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Using Improved SPA and ICS-LSSVM for Sustainability Assessment of PV Industry along the Belt and Road

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Abstract: Scientific and timely sustainability evaluation of the photovoltaic industry along the Belt and Road is of great significance. In this paper, a novel hybrid evaluation model is proposed for accurate and real-time assessment that integrates modified set pair analysis with least squares support vector machine that combines improved cuckoo search algorithm. First, the indicator system is set from five principles, namely economy, politics, society, ecological environment and resources. Then, the traditional approach is established through modifying set pair analysis on the basis of variable fuzzy set coupling evaluation theory. A modern intelligent assessment model is designed that integrates improved cuckoo search algorithm and least squares support vector machine where the concept of random weight is introduced in improved cuckoo search algorithm. In the case analysis, the relative errors calculated by the proposed model all fluctuate in the range of $[-3\%, 3\%]$, indicating that it has the strongest fitting and learning ability. The empirical analysis verifies the scientificity and precision of the method and points out influencing factors. It provides a new idea for rapid and effective assessment of PV industry along the Belt and Road, as well as assistance for the sustainable development of this industry. This paper innovatively proposes the sustainability evaluation index system and evaluation model for the photovoltaic industry in countries along the Belt and Road, thus contributing to the promotion of sustainable development of the photovoltaic industry in countries along the Belt and Road.

Keywords: the Belt and Road; photovoltaic industry; sustainability evaluation; modified set pair analysis; improved cuckoo search algorithm; least squares support vector machine



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1. Introduction

With the increasing attention paid to global warming all over the world, clean and renewable energy, such as photovoltaic (PV) energy, has become of great importance [1]. The development of the PV industry demands unity and cooperation of all countries. The initiative known as “the Belt and Road” is one of the momentous links that cohere the countries along the road to promote the growth of the PV industry [2]. In the past seven years, this proposal has facilitated close energy cooperation, especially in the field of renewable energy such as PV [3]. However, uneven comprehensive national strength and resources bring about significant differences in the sustainable development of the PV industry in these countries. Some countries are faced with many problems that seriously affect the development and exploitation of solar energy resources. Hence, the sustainable growth of the PV industry has become a hot issue in current research [4]. This study conducts a sustainable development evaluation of the PV industry in the countries along the Belt and Road so as to provide a reference for PV escalation.

While various studies have considered sustainability evaluation, few studies have focused on the PV industry along the Belt and Road. Considering the similarities between the PV industry and other fields in sustainability assessment such as influential factors,

it is of great necessity to study the existing research [5]. Reference [6] established a small hydropower sustainability estimation index system for countries along the Belt and Road. Analytic hierarchy process (AHP) combined with fuzzy comprehensive evaluation model was employed to realize the evaluation. Reference [7] accomplished the site selection from the perspective of sustainability assessment. Although this study mentioned PV power station evaluation, it was focused on the micro level of the project and unconcerned with the whole PV industry. The core issue of sustainable development is the coordinated growth of economy, society and environment, according to [8]. This study followed the concept of the Chinese sustainable development index system (CSDIS) to form the indicator system. Natural discontinuity classification, exploratory spatial data analysis and geographic detector analysis were utilized to explore urban sustainability and coordination degree. Reference [9] studied the sustainability of private internal combustion vehicles replaced with shared electric vehicles. Despite the lack of research on sustainable estimation aiming at the PV industry, these studies have a certain reference value for the establishment of an indicator system in this paper.

The existing evaluation approaches are of great significance to the sustainable development assessment of PV industries and are mainly divided into traditional estimation methods and modern intelligent algorithms [10]. Conventional evaluation models incorporate subjective and objective modes [11]. For instance, expert assessment, fuzzy analytic hierarchy process and network analytic hierarchy process are employed for subjective determination, while entropy weight method, principal component analysis, grey correlation analysis, matter-element extension model and set pair analysis (SPA) are all used for objective estimation [12]. Additionally, intelligent algorithms chiefly comprise artificial neural network (ANN), support vector machine (SVM), least squares support vector machine (LSSVM), etc. [13]. Considering the mature theory and accurate calculation of traditional models [14], as well as quick data processing of intelligent techniques [15], this paper integrates these two methods for sustainability evaluation of the PV industry in the countries along the Belt and Road.

First of all, the entropy weight method is used to determine the index weight so as to quantify the estimation and reduce the deviation caused by human factors [16]. SPA is able to describe the internal correlation via connection degree [17]. However, the variable fuzzy set method (VFSM) can illustrate the dynamic of clusters in detail [18]. In line with the aforementioned two techniques, the modified SPA is utilized in this study. With regard to the evaluation approaches, the drawbacks of low convergence speed and ease of becoming trapped in local optima limit the application of ANN [19]. SVM needs to transform the solving process into quadratic programming via kernel function [20], which results in low efficiency and convergence precision [21]. LSSVM takes advantage of least squares linear system as the loss function so that the process of quadratic programming can be avoided [22]. Meanwhile, the transformation of evaluation problems into equations and the conversion of inequality constraints into equality ones contribute to the enhancement of estimation accuracy and speed [23]. Hence, LSSVM is selected here for research. Due to the blind selection of penalty coefficient and kernel parameters in LSSVM, it is of great significance to apply an appropriate technique to optimize these values [24]. Cuckoo search (CS) algorithm is a novel heuristic algorithm proposed by Yang Xinshe and S. Deb in 2009. In comparison with particle swarm algorithm and genetic algorithm, this technique is inspired by the cuckoo breeding method and presents satisfactory performance in optimization problems [25,26]. CS is commonly used in project scheduling, engineering optimization, etc. It has been a hot issue on the basis of simple structure and few control parameters. However, it is noteworthy that CS can easily fall into optima [27]. Thus, random weight is introduced to change the update mode of nest position, which is conducive to improving convergence speed and realizing global optimal search.

The main contributions of this paper are the following:

- (1) The indicator system of sustainability evaluation on PV industry in countries along the Belt and Road is constructed from five aspects: economy, politics, society, ecological

environment and resources, and the question of what the aspects of sustainability of the PV industry in countries along the Belt and Road are is answered.

- (2) The evaluation index weights are determined based on the entropy weight method, and the evaluation results are obtained by designing an improved SPA model from the perspective of the classical evaluation method.
- (3) The basic cuckoo algorithm is improved by using random weights, and the improved algorithm is used to optimize the LSSVM and establish an intelligent evaluation model. It provides decision support to promote the sustainable development of the PV industry in countries along the Belt and Road.

All in all, this paper establishes an index system for sustainability evaluation of the PV industry in the countries along the Belt and Road. Moreover, a comprehensive evaluation model incorporating modified SPA and ICS-LSSVM is proposed in this study. The rest of the paper is organized as follows: Section 2 selects the indicators and provides a brief description. Section 3 introduces the methodology of entropy weight method, modified SPA, ICA and LSSVM in detail. The evaluation model that integrates modified SPA with ICS-LSSVM is constructed in Section 4. Section 5 provides the results of an experimental study conducted to verify the effectiveness of this novel technique and analyzes the sustainability of the PV industry. The study is concluded in Section 6.

