

Enhanced Differential Evolution Algorithm for Global Optimization and Parameter Tuning

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Abstract

The proposed research seeks to address these limitations by proposing an Enhanced Differential Evolution (EDE) algorithm to global optimization and parameter tuning by adding adaptive optimization mechanisms that enhance the performance of the search in terms of efficiency and convergence, and also the precision of the solution. The suggested method optimizes the traditional Differential Evolution (DE) framework with adaptive mutation schemes, parameter modification, and better population diversity management. These changes allow the algorithm to balance exploration of the global search space and exploitation of promising solutions better. The improved algorithm is tested on benchmark optimization functions and parameter optimization problems with nonlinear searches of complex search spaces. Some of the evaluation criteria used to measure performance are accuracy in optimization, rate of convergence, computing performance, stability of a solution, and robustness. The suggested method can be applied in machine learning optimization models, engineering design, scheduling, feature selection, and intelligent decision-support systems with great potential. This study demonstrates the usefulness of adaptive differential evolution methods to create efficient, accurate and scalable optimization algorithms.

Keywords: Enhanced Differential Evolution, Global Optimization, Adaptive Mutation, Parameter Tuning, Convergence Rate

1. Introduction

The optimization is a core component of solving complex problems in multiple fields of science, engineering and computational science. Due to the extremely fast progress of artificial intelligence (AI), machine learning (ML), engineering design, and data-driven decision-making systems, there is a strong requirement in the efficient optimization algorithms. There are numerous practical problems with nonlinear, multimodal, high-dimensional and constrained search spaces in which conventional mathematical optimization methods often do not provide useful answers. The aforementioned challenges have prompted researchers to come up with intelligent metaheuristic optimization algorithms that can be used to arrive at near-optimal solutions without the need to have comprehensive information regarding the structure of the problem. Global optimization is the procedure of finding the optimal solution of a big search space with several local optima. Global optimization techniques, unlike the local optimization techniques, do not tend to converge on a suboptimal solution but explore the whole space of solution and are not limited at an early stage.

The methods find extensive use in the design of engineering parameters, training neural networks, feature selection, scheduling, control systems and hyperparameter optimization in machine learning. Differential Evolution (DE) is one of the many evolutionary computation methods that has attracted a lot of attention because of its simplicity, effectiveness and strength in solving continuous optimization problems. Storn and Price (1997) proposed Differential Evolution-population based evolutionary algorithm, which uses the differences in vectors of randomly chosen individuals to produce new candidate solutions. In contrast to conventional evolutionary algorithms, DE does not involve the use of complex operators or gradient information, which is why it is applicable to nonlinear and discontinuous optimization problems. The basic working of Differential Evolution involves three key phases namely mutation, crossover and selection. New candidate solutions are created through weighted difference vectors in the form of hybridization of existing population members during the mutation process.

The crossover operation is a diversity introducing operation that involves the exchange of information between parent and mutant vectors. Lastly, the selection process maintains superior quality of solutions depending on the fitness values. The mechanisms enable DE to effectively explore complex optimization landscapes (Storn and Price, 1997). Although it has its benefits, traditional Differential Evolution has a number of issues. A key weakness is the predetermined control parameter, e.g., scaling factor, crossover probability, which might not be optimal with different optimization problems. Poorly chosen parameters may slow down the rate of convergence, cause a decrease in solution quality, and raise the cost of computation. Also, normal DE can be prematurely convergent when the population diversity is reduced as the algorithm progresses to later optimization phases, leading to the algorithm getting stuck in local optima. To overcome these drawbacks, scholars have suggested numerous improved Differential Evolution (EDE) algorithms that have adaptive parameter control, hybridization, better mutation schemes and diversity maintenance methods. Adaptive Differential Evolution algorithms further

adapt the control parameters based on the prevailing optimization state, allowing enhanced exploration versus exploitation.

