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Comparative Analysis of Population Initialization Strategies in Metaheuristic Optimization

Zainab O. Falah, Maytham Alabbas

Department of Computer Science, College of Computer Science and Information Technology, University of Basrah, Basrah, Iraq
E-mails: zainab.obaid@uobasrah.edu.iq ma@uobasrah.edu.iq (corresponding author)

Abstract**:** *Metaheuristic algorithms depend on population initialization to ensure an effective balance between exploration and exploitation in complex search spaces. Randomly initialized populations result in uneven coverage and premature convergence, especially in high-dimensional or multimodal problem landscapes. In this study, we investigate traditional and seven advanced population initialization techniques, including quasi-random sequence, chaotic map, opposition-based, knowledge-based, hybrid, and machine learning-based approaches. We discuss their theoretical foundations, computational complexity, and practical effectiveness. Findings suggest quasi-random initialization improves convergence for medium-dimensioned problems, chaotic population initialization improves convergence for multimodal search landscapes, and machine learning techniques adapt to very-high-dimensional optimization problems. Advanced techniques increase computational cost but significantly improve convergence rate and algorithm robustness. Such insights can assist researchers and practitioners in selecting appropriate initialization techniques for the complexity of their problems, and also indicate the direction of future research into intelligent and adaptive initialization techniques.*

Keywords**:** *Metaheuristic optimization, Population initialization, Quasi-random sequences, Chaotic maps, Machine learning-guided initialization.*

1. Introduction

Metaheuristic algorithms are nature-inspired optimization methods for solving complex, nonconvex, and high-dimensional problems where traditional techniques fail [1]. They efficiently explore poorly understood search spaces and are mainly classified into population-based methods, including evolutionary algorithms and swarm intelligence approaches, which maintain diversity and reduce the risk of local optima through collective solution search [2]. By maintaining a population of candidate solutions that evolve through iterations, metaheuristics balance exploration (searching new areas) and exploitation (refining known solutions) [3].

A critical aspect of this process is population initialization, which sets the starting distribution of solutions in the search space. The initial population influences the search by diversity and local optima avoidance [4]. The initial population influences the exploration of the search space, computational cost, and convergence speed. Randomly generated initial population is common in most metaheuristic optimization algorithms. Random population initialization can result in a non-uniform and non-diverse population and premature convergence to local optima, which results in poor quality of solutions [5]. Advanced population initialization methods include chaotic mappings (logistic, tent, and sinusoidal mappings), Low-Discrepancy Sequences (LDS), knowledge-based or hybrid approaches, and filter-based feature selection (applying statistical or heuristic criteria for selection of relevant features) [6]. These methods enhance population diversity, uniformity, and coverage of the search space, leading to rapid convergence to the optimal solution. Population initialization can be tailored to the problem at hand. In feature selection problems, knowledge or filter-based rankings can be used to form a promising initial population. Comparative studies show that well-designed population initialization techniques enhance the algorithm's optimization performance in terms of solution quality, convergence speed, and robustness across a wide range of benchmark functions and real-world problems [7]. This survey explores advanced population initialization techniques, classifies them, identifies their theoretical foundations, and compares their performance while pointing out challenges for future research. The contributions of the work are an analysis of current work and gaps in future research.

We conducted a systematic literature search across major academic databases, including ScienceDirect, IEEE Xplore, Scopus, and Google Scholar, focusing on English-language and peer-reviewed publications from 2021 up to 2026. The search strategy employed combinations of the following keywords: “population initialization”/ “initial population”; “metaheuristic”/ “evolutionary algorithm”/ “swarm intelligence”/ “population-based”; and one or more technique-specific terms (e.g., “random”, “Latin hypercube sampling”, “quasi-random sequences”, “chaotic maps”, “opposition-based learning”, “hybrid”, “machine-learning-guided”). We explicitly limited queries to the title and abstract fields to increase precision and reduce noise. The initial search yielded hundreds of papers. After screening for duplicates and non-relevant sources, 254 papers underwent full-text assessment, of which 86 met the inclusion criteria (i.e., empirical validation with quantitative benchmark or real-world results).

