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SE-DEA-SVM evaluation method of ECM operational disposition scheme

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Abstract: Operational disposition of electronic countermeasures (ECM) is a hot topic in modern warfare research. Through fully analyzing the characteristics and shortcomings of the traditional operational disposition scheme, a super-efficient data envelopment analysis support vector machine (SE-DEA-SVM) method for evaluating the operational configuration scheme of ECM is proposed. Firstly, considering the subjective and objective factors affecting the operational disposition of ECM, the index system of operational disposition scheme is established, and we explain the solution method of terminal indexs. Secondly, the evaluation and algorithm process of SE-DEA-SVM evaluation method are introduced. In this method, the super-efficient data envelopment analysis (SE-DEA) model is used to calculate the weight of index system, and the support vector machine (SVM) method combined with the training samples of evaluation index is used to obtain the input-output model of evaluation value of combat configuration. Finally, by an example (obtaining five schemes), we verify the SE-DEA-SVM evaluation method and analyze the results. The efficiency analysis, comparison analysis, and error analysis of this method are carried out. The results show that this method is more suitable for military evaluation with small samples, and it has high efficiency, applicability, and popularization value.

Keywords: electronic countermeasures (ECM), operational disposition, plan evaluation, super-efficiency data envelopment analysis (SE-DEA), support vector machine (SVM).

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1. Introduction

Operational disposition refers to the specific arrangement made by the commander for the division of tasks, the formation and configuration of combat troops [1]. Electronic countermeasures (ECM) is the key factor that determines the success or failure of modern warfare, and its operational disposition scheme is also the key content of the operational plan of joint and combined operations commanders. Therefore, it has become one of the research hotspots in the field of operational command and decision-making to accurately and quickly evaluate the operational disposition scheme of ECM.

The evaluation of ECM operational disposition scheme is a multi-objective nonlinear decision-making problem with variable influencing factors, large uncertainty, and many targets. At present, the following three methods can be summarized in the study of operational disposition scheme evaluation.

(i) Many scholars have statically evaluated the index system that affects operational disposition and optimized different disposition schemes by sorting the evaluation results. Hou et al. [2] combined fuzzy weight determination method and analytic hierarchy process (AHP) to evaluate the combat indexes of different anti-ship weapon disposition schemes by Fuzzy-AHP, and obtained the anti-ship force disposition scheme with high combat efficiency and good safety by scheme sequencing comparison. In [3−5], Charnes, Cooper and Rhodes model based on data envelopment analysis (DEA-CCR) method, Banker, Charnes and Cooper model based on data envelopment analysis (DEA-BBC) method, and the super-efficient data envelopment analysis (SE-DEA) model are used to evaluate and optimize the operational disposition scheme of communication ECM respectively. This method determines the weight value of the index system through the iteration of the efficiency index of the model, and does not need to manually determine the weight subjectively, which provides a good reference idea for the evaluation of influencing factor in the operational disposition of ECM. Zheng et al. [6] modeled the index system of the factors affecting the radar combat network configuration, and the back-propagation (BP) neural network is improved by using particle swarm optimization (PSO) algorithm and the deployment scheme is evaluated and optimized, which

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has good convergence effect and prediction accuracy.

(ii) Battlefield scenario modeling is carried out based on the combat characteristics of different forces, and the planning and solving are carried out with combat efficiency and combat consumption as the objectives, so that the specific values of various elements of the operational disposition scheme can be obtained through solving. Zhao et al. [7,8] modeled the operational disposition of air defense operations dynamically, solved multiple configuration schemes using the Memetic algorithm, and obtained the optimal configuration area and multiple disposition scheme elements such as the mobile route of weapons and equipment. Wen et al. [9] and Chen et al. [10] modeled the operational disposition for the terminal defense problem of missile positions, and regarded the fire coverage as the optimization target of the model. They used the genetic PSO hybrid algorithm and the artificial potential field method to optimize the number of combat troops and the configuration method. Zak et al. [11] and Deng et al. [12] modeled the operational disposition of air defense operations and anti-submarine warfare based on game theory, and different operational disposition schemes are optimized by using dynamic game theory methods according to the operational planning process.

(iii) The "distributed combat" technology put forward by the U.S. military as the leader solves the centrality and energy value of the combat nodes in the battlefield through the network deployment of the battlefield and the method of rasterizing the combat situation, integrates the network optimization method into the evaluation and optimization of the operational disposition scheme. Rawat et al. [13] analyzed and modeled the combat network configuration scheme based on the improved genetic algorithm, optimized the model by analyzing the service utility value of the network nodes, and obtained a good network deployment performance evaluation scheme. Ran et al. [14] modeled the operational disposition problem in aviation operations on a network, solved the time factor and information smoothness of network nodes optimally by multi-objective bat algorithm, and obtained the optimal solution set of multi-schemes. Qiao et al. [15] proposed the deterministic sequencing of learning and coverage (DSLC) algorithm on the basis of [13], which improves the situation that the optimization process may enter local optimum, and further improves the networking configuration effect.

The above-mentioned methods provide a solution to the evaluation and optimization of operational disposition schemes and also provide a reference for the follow-up study of similar problems. However, there are still the following shortcomings: Firstly, the static scheme optimization evaluation method does not fully consider the battlefield change factors in the selection of index sets, so the evaluation timeliness is not strong. Second, the scheme optimization method of the planning solution does not fully consider the subjective judgment factors of the commander on the battlefield conditions, and the scheme evaluation process can not well reflect the superior's combat efforts. Third, when evaluating the operational disposition scheme by the network optimization method, there is still a certain gap between the feature values and the utility values of each combat node and the actual battlefield, which can not fully reflect the influencing factors of the operational disposition scheme.

