Evaluation of Emission Reduction Performance of Power Enterprises Based on Least Squares Support Vector Machine

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Abstract: *In response to the increasingly severe environmental pollution problem at present, many traditional power companies are facing the promotion of environmental protection work. The promotion of Energy Conservation and Emission Reduction (ECER) work needs sufficient theory and data support. Therefore, this study proposes a performance evaluation model for ECER in power enterprises based on the improved lion swarm algorithm optimized Least Squares Support Vector Machine (LSSVM). The evaluation index system has been reconstructed according to the current environment and era characteristics. The LSSVM has been used to evaluate the ECER work of power enterprises, and the training efficiency of Lion Swarm Optimization (LSO) algorithm has been solved using chaos theory. An improved LSO algorithm is utilized to improve the parameter selection problem of the LSSVM model, to achieve a scientific and objective evaluation of the ECER performance of power enterprises. The research findings denote that the algorithm put forward in this study has better training efficiency, higher accuracy and stability, as well as better response time. It also exhibits minimal errors in simulation experiments. In summary, the ECER performance evaluation model proposed by this research institute can effectively output correct scoring results, providing data support for the promotion of environmental protection work.*

Keywords: *Power generation enterprise, evaluation indicators, least squares support vector machine, Lion swarm optimization algorithm, chaos theory.*

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1. Introduction

As the continuous growth of human technology and science, environment pollution and energy shortage have become the most urgent issues that humanity will face until the 21st century. The series of accompanying problems it brings are extremely serious, such as various natural disasters and energy shortages, constantly threatening many aspects of human agriculture, energy, ecology, and even directly threatening human survival and development [1, 3]. As an essential component of human production and daily life, the power generation enterprise is also an important source of energy consumption and pollutant emissions. Therefore, Energy Conservation and Emission Reduction (ECER) work in the power generation enterprise urgently needs improvement [7]. In general, maintaining reasonable energy output while reducing emissions is a difficult goal to achieve, and these two goals are inherently conflicting. How to improve the energy utilization efficiency of the power generation enterprise while reducing pollutant emissions is currently a research hotspot [4, 12]. The orderly promotion of systematic ECER work in the power generation enterprise often requires the construction of a more objective and scientific evaluation index system. A scientific evaluation of ECER work in the power generation enterprise is needed to provide effective data support for the further promotion of low-carbon work. Therefore, based on the current research on ECER in the power generation enterprise, this study combines relevant environmental issues and redefines the concept of ECER. It reorganizes the theory and work related to ECER in the power enterprise, thereby establishing a scientific and objective evaluation index for ECER in the power enterprise. Furthermore, a Least Squares Support Vector Machine (LSSVM) model based on improved Lion Swarm Optimization (LSO) algorithm is used to evaluate the ECER effectiveness of the power generation enterprise. The LSO algorithm is improved to enhance its local search ability and its update iteration performance. The improved LSO algorithm is utilized to improve the LSSVM model to overcome the problem of model parameter selection in practical applications, thereby further ensuring the global optimality of its solution. There are two innovative points in this study. The first point is to optimize the LSO algorithm by combining chaotic search algorithm. The second point is to improve the minimum Support Vector Machine (SVM) model using an LSO algorithm. This study is composed of four parts. The first part is a summary and review of relevant research fields. The second part is the construction of the model and evaluation index system proposed in this study. The third part is the validation and evaluation of the model proposed in this study. The fourth part is a summary of the research content.

2. Related Works

In the current global energy crisis situation, low-carbon development and ECER have become the focus of research, and many related theories have been proposed. Currently, many scholars are dedicating themselves to studying the low-carbon development path of the energy and power enterprise in the future, and striving to improve pollution reduction and energy conservation in the existing energy system as much as possible. Yan *et al*. [21] proposed an optimal carbon growth method using aldehyde alcohol condensation to further reduce carbon emissions in the fine chemical industry, which achieved the generation of new carbon bonds without the use of fossil fuels. Daggash and Dowell [5] used Nigeria as an example to explore the growth of fossil fuels and low-carbon energy in the South Sahara region, and found that renewable resources contribute to achieving more equitable distribution and development of socio-economic resources. Sun *et al*. [18] constructed a green finance innovation system and studied the significant role of the green finance innovation system in current social development. The experimental outcomes denoted that their proposed solution directly reduced carbon emissions by 30%. Lu [11] utilized three different manners to explore the influence of central environmental protection inspectors on cross-border water pollution. The research findings expressed that central environmental protection inspectors could effectively reduce the severity of cross-border water pollution, providing data and theory support for solving cross-border pollution. Sánchez *et al*. [16] proposed a renewable power system using ammonia as energy source, which solved the energy storage problem in renewable energy systems. After evaluation, the feasibility of ammonia as a clean energy storage was demonstrated in this scheme. Ishaq and Dincer [8] proposed a clean methanol generation system based on renewable energy, which effectively realized the cycle of clean energy. The experiment outcomes indicated that the system had high energy utilization efficiency and conversion efficiency, and this study provided extremely significant technical support for the promotion of clean energy.

