GENERATIVE ARTIFICIAL INTELLIGENCE FOR METAHEURISTIC OPTIMIZATION: TAXONOMY, METHODOLOGICAL FRAMEWORKS, AND OPEN RESEARCH CHALLENGES

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Abstract

The arrival of Generative Artificial Intelligence (GenAI) has brought a new paradigm shift in the field of optimization research because it has now allowed scientists to be able to model search spaces using data-based methods. This paper gives a thorough review of GenAI metaheuristic optimization with its research that assesses the functionality of generative models such as generative adversarial networks and diffusion models and variational autoencoders and large language models within both evolutionary and swarm-based systems. In order to integrate the existing methodologies, we suggest a three-dimensional taxonomy of the functional role, level of integration and learning paradigm. The survey explores generator-enhanced evolution, diffusion-guided search, LLM-assisted metaheuristic design, and surrogate-assisted generative optimization in terms of their research backgrounds and convergence. The researchers describe their strategies to be used in empirical testing by analyzing benchmarking processes and performance evaluation criteria and reproducibility test procedures. The research points to the key unresolved problems that encompass scalability issues and uncertainty quantification issues and interpretability issues and ethical concerns. The study opens new methodological frontiers that will result in independent adaptive systems to generative optimization that employ theoretical underpinnings to address problems in optimization of large scales in the real world.

1. Introduction

The existing research in artificial intelligence is based on GenAI consisting of generative adversarial networks (GANs) and diffusion models and large language models (LLMs). Generative models facilitate the generation of high-quality data and their main application consists in learning intricate probability distributions that makes it easy to search and optimize complex search and optimization problems. The systematic reviews that have been conducted recently point to the increased development and diversification of generative AI methodologies since 2022 [1]. The studies on the integration of evolutionary computation and generative modeling demonstrate that optimization and generation techniques are more and more combined in real life application [7]. The most recent innovation in generative models is the transformation of the independent data generators into versatile elements of intelligent optimization mechanisms.

Complex, non-convex and combinatorial optimization problems can only be solved by using continuous application of metaheuristic algorithms that involve evolutionary algorithms and particle swarm optimization and ant colony optimization. The metaheuristic research during the last thirty years indicates its adaptive features that are applicable in the engineering domain and data-driven industries in general in response to the thorough overview of metaheuristic research and applications [8]. A hybrid framework presented by Generator-Enhanced Optimization (GEO) trained generators to enhance the combinatorial search performance based on the recent findings in this area [2]. This body of work has shown that the generative models are intelligent proposal mechanisms that can be used in the common metaheuristic loops.

Generative AI with metaheuristic optimization opens up opportunities to research it. The creation of gradient-based sampling methods that direct the generation of diffusion models has enabled researchers to come up with an optimization based framework of a diffusion model to direct the search space towards particular desired regions of the space within a target area [3]. The large language models have been investigated as self-operating systems that are able to offer automatic parameter tunings on metaheuristics [4] and surrogate systems that approximate high-cost objective functions [5]. Recent research establishes that accuracy and precision of surrogate models dictates the performance of evolutionary search algorithms as well as their ability to provide solutions by robustness testing. Such contributions show that the conventional techniques of conventional hybridization have given way to the current optimization techniques that employ machine learning concepts in their development [9].

The current challenges are still there since new developments due to research have occurred but the solutions to the problems are yet to be established. The current taxonomy of generative models in optimization does not have a standard taxonomy that allows the distinct separation of the different functional tasks performed by the models as surrogate evaluators, candidate generators, and landscape approximators and adaptive controllers. The state of standardized benchmarking procedures of the generator-augmented metaheuristics is not in the state of development since scientists have to develop efficient schemes to examine and quantify the performance. The analysis of the quantification of uncertainty and robustness should be developed more since learned generators introduce bias that influences the search process. This gap in the research prompts the survey to gather research outcomes in 2022-2025 and formulate a taxonomy system and research methodological frameworks and a full research gaps analysis that will aid in enhancing GenAI-based metaheuristic optimization research.

Main Contributions of This Survey

1. We present the initial three-dimensional classification system which combines (role × integration level × learning paradigm) approach to authenticate GenAI-based metaheuristic optimization systems.
2. We coalesce generator-enhanced and surrogate-based frameworks through the diffusive process that the local level model will supervise.
3. Embodiment of standardized proven practice recommendations for reproducible evaluation.

