	10,003.638	67.00%	404,518.5
2025	1,337,665.6	140,187.92	8,278.814	67.89%	416,826

Table 1. Continued

Year	Steel apparent consumption (Mt)	Steel net exports (Mt)	Iron ore price (USD/dmtu)	BDI (annual close)	USD exchange rate (avg)
2014	730.4	81.2	96.95	782	6.1434
2015	689.8	102.1	55.85	474	6.2275
2016	699.3	98.9	58.42	928	6.6445
2017	791.5	65.6	71.76	1,476	6.7588
2018	854	59	69.75	1,406	6.616
2019	925.6	52.2	93.85	1,281	6.9084
2020	1,025.1	16.2	108.92	1,301	6.9008
2021	975.5	39.7	161.71	2,379	6.449
2022	944.1	53.9	121.3	1,723	6.7372
2023	922.5	85.2	120.57	2,087	7.084
2024	874	108.7	109.4	990	7.1975
2025	813.4	126.8	100.18	2,023	7.1898

Table 2. Descriptive statistics of variables (data includes 2014-2025)

Variable	Description	Mean	Std. Dev.	Min	Max
Y	Iron ore demand (10,000 t)	127,356.6	10,971.3	110,626.1	142,236.2
X_1	GDP (billion yuan)	102,703.9	26,893.7	65,578.2	140,187.9
X_2	Real estate investment (billion yuan)	108,591.4	18,140.5	82,788.1	137,633.3
X_3	Urbanization rate (%)	62.9	4.0	55.8	67.9
X_4	Industrial output (billion yuan)	1,205,799.3	128,481.0	1,057,327.3	1,396,450.4
X_5	Steel apparent consumption (Mt)	853.5	101.6	689.8	1,025.1
X_6	Steel net exports (Mt)	74.2	30.9	16.2	126.8
X_7	Iron ore price (USD/dmtu)	102.2	30.9	55.9	161.7
X_8	BDI (annual close)	1,479.7	581.8	474.0	2,379.0
X_9	USD exchange rate (avg)	6.72	0.36	6.14	7.20

4.2. Experimental design

To evaluate the forecasting performance of the proposed AOA-LSSVM model, this study adopts a hold-out validation strategy. The dataset (from 2014 to 2025) is partitioned into a training set and a testing set. The training set comprises the first eight years (2014-2021), which are used to calibrate the model parameters. The testing set comprises the remaining four years (2022-2025), which are reserved for out-of-sample evaluation. This split ensures that the model is trained on a sufficiently long historical period while retaining a meaningful number of future years for validation.

Prior to model training, all variables are normalized using min-max scaling to the range [0, 1] to eliminate the influence of different units of measurement and to facilitate the convergence of the optimization algorithm. The normalization formula is Equation (9):

$$S_i = \frac{S-S_{min}}{S_{max}-S_{min}} \quad (9) \tag{9}$$

where S is the original value, S_{min} and S_{max} are the minimum and maximum values of the respective variable over the training period, S_i is the normalized value.

For the LSSVM model, the regularization parameter γ and the kernel parameter σ (the width of the radial basis function kernel) are critical determinants of forecasting performance. In the standard LSSVM approach, these parameters are typically selected via grid search or cross-validation, which can be computationally expensive and may not guarantee global optimality. In the proposed AOA-LSSVM model, the Archimedes Optimization Algorithm is employed to automatically search for the optimal parameter combination (γ, σ) that minimizes the prediction error on the training set. The AOA is a population-based metaheuristic inspired by the physical laws of buoyancy and Archimedes' principle. It operates by simulating the behavior of objects immersed in a fluid, where each candidate solution is treated as an object with a certain volume, density, and acceleration. Through iterative updates of these physical properties, the algorithm converges to the global optimum. The population size is set to 20, and the maximum number of iterations is 100, consistent with the parameter settings in the benchmark study. The fitness function is defined as the root mean square error between the predicted and actual iron ore demand values on the training set.

