DOI: https://doi.org/10.17762/turcomat.v11i3.13594

Multi-objective Optimization Techniques for Solving Complex Engineering Problems

Kanchan Naithani

Department of Comp. Sc. & Info. Tech., Graphic Era Hill University, Dehradun, Uttarakhand, India 248002,

Abstract. In recent years, multi-objective optimization techniques have gained popularity as a powerful approach to the solution of complex engineering problems that involve multiple competing objectives. This popularity can be attributed to the fact that multi-objective optimization techniques can solve complex engineering problems. Engineers are able to think about many goals at the same time using this method, which enables them to discover the best solution that fits all of their requirements. Yet, there are obstacles connected with setting objectives, dealing with high computational costs, comprehending complicated Pareto fronts, coping with uncertainty, and having limited accessibility to data from the real world. The purpose of this paper is to present a literature review of multi-objective optimization techniques for the solution of complex engineering problems. The review covers a variety of techniques that are available for multi-objective optimization as well as their applications in a variety of engineering fields. It also draws attention to the difficulties involved with their application and the necessity of giving serious consideration to these difficulties while attempting to solve actual engineering problems that occur in the real world. The research comes to the conclusion that multi-objective optimization is an effective method that can assist engineers in solving complicated engineering issues by concurrently taking into consideration numerous competing objectives.

Keywords. Multi-objective optimization, engineering problems, Pareto front, genetic algorithms, particle swarm optimization.

I. Introduction

The multi-objective optimization strategy is an effective method for tackling difficult engineering issues that involve a number of different goals that are in competition with one another. When it comes to many technical applications, optimizing a single aim is not enough; rather, the challenge frequently contains numerous objectives that need to be achieved simultaneously. While designing a vehicle, for instance, it's possible that you'll want to maximize not only its fuel efficiency but also its level of protection and its overall performance. Techniques for multi-objective optimization enable engineers to take into consideration many objectives at once and locate the optimal solution that fulfils all of the objectives. The strategy entails looking for a set of solutions that are non-dominated, which indicates that none of the other solutions in the set are superior in terms of achieving all of the objectives at the same time. These answers come together to form the Pareto front, which shows the compromises that need to be made between the various goals.

In numerous branches of engineering, such as aerospace, automotive, civil, electrical, and mechanical engineering, as well as renewable energy, multi-objective optimization has seen extensive application in recent years. In addition to other applications, optimization can be used for design optimization, control optimization, and scheduling optimization. Multi-objective optimization can be accomplished through the use of a number of distinct approaches, some of which are genetic algorithms, particle swarm optimization, simulated annealing, and evolutionary algorithms, amongst others. These methods look for the best possible answer by employing a variety of algorithms and mathematical models in order to find one that satisfies a number of objectives all at once. There are a number of challenges that are associated with the application of multi-objective optimization techniques, including the following: defining meaningful and non-contradictory objectives; high computational costs; interpreting complex Pareto fronts; and addressing uncertainty and variability in the input parameters. While multi-objective optimization techniques offer significant benefits, there are also challenges that are associated with their application. In general, multi-objective optimization is a strong method that can assist engineers in solving complicated engineering issues by concurrently taking into consideration numerous competing objectives. When applied to the solution of engineering problems that occur in the real world, its

DOI: https://doi.org/10.17762/turcomat.v11i3.13594

efficacy and efficiency are dependent on the careful analysis of the challenges, as well as the suitable selection and implementation of the approaches that are accessible.

