Digital Investment Risk Evaluation Model of Power Grid Enterprises Based on FAHP-AOA-LSSVM

Xinyi Lan[1](✉), Xinping Wu[2], Qiuzhe Ma[2], Wenqing Liu[1], and Jinchao Li[1]

[1] Institute of Economic and Management, North China Electric Power University, Beijing, China
905806800@qq.com, lijc@ncepu.edu.cn

[2] Engineering Data Center Digital Planning Division, State Power Economic Research Institute, Beijing, China

Abstract. The digital transformation of the economy represents the general trend. In order to effectively control the investment risk of grid digitization projects and adopt risk-coping strategies with foresight, construct an investment risk evaluation model for grid digitization projects by optimizing the kernel function parameters and regularization parameters of least squares support vector machines through the Archimedes algorithm. Questionnaires and expert judgment are used to analyze the risk factors facing digitization projects' investment environment and establish an investment risk evaluation system. A fuzzy hierarchical analysis method is applied to evaluate the investment risk of 40 completed projects according to the actual engineering situation, and the evaluation results are normalized and processed as the input vector of the evaluation model for training. The results show that the Archimedes optimization algorithm improves the least squares support vector machine model prediction with an average absolute percentage error of 3.5026%, which can more accurately assess the riskiness of digital projects and provide a reference basis for digital project investment risk control.

Keywords: digital project investment risk · fuzzy hierarchical analysis · Archimedean optimization algorithm · least squares support vector machine

1 Introduction

Digital technology is driving the digital transformation of industries. Power grid enterprises in this new situation need to create favorable conditions for digital transformation and focus on the benefits of digital transformation. However, due to the significant investment amount and long investment cycle of digital projects, there are many risk factors in the investment process. How to scientifically and effectively evaluate and avoid investment risks and increase income is vital.

The current relevant research mainly draws on mathematics, operations research, economics, and computer science to analyze and evaluate risks, such as arbitrage pricing theory, mathematical statistics, the Monte Carlo method [1], fuzzy mathematics [2],

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grey system theory [3] and other methods. Demong N Lu J, Hussain F [4] proposed a new uncertainty measure for risk factors based on multidimensional data models and data mining techniques. Das I, Bhattacharya K, Canizares C [5] established a novel relationship between the sensitivity index and investors' profit to assess project investment risk.

Most of the above evaluation methods use empirical risk minimization and require extensive sample support, which only applies to more data in the current investment risk evaluation. The least squares support vector machine (LSSVM) has been widely used in regression and classification in recent years. It is based on the structural risk minimization theory, overcomes the dependence on large samples, and better solves the problems of small samples and high dimensions. In addition, Archimedes optimization algorithm (AOA) performs well in solving random optimization problems. Based on LSSVM and AOA, this paper constructs an investment risk evaluation model to provide a decision-making reference for digital project investment risk control.

2 Fuzzy Analytic Hierarchy Process

The FAHP method is mainly based on the subjective experience of experts. Its main steps are as follows.

2.1 Establish Judgment Matrix

Determine the evaluation object's factor set and comment set and record them as $U = \{u_1, u_2, \cdots, u_n\}$. The comment set is divided into 5 levels according to the level of contribution and recorded as $V = \{v_1, v_2, \cdots, v_5\}$ in the order of good, better, average, bad, and worse.

2.2 Determine the Membership Function

After the range transformation, each index value is between 0 and 1. Use $\{1, 0.75, 0.5, 0.25, 0\}$ to represent good, better, average, bad, and worse in the comment set, that is, $V = \{1, 0.75, 0.5.0.25.0\}$. Select the normal membership function $\mu_a = e\{-[(x-a)/\sigma]^2\}$ as the membership function of each evaluation index to the comment set, where σ is the standard deviation of the value of the comment set, $a = \{1, 0.75, 0.5, 0.25, 0\}$.

2.3 Single-Factor Evaluation

According to the membership formula, calculate the membership of each index value to the 5 comments of good, better, average, bad, and worse, and normalize to get the matrix M. The calculation formula is

$$y_{ij} = x_{ij} / \sum_{j=1}^{n} x_{ij} \tag{1}$$

where: $1 \leq i \leq m = 9, \quad 1 \leq j \leq n = 3$.

