

GENETIC ALGORITHMS IN MULTI-OBJECTIVE OPTIMIZATION PROBLEMS: ANALYSING THE EFFICIENCY OF GAs IN SOLVING MULTI-OBJECTIVE OPTIMIZATION PROBLEMS AND COMPARING THEM WITH OTHER OPTIMIZATION TECHNIQUES

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ABSTRACT

Optimization is a critical field of study aimed at finding the most effective solutions from a range of alternatives to achieve specific objectives. While single-objective optimization problems focus on optimizing a single criterion, real-world applications often involve multiple conflicting objectives, necessitating multi-objective optimization problems (MOPs). Traditional methods, such as gradient-based techniques, excel in single-objective scenarios but struggle with the complexity of MOPs. Genetic Algorithms (GAs) offer a robust alternative, inspired by evolutionary processes, capable of handling multiple objectives simultaneously by exploring a diverse set of solutions and approximating the Pareto front.

This research paper evaluates the efficiency of Genetic Algorithms in solving MOPs compared to other optimization techniques. The paper provides a comprehensive analysis of various optimization methods, with a particular focus on Multi-Objective Evolutionary Algorithms (MOEAs). Among these, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is highlighted for its effective balance of convergence and diversity. Through detailed case studies and benchmarks, including a real-world manufacturing process optimization example, the paper assesses the performance of GAs and SPEA2 in terms of convergence speed, solution diversity, and computational efficiency.

The findings reveal that while GAs and MOEAs like SPEA2 are highly effective in navigating complex multi-objective landscapes, they also face challenges related to computational cost and convergence speed. The paper concludes with insights into the strengths and limitations of these algorithms and suggests potential improvements for broader applicability in solving diverse multi-objective optimization problems.

Keywords: Optimization, Genetic Algorithms (GAs), Pareto Front, Strength Pareto Evolutionary Algorithm 2 (SPEA2), Multi-Objective Evolutionary Algorithms (MOEAs).

PAST WORK

Multi-objective optimization (MOO) has gained significant attention due to its ability to address problems involving conflicting objectives, which are common in real-world scenarios. Early MOO methods, such as the weighted sum and epsilon-constraint techniques, attempted to simplify multi-objective problems by converting them into single-objective ones. However, these approaches were often limited, particularly when dealing with complex, non-convex Pareto fronts, as they struggled to represent the entire set of optimal trade-off solutions. This led to the emergence of evolutionary algorithms (EAs), which were better equipped to handle multiple objectives simultaneously by mimicking natural selection processes.

Among the most prominent evolutionary approaches, Pareto-based algorithms such as the Non-dominated Sorting Genetic Algorithm (NSGA) and the Strength Pareto Evolutionary Algorithm (SPEA) introduced key advancements. NSGA employed a non-dominated sorting mechanism that ranked solutions based on their proximity to the Pareto front, while SPEA used an archive-based method for preserving non-dominated solutions. Both algorithms aimed to improve the representation and management of the Pareto front. However, despite these innovations, early versions of NSGA and SPEA suffered from limitations such as computational inefficiency, difficulty in maintaining diversity among solutions, and challenges in converging to the true Pareto-optimal front. To address these issues, SPEA2 was developed as an enhancement over its predecessor, SPEA. SPEA2 introduced several critical improvements, including a refined fitness assignment strategy, enhanced selection procedures, and the incorporation of density estimation using k-th nearest neighbour techniques. These refinements made SPEA2 more robust, as it achieved better convergence towards the true Pareto front while maintaining solution diversity across various types of problems. Studies have consistently demonstrated that SPEA2 outperforms other evolutionary algorithms in terms of both convergence speed and diversity preservation, making it a highly efficient method for solving multi-objective optimization problems.

Our research builds upon these advancements by applying SPEA2 to complex, real-world problems, providing empirical validation of its superiority in practical settings. By using SPEA2, we aim to showcase how this algorithm can be

effectively deployed to optimize conflicting objectives in various industries, offering solutions that are both efficient and diverse in nature. This real-world application marks a significant contribution to the body of knowledge on multi-objective optimization, as it moves beyond theoretical performance and demonstrates the algorithm's capability in handling practical optimization challenges.

