Jurnal CoreIT, Vol.10, No.2, December 2024
ISSN 2460-738X (Print)
ISSN 2599-3321 (Online)

Review of Original Differential Evolution Algorithm: Research Trends, Original Setting Parameters

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ABSTRACT. Differential Evolution (DE) has emerged as a widely embraced optimization algorithm, consistently showcasing robust performance in the IEEE Congress on Evolutionary Computation (CEC) competitions. This study aims to pinpoint key regulatory parameters and manage the evolution of DE parameters. We conducted an exhaustive literature review spanning from 2010 to 2021 to identify and analyze evolving trends, parameter settings, and ensemble methods associated with the original differential evolution. Our meticulous investigation encompasses 1,210 publications, including 543 from ScienceDirect, 12 from IEEE Xplore, 424 from Springer, and 231 from WoS. Through an initial screening process involving skimming title and abstract to identify relevant subsets and eliminate duplicate entries, we excluded 762 articles from full-text scrutiny, resulting in 358 articles for in-depth analysis. Our findings reveal a consistent utilization of tuning parameters, self-adaptive mechanisms, and ensemble methods in the final collection. These results enhance our understanding of DE's success in CEC competitions and offer valuable insights for future research and algorithm development in optimization fields.

Keywords: Review of original, Differential evolution (DE), original differential evolution

Received July 2024 / **Revised** October 2024 / **Accepted** October 2024

INTRODUCTION

The theoretical underpinnings of Differential Evolution (DE) research, including DE theories and their benefits and drawbacks, are explained in this chapter. The research was conducted to address DE's shortcomings, mutation strategies, and control parameter setting.

Since Storn and Price first introduced DE, research has been conducted to improve its performance[1]. DE's two-phase operation has a positive impact on its success. i. e. exploration and exploitation[2]. The majority of DE research has demonstrated that exploration and exploitation in DE are impacted by the setting of control parameters like scale factor (F), cross overate(CR), and population size (NP). The research on adaptive differential evolution examines the impact of CR and F on two phases [3]. When large F is selected, exploration ability increases while exploitation ability decreases, and vice versa. Although a large F may maintain a diversity of solutions, it can potentially hinder the algorithm's optimization capability..

Since 2005, numerous of Differential Evolution (DE) variants have consistently distinguished themselves by securing a place among the top three algorithms in the CEC competitions year after year. However, in 2013, DE experienced a deviation by achieving 4th place. Although this was a singular occurrence, it highlights the dynamic nature of algorithmic performance and underscores the need for ongoing efforts to refine and optimize DE to meet the diverse challenges in the ever-evolving landscape of computational intelligence competitions.

The structure of this paper is as follows: section 1. Methodology 1.2 search strategy, 2. Data collection process 2.1. Assessment of the study quality, and data synthesis and 2.2 The result of literature taxonomy

DOI: 10.24014/coreit.v10i2.29903

of differential evolution algorithm, and 1.3 search strategy. Section 3.Research result, 3.1 Journals with important articles, 3.2. Differential original structure, 3.3 Review on effort done for modification of original DE, 3.4 Parameter tuning, 3.5 Self-adaptive, and 3.6 Ensemble, and last section 4. Conclusion and future works.

METHODS

Search strategy

The article search utilized four digital databases: (1) the Springer Link database, (2) the IEEE Xplore library of engineering and technology technical literature, (3) the IEEE Xplore database, and (4) the Web of Science (WoS) service, which indexes cross-disciplinary scientific research, sociological studies, arts, and humanities. This choice was made to give a wider perspective on researchers' efforts across a diverse but relevant range of fields, to include both theoretical and technical literature.

Table 1. Result search journal in databases

Stage	Query	Search Engine	articles	Remarks
1	"Differential Evolution" AND ("Self adaptive" OR "Self-adaptive" OR "Self-adapting" OR "Self-adapting" OR "Self adjust" OR "Self-adjust" OR "Self-adjusting" OR "Self-adjusting") AND ("Control parameters" OR parameters) AND ensemble	Web of Science Springer IEEE	231 424 12	Years: 2010 – 2023. Exclude Proceedings
2	"Differential Evolution" AND ("Self adaptive" OR "Self-adaptive" OR "Self-adapting" OR "Self adjust" OR "Self-adjust") AND ("Control parameters" OR parameters) AND ensemble	Science Direct	543	Years: 2010 – 2023. Exclude Proceedings

The tabulation of search results for ScienceDirect is shown in Table 1 via using the search fields on the Springer and WoS databases. The search employs the fourth set of keywords. Differential Evolution was in category one, Self-adaptive were included in the second category, whereas Adaptive on its own category. Keyword parameters involved includes "Automatically adjust" & "Self-adjusting". By using the "OR" operator, "Self-adjusting" is combined. In the third group, there were "control parameters". By using the "OR" operator and the final filter "ensemble," "parameters" are combined. Using AND, the fourth group is combined. Table 2 displays the exact query text. In addition, each search engine has options that can be used to filter out book chapters and other documents besides journal and conference articles, such as reports. These two venues is determined to be the most likely to contain current and appropriate scientific works pertinent to this study on the emerging trend of DE.

