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Evaluation of Sino Foreign Cooperative Education Project Using Orthogonal Sine Cosine Optimized Kernel Extreme Learning Machine

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ABSTRACT This study aims to propose an efficient evaluation model for Sino foreign cooperative education projects, which can offer a reasonable reference for universities to deepen reform and innovation of education and further enhance the level of international education. The core engine of the model is the kernel extreme learning machine (KELM) model integrated with orthogonal learning (OL) strategy optimization. The introduction of the OL mechanism is to further strengthen the optimization capabilities of the basic SCA, which is devoted to promoting the KELM model to select the optimal parameter combination and feature subset and further enhance the KELM evaluation capability of Sino foreign cooperative education projects. To examine the performance of the proposed method, OLSCA is evaluated on 23 benchmark problems, comparison with eight other well-known methods. The experimental results have shown that the proposed OLSCA is prominently superior to existing methods on most functional problems. Meantime, OLSCA-KELM is compared against other machine learning approaches in dealing with the evaluation of education projects of Sino foreign cooperation. The simulation results illustrate that the presented OLSCA-KELM obtains better performance of classification and higher stability on all four indicators. Therefore, it is evident that the presented OLSCA-KELM can be an effective solution for the evaluation of Sino foreign cooperative education projects.

INDEX TERMS Sine cosine algorithm, swarm intelligence, sino foreign cooperative education project, Kernel extreme learning machine, parameter optimization.

I. INTRODUCTION

A. MOTIVATION

In recent years, Sino foreign cooperation in running schools has been developing rapidly in the ground of the rapid development of China's higher education and the deepening of education reform. In order to better promote the connotative development of school running units, China's competent education department has launched the qualification assessment work, and so far, has completed the assessment of 882 school running units. In fact, evaluation has become an essential link and means in the process of educational management. In essence, the evaluation by the competent department of education is to realize the reasonable allocation of educational resources and influence the coordinated development of higher education itself through the structure of resource allocation. However, as an important way of qualitative evaluation, evaluation by experts has inevitable subjectivity and uncertainty. Therefore, it is essential to make an in-depth analysis of the evaluation results of experts, which is helpful

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to enhance the dependability of evaluation results. At present, a large number amount of data has been gathered after years of evaluation of Sino foreign cooperative education. We can use these data for deep mining and analysis to build an intelligent predictive model. Through this model, the factors that affect the reliability of the experts' evaluation can be found out in the data set, and further analyze the potential correlation between the factors to carry out the meta-evaluation of the experts. To select and organize appropriate experts for fair evaluation and evaluation, form a supervision and monitoring system, ensure the normal and smooth evaluation process, and ensure that the evaluation results are fair, scientific, and credible.

As far we know, before OLSCA-KELM, few types of research on evaluating the Sino-foreign cooperative education project are proposed through machine learning methods.

In this paper, we introduced an enhanced kernel extreme learning machine (KELM) for constructing an intelligent prediction model for evaluation of Sino foreign cooperation in education projects. In the established KELM model, an orthogonal learning (OL) strategy improved sine cosine algorithm (SCA) was designed to decide the significant parameters of KELM and perform the feature selection task simultaneously. The resultant OLSCA and OLSCA-KELM have been rigorously evaluated on 23 benchmark problems and the real-life dataset by comparing other well-known approaches, respectively. The simulation results have proved that the proposed OLSCA can achieve significantly more excellent results than other approaches on most functions, and the OLSCA-KELM can reach the best performance results than other methods per four evaluation metrics on the real-life dataset.

B. LITERATURE REVIEW

There are mainly two kinds of project evaluation methods in the literature; one is the traditional statistical method; the other is based on an artificial intelligence method.

The main work of traditional statistical methods is as follows: an Analytic Hierarchic Process (AHP) based judgment model for R&D project evaluation, was proposed by Kumar [1]. The results have shown that AHP had a better performance than scoring charts and utility models in priority setting. Cates and Mollaghasemi [2] introduced the Simulation Technique, which improved visibility may result in enhancing project risk management and enhancing project completion performance. Talias [3] revealed that the Pearson index and Gittins index were significant as to be a strategic decision-making tool for the selection of R&D projects [3]. Jung and Seo [4] provided to use the analytic network process (ANP) for project evaluation. Their method showed that the ANP could produce the final priorities of projects concerning benefits and costs when between programs and evaluation criteria were interdependencies. Wang *et al.* [5] proposed to use the Least Squares Monte-Carlo simulation to evaluate risky projects with real fuzzy options. It is shown that the proposed methodology can determine values whether there is an analytic solution or not. Morimoto [6] presented to incorporate socio-environmental considerations into project assessment models by using multi-criteria analysis. Kim *et al.* [7] developed an AHP method for project evaluation. Solution Map was introduced, and the Solution Tool was suggested in order to utilize the evaluation results effectively. He *et al.* [8] proposed novel q-rung picture fuzzy aggregation operators, and the effectiveness was validated on the best project selection example. In order to help project practitioners to select an appropriate project evaluation criterion for the projects, Haass and Guzman [9] proposed a meta-framework by considering the strengths and limitations of their preferred project evaluation model as well as making project evaluators aware of the underlying logics associated with diverse project evaluation approaches. The results proved that narrative analysis and actor-network theory were likely to be powerful tools for coping with the projects' uncertainty and complexity.

The artificial intelligence methods-based evaluation approaches are as follows. Bodea [10] presented the specific ways in which indicators and artificial intelligence methods and tools can be applied to the evaluation of research projects and programs. Seo *et al.* [11] proposed to use particle swarm optimization-based clustering analysis for project evaluation. Zhu *et al.* [12] proposed to use multi-granular linguistic labels to transform the evaluation problem to multiple-criteria decision-analysis problem and developed an estimation model using maximal group consistency with the minimal evidence distance of Dempster-Shafer theory for incomplete evaluation items. Zhang *et al.* [13] proposed to use several machine learning models for funding evaluation prediction. The experimental results proved that SVM could achieve the best results. Sun *et al.* [14] offered a new model for the evaluation of the university project; in this scheme, partial least squares and dynamic bp network group algorithms were developed for evaluation Sayadi *et al.* [15] proposed a model that used an artificial neural network (ANN) to predict the Net Present Value (NPV) was the most popular economic indicator in the evaluation of the investment projects. He *et al.* [8] proposed novel q-rung picture fuzzy aggregation operators, and the effectiveness was validated on the best project selection example. Smith [16]applied linguistic-preference models based on fuzzy relations in the context of multiple factor project assessment. Imoto *et al.* [17] proposed to use a method based on the principal component model, dual scaling, AHP, and fuzzy regression analysis for R&D project evaluation. In order to improve cost estimation and accuracy, Kiliç and Kaya [18] presented the Evolutionary Fuzzy Neural Inference Model (EFNIM)-based on an artificial intelligence approach. In this scheme, Genetic Algorithms, Fuzzy Logic, and Neural Networks were combined for effectively finding the best solutions in complex problems. Kiliç and Kaya [18] proposed models for the investment project evaluation problem based on type-2 fuzzy sets. Mohagheghi *et al.* [19] proposed a new model that used a new interval type-2 fuzzy optimization method for R&D

project portfolio selection under uncertainty and applied lower semi-variance to consider the risk of proposed projects. Zhou *et al.* [20] proposed to enhance the trapezoidal interval type-2 fuzzy sets (IT2FSs) by using the in center point of fuzzy sets. In addition, the proposed method was validated on an investment project assessment.

C. CONTRIBUTION AND PAPER ORGANIZATION

The main contribution of this study is described as bellow:

a) An orthogonal learning strategy is incorporated into SCA to enhance its searchability.
b) The proposed OLSCA can realize significant, more excellent results than other well-known approaches on 23 benchmark problems.
c) The OLSCA used to optimize the two critical parameters of KELM, and the best prediction model OLSCA-KELM is established.
d) The proposed OLSCA-KELM can realize more excellent performance compared to other competitive peers for the prediction of the Sino foreign cooperative education project.

The remaining part of the article is organized as follows. Section 2 presents brief descriptions of KELM, SCA, OLSCA method, and the proposed OLSCA-KELM model. The data description and experimental setup are displayed in detail in Section 3. Section 4 shows the experimental results of OLSCA on benchmark functions and the OLSCA-KELM on the real-life dataset. The discussions on the results are delivered in Section 5. The conclusions and future work's suggestions are present in Section 6.