Since machine learning methods were proposed, they have received much attention. Machine learning algorithms involve many disciplinary fields and are the core of artificial intelligence. They now have an extremely broad development space and have been widely applied. Their core lies in the simulation and implementation of human behavior. Pandit *et al*. [14] proposed an efficient multi-catalytic prediction method using density functional theory for the field of electrocatalysts used in hydrogen evolution reactions. The experimental findings indicated that this method could effectively screen catalysts with active properties. Bones *et al*. [2] proposed a medical image segmentation method using machine learning to address the current issue of limited clinical applicability of renal self-labeling MRI due to post-processing. Research outcomes expressed that this method could overcome observer limitations and had wider clinical applicability. Jame *et al*. [9] proposed a prediction method using supervised machine learning to address the optimal concentration of bromine doping in Tai Yanni devices. The experiment findings demonstrated that the method effectively predicted the optimal bromine concentration and further studied the impact of bromine concentration on device performance, providing technical support for improving the performance of the solar cell capacitor and effectively promoting the improvement of solar resource utilization. Munonye and Peter [13] proposed a supervised machine learning method to detect vulnerabilities in applications that currently integrated the OAuth framework in enterprises. The research findings showed that the method achieved an accuracy of over 90% and the vulnerabilities obtained had a matching degree of 54% compared to actual vulnerabilities. This method effectively proposed a machine learning based vulnerability detection method, which effectively reduced manpower consumption in vulnerability mining work, successfully improved the detection and mining efficiency of vulnerabilities, and was of great significance for improving network security. Vecchi *et al*. [20] proposed an upper optimal scalable probability approximation algorithm for classification problems in small data systems, effectively solving the problem of lack of robustness faced by machine learning and deep learning tools in such problems. In experiments, their proposed method outperformed existing learning methods in terms of various numerical values, achieving more accurate prediction results using lower computational resources. Sebastian *et al*. [17] proposed a prediction model using machine learning algorithms for unstable situations in cage dynamics. The experimental results indicated that the model could effectively predict its invisible load and related physical characteristics, further demonstrating the higher quality of simulation models and training data using machine learning compared to ordinary methods.

Based on the current carbon neutrality goals and the difficulties in optimizing the architecture of existing power enterprises, this study proposes a LSSVM model based on LSO algorithm to assess the ECER performance. To evaluate the ECER performance of power enterprises more scientifically, reasonably, and objectively, based on existing literature knowledge, preliminary performance evaluation indicators for ECER in power enterprises have been compiled. Based on the existing situation and current environmental characteristics, better performance evaluation indicators for ECER in power enterprises have been optimized and improved, thereby enhancing the credibility of the performance evaluation method proposed by this research institute.

3. ECER Performance Evaluation of Power Enterprises Based on LSSVM Model with Improved LSO Algorithm

At present, traditional power enterprises need stronger theoretical support and more accurate data support to promote energy greening, to make targeted ECER improvements. In this study, an improved LSO algorithm combined with a LSSVM model is used to assess the ECER performance, based on the principles of science, rationality, objectivity, and accuracy.

3.1. Construction of ECER Performance Evaluation Index System for Power Enterprises

To objectively evaluate the ECER performance and make the evaluation results more credible, scientific evaluation indicators should be selected specifically for their work, and an effective evaluation index system should be established. This study starts from the existing environment, combines with the current actual situation, and uses existing literature as theoretical support to reconstruct the performance evaluation indicators for ECER of power enterprises based on comprehensiveness, effectiveness, and availability. The reconstructed indicators include six primary indicators: low-carbon power supply structure indicators (proportion of non-fossil energy generation), power generation technology and economic indicators (equipment and energy usage of power plants), pollutant emissions indicators (emissions of greenhouse gases and other pollutants), comprehensive resource utilization indicators (utilization of coal, water and desulfurization stones), ECER innovation mechanism indicators (carbon trading situation), and ECER management indicators ECER. These six primary indicators almost completely cover all aspects of the ECER performance of power enterprises, and can comprehensively reflect the energy-saving and emission reduction benefits of power enterprises.

Table 1. ECER performance of power enterprises evaluation index system.

Primary indicators	Code	Secondary indicators	Unit	Code
Low-carbon power supply structure	A	Proportion of clean energy generation	%	X_1
		Proportion of installed capacity of non-fossil energy generation	%	X_2
		Proportion of new energy power generation capacity added	%	X_3
Technical and economic indicators of power generation	B	Average utilization hours of power generation equipment	h	X_4
		Station service power consumption rate	%	X_5
		Standard coal consumption for power generation	g/kWh	X_6
		Standard coal consumption for power supply	g /kWh	X_7
Pollutant discharge index	C	SO_2 emissions per unit of power generation	g/kWh	X_8
		NO_X emissions per unit of power generation	g/kWh	X_9
		Soot emission per unit of power generation	g/kWh	X_{10}
		Wastewater discharge per unit of power generation	g/kWh	X_{11}
Indicators of comprehensive utilization of resources	D	Comprehensive utilization rate of fly ash	%	X_{12}
		Reuse rate of industrial water	%	X_{13}
		Desulfurization gypsum utilization rate	%	X_{14}
Indicators of innovative mechanisms for ECER	E	Implementation of the power generation rights trading mechanism	-	X_{15}
		Implementation of the carbon trading mechanism	-	X_{16}
		Implementation of the emission trading mechanism	-	X_{17}
		Implementation of the pricing and tax mechanism	-	X_{18}
ECER management indicators	F	Implementation of energy-saving power generation scheduling	-	X_{19}
		ECER supervision	-	X_{20}
		Construction of laws and regulations on ECER	-	X_{21}
		Organization and leadership of ECER work	-	X_{22}
		The setting and implementation of ECER targets	-	X_{23}

In response to the current environmental factors related to ECER in power enterprises, combined with existing relevant literature and materials, and considering the design concept of the evaluation index system, this study has preliminarily established a performance evaluation index system for ECER in power enterprises, as shown in Table 1. It starts from six aspects: low-carbon power supply structure indicators, power generation technology and economy indicators, pollutant emission indicators, resource comprehensive utilization indicators, ECER innovation mechanism indicators, and ECER management indicators. On the one hand, the importance of low-carbon energy transformation itself for power enterprises is considered. On the other hand, it is also evaluated from the organizational structure of power enterprises, further making the evaluation of ECER performance for power enterprises more comprehensive and objective, making it more informative and practical. However, from Table 1, the evaluation index system for ECER of power enterprises constructed in this study has a large number, reaching a total of 23 evaluation indicators. If the indicator system is directly used, it will increase the complexity of the model, thereby increasing the amount of parameters and computational load of the model, and even affecting the model's output results accuracy. Therefore, it is necessary to reduce the evaluation index system preliminarily constructed by our research institute. This study chose to use rough sets for reduction processing, and the reduction findings are expressed in Table 2 [10].

Table 2. Reduction findings of performance evaluation index system of ECER performance of power enterprises evaluation index system.