In Figure 1 the first search, 1,210 publications from 2010 to 2023 were found, including 231 from ScienceDirect. 12 from IEEE Xplore. A total of 424 from Springer and 543 from WoS. The articles were examined twice; the first round involved skimming the title and abstract to identify the most pertinent list of articles and to weed out duplicates. 762 articles are excluded from full-text reading, leaving 358 items out for a variety of reasons. There were 358 articles in the final collection that was included.

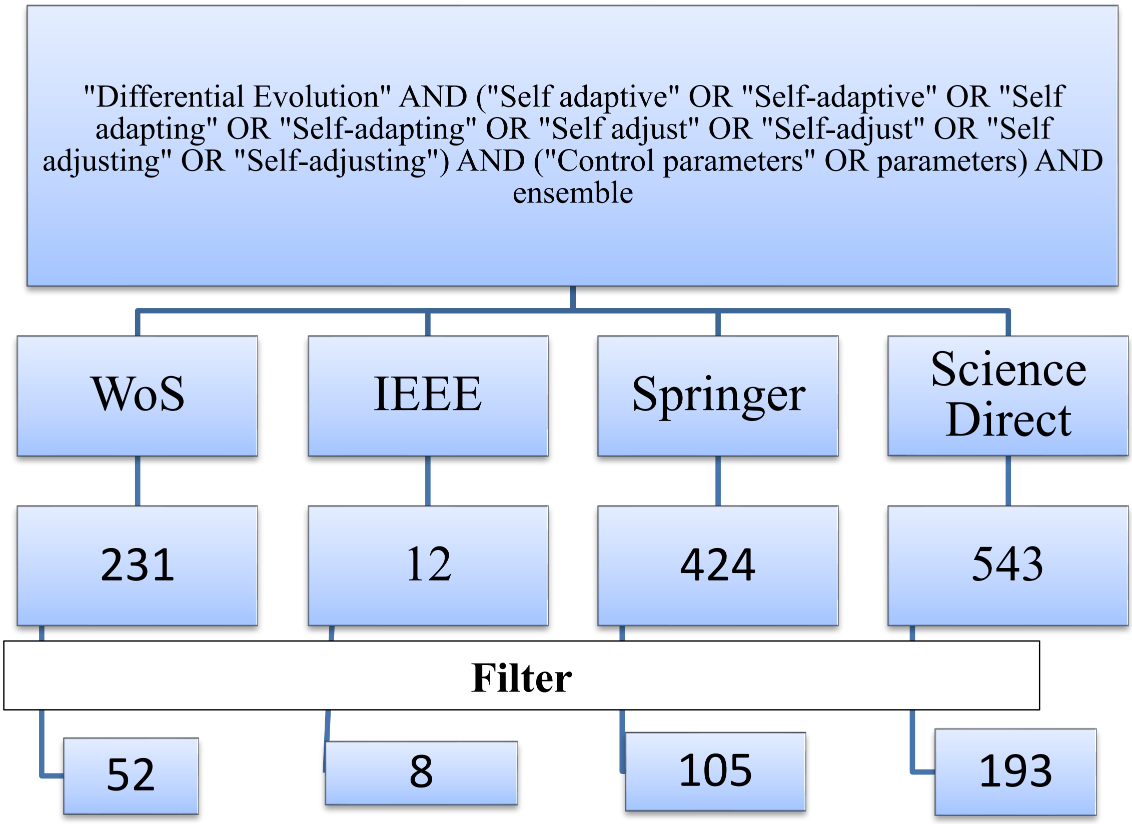

Figure 1. Flowchart of a systematic review of study selection

Regarding the application of the filter across databases, it appears that the filtering process was applied uniformly across all databases, including WoS, even though the figure does not show a specific reduction for WoS. The absence of filtered WoS results in the figure might be a visualization oversight, as the same two-stage filtering was applied to articles from all databases. Therefore, the filtering was not limited to IEEE, Springer, and ScienceDirect but was applied consistently across all sources, including WoS, ensuring that only the most relevant studies were retained in the final analysis.