2. Index System

2.1. Establishment Principles

In accordance with construction experience, the indicator system of sustainability evaluation on PV industry in countries along the Belt and Road is established based on the following principles [28]:

- (1) Sustainability: the promotion of PV power stations can not only acquire economic benefits, but also reduce poverty and promote social development on the premise of ecological protection. Thus, in index selection, it is necessary to take both protection and development into account.
- (2) Systematicness: the evaluation index system should be treated as a whole in order to interrelate the indicators and endue the system with rigorous structure and complete content.
- (3) Pragmatism: key factors should be selected and appropriate assessment standards should be set in line with the inherent development law of the PV industry and data availability.

2.2. Index Selection

Based on the aforementioned principles as well as existing literature and data collection [29–31], this study establishes the evaluation index system of PV industry along the Belt and Road from five aspects, namely economy, politics, society, ecological environment and resources, as listed in Table 1.

Table 1. Index system of sustainability evaluation in countries along the Belt and Road.

First-Grade	Second-Grade	Indexes	
Economy	Gross domestic product (GDP)	x_1	
	Per capita GDP	x_2	
	GDP growth rate	x_3	
	Political stability	x_4	
Politics	National political openness	x_5	
	Support of national policies for PV industry	x_6	
	National perception index	x_7	
Society	Urbanization rate	x_8	
	Human development index (HDI)	x_9	
Ecological Environment	Power supply and demand	x_{10}	
	CO ₂ emissions	x_{11}	
	Biodiversity	x_{12}	
	Emphasis on environmental protection	x_{13}	
	Solar radiation conditions	x_{14}	
	Meteorological conditions	x_{15}	
	Engineering geological conditions	x_{16}	
	Total primary energy consumption	x_{17}	
	Resources	Per capita consumption of primary energy	x_{18}
		Renewable energy consumption	x_{19}
Total power generation		x_{20}	
PV power generation		x_{21}	
Proportion of PV power generation		x_{22}	

2.3. Index Description

This paper elaborates on the definition of indicators as follows:

- (1) Gross domestic product (GDP) refers to the production activity achievement of all resident units in a country (or) region during a period of time, which is calculated in terms of the national market price. GDP is commonly recognized as the most appropriate indicator to measure a national economy. As a comprehensive statistical index in an accounting system, GDP reflects the economic strength and market scale in a country (or region).
- (2) Per capita GDP equals the ratio of GDP in a country or region during the accounting period (usually one year) to the corresponding permanent population.
- (3) GDP growth rate stands for the annual increasing ratio calculated via GDP at a comparable price.
- (4) Political stability is affected by regime change, ethnic contradictions and so on.
- (5) National political openness represents the openness scale and level of a country to other countries in politics.
- (6) Support of national policies for the PV industry indicates the relevant policies in a country aimed at PVs.
- (7) National perception index takes entrepreneurs, risk analysts and general public as survey objects to assess the integrity and bribery of government officials.
- (8) Urbanization rate generally utilizes demographic indicators, namely the proportion of urban population in the total population (including agriculture and non-agriculture).
- (9) Human development index (HDI) is a comprehensive indicator obtained from three basic variables, namely life expectancy, education level and life quality.
- (10) Power supply and demand identify the electricity development in a country.
- (11) CO₂ emissions equal the gross carbon emission in a country.
- (12) Biodiversity can be judged via national representative species, threatened status and diverse habitat types.
- (13) Emphasis on environmental protection is chiefly determined by the formulation and implementation of related policy.
- (14) Solar radiation conditions incorporate the amount of solar radiation, sunshine hours and peak sunshine hours.
- (15) Meteorological conditions refer to various hydrothermal states. This study mainly analyzes annual average wind speed, annual average wind speed, historical maximum

- instantaneous wind speed, annual average temperature, extreme maximum temperature, extreme minimum temperature, annual average rainfall, annual average relative humidity, annual frost-free period, annual average evaporation, annual thunderstorm days and special climate impact in the construction sites of PV generation projects.
- (16) Engineering geological conditions comprise basic geological structure, underground hydrological conditions and negative impacts.
 - (17) Total primary energy consumption represents the amount of primary energy consumed by a country or region during a certain period of time.
 - (18) Per capita consumption of primary energy is equivalent to the ratio of primary energy consumption to the corresponding permanent population in a country or region during the accounting period (usually one year).
 - (19) Renewable energy consumption equals the amount consumed by a country or region in a certain period of time.
 - (20) Total power generation includes thermal power, hydropower, nuclear energy and other modes (such as geothermal power, PV, wind, tidal power and bioenergy) from all electricity industry plants, self-owned power plants and rural small electric stations.
 - (21) PV power generation identifies total electricity generated from PV stations.
 - (22) Proportion of PV power generation equals the ratio of PV electricity generation to gross amount in a country.

3. Methodology

3.1. Entropy Weight

As a common technique for objective weight calculation, the principle of entropy weight comes from thermodynamics. Entropy is a measure of system uncertainty. A larger entropy corresponds to a more chaotic system and less information [32]. Suppose the system stays in n states, the probability of each state is expressed as $P_i (i = 1 \rightarrow n)$. Thus, the entropy weight can be computed by Equation (1):

$$E = - \sum_{i=1}^n P_i \ln p_i \quad (1)$$

where $P_i (i = 1 \rightarrow n)$ satisfies the conditions $0 \leq P_i \leq 1$ and $\sum_{i=1}^n P_i = 1$.

The specific procedures of entropy weight are presented as follows [33]:

- (1) Establishment of standardized judgment matrix

The standardized judgement matrix is constructed based on the standardized data.

- (2) Information entropy calculation of each index

$$H_j = -k \sum_{i=1}^m f_{ij} \ln f_{ij} \quad (2)$$

$$f_{ij} = \frac{x_{ij}^*}{\sum_{i=1}^m x_{ij}^*} \quad (3)$$

$$k = \frac{1}{\ln m} \quad (4)$$

if $f_{ij} = 0$,

$$\ln f_{ij} = 0 \quad (5)$$

- (3) Index weight

$$w_j = \frac{1 - H_j}{\sum_{j=1}^n (1 - H_j)} \quad (6)$$

where $0 \leq w_j \leq 1, \sum_{j=1}^n w_j = 1$.

3.2. Modified SPA

SPA is modified in this paper via variable fuzzy set coupling evaluation theory which takes the multiscale fuzzy relationship between the indicators and grade as well as the influence of indexes on evaluation object. The basic steps are listed as follows:

- (1) Determine the evaluation index and estimation grade as $x_{im} = 1, 2, \dots, m$ and $[h_{ig-1}, h_{ig}] (i = 1, 2, \dots, m; g = 1, 2, \dots, C)$, respectively, where m and C equal the number of indicators and grades.
- (2) In virtue of basic principles of SPA [34], set x_{ij}, h_{ig} as the set pair and conduct analysis from the perspective of identity, discrepancy and opposition. The connection degree μ_{ijg} between grade g and the j -th sample in index i is calculated as follows:

$$\mu_{ijg} = a + bI + cJ \tag{7}$$

where a, b, c represent the degree of identity, discrepancy and opposition, respectively. $a + b + c = 1$. I is the discrepancy coefficient determined based on research object; $I \in [-1, 1]$. J is the opposition coefficient; $J = -1$.