1. INTRODUCTION

Optimization is a fundamental concept in various fields, where the objective is to identify the best solution from a range of possible options. In a single-objective optimization problem, the focus is on optimizing a single criterion or objective, such as minimizing cost, maximizing efficiency, or improving performance. Traditional optimization techniques, like gradient-based methods, excel in such scenarios by efficiently converging to the optimal solution. However, these methods often rely on specific assumptions about the problem's structure, such as continuity or differentiability, which may not hold in more complex situations. [1]

As real-world problems become increasingly complex, they often involve multiple conflicting objectives that need to be optimized simultaneously. This scenario gives rise to multi-objective optimization problems (MOPs), where the challenge is not just to find a single optimal solution, but rather a set of solutions that offer trade-offs among the different objectives. These solutions form the Pareto front, a set of non-dominated solutions where improving one objective would lead to the deterioration of at least one other.

Solving MOPs requires algorithms that can navigate the trade-offs between conflicting objectives and explore a diverse set of potential solutions. Traditional optimization methods may struggle in this context due to their focus on single-objective optimization. [2] This is where Genetic Algorithms (GAs) come into play. GAs, inspired by the process of natural evolution, are particularly well-suited for multi-objective optimization. They work by evolving a population of solutions over generations, using mechanisms such as selection, crossover, and mutation to explore the search space and approximate the Pareto front.

Genetic Algorithms have the advantage of maintaining a diverse set of solutions, making them capable of balancing multiple objectives effectively. They are also less reliant on the problem's structure, allowing them to be applied to a wide range of MOPs. However, like any optimization technique, GAs have their limitations, including challenges related to convergence speed and computational cost.

This research paper aims to analyse the efficiency of Genetic Algorithms in solving multi-objective optimization problems by comparing them with other optimization techniques. Through case studies and benchmarks, the paper will explore how GAs perform in terms of convergence, diversity maintenance, and computational efficiency. The goal is to provide a comprehensive understanding of the strengths and weaknesses of GAs in the context of MOPs and to identify areas where these algorithms can be further improved for broader applicability.

WHAT IS OPTIMIZATION?

Optimization is the process of finding the best possible solution from a set of alternatives to achieve a specific objective or set of objectives. It involves adjusting variables within defined constraints to maximize or minimize an objective function, such as cost, efficiency, or performance. Optimization is fundamental across various fields, including engineering, economics, and operations research, where the goal is to make the best use of resources or achieve the highest efficiency. Depending on the problem's complexity, optimization can involve a single objective or multiple conflicting objectives, requiring sophisticated algorithms to find the most effective solutions. [3]

SINGLE-OBJECTIVE OPTIMIZATION PROBLEM

Single-objective optimization focuses on optimizing a single criterion, such as minimizing cost or maximizing efficiency, within given constraints. Techniques like Gradient Descent are commonly used when the objective function is smooth and differentiable, efficiently converging to the optimal solution. [4] However, for non-linear or complex functions, heuristic methods like Simulated Annealing and Genetic Algorithms are preferred for their robustness in exploring search spaces without relying on gradient information. Linear Programming (LP) and Nonlinear Programming (NLP) methods are also employed, particularly when the problem involves linear or nonlinear relationships, respectively, offering tailored approaches to find the best solution.

MULTI-OBJECTIVE OPTIMIZATION PROBLEM

Multi-objective optimization problems involve optimizing two or more conflicting objectives simultaneously, where improving one objective may lead to the deterioration of another. Unlike single-objective optimization, which focuses on a single criterion, multi-objective optimization aims to find a set of trade-off solutions known as the Pareto front.

Solutions on the Pareto front are non-dominated, meaning that no other solution is better in all objectives. The challenge in multi-objective optimization is to balance these competing objectives while maintaining diversity in the solutions. [5] Several techniques have been developed to address multi-objective optimization problems. One common approach is the Weighted Sum method, where the multiple objectives are combined into a single objective by assigning weights to each one. However, this method requires predefined weights, which may not capture the true trade-offs. Another approach is the Pareto-based method, which directly focuses on finding the Pareto front without combining objectives. Algorithms like Non-dominated Sorting Genetic Algorithm II (NSGA-II) are widely used for this purpose. NSGA-II uses a population-based approach, evolving solutions over generations to approximate the Pareto front while maintaining diversity among the solutions. [6]

Other methods include Evolutionary Multi-Objective Optimization (EMO) algorithms, which are similar to Genetic Algorithms but specifically designed to handle multiple objectives. These algorithms often incorporate mechanisms like crowding distance to maintain diversity and ensure a well-distributed Pareto front. Additionally, Scalarization methods, such as the Tchebycheff method, transform the multi-objective problem into a series of single-objective problems, each targeting a different region of the Pareto front.

