International Journal for Housing Science and Its Applications
Publish August 5, 2025. Volume 46, Issue 3 Pages 4340-4351

https://doi.org/10.70517/ijhsa463371

Research on grid investment efficiency assessment and optimization scheme based on hierarchical regression modeling

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Abstract The power grid is an essential infrastructure for social and economic development, and the development of the power grid has always been a matter of national importance. The steady and rapid development of the world economy in recent years, the rapid development of the economy has also brought the development of the electric power business. This paper establishes the evaluation indexes in the evaluation of grid investment efficiency, the relationship between the indexes and the impact on the final comprehensive post-evaluation, and proposes a comprehensive post-evaluation model based on the improved hierarchical analysis method (AHP) and support vector machine regression (SVR). The improved AHP method is utilized to determine the weights of each evaluation index in the comprehensive post-evaluation index system, and then the comprehensive evaluation is carried out by SVR to improve the accuracy of the evaluation results. By setting the model parameters and using the MSE, RMSE, and MAE assessment methods to evaluate the grid investment benefit assessment model of AHP-SVR, the MSE was 1.64%, the RMSE was 4.21%, and the MAE was 12%. The assessment model is used to predict and analyze the investment efficiency of the grid enterprise in October 20232023, and the results are in line with the actual situation, providing targeted optimization suggestions for the investment efficiency of the grid enterprise.

Index Terms hierarchical analysis, support vector machine regression, grid investment efficiency, assessment model

I. Introduction

Under the macro background of rapid development of electric power economy and increasing national investment in power grid, the enthusiasm of power grid enterprise investment has been rising, and therefore the various benefits generated by the investment of power grid enterprises have also been growing [1], [2]. At present, China's power grid investment is in a critical period from the pursuit of speed to the pursuit of quality and efficiency of the transformation, so in the power grid investment scale is relatively large but the growth rate has slowed down under the premise of the grid investment generated by the identification of the various benefits as well as the measurement of the power grid investment is of great significance [3]-[5].

Maximizing investment benefits as far as possible is the main goal of grid investment decision-making, and the level of benefits of grid investment is one of the important bases for decision-making on the direction and scale of grid investment [6]. Benefit-oriented grid investment should first accurately grasp the various benefits generated by the invested funds, and then reasonably measure and plan the investment benefits that may be generated in the future [7], [8]. However, we also need to realize that there are some imminent problems in the management of grid investment and construction, in order to better solve them, we must seek a set of feasible investment optimization and comprehensive benefit assessment system, do a good job of the relevant benefit assessment work, and promote the cause of the distribution network towards a stable and healthy direction [9]-[12]. Therefore, the comprehensive consideration of the economic, social and environmental benefits of grid investment, the use of scientific methods for objective simulation analysis and applied research, has become an inevitable trend of modern grid development and construction investment decision-making [13]-[15].

In this paper, a comprehensive post-evaluation model based on improved hierarchical analysis method support vector machine regression is proposed, and the framework of grid investment efficiency assessment index system is constructed, and the assessment index system contains one level 1 index, four level 2 indexes and 18 level 3 indexes. Then the 1135 samples are processed to prepare the experimental data, the distribution of the 1135 experimental sample data is analyzed, and the parameters of the model are set. The AHP-SVR model is evaluated by analyzing the main several evaluation methods based on error analysis, determining the error evaluation statistics of several evaluation methods using MSE, RMSE, and MAE, and determining the optimal parameters of the AHP-SVR-based evaluation model. At the same time, the data of the evaluation indexes are used as the input of the risk assessment model, and four machine learning algorithms, namely, random forest regression, BP neural network regression, and K nearest neighbor regression, are selected for comparison.

II. Assessment of grid investment benefits based on hierarchical regression modeling

II. A. Indicator system for evaluating the efficiency of power grid investment

II. A. 1) Principles for the construction of the indicator system

The basic principles of grid investment efficiency evaluation are objectivity, impartiality and science. On this basis, the principles for the construction of the grid investment efficiency evaluation index system are as follows:

(1) Impartiality

Impartiality should be carried through the whole process of evaluation of the investment efficiency of power distribution grid to avoid the evaluator from making non-objective evaluation when discovering problems, analyzing reasons and drawing conclusions, so as to ensure the objectivity and scientificity of the index system.

(2) Independence

Independence is the sign of legitimacy of grid investment efficiency evaluation, meaning that the selection of evaluation indicators should be carried out independently without any interference. It is an important guarantee for the fairness and objectivity of the evaluation of grid investment efficiency.