This paper evaluates various approaches to initializing populations in metaheuristic algorithms. Section 2 presents a taxonomy of eight groups for initialization and compares their benefits. Section 3 analyses these methods through their theoretical foundations, which include diversity, computational complexity, robustness, and so on. Section 4 discusses algorithm sensitivity and dimensionality effects, along with a computational trade-off analysis, empirical validation, and recommendations for use cases. Ultimately, Section 5 presents conclusions and indications of future research possibilities.

2. Taxonomy of population initialization methods

This section synthesizes all the described population initialization strategies, detailing their mechanisms and highlighting their comparative advantages and limitations.

2.1. Random initialization

Random initialization is the standard and most rudimentary way of creating the initial population, using randomly generated solutions within the bounds of the search space – using uniform, normal, or other types of distributions [8-10] – and is the most commonly employed initialization method in most optimization algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Biogeography-Based Optimization (BBO), Water Wave Optimization (WWO), Backtracking Search Algorithm (BSA), etc., [10-13]. Random initialization has the advantages of simplicity and unbiased population coverage of the search space [9, 14]; its disadvantages, however, include producing an uneven distribution of search efforts across some regions, rendering the search space inadequately covered, as well as a lack of diversity among solutions within the population, resulting in both premature convergence and local optima [15-17].

2.2. Stratified random initialization

Stratified random initialization includes techniques such as Latin Hypercube Sampling (LHS) and Orthogonal Array Sampling. Approaches like stratified sampling break the search space into strata or intervals [18]. This ensures a more uniform and representative sampling of the initial population. In a setup involving LHS, one sample is placed per stratum per variable [19]. Orthogonal arrays, on the other hand, combine balanced combinatorial designs to cover the space efficiently [20]. The principal benefits are diversity enhancement and exploration by preventing clustering, computational efficiency for medium-scale issues, superior performance for continuous optimization, and a lower risk of premature convergence through structured coverage [21-24]. Nevertheless, there are some limitations, which consist of an insufficient number of studies showing the initialization effect, difficulty in scaling to high-dimensional or constrained settings without modifications, underutilization in recent literature (generally orthogonal methods), and ineffectiveness in discrete or highly irregular landscapes [25, 26].

2.3. Quasi-random initialization

Initialization using quasi-random (low-discrepancy) sequences, such as Sobol, Halton, Well Equidistributed Long-period Linear (WELL), Knuth, Good Point Set (GPS), and Torus, generates an initial population that is more spaced out in the search space than random methods [27-29]. This method has the effect of increasing standardized diversity as well as the exploration ability of the population by improving the early phase of optimization. The convergence speed and the quality of the solution are generally better [29-31]. Yet, this benefit is diminished with time, as the performance gap between quasi-random initialization and random initialization reduces when the algorithm is given a large number of iterations to explore the search space thoroughly [32, 33].

2.4. Chaotic initialization

Chaotic initialization techniques employ chaotic maps (such as logistic, tent, sinusoidal, or other chaotic sequences) to create the initial population. The presence of disorderly behavior in these maps, such as ergodicity, non-repetition, randomness, and so forth, helps individuals spread more uniformly and promotes diversity [34, 35]. Examples include sinusoidal chaotic mapping for the Seagull Optimization Algorithm (SOA) [36], the tent chaotic map for Harris Hawks Optimization (HHO) [37], the logistic map for the Whale Optimization Algorithm (WOA) [38], and chaotic mapping for Tuna Swarm Optimization (TSO) [39]. Enhanced search speed, prevention of local optima, and faster convergence are the benefits [40]. Nonetheless, their limitations, such as potential sensitivity to map selection and increased computational overhead in some cases, have not been explored [41, 42].