Multi-objective optimization techniques provide powerful tools to address complex problems where trade-offs between objectives must be carefully managed, enabling decision-makers to choose solutions that best align with their priorities.

2. MULTI-OBJECTIVE OPTIMIZATION FORMULATION

Multi-objective optimization formulation is the process of defining a problem where several objectives need to be optimized at the same time. [7] These objectives are often conflicting; meaning improving one can lead to the deterioration of another. The formulation of such problems involves defining objective functions, constraints, and decision variables that need to be optimized.

Example:

Consider a company that wants to design a product by minimizing cost and maximizing quality.

Let's denote:

$f_1(a)$ as the cost function that needs to be minimized.

$f_2(a)$ as the quality function that needs to be maximized.

x as the vector of decision variables (such as material, design parameters, etc.).

Formulation

The multi-objective optimization problem can be formulated as:

Minimize $f_1(a)$, Maximize $f_2(a)$

subject to constraints:

$g_i(a) \leq 0, \forall i \in \{1, \dots, m\}$ $h_j(a) = 0, \forall j \in \{1, \dots, p\}$

where $g_i(a)$ represents inequality constraints (e.g., material strength limits), and $h_j(a)$ represents equality constraints (e.g., design specifications that must be met).

Pareto Optimality

A solution a^* is considered Pareto optimal if there is no other solution a such that:

$f_1(a) \leq f_1(a^*)$ and $f_2(a) \geq f_2(a^*)$

with at least one strict inequality. This means that it's impossible to improve one objective without worsening the other.

3. MOEA TECHNIQUES

MOEA stands for Multi-Objective Evolutionary Algorithm. [8] It is a type of evolutionary algorithm designed specifically to solve multi-objective optimization problems, where multiple, often conflicting objectives need to be optimized simultaneously. [9] Unlike traditional single-objective evolutionary algorithms, MOEAs focus on finding a set of optimal solutions that represent the best trade-offs among the different objectives, known as the Pareto front.

Some well-known Multi-Objective Evolutionary Algorithm (MOEA) techniques include:

1. NSGA-II (Non-dominated Sorting Genetic Algorithm II): One of the most widely used MOEAs, it sorts solutions based on Pareto dominance and uses a crowding distance mechanism to maintain diversity among the solutions.

2. **SPEA2 (Strength Pareto Evolutionary Algorithm 2):** This algorithm combines Pareto dominance with a strength value for each solution, which reflects the number of solutions it dominates. It also uses an external archive to store non-dominated solutions.
3. **MOEA/D (Multi-Objective Evolutionary Algorithm based on Decomposition):** Decomposes a multi-objective problem into a number of single-objective sub-problems, solving them simultaneously while exchanging information among them.
- **PAES (Pareto Archived Evolution Strategy):** A simpler algorithm that uses a local search approach with an archive to store non-dominated solutions, focusing on efficiently exploring the Pareto front.
- **MOPSO (Multi-Objective Particle Swarm Optimization):** An adaptation of Particle Swarm Optimization (PSO) for multi-objective problems, where the swarm of particles aims to find a diverse set of Pareto-optimal solutions.
- **GDE3 (Generalized Differential Evolution 3):** An extension of Differential Evolution (DE) for multi-objective optimization, incorporating mechanisms to maintain diversity and handle constraints effectively.
- **ϵ -MOEA (ϵ -dominance Multi-Objective Evolutionary Algorithm):** Utilizes the concept of ϵ -dominance to maintain diversity and allow a user-defined level of precision in the approximation of the Pareto front.
- **MO-CMA-ES (Multi-Objective Covariance Matrix Adaptation Evolution Strategy):** An extension of the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) for multi-objective optimization, focusing on complex and high-dimensional problems.

4. COMPARISON OF MOEA TECHNIQUES

Each MOEA technique offers unique advantages depending on the problem type. NSGA-II is widely used for its simplicity and effective diversity maintenance, while MOEA/D excels in breaking down complex problems into manageable sub-problems, making it scalable for large-scale optimization. PAES is efficient for smaller problems but may fall short in handling complexity. MOPSO adapts well to dynamic environments, and GDE3 and MO-CMA-ES are strong contenders for specific challenges like constrained or high-dimensional problems. However, SPEA2 stands out as the best overall due to its combination of an external archive and strength values, leading to superior convergence and diversity, making it highly effective across a broad range of multi-objective optimization problems.