In line with the simple calculation of connection degree and fuzziness of evaluation object and standard, a membership function is adopted to confirm μ_{ijg} which avoids calculating a, b, c in Equation (6) directly. If they belong to the same grade, $\mu_{ijg} = 1$. If they pertain to the adjacent level, $\mu_{ijg} \in [-1, 1]$. Additionally, if they are attributed to separate grades, $\mu_{ijg} = -1$. The connection degree is computed by Equation (8) [35]:

$$\mu_{ijg} = \begin{cases} 1 - 2 \cdot \left| \frac{h_{ig-1} - x_{ij}}{h_{ig-1} - h_{ig-2}} \right| & x_{ij} \in \text{adjacent standard set } g - 1 \\ 1 & x_{ij} \in \text{adjacent standard set } g \\ 1 - 2 \cdot \left| \frac{x_{ij} - h_{ig}}{h_{ig+1} - h_{ig}} \right| & x_{ij} \in \text{adjacent standard set } g + 1 \\ -1 & x_{ij} \in \text{other standard set} \end{cases} \tag{8}$$

where μ_{ijg} takes full advantage of the information in x_{ij} and h_{ig} from three aspects, namely identity, discrepancy and opposition.

- (3) The connection degree u_{jg} between j -th sample and assessment grade g is acquired on the foundation of μ_{ijg} and ω_i [34].

$$\mu_{jg} = \sum_{i=1}^m \omega_i \mu_{ijg} \tag{9}$$

where $\omega_i \in [0, 1]$ is the weight of i -th index. $\mu_{jg} \in [-1, 1]$. If u_{jg} approximates -1 , it indicates the consistency between j -th sample and assessment grade g is small. If u_{jg} approximates 1, it demonstrates the consistency is great.

- (4) The relative membership γ_{jg} is computed between j -th sample and evaluation grade g where μ_{jg} is deemed as the relative difference in VFSM [36].

$$\gamma_{jg} = (1 + \mu_{jg}) / 2 \tag{10}$$

In accordance with the principle of maximum membership degree, γ_{jg} is used for evaluation. The eigenvalue h_j^* is taken as an alternative for result recognition due to estimation precision.

$$h_j^* = \sum_{g=1}^C g \left| \gamma_{jg} / \sum_{g=1}^C \gamma_{jg} \right| \tag{11}$$

where h_j^* is the eigenvalue of the j -th sample. A larger eigenvalue corresponds to better sustainability. $h_j^* \in [1, C]$.

3.3. Improved CS (ICS)

3.3.1. CS

CS is a novel heuristic algorithm proposed in 2009 [37]. The core idea of this technique is brood parasitism behavior and Levy flight mode.

(1) Brood parasitism behavior

On the foundation of long-term observation and research of entomologists, cuckoos do not raise their offspring, but secretly put their nestlings in other birds' nests. If they are not detected by the nest owner, their offspring will be brought up. This is also known as nest parasitism, which is a special breeding method different from other birds. Cuckoos do not build nests or hatch their young eggs all the time; instead, they search for birds with similar egg shapes and sizes along with feeding periods and habits. Cuckoos quickly lay their eggs in the nests of orioles and skylarks when they watch other birds leave the nests and allow these birds to hatch on their own behalf. Due to the similar color and size, cuckoos remove one egg from the original nest before laying eggs, so that other birds substitute for cuckoos to feed the young. The CS algorithm simulates cuckoos' nest search and brood parasitic behavior where the selected nests are perceived as solution distribution in space. Moreover, the nest position symbolizes the fitness value and the process of nest search represents the optimization procedures.

(2) Levy flight

Levy flight adopted in CS belongs to random walk that satisfies heavy-tailed stable distribution where short-distance exploration alternates with occasional long-distance walking. This approach is able to increase search space, expand population diversity and escape local optima. As a continuous probability distribution, Levy flight is named after Paul Levy. Several vital parameters are listed here: characteristic index α , scale σ , displacement χ and direction β . The definition of Levy distribution is Fourier transformation of its characteristic function $\varphi(t)$ [38]:

$$\begin{aligned} p_{\alpha,\beta}(k; \mu, \sigma) &= F\{p_{\alpha,\beta}(x; \mu, \sigma)\} = \int_{-\infty}^{\infty} dx e^{ikx} p_{\alpha,\beta}(x; \mu, \sigma) \\ &= \exp\left[iuk - \sigma^\alpha |k|^\alpha \left(1 - i\beta \frac{k}{|k|} \omega(k, \alpha)\right)\right] \end{aligned} \quad (12)$$

$$\text{where } \omega(k, \alpha) = \begin{cases} \tan \frac{\pi\alpha}{2}, & \alpha \neq 1, 0 < \alpha < 2 \\ -\frac{2}{\pi} \ln|k|, & \alpha = 1 \end{cases}.$$

The probability density function of Levy flight distribution is shown in Equation (13):

$$p_{\alpha,\beta}(x) = \begin{cases} \frac{1}{\sqrt{2\pi}} x^{-\frac{2}{\alpha}} \exp\left(-\frac{1}{2x}\right), & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (13)$$

where $\alpha = \frac{1}{2}, \beta = 1$.

Equation (14) presents the probability density function of jump distribution in Levy flight [39].

$$\lambda(x) \approx |x|^{-1-\alpha}, 0 < \alpha < 2 \quad (14)$$

It is a remarkable fact that there exists a great jump in Levy flight owing to its second-moment divergence.

3.3.2. Improved CS

CS has been successfully adopted in many fields, such as nonlinear optimization. This approach has advantages of good local and global convergence, few parameters, strong robustness and high search efficiency. However, the drawback of easily falling into local optima limits the application of CS. Thus, random weight is introduced in this paper to change the update mode of bird nest position so as to enhance the convergence speed and realize global optimal search.

Random weight is a dynamic method of weight selection. It randomly determines a weight value, i.e., a larger or smaller weight, from the Gaussian distribution each time. This technique can prevent the CS algorithm from becoming trapped in local optima at the initial stage of the search. Simultaneously, the random occurrence of larger and smaller weights brings about the improvement of convergence speed and precision. Equation (15) generates a number in $[0.5, 1]$.

$$w = 0.5 + \frac{randm(\cdot)}{2} \quad (15)$$

where $randm(\cdot)$ represents a random number that obeys normal distribution.

$$w = r(rmin_{max} * normrnd(\cdot) + \sigma * randm(\cdot))_{min} \quad (16)$$

where $rmin_{max}$ represent the maximum and minimum of the randomly selected weights, $normrnd$ is the random number and σ equals the bias.