(3) Practical

Grid investment efficiency evaluation index system must be applied in practice, that is, with a strong practicality, so that the evaluation can make the evaluation results have a positive effect on decision-making. Therefore, the evaluation index system should focus on key indicators, reflecting the strong professionalism and practicality of the evaluation of grid investment efficiency.

II. A. 2) Construction of evaluation index system

Considering the actual working situation of grid investment efficiency evaluation and the availability of index data, this paper establishes a set of index system that is highly operable and in line with the actual evaluation of grid investment efficiency, as shown in Table 1.

Table 1: Network investment benefit evaluation index system

Primary indicator	Secondary indicator	Tertiary index
Network investment benefit	Production service benefits	Number of service users
		Per capita operating number
		Per capita transformer capacity
		Per capita distribution line
	Production efficiency	Line loss
		Power supply reliability
		Total voltage qualification
		Network line interconnection rate
		Smart meter coverage
	Economic benefit	Annual growth rate for sales
		Unit power grid assets to sell electric revenue
		Unit grid investment increase load
		The unit grid investment increases the sales
	Social and environmental benefits	Renewable energy generation
		Address the number of non-electric population
		economizing
		Co2 reduction
		Sulfur dioxide emission reduction

II. A. 3) Meaning and measurement of evaluation indicators

1. Indicators of production service effectiveness

(1) Number of service users

The number of service users refers to the total number of customers covered by the distribution network power supply service of a county-level power supply enterprise.

(2) Number of business households per capita

The number of business households per capita refers to the average number of users per person in charge of the power supply enterprises at the end of the year, calculated as follows:

Number of business households per capita = number of customers in the city/number of people in the company at the end of the period

(3) Transformer capacity per capita

Per capita transformer capacity refers to the average power supply enterprises per person share of the transformer capacity, the formula is:

Per capita transformer capacity = total transformer capacity of power supply enterprises / number of companies at the end of the period

(4) Distribution lines per capita

Per capita distribution line refers to the length of distribution line shared by each person in the power supply enterprise on average, and the calculation formula is as follows:

Per capita distribution line = total distribution line length of the power supply enterprise/number of employees at the end of the period.

2. Production and operation efficiency indicators

(1) Reliability of power supply

The ability of the power supply system to continue to supply electricity is defined as the reliability of the power supply refers to, is the power supply enterprises to assess the quality of the power supply system power an important indicator, reflecting the power supply enterprises to meet the social demand for electricity to meet a degree.

(2) Comprehensive voltage pass rate

Comprehensive voltage pass rate = actual operating voltage within the permissible voltage deviation cumulative operating time/corresponding total operating time * 100%. According to China's power quality requirement standard, the terminal voltage is allowed to fluctuate 5% above and below the rated range.

(3) Grid line interconnection rate

In order to improve the electrification level, reduce the consumption of fossil energy, increase the proportion of renewable energy power consumption, and achieve sustainable development, the State promotes the interconnection of power grids in order to improve the national power supply and demand situation. The interconnection rate of grid lines refers to the percentage of distribution grids in the region that are interconnected to the total distribution grids in the region.

3. Indicators of Economic Benefits of Investment

(1) Annual growth rate of electricity sales

Annual growth rate of electricity sales refers to the average annual growth rate of electricity sales of a power supply company.

(2) Revenue from electricity sales per unit of grid assets

Revenue from electricity sales per unit of grid assets refers to the average revenue from electricity sales per unit of assets of a power supply enterprise (in yuan/yuan), calculated by the formula:

Revenue from electricity sales per unit of grid assets = total annual revenue from electricity sales of the power supply enterprise / total assets of the grid

(3) Unit grid investment to increase the supply load

Unit grid investment load refers to the average power supply enterprise per unit of investment in the growth of the power supply load (unit of kilowatts / million yuan), the formula is:

Unit grid investment load = total annual increase in the power supply enterprise load / total investment in the grid

(4) unit of grid investment in electricity sales

Unit grid investment in electricity sales refers to the average power supply enterprises per unit of investment growth in electricity sales (in kWh / yuan), the formula is:

Unit grid investment in electricity sales = total annual increase in electricity sales of power supply enterprises / total investment in the grid

4. Social and Environmental Benefit Indicators

(1) Renewable Energy Generation

Renewable energy power generation refers to the amount of electricity generated by using renewable energy to generate electricity, generally including hydroelectric power generation, wind power generation, biomass power generation, solar power generation, ocean energy power generation and geothermal energy power generation, etc., in 10,000 kWh.

(2) Number of people without electricity resolved

The number of people without electricity is the number of residential users who have solved the problem of no electricity due to the regional construction of distribution grids, and the unit is ten thousand people.