2.4 Determine the Weight Vector

Apply FAHP to give the weight of the three levels to the secondary indicators. Collect the expert scoring, use the 1–9 scale method to record, and set the scoring latitude fruit as matrix B, according to formula (2) to calculate to get the weight coefficient as $\lambda_{\max}$. The calculation formula is

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(BM)_t}{nM_t} \tag{2}$$

2.5 Consistency Test

Calculate the consistency indicator CI. Set to α by formula (3), where n is the order of the short judgment array, that is the total number of indicators. Check the table to get random consistency index RI, set to β by formula (4), and calculate consistency ratio CR, set to γ, from which to determine whether to pass the consistency test

$$\alpha = (\lambda_{\max} - n)/(n - 1) \tag{3}$$

$$\gamma = \alpha/\beta \tag{4}$$

If the calculation result meets $\gamma < 0.1$, the judgment matrix can be considered acceptable through the consistency test. Otherwise, modify the judgment matrix until it meets $\gamma < 0.1$. If the consistency check is passed, the weight vector can be calculated.

3 AOA's Improved Risk Evaluation Model of LSSVM

LSSVM is an extension of a Support Vector Machine (SVM). It improves the model's generalization ability through machine learning and avoids some limitations of neural networks.

AOA automatically searches the optimal value of kernel function and regularization parameters. AOA improved the LSSVM model, which combines both advantages, still has high prediction accuracy when the number of investment risk samples is small and applies to the evaluation of investment risk of power grid digital projects.

3.1 Principle of LSSVM Evaluation

The least squares support vector machine (LSSVM) is an improved traditional support vector machine model. It uses the least squares linear equation as its loss function to transform the inequality constraints of the standard SVM into equality constraints [6, 7].

The general formula of the LSSVM regression function model is:

$$f(x) = m^{\mathrm{T}}\varphi(x) + b \tag{5}$$

where m is the weight vector of the feature space; $\varphi(x)$ is the kernel function of LSSVM; b is the amount of deviation.

Obtaining the exact value of the m, b in Eq. (5), following the principle of structural risk minimization, converts the LSSVM optimization problem to:

$$\begin{cases} \min J(m, b, e) = \frac{1}{2}\|m\|^2 + \frac{1}{2}j\sum_{i=1}^{\pi} e_i^2 \\ \text{s. t.} y_i = m^{\mathrm{T}}\varphi(x_i) + b + e_i \end{cases} \tag{6}$$

e_i is the regression error vector; j is the regularization parameter. Optimization of Eq. (6) by introducing Lagrange λ_i multipliers give:

$$L(\omega, b, e, \lambda) = J(m, b, e) - \sum_{i=1}^{x} \lambda_i \left[m^{\mathrm{T}}\varphi(x_i) + b + e_i - y_i\right] \tag{7}$$

Derive the solution using the KKT condition:

$$\begin{cases} \frac{\partial J}{\partial m} = 0 \to \sum_{i=1}^{i} \lambda_i \varphi(x_i) \\ \dfrac{\partial J}{\partial m} = 0 \to \displaystyle\sum_{i=1} \lambda_i = 0 \\ \frac{\partial J}{\partial m} = 0 \to \lambda_i = j_{e_i} \\ \frac{\partial J}{\partial m} = 0 \to m^{\mathrm{T}}\varphi(x_i) + B + e_i - y_i = 0 \end{cases} \tag{8}$$

Eliminating m and e_i in the above equation yields the LSSVM load forecasting model:

$$f(x) = \sum_{i=1}^{N} \lambda_i K\left(x_i, x_j\right) + b \tag{9}$$

In Eq. (10), A is the kernel function, and in this paper, the radial basis function is taken as the kernel function, and its expression is as follows:

$$K(x_i, y_i) = \exp\left(\frac{-x_i - y_i^2}{2\sigma^2}\right) \tag{10}$$

where σ is the width factor of the kernel function.

3.2 AOA Search for Optimal Solutions of LSSVM Parameters

AOA is a population-based algorithm. During the search process, each object will be initialized with its random position in the fluid. After evaluating the fitness of the initial population, AOA starts the iteration until it meets the termination conditions. In each iteration, AOA updates the density and volume of each object. The acceleration of an object is updated based on its collision with any other adjacent object. Then, determine the new location of the object.