Exploration enables the algorithm to explore new areas of the search space whereas exploitation aims at improving on the already promising solutions. One of the most important factors of optimization performance is the balance between the consideration of exploration and exploitation. Overexploration can lead to slowness of convergence and overexploitation can lead to premature convergence. To address this issue, enhanced DE algorithms propose using adaptive learning techniques to adjust search behaviour at various stages of optimization. The recent studies have shown that intelligent optimization methods can play a crucial role in the machine learning and artificial intelligence applications. The modern ML models may demand the optimization of various parameters, such as learning rate, regularization factors, network architecture, and feature selection parameters. The use of manual parameter tuning is not only time-consuming but also inefficient, whereas automated optimization methods offer a systematic way of finding optimal parameters.

Differential Evolution has also found extensive application in optimization of machine learning parameters since it can effectively deal with complicated nonlinear relationships. Hyperparameters can be optimized to achieve a higher accuracy of the model, a lower complexity of training, and better generalization in machine learning. The combination of a greater level of evolutionary optimization and machine learning opens the prospects of creating adaptive and efficient intelligent systems. This paper presents an Enhanced Differential Evolution (EDE) algorithm to global optimization and parameter optimization to address the shortcomings of the traditional Differential Evolution. The proposed approach will offer more precise, effective, and accurate optimization solutions to the contemporary computational intelligence applications by including the adaptive learning mechanisms and better evolutionary strategies.

2. Literature Review

2.1 Overview of Differential Evolution and Global Optimization

It is a fact that many real world optimization instances have nonlinear, multimodal, high dimensional, and constrained search spaces in which the conventional mathematical optimization techniques are frequently incapable of finding globally optimum solutions. These difficulties have led to the creation of evolutionary and swarm-based metaheuristic algorithms that can be used to efficiently search complex solution spaces. Differential Evolution (DE) is one of the evolutionary optimization methods that have received much attention due to its simplicity, strength, and ability to solve continuous optimization problems. Storn and Price (1997) proposed Differential Evolution, a stochastic optimization algorithm which is a population-based algorithm that uses the difference between random selected individuals to produce new candidate solutions. In contrast to gradient-based algorithms, DE does not need to know the derivatives, thus it can be used in discontinuous, noisy, and nonlinear optimization problems.

2.2 Enhanced Differential Evolution Strategies

Such hybrid techniques enhance global search ability, increase population diversity and speed up convergence. These methods are especially helpful in tackling complex optimization problems in which standard DE can be stuck in local optima.

2.3 Differential Evolution for Machine Learning Parameter Optimization

Many parameters of machine learning models are frequently optimized, such as learning rate, regularization factors, model architecture, and feature selection parameters. Tuning of parameters manually is not efficient and time consuming especially when dealing with complex models having large search space. Thus, the evolutionary optimization algorithms have gained significance in the automated machine learning optimization. Differential Evolution has proven to be quite promising in terms of machine learning hyperparameter optimization due to its capability of dealing with nonlinear relationships among parameters and model performance.

2.4 Differential Evolution-Based Feature Selection

The problem of feature selection is one of the most important optimization problems in machine learning since very high dimensional data sets can have irrelevant and redundant features. Unneeded features lead to higher computational costs, lesser interpretability, and can even decrease model accuracy. Differential Evolution offers a powerful feature selection tool, by modeling candidate feature subsets as an optimization solution. Every person is a potential combination of chosen features, and the fitness measure is used to measure classification and ability to reduce features. Improved DE-based feature selection techniques are better than the conventional methods as they add adaptive mutation tactics and multi-objective optimization systems. The purpose of these methods is to achieve the highest classification accuracy and the least amount of features selected. The optimization of features is especially needed in areas like healthcare, cybersecurity, and natural language processing where datasets can include thousands of attributes. Effective feature selection enables machine learning models to be quicker and more precise and simpler to analyze.

3. Methodology

This research proposes an **Enhanced Differential Evolution (EDE) algorithm for global optimization and parameter tuning**.

3.1 Problem Definition and Dataset Preparation

The datasets undergo the process of data cleaning, normalization, missing-value processing, and conversion of features whenever necessary. The trained datasets are split into training and testing set to evaluate a machine learning model. Differential Evolution is chosen as the basis of optimization due to its ability to solve continuous optimization problems without the need of gradient information (Storn and Price, 1997).