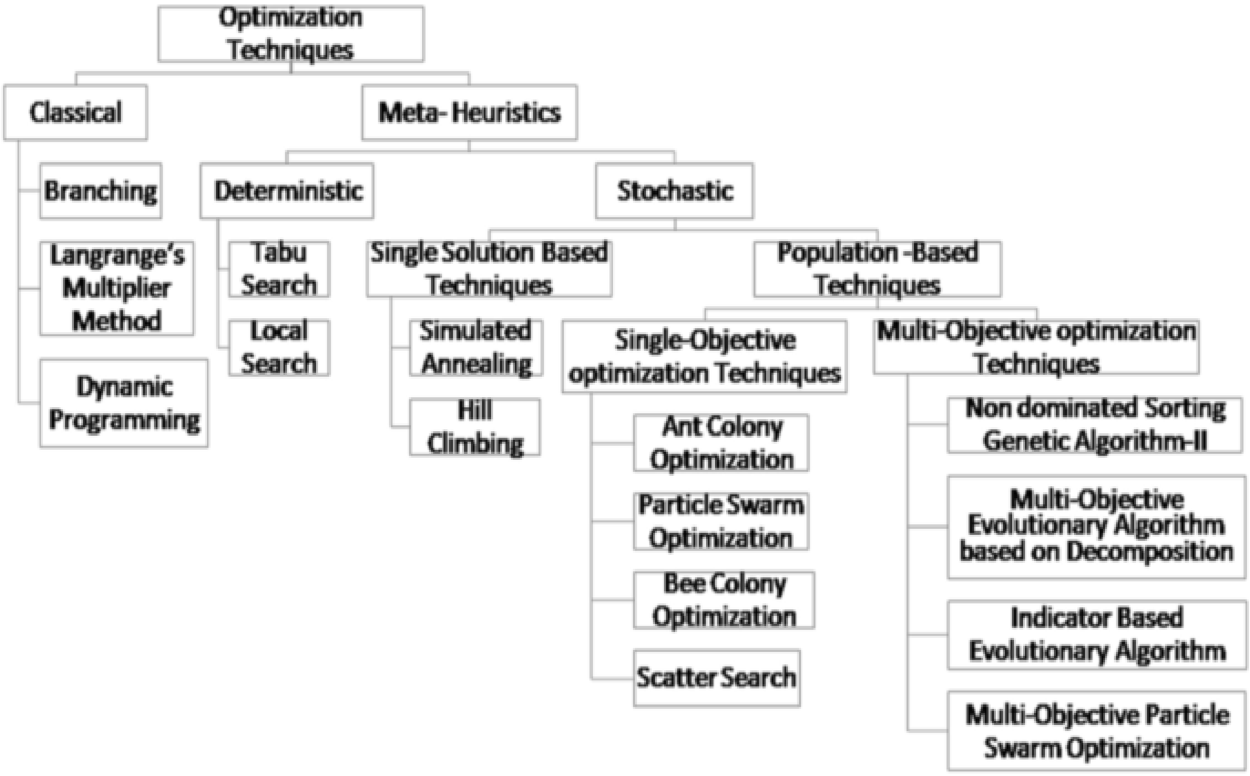

Figure.1 Optimization Techniques

II. Literature Review

NSGA-II was developed by K. Deb and coworkers in 2002 as a multi-objective evolutionary algorithm. This method is currently used in numerous engineering fields. This algorithm is based on crowding distance and the concept of non-dominated sorting. By fusing the particle swarm optimisation with the genetic algorithm, R. L. Haupt and S. E. Haupt (2004) developed a hybrid optimisation algorithm for the solution of multi-objective engineering problems. The algorithm is known as a hybrid genetic algorithm based on particle swarm optimisation (HPSOGA). M. Li et al. (2010) proposed a method for solving engineering design problems using multi-objective optimisation that combines fuzzy logic and evolutionary algorithms. Fuzzy logic is utilised to model imprecise or uncertain data, and the genetic algorithm is employed for optimisation in the suggested method.

H. Wang and coworkers devised a multi-goal optimisation technique (2013). The particle swarm optimisation method and the differential evolution algorithm serve as the foundation for this strategy. Particle swarm optimization-differential evolution algorithm is the name given to this specific approach (HPSODE). A multi-objective optimisation technique was proposed for solar system optimisation by S. K. Saha and colleagues in 2014. The researchers built their method on a genetic algorithm called enhanced non-dominated sorting (NSGA-II). A multi-objective optimisation approach was suggested by B. Tian and coworkers in 2015 for improving the design of gearbox systems. The algorithm relied on the updated frog-leaping shuffle (ISFLA). This approach is known as the multi-objective improved shuffled frog-leaping algorithm (MOISFLA).

