

RESEARCH ON THE GREEN INNOVATION EFFECT OF HIGH-TECH INDUSTRIAL AGGLOMERATION BASED ON WAVELET-QUANTUM CUCKOO OPTIMIZATION SUPPORT VECTOR MACHINE

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This study explores the technical advantages of Support Vector Machine (SVM) method and emphasizes the necessity of integrating intelligent optimization algorithms to enhance parameter optimization and overall model performance. The connotation and characteristics of wavelet transform are discussed, with particular focus on the role of wavelet denoising in processing evaluation data related to the green innovation effects of high-tech industrial agglomerations. Drawing on the principles of SVM regression and the cuckoo search algorithm, a Quantum Cuckoo (QC)-optimized SVM model is developed and applied to predict the green innovation effects of high-tech industrial agglomerations in China. Simulation experiments yield three key findings: First, the cuckoo-optimized SVM exhibits significantly superior performance in evaluating the green innovation effects of industrial agglomerations compared to the wavelet SVM and standard SVM. Second, the wavelet-cuckoo optimized SVM model outperforms the standard cuckoo-optimized SVM in assessing the green innovation effects of industrial agglomerations. Third, the performance of the quantum wavelet Principal Component Analysis (PCA) cuckoo SVM is influenced by the selection of the basis wavelet and the proportion of principal components. When Daubechies-3(DB3) is adopted as the basis wavelet and the principal component proportions are set to 97% and 96%, the model achieves more accurate results than the wavelet-cuckoo optimized SVM and the PCA-cuckoo optimized SVM. However, altering the basis wavelet or the principal component proportions leads to suboptimal simulation outcomes compared to those obtained with DB3 and principal component proportions of 97% and 96%.

Keywords: Quantum Cuckoo-Optimized Support Vector Machine, Wavelet Transform, Green Innovation, High-Tech Industrial Agglomerations

1. Introduction

High-tech industrial agglomeration is widely recognized for accelerating innovation development through economies of scale and knowledge-technology spillover effects, while also exerting a substantial impact on green development.

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Consequently, the measurement of its green innovation effects cannot be overlooked. Nevertheless, traditional methods for evaluating green innovation effects suffer from several limitations. For instance, the Analytic Hierarchy Process (AHP) and Expert Analysis Method are highly susceptible to subjective factors, whereas the Entropy Evaluation Method imposes strict requirements on data quality. In recent years, econometric analysis methods—such as panel data analysis and spatial econometric analysis—have been extensively applied in academic research. While these methods are well-suited for mechanism analysis, they lack integration with information technology approaches.

In recent years, wavelet transform [1], SVM [2], and QC algorithms [3] have demonstrated robust nonlinear modeling and global optimization capabilities, making them effective tools for processing non-stationary data and multi-scale information. Owing to their strengths in nonlinear modeling, feature extraction, and parameter optimization, these methods have gradually been introduced into interdisciplinary fields such as economic management and environmental governance, where they have exhibited notable adaptability and high-precision evaluation performance. This study leverages the technical advantages of these intelligent algorithms to construct a high-performance predictive model for green innovation effects.

A variety of approaches have been employed to measure green innovation. Xie et al. calculated the ratio of green technology patent applications and authorizations to firms' R&D investment to measure enterprise-level green innovation efficiency [4]. Zhang et al. utilized the Stochastic Frontier Analysis (SFA) model to evaluate technological progress and green innovation efficiency [5]. Zhang et al. applied Epsilon-based Measure (EBM) model and concluded that environmental regulations significantly promoted innovation efficiency [6]. Zhang Jifeng et al. [7] and Shen et al. [8] adopted the Super-Slack Based Measure Data Envelopment Analysis (Super-SBM DEA) model to measure green technology innovation efficiency. Fried et al. developed a three-stage DEA model that effectively minimizes environmental and stochastic interference in efficiency evaluations [9]. Luo et al. applied the Malmquist DEA method to panel data, revealing a consistent improvement in innovation levels [10]. Zeng et al. employed the Malmquist–Luenberger index [11]. In recent years, SVM has attracted considerable attention from scholars. However, the performance of SVM is highly dependent on parameter selection, and inappropriate parameter settings can severely restrict its modeling capabilities. To address this limitation, intelligent optimization algorithms have been introduced to improve parameter selection and thereby enhance overall model performance [12]. The Quantum Cuckoo Search (QCS) algorithm offers unique advantages in parameter optimization, including a small number of parameters, ease of implementation, strong global search ability, high robustness, and fast convergence—characteristics that have led to its

widespread adoption by scholars worldwide. Meanwhile, the development of quantum technology has exerted a significant influence on Artificial Intelligence (AI) algorithms. The QCS algorithm is derived from the integration of the traditional Cuckoo Search (CS) algorithm and quantum computing theory [13]. Considering the time-frequency localization characteristics of wavelet transform, the hybrid model formed by combining wavelet transform with SVM can expand the application boundaries of intelligent computing. This paper aims to investigate the green innovation effects of high-tech industrial agglomeration using a Wavelet Transform-QCS Optimized SVM model.

2. Method

2.1 Wavelet Transform

2.1.1 Definition of Wavelet Transform

The wavelet transform, developed in the 1980s by French scientists, is an emerging technology rooted in multiple analytical disciplines—including Fourier analysis and functional analysis—and possesses profound theoretical significance and broad application value.

Compared with the windowed Fourier transform, the wavelet transform compensates for its shortcomings. It retains the localization advantage of the windowed Fourier transform while addressing the issue of fixed windows.

