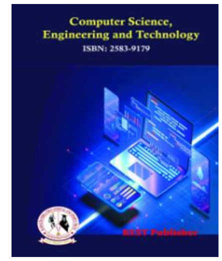
Computer Science, Engineering and Technology

Vol: 3(3), September 2025

REST Publisher; ISSN: 2583-9179

Website: https://restpublisher.com/journals/cset/

DOI: https://doi.org/10.46632/cset/3/3/11



Decision Support in Optimization: A Comparative Review of Techniques for Engineering Applications

Thilagavathi R

Velalar College of Engineering and Technology (Autonomous), Erode, Tamil Nadu, India.

Corresponding Author Email: rthilaga.vcet@gmail.com

Abstract: *Introduction: Optimization plays a vital role in engineering, where complex systems must be designed for maximum efficiency, cost-effectiveness, and reliability. Given the wide range of optimization techniques available, it is impractical to cover them all in a single discussion. Therefore, this review highlights a selection of optimization methods that are widely used in engineering. Each technique is examined in terms of its operational mechanics, applications, advantages, and limitations in supporting informed decision-making in problem solving. Research significance: Understanding the various optimization strategies is crucial in engineering and applied sciences, where the outcomes often affect cost, performance, and safety. This review emphasizes frequently used optimization techniques, avoiding narrow or highly specialized methods to maintain broad relevance. Designers and engineers can benefit from a structured comparison of these methods, improving their ability to match the most appropriate approach to a given problem, thereby improving solution quality and resource efficiency in real-world situations. Methology: Alternatives: Gradient Descent Optimization, Genetic Algorithm, Simulated Annealing, Linear Programming (LP), Particle Swarm Optimization (PSO), Conjugate Gradient Method. Evaluation Parameters: Quality of material, Additional discount on quantity, Warranty period, Reliability. Result: The results show that Conjugate Gradient Method received the highest ranking, whereas Gradient Descent Optimization received the lowest ranking. Conclusion: Conjugate Gradient Method has the highest value for optimization according to the EDAS approach.*

Key words: *Optimization techniques, Genetic Algorithm, Particle Swarm Optimization, Engineering Design, EDAS Method.*