2.5. Opposition-based initialization

Opposition-Based Initialization (OBI) forms the initial solutions using a candidate's opposite (lens-imaged) position in the search space, as this fills in unvisited areas and increases exploratory power [43]. Enhanced variations of the Salp Swarm Algorithm (SSA) utilize OBI to increase convergence and exploration, while some other enhanced versions utilize Opposition-Based Learning (OBL) at different points in the algorithm [44]. The OBL approach has also been applied to both the initialization and the updating of solutions within the Equilibrium Optimizer (EO) algorithm, so that it has improved performance, particularly when applied to high-dimensional problems [45]. Some of the advantages include receiving a higher-quality initial population, increased exploration of the search space, an improved ability to avoid becoming trapped in a local optimum, and improved performance on potentially deceptive optimization problems [46, 47], while some limitations include dependence on the type of problems being solved, requiring additional tuning or computations in some cases, and not being effective across all metaheuristic landscapes [43, 48].

2.6. Knowledge-based/heuristic initialization

Knowledge-based initialization (heuristic initialization) employs heuristic knowledge, expert design, and problem-specific information to produce the initial population instead of generating it randomly [49, 50]. One such example is knowledge-based local search operators, which aim to increase the quality of the solution during the search process [51]. Another example is heuristic rules such as Shortest Processing Time (SPT), Longest Processing Time (LPT), and First-Come-First-Served (FCFS), which are embedded in hybrid initialization methods for scheduling problems [52]. It leads to improved quality of the initial solution, faster convergence due to a more reliable starting point, applicability to a wide range of complex problems, and the ability to address scalability through a more generalized initial seed [49, 53]. Nonetheless, limitations exist in that they are strongly reliant on problem-specific knowledge, which may not generalize. Furthermore, the potential introduction of bias may limit exploration while requiring additional expertise or tuning. Finally, performance varies across optimization landscapes [54, 55].

2.7. Hybrid initialization

Hybrid initialization is a concept where a combination of two or more initialization strategies, often involving a mix of heuristic, random, and knowledge-based approaches, is employed to generate the initial population, which is a critical component in the optimization process [56]. This concept aims to leverage the benefits of different techniques to generate a highly effective initial population, a vital component in the exploration and exploitation of the solution search space [53, 57]. Some examples include the integration of symmetric LHS with reverse-based learning, which results in a well-dispersed initial population for the optimization process [58]; the integration of a hybrid fuzzy rough set with binary whale optimization, which results in an effective solution in the selection of features in a high-dimensional feature selection problem [59]; and the integration of a greedy construction stage before a subsequent heuristic or metaheuristic optimization stage, among others [60]. The benefits of this concept include better diversity and quality in the initial population, faster convergence due to the ability to start the optimization process with a better population, a better ability to tackle complex optimization problems, and better robustness as opposed to the application of a single optimization technique. This is shown by its application in benchmarks such as the CEC benchmarks, as well as in real-world applications such as the optimization of a pressure vessel, among others [61-63]. However, some of the challenges associated with the application of this concept include the computational cost due to the complexity of the optimization process, its sensitivity, which often requires substantial tuning, and its application being dependent on the expertise of the practitioner, among others [53, 62, 64].

2.8. Machine Learning-guided (ML-guided) initialization

ML-guided initialization exploits machine learning methodologies, such as reinforcement learning, supervised learning, clustering, fuzzy rough sets, and surrogate models, for identifying potentially useful regions or data structures in the search space. This results in the generation of high-quality initial populations for better performance of metaheuristic optimization algorithms [53, 59]. Some examples of ML-guided initialization methodologies include the use of smart sampling using modified quadratic interpolation or nonlinear simplex search for DE optimization algorithms [65], clustering for partitioning the search space for better initialization of the population for optimization problems [66], and the use of fuzzy rough set theory for initialization of the population for high-dimensional feature selection problems using metaheuristic optimization algorithms [67]. The advantages of using ML-guided initialization for optimization problems include fewer function evaluations needed to achieve the global optimum, better success rates compared to random or OBI, better diversity of the population using data-driven structuring of the search space, and better handling of complex or high-dimensional problems [59, 68]. The disadvantages of using ML-guided initialization for optimization problems include the increased computational cost of the learning or modeling step, the need for quality training data or models for better performance, and the limited generalizability of ML-guided initialization for solving a wide range of optimization problems [53, 59].