Definition 1: For a function $\psi(t) \in L^2(\mathbb{R})$, where $L^2(\mathbb{R})$ denotes the space of square-integrable functions, let its Fourier transform be $\hat{\psi}(\omega)$ satisfies the following "admissibility condition" (Formula 1):

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \quad (1)$$

then $\psi(t)$ is referred to as a mother wavelet, also known as a fundamental wavelet [14].

2.1.2 Principle of Wavelet Denoising for Data on Green Innovation Effects of High-Tech Industrial Agglomeration

The evaluation of green innovation effects in high-tech industrial agglomeration constitutes a complex system, in which data signals are typically nonlinear and exhibit non-stationary characteristics.

Fig. 1 presents a schematic diagram of wavelet signal decomposition for processing data related to the green innovation effects of high-tech industrial agglomeration. The wavelet denoising process is conducted in accordance with the workflow illustrated in Fig. 1.

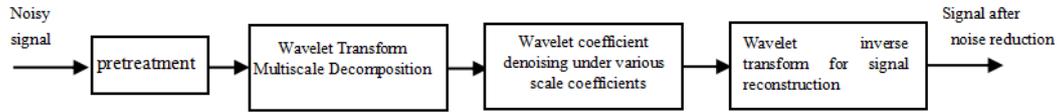


Fig. 1. Flow Chart of Wavelet Denoising Processing for Green Innovation

The initial noise-containing signal for evaluating the green innovation effects of high-tech industrial agglomeration is decomposed into different frequency components layer by layer using wavelet transform. Compared with the original signal, the decomposed signal exhibits smoother and more stable frequency components, which provide significant advantages for subsequent data analysis [15].

2.2 Regression Principle of SVM

2.2.1 Concept of SVM

The theoretical foundations of SVM are the VC dimension theory and the principle of structural risk minimization. This method aims to find the optimal solution by balancing model complexity and learning ability.

Definition1: Given a set of samples $x_1, x_2, x_3, \dots, x_n$ with corresponding labels y_i to show, (x_i, y_i) , where $x_i \in R_d$ and $y_i \in \{+1, -1\}$, $i=1, \dots, n$, the expression of a hyperplane is $w \cdot x + b = 0$. To accurately classify different samples and maximize the sample margin, the optimization problem is formulated as follows (Formula 2):

$$y_i[(w \cdot x_i) + b] - 1 \geq 0 \tag{2}$$

$i=1, \dots, n$, while minimizing the objective function $\phi(w) = \frac{1}{2} \|w\|^2$. The training samples that lie on the margin boundaries at this point are referred to as support vectors.

2.2.2 Principle of SVM Regression

As shown in Fig. 2, let n denote the number of indicators and m denote the number of training points.

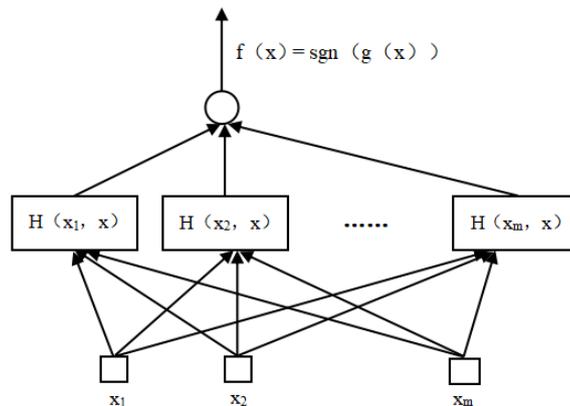


Fig. 2. Schematic diagram of the optimal classification surface SVM under linear separability

The set of training points is denoted as $D = \{(x_1, y_1)(x_2, y_2) \cdots (x_m, y_m)\}$. For samples that are linearly inseparable in low-dimensional space, SVM maps them to a high-dimensional space through kernel functions to achieve nonlinear separability, then constructs the optimal hyperplane and decision function to determine the output y corresponding to a new input x .

The principle of SVM for nonlinear regression can be summarized as follows:

Given a training set $D = \{(x_i, y_i) | x_i \in R^d, y_i \in R\}, i = 1, 2, \dots, l$, SVM maps the original variable x to a high-dimensional space $\varphi(\cdot)$, calculate the weight vector ω and bias term b in this high-dimensional space, and send $f(x) = \omega^T \varphi(x) + b$ to minimize structural risk, is $\min \frac{1}{2} \omega^T \omega$.

To address the problem of nonlinear regression, non-negative slack variables ξ_i and a penalty factor C are introduced. The optimization problem is then formulated as follows (Formulas 3 and 4):

$$\min \left(\frac{1}{2} \omega^T \omega + C \sum_{i=1}^l (\xi_i + \xi_i^*) \right) \tag{3}$$

$$\begin{cases} y - \omega^T \varphi(x_i) - b \leq \varepsilon + \xi_i \\ \omega^T \varphi(x_i) + b - y \geq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{4}$$

where ξ_i and ξ_i^* as upper and lower boundaries for controlling output constraints.

The optimization problem of the convex quadratic function is solved using Lagrange multipliers (Formula 5):

$$\begin{aligned} L = & \frac{1}{2} \omega^T \omega + C \sum_{i=1}^l (\xi_i + \xi_i^*) - \sum_{i=1}^l \alpha_i (\varepsilon + \xi_i - y + (\omega^T \varphi(x_i)) + b) \\ & - \sum_{i=1}^l \alpha_i (\varepsilon + \xi_i + y - (\omega^T \varphi(x_i)) - b) - \sum_{i=1}^l (\eta_i \xi_i + \eta_i^* \xi_i^*) \end{aligned} \tag{5}$$

where α_i is a Lagrange multiplier. After excluding zero multipliers and retaining non-zero ones, the non-zero Lagrange multipliers are denoted as α_i^0, α_i^0 , which correspond to the support vectors obtained from training [16-17].