II. METHODS

A. KERNEL EXTREME LEARNING MACHINE (KELM)

Like other supervised learning approaches [21]–[25], extreme learning machine (ELM) [26] has got more attention in recent years. ELM theories show that the hidden layer needs no learning, but the parameters of input weights and bias values of single-hidden layer feedforward networks can be obtained randomly during the training, and the output weights also can be achieved by some learning criteria. After that, compared with the previous training approaches, ELM can significantly improve both learning speed and performance. Due to the effectiveness of ELM, it has been applied to solve a large number of practical problems such as medical analysis and diagnosis [27]–[32], face recognition [33].

KELM [34] is constructed based on the above ELM by introducing the radial basis function (RBF) kernel functions. KELM has also found its applications in many scenarios [35]–[40]. RBF kernel is selected because it can map samples to higher-dimensional spaces, and can handle samples if the relationship between class labels and properties is non-linear. Meanwhile, the RBF kernel also has the advantage of fewer parameters. When RBF kernel is used, only two parameters C and γ(C represents the penalty factor and γ represents the kernel parameter) should be considered, but the selection of parameters has a great influence on the prediction results [37], [41]–[43]. In this study, the proposed OLSCA has been applied to identify the two parameters of KELM adaptively; the resultant OLSCA-KELM has applied to evaluate the Sino foreign cooperative education project.

B. SCA

There are many analytical and metaheuristic algorithms (MAs) in the literature that can be utilized for special or general-purpose problems [44]–[48], which can be more efficient for traditional gradient-based approaches [49]–[51], [53]. Some popular and new MAs are particle swarm optimization (PSO) [55], [56], bacterial foraging optimization (BFO) [57]–[59], gray wolf optimizer (GWO) [59], moth-flame optimization (MFO) [61], teaching-learning-based optimizer (TLBO) [52], grasshopper optimization algorithm (GOA) [62], [63], whale optimization algorithm (WOA) [64]–[66], Harris hawks optimizer (HHO) [67] and fruit fly optimization algorithm (FOA) [68]–[70]. These MAs have been adopted in various applications like the pharmaceutical industry, job scheduling, energy management, engineering design, machine learning and medical diagnosis [36], [71]–[75] due to the competitive global optimization capacity. Among these MAs, SCA has been tailored to many optimization problems and applications because of its simplicity and flexibility.

SCA begins with a group of random solutions, and then use the positive cosine to update the position of the population alternately. The updating formula of the algorithm is as follows:

$$X_{t+1} = X_t + r_1 \cdot \sin(r_2) \cdot |r_3 \cdot P_t - X_t| \tag{1}$$

$$X_{t+1} = X_t + r_1 \cdot \cos(r_2) \cdot |r_3 \cdot P_t - X_t| \tag{2}$$

The above two equations are applied to SCA in the following manner:

$$X_{t+1} = \begin{cases} X_t + r_1 \cdot \sin(r_2) \cdot |r_3 \cdot D_t - X_t| & rand < 0.5 \\ X_t + r_1 \cdot \cos(r_2) \cdot |r_3 \cdot D_t - X_t| & \text{otherwise} \end{cases} \tag{3}$$

where t is responsible for the number of current iterations, X_{t+1} represents the location of the next generation. X_t is the location of the current search agent. P_t is the current best location, where $r_3 \in [0, 1]$ and r_2 is a random number in the range of $[0, 2\pi]$. And r_1 decreases linearly from 2 to 0. This parameter will reduce the search range with the increase of iterations, and improve the efficiency of the algorithm. In conclusion, the mathematical definition of vector r_1 is as follows:

$$r_1 = 2 - 2(\frac{t}{T}) \tag{4}$$

where T denotes a predefined maximum number of iterations. r_3 is a vector, which provides a weight for D_t, emphasizing the two stages of exploration and exploitation. At the same time, it can also prevent the premature convergence of SCA. Moreover, *rand* enables SCA to switch between sine and cosine and prevents SCA from prematurity.

C. OLSCA

Since its inception, SCA has been extensively utilized in various applications such as wind speed forecast [76], time series prediction [77], prediction of the intention of students for postgraduate entrance examination [78], and prediction of the entrepreneurial intention of students [79]. Moreover, many improved SCA variants have been proposed to improve its performance. Issa *et al.* [80] proposed an enhanced version of SCA, combining SCA with PSO. Nenavath and Jatoth [81] developed a hybrid SCA integrated with a differential evolution algorithm. Abd Elaziz *et al.* [82] introduced an enhanced SCA (OBSCA) by using oppositional learning strategy (OBL), in which oppositional learning strategy has increased the search range of the search space to a great extent. Qu *et al.* [83] designed an enhanced SCA, including three optimization strategies. Kumar *et al.* [84] introduced mixed Cauchy and Gaussian distributions into the SCA and proposed an improved SCA (CGSCA). Long *et al.* [85] proposed an inertia weight-based position updating equation and a nonlinear conversion parameter strategy to improve the SCA. Chen *et al.* [86] proposed to use the orthogonal learning mechanism and multi-population strategy to improve the SCA. Guo *et al.* [87] proposed to combine the Riesz fractional derivative and the OBL strategy with SCA. Gupta and Deep [88] proposed to incorporate the leading guidance mechanism and simulated quenching algorithm into SCA and used the proposed method to train a multilayer perceptron. Chen *et al.* [89] proposed a multi-strategy enhanced SCA, which combined multiple control mechanisms such as Cauchy mutation operator and chaotic local search mechanism, OBL strategy and DE Operator to improve better exploration and local optima avoidance ability of SCA.

In this work, the OL mechanism was developed to obtain an excellent performance than the original SCA and prevent the SCA from falling into local optimum (LO). In this paper, the orthogonal design [90], which is a well-known mathematical concept belongs to the computational intelligence community, is used to improve the individual position updating function of the SCA. T_2 is randomly composed of three different populations. The three populations are mixed as follows:

$$T_2 = X_{k_1}^j + r_4 \cdot (X_{k_2}^j - X_{k_3}^j) \tag{5}$$

where r_4 is a random number in the range of [0,1], k_1, k_2, k_3 refer to a random integer in the range of $[1, N]$. Furthermore, N indicates the number of search agents. j refer to the dimension.

The other is the updated location of the solution. First, the solution vector is divided into K groups, each group matching to a factor. Second, Q levels are constructed in each dimension. Finally, M test solutions are generated by using the orthogonal array $L_M\left(Q^K\right)$.The specific steps are as follows:

1. *Vector grouping:* Each dimension directly matched to a factor when the dimension of the solution vectors was not high. Otherwise, the grouping is required to reduce the number of factors.
2. *Level construction:* Q levels using $x_{i,d}$ and $x_{j,d}$ are constructed in each dimension $d = 1, 2, \ldots, D$. The formula of the construction was as follow:

$$Level_q = x_{i,d} + \frac{q-1}{Q-1}\left(x_{j,d} - x_{i,d}\right) \tag{6}$$

3. *Generating new solutions:* generate feasible candidate solutions using vector grouping, dimension level construction, and previously generated orthogonal array $L_M\left(Q^K\right)$.
4. *Generating the best predictive solution*: Through the analysis of the fitness value of the orthogonal design combination test, the optimal level combination test, that is, the optimal prediction solution is found.

Algorithm 1 Construction of Orthogonal Array $L_M\left(Q^K\right)$

for $\{i = 1 : J\}$ do
  $j = \frac{Q^{i-1}-1}{Q-1} + 1$
  for $\left\{k = 1 : Q^J\right\}$ do
    $a_{k,j} = \left\lfloor \frac{k-1}{Q^{J-i}} + 1 \right\rfloor mod Q$
  end
end
for $\{i = 2 : J\}$ do
  $j = \frac{Q^{i-1}-1}{Q-1} + 1$
for $\{m = 1 : j-1\}$ do
  for $\{n = 1 : Q-1\}$ do
    $a_{j+(m-1)(Q-1)+n} = a_{m*n} + a_j \ mod \ Q$
  end
end
end
$a_{i,j} = a_{i,j}+1 1 \le i \le M \ and \ 1 \le j \le K$

The characteristics of the fractional experiment can adequately find the best level combination, which is the principle of orthogonal design. If an experiment is carried out, the results will rely on K factors, and each factor will be divided into Q levels. When the optimal level for each factor needs to find out, one method is to experiment with all levels of all factors. If the number of factors and levels is relatively small, the best level for each factor will be found out in this way. Q^k is the number of experimental combinations.