1) **Initialization.**

Initialize the positions of all objects using Eq. (11).

$$O_i = lb_i + rand \times (ub_i - lb_i); i = 1, 2, \ldots, N \tag{11}$$

where O_i is the location of the ith object among N individuals, and lb_i and ub_i are the lower and upper limits of the search space, respectively.

Initialize the volume (vol) and density (den) of the ith object using Eq. (12):

$$\begin{aligned} den_i &= rand \\ vol_i &= rand \end{aligned} \tag{12}$$

where rand is a randomly generated D-dimensional vector between [0,1].

Finally, the acceleration of the object (acc) is initialized using Eq. (13):

$$\mathrm{acc_i} = \mathrm{lb_i} + \mathrm{rand} \times (\mathrm{ub_i} - \mathrm{lb_i}) \tag{13}$$

In this step, the initial overall is evaluated and the object with the best fitness value is selected. Assign x_{best} , den_{best} , vol_{best} and acc_{best} .

2) **Updating density and volume.**

The density and volume of the ith object at the t + 1st iteration is updated using Eq. (14):

$$\begin{aligned} \mathrm{den}_i^{t+1} &= \mathrm{den}_i^{\mathrm{t}} + \mathrm{rand} \times \left(\mathrm{den_{best}} - \mathrm{den_i^t}\right) \\ \mathrm{vol_i^{t+1}} &= \mathrm{vol}_i^{\mathrm{t}} + \mathrm{rand} \times \left(\mathrm{vol_{best}} - \mathrm{vol_i^t}\right) \end{aligned} \tag{14}$$

where den_{best} and vol_{best} are the best densities and volumes of the objects found so far; rand is a random number between [0,1].

3) **Transfer operator and density operator.**

TF converts search from exploration to development and uses the Eq. (15) to define:

$$\mathrm{TF} = \exp\left(\frac{\mathrm{t} - \mathrm{t_{max}}}{\mathrm{t_{max}}}\right)_{\max} \tag{15}$$

where the transfer factor gradually increases until it reaches 1; t and $t_{\max}$ denote the current and maximum number of iterations, respectively. Similarly, the decreasing density factor d contributes to the global to local search of AOA, which decreases over time using Eq. (16).

$$d^{t+1} = \exp\left(\frac{t_{\max} - t}{t_{\max}}\right) - \left(\frac{t}{t_{\max}}\right) \tag{16}$$

d^{t+1} decreases as the number of iterations increases.

4) **Exploration phase.**

a) *Collision between objects.*

If TF $\leq$ 0.5, a collision between objects occurs, choose an object (mr) at random and update the object acceleration for t + 1 iterations using Eq. (17).

$$\mathrm{acc_i^{t+1}} = \frac{\mathrm{den_{mr}} + \mathrm{vol_{mr}} \times \mathrm{acc_{mr}}}{\mathrm{den}_i^{\mathrm{t+1}} \times \mathrm{vol}_i^{\mathrm{t+1}}} \tag{17}$$

where den_i , vol_i and acc_i are the density, volume and acceleration of object i, respectively.acc_{mr}, den_{mr} and vol_{mr} are the random object's acceleration, density, and volume, respectively.

b) *No collision between objects.*

If TF > 0.5, no collision between objects, update t + 1 iterations of object acceleration using the Eq. (18):

$$\mathrm{acc}_{\mathrm{i}}^{\mathrm{t}+1} = \frac{\mathrm{den}_{\mathrm{best}} + \mathrm{vol}_{\mathrm{best}} \times \mathrm{acc}_{\mathrm{best}}}{\mathrm{den}_{i}^{\mathrm{t}+1} \times \mathrm{vol}_{1}^{\mathrm{t}+1}} \tag{18}$$

where acc_{best} is the optimum acceleration of the object.

c) *Normalized acceleration.*

Standardize the acceleration using formula (19) to calculate the percentage change:

$$\mathrm{acc}_{i-\mathrm{norm}}^{t+1} = u \times \frac{\mathrm{acc}_{i}^{t+1} - \min(\mathrm{acc})}{\max(\mathrm{acc}) - \min(\mathrm{acc})} + 1 \tag{19}$$

where u and l are the normalized range, set to 0.9 and 0, respectively $\mathrm{acc}_{i-\mathrm{norm}}^{t+1}$ determines the percentage of steps that each agent will change.