To map the input data to a high-dimensional space, kernel functions are employed. By selecting an appropriate kernel function $k(x, y) = \varphi(x) \cdot \varphi(y)$, the inner product operation in the high-dimensional space is simplified. The SVM regression function is defined as follows (Formula 6):

$$f(x) = \sum_{i=1}^l (\alpha_i - \alpha_i^*) k(x_i, x) + b \quad (6)$$

Typically, the Radial Basis Function (RBF) is widely used as the kernel function (Formula 7):

$$k(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) = \exp(-\gamma\|x - y\|^2) \quad (7)$$

where $\gamma = \frac{1}{2\sigma^2}$ is a kernel function parameter.

σ is a kernel function parameter. The smaller the kernel function parameter, the better the fit. If the kernel function parameter is too small, it may reduce the generalization ability [18].

Different kernel functions serve distinct functions in SVM, making the selection of the kernel parameter γ a critical consideration in practical applications. The academic community generally prefers the RBF kernel due to its excellent adaptability. Its performance varies with the parameter γ : when γ is large, the RBF kernel behaves similarly to the polynomial kernel, while a smaller γ causes it to approximate the linear kernel. Therefore, the RBF kernel is selected for this study.

With respect to other parameters, the penalty factor for samples and the radial action range of the kernel are determined by C and σ , respectively. The selection of SVM parameters has a significant impact on training results, yet no universally accepted methodology exists for parameter optimization. With the development of artificial intelligence, integrating AI-based optimization techniques into SVM parameter tuning has emerged as a promising research direction. In this study, the strong global search capability of the QCS algorithm is employed to optimize SVM parameters, followed by comparative analyses.

Additionally, considering the data requirements for predicting the green innovation effects of high-tech industrial agglomerations, wavelet transform technology is used for data preprocessing to reduce noise interference and improve evaluation accuracy.

2.3 QCS-Optimized SVM

2.3.1 Cuckoo Search (CS) Algorithm

The CS algorithm was first proposed by the renowned British scholar Yang and his collaborators. This heuristic optimization technique is inspired by the brood parasitism behavior of cuckoos and their Lévy flight search patterns. The algorithm is based on three core assumptions: First, each cuckoo lays exactly one egg at a time and selects a random nest from the population to place it. Second, nests containing the highest-quality eggs (i.e., those corresponding to the best solutions) are retained to form the next generation, ensuring evolutionary progress. Third, host birds have a probability P_a of detecting foreign eggs; if detected, the host may either discard

the egg or abandon the nest, leading to the establishment of a new nest at a random location. Based on these principles, the position update formula of the CS algorithm is mathematically defined as follows (Formula 8):

$$X_i^{t+1} = X_i^t + 0.01L(s, \lambda) \tag{8}$$

where, $0.01L(s, \lambda) = \frac{\lambda \Gamma(\lambda) \sin(\frac{\pi\lambda}{2})}{\pi} \times \frac{1}{s+\lambda}$, $s > 0$. In this formula, s denotes the step size, with an initial step size of $s_0 = 0.01$; λ represents an exponent that defines the probability distribution function, $1 < \lambda \leq 3$; $L(s, \lambda)$ denotes the random search path. The random solution at random times is denoted as X_i^t [19-20]; and X_i^{t+1} represents the result calculated according to the step size in the next step.

2.3.2 Fundamental Principles of the Basic Cuckoo Search Algorithm

The CS algorithm is a novel heuristic optimization method whose core principle is to determine the position of new nests based on Lévy flights. For example, the CS algorithm calculates a new solution x_i according to the Lévy flight trajectory, as described by Formula (9):

$$x_i^{t+1} = x_i^t + \alpha \oplus \text{Lévy}(\lambda) \tag{9}$$

$$\text{Lévy}(\lambda) \sim u = t^{-\lambda} \quad (1 < \lambda \leq 3)$$

It is important to clarify that in Formula (9), "Lévy flight" refers to a composite flight pattern consisting of alternating "short flights" and "long flights". Specifically, short flights denote brief, localized movements by the cuckoo, enabling fine-grained exploration of the solution space; long flights represent rare, long-range jumps that allow the cuckoo to escape local optima and explore distant regions of the search space [21].

2.3.3 QCS Algorithm and Its Application in SVM Optimization

The principle of the QCS algorithm and its application in SVM optimization are illustrated in Fig. 3 below.

The schematic diagram of the QCS algorithm combined with the optimized SVM model primarily illustrates the following characteristics:

First, wavelet transform is integrated with PCA to evaluate their synergistic effect on dimensionality reduction. The DB3 wavelet is selected as the basis function due to its balanced performance in smoothness and compact support.

Second, the Cuckoo Search optimization method adopts a global search strategy based on Lévy flights to implement a dynamic parameter-tuning mechanism. This strategy enhances the balance between exploration and exploitation of the algorithm and accelerates its convergence toward optimal solutions [22].

