

Article

A Data-Driven Evolutionary Optimization Approach for Complex Chinese Text Analysis via Surrogate Model Management

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Abstract

With the rapid growth of Chinese social media data, many language-driven analytical tasks, such as sentiment analysis and malicious account detection, are increasingly formulated as computationally expensive optimization problems, particularly in the context of hyperparameter tuning for deep learning models. Due to the intrinsic characteristics of Chinese text, including implicit word boundaries, strong context dependency, and high linguistic variability, the resulting feature representations are often high-dimensional, sparse, and heterogeneously distributed. From an optimization perspective, these properties induce highly irregular, non-smooth, and multimodal objective landscapes, posing significant challenges to conventional surrogate-assisted data-driven evolutionary algorithms (DDEAs). To address this problem, this paper proposes a Normal Selection-based data-driven evolutionary algorithm (NSEA) for improving surrogate-assisted optimization under complex conditions. Specifically, a Normal distribution-based selection strategy (NSS) is developed to enable probabilistic selection of surrogate models, balancing exploitation of high-performing models and exploration of alternative candidates, thereby alleviating premature convergence in multimodal search spaces. In addition, an exponential weighting ensemble (EWE) method is introduced to aggregate surrogate models based on their relative ranking performance, which enhances the stability and generalization capability of fitness approximation across different regions of the search space. Extensive experiments on benchmark functions demonstrate that the proposed NSEA consistently outperforms several state-of-the-art DDEAs in terms of optimization accuracy and robustness. Furthermore, a real-world application of cheating official account (COA) detection on Chinese social media is conducted, in which the hyperparameter optimization of a heterogeneous graph transformer (HGT) model is formulated as an EOP. The results further prove the effectiveness and practical applicability of the NSEA in complex data-driven scenarios. Overall, this study provides an effective optimization framework for handling EOPs with complex and multimodal characteristics and offers a feasible computational approach for tasks associated with large-scale Chinese textual data.

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This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.**Keywords:** expensive optimization; surrogate-assisted optimization; evolutionary computation; evolutionary algorithm; Chinese information processing; social media mining

1. Introduction

Over the past decades, data-driven evolutionary algorithms (DDEAs) have become an effective paradigm for solving expensive optimization problems (EOPs), where fitness

evaluations are computationally costly, time-consuming, or even infeasible [1–5]. By constructing surrogate models from a limited number of evaluated samples, DDEAs approximate the underlying objective function and significantly reduce the reliance on expensive evaluations. Due to these advantages, DDEAs have been widely applied to a variety of complex optimization tasks under restricted computational budgets [6–8].

In the field of digital strategy, large-scale social media text analysis tasks, such as public opinion analysis, user profiling, and abnormal behavior detection, have become increasingly important. Chinese is characterized by strong paratactic features, where logical relationships are often implicitly conveyed through word order, functional words, and semantic context rather than explicit conjunctions. In addition, Chinese lacks explicit word boundary markers and rich inflectional morphological variations. As a result, semantic representations in Chinese social media text are highly context-dependent and easily influenced by emerging internet slang, neologisms, and rapidly evolving online expressions. These characteristics often lead to sparse, heterogeneous, and noisy feature representations, thereby increasing the complexity of downstream learning and optimization tasks.

In recent years, many expensive optimization problems have emerged from data-intensive learning systems, particularly deep neural network-based text analysis frameworks. For downstream models such as convolutional neural networks (CNNs) and graph-based architectures, hyperparameter optimization often involves high-dimensional, non-convex, and computationally expensive search spaces. Existing optimization methods may suffer from insufficient search diversity, premature convergence, or unstable surrogate participation when handling irregular multimodal landscapes. Therefore, developing more robust and adaptive surrogate-assisted evolutionary optimization methods has become increasingly important for improving optimization efficiency and model generalization performance [5–11].

Under these conditions, conventional DDEAs face several limitations. Since surrogate models are constructed from limited samples, their approximation performance may degrade when the underlying objective function is highly complex and irregular. In particular, relying on a single surrogate model may lead to insufficient generalization, especially when different regions of the search space exhibit distinct characteristics [12–15]. Moreover, deterministic or greedy model selection strategies tend to focus excessively on a small subset of surrogate models, thereby restricting exploration and increasing the risk of premature convergence in multimodal optimization landscapes [16–22]. In addition, traditional ensemble methods based on absolute error measures may not adequately reflect the relative performance differences among surrogate models across different regions of the search space, thereby limiting their effectiveness in complex optimization scenarios [22–25].

To address these challenges, this paper proposes a Normal Selection-based data-driven evolutionary algorithm (NSEA) that focuses on improving surrogate model management in complex, multimodal optimization settings. Specifically, a Normal distribution-based selection strategy (NSS) is introduced to enable probabilistic selection of surrogate models. By incorporating stochasticity into the selection process, the NSS promotes both high-performing models that exploit and alternative candidates that explore, thereby enhancing search diversity and avoiding premature convergence. Furthermore, an exponential weighting ensemble (EWE) method is developed to aggregate multiple surrogate models based on their relative ranking performance. Compared with traditional aggregation methods, the proposed ranking-based strategy better captures the relative effectiveness of surrogate models and improves the stability of fitness approximation in different regions of the search space.

Here, the contributions of this paper are summarized as follows:

First, the NSS is proposed to improve surrogate model selection through a probabilistic mechanism, effectively improving the diversity of the surrogate through probabilistic surrogate participation in complex optimization landscapes.

Second, the EWE method is developed to enhance aggregation performance by leveraging ranking-based weighting, making it more suitable for multimodal optimization problems.

Third, by integrating the NSS and EWE, a novel NSEA framework is developed to effectively address EOPs with complex, irregular objective functions.

Extensive comparisons on test problems and real-world instances with Chinese textual data demonstrate that the proposed method consistently outperforms several cutting-edge DDEAs, which show its potential. This paper is organized as follows: Section 2 presents the review on related DDEAs. The proposed NSEA is detailed in Section 3, while the experimental settings, benchmark problems, and comparative performance analysis are given in Section 4. The conclusions and future work are finally detailed in Section 5.

2. Background and Related Work

2.1. Data-Driven Evolutionary Algorithm

In essence, DDEAs aim to minimize expensive FEs via leveraging surrogates constructed from available data, thereby improving search efficiency [5]. By learning approximate mappings from previously evaluated solutions, surrogate models can replace a substantial portion of costly real evaluations during the evolutionary process so as to reduce expenses. Hence, DDEAs generally can be more widely used than conventional EAs when addressing resource-demanding optimization problems.

Nevertheless, the success of DDEAs critically depends on maintaining an appropriate trade-off between predictive accuracy and generalization capability. Surrogates that focus excessively on fitting limited training data may suffer from overfitting and poor extrapolation performance, whereas overly generalized models may produce inaccurate fitness estimates that misguide the search process.

From a structural perspective, a standard DDEA framework typically consists of two essential components: a Model Management (MM) and an Evolutionary Optimization (EO) part. The MM aims to construct, maintain, and adaptively refine surrogate models through appropriate strategies, ensuring reliable approximations of the underlying objective problem. The EO uses these surrogates within the evolution to support candidate generation, fitness estimation, and selection decisions. Through iterative feedback from the DDEO, the SMM can continuously refine surrogate models, thereby enhancing their predictive accuracy and adaptability.

Based on whether additional FEs are permitted during evolution, DDEAs are commonly classified into online or offline categories. Online ones allow for a limited number of real FEs. The newly obtained evaluation results are incorporated to progressively update and improve surrogate models, making online approaches particularly suitable for scenarios with constrained but nonzero evaluation budgets. In contrast, offline DDEAs rely exclusively on pre-evaluated datasets and prohibit any further real FEs during the search. This paradigm is typically adopted when evaluations are prohibitively expensive and time-consuming.

Despite differences in mechanisms, the two categories above share the fundamental goal of reducing costly evaluations by maximizing the use of available data so as to enable efficient and effective optimization.

2.2. Related Work on Enhanced DDEAs

Many techniques have been developed to improve the performance of DDEAs [6]. As this study focuses specifically on offline optimization, the following review centers on

representative offline DDEA approaches, emphasizing their distinguishing characteristics and inherent limitations.

Offline DDEAs operate exclusively on a fixed, pre-collected dataset and do not permit additional FEs during the optimization process. Consequently, their effectiveness depends critically on how efficiently the data is utilized. The quantity and the quality of the offline dataset directly influence surrogate model fidelity and, ultimately, optimization performance [6]. The intrinsic constraints of limited and imperfect data may therefore introduce bias or degrade solution quality. For example, Lin et al. [26] showed that increasing noise levels significantly impair DDEA performance. To alleviate common data-related issues, such as noise contamination, missing entries, and class imbalance, various preprocessing strategies have been proposed. In blast furnace optimization, for instance, local regression techniques were employed to denoise observational data and enhance surrogate reliability [5].