Primary indicators		Secondary indicators		
Name	**Code**	**Name**	**Implication**	**Code**
Low-carbon power supply structure	A	Proportion of clean energy generation	The ratio of clean energy generation and electricity generation to total electricity generation	X_1
		Proportion of new energy power generation capacity added	New energy generation accounts for the proportion of all new power generation	X_3
Technical and economic indicators of power generation	B	Standard coal consumption for power generation	The amount of standard coal consumed for each kilowatt-hour of electricity generated by power generation enterprises	X_6
		Standard coal consumption for power supply	The average standard coal amount consumed for every 1kWh of electricity supplied by the power plant	X_7
Pollutant discharge index	C	NOx emissions per unit of power generation	The NOx emissions for each kilowatt-hour of electricity generated by the power generation enterprise	X_9
		Soot emission per unit of power generation	The soot emission of electricity per kilowatt-hour of power generation enterprises	X_{10}
Indicators of comprehensive utilization of resources	D	Comprehensive utilization rate of fly ash	The ratio of the annual utilization and production of fly ash	X_{12}
		Desulfurization gypsum utilization rate	The ratio of the annual utilization capacity and the production capacity of desulfurized gypsum	X_{14}
Indicators of innovative mechanisms for ECER	E	Implementation of the carbon trading mechanism	The impact of the carbon trading mechanism on the emission reduction benefits	X_{16}
ECER management indicators	F	The setting and implementation of ECER targets	Benefits and achievements of ECER in electric power enterprises	X_{23}

By Table 2, the evaluation system covers low carbon power supply structure, power generation technical and economic indicators, pollutant emissions index, comprehensive utilization of resources, ECER innovation mechanism indicators and ECER management index six aspects, can fully reflect the energy conservation and emissions reduction performance of electric power enterprises, and avoid the index of high complexity and low accuracy. On the premise of covering all aspects of ECER, the above index system has deleted the highly repetitive indicators. Take the proportion of clean energy power generation and the proportion of new energy power generation capacity as an example, these two indicators not only reflect the proportion of new energy power generation, but also reflect the proportion of fossil energy power generation. If too many evaluation data metrics are directly input into the model, it will be difficult to make the model structure too complex. Therefore, this study uses rough sets to reduce the preliminarily established performance evaluation index system for ECER in power enterprises. After reduction, the number of indicators is 10, which is still relatively large. Therefore, further processing is carried out on them. Due to the common influencing factors among the 10 indicators in Table 2, in order to further simplify the evaluation index, the study used the principal component analysis method to extract the common factors of each index and calculate the contribution degree of each index. The index with the total variance contribution of more than 85% will be used as the final evaluation index. In this study, objective mathematical statistical methods are used to extract the common factor matrix, resulting in the common factor correlation statistical table shown in Table 3.

Table 3. Correlation analysis between 10 indicators and common factors.

Indicator code	Common factor serial number				Total cost of the common factor
	1	2	3	4	
X_1	**0.659**	**0.625**	**-0.514**	**0.246**	**1.016**
X_3	0.275	0.487	0.116	0.017	0.895
X_6	0.114	0.659	0.159	-0.436	0.496
X_7	**0.395**	**0.294**	**-0.184**	**0.682**	**1.187**
X_9	0.178	0.296	-0.422	0.468	0.52
X_{10}	**0.658**	**0.284**	**-0.148**	**0.592**	**1.386**
X_{12}	0.483	0.562	0.284	-0.684	0.645
X_{14}	0.153	0.345	-0.648	0.632	0.482
X_{16}	0.154	0.653	-0.523	0.538	0.822
X_{23}	**0.157**	**0.593**	**0.452**	**0.128**	**1.33**

Table 4. Reliability and validity testing.

Project		Value
KMO inspection		0.897
Bartlett sphericity test	Approximate chi-square	7684.21
	DF	0.815
	Significance	0.000

All indicators in the performance assessment metrics system for ECER constructed in this study can be directly obtained from power enterprises, and their practical application feasibility is good. The final reduction results are four indicators. To demonstrate the reliability and validity of the reduced indicator system, this study utilize Kaiser-Meyer-Olkin (KMO) test and Bartlett method to test the reduced performance evaluation indicator system for ECER in power enterprises. The research outcomes are denoted in Table 4. From Table 4, the ECER performance evaluation index system of power enterprises obtained after reduction in this study has strong objectivity, and its rationality and feasibility for practical analysis are also strong.

In summary, while ensuring the reliability and validity of performance evaluation, after reducing the preliminarily constructed indicator system, X1: proportion of clean energy generation (%), X7: standard coal consumption for power supply (g/kWh), X10: smoke and dust emissions per unit of power generation (g/kWh), and X23: formulation and implementation of

ECER goals are ultimately selected. The questionnaire survey method is used by inviting experts to rate the indicators. The weight values corresponding to each indicator are obtained and used as the input vector of the model. By inputting them into the model, learning and training can be achieved. Finally, based on the output results of the model, the analysis and evaluation of ECER performance of power enterprises can be achieved.

3.2. Construction of LSSVM Model Based on Improved LSO Algorithm

LSO algorithm is an intelligent algorithm that imitates hunting behavior in the context of lion society [19]. It achieves information sharing within the population through the utilization of group intelligence, and seeks the optimal solution together among individuals through mutual cooperation. Usually, the LSO algorithm first initializes the position x_i of each lion in the lion swarm and the amount of Lions N in the lion swarm, including female Lions and young masters, and confirms the maximum amount of iterations T and dimension D. It sets the current position x_i of the individual as the optimal x_{ibest} position, and the optimal position x_{best} of the swarm as the optimal position x_{king} of the Lion king. Therefore, the update on the position and fitness of the unknown lion king and are shown in Equation (1).

$$x_i^{k+1} = g^k\left(1+y\left\|p_i^k - g_i^k\right\|\right) \tag{1}$$

In Equation (1), x_i^{k+1} means the position of the k+1 generation lion; p_i^k indicates the historical optimal position of the ith generation lion and the kth generation lion; g_i^k means the population optimal position of the ith generation lion and the kth generation lion. The update on the position and fitness of the lioness is shown in Equation (2).