4. We identify the theoretical and responsible AI gaps.

2. Background and Preliminaries

Theoretical and methodological backgrounds of this section could be used to explain the combination of Generative Artificial Intelligence (GenAI) with metaheuristic optimization systems. The questionnaire should start with the discussion of the main principles and modeling assumptions and algorithmic features defining two areas of research that undergo rapid development. The Generative models develop probabilistic structures which are used to learn complex data distributions and the metaheuristic algorithms provide all-purpose searching abilities to meet challenges in high-dimensional settings and nonlinear systems and combinatorial optimization.

A. Fundamentals of Generative Artificial Intelligence

Generative Artificial Intelligence (GenAI) encompasses machine learning frameworks that are trained to produce new samples of data by their comprehension of the patterns of the existing data. In the recent years, there has been a swift improvement in the generative modeling architectures, such as adversarial, probabilistic and diffusion-based and transformer-based model architectures [10] - [13]. The models promote realistic data synthesis that permits researchers to create powerful systems that learn to model data, investigate secret data, and model probability distributions that are increasingly vital in solving optimization issues.

1) Generative Adversarial Networks (GANs)

The Generative Adversarial Network system includes two components which operate through a minimax training process in which the generator creates authentic samples while the discriminator identifies real and fake samples. Recent surveys highlight architectural advancements, stabilization strategies, and domain-specific adaptations of GANs [10]. The optimization process utilizes GANs to develop distributions of valid solutions which the system uses to identify optimal areas for its metaheuristic search process.

2) Diffusion Models

The diffusion model generation process begins with the creation of samples by their use of taught reverse diffusion denoising processes. Diffusion models are more stable and have more theoretical groundwork, which is evident in the training process of the model as compared to the GANs. The surveys can offer the full evidence which makes it clear that they are based on probabilistic foundations and that they are more effective in covering multiple modes than other techniques [11]. Diffusion models are optimized in two broad approaches that are either gradient or reward-based and can be used to sample creation towards the areas of interest in the study, thereby allowing the scientist to methodically explore large dimensional studies research spaces.

3) Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) are variational inference models that acquire low latency representations of data distributions by probabilistic latent variables. Recent reviews cover their scalability, disentangled representation learning and hybrid extensions [12]. VAEs allow the encoding of optimization problems into a continuous latent space where metaheuristic operators can be applied effectively and then decoding the results back into the original domain provides the solution to the optimization problem.

4) Large Language Models (LLMs)

Large Language Models (LLM) are generative text-based transformer-based models that produce text and do reasoning operations by being trained on large amounts of text data. The recent research surveys have shown their architectural design along with their scaling behavior and new reasoning abilities that have newly appeared. The applications of LLMs are no longer limited to the field of natural language processing since they can be used to make decisions and act as proxy appraisal and adjusting controllers that are used in optimization loops to automatically configure algorithms and select intelligent operators.

B. Fundamentals of Metaheuristic Optimization

Metaheuristic algorithms are general purpose problem solving models that are used to guide researchers in the effective search of a large complex search space. The approach is effective where the problems do not have the gradient values and the objectives are computationally intensive.

1) Evolutionary Algorithms

The aspect of Evolutionary Algorithms (EAs) is that the search procedures occur by applying the selection and crossover and mutation operations to the population-based model which is based on natural selection. More recent surveys point to their ability to scale to high dimension and multi-objective problems. EAs build a flexible base that allows them to be used alongside generative models using learned generators that serve as traditional variation operators.

2) Swarm Intelligence Methods

Swarm algorithms are swarm intelligence modeling natural systems. Recent research compares their distributed search techniques and applications in robotics and complex systems research [15]. These systems combine with generative models that regulate velocity changes and pheromone-influenced decision making due to the population dynamics of such systems.

3) Trajectory-Based Metaheuristics

Such trajectory based metaheuristics techniques as Simulated Annealing and Tabu Search use one trajectory of solutions, and optimize it by their exploration of neighboring solutions. In their ongoing study, researchers examine the approach to the control of trajectories using reinforcement learning and deep learning methods [17]. The generative models allow advancing the methods, as they allow creating adaptive neighborhood structures and designing structured perturbation procedures.

