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Evaluation of missile electromagnetic launch system based on effectiveness

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Abstract. To solve the problems of strong infrared radiation, poor continuous combat capability of the system, serious ablation of the launching device, and environmental pollution of the existing missile launching system, electromagnetic launch system (EMLS) has been studied for missile launch system. Combining the situation that the current research on missile electromagnetic launch system (MEMLS) mainly focuses on the key technical points and the deficiencies in the previous research on MEMLS, this paper establishes an effectiveness prediction model based on GRA-PCA-LSSVM, and discusses the investment efficiency of the system based on DEA. The experimental results prove that the established model is reasonable, effective and superior, and provides a reference for the further improvement and development of MEMLS.

Keywords: MEMLS, Grey relation analysis (GRA), Principal component analysis (PCA), Least square support vector machine (LSSVM), Data Envelopment Analysis (DEA)

1. Introduction

Electromagnetic launch system (EMLS) is a launching technology that uses electromagnetic energy to convert it into payload kinetic energy [1]. EMLS can convert electrical energy into the kinetic energy required by the load in a short time, and push objects to reach a certain speed quickly [2]. Since it can effectively solve the problems of strong infrared radiation, poor continuous combat capability of the system, serious ablation of the launcher, and environmental pollution of the existing system, missile electromagnetic launch system (MEMLS) is a current research hotspot.

The current research on MEMLS concentrates on technical points such as pulse energy storage power supply, pulse power discharge, motor control, etc. There are few studies on the whole system evaluation. The author has studied the effectiveness evaluation method of MEMLS and proposed a new evaluation model for the two-level indicators of the system [3]. However, the system has many evaluation indicators and the model is quite complex, so the effectiveness value of the design scheme cannot be calculated quickly, and the investment efficiency of the design scheme is not discussed.

Aiming at the problem of too many evaluation indexes, Wang used gray correlation analysis (GRA) and support vector machine (SVM) to study and optimize the performance of asphalt pavement [4]; Yu proposed an improved principal component analysis (PCA) model to study the fault detection of nuclear power station sensors [5]. For the study of prediction model, Chung used multi-channel convolutional neural network optimized by genetic algorithm to predict the stock market [6]; Stoichev used multiple regression model to study the pollution of metals and quasi metals in surface sediments [7]; Liu used SVM model optimized by particle swarm optimization to analyze and predict PM2.5 [8]. To solve the problem of investment efficiency, Yeung used data envelopment analysis (DEA) to study the efficiency of Brazilian courts [9]; Yang used DEA to evaluate the

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efficiency of China's industrial waste gas treatment [10].

Existing research models only solve part of the problems, and there are few in the field of MEMLS. This paper evaluates MEMLS based on effectiveness, focusing on the rapid calculation of effectiveness model and system investment efficiency. The main innovations are as follows.

(1) From the perspective of the system, this paper conducts further research on the effectiveness calculation model of MEMLS, which makes up for the lack of most research focusing on specific technologies.

(2) This paper establishes the effectiveness calculation model of GRA-PCA-LSSVM, which can quickly calculate the effectiveness value of MEMLS.

(3) This paper uses the DEA model to study the investment efficiency of MEMLS, and proposes suggestions for improvement of the design scheme.

(4) This paper supplements the deficiencies of the previous research, which is innovative and practical.

The main structure of this paper is as follows: Section 1 introduces the basic concepts and advantages of EMLS and MEMLS, and points out the status and shortcomings of the current research of MEMLS; Section 2 establishes a model for fast calculation of effectiveness and investment efficiency of MEMLS; Section 3 combines the existing sample data to apply and verify the model, which proves the effectiveness of the model and methods; Section 4 summarizes this paper.

2. System evaluation model based on effectiveness

This section mainly introduces the model established in this paper for MEMLS evaluation. The steps and methods of model establishment are shown in Fig. 1.

The effectiveness evaluation model in Fig. 1 has been studied in the early stage [3], and is used directly as a model here.

2.1. *Effectiveness calculation model based on GRA-PCA-LSSVM*

To solve the problem that the original effectiveness evaluation model is too complicated, firstly establish a fast calculation model of effectiveness based on GRA-PCA-LSSVM, which is convenient to directly obtain the effectiveness value from the design scheme of MEMLS.