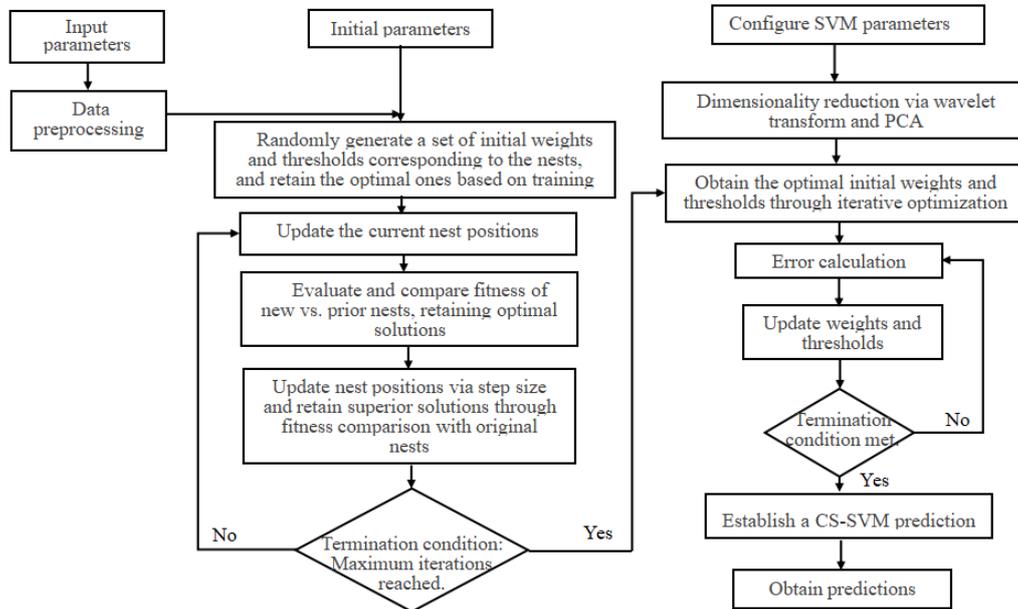


Fig. 3. Schematic Diagram of QCS Algorithm and SVM Optimization

Third, quantum computing methodologies are introduced by integrating quantum computational principles to construct a QCS-SVM model. During the analytical process, this model is further combined with wavelet transform and PCA to achieve dimensionality reduction. Additionally, the percentage of retained principal components is dynamically adjusted to examine the influence of different component ratios on simulation results [23].

3. Simulation experiments

3.1 Data Sources

This study takes 30 provinces and municipalities in China (including Shanghai, Yunnan, Inner Mongolia, Beijing, Jilin, Sichuan, Tianjin, Ningxia, Anhui, Shandong, Shanxi, Guangdong, Guangxi, Hainan, Jiangxi, Hebei, Henan, Zhejiang, Hunan, Hubei, Gansu, Fujian, Guizhou, Chongqing, Shaanxi, Qinghai, Heilongjiang, and Xinjiang) from 2006 to 2022 as research samples to evaluate the green innovation performance of high-tech industrial agglomeration. (Tibet is excluded due to incomplete data availability.) Sample data are sourced from the China Statistical Yearbook, Provincial Statistical Yearbooks, China City Statistical Yearbook, the EPS database, and national and local socioeconomic statistical bulletins. Following the principles of scientific rigor, comprehensiveness, and comparability, an indicator system comprising 18 features is constructed, including: industrial added value (X1), number of authorized green patents (X2), industrial "three wastes" (X3), number of patent applications in high-tech industries (X4), per

capita water consumption (X5), year-end employed population (X6), built-up area (X7), sales revenue of new products (X8), waste gas treatment capacity (X9), soot and dust emissions (S1), number of employees in electronic and communication equipment manufacturing (S2), number of employees in medical equipment and instrument manufacturing (S3), number of employees in pharmaceutical manufacturing (S4), number of urban employees in information transmission, software, and IT services (S5), number of employees in high-tech industries (S6), expenditure on new product development (S7), internal expenditure on R&D (S8), and number of R&D personnel (S9). Table 1 presents the standardized average values of the selected indicators for the research samples during 2021–2022.

Table 1

Data on the 2021-2022 Evaluation Index System for Green Innovation in China's High-tech Industry Clusters