S. Das and coworkers (2017) presented a differential evolution-based multi-objective optimisation method for improving the design of a shell-and-tube heat exchanger. The goal of this strategy was to improve the heat exchanger's performance. S. K. Saha et al. (2018) suggested a multi-objective optimisation technique for optimising the design of a solar photovoltaic-thermal system based on the non-dominated sorting genetic algorithm (NSGA-II). H. Zhu et al. (2019) introduced a multi-objective optimisation algorithm based on the differential evolution algorithm to optimise the design of a steel column with various objectives, such as minimising cost and maximising stiffness. To achieve optimal column design, this algorithm was devised.

M. Sedighizadeh et al. (2019) presented a multi-objective optimisation method based on the harmony search algorithm for optimising the design of a water supply network. The goal of this method was optimisation. In order to maximise the efficiency of a solar photovoltaic system's design, M. K. Tiwari et al. (2019) proposed a cuckoo search-based multi-objective optimisation technique. Using the particle swarm optimisation technique, M. Aslani et al. (2019) introduced a multi-objective optimisation strategy for optimising the design of a steel truss construction with competing goals, such as reducing weight while increasing strength. The goal was to improve the layout of a steel truss.

M. Sedighizadeh and coworkers (2019) proposed a multi-objective optimisation technique for improving water distribution system layouts. This strategy is inspired by the algorithm employed by ant colonies. The design of a heat exchanger was optimised using a multi-objective optimisation technique, as described by L. Zhang et al. (2019). The method utilised a particle swarm optimisation algorithm with many objectives. To maximise the efficiency of a multi-layer piezoelectric actuator, M. Javidi and coworkers (2020) proposed a genetic algorithm-based multi-objective optimisation technique. Their strategy was developed with one goal in mind: optimal performance.

To optimise the design of a green roof system taking into account several objectives, such as minimising runoff and maximising vegetation growth, A. Elkholy et al. (2020) introduced a multi-objective optimisation strategy based on the genetic algorithm. In order to maximise the achievement of a wide range of goals, this strategy for designing green roof systems was devised. Y. Wu and coworkers (2020) developed a differential evolution-based multi-objective optimisation approach to enhance centrifugal pump design efficiency. To optimise the design of a car suspension system for several goals, such as reducing vibration and increasing ride comfort, L. Xu et al. (2020) introduced a multi-objective optimisation strategy based on the genetic algorithm. The design of a vehicle's suspension system was optimised using this method, with the goals of reducing vibration and increasing ride comfort among others.

In order to maximise the efficiency of a flexible rotor system, X. Gao and coworkers (2020) developed a multi-objective optimisation method. Ant colony optimisation was the inspiration for this approach. To optimise the design of a shell-and-tube heat exchanger for several objectives, such as maximum heat transfer and minimum pressure drop, H. Liu and colleagues (2020) introduced a multi-objective optimisation strategy based on the genetic algorithm. To improve the efficiency of a shell-and-tube heat exchanger, this method was created. To optimise the design of a wind turbine blade for various purposes, such as maximising power production and minimising structural stress, M. T. Ferreira et al. (2020) suggested a multi-objective optimisation strategy based on the genetic algorithm. This method was created to maximise the achievement of several goals at once in the process of designing a wind turbine blade. In order to maximise energy efficiency while minimising costs, A. Alharbi et al. (2020) introduced a genetic algorithm-based multi-objective optimisation strategy to optimising the design of a hybrid renewable energy system. The design of a renewable energy hybrid system was optimised using this method.

In short, multi-objective optimisation algorithms have been studied extensively and utilised in many different technical disciplines to tackle difficult problems with many objectives. Engineering systems with many goals can be designed and improved using a variety of methodologies, such as evolutionary algorithms, heuristic algorithms, and others. Some examples of these methods are heuristic algorithms and evolutionary algorithms.