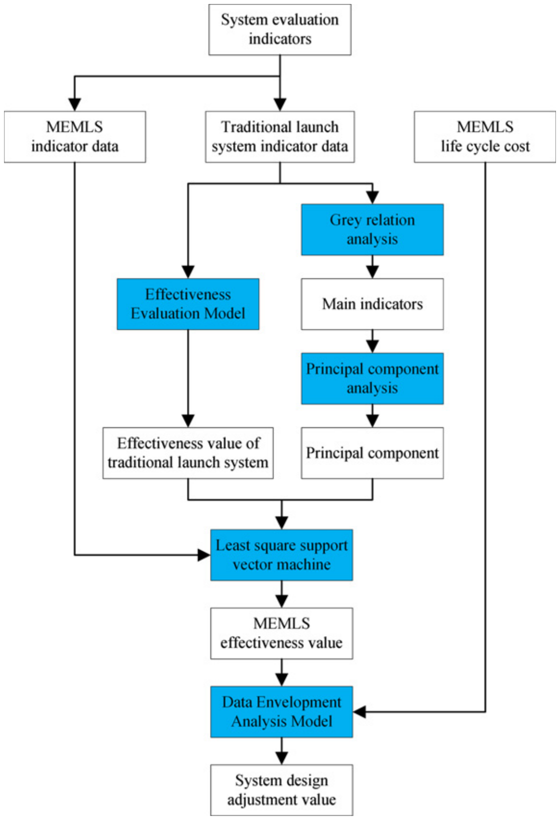

Fig. 1. Evaluation model based on effectiveness.

2.1.1. *GRA*

When evaluating the system, there are too many original evaluation indicators, which will lead to the redundancy of information and the complexity of the process. Therefore, it is necessary to select the main indicators. Grey system theory was founded in 1982 by Professor Deng Julong of China. It is a system control theory about the incomplete or uncertain internal system [11]. GRA is a multi-factor statistical analysis method in grey system theory, which judges the correlation degree according to the similarity degree of the changing trends between factors. Because of its simple calculation and low sample requirements, GRA has been widely used in industry, materials, and agriculture [12–14]. The steps of GRA are as follows.

Step 1: Determine the parent sequence and subsequence in the system. The parent sequence is a sequence that reflects the characteristics of the system's behavior, and the subsequence is a sequence that affects the characteristics of the system's behavior.

Step 2: Dimensionless processing of the parent sequence and subsequence. In the analysis process, different dimensions may lead to errors in the results. Generally, the sequence is processed by the averaging method to remove dimensions.

Step 3: Calculate the correlation coefficient of the factors corresponding to the sub-sequence and the parent sequence, as shown in formula (1).

$$\xi(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}, \begin{cases} i = 1, 2, \cdots, m \\ k = 1, 2, \cdots, n \end{cases} \quad (1)$$

In the formula: m is the number of subsequences; n is the number of samples; $x_0(k)$ is the k-th sample value of the parent sequence after dimensionless processing; $x_i(k)$ is the k-th sample of the i-th subsequence after dimensionless processing Value; ρ is the resolution coefficient, reflecting the size of the resolution, usually 0.5.

Step 4: Calculate the degree of relevance and sort to obtain the degree of relevance of each sub-sequence to the parent sequence, as shown in formula (2).

$$r_i = \frac{1}{n} \sum_{k=1}^{n} \xi(x_0(k), x_i(k)), i = 1, 2, \cdots, m \quad (2)$$

2.1.2. PCA

PCA is a multivariate statistical analysis method that converts multiple interrelated indicators into a few comprehensive indicators. In the research of multiple indicators, Since there is often a certain correlation between the indicators, the data will overlap with information, which is more complicated for high-dimensional research. PCA adopts the method of dimensionality reduction, and uses a small number of comprehensive factors to express all the original indicators, and requires that the original indicator information is reflected as much as possible, and the factors are not related to each other. PCA has been widely used in environmental science, agriculture and industry [15–17]. The steps of PCA are as follows.

Step 1: Standardize the original data to eliminate the influence of different dimensions and orders of magnitude on the analysis results.

Step 2: Perform correlation analysis on the processed sample matrix to obtain the correlation coefficient matrix, and determine whether PCA can be performed.

Step 3: From the correlation coefficient matrix, the eigenvalue and variance are calculated by the Jacobian method, and the principal component variance contribution rate and cumulative contribution rate are calculated.

Step 4: Select the principal component according to the specific requirements of the eigenvalue or the cumulative contribution rate of the principal component to complete the PCA. The general mathematical model of PCA results is shown in formula (3).

$$\begin{aligned} Z_1 &= a_{11}X_1 + a_{12}X_2 + \cdots + a_{1n}X_n \\ Z_2 &= a_{21}X_1 + a_{22}X_2 + \cdots + a_{2n}X_n \\ &\vdots \\ Z_l &= a_{l1}X_1 + a_{l2}X_2 + \cdots + a_{ln}X_n \end{aligned} \quad (3)$$

In the formula: Z_l is the main component; X_n is the normalized raw data; a_{ij} is the main component coefficient.