In practice, an orthogonal array can be computed by specific M, K, and Q. Here, M indicates the number of experimental combinations. The pseudo-code below presents the approach of constructing an orthogonal array $L_M\left(Q^K\right) = \left(a_{i,j}\right)_{M\times K}$. There are two limitations in this approach: (1) Q must be a prime number, and (2) $M = Q^J$, where J is a positive integer and must meet the following conditions:

$$K = \left(\frac{Q^J - 1}{Q-1}\right) \tag{7}$$

Algorithm 2 Pseudo Code of OLSCA

Begin
Initialize the population $X_i (i = 1, 2, \ldots, N)$;
Initialize Q, F, population dimension D, best position P, and maximum number of iterations T;
Compute the fitness function;
Select the best solution P;
While $(t \le T)$
Update r_1
For $i = 1$: N
  For $j = 1$: D
    Update r_2, r_3
    Update X_i by using Eq. (3);
  End for
Update T_2 by using Eq. (5);
Use orthogonal strategy;
Make a greedy choice and choose the best position;
End for
Evaluate the fitness of all agents;
Update P if any better solution is achieved;
$t = t+1$;
End while
Output the global best position P;
End

where K is not less than the number of variables n. If K is not equal to n, the front $K - n$ columns will be selected to form an orthogonal array. In an orthogonal array, $j= 1, 2, \frac{Q^2-1}{Q-1}+1, \ldots, \frac{Q^{J-1}-1}{Q-1} + 1$ are the essential columns; the remaining columns are non-basic columns.

According to the above policies, these policies are integrated into SCA that can effectively improve the performance of SCA. The introduction of OL strategy increases the population diversity of SCA and avoids SCA falling into LO prematurely. Here, the orthogonal coefficient $Q = 3$, $F = 4$. The pseudo-code of OL is shown in Algorithm 2.

It should be noted that the time complexity of OLSCA is primarily correlated with the dimensions of the particular optimization assignments (d), the population size (n), levels (Q), rows (M), factors (F), and the number of algorithm iterations (T). To analyze the efficiency of the OLSCA, in accordance with the procedure of OLSCA, the time complexity analysis is evaluated as follows:

(1) The time complexity for the process of initialization is O(*Initialize*).

(2) The time complexity of calculating the fitness values of the initial search individuals is $O(d)$.

(3) The time complexity of updating position with sine and cosine formula is $O(T\times(n\times d))$.

(4) The time complexity of updating the position of T_2 in each iteration is $O(T \times (d))$.

(5) The computational complexity of executing orthogonal strategy in each iteration is $O(T \times (d \times M + M \times F + Q \times M \times F + M + 1))$.

(6) The computational complexity of updating the new population in each iteration is $O(T\times(d))$

It is not necessary to take O (*Calculate the fitness values*) into account because of the computational complexity of different optimization methods also diverse. Due to different optimization cases have different computational complexities, there is no need for consideration of O (*Calculate the fitness values*). In total, the time complexity of OLSCA is $O(\text{OLSCA}) = O(n \times d) + O(d) + T \times (O(n\times d)+2O(d)+O\,(d\times M+M\times F+Q\times M\times F+M+1))$.

D. OLSCA-KELM

The proposed OLSCA-KELM method is described in this part. The flowchart of OLSCA-KELM is illustrated in Figure 1. The core prediction engine is the KELM model. Mapping the aggregated data of the input space to another hidden layer space through the RBF kernel. To obtain the optimal two parameters and feature subsets, the two parameters (penalty coefficient C and kernel width γ) and n features of the space are updated through OLSCA. When applying OLSAC to feature selection, it is necessary to convert the continuous space into a binary space through a sigmoid function and adopt 0.5 as the dividing line to determine whether to select or discard the feature. The classification accuracy is set as the objective function for evolving. Finally, the obtained optimization parameters and features were used for the KELM decision. The procedures of OLSCA-KELM are shown below:

Procedure 1: Aggregate all relevant data of Sino foreign cooperative education projects.

Procedure 2: Split the data according to the 10-fold CV strategy. Ten percent of the data is defined as test data, and the remaining ninety percent is set as training data. This process is performed ten times.

Procedure 3: Test data and training data are normalized to the scope [−1,1].

Procedure 4: Encode n features into n dimensions of the agent with a value of 0 or 1. Then perform the initialization of the number of iterations and population size and encoding C and γ into the two dimensions of the initial individual.

Procedure 5: Define the probe field and calculate the exact value of the fitness function.

Procedure 6: Compare the optimal fitness value and output fitness function value to set the optimal fitness function value.

Procedure 7: Preserve the optimal position obtained with the optimal fitness function value and substitute the current position if a better position is acquired.

Procedure 8: Output the optimal C and γ parameter values and feature subsets at the end of the iteration. Otherwise, go back to procedure 5.

Procedure 9: After obtaining the feature subset and the optimal C and γ parameters, retrain KELM using the training data.

Procedure 10: Apply the final OLSCA-KELM model for unknown sample prediction problems.

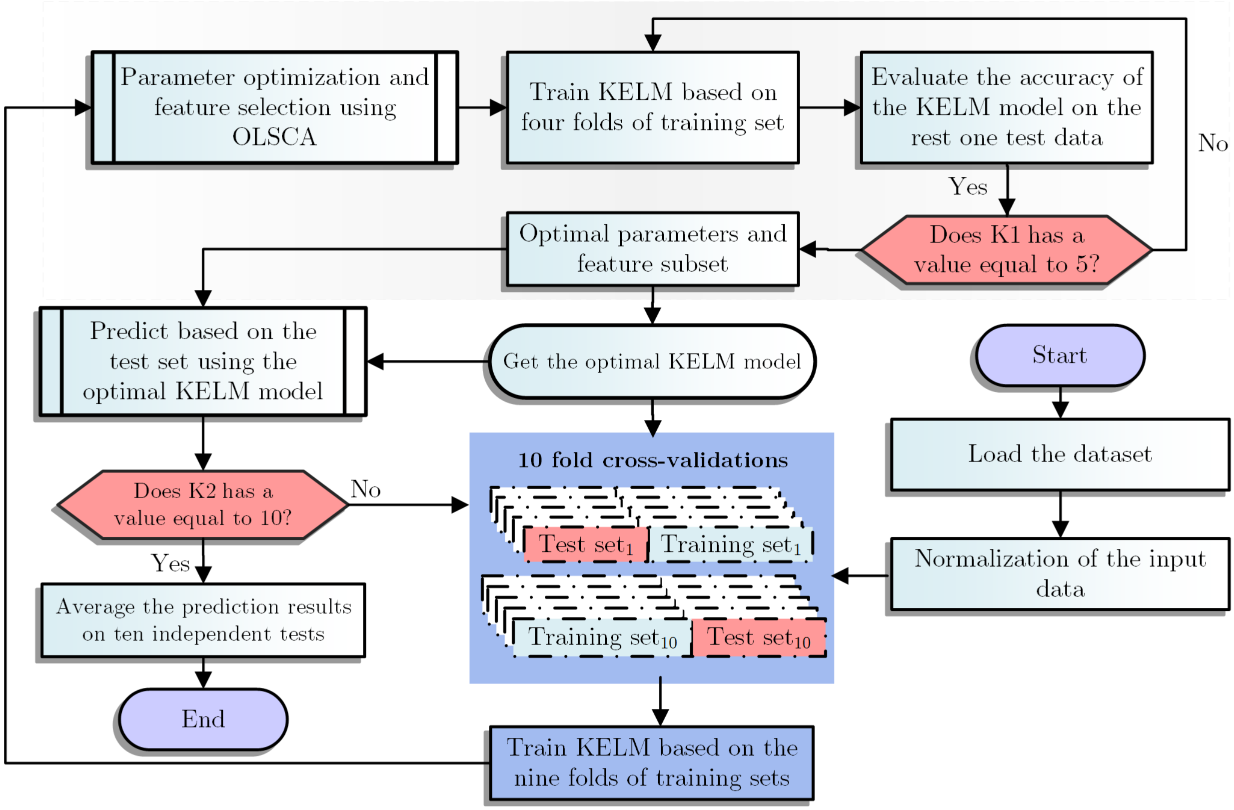

FIGURE 1. Flowchart of OLSCA-KELM.