	X1	X2	X3	X4	X5	X6	X7	X8	X9	S1	S2	S3	S4	S5	S6	S7	S8	S9
SH	0.2	0.3	0.2	0.1	0.9	0.2	0.2	0.7	0.9	0.0	0.1	0.2	0.3	0.5	0.1	0.1	0.2	0.1
YN	0.1	0.1	0.5	0.0	0.8	0.4	0.2	0.7	0.8	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0
NM	0.2	0.1	0.8	0.0	0.8	0.2	0.2	0.7	1.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
BJ	0.1	0.4	0.0	0.1	0.8	0.2	0.0	0.6	0.9	0.0	0.0	0.2	0.4	1.0	0.1	0.2	0.1	0.1
JL	0.1	0.0	0.2	0.0	1.0	0.2	0.2	0.5	0.9	0.2	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0
SC	0.3	0.2	0.6	0.1	0.8	0.7	0.5	0.6	0.9	0.3	0.1	0.1	0.5	0.3	0.2	0.1	0.1	0.1
TJ	0.1	0.1	0.1	0.0	0.9	0.1	0.2	0.5	0.8	0.0	0.0	0.1	0.2	0.1	0.0	0.0	0.0	0.0
NX	0.0	0.0	0.2	0.0	1.0	0.0	0.1	0.5	0.8	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
AH	0.3	0.2	0.5	0.1	0.8	0.5	0.4	0.8	0.8	0.0	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.1
SD	0.6	0.5	0.8	0.1	0.9	0.8	0.9	0.9	1.0	0.2	0.1	0.3	1.0	0.2	0.1	0.1	0.2	0.2
SX	0.2	0.1	1.0	0.0	0.0	0.2	0.2	0.9	1.0	1.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
GD	1.0	0.9	0.8	1.0	0.9	1.0	1.0	0.8	0.9	0.0	1.0	1.0	0.7	0.8	1.0	1.0	1.0	1.0
GX	0.1	0.1	0.3	0.0	0.9	0.4	0.3	0.8	0.9	0.1	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0
HS	1.0	1.0	0.7	0.4	0.9	0.2	0.2	0.8	0.9	0.0	0.4	1.0	1.0	0.3	0.6	0.4	0.6	0.5
JX	0.2	0.1	0.3	0.1	0.8	0.7	0.7	0.8	1.0	0.0	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.1
HB	0.3	0.2	0.8	0.0	0.8	0.3	0.3	0.8	0.9	0.6	0.0	0.1	0.4	0.1	0.1	0.0	0.0	0.0
HN	0.4	0.2	0.7	0.1	0.9	0.5	0.3	0.8	0.9	0.1	0.1	0.2	0.5	0.2	0.2	0.0	0.1	0.1
ZJ	0.6	0.5	0.4	0.2	0.9	0.7	0.5	0.8	0.8	0.6	0.2	0.7	0.7	0.3	0.3	0.2	0.3	0.3
HN	0.0	0.0	0.0	0.0	0.8	0.6	0.5	1.0	1.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
HB	0.4	0.3	0.5	0.1	0.9	0.1	0.1	0.5	0.8	0.0	0.1	0.1	0.5	0.2	0.1	0.1	0.2	0.1
HN	0.3	0.1	0.3	0.1	0.9	0.5	0.4	0.4	0.6	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.1
GS	0.1	0.0	0.2	0.0	0.8	0.5	0.3	0.8	0.8	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
FJ	0.4	0.2	0.4	0.1	0.8	0.2	0.1	0.8	0.9	0.0	0.1	0.1	0.2	0.1	0.1	0.1	0.2	0.2
GZ	0.1	0.0	0.4	0.0	0.8	0.3	0.3	0.6	0.7	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
LN	0.2	0.1	0.7	0.0	0.8	0.0	0.0	0.5	0.8	0.0	0.0	0.1	0.2	0.1	0.0	0.0	0.0	0.0
CQ	0.2	0.1	0.2	0.0	1.0	0.3	0.2	0.3	0.0	0.0	0.1	0.1	0.2	0.1	0.1	0.0	0.1	0.1
sx2	0.3	0.1	0.4	0.0	0.8	0.3	0.4	0.7	0.8	0.2	0.0	0.1	0.2	0.1	0.1	0.1	0.1	0.1
QH	0.0	0.0	0.3	0.0	0.9	0.2	0.3	0.5	0.8	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
HLJ	0.1	0.1	0.3	0.0	0.9	0.3	0.2	0.4	0.7	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0
XJ	0.1	0.0	0.3	0.0	1.0	0.0	0.0	0.6	0.7	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

3.2 Comparison of Denoising Performance Using Different Wavelet Bases

To evaluate the denoising performance of different wavelet bases on signals, experiments were conducted in MATLAB. Several wavelet families were tested, including Haar and Daubechies (db). In this study, the original signal is denoted as

S, the denoised signal as DS, and the residual as S-DS. Figures 4 and 5 present the denoising results for selected wavelet functions. The DB wavelets exhibited superior performance in feature extraction and signal smoothing; thus, DB wavelets were selected for subsequent analysis.

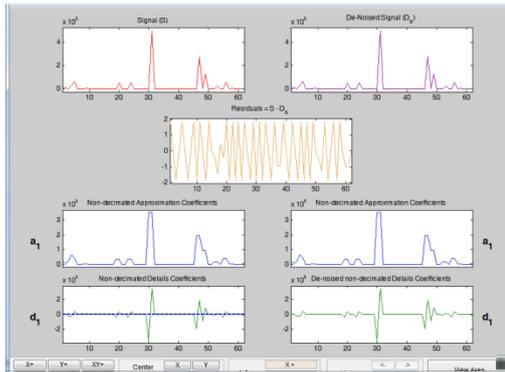


Fig. 4. Wavelet basis function DB denoising

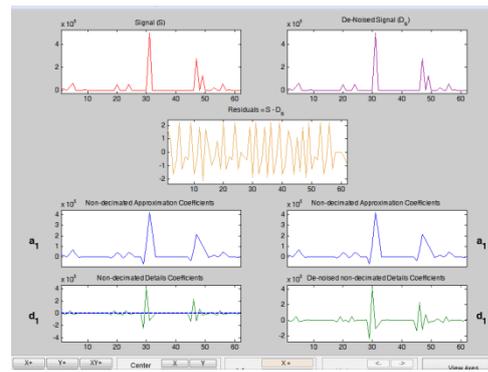


Fig. 5. Wavelet basis function SYM denoising

3.3 Experimental Simulation of Wavelet-PCA QC-Optimized SVM for Green Innovation Effects of High-Tech Industrial Agglomeration

3.3.1 Wavelet-PCA Cuckoo-Optimized SVM Experiment

The experimental results of the Wavelet-PCA Cuckoo-Optimized SVM are presented in Table 2.

Table 2

Wavelet-PCA Cuckoo-Optimized SVM Experiment

Method	R ²	MSE	
SVM	0.7839	0.0194	
Wavelet-SVM	0.7834	0.0195	
Cuckoo-Optimized SVM	0.8721	0.0115	
Wavelet-Cuckoo-Optimized SVM	0.8794	0.0108	
PCA Cuckoo Optimization	0.8794	0.0108	
Quantum Wavelet PCA Cuckoo Optimization	0.8818	0.0110	DB3,97%PCA
	0.8950	0.0094	DB3,96%PCA
	0.7754	0.0205	DB3,98%PCA
	0.7290	0.0234	DB3,95%PCA
	0.7419	0.0255	DB4,97%PCA
	0.8582	0.0133	DB4,95%PCA
	0.8252	0.0170	DB5,97%PCA
	0.8495	0.0144	DB5,95%PCA

3.3.2 Simulation Diagrams of Wavelet-PCA QC-Optimized SVM

(1) Simulation Results of Cuckoo-Optimized SVM and Wavelet-Cuckoo-Optimized SVM Experiments (Figs. 6-7):