2.1.3. LSSVM

Least Square Support Vector Machine (LSSVM) is an extension of SVM. LSSVM takes the quadratic loss function as the empirical risk, and replaces the inequality constraints with equality constraints, transforming the training of the model into the calculation of linear equations, reducing the computational complexity [18]. Because of its superiority, LSSVM is widely used in meteorology, materials science, industry and other fields [19–21]. The establishment process of the LSSVM model is as follows.

Suppose that the number of samples is n, x_i is the m-dimensional input vector, and y_i is the output vector. Construct the optimal linear regression function as formula (4).

$$f(x) = \omega^{\mathrm{T}}\varphi(x) + b \quad (4)$$

In the formula: ω is the weight vector; b is the offset; $\varphi(x)$ is the nonlinear mapping.

According to the principle of structural risk minimization, the objective function can be expressed as formula (5).

$$\min \frac{1}{2}\omega^{\mathrm{T}}\omega + \frac{\lambda}{2}\sum_{i=i}^{n} e_i^2 \quad (5)$$

Where: λ is the regularization parameter; e_i is the prediction error vector of the training set.

The constraint condition is formula (6).

$$y_i = \omega^{\mathrm{T}}\varphi(x_i) + b + e_i \tag{6}$$

The Lagrangian function is used to transform the problem into the dual space, as in formula (7).

$$L = \frac{1}{2}\omega^{\mathrm{T}}\omega + \frac{\lambda}{2}\sum_{i=i}^{n} e_i^2 - \sum_{i=1}^{n}\alpha_i[\omega^{\mathrm{T}}\varphi(x_i) + b + e_i - y_i] \tag{7}$$

In the formula: α_i is the Lagrange multiplier. According to the KKT condition, the formula (8) can be obtained.

$$\begin{cases} \omega = \sum_{i=1}^{n}\alpha_i\varphi(x_i) \\ \sum_{i=1}^{n}\alpha_i = 0 \\ \alpha_i = \lambda e_i \\ \omega^{\mathrm{T}}\varphi(x_i) + b + e_i - y_i \end{cases} \tag{8}$$

Eliminate ω and e_i in formula (8) to obtain formula (9).

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1, x_1) + \frac{1}{c} & \cdots & K(x_1, x_1) \\ \vdots & \vdots & & \vdots \\ 1 & K(x_n, x_n) & \cdots & K(x_n, x_n) + \frac{1}{c} \end{bmatrix} \begin{bmatrix} b \\ \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_n \end{bmatrix} \tag{9}$$

In the formula: $K(x_i, x_j) =< \varphi(x_i), \varphi(x_j) >$ is the kernel function. Generally take the radial basis kernel function as equation (10).

$$K(x_i, x_j) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\mu^2}\right) \tag{10}$$

In the formula: μ is the nuclear parameter.

Finally, the prediction model of LSSVM is

$$y(x) = \sum_{i=1}^{n}\alpha_i K(x_i, x_j) + b \tag{11}$$

2.2. *Evaluation of system investment efficiency based on DEA model*

The DEA method is a non-parametric method used to evaluate the relative effectiveness of decision-making units (DMUs) with the same type of multiple inputs and multiple outputs. At present, DEA research is relatively mature and widely used in economics, sociology and industry [22–24].

2.2.1. *Overall effectiveness evaluation model (CCR)*

Suppose there are a total of s DMUs, each DMU has p inputs and q outputs, $x_k = (x_{1k}, x_{2k}, \cdots, x_{pk})^{\mathrm{T}}$ represents the input vector of the k-th DMU, $y_k = (x_{1k}, x_{2k}, \cdots, x_{qk})^{\mathrm{T}}$ represents the output vector of the k-th DMU, and x_0 and y_0 represent the input and output vectors of the DMU_0. From the literature [25], the BCC model is:

$$\begin{cases} \min\theta \\ s.t. \sum_{k=1}^{s}\lambda_k x_k + s^- = \theta x_0 \\ \sum_{k=1}^{s}\lambda_k x_k - s^+ = y_0 \\ s^- \geq 0, s^+ \geq 0 \end{cases} \tag{12}$$

In the formula: s^- and s^+ are slack variables; λ_k is a general variable.

To simplify the calculation, the non-Archimedean infinitesimal quantity is introduced, then the formula (12) becomes

$$\begin{cases} \min[\theta - \varepsilon(\hat{e}^{\mathrm{T}}s^- + \hat{e}^{\mathrm{T}}s^+)] \\ s.t. \sum_{k=1}^{s}\lambda_k x_k + s^- = \theta x_0 \\ \sum_{k=1}^{s}\lambda_k x_k - s^+ = y_0 \\ s^- \geq 0, s^+ \geq 0 \end{cases} \tag{13}$$

If the optimal solutions of the model are λ^*, s^{-*}, s^{+*} and θ^*, then there are the following conclusions.