III. EXPERIMENTAL DESIGNS

A. DATA COLLECTION

The data involved in this paper mainly includes 1056 evaluation results by experts with 160 Sino foreign cooperative education projects in 2018 and 2019. The data set contains seven first-level indicators and 22 second-level indicators including F1:(Internal benefits), F2:(External benefits), F3:(School characteristics), F4:(Quality appraisal of graduation achievements), F5:(Management institutions), F6:(Syllabus and teaching textbooks), F7:(Teaching methods), F8:(Teaching plan), F9:(Teaching facility), F10:(Teaching documents and archives), F11:(Teaching quality supervision), F12:(Training objectives program), F13:(Training objectives), F14:(Social evaluation), F15:(Teacher training), F16:(Teacher evaluation and appointment), F17:(Teacher status), F18:(Diplomas and certificates management), F19:(Student satisfaction), F20:(Enrollment and student status management), F21:(Policy environment), F22:(Bankroll management). The decision attribute is obtained by summing the scores of each attribute. Through consultation with experts, it is agreed that when the total score of all attributes is less than or equal to 75, the evaluation result is marked as unqualified, and when the total score is equal to or higher than 75, the evaluation result is marked as good. The score range of each attribute is as follows: F1, F2, F3:0-2, F6, F7, F8, F9, F10, F12, F13, F14, F15, F18, F21:0-4, F5, F19, F20, F22:0-5, F11, F16, F17:0-6, F4:0-12. The detailed description of 22 factors with the mean value and standard deviation of each factor is shown in Table 1. The evaluation indicators of the Sino foreign cooperative education project are given in Figure 2.

B. EXPERIMENTAL SETUP

The examinations are performed under the MATLAB R2018 software. The experimental data are normalized into [−1,1] before the classifier is constructed. Besides, an unbiased estimate of experimental results is attained by using the k-fold cross-validation (CV). The value of k is commonly set to 10 in the literature [91], [36], so we also set it to 10, in which the experimental data were divided into 10 subsets, one of 10 subsets was used as the testing set, and the other nine subsets were put together to form the training set. The code of KELM, SVM, and random forest (RF) was obtained from a public source.[1] K-nearest neighbor (KNN) method is implemented from scratch. All parameters were determined by trial and error approach [95], [96]. The search range of penalty coefficient and kernel bandwidth in SVM and KELM are set to [−10, 10]. The number of trees and variables in RF was set to 500 and 3, respectively. The best nearest neighbors in KNN was set to 1.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. BENCHMARK FUNCTION VALIDATION

In order to study the performance of the proposed strategy, some competitive MAs, including the MSCA [83], OBSCA,

[1] http://www3.ntu.edu.sg/home/egbhuang, https://www.csie.ntu.edu.tw/~cjlin/libsvm/, and https://code.google.com/archive/p/randomforest-matlab

TABLE 1. Description of 22 attributes.

Feature	Brief description	Mean	Std deviation
F1	Internal benefits (IB)	1.9252	0.5713
F2	External benefits (EB)	1.9177	0.6317
F3	School characteristics (SC)	2.2426	0.8750
F4	Quality appraisal of graduation achievements (QAGA)	6.6289	2.7697
F5	Management institutions (MI)	3.8213	0.7174
F6	Syllabus and teaching textbooks (STT)	3.0023	0.5881
F7	Teaching methods (TM)	2.9797	0.5691
F8	Teaching plan (TP)	2.9364	0.6540
F9	Teaching facility (TF)	3.1303	0.5468
F10	Teaching documents and archives (TDA)	3.1635	0.5609
F11	Teaching quality supervision (TQS)	4.3866	0.8073
F12	Training objectives program (TTOP)	3.1187	0.5488
F13	Training objectives (TO)	3.3370	0.5153
F14	Social evaluation (SE)	2.8244	0.7395
F15	Teacher training (TT)	2.8878	0.6205
F16	Teacher evaluation and appointment (TEA)	4.3350	0.8430
F17	Teacher status (TS)	4.1764	0.9524
F18	Diplomas and certificates management (DCM)	3.2399	0.6225
F19	Student satisfaction (SS)	3.6105	0.7982
F20	Enrollment and student status management (ESSM)	3.8259	0.8100
F21	Policy environment (PE)	3.1356	0.5648
F22	Bankroll management (BM)	3.7665	0.8018

TABLE 2. Parameters for involved methods.

Method	Parameters
SCA	a=2
PSO	w=1; c_1=2; c_2=2
FA	$\varepsilon = 0.2$; φ_0=1; $\gamma = 1$
MFO	b=1; t= [-1 1]; a∈[-1 -2]
BA	A=0.5; r=0.5
CESCA	a=2; $r_3 = chaotic\ sequence$
OBSCA	a=2
MSCA	a=2, $wMax$=0.9, $wMin$=0.4, $epsilon$=30, $lambda$=0.01, $beta$=1.5
OLSCA	a=2, Q=3, F=4

chaos enhanced SCA (CESCA) [78], bat algorithm (BA) [92], MFO, firefly algorithm (FA) [93], PSO and SCA are made a comparison on 23 well-known benchmark functions. The full parameter values of these involved algorithms are reported in Table 2. These unimodal and multimodal functions in Tables 3-5 are extensively applied in the literature. Dim represents the dimensionality of the objective functions selected, Range is responsible for the boundary of the function's search space, and f_{min} is used for the optimal values of functions in the table

TABLE 3. Unimodal benchmark functions.

Function	Dim	Range	$f_{\min}$
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[-100, 100]	0
$f_2(x) = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\|$	30	[-10, 10]	0
$f_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_j)^2$	30	[-100, 100]	0
$f_4(x) = max_i\{\|x_i\|, 1 \le i \le n\}$	30	[-100, 100]	0
$f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	[-30, 30]	0
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[-100, 100]	0
$f_7(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	30	[-1.28, 1.28]	0

Besides, the value of the dim is set to 30, the size of the population is fixed to 30, and the maximum iteration number is 1000. The average results (AVG) and the standard deviation (STD) are illustrated, which are computed by the best position

FIGURE 2. Evaluation indicator system of Sino foreign cooperative education project.

TABLE 4. Multimodal benchmark functions.

Function	Dim	Range	f_{min}
$f_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i \rvert})$	30	[-500,500]	- 418.9829×5
$f_9(x) = \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[-5.12,5.12]	0
$f_{10}(x) = -20\exp\{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i}\} - exp\{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\} + 20 + e$	30	[-32,32]	0
$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,600]	0
$f_{10}(x) = \frac{\pi}{n}\{10\sin(ay_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10sin^2(\pi y_{i+1})] + (y_n - 1)^2 + \sum_{i=1}^{n}\mu(x_i, 10,100,4)\}$	30	[-50,50]	0
$f_{13}(x) = 0.1\{sin^2(3\pi x_i) + \sum_{i=1}^{n}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + sin^2(2\pi x_n)] + \sum_{i=1}^{n}\mu(x_i, 5,100,4)$	30	[-50,50]	0

found using six methods over 30 independent runs. In order to guarantee the fairness of experiments, the competitors of the testing environment are set in accordance with the proposed algorithm.

For conducting a fair comparison, the same testing environment is employed for competitors and the proposed algorithm.

OLSCA presents the lowest mean values of 23 functions, as illustrated in Table 6. In other words, the presented algorithm has a better superiority than other competitors on 23 problems according to the AVG index. Moreover, the curves declined rapidly indicated that the proposed method has a faster convergence speed in early evolution so that it can provide superior results on F9 and F11. Besides, the results on F1, F2, F5, F6, F12, F13, F14, F15, and F21 have proved the ability of the proposed method for obtaining the highest quality solutions. Followed by MSCA, CESCA, MFO, and FA, they present the lowest average of two, six, four, and three functions, respectively.

The statistical comparison performance of the OLSCA against other competitive algorithms was verified by using the Friedman test. For further statistical comparison, the ranks of six algorithms are shown in Table 7, according to the ARV (the average ranking value) index. According to the statistic values of ARV, it is evident that the proposed

TABLE 5. Simple multimodal functions.

