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Enhancing Multi-Objective Optimization Through Differential Evolution and Rough Sets Theory: A Novel Proposal

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Abstract
This study presents a unique method based on Rough Sets Theory (RST) and Differential Evolution (DE) to improve multi-objective optimization. In many different domains where it is necessary to simultaneously optimize conflicting objectives, multi-objective optimization problems are common. The research provides a novel approach to multi-objective optimization dubbed DEMORS (Differential Evolution for Mult objective Optimization with Random Sets), which consists of two phases: a local search phase using rough sets following the first Differential Evolution-based phase. Empirical analysis shows that DEMORS performs better on nine benchmark issues than the state-of-the-art NSGA-II algorithm, albeit with larger variability and overall better mean values. The computational studies, which used 3000 fitness function evaluations each run, showed that DEMORS is a good stand-in for real-world applications with high processing costs since it efficiently converges to the true Pareto front with fewer evaluations. The performance measurements, namely SSC, standard deviation of crowding distances, and unary additive epsilon indicator, further validate the efficacy of DEMORS in providing a computationally efficient and competitive solution for multi-objective optimization problems. By providing a viable framework that combines the best aspects of both DE and RST, this research advances the field of multi-objective optimization and opens the door to more effective and dependable optimization solutions in real-world settings.

Keywords: *Multi-Objective, Optimization, Differential, Evolution, Rough Set, Theory*

I. INTRODUCTION

A basic difficulty in many domains, including operations research, engineering, and finance, is multi-objective optimization (MOO), which requires decision-makers to simultaneously optimize many competing objectives. MOO, as contrast to single-objective optimization, calls for identifying a collection of solutions—often referred to as Pareto-optimal solutions—that reflect trade-offs between conflicting objectives. MOO is complicated because it requires balancing these goals while navigating a high-dimensional decision space, which presents difficult algorithmic and computational problems. The three main traditional approaches to MOO—mathematical programming, swarm intelligence, and evolutionary algorithms—each have their own benefits and drawbacks. As a reliable evolutionary algorithm, Differential Evolution (DE) has gained popularity. It is renowned for its ease of use, effectiveness in global optimization, and capacity to manage complex, noisy optimization situations. Through mutation, crossover, and selection processes, DE keeps a population of candidate solutions that grow across iterations, efficiently exploring and utilising the search space to converge towards optimal or nearly optimal answers. However, Rough Sets Theory (RST) offers a mathematical framework for handling imprecision and uncertainty in decision-making. RST, which has its roots in data mining and artificial intelligence, makes complicated decision systems easier to analyses by reducing and simplifying data while maintaining its most important features. RST is very helpful in managing different and unclear optimization aims since it defines discernibility matrices and equivalency relations, which enable the construction of decision rules that classify data into distinct groups. In order to improve MOO capabilities, a novel technique integrating DE and RST is proposed in this study. Premature convergence, low diversity of solutions, and ineffective exploration of the Pareto-optimal front are some of the issues in MOO that are intended to be addressed by the combination of DE's evolutionary principles and RST's capacity to handle uncertainty. Our suggested method aims to enhance the convergence speed and solution quality in MOO tasks by fusing the exploration-exploitation balance of DE with the uncertainty managing capabilities of RST.

The primary goals of this research are twofold: first, to create a hybrid DE-RST framework specifically designed for MOO that takes advantage of the complementary advantages of both approaches; and second, to compare the suggested strategy's performance to current cutting-edge MOO algorithms empirically and validate it. Our goal is to show the effectiveness and competitiveness of the DE-RST technique in generating well-distributed, high-quality Pareto-optimal solutions through extensive tests on common benchmark problems. This work advances the field of multi-objective optimization by providing a new and efficient framework that uses uncertainty management and evolutionary computation. The combination of DE and RST broadens the methodological toolbox for MOO and creates new opportunities to tackle challenging real-world optimization issues in a variety of application domains.

II. REVIEW OF LITREATURE

Abdolrazzagh-Nezhad, Radgohar, and Salimian (2020) propose an enhanced cultural algorithm (CA) aimed at solving the multi-objective attribute reduction problem using rough set theory (RST). The study addresses the challenge of feature selection in data mining and pattern recognition, where the goal is to identify a minimal subset of attributes that retains the essential information. By integrating CA with RST, the authors enhance the algorithm's ability to handle uncertainty and complexity inherent in attribute reduction tasks. The experimental results demonstrate the effectiveness of their approach in producing Pareto-optimal solutions that balance attribute subset size with classification accuracy, highlighting its potential in improving computational efficiency and decision-making processes in data-intensive applications.