DATA COLLECTION PROCESS

The study that served as the foundation for this article's data collection only looked at closely related DE issues. Self-adaptive is among them, apart from setting changes for parameters and hybrid evolutionary algorithms-based DE techniques. According to the characteristics examined (year of publication), the total number of articles collected is meticulously categorized into a systematic review table, consisting of field of study, description, methodology, motivation, challenges, additional work or suggestions. Tables are utilized to analyze the summaries of these articles. Using the fundamental taxonomy, all articles were grouped. The information on the research purpose for that particular sector is contained in the data table highlighted by the aforementioned criteria. The issues addressed, suggestions for future growth. Also enforced were the variables that affected the control parameters and mutation methods. Finding out how any changes to parameter settings will affect the entire evolution stage is the main goal of this inspection phase after gathering a large number of pertinent papers and making them available on WoS, ScienceDirect, Springer, and IEEE Explore. Top priority is given to these areas, with a condensed summary provided of the analysis of the articles received.

Assessment of the Study's Quality and Data Synthesis

Making decisions based on synthesis results and evaluating the reliability of inferences are supported by assessing the quality of a piece of research. Data synthesis aims to compile data from various studies to address the particular research questions under investigation. A strong case can be made with the help of multiple pieces of evidence. To combine data gathered from different research topics, this review's data includes both quantitative and qualitative data. There were several techniques employed. The information was organized using the queries and the narrative synthesis methodology. To increase the accuracy statistics and distribution of differential evolution, additional visual tools were used, including bar graphs, pie chart, and table illustrations.

The result of the Literature Taxonomy of Differential Evolution Algorithm

In order to conduct additional research, the author created network and density visualization maps using "VOSviewer". Circular shapes and labels make up a network visualization and the links (relationship between the items) that link them. Based on the colours they were assigned, objects are grouped into clusters. Figure 2 displays a visualization of keyword co-occurrences in peer-reviewed articles. Numerous words are associated with optimization, overall improvement, and the use of evolutionary algorithms. However, most frequently used is the phrase "differential evolution". Figure 4 shows a network of words that were taken from peer-reviewed paper titles and abstracts. The number of connections indicates how many articles contain two phrases together. Here, along with other words like "ensemble," "benchmark problem," and "technique," the word "model" is the one that appears the most.

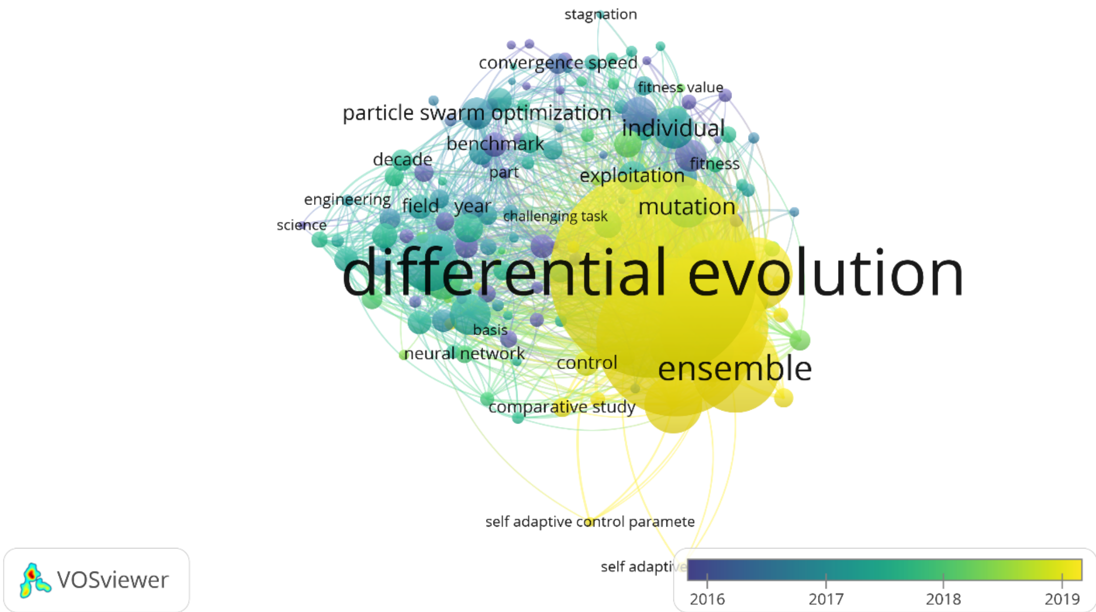

Figure 2. Visualization of the keyword network

1,210 publications from 2010 to 2023 were returned by the initial search, including 543 from ScienceDirect, 12 from IEEE Xplore, 424 from Springer and 231 from WoS. The articles were examined twice; the first time, the title and abstract were skimmed for the most pertinent list of articles and to weed out duplicates. 1,210 articles are excluded from full-text reading, leaving 762 items out for a variety of reasons. A total of 358 pieces made up the final collection.