Random weight obeys Gaussian distribution, namely $w \sim N(\theta, \sigma)$. The stochastic appearance of larger and smaller weights contributes to optimum determination as well as the balance of local and global search. Hence, random weight is combined with CS algorithm in this study to update bird nest position. The specific procedures of ICS are listed as follows:

Step 1: Determine the optimization function $f(x)$ where d is the dimension, $[-l, l]$ is the domain, P_0 represents the discovery probability (namely the possibility of a new nest replacing the old one) and n equals the number of population. Randomly generate $(x_1, x_2, \dots, x_n)^T$ and the initial nest positions as $S_i (i = 1, 2, \dots, n)$.

Step 2: Calculate the objective function f_i of each nest and record the current optimum.

Step 3: Keep the optimal position S_i^t of the previous nest and randomly generate the weight as $w \sim N(\theta, \sigma)$. The nest position is updated according to Equation (17):

$$S_i^{(t+1)} = w * S_i^t + \alpha \oplus Levy(\lambda) \quad (17)$$

where t equals the number of iterations, α represents the step length and \oplus means entrywise multiplication. It describes a random walk where the first term in the current equation and the second term in the transition probability equation determine the position of the next generation. Levy flight belongs to a random search path whose step length satisfies Levy distribution.

Step 4: Compare S_i^{t+1} with S_i^t . If S_i^{t+1} is superior to S_i^t , namely $f_i^{t+1} > f_i^t$, S_i^{t+1} is regarded as the optimal position.

Step 5: Compare discovery probability P_0 with the random number r of possibility that a host bird can discover an alien egg. If $r \leq P_0$, the optimal position is obtained. Otherwise, repeat Step 2 to update the nest positions.

Step 6: Output the global optimum.

3.4. LSSVM

As an extension of SVM, LSSVM owns two principal characteristics: (i) equality constraints are utilized to replace the inequality ones in SVM; (ii) kernel function is adopted to transform prediction problems into solving equations. These two aspects can greatly improve assessment accuracy and speed [40].

The training sample is set as $T = \{(x_i, y_i)\}_{i=1}^N$ where N stands for the total number. The regression model is established as Equation (18):

$$y(x) = \overset{T}{w} \bullet \phi(x) + b \quad (18)$$

where $\phi(\cdot)$ is employed to map the training sample into a high-dimensional space. w equals the weighted vector and b is the bias.

Equation [19] presents the transformation of the optimization problem [41]:

$$\min \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{i=1}^N \xi_i^2 \tag{19}$$

$$y_i = w^T \phi(x_i) + b + \xi_i, i = 1, 2, 3, \dots, N \tag{20}$$

where γ represents the penalty parameter that can be applied to balance the accuracy as well as complexity. ξ_i is the estimation error.

The Lagrange function is exploited here to solve the problem above.

$$L(w, b, \xi_i, \alpha_i) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{i=1}^N \xi_i^2 - \sum_{i=1}^N \alpha_i \left[w^T \phi(x_i) - y_i \right] \tag{21}$$

where α_i equals Lagrange multipliers. Equation (22) is derived via derivation of each variable and making it zero.

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^N \alpha_i \phi(x_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^N \alpha_i = 0 \\ \frac{\partial L}{\partial \xi_i} = 0 \rightarrow \alpha_i = \gamma \xi_i \\ \frac{\partial L}{\partial \alpha_i} = 0 \rightarrow w^T + b + \xi_i - y_i = 0 \end{cases} \tag{22}$$

Through eliminating w and ξ_i , the transformation of the optimization problem is achieved in Equation (23).

$$\begin{bmatrix} 0 & e_n^T \\ e_n & \Omega + \gamma^{-1} \cdot I \end{bmatrix} \cdot \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{23}$$

$$\Omega = \phi^T(x_i)\phi(x_i) \tag{24}$$

$$e_n = [1, 1, \dots, 1]^T \tag{25}$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_n \end{bmatrix} \tag{26}$$

$$y = [y_1, y_2, \dots, y_n]^T \tag{27}$$

Accordingly, Equation (28) is obtained as follows:

$$y(x) = \sum_{i=1}^N \alpha_i K(x_i, x) + b \tag{28}$$

where $K(x_i, x)$ represents the kernel function that meets the Mercer condition. In view of the wide convergence domain and application of radial basis function (RBF), it is selected as the kernel function of LSSVM as listed in Equation (29)

$$K(x_i, x) = \exp\left\{-\|x - x_i\|^2 / 2\sigma^2\right\} \tag{29}$$

where σ^2 is the kernel width that reflects the characteristics of the training data set and affects the generation capability of the system.

To sum up, the appropriate determination of kernel parameter σ^2 and penalty parameter γ is of great significance to enhance the learning and generalization ability of LSSVM.

4. Evaluation Method Combining Modified SPA with ICS-LSSVM

A hybrid evaluation approach integrating modified SPA with ICS-LSSVM is constructed in this paper where modified SPA is employed to derive traditional results and ICS is adopted to optimize the parameters in LSSVM. The assessment framework is displayed in Figure 1. The specific procedures are as follows:

- (1) Implement index classification and standardization. This paper applies the targeting standardization method for different indicators to transform them with the same nature. The indexes involved in this study mainly incorporate the minimal and maximal types. Besides, they can also be divided into quantitative and qualitative indicators.