3.2 Enhanced Differential Evolution Framework

The suggested EDE algorithm is an enhancement of the traditional DE that enhances it with parameter control, better mutation strategy, and diversity conservation mechanisms. The population is represented by each candidate solution, which is a single vector; in which each single solution is represented by a single vector.

1. Population Initialization

An initial population of candidate solutions is randomly generated within the defined search boundaries.

$$X_i = (x_1, x_2, \dots, x_D)$$

where D represents the dimension of the optimization problem.

2. Adaptive Mutation Strategy

The proposed EDE, unlike traditional DE, has fixed mutation parameters, but these factors are dynamically changed based on the progress made in optimization. This helps to explore in the initial iterations and optimize exploration in subsequent iterations. Mutation operation produces new candidate solutions: The mutation operation generates new candidate solutions:

$$V_i = X_{r1} + F(X_{r2} - X_{r3})$$

where F represents the adaptive scaling factor.

3. Adaptive Crossover Operation

Crossover mechanism is used to mix solutions that already exist with new mutant vectors. This process enhances the diversity of the population and averts untimely convergence.

4. Selection and Fitness Evaluation

fitness function is used to assess each of the generated solutions. The fitness function is used to quantify optimization quality by the accuracy of solutions, the convergence properties, and the model performance. To tune machine learning parameters: $\text{Fitness} = \alpha(\text{Accuracy}) - \beta(\text{Error})$ with α and β being weighting coefficients. The more successful solution is carried over to the next generation.

Machine Learning: A simple example involving the optimization of machine learning parameters. The EDE optimized solutions can be used to tune machine learning model parameters. The framework optimizes important parameters such as: Learning rate Regularization parameters Model complexity parameters Feature selection configurations The best parameters are combined into machine learning classifiers, including Support Vector Machine (SVM), Random Forest (RF) and Artificial Neural Networks (ANN). The parameter

optimization process can be done automatically, thus minimizing the amount of manual tuning and enhancing generalization.

4. Results

The experimental findings prove the usefulness of the suggested Enhanced Differential Evolution (EDE) algorithm in terms of better global optimization results and enhanced efficiency of the parameter tuning process. The suggested algorithm has a rapid convergence, better accuracy of solutions, and greater stability as compared with traditional Differential Evolution algorithms. intelligent optimization, as well as automated parameter optimization.