In order to fully consider the subjective decision-making of commanders and the objective situation of the battlefield and to avoid the shortcomings of the above methods, a super-efficient data envelopment analysis support vector machine (SE-DEA-SVM) evaluation method is proposed. By comprehensively considering quantitative and qualitative indicators, the optimization problem of the evaluation of ECM combat configuration scheme based on small sample data sets is successfully solved.

The main innovations and contributions of this paper are as follows:

(i) The index system affecting the disposition of ECM is constructed. When considering the index factors, the subjective and objective factors are integrated, and all factors are fully considered, thus avoiding the intersection of end indicators.

(ii) An SE-DEA-SVM evaluation algorithm is proposed. The SE-DEA model is used to determine the number of initial factors and the weight of each index, calculate the exponential index weight and multiplied by the normalized exponential matrix. The result is used as the input of the support vector machine (SVM). The trained SVM is used to evaluate the input sample data, so as to obtain the final evaluation expectation. This method makes full use of the characteristics of data envelopment analysis (DEA) model and SVM model, avoids subjective deviation, and is suitable for the evaluation of small samples of military programs.

(iii) The SE-DEA-SVM evaluation algorithm is used to evaluate and optimize the set of operational disposition scheme, and compared with three similar comparable algorithms, the advantages of the evaluation algorithm proposed in this paper are obtained.

The rest of this paper is organized as follows: Section 2 briefly introduces the comprehensive evaluation index system of ECM disposition scheme, and gives the calculation method of terminal index. In Section 3, an SE-DEA-SVM evaluation method is proposed and the specific steps of the algorithm are given. A simulation example is given in Section 4, and the optimization results of scheme evaluation are given by using the algorithm proposed in this paper and comparison algorithms. Conclusions are drawn in Section 5.

2. Comprehensive evaluation index of ECM operational disposition scheme

2.1 Index system construction

ECM operational disposition refers to the deployment of ECM troops within a military organization according to various operational requirements. In the current combat process, the electronic countermeasure commander will implement a reasonable combat configuration according to the enemy's threat, the millitary's combat intention, combat mission, troop composition, task division, combat capability and battlefield conditions. The basic requirements are as follows [16]:

(i) The deployment should be determined according to the operational intention and preliminary determination of the superior.

(ii) It is conducive to give play to the combat capability of electronic countermeasure equipment.

(iii) Promote coordination and support with the combined forces.

(iv) It can give full play to the flexible advantage of ECM forces.

(v) It is conducive to improve the battlefield survivability of ECMs equipment.

Considering the above requirements, the main considerations for the disposition of ECMs forces can be summarized into three aspects, namely, the exertion of operational effectiveness, the security of disposition scheme, and the convenience for command and control. Based on these three aspects, our study comprehensively analyzes the factors that affect the disposition of ECM combat forces. The exertion of combat effectiveness can be summarized as operational (jamming) efficiency index (A_2) and environmental factor index (A_4) in the first-level index. And the security of the disposal scheme is summarized as the safety index (A_3) in the first-level index. Command and control is summarized as the command efficiency index (A_1) and the subjective factor index (A_5) in the first-level index. The two-level indicators under each first-level indicator are further refined according to the nature of the first-level indicators.

In summary, we established the comprehensive evaluation index system of the operational disposition scheme of the ECM, as shown in Fig. 1.

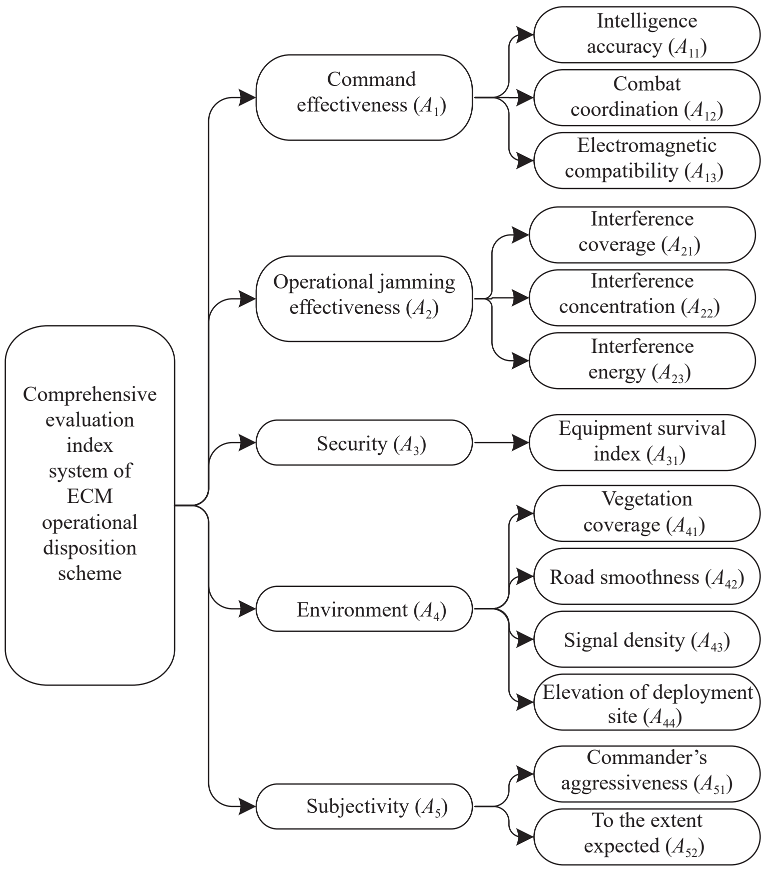


Fig. 1 Comprehensive evaluation index system of ECM operational disposition scheme

The index system is divided into two levels, with five indicators at the first-level indicating the factors (denoted by A_1 to A_5, respectively) affecting the reasonable disposition of ECM operations. The secondary level is the final index for comprehensively evaluating the operational disposition scheme of the ECM, with 13 items in total. End indicators A_{51} and A_{52} are qualitatively determined indicators, and the remaining end indicators are quantitatively determined indicators.