To address computational inefficiency arising from large-scale or redundant datasets, clustering and data-mining techniques are often applied to compress or restructure the data [5]. Conversely, when data are lacking for training accurate surrogates, generative data may provide a complementary solution. Li et al. [15] introduced a sample generation approach that enhanced the surrogate under sparse-data conditions. Similarly, data perturbation methods [14] have been adopted to create diverse training subsets that enhance model robustness and address the problem of data scarcity. Huang et al. [22] proposed the TT-DDEA that incorporates pseudo-data to expand the sample set by labeling high-confidence unlabeled samples. Nevertheless, the effectiveness of synthetic data augmentation strongly depends on the fidelity of the generative mechanism; poorly aligned generation strategies may distort the problem landscape and introduce modeling bias [15].

Beyond data-oriented improvements, considerable effort has been devoted to advancing modeling techniques. Ensemble learning has emerged as a prominent strategy for improving predictive robustness by combining multiple base learners, either homogeneous or heterogeneous. For example, DDEA-SE [21] adopts a bagging scheme to construct a large pool of radial basis function neural networks (RBFNNs). The subset of RBFNN is used as the surrogate. In contrast, BDDEA [15] employs a boosting mechanism that sequentially trains and integrates models to progressively enhance prediction accuracy. Other methods emphasize structural diversity among base learners. The SRK-DDEA algorithm [12], for instance, integrates multiple RBFNNs with distinct radial basis functions and applies surrogate-assisted ranking to evaluate candidate solutions. Collectively, these studies underscore the importance of ensemble in strengthening accuracy and overall algorithm performance.

Despite the effectiveness of existing ensemble-based DDEAs, several research gaps remain insufficiently addressed. First, most current ensemble frameworks employ deterministic surrogate selection mechanisms, in which only the top-performing models are repeatedly used during optimization. Although such strategies improve local prediction accuracy, they may reduce ensemble diversity and increase the risk of premature convergence in highly multimodal landscapes. Second, some existing approaches incorporate ranking information for surrogate evaluation; however, ranking is typically used only for candidate assessment rather than adaptive surrogate participation control. In addition, many weighting strategies depend directly on absolute prediction errors, which may become unstable when surrogate performance varies significantly across different regions of the search space. Unlike these studies, the proposed NSEA introduces a Normal distribution-guided probabilistic surrogate selection mechanism that preserves diversity by maintaining stochastic participation opportunities for non-dominant models. Furthermore, the proposed EWE mechanism uses exponential ranking-based weighting rather than relying directly on absolute errors, thereby improving robustness and aggregation stability across heterogeneous optimization landscapes.

More recently, alternative learning paradigms have attracted attention [27–31]. Huang et al. [32] studied CL-DDEA, which adopted contrastive ensemble learning to learn relational information among candidate solutions. Hao et al. [33] proposed a relation-based surrogate framework to reduce dependence on direct function evaluations. In addition, Sun et al. [34] explored symbolic regression as an interpretable and flexible surrogate modeling technique for data-driven evolutionary optimization.

3. The Proposed NSEA

In this study, the proposed surrogate management strategies are designed to address optimization problems arising from complex data sources, such as large-scale textual data. In particular, the variability and high dimensionality of Chinese textual data often lead to complex, multimodal objective functions. Therefore, the proposed methods focus on improving model selection and aggregation mechanisms to enhance robustness and generalization in such challenging optimization scenarios.

3.1. The Architecture of NSEA

Figure 1 is the architecture of the NSEA, which comprises the EO process and the NS-based MM. The EO component adheres to a standard EC paradigm, including population initialization, variation, fitness evaluation, and selection. Consequently, the NSEA maintains broad compatibility with a wide range of EC algorithms and can be seamlessly integrated with different evolutionary optimizers.

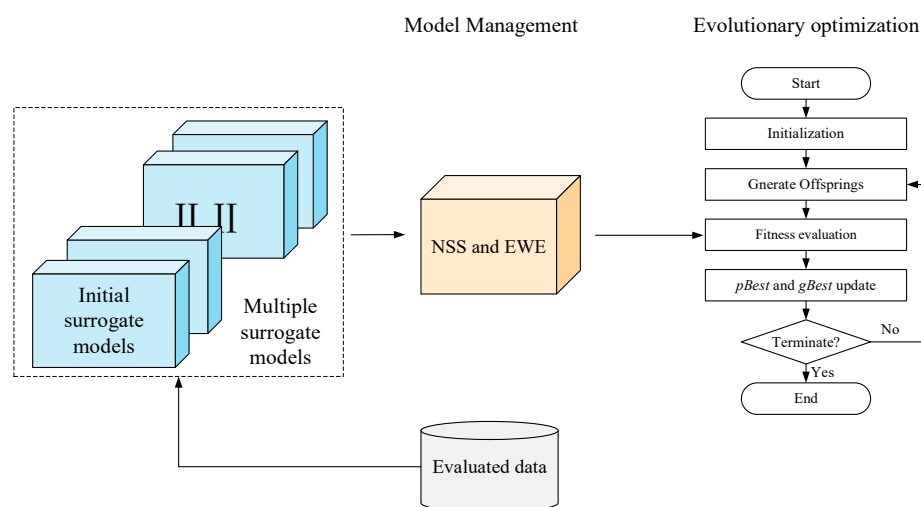


Figure 1. The overall framework of the NSEA.

The primary distinction between the NSEA and conventional EC frameworks lies in the evaluation mechanism. Rather than performing computationally expensive FEs, the proposed approach employs an NS-based ensemble to estimate fitness values. This surrogate-driven evaluation can provide the optimizer with informative search directions, thereby substantially reducing reliance on real evaluations.

The core innovation of the NSEA is embedded in its MM. It combines the NSS with the EWE mechanism. Specifically, multiple surrogate models are first trained using the available evaluated samples, and their predictive errors are subsequently estimated. These error measures are transformed into metrics that govern the ensemble selection.

Guided by the above, the EO module iteratively searches until the algorithm stops. Detailed descriptions of the surrogate training procedure, the NSS mechanism, and EWE are provided in the subsequent sections.

3.2. Base Model Initialization

Motivated by the strong performance of ensemble-based techniques in solving EOPs, the proposed NSEA employs a multi-surrogate ensemble to approximate fitness values. The key feature that differentiates the NSEA from existing ensemble-based DDEAs is its novel NSS mechanism. Instead of relying on deterministic or greedy aggregation schemes, the NSS introduces a probability-driven selection strategy that favors surrogate models with lower prediction errors. This design improves predictive precision while preserving generalization capability.

At the initialization stage, S surrogate models are constructed, as described in Algorithm 1. The data subset is sampled from the original evaluated dataset. Specifically, each data instance is independently sampled from a Bernoulli distribution over $\{0, 1\}$; instances associated with a sampled value of 1 will be added in the subset. This randomized sampling process enhances surrogate diversity even when identical base-learner structures are used.

Algorithm 1: Base Model Initialization

Input: A —the set of training data; S —the base model number.

Output: $J_1, J_2, \dots, J_s$ —the S initialized surrogates;

```

1: Begin
2:   For  $i = 1: S$  Do
3:     Set  $B$  as empty;
4:     For each  $x$  from  $A$ 
5:       Obtain a value via a Bernoulli distribution over  $\{0, 1\}$ ;
6:       If the value is 1
7:          $B \leftarrow x$ ;
8:       End If
9:     End For
10:    Build  $J_i$  with  $B$ ;
11:    Compute  $mae_i$ ;
12:  End For
13: End

```

To achieve both efficiency and approximation power, the NSEA uses RBFNNs. The sampled subsets are adopted to build independent RBFNNs, yielding S surrogate models for subsequent ensemble prediction. After training, model accuracy is assessed using mean absolute error (MAE). For the i -th surrogate, the MAE, i.e., mae_i , will be computed as follows:

$$mae_i = \frac{1}{|A|} \sum_{x \in A} |f(x) - J_i(x)| \quad (1)$$

where A is the dataset, $J_i(x)$ is the predicted fitness of surrogate J_i on data x .

Although all ensemble members share the same RBFNN architecture, potential reductions in structural diversity are alleviated through two complementary mechanisms: stochastic data sampling during model construction and probabilistic model selection under the NSS. These components encourage dynamic variation in model participation across evolutionary iterations, thereby maintaining ensemble flexibility. Furthermore, RBFNNs possess strong nonlinear approximation capabilities, enabling effective learning when trained on heterogeneous data subsets. Notably, ensemble aggregation in the NSEA is conducted using relative ranking rather than absolute error magnitudes. This ranking-based weighting improves robustness and reduces sensitivity to outliers or extreme prediction deviations. Consequently, despite employing homogeneous base learners, the integration of randomized

sampling, probability-based selection, and ranking-oriented aggregation enables the ensemble to maintain adequate diversity, strong generalization, and high predictive accuracy.

Overall, Algorithm 1 describes the initialization procedure of the surrogate ensemble. Specifically, multiple surrogate models are constructed from randomly generated training subsets of the original dataset. For each surrogate model, a Bernoulli sampling strategy is used to probabilistically select training samples from dataset A, thereby increasing surrogate diversity and reducing overreliance on a single training distribution. Each sampled subset is subsequently used to train an individual surrogate model J_i , and the corresponding prediction error mae_i is computed for subsequent surrogate evaluation and selection.