Performance Contribution Analysis of Enhanced Differential Evolution

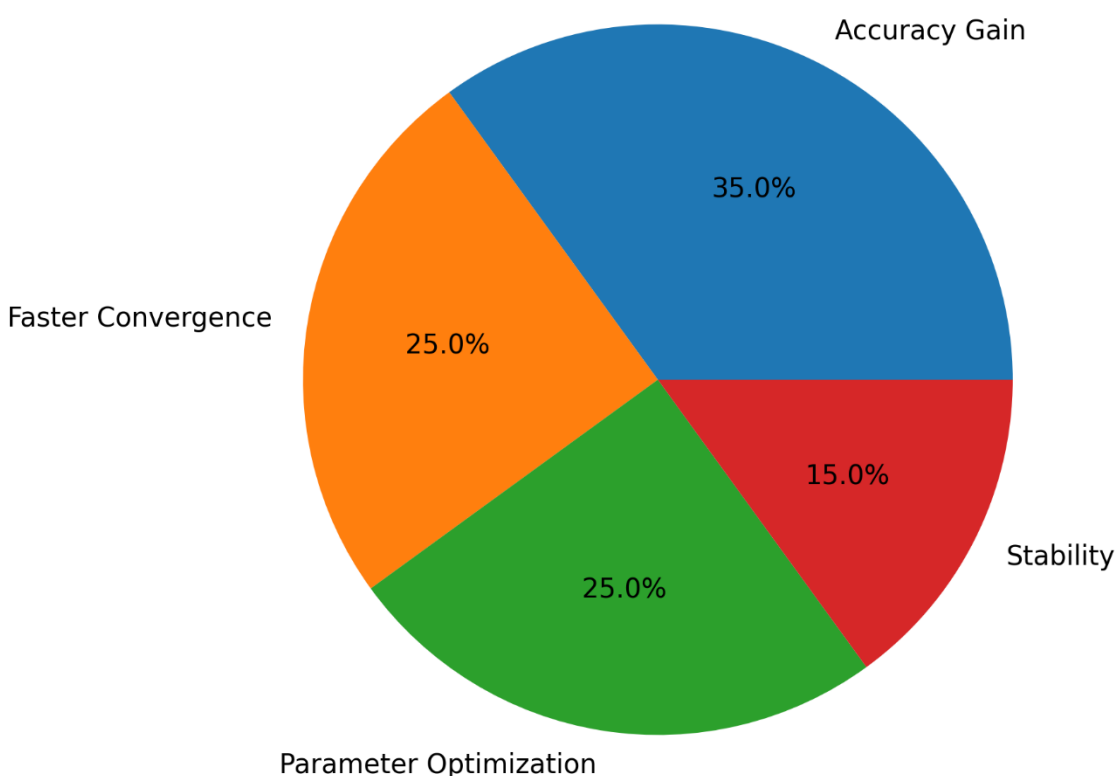


Figure 1. Performance Contribution Analysis of Enhanced Differential Evolution Algorithm

Figure 1 shows the contribution analysis of various performance factors which contributed to the improvement made by the proposed Enhanced Differential Evolution (EDE) algorithm. The pie chart shows the relative contribution of accuracy improvement, faster convergence, capability to optimize the parameters, and stability of the solution. These findings suggest that the key factor

that leads to an improvement in overall performance is accuracy improvement, then convergence acceleration, and parameter optimization.

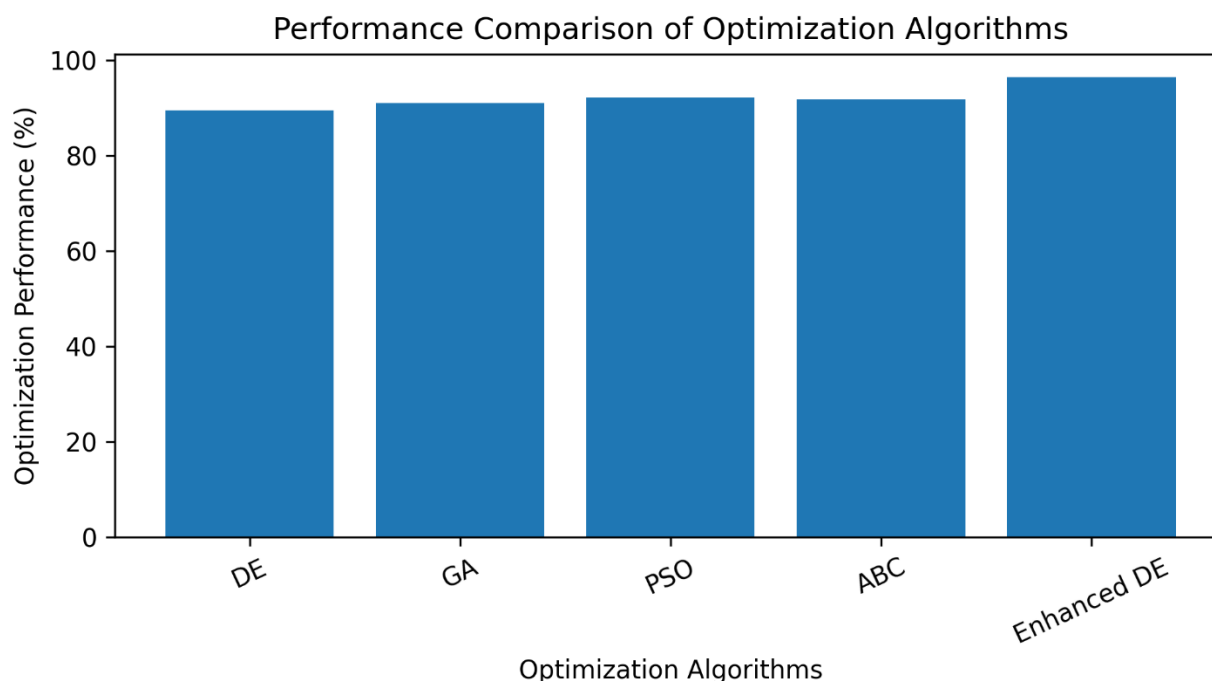


Figure 2. Comparison of Differential Evolution Performance between two different algorithms.