2.2 Terminal index calculation method

Among the 13 end indicators, the qualitative indicators are measured by the unary semantic scale method [17], and the levels are divided into five levels, as shown in Table 1.

Table 1 Semantic level table

Metric	Expression level				
	high (++)	higher (+)	medium (−)	Lower (×)	Low (××)
Interval range	(0.8,1]	(0.6,0.8]	(0.4,0.6]	(0.2,0.4]	(0,0.2]

For example, when solving the expected task degree index A_{52}, the results are derived from different schemes and scores, the normalized data value is taken as the interval range value, that is, the end index value is obtained.

The following gives the solutions of the 11 quantitative indices:

(i) Intelligence accuracy (A_{11}). The ratio of our reconnaissance intelligence data to the enemy actual data in battle. Data generally includes the type, quantity and deployment location of enemy equipment.

(ii) Combat coordination (A_{12}) [18]. It can be solved by the following equation:

$$A_{12}=\frac{0.5\mathrm{C}_n^2-M}{0.5\mathrm{C}_n^2} \tag{1}$$

where $0.5\mathrm{C}_n^2$ represents the number of paired communication path between the ECM devices; M represents the number of communication distance exceeding the maximum communication distance of the devices in these communication paths.

(iii) Electromagnetic compatibility (A_{13}). The ratio of the number of all ECM equipment performing combat missions to the number of all equipment that can perform combat missions simultaneously without frequent interference.

(iv) Interference coverage (A_{21}) [19]. It can be solved by the following equation:

$$A_{21}=\begin{cases}\dfrac{s'}{S}, \text{ communication interference}\\ \dfrac{S-s'}{S}, \text{ ground-to-ground radar interence}\\ \dfrac{\theta'}{\theta}, \text{ ground-to-air radarinterence}\end{cases} \tag{2}$$

where s' represents the overlapping area of the actual communication (radar) interference suppression area and a planned interference task area corresponding to a certain disposition scheme; s represents the planned interference task area; θ represents the designated interference shielding angle range of the planned interference task; θ' represents the overlapping part of the actual radar interference shielding angle corresponding to a certain configuration scheme and the planned interference task.

(v) Interference concentration (A_{22}). It can be solved by the following equation:

$$A_{22}=\begin{cases}\displaystyle\sum_i \frac{iS_i}{S}, \text{ communication}\\ \quad\text{ground-to-ground radar interference}\\ \displaystyle\sum_i \frac{i\theta_i}{\theta}, \text{ ground-to-air radar interference}\end{cases} \tag{3}$$

where S_i and θ_i respectively represent the actual communication (radar) interference suppression area and radar interference cover angle of the ith ECM equipment in the combat mission area.

(vi) Interference energy (A_{23}). The total interference powers of all ECM equipment in a certain disposition scheme.

(vii) Equipment survival index (A_{31}). It can be solved by the following equation:

$$A_{31}=\frac{n-\sum_{i=1}^{n}\partial_i}{n} \tag{4}$$

where ∂_i indicates that the millitary's ith ECM equipment is within the range of enemy fire damage.

(viii) Environment (A_4). The four end indicators of environmental factors are extracted and determined directly from the geographic location information of the combat area.

3. SE-DEA-SVM evaluation method

In recent years, with the continuous development of military technology, the solution to military evaluation problems have become more refined and specialized. The traditional method of subjective judgment is no longer applicable, and the more scientific evaluation and optimization method are gradually applied to this kind of problems. DEA is one of the most outstanding methods. DEA establishes the linear programming model of the decision making unit (DMU) and obtains the optimal scheme corresponding to DMU based on the optimal solution. At first, when DEA was applied to military evaluation, there were two main models, CCR and BBC [20,21]. On this basis, many scholars have brought time into the evaluation process, and put forward two-stage DEA model [22] and a three-stage DEA model [23]. At present, the combination of artificial intelligence (AI) and DEA model has produced many effective and feasible evaluation methods. For example, DEA-machine learning (DEA-ML) method [24], DEA-BP neural network (BPNN) [25], integrated DEA-genetic algorithm (DEA-GA) and BPNN DEA (BPNN-DEA) [26], etc. Inspired by the above, we combine SVM and SE-DEA model [27] to solve the ECM operational disposition scheme evolution problem.

3.1 Evaluation method framework

In this paper, the evaluation method of ECM operational disposition scheme is mainly divided into two parts: SE-DEA and SVM model. The input variables are the established evaluation index system and sample data of combat disposition, the output variables are the expectation of force disposition, that is, the sorting basis of combat disposition schemes. The SE-DEA model is mainly to determine the weight values of the end indicators in the evaluation index system. The SVM model trains the model through the sample data of ECM combat disposition, selects the optimal model parameters, and carries out regression analysis on the weight values of different schemes determined in SE-DEA model, so as to obtain the expected value of force disposition, then evaluates and optimizes the schemes. The evaluation process is shown in Fig. 2.