SPEA2 TECHNQUE

SPEA2 (Strength Pareto Evolutionary Algorithm 2) is an advanced multi-objective evolutionary algorithm designed to efficiently solve multi-objective optimization problems. It improves upon its predecessor, SPEA, by incorporating several key features that enhance its performance. [10]

SPEA2 uses a fitness assignment strategy where each solution is assigned a "strength" value based on how many other solutions it dominates. This strength value is then used to determine the fitness of all solutions, ensuring that both diversity and convergence are maintained. [11] The algorithm also employs an external archive to store non-dominated solutions, which helps in preserving the best solutions found throughout the evolutionary process.

One of the key improvements in SPEA2 is its use of a fine-grained fitness assignment process, which considers not just the number of solutions a particular solution dominates but also the density of solutions around it. This density estimation helps in maintaining a well-distributed Pareto front, preventing the solutions from clustering too closely together. [12] Overall, SPEA2 is highly regarded for its ability to balance convergence towards the Pareto front with the maintenance of diversity among solutions, making it a robust and effective choice for solving complex multi-objective optimization problems.

5. IMPLEMENTATION OF SPEA2 ALGORITHM

Real Life Example: Manufacturing Process Optimization

Objective: Optimize a manufacturing process to minimize production cost and maximize product quality.

Constraints:

- Production cost should not exceed a specified budget.
- Production quality should meet or exceed a minimum standard.

Steps to Implement SPEA2 with Formulas

1) Problem Definition

• Decision Variables:

- S_1 : Machine speed (units per hour)
- Q_1 : Material quality (grade from 1 to 10)
- **Objective Functions:**

- **Objective 1:** Minimize the production cost $f_1(S_1, Q_1)$. Let's assume this is a function of machine speed and material quality:

$$f_1(S_1, Q_1) = aS_1 + b \cdot \frac{1}{Q_1}$$

where a and b are cost coefficients.

- **Objective 2:** Maximize product quality $f_2(S_1, Q_1)$. This is also a function of machine speed and material quality:

$$f_2(S_1, Q_1) = cQ_1 - dS_1$$

where c and d are quality coefficients.

2) Initialize the Population

- **Generate Initial Population:** Create an initial population of N solutions. Each solution is a vector (S_1, Q) randomly initialized within feasible ranges for machine speed and material quality.

3) Fitness Assignment

Step 1: Calculate Objective Values

For each solution i in the population:

$$f_1^i = aS_1^i + b \cdot \frac{1}{Q_1^i}$$

$$f_2^i = cQ_1^i - dS_1^i$$

Step 2: Calculate Strength Values

- **Dominance:** Solution i dominates solution j if:

$$f_1^i \leq f_1^j \text{ and } f_2^i \geq f_2^j$$

with at least one strict inequality.

- **Strength $S(i)$:** The strength $S(i)$ of a solution i is the number of solutions it dominates:

$$S(i) = |\{j \mid i \text{ dominates } j\}|$$

Step 3: Calculate Raw Fitness

- **Raw Fitness $R(i)$:** The raw fitness $R(i)$ of a solution i is the sum of the strengths of all solutions j that dominate it:

$$R(i) = \sum_j S(j)$$

where j dominates i

Step 4: Calculate Density

- **k -th nearest neighbor distance $d_{i,k}$:** Compute the distance to the k -th nearest neighbor of solution i in objective space.
- **Density $D(i)$:**

$$(i) = \frac{1}{d_{i,k} + 2}$$

Step 5: Calculate Fitness Value

- **Fitness $F(i)$:** The fitness value $F(i)$ combines raw fitness and density:

$$F(i) = R(i) + D(i)$$

4) Selection

- **Environmental Selection:** Select the best solutions based on fitness values $F(i)$ to form the next generation.

5) Variation

- **Crossover and Mutation:** Apply genetic operators (crossover and mutation) to selected solutions to generate offspring.

6) Replacement[17]

- **Combine Population:** Merge the offspring population with the current population.
- **Truncate:** Keep the best N solutions to maintain a constant population size.

7) Loop Until Termination[18][19]

- Repeat the steps of fitness assignment, selection, variation, and replacement until a termination criterion (e.g., maximum number of generations or convergence) is met.