1. INTRODUCTION

Since there are so many optimization strategies accessible, it is not practical to address them all in this debate. As a result, techniques that are commonly employed in engineering optimization are highlighted. By purposefully omitting particular categories like linear programming, convergent optimization, multi-objective, and multidisciplinary techniques, the review preserves a broad viewpoint. The advantages and disadvantages of the different approaches are examined, and suggestions are made to assist designers in selecting the best approach for their specific issue. A succinct synopsis of a typical approach is provided where appropriate to bolster the discussion of each technique area. [2] Critics of this shift in methodology have pointed out that the underlying assumption of adaptation is untestable and, as a result, lacks scientific legitimacy. Critics contend that rather than being a pursuit of truth, the emphasis on functional explanations through optimization has evolved into an artistic endeavor. The absence of a strong theoretical basis for the application of maximum principles in biology raises a related issue, suggesting that optimization cannot take the role of a reliable genetic model. [3] Utilizing resources effectively has become more crucial because to the growing demand for food, fiber, and other necessities worldwide as well as the depletion of existing resources. Finding the most effective use of these resources is made possible via optimization techniques. A thorough analysis of numerous programming techniques used to various optimization issues is presented in this review study. The earlier assessments are divided into nine sections, each of which deals with solutions to topical, real-world problems. [4] The two writers decided to co-author both of the optimization papers they were invited to present, both retrospective and prospective, after recognizing that a collaborative effort would better address the field's wide reach and represent their respective areas of competence. This first paper aims to give a broad introduction of optimization with a focus on the most extensively studied and used methods, namely dynamic optimization, optimization under uncertainty, Nonlinear programming (NLP) and mixed-integer nonlinear programming (MINLP). [5] Instead of directly constraining basic representations, this study advocates a theoretical paradigm where basic representations are completely formed by grammar-related optimization. This viewpoint has important ramifications for underlining, altering the way this and other fundamental structure elements are employed. This research specifically shows that emphasizing only occurs when there are several surface options, each of which can be predicted in terms of context or default grammar rules, within the framework of optimization theory. [6] The theory of communication optimization operates in a number of fundamental processes. In order to properly construct the message, it starts with a deep grasp of the audience and context. It then entails creating strategic communication plans through the use of efficient procedures and the selection of relevant media. A crucial element is the integration of feedback mechanisms to continuously assess and improve communication. The theory also emphasizes how important education and training are for improving communication abilities both inside and outside of organizations. [7] Test functions are essential for assessing and contrasting the performance of novel optimization techniques. There is no widely recognized standard set of test functions, despite the fact that there are many available in the literature. To ascertain how well novel optimization techniques, perform on various issue types, it is crucial to test them using a range of functions with various attributes. Here, we introduce a collection of test problems designed especially for unconstrained optimization. [8] Current research in optimal structural design generally follows two primary directions. The first focuses on investigating the fundamental principles of structural optimization. This involves analyzing the mathematical properties of the governing equations to gain broad, generally applicable insights through numerical experiments using analytical methods and example problems. The second research direction focuses on developing efficient numerical methods for optimizing complex, real-world structures. [9] A new area of discrete optimization is logic-based optimization. Its main objective is to create symbolic representations that enhance discrete constraint modeling and facilitate the creation of more effective solution techniques, with the ultimate goal of lowering the computing complexity of optimization problems, both continuous and discontinuous. Following a succinct overview of logic representations, logic-based optimization approaches is reviewed. [10] The creation One of the most notable instances of the collaboration between operations research and computer science is the use of discrete-event simulation software. The fact that most discrete-event simulation packages now incorporate some form of "optimization" process shows how optimization approaches have recently become widely used in simulation practice, especially in commercial software. This article's main argument, however, is that simulation optimization research, which concentrates on theoretical convergence results and the stochastic aspects of discrete-event simulation, differs from recent software developments, which usually implement broader algorithms borrowed from deterministic optimization metaheuristics (e.g., genetic algorithms, tabu search, artificial neural networks) through specialized, mathematically sophisticated algorithms. [11] Key operational variables in psychological optimization theory include evaluating psychological well-being, evaluating the efficacy of stress-reduction techniques, and analyzing the caliber of social support. Usually, surveys, self-report tools, and data analysis on mental health are used to quantify these characteristics. The ensuing knowledge aids in understanding how people preserve their psychological well-being and guides the creation of interventions meant to enhance mental and emotional health. [12] Information that facilitates the creation of optimization programs, comprehension of optimization tools, and efficient problem formulation is the author's stated objective. The material is well suited to this function as an introductory textbook. To comprehend the content, readers should be familiar with the fundamentals of linear algebra. [13] Experiments on a range of difficult optimization test problems demonstrate that the PSO method may successfully escape from local minima and locate a global minimum when supplemented with the suggested stretching technique (SPSO). The stretching strategy increases the likelihood of success by promoting stable convergence. The increased success rates of SPSO, which show a higher likelihood of the algorithm attaining the genuine global minimum of the objective function, justify its higher computational cost. [14] Tools like experimental design and optimization are crucial for methodically examining a range of issues encountered in industries including manufacturing, research, and development. Random experimentation can produce uneven and uninformative results. Experiments must therefore be properly planned in order to guarantee that pertinent and useful data is collected. [15] The receding horizon heuristic (RHH), a metaheuristic used in the suggested approach, was motivated by the popular process management method called retreating horizon control (RHC) or model predictive control (MPC). RHC uses a model to iteratively solve a finite-horizon optimization problem. The system's present state is assessed at each time step t, and a control method that minimizes the cost across a brief future interval [t, t + T] is chosen. Only the initial control action (at time t) is utilized, though. The optimization procedure is then repeated when the system is reassessed at time t + 1. [16] Both industry and scientific research find optimization challenges to be highly relevant. Train scheduling, timetables, shape optimization, difficulties in designing telecommunications networks, and computational biology are a few real-world examples. Many of these intricate issues have been reduced to benchmark test cases in order to aid scientific investigation. One such example is the well-known traveling salesman problem (TSP), which simulates the scenario in which a salesman has to visit cities once. [17] The methods for cover order and homogenize order depend on having fewer inputs, which is a subtle aspect of the order scan. Understanding the functional dependencies (FDs) and application predicates is necessary to accomplish this reduction. However, since these components are acquired as properties during the optimization planning stage, they are not accessible during the order scan. [18] The evolution of NP-completeness theory has been heavily influenced by optimization, and many of the issues covered in [Ka, GJ] have their roots in optimization settings. Nevertheless, optimization problems are not particularly covered by the NP-completeness paradigm and formalism. An optimization issue must be converted into a decision problem by placing a limit on its objective function in order to be included in this framework. While it is technically possible to reduce NP-complete optimization problems to one another, these reductions frequently entail intermediate non-optimization issues like SAT and overlook crucial elements like the cost function's value and the problem's approximation.

2. MATERIALS AND METHOD

Alternatives:

Gradient Descent Optimization: Gradient Descent is an iterative optimization process that moves in the direction of the negative gradient in order to minimize a function. By lowering the error between expected and actual values, it is frequently employed in deep learning and machine learning to train models. The learning rate, often known as the step size, is crucial in regulating the precision and speed of convergence.

Genetic Algorithm: Natural selection serves as the inspiration for heuristic search techniques like genetic algorithms. It creates a set of potential solutions in the direction of the ideal answer via processes including crossover, mutation, and selection. In domains like artificial intelligence, economics, and engineering, genetic algorithms are very helpful for resolving intricate optimization issues with wide search spaces.