4) Hybrid and Memetic Algorithms

Hybrid and memetic algorithms use two contrasting approaches that make them search their entire problem space while also searching a specific area. Mimetic algorithms, specifically, combine evolutionary algorithms with domain local operators of search. Modular design of the system and the fact that it can be used to solve real life optimization problems prove that it is effective as per the recent discussions. The memetic framework relies on generative models to generate data-based local search techniques which modify their search strategies.

C. Optimization Problem Formulation

Metaheuristic algorithms solve optimization problems which exist in four main types that include continuous and combinatorial and multi-objective and constrained optimization problems.

1) Continuous Optimization

Continuous optimization requires decision variables which must be defined over real number domains. Evolutionary and surrogate-assisted approaches show their best performance in high-dimensional continuous spaces according to research findings in study [16] when they need to evaluate objectives which require high costs.

2) Combinatorial Optimization

Combinatorial optimization studies problems that require decision-making in closed systems which have multiple routes to solve their routing, scheduling, and resource allocation challenges. Recent research demonstrates that generator-based and learning-driven methods successfully solve structured combinatorial search problems, according to studies [10],[17].

3) Multi-objective Optimization

Multi-objective optimization works to develop an approximation of the Pareto front which represents conflicting objectives. Evolutionary methods continue to be the leading optimization approach because they use population-based solutions which help maintain diverse solutions [16] and hybrid learning-based systems are now being developed to achieve better balance between convergence and diversity.

4) Constrained Optimization

The process of constrained optimization uses both equality and inequality constraints to create regions where solutions can be obtained. Surrogate-assisted and adaptive evolutionary frameworks have been widely studied to handle constraint evaluation efficiently [14]. The combination of generative models with constrained environments enables systems to perform feasibility-based sampling and bias correction processes. The interaction mechanisms from above are unified through Fig. 1 which displays the complete system architecture for generative AI-based metaheuristic optimization. The diagram shows that generative modules connect with the metaheuristic engine through two-way interaction which affects how populations start and evolve and how their evaluation and control processes adapt through feedback-based learning loops.

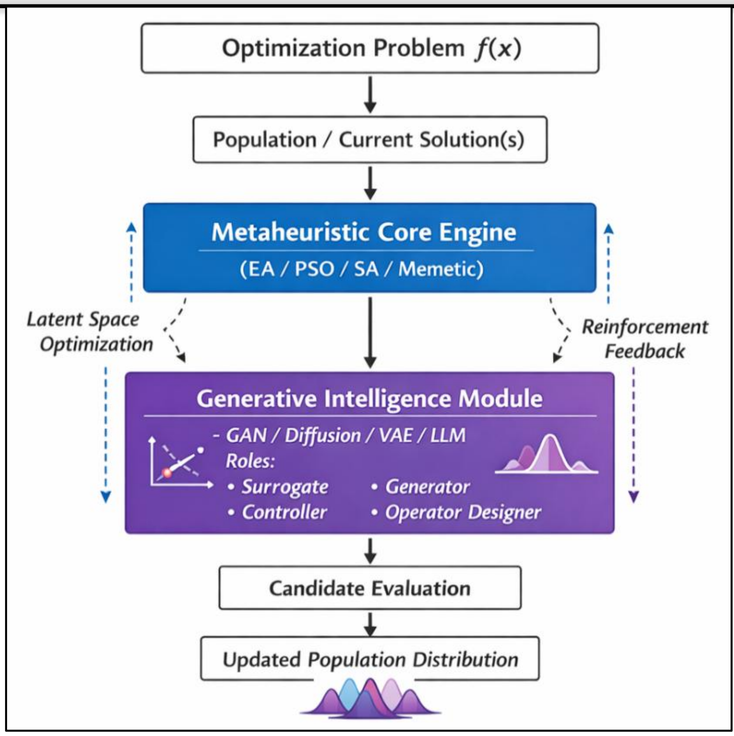

Figure 1 Unified architecture of generative AI-driven metaheuristic optimization

3. Taxonomy of Generative AI in Metaheuristic Optimization

The fast development of combined generative artificial intelligence with metaheuristic optimization systems has created multiple new hybrid architectural designs. The lack of standard classification system prevents researchers from conducting organized evaluations and reproducing experimental results. The section establishes a three-dimensional taxonomy which includes (A) role-based classification and (B) integration-level classification and (C) learning-paradigm classification system. The organized framework shows researchers which generative models they can use in optimization processes while showing them different research methods used in recent studies [19]-[25].