$$x_i^{k+1} = \frac{p_i^k + p_c^k}{2}\left(1+\alpha_f \gamma\right) \tag{2}$$

In Equation (2), γ denotes a random number with a normal distribution of $N(0, 1)$, and p_i^k means the historical optimal position of a hunting partner randomly selected from the kth generation of female Lions. Furthermore, it randomly generates q within the (0, 1) range, and then updates the position of the lion cubs, as shown in Equation (3).

$$x_i^{k+1} = \begin{cases} \dfrac{g^k + p_i^k}{2}\left(1+\alpha_c \gamma\right), 0 < q \le \dfrac{1}{3} \\ \dfrac{p_m^k + p_i^k}{2}\left(1+\alpha_c \gamma\right), \dfrac{1}{3} \le q < \dfrac{2}{3} \\ \dfrac{\bar{g}^k + p_i^k}{2}\left(1+\alpha_c \gamma\right), \dfrac{2}{3} \le q < 1 \end{cases} \tag{3}$$

The optimal position x_{ibest} and x_{best} of the lion swarm are iteratively calculated according to the above formulas. When the set number of iterations or accuracy is arrived, the final result x_{best} and its corresponding fitness value are output. To further improve the convergence speed of the LSO algorithm, chaos algorithm is chosen to improve it. This study adopts Tent chaotic mapping to improve the LSO algorithm, which can better utilize the characteristics of ergodicity and effectively improve the speed of update iteration, which can greatly improve the local search ability of the lion swarm algorithm. Introduce Tent chaos map into the LSO algorithm can transform the variable value in the optimization space into the value interval in the chaotic variable, which improves the utilization efficiency of ergodicity and then improves the convergence speed of LSO algorithm. Firstly, the optimal individual of the lion cub is changed, and the calculation is indicated in Equation (4).

$$Z = (x-l)/(u-l) \tag{4}$$

The purpose of Equation (4) is to transform the variable values in the optimization space of the lion swarm algorithm into the value interval in the chaotic variable. u and l represent the two ends of the interval, respectively, where $[u, l]$ represents the spatial range of the search. Then it transforms the variables of the tent chaotic map, as shown in Equation (5).

$$y = x + \left((u-l)/2\right)\cdot(2\cdot z-1) \tag{5}$$

In Equation (5), y indicates the new positional individual, and z denotes the optimal young lion individual whose optimization space variable value interval is transformed into the chaotic variable value interval. Then, by calculating the fitness of the position individual y, the remaining original individual x is compared, and the optimal individual x_{best} is selected for replacement. Then, a loop iteration is performed until the conditions are met before ending the algorithm. The algorithm flowchart is shown in Figure 1.

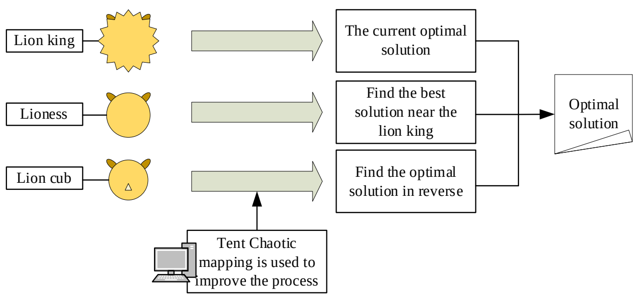


Figure 1. Tent chaotic mapping improved LSO algorithm.

The SVM model, as a typical model in machine learning, its basic idea is to transform the algorithm for finding the optimal hyperplane into an algorithm problem for finding the optimal solution. As shown in Figure 2, it is a schematic diagram of the optimal hyperplane in SVMs, where L is the optimal hyperplane, and the points on the l_1 and l_2 planes are different sample points on the distance from the optimal plane, which can be defined as support vectors.

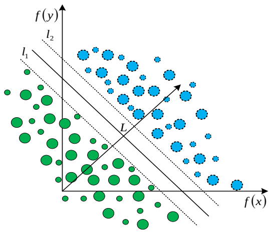


Figure 2. Schematic representation of the optimal hyperplane.

The optimal classification hyperplane used can be described as shown in Equation (6).

$$\begin{cases} (\omega x)+b=0, \|\omega\|=1 \\ y=\begin{cases} +1, (\omega x)-b \geq \Delta \\ -1, (\omega x)-b \leq -\Delta \end{cases} \end{cases} \tag{6}$$

In Equation (6), Δ means the sample interval and $(\omega x)+b$ denotes the hyperplane. If these vectors all belong to a sphere with a radius of R, then for the Δ interval classification hyperplane set, the calculation of its *VC* dimension bound h is shown in Equation (7).

$$h \leq \min\left(\left[\frac{R^2}{\Delta^2}\right], l\right)+1 \tag{7}$$

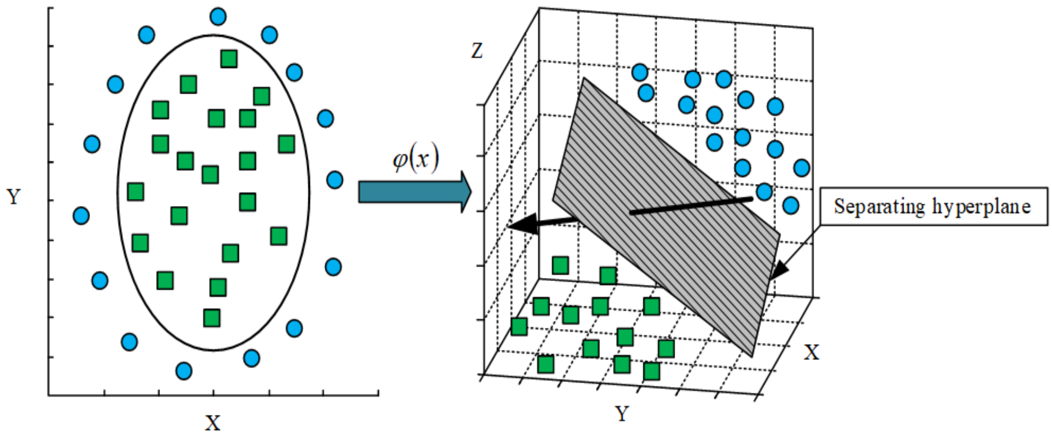
From Equation (7), the inherent structural minimization feature in the SVM model can fundamentally ensure that its empirical risk is minimized, and it selects the optimal hyperplane based on the principle of maximizing the Δ interval, thereby achieving control over the *VC* dimension of the function set. It further establishes the regression theory of the SVM model and add the insensitive loss function ε. Firstly, the training sample set is given as shown in Equation (8).