Function	Dim	Range	f_{min}
$f_{14}(x) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}\right)$	2	[-65,65]	1
$f_{15}(x) = \sum_{i=11}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]$	4	[-5,5]	0.00030
$f_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	[-5,5]	-1.0316
$f_{17}(x) = (x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6)^2 + 10\left(1 - \frac{1}{8\pi}\right)cosx_1 + 10$	2	[-5,5]	0.398
$f_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2 \times (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	2	[-2,2]	3
$f_{19}(x) = -\sum_{i=1}^{4} c_i exp(-\sum_{j=1}^{3} a_{ij}(x_j - p_{ij})^2)$	3	[1,3]	-3.86
$f_{20}(x) = -\sum_{i=1}^{4} c_i exp(-\sum_{j=1}^{6} a_{ij}(x_j - p_{ij})^2)$	6	[0,1]	-3.32
$f_{21}(x) = -\sum_{i=1}^{5}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0,10]	-10.1532
$f_{22}(x) = -\sum_{i=1}^{7}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0,10]	-10.4028
$f_{23}(x) = -\sum_{i=1}^{10}[(X - a_i)(X - a_i)^T + c_i]^{-1}$	4	[0,10]	-10.5363

OLSCA performs better than other methods on twenty-three benchmark tasks when searching for function minimum, followed by OBSCA, FA, MSCA, CESCA, MFO, SCA, and BA, while PSO has the worst performance. Table 8 presents the statistical results of the Wilcoxon signed-rank test [94] further to evaluate the significant improvement for the proposed OLSCA. The proposed OLSCA is obviously better than SCA on 23 functions, as seen from the table. Compared with the existing SCA variants, 18 out of 23 function tests of OLSCA are better than MSCA, 16 are better than OBSCA, 17 are better than CESCA, 3 are the same as MSCA, 4 are the same as OBSCA, 4 are the same as CESCA, 2 are inferior to MSCA, 3 are inferior to OBSCA, 2 are inferior to CESCA. What is more, it can be seen that the experimental results of the OLSCA have superior performance better than those obtained by FA, BA, PSO, and MFO algorithms on all the test functions. In a word, it is evident that the proposed OLSCA yields the best results on these test functions, compared with FA, BA, PSO, MFO, and three other algorithms.

Besides, to demonstrate the significant superiority of the OLSCA, Figure 3 presents the convergence rates of MSCA, OBSCA, CESCA, BA, MFO, FA, PSO and SCA on 23 benchmarks. as shown, regarding the problems of F1, F2, F6, F12, F13, F14, F15, F21, and F23, the results of convergence curve also prove that the proposed method can successfully enhance the convergence rate of SCA, comparing with other popular algorithms. In addition, the developed OLSCA can achieve the optimal solution when dealing with F1, F2, F6, F12, and F13. Because F12 and F13 belong to multimodal benchmark functions, it should be noted that there are many LO. Even though OLSCA is under such circumstances, the curves of OLSCA declined rapidly and it can obtain the optimal position. It proves that OL based SCA has superior exploration to avoid the LO. As a result, the proposed OLSCA has a distinct advantage compared with the original SCA.

B. PREDICTION RESULTS OF SINO FOREIGN COOPERATIVE EDUCATION PROJECT

In this experiment, we conducted an evaluation of the effectiveness of the OLSCA-KELM model. The detailed results are tabulated in Table 9. From the table, it is evidently seen that the accuracy of classification obtained by OLSCA-KELM with feature selection (FS) is 95.83%, the Matthews' correlation coefficient (MCC) is 93.31%, the sensitivity is 96.58%, the specificity is 94.65%, and the variance of each is 0.0210, 0.0436, 0.0262 and 0.0471 respectively.

In addition, in the experiment, we can see that OLSCA can automatically obtain the optimal parameters and feature subset of KELM, which shows that the addition of OL strategy makes SCA have stronger search ability and accuracy. In order to prove the effectiveness of this method, we propose a comparative study with five other effective machine-learning models, including OLSCA-KELM with FS, OLSCA-KELM without FS, SCA-KELM, KNN, RF, and SVM. The boxplot of these six methods is shown in Figure 4. The results show that OLSCA-KELM with the FS model is better than OLSCA-KELM without FS and OLSCA-KELM model in four evaluation metrics, and its variance is also smaller than OLSCA-KELM without FS and SCA-KELM model. This means that the proposed OLSCA can assist the KELM model to achieve better performance and stability.

Regarding the ACC index, OLSCA-KELM with the FS model has gained the best evaluation effect, which is 2.65% higher than the second-ranked RF method. While OLSCA-KELM without FS, which is 3.02% lower than OLSCA-KELM with FS. The difference between SCA-KELM and SVM is minimal. The calculation result of KNN model is the worst with the largest variance of 0.0351, indicating that the KNN model is not stable in solving this problem.

In terms of the MCC index, OLSCA-KELM with the FS model still achieves the best results. The second follower is RF and OLSCA-KELM without FS. Compared with OLSCA-KELM with FS, OLSCA-KELM without FS is 6.73% lower. The results of SVM and SCA-KELM are very close, KNN performs worst, and its variance is the largest with a value of 0.0898.

In terms of sensitivity evaluation indexes, OLSCA-KELM with FS model has the best evaluation effect, followed by RF

TABLE 6. Comparison results of the OLSCA and the other eight peers.

	F1		F2		F3	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	**1.3976E-51**	**3.0525E-51**	**2.3778E-42**	**5.7040E-42**	2.4699E+01	2.6119E+01
MSCA	7.2823E-04	1.1059E-03	2.7330E-03	3.0422E-03	4.0610E+03	1.4872E+03
OBSCA	4.5430E-27	2.3676E-26	8.1561E-27	1.5896E-26	2.2805E-04	1.0799E-03
CESCA	1.4344E-35	3.0025E-35	7.9223E-21	3.3770E-20	**4.0452E-24**	**1.9988E-23**
BA	1.3848E+01	2.0584E+00	1.2015E+03	6.4425E+03	6.0529E+01	1.3634E+01
MFO	3.3333E+03	5.4667E+03	3.9334E+01	2.5855E+01	1.6796E+04	1.0760E+04
FA	2.9736E-03	8.2894E-04	1.3335E-01	7.3642E-02	8.2646E+02	3.2277E+02
PSO	1.2509E+02	1.3241E+01	7.4745E+01	1.6384E+01	4.0184E+02	6.5283E+01
SCA	2.1310E-02	3.9643E-02	3.3512E-05	9.2357E-05	2.9270E+03	2.1574E+03
	F4		F5		F6	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	1.8065E-03	1.1750E-03	**2.3693E+01**	**2.0980E-01**	**1.0563E-04**	**3.9264E-05**
MSCA	2.9128E+01	4.9789E+00	2.0342E+02	3.2767E+02	1.4386E+00	6.6687E-01
OBSCA	6.4991E-06	1.1774E-05	2.8124E+01	3.1290E-01	4.3935E+00	2.5047E-01
CESCA	**1.2770E-15**	**2.0718E-15**	2.8450E+01	4.2997E-01	5.1590E+00	1.7367E-01
BA	1.8779E+00	2.6644E-01	3.7959E+03	1.0259E+03	1.4749E+01	1.8170E+00
MFO	6.5124E+01	8.4085E+00	2.6802E+06	1.4610E+07	2.9901E+03	5.3238E+03
FA	6.4698E-02	1.4992E-02	1.8241E+02	4.0927E+02	2.6245E-03	8.8089E-04
PSO	4.4611E+00	4.0091E-01	1.4398E+05	4.8468E+04	1.3080E+02	1.5881E+01
SCA	2.2835E+01	9.2310E+00	1.0942E+03	3.3065E+03	4.6141E+00	5.4565E-01
	F7		F8		F9	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	7.1179E-03	2.2302E-03	-5.5175E+03	1.0203E+02	**0.0000E+00**	**0.0000E+00**
MSCA	3.7206E-01	1.3402E-01	**-3.3630E+305**	**6.5535E+04**	1.4575E+01	4.4115E+00
OBSCA	3.1691E-03	1.9192E-03	-3.8719E+03	2.8748E+02	3.5479E-04	1.9433E-03
CESCA	**9.8851E-05**	**9.5093E-05**	-3.5129E+03	3.5987E+02	**0.0000E+00**	**0.0000E+00**
BA	1.2930E+01	6.2161E+00	-7.3119E+03	8.4119E+02	2.7492E+02	3.1498E+01
MFO	2.8525E+00	5.0828E+00	-8.6407E+03	9.0770E+02	1.6147E+02	3.2533E+01
FA	7.1643E-03	3.1220E-03	-6.7773E+03	7.8916E+02	3.9269E+01	1.6231E+01
PSO	1.1075E+02	2.2580E+01	-6.5198E+03	8.2642E+02	3.6885E+02	2.3891E+01
SCA	2.7774E-02	2.0084E-02	-3.9484E+03	2.3427E+02	8.5474E+00	1.2615E+01
	F10		F11		F12	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	1.0599E-14	1.6714E-14	**0.0000E+00**	**0.0000E+00**	**4.2300E-06**	**1.5170E-06**
MSCA	2.0341E+00	9.4253E-01	1.3421E-01	8.4157E-02	2.3913E-01	2.3504E-01
OBSCA	5.2699E-15	4.6353E-15	2.3327E-12	1.0500E-11	4.7975E-01	6.5930E-02
CESCA	**2.4277E-15**	**1.7906E-15**	**0.0000E+00**	**0.0000E+00**	6.4062E-01	9.0299E-02
BA	4.7384E+00	2.6349E+00	5.7427E-01	4.9837E-02	1.1072E+01	5.0250E+00
MFO	1.5532E+01	6.8383E+00	2.7160E+01	5.8874E+01	8.5333E+06	4.6739E+07
FA	1.4184E-02	2.3064E-03	3.9527E-03	1.9321E-03	2.5402E-05	1.1801E-05
PSO	8.3956E+00	3.6871E-01	1.0295E+00	9.3185E-03	4.8344E+00	8.0833E-01
SCA	1.1565E+01	9.7190E+00	3.0927E-01	3.1955E-01	1.7956E+02	7.0257E+02
	F13		F14		F15	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	**6.7039E-05**	**2.2091E-05**	**1.0641E+00**	3.6225E-01	**4.3011E-04**	3.1780E-04
MSCA	8.3623E-01	2.7544E-01	1.1353E+00	**3.4277E-01**	1.0282E-03	3.0194E-04
OBSCA	2.4186E+00	1.1536E-01	1.7923E+00	9.8811E-01	6.9045E-04	**1.2014E-04**
CESCA	2.5600E+00	6.1043E-02	1.6654E+00	9.1092E-01	5.2062E-04	3.1155E-04
BA	2.2889E+00	3.5855E-01	4.0426E+00	3.4907E+00	6.7719E-03	1.2296E-02
MFO	1.3669E+07	7.4867E+07	1.9877E+00	1.4904E+00	2.5907E-03	5.0240E-03
FA	3.2280E-04	1.4029E-04	1.4332E+00	7.1939E-01	1.3665E-03	3.5897E-03
PSO	2.3316E+01	3.5371E+00	1.9550E+00	1.4300E+00	1.1460E-03	2.0892E-04
SCA	1.3950E+03	5.0051E+03	1.3950E+00	8.0711E-01	1.0637E-03	3.9007E-04
	F16		F17		F18	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	**-1.0316E+00**	1.3657E-10	**3.9789E-01**	5.4326E-09	**3.0000E+00**	1.7057E-08
MSCA	**-1.0316E+00**	**4.9992E-16**	**3.9789E-01**	3.2434E-16	**3.0000E+00**	2.9578E-05
OBSCA	**-1.0316E+00**	2.4313E-06	3.9836E-01	5.3354E-04	**3.0000E+00**	2.5031E-05
CESCA	**-1.0316E+00**	3.7841E-05	3.9908E-01	1.2931E-03	**3.0000E+00**	1.7877E-05
BA	-1.0311E+00	3.8304E-04	3.9814E-01	1.6633E-04	3.0317E+00	3.0519E-02
MFO	**-1.0316E+00**	**6.7752E-16**	**3.9789E-01**	**0.0000E+00**	**3.0000E+00**	**1.7080E-15**