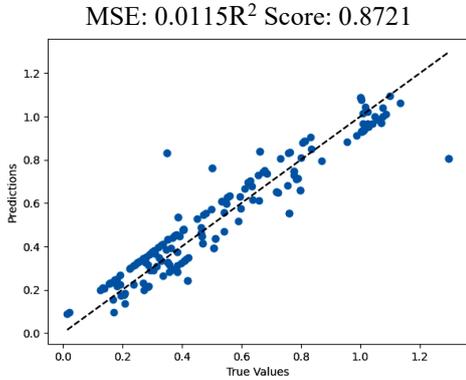


Fig. 6. Simulation Results of Cuckoo-Optimized SVM

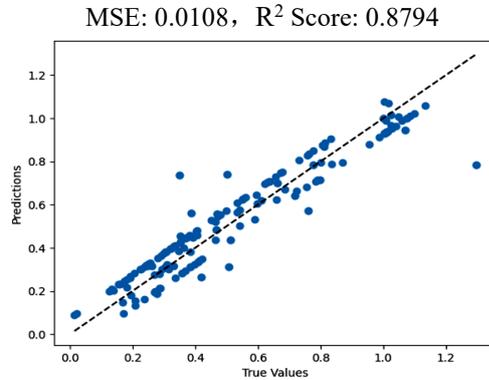
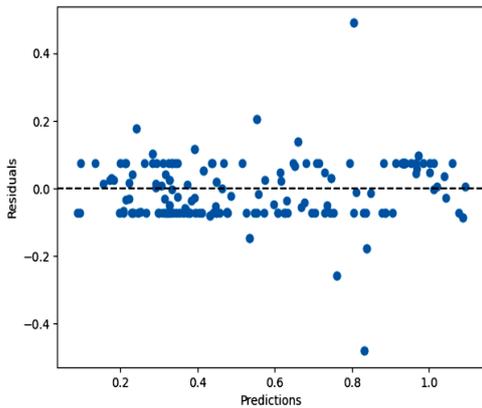


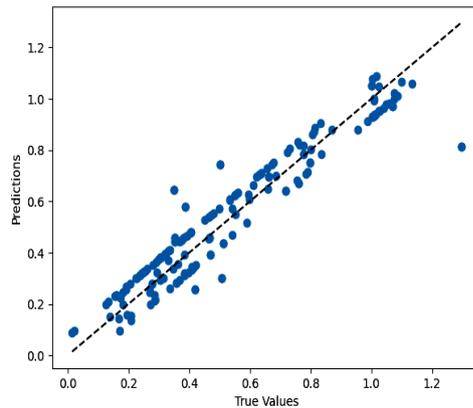
Fig. 7. Wavelet-Cuckoo-SVM Simulation Results

(2) Simulation Results of Wavelet-PCA QC-Optimized SVM

The following figures (Figs. 8-9) present the simulation diagrams of the Cuckoo-Optimized SVM and Wavelet-PCA QC-Optimized SVM experiments.



MSE:0.0110 R^2 : 0.8818
Fig. 8. PCA-Cuckoo-SVM Simulation Results



MSE: 0.0094 R^2 Score: 0.8950
Fig. 9. Wavelet-PCA QC Optimized SVM Simulation Results

3.3.3 Evaluation Results of Green Innovation in China's High-Tech Industrial Agglomeration

Fig. 10 displays the average green innovation values of high-tech industrial agglomeration in 30 Chinese provinces and municipalities (Shanghai, Yunnan, Inner Mongolia, Beijing, Jilin, Sichuan, Tianjin, Ningxia, Anhui, Shandong, Shanxi, Guangdong, Guangxi, Hainan, Jiangxi, Hebei, Henan, Zhejiang, Hunan, Hubei, G

ansu, Fujian, Guizhou, Chongqing, Shaanxi, Qinghai, Heilongjiang, Xinjiang) during 2021–2022.

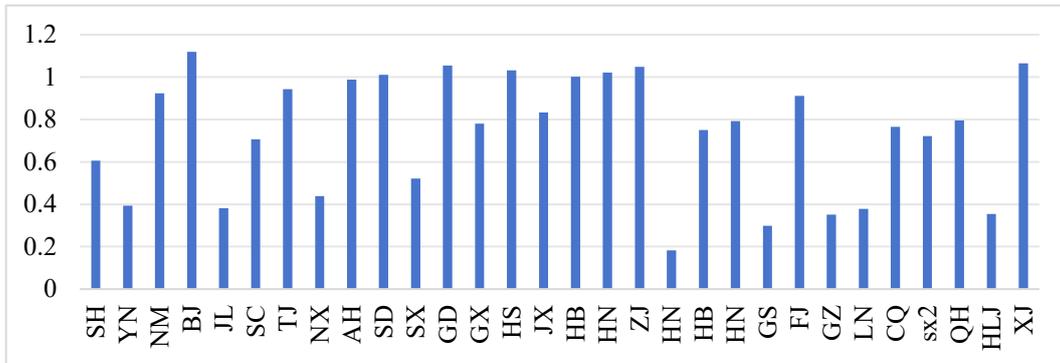


Fig. 10. The average value of Green Innovation in High-Tech Industrial Agglomeration in China (2021–2022)