$$(X_1, y_1), (X_2, y_2), \cdots, (X_n, y_n) \tag{8}$$

In Equation (8), X_i is the input vector, AND $X_i \in R^n$. y_i are the output vectors, and $y_i \in R$. The definition of the insensitive loss function is shown in Equation (9).

$$|y-f(x)|_\varepsilon = \begin{cases} 0, |y-f(x)| \leq \varepsilon \\ |y-f(x)|-\varepsilon \end{cases} \tag{9}$$

In Equation (9), $f(x)$ is the regression estimation function, and the output value of X is y. The foundation of SVM regression theory is the mapping $f: R^n \rightarrow R$ from R^n in the input space to R in the output space, thus enabling $f(x)=y$. Assuming that the obtained sample is within its region, the loss is 0. If the obtained sample is not within the region, a linear penalty will be applied to it, which can obtain a solution with strong robustness. The regression principle of SVM is shown in Figure 3.



a) Complex in low dimensions.

b) Simple in higher dimensions.

Figure 3. SVM regression schematic.

To further enhance the computational efficiency of the model and reduce its computational load, this study adopts a variant algorithm of SVM, namely LSSVM [15]. LSSVM integrates the core ideas of SVMs, and still has advantages such as structural risk minimization and kernel functions. LSSVM can transform the model solving process into solving equation variance, and transform the solving quadratic programming problem in standard SVM into solving linear relationship issues. The given data training set is shown in Equation (10).

$$\{(x_k, y_k) | k=1,2,\cdots,n\} \tag{10}$$

In this training set, n means the total number of training samples; x_k denotes the input data, and $x_k \in R^n$; y_k are the output data, and $y_k \in R^n$. Then, the nonlinear mapping $y_k \in R^n$ is utilized to map the high order feature space of the sample, as shown in Equation (11).

$$y(x)=\omega^T \cdot \phi(x)+b \tag{11}$$

In Equation (11), ω refers to the weight vector and b indicates the paranoia. The objective optimization function is shown in Equation (12).

$$\min_{\omega,b,e}(\omega,b,e)=\frac{1}{2}\omega^T\omega+\frac{1}{2}C\sum_{k=1}^{n}e_k^2 \tag{12}$$

In Equation (12), C expresses the regularization parameter used to control the degree of penalty for errors, and e_k means the relaxation variable. The constraint conditions are shown in Equation (13).

$$\begin{cases} y_k = \omega^T \phi(x_k) + b + e_k \\ k = 1, 2, \cdots, n \end{cases} \tag{13}$$

Furthermore, the Lagrangian function is defined to solve the above problem, as shown in Equation (14).

$$L(\omega, b, e, \alpha) = \varphi(\omega, e) - \sum_{k=1}^{n} \left\{ \alpha_k \left[\omega^T \phi(x_k) + b + e_k - y_k \right] \right\} \tag{14}$$

In Equation (14), α_k indicates the Lagrange multiplier, and $\alpha_k \in R$ is optimized to make that the partial derivative of ω, b, e_k, α_k is 0, as shown in Equation (15), after optimization.

$$\begin{cases} \omega = \sum_{k=1}^{n} \alpha_k \phi(x_k) \\ \sum_{k=1}^{n} \alpha_k = 0 \\ \alpha_k = e_k \gamma \\ \omega^T \phi(x_k) + b + e_k - y_k = 0 \end{cases} \tag{15}$$

The above problem is transferred into a linear equation which is solved to obtain α and b, then the corresponding LSSVM optimal linear regression function is shown in Equation (16).

$$f(x) = \sum_{k=1}^{l} \alpha_k K(x, x_i) + b \tag{16}$$

In Equation (16), according to Mercer's conditions, $K(x, x_i) = \phi(x)^T \phi(x_l)$ is its kernel function. For the LSSVM model, based on the system process and data characteristics, the RBF kernel function is ultimately selected, which has the advantages of simple structure and easy parsing. Its expression is shown in Equation (17).

$$K(x, x_i) = \exp\left(-\frac{|x - x_i|^2}{2\sigma^2} \right) \tag{17}$$

In Equation (17), σ is the kernel function width, and its value requirements are relatively strict. A larger kernel function width will result in a relatively greater degree of mutual influence between support vectors, which will result in the model's accuracy not meeting the requirements. A smaller kernel function width will make the mutual relationships between support vectors more relaxed, making the machine learning process more complex. To address this issue, the improved LSO algorithm proposed in the previous section is used to obtain values, thereby utilizing the improved LSO algorithm to improve LSSVM. The final operational flowchart is shown in Figure 4.