TABLE 6. *(Continued.)* **Comparison results of the OLSCA and the other eight peers.**

FA	**-1.0316E+00**	1.5509E-09	**3.9789E-01**	4.7046E-10	**3.0000E+00**	1.5634E-08
PSO	-1.0304E+00	1.1833E-03	3.9874E-01	8.8560E-04	3.0931E+00	1.0482E-01
SCA	**-1.0316E+00**	2.0279E-05	3.9868E-01	8.7035E-04	**3.0000E+00**	1.8891E-05
	F19		F20		F21	
	AVG	STD	AVG	STD	AVG	STD
OLSCA	**-3.8628E+00**	9.2109E-09	-3.2348E+00	5.3475E-02	**-9.6434E+00**	1.5555E+00
MSCA	-3.8596E+00	3.9272E-03	-3.1640E+00	1.5397E-01	-4.4856E+00	3.3819E+00
OBSCA	-3.8614E+00	8.5992E-04	-3.2285E+00	**3.5294E-02**	-8.8475E+00	**8.5993E-01**
CESCA	-3.8535E+00	4.2700E-03	-2.8506E+00	3.3703E-01	-2.8464E+00	2.0042E+00
BA	-3.8474E+00	1.0962E-02	-2.9026E+00	1.1817E-01	-4.7709E+00	2.8754E+00
MFO	**-3.8628E+00**	**2.7101E-15**	-3.2159E+00	5.9124E-02	-6.3781E+00	3.0699E+00
FA	**-3.8628E+00**	4.4994E-10	**-3.2699E+00**	6.0590E-02	-7.5718E+00	3.4986E+00
PSO	-3.8506E+00	1.0143E-02	-2.8974E+00	1.7974E-01	-3.9990E+00	1.3363E+00
SCA	-3.8546E+00	2.1672E-03	-2.9512E+00	3.0645E-01	-2.6123E+00	1.9970E+00
	F22		F23			
	AVG	STD	AVG	STD		
OLSCA	-1.0049E+01	1.3485E+00	-1.0176E+01	1.3720E+00		
MSCA	-4.7405E+00	2.7305E+00	-4.8366E+00	3.3246E+00		
OBSCA	-8.9041E+00	8.0107E-01	-8.8329E+00	8.3207E-01		
CESCA	-3.6334E+00	1.8516E+00	-3.9037E+00	1.7021E+00		
BA	-5.4877E+00	2.9897E+00	-5.1672E+00	3.0920E+00		
MFO	-7.1361E+00	3.3948E+00	-7.5592E+00	3.7528E+00		
FA	**-1.0403E+01**	**9.0057E-07**	**-1.0536E+01**	**8.5520E-07**		
PSO	-5.0047E+00	1.7429E+00	-4.4985E+00	1.3404E+00		
SCA	-3.7886E+00	2.1229E+00	-3.8009E+00	1.8257E+00		

TABLE 7. **Ranking of comparison results between OLSCA and other eight peers.**

Function	**OLSCA**	MSCA	OBSCA	CESCA	BA	MFO	FA	PSO	SCA
Ranking	**2.043478**	4.608696	3.565217	4.695652	6.608696	6.086957	3.565217	7.347826	6.347826
ARV	**1**	4	2	5	8	6	2	9	7

TABLE 8. **Wilcoxon test results of OLSCA and other peers.**

Function	MSCA	OBSCA	CESCA	BA	MFO	FA	PSO	SCA
F1	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F2	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F3	1.7344E-06	1.7344E-06	1.7344E-06	3.1123E-05	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F4	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F5	2.8786E-06	1.7344E-06	1.7344E-06	1.7344E-06	3.1817E-06	1.7344E-06	1.7344E-06	1.7344E-06
F6	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.8910E-04	1.7344E-06	1.7344E-06	1.7344E-06
F7	1.7344E-06	2.6033E-06	1.7344E-06	1.7344E-06	1.7344E-06	8.7740E-01	1.7344E-06	5.2165E-06
F8	1.7344E-06	1.7344E-06	1.7344E-06	1.9209E-06	1.7344E-06	1.7344E-06	3.8822E-06	1.7344E-06
F9	1.7344E-06	1.0000E+00	1.0000E+00	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F10	1.7344E-06	1.5625E-02	4.3968E-05	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F11	1.7344E-06	2.5000E-01	1.0000E+00	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F12	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F13	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F14	4.4919E-02	2.6033E-06	1.3601E-05	2.8786E-06	3.8203E-01	1.7138E-01	4.8969E-04	1.7988E-05
F15	1.4936E-05	1.0444E-02	1.8326E-03	4.2857E-06	1.7988E-05	5.3197E-03	4.7292E-06	5.3070E-05
F16	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	5.2165E-06	1.7344E-06	1.7344E-06
F17	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	2.1630E-05	1.7344E-06	1.7344E-06
F18	2.1266E-06	1.9209E-06	1.7344E-06	1.7344E-06	1.7344E-06	9.2626E-01	1.7344E-06	1.7344E-06
F19	2.0589E-01	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06	1.7344E-06
F20	7.8647E-02	9.0993E-01	1.7344E-06	1.7344E-06	8.9364E-01	5.0383E-01	1.7344E-06	1.7344E-06
F21	5.3070E-05	2.7653E-03	1.7344E-06	5.2165E-06	3.3789E-03	1.2544E-01	1.7344E-06	1.7344E-06
F22	1.3601E-05	3.5888E-04	1.7344E-06	6.9838E-06	2.8486E-02	2.7029E-02	1.7344E-06	2.1266E-06
F23	2.5967E-05	3.5888E-04	1.7344E-06	1.9729E-05	2.2102E-01	5.1931E-02	1.7344E-06	1.7344E-06
+/−/=	18/3/2	16/4/3	17/4/2	22/1/0	13/0/0	15/5/3	13/4/6	23/0/0

model, with a difference of only 0.2%, followed by OLSCA-KELM without FS which is 1.5 percentage points lower than OLSCA-KELM with FS, SVM and KNN have little difference, only 0.01 percentage points, OLSCA-KELM model has the worst results, but SVM has the largest variance, reaching 0.0473.