(3) Amount of standard coal saved

The amount of standard coal saved refers to the amount of standard coal saved compared to conventional thermal power generation due to the use of renewable energy.

(4) Carbon Dioxide Emission Reduction

Carbon dioxide emission reduction refers to the amount of carbon dioxide in tons that will be reduced as a result of the use of renewable energy to generate electricity, as compared to traditional thermal power generation.

(5) Emission reduction of sulfur dioxide

Emission reduction of sulfur dioxide refers to the amount of sulfur dioxide reduced due to the use of renewable energy power generation, compared with traditional thermal power generation, in tons.

II. B.Improvement of the methodology for assigning indicators in hierarchical analysis

II. B. 1) Improvement of the AHP method principle

The traditional AHP method [16] to determine the weights of evaluation indicators is widely used AHP method of 1-9 scale, but there are many factors affecting each evaluation indicator in the grid investment, and 1-9 scale is only more effective for the sorting problem under a single criterion, which leads to the determination of the weights of the evaluation indicators with low accuracy, so this paper proposes an improved hierarchical analysis method of scaling that is, In(9e/9)- In(17e/1), the application of this scale weight calculation results are more scientific.

II. B. 2) Basic Steps for Improving the AHP

Step 1: Establish a hierarchical analysis model, on the basis of an in-depth analysis of the problems to be studied, the evaluation indicators of the impact problem are divided into different levels, and a multilevel evaluation model is established.

Step 2: Construct judgment matrix R, and set the set of evaluation indicators $A=\{a_1,a_2,\cdots a_i,\cdots a_n\}$ for the evaluation model to be compared in terms of their importance, where a_i is the first $i(i=1,2.....i,....n)$ of the indicators that need to be compared, where n is the total number of evaluation indicators, two-by-two comparisons are made between the factors at the same level regarding the importance of a criterion at the previous level to determine their importance, and the two-by-two comparison judgment matrix is constructed as R:

$$R=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \text{And meet the conditions} \begin{cases} r_{ij}=1, i=j \\ r_{ij}=1/r_{ij} \end{cases} \tag{1}$$

The elements $a_1,a_2,...a_n$ metric weights are respectively

$w_1,w_2,\ldots w_n$, denotes the degree of affiliation of the indicator a_i is more important than the indicator a_j, and the larger the r_{ij}, the greater the degree of affiliation of the indicator a_i is more important than the indicator a_j, and if $r_{ij}=1$, it means that the two indicators have the same important affiliation.

Step 3: Calculate the weights, using the square root method of the judgment matrix by row elements of the product, and then open n times, formula (2) is as follows:

$$w_i=\sqrt[n]{\prod_{j=1}^{n} a_{ij}} \text{ And meet the conditions } (i,j=1,2,\cdots,n) \tag{2}$$

Normalization leads to the weighting coefficients W_i:

$$W_i=\frac{W_i}{\sum_{i=1}^{n} W_i} \tag{3}$$

The weight vector is:

$$W=(w_i,w_2,\cdots,w_n) \tag{4}$$

The maximum eigenvalue λ_{max} of the judgment matrix R is computed using MATLAB, the test formula (5) is applied to find the consistency index CI, and formula (6) is used to find the random consistency ratio CR:

$$CI = (\lambda_{max} - n)/(n-1) \tag{5}$$

$$CR = CI / RI \tag{6}$$

RI is the average random consistency index, when CR<0.10, the judgment matrix has satisfactory consistency, and vice versa, the judgment matrix is adjusted.

II. C.AHP-SVR grid investment efficiency assessment model

II. C. 1) Support Vector Regression Algorithm and Steps

Given a series of hypothetical investment efficiency samples $T = \{(x_1, y_1), \cdots, (x_i, y_i)\} \in (X \times R)$, introduce the relaxation factor ξ, and support the vector regression [17] problem which is to find the optimal solution to the following quadratic programming problem:

$$\min \frac{1}{2} \| \omega \|^2 + C\sum_{i=1}^{n}(\xi_i^- + \xi_i^+) \tag{7}$$

$$s.t. \begin{cases} y_i - (w \cdot x_i) - b \le \varepsilon + \xi_i^- \\ (w \cdot x_i) + b - y_i \le \varepsilon + \xi_i^+ \\ \xi i^-, \xi i^+ \ge 0 \end{cases} \tag{8}$$

The ε in Eq. (7) is the maximum error allowed by the regression, the first term in Eq. (8) is to make the regression function flatter and better generalized, and the second term is to reduce the error, with the constant $C > 0$ controlling the degree of penalty for samples that exceed the error ε.