For comparative purposes, this study also implements a standard LSSVM model without parameter optimization, using the same training and testing data. Both models are implemented in the MATLAB environment. The AOA-LSSVM model follows the procedure described in Section 3. After the optimal (γ, σ) are identified by AOA, the LSSVM model is retrained with these optimized parameters and then applied to generate forecasts for the testing period (2022-2025). The standard LSSVM model uses parameters selected via a simple grid search over a predefined range.

4.3. Evaluation metrics

We employ widely used performance metrics Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to assess and compare the forecasting accuracy of the two models. These metrics are defined in Equations (10)-(12).

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t| \quad (10) \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \quad (11) \tag{11}$$

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100\% \quad (12) \tag{12}$$

where y_t is the demand observation of iron ore at time t, $\hat{y}_t$ is the forecasted value, and n is the number of observations in the testing set. Lower values of these metrics indicate better forecasting performance. MAPE is particularly informative as it provides a scale-independent measure of relative prediction accuracy.

4.4. Results and analysis

Table 3 reports the forecasting results for both models over the 2022-2025 period, along with the actual iron ore demand values. The AOA-LSSVM model consistently produces forecasts that are closer to the actual values than those of the standard LSSVM model for all four testing years. For 2022, the AOA-LSSVM forecast is 134,331.71 ten thousand tonnes, compared to the actual value of 138,212.45, while the LSSVM forecast is 134,128.36. For 2023, the AOA-LSSVM forecast is 131,408.90 (actual: 139,537.28), and the LSSVM forecast is 130,869.44. For 2024, the AOA-LSSVM forecast is 128,619.64 (actual: 136,277.92), and the LSSVM forecast is 128,172.40. For 2025, the AOA-LSSVM forecast is 123,371.69 (actual: 133,766.56), and the LSSVM forecast is 122,279.58.

Table 3. Forecasting results for 2022-2025 (ten thousand tonnes)

Year	Actual Demand	AOA-LSSVM Forecasted Demand	LSSVM Forecasted Demand
2022	138,212.45	134,331.71	134,128.36
2023	139,537.28	131,408.90	130,869.44
2024	136,277.92	128,619.64	128,172.40
2025	133,766.56	123,371.69	122,279.58

Table 4 presents the summary error statistics for both models. The AOA-LSSVM model achieves a MAE of 7,515.57, an RMSE of 7,871.36, and a MAPE of 5.51%. In comparison, the standard LSSVM model yields a MAE of 8,086.11, an RMSE of 8,506.78, and a MAPE of 5.93%. The AOA-LSSVM model reduces the MAE by 570.53, leading to a 7.05% improvement and the RMSE by 635.42, leading to a 7.47% improvement compared to the standard LSSVM model. The MAPE is reduced by 0.42 percentage points, which leads to a 7.08% relative improvement.

Table 4. Forecasting accuracy

Metric	AOA-LSSVM	LSSVM	Improvement
MAE	7,515.57	8,086.11	570.53 (7.05%)
RMSE	7,871.36	8,506.78	635.42 (7.47%)
MAPE (%)	5.51	5.93	0.42 (7.08%)

These results demonstrate that the AOA-based parameter optimization consistently enhances the forecasting accuracy of the LSSVM model. The improvement is attributable to the AOA's ability to effectively search the parameter space and identify the optimal (γ, σ) combination that minimizes the training error, thereby avoiding the suboptimal parameter selections that may occur with manual or grid-search approaches. The relatively modest but consistent improvements across all three metrics suggest that the AOA-LSSVM model offers a reliable and robust alternative for iron ore demand forecasting.

It is worth noting that both models exhibit larger absolute errors in the years of the testing period (2024 and 2025), which may reflect the increasing uncertainty in China's iron ore market due to structural economic transitions, policy shifts, and global commodity market volatility. The MAPE values below 6% for both models indicate that the LSSVM framework, with or without AOA optimization, provides a reasonably accurate approximation of the underlying demand dynamics. However, the superior performance of the AOA-LSSVM model across all metrics confirms the value of integrating metaheuristic optimization into the forecasting pipeline.