5) ***Position update.***

If TF ≤ 0.5(exploration phase), the position of the i-th object at generation t + 1 is calculated using Eq. (20).

$$\mathrm{x}_{\mathrm{i}}^{\mathrm{t}+1} = \mathrm{x}_{\mathrm{i}}^{\mathrm{t}} + \mathrm{C}_1 \times \mathrm{rand} \times \mathrm{acc}_{\mathrm{i-norm}}^{\mathrm{t}+1} \times \mathrm{d} \times \left(\mathrm{x}_{\mathrm{rand}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{t}}\right) \tag{20}$$

where $C_1 = 2$. Otherwise, if $TF > 0.5$(development phase), the object will update its position using Eq. (21).

$$\begin{aligned}\mathrm{x}_{\mathrm{i}}^{\mathrm{t}+1} = {} & \mathrm{x}_{\mathrm{best}}^{\mathrm{t}} + \mathrm{F} \times \mathrm{C}_2 \times \mathrm{rand} \times \mathrm{acc}_{\mathrm{i-norm}}^{\mathrm{t}+1} \times \mathrm{d} \\ & \times \left(\mathrm{T} \times \mathrm{x}_{\mathrm{best}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{t}}\right)\end{aligned} \tag{21}$$

where $C_2 = 6$; T increases with the number of iterations and is proportional to the transfer operator, defined by $T = C3 \times TF$. In the range $[C3 \times 0.3, 1]$, T increases with iteration and starts at a certain percentage from the best position.

F is the sign for changing the direction of movement using Eq. (22).

$$F = \begin{cases} +1 \text{ if } \mathrm{P} \le 0.5 \\ -1 \text{ if } \mathrm{P} > 0.5 \end{cases} \tag{22}$$

of which $P = 2 \times \mathrm{rand} - C_4$.

6) **Adaptation function.**

Use the objective function f to evaluate each object and remember the optimal solution found so far. Assign x_{best}, den_{best}, vol_{best} and acc_{best}.

4 Construction of Risk Evaluation Index System for Power Grid Digital Investment

4.1 Questionnaire Design and Data Sources

In this study, experts from different departments and grades are covered in the questionnaire distribution to compare their perceptions of the various risk factors for digitizing the companies listed in the questionnaire. The experts' compositions are shown in Table 1, and the specific quantitative indicators of the questionnaire are shown in Tables 2 and 3.

Table 1. List of experts

Name	Category	Number (persons)	Percentage (%)
Title	Professor of engineering	20	50
	Senior engineer	16	40
	Engineer	4	10
Academic qualifications	PhD	10	25
	Master	30	75
Years of work	Less than 5 years	4	10
	5˜9 years	4	10
	10˜19 years	12	30
	20˜29 years	8	20
	More than 30 years	12	30
Total		40	100

Table 2. Quantitative values for importance, applicability, and familiarity of indicators

Importance	Quantified value	Applicabiliy	Quantified value	Familiarity	Quantified value
Very important	1	Very applicable	1	Very familiar	1
Important	0.8	Applicable	0.8	Familiar	0.8
Generally	0.6	Generally	0.6	Generally	0.6
Not very important	0.4	Not very applicable	0.4	Not very familiar	0.4
Not important	0.2	Not applicable	0.2	Unfamiliar	0.2

Table 3. Quantitative values for the basis of judgement

Basis of judgement	Quantified value
Practical experience	0.8
Theoretical basis	0.6
National and international literature on digital projects	0.4
Professional intuition	0.2

4.2 Expert Evaluation

The motivation factor for experts is obtained by examining the return of questionnaires, which is calculated as follows:

$$\textit{Expert motivation factor} = \frac{\textit{number of questionnaires returned}}{\textit{total number of questionnaires distributed}} \tag{23}$$

The expert's authority coefficient (Cr) is influenced by two factors: the expert's familiarity with the content of the indicator (Cs) and the basis for judging the indicator (Ca). When $Cr \geq 0.7$, the evaluation result is considered valid. Its calculation formula is:

$$\mathrm{Cr} = \frac{(\mathrm{Cs} + \mathrm{Ca})}{2} \tag{24}$$

The coefficient of coordination of experts' opinions is expressed by variation $C.V$. The smaller the value of $C.V$, the higher the experts' coordination degree and the higher the reliability of the consultation results. The coefficient of variation is generally considered to be less than 0.25 and is calculated as follows:

$$\mathrm{C.V} = \frac{\mathrm{SD}}{\mathrm{MN}} \times 100\% \tag{25}$$

SD--standard deviation
MN--mean

1) **Screening methods and basis.**

The evaluation indicators for power grid digitization projects are selected by combining the boundary value and expert methods. This paper mainly adopts three boundary values: the arithmetic mean boundary value, the full score frequency boundary value, and the variation coefficient boundary value. The calculation formula is as follows.