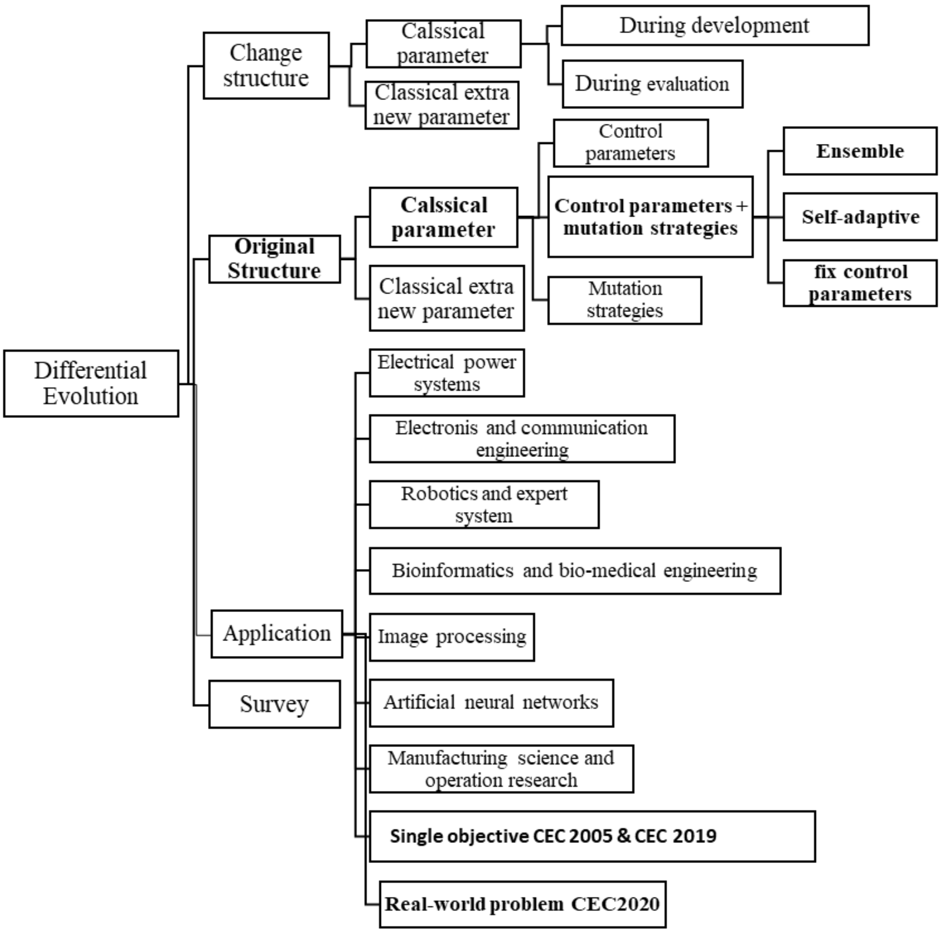

Figure 3. Taxonomy of Differential Evolution

Figure 3, by the author provides results of journal reviews from 2010 to 2021. DE is the focus of this study. There are various change structures in DE original framework, in terms of their application and survey. The classical and classical extra parameters make up the change structure[4–12]. The original structure's DE division is transformed into new parameters added to the classical parameters.

RESULT AND DISCUSSION

Journals with Important Articles

This review of the literature includes 60 original papers that examine the effectiveness of software defect prediction. Figure 6 summarizes the distribution studies conducted over the years and shows how the distribution over time demonstrates the evolution of interest in software fault prediction. More studies have been published since 2010. They advocate including more recent and pertinent investigations. Figure 4 shows how important the field of differential evolution is for the most recent date.