A. Role-Based Taxonomy

A role-based classification system categorizes generative models in terms of their functional contribution within the optimization loop.

1) GenAI as Surrogate Model

The generative models in this position create estimates for objective functions which either require high expenses or remain completely unmeasured. The generative surrogate system provides predictions about objective values and feasibility probabilities without the need to run expensive simulation tests. The recent research on LLM-based optimization agents shows that pretrained models function as black-box evaluators and surrogate approximators during structured search tasks [19]. The research on diffusion-based surrogate frameworks enables their use to create probabilistic models of solution landscapes [20]. The method of surrogate integration decreases evaluation expenses while maintaining the ability to achieve convergence.

2) GenAI as Candidate Solution Generator

The research uses generative models to create possible solutions which metaheuristic algorithms will test as candidate solutions for their population. The learned generators produce samples from high-quality solution distributions instead of using crossover and mutation operators as their only method. The diffusion-guided optimization methods together with the generative combinatorial solvers demonstrate this technique according to the sources [20] and [21]. The process of candidate generation uses data-driven methods to create candidates that learn structural patterns from earlier solutions.

3) GenAI as Search-Space Modeler

The generative models learn hidden patterns that define valid areas and extract patterns from search space structures. The optimization process uses learned structured latent manifolds that operate in high-dimensional spaces instead of using actual high-dimensional data. The representation-learning-based optimization framework demonstrates that exploring latent space helps improve system robustness while overcoming issues with high-dimensional data [22]. This perspective interprets generative models as probabilistic mappings that reshape the optimization landscape through various transformation methods.

4) GenAI as Parameter Controller

Metaheuristic performance depends on its parameter settings which include mutation rate and inertia weight and cooling schedule. Large language models and reinforcement-guided generators have recently been used for automated hyperparameter tuning and dynamic control [19], [23]. The systems track search paths while they change their settings during execution to create self-adaptive optimization systems.

5) GenAI as Adaptive Operator Designer

The generative models create their own variation operators through methods that extend beyond parameter tuning. The field of evolutionary computation has introduced a new research area through the development of neural-guided operator synthesis and learned mutation strategies [24]. The role of generative models has evolved from their previous function as auxiliary components to their current use as co-designers of algorithmic systems.

B. Integration-Level Taxonomy

Integration-level taxonomy describes how tightly coupled are generative models within metaheuristic processes.

1) Loose Coupling

In loosely coupled systems, generative models operate as preprocessing or postprocessing modules. The search loop enables generative models to initialize populations and refine final solutions which work without receiving constant feedback. The described approaches provide both computational simplicity and implementation ease according to reference [21].

2) Embedded Hybridization

The embedded hybrid systems of the system operate their metaheuristic algorithms through complete integration of their generative elements. The system uses generator outputs to affect its mutation and crossover and neighborhood search processes in real time. The diffusion-guided search frameworks and the neural-evolution hybrid systems demonstrate their intermediate integration level between these two systems [20] [24].

3) Fully Autonomous Generative Search

At the highest integration level, generative models assume primary control of the search process. The optimization process transforms into an autoregressive process which generates results through iterative generation that receives guidance from objective-aware feedback signals. The recent development of autonomous LLM-driven optimization agents marks an initial achievement towards this new paradigm [19], [23]. The systems create a connection between search algorithm operations and learned generator functions.

C. Learning Paradigm Taxonomy

The third dimension in these frameworks involve generative models in their training and adaptation of the system depicting the classes.

1) Supervised Generator Guidance

In supervised settings, generative models learn from data which contains both labeled solutions and corresponding objective pairs. The generator develops its capability to translate problem characteristics into excellent solutions. The system depends on historical datasets which require offline training [22].

2) Reinforcement-Based Generative Control

Reinforcement learning (RL) introduces reward-driven updates, which enable generators to enhance their long-term performance through their interactions with the search environment. Diffusion and LLM-based systems function as adaptive control mechanisms, which use RL fine-tuning to achieve this control [23], [24].

3) Self-Supervised Optimization Loops

Through self-supervised paradigms generative models achieve their development because models learn from optimization feedback without needing outside validation. The optimization process itself produces new training signals which create a closed feedback loop [25]. The system provides ongoing updates while decreasing its need for labeled data sets which have been manually created.