Simulated Annealing: The probabilistic optimization method known as "simulated annealing" was motivated by the metallurgical annealing process. By accepting worst-case solutions with a continuously declining probability, it looks for a global optimum. This keeps one from becoming trapped in local minima. It works well for handling big, complicated solution spaces and may be applied to both discrete and continuous optimization problems.

Linear Programming (LP): Linear programming is a mathematical method used to optimize a linear objective function, subject to a set of linear equality and inequality constraints. It is widely used in operations research, economics, logistics, and manufacturing to determine the best outcome, such as maximum profit or minimum cost. The feasible region formed by the constraints is convex, which ensures efficient solvability using algorithms such as the simplex method.

Particle Swarm Optimization (PSO): Partition Swarm Optimization is a population-based optimization method that draws inspiration from fish or bird social behavior. Every possible solution, referred to as a particle, modifies its location according on both its own and its neighbors' experiences. Because of its ease of use and effectiveness, PSO is utilized in many machine learning and engineering applications. It effectively searches the search space to identify the global optimum.

Conjugate Gradient Method: The parallel Large systems of linear equations can be solved using the gradient approach, particularly those that result from sparse matrices or discrete partial differential equations. It is an iterative technique that works well with positive-definite and symmetric matrices. By minimizing a quadratic function, it converges faster than the basic gradient descent, making it useful in scientific computing and numerical optimization.

Evaluation parameters:

Material quality: The quality of a material refers to the degree to which a material meets specific standards and performance requirements. It includes properties such as strength, durability, and stability. High-quality materials improve product performance, reliability, and lifespan, making them important in the manufacturing, construction, and engineering industries. Material quality is often assessed through testing and certification processes.

Additional discount on quantity: A price reduction offered to buyers who purchase goods in large quantities. It encourages bulk purchasing and helps sellers increase sales volume or reduce inventory. This type of discount benefits both parties – buyers gain cost savings, while sellers gain economies of scale and customer loyalty. It is commonly used in wholesale and B2B transactions.
Warranty period: The time frame within which a manufacturer or seller promises to fix or replace a product is known as the warranty term. in the event of defects or failures. It assures customers of the product's reliability and protects them from financial loss. Warranty terms vary by product type and industry, and are often legally binding in consumer contracts.
Reliability: The capacity of a system, part, or product to carry out its intended function under given circumstances for a predetermined amount of time is referred to as reliability. It is a key factor in engineering, manufacturing, and service quality, affecting user satisfaction and maintenance costs. Higher reliability means fewer failures and longer operational life, and is often measured using metrics such as Mean Time Between Failures.

EDAS Method: Making decisions entails weighing several options and deciding which is best. Under the presumption of perfect rationality, the EDAS approach is frequently applied to multi-attribute decision-making problems. However, people frequently display poor reasoning in real-world scenarios. A more practical framework is offered by Prospect Theory (PT), which describes how people make decisions based on their perceived advantages and losses in relation to a reference point. This study presents an enhanced EDAS approach that incorporates Prospect Theory and shows better practical results. [20] The EDAS approach works well for addressing random issues because it uses the arithmetic mean to determine the average solution. A random variant of the EDAS approach is presented in this study. It is intended for use in scenarios where the alternatives' performance values under each criterion have a normal distribution. To take into consideration the ambiguity in the data used for decision-making, the suggested method enables the computation of optimistic and pessimistic assessment scores. A graphical example and a real world case study on assessing bank branch performance are provided to illustrate the approach. [21] Even though a variety of techniques have been created to address stochastic MCDM challenges, the majority of them fall short in integrating the essential characteristics of statistical distributions into MCDM techniques. Because of this, current approaches frequently entail intricate computations and offer decision makers reliable results. This study suggests an algorithm that combines the EDAS approach with the characteristics of the normal distribution to address this issue. [22] For organizational selection issues, a number of multi-criteria decision-making (MCDM) techniques have been put forth. Two MCDM approaches that are applied in a variety of domains in the literature are MACBETH and EDAS. This paper's integration of the MACBETH and EDAS methodologies is its distinctive addition. This study is the first to combine these two methods in the literature. [23] This study shows how combining hesitant fuzzy sets (HFSs) can be used to evaluate the average solution (EDAS) technique. Three rival private hospitals are evaluated using a number of contradictory standards in order to identify the best one. Healthcare providers frequently ignore the assessment of service quality, despite its significance to human well-being. [24] This approach's earlier iterations are not appropriate for solving MCGDM problems requiring interval type-2 fuzzy sets (IT2FSs). We present an expanded EDAS approach with IT2FSs (EDAS-IT2FSs) in this work. To illustrate the process and functionality of the suggested approach, a numerical example is presented. To evaluate the reliability and consistency of the ranking findings, a comparison and sensitivity analysis are also carried out. According to the analysis, the suggested expanded EDAS approach is consistent with other current approaches and stable across a range of criterion weights. [25] This can be accomplished by applying the MCDM approach, also known as the mean solution (EDAS) method, to mathematically analyze a particular scenario. This study examines the agricultural conditions in a specific region, taking into account a number of factors associated with crop water management. By examining various crops with differing lengths, water consumption, yield, and market pricing, the EDAS method helps farmers determine the most effective water management techniques. [26] The EDAS approach uses an average solution to assess alternatives. The central aggregates of extended hesitant fuzzy linguistic term sets (EHFLTSs) are analyzed in order to derive this average solution. These average solutions (EHFLTSs) are computed using the EHFL-OWA and EHFL-COWA operators. The likelihood degree formula for comparing EHFLTSs is carefully examined because there is no standard distance formula for extended fuzzy linguistic term sets. For every criterion, the positive agreement degree (PDA) and negative agreement degree (NDA) are determined using this formula. Lastly, a comparison between the TOPSIS approach and the extended EHFL-EDAS method is made. [27] Type-2 fuzzy, intuitionistic fuzzy, and conventional fuzzy versions of the EDAS approach have previously been developed. The interval-valued neutrosopic version of the EDAS approach, which we enhance in this study, enables us to take into account an expert's doubt, falsehood, and truth all at once. Prioritizing the United Nations national sustainable development objectives is done using the suggested approach, and the method's robustness is evaluated using a sensitivity analysis. To confirm the method's effectiveness, it is also contrasted with the intuitionistic fuzzy TOPSIS method. [28] Using Ghana as a case study, this study examined the obstacles to the growth of renewable energy (RE) using the MULTIMOORA-EDAS approach. Ghana has implemented laws and initiatives to make use of its plentiful renewable energy resources in order to lower harmful emissions and promote economic growth, much like other growing economies. In order to facilitate a swift transition to a sustainable energy market, the nation's Renewable Energy Adoption Policy seeks to remove obstacles to the growth of renewable energy sources, draw in investment, and develop local knowledge.