Hancer (2019) presents a novel approach that combines fuzzy kernel feature selection with the multi-objective differential evolution (MODE) algorithm. The study addresses feature selection challenges in pattern recognition and classification tasks, where traditional methods often struggle with high-dimensional and noisy datasets. By leveraging fuzzy kernel methods to enhance the discriminative power of features and integrating them with MODE, the proposed algorithm aims to improve the robustness and accuracy of feature selection outcomes. Experimental evaluations on benchmark datasets demonstrate that the approach effectively balances multiple objectives such as feature relevance and redundancy, showcasing its potential to enhance the performance of machine learning models in real-world applications.

Hancer (2020) introduces an innovative multi-objective differential evolution (MODE) approach tailored for simultaneous clustering and feature selection tasks. The research addresses the dual challenge of partitioning data into meaningful clusters while identifying relevant features that contribute to cluster quality and interpretability. By formulating clustering and feature selection as concurrent optimization objectives, the proposed MODE approach aims to uncover hidden patterns in data and improve the overall understanding of complex datasets. Empirical evaluations across various datasets demonstrate that the method achieves competitive clustering accuracy and feature selection effectiveness compared to existing approaches, underscoring its potential utility in exploratory data analysis and knowledge discovery tasks.

Hancer's (2020) study introduces new filter approaches for feature selection by integrating differential evolution (DE) with fuzzy rough set theory (FRST). The research focuses on enhancing the efficiency and effectiveness of feature selection processes in data mining and pattern recognition applications. Filter methods are particularly valuable in preprocessing stages where feature subsets are evaluated independently of specific learning algorithms. By leveraging DE, which is known for its robustness in optimization tasks, and FRST, which handles uncertainty and vagueness in data through fuzzy logic, the proposed approaches aim to identify optimal feature subsets that maximize classification accuracy while minimizing computational overhead. Experimental evaluations on benchmark datasets demonstrate that the hybrid methods outperform traditional filter techniques, illustrating their potential to streamline feature selection workflows and improve the performance of machine learning models in diverse domains.

Meenachi and Ramakrishnan (2020) present a novel approach that integrates differential evolution (DE) and ant colony optimization (ACO) for global optimal feature selection in cancer data classification. The study addresses the critical need for accurate and interpretable models in biomedical informatics, where identifying relevant biomarkers from high-dimensional data is paramount for disease diagnosis and prognosis. By combining DE's capability to efficiently explore solution spaces and ACO's ability to mimic natural optimization processes, the proposed method seeks to identify informative features while minimizing the risk of overfitting and improving generalization performance. Additionally, fuzzy rough set theory (FRST) is employed to handle imprecision and uncertainty in medical data, ensuring robust feature subset selection that aligns with clinical insights. Experimental results on cancer datasets demonstrate that the hybrid approach achieves competitive classification accuracy compared to state-of-the-art methods, underscoring its potential to aid clinicians and researchers in identifying predictive biomarkers and enhancing decision support systems in healthcare applications.

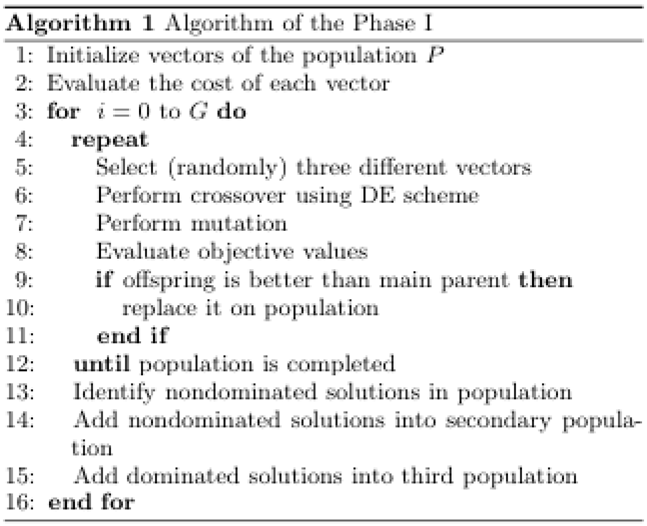
III. OUR PROPOSED APPROACH

DEMORS (Differential Evolution for Multiobjective Optimization with Irregular Sets), the strategy we propose, is parted into two phases, every one of which requires a set number of wellness capability assessments.