(1) If $\theta^* < 1$, then DMU_0 is not DEA effective. This scheme neither meets the requirements of the best technical efficiency nor the constant return of scale.

(2) If $\theta^* = 1$, and at least one of s^{-*} and s^{+*} is not 0, then DMU_0 is weak DEA effective, that is, it is not both technically effective and scale effective.

(3) If $\theta^* = 1$ and $s^{-*} = s^{+*} = 0$, then DMU_0 is DEA effective, that is, both technical efficiency and scale efficiency are satisfied.

2.2.2. *Technical effectiveness evaluation model (BCC)*

The BCC model is used to evaluate the relative technical effectiveness. Similarly, the calculation model can be obtained as follows.

Table 1
MEMLS effectiveness evaluation indicators table

Target layer	First-level indicator layer	Second-level indicator layer
Effectiveness evaluation of MEMLS	Launch capability U_1	Thrust control accuracy U_{11}
		Robustness during launch U_{12}
		Maximum thrust U_{13}
		Acceleration time U_{14}
		Initial ejection velocity U_{15}
	Confrontation capability U_2	Infrared radiation intensity U_{21}
		Electromagnetic anti-interference ability U_{22}
		Electromagnetic compatibility of own system U_{23}
		Initial anti-interception rate U_{24}
	State loss U_3	Energy utilization rate U_{31}
		Ablation degree of the launcher U_{32}
		Environmental pollution degree U_{33}
		Spare parts replacement rate U_{34}
	Expanding ability U_4	Ejection power unit weight U_{41}
		Launcher weight U_{42}
		Space-ratio performance U_{43}
		Continuous combat capability U_{44}
		Universality of launch system U_{45}

$$\begin{cases} \max[\theta - \varepsilon(\hat{e}^{\mathrm{T}}s^- + \hat{e}^{\mathrm{T}}s^+)] = V \\ s.t. \sum_{k=1}^{s} \lambda_k x_k + s^- = \theta x_0 \\ \sum_{k=1}^{s} \lambda_k = 1 \\ \lambda_k \geq 0, s^- \geq 0, s^+ \geq 0 \end{cases} \tag{14}$$

If the optimal solutions of the model are λ^*, s^{-*}, s^{+*} and θ^*, when $\theta^0 = 1$ and $s^{-0} = s^{+0} = 0$, DMU_0 is technically effective, otherwise it is not technically effective.

2.2.3. *Scale effectiveness evaluation model*

Scale validity refers to verifying whether the DMU is at the optimal scale level, and it can be judged whether it is in a state of increasing, constant or decreasing scale. The scale efficiency of DMU is represented by $Q = \frac{\theta}{V}$. Calculate $K = \sum_{k=1}^{s} \lambda_k$. When $K = 1$, the scale efficiency is unchanged; when $K < 1$, the scale efficiency increases; when $K > 1$, the scale efficiency decreases.

3. Evaluation of MEMLS based on effectiveness

3.1. *Effectiveness calculation based on GRA-PCA-LSSVM*

From the author's previous research [3], the effectiveness evaluation indicators of MEMLS can be obtained as shown in Table 1. From the related research of the subject, 64 sets of sample data for traditional launch methods can be obtained as shown in Table 2. Each set of data includes 18 evaluation indicators and the effectiveness value.

Due to the large number of indicators and the complexity of the evaluation method in literature [3], it needs to be simplified. First, perform a statistical description of the sample data as shown in Table 3, and make an indicator correlation strength diagram as shown in Fig. 2. The horizontal and vertical coordinates of Fig. 2 are indicator numbers, the color indicates the intensity of correlation, and the right side is the intensity and color contrast scale. It can be seen from Fig. 2 that there is a certain correlation between the indicators, so it can be considered to select and reduce the dimensionality of the indicators through GRA-PCA.

According to formulas (1)-(2), the correlation between each indicator and effectiveness is calculated, as shown in Table 4. The main indicators are selected with the degree of correlation > 0.7, that is, U_{11}, U_{12}, U_{13}, U_{15}, U_{22}, U_{24}, U_{31} and U_{41}.

After GRA, in order to further reduce the number of indicators and simplify the model, PCA was performed on the selected 8 indicators. According to Section 2.1.2, the correlation coefficient matrix is calculated as shown in Table 5, and the variance contribution rate of each principal component is calculated as shown in Table 6.