An analysis of the average green innovation values of high-tech industrial agglomeration in 30 Chinese provinces and municipalities from 2021 to 2022 reveals the following: The top 10 regions in terms of green innovation are Beijing (BJ, 1.119), Xinjiang (XJ, 1.065), Guangdong (GD, 1.055), Zhejiang (ZJ, 1.048), Hainan (HS, 1.032), Henan (HN, 1.021), Shandong (SD, 1.011), Hebei (HB, 1.002), Anhui (AH, 0.988), and Tianjin (TJ, 0.943). The bottom 8 regions are Ningxia (NX, 0.439), Yunnan (YN, 0.394), Jilin (JL, 0.381), Liaoning (LN, 0.379), Heilongjiang (HLJ, 0.354), Guizhou (GZ, 0.351), Gansu (GS, 0.299), and Hunan (HN, 0.183). The remaining regions exhibit medium-level green innovation, with values of 0.923 (Inner Mongolia, NM), 0.912 (Fujian, FJ), 0.833 (Jiangxi, JX), 0.795 (Qinghai, QH), 0.792 (Hainan, HN), 0.781 (Guangxi, GX), 0.766 (Chongqing, CQ), 0.751 (Hubei, HB), 0.721 (Shaanxi, sx2), 0.707 (Sichuan, SC), 0.605 (Shanghai, SH), and 0.521 (Shanxi, SX).

4. Result

- (1) In the evaluation of green innovation effects of industrial agglomeration, the simulation results of the Cuckoo-Optimized SVM are significantly superior to those of the Wavelet-SVM and standard SVM. The R^2 values of the Cuckoo-Optimized SVM, Wavelet-SVM, and standard SVM are 0.8721, 0.7834, and 0.7839, respectively, with corresponding MSE values of 0.0115, 0.0195, and 0.0194.
- (2) The Wavelet-Cuckoo-Optimized SVM outperforms the standard Cuckoo-Optimized SVM in evaluating the green innovation effects of industrial agglomeration. Additionally, the Wavelet-Cuckoo-Optimized SVM and

PCA-Cuckoo-Optimized SVM yield identical evaluation results, with an R^2 value of 0.8794 and an MSE value of 0.0108.

- (3) The simulation results of the Quantum Wavelet-PCA Cuckoo-Optimized SVM in evaluating the green innovation effects of industrial agglomeration are influenced by the selection of wavelet basis and the proportion of principal components, with specific findings as follows:

First, when the DB3 wavelet basis is used with 97% and 96% principal components, the Quantum Wavelet-PCA Cuckoo-Optimized SVM achieves higher accuracy than both the Wavelet-Cuckoo-Optimized SVM and PCA-Cuckoo-Optimized SVM, with R^2 values of 0.8818 and 0.8950, and MSE values of 0.0110 and 0.0094, respectively (see Fig. 9).

Second, when the DB3 wavelet basis was used with 98% and 95% principal components, the performance of the Quantum Wavelet-PCA Cuckoo-optimized SVM was inferior to that of the Wavelet-Cuckoo-optimized SVM and PCA-Cuckoo-optimized SVM, with R^2 values decreasing to 0.7754 and 0.7290 and MSE values increasing to 0.0205 and 0.0234, respectively.

Third, when the DB4 wavelet basis is used with 97% and 95% principal components, the Quantum Wavelet-PCA Cuckoo-Optimized SVM again underperforms compared to the Wavelet-Cuckoo-Optimized SVM and PCA-Cuckoo-Optimized SVM, with R^2 values of 0.7419 and 0.8582, and MSE values of 0.0255 and 0.0133, respectively.

Finally, when the DB5 wavelet basis is used with 97% and 95% principal components, the Quantum Wavelet-PCA Cuckoo-Optimized SVM remains less accurate than the Wavelet-Cuckoo-Optimized SVM and PCA-Cuckoo-Optimized SVM, with R^2 values of 0.8252 and 0.8495, and MSE values of 0.0170 and 0.0144, respectively.

5. Conclusions

This study integrates the Cuckoo Search algorithm with the SVM method to leverage the optimization capability of the former for refining SVM parameters. Furthermore, by incorporating quantum computing and wavelet transform, a Wavelet-QCS Optimized SVM model is constructed and applied to predict the green innovation effects of high-tech industrial agglomerations in China. The results indicate that the Wavelet-Cuckoo-Optimized SVM outperforms the standard Cuckoo-Optimized SVM. Additionally, the simulation results of the Quantum Wavelet-PCA Cuckoo-Optimized SVM in evaluating the green innovation effects of industrial agglomeration are influenced by the selection of wavelet basis functions and the proportion of principal components. Future research could focus on conducting a convergence analysis of the Quantum Wavelet-PCA Cuckoo-Optimized SVM algorithm.

This paper proposes an evaluation method for green innovation in high-tech industrial agglomeration, integrating wavelet transform, PCA dimensionality reduction, and a quantum-inspired cuckoo optimization algorithm for SVM. The innovations of this study are reflected in three aspects:

First, a quantum-inspired optimization algorithm is employed to optimize SVM parameters, effectively avoiding local optima.

By replacing the traditional manual grid search method, the quantum entanglement-based optimization algorithm efficiently explores the global parameter space through simulated quantum randomness, identifying the optimal C and gamma parameters for SVM, thereby significantly enhancing model performance.

Second, wavelet transform ensures model robustness.

Through multi-scale feature extraction via wavelet analysis, the method thoroughly captures deep-level information from the raw data on green innovation in high-tech industrial agglomeration. Wavelet basis functions are applied to construct feature vectors from wavelet coefficients, addressing potential anomalies in wavelet transforms and ensuring robustness. Moreover, the adaptive nature of wavelet transform accommodates samples of varying lengths, automatically extracting multi-resolution features, which eliminates the tediousness and subjectivity associated with manual feature design.

Third, PCA enables intelligent dimensionality reduction. By preserving 95%, 97%, and 98% of feature variance, PCA significantly reduces computational complexity and effectively mitigates the "curse of dimensionality".

The integrated evaluation approach-combining wavelet transform, PCA, and quantum-inspired cuckoo-optimized SVM-achieves automated integration of feature engineering, parameter optimization, and model training, demonstrating strong robustness and adaptability. This method holds considerable potential for further development and application in related fields.