Our DE-based MOEA is utilized in Stage I to assess 2000 wellness capabilities. In Stage II, 1000 wellness capability assessments are led utilizing a nearby pursuit system in view of rough sets theory, determined to upgrade the responses created in Stage I. In the wake of leading countless examinations, these two qualities — the 2000 and 1000 wellness capability assessments, which address a 65%-35% equilibrium — not entirely settled. These two phases are made sense of in more profundity underneath.

Phase I : Use of Differential Evolution

Algorithm 1 shows the pseudo-code of our recommended DE-based MOEA. In our strategy, three populaces are kept up with: the essential populace (used to pick the guardians), an optional (outside) populace used to clutch the nondominated arrangements found, and a third populace used to clutch the ruled arrangements separated from the subsequent populace.



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Algorithm 1 Algorithm of the Phase I
Initialize vectors of the population $P$
Evaluate the cost of each vector
for $i = 0$ to $G$ do
  repeat
    Select (randomly) three different vectors
    Perform crossover using DE scheme
    Perform mutation
    Evaluate objective values
    if offspring is better than main parent then
      replace it on population
    end if
  until population is completed
  Identify nondominated solutions in population
  Add nondominated solutions into secondary population
  Add dominated solutions into third population
end for
```

We start by making 25 people indiscriminately, then we utilize those people to make 25 youngsters. Two determination systems in Stage I are set off by the all out number of ages and a choice tension managing boundary named sel2 ∈ [0, 1]. For example, if sel2 = 0.6 and Gmax = 200 is the all out number of ages, then an irregular determination will be utilized for the initial 120 ages (or 60% of Gmax), and an elitist choice will be utilized for the last 80 ages. A solitary parent is picked as the reference in both the irregular and elitist choice cycles.

The kids created by the three unmistakable guardians are contrasted with this parent. During the creating system, this strategy guarantees that each parent of the essential populace will act as a kind of perspective parent only a single time. Following is a portrayal of both determination techniques:

1. Arbitrary Determination: From everyone, three unmistakable guardians are picked aimlessly.
2. Elitist Determination: From the optional populace, three particular guardians are picked. It is essential for these three guardians to be near each other. If no gathering of three individuals meets this rule, a gathering of three individuals is picked indiscriminately from the optional populace. The accompanying articulation is utilized to evaluate closeness:

$$f\ close = \sqrt{\frac{\sum_{i=0}^{FUN}\left(X_{i,max} - x_{i\ \min}\right)^2}{2\ FUN}}$$

were

FUN is equivalent to the amount of objective capabilities.

In the auxiliary populace, Xi,max addresses the upper bound of the I-th objective capability.

Xi,min is the lower bound of the auxiliary populace's I-th objective capability.

In Stage I, recombination is completed by following this convention: The age of the kid vector −→h for each parent vector −→pi ; I = 0, 1, 2,...,P − 1 (P = populace) is finished as follows:

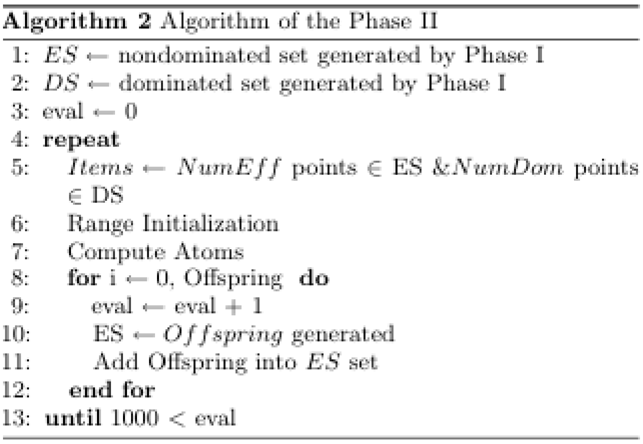
$$\left(\boldsymbol{x} \in \cup\ (\boldsymbol{0},\boldsymbol{1})\right)\left\{\boldsymbol{h_j} = \boldsymbol{p_r 1}, \boldsymbol{j} + \boldsymbol{F}(\boldsymbol{P_{r1,j}} + \boldsymbol{F}(\boldsymbol{P_{r2,j-P_r3,j})}\quad \boldsymbol{If\ x < P}$$

Pareto front, and each point overwhelmed by this new competitor is disposed of from the set. A point is at last remembered for this populace on the off chance that it isn't overwhelmed here. Like the subsequent populace, a dad predominance network will be made to oversee and ensure a fair circulation of focuses on the off chance that the third populace develops to a size of 100 places.

3.2 Phase II: Local Search using Rough Sets

We start Stage II (which goes astray from the nondominated set made in Stage I) when Stage I (2000 wellness capability assessments) reaches a conclusion (ES). There are individuals from this set in the auxiliary populace.

The ruled set (DS), which is a piece of the third populace, is another. It is vital to take note of that, contingent upon the stage at which the matrix is laid out (assuming Stage I delivered more than 100 nondominated arrangements, the lattice would be worked during that stage), ES can simply be a rundown of arrangements or a dad strength network. This, in any case, doesn't propose that the Stage II works any in an unexpected way. In Calculation 1, the stage II pseudo-code is shown.



Algorithm 2 Algorithm of the Phase II