This taxonomy illustrates the evolution from simple random approaches to sophisticated ML-guided methods, highlighting how each category presents distinct trade-offs between implementation complexity, computational cost, and optimization performance. These trade-offs are summarized in Table 1.

Table 1. Population initialization categories in terms of their mechanisms, strengths, and limitations

Method	Core mechanism	Examples	Strengths	Limitations
Random	Uniform random sampling within bounds	Standard GA, PSO, DE	Simple, fast, and ensures baseline diversity	May produce low-quality solutions, uneven coverage, and poor early convergence
Stratified random	Divide the search space into strata and sample randomly within each	LHS, OAS	Better coverage than pure random; reduces clustering	Added complexity; benefits diminish in very high dimensions
Quasi-random	Low-discrepancy sequences for uniform coverage	Sobol, Halton, WELL, Knuth, Torus, GPS	Uniform, repeatable, good in low dimensions	Correlation issues in high dimensions may require scrambling
Chaotic	Use chaotic maps with ergodicity to generate sequences	Logistic, Tent, Sine, Ikeda maps	High diversity, ergodic, pseudo-random, avoids premature convergence, and notable gains on multimodal landscapes	Parameter sensitivity; may require tuning the map type to the problem
Opposition-based	Generate both candidates and their opposites; select the better	OBL, GOP, dynamic OBL	Improves quality while maintaining diversity; faster convergence	Gains depend on problem symmetry; less effective if opposition points are poor, extra tuning/effort
Knowledge-based/ Heuristic	Use domain rules, heuristics, or known feasible solutions	FIFO, LPT, SPT	High-quality starts; faster convergence; problem-specific robustness	Requires domain expertise; may reduce diversity; risk of bias toward local optima
Hybrid	Combine multiple strategies	Logistic-Tent chaos + OBL; global/local heuristic + random	Enhanced diversity, robust, adaptable to problems	More complex design; higher computational overhead, needs balancing

3. Theoretical considerations

The current theoretical comparison between the different population initialization methods in metaheuristics considers the properties of diversity, convergence, efficiency, and robustness against bias.

Diversity within the initial population plays a very important role in ensuring effective exploration of the search space and preventing premature convergence to suboptimal solutions [69, 70]. Although random initialization of populations is a popular choice, it does not ensure sufficient diversity within the search space, particularly in high-dimensional search spaces. This may cause local optimization problems [7, 71]. To overcome these limitations of random initialization, various innovative methods, such as LHS, chaotic mapping, OBL, and hybrids of these, have been proposed to ensure sufficient diversity within the search space. Furthermore, diversity-preserving mechanisms, such as elite crossing, chaotic sequences, and distributed search, have also been proposed to enhance search space exploration efficiency and prevent premature convergence [70, 72].

Exploration of the search space by optimization algorithms allows them to explore unknown regions of the search space, while exploitation of the search space helps optimization algorithms converge to optimal solutions. Therefore, a good optimization algorithm must ensure a fair balance between exploration and exploitation to achieve global optimality [73]. Various innovative initialization methods ensure sufficient diversity within the search space in the early stages of optimization, while adaptive parameter control and hybrids ensure a smooth transition from exploration to exploitation in the later stages of optimization [72]. However, improper initialization may cause optimization algorithms to converge slowly or may prevent sufficient search space exploration. Dynamic optimization algorithms that use a combination of chaos theory, OBL, and elite search have shown promising results in improving the exploration–exploitation balance of optimization algorithms [7].

Costs differ among initialization methods: simple random or uniform initialization is low cost but frequently does not provide a sufficiently diverse high-dimensional population [15], while initialization based on LHS, chaotic mappings, or learning is high cost but yields populations that reduce the cost of function evaluations [70]. There is, therefore, a trade-off between the initialization process and the efficiency of the optimization process as a whole; more sophisticated processes may be high-cost but can also provide increased optimization efficiency [7].

Initialization bias is a phenomenon in which the initial population is not adequately distributed, which can limit the ability of the optimization method to effectively search for global optima [12]. To address this, techniques such as low-correlation sampling, which include methods such as LHS and Gibbs sampling, OBL, and hybrid approaches combining random and deterministic sampling, are used to improve the quality of the population and limit bias [74]. These powerful initialization techniques are particularly useful for high-dimensional optimization problems, as bias and premature convergence are common [7].