3.3. Normal Distribution-Based Selection Strategy

The NSS selects surrogate models that simultaneously ensure predictive accuracy and diversity. Its design is motivated by the need to effectively handle complex and multimodal optimization landscapes, where different regions of the search space may exhibit distinct characteristics. In such scenarios, relying on a fixed or deterministic selection mechanism may lead to premature convergence, as the optimization process may overly focus on a small subset of surrogate models that perform well in limited regions but fail to generalize across the entire search space. To address this issue, the NSS adopts a probabilistic selection framework based on the Normal distribution. Specifically, surrogate models with better predictive performance are assigned higher probabilities of being selected, while other models still retain a nonzero probability of participation. It balances exploitation of high-quality surrogate models and exploration of alternative candidates, thereby improving the adaptability of the ensemble in complex and multimodal optimization environments. This is particularly beneficial in optimization problems induced by complex data distributions, such as those arising from large-scale textual data.

In contrast to deterministic or greedy selection mechanisms, which may prematurely concentrate on a small set of models, the NSS employs a probabilistic framework derived from the Normal distribution. This stochastic mechanism enables controlled exploration among candidate models according to their estimated prediction errors, thereby enhancing robustness and mitigating overfitting. Specifically, models with lower prediction errors are assigned higher selection probabilities, while those with comparatively larger errors retain a nonzero probability of being selected. Such a design promotes the exploitation of accurate predictors without eliminating alternative models, thus preserving ensemble diversity and supporting generalization.

The Normal distribution was adopted in the NSS because it provides a balanced compromise between exploitation and exploration during surrogate participation. Specifically, surrogate models with better predictive performance obtain higher selection probabilities, while lower-ranked surrogates still retain non-zero opportunities to participate. This probabilistic characteristic helps preserve ensemble diversity and avoids excessive dependence on only a few dominant surrogate models. Compared with uniform random selection, the proposed strategy introduces adaptive selection pressure toward higher-quality surrogates. Meanwhile, unlike deterministic greedy selection or sharply concentrated probabilistic schemes, the Normal distribution exhibits smoother probability transitions and more stable stochastic behavior, which is beneficial for maintaining robustness in multimodal optimization landscapes. In addition, the symmetric and continuous nature of the Normal distribution is well-suited for modeling differences in performance among surrogate models ranked by prediction error. Therefore, the NSS can effectively balance surrogate exploitation and diversity preservation during the optimization process.

The NSS jointly considers two critical factors: model reliability and ensemble diversity. Reliability is quantified by the prediction error mae_i , which directly reflects the approx-

imation quality of the i -th surrogate. To maintain diversity, the NSS adopts a probability-based sampling scheme that favors models with smaller errors while avoiding exclusive reliance on them.

The selection score of model i , denoted as r_i , is computed as follows:

$$r_i = e_i + \text{Normal}(0, 1) \quad (2)$$

where $\text{Normal}(0, 1)$ denotes a Gaussian random variable with mean 0 and variance 1. The introduced Normal random term is used to probabilistically perturb surrogate participation probabilities, thereby preventing overly deterministic surrogate selection and preserving stochastic ensemble diversity during the optimization process. The term e_i represents a normalized quantity derived from the prediction error and is defined to be:

$$e_i = -\log mae_i \quad (3)$$

Through this normalization process, a larger mae_i yields a smaller e_i , thereby reducing the likelihood of selecting less accurate models. Based on the computed scores r_i , the top K models with the largest values are chosen to perform ensemble prediction. By integrating normally distributed randomness into the selection procedure, the NSS ensures that highly accurate models are preferentially selected, while others have a finite probability of participation. Such a probabilistic yet accuracy-aware mechanism effectively keeps the reliable surrogates with diverse alternatives, thereby enhancing both ensemble generalization and overall optimization performance.

From an optimization perspective, the complex characteristics of data-driven tasks (e.g., those induced by large-scale textual data) often lead to the presence of numerous pseudo-modes in the objective landscape. These pseudo-modes are typically caused by minor variations in input representations, which may produce locally competitive but globally suboptimal solutions, thereby misleading the search process and increasing the risk of premature convergence. The proposed NSS mechanism can be interpreted as a regularized exploration strategy for such multimodal landscapes. By introducing controlled stochasticity through a Normal distribution-based selection scheme, the NSS maintains a non-zero probability of selecting less competitive surrogate models. This design prevents the optimization process from over-relying on a small subset of surrogates that perform well only in specific regions of the search space, while improving robustness and generalization across heterogeneous data patterns.

3.4. Exponential Weighting Ensemble

EWE sums the surrogate results to produce the final evaluation, explicitly incorporating each model's relative accuracy via a weighting scheme. For a x , the final evaluation $En(x)$ computes as follows:

$$En(x) = \sum_{J_i \in \text{Models}} \text{weight}_i \cdot J_i(x) \quad (4)$$

where the weight_i is derived as follows:

$$\text{weight}_i = \frac{et_i}{\sum_{J_k \in \text{Models}} et_k} \quad (5)$$

where the et_i is:

$$et_i = e^{-\frac{1}{(L - \text{rank}(i|I) + 1)}} \quad (6)$$

where $rank(i|I)$ represents the rank of model i within the selected set $Models$, according to the mae_i . A smaller mae_i corresponds to a higher ranking (i.e., a smaller rank value). Notably, only the ranking coefficients for models in subset I are used to compute the aggregation weights. This ranking-based weighting mechanism assigns greater influence to more reliable models while preserving relative contributions from other selected models. As a result, the ensemble prediction benefits from improved accuracy and enhanced robustness, while avoiding excessive sensitivity to absolute error magnitudes. Such characteristics are commonly observed in optimization tasks associated with high-dimensional and heterogeneous data sources.

From an optimization perspective, data-driven problems with heterogeneous feature representations often involve multiple underlying patterns at different granularities, leading to significant variation in the absolute prediction errors of surrogate models. In such scenarios, different surrogate models may exhibit complementary strengths across regions of the search space, even if their overall error magnitudes differ substantially. The proposed EWE mechanism addresses this issue by adopting an exponential-weighted ranking strategy. Instead of relying on absolute prediction errors, which can be sensitive to scale differences and outliers, EWE leverages the relative ranking of surrogate models within the selected set. This design emphasizes the consistency of relative performance rather than absolute accuracy, resulting in more stable and robust aggregation. Consequently, the ensemble can effectively integrate diverse surrogate models and better adapt to heterogeneous and multimodal optimization landscapes.

3.5. The Normal Selection-Based Data-Driven Evolutionary Algorithm

This section presents the NSEA, and the corresponding procedure is summarized in Algorithm 2. The NSEA consists of several key stages. The algorithm first performs an initialization process, including population initialization and surrogate model construction. Specifically, S surrogates are trained on the initially evaluated dataset using the procedure described in Algorithm 1. Subsequently, the prediction errors of each surrogate model are calculated on the original dataset to support the subsequent model selection process using the NSS mechanism. After initialization, three operations are iteratively executed: (1) NSS, (2) offspring generation, and (3) environmental selection.

Algorithm 2: NSEA

Input: A —pre-evaluated dataset;
 S —number of surrogate models constructed initially;
 K —number of surrogate models selected for ensemble prediction;
Output: xb —best solution obtained;
 1: **Begin**
 2: Build S models from A according to Algorithm 1;
 3: Generate the initial population;
 4: **While** not stop met
 5: Perform NSS;
 6: Estimate the fitness values of all current individuals using the ensemble prediction as Equation (4);
 7: Produce offspring through crossover and mutation operators;
 8: Evaluate the offspring using the same surrogate ensemble;
 9: Merge parent and offspring populations, and retain the top-performing individuals to form the next generation;
 10: Record the current best individual as xb ;
 11: **End While**
 12: **End**

In each generation, K surrogate models are selected probabilistically using the NSS. Based on the selected models, high-quality individuals are stored to form the next generation. Once the termination criterion is met, the NSEA outputs the best solution.

4. Experimental Studies

4.1. Experiment Setup

To systematically evaluate the effectiveness of the proposed NSEA, five widely recognized benchmark problems are adopted. These test functions, labeled EOP1 to EOP5 in Table 1, are popular in DDEA research because of their heterogeneous characteristics and optimization difficulty [21]. Specifically, EOP1 is adopted to evaluate convergence efficiency. In contrast, EOP2, EOP3, EOP4, and EOP5 are characterized by numerous local optima, thereby posing significant challenges to optimization algorithms. Collectively, these benchmarks represent a diverse range of search landscapes and provide a comprehensive evaluation of the NSEA's exploration and exploitation capabilities. The EOP1 to EOP5 is tested with 10, 30, 50, and 100 dimensions to examine scalability.

Table 1. The problem set.

ID	Basic Function	Dimension Settings	Optimal Value
EOP1	Ellipsoid	10/30/50/100	0
EOP2	Rosenbrock		0
EOP3	Ackley		0
EOP4	Griewank		0
EOP5	Rastrigin		0

The unified experimental protocol is: First, LHS [35] is utilized to sample $11 \times D$ sample points, where D represents the dimensionality. These samples serve as the available dataset for all DDEAs under comparison. Surrogate models are trained solely on this dataset and subsequently used in the evolution.