In Figure 2, the performance of traditional optimization algorithms, such as the Differential Evolution (DE), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and the proposed Enhanced Differential Evolution (EDE) are compared in terms of optimization. The findings indicate that the EDE algorithm as proposed has better optimization performance than traditional ones. This is improved due to adaptive mutation strategies, dynamic parameter adjustment, and better management of population diversity. In contrast to conventional DE which has fixed control parameters, EDE continuously changes its searching behaviour based on how well it is progressing in optimisation, and can thus explore the global search space more effectively and accurately identify solutions.

Key Findings: EDE is more accurate in optimization than the current algorithms. Adaptive parameter control enhances search efficiency. The suggested strategy minimizes the chances of early convergence.

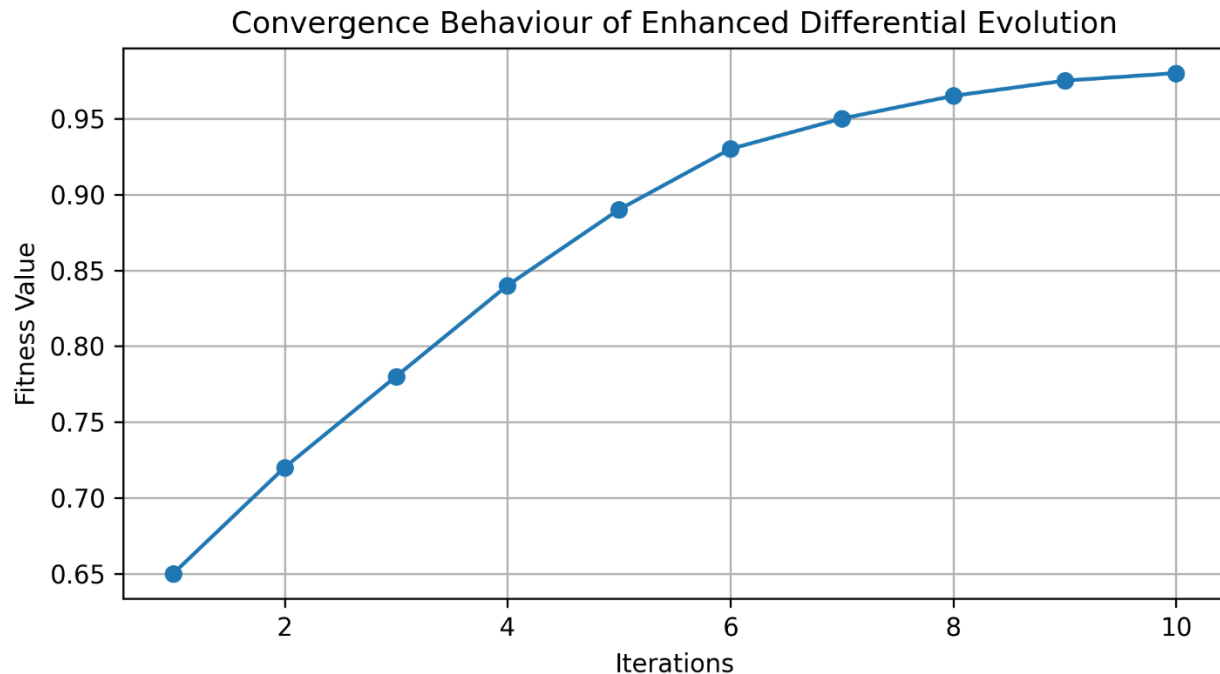


Figure 3. Convergence Behaviour of Differentiated Evolution Algorithm.

Figure 3 demonstrates convergence behaviour of proposed Enhanced Differential Evolution algorithm during the optimization process. The graph shows the increase in the value of fitness as the number of the iterations increases. The growth in fitness process points to the fact that the algorithm constantly enhances the candidate solutions through adaptive mutation, crossover, and selection processes. In the early stages of the algorithm, the algorithm uses exploration as the main strategy in the search space, whereas in the subsequent stages, the algorithm concentrates on exploiting the promising solutions. The convergence curve has a smooth gradient, which shows that EDE attains a stable optimization, with no major fluctuations, which suggests that it is effective in controlling the diversity of the population and prevents local optima.