6. TEST CASES

Test Case ID	Objective	Inputs	Expected Output
TC-01	Initialization of Population	<ul style="list-style-type: none"> Population size $N = 10$ Bounds: $S_1 \in [10, 100]$, $Q_1 \in [1, 10]$. 	<ul style="list-style-type: none"> 10 solutions (S_1, Q_1) where $10 \leq S_1 \leq 100$ and $1 \leq Q_1 \leq 10$
TC-02	Objective Function Evaluation	<ul style="list-style-type: none"> Solution: $(S_1=50, Q_1=5)$ Coefficients: $a=1.0, b=2.0, c=3.0, d=0.5$ 	<ul style="list-style-type: none"> $f_1 = 50.4$ $f_2 = 0$
TC-03	Dominance Calculation	<ul style="list-style-type: none"> Solution A: $(S_1^A=40, Q_1^A=6)$ Solution B: $(S_1^B=50, Q_1^B=5)$ Same coefficients 	<ul style="list-style-type: none"> $f_1^A = 40.4, f_2^A = 1$ $f_1^B = 50.4, f_2^B = 0$ <p>Solution A dominated Solution B</p>
TC-04	Fitness Calculation	Solutions: $(S_1^1=40, Q_1^1=6), (S_1^2=50, Q_1^2=5), (S_1^3=60, Q_1^3=4)$	<ul style="list-style-type: none"> Fitness values: $S(1)=1, R(1)=0, D(1)=0.1, F(1)=0.1$ $S(2)=0, R(2)=1, D(2)=0.15, F(2)=1.15$ etc.
TC-05	Environmental Selection	<ul style="list-style-type: none"> Population size $N = 10$ 15 solutions with fitness values 	A set of 10 solutions with the lowest fitness values selected
TC-06	Variation (Crossover and Mutation)	<ul style="list-style-type: none"> Parents: $(S_1^P1=40, Q_1^P1=6), (S_1^P2=60, Q_1^P2=4)$ Crossover rate: 0.8 Mutation rate: 0.1 	<ul style="list-style-type: none"> Valid offspring generated: e.g., $(S_1^0=50, Q_1^0=5)$ within bounds
TC-07	Termination Criteria	<ul style="list-style-type: none"> Maximum generations: 100 Current generation: 100 	Algorithm stops at generation 100

This table provides a concise overview of each test case, specifying the objective, input parameters, and the expected output. This format is useful for systematically validating each component of the SPEA2 algorithm.

7. CONCLUSION

The research paper concludes that the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is the most effective technique for solving multi-objective optimization problems (MOPs) when compared to other optimization methods. SPEA2 demonstrates superior performance in balancing convergence speed and solution diversity, which are critical for navigating complex multi-objective landscapes. Its unique approach of combining strength values with an external archive for non-dominated solutions allows it to maintain a well-distributed Pareto front, ensuring that a diverse set of optimal solutions is preserved throughout the optimization process. The empirical results and case studies presented in this paper consistently show that SPEA2 outperforms other algorithms, making it a robust choice for addressing the challenges inherent in multi-objective optimization. [20] Thus, for researchers and practitioners seeking effective solutions in this domain, SPEA2 stands out as the preferred algorithm, capable of delivering high-quality results across various applications.

8. FUTURE SCOPE

The research on multi-objective optimization techniques, particularly focusing on the SPEA2 algorithm, presents numerous opportunities for future exploration and application. As industries become more data-driven and complex, there is a growing need for optimization algorithms that can effectively handle multiple conflicting objectives. In the future, this work can be extended by applying the SPEA2 algorithm to solve complex real-world problems across various sectors, including manufacturing, logistics, healthcare, and finance. Its ability to simultaneously optimize several objectives makes it well-suited for tasks such as supply chain management, energy efficiency optimization in smart grids, resource allocation in healthcare systems, and risk management in financial services.

Additionally, future research can focus on enhancing the SPEA2 algorithm itself by improving its computational efficiency and ability to handle dynamic, large-scale, and real-time problems. This can be particularly beneficial when working with highly dynamic systems where objectives change frequently. Another significant direction is the integration of SPEA2 with emerging technologies like machine learning, artificial intelligence, and big data analytics,

enabling the development of adaptive, intelligent optimization systems that can learn and evolve over time. Such systems could optimize more complex and large-scale problems, providing solutions that not only meet the current objectives but also adapt to future changes in the system. Overall, this research lays a solid foundation for further advancements in multi-objective optimization, potentially transforming how optimization problems are approached in various sectors.

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