The convex optimization problem obtained in Eq. (8) is transformed into a problem of finding the vectors" in a quadratic programming optimization, i.e., finding the required vectors $w - \sum_{i}^{n}(a_i^* - a_i)x_i$, a_i^*, a_i are Lagrange multipliers, and with the introduction of the kernel function, the optimization objective function becomes the following pairwise optimization problem:

$$\min \frac{1}{2}\sum_{i,j=1}^{n}(a_i^* - a_i)(a_j^* - a_i)K(x_i, x_i) + \varepsilon\sum_{i=1}^{n}(a_i^* + a_i) - \sum_{i=1}^{n} y_i(a_i^* - a_i) \tag{9}$$

The corresponding regression function equation also becomes:

$$f(x) = \sum_{i=1}^{n}(a_i^* - ai)K(x_i, x) + b \tag{10}$$

where the kernel function $K(x_i, x) = \Phi(x_i) \cdot \Phi(x)$ is an arbitrary symmetric function satisfying Mercer conditioning. Different forms of kernel functions can be chosen to generate different support vector machines, and the commonly used kernel functions are: RBF function, polynomial function, Sigmoid function and linear function.

In a support vector regression machine, y_i is real-valued and $y_i \in \{-1,1\}$ for all i-values, it is possible to perform SVM classification or regression on the same data set.

When SVR is in the range of $y_i \in \{-1,1\}$, the optimal solution of Eq. (7) is $W - \xi^- - \xi^+ - 0$ if $\varepsilon \ge 1$. Thus to pay strict attention to the case $\varepsilon < 1$, then the main result is that when ε is sufficiently close to 1, then $C_r = (1-\varepsilon)C_\varepsilon$ holds, when the SVC is regarded as a special case of the SVR.

From the above, it can be seen that the parameter ε and the parameter C are free parameters in the support vector regression machine, and the process of nonlinear regression using SVR is further complicated by the fact that the two parameters must be adjusted simultaneously.

The steps of applying to conduct grid investment efficiency assessment are as follows:

1. Select the successful examples of applying the AHP-SVR method of assessment as a sample bank for support vector regression machine training.
2. Normalize the data, where the input data and output data of the investment benefits assessed by SVR-AHP have been guaranteed to take values in the range of [0,1] interval.

3. Select the appropriate kernel function and related parameters, and establish the optimal model.
4. Apply the optimal model for training, the error meets the requirements, save the model, otherwise return to the previous step to retrain the model parameters.
5. Apply the optimal model to evaluate the grid investment benefits.
6. The evaluated samples are deposited into the identification sample library.

II. C. 2) Selection of the kernel function

In the medium SVR, parameter selection has a relatively large impact on the learning and predictive ability, and is crucial for constructing the regression function. Model selection is mainly: (1) the choice of the kernel function and its corresponding parameters; (2) the choice of the tolerance error of the two parameter approximation of the SVR itself ε, the penalty parameter C.

There are four commonly used kernel functions for SVM as follows:

(1) Linear kernel function:

$$K(x,x_i)=u*v \tag{11}$$

(2) Polynomial kernel functions:

$$K(x,x_i)=(s(x\cdot x_i)+c)^d \tag{12}$$

At this point, a polynomial classifier of order d is obtained, and d is usually taken from 1 to 10.

(3) Radial basis kernel function:

$$K(x,x_i)=\exp(-\frac{|x-x_i|^2}{\sigma^2}) \tag{13}$$

The center of each radial basis function corresponds to a support vector machine, the network structure and its network weights determined automatically by the algorithm. The σ is usually taken as 0.001~0.006.

(4) Sigmoid kernel function:

$$K(x,x_i)=\tanh(s(x\cdot x_i)+c) \tag{14}$$

At this point the SVM implements a two-layer multilayer perceptron neural network, at which time the network weights and the number of hidden nodes of the network are automatically determined by the algorithm.

The choice of RBF function as the kernel function in this study is mainly based on the following points

A) The radial basis function maps the data nonlinearly to the high-dimensional feature space, which can deal with the situation when the feature variables and the categorical variables are in a nonlinear relationship;

B) The linear function can be regarded as a special case of the radial basis function, in addition, for definite parameters, the Sigmoid function behaves similarly to the radial basis function;

C) Radial basis functions have fewer parameters, simplifying the complexity of model selection;

D) Radial basis functions have smaller numerical differences.