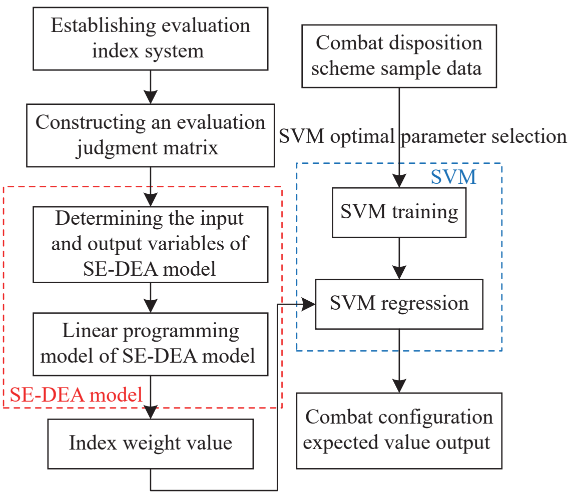


Fig. 2 A illustration of SE-DEA-SVM evaluation flow

3.2 Algorithm steps

The algorithm is set in the following steps:

Step 1 The judgment matrix of the model is decided by the hierarchical relationship of the index system. Set that terminal indexes as $c_1,c_2,\cdots, c_{13}$, every two terminal indexes are compared with each other, and the model judgment matrix $\boldsymbol{A}=(a_{ij})_{13\times 13}$ is obtained.

$$\boldsymbol{A}=\begin{pmatrix} 1 & a_{1,2} & \cdots & a_{1,13} \\ 1/a_{1,2} & 1 & \cdots & a_{2,13} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1,13} & 1/a_{2,13} & \cdots & 1 \end{pmatrix} \tag{5}$$

where a_{ij} $(i, j=1,2,\cdots,13)$ represents the result of quotient comparison between terminals c_i and c_j. Obviously, this matrix is a symmetric matrix.

Step 2 The DMU of the SE-DEA model is determined. According to the structure of judgment matrix $\boldsymbol{A}$, take the matrix as the initial value of the model and $\text{DMU}_{ij}= a_{ij}$. Let the DMU input variable be $\boldsymbol{x}_{ij}= [x_{1i}, x_{2i},\cdots, x_{13,i}]^{\mathrm{T}}$, the output variable be $\boldsymbol{y}_{ij}= [y_{1i}, y_{2i},\cdots, y_{13,i}]^{\mathrm{T}}$, where x_{ij} represents input variable of decision unit j under index i, and y_{ij} represents output variable of decision unit j under index i.

Step 3 The SE-DEA model is used to calculate the terminal index weight. The general form of dual transformation of SE-DEA model is shown in (6), where ε, s^-, and s^+ are input and output relaxation variables and x_0 and y_0 are internal input and output. In this paper, ε is calculated by taking 10^{-6}.

$$\min\left[\theta-\varepsilon\left(\sum_{i=1}^{13}s_i^-+\sum_{r=1}^{13}s_r^+\right)\right]$$
$$\text{s.t.}\begin{cases}\displaystyle\sum_{j=1,j\neq k}^{13}\lambda_j x_{ij}+s_i^-=\theta x_0\\ \displaystyle\sum_{j=1,j\neq k}^{13}\lambda_j y_{rj}-s_r^+=y_0\\ s^-,s^+,\lambda_j\geqslant 0,\ j=1,2,\cdots,13\end{cases} \tag{6}$$

Because the terminal index in the evaluation index system established in this paper can not distinguish the input and output indexes of the model well, in order to facilitate the calculation and evaluation, this paper sets all the input indexes as 1, which is convenient for the discussion and evaluation of the terminal index. Thus, the model becomes

$$\min\left[\theta-\varepsilon\left(\sum_{i=1}^{13}s_i^-+\sum_{r=1}^{13}s_r^+\right)\right]$$
$$\text{s.t.}\begin{cases}\displaystyle\sum_{j=1,j\neq k}^{13}\lambda_j x_{ij}+s_i^-=\theta\\ \displaystyle\sum_{j=1,j\neq k}^{13}\lambda_j y_{rj}-s_r^+=y_0\\ \displaystyle\sum_{j=1,j\neq k}^{13}\lambda_j=1\\ s^-,s^+,\lambda_j\geqslant 0,\ j=1,2,\cdots,13\end{cases}. \tag{7}$$

The judgment criteria of this model are as follows:

(i) When $\theta\geqslant 1$, $s^-=s^+=0$, it is considered that the ($j0$)th decision unit is DEA effective ($j0$ is the serial number of the decision unit), the weight of the terminal indicators is reasonable. The higher the value of θ is, the more rational it is.

(ii) When $\theta\geqslant 1$, $s^+\neq 0$ or $s\neq 0$, the $j0$ decision unit DEA is weakly efficient, and the final index weight is acceptable.

(iii) When $\theta<1$ or $s^+\neq 0$, $s\neq 0$, the ($j0$)th decision unit DEA is said to be invalid, and the weight of the end index is unreasonable, and it needs to be re-scored.

Step 4 Initialize the SVM model. The weight vectors of the N evaluation schemes obtained through Step 3 are $\boldsymbol{\omega}_1, \boldsymbol{\omega}_2, \cdots, \boldsymbol{\omega}_p, \cdots, \boldsymbol{\omega}_N$, where $\boldsymbol{\omega}_p=(\omega_1^{(p)}, \omega_2^{(p)}, \cdots, \omega_{13}^{(p)})$, ($p=1,2,\cdots,N$). Before indicators are brought into the model, numerical normalization is required for all indicator values. The normalization formula is

$$\bar{\omega}_j^{(p)}=\frac{\omega_j^{(p)}-\min\ \omega_j^{(p)}}{\max\ \omega_j^{(p)}-\min\ \omega_j^{(p)}}. \tag{8}$$

Training SVM with the processed operational disposition sample index data and determining the optimal penalty parameter c and a kernel function parameter g of SVM model by cross-validation (CV) method [28,29], wherein the kernel function takes the radial basis function, and SVM model's offset parameter set as b.

$$K(x,x_i)=\exp(-\gamma\|x-x_i\|^2) \tag{9}$$

where $\gamma>0$.