Here, the cumulative contribution rate > 90% is taken as the target, so 6 principal components need to be extracted, and the corresponding coefficients of

Table 2
Effectiveness and indicators data of missile launch system

No.	Indicators																		
	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{21}	U_{22}	U_{23}	U_{24}	U_{31}	U_{32}	U_{33}	U_{34}	U_{41}	U_{42}	U_{43}	U_{44}	U_{45}	E
1	0.9	0.6	250	15	35	25	0.9	0.5	0.7	0.8	0.9	0.4	0.6	350	6	0.4	0.6	0.2	0.6371
2	0.7	0.6	250	10	35	25	0.9	0.5	0.6	0.7	0.9	0.4	0.3	350	3	0.6	0.4	0.2	0.6239
3	0.5	0.6	250	10	35	25	0.9	0.5	0.6	0.5	0.9	0.4	0.3	350	3	0.3	0.4	0.2	0.5851
4	0.5	0.6	250	20	35	25	0.9	0.7	0.7	0.8	0.9	0.8	0.7	350	3	0.3	0.5	0.2	0.6669
5	0.5	0.6	250	10	40	25	0.9	0.7	0.8	0.5	0.9	0.4	0.3	350	6	0.3	0.7	0.2	0.5997
6	0.7	0.9	250	20	35	25	0.9	0.4	0.7	0.9	0.9	0.4	0.6	350	6	0.3	0.5	0.2	0.6152
7	0.9	0.5	250	20	35	25	0.9	0.4	0.8	0.9	0.7	0.8	0.6	350	3	0.3	0.5	0.2	0.6534
8	0.9	0.5	250	10	35	25	0.9	0.4	0.6	0.9	0.4	0.4	0.3	350	3	0.5	0.7	0.2	0.6059
9	0.5	0.9	250	20	37	25	0.9	0.4	0.6	0.9	0.8	0.4	0.3	350	7	0.4	0.5	0.5	0.5896
10	0.9	0.5	250	10	35	25	0.9	0.4	0.6	0.9	0.7	0.4	0.6	350	7	0.5	0.5	0.5	0.6361
11	0.5	0.5	250	15	40	25	0.6	0.4	0.6	0.9	0.4	0.6	0.6	350	7	0.6	0.5	0.2	0.5514
12	0.9	0.5	250	10	37	25	0.5	0.4	0.8	0.9	0.4	0.4	0.7	400	7	0.4	0.5	0.5	0.6015
13	0.9	0.5	250	20	35	25	0.6	0.4	0.7	0.9	0.6	0.6	0.3	300	7	0.6	0.5	0.5	0.5741
14	0.9	0.7	250	10	35	25	0.6	0.7	0.6	0.9	0.6	0.8	0.3	500	7	0.4	0.5	0.2	0.6240
15	0.7	0.5	250	20	37	25	0.6	0.5	0.6	0.9	0.6	0.8	0.3	300	7	0.4	0.7	0.7	0.6026
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
61	0.6	0.9	150	10	39	10	0.5	0.9	0.6	0.7	0.4	0.9	0.3	500	9	0.8	0.5	0.2	0.6366
62	0.6	0.9	150	10	39	16	0.5	0.9	0.7	0.5	0.4	0.9	0.7	300	9	0.8	0.5	0.7	0.6847
63	0.6	0.5	150	10	39	10	0.7	0.9	0.7	0.7	0.8	0.9	0.3	480	9	0.8	0.5	0.2	0.6637
64	0.6	0.7	150	20	39	16	0.6	0.9	0.6	0.5	0.4	0.9	0.6	480	9	0.8	0.5	0.2	0.5855

Table 3
Mathematical statistics of the original data of MEMLS

Evaluation Indicator	Minimum	Maximum	Average	Standard deviation
U_{11}	0.50	0.90	0.6375	0.15379
U_{12}	0.50	0.90	0.6547	0.16323
U_{13}	150.00	250.00	195.4688	41.01605
U_{14}	10.00	20.00	15.3906	4.07321
U_{15}	35.00	40.00	37.0937	1.96573
U_{21}	10.00	25.00	18.7812	6.62719
U_{22}	0.40	0.90	0.6047	0.15779
U_{23}	0.40	0.90	0.6156	0.16351
U_{24}	0.60	0.90	0.7625	0.12536
U_{31}	0.50	0.90	0.6844	0.16057
U_{32}	0.40	0.90	0.5859	0.17716
U_{33}	0.40	0.90	0.6141	0.18845
U_{34}	0.30	0.80	0.4953	0.18724
U_{41}	300.00	500.00	380.9375	72.93656
U_{42}	3.00	9.00	5.8125	2.30166
U_{43}	0.30	0.80	0.5297	0.15704
U_{44}	0.40	0.90	0.5750	0.17817
U_{45}	0.20	0.70	0.4000	0.21381

6 principal components and 8 main indicators can be obtained as shown in Table 7.

According to Table 7 and formula (3), the calculation expression of the principal components can be obtained as follows.