3. ANALYSIS AND DISCUSSION

TABLE 1. Optimization

	Quality of material	Additional discount on quantity	Warranty period	Reliability
Gradient Descent Optimization	86.00	139.53	29.15	98.00
Genetic Algorithm	69.00	142.97	33.69	76.00
Simulated Annealing	47.00	144.00	29.18	37.00
Linear Programming (LP)	83.00	207.00	50.00	50.00
Particle Swarm Optimization (PSO)	79.00	128.28	24.60	82.00
Conjugate Gradient Method	67.00	186.41	27.96	67.00
AVj	71.83333	158.03167	32.43000	68.33333

Table 1 presents a comparative analysis of various optimization techniques based on four key parameters: quality of material, additional discount on quantity, warranty period, and reliability. Among the methods evaluated, Gradient Descent Optimization stands out with a high material quality score of 86 and the highest reliability of 98, indicating its consistency in delivering dependable results. Genetic Algorithm also performs well, especially in providing a longer warranty period of 33.69 and a relatively high discount rate, though its reliability is lower at 76. Simulated Annealing, while offering the highest discount (144), has the lowest scores in both material quality and reliability, suggesting potential trade-offs in performance. Linear Programming provides the longest warranty period (50) and the highest discount (207), but its reliability remains moderate at 50. Particle Swarm Optimization (PSO) strikes a balance with competitive values in quality and reliability, though its warranty and discount are less impressive. The Conjugate Gradient Method has moderate values across all metrics, with its highest strength being the discount offered (186.41). On average (AVj), the methods yield a material quality of 71.83, a discount of 158.03, a warranty of 32.43, and reliability of 68.33. Overall, Gradient Descent appears to offer the best trade-off between performance and reliability.