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REFERENCES

- [1] *Wils M, Sharma M, Moonen M.* Per-Wavelet Equalization for Discrete Wavelet Transform Based Multi-Carrier Modulation Systems. *IEEE Open Journal of Signal Processing*, vol.4, 2023, pp. 52-60.
- [2] *Ravikumar S, Jeyalakshmi S, Sekar S, et al.* An efficient intelligent task management in autonomous vehicles using AIOT and optimal kernel adaptive SVM, *Engineering Applications of Artificial Intelligence*, vol.126, 2023, pp.106832.

- [3] *Alkhateeb F, Abed-Alguni B H, Al-Rousan M H*, Discrete hybrid cuckoo search and simulated annealing algorithm for solving the jobshop scheduling problem, *The Journal Supercomputing*, vol.78, no. 4, 2022, pp. 4799-4826.
- [4] *Xie Xianjun, Yu Junli, Ding Sheng, et al.* The Impact and Mechanism of Interest Rate Marketization on the Quality and Efficiency of Enterprise Green Technology Innovation. *Science and Technology Management Research*, vol.44, no. 6, 2024, pp.206-213.
- [5] *Zhang Q, Yan F H, Li K, et al.* Impact of market misallocations on green TFP: evidence from countries along the Belt and Road. *Environmental Science and Pollution Research*, vol. 26, no. 34,2019, pp.35034-35048.
- [6] *Zhang J X, Ouyang Y, Ballesteros-Perez P, et al.* Understanding the impact of environmental regulations on green technology innovation efficiency in the construction industry. *Sustainable Cities and Society*, vol.65, 2021, pp. 1-12.
- [7] *Zhang Jifeng, Wang Hongrui, Sun Jun.* Influence of Two-way FDI Coordination on Green Technology Innovation Efficiency: Based on Mediation Effect of Yangtze River Delta Market Integration. *Science and Technology Management Research*, vol.43, no.9, 2023, pp. 197-205.
- [8] *Shen T, Li D, Jin Y, et al.* Impact of environmental regulation on efficiency of green innovation in China. *Atmosphere*, vol.13, no.5, 2022, pp.767-775.
- [9] *Fried H O, Lovell C A K, Schmidt S S, et al.* Accounting for environmental effects and statistical noise in data envelopment analysis. *Journal of Productivity Analysis*, vol.17,2022, pp.157-174.
- [10] *Luo Q L, Miao C L, Sun L Y, et al.* Efficiency evaluation of green technology innovation of China's strategic emerging industries: An empirical analysis based on Malmquist-data envelopment analysis index. *Journal of Cleaner Production*, vol. 238, 2019, pp.117782.
- [11] *Zeng J Y, Škare M, Lafont J.* The co-integration identification of green innovation efficiency in Yangtze River Delta region. *Journal of Business Research*, vol. 134, no.5, 2021, pp.252-262.
- [12] *Chandra M A, Bedi S S.* Survey on SVM and their application in image classification. *International Journal of Information Technology*, vol.13, 2021, pp. 1-11.
- [13] *Yin Zhendong, Wang Li, Zhang Yaojia, Gao Yang.* Parameter identification of DC arc models using chaotic quantum cuckoo search *Journal, Applied Soft Computing*.vol.108, 2021, pp.107451.
- [14] *Zou W, Gao H, Yang W, Liu T.* Wave-Mamba: Wavelet statespacemodelforultra-high-definitionlow-lightimageenhancement, *Proceedings of the 32nd ACM International Conferenceo Multimedia*. New York, USA, 2024, pp. 1534-154.
- [15] *LIU Chong, MA Lixiu, PAN Jinfeng, et al.* PD signal denoising based on VMD and improved wavelet threshold. *Modern electronics technique*, vol. 44, no. 21, 2021, pp.45-50.
- [16] *Sun G, Rong X, Zhang A, et al.* Multi-scale Mahalanobis kernel-based support vector machine for classification of high-resolution remote sensing images, *Cognitive Computation*, vol.3,2021, pp.787-794.
- [17] *Han F.* Feature recognition of spoken Japanese input based on support vector machine, *Journal of Intelligent & Fuzzy Systems*, vol.40,2021, pp.2181-2192.
- [18] *Jeong K, Choi S.* Takagi-Sugeno Fuzzy observer-based magnetorheological damper fault diagnosis using a support vector machine, *IEEE Transactions on Control Systems Technology*, vol. 30, no. 4,2022, pp.1723-1735.
- [19] *Dao T P, Huang S C, Thang P T.* Hybnd Taguchi-cuckoo search algorithm for optimization of a compliant focus positioning platform. *Applied Soft Computing*, vol.57, 2017, pp.526 - 538.
- [20] *Mosharraf SIM, Adnan MA.* Improving lookup and query execution performance in distributed big data systems using cuckoo filter. *Journal of Big Data*, vol.9, no.1, 2022, pp.12.

- [21] *Zhao YK, Dai WC, Wang SR, Xi L, Wang SQ, Zhang F.* A review of cuckoo filters for privacy protection and their applications. *Electronics*, vol.12, no.13, 2023, pp.2809.
- [22] *Gao S Z, Gao Y, Zhang Y, et al.* Adaptive cuckoo algorithm with multiple search strategies, *Applied Soft Computing*, vol.106,2021, pp.107181.
- [23] *Zhu Haihong, Luo Ning, Li Xiaoping.* A quantum-inspired cuckoo co-evolutionary algorithm for no-wait flow shop scheduling. *IET Collaborative Intelligent Manufacturing*, vol.3, no.2, 2021, pp.105-118.