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Mutual Operator Patterns in Engineering Metaheuristics: A Review of Classical Engineering Design Optimization Problems

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Abstract: *Optimization problems arising from engineering design applications exhibit nonlinear objective functions, multimodal search spaces, interactivity among variables, and tight constraints on feasible solutions; all of which have made classical approaches to deterministic optimization infeasible. Consequently, metaheuristic algorithms have emerged as effective means for tackling classic engineering benchmark problems such as pressure vessel design, tension and compression spring design, welded beam design, and speed reducer design. However, recent developments in the fast-growing field of hybrid metaheuristics have been plagued with excessive development of optimization algorithms whose novel methodology revolves merely around the search metaphor used. In this context, the present paper conducts a review of metaheuristics for engineering design optimization with emphasis on hybridization at the operator level. The review critically evaluates the use of main operator types that make up the structure of today's engineering optimizers, including: exploration operators, exploitation operators, constraint handling operators, repair operators, diversity preserving operators, and adaptative control operators. Additionally, common operator usage patterns observed in successful metaheuristics are identified, such as: cooperation between exploration and exploitation operators, diversified search with repair operators, chaotic initialization, Lévy flight perturbation, memetic refinement, and adaptive operator sequencing. Also, the study covers new trends regarding hyper-heuristics, reinforcement learning guided operators' selection, and adaptive operator ecosystems. The findings of the analysis indicate that operator cooperation, compatibility and adaptiveness, not the metaheuristic algorithm's metaphor, play a predominant role in achieving optimal results. Lastly, several challenges concerning open questions and directions for future research in this area are discussed, such as those relating to operator compatibility theory, explainability, benchmarking inconsistency, scalability issues, and autonomous optimization systems.*

Keywords: Exploration and exploitation, Engineering Metaheuristic algorithms, Operator-level hybridization, Hybrid optimization.

1. Introduction

Efficiency and optimization represent two vital concepts in engineering systems, whereby engineering optimization problems try to achieve an optimal solution with respect to cost efficiency and robustness amidst various physical constraints [1], [2]. Engineering optimization problems often feature several attributes including nonlinearity, multimodality, mixed variables, and complex feasible spaces. These make it difficult to apply traditional algorithms in solving engineering optimization problems [1], [2]. Hence, classical engineering optimization problems, namely pressure vessel design, tension/compression spring design, welded beam design, and speed reducer design, are frequently used as test problems due to nonlinear interactions among realistic variables [3].

Traditional engineering optimization approaches depend on gradient-based searching, convexity, and differentiation of the objective function; therefore, they are ill-suited to problems with nonlinearity and discontinuity [1]. In recent years, many authors have looked into the use of metaheuristics for optimization since they are stochastic, do not require derivatives of the objective function, and can handle problems related to complex engineering systems, manufacturing scheduling, logistics management, and intelligent system control [1], [2], [3]. Many optimization algorithms have been developed in the last decades including Particle Swarm Optimization (PSO), Differential Evolution (DE), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), and Cuckoo Search (CS), among many others [1].

The reason behind creating hybrid optimization algorithms has been stated by the NFL theorem, which implies that no algorithm performs better than other algorithms in all problem domains and hence no universal solver exists for all problems [1]. Modern day optimization employs several search mechanisms in order to improve efficiency and effectiveness via improved convergence and feasibility preservation. This includes exploration and exploitation, adaptation of parameters, infeasibility-fixing operations, diversification based on chaotic search and Lévy flight behaviors [4]. Engineering optimization problems also necessitate effective search mechanisms to traverse complex feasible regions and nonlinear constraints; thus, feasibility preservation is achieved through adaptive penalty functions, infeasibility-fixing operations, and projection mechanisms [4]. In addition, recent optimization trends have incorporated dynamism into optimization algorithms, learning-guided searches, and hyper-heuristics that coordinate low-level search algorithms depending on the optimization domain [6], [7], [8].

Nevertheless, much of the literature review on optimization focuses on classification and behavior of search operators without detailed analysis of interactions between operators. Therefore, little research has been conducted on understanding the interactions between search operators in hybrid optimization algorithms and their application to engineering optimization problems. The purpose of this study is to bridge this gap through investigation of the interactions between search operators in hybrid optimization algorithms with regards to engineering optimization problems.