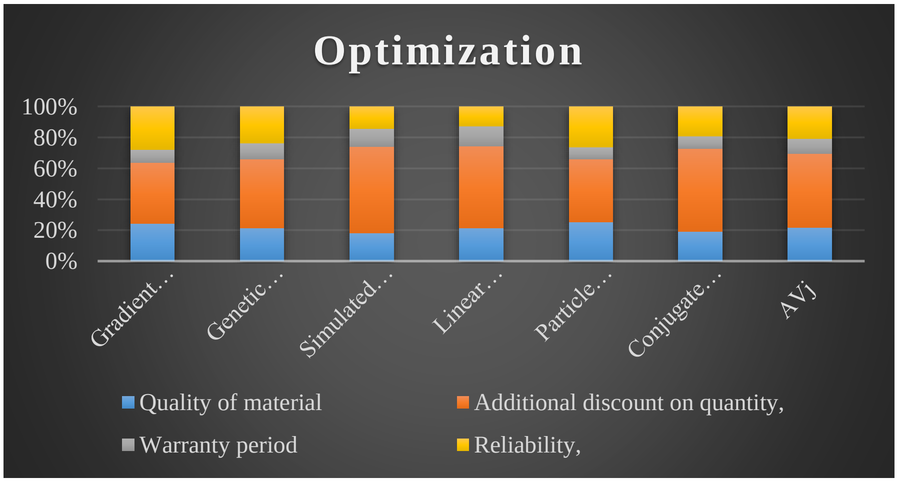


FIGURE 1. Artificial Intelligence

Figure 1 illustrates the performance of six optimization methods across four criteria: quality of material, additional discount on quantity, warranty period, and reliability. Linear Programming (LP) leads in discount and warranty, showing its strength in cost efficiency and support. Gradient Descent Optimization excels in quality and reliability, indicating consistent performance. Genetic Algorithm performs close to average across all metrics. Simulated Annealing scores the lowest in quality and reliability, reflecting weaker outcomes. Particle Swarm Optimization (PSO) offers a strong balance in quality and reliability but lags in warranty. Conjugate Gradient Method performs moderately in all aspects.

TABLE 2. Positive Distance from Average (PDA)

	Positive Distance from Average (PDA)			
Gradient Descent Optimization	0.19721578	0	0.10114092	0
Genetic Algorithm	0	0	0	0
Simulated Annealing	0	0	0.10021585	0.45853659
Linear Programming (LP)	0.15545244	0.309864057	0	0.26829268
Particle Swarm Optimization (PSO)	0.09976798	0	0.24144311	0
Conjugate Gradient Method	0	0.179573714	0.13783534	0.0195122

Table 2 displays the Positive Distance from Average (PDA) values for six optimization methods across four criteria: quality of material, additional discount on quantity, warranty period, and reliability. PDA values indicate how much each method positively deviates from the average performance, highlighting their relative strengths. Gradient Descent Optimization shows strong performance in material quality (0.1972) and reliability (0), indicating it meets or slightly exceeds the average in both aspects. Genetic Algorithm has zero PDA values across all criteria, meaning its performance is exactly at the average, neither better nor worse. Simulated Annealing stands out in warranty period (0.1002) and shows a significant deviation in reliability (0.4585), suggesting it lags behind in consistency. Linear Programming exhibits noticeable strength in discount (0.3099) and material quality (0.1555), although it performs moderately in reliability. Particle Swarm Optimization shows moderate positive distances in material quality (0.0998) and warranty period (0.2414), indicating its balanced advantage. The Conjugate Gradient Method also shows slight strengths in discount (0.1796) and warranty period (0.1378).

TABLE 3. Negative Distance from Average (NDA)

	Negative Distance from Average (NDA)			
Gradient Descent Optimization	0	0.117076	0	0.434146
Genetic Algorithm	0.039443	0.095308	0.0388529	0.112195
Simulated Annealing	0.345708	0.08879	0	0
Linear Programming (LP)	0	0	0.5417823	0
Particle Swarm Optimization (PSO)	0	0.188264	0	0.2
Conjugate Gradient Method	0.067285	0	0	0

Table 3 presents the Negative Distance from Average (NDA) for six optimization techniques across four parameters: quality of material, additional discount on quantity, warranty period, and reliability. NDA values indicate how far each method falls below the average, thus revealing their weaknesses. Gradient Descent Optimization performs well overall but has a significant drop in reliability (0.4341), indicating that despite high scores in other areas, its reliability is below average. Genetic Algorithm shows minor underperformance in all four parameters, particularly in reliability (0.1122), suggesting it remains close to average but lacks standout strengths. Simulated Annealing displays the highest negative deviation in quality of material (0.3457), although it has no shortfall in warranty or reliability. Linear Programming exhibits a major weakness in warranty period (0.5418), the highest negative deviation in the table, indicating a significant drop below average in that aspect. Particle Swarm Optimization shows below-average performance in discount (0.1883) and reliability (0.2), despite strengths elsewhere. The Conjugate Gradient Method underperforms slightly in material quality (0.0673), but fares reasonably in other areas.

TABLE 4. Weight

	Weight			
Gradient Descent Optimization	0.25	0.25	0.25	0.25
Genetic Algorithm	0.25	0.25	0.25	0.25
Simulated Annealing	0.25	0.25	0.25	0.25
Linear Programming (LP)	0.25	0.25	0.25	0.25
Particle Swarm Optimization (PSO)	0.25	0.25	0.25	0.25
Conjugate Gradient Method	0.25	0.25	0.25	0.25

Table 4 presents the weight distribution for evaluating six optimization techniques based on four criteria: quality of material, additional discount on quantity, warranty period, and reliability. Each criterion is assigned an equal weight of 0.25 for all methods, indicating that all parameters are considered equally important in the decision-making process. This balanced weighting ensures a fair and unbiased comparison, where no single attribute disproportionately influences the overall evaluation. By treating each criterion with equal significance, the analysis allows a holistic assessment of each optimization method's performance. This approach is especially useful when the context does not prioritize any one factor over others. Consequently, the final ranking or selection of the best method will be based solely on the performance data (from PDA and NDA), rather than weight-induced preference. This promotes transparency and objectivity in multi-criteria decision-making.