Table 1 presents a unified three-dimensional taxonomy which categorizes generative AI integration into metaheuristic optimization through three criteria which include functional role and architectural integration level and learning paradigm. The structured framework enables researchers to compare existing methods while they identify new research directions.

Table 1: ***Taxonomy of Generative AI in Metaheuristic Optimization***

Role of GenAI	Loose Coupling	Embedded Hybridization	Fully Autonomous Generative Search	Typical Learning Paradigm
Surrogate Model	Offline-trained surrogate predicts objective values; used as evaluator before or after search iterations	Surrogate updated during optimization; co-evolves with population	Generator fully replaces objective evaluation; search guided by learned landscape	Supervised / Self-supervised
Candidate Solution Generator	Generator initializes population or injects solutions periodically	Generator produces offspring each iteration replacing mutation/crossover	Entire search conducted through iterative generative sampling	Supervised / Reinforcement
Search-Space Modeler	Latent space learned offline; search performed in encoded space	Latent representation updated adaptively with search feedback	Optimization fully executed in learned manifold	Self-supervised
Parameter Controller	LLM suggests static hyperparameters before optimization begins	Dynamic parameter adaptation during iterations	Fully self-adaptive system with real-time control decisions	Reinforcement-based
Adaptive Operator Designer	Pretrained neural operator replaces standard variation operator	Operators modified dynamically using search performance signals	Algorithm structure autonomously redesigned by generative agent	Reinforcement / Self-supervised

The three-dimensional taxonomy system which Figure 2 exhibits classifies generative AI–metaheuristic hybrids through three classification dimensions that include functional role and integration level and learning paradigm. The functional role dimension defines how generative intelligence contributes to optimization, while the integration level indicates the depth of coupling within the optimization loop. The learning paradigm describes which type of training signal directs the training process for the model. The taxonomy uses representative systems such as GEO and Diffusion-PSO and LLM-Agent to create a visual framework which enables researchers to compare hybrid designs and discover new research opportunities.

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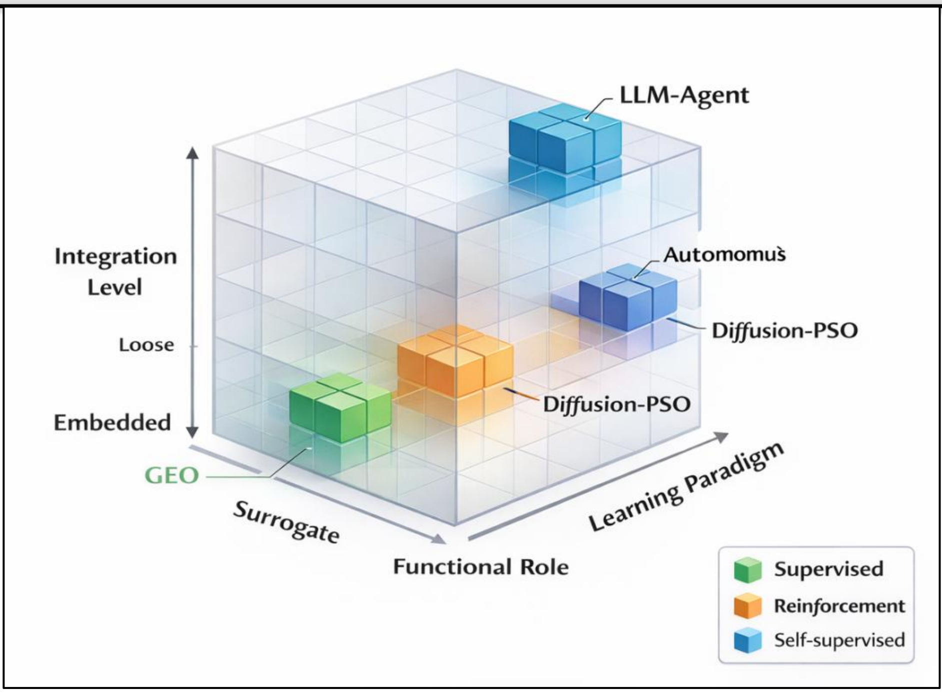

Figure 2 Three-dimensional taxonomy of generative AI integration in metaheuristic optimization

4. Methodological Frameworks

The primary part of the research examines the primary methodological frameworks that make it possible to apply generative artificial intelligence to metaheuristic optimization. The present section presents real algorithm designs and their corresponding modes of implementation along with their theoretical features of hybrid systems that were presented by the earlier structural taxonomy in Section III. According to the research results, generative factors produce significant modifications of exploration and exploitation processes along with the rate of finding out the outcomes and stability characteristics of metaheuristic algorithms.