The current study explores interactions between search operators of hybrid optimization algorithms utilized in engineering optimization problems. This involves discussions on interactions between search operators of hybrid algorithms in four classical engineering optimization test problems:

- pressure vessel design,
- tension/compression spring design,
- welded beam design,
- speed reducer design.

In this study, the focus point will shift from previous research where algorithms were primarily classified in certain categories to the discussion of particular components of optimization processes. Operators for the following characteristics will be analyzed: exploration, exploitation, diversity maintenance, repairing, adaptive control, and constraint handling. The purpose of this study is to shed light on the operator-level hybridization strategy applied in solving engineering optimization issues regardless of the algorithm utilized.

The main contributions of this research paper can be summarized in the following five points:

1. Proposing a new hybridization method based on operators used for solving engineering optimization problems;
2. Identification and classification of operator patterns used for solving classical engineering optimization benchmarks;
3. Classification of operators associated with exploration, exploitation, diversity maintenance, repairing, adaptive control, and constraint handling in engineering optimization problems;
4. Studying the links between problem-specific properties and operator-level hybridization strategies;
5. Future perspectives of adaptive optimization ecosystems, hyper-heuristics, reinforcement learning in operator-level hybridization, and evolutionary approaches in operator-based engineering optimization hybridization.

As for the manuscript's structure, there are eight chapters in total. Chapter 2 deals with engineering optimization benchmark problems. Chapter 3 describes operator-level hybridization and its classifications. Chapter 4 highlights typical operator patterns in engineering optimization problems. Chapter 5 presents operators' taxonomy and classification concerning problems. Chapter 6 discusses how the discovered operator patterns influence engineering optimization progress. Chapter 7 identifies research challenges of operator-based hybridization strategies. Chapter 8 explores emerging trends in optimization ecosystem and intelligence through an operator-based approach. Chapter 9 concludes the paper.

2. Classical Engineering Design Problems

The application of classical design optimization problems for assessing the robustness, convergent behavior, and ability of metaheuristics to solve problems with multiple constraints is widespread in literature. The reason for that lies in the fact that such problems reflect realistic situations involving nonlinear objectives, multimodalities, various variables types, and numerous constraints [1], [2], [3], [5]. Pressure vessel, tension/compression spring, welded beam, and speed reducer design optimization problems serve as common benchmarks due to their complex nature, such as highly coupled variables, active nonlinear constraints, small feasible areas, and multimodal landscapes [2], [4], [5].

2.1 Pressure Vessel Design Problem

The pressure vessel design problem involves finding an optimal design with minimal production costs subject to nonlinear constraints associated with thickness, volume, and shape [2], [5]. Optimization algorithms used in such a problem typically include repair operators, penalty functions, chaotic initialization, and diversification techniques to facilitate the search for feasible solutions and improve convergence stability [3], [4], [9].

2.2 Tension/Compression Spring Design Problem

Problem statement for designing a compression/tension spring involves minimizing weight under stress, deflection, and natural frequency restrictions [2], [5]. Considering the extremely sensitive feasible region of this problem, most optimal algorithms usually consider local search, adaptive penalty methods, and feasible improvement techniques [2], [4], [5].

2.3 Welded Beam Design Problem

The optimization problem for the welded beam is aimed at minimizing manufacturing costs subject to stress, buckling, and deflection constraints [2], [5]. As several constraints could be binding close to the optimal solution, it is common practice in hybrid metaheuristics to incorporate repairs, penalty function modifications, local search algorithms, and diversification techniques [3], [4], [9].

2.4 Speed Reducer Design Problem

The optimization problem for designing speed reducers is to reduce the weight of gearboxes under nonlinear mechanical and geometrical constraints involving shaft sizes and stresses [2], [5]. Because of the increased dimensionality and complexity involved due to the interdependence between the parameters, modern approaches to solving such problems frequently include adaptive operator control, multi-approach strategy, Levy-flight diversity generation, and means of ensuring population diversity [3], [5].

2.5 Comparative Characteristics of Classical Engineering Design Problems

The test problems differ in sizes and goals of optimization, but they have some optimization characteristics in common which make them appropriate for assessing the new operators. Some of the main optimization characteristics of these four test problems are outlined in Table 1.