Step 5 Evaluating the optimal scheme according to the operational disposition expectation value calculated by SVM. In this paper, we use the framework of SVM algorithm for sample training and expected fitting, which is proposed by Viswanathan et al. [30] and Shalev-Shwartz et al. [31]. The structure of the expected value calculation model for operational disposition of SVM is shown in Fig. 3.

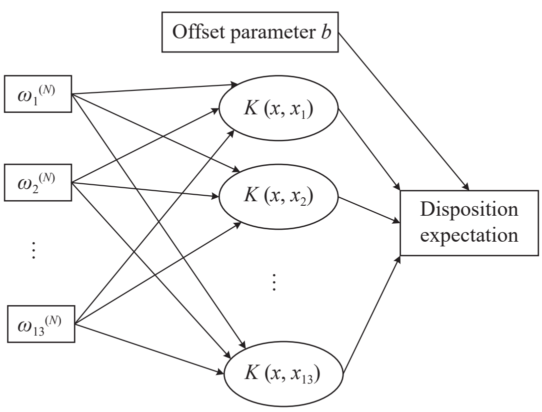


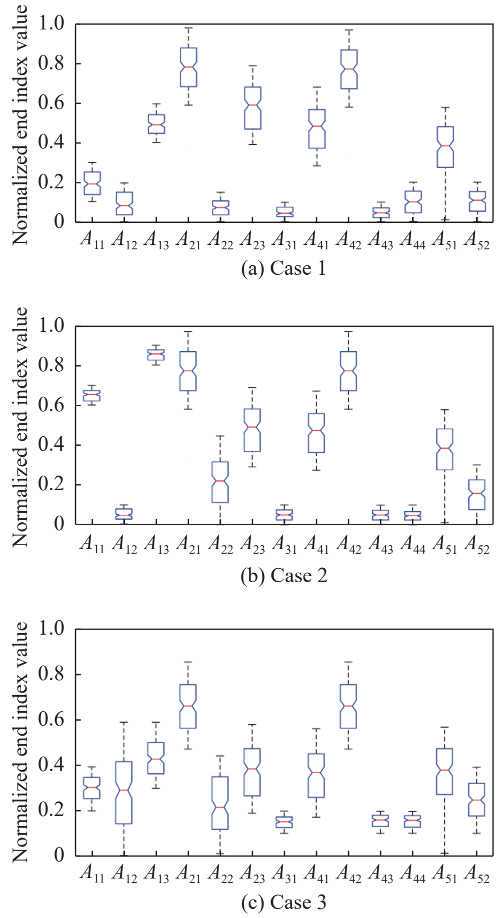
Fig. 3 Structure of the expected value calculation model for operational disposition of SVM

Through the calculation of SVM model, the expected output of the operational disposition of each scheme can be obtained, and the optimal scheme can be obtained by comparing and sorting.

4. Case studies and conclusion analysis

4.1 Case building

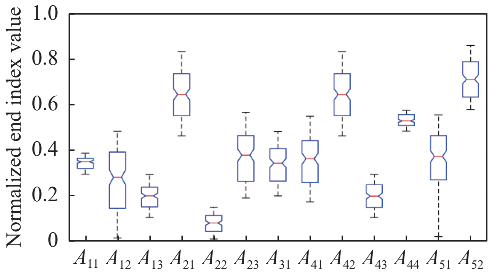
Based on 100 sets of ECM operational disposition data (five operational disposition schemes, 20 sets for each scheme) obtained from practical research, the expected output of each set of operational disposition is obtained according to SE-DEA-SVM model, thus evaluating and optimizing an ECM operational disposition scheme. In 100 sets of data, each set of data corresponds to the end index of the comprehensive evaluation of deployment scenarios established in this paper, which has 13 elements in total. Because of the large amount of data, it is not listed in this paper, and the statistical distribution of normalized index value data is used for intuitive explanation. Fig. 4(a)−Fig. 4(e) are boxplot diagrams composed of 100 groups of data of 13 end indexes of five cases. It can be seen that the normalized final index value data is relatively stable, and it is suitable for training sample and input data of SVM.



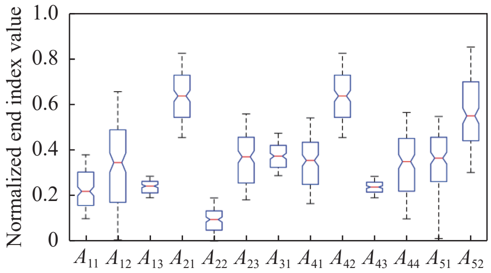
(a) Case 1

(b) Case 2

(c) Case 3



(d) Case 4



(e) Case 5

Fig. 4 100 group normalized sample data statistical boxplot with five cases

The standardized end indexes of the five operational disposition schemes to be evaluated are shown in Table 2.

Table 2 End of the five schemes to be evaluated

Index	Case 1	Case 2	Case 3	Case 4	Case 5
A_{11}	0.4230	0.6500	0.2546	0.3463	0.3453
A_{12}	0.0100	0.1700	0.9400	0.1900	0.6100
A_{13}	0.1200	0.2300	0.1500	0.2100	0.2900
A_{21}	0.1800	0.4800	0.1700	0.0700	0.1800
A_{22}	0.1200	0.1200	0.0200	0.2800	0.0940
A_{23}/W	9800	1100	5300	1500	9000
A_{31}	0.9800	0	0.7000	0.7200	0.9800
A_{41}	0.2600	0.2700	0.5500	0.1400	0.3700
A_{42}	0.4000	0.4200	0.6200	0.3500	0.5500
A_{43}/s^{-1}	0.3000	0.3200	0.8300	0.1500	0.9500
A_{44}/m	2800	400	4200	5000	4600
A_{51}	0.1200	0.1200	0.0200	0.2800	0.0940
A_{52}	0.1800	0.4800	0.0700	0.2700	0.1800

All compared methods are coded in Matlab language and executed on an Intel Core i7 2.6-GHz PC with 32 GB of memory.