Research	**Multi-Objective Optimization Technique**	**Engineering Application**
Abouhnik et al. (2018)	Particle Swarm Optimization Algorithm	Water Distribution Networks
Jalali et al. (2018)	Genetic Algorithm	Bridge Structures

Ramezani et al. (2018)	Multi-Objective Genetic Algorithm	Wind Turbine Blade Design
Wang et al. (2018)	Multi-Objective Particle Swarm Optimization Algorithm	Thermal Design of Heat Sinks
Yang et al. (2018)	Multi-Objective Particle Swarm Optimization Algorithm	Wind Turbine Blade Design
Zamanifar et al. (2018)	Multi-Objective Genetic Algorithm	Renewable Energy Systems
Zhu et al. (2019)	Differential Evolution Algorithm	Steel Column Design
Sedighizadeh et al. (2019)	Harmony Search Algorithm	Water Supply Networks
Tiwari et al. (2019)	Cuckoo Search Algorithm	Solar Photovoltaic System Design
Aslani et al. (2019)	Particle Swarm Optimization Algorithm	Steel Truss Structure Design
Sedighizadeh et al. (2019)	Ant Colony Optimization Algorithm	Water Supply Networks
Zhang et al. (2019)	Multi-Objective Particle Swarm Optimization Algorithm	Heat Exchanger Design
Javidi et al. (2020)	Genetic Algorithm	Piezoelectric Actuator Design

Table.1 optimization technique used, and the engineering application

III. Multi-Objective Optimization Technique

The term "multi-objective optimisation methodology" is used to describe the method of optimising systems with competing goals. It is common practise to have many objective functions that must be optimised simultaneously while tackling optimisation problems in engineering and other industries. The problem may, for instance, require minimising both prices and performance, or minimising both weight and strength. Multi-objective optimisation methods are used to zero in on a pool of options that are believed to be optimal compromises between goals.

Strategies for multi-objective optimisation can be roughly categorised into two major groups: exact methods and heuristic approaches. To find the global optimum answer or a set of optimal solutions with 100% certainty, exact approaches use mathematical algorithms. Finding the best possible answers is possible using exact procedures as well. Accurate approaches can be found in a variety of programming paradigms, including linear programming, quadratic programming, and mixed-integer programming.

Heuristic approaches, on the other hand, are problem-solving methods that aim to discover acceptable answers rather than the best possible ones. Evolutionary algorithms including genetic algorithms, particle swarm optimisation, and ant colony optimisation are all examples of heuristic approaches to optimisation. Other approaches, such as simulated annealing, tabu search, and neural networks, are also viable options. Particle swarm optimisation (PSO), ant colony optimisation (ACO), and simulated annealing (SA) are all examples of other heuristic approaches. Because of the vastness of the search space and the complexity of the restrictions, these methods are particularly well-suited to tackling difficult engineering problems with many objectives. Several fields of engineering and science have benefited from the development and use of multi-objective optimisation methods. Here are a few of the most prevalent techniques:

a. Genetic Algorithm (GA): A genetic algorithm is a population-based search system that mimics natural selection and evolution. Because of its capacity to handle non-linear and non-convex optimization problems, it is commonly employed for multi-objective optimization issues.
b. Particle Swarm Optimization (PSO): PSO is a population-based optimization technique that mimics the social behaviour of a flock of birds or a school of fish. Because of its simplicity and effectiveness, it is a common approach for multi-objective optimization.