Overall, theoretical and empirical evidence support that initialization matters for metaheuristic performance. Richly diverse and uniformly distributed initial populations enhance search coverage, reduce premature convergence, and ensure a good exploration-exploitation balance for the search, even in high-dimensional spaces. Random initialization is cheap but inferior to other approaches because it lacks diversity and is biased. LHS, chaotic, opposition-based, and hybrid initializations enhance coverage and convergence speed at a higher cost. However, consistent with discrepancy theory and the no-free-lunch theorems, no single initialization scheme can be expected to outperform all others across all problems. Therefore, properly designed and problem-tailored initialization is still a requirement for a high-performing metaheuristic.

4. Comparative analysis and sensitivity

Comparative analysis and sensitivity studies of population initialization methods in metaheuristic algorithms reveal important differences related to settings, such as algorithm sensitivity to initialization, population size, and iteration budget, diversity versus quality, dimensionality, cost, and supporting studies.

4.1. Algorithm sensitivity

Metaheuristic algorithms are sensitive to initialization with respect to exploration-exploitation, convergence, and solution quality. Earlier work shows that quantum-inspired, chaotic, and LHS-based initializations yield significantly improved search space coverage, convergence, and solution quality compared with biased or conventional initialization methods [75, 76]. Population initialization methods have a clear impact on the search process in metaheuristic algorithms.

4.2. Population size and iteration trade-offs

Population size and iteration budget are related to exploration, exploitation, and cost in metaheuristic algorithms. Sensitivity analysis studies show that improved performance gains from increased population size and iteration budget only go so far – they reach a limit in positive performance gain, beyond which further improvement is negligible relative to cost. Differences between algorithms (e.g., PSO has population size sensitivity, Cuckoo Search (CS) does not; Differential Evolution (DE) favors iteration budgets over population size) indicate the need to tune these parameters with respect to population diversity, convergence, and cost. [77-79].

4.3. Trade-off between diversity and quality

The diversity and quality of the initial population play an important role in the effectiveness of metaheuristic algorithms, as these improve exploration, accelerate convergence, and prevent premature convergence to local optima. Although random population initialization results in low diversity, especially for complex problems, other techniques such as chaotic systems, LHS, and OBL improve population diversity and quality, resulting in improved convergence behavior. In addition, using hybrid, rule-based, and knowledge-based techniques for population initialization further improves solution quality, though this is dependent on problem complexity and data. Therefore, the selection of an appropriate population initialization technique becomes critical for achieving effective and optimal optimization results. [19, 80, 81].

4.4. Dimensionality issues

High-dimensional search spaces hinder the achievement of uniform and effective initial population distributions, as random methods tend to create inhomogeneous particles and unstable performance, while increasing the population size increases computational cost. [82]. Although quasi-random methods and LHS have been found to improve performance, their effectiveness decreases, or their costs increase with higher dimensions, as the curse of dimensionality reduces the performance differential among initialization methods and limits exploration. [15, 83, 84]. Advanced methods, such as Gibbs sampling and filter-based initialization methods, are more robust for maintaining diversity and solution quality for high-dimensional optimization and feature selection problems. [15, 59].

4.5. Computational overhead

Initialization methods vary significantly with regard to computational overhead; for instance, simple stochastic methods tend to have minimal computational overhead, typically linear ($O(1)$) for each solution generated. As a result, they are fast but may require additional iterations due to the lower-quality solutions generated initially. In contrast, advanced techniques like anti-symmetric learning, LHS, and knowledge-based methods have higher overhead, especially for high-dimensional search spaces; however, they have the potential to improve convergence speed and consequently reduce total computational time. [53, 59, 82, 84]. Although computational time generally increases with problem dimensionality, differences between initialization methods for a given algorithm tend to be small and problem-dependent, emphasizing a trade-off between initialization time and optimization efficiency that requires empirical evaluation [83, 85, 86].