To mitigate stochastic effects, each DDEA run 20 times on every problem, and the mean performance over all runs is reported. The Wilcoxon rank-sum test with $\alpha = 0.05$ is adopted to evaluate significance. For ease of comparison, three symbols are used: “+” indicates that the NSEA significantly outperforms the compared ones, “ $\approx$ ” denotes no statistically significant difference, and “−” indicates that the NSEA is significantly worse.

To ensure a rigorous statistical comparison across multiple algorithms, the Wilcoxon rank-sum test was used for pairwise performance analysis. Furthermore, given the potential family-wise Type I error from multiple hypothesis testing, the Holm post hoc correction was applied to adjust the statistical significance levels. The corrected results provide more reliable comparative conclusions regarding algorithm performance differences.

4.2. Compared Data-Driven Evolutionary Algorithms

To fully assess the performance of the NSEA, four DDEAs are in comparison, including DDEA-SE [21], DDEA-PES [14], BDDEA [15], and ESCO [36]. These methods represent typical ensemble DDEAs that combine multiple surrogate models with diverse strategies for model selection, making them suitable and challenging baselines for evaluating the effectiveness of the NSEA.

All baseline methods repeated using their publicly released source code to minimize potential discrepancies caused by implementation differences. In addition, the NSEA employs the same operators [37,38] as those used in the baseline algorithms to provide fair comparisons.

4.3. Comparison Results

The comparisons result between the NSEA and the advanced DDEAs are given in Table 2. Overall, the results show that the NSEA achieves competitive or superior performance across most test instances and dimensional settings.

Table 2. The result of the NSEA and DDEAs.

<i>D</i>	ID	NSEA	DDEA-SE	DDEA-PES	BDDEA	ESCO
10	EOP1	0.69 ± 0.32	$0.97 \pm 0.47 (+)$	$1.42 \pm 0.61 (+)$	$1.10 \pm 0.41 (+)$	$10.23 \pm 5.96 (+)$
	EOP2	24.45 ± 5.81	$27.82 \pm 5.38 (+)$	$29.86 \pm 7.96 (\approx)$	$34.62 \pm 7.61 (+)$	$42.40 \pm 10.01 (+)$
	EOP3	5.46 ± 0.94	$6.04 \pm 0.78 (\approx)$	$6.52 \pm 1.48 (+)$	$6.68 \pm 0.66 (+)$	$8.61 \pm 1.64 (+)$
	EOP4	1.32 ± 0.11	$1.30 \pm 0.14 (\approx)$	$1.32 \pm 0.13 (\approx)$	$1.25 \pm 0.12 (\approx)$	$5.21 \pm 2.08 (+)$
	EOP5	65.33 ± 21.28	$60.10 \pm 18.55 (\approx)$	$60.45 \pm 16.77 (\approx)$	$65.93 \pm 22.98 (\approx)$	$45.65 \pm 8.02 (-)$
+/ $\approx$ /−		NA	2/3/0	2/3/0	3/2/0	4/0/1
30	EOP1	3.59 ± 0.88	$3.93 \pm 1.22 (\approx)$	$5.37 \pm 1.41 (+)$	$7.07 \pm 2.27 (+)$	$22.58 \pm 5.79 (+)$
	EOP2	57.80 ± 3.87	$56.50 \pm 4.24 (\approx)$	$70.19 \pm 8.85 (+)$	$68.62 \pm 7.41 (+)$	$77.89 \pm 11.18 (+)$
	EOP3	4.63 ± 0.44	$4.84 \pm 0.54 (\approx)$	$5.47 \pm 0.37 (+)$	$5.61 \pm 0.68 (+)$	$5.96 \pm 0.38 (+)$
	EOP4	1.20 ± 0.05	$1.25 \pm 0.08 (+)$	$1.26 \pm 0.09 (+)$	$1.39 \pm 0.11 (+)$	$5.31 \pm 0.94 (+)$
	EOP5	122.59 ± 39.18	$116.12 \pm 26.47 (\approx)$	$148.59 \pm 29.59 (\approx)$	$155.37 \pm 40.64 (+)$	$121.91 \pm 22.10 (\approx)$
+/ $\approx$ /−		NA	1/4/0	4/1/0	5/0/0	4/1/0
50	EOP1	8.59 ± 3.53	$13.67 \pm 4.83 (+)$	$14.40 \pm 4.20 (+)$	$13.31 \pm 3.28 (+)$	$103.22 \pm 24.75 (+)$
	EOP2	82.84 ± 5.20	$82.64 \pm 4.10 (\approx)$	$110.15 \pm 10.76 (+)$	$98.20 \pm 9.89 (+)$	$359.95 \pm 83.72 (+)$
	EOP3	4.29 ± 0.27	$4.89 \pm 0.31 (+)$	$4.88 \pm 0.42 (+)$	$4.75 \pm 0.32 (+)$	$8.23 \pm 0.72 (+)$
	EOP4	1.21 ± 0.05	$1.88 \pm 0.21 (+)$	$1.32 \pm 0.07 (+)$	$1.42 \pm 0.08 (+)$	$15.32 \pm 3.41 (+)$
	EOP5	151.04 ± 25.25	$180.27 \pm 31.22 (+)$	$236.29 \pm 50.99 (+)$	$196.32 \pm 30.72 (+)$	$198.09 \pm 22.72 (+)$
+/ $\approx$ /−		NA	4/1/0	5/0/0	5/0/0	5/0/0
100	EOP1	67.85 ± 30.55	$277.25 \pm 75.01 (+)$	$342.17 \pm 159.30 (+)$	$56.16 \pm 12.75 (\approx)$	$285.28 \pm 56.63 (+)$
	EOP2	171.32 ± 17.90	$241.90 \pm 26.60 (+)$	$497.68 \pm 198.52 (+)$	$195.45 \pm 19.60 (+)$	$289.10 \pm 52.18 (+)$
	EOP3	4.11 ± 0.24	$7.17 \pm 0.68 (+)$	$5.22 \pm 0.61 (+)$	$4.71 \pm 0.24 (+)$	$5.68 \pm 0.23 (+)$
	EOP4	2.09 ± 0.74	$18.55 \pm 1.83 (+)$	$3.93 \pm 2.02 (+)$	$1.86 \pm 0.24 (\approx)$	$15.43 \pm 2.32 (+)$
	EOP5	427.82 ± 124.22	$778.40 \pm 88.47 (+)$	$913.89 \pm 132.32 (+)$	$427.08 \pm 149.41 (\approx)$	$423.69 \pm 39.74 (\approx)$
+/ $\approx$ /−		NA	5/0/0	5/0/0	2/3/0	4/1/0

For the 10-dimensional problems, the NSEA performs competitively with the compared algorithms. Specifically, it significantly outperforms DDEA-SE, DDEA-PES, and BDDEA on EOP1, while achieving comparable results on EOP2-EOP5 in most cases. Compared with ESCO, the NSEA shows clear superiority on four out of five problems, indicating that the proposed method can effectively handle low-dimensional EOPs. The statistical summary further shows that the NSEA obtains 2/3/0 better/similar/worse results against DDEA-SE and DDEA-PES, and 3/2/0 against BDDEA, suggesting stable performance advantages.

When the dimension is 30, the advantage of the NSEA becomes more evident. The NSEA significantly outperforms DDEA-PES and BDDEA on most test problems, achieving 4/1/0 and 5/0/0 better/similar/worse results, respectively. In comparison with DDEA-SE, the NSEA still maintains comparable performance on several instances. Meanwhile, ESCO shows noticeably worse results on almost all problems.

For the 50-dimensional EOPs, the NSEA consistently achieves the best performance across almost all benchmark problems. It significantly outperforms all compared algorithms on EOP1, EOP3, EOP4, and EOP5, while maintaining comparable results on EOP2 against DDEA-SE. The better/similar/worse results statistics (4/1/0 against DDEA-SE and 5/0/0 against the other algorithms) further confirm the robustness and scalability of the proposed NSEA.

As for the 100-dimensional case, the NSEA still maintains strong competitiveness. It significantly outperforms DDEA-SE and DDEA-PES on all test problems, achieving a 5/0/0 better/similar/worse results record against both methods. Compared with BDDEA and ESCO, the NSEA also shows clear advantages on most problems while remaining comparable on a few instances. These results indicate that the proposed NSEA maintains strong optimization capability even in very high-dimensional search spaces.

In summary, the results show that the NSEA consistently achieves superior or highly competitive performance compared with several state-of-the-art DDEAs across different dimensional settings. Particularly as the problem dimensionality increases, the advantages of the NSEA become more pronounced, suggesting that the proposed algorithm possesses strong scalability and robustness for high-dimensional expensive optimization problems.

4.4. Ablation Study for Component Analysis

To study the effectiveness of the proposed NSS and EWE, this part compares the NSEA with its variants that do not have the NSS or EWE. For simplicity, the NSEA without the NSS and EWE is denoted as NSEA-w/o-N and NSEA-w/o-E, respectively. To be specific, the NSEA-w/o-N uses a greedy method for model selection instead of the NSS, while the NSEA-w/o-E uses an average weighted method instead of EWE. The results are shown in Table 3.