TABLE 5. Weighted PDA, SPi

	Weighted PDA				SPi
Gradient Descent Optimization	0.0493039	0	0.02529	0	0.07459
Genetic Algorithm	0	0	0	0	0
Simulated Annealing	0	0	0.02505	0.11463	0.13969
Linear Programming (LP)	0.0388631	0.07747	0	0.06707	0.1834
Particle Swarm Optimization (PSO)	0.024942	0	0.06036	0	0.0853
Conjugate Gradient Method	0	0.04489	0.03446	0.00488	0.08423

Table 5 displays the Weighted Positive Distance from Average (Weighted PDA) and the Summed Preference Index (SPi) for six optimization methods. Weighted PDA is calculated by multiplying the PDA values by their respective weights (0.25 each), reflecting each method's positive deviation in a balanced manner. The SPi, obtained by summing these weighted values, indicates the overall strength of each method. Gradient Descent Optimization achieves an SPi of 0.07459, showing a modest advantage mainly in material quality and warranty. Genetic Algorithm scores zero across all parameters, meaning its performance aligns exactly with the average. Simulated Annealing gains a higher SPi of 0.13969 due to strong contributions from warranty and reliability. Linear Programming stands out with the highest SPi of 0.1834, primarily due to strong discount and reliability performance. Particle Swarm Optimization and Conjugate Gradient Method have comparable SPi values of 0.0853 and 0.08423 respectively, indicating moderate positive performance.

TABLE 6. Weighted NDA, SNi

	Weighted NDA				SNi
Gradient Descent Optimization	0	0.02927	0	0.10854	0.13781
Genetic Algorithm	0.00986	0.02383	0.00971	0.02805	0.07145
Simulated Annealing	0.08643	0.0222	0	0	0.10862
Linear Programming (LP)	0	0	0.13545	0	0.13545
Particle Swarm Optimization (PSO)	0	0.04707	0	0.05	0.09707
Conjugate Gradient Method	0.01682	0	0	0	0.01682

Table 6 presents the Weighted Negative Distance from Average (Weighted NDA) and the Summed Negative Index (SNi) for six optimization methods. Weighted NDA values reflect how much each method falls below the average, adjusted by equal weighting (0.25 per criterion). The SNi is the sum of these values, representing the overall weakness of each method. Gradient Descent Optimization has an SNi of 0.13781, mainly due to lower reliability, despite strong performance in other areas. Genetic Algorithm shows a moderate SNi of 0.07145, indicating consistent but slightly below-average performance across all criteria. Simulated Annealing has a high SNi of 0.10862, largely due to a significant drop in material quality. Linear Programming shows the highest single-criterion weakness in warranty

(0.13545), which is its total SNi. Particle Swarm Optimization's SNi of 0.09707 reflects its shortcomings in discount and reliability. Conjugate Gradient Method shows minimal overall weakness with the lowest SNi of 0.01682, indicating balanced performance.

TABLE 7. NS Pi, NS Pi, ASi

	NSPi	NSPi	ASi
Gradient Descent Optimization	0.4067	0	0.203349
Genetic Algorithm	0	0.48152	0.240759
Simulated Annealing	0.76165	0.21176	0.486702
Linear Programming (LP)	1	0.01713	0.508563
Particle Swarm Optimization (PSO)	0.46511	0.29563	0.380372
Conjugate Gradient Method	0.45927	0.87793	0.6686

Table 7 presents the normalized scores for each optimization method: NSPi (Normalized Summed Preference Index), NSNi (Normalized Summed Negative Index), and ASi (Aggregate Score Index). NSPi represents the relative strength, while NSNi indicates the relative weakness. The ASi is calculated by averaging NSPi and the complement of NSNi, thus reflecting the overall performance balance. Linear Programming (LP) stands out with the highest ASi score of 0.5086, suggesting it is the best overall performer, due to its highest positive score and lowest negative influence. Simulated Annealing follows with an ASi of 0.4867, despite having high negative values—it compensates with strong positive deviations. Conjugate Gradient Method ranks third (0.6686 ASi) mainly due to its very low weakness score (high NSNi complement). Gradient Descent and Genetic Algorithm perform moderately, with ASi values of 0.2033 and 0.2407 respectively. Particle Swarm Optimization (PSO) shows a balanced profile with an ASi of 0.3803, making it a solid middle-ground choice.