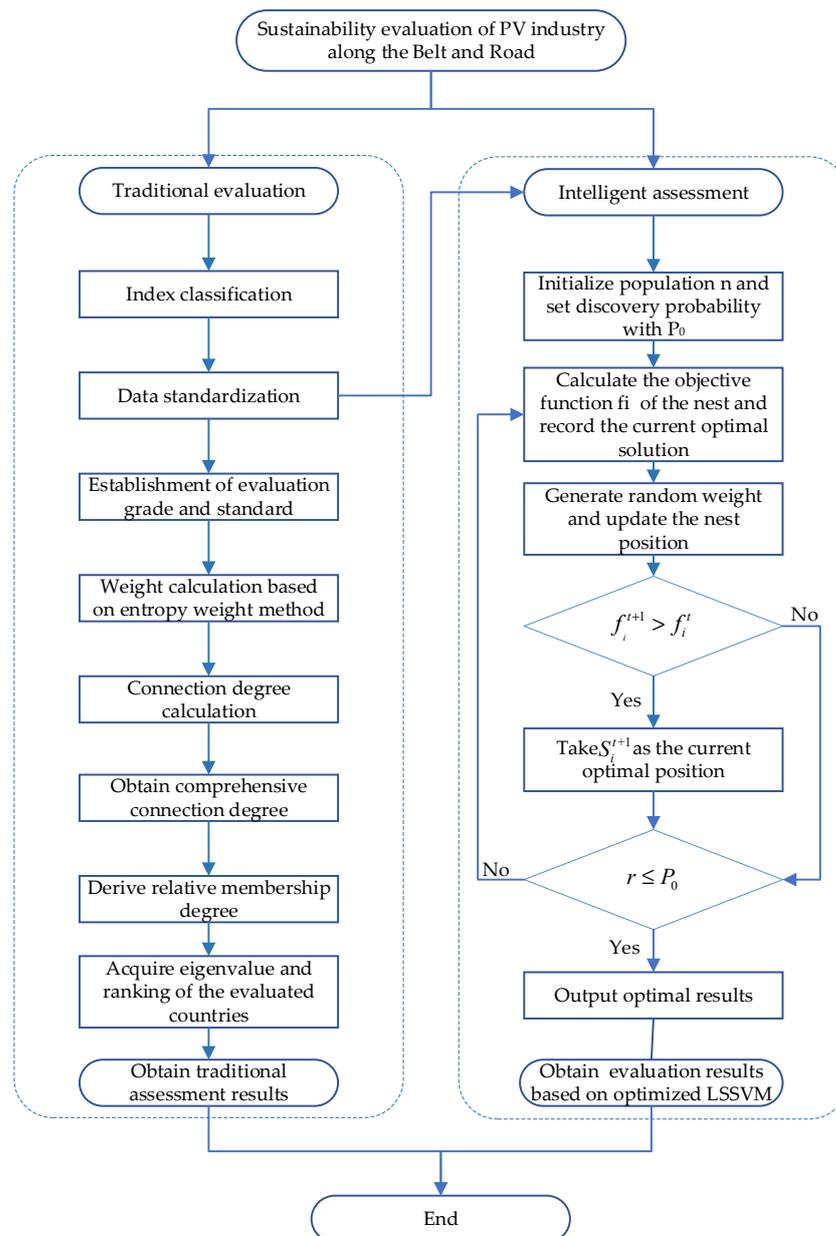


Figure 1. The assessment framework of the proposed model.

The standardization for a maximal index is as follows:

$$x_{ij}^* = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad (30)$$

The standardization for a minimal index is as follows:

$$x_{ij}^* = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \quad (31)$$

where x_{ij}^* is the normalized value of x_{ij} . $\max\{x_{ij}\}$, $\min\{x_{ij}\}$ are the maximum and minimum values, respectively.

- (2) Establish evaluation grade and standard. The assessment level and classification standard of indicators are determined on the basis of obtained data and expert suggestions.
- (3) Derive traditional evaluation results based on entropy weight method and modified SPA.
- (4) Initialize the parameters in ICS and LSSVM algorithm and optimize the parameters in LSSVM via ICS. The key parameters of LSSVM have a crucial impact on the estimation precision. Therefore, this study utilizes ICS to search for the optimal parameters in LSSVM. If the conditions are satisfied, the optimal parameters are acquired. Through training and testing, the final evaluation model for sustainable development of the PV industry in the countries along the Belt and Road is established.
- (5) Output intelligent assessment results. This study carries out the simulation according to the proposed intelligent technique to assess the sustainability of the PV industry along the Belt and Road. Additionally, the intelligent evaluation results are compared with the traditional ones here.

5. Experimental Study

5.1. Classification and Standardization of Evaluation Indexes

The assessment indicators are classified as illustrated in Table 2, which offers the basis of data standardization. Classification I divides the indicators into maximal and minimal ones, while Classification II separates the indexes into quantitative and qualitative ones.

Table 2. Classification results of indicators.

Indexes	Classification I	Classification II
Gross domestic product (GDP)	maximal	quantitative
Per capita GDP	maximal	quantitative
GDP growth rate	maximal	quantitative
Political stability	maximal	qualitative
National political openness	maximal	qualitative
Support of national policies for PV industry	maximal	qualitative
National perception index	maximal	qualitative
Urbanization rate	maximal	quantitative
Human development index (HDI)	maximal	quantitative
Power supply and demand	maximal	qualitative
CO ₂ emissions	minimal	quantitative
Biodiversity	maximal	qualitative
Emphasis on environmental protection	maximal	qualitative
Solar radiation conditions	maximal	qualitative
Meteorological conditions	maximal	qualitative
Engineering geological conditions	maximal	qualitative
Total primary energy consumption	maximal	quantitative
Per capita consumption of primary energy	maximal	quantitative
Renewable energy consumption	maximal	quantitative
Total power generation	maximal	quantitative
PV power generation	maximal	quantitative
Proportion of PV power generation	maximal	quantitative

In this study, 15 countries are selected, including Indonesia, Singapore, Malaysia, Thailand and Saudi Arabia. The experimental data are derived from expert scoring method along with actual data analysis. Table 3 exhibits the standardization results in accordance with Equations (30) and (31).

Table 3. Data standardization.

Index	Indonesia	Singapore	Malaysia	Thailand	Saudi Arabia	Qatar	Greece	India	Pakistan	Bengal	Kazakhstan	Russia	Ukraine	Poland	Romania
x ₁	0.3556	0.0804	0.0777	0.1436	0.2354	0.0081	0.0207	1.0000	0.0458	0.0548	0.0103	0.5695	0.0000	0.1628	0.0355
x ₂	0.0446	1.0000	0.1584	0.1020	0.3418	0.9508	0.2861	0.0127	0.0000	0.0089	0.1334	0.1611	0.0371	0.2253	0.1819
x ₃	0.6242	0.1092	0.5378	0.3037	0.0612	0.0000	0.2461	0.5234	0.1405	1.0000	0.5618	0.1825	0.4094	0.5666	0.5198
x ₄	0.3667	0.9667	0.2667	0.0000	0.6000	0.6333	0.7333	0.6667	0.6333	0.5000	0.7667	1.0000	0.0000	0.8333	0.2667
x ₅	0.2778	0.9444	0.4722	0.2222	0.0000	0.1944	0.9167	0.5000	1.0000	0.8056	0.7778	0.6667	0.5278	0.5278	0.5000
x ₆	0.0000	0.7174	0.7391	0.8913	0.5217	0.2609	1.0000	0.7826	0.6304	0.6087	0.5435	0.2609	0.6957	0.3043	0.8261
x ₇	0.0250	1.0000	0.1500	0.0250	0.0250	0.0000	0.4000	0.1000	0.4750	0.3000	0.2500	0.2000	0.5000	0.3500	0.2250
x ₈	0.3030	1.0000	0.6212	0.2424	0.7576	0.9848	0.6818	0.0000	0.0455	0.0455	0.3485	0.6061	0.5303	0.3939	0.3030
x ₉	0.4226	1.0000	0.6640	0.5774	0.7795	0.7638	0.8688	0.2310	0.0000	0.1969	0.7034	0.7008	0.5827	0.8478	0.7113
x ₁₀	0.0000	1.0000	0.4516	0.3871	0.5484	0.2258	0.4194	0.6129	0.2903	0.0000	0.1290	0.8387	0.4194	0.9677	0.9355
x ₁₁	0.7670	0.9384	0.9278	0.9041	0.7886	0.9867	0.9995	0.0000	0.9470	0.9851	0.9297	0.3933	0.9523	0.9031	1.0000
x ₁₂	0.6429	0.6071	0.7857	0.6786	0.0000	0.0357	0.8214	0.8571	1.0000	0.4643	0.1786	0.9643	0.4286	0.8214	0.9286
x ₁₃	0.4286	1.0000	0.6286	0.2857	0.1714	0.2286	0.9429	0.2000	0.0000	0.1714	0.2857	0.6000	0.2857	0.7714	0.7429
x ₁₄	0.2727	0.6364	0.3939	0.5455	0.0606	0.4242	0.2727	0.2424	0.2727	0.8182	0.9394	1.0000	0.4848	0.0000	0.7576
x ₁₅	0.8250	0.7000	0.0000	0.4750	0.3500	0.4750	0.9250	0.9500	1.0000	0.5500	0.0000	0.5750	0.6000	0.1250	0.0500
x ₁₆	0.2326	0.0930	0.1395	0.0698	0.0465	0.6744	0.4186	0.0000	0.2791	0.6744	0.3953	0.6744	1.0000	0.6744	0.4186
x ₁₇	0.2358	0.0729	0.0945	0.1355	0.3005	0.0264	0.0000	1.0000	0.0732	0.0185	0.0593	0.8709	0.0687	0.0951	0.0067
x ₁₈	0.0314	0.8540	0.1743	0.0992	0.4424	1.0000	0.1402	0.0200	0.0080	0.0000	0.2222	0.2751	0.0947	0.1451	0.0853
x ₁₉	0.3195	0.0041	0.0207	0.2365	0.0124	0.0000	0.0871	1.0000	0.0456	0.0000	0.0041	0.0124	0.0373	0.2033	0.0788
x ₂₀	0.1526	0.0036	0.0811	0.0913	0.2045	0.0000	0.0011	1.0000	0.0581	0.0272	0.0396	0.7082	0.0701	0.0764	0.0072
x ₂₁	0.0011	0.0032	0.0162	0.1070	0.0378	0.0000	0.0854	1.0000	0.0249	0.0076	0.0054	0.0205	0.0616	0.0141	0.0357
x ₂₂	0.0000	0.0421	0.0545	0.3335	0.0590	0.0085	1.0000	0.3700	0.1065	0.0517	0.0304	0.0068	0.2321	0.0493	0.3557