$$\begin{aligned} &\textit{Index mean limit} = \textit{mean arithmetic mean of} \\ &\textit{indicators} - \textit{standard deviation of indicators} \end{aligned} \tag{26}$$

$$\begin{aligned} &\textit{Full scale frequency limit} = \textit{mean of} \\ &\textit{the arithmetic mean of the full frequency of} \\ &\textit{the indicator} - \textit{standard deviation} \end{aligned} \tag{27}$$

$$\begin{aligned} & Variation coefficient limit = mean\ of\ the\ arithmetic \\ & mean\ of\ the\ coefficient\ of\ variation\ of\ the \\ & indicator + standard\ deviation \end{aligned} \tag{28}$$

2) **Boundary value analysis.**
a) *Experts' motivation coefficient.*

In the first round of expert consultation, 40 questionnaires were distributed to 40 experts, of which 36 questionnaires were effectively collected, with an effective recovery rate of 90%. The positive coefficients of experts in the two rounds were calculated to be 0.9 and 1.0, respectively. The positive coefficients of experts were high, indicating that the experts who participated in the consultation were more concerned about the research content of this paper and were more active in participating.

b) *Coefficient of experts' authority.*

The authority degree coefficient of experts was calculated by obtaining the self-assessment data of experts, and the calculation results are shown in Table 4.

Table 4. Index authority coefficient table

Indicator name	Ca	Cs	Cr
Financing risk A_1	0.78	0.80	0.79
Interest rate risk A_2	0.84	0.74	0.79
Market competition A_3	0.76	0.80	0.78
Change in demand A_4	0.74	0.88	0.81
Policy adjustments B_1	0.76	0.86	0.81
Default risk B_2	0.78	0.86	0.82
Contractual disputes B_3	0.80	0.80	0.80
Design failure C_1	0.80	0.82	0.81
Design input C_2	0.72	0.82	0.77
Quality defects C3	0.74	0.88	0.81
Organizational coordination D_1	0.72	0.88	0.80
Resource allocation D_2	0.72	0.88	0.80
Decision-making errors D_3	0.70	0.86	0.78
Management capacity D_4	0.74	0.92	0.83
Corporate culture D_5	0.70	0.86	0.78
Average value	0.76	0.84	0.80

Table 5. Delphi expert opinion coordination coefficient

Correlation coefficient	Round 1	Round 2
Coordination coefficient W	0.299	0.616
X	48.800	123.109
P	0.000	0.000

The calculation results show that the index authority coefficient is more significant than 0.7, which can judge that the expert authority is high and the research results are reliable.

c) Coordination coefficient of experts.

Through the calculation, the coordination coefficient is 0.299 for the first round of expert consultation and 0.616 for the second round of expert consultation, which indicates that with the increase in the number of talks, the experts' understanding of the indicators can continuously converge. The coefficient of coordination test value P is 0.000, which means that the coefficient of coordination of experts' opinions is high, and the calculation result is desirable. The detailed calculation results are shown in Table 5.

d) *Calculation of boundary values.*

The results of the calculation of the threshold values of the investment risk evaluation indicators of the power grid digitization project are shown in Table 6. The indicators were selected when the indicators' full score rate and arithmetic mean were more significant than the corresponding threshold values, and the coefficient of variation was less than the threshold value.

According to the statistical results, the indicator of corporate culture does not meet the three threshold criteria, so it is deleted from the evaluation indicator system. Although interest rate risk, contract dispute, and organization and coordination do not meet the threshold, the coefficient of variation of interest rate risk and contract dispute is small, which means that experts' recognition tends to be consistent. The average value of both indicators is above 8.5. The average weight of organization and coordination indicators reaches 9 points, which means that experts have a high recognition of this indicator, so all three indicators are retained. After the first round of index adjustment, all experts' opinions tended to be consistent in the second round of expert consultation. Finally, it obtains the power grid digital project's investment risk evaluation index system.