TABLE 8. Rank

	Rank
Gradient Descent Optimization	6
Genetic Algorithm	5
Simulated Annealing	3
Linear Programming (LP)	2
Particle Swarm Optimization (PSO)	4
Conjugate Gradient Method	1

Table 8 presents the final ranking of the six optimization techniques based on their overall performance metrics. The Conjugate Gradient Method secures the 1st rank, indicating the best balance of strengths and minimal weaknesses across all criteria. Linear Programming (LP) follows in 2nd place, showing strong performance, particularly in positive deviations. Simulated Annealing ranks 3rd, reflecting solid gains despite some weaknesses. Particle Swarm Optimization (PSO) takes 4th, offering balanced performance. The Genetic Algorithm is ranked 5th, suggesting average effectiveness across parameters. Gradient Descent Optimization ranks 6th, largely due to its higher negative deviations, especially in reliability.

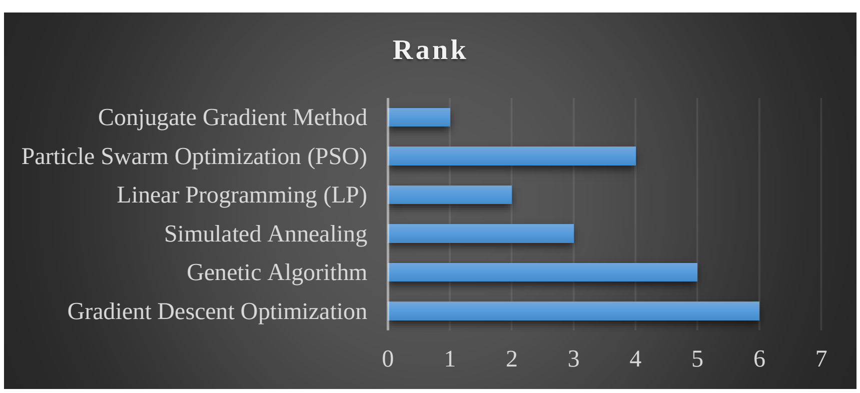


FIGURE 2. Rank

Figure 2 the Conjugate Gradient Method is ranked 1st, indicating it outperforms others in terms of balance between strengths and weaknesses. Linear Programming (LP) and Simulated Annealing follow in 2nd and 3rd places, respectively, showing strong but slightly less optimal results. Particle Swarm Optimization (PSO) is ranked 4th, suggesting moderate performance. Genetic Algorithm comes 5th, performing close to average. Gradient Descent Optimization is placed last at 6th, mainly due to higher negative deviation, particularly in reliability. The graph clearly highlights relative efficiencies.

4. CONCLUSION

Optimization plays a vital role in a variety of domains, from engineering and economics to psychology and environmental management. Given the vast number of optimization techniques available, it is impractical to explore them all within the scope of a single discussion. Therefore, this review strategically highlights several widely used and fundamental techniques, while deliberately avoiding specialized categories such as linear programming, convergent optimization, and multidisciplinary approaches. The aim is to provide a broad but insightful overview, equipping designers and decision makers with the conceptual tools necessary to select the method most appropriate for their unique problems. Among the methods discussed, classical approaches such as gradient descent and the parallel gradient method provide powerful solutions to persistent optimization problems, especially in machine learning and scientific computing. Population-based methods include particle swarm optimization and genetic algorithms bring robustness and flexibility to complex search spaces. Simulated annealing, with its ability to escape local minima, is an excellent choice for problems with abundant local optimization. Each of these methods offers unique strengths be it simplicity, global search capabilities or convergence speed with limitations that need to be carefully considered in practical applications. Modern frameworks such as the EDAS (Estimation Based on Distance from Average Solutions) method, especially when combined with fuzzy logic, prospect theory or interval type-2 fuzzy sets, further extend optimization to multi-criteria decision making. These improvements better capture the ambiguity and uncertainty present in real-world situations, such as assessing service quality in healthcare or prioritizing sustainable development goals. In addition, the influence of optimization extends to structural engineering, communication theory, operations research and computational biology, emphasizing its versatility. Critics of the theoretical foundations of optimization, particularly in biology and adaptive systems, warn that optimization can function more as a metaphorical or heuristic model than as an experimental scientific framework. Nevertheless, its practical application in resource management, industrial process design, and strategic decision-making remains undeniable. Ultimately, the value of optimization lies not only in the mathematical rigor behind its methods, but also in its adaptability to a variety of contexts and data formats. The collaborative effort to synthesize both retrospective and prospective optimization perspectives represents a growing field one that continues to grow in scope and relevance. With continued advances in computational power and algorithm development, optimization will be central to solving tomorrow’s most important technological and societal challenges.