Table 1: The major characteristics of the four benchmark problems

Problem	Variables	Main Difficulty	Typical Operator Requirement
Pressure vessel	4	Narrow feasible region	Exploration + repair
Spring design	3	Sensitive constraints	Local exploitation
Welded beam	4	Multiple active constraints	Constraint handling
Speed reducer	7	High dimensionality	Adaptive exploration

Considering the wide range of possible applications, it may be concluded that one of the major simplifications was observed during the implementation of metaheuristic approaches and adaptive techniques [3], [4], [5]. It is worth mentioning that the basis for such simplification is the operator-oriented technique approach, which was used to solve these issues.

3. Operator-Level Hybridization

Operator hybridization can be considered as an approach whereby the use of operators belonging to different optimization algorithms takes place. In contrast to the hybridization of algorithms, which involves the application of full-fledged algorithms, operator hybridization refers to the cooperation of operators used in optimization procedures, such as those relating to diversification, local search, repairing, and scheduling [2], [5]. There are five main types of operators:

- exploration operators,
- exploitation operators,
- constraint-handling operators,
- diversity-preservation operators,
- adaptive operators.

3.1 Exploration Operators

The exploration operators are responsible for performing the global search procedure, which expands the exploration area in the search space to prevent premature convergence [1], [3]. There are different types of exploration, including differential evolution mutation, Levy flight disturbance, chaotic search, spiral search, and opposition-based learning [2], [3]. Recent studies have shown that using chaotic operators and Levy flight disturbance can increase diversity and achieve higher stability in the convergence process [3], [4], [10].

3.2 Exploitation Operators

Exploiters focus mainly on the development and acceleration of convergence around potential solutions [1], [5]. Some of the commonly used exploiters include local search, simulated annealing, variable neighborhood search (VNS), tabu search, and simplex [4], [5], [11]. Several effective optimization approaches in engineering make use of exploiters in a population-based setting [4], [5].

3.3 Constraint-Handling Operators

Constraint-handling plays an important role in maintaining feasibility through the whole optimization process and is especially useful when the problem under consideration has a limited feasible domain and nonlinear constraints [7], [12]. Examples of such strategies include the penalty function approach, repair methods, feasibility rules, adaptive penalties, and the ε-constraint approach [12]. The current scientific trend in this field suggests adaptive repairing and feasibility preservation strategies owing to their superior convergence characteristics [4], [12].

3.4 Diversity-Preservation Operators

The Diversity-preservation operators ensure that the population diversity is sustained and population stagnation is also avoided during the whole process of optimization [1], [3]. Some of these operators include random restart, mutations explosion, chaos perturbation, fitness sharing, oppositional learning, and the use of Lévy flights [2], [3]. The importance of these operators is very high in multimodal optimization [12].

3.5 Adaptive Operators

The operations detailed above adapt the search approach used by the algorithm based on the current status of the search process and whether or not the algorithm converges [3], [11]. There are several types of adaptation strategies, such as parameter adaptation, self-adaptation of mutation rate, inertia weight adaptation, reinforcement learning of operator choice, and hyper-heuristics [3], [11]. Modern optimization algorithms make use of artificial intelligence approaches to coordinate operators using machine learning techniques [6], [13], [14].

3.6 Operator-Level Hybridization Architectures

In the case of modern optimization problems, where most of them utilize engineering optimizers, architectures that include multiple operators have become increasingly common. Here, exploration, exploitation, repair, diversification, and adaptive operators work at the same time to produce better outcomes [2], [3]. The reason for this preference is that there is rarely a need for only one approach since a combination of operators is required. A generalized operator-level hybridization architecture is illustrated in Figure 2 below.