In the formula: U_{11}, U_{12}, U_{13}, U_{15}, U_{22}, U_{24}, U_{31} and U_{41} represent normalized data values.

According to formula (15), Table 2 can be transformed into Table 8.

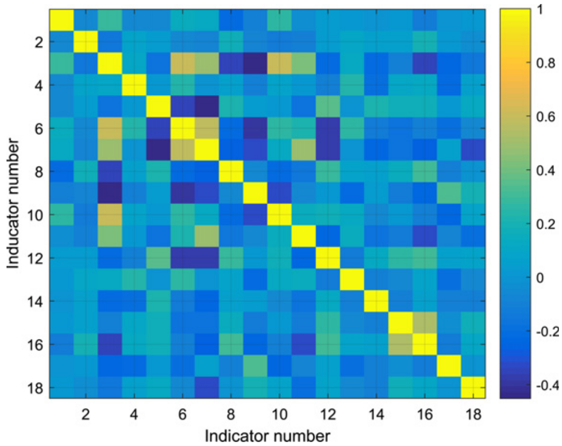

Fig. 2. Indicator correlation strength diagram.

$$
\begin{aligned}
Z_1 &= 0.411U_{11} - 0.179U_{12} + 0.864U_{13} - 0.387U_{15} \\
&\quad + 0.698U_{22} - 0.597U_{24} + 0.645U_{31} - 0.340U_{41} \\
Z_2 &= 0.285U_{11} + 0.024U_{12} + 0.182U_{13} + 0.704U_{15} \\
&\quad - 0.449U_{22} - 0.234U_{24} + 0.521U_{31} + 0.471U_{41} \\
Z_3 &= -0.250U_{11} + 0.848U_{12} - 0.016U_{13} - 0.027U_{15} \\
&\quad + 0.128U_{22} - 0.483U_{24} - 0.105U_{31} + 0.153U_{41} \\
Z_4 &= 0.772U_{11} + 0.314U_{12} - 0.102U_{13} - 0.225U_{15} \\
&\quad + 0.029U_{22} + 0.264U_{24} - 0.099U_{31} + 0.206U_{41} \\
Z_5 &= 0.121U_{11} + 0.325U_{12} + 0.029U_{13} + 0.237U_{15} \\
&\quad - 0.244U_{22} + 0.163U_{24} + 0.133U_{31} - 0.754U_{41}
\end{aligned}
$$

Table 4
Correlation degree of each indicator and effectiveness

Indicator	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{21}	U_{22}	U_{23}	U_{24}
correlation	0.7165	0.7155	0.7206	0.6571	0.8688	0.5897	0.7112	0.6775	0.7616
Indicator	U_{31}	U_{32}	U_{33}	U_{34}	U_{41}	U_{42}	U_{43}	U_{44}	U_{45}
correlation	0.7348	0.6675	0.6729	0.5925	0.7464	0.5944	0.6618	0.6647	0.4983

Table 5
Correlation coefficient matrix of PCA

		U_{11}	U_{12}	U_{13}	U_{15}	U_{22}	U_{24}	U_{31}	U_{41}
Correlation coefficient	U_{11}	1.000	–0.051	0.284	–0.054	0.137	–0.091	0.268	–0.020
	U_{12}	–0.051	1.000	–0.138	0.038	–0.084	–0.069	–0.112	0.056
	U_{13}	0.284	–0.138	1.000	–0.158	0.494	–0.444	0.604	–0.207
	U_{15}	–0.054	0.038	–0.158	1.000	–0.452	0.047	0.015	0.208
	U_{22}	0.137	–0.084	0.494	–0.452	1.000	–0.328	0.122	–0.235
	U_{24}	–0.091	–0.069	–0.444	0.047	–0.328	1.000	–0.329	0.033
	U_{31}	0.268	–0.112	0.604	0.015	0.122	–0.329	1.000	–0.061
	U_{41}	–0.020	0.056	–0.207	0.208	–0.235	0.033	–0.061	1.000

Table 6
Variance contribution rate of PCA

Principal component	Variance	Contribution rate / %	Cumulative contribution rate / %
1	2.472	30.899	30.899
2	1.360	17.006	47.905
3	1.067	13.336	61.241
4	0.894	11.171	72.411
5	0.850	10.622	83.034
6	0.610	7.627	90.660
7	0.480	5.999	96.659
8	0.267	3.341	100.000

$$Z_6 = -0.262U_{11} + 0.168U_{12} + 0.102U_{13} - 0.356U_{15} - 0.185U_{22} + 0.344U_{24} + 0.453U_{31} + 0.136U_{41} \tag{15}$$

The principal components are used as input, and the effectiveness is used as output, and regression fitting is performed. According to formulas (4)-(11), model training is performed and compared with PSOSVM and BP neural network algorithms. Select 85% of the samples as the training set and 15% of the samples as the test set. The fitting effect of the training set is shown in Fig. 3 and the fitting effect of the test set is shown in Fig. 4.