REFERENCES

[1]. Venter, Gerhard. "Review of optimization techniques." (2010).
[2]. Smith, J. Maynard. "Optimization theory in evolution." Annual review of ecology and systematics 9 (1978): 31-56.
[3]. Singh, Ajay. "An overview of the optimization modelling applications." Journal of Hydrology 466 (2012): 167-182.
[4]. Biegler, Lorenz T., and Ignacio E. Grossmann. "Retrospective on optimization." Computers & Chemical Engineering 28, no. 8 (2004): 1169-1192.
[5]. Inkelas, Sharon. "The consequences of optimization for underspecification." (1994).
[6]. Rachmad, Yoesoep Edhie. "Communication Optimization Theory." (2022).
[7]. Yang, Xin-She. "Test problems in optimization." arXiv preprint arXiv:1008.0549 (2010).
[8]. Olhoff, Niels, and J. E. Taylor. "On structural optimization." (1983): 1139-1151.
[9]. Grossmann, Ignacio E., and Lorenz T. Biegler. "Part II. Future perspective on optimization." Computers & Chemical Engineering 28, no. 8 (2004): 1193-1218.
[10]. Fu, Michael C. "Optimization for simulation: Theory vs. practice." INFORMS Journal on Computing 14, no. 3 (2002): 192-215.
[11]. Rachmad, Yoesoep Edhie. "Psychological Optimization Theory." (2022).
[12]. Everitt, Brian. "Introduction to optimization methods and their application in statistics." (2012).

[13]. Parsopoulos, Konstantinos E., and Michael N. Vrahatis. "Recent approaches to global optimization problems through particle swarm optimization." Natural computing 1 (2002): 235-306.

[14]. Lundstedt, Torbjörn, Elisabeth Seifert, Lisbeth Abramo, Bernt Thelin, Åsa Nyström, Jarle Pettersen, and Rolf Bergman. "Experimental design and optimization." Chemometrics and intelligent laboratory systems 42, no. 1-2 (1998): 3-40.

[15]. Boschetti, Marco A., Vittorio Maniezzo, Matteo Roffilli, and Antonio Bolufé Röhler. "Matheuristics: Optimization, simulation and control." In International workshop on hybrid metaheuristics, pp. 171-177. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009.

[16]. Blum, Christian. "Ant colony optimization: Introduction and recent trends." Physics of Life reviews 2, no. 4 (2005): 353-373.

[17]. Simmen, David, Eugene Shekita, and Timothy Malkemus. "Fundamental techniques for order optimization." In Proceedings of the 1996 ACM SIGMOD International Conference on Management of Data, pp. 57-67. 1996.

[18]. Papadimitriou, Christos, and Mihalis Yannakakis. "Optimization, approximation, and complexity classes." In Proceedings of the twentieth annual ACM symposium on Theory of computing, pp. 229-234. 1988.

[19]. Huang, Yuhan, Rui Lin, and Xudong Chen. "An enhancement EDAS method based on prospect theory." Technological and Economic Development of Economy 27, no. 5 (2021): 1019-1038.

[20]. Keshavarz Ghorabaee, Mehdi, Maghsoud Amiri, Edmundas Kazimieras Zavadskas, Zenonas Turskis, and Jurgita Antucheviciene. "Stochastic EDAS method for multi-criteria decision-making with normally distributed data." Journal of Intelligent & Fuzzy Systems 33, no. 3 (2017): 1627-1638.

[21]. Kundakcı, Nilsen. "An integrated method using MACBETH and EDAS methods for evaluating steam boiler alternatives." Journal of Multi-Criteria Decision Analysis 26, no. 1-2 (2019): 27-34.

[22]. Kutlu Gündoğdu, Fatma, Cengiz Kahraman, and Hatice Nida Civan. "A novel hesitant fuzzy EDAS method and its application to hospital selection." Journal of Intelligent & Fuzzy Systems 35, no. 6 (2018): 6353-6365.

[23]. Torkayesh, Ali Ebadi, Muhammet Deveci, Selman Karagoz, and Jurgita Antucheviciene. "A state-of-the-art survey of evaluation based on distance from average solution (EDAS): Developments and applications." Expert systems with applications 221 (2023): 119724.

[24]. Ghorabaee, Mehdi Keshavarz. "Multi-criteria group decision-making using an extended EDAS method with interval type-2 fuzzy sets." (2017).

[25]. Sudha, A. Sahaya. "Application of EDAS method on water requirement in agriculture." Management 8, no. 9 (2019): 20-22.

[26]. Feng, Xiangqian, Cuiping Wei, and Qi Liu. "EDAS method for extended hesitant fuzzy linguistic multi-criteria decision making." International Journal of Fuzzy Systems 20, no. 8 (2018): 2470-2483.

[27]. Karaşan, Ali, and Cengiz Kahraman. "A novel interval-valued neutrosophic EDAS method: prioritization of the United Nations national sustainable development goals." Soft Computing 22 (2018): 4891-4906.

[28]. Asante, Dennis, Zheng He, Nana Osae Adjei, and Bismark Asante. "Exploring the barriers to renewable energy adoption utilising MULTIMOORA-EDAS method." Energy Policy 142 (2020): 111479.