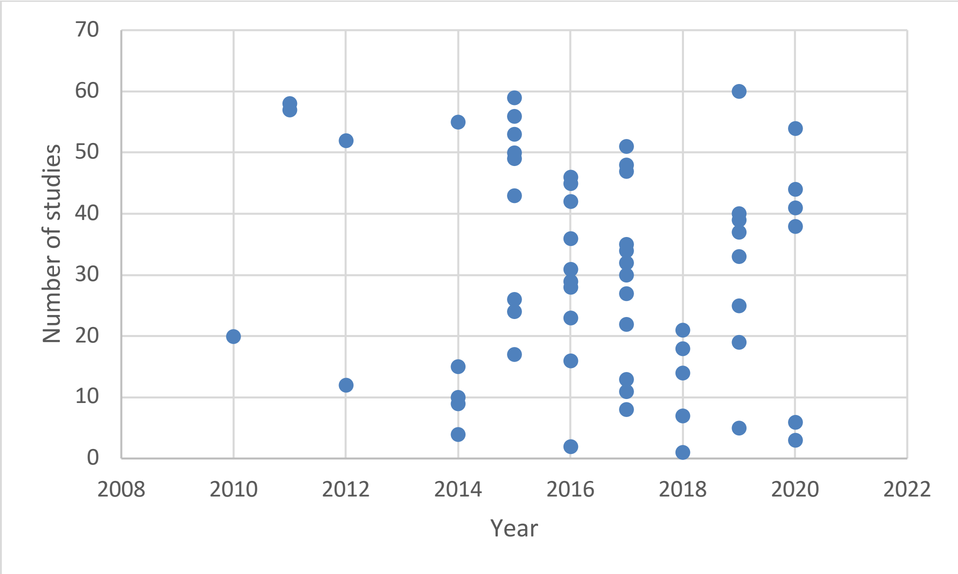

Figure 4. Distribution of Study Time

Based on the chosen primary research works, Figure 5 illustrates the prominent journals in the realm of differential evolution. It's important to mention that the graph doesn't encompass conference proceedings.

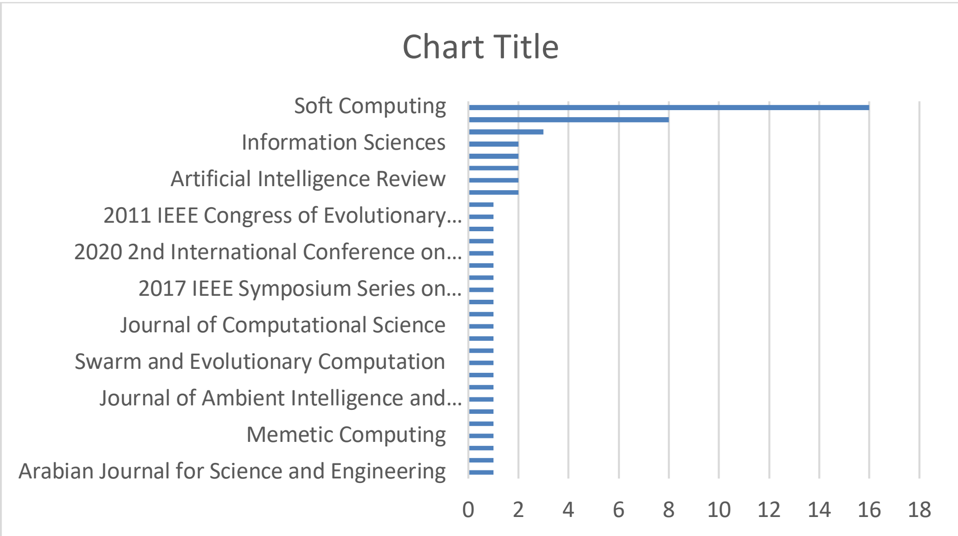

Figure 5. Publication in Journals and Distribution of Selected Studies

In Table 2, the most frequently cited differential evolution on original parameters journals are listed along with their Scimago Journal Rank (SJR) scores and Q categories (Q1-Q2) by SJR value, journal publications are arranged alphabetically.

Tabel 1. The Selected Journals' Scimago Journal Rank (SJR)

No	Journal Publication	SJR	Q Catagory
1	Information Sciences	Q1	1.52
2	Computers and Operations Research	Q1	1.51
3	Swarm and Evolutionary Computation	Q1	1.46
4	Expert Systems with Applications	Q1	1.37
5	Applied Soft Computing	Q1	1.29
9	Artificial Intelligence Review	Q1	1.20
6	PLOS ONE	Q1	0.99
7	Applied Mathematics and Computation	Q1	0.97
10	Memetic Computing	Q1	0.83
15	Applied Intelligence	Q2	0.79
11	Optimization Letters	Q1	0.72
12	Neural Computing and Applications	Q1	0.71
8	Journal of Computational Science	Q1	0.70
13	International Journal of Machine Learning and Cybernetics	Q1	0.68
16	Soft Computing	Q2	0.63
17	Chemometrics and Intelligent Laboratory Systems	Q2	0.60
14	Journal of Ambient Intelligence and Humanized Computing	Q1	0.59
18	The Journal of Supercomputing	Q2	0.45
19	Natural Computing	Q2	0.41
20	Frontiers of Computer Science	Q2	0.41
21	Arabian Journal for Science and Engineering	Q2	0.36
22	OPSEARCH	Q2	0.35
23	Evolutionary Intelligence	Q2	0.32

Differential original Structure

The impact of CR on the functionality of DE has been documented in earlier studies. The quality of optimal solutions degrades with increasing CR, while algorithmic performance becomes unresponsive with decreasing CR. Despite the fact that there is no particular regulation for setting F and CR. The algorithm's functionality is determined by the setting [13]. $F \in [0.5, 1.0)$ and $CR \in [0.6, 1.0]$ are the only general conclusion that can be drawn from the given parameters. However, given that an effective parameter setting depends on problems the conclusion isn't guaranteed to hold true for all situations[14] similar to the majority of EAs. The development of promising solutions is hampered by using a small NP thus causes premature convergence and stagnation [15].