First, the comparison between the NSEA and the NSEA-w/o-N clearly highlights the importance of the NSS. For all dimensional settings, the NSEA significantly outperforms the NSEA-w/o-N on all five test problems. In particular, the performance degradation of the NSEA-w/o-N becomes more pronounced as the dimensionality increases. For example, on EOP1 and EOP5 at 50D and 100D, the optimization errors of the NSEA-w/o-N are several times larger than those of the NSEA. This indicates that the greedy model selection strategy used in the NSEA-w/o-N is insufficient for effectively identifying suitable surrogate models during the optimization process. In contrast, the NSS can adaptively select more appropriate models, thereby significantly improving the overall optimization performance.

Second, the comparison between the NSEA and the NSEA-w/o-E shows the contribution of the proposed EWE strategy. In most cases, the NSEA achieves either significantly better or comparable performance than the NSEA-w/o-E. Specifically, the NSEA obtains 1/4/0, 1/4/0, 4/1/0, and 0/5/0 better/similar/worse results on 10D, 30D, 50D, and 100D problems, respectively. Although the performance difference is less dramatic than that observed for the NSS, the results still show that the proposed EWE can provide noticeable improvements in several cases, particularly on higher-dimensional problems such as the 50D instances. This suggests that the weighting mechanism used in EWE can better exploit the complementary strengths of different surrogate models compared with the simple average weighting strategy.

To sum up, this study shows that both the NSS and EWE contribute positively to the performance of the NSEA. Among them, the NSS plays a more critical role by significantly improving model selection quality, while EWE further enhances the robustness and accuracy of the ensemble. The combination of these two mechanisms enables the NSEA to achieve superior optimization performance on EOPs across different dimensions.

Table 3. The results of the NSEA and its variants without the NSS or EWE.

<i>D</i>	ID	NSEA	NSEA-w/o-N	NSEA-w/o-E
10	EOP1	0.69 ± 0.32	$6.21 \pm 3.40 (+)$	$0.82 \pm 0.32 (\approx)$
	EOP2	24.45 ± 5.81	$42.34 \pm 21.25 (+)$	$30.71 \pm 7.76 (+)$
	EOP3	5.46 ± 0.94	$9.39 \pm 1.73 (+)$	$5.31 \pm 0.84 (\approx)$
	EOP4	1.32 ± 0.11	$3.95 \pm 1.15 (+)$	$1.34 \pm 0.10 (\approx)$
	EOP5	65.33 ± 21.28	$95.61 \pm 18.97 (+)$	$52.85 \pm 11.90 (\approx)$
+/ $\approx$ /–		NA	5/0/0	1/4/0
30	EOP1	3.59 ± 0.88	$20.35 \pm 6.36 (+)$	$4.84 \pm 1.69 (\approx)$
	EOP2	57.80 ± 3.87	$73.95 \pm 27.64 (+)$	$56.13 \pm 4.87 (\approx)$
	EOP3	4.63 ± 0.44	$7.39 \pm 1.17 (+)$	$5.12 \pm 0.45 (+)$
	EOP4	1.20 ± 0.05	$3.61 \pm 1.07 (+)$	$1.23 \pm 0.09 (\approx)$
	EOP5	122.59 ± 39.18	$219.96 \pm 40.27 (+)$	$116.01 \pm 27.74 (\approx)$
+/ $\approx$ /–		NA	5/0/0	1/4/0
50	EOP1	8.59 ± 3.53	$47.27 \pm 16.48 (+)$	$10.10 \pm 2.42 (+)$
	EOP2	82.84 ± 5.20	$96.54 \pm 15.69 (+)$	$87.50 \pm 7.59 (+)$
	EOP3	4.29 ± 0.27	$6.56 \pm 0.60 (+)$	$4.39 \pm 0.36 (\approx)$
	EOP4	1.21 ± 0.05	$4.42 \pm 0.74 (+)$	$1.26 \pm 0.08 (+)$
	EOP5	151.04 ± 25.25	$317.41 \pm 78.53 (+)$	$172.40 \pm 30.30 (+)$
+/ $\approx$ /–		NA	5/0/0	4/1/0
100	EOP1	67.85 ± 30.55	$277.08 \pm 118.67 (+)$	$74.93 \pm 69.79 (\approx)$
	EOP2	171.32 ± 17.90	$268.89 \pm 80.06 (+)$	$169.38 \pm 15.82 (\approx)$
	EOP3	4.11 ± 0.24	$7.12 \pm 0.75 (+)$	$4.27 \pm 0.20 (\approx)$
	EOP4	2.09 ± 0.74	$18.13 \pm 17.85 (+)$	$2.32 \pm 0.82 (\approx)$
	EOP5	427.82 ± 124.22	$802.31 \pm 121.77 (+)$	$408.84 \pm 96.25 (\approx)$
+/ $\approx$ /–		NA	5/0/0	0/5/0

4.5. Parameter Study of NSEA

To get the effectiveness of K settings, this paper compares the NSEA with its variants using different K values. In particular, the NSEA variants with K = 20, 100, 200, 300, and 400 are compared, with K = 300 as the original setting. The comparison results are shown in Table 4.

The experimental results of the NSEA with different K settings are presented in Table 4. Overall, the results indicate that the performance of the NSEA is relatively stable under different K, while the original setting K = 300 achieves consistently competitive results across most test cases.

For the 10-dimensional EOPs, the performance differences among different K settings are relatively small. However, the variants with smaller K values (e.g., K = 20 and K = 100) tend to show slightly inferior performance on several problems, such as EOP1 and EOP2. This suggests that selecting too few models for the ensemble may limit the diversity of the surrogate models, thereby reducing the effectiveness of the ensemble learning process. In contrast, K = 300 achieves better or comparable performance on most problems, as reflected by the better/similar/worse results.

Table 4. The results of the NSEA variants using Different K.

D	ID	K = 300	K = 20	K = 100	K = 200	K = 400
10	EOP1	0.69 ± 0.32	1.19 ± 0.64 (+)	0.69 ± 0.33 (≈)	0.99 ± 0.42 (≈)	0.96 ± 0.34 (+)
	EOP2	24.45 ± 5.81	29.41 ± 5.42 (+)	29.49 ± 4.90 (+)	25.90 ± 4.88 (≈)	31.34 ± 4.96 (+)
	EOP3	5.46 ± 0.94	5.54 ± 0.69 (≈)	5.56 ± 1.32 (≈)	5.29 ± 0.58 (≈)	5.42 ± 0.61 (≈)
	EOP4	1.32 ± 0.11	1.37 ± 0.23 (≈)	1.27 ± 0.12 (≈)	1.30 ± 0.14 (≈)	1.24 ± 0.10 (≈)
	EOP5	65.33 ± 21.28	52.98 ± 16.57 (≈)	61.34 ± 27.77 (≈)	51.03 ± 26.40 (≈)	67.70 ± 32.04 (≈)
+ / ≈ / −		NA	2/3/0	1/4/0	0/5/0	2/3/0
30	EOP1	3.59 ± 0.88	4.45 ± 1.52 (≈)	4.91 ± 1.78 (+)	4.09 ± 0.81 (+)	4.69 ± 1.53 (+)
	EOP2	57.80 ± 3.87	52.17 ± 5.79 (−)	59.05 ± 3.84 (≈)	54.81 ± 5.64 (≈)	56.62 ± 5.80 (≈)
	EOP3	4.63 ± 0.44	5.05 ± 0.51 (+)	4.72 ± 0.33 (≈)	4.74 ± 0.28 (≈)	4.84 ± 0.51 (≈)
	EOP4	1.20 ± 0.05	1.21 ± 0.03 (≈)	1.24 ± 0.08 (≈)	1.19 ± 0.05 (≈)	1.22 ± 0.06 (≈)
	EOP5	122.59 ± 39.18	119.24 ± 15.25 (≈)	108.10 ± 25.61 (≈)	119.51 ± 31.65 (≈)	122.47 ± 11.55 (≈)
+ / ≈ / −		NA	1/3/1	1/4/0	1/4/0	1/4/0
50	EOP1	8.59 ± 3.53	8.57 ± 1.90 (≈)	9.27 ± 1.82 (≈)	8.33 ± 2.24 (≈)	7.70 ± 2.19 (≈)
	EOP2	82.84 ± 5.20	83.22 ± 4.22 (≈)	81.65 ± 4.76 (≈)	81.41 ± 6.28 (≈)	81.54 ± 6.86 (≈)
	EOP3	4.29 ± 0.27	4.43 ± 0.39 (≈)	4.38 ± 0.23 (≈)	4.33 ± 0.18 (≈)	4.34 ± 0.38 (≈)
	EOP4	1.21 ± 0.05	1.24 ± 0.07 (≈)	1.19 ± 0.05 (≈)	1.17 ± 0.04 (−)	1.21 ± 0.03 (≈)
	EOP5	151.04 ± 25.25	142.07 ± 25.18 (≈)	135.62 ± 19.74 (−)	153.15 ± 29.59 (≈)	148.46 ± 24.08 (≈)
+ / ≈ / −		NA	0/5/0	0/4/1	0/4/1	0/5/0
100	EOP1	67.85 ± 30.55	78.32 ± 53.24 (≈)	75.14 ± 43.54 (≈)	70.28 ± 27.91 (≈)	44.75 ± 15.97 (−)
	EOP2	171.32 ± 17.90	176.66 ± 13.23 (≈)	174.84 ± 19.96 (≈)	189.22 ± 26.66 (+)	177.57 ± 24.55 (≈)
	EOP3	4.11 ± 0.24	4.23 ± 0.24 (≈)	4.24 ± 0.25 (≈)	4.14 ± 0.18 (≈)	4.15 ± 0.36 (≈)
	EOP4	2.09 ± 0.74	1.99 ± 0.31 (≈)	1.72 ± 0.23 (−)	1.77 ± 0.35 (≈)	1.67 ± 0.33 (≈)
	EOP5	427.82 ± 124.22	433.53 ± 126.14 (≈)	458.79 ± 144.77 (≈)	423.80 ± 112.00 (≈)	417.51 ± 103.49 (≈)
+ / ≈ / −		NA	0/5/0	0/4/1	1/4/0	0/4/1

When the dimension increases to 30, a similar trend can be observed. Although some NSEAs achieve comparable results on several problems, K = 300 still shows stable performance across the majority of test instances. In particular, smaller ensemble sizes occasionally lead to performance degradation due to insufficient model diversity, while larger ensemble sizes do not provide clear additional benefits.