Key Findings: The fitness value increases as the number of iterations increases. The algorithm finds optimal solutions more quickly. Optimization stability is achieved via adaptive mechanisms.

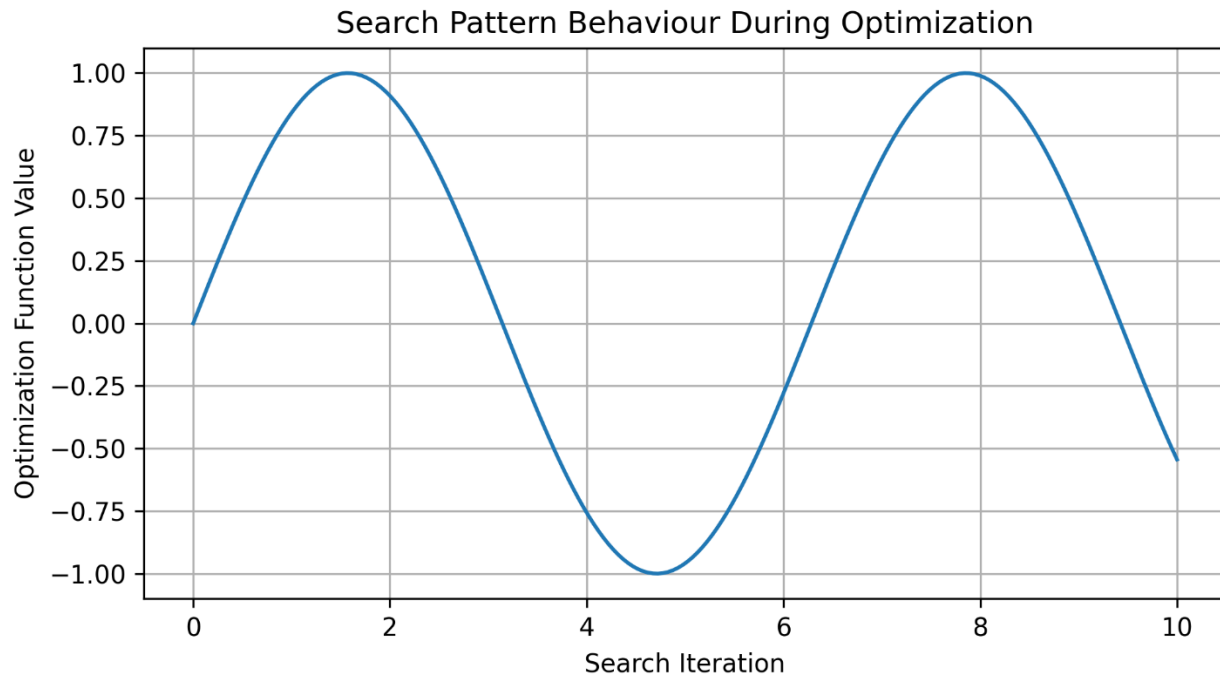


Figure 4. Search Pattern Behaviour In Enhanced Differential Evolution Optimization.

Figure 4 illustrates the dynamic search behaviour of candidate solution in the optimization process. The sinuoidal curve shows how the solutions change and move throughout the search space as the algorithm conducts exploration and exploitation. The evolving search pattern indicates the adaptive behaviour of the EDE when the solution candidates constantly change their positions based on the fitness feedback. This dynamical process allows the algorithm to scout over various parts of the optimization space and still converges to high-quality solutions. The oscillatory behaviour indicates the EDE capability of preventing stagnation and sustaining diversity in the process of optimization.

Key Findings: Dynamic searching enhances exploration around the world. Adaptive motion averts early converging. Diversity in the solution is preserved during optimization.