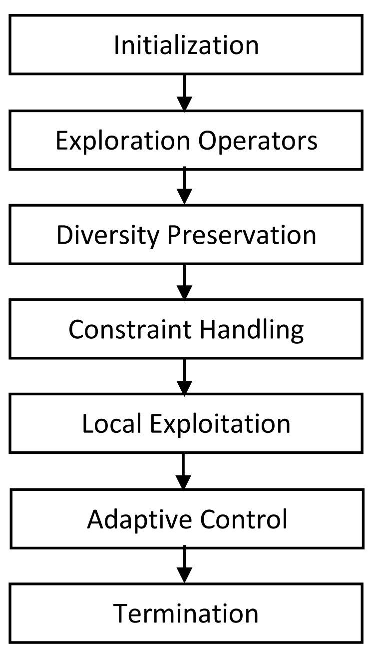

Figure 2: A generalized operator-level hybridization architecture

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4. Mutual Operator Patterns

4.1 Exploration–Exploitation Cooperation

One of the common approaches uses global diversification combined with local exploration. Exploration algorithms include differential evolution mutation, levy flight perturbation, chaotic search, and swarm intelligence. As for local exploration, some algorithms that could be used include simulated annealing, variable neighborhood search, tabu search, and simplex search [3], [5].

Such an approach is consistently found in the following optimization tasks:

- design optimization of a pressure vessel,
- design optimization of a spring,
- design optimization of a welded beam,
- design optimization of a speed reducer.

The process of diversification helps at the early stage of the search process, while local search becomes more important when approaching possible solutions [4]. The above approach could be depicted using the following diagram:

Global Exploration

+

Local Exploitation

4.2 Exploration–Repair Cooperation

For engineering applications with tight constraint specifications, the use of exploration-based approaches coupled with feasible solution recovery techniques is very common. A hybrid approach may involve chaotic perturbation, Lévy Flight diversification, or mutation using Differential Evolution, along with:

- Feasibility repair,
- Projection repair,
- Adaptive penalties,
- Stress repair [4], [12].
- Such an approach is very relevant for:
- Pressure vessel design optimization,
- Welded beam design optimization,

because constraint violation often occurs near the optimal solutions [4], [9]. The general pattern can be formulated as:

Exploration Operators

+

Repair Operators

4.3 Chaos-Assisted Diversification

The concept of chaos operators is known to be an approach which is actively used to improve metaheuristics in modern engineering [2], [3]. Mappings like logistic, tent, sine, and Chebyshev mappings are often used to provide diversification and to enable exploration.

Current research shows that chaos-based optimization demonstrates significant advantages in terms of:

- diversification ability,
- stability of convergence,

- avoiding local optima,

especially when dealing with multi-modal optimization problems [11]. The basic idea behind chaos-based optimization can be stated as follows:

Chaotic Initialization

+

Metaheuristic Search

4.4 Lévy-Flight Diversification

The Lévy flight operator is another example of the frequently encountered operators in engineering optimizations. The diversification technique based on Lévy flight allows large jumps and helps to escape local optimums [2], [3]. The generalized hybrid technique can be written as follows:

Base Search Operators

+

Lévy Diversification

This structure commonly appears in:

- Differential Evolution frameworks,
- swarm-based optimizers,
- memetic optimization systems,
- adaptive hybrid metaheuristics [4], [5], [11].

4.5 Memetic Local Refinement

In memetic algorithms for optimization, the incorporation of global search by population approaches together with local search strategies helps improve convergence precision [11]. Local search approaches widely used include:

• Hill Climbing

• Simulated Annealing

- Simplex Search
- Variable Neighborhood Search
- The application of these approaches proves helpful in cases like:
- Springs Design
- Welded Beam Problem, in which precise feasible solutions need to be found near the boundary constraints [4], [12].

Population-Based Search

+

Local Refinement

4.6 Adaptive Operator Control

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Operator scheduling is becoming a prevalent approach for modern hybrid metaheuristic algorithms [11]. The current schemes modify their operators' activation and parameter values based on:

- convergence characteristics,
- diversification status,
- fitness enhancement,
- search-state feedback.

Current studies have shown a growing trend toward incorporating reinforcement learning, hyper-heuristics, and machine-learning approaches in scheduling operators to dynamically manage operator cooperation during the entire optimization procedure [6], [14]. Adaptive control systems usually follow this general structure:

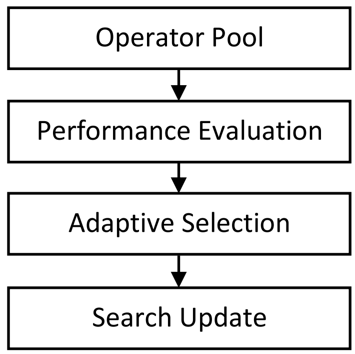

Figure 3: Adaptive control framework architecture

4.7 Unified Mutual Operator Architecture

As can be seen from the review of the literature, several optimizers use a common approach to hybridization, which includes:

- diversity,
- intensification,
- feasibility, and
- cooperation.