It can be intuitively obtained from Fig. 3 and Fig. 4 that the effect of the LSSVM model is better than that of PSOSVM and BP neural network. In order to get a specific comparison, calculate the mean square error (MSE) of the training set and the test set, as shown in Table 9.

It can be seen from Table 9 that the MSE of the training and test sets using the LSSVM model is the smallest, and the running time is the fastest, which can be further applied to the MEMLS design.

Each indicator value of the MEMLS design scheme is obtained from the research of the subject, and the effectiveness value is obtained through the pre-trained LSSVM model, as shown in Table 10.

Table 7
Principal component coefficient

Indicators	Principal component					
	1	2	3	4	5	6
U_{11}	0.411	0.285	–0.250	0.772	0.121	–0.262
U_{12}	–0.179	0.024	0.848	0.314	0.325	0.168
U_{13}	0.864	0.182	–0.016	–0.102	0.029	0.102
U_{15}	–0.387	0.704	–0.027	–0.255	0.237	–0.356
U_{22}	0.698	–0.449	0.128	0.029	–0.244	–0.185
U_{24}	–0.597	–0.234	–0.483	0.264	0.163	0.344
U_{31}	0.645	0.521	–0.105	–0.099	0.133	0.453
U_{41}	–0.340	0.471	0.153	0.206	–0.754	0.136

Table 8
Effectiveness and principal components data of MEMLS

No.	Principal component						E
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	
1	2.8840	–0.4945	–0.3521	1.1770	0.2571	–0.3028	0.6371
2	2.5919	–0.9309	0.3985	–0.0433	0.6588	–0.5791	0.6239
3	1.7415	–1.8053	0.8395	–0.9752	1.0095	–0.8654	0.5851
4	2.2044	–1.1306	0.2770	–0.9479	0.5988	0.5689	0.6669
5	0.5092	–0.5886	0.0280	–1.2162	0.0737	–1.3226	0.5997
6	2.5900	–0.4967	1.4089	0.6603	–0.3102	0.8904	0.6152
7	2.9061	–0.3887	–1.2914	1.1311	0.2423	0.2773	0.6534
8	3.5122	–0.0692	–0.5458	0.6849	0.5242	–0.4248	0.6059
9	2.3028	–0.0406	2.0698	–0.9002	–0.2601	0.5115	0.5896
10	3.5122	–0.0692	–0.5458	0.6849	0.5242	–0.4248	0.6361
...	...	...	...	...	...	...	...
61	–1.1979	1.6010	2.0404	0.1202	0.6631	–0.2537	0.6366
62	–1.4189	–0.2224	1.3889	–0.1226	–1.5413	–1.1040	0.6847
63	–0.5998	0.7927	–0.2291	–0.4926	1.4972	–0.7784	0.6637
64	–1.2283	0.6651	1.1983	–0.1970	1.2183	–1.4377	0.5855

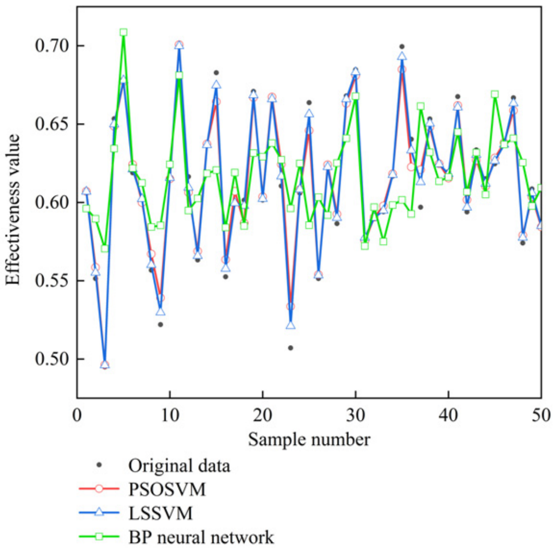

Fig. 3. Fitting diagram of the training set of effectiveness value.

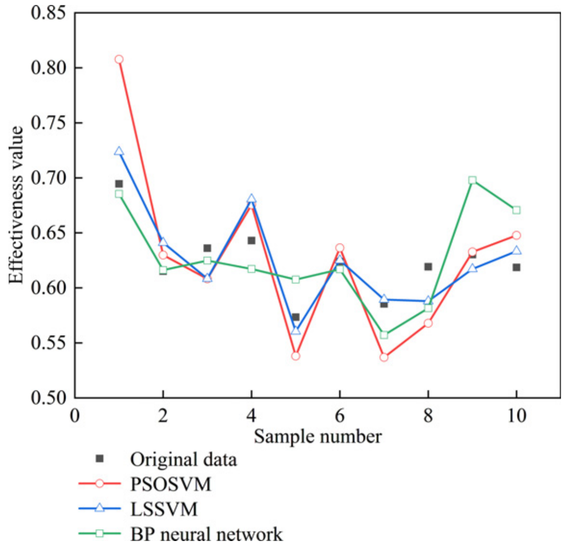

Fig. 4. Fitting diagram of the test set of effectiveness value.