5 Example Analysis

In this paper, 40 projects that have been put into use are selected and the FAHP method is used to evaluate the investment risk of these projects. The evaluation values of 30 projects were randomly selected as the subject data set for machine training; the evaluation values of the remaining 10 projects were used as the testing group to test the accuracy of the AOA-LSSVM model.

Table 6. Calculation results of mean index value, full score frequency, and coefficient of variation

Indicator Name	Mean index value	Full score frequency	Coefficient of variation
Financing risk A_1	8.8	0.7	0.103
Interest rate risk A_2	8.6	0.3	0.102
Market competition A_3	8.6	0.9	0.103
Change in demand A_4	9.6	0.9	0.1
Policy adjustment B_1	8.6	0.5	0.103
Default risk B_2	8.6	0.4	0.117
Contractual disputes B_3	8.6	0.2	0.1
Design failures C_1	9.5	0.9	0.112
Design input C_2	8.5	0.4	0.112
Quality defects C_3	8.8	0.4	0.1
Organization and coordination D_1	9	0.7	0.189
Resource allocation D_2	9.1	0.7	0.103
Decision-making failures D_3	9.4	0.7	0.103
Management capability D_4	9.4	0.7	0.103
Corporate culture D_5	7.1	0.19	0.191
Mean	8.86	0.58	0.11
Standard deviation	0.57	0.23	0.03
Boundary value	8.29	0.35	0.14

5.1 Determining the Evaluation Value of the Project

Select 40 projects that have been put into use, and invite experts who participate in the whole process and have rich theoretical knowledge reserves and project practice experience to evaluate. Indicator set U = {financing risk, interest rate risk, market competition,…, decision errors, management capability, corporate culture} = {u1, u2, u3,…, u13, u14, u15}. The set of comments is divided into 5 levels according to the experts' ratings to obtain the set of comments V = {good, good, fair, poor, poor} = {v1, v2, v3, v4, v5}.

Using the 1–9 scaling method to establish the expert scoring judgment matrix, according to the formulae (2–2)-(2–4), the primary indicator weight vector $W_{FAHP_1} = (0.27,$

Table 7. Evaluation values of the 40 items

Item No.	Evaluation Value	Item No.	Evaluation Value
1	2.017922	21	8.005491
2	5.003279	22	4.001264
3	5.995624	23	6.011407
4	9.011791	24	8.010862
5	8.01465	25	4.990676
6	2.996424	26	3.015078
7	6.010327	27	6.009584
8	4.010717	28	2.000736
9	2.001183	29	8.009256
10	3.003449	30	8.013381
11	2.016726	31	6.993379
12	5.003302	32	6.993379
13	4.003609	33	5.829024
14	4.014759	34	4.887348
15	3.998652	35	4.228852
16	1.997392	36	4.136491
17	7.017969	37	3.276849
18	3.007059	38	1.833859
19	2.997074	39	5.680884
20	5.013349	40	5.743852

0.12, 0.30.0.31) and each indicator weight vector W_{FAHP_1} = (0.08, 0.05, 0.11, 0.10, 0.10,0.06, 0.02, 0.03, 0.07, 0.07, 0.07, 0.07, 0.08, 0.09, 0.10, 0.11), and finally the evaluation value of each item was obtained as shown in Table 7.

5.2 Parameter Setting

The initial parameters of the AOA algorithm were C1 = 2, C2 = 6, C3 = 1, C4 = 2, u = 0.9, l = 0.1, the number of populations was 30, the maximum number of iterations was 40, and the values of the regularization factor and kernel parameters were [0.6,190] and [0.1,195] respectively. The risk factor scores of the 40 items are used as the input vector for the AOA-LSSVM model, with items numbered 1–30 as the training set, and items numbered 31–40 as the test set of the model.

5.3 Analysis of Results

Based on the Matlab2022 platform for simulation analysis, the optimal value of regularization parameter c in LSSVM is 190, and the optimal value of kernel function parameter