Here, the performance of the algorithm depends not on the parent algorithm itself, but rather on the cooperation between the operators [2], [3], [5].

5. Comparative Operator Taxonomy

In this chapter, brief explanations are given for the different operators used for optimizing problems in the field of engineering [3], [5]. There are six main types of hybrid operators, which include the following:

1. Exploration Operators
2. Exploitation Operators
3. Constraint Handling Operators
4. Diversity Operators
5. Adaptive Operators
6. Repair Operators

The connections between these operators are represented in Figure 4. More information about the operators will be explained in future chapters of this paper.

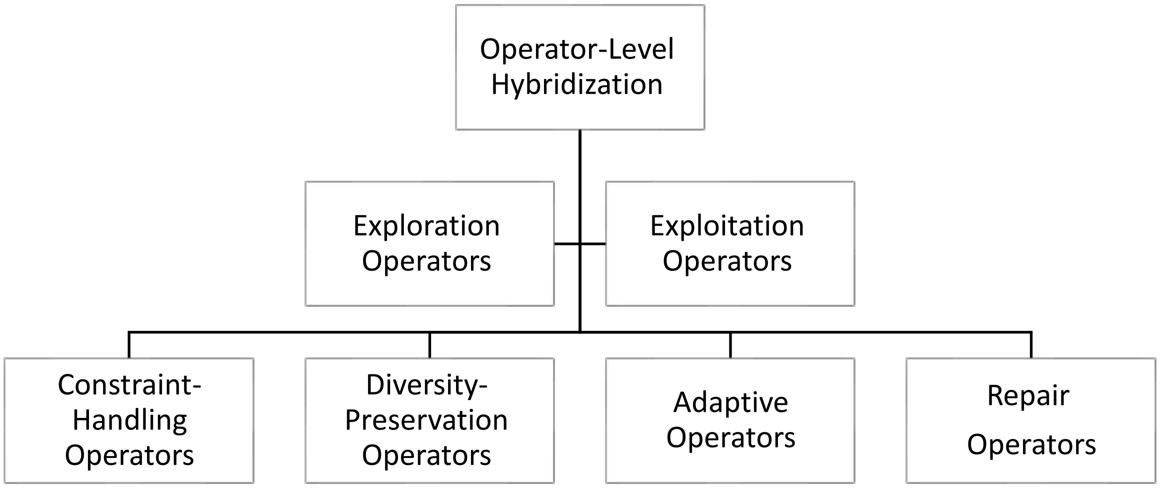

Figure 4: Operator-Level Hybridization framework

5.1 Exploration Operator Taxonomy

Table 2 summarizes the major exploration operators identified in the literature.

Table 2: The major exploration operators identified in the literature

Exploration Operator	Main Function	Common Applications
Differential Evolution mutation	Global perturbation	Pressure vessel, speed reducer
Lévy-flight search	Long-distance jumps	Multimodal optimization
Chaotic search	Diversity enhancement	Welded beam
Opposition-based learning	Search-space expansion	Spring design
Swarm movement operators	Population exploration	General engineering optimization
Spiral search	Nonlinear exploration	Spring optimization

5.2 Exploitation Operator Taxonomy

Table 3 summarizes the most common exploitation operators used in engineering optimization literature.

Table 3: The engineering optimization exploitation operators

Exploitation Operator	Main Function	Typical Problems
Local search	Neighborhood refinement	All engineering problems
Simulated annealing	Controlled local search	Pressure vessel
Variable Neighborhood Search	Adaptive exploitation	Spring design
Tabu Search	Guided local refinement	Welded beam
Simplex search	Precision optimization	Speed reducer
Hill climbing	Fine local adjustment	Spring optimization

5.3 Constraint-Handling Operator Taxonomy

Table 4 summarizes the major constraint-handling operators used in engineering metaheuristics.