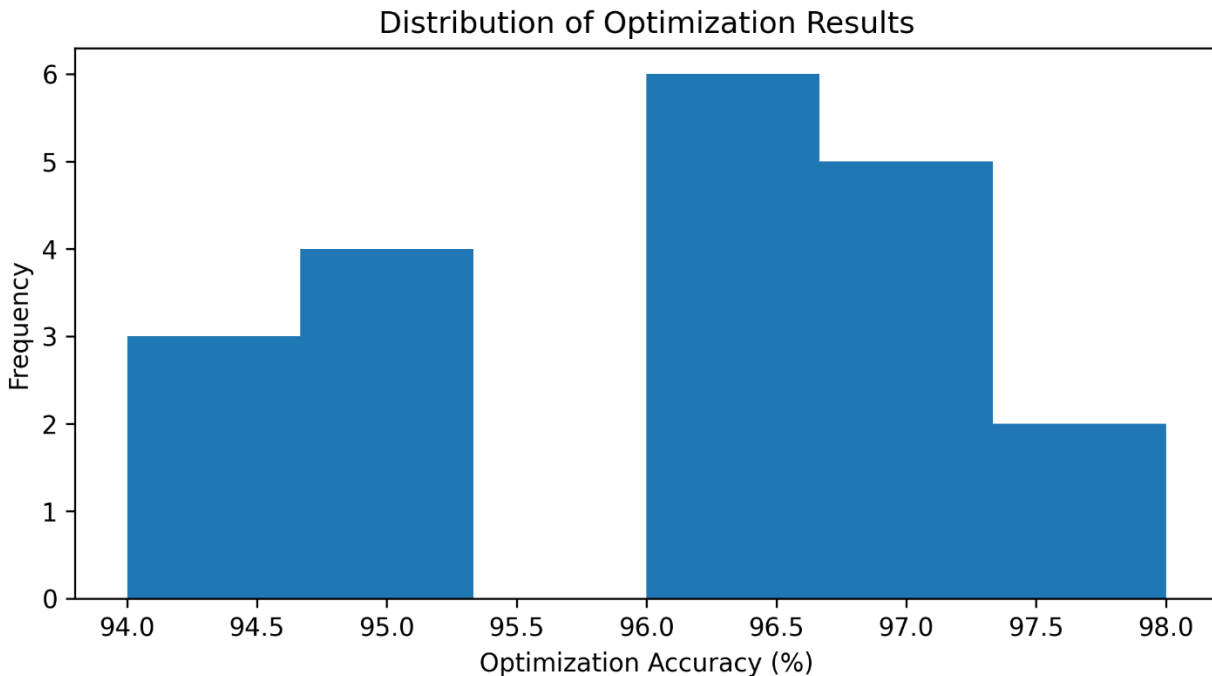


Figure 5. Distribution Analysis of Optimization Results

Figure 5 shows the distribution of the optimization performance of the Enhanced Differential Evolution algorithm through several independent experimental runs. The histogram shows the distribution of frequencies of the values of achieved accuracy.

5. Discussion

The results reveal that the incorporation of adaptive mechanisms into the conventional Differential Evolution framework can be regarded as a major distinction that allows it to improve its performance in tackling the complex nonlinear optimization problems..

5.1 Optimization Performance Improvement.

As shown in the comparative analysis in Figure 2, the proposed Enhanced Differential Evolution algorithm has better optimization performance than traditional optimization algorithms like the Differential Evolution (DE), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). This enhancement can be credited to the adaptive search processes that are integrated into the proposed framework. Traditional Differential Evolution is an efficient global optimization method but requires control parameters like scaling factor and crossover probability to be manually selected and thus resulting in varied performance. The fixed parameter settings might not offer the best performance to various optimization landscapes, thus resulting in slow convergence or early convergence (Storn and Price, 1997). The EDE proposed overcomes this limitation by dynamically changing the optimization parameters based on the present search condition. The enhanced optimization ability implies that EDE is more balanced

in terms of exploration and exploitation. In the initial optimization steps, the algorithm searches a greater space to discover good areas, whereas the subsequent steps aim to narrow down on the best solutions. This adaptive behaviour enables the algorithm to give superior solutions using fewer iterations.

5.2 Performance Contribution and Optimization Factor Analysis.

The fact that the proposed adaptive optimization strategy is able to identify high-quality solutions with the huge contribution of accuracy improvement proves that the proposed strategy is effective. The enhancement in convergence performance implies that the algorithm is able to efficiently work over complex search spaces without having to use huge amounts of computation. Optimization of parameters is crucial since the evolutionary algorithms are very sensitive to the choice of parameters.