II. C. 3) SVR parameter selection based on RBF kernel

The significance of the values of the two parameters, the penalty parameter C and the tolerated error of the pass approximation ε, is that a larger C and a smaller ε indicate a high level of training accuracy but poor generalization ability, while a smaller C and a larger ε indicate a high level of generalization ability. Optimizing these parameters can be determined by means of an interaction test. This is done by first fixing a parameter and letting the other parameters vary, and choosing the smallest of these as the optimized value for that parameter. The role of C is to adjust the ratio of confidence range and empirical risk of the learning machine in the determined data subspace in order to optimize the generalization ability of the learning machine, with the optimal C varying in different data subspaces. In the determined data subspace, a small value of C indicates a small penalty for empirical error, a small complexity of the learning machine and a large value of empirical risk; and vice versa.

II. C. 4) AHP-SVR assessment model

Applying the AHP-SVR model to investment benefit assessment has the following advantages.

(1) Grid investment benefit assessment is a more complex process involving various factors, and there is not a completely linear relationship between the influencing factors and the measurement results. While the AHP-SVR

model has a strong nonlinear mapping ability, its ability to learn from experience is strong, and the classification and prediction accuracy is high.

(2) In view of the simplicity of the input and output of the AHP-SVR model, its use in the evaluation of grid investment efficiency, without the need for the traditional statistics and weighting of the raw data of the expert scores, and only need to input the raw data into the model through the training to get the comprehensive evaluation results, so as to make the evaluation results more objective and real, and make the evaluation process more simple and practical.

(3) The AHP-SVR model has a strong adaptive ability, can continuously accept new samples and learn continuously in order to adjust the model, which can provide continuously updated rolling data training model for grid investment benefit assessment, make the assessment results more in line with the reality, and form a dynamic assessment process.

III. Modeling and experimental comparative analysis

III. A. Experimental preparation

III. A. 1) Preparation of experimental data

In this paper, weka toolkit1 is used as the secondary development toolkit for the experiment. Before the experiment, 1135 samples need to be formatted. In Weka, a dataset is realized by weka.core.Instances. Each sample in the dataset is realized by weka.core.Instance.

III. A. 2) Distribution of experimental data

In order to be able to better establish the model and set the parameters of the model, this paper analyzes the distribution of the data of 1032 experimental samples, with the highest value of 100 and the lowest value of 0. There is a certain positive correlation between the assessment characteristics C_i and the assessment score, so in addition to using hierarchical analysis, this paper compares the use of linear regression and other methods to carry out experiments.

III. A. 3) Model evaluation methodology

The assessment model used in this paper is mainly based on regression analysis, so error estimation is usually the main focus when assessing the model. There are mainly the following assessment methods based on error analysis.

(1) Mean square error (MSE) analysis assessment method:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \tag{15}$$

Mean Square Error Analysis (MSE) is the expected value of the square of the difference between the predicted value of a parameter and the true value of the parameter, abbreviated as MSE.MSE is a convenient and practical way to measure the average error, and MSE can assess the degree of variation in the data, and the smaller the value of the MSE, the more accurate the prediction model established to describe the experimental data. Where m denotes the number of samples, y_i denotes the expert assessment score of the i th sample, and $\hat{y}_i$ denotes the prediction result score of the assessment model.

(2) Root Mean Square Error (RMSE) analysis assessment method

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{16}$$

where m denotes the number of samples, y_i denotes the expert assessment scoring of the i th sample, and $\hat{y}_i$ denotes the prediction result score of the assessment model.

(3) Mean Absolute Error (MAE) Analysis and Evaluation Method

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|(y_i - \hat{y}_i)| \tag{17}$$

The MAE is called the mean absolute dispersion, also known as the mean absolute deviation, and is the average value of the absolute values of the differences between all individual observations and the arithmetic mean selected. The mean absolute error analysis and assessment method can better avoid the problem of each error canceling each other out and thus affecting the assessment results, thus accurately reflecting the actual prediction error. Where m denotes the number of samples, y_i denotes the expert assessment score of the i th sample, and $\hat{y}_i$ denotes the prediction score of the assessment model.

(4) R-square value analysis assessment method

$$R^2(y_i, \hat{y}_i) = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \overline{y}_i)^2} \tag{18}$$

The R-squared value, also known as the coefficient of determination, reflects the proportion of all changes in the dependent variable, which can be explained by the independent variables through a regression relationship; the higher the value, the better the model. In this section, the model will be evaluated using the error evaluation statistics of MSE, RMSE, and MAE, which are several evaluation methods based on error analysis.

III. B. Analysis of the experimental results of the assessment model

III. B. 1) AHP-SVR hyperparameter-based selection

When building a model based on AHP-SVR, once the form of the kernel function is determined, multiple hyperparameters will be adjusted accordingly in the model, and the accuracy of the model is greatly affected by the values of the hyperparameters. When the kernel function is selected as RBF, the hyperparameters that need to be adjusted for the SVR model are the regularization parameter γ, the insensitivity parameter ε and the RBF kernel parameter gamma.