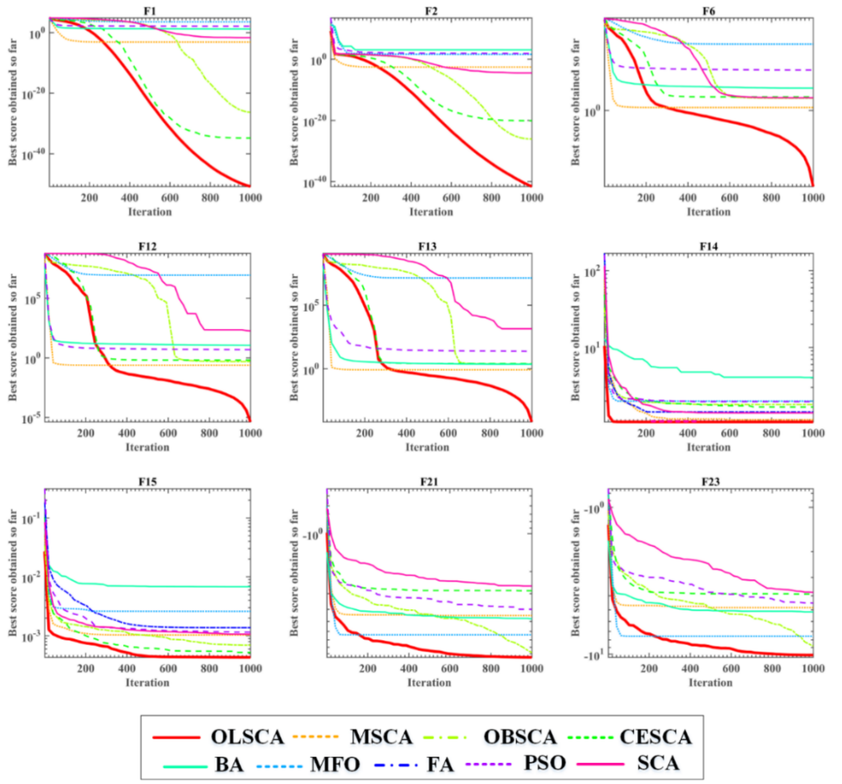

FIGURE 3. Convergence curves of 9 selected benchmark functions.

TABLE 9. The detailed results of OLSCA-KELM.

Fold	Selected feature subset	ACC	MCC	Sensitivity	Specificity
No.1	{2, 3, 6, 7, 8, 10, 11, 13, 14, 18, 19, 20, 22}	0.9623	0.9247	0.9385	1.0000
No.2	{2, 3, 6, 8, 10, 11, 14, 16, 17, 18, 19, 22}	0.9714	0.9387	0.9701	0.9737
No.3	{2, 3, 6, 11, 15, 16, 17, 18, 19, 20}	1.0000	1.0000	1.0000	1.0000
No.4	{2, 3, 6, 8, 11, 12, 13, 14, 15, 18, 19, 20, 21}	0.9429	0.8826	0.9672	0.9091
No.5	{1, 2, 3, 8, 9, 13, 14, 16, 17, 18, 19, 20, 21, 22}	0.9429	0.8817.	0.9375	0.9512
No.6	{1, 2, 3, 4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16, 18, 19, 20, 21}	0.9623	0.9212	0.9429	1.0000
No.7	{3, 4, 5, 9, 11, 12, 14, 15, 17, 18, 19, 20}	0.9245	0.8464	0.9333	0.9130
No.8	{2, 3, 6, 9, 11, 12, 14, 15}	0.9714	0.9381	1.0000	0.9189
No.9	{2, 3, 4, 5, 6, 7, 10, 11, 14, 16}	0.9434	0.8736	0.9857	0.8611
No.10	{1, 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21}	0.9623	0.9243	0.9828	0.9375
AVG.	-	0.9583	0.9131	0.9658	0.9465
STD	-	0.0210	0.0436	0.0262	0.0471

In terms of specificity index, the result of OLSCA-KELM with the FS model is the best, and the variance is the smallest. There is no significant difference among the models of OLSCA-KELM without FS, SCA-KELM, RF, and SVM. The difference between OLSCA-KELM without FS and OLSCA-KELM with FS is 5.78%, the worst is KNN, only 87.85%, and the variance is also the largest, reaching 0.1222.

In order to illustrate the convergence of the proposed OLSCA-KELM algorithm, the inclination that the accuracy changes with regard to the population iteration were recorded. In Figure 5, it is found that after several iterations, the OLSCA-KELM with the FS model can quickly and continuously avoid the problem of premature convergence to reach the optimal precision, which shows that the OLSCA-KELM with FS method has strong local search ability and global search ability. The reason is that the introduction of the OL mechanism makes the algorithm enhance the local search ability and global search ability, and makes the hybrid model keep a better balance status between exploration and exploration.

By observing the curve that is shown in Figure 5, it is found that the OLSCA-KELM without the FS model needs more iteration to converge, and the accuracy is not as high as OLSCA-KELM with FS. The accuracy of OLSCA-KELM is the lowest among all algorithms, far less than that of OLSCA-KELM with the FS model, and it is not obvious with the improvement of iteration accuracy, so it tends to trap into the LO.

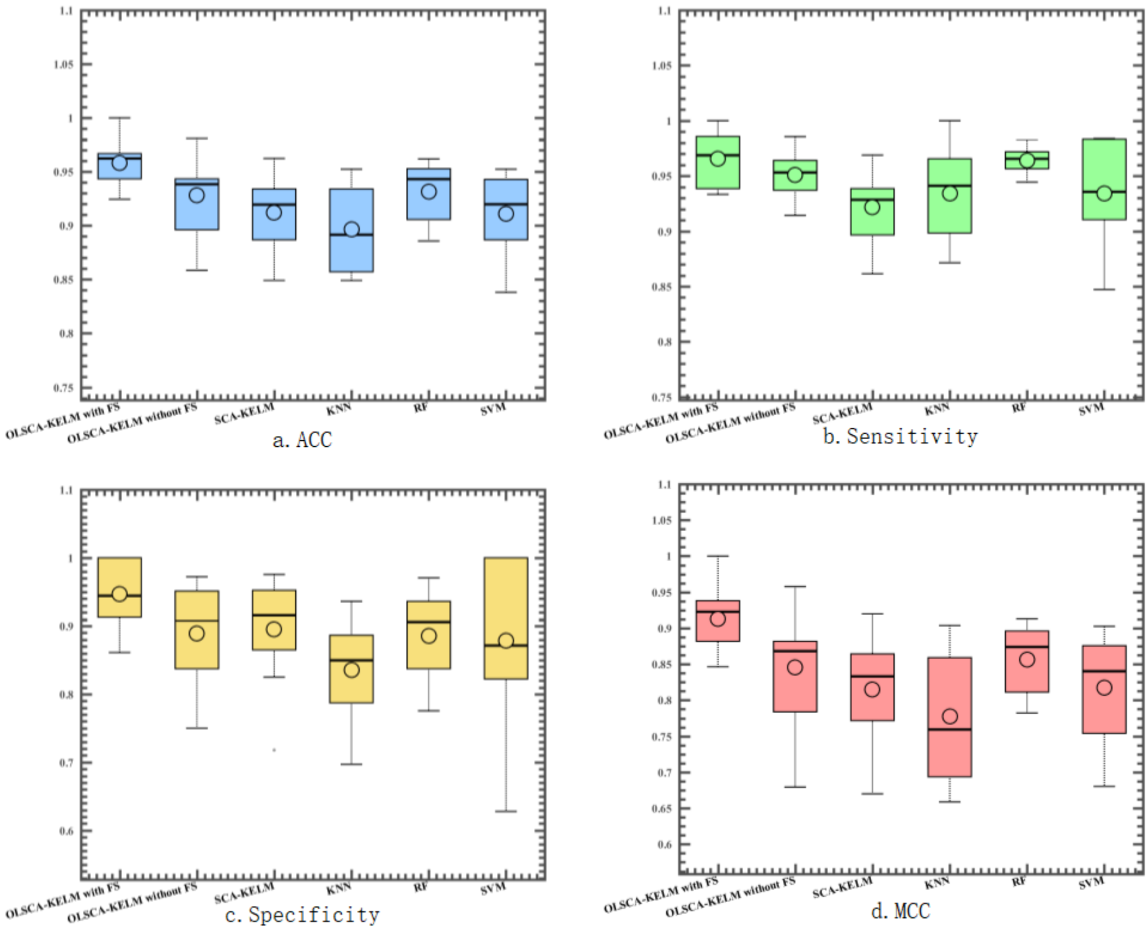

FIGURE 4. Boxplot of the six methods on four evaluation metrics.