Table 4: The major engineering metaheuristics constraint-handling operators

Constraint Operator	Main Function	Common Applications
Static penalty	Constraint penalization	General constrained optimization
Adaptive penalty	Dynamic feasibility control	Engineering benchmarks
Repair operators	Feasibility correction	Welded beam, pressure vessel
Feasibility dominance	Constraint prioritization	Spring optimization
Projection methods	Feasible-space mapping	Highly constrained problems
ε-constrained methods	Constraint relaxation	Nonlinear optimization

5.4 Diversity-Preservation Operator Taxonomy

Table 5 summarizes the major diversity-preservation operators identified in the literature.

Table 5: The diversity-preservation operators

Diversity Operator	Main Function	Typical Applications
Lévy-flight diversification	Long-range perturbation	Multimodal optimization
Chaotic perturbation	Diversity enhancement	General engineering optimization
Random restart	Escape stagnation	Highly constrained problems
Mutation bursts	Population diversification	Evolutionary optimization
Crowding mechanisms	Population spreading	Multi-solution optimization
Fitness sharing	Diversity preservation	Multi-modal search

5.5 Adaptive Operator Taxonomy

Table 6 summarizes the major adaptive operators identified in recent literature.

Table 6: The major adaptive operators

Adaptive Operator	Main Function	Typical Applications
Adaptive inertia weight	Exploration–exploitation balance	PSO-based frameworks
Adaptive mutation	Dynamic perturbation control	Evolutionary optimization
Success-history adaptation	Operator learning	Differential Evolution
Reinforcement-learning selection	Dynamic operator scheduling	Hyper-heuristics
Adaptive crossover	Diversity management	Evolutionary search

Self-adaptive parameters	Autonomous optimization	Hybrid frameworks

5.6 Repair Operator Taxonomy

Table 7 summarizes the most common repair operators used in engineering optimization literature.

Table 7: The engineering optimization repair operators

Repair Operator	Main Function	Typical Applications
Bound correction	Variable feasibility	General optimization
Stress correction	Structural feasibility	Welded beam
Thickness correction	Geometric feasibility	Pressure vessel
Projection repair	Feasible-space mapping	Constrained optimization
Feasibility restoration	Constraint recovery	Engineering benchmarks
Local repair search	Feasible local refinement	Hybrid optimization

5.7 Problem-to-Operator Mapping Analysis

Table 8 presents a generalized mapping between engineering benchmark problems and suitable operator categories.

Table 8: The generalized mapping between engineering benchmark problems and suitable operator categories.

Problem	Dominant Difficulty	Most Important Operator Types
Pressure vessel	Narrow feasible region	Exploration + repair
Spring design	Sensitive local constraints	Exploitation + feasibility
Welded beam	Multiple active constraints	Constraint handling + repair
Speed reducer	High dimensionality	Adaptive exploration

As follows from this classification, it may be stated that the efficiency of an optimization procedure depends significantly on the following aspects:

- the optimization problem itself,
- constraints imposed on the problem,
- geometry of the search domain,
- interactions between different variables.

Therefore, there cannot exist some universal set of operators effective for each engineering problem [3], [5]. On the contrary, efficient hybrid meta-heuristic algorithms usually combine several different classes of operators into a single algorithmic scheme.

5.8 Unified Comparative Taxonomy Framework

Based on the literature analysis presented throughout this review, a generalized operator-level taxonomy framework can be formulated as shown in figure 5:

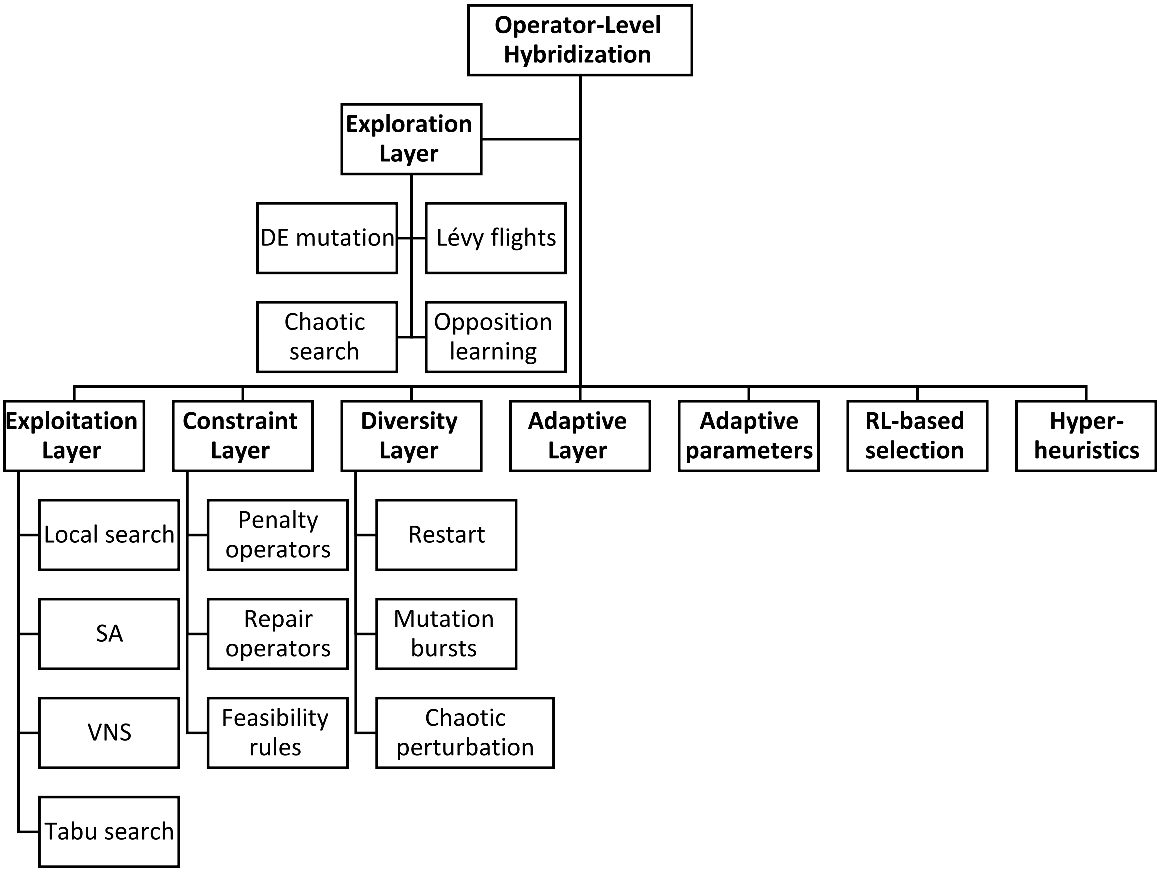

Figure 5: Unified Comparative Taxonomy Framework

These observable characteristics of modern optimization techniques used in engineering, according to the above classification, include:

- Environment of the operator;
- Scheduling of the operator;
- Hybridizing of the operator; and
- Collaboration of operators [11].

Therefore, the classification of operators applied for comparison in the above section is based on the main theme from the literature review, according to which the efficiency of meta-heuristics in engineering does not depend on the type of algorithm but rather on the application thereof.

6. Discussion

Considering the current literature devoted to optimization algorithms that are useful in addressing the task, one can outline some of the most significant features of algorithms and functions that allow efficient operation. In particular, those features are: diversification; local search operators' modification; providing feasibility of obtained solutions; and coordinated search [1], [2], [3], [4], [5], [6], [7], [12]. First of all, it should be stated that the usage of operators plays a key role in successful functioning. Effectiveness of those operators depends on the following aspects: the geometry of the feasible set, the nature of constraints, the problem multimodality, and high dimensionality of the objective function.

In this regard, one should note that peculiarities of optimization algorithms lead to different behavior of its operators and hybrid algorithms appear. That means, for instance, that due to relatively low cardinality of the feasible set in problems like pressure vessel design and spring design, the designing of such an operator that would integrate local search and repair is needed. Additionally, taking into consideration the need to overcome high dimensionality in such a problem as speed reducer optimization, the usage of several operators becomes inevitable. Furthermore, since a large number of nonlinear constraints makes weld beam optimization a highly complex process, the usage of repairing operator becomes necessary. Hence, there arises some interaction between the operators which depends on the specifics of the problem.