In determining the AHP-SVR grid investment benefit assessment model, the accuracy of the model will be affected by these three parameters to a certain extent, for determining the parameters of many methods, but there is no set of more standardized methods, combined with the experimental data in this paper, the traversal method is used for the selection of the parameters, the parameters are selected using the Mean Absolute Error (MAE) to assess the experiments in this paper.

(1) Parameter ε value of the experiment and analysis

Figure 1 shows the experimental results of model MAE when different values of ε are taken, from which it can be seen that the MAE error will gradually increase during the gradual increase of ε, but the gradual decrease of ε will not bring about an infinite decrease of MAE, only that the decrease of ε will lead to the computational efficiency of the model, the convergence speed decreases, so choose a suitable ε value, for the efficiency and accuracy of the experiment is particularly important, this paper in the experimental process, ε take the value of 0.0001.

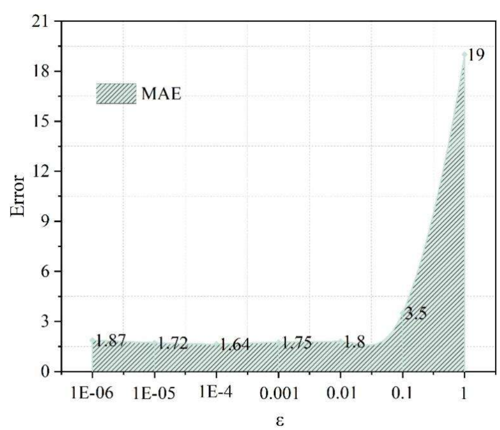


Figure 1: Model mae experiment results of different values of ε

(2) Parameter γ and nuclear parameter gamma value of the experiment and analysis

Figure 2 shows a heat map of the experimental results of the model MAE for the parameter γ with the value of gamma, from which it can be seen that in the case of a fixed gamma, the increase in the value of γ increases the overall average absolute error of the model is decreasing, and then it will stabilize in the range of a definite value, but the time efficiency will also grow exponentially; With a fixed γ value, the value of gamma is taken to increase or decrease continuously with it, and the mean absolute error decreases.

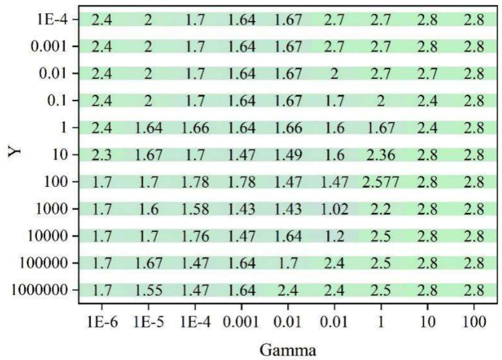


Figure 2: Parameters γ and gamma values

Combined with the experiments and analysis above, it can be seen that the regularization parameter γ=1000, the insensitivity parameter ε=0.0001, and the RBF kernel parameter gamma=0.01 are chosen as the optimal parameters in the modeling process.

III. B. 2) Analysis of AHP-SVR based experimental results

After the optimal parameters of the model are determined, the optimal parameters can be used to evaluate the grid investment benefits. In the experiment, because the hierarchical analysis method (AHP) is the most traditional evaluation and analysis method, the certainty and predictability of its results are more stable, and it is also used by more researchers and scholars, therefore, this paper takes the hierarchical analysis method (AHP) as the BaseLine of the experiment.

In order to better verify the effectiveness of the AHP-SVR model, a comparison experiment is carried out based on linear regression and multilayer perceptual machine, in which the parameters of linear regression are set as follows: Ridge=1.0E-8, batchSize=100; and the parameters of the multilayer perceptual machine are set as follows: learning rate learningRate=0.3, and the kinetic energy parameter momentum=0.2.

The experiments are shown in Table 2 and Figure 3, and the experimental results show that the method based on hierarchical analysis combined with support vector machine regression proposed in this paper is the most effective, with an average absolute error (MAE) of 1.64%, a root-mean-square error (RMSE) of 4.21%, and a mean-square error (MSE) of 12%. And compared to the benchmark AHP method all the evaluation indexes are greatly improved, and all of them are greater than the other comparison methods, so the method proposed in this paper is effective.