5.2. Evaluation Grade and Standard

Considering the assessment indicators on the sustainability of PV industry along the Belt and Road and specialist recommendations, the evaluation grades are divided into three levels, namely good, general and bad. Table 4 lists the classification standard.

5.3. Traditional Evaluation Using Entropy Weight and Modified SPA

Table 5 manifests the weight calculated via the entropy weight approach. The connection degree of three levels are acquired through SPA as follows:

$$u_{ij1} = \begin{bmatrix} -1.0000 & 0.8034 & \dots & 1.0000 \\ 1.0000 & -1.0000 & \dots & 0.4016 \\ \vdots & \vdots & \vdots & \vdots \\ 1.0000 & 1.0000 & \dots & -1.0000 \end{bmatrix}$$

$$u_{ij2} = \begin{bmatrix} 0.8925 & 1.0000 & \dots & 0.6593 \\ 0.1636 & -1.0000 & \dots & 1.0000 \\ \vdots & \vdots & \vdots & \vdots \\ -0.8428 & 0.6218 & \dots & 0.8596 \end{bmatrix}$$

$$u_{ij3} = \begin{bmatrix} 1.0000 & -0.8034 & \dots & -1.0000 \\ -1.0000 & 1.0000 & \dots & -0.4016 \\ \vdots & \vdots & \vdots & \vdots \\ -1.0000 & -1.0000 & \dots & 1.0000 \end{bmatrix}$$

Tables 6 and 7 show the comprehensive connection degree and relative membership degree, respectively. Besides, the eigenvalues and ranking of the evaluated countries are displayed in Table 8 and Figure 2.

Table 4. Positive and negative solutions.

Index	Bad		General		Good	
	Lower Limit	Upper Limit	Lower Limit	Upper Limit	Lower Limit	Upper Limit
Gross domestic product (GDP)	0	3014	3014	10198	10198	28689
Per capita GDP	0	7107	7107	26533	26533	65233
GDP growth rate	0	2	2	4	4	8
Political stability	0	79	79	88	88	97
National political openness	0	73	73	83	83	94
Support of national policies for PV industry	0	72	72	84	84	97
National perception index	0	65	65	75	75	99
Urbanization rate	0	54	54	74	74	100
Human development index (HDI)	0	0.7357	0.7357	0.8380	0.8380	0.9380
Power supply and demand	0	69	69	79	79	90
CO ₂ emissions	805	2480	164	805	0	164
Biodiversity	0	68	68	77	77	83
Emphasis on environmental protection	0	71	71	81	81	95
Solar radiation conditions	0	73	73	83	83	95
Meteorological conditions	0	70	70	83	83	96
Engineering geological conditions	0	66	66	79	79	99
Total primary energy consumption	0	3	3	13	13	34
Per capita consumption of primary energy	0	76	76	282	282	714
Renewable energy consumption	0	0.0203	0.0203	0.3210	0.3210	1.2100
Total power generation	0	91	91	514	514	1559
PV power generation	0	3	3	10	10	46
Proportion of PV power generation	0	0.4559	0.4559	2.4712	2.4712	7.9681
Gross domestic product (GDP)	0	3014	3014	10198	10198	28689

Table 5. Indicator weight.

Indicator	Weight	Indicator	Weight
Gross domestic product (GDP)	0.0738	Biodiversity	0.0186
Per capita GDP	0.0616	Emphasis on environmental protection	0.0235
GDP growth rate	0.0252	Solar radiation conditions	0.0219
Political stability	0.0208	Meteorological conditions	0.0284
National political openness	0.0164	Engineering geological conditions	0.0310
Support of national policies for PV industry	0.0135	Total primary energy consumption	0.0764
National perception index	0.0415	Per capita consumption of primary energy	0.0600
Urbanization rate	0.0266	Renewable energy consumption	0.1022
Human development index (HDI)	0.0135	Total power generation	0.0925
Power supply and demand	0.0270	PV power generation	0.1444
CO ₂ emissions	0.0085	Proportion of PV power generation	0.0729

Table 6. Comprehensive connection degree.

Country	First-Level	Second-Level	Third-Level
Indonesia	0.3239	0.3602	−0.3239
Singapore	0.2494	−0.0852	−0.2494
Malaysia	0.5881	0.7371	−0.5881
Thailand	0.3094	0.9292	−0.3094
Saudi Arabia	0.2766	0.7489	−0.2766
Qatar	0.5449	−0.1565	−0.5449
Greece	0.1943	0.4345	−0.1943
India	−0.4085	−0.3115	0.4085
Pakistan	0.6449	0.4026	−0.6449
Bengal	0.6922	0.1749	−0.6922
Kazakhstan	0.6424	0.4178	−0.6424
Russia	−0.0374	0.2092	0.0374
Ukraine	0.4940	0.7515	−0.4940
Poland	0.2389	0.5999	−0.2389
Romania	0.4044	0.5361	−0.4044

Table 7. Relative membership degree.