However, increasing NP too much can slow down convergence or lead to many ineffective solutions [16]. If DE is applied to a noisy, high-dimensional optimization problem, then parameter setting becomes even more critical. Researchers have developed various techniques to address the challenge of high-dimensional optimization. The ability to identify promising new solutions will increase as the population grows. An issue with a fitness landscape that varies over time is referred to as a noisy optimization problem. In other words, the global optimum has shifted or changed. This change is difficult to predict in advance because DE operates within a noisy fitness function. Deterministic F alone might not be sufficient. In other words, the F, CR, and NP settings have an impact on the generation of the solution space, which ultimately has an impact on the convergence and robustness of DE in problem-solving. The related work has been distilled into a self-adaptation scheme and ensemble strategies by Rammohan Mallipeddi and Suganthan, who also propose various DE parameter tuning techniques [17]. Nevertheless, the researchers offer some suggested ranges for the pre-conditions and the control parameters. The setting is not justified in a logical and consistent manner.

The suggested research area consists of the studies in Figure 3. DE classical parameters are made up of control parameters and mutation strategies. The control parameter is divided into an ensemble in this study area, involving control parameters that are both self-adaptive and fixed particularly in the ensemble region[11], [18–21].

Storn and Price's original algorithm has been improved through research into the modification of the original DE. The majority of traditional DE research has demonstrated the setting of control parameters like F, CR, and NP [22]. Setting parameters is a contentious issue that is essential for spreading better values and identifying the best solutions. The values of the control parameters CR and F are not determined by any particular rules. In spite of this, Mallipeddi's DE is affected by the setting [23]. As an illustration, an enormous value of F improves exploitation but decreases exploration, and vice versa. The quality of optimal solutions declines as CR rises, and the algorithm becomes unresponsive as it falls. By maintaining a fixed population size and scale factor to avoid early convergence and stagnation, the significance of F and CR in affecting the convergence velocity and robustness of the search process is tested [24].

Review on Effort done for Modification of original DE

Since DE's founding in 1995, there has been much discussion about the value of exploration and exploitation. The primary agenda created by these two factors is dealing with problems involving large-scale global optimization (LSGO). The common metaheuristic algorithms utilizing DE are involved in these issues such as the size restriction on search spaces and the curse of dimensions. The majority of algorithms perform worse when dealing with high-dimensional problems. The complexity of the landscape involved and characteristic modification increase as the problem dimension gets bigger[16]. Alongside the growth of the problem space, the search space also expands. An algorithm's capacity to efficiently search the entire search space is a requirement for optimization. It consequently results in high costs and increased time consumption[16].

Control parameters and evolutionary operators have a significant impact on how DE strategies behave, according to Yiqiao, who attempted to implement exploration steps using hybrid linkage crossover [25]. Due to DE's linkage blindness, the search process was not effectively guided by the problem-specific linkages. The use of swarm intelligence and evolutionary algorithms for optimization in dynamic environments is problematic because the algorithm must be able to recognize and track optimal positions in such environments [26]. Based on the characteristic that varies from method to method, the population set is skewed toward the new set point. The forced redirecting towards randomness would not ensure that the solution steps would replicate an ideal solution [27]. The goal of the local search producer is to hasten the exploitation of local optima without reducing the algorithm's ability to explore the entire world. The shortcomings of attempting to strike a balance between exploration and exploitation are also highlighted [3], in which reducing the convergence rate enhances the algorithm's capacity for exploration. Through global exploration and local exploitation stages, Mallipeddi's research on ensemble mutation strategies also aims to address constrained optimization in order to take advantage of the compatibility between constraint handling techniques [28].

Parameter Tuning

For early adaptations of DEs, the process occasionally skips over control parameters during the evolution phase. They were considered to have little bearing on overall processes, acting more as a catalyst for outside factors. However. Since achieving optimum convergence required more objective functions. To achieve the desired result, it was decided that the process should take into account the value of the control parameters [29].

Heuristic techniques are used to gradually change the control settings while taking into account valid data about the advancement. Heuristic rules exist in a lower dimensional space and are suitable for solitary functions. Nevertheless, they fall short of supplying sufficient convergence for a subsequent multi-dimensionality problem [30]. When effervescent processes are included in evolutionary processes, parameter tuning is added to the evolution process, allowing the secondary parameters to be adjusted with ease. The tuning and parameter control techniques are the two main ways to choose initial parameter values [31].