One more important characteristic of modern algorithms is their adaptability. Adaptability allows controlling the degree of diversification, increases the effectiveness of local search, and allows tuning parameters in order to enhance convergence and diversity. For instance, examples of adaptive operators are:

- adaptive parameter control;
- hyper-heuristic scheduling;
- operator selection using reinforcement learning;
- adaptive search using machine learning.

Thus, in the next stage, the idea is to develop adaptive operators to facilitate inter-operator interaction flexibly.

Since nowadays optimization problems tend to become even more sophisticated and require vast resources, the issues associated with the convergence stability become critical [7], [8], [12]. As a result, feasible solution diversity can be obtained by using diversification, modularity, repair and penalty terms. Therefore, it can be assumed that flexible inter-operator interaction might become a key direction in developing hybrid algorithms.

Despite that, one should acknowledge that there is a lack of theory about how hybrid algorithms should be created. Currently, algorithms are empirically designed. The issue of how operator interaction and adaptability should take place is not studied systematically. Benchmarking discrepancies may appear because of various setups.

Thus, adaptability along with controlled inter-operator interaction might become the leading principle in developing hybrid algorithms.

7. Open Research Challenges

Despite recent progress in hybridizing meta-heuristic methods to optimize solutions, some issues have to be discussed from the scientific standpoint. First of all, it should be mentioned that modern optimization science is based on empirical research, and its hybridization is also performed manually, thus lacking the necessary theoretical foundations for the effectiveness and scalability of optimizations due to black-box methods.

First, the theoretical aspects and interpretation of operator-level hybridizations remain insufficient. Also, hybridization itself often occurs along with a failure to perform a proper analysis of such theoretical characteristics as compatibility, convergence speed, and adaptability. Along with the theoretical constraints, a lack of transparency in the algorithm remains an issue since adaptive methods of hybridization, just like any others, can be considered black-boxes.

Second, reproducibility and benchmarking remain relevant topics within the sphere of optimization. There are several issues: first of all, various algorithms use different parameters, initial values, stopping conditions, feasibility checking methods, and performance measures. Furthermore, the output produced by an algorithm usually includes a single scalar value without any additional information on such criteria as convergence speed, stability, solution identification ability, etc.

Third, scalability remains one of the issues. Many algorithms are tested on low-dimensional problems while experiencing difficulties when solving higher dimensional tasks. Scalability of an optimization algorithm implies a balance between effectiveness and computational complexity depending on the dimensions of the problem.

Fourth, autonomous coordination should be discussed. Currently, dozens of operators are used for performing operations during a single optimization run, and there are no efficient policies of coordination that are based on handcrafted components, hence requiring autonomous coordination of operators.

Fifth, along with the development of the field, the phenomenon of redundant structure becomes increasingly noticeable. More and more scientists disapprove of metaphorical algorithms and call for getting rid of metaphors.

8. Future Directions

Current trends in optimization focus on optimizing operators' intelligence depending on properties of the particular algorithm used for optimization [6], [13], [14].

Firstly, a whole new approach must be implemented in order not to have any interference between searches while performing searches for local search, constraints, and operators. The following methods may be used in that case:

- hyper-heuristics
- reinforcement learning for operators
- machine learning optimization
- operator coordination

They help to select the optimal operator to use during search in particular search situation.

Secondly, the performance of all operators needs to be analyzed in certain situations using:

- surrogate-assisted optimization
- learning-based predictions
- landscape learning
- optimization memories
- state prediction

This helps to achieve flexibility and effectiveness of optimization process with plenty of possibilities for experimenting and hybridizing with other operators.

Finally, optimization algorithms might be incorporated into self-managing engineering systems through:

- digital twins
- cyber-physical systems
- Industry 4.0 cases
- real-time engineering systems

Coordinated searches become a necessity due to the highly volatile environment of such frameworks. Therefore, the main trend in optimization currently is developing intelligent self-management technologies of optimization.

9. Conclusion

In this research paper, a review of hybrid meta-heuristic algorithms is performed through the lens of operators in relation to their use in solving traditional engineering design optimization problems. It highlights common operator classes, which include those relating to diversification, intensification, solution retention, and coordination, for successful optimization processes. These results highlight the significance of operator cooperation based on problem knowledge in the development of future engineering optimization algorithms.

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