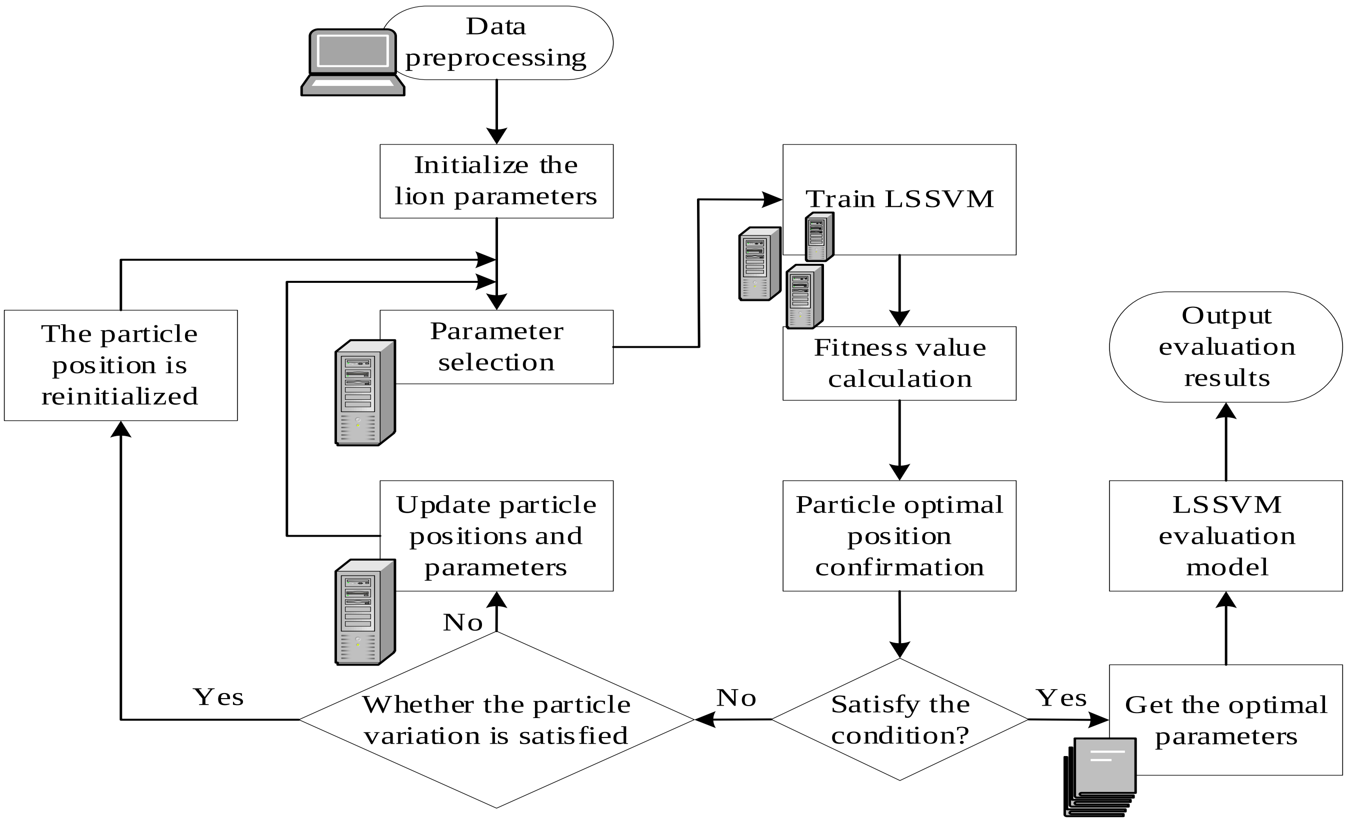


Figure 4. Improved algorithm of the optimization of power enterprise performance evaluation of ECER of LSSVM model process.

4. Evaluation of ECER Performance Evaluation Model for Power Enterprises Based on Improved LSO Algorithm LSSVM

To verify the availability and effectiveness of the ECER performance evaluation model for power enterprises based on improved LSO algorithm optimized LSSVM proposed by our research institute, this study obtained several years of ECER work related data of a certain power enterprise with consent, and divided it into test and training sets. The data set has a total of 12,858 pieces of data, including carbon trading data, power generation data, new energy generation, resource utilization, etc. Since this data set is the internal data of power enterprises, the research does not provide data download methods and download links here for the purpose of safeguarding the interests of power companies. To fully demonstrate the proposed method's superiority, LSSVM and SVM models were selected as comparisons with the LSO-LSSVM model. To ensure the objectivity of the experiments in this study, all algorithms in this study had the same operating environment and set the same conditions. As shown in Table 5, the software and hardware environments for the experiment in this study are presented.

Table 5. Software and hardware environment.

Software and hardware environment name	Parameter specification
Device type	Deep learning server
Processor	Intel(R) Xeon(R) CPU E5-2660 v2@ 2.20Ghz
Graphics card	Nvidia GTX 2080 8G *2
Internal memory	120GB
Operating system	Ubuntu 18.04
Experimental platform	Python 3.8.2 Matlab 2016b

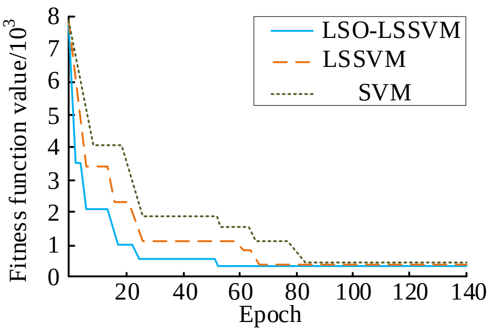


Figure 5. Comparison of iterative curves.

Firstly, using the test set in this study, three algorithms were trained and learned, and their fitness curves were tested for changes with the number of iterations to compare their convergence performance. The experimental results are expressed in Figure 5. From Figure 5, the LSO-LSSVM algorithm only required 51 iterations when reaching the fitness curve value, while the LSSVM and SVM models required 68 and 82 iterations, respectively. This result indicated that the proposed algorithm had good convergence effectiveness, and its training efficiency has been improved through the improvement of the LSO algorithm.

A detailed test was conducted on the convergence of the three algorithms. To avoid the impact of experimental errors as much as possible, five tests were conducted, and the average and standard deviation of their convergence were taken separately. The experimental findings are denoted in Table 6. From Table 6, the LSO-LSSVM model had the best numerical values, further proving the excellent convergence effectiveness of the proposed model. It had better training efficiency and effectively reduced training time and cost.

Table 6. The mean and standard deviation of convergence of the three algorithms.