4.6. Empirical evidence

Significant research efforts have shown that initialization methods can significantly affect optimization performance and convergence behavior, especially for algorithms like PSO and DE, for which some probability-based and deterministic initialization methods have been shown to outperform others [11, 86]. Nevertheless, benchmark experiments and statistical analyses have also shown that, as the number of iterations and dimensionality increase for algorithms like PSO, DE, ABC, and GWO, differences in optimization performance among various initialization methods tend to vanish significantly, and none outperforms the others [83, 86]. Overall, comprehensive benchmarking and comparative analyses have confirmed that, although significant improvements in optimization speed and solution quality have been reported for some optimization algorithms by employing suitable initialization methods, these improvements remain problem-dependent and algorithm-specific [11, 87-89].

Table 2 summarizes the best and worst choices for different aspects, including simplicity, space-filling properties, performance in high and low dimensions, speed, reproducibility, theoretical guarantees, and suitability when no prior knowledge is available.

Table 2. Comparative evaluation: best and worst population initialization methods across key performance aspects

Aspect	Best choices	Worst Choices
Simplicity	Random, Chaotic	ML-guided, Knowledge-based
Space-filling	Quasi-random, Stratified random	Random, Heuristic
High dimensions	Quasi-random, Chaotic	Random, Heuristic
Low dimensions	Stratified random, Heuristic	Random, ML-guided
Speed	Random, Chaotic	ML-guided, Knowledge-based
Reproducibility	Quasi-random, Chaotic	Heuristic, ML-guided
Theoretical guarantees	Quasi-random, Stratified random	Heuristic, Knowledge-based
No prior knowledge	Random, Quasi-random	Knowledge-based, ML-guided

Table 3 presents the primary and alternative choices for various scenarios, including general-purpose optimization, high dimensions (D>50), very high dimensions (D>100), low dimensions (D<10), fast initialization requirements, maximum uniformity, sequential optimization, unknown problem structure, limited budget, and real-time applications.

Table 3. Recommended population initialization strategies: primary and alternative choices for specific optimization scenarios with key considerations

Use case	Primary choice	Alternative	Key considerations
General purpose	Random, Chaotic	Quasi -random, Hybrid	Primary: Random is most common; chaotic improves diversity and convergence Alternative: Quasi-random best uniformity; Hybrid is more robust
High dimensions (D>50)	Chaotic, Quasi-Random	Opposition-Based, Hybrid	Primary: Chaotic and quasi-random methods enhance coverage and diversity Alternative: Opposition lightweight and jumps to good regions; Hybrid adaptive
Very high dimensions (D>100)	Quasi-random, Chaotic	Hybrid, Knowledge-based	Primary: Uniformity and diversity are critical; quasi-random and chaotic are preferred Alternative: Hybrid scales; Knowledge-based reduces effective dimension
Low dimensions (D<10)	Stratified random, Random	Heuristic, Quasi-random	Primary: Simpler methods suffice; stratified can be effective Alternative: Heuristic is very effective with domain knowledge; Quasi-random extra uniformity
Fast initialization needed	Random, Chaotic	Quasi-random, Opposition-Based	Primary: Random and chaotic are the fastest Alternative: Quasi-random slower; Opposition very quick and diverse
Maximum uniformity	Quasi-random, Stratified random	Chaotic, Opposition-based	Primary: Statistical methods outperform random for uniformity Alternative: Chaotic dynamic coverage; Opposition good spread, less statistical uniformity
Sequential optimization	Heuristic, Hybrid	Random, Opposition-based	Primary: Heuristics can leverage sequential structure Alternative: Random, unbiased; Opposition quick diversity per step
Unknown problem structure	Random, Chaotic	Quasi-random, Opposition-based	Primary: Diversity is prioritized; random and chaotic are robust Alternative: Quasi-random structured coverage; Opposition doubles spread instantly
Limited budget	Random, Opposition-based	Quasi-random, Lightweight hybrid	Primary: Simpler methods reduce computational cost Alternative: Quasi-random better coverage per evaluation; Lightweight hybrid still cheap
Real-time applications	Random, Chaotic (hardware-accelerated only)	Hybrid, ML-guided (fast inference)	Primary: Hardware-accelerated chaotic methods offer speed and diversity Alternative: Pruned hybrid or lightweight ML inference adaptive and quick