Figure 6 illustrates the statistical results of the frequency for each feature that appeared in each feature subset during the 10-fold CV procedure. Seven features, including MI, TS, TTOP, STT, SS, SE, and IB, are shown to be the most common factors chosen by the proposed OLSCA-KELM during the feature selection procedure. Therefore, the factors 'management institutions', 'teacher status', 'training objectives programs', 'syllabus and teaching textbooks', 'student satisfaction', 'social evaluation', and 'internal benefits' may play an important role in the evaluation of Sino foreign cooperative education project. Therefore, it is worthy of paying more attention to these factors when updating the policies and rules for the evaluation of the Sino foreign cooperative education project.

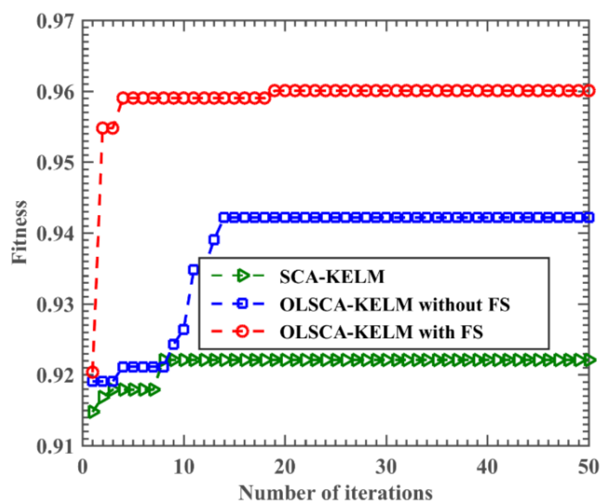

FIGURE 5. Convergence plot of three methods.

V. DISCUSSIONS

The machine learning methods were adopted to select the key factors of Sino foreign cooperation projects. From the experimental results found in the study, the most important characteristics include 'management institutions', 'teacher status', 'training objectives programs', 'syllabus and teaching textbooks', 'student satisfaction', 'social evaluation', and 'internal benefits. In the actual evaluation process, these characteristics do have a significant impact on experts' evaluation.

The management agency plays an essential part in determining the success or failure of the project in actual operation.

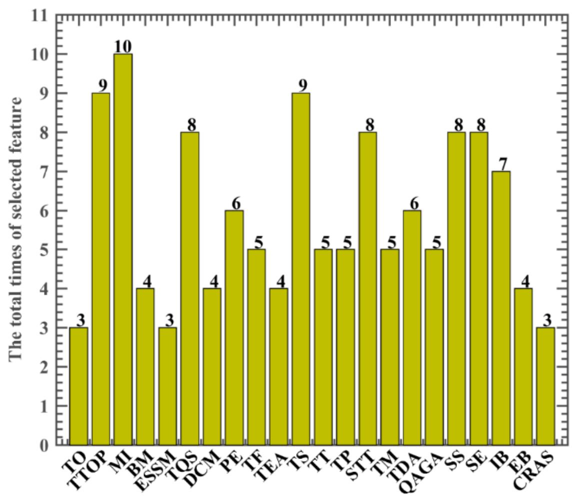

FIGURE 6. Frequency of 22 features selected by the OLSCA-KELM.

The final evaluation results of projects with high scores given by management agencies are very satisfactory. Focus on the management institutions can make full use of management and supervision and form regular meetings, rules of procedure, and other related systems. Through the open platform, the school running level and category, primary setting, course content, enrollment scale, and other primary school running information can be regularly announced to the society, and an effective communication mechanism can be established with students to provide satisfactory services. Foreign high-quality educational resources refer to educational resources with high standards and school-running characteristics worldwide, and at the same time have certain leading advantages in education and teaching concepts, talent training models, courses, teaching materials, teaching methods, education management systems, teachers, management teams and quality assurance system. In the field of higher education, foreign high-quality educational resources are generally represented as disciplines and professions with the distinctive or existing school running experience. The introduction of high-quality education resources, especially foreign high-quality teachers, courses, teaching materials, and training programs, directly affects the improvement of student training quality. The teaching staff of both parties shall meet the requirements of education and teaching, including the reasonable size of the teaching staff, academic structure, teaching experience, and practical experience. At the same time, four ''one-third'' principles need to be formed, that is, the introduction of foreign courses and professional core courses should account for more than one-third of all courses and core courses of Sino foreign cooperative education programs. It is one of the critical indicators for evaluation that more than a third of the total courses and teaching hours of Sino foreign cooperative education programs should be core courses and teaching hours of majors. Student satisfaction is a yardstick that reflects the quality and level of running a school. By designing a student satisfaction questionnaire, taking current students and graduates as survey objects, the students' satisfaction with the Sino foreign cooperative education project is investigated from fifteen dimensions, including the level of teachers, curriculum settings, teaching effectiveness, and students' satisfaction with self-growth and development and self-confidence in the future, graduates' evaluation and satisfaction with their career development. The results of the survey are provided to experts for reference through quantified data. Through investigation, it was found that the students believed that the school-run unit should improve in the aspects of curriculum arrangement, teaching planning, service level, etc., and the expert ratings and written opinions explained related issues. The social reputation survey is mainly for the society, especially to understand the students, parents, teachers, and other stakeholders of the Sino foreign cooperative education project from five dimensions. After research, it is found that projects with higher expert scores will make all sectors of society generally believe that the majors established by the project meet market demand, so the education and teaching environment, management system, and overall evaluation of the project will also be higher. It is the original intention of Sino foreign cooperation in running schools that the introduced educational resources have better influence and radiating effect on the teaching practice, discipline construction, scientific research, teaching reform, and teacher capacity building of school-run units, and have also created innovation in the management system of school-run units enhancement. At the same time, this will help improve the internal benefits of the school, promote the introduction, absorption, and integration of high-quality educational resources, promote the connotative development of the main body of the school and increase the depth and breadth of exchanges in the humanities, scientific research, and academic fields between China and foreign countries.

Several limitations to this study need further discussion. First, the sample involved in this study is limited. It is essential to collect more samples to train a more unbiased learning model. Future research will consider a wider variety of assessments. In addition, the attributes involved in this article are relatively limited, and future research will consider more attributes that affect the reliability of experts' assessment.

VI. CONCLUSION AND FUTURE WORKS

This study proposes an effective OLSCA-KELM hybrid model to evaluate Sino foreign cooperative education projects. The main innovation of the proposed method is that the OL mechanism is introduced into SCA to further balance the global and local search capacity of SCA, and the optimal prediction model of the kernel learning machine is built to resolve optimization problems. First, the proposed OLSCA is compared with some competitive peers on 23 benchmark problems to verify its efficacy. The simulation shows that the proposed method has achieved a more excellent and stable performance on these benchmark problems. In addition, superior parameters and the subset of features can be obtained by applying the proposed OLSCA integrated with KELM. According to the experimental results, it is evident that the evaluation of Sino foreign cooperative education exhibits higher prediction accuracy and more stable performance compared with other machine learning methods.

In our future work, several aspects need to explore further. First, we can try to use the proposed OLSCA-KELM to predict other similar problems, such as fund project evaluation. Besides, the proposed method is expected to apply in different practical problems such as image segmentation and optimization of solar photovoltaic cells.

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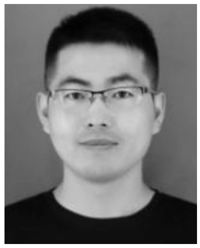

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