Number of experiments		LSO-LSSVM	LSSVM	SVM
1	Mean	**5.84E-05**	8.69E-05	7.84E-02
	Standard	**6.09E-06**	7.49E-04	5.61E-03
2	Mean	**3.81E-05**	5.16E-04	4.97E-03
	Standard	**6.95E-05**	4.18E-03	5.82E-02
3	Mean	**4.26E-06**	6.44E-05	4.69E-03
	Standard	**3.46E-04**	5.62E-02	6.29E-03
4	Mean	**5.69E-05**	4.32E-04	6.48E-03
	Standard	**7.27E-05**	1.39E-03	7.81E-02
5	Mean	**6.34E-04**	5.10E-03	5.69E-02
	Standard	**4.24E-05**	4.37E-03	7.62E-02

The F1 and Recall values of the three algorithms were tested, and the research outcomes are shown in Figure 6. From Figure 6, the highest F1 value of the LSO-LSSVM model proposed in this study was 0.978, while the LSSVM and SVM models were 0.948 and 0.931, respectively. The model proposed in this study had a relatively leading numerical value. Its Recall value reached 0.958, leading the LSSVM and SVM models by 0.026 and 0.048, respectively.

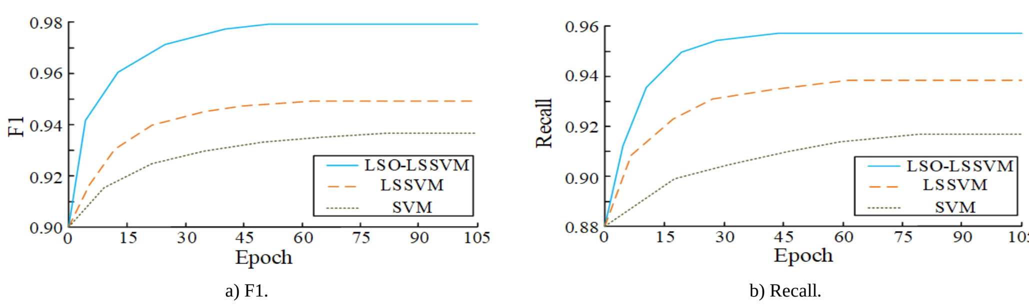


Figure 6. F1 and Recall of three algorithms.

The Area Under the Curve (AUC) values and accuracy of the three algorithms were tested to derive the performance of each algorithm. To minimize the impact of error values, each algorithm was trained to its optimal state and tested using the same training set and testing data set. To minimize errors, each algorithm was tested 10 times and the average value was taken for comparison. The test outcomes are expressed in Table 7. Where, the LSO-LSSVM mode had an AUC value of 0.952, which was 0.020 and 0.038 higher than the LSSVM and SVM models, respectively. The accuracy of the LSO-LSSVM model proposed in this study reached 0.983, while the average accuracy values of the LSSVM and SVM models were 0.940 and 0.924, respectively. The model proposed in this study led by 0.043 and 0.059, respectively.

Table 7. F1 values and accuracy of the three algorithms.

Index	Number of experiments	Model		
		LSO-LSSVM	LSSVM	SVM
AUC	1	0.959	0.927	0.912
	2	0.948	0.921	0.914
	3	0.941	0.937	0.926
	4	0.958	0.904	0.902
	5	0.961	0.924	0.931
	6	0.949	0.935	0.913
	7	0.951	0.938	0.927
	8	0.947	0.941	0.903
	9	0.953	0.942	0.908
	10	0.957	0.952	0.901
	Average value	**0.952**	**0.932**	**0.914**
Accuracy	1	0.978	0.957	0.925
	2	0.981	0.941	0.917
	3	0.978	0.93	0.924
	4	0.983	0.928	0.911
	5	0.991	0.945	0.927
	6	0.982	0.921	0.923
	7	0.986	0.931	0.925
	8	0.992	0.924	0.932
	9	0.985	0.958	0.936
	10	0.974	0.968	0.915
	Average value	**0.983**	**0.940**	**0.924**

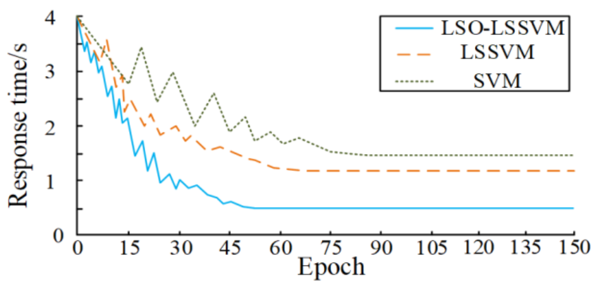


Figure 7. Response of three algorithms.

The response time of three algorithms and the relationship between their iteration time and response time were tested, and the calculation time of several algorithms in practical applications was compared. The test results are shown in Figure 7. Where, the response time of the three models gradually decreased and tended to stabilize with the increase of iteration times. The LSO-LSSVM model proposed in this study ultimately achieved a response time of 0.51 seconds, which was reduced by 0.98 seconds and 1.31 seconds compared to the LSSVM and SVM models, respectively, and reduced by 66% and 72% of the response time. This indicated that the LSO-LSSVM model proposed in this study could output evaluation results quickly, had high computational efficiency, and could greatly save time and cost.

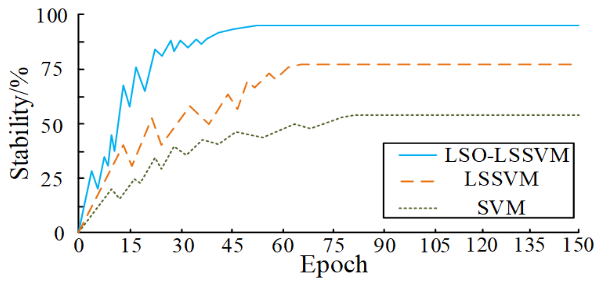


Figure 8. Stability of three algorithms.

The stability of the three algorithms was tested, and the test findings are illustrated in Figure 8. From the figure, the stability of the LSO-LSSVM algorithm proposed in this study reached a peak of stability and remained stable as the number of iterations increased. Its stability ultimately reached 96%, leading by 23% and 45% compared to the LSSVM and SVM models, respectively. This indicated that this study could maintain high stability in practical applications, effectively reduce the resources and time wasted due to crashes, and thus improve efficiency.