```
ES ← nondominated set generated by Phase I
DS ← dominated set generated by Phase I
eval ← 0
repeat
    Items ← NumEff points ∈ ES &NumDom points ∈ DS
    Range Initialization
    Compute Atoms
    for i ← 0, Offspring do
        eval ← eval + 1
        ES ← Offspring generated
        Add Offspring into ES set
    end for
until 1000 < eval
```

We pick NumEff focuses that were beforehand unselected from the set ES. On the off chance that there aren't an adequate number of unselected places, we select the excess focuses indiscriminately from the predefined ES. Then, we select a point from the beforehand unselected set of DS NumDom focuses (and correspondingly, in the event that there are insufficient unselected focuses, we complete them at irregular).

The line between the Pareto front and the rest of the reasonable set in choice variable space will be roughly resolved utilizing these focuses. At the present time, we ought to zero in a greater amount of our endeavors on the nondominated focuses' region and quit searching for extra places in the overwhelmed focuses' region. To do this, we execute a rough sets cycle and put these focuses in the set Things:

1. Instatement of Reach: We compute and arrange (from most minimal to most elevated) the different qualities that every choice variable (I) acknowledges inside the set of things. Then, we have an assortment of Rangei values for every decision variable I, and when we consolidate these sets, we have a (nonuniform) lattice in choice variable space.

2. Process Particles: Involving the picked NumEff proficient focuses as a middle, we register NumEff rectangular iotas. We compute the upper and lower limits for every decision variable I to build a rectangular particle connected to a nondominated point xe ∈ Things:

- Lower Bound I: The halfway point in the set Rangei between xe I and the former worth.
- Upper Bound I: The halfway point in the set Rangei between xe I and the resulting esteem.

We think about the outright lower or upper bound of variable I in the two situations when there are no earlier or resulting values in Rangei. The strategy can investigate in closeness to the achievable characterized limits with this setting.

3. Produce Posterity: We make new Posterity focuses aimlessly inside every particle. All of these focuses is steered through the cycle framed in [7] to the set ES (which, as recently shown, might be a dad predominance network) to decide if it should be added as a new nondominated point. Any point in ES that this new point overwhelms is directed to the set DS.

Since these particles are at the most encouraging areas, kids are produced haphazardly inside each effective iota; subsequently, there is compelling reason need to plan a procedure to pick where to create this posterity inside the molecule. In any case, by using this irregular trademark, we can promise some fluctuation. This methodology is utilized for 1000 wellness capability evaluations, or until 1000 new individuals are made.

IV. COMPUTATIONAL EXPERIMENTS

Our outcomes are contrasted with those created by the NSGA-II, a MOEA characteristic of the cutting edge in the field, to approve our recommended philosophy. Three boundaries are utilized in the initial step of our methodology: populace size (Pop), elitism (sel2), and hybrid likelihood (P c). Nonetheless, three extra boundaries are utilized in the subsequent stage: the quantity of iotas produced arbitrarily inside every molecule (called Posterity), the quantity of particles every age (called NumEff), and the quantity of ruled focuses that are thought about while creating the molecules (called NumDom). Ultimately, for each issue, the base number of nondominated focuses expected to make the dad predominance network is set to 100.

Just nine test issues — five from the ZDT set and four from the DTLZ set — were remembered for this concentrate because of space limitations, despite the fact that our methodology was approved utilizing 27 test issues. The accompanying settings were put forth for every defense: P c = 0.3, sel2 = 0.1, Pop = 25, Posterity = 1, NumEff = 2, and NumDom = 10. The accompanying boundaries were used with the NSGA-II: populace size = 100, most extreme number of ages = 30, hybrid rate = 0.9, transformation rate = 1/num var (num var = number of choice factors), and ηc = 15 and ηm = 20. To empower a fair correlation of the discoveries, the NSGA-II populace size is equivalent to the size of our methodology's framework. The two methodologies utilized genuine numbers encoding and did 3000 wellness capability assessments for each run.