Self-Adaptive

For unrestricted optimization problems, Zhiwei and Jingming proposed a differential evolution algorithm with self-adaptive strategy and control parameters [32]. It has been demonstrated that this approach can solve problems involving constraints and multiple objectives while also adapting to different evolutionary stages based on prior experience. The ability of surrogate models to approximate the fitness function in control parameters was also demonstrated by Xiaofen and Tang using a self-adaption scheme[33]. This approach demonstrates how self-adaptation could outperform other adaptive DE variants in terms of performance.

Elsayed additionally utilized a self-adaptive combined strategies algorithm for constrained optimization using DE [2]. The fulfillment of particular mathematical properties is not necessary for this method. Robust to dynamic changes, it organizes itself adaptably and has greater accessibility in real-world use. To address other optimization issues, Laizhong and Genghui imposed adaptive DE algorithms with novel mutation strategies in numerous sub-populations. Including multi-objective optimization with constraints[34].

The improvisation for self-adaptive approaches is concentrated on the aim of exploitation or exploration. To the fullest extent possible, these conditions cannot coexist. The work specialization already in place is typically enhanced by DE stages[35]. Incorporating adaptive factors into the selection of the parents who go through mutation to produce offspring is another aspect of modifications. as demonstrated by the work by Das and Mallipeddi to identify the p-best mutation strategy using adaptive evolutionary programming[36]. In addition to changes to the variable itself. In order to implement targeted population distribution and solution-searching strategies for offspring generation, DE modifies population size. Throughout this procedure, hybrid approaches were used [15][37][38][39].

Global numerical optimization is viewed as being inferior to adaptive strategy[40]. Venske developed Protein Structure Prediction as a multi-objective optimization problem and applied ADEMO/D (Adaptive Differential Evolution for Multi-objective Problems based on Decomposition) to the optimizer problem[40]. By taking first place in the CEC2009 multi-objective optimization competition, this decomposition-based framework based on the classification of protein structures proved to have superior performance. A complicated multi-objective optimization problem was also shown to be amenable to it.

Adaptive methods have been viewed as unconventional performance improvements for multiple dimensionality issues and convergence speed in the context of optimization. In order to test his adaptive hybrid DE, Asafuddoula created the AH-DE, which uses binomial crossover for exploration and exponential crossover for exploitation. It was tested on 40 mathematical benchmarks as well as two shape-matching problems [40]. The findings indicate that hybrid DE inherits the advantages of numerous tried-and-true tactics. In accordance with Kusakci and Can, Ali Osman used an adaptive penalty-based covariance matrix adaptation evolution strategy in addition to an adaptive weight adjustment scheme [41]. To fix the flaw in the numerical optimization problems, Yu Xue demonstrated an ensemble algorithm with self-adaptive learning techniques[42]. Experimental evidence shows that the strategy and parameter adaptation significantly boost the efficiency of evolutionary algorithms.

The DE field and nature-inspired algorithms are not the only areas where self-adaptive techniques are used. Particle swarm organization and opposition-based sampling are just two examples of algorithms that have had their evolution and crossover stages hybridized[43][44]. With the help of opposition-based sampling for distance to optima (OBS-DTO), Rahhamayan developed a Euclidean distance-to-optimal solution[44]. Studies comparing the two have shown that the convergence speed of opposition-based differential evolution is faster than that of differential evolution[42].

Assimilation of non-invasive quantities into coronary artery simulations from non-invasive clinical targets is accomplished by Tran's automatic Bayesian approach to parameter estimation, which is based on adaptive Markov Chain Monte Carlo sampling[45]. The covariance matrix-based migration was developed by Chen to reduce the dependence of biogeography-based optimization (BBO) on the coordinate system [34]. This study was conducted based on the theory that covariance matrix learning (CML) efficiently adapts the search to the topography of the optimization function. For the DE framework, Poikolainen proposed a method to carry out an intelligent initialization for a population-based algorithm using cluster-based population initialization [40].

Zhang implemented a new associative model based on variable-mode decomposition and learning to enhance prediction performance for short-term wind energy forecasting in China's Jiangsu province[46]. Ikeda successfully utilized a genetic algorithm DE to establish frameworks for optimizing energy system operating schedules, incorporating internal Particle Swarm Optimization (m-PSO) for mutation, cuckoo search, and self-adaptive learning bat algorithm [47]. Ikeda also used the algorithm DE to establish frameworks for optimising energy system operating schedules, applying internal Particle Swarm Optimization (m-PSO) for mutation, cuckoo search, and the self-adaptive learning bat algorithm[47].