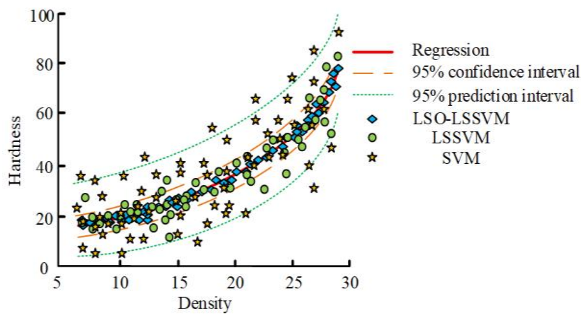


Figure 9. The fit degree of the three algorithms.

Then, simulation experiments were conducted on the three algorithms to test their fit to verify their reliability and validity in practical applications. The test outcomes are indicated in Figure 9. From the figure, the LSO-LSSVM model had the best fit performance, reaching 98.6%, which was 7.34% and 18.78% higher than the LSSVM and SVM models, respectively. This indicated that the proposed model performed better in practical applications and could output more accurate results.

Finally, simulation experiments were conducted to conduct actual tests on the three algorithms. Fifteen sets of data were selected, with scores ranging from 0 to 10, indicating that the ECER performance of power enterprises ranged from the worst to the best. The data was input into the three algorithms for actual testing of error values, and the test findings are expressed in Table 8. From Table 8, the LSO-LSSVM algorithm proposed in this study had excellent error performance, with an average error of only 0.14. Compared to the LSSVM and SVM models, it has decreased by 0.45 and 0.77, respectively. It performed well in practical use and could output scoring data with great accuracy. In summary, the LSO-LSSVM based performance evaluation model for ECER in power enterprises proposed by this research institute has shown excellent performance and high accuracy in practical applications. The output data could also accurately reflect the actual situation of its ECER work, which had strong usability and practical significance.

Table 8. The average error of the three algorithms.

Sample number	LSO-LSSVM	LSSVM	SVM	Actual evaluation result
1	9.7	9.4	8.9	9.8
2	8.9	8.5	8.2	9.1
2	8.7	9.5	8.1	8.9
4	8.5	9.7	9.8	8.7
5	6.4	8.2	7.9	6.7
6	7.5	7.5	8.2	7.2
7	5.4	5.6	6.4	5.4
8	6.5	6.1	5.1	6.6
9	5.1	4.5	6.7	5.2
10	3.8	4.5	4.8	3.9
11	8.5	7.6	7.2	8.4
12	9.2	8.9	8.4	9.2
13	7.5	7.2	7.5	7.6
14	8.0	7.5	7.7	8.1
15	8.3	8.1	8.1	8.5
Average error	**0.14**	**0.59**	**0.91**	-

In order to further explore the evaluation effect of the energy saving and emission reduction of the proposed algorithm, the study compares it with the energy saving and emission reduction evaluation models of other power plants (PSO-LSSVM and BACA). Table 7 of each algorithm the accuracies of the three algorithms are shown in Table 9.

Table 9. Accuracy of each algorithm.

Sample number	LSO-LSSVM	PSO-LSSVM	BACA
1	0.975	0.945	0.928
2	0.979	0.941	0.924
2	0.985	0.946	0.927
4	0.982	0.949	0.928
5	0.989	0.953	0.922
6	0.983	0.957	0.926
7	0.987	0.952	0.929
8	0.991	0.956	0.932
9	0.986	0.951	0.936
10	0.981	0.948	0.931
11	0.978	0.946	0.928
12	0.974	0.941	0.934
13	0.973	0.947	0.929
14	0.977	0.951	0.926
15	0.984	0.953	0.925
Average accuracy	**0.982**	**0.949**	**0.928**

According to Table 9, the average accuracy of LSO-LSSVM and PSO-LSSVM and Boundary Awareness and Content Adaptation (BACA) were 0.982,0.949 and 0.928, respectively. It can be seen that the proposed LSO-LSSV algorithm outperforms other algorithms in the evaluation of energy saving and emission reduction in power plants.

5. Conclusions

The current environmental pollution is becoming increasingly serious, and the ECER work of traditional power enterprises is imperative. Therefore, this study proposed a performance evaluation model for ECER in power enterprises based on LSO-LSSVM, and reconstructed a more realistic evaluation index system for evaluation. Based on the characteristics of the data and the actual situation, the LSSVM model was selected, and an improved LSO algorithm was used to address its parameter selection problem. The experimental outcomes illustrated that the LSO-LSSVM model proposed in this study exhibited good convergence performance, requiring only about 51 iterations to reach the optimal fitness curve value. The improved LSO algorithm greatly improved its training efficiency. The highest F1 and Recall values were 0.978 and 0.958, respectively. Its AUC value reached 0.952, with an accuracy of 0.983, both ahead of the other two algorithms. Its response time ultimately stabilized at 0.51 seconds, which was reduced by 0.98 seconds and 1.31 seconds compared to LSSVM and SVM models, respectively. Its stability ultimately reached 98.6%, higher than the other two models. It is fitting degree reached 98.6%, which was 7.34% and 18.78% higher than LSSVM and SVM models, respectively. In the simulation experiment, its average error was only 0.14, indicating excellent performance. At the same time, compared with the wind power generation estimation method of power enterprises based on the prediction generalized autoregressive score model with exogenous variables *x* in literature [6], the proposed method can more accurately reflect the energy saving and emission reduction efficiency of new energy generation in power enterprises, rather than only analyze the new energy generation. The above findings illustrated that the performance evaluation model for ECER in power enterprises based on improved LSO-LSSVM model proposed in this study had excellent performance in all aspects, and could output extremely accurate results in practical use, providing accurate data support for ECER work in power enterprises. However, in this study, the impact of objective factors such as regional factors and economic conditions on power enterprises was not considered. Therefore, in order to build a more reasonable evaluation system of ECER effect of power enterprises, the influence of regional factors and economic conditions will be added to the evaluation system in the future, so as to build a more universal performance evaluation system of ECER performance of power enterprises.

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