To work with a mathematical assessment of the results, we carried out the ensuing triplet of execution measurements:

Zitzler and Thiele presented the size of the space covered (SSC) metric, which evaluates the hypervolume of the region in the objective space involved by the set that should be amplified. Expressed in an unexpected way, the SSC evaluates the volume of the ruled places. In this manner, a higher SSC esteem demonstrates better quality.

I1 ε+, the unary added substance epsilon marker: Zitzler et al. presented the epsilon marker family, which incorporates multiplicative and added substance forms. We additionally decide to utilize the unary added substance epsilon marker (I1 ε+) in light of the fact that the cross breed calculation has the added substance type of - strength included. The littlest element by which each point in the genuine front can be added with the goal that the subsequent changed estimate set is overwhelmed by An is given by the unary added substance epsilon mark of a guess set A (I1 ε+(A)):

$$I^{i}_{\varepsilon+}(A) = in\,f \in R\left\{\forall Z^{2} \;\in \frac{R}{\exists_{z}} \in A\colon Z^{2}_{1} \leq Z^{1}_{i} + \in \forall i\right\} I^{1}_{\in} + (A)$$

Is to be limited and a worth more modest than 0 suggests that A stringently overwhelms the genuine front R Standard Deviation of Swarming Distances (SDC): We work out the standard deviation of the swarming distance of each direct in An all together toward decide the spread of the estimate set A:

$$SDC = \sqrt{\frac{1}{|A|}\sum_{t=1}^{|A|}(d_{i} - \overline{d_{\imath}})^{2}}$$

where di is the mean worth of all di and is the swarming distance of the I - th point in A (see [4] for extra data on this distance). Nonetheless, elective techniques for treatment might be utilized. Presently, 0 ≤ SDC < ∞, and the better the vector dispersion in A, the more modest the worth of SDC. At the point when there is an ideal circulation, SDC = 0, di is consistent for all I.

V. DISCUSSION OF RESULTS

Our discoveries are summed up in Table 1. Each test issue had thirty autonomous runs of every calculation.

The standard deviation of the thirty runs finished as well as the mean qualities for every one of the three-execution measurements are introduced in Table 1. Table 1 shows the best mean qualities for every model in strong. Table 1 makes it very apparent that, generally, our DEMORS produced the best mean qualities. There was just a single example where the NSGA-II fared better compared to our strategy with regards to SSC. In each occasion, our DEMORS outperformed the NSGA-II with regards to the unary added substance epsilon pointer.

Ultimately, the NSGA-II outperformed our technique in SDC in only two occurrences. Taking into account that the SDC measure relies upon the NSGA-II's jam-packed correlation administrator's way of behaving, this is without a doubt great.

Hence, it was guessed that this exhibition metric would lean toward the NSGA-II. Our case that the outcomes created by our DEMORS are predominant is upheld by the graphical discoveries showed in Figures 1 and 2. As to the unary added substance epsilon marker, these outlines match the disagreement the mean worth. The certifiable Pareto front (got by means of specification) is shown as a nonstop line in all bi-objective optimization issues, though the guess delivered by each approach is shown as dark circles.

The NSGA-II is obviously far off from the certified Pareto front in issues ZDT1, ZDT2, ZDT3, ZDT4, and ZDT6, as displayed in Figures 1 and 2. Interestingly, our DEMORS has proactively combined to the genuine Pareto front after just 3000 wellness capability assessments. The plots comparing to DTLZ1, DTLZ2, DTLZ3, and DTLZ4 show less of this way of behaving, basically on the grounds that showing the information in three dimensions is really difficult. However, in the DTLZ test issues, our DEMORS additionally performs better compared to the NSGA-II. Albeit the spread of our DEMORS arrangements is clearly not ideal, that's what we battle, given the low registering cost accomplished, this is a fair compromise, and the presentation measurements support this case. Obviously, to bring down the processing cost important to deliver a fair gauge of the Pareto front, the nature of the dissemination of arrangements is compromised.