For the 50-dimensional problems, the differences among various K settings become even less pronounced. Most NSEAs achieve statistically similar results on the majority of benchmark problems, indicating that the NSEA is robust to moderate changes in the ensemble size. Nevertheless, the setting K = 300 maintains competitive performance without suffering from the occasional performance fluctuations observed in some smaller or larger K configurations.

When the dimension further increases to 100, the performance remains generally consistent across different K values. Although certain variants occasionally achieve slightly better results on specific problems (e.g., K = 400 on EOP1), these improvements are not consistent across all test cases. Overall, the results show that the proposed method is not highly sensitive to the choice of K, provided that the ensemble size is sufficiently large.

In summary, the parameter study demonstrates that the NSEA exhibits strong robustness with respect to the parameter K. While very small ensemble sizes may slightly degrade performance due to limited model diversity, excessively large ensembles do not necessarily bring additional improvements. The default setting K = 300 provides a good balance

between ensemble diversity and computational efficiency, leading to stable and competitive optimization performance across different dimensional settings.

From a methodological perspective, the parameter K controls the balance between ensemble diversity and computational overhead during surrogate aggregation. A relatively small K may limit surrogate diversity and increase the risk of insufficient approximation robustness, whereas an excessively large K may introduce redundant surrogate participation and additional computational cost without consistently improving prediction quality. The experimental results indicate that $K = 300$ provides a favorable trade-off between optimization stability, ensemble diversity, and computational efficiency across different dimensional settings. Therefore, $K = 300$ is adopted as the default configuration in this study.

4.6. Study on Cheating Official Accounts Mining

To demonstrate the practical applicability of the NSEA, it is applied to the detection of cheating official accounts (COAs) on Chinese social media platforms. With the rapid growth of online information ecosystems [39–42], official accounts have become a major channel for content dissemination. However, this expansion has also enabled malicious entities to create COAs that have illicit activities, including fake reviews, traffic manipulation, advertising fraud, and online scams [43–46]. Accurately identifying such accounts is therefore crucial for preserving the credibility and governance of digital platforms.

Recent research indicates that heterogeneous graph transformer (HGT) models are well-suited for capturing complex relational structures in COA detection, particularly when integrated with Chinese textual feature analysis [47,48]. Nevertheless, the performance of HGT is highly dependent on hyperparameter settings. Because configuration requires full model training, which incurs considerable computational overhead, the hyperparameter tuning process naturally constitutes an EOP. Furthermore, the high dimensionality and heterogeneity of textual features often yield a complex, multimodal search landscape, making this task an appropriate benchmark for evaluating the effectiveness of the NSEA.

Recent advances in text classification have increasingly incorporated transformer-based and graph-based deep learning architectures to improve semantic representation and contextual dependency modeling. For example, transformer-based text analysis frameworks have demonstrated strong effectiveness in automated defect monitoring and semantic feature extraction for complex engineering text data [49]. In addition, graph neural network (GNN)-driven text classification methods further enhance relational information learning by modeling structural dependencies among textual entities and contextual features [50]. These approaches provide powerful representation learning capabilities for complex text analysis tasks. However, such deep architectures often involve high-dimensional hyperparameter spaces and substantial computational training costs, making efficient hyperparameter optimization increasingly important. It should be noted that the primary focus of this study is the development of a surrogate-assisted expensive optimization framework rather than the design of state-of-the-art text classification architectures. Accordingly, the HGT-based classification model is employed as a representative computationally intensive optimization target to validate the effectiveness of the proposed NSEA framework. The integration of transformer-based or graph-based text classification architectures into the proposed optimization framework remains an important direction for future investigation. Therefore, instead of proposing a new text classification architecture, the present study focuses on developing an efficient surrogate-assisted, expensive-optimization framework for computationally intensive model optimization.

In this study, a real-world dataset provided by WeChat is utilized, comprising 32,021 legitimate official accounts and 5391 COAs. The optimization objective is to iden-

tify the hyperparameter configuration that maximizes the classification performance of the HGT model. The collected WeChat (8.0.43) dataset was randomly split into training, validation, and test sets at 70:15:15. The training set was used for model training, the validation set for hyperparameter optimization, and the test set for final performance evaluation. The dataset labeling process was conducted manually according to predefined annotation criteria for COA identification. To improve annotation consistency, ambiguous samples were re-examined and verified by multiple annotators before final label assignment. Considering the potential class imbalance in the WeChat COA detection dataset, Micro-F1 and Macro-F1 were adopted as the primary evaluation metrics. Specifically, Micro-F1 evaluates the overall classification performance by aggregating contributions from all classes, while Macro-F1 computes the average F1-score across classes and is more sensitive to minority-class performance. The combined use of these metrics provides a more comprehensive assessment of classification effectiveness under imbalanced data distributions.

The optimization process focused on critical HGT hyperparameters, including dropout rate, learning rate, and text embedding dimension. These hyperparameters were selected because they substantially influence model generalization capability, optimization stability, and semantic representation performance. Relatively broad search intervals were intentionally adopted to better simulate realistic hyperparameter optimization scenarios and avoid restrictive prior assumptions. In particular, the learning rate was explored over a range of 1×10^{-6} to 1, while the embedding dimension varied from 32 to 1024 to capture different representation capacities. Such heterogeneous, high-dimensional search spaces significantly increase the computational burden of exhaustive tuning, motivating the use of surrogate-assisted optimization methods.

For feature construction, Chinese text must first be segmented into words, a non-trivial task due to the absence of explicit word boundaries in Chinese. Unlike English or other alphabetic languages, Chinese relies on word boundaries that are implicitly determined by semantic and syntactic contexts. To address this, we employ a hybrid segmentation strategy that combines a dictionary-based maximum-matching algorithm with a statistical language model. However, social media text frequently introduces neologisms and cyber-slang (e.g., 'YYDS', 'jué jué zi') that are absent from standard dictionaries. To mitigate out-of-vocabulary (OOV) issues, we implement a character-aware word embedding mechanism that captures sub-character radical and stroke-level information, allowing the model to generalize to unseen word formations, a capability critical for processing evolving Chinese internet vocabulary. Moreover, in social media contexts, Chinese punctuation marks often exhibit compensatory semantic and pragmatic functions. Features such as punctuation density, repetitive punctuation sequences, and special combinations (e.g., consecutive exclamation marks) can provide important cues for identifying emotionally provocative expressions and unnatural pragmatic patterns commonly associated with malicious or deceptive online behaviors. For instance, the full stop (。) indicates a neutral or declarative boundary, while the exclamation mark (!) signals strong emotion or urgency, and the ellipsis (.....) often implies hesitation, irony, or deliberate omission. In the context of cheating official accounts, exaggerated emotional expression or abrupt punctuation patterns frequently serve as linguistic cues of inauthenticity. To incorporate these features, we extract punctuation density, sequence, and type distributions as auxiliary input channels to the TextCNN [51].

We argue that generic, language-agnostic preprocessing pipelines, when applied directly to Chinese text, inevitably lose critical information due to their neglect of the multi-level (character–word–phrase) semantic construction of Chinese and the strong emotional load carried by its punctuation system. In response, our customized pipeline explicitly preserves these linguistically meaningful cues. After segmentation and punctua-

tion feature extraction, word-level embeddings are obtained using a self-constructed corpus specifically built from WeChat public accounts, ensuring domain relevance. Finally, TextCNN [51] is employed to aggregate word-level embeddings and punctuation features into sentence-level representations, which are then used as node features in the heterogeneous graph transformer (HGT) model. At the beginning of the optimization procedure, 30 candidate solutions are generated using Latin hypercube sampling (LHS). The performance of the resulting models is assessed using both micro-F1 and macro-F1 scores. All experiments for the COA detection task were conducted on a workstation equipped with an NVIDIA RTX 4090 GPU, Intel Xeon CPU, and 128 GB RAM. For each hyperparameter configuration, the HGT model was trained with the Adam optimizer, using an initial learning rate selected from the candidate search space. During optimization, the initial candidate solutions were generated using Latin hypercube sampling, and the optimization process was executed for 100 generations with a population size of 30. To reduce stochastic bias, all experiments were independently repeated 20 times using different random seeds, and the average performance was reported. In terms of computational cost, a complete optimization run required approximately 8 h on average, whereas exhaustive manual tuning would require substantially higher computational resources.