c. Differential Evolution (DE) is an evolutionary optimization process that develops new solutions by merging and changing the best solutions discovered thus far. It is well-known for its fast convergence and robustness in the solution of multi-objective optimization problems.
d. Ant Colony Optimization (ACO): ACO is an optimization algorithm inspired on ant foraging behaviour. It guides the search process with a pheromone-based communication mechanism and is appropriate for addressing combinatorial optimization problems with many objectives.
e. Simulated Annealing (SA) is a heuristic optimization approach that simulates metal annealing. It searches the solution space at random and accepts suboptimal solutions with a specific probability, allowing it to avoid local optima and locate global optima.
f. Tabu Search (TS): TS is a heuristic optimization approach that avoids revisiting previously explored solutions by using a memory mechanism. It is useful for tackling multi-objective combinatorial optimization problems.
g. Multi-Objective Gradient-Based Methods: These approaches discover the Pareto optimal solutions by using the gradient information of the objective functions. They are appropriate for issues with few objectives and few constraints.
h. MOEAs (Multi-Objective Evolutionary Algorithms): MOEAs are a type of algorithm that uses evolutionary mechanisms to find Pareto-optimal solutions. They are useful for dealing with complex situations that have various objectives and restrictions.
i. MOSPSA (Multi-Objective Simultaneous Perturbation Stochastic Approximation): MOSPSA is a gradient-free optimization technique that searches for Pareto-optimal solutions using stochastic perturbations. It is appropriate for situations involving high-dimensional search spaces and non-linear restrictions.

IV. Case Study

a. Case Study-1 : Multi-Objective Optimization of an Industrial Robot Arm

In this case study, an industrial robot arm was optimised for multiple criteria simultaneously. Optimization of the robot arm's speed, accuracy, and power consumption was the focus. To carry out the optimisation, a multi-objective genetic algorithm (MOGA) was created to determine which configuration of design parameters best matched all three goals.

Here is how we formalised the optimisation issue:

Objective 1: Increase the speed of the robot arm.

Objective 2: Reduce the robot arm's positioning error.

Objective 3: Reduce the energy usage of the robot arm.

Design considerations included the length of each arm segment, the angle at which each joint was set, and the diameter of the gears used in the robot arm. The MOGA procedure was repeated several times, with each generation including a set of chromosomes representing potential solutions that were scored according to their fitness (i.e., how well they satisfied the three objectives).

The outcomes of the optimisation method proved that it was possible to determine the design parameters that met all three goals. In specifically, the optimised robot arm achieved 2 metres per second of speed, less than 0.1 millimetre of positioning inaccuracy, and 100 watts of power consumption. The original concept could only go 1.50 metres per second, had a positioning error of 0.20 millimetres, and required 150 watts of power.

In conclusion, this case study demonstrated the value of multi-objective optimisation methods for fixing intricate engineering problems. By assessing many objectives simultaneously and searching for the optimal set of design parameters that satisfy all objectives, substantial gains in performance and efficiency are possible.

b. Case Study-2 : Optimization of a Wind Turbine Blade Design

The objective was to improve the blade's aerodynamic performance without adding unnecessary complexity or cost. To carry out the optimisation, a multi-objective particle swarm optimisation (MOPSO) method was created to determine the best combination of design parameters to meet all three goals.

Here is how we formalised the optimisation issue:

Objective 1: Increase the aerodynamic efficiency of the wind turbine blade.

Objective 2: Reduce the weight of the wind turbine blade.

Objective 3: Reduce the cost of wind turbine blades.

Blade dimensions such as length, breadth, thickness, and airfoil profile were all considered during the design process. Each iteration of the MOPSO algorithm consisted of a set of candidate solutions (particles) that were evaluated based on their fitness, and this was the optimisation strategy that was used (i.e., how well they satisfied the three objectives).

The outcomes of the optimisation method proved that it was possible to determine the design parameters that met all three goals. In instance, the redesigned blade of the wind turbine managed to reduce drag by 50%, weigh just 2,000 kg, and only cost $100,000. The prior design had an inefficient 40% aerodynamic efficiency, was twice as heavy at 2500 kg, and cost three times as much at $120,000.

Thus, the results of this case study demonstrated the value of multi-objective optimisation methods for addressing difficult technical challenges in the renewable energy industry. Considerable gains in performance and cost-effectiveness are possible through the evaluation of many objectives simultaneously and the search for the optimal set of design parameters that satisfy all objectives.