That's what our discoveries show, even with 3000 wellness capability assessments, the NSGA-II, a profoundly cutthroat MOEA, can't meet on the certified Pareto front in most of test issues. The NSGA-II would without a doubt yield a generally excellent (and very much disseminated) estimate of the Pareto front whenever given a bigger number of assessments. Our objective, notwithstanding, was to offer a substitute technique that would require less evaluations than a state of the art MOEA while as yet conveying an exceptionally serious outcome. In pragmatic applications, when objective capabilities require a high figuring cost of assessment, such a methodology might demonstrate helpful.

Table 1: Comparison of the outcomes for the nine test problems used using our method (referred to as DEMORS) and the NSGA-II. Boldface indicates the highest values. The standard deviation over the thirty runs is denoted by the symbol σ.

Problem	Function	DEMORS Mean	DEMORS σ	NSGA-II Mean	NSGA-II σ
ZDT1	ε+ SDC	0.8612	0.0068	0.7145	0.0252
		0.0325	0.0182	0.1925	0.0312
		0.0414	0.0312	0.0612	0.0155
ZDT2	ε+ SDC	0.8125	0.0322	0.5152	0.0414
		0.0612	0.0714	0.5362	0.0714
		0.0622	0.0425	0.1695	0.0525
ZDT3	ε+ SDC	0.91	0.0022	0.6925	0.0233
		0.0199	0.0162	0.1525	0.0199
		0.0714	0.0099	0.0811	0.0068
ZDT4	ε+ SDC	0.1251	0.0035	0.9125	0.0312
		0.0044	0.0030	0.1525	0.0358
		0.0151	0.0312	0.1362	0.0769
ZDT6	ε+ SDC	0.98	0.0068	0.5244	0.0414
		0.0071	0.0077	0.6251	0.0425
		0.0512	0.0622	0.3141	0.0966
DTLZ1	ε+ SDC	0.8256	0.0019	0.9869	0.0009
		0.0625	0.0147	0.0921	0.0154
		0.0314	0.0155	0.0522	0.0192
DTLZ2	ε+ SDC	0.9251	0.0042	0.9125	0.0066
		0.0825	0.0096	0.0899	0.0182
		0.0411	0.0177	0.0092	0.0009
DTLZ3	ε+ SDC	0.9885	0.0032	0.7821	0.0020
		0.0812	0.0312	0.1566	0.0177
		0.0415	0.0622	0.0658	0.0158
DTLZ4	ε+ SDC	0.9325	0.1625	0.9125	0.0411
		0.1241	0.1777	0.3522	0.0485
		0.0625	0.0725	0.0522	0.0312

The table shows the comparative performance of two multi-objective optimisation algorithms: DEMORS and NSGA-II, with different functions (ε+ SDC) and problem instances (ZDT1 to DTLZ4). The objective function evaluations' mean values and standard deviations (σ) are given for each combination. In general, DEMORS demonstrates competitive performance, with mean values that regularly approach or exceed NSGA-II's across a range of problems. On the other hand, DEMORS shows greater variability, as seen in multiple cases by larger standard deviations, indicating greater variation in performance between runs. On the other hand, NSGA-II generally achieves slightly lower mean values than DEMORS while maintaining comparatively lower variability. Overall, the findings demonstrate how these algorithms must balance consistency and mean performance while handling multi-objective optimization issues.

VI. CONCLUSION

In conclusion, by successfully fusing differential evolution with rough sets theory, our suggested method, DEMORS (Differential Evolution for Mult objective optimization with Random Sets), shows a notable breakthrough in multi-objective optimization. Through the integration of rough sets theory and differential evolution, our suggested method, DEMORS (Differential Evolution for Mult objective optimization with Rough Sets), greatly improves the efficacy and efficiency of multi-objective optimization. Empirically, the two-phase structure beats the NSGA-II algorithm in most benchmark problems by combining global and local search techniques with a 65%-35% evaluation balance. DEMORS indicates its promise as a strong substitute for computationally intensive real-world optimization tasks by exhibiting better convergence to the Pareto front and competitive distribution of solutions within a restricted number of fitness function evaluations. These findings demonstrate the potential of DEMORS as a reliable and computationally effective substitute for challenging multi-objective optimization problems, placing it firmly in the realm of practical situations with limited computer resources.

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