4.2 Case solving

According to the steps of solving the model, take the first group of five groups of data as an example, and solve the case step by step. Firstly, according to the index system at all levels in Fig. 1, we establish the judgment matrix $\boldsymbol{A}=(a_{ij})_{13\times 13}=\beta(\boldsymbol{A}_p)\beta(\boldsymbol{A}_{pq})$, where p=1,2,$\cdots$,5, q is the numerical serial number of end indexes under the first-level index, $\beta(\boldsymbol{A}_p)$ is the first-level index weight, and $\beta(\boldsymbol{A}_{pq})$ is the end indicator weight. Since terminal indicators A_{23} and A_{44} are actual value indicators, normalization calculation is required according to (8) before the indicator value is brought into model (6) and (7), normalized values for all indicators are presented in Table 3.

Table 3 Normalized values for all indicators

Index	Case 1	Case 2	Case 3	Case 4	Case 5
A_{11}	0.4259	1	0	0.2319	0.2294
A_{12}	0	0.1720	1	0.1935	0.6452
A_{13}	0	0.6471	0.1765	0.5294	1
A_{21}	0.2683	1	0.2439	0	0.2683
A_{22}	0.3846	0.3846	0	1	0.2846
A_{23}/W	1	0	0.4828	0.0459	0.0919
A_{31}	1	0	0.7143	0.7347	1
A_{41}	0.2927	0.3170	1	0	0.5609
A_{42}	0.1852	0.2593	1	0	0.7407
A_{43}/s^{-1}	0.1875	0.2125	0.8500	0	1
A_{44}/m	0.5217	0	0.8261	1	0.9130
A_{51}	0.3846	0.3846	0	1	0.2846
A_{52}	0.2683	1	0	0.4878	0.2683

Then the data of the five schemes to be evaluated are brought into the SE-DEA model, the SE - DEA model obtained here is

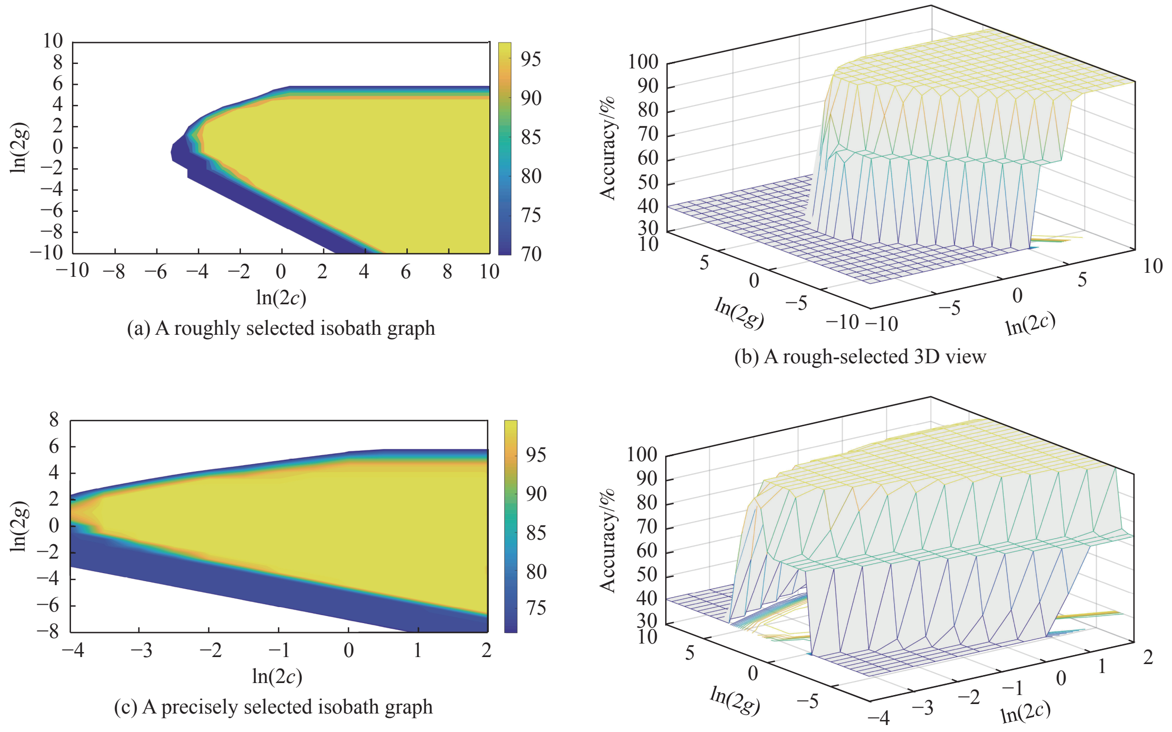
$$\min\left[\theta-10^{-6}\left(\sum_{i=1}^{13}s_i^-+\sum_{r=1}^{13}s_r^+\right)\right]$$

$$\text{s.t.}\begin{cases}\displaystyle\sum_{j=2}^{13}\lambda_j+s_1^-=1\\ \displaystyle\sum_{j=1,j\neq 2}^{13}\lambda_j+s_2^-=1\\ \quad\vdots\\ \displaystyle\sum_{j=1}^{12}\lambda_j+s_{13}^-=1\\ (\lambda_j)_{1\times 12}(y_{rj})_{12\times 1}-s_1^+=0.423,\ j\neq 1\\ (\lambda_j)_{1\times 12}(y_{rj})_{12\times 1}-s_2^+=0.010,\ j\neq 2\\ \quad\vdots\\ (\lambda_j)_{1\times 12}(y_{rj})_{12\times 1}-s_{13}^+=0.180,\ j\neq 13\\ \displaystyle\sum_{j=1,j\neq k}^{13}\lambda_j=1\\ s^-,s^+,\lambda_j\geqslant 0,j=1,2,\cdots,13\end{cases}. \tag{10}$$

After calculation, the weight of each index in Case 1 is

0.0043, 0.0056, 0.3149, 0.1750, 0.00427, 0.00629, 0.00047, 0.0022, 0.0022, 0.0050, 0.0003, 0.0072, 0.0022, 0.0309, 0.1228, 0.0050, 0.0003, 0.0072, $\theta_1^*=1.214$.