Ensemble

In order to address optimization issues, the evolutionary algorithm has recently come to embrace the ensemble method specifically those that occur in multimodal contexts. Using a collection of niching techniques, Mallipeddi creates four parallel populations that are connected by a single niching method[23]. These populations use genetic algorithms as their search technique. It employs the niching approach. Each merged group's parents would be chosen by each population for the subsequent generation. By using this technique, the best progeny will be retained in accordance with niching's selection criteria[48]. By using this method, the best offspring created in the ideal conditions would be preserved.

To enhance its already positive qualities, particularly in terms of simplicity, robustness, and computing effectiveness, DE has been impaled with a variety of variable generation techniques and adaptive machineries. When optimizing a wide variety of objective functions, DE produces exceptional results in terms of ultimate accuracy, computational speed, and resilience[49]. DE and its variants, such as Self-adaptive Different Evolution[50]. EPSDE an ensemble of multiple DE variants (EDEV) [51] produce significantly better global optima results than genetic and particle swarm optimization algorithms (Arya et al., 2012). On the other hand, DE is still plagued by a number of parameter setup issues, particularly the dimensionality of the problems and the scale factor, crossover rate, and population size. The effects of these problems seem to be more pronounced during the stages of solutions with both many and singular goals.

Ensemble-based DE could be seen as an effort to fit the mutation and crossover strategies in a smaller space while keeping a constant convergence rate. The ensemble learning paradigm can be used to correct complex data series for data types with a wider range of irregularity and unpredictability. For a larger population, ensemble methods are useful in promoting a higher convergence rate[51] [42]. Due to the focus on developing a successful model, ensemble methods also have the ability to improve the stability of overall prediction performance by reducing the variance of estimated errors[53]. This method works effectively and efficiently for changing various control parameters or strategies online [54]. A measure to lessen DE's performance deficiencies in noisy problems is the randomization strategy [55]. The ensemble-based approach enables DE to choose its parameter control and adjust it to take into account the most viable solution, typically within a predicted range. In a number of earlier works, the effects of population size, dimensionality, and mutation strategies have also been discussed in relation to how to best use the convergence rate and computational time to achieve global convergence. The effects of ensemble methods on population size, however, need to be further studied because the topic has not received enough attention[56][57][58][59].

CONCLUSION

In this review, we examined the research trends and original setting parameters of the Differential Evolution (DE) algorithm. Through an extensive analysis of 1,210 publications, we identified key regulatory parameters, self-adaptive mechanisms, and ensemble methods that contribute to the success of DE in optimization fields, particularly in the IEEE Congress on Evolutionary Computation (CEC) competitions. Our findings reveal a consistent utilization of tuning parameters, self-adaptive mechanisms, and ensemble methods in the DE variants analyzed. The control parameters F (mutation factor), CR (crossover rate), and NP (population size) were identified as crucial factors affecting the exploration and exploitation abilities of DE. The research also highlighted the impact of large F values on exploration and exploitation trade-offs, emphasizing the need for careful parameter setting to ensure effective optimization.

Furthermore, our study observed the dynamic nature of algorithmic performance, as evidenced by DE's occasional deviation from top rankings in the CEC competitions. This underscores the importance of ongoing efforts to refine and optimize DE to meet diverse challenges in the evolving landscape of computational intelligence competitions.

Future Work:

Based on the outcomes of this systematic literature review, several directions for future research and algorithm development in DE and optimization fields can be suggested:

1. Investigation of Novel Parameter Setting Methods: Further research can focus on developing innovative methods for automatically setting the control parameters in DE. This can include adaptive or self-adjusting mechanisms that dynamically adjust the parameter values during the optimization process based on problem characteristics or performance feedback.
2. Hybridization with Other Optimization Techniques: Exploring hybrid approaches by combining DE with other metaheuristic or machine learning algorithms can be a promising avenue. This can potentially enhance the performance and convergence speed of DE, particularly in solving complex and large-scale optimization problems.
3. Benchmarking and Comparative Studies: Conducting comprehensive benchmarking experiments and comparative studies can provide deeper insights into the strengths and weaknesses of different DE variants. This can help researchers and practitioners in selecting the most suitable DE configuration for specific problem domains and settings.
4. Real-World Applications: Applying DE and its variants to real-world optimization problems in various domains, such as engineering, finance, and healthcare, can validate their effectiveness and practical applicability. This can involve addressing specific challenges and constraints encountered in real-world scenarios.
5. Theoretical Analysis and Understanding: Further theoretical analysis and understanding of DE's behavior, convergence properties, and exploration-exploitation trade-offs can contribute to advancing our knowledge of this algorithm. This can lead to the development of more efficient and effective DE variants.

By pursuing these future research directions, we can continue to enhance the performance, versatility, and applicability of DE in solving complex optimization problems across different domains.

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