The empirical results provide several important insights. First, the AOA-LSSVM model effectively captures the nonlinear relationships between iron ore demand and its multifaceted drivers. The inclusion of both domestic economic indicators (GDP, real estate investment, urbanization, industrial output) and international market factors (steel trade, iron ore price, shipping costs, exchange rates) enables the model to account for the complex interplay of forces shaping China's iron ore consumption. Second, the consistent improvement of the AOA-LSSVM over the standard LSSVM underscores the critical role of hyperparameter optimization in machine learning-based forecasting. The AOA's global search capability proves particularly valuable in navigating the non-convex parameter landscape of the LSSVM model. Third, the forecasting errors, while modest, suggest that further improvements may be achievable through the incorporation of additional predictors (e.g., policy variables, technological change indicators) or the use of ensemble methods that combine multiple forecasting models.

The practical implications of these findings are significant. For policymakers and industry planners, the AOA-LSSVM model offers a tool for generating more accurate demand projections, which can inform decisions regarding iron ore import strategies, and resource security planning. For mining companies and trading firms, improved demand forecasts can enhance procurement planning, inventory management, and risk mitigation strategies in the face of volatile global markets.

5. Conclusion

This study proposes a hybrid forecasting framework that integrates the Archimedes Optimization Algorithm (AOA) with Least Squares Support Vector Machine (LSSVM) to predict China's annual iron ore demand. The motivation for this work arises from the difficulty of adequately capturing the complex nonlinear relationships between iron ore demand and its multifaceted economic, industrial, and market drivers.

To construct the forecasting model, this study assembles a comprehensive dataset spanning 2014 to 2025, comprising ten explanatory variables that reflect both domestic economic conditions, including GDP, real estate investment, urbanisation rate, industrial output, and steel apparent consumption, international market factors, namely steel net exports, iron ore spot prices, the Baltic Dry Index, and the USD exchange rate. The dataset is partitioned into a training set (2014-2021) and a testing set (2022-2025) to evaluate out-of-sample forecasting performance. The AOA is employed to automatically search for the optimal hyperparameter pair (γ, σ) of the LSSVM model, with the fitness function defined as the minimisation of the root mean square error on the training set. The optimised model is then validated against the test set and benchmarked against the standard LSSVM model without parameter optimization.

The empirical results demonstrate that the proposed AOA-LSSVM model outperforms the standard LSSVM across all three evaluation metrics. Specifically, the AOA-LSSVM model reduces the Mean Absolute Error (MAE) by 570.53 (a 7.05% improvement), the Root Mean Square Error (RMSE) by 635.42 (a 7.47% improvement), and the Mean Absolute Percentage Error (MAPE) by 0.42 percentage points (a 7.08% relative improvement). These improvements, while modest in absolute magnitude, are consistent across all four testing years, confirming the robustness of the AOA-based parameter optimization approach. The enhanced performance is attributable to the AOA's ability to effectively navigate the non-convex parameter space and identify the global optimal parameter combination, thereby avoiding the suboptimal selections that characterise manual or grid-search approaches.

This study contributes to the growing body of literature on hybrid forecasting models by demonstrating the effectiveness of integrating meta-heuristic optimization with LSSVM for mineral resource demand forecasting. The AOA-LSSVM framework offers a computationally efficient and robust alternative to traditional approaches, particularly in contexts where sample sizes are limited and the underlying data-generating process is characterized by nonlinearities and structural breaks. From a practical standpoint, the proposed model provides policymakers and industry planners with a tool for generating more accurate demand projections, which can inform strategic decisions regarding iron ore import planning, and resource security. For mining companies and commodity trading firms, improved demand forecasts can enhance procurement planning, inventory management, and risk mitigation strategies in the face of volatile global markets. The main limitation of this study is the small sample size. The sample size of 12 annual observations limits the generalisability of the findings and constrains the complexity of models that can be reliably estimated, which should be addressed in the future study.

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