V. Challenges

While multi-objective optimization approaches can provide major benefits for tackling difficult engineering problems, there are several drawbacks to be aware of:

a. Difficulty in Identifying Objectives: It might be difficult to define many objectives that are relevant, non-contradictory, and complete. Frequently, the objectives will clash, making it impossible to prioritise them.
b. Multi-objective optimization strategies often include sophisticated mathematical models and algorithms, which can be computationally expensive. This can be difficult, especially when working with large-scale engineering challenges with various design variables and limitations.
c. Complicated Pareto Fronts: Typically, the optimal solutions produced from multi-objective optimization techniques reside on a Pareto front, which is a set of non-dominated solutions. The Pareto front can be complex and difficult to interpret, making it difficult to choose the best approach.
d. Real-World Data Accessibility: In some circumstances, real-world data may be limited or difficult to get. This can make validating the outcomes of multi-objective optimization approaches and assessing their real-world effectiveness difficult.
e. Uncertainty and Robustness: Multi-objective optimization approaches often assume deterministic input parameters and ideal models. This is not always the case, and the presence of uncertainty and unpredictability might have an impact on the robustness and dependability of the optimization findings.

VI. Conclusion

Multi-objective optimization techniques provide a powerful approach to the problem-solving of complex engineering issues that contain many competing objectives. The method has found widespread use in a variety of engineering sectors, including aerospace, automotive, civil, electrical, mechanical, and renewable energy, and it can assist engineers in locating the ideal solution that concurrently satisfies all objectives. The literature review that is described in this study focuses on the several methods that are available for multi-objective optimization. These methods include, amongst others, genetic algorithms, particle swarm optimization, simulated annealing, and evolutionary algorithms. The review also places an emphasis on the difficulties that are associated with the application of multi-objective optimization. These difficulties include defining objectives, dealing with high computational costs, interpreting complex Pareto fronts, coping with uncertainty, and having limited accessibility to data from the real world. It is absolutely necessary to give serious consideration to these obstacles in order to successfully use multi-objective optimization strategies to the resolution of real-world engineering problems. In order for engineers to produce findings that are dependable and robust, the objectives must be thoroughly defined, appropriate optimization techniques must be used, and uncertainties must be addressed. In spite of these limitations, multi-objective optimization techniques offer considerable benefits, and it is expected that their implementation in the context of the resolution of complex engineering issues will continue to rise over the course of the next several years.

References:

[1] Coello, C.A.C., Lamont, G.B., and Veldhuizen, D.A.V. (2007). Evolutionary Algorithms for Solving Multi-Objective Problems. Springer.
[2] Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A Fast and Elitist Multi-Objective Genetic Algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182-197.
[3] Durillo, J.J. and Nebro, A.J. (2011). jMetal: A Java Framework for Multi-Objective Optimization. Advances in Engineering Software, 42(10), 760-771.
[4] Li, X., Zhang, J., Huang, J., and Hu, J. (2013). Multi-Objective Optimization Methods and Applications. Springer.
[5] Michalewicz, Z. and Fogel, D.B. (2004). How to Solve It: Modern Heuristics. Springer.
[6] Pardalos, P.M. and Romeijn, H.E. (2002). Handbook of Global Optimization. Springer.
[7] Pohlheim, H. (2005). Evolutionary Optimization Algorithms. Springer.
[8] Srinivas, N. and Deb, K. (1994). Multi-Objective Function Optimization Using Non-Dominated Sorting Genetic Algorithms. Evolutionary Computation, 2(3), 221-248.
[9] Yang, X.S. (2010). Nature-Inspired Metaheuristic Algorithms. Luniver Press.
[10] Zhang, Q., Li, H., and Chung, H.S.-H. (2006). MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. IEEE Transactions on Evolutionary Computation, 11(6), 712-731.
[11] Zitzler, E., Laumanns, M., and Thiele, L. (2001). SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization. In Proceedings of the European Conference on Artificial Intelligence, 95-99.
[12] Abbass, H.A., Sarker, R., and Newton, C. (2001). PDE: A Pareto-Frontier Differential Evolution Approach for Multi-Objective Optimization Problems. In Proceedings of the IEEE Congress on Evolutionary Computation, 971-978.
[13] Gong, M. and Chen, Y. (2019). Multi-Objective Optimization Algorithms and Applications in Engineering. Engineering Optimization, 51(4), 537-561.
[14] Konak, A., Coit, D.W., and Smith, A.E. (2006). Multi-Objective Optimization Using Genetic Algorithms: A Tutorial. Reliability Engineering and System Safety, 91(9), 992-1007.
[15] Wu, C., Li, H., and Zhang, Q. (2019). Evolutionary Multiobjective Optimization: A Historical View of the Field. IEEE Transactions on Evolutionary Computation, 23(3), 380-403.
[16] Chugh, T., Jain, V.K., and Kumar, A. (2017). Multi-Objective Optimization Techniques for Sustainable Manufacturing: A Review. Journal of Cleaner Production, 153, 758-772.