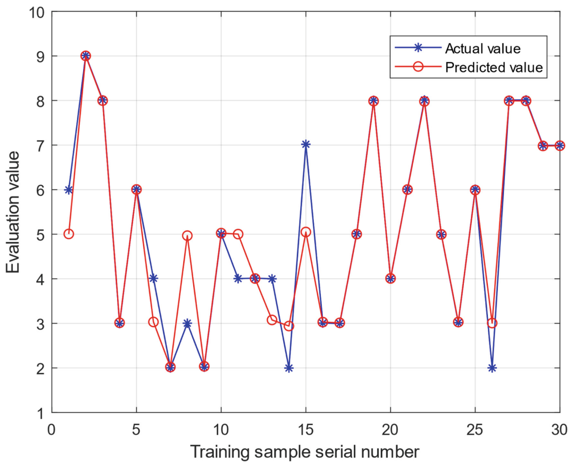

Fig. 1. Comparison of predicted and actual values for the training set of the AOA-LSSVM model

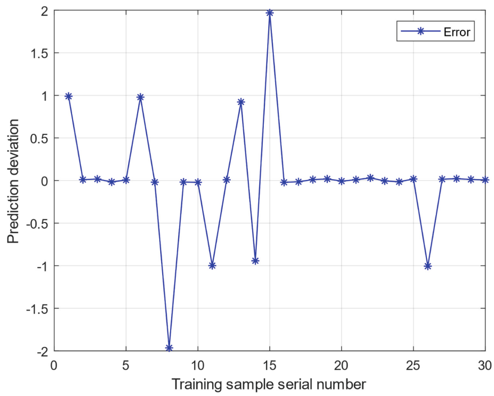

Fig. 2. Prediction error plot for the training set of the AOA-LSSVM model

is 0.1 through AOA algorithm search and optimization. Error evaluation index consists of mean square error, mean absolute error, root mean square error, mean absolute percentage error, and goodness of fit. The evaluation values and errors of the training set predictions are shown in Fig. 1 and Fig. 2. The training set errors are calculated as shown in Table 8. As the graphs show, the training set's prediction error does not fluctuate by more than 2%, and the fit is over 90%, so the training effect of small samples is good. The evaluation values and errors of the test set predictions are shown in Fig. 3 and Fig. 4. The test set errors are calculated as shown in Table 9. As can be seen from the graphs, the test set prediction error fluctuates by no more than 1%, and the fit exceeds 90%, with good prediction results for small samples, indicating that the AOA-LSSVM model has high prediction accuracy and can be used to predict the investment risk value of digital projects.

Table 8. Training set error

MSE	MAE	RMSE	MAPE	R2
0.4475	0.3366	0.6690	9.5787%	0.9029

Table 9. Test set error

MSE	MAE	RMSE	MAPE	R2
0.16068	0.20014	0.40085	3.5026%	0.91224

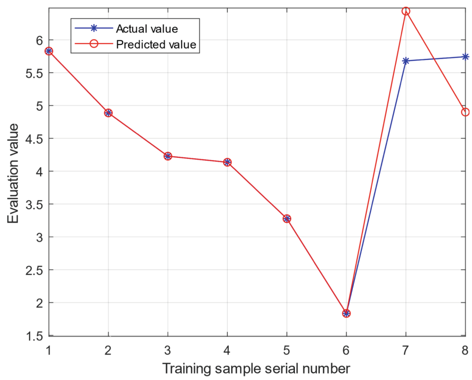

Fig. 3. Comparison of predicted and actual values for the test set of the AOA-LSSVM model

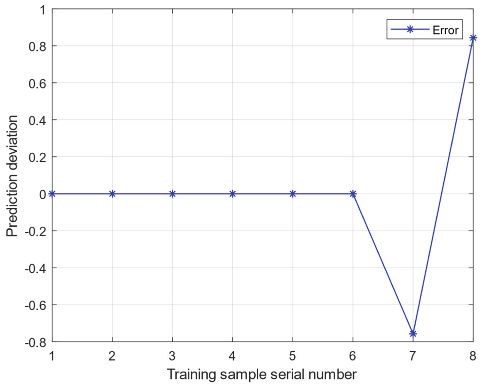

Fig. 4. Prediction error plot for the test set of the AOA-LSSVM model

6 Conclusion

(1) This paper analyzes the questionnaire results by combining the boundary value and expert methods to ensure that the risk evaluation system of digital project investment is objective, scientific, and comprehensive.
(2) AOA algorithm is used to search for the optimal solution of the super parameters in LSSVM, which avoids the empiricism and randomness of LSSVM parameter selection and is conducive to improving the accuracy of investment risk evaluation.
(3) LSSVM overcomes the dependence on large samples and still has good applicability for less investment risk data. It can be applied to other projects, providing reference ideas for investment risk early warning control.

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