Table 2: The results of the evaluation model of the investment benefit of the grid

Experimental method	MSE (%)	MAE (%)	RMSE (%)
AHP (baseLine)	34.31	5.3	7.7
Multi-layer perceptron (MP)	19.0457	3.97	5.6
Linear regression (LR)	15.5409	2.01	4.56
SVR	15.2873	1.96	4.72
MP-AHP	19.1475	2.57	5.07
LR-AHP	14.2218	1.94	4.74
AHP-SVR	11.9534	1.64	4.21

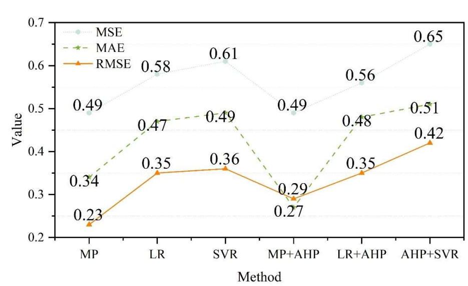
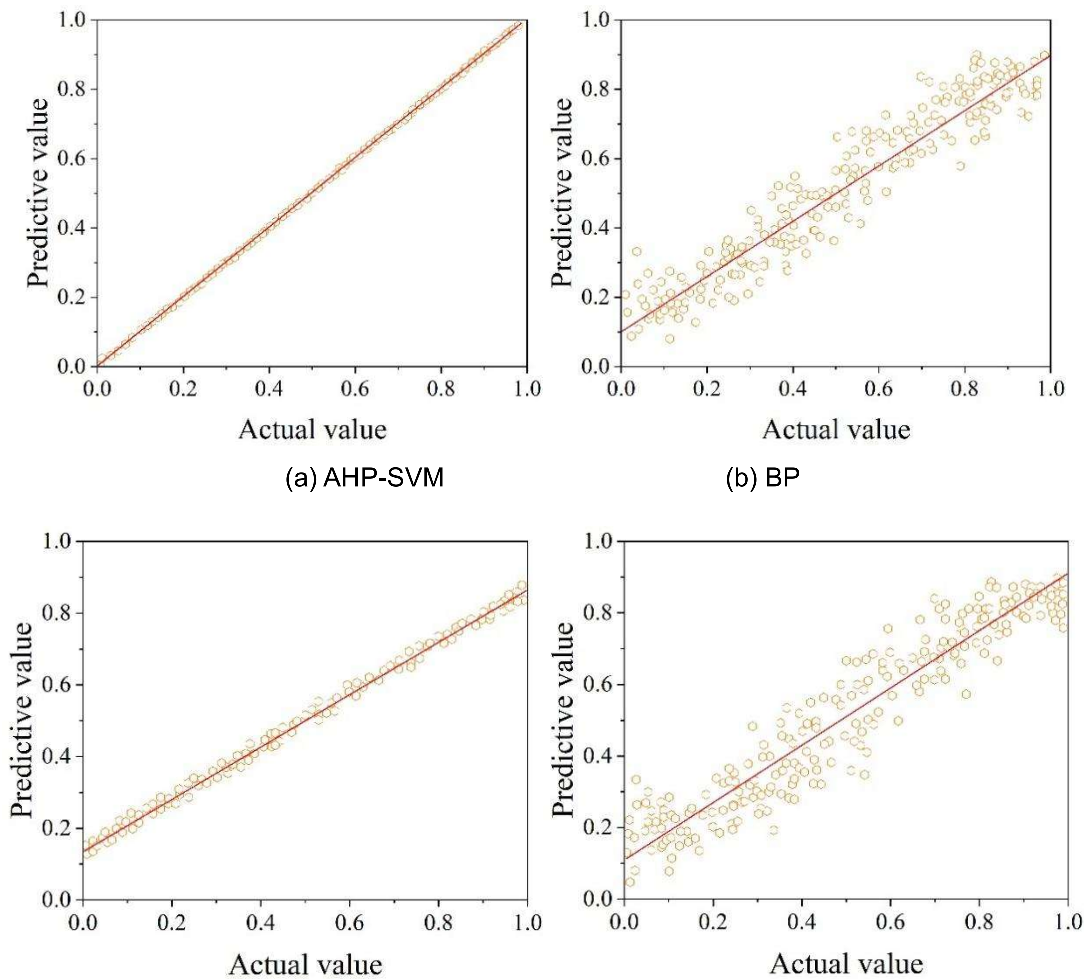


Figure 3: A variety of methods compared with the baseline method

III. C. Analysis of the assessment of the benefits of investment in electricity grids

III. C. 1) Predictive performance analysis

A comparison of linear regression analysis using using Random Forest (RF), BP Neural Network (BP), K Nearest Neighbor Regression (KNN) and methods was used and the results are shown in Figure 4. As can be seen from the figure, the fit of the hierarchical analysis based combined with support vector machine regression method is better than the other three methods and can be used for the prediction of grid investment benefits.