Next, the SVM initialization is performed. The first 80 groups in the 100 groups of force configuration exercise data are used as the SVM training set, and the last 20 groups are used as the test set. The parameters c and g of the SVM are roughly selected within the range of [−10,10] by the K-fold cross validation (K-CV) method, and the results are shown in Fig. 5(a) and Fig. 5(b), which are the isobath graph and the 3D curved surface graph of the selected results, respectively. Then, according to the image range, the accurate selection of narrowing range is carried out, and the results is shown in Fig. 5(c) and Fig. 5(d), finally the optimal values of c and g are 0.0884 and 1.



(a) A roughly selected isobath graph

(b) A rough-selected 3D view

(c) A precisely selected isobath graph

(d) Precisely selected 3D view

Fig. 5 Illustration of the selecting result of SVM parameters by K-CV method

Finally, the weight value obtained by SE-DEA model is dot-multiplied with the end index value. After the SVM model is used to calculate the result, the expected value output of troop deployment for the five schemes to be evaluated is obtained, which is 0.6873, 0.6476, 0.6545, 0.6438, 0.6672, respectively. Comparison and ranking of the best cases are Case 1>Case 5>Case 3>Case 2>Case 4, where “>” means non-inferior.

4.3 Result discussion

4.3.1 Model efficiency analysis

SE-DEA-SVM algorithm is used to solve the models of the five cases, the relative efficiency and relaxation variables are obtained, as shown in Table 4.

Table 4 Results of SE-DEA efficiency evaluation

Case	Relaxation variable S^+													S^-	θ
	S_1^+	S_2^+	S_3^+	S_4^+	S_5^+	S_6^+	S_7^+	S_8^+	S_9^+	S_{10}^+	S_{11}^+	S_{12}^+	S_{13}^+		
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1.214**
2	**0.55465**	**0.76000**	2.45000	15.2000	112	**1.27000**	**1.39000**	**0.34000**	**0.34000**	**1.75000**	0.05000	0.85000	**1450**	0	0.991
3	0.54230	0.71000	2.43000	15.6000	**127**	0.80000	0.60000	0.28000	0.28000	0.64000	0.04000	**1.92000**	1065	0	1.051
4	0.48050	0.15000	**2.61000**	**17.6000**	121	1.06000	0.51000	0.31000	0.31000	0.04998	**0.06000**	1.58000	1295	0	0.847
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.169

In Table 4, the optimal value of each parmeter for each of the five cases are in bold. Since the input variables are set to 1, the output relaxation variables S^- are all 0. According to the evaluation standard of SE-DEA-SVM model, it can be seen from the value of θ^* that the weight values of Case 1 and Case 5 are effective, Case 3 is weak and Case 2 and Case 4 are invalid. Case 2 and Case 4 need to adjust the index weight and determine the result weight again. We use the projection method [32,33] to deal with this kind of problems, in order to adjust the parameters of the model. The operation method are as follows:

$$\hat{x}^* = \theta^* x^* - s^-, \tag{11}$$

$$\hat{y}^* = y^* + s_j^-, \tag{12}$$

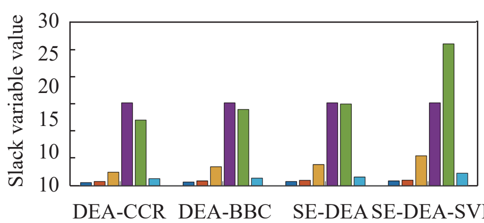
where $(\hat{x}^*, \hat{y}^*)$ is the projection of (x^*, y^*) corresponding to the optimal decision unit DMU* on the relatively efficient surface of the DEA model. According to the above two formulas, the scheme indexes of Case 2, Case 3, and Case 4 are adjusted, the values of θ^* are calculated again to be 1.235, 1.092, 0.828, respectively. In this way, the index weights of Case 2 and Case 3 meet the current conditions. In Case 4, the scheme index is constantly adjusted, and the solution θ^* is 1.112. Up to now, the weight of all schemes have met the requirements. Through this method, the deviation of index weight caused by subjective factors can be avoided to a great extent.

4.3.2 Algorithm comparison analysis

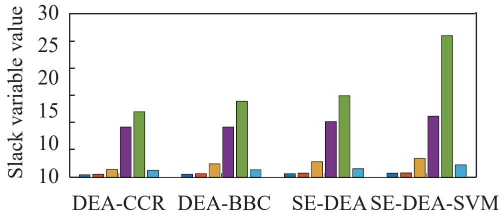
In order to further illustrate the feasibility and efficiency of the evaluation method in this paper, the last four groups of data in each case sample (a total of 20 groups) are used as test samples to compare this method with the DEA-CCR method [3], the DEA-BBC method in [4], and the SE-DEA method in [5]. It should be noted that the three DEA methods used evaluation indexes A_{31}, A_{41}, A_{42}, A_{43}, A_{44}, A_{51}, A_{52} are used as model inputs, and A_{11}, A_{12}, A_{13}, A_{21}, A_{22}, A_{23} are used as model outputs.