3.2. Analysis of investment efficiency based on DEA

The whole life cycle cost and the cost of each stage of the MEMLS design scheme are obtained from the research of the subject. Obtain the effectiveness value from Table 10, and calculate the effectiveness -cost ratio, as shown in Table 11.

According to equations (12) - (14), the overall efficiency and pure technical efficiency of MEMLS are calculated, and its scale benefit and K value are calculated, as shown in Table 12.

According to Table 12, the following conclusions can be drawn.

Table 9
Performance comparison

Performance	PSOSVM	LSSVM	BP neural netwok
Optimal Parameters	Maxgen = 300 Sizepop = 50	Gam = 400 Sig2 = 5	Hidden layer = 10 Learning rate = 0.01 MaxEpochs = 5000
Train-MSE	7.8520e-05	2.0358e-05	0.0014
Test-MSE	0.0022	5.2525e-04	0.0012
Time	66.009s	0.535s	1.710s

Table 10
Design indicators and effectiveness values of MEMLS

Scheme Number	U_{11}	U_{12}	U_{13}	U_{15}	U_{22}	U_{24}	U_{31}	U_{41}	E
1	0.9	0.8	200	37	0.9	0.8	0.8	350	0.6779
2	0.8	0.9	200	37	0.7	0.8	0.9	350	0.6082
3	0.8	0.8	250	37	0.7	0.8	0.8	300	0.6416
4	0.8	0.8	200	37	0.7	0.9	0.9	350	0.6665
5	0.8	0.8	200	37	0.7	0.8	0.8	350	0.5564

Table 11
Cost and effectiveness data of MEMLS

Scheme Number	Investment indicators (100 million yuan)				Output indicators	
	Development cost	Production cost	Use and guarantee cost	*LCC*	*E*	*E/LCC*
1	1.2	3.5	7.2	11.9	0.6779	0.0570
2	1.2	3.6	6.5	11.3	0.6082	0.0538
3	1.4	3.8	6.0	11.2	0.6416	0.0573
4	2.2	3.8	6.9	12.9	0.6665	0.5167
5	1.6	4.0	5.5	11.1	0.5564	0.0501

Table 12
Calculation results using DEA model

Scheme Number	overall efficiency	pure technical efficiency	scale benefit	K
1	1	1	1	1
2	0.9599	1	0.9599	0.9117
3	1	1	1	1
4	1	1	1	1
5	0.9462	1	0.9462	0.8672

(1) From the perspective of overall efficiency, schemes 1, 3, and 4 are all effective, and schemes 2, 5 have efficiency values < 1, and there is room for adjustment.

(2) From the point of view of pure technical efficiency, the five programs are all at a relatively high level.

(3) From the perspective of returns to scale, schemes 1, 3, and 4 remain unchanged and are the optimal level of investment scale, while schemes 2, 5 are incremental and need to be adjusted.

Therefore, the cost of the MEMLS design scheme is adjusted, and the results are shown in Table 13.

4. Conclusion

This paper takes MEMLS as the research object. Based on the previous research, a fast calculation model based on GRA-PCA-LSSVM is established, and the rationality and superiority of the calculation model are verified. At the same time, based on the DEA model, the investment efficiency of the MEMLS scheme is analyzed. The conclusions of this paper are as follows:

(1) Through GRA-PCA, the main indicators of system evaluation can be effectively extracted and the dimensionality of the input vector can be reduced, which is reasonable and necessary.

(2) LSSVM can effectively construct the performance prediction model of MEMLS. Compared with other methods, this model has higher accuracy and shorter calculation time.

(3) Through the DEA model, the input and output of the MEMLS program can be adjusted, and the method is effective and feasible.

(4) In the existing 5 design schemes of MEMLS, it is necessary to adjust the life cycle cost of schemes 2 and 5 to achieve the best investment scale level.

Table 13
Cost adjustment plan of MEMLS (100 million yuan)

Scheme Number	Development cost	Production cost	Use and guarantee cost	*LCC*
2	1.2000	3.4176	6.5000	11.1176
5	1.3009	3.5106	5.5000	10.3116

In the next step, the specific scheme design and deployment scale of MEMLS will be studied.

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