(a) AHP-SVM (b) BP

(c) KNN (d) RF

Figure 4: Linear regression analysis of the algorithm

III. C. 2) Application test results

The AHP-SVR model is used to evaluate the sample test data of 20 grid companies in October 2023, and the results of investment benefit prediction are shown in Figure 5. From the figure, it can be seen that the AHP-SVR risk assessment model can accurately predict the investment benefits of the grid at the beginning of October 2023.The average value of the investment benefits of the 20 companies in October 2023 is 0.636, and the overall investment benefits are in the medium range. The analysis of the investment benefits of the first 10 companies in October 2023 shows that the average benefit value is 0.679, and the 10 companies in the second 10 October The average benefit value is 0.593, thus the overall investment benefit of the top 10 companies in October 2023 is greater. After investigation, it was found that there were 7 data above the high efficiency warning reference value of 0.792 in October 2023, accounting for 35% of the total data. The data with benefit values higher than the high efficiency warning reference value in the April-September data only accounted for 9.6% of the total data, so the percentage of high efficiency data in October has increased significantly, and the overall benefit value has risen significantly. Therefore, relevant investment enterprises need to focus on the market development trend in this period.

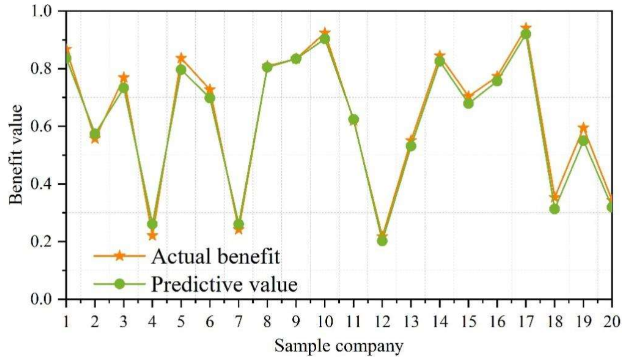


Figure 5: The prediction value and the actual benefit value of the AHP-SVR assessment model

III. D. Recommendations for the optimization of power grid investment strategies

1. Establishment of follow-up adjustment mechanism

Grid enterprises should organize research in advance of the determination of transmission and distribution tariff parameters, finance, development, marketing, operation and inspection, scheduling and other departments to set up a transmission and distribution tariff reform expert review group, review and evaluation of tariff parameters, and coordinate and promote coordination work. At the same time should pay attention to cross-provincial and cross-regional project tariff approval and progress of major projects, the establishment of a single tracking mechanism, close tracking of extra-high voltage and other cross-provincial and cross-regional project transmission and distribution tariff approval, tracking of major projects in the preliminary feasibility study, investment arrangements[18]-[20] , the investment body set up to achieve timely follow-up of the investment strategy and management adjustments.

2. Establish reasonable competition concept

Grid enterprises should strive for quality market space, enhance core competitiveness, plan the grid layout in advance in quality parks where fierce market competition is expected, accelerate the construction and deployment by combining near and far, and prevent the loss of stock market and stock users. For parks with dense user line assets, combined with user expansion and grid layout, ensure that the incremental distribution market is not lost and the stock distribution market is not lost by adjusting and reconnecting the user line or adopting the repurchase of high-quality user assets.

3. Timely organization of thematic investment strategy research

For the transmission and distribution tariff reform, investment effectiveness regulation, incremental distribution network and other market competition, as well as the improvement of business environment and other topics, grid enterprises should continue to carry out special investment strategy research, timely tracking of reform policies, market environment and other latest developments, keen to grasp, ahead of the organization of the relevant departments, units, to carry out the relevant thematic investment strategy research, to provide strong support for the investment decision-making.

IV. Conclusion

This paper constructs a grid investment efficiency assessment model based on AHP-SVR to assess the value of investment efficiency of grid enterprises, from the establishment of grid investment efficiency index system, the construction of AHP model and the improvement of the model, the AHP assessment of the formation of the samples to the construction and optimization of the SVR model, and verifies the feasibility of the AHP-SVR assessment model with examples. The experimental results show that the method based on hierarchical analysis combined with support vector machine regression proposed in this paper is the most effective, with an average absolute error of 1.64%, a root mean square error of 4.21% and a mean square error of 12%. It is superior to other comparative methods. Applying the AHP-SVR method to the grid investment benefit analysis in October 2023, it is found that the proportion of high-efficiency data in October increased significantly, and the overall benefit value increased significantly.

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