5. Conclusion

Metaheuristic algorithms have access to a wide range of population initialization techniques, ranging from simple random-based to sophisticated chaos-based, knowledge-based, or hybrid-based techniques. The choice of the population initialization strategy may have an impact on the performance of the algorithm in terms of diversity preservation, convergence speedup, or escape from local optima. The latest trends in population initialization techniques are based on the inclusion of chaos theory, LDSs, or the use of hybrid techniques to increase the quality or effectiveness of the population initialization process. Based on the taxonomy presented in this paper, it appears that none of the population initialization techniques are universally superior for all problem classes or algorithmic contexts. Quasi-random sequences, such as Sobol or Halton sequences, are found to be effective population initialization techniques for low- up to medium-dimensional problem spaces, especially when compared to random-based techniques with minimal computational overhead [90]. Stratified sampling-based techniques, such as LHS, are found to be particularly well-suited for continuous optimization problems that require uniform coverage of the solution space. For high-dimensional problems, ML-based or knowledge-based techniques are also found to be particularly well-suited for population initialization. Chaotic population initialization techniques have also shown significant promise for improving the performance of optimization algorithms for multimodal problems by exploiting the ergodicity of chaotic sequences for diversity preservation or convergence speedup in a wide range of application domains [91-93]. There are critical trade-offs between simplicity, computational cost, and performance. Though random initialization is computationally cheap, there are possible issues with uneven coverage of the search space. On the other hand, complex initialization methods improve the quality of the initial population, which is, however, accompanied by an increase in the cost of initialization. This cost is worthwhile only when function evaluation is expensive or when the population size is small. It is also noteworthy that the effect of initialization is most significant in the early stages of the optimization process, where exploration is dominant. As the number of iterations or population size increases, the effect of initialization decreases, although the rate at which this effect decreases is problem-dependent. Dimensionality significantly influences the effectiveness of optimization techniques. Though structured initialization techniques are better than random initialization in low-dimensional optimization, the advantage decreases with an increase in dimensionality, such that the effect is less significant in high-dimensional optimization, where the curse of dimensionality is prevalent. On the other hand, the diversity-quality trade-off is problem-dependent. For unimodal optimization, there is a greater need to exploit better-quality solutions with less diversity, while, on the contrary, diversity is much more important in multimodal optimization, where there is a greater risk of premature convergence. Therefore, effective optimization requires the use of adaptive techniques that are able to balance the diversity quality trade-off according to the nature of the problem being optimized [94]. Future research directions include the use of adaptive initialization techniques that are able to adjust the diversity-quality ratio according to the feedback received from the landscape and dimensionality, and the use of automated selection techniques. Furthermore, integration with ML techniques, especially reinforcement learning, is also a possible direction for future research [95]. However, there is a need to consider the no-free-lunch theorem, which states that there is no universal optimization solution, as the effectiveness of an optimization solution is problem-dependent, as well as its properties and computational cost.

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List of abbreviations

Abbreviature	Full term		Abbreviature	Full term
BBO	Biogeography-Based Optimization		ML	Machine Learning
BSA	Backtracking Search Algorithm		OBI	Opposition-Based Initialization
CS	Cuckoo Search		OBL	Opposition-Based Learning
DE	Differential Evolution		PSO	Particle Swarm Optimization
EO	Equilibrium Optimizer		SOA	Seagull Optimization Algorithm
FCFS	First-Come-First-Served		SPT	Shortest Processing Time
GA	Genetic Algorithms		SSA	Salp Swarm Algorithm
GPS	Good Point Set		TSO	Tuna Swarm Optimization
HHO	Harris Hawks Optimization		WELL	Well Equidistributed Long-Period Linear
LDS	Low-Discrepancy Sequences		WOA	Whale Optimization Algorithm
LHS	Latin Hypercube Sampling		WWO	Water Wave Optimization
LPT	Longest Processing Time			

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