Country	First-Level	Second-Level	Third-Level
Indonesia	0.6619	0.6801	0.3381
Singapore	0.6247	0.4574	0.3753
Malaysia	0.7941	0.8685	0.2059
Thailand	0.6547	0.9646	0.3453
Saudi Arabia	0.6383	0.8745	0.3617
Qatar	0.7724	0.4217	0.2276
Greece	0.5971	0.7173	0.4029
India	0.2957	0.3443	0.7043
Pakistan	0.8225	0.7013	0.1775
Bengal	0.8461	0.5874	0.1539
Kazakhstan	0.8212	0.7089	0.1788
Russia	0.4813	0.6046	0.5187
Ukraine	0.7470	0.8758	0.2530
Poland	0.6195	0.7999	0.3805
Romania	0.7022	0.7680	0.2978

Table 8. Eigenvalue and ranking.

Country	Eigenvalue	Ranking
Indonesia	1.8072	8
Singapore	1.8289	7
Malaysia	1.6853	11
Thailand	1.8425	6
Saudi Arabia	1.8524	5
Qatar	1.6168	14
Greece	1.8869	3
India	2.3039	1
Pakistan	1.6209	13
Bengal	1.5639	15
Kazakhstan	1.6241	12
Russia	2.0233	2
Ukraine	1.7367	10
Poland	1.8673	4
Romania	1.7713	9
Average	1.8021	-

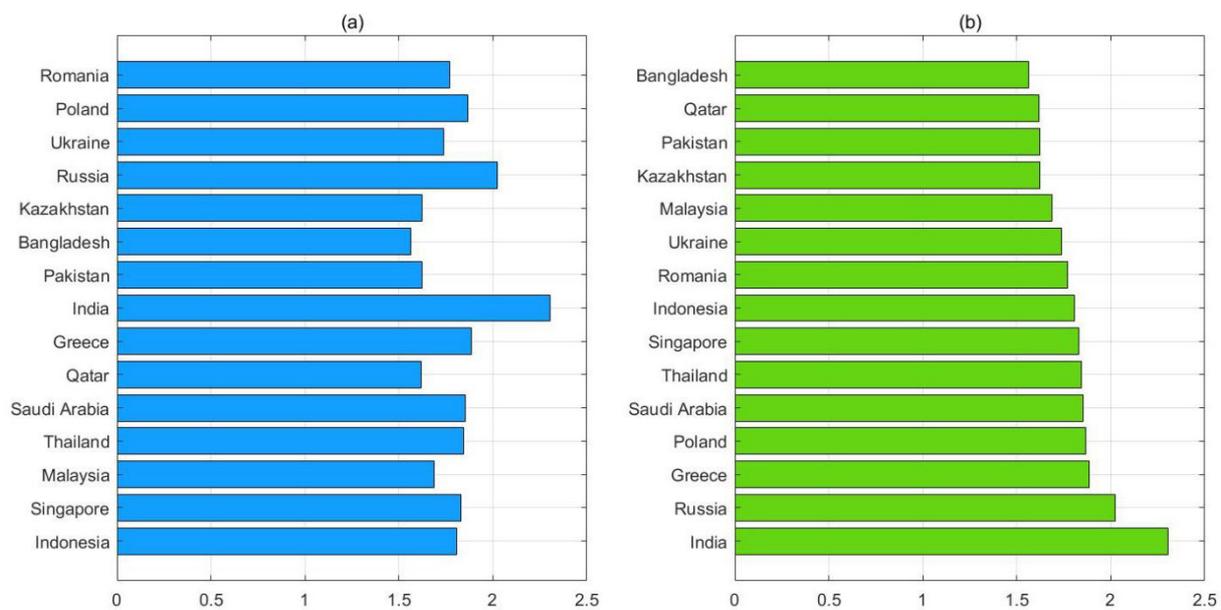


Figure 2. Results of eigenvalues. Note: (a) shows the disordered eigenvalues; (b) shows the ranking results.

It can be seen that the assessment results of eight countries, namely Indonesia, Singapore, Thailand, Saudi Arabia, Greece, India, Russia and Poland are superior to the average level. India presents the optimal PV industry sustainability and is followed by Russia; their eigenvalues are both higher than 2. It is worth noting that the GDP of India is the highest at USD 2868.9 billion while Russia ranks second with a GDP of USD 1700 billion. Furthermore, these two countries also have advantages in total primary energy consumption, renewable energy consumption, total power generation and PV power generation. Hence, strong economic strength and adequate resources play an important part in the sustainable development of the PV industry, which also explains why the sustainability levels of the other six countries are better than the average value.

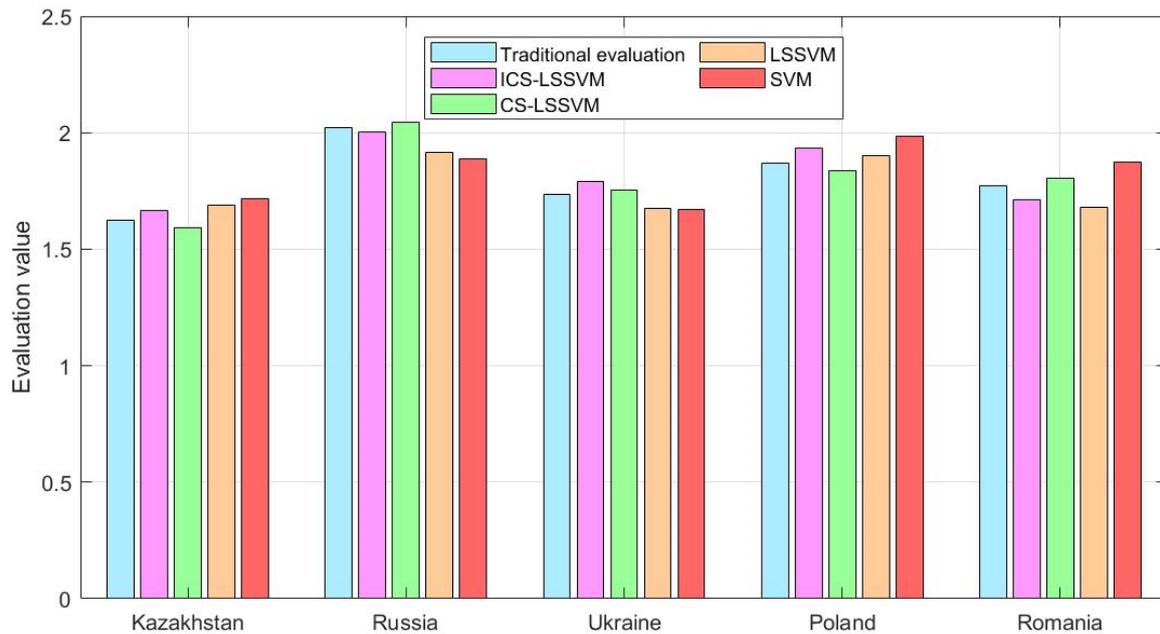
As for the countries with worse-than-average sustainability, the prime influential factors that restrict the sustainable growth of the PV industry are backward economy, total renewable energy consumption and PV power generation. It should be pointed out that human activities and natural forces have an impact on the trend of these complicated and nonlinear indicators, which brings about uncertainty together with temporal and spatial differences. Therefore, countries along the Belt and Road should be classified to enhance the sustainability of the PV industry. Meanwhile, the effectiveness of this established model based on modified SPA is verified in this study. It also provides a reference for sustainability estimation of the PV industry in other countries.