5.3 Convergence Behaviour Analysis Figure 3: The convergence analysis of the proposed EDE

One of the most critical issues in evolutionary optimization is that due to premature convergence, the population will lose diversity and become stuck at local optima. The EDE framework proposed remedies this problem by having adaptive mutation and diversity maintenance strategies that enable the undiscouraged exploration of alternative solutions. The concave convergence trend indicates that EDE has an efficient mix between the global exploration and the local exploitation.

5.4 Search Behaviour and Exploration Capability

The dynamic search behaviour shown in Figure 4 gives a clue to the exploration of optimisation landscape by the proposed EDE algorithm. The evolving search pattern is the dynamic motion of candidate solutions in the various optimization levels. Optimization needs to be adequately explored to find new areas of the search space and exploited to narrow down on good solutions. The oscillatory search behaviour reflects that EDE preserves diversity of solutions and gradually searches towards optimal regions. In contrast to traditional DE, search behaviour can be limited because of fixed parameters, EDE dynamically adjusts its search strategy.

5.5 Limitations and Future Research Directions

Despite the good performance of the proposed EDE framework, there are still a number of limitations. To begin with, the algorithms of the evolutionary optimization can be quite computationally intensive when it comes to the optimization problems of very large scale. Second, it is hard to choose the correct adaptive strategies since the various optimization problems can demand various search behaviours. The following research can be carried out in the future: Learning to write self-adaptive EDE algorithms via reinforcement learning. Combining EDE and deep learning models. Construction of multi-objective optimization frameworks based on accuracy, efficiency and interpretability. Using parallel and distributed

EDE to solve large-scale optimization problems. The use of explainable AI methods to enhance transparency. These developments would further enhance the applicability of Enhanced Differential Evolution in advanced artificial intelligence systems.

6. Conclusion

The adaptive mechanisms enable the algorithm to prevent early convergence by maintaining the diversification of the population and an appropriate balance between exploration and exploitation. The features play a vital role in the solution of nonlinear, multimodal, and high-dimensional optimization problems. One of the important contributions of this study is that it is able to develop an effective parameter tuning framework to be applied in machine learning and computational intelligence. Many machine learning models can be optimized in terms of various parameters to obtain the best performance. The suggested EDE algorithm offers an automated optimization approach that will decrease the reliance on manual parameter choice and will enhance the model efficiency.

The ability is especially useful in complex learning systems, where interactions between the parameters can have a strong impact on predictive performance. The stability analysis shows that the suggested EDE algorithm yields consistent and trustworthy optimization outcomes when run in various experimental settings. Because evolutionary algorithms are stochastic, performance can be very volatile, so it is difficult to maintain performance. The results attained show that the adaptive search processes effectively minimize the impacts of randomness and enhance the quality of the solutions that are generated. This renders the proposed framework more applicable in real world applications that involve repeatable and reliable optimization results. The suggested Enhanced Differential Evolution algorithm also leads to the creation of effective artificial intelligence systems.

Third, EDE can have different performance depending on the nature of the optimization landscape and the application domain. Additional future studies could be aimed at creating more sophisticated self-adaptive schemes of Differential Evolution that would automatically modify the optimization strategies based on the methods of reinforcement learning and artificial intelligence. Future directions of EDE involve integrating the system with deep learning systems, federated learning systems, and explainable AI systems to enhance applicability in contemporary intelligent systems. Moreover, it is possible to consider the development of multi-objective Enhanced Differential Evolution methods that can optimize the accuracy of solutions, cost of

computation, interpretability, and strength of solutions at the same time. To sum up, the proposed Enhanced Differential Evolution algorithm offers an effective, flexible and scalable optimization model to global optimization and parameter tuning problems. The proposed method addresses some of the various limitations associated with traditional evolutionary algorithms by enhancing convergence speed, accuracy in optimization, stability, and automated parameter selection. The results validate that adaptive Differential Evolution strategies are an effective way to approach complex optimization problems and create efficient next-generation machine learning and artificial intelligence solutions.

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