Table 5 summarizes the comparative performance of the NSEA against several representative DDEAs, with the default HGT configuration also reported as a reference baseline.

Table 5. Comparisons for COA mining.

Model	Macro F1	Micro F1
Original	43%	88%
DDEA-SE	48%	93%
BDDEA	47%	92%
DDEA-PES	46%	92%
NSEA	52%	94%

The comparative results for COA detection are presented in Table 5. It can be observed that all surrogate-assisted optimization methods significantly improve the performance of the baseline HGT model, confirming the necessity of hyperparameter optimization for this task. Specifically, the default HGT model achieves a macro-F1 of 43% and a micro-F1 of 88%, indicating that although it performs reasonably well on the majority class, its ability to accurately identify minority-class COAs remains limited. After applying DDEA-based optimization methods, consistent improvements are observed. For instance, DDEA-SE-HGT achieves 48% macro-F1 and 93% micro-F1, while BDDEA-HGT and DDEA-PES-HGT also yield noticeable gains. These results demonstrate that surrogate-assisted evolutionary approaches are effective in exploring the hyperparameter space of HGT and enhancing classification performance.

Among the compared methods, the NSEA-HGT achieves the best performance, with macro-F1 of 52% and micro-F1 of 94%. Compared with the baseline HGT, this corresponds to an improvement of 9 percentage points in macro-F1 and 6 percentage points in micro-F1. More importantly, compared with other DDEA-based methods, the NSEA still shows clear advantages, particularly in terms of macro-F1. This indicates that the NSEA is more effective at improving detection performance for the minority class (i.e., COAs), which is crucial in imbalanced classification scenarios.

The superior performance of the NSEA can be attributed to its enhanced surrogate ensemble mechanism. On the one hand, the NSS enables more accurate selection of informative surrogate models, thereby improving the quality of fitness approximation during

the optimization process. On the other hand, the EWE mechanism effectively integrates multiple surrogate models by assigning adaptive weights, thereby allowing the algorithm to better capture the complex, heterogeneous relationships in the search space. As a result, the NSEA can more efficiently locate high-quality hyperparameter configurations for the HGT model.

In addition, the results also demonstrate the robustness of the NSEA in handling real-world EOPs with high dimensionality and complex feature representations. The consistent improvements across both macro-F1 and micro-F1 metrics indicate that the proposed method not only enhances overall classification accuracy but also improves class-balanced performance.

In summary, the experimental results on the real-world COA detection task further show the effectiveness of the NSEA. By efficiently optimizing the hyperparameters of a complex graph-based model, the NSEA significantly improves detection performance and offers a promising solution for combating malicious behavior on large-scale social media platforms.

4.7. Study on More Complex Problems

To better evaluate the NSEA, this part compares the NSEA and other DDEAs on IEEE CEC 2025 Competition Benchmark problems [52], which include 29 highly complex problems with shifted, rotation, and transformation characteristics. The experimental setup is the same as that of the above study. The experimental results are given in Table 6.

The results show that the proposed NSEA achieves highly competitive performance across the 29 benchmark problems. Specifically, compared with DDEA-SE, the NSEA achieves better results on 10 problems while showing statistically similar performance on the remaining 19. Against DDEA-PES, the NSEA performs better on 4 problems, ties on 23 problems, and is inferior on only 2 problems. Similarly, compared with BDDEA, the NSEA obtains superior performance on 8 problems, comparable performance on 19 problems, and worse performance on only 2 problems. These results verify the effectiveness and robustness of the proposed NSEA in handling complex optimization landscapes.

Overall, the experimental results on the IEEE CEC 2025 Competition benchmark suite demonstrate that the NSEA possesses strong optimization capability, robustness, and generalization performance for solving highly complex expensive optimization problems. Therefore, the proposed NSEA can serve as a promising and effective DDEA framework for practical large-scale and complicated optimization tasks.

Table 6. The result of the NSEA and DDEAs on Complex Problems.

ID	NSEA	DDEA-SE	DDEA-PES	BDDEA
P1	$1.01 \times 10^{10} \pm 2.19 \times 10^9$	$1.29 \times 10^{10} \pm 1.52 \times 10^9 (+)$	$1.16 \times 10^{10} \pm 1.94 \times 10^9 (\approx)$	$1.06 \times 10^{10} \pm 1.34 \times 10^9 (\approx)$
P2	$8.14 \times 10^7 \pm 1.36 \times 10^8$	$1.65 \times 10^8 \pm 4.49 \times 10^8 (\approx)$	$2.41 \times 10^9 \pm 3.46 \times 10^9 (\approx)$	$1.80 \times 10^9 \pm 2.74 \times 10^9 (+)$
P3	$1.67 \times 10^3 \pm 3.46 \times 10^2$	$2.09 \times 10^3 \pm 4.28 \times 10^2 (+)$	$1.95 \times 10^3 \pm 3.60 \times 10^2 (\approx)$	$1.41 \times 10^3 \pm 2.62 \times 10^2 (\approx)$
P4	$6.43 \times 10^2 \pm 2.57 \times 10^1$	$6.41 \times 10^2 \pm 2.26 \times 10^1 (\approx)$	$6.46 \times 10^2 \pm 2.42 \times 10^1 (\approx)$	$6.37 \times 10^2 \pm 2.04 \times 10^1 (\approx)$
P5	$6.79 \times 10^2 \pm 2.09 \times 10^1$	$6.78 \times 10^2 \pm 2.01 \times 10^1 (\approx)$	$6.88 \times 10^2 \pm 1.31 \times 10^1 (\approx)$	$6.67 \times 10^2 \pm 1.78 \times 10^1 (\approx)$
P6	$8.32 \times 10^2 \pm 2.54 \times 10^1$	$8.51 \times 10^2 \pm 2.01 \times 10^1 (\approx)$	$8.46 \times 10^2 \pm 1.48 \times 10^1 (\approx)$	$8.32 \times 10^2 \pm 2.08 \times 10^1 (\approx)$
P7	$8.98 \times 10^2 \pm 3.31 \times 10^1$	$9.19 \times 10^2 \pm 1.74 \times 10^1 (\approx)$	$9.12 \times 10^2 \pm 2.00 \times 10^1 (\approx)$	$9.13 \times 10^2 \pm 2.01 \times 10^1 (\approx)$
P8	$2.02 \times 10^3 \pm 4.28 \times 10^2$	$2.48 \times 10^3 \pm 4.44 \times 10^2 (\approx)$	$2.49 \times 10^3 \pm 3.52 \times 10^2 (\approx)$	$2.23 \times 10^3 \pm 5.77 \times 10^2 (\approx)$
P9	$4.96 \times 10^3 \pm 4.33 \times 10^2$	$4.72 \times 10^3 \pm 6.63 \times 10^2 (\approx)$	$4.43 \times 10^3 \pm 6.55 \times 10^2 (\approx)$	$4.82 \times 10^3 \pm 6.05 \times 10^2 (\approx)$
P10	$1.69 \times 10^6 \pm 3.45 \times 10^6$	$3.57 \times 10^7 \pm 7.11 \times 10^7 (+)$	$1.35 \times 10^7 \pm 1.08 \times 10^7 (+)$	$5.35 \times 10^7 \pm 3.70 \times 10^7 (+)$
P11	$1.00 \times 10^9 \pm 6.47 \times 10^8$	$6.24 \times 10^8 \pm 3.42 \times 10^8 (\approx)$	$7.29 \times 10^8 \pm 5.79 \times 10^8 (\approx)$	$1.56 \times 10^8 \pm 1.72 \times 10^8 (-)$

Table 6. Cont.