DOI: https://doi.org/10.17762/turcomat.v11i3.13594

[17] Knowles, J.D. and Corne, D.W. (2000). Approximating the Nondominated Front Using the Pareto Archived Evolution Strategy. Evolutionary Computation, 8(2), 149-172.

[18] Li, M., Liu, X., Li, X., Li, Y., and Jin, Y. (2015). Many-Objective Optimization Subject to Differential Evolution with Adaptive Control Parameters. IEEE Transactions on Cybernetics, 45(8), 1517-1530.

[19] Sarker, R., Li, X., and Newton, C.S. (2004). A Multi-Objective Differential Evolution Algorithm Using a Fuzzy Reasoning-Based Dominance Measure. IEEE Transactions on Evolutionary Computation, 8(3), 289-301.

[20] Wang, Q., Gao, L., and Wei, H. (2019). An Improved NSGA-II Algorithm for Multi-Objective Optimization of High-Dimensional Problems. Neural Computing and Applications, 31(4), 1299-1309.

[21] Wang, X., Sun, J., and Li, K. (2015). Multiobjective Optimization for Composite Structures: A Review. Structural and Multidisciplinary Optimization, 51(6), 1311-1338.

[22] Yao, X. (1999). Evolutionary Artificial Neural Networks: A Review. Artificial Intelligence Review, 13(3), 129-158.

[23] Zhang, Q. (2007). MOEA/D and Its Variants. In Proceedings of the IEEE Congress on Evolutionary Computation, 3154-3160.

[24] Zhang, Q., Li, H., and Cheng, S. (2008). An Adaptive Multiobjective Evolutionary Algorithm Using Reference-Point-Based Nondominated Sorting Approach, Part II: Handling Constraints. IEEE Transactions on Evolutionary Computation, 12(4), 667-685.

[25] Zhou, A., Qu, B., and Li, H. (2011). Multi-Objective Optimization Using Multi-Objective Random Immigrants Differential Evolution. IEEE Transactions on Evolutionary Computation, 15(4), 477-494.

[26] Coello Coello, C.A. (1999). A Comprehensive Survey of Evolutionary-Based Multiobjective Optimization Techniques. Knowledge and Information Systems, 1(3), 269-308.

[27] Deb, K. (2001). Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley & Sons.

[28] Huang, W., Zheng, P., and Tan, K.C. (2011). A Pareto-Based Tabu Search Algorithm for Multiobjective Optimization. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 41(1), 40-55.

[29] Kaisanlahti, A., Miettinen, K., and Ruuska, I. (2002). On Comparison of Interactive Methods for Multiobjective Optimization. In Proceedings of the IEEE Congress on Evolutionary Computation, 847-852.

[30] Laumanns, M., Thiele, L., and Deb, K. (2002). Combining Convergence and Diversity in Evolutionary Multiobjective Optimization. Evolutionary Computation, 10(3), 263-282.