Evaluate and optimize the schemes by using the model efficiency parameters. Firstly, the DEA efficiency of the model is calculated and the result is shown in Fig. 6.

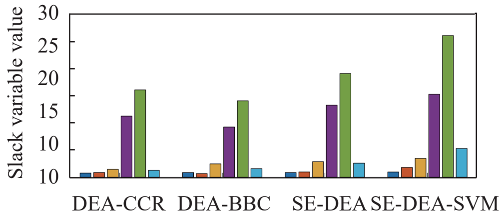
Comparing the three model algorithms with SE-DEA-SVM, the expectation value of 20 sets of test set indicators in five cases are shown in Fig. 7.



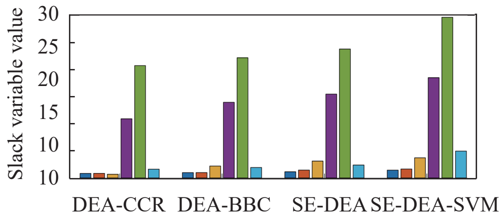
(a) Case 1



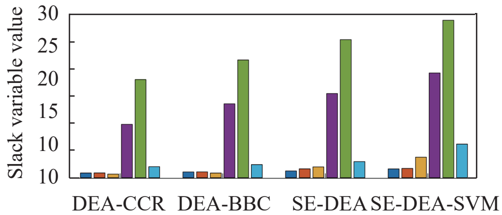
(b) Case 2



(c) Case 3



(d) Case 4



(e) Case 5

: S_1^+; : S_2^+; : S_3^+; : S_4^+; : S_5^+; : S_6^+.

Fig. 6 Comparison of DEA efficiency results for solving test sets with four methods

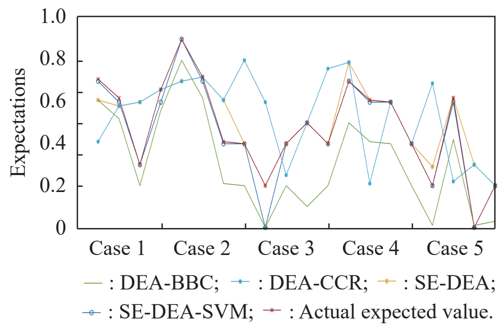


Fig. 7 Comparison of expectation value of test set indexes under four methods

It can be seen from Fig. 6 and Fig. 7 that the SE-DEA-SVM model proposed in this paper is most effective in solving the optimization problem of the evaluation of operational disposition scheme. The reason is that the SE-

DEA model has good objectivity when solving index weights, and SVM performs well when dealing with small sample data. The combination of the two is very suitable for solving the evaluation problem of small samples in military category. In addition, the SE-DEA-SVM model has strong generalization ability, and the expected result is very close to the actual expectation value.

4.3.3 Error analysis

In this part, we mainly compare and analyze the absolute error between the expected and actual values of the test set, the average semantic level of the operational disposition expectation and the fault tolerance performance of various method.

The expected values of 20 sets of test set data solved by this method is compared with the actual expected values, and the formula for calculating the average absolute error is as follows:

$$\Delta = \frac{1}{20}(E_{\text{method}} - E_{\text{fact}}) \tag{13}$$

where E_{method} and E_{fact} represent the expected values obtained by the model algorithms and the actual expected values of the test set data, respectively.

When solving the semantic level, 20 sets of expected values are converted into the semantic level of the disposition scheme by using the semantic conversion interval in Table 1 and then the average value is calculated to get the average semantic level of the four methods.

When solving the fault tolerance performance of the model, the Matlab function rand(1,13) is used to generate a random wave vector containing 13 elements and add a set of test data. Comparing the expected values of the four methods with the expected values of the waveless solution, the fault-tolerant performance of each method is obtained. The values in [0,0.1] are recorded as good fault tolerance, and others are poor. Table 5 shows the relative error values, expected average semantic level and fault tolerance performance of these four methods.

Table 5 Comparison of error analysis results of four methods

Compare items	DEC-CCR	DEC-BBC	SE-DEA	SE-DEA-SVM
Absolute error	−0.012	0.010	−0.004	−0.001
Semantic level	+	+	++	++
Fault freedom	×	×	√	√

Through comparison, the SE-DEA-SVM method established in this paper has a high accuracy and good fault-tolerant performance in the output results of the model, meets the evaluation accuracy and related requirements of electronic countermeasures operational disposition scheme, and has good applicability and generalization potential.

5. Conclusions

In this study, a multi-level evaluation index system of deployment scheme is constructed based on the research background of ECM operational disposition and 13 terminal indexes of the system are calculated by combining qualitative and quantitative means, and the final weight values of the index system are solved by DEA combining the SE-DEA model with the SVM model. 100 sets of sample data are used as a training set and a test set of the SVM model respectively, the index values are used as training inputs and the expected values are used as training outputs to deploy and initialize the SVM, so as to obtain the SVM model with good regression ability. Then, the indexes of ECM operational disposition scheme to be evaluated are carried to SVM to obtain the final evaluation result. Finally, we analyze the efficiency of the evaluation results obtained by SE-DEA-SVM method. The invalid result is obtained by efficiency analysis, and then iteratively update model parameters and make the expected solution again. By comparing different model algorithms with SE-DEA-SVM, it is concluded that the evaluation method proposed in this paper has good applicability and generalization in small sample military evaluation, and can provide accurate and rapid quantitative decision-making methods for commanders at all levels in combat planning. In the future, we will study from the following two aspects. First, enhancing the evaluation model of the battlefield dynamic configuration scheme and studying the improvement method of the evaluation model after the configuration scheme changes in different operational stages. Second, studying the adaptability of the model to large-scale data and keeping good robustness of the model even in the case of large-scale battlefield data.

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