ID	NSEA	DDEA-SE	DDEA-PES	BDDEA
P12	$1.01 \times 10^8 \pm 5.75 \times 10^7$	$5.00 \times 10^8 \pm 1.65 \times 10^8 (+)$	$2.04 \times 10^8 \pm 1.69 \times 10^8 (\approx)$	$5.82 \times 10^8 \pm 1.64 \times 10^8 (+)$
P13	$2.33 \times 10^8 \pm 2.88 \times 10^8$	$1.92 \times 10^9 \pm 8.36 \times 10^8 (+)$	$6.10 \times 10^8 \pm 4.56 \times 10^8 (\approx)$	$1.69 \times 10^9 \pm 3.22 \times 10^8 (+)$
P14	$4.71 \times 10^8 \pm 5.73 \times 10^8$	$3.53 \times 10^9 \pm 2.62 \times 10^9 (+)$	$2.87 \times 10^9 \pm 1.37 \times 10^9 (+)$	$5.54 \times 10^9 \pm 2.91 \times 10^9 (+)$
P15	$2.93 \times 10^3 \pm 3.57 \times 10^2$	$3.55 \times 10^3 \pm 5.46 \times 10^2 (+)$	$3.38 \times 10^3 \pm 6.17 \times 10^2 (\approx)$	$3.84 \times 10^3 \pm 4.67 \times 10^2 (+)$
P16	$2.71 \times 10^3 \pm 2.88 \times 10^2$	$2.69 \times 10^3 \pm 3.99 \times 10^2 (\approx)$	$2.66 \times 10^3 \pm 3.30 \times 10^2 (\approx)$	$4.00 \times 10^3 \pm 3.13 \times 10^3 (\approx)$
P17	$1.38 \times 10^9 \pm 5.88 \times 10^8$	$3.34 \times 10^9 \pm 9.36 \times 10^8 (+)$	$2.36 \times 10^9 \pm 1.10 \times 10^9 (\approx)$	$2.23 \times 10^9 \pm 8.65 \times 10^8 (\approx)$
P18	$1.35 \times 10^8 \pm 2.82 \times 10^8$	$8.65 \times 10^8 \pm 3.02 \times 10^8 (+)$	$7.38 \times 10^8 \pm 4.61 \times 10^8 (+)$	$2.63 \times 10^9 \pm 7.67 \times 10^8 (+)$
P19	$3.25 \times 10^3 \pm 2.99 \times 10^2$	$2.95 \times 10^3 \pm 1.98 \times 10^2 (\approx)$	$2.89 \times 10^3 \pm 1.80 \times 10^2 (-)$	$2.93 \times 10^3 \pm 2.42 \times 10^2 (-)$
P20	$2.46 \times 10^3 \pm 3.36 \times 10^1$	$2.45 \times 10^3 \pm 2.36 \times 10^1 (\approx)$	$2.45 \times 10^3 \pm 2.64 \times 10^1 (\approx)$	$2.44 \times 10^3 \pm 2.55 \times 10^1 (\approx)$
P21	$3.15 \times 10^3 \pm 3.93 \times 10^2$	$3.56 \times 10^3 \pm 4.12 \times 10^2 (\approx)$	$3.23 \times 10^3 \pm 3.63 \times 10^2 (\approx)$	$3.18 \times 10^3 \pm 3.07 \times 10^2 (\approx)$
P22	$2.91 \times 10^3 \pm 1.05 \times 10^2$	$2.83 \times 10^3 \pm 4.48 \times 10^1 (\approx)$	$2.90 \times 10^3 \pm 6.38 \times 10^1 (\approx)$	$2.85 \times 10^3 \pm 2.82 \times 10^1 (\approx)$
P23	$3.06 \times 10^3 \pm 6.53 \times 10^1$	$3.04 \times 10^3 \pm 3.30 \times 10^1 (\approx)$	$3.09 \times 10^3 \pm 4.70 \times 10^1 (\approx)$	$3.00 \times 10^3 \pm 6.09 \times 10^1 (\approx)$
P24	$3.89 \times 10^3 \pm 6.39 \times 10^1$	$3.96 \times 10^3 \pm 2.46 \times 10^2 (\approx)$	$3.95 \times 10^3 \pm 2.66 \times 10^2 (\approx)$	$3.75 \times 10^3 \pm 9.43 \times 10^1 (\approx)$
P25	$5.01 \times 10^3 \pm 2.87 \times 10^2$	$4.96 \times 10^3 \pm 1.47 \times 10^2 (\approx)$	$5.12 \times 10^3 \pm 1.60 \times 10^2 (\approx)$	$5.10 \times 10^3 \pm 2.49 \times 10^2 (\approx)$
P26	$3.72 \times 10^3 \pm 1.71 \times 10^2$	$3.85 \times 10^3 \pm 2.57 \times 10^2 (\approx)$	$3.83 \times 10^3 \pm 2.83 \times 10^2 (\approx)$	$3.69 \times 10^3 \pm 1.59 \times 10^2 (\approx)$
P27	$3.95 \times 10^3 \pm 8.76 \times 10^1$	$4.02 \times 10^3 \pm 1.03 \times 10^2 (\approx)$	$4.03 \times 10^3 \pm 7.68 \times 10^1 (\approx)$	$4.00 \times 10^3 \pm 7.45 \times 10^1 (\approx)$
P28	$2.04 \times 10^4 \pm 1.28 \times 10^4$	$2.31 \times 10^4 \pm 2.53 \times 10^4 (\approx)$	$9.37 \times 10^3 \pm 3.85 \times 10^3 (-)$	$2.96 \times 10^4 \pm 4.02 \times 10^4 (\approx)$
P29	$2.95 \times 10^8 \pm 1.28 \times 10^8$	$7.08 \times 10^8 \pm 3.02 \times 10^8 (+)$	$6.98 \times 10^8 \pm 3.46 \times 10^8 (+)$	$1.29 \times 10^9 \pm 5.57 \times 10^8 (+)$
+/-/-	NA	10/19/0	4/23/2	8/19/2

4.8. Discussion

The experimental results demonstrate that the proposed NSEA achieves superior performance across a range of benchmark functions and real-world tasks. This improvement can be attributed to the complementary design of the NSS and EWE, which jointly enhance the adaptability and stability of surrogate-assisted optimization in complex and multimodal landscapes. In particular, the NSS effectively alleviates premature convergence by maintaining diversity in model selection, while EWE improves aggregation consistency across different regions of the search space.

It should be noted that the exploration–exploitation discussion in the present study is mainly derived from algorithmic design rationale and empirical optimization behavior, rather than explicit behavioral landscape analysis. More rigorous characterization approaches, including diversity evolution analysis [53], attraction basin analysis [54], and trajectory-based search behavior analysis [55], were not included in the current work.

Therefore, although the proposed NSS and EWE mechanisms are intended to improve surrogate diversity and ensemble robustness, the detailed dynamics of successful exploration [56], deceptive exploration [57], and exploitation efficiency [58] remain to be further investigated. Future work will incorporate more advanced landscape-aware behavioral analysis techniques to better understand the optimization dynamics of the proposed framework.

From a broader perspective, the effectiveness of the proposed method is closely related to the characteristics of data-driven optimization problems induced by large-scale textual data. In Chinese social media scenarios, textual content often exhibits high-dimensional representations, uneven distribution patterns, and significant variability in expression. These properties lead to complex, multimodal objective functions in downstream tasks, such as model training and hyperparameter optimization. The proposed

NSEA provides a robust mechanism to address these challenges by improving both model selection and aggregation strategies.

Furthermore, the application to COA detection demonstrates that the proposed framework can serve as a practical computational tool for analyzing Chinese textual data. By formulating model configuration as an optimization problem, the NSEA enables efficient exploration of model parameter spaces under limited computational budgets. This is particularly valuable for large-scale platform governance tasks, where both efficiency and reliability are critical.

Despite the encouraging experimental results, several limitations of the present study should be acknowledged. First, the current validation is limited to benchmark functions and a real-world COA detection task. Although these experiments cover both synthetic and practical optimization scenarios, they may not fully represent the diversity of expensive optimization problems encountered in broader applications. Second, the proposed framework is currently evaluated primarily using RBFNN-based surrogate ensembles. The effectiveness of the proposed NSS and EWE mechanisms when integrated with other surrogate architectures, such as Gaussian processes or deep surrogate models, remains to be further investigated. In addition, the real-world application considered in this work focuses specifically on Chinese social media analysis. The performance and adaptability of the proposed method in other domains, datasets, and optimization settings require additional validation.

Overall, the proposed method not only advances surrogate-assisted evolutionary optimization but also offers a feasible computational approach for handling complex optimization problems arising from Chinese text-driven applications.

5. Conclusions

This study addresses the overfitting issue commonly encountered when surrogate models are trained on a limited number of evaluated samples, a persistent bottleneck in DDEAs. This paper proposes a novel framework termed NSEA, which integrates an NSS and an EWE mechanism into surrogate model management. Specifically, the NSS probabilistically selects surrogate models by jointly considering predictive accuracy and diversity, thereby balancing exploitation and exploration. The selected models are then aggregated using EWE, thereby enhancing the stability and reliability of fitness estimation. Through this dual-strategy design, the proposed method effectively mitigates overfitting and strengthens the robustness of surrogate-based optimization.

Extensive experiments on benchmark functions and a real-world application validate the effectiveness and robustness of the proposed method. In particular, the application to Chinese social media data demonstrates that the NSEA can effectively handle optimization problems arising from high-dimensional, heterogeneous textual features, achieving superior performance in hyperparameter optimization tasks.

From an application perspective, this study demonstrates how domain-specific data characteristics, such as those arising from large-scale textual analysis, can be effectively incorporated into surrogate-assisted evolutionary optimization. Rather than relying solely on generic modeling assumptions, the proposed framework leverages insights into data heterogeneity and representation variability to guide surrogate model management. The effectiveness of the proposed NSEA, supported by the NSS and EWE mechanisms, has been validated across both benchmark problems and a real-world COA detection task, demonstrating its robustness and practical applicability.

In future work, the proposed framework can be extended to a wider range of data-intensive optimization tasks involving heterogeneous and multimodal representations, including applications in large-scale text analysis and other complex real-world scenar-

ios [59,60]. In addition, integrating more advanced deep learning architectures and exploring adaptive or online optimization strategies may further improve the flexibility and scalability of the proposed approach.

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