5.4. Intelligent Evaluation Based on ICS-LSSVM and Comparative Analysis

Here, the data of 5 countries, namely Kazakhstan, Russia, Ukraine, Poland and Romania, are taken as test samples while the other 10 countries are selected as training samples. Simultaneously, four assessment techniques, namely ICS-LSSVM, CS-LSSVM, LSSVM and SVM, are involved in this study to make a comparison. The estimation results of the test samples are exhibited in Table 9 and Figure 3.

Table 9. Estimation results of the test samples.

Country	Traditional Evaluation Result	SVM		LSSVM		CS-LSSVM		ICS-LSSVM	
		Result	Error	Result	Error	Result	Error	Result	Error
Kazakhstan	1.6241	1.7168	5.71	1.6910	4.12	1.6657	2.56	1.5908	−2.05
Russia	2.0233	1.8900	−6.59	1.9169	−5.26	2.0037	−0.97	2.0427	0.96
Ukraine	1.7367	1.6728	−3.68	1.6731	−3.66	1.7916	3.16	1.7518	0.87
Poland	1.8673	1.9842	6.26	1.9020	1.86	1.9358	3.67	1.8382	−1.56
Romania	1.7713	1.8726	5.72	1.6794	−5.19	1.7132	−3.28	1.8064	1.98

**Figure 3.** Comparison of estimation results.

As displayed in Figure 3 and Table 4, the evaluation result derived from ICS-LSSVM is the closest to the traditional assessment value. The accuracy and stability of the intelligent estimation approach have been proved in this study. In contrast with SVM, the estimation values of LSSVM are closer to the conventional ones. The cause lies in the fact that LSSVM employs kernel function to transform prediction problems into equations. The precision and classification capability of LSSVM is superior, especially in coping with unstable data.

Figure 4 illustrates the relative errors of the four techniques. It can be found that ICS-LSSVM has the strongest fitting and learning ability. The number of relative errors ranging in $[-3\%, 3\%]$ of ICS-LSSVM, CS-LSSVM, LSSVM and SVM is equivalent to 5, 2, 1 and 0, respectively. There exist two countries in ICS-LSSVM and only one country in CS-LSSVM with a relative error within $[-1\%, 1\%]$. In line with the absolute value, the maximum of relative errors is -2.05% , 3.67% , -5.26% and -6.59% for ICS-LSSVM, CS-LSSVM, LSSVM and SVM, respectively, while the corresponding minimum of relative errors is 0.87% , -0.97% , 1.86% and -3.68% . The study demonstrates that the proposed approach has the strongest nonlinear fitting ability together with the most satisfactory accuracy and robustness.

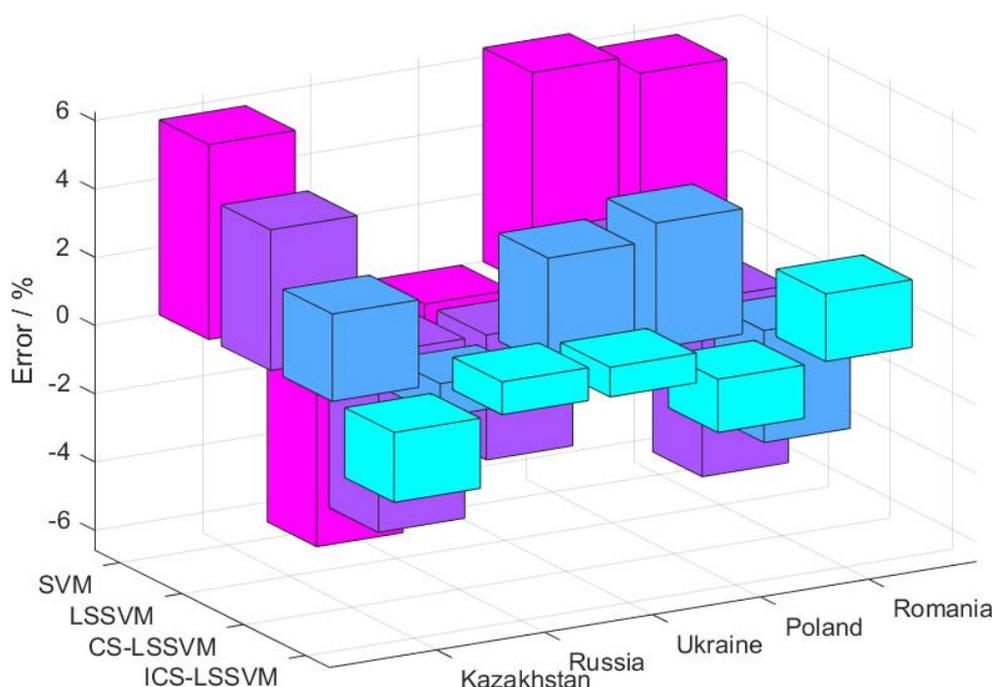


Figure 4. Comparison of relative errors.

To sum up, this paper introduces ICS to fine-tune the parameters in LSSVM so as to reduce the evaluation errors. The experimental study verifies the effectiveness and stability of the established model. Simultaneously, intelligent assessment approaches have advantages in workload reduction, efficiency improvement and rapid calculation.

6. Conclusions

In order to guarantee the sustainable development of the PV industry along the Belt and Road, in this study, assessment indicators were selected from five aspects, namely economy, politics, society, ecological environment and resources, based on the principles of sustainability, systematization and pragmatism. Then, the variable fuzzy set coupling evaluation theory was employed to modify the SPA process considering the multiscale fuzzy relationship between indicators and grade standards. This traditional assessment method is conducive to acquiring exact results. Additionally, this study established a novel technique integrating ICS with LSSVM where random weight is utilized to modify CS. The intelligent evaluation model built in this study was shown to have the strongest fitting and learning ability; the relative errors all fluctuate in the range of $[-3\%, 3\%]$, and the relative errors of two countries are in the range of $[-1\%, 1\%]$. Based on this fast and accurate calculation, this paper not only offers new ideas for rapid and effective sustainability estimation, but also provides a reference for the sustainable growth strategy of the PV industry in the countries along the Belt and Road. The constructed index system and evaluation model can solve the problems considered in this paper and are also applicable to the sustainability evaluation of the PV industry in other countries or regions. The study presents a certain degree of generalizability.

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Abbreviations

AHP	Analytic hierarchy process
ANN	Artificial neural network
CS	Cuckoo search algorithm
CSDIS	Chinese sustainable development index system
GDP	Gross domestic product
HDI	Human development index
ICS	Improved cuckoo search algorithm
LSSVM	Least squares support vector machine
PV	Photovoltaic
SPA	Set pair analysis
SVM	Support vector machine
VFSM	Variable fuzzy set method

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