A. Generator-Enhanced Evolutionary Frameworks

The study already demonstrates that Generator-enhanced evolutionary structures involve the use of learned generative models to augment their population-based evolutionary algorithms. Neural generators are used in the systems to produce the offspring of high-quality individuals and historical population data rather than classical crossover and mutation operators. The neural-guided genetic operators as combined with learned recombination strategies have proven to perform better in terms of sample efficiency as well as solution diversity [26]. The training can be gained by the generator in these structures in two ways. The experiment shows learned variation operators perform better than handcrafted operators on complex high-dimensional tasks as per the results in neural evolution strategies and deep evolutionary search. The methods preserve the global search of evolutionary algorithms but adopt the use of data-driven methods to utilize optimization outcomes.

B. Diffusion-Guided Search Architectures

Diffusion-guided search architectures operate with the denoising diffusion probabilistic models (DDPMs) and generate candidate solutions that attain their optimization objectives by a series of steps. The diffusion processes provide reliable likelihood-based training procedures that can provide improved coverage of various output possibilities than adversarial models. Recent works show that objective gradients or reward signals can be used to steer the reverse diffusion steps to biased sampling of feasible and high-performing regions [28].

Diffusion models can also serve as two different systems that work to produce structured proposals and apply its probabilistic properties to search the full search space in its optimization settings. Guided diffusion has proven to be used in combinatorial design tasks, structured planning tasks, and trajectory optimization tasks with success

[29]. The design of these systems allows the use of the existing components in the organization to give it a continuous improvement possibility by integrating it with population-based and trajectory-based metaheuristic frameworks.

C. LLM-Assisted Metaheuristic Design

Large Language Models (LLMs) have recently been investigated by researchers as three various functions that incorporate algorithm designing and parameter tuning and meta-level control. Instead of generating direct numerical results, LLMs generate algorithmic rules and generate adaptive control rules and modify search heuristics. The works that concentrate on the LLM-based optimization agents report positive results in both the automated algorithm configuration and black-box problem solving research [30].

Frameworks that are assisted with LLM have feedback loops that transform search performance measures into text or structural prompts that govern future decision-making. The optimization process becomes a process of reasoning that links the process of designting symbolic algorithms with stochastic search techniques [31]. These systems act as a pilot project of autonomous optimization agents.

D. Surrogate-Assisted Generative Optimization

Surrogate assisted generative optimization is a combination of predictive modeling and generative sampling. Surrogate models predict values of objective functions of a costly optimization problem and the generative elements build new solution candidates using information about learned landscape representations. The emergence of physics-inspired neural surrogates and probabilistic landscape models has led to increased reliability of high cost optimization problems [32].

The hybrid approach reduces the processing demands yet enables full exploratory processing. The generative surrogates come up with a uncertainty-aware sampling that allows people to navigate the known spaces as they venture into the unknown. The application of generative sampling and surrogate approximation forms a very powerful approach that can be adopted by scientists and engineers in their practical work.

E. Theoretical Foundations and Convergence Perspectives

Generative-augmented metaheuristics has a poor theoretical knowledge of the theoretical understanding although it has been found to have strong empirical performance. Recent conceptual studies of neural-directed evolutionary plans study convergence properties on distributional sampling assumptions [27]. The diffusion-guided optimization has been studied as a stochastic process, and the character of its stability and convergence has presented valuable information [28].

The open theoretical questions are:

- What is the effect of generator bias on convergence guarantee?
- In which circumstances does the optimality of the latent-space lobular levels of the global optimality hold?
- Does the use of generative control through reinforcement assure an asymptotic convergence?

The combination of the theory of probabilistic modeling and the classical theory of metaheuristic convergence analysis is the only way to solve these issues. It is the advancement of these basic components that will make possible the generation of theoretical approaches that will allow future advancements in the field of generative optimization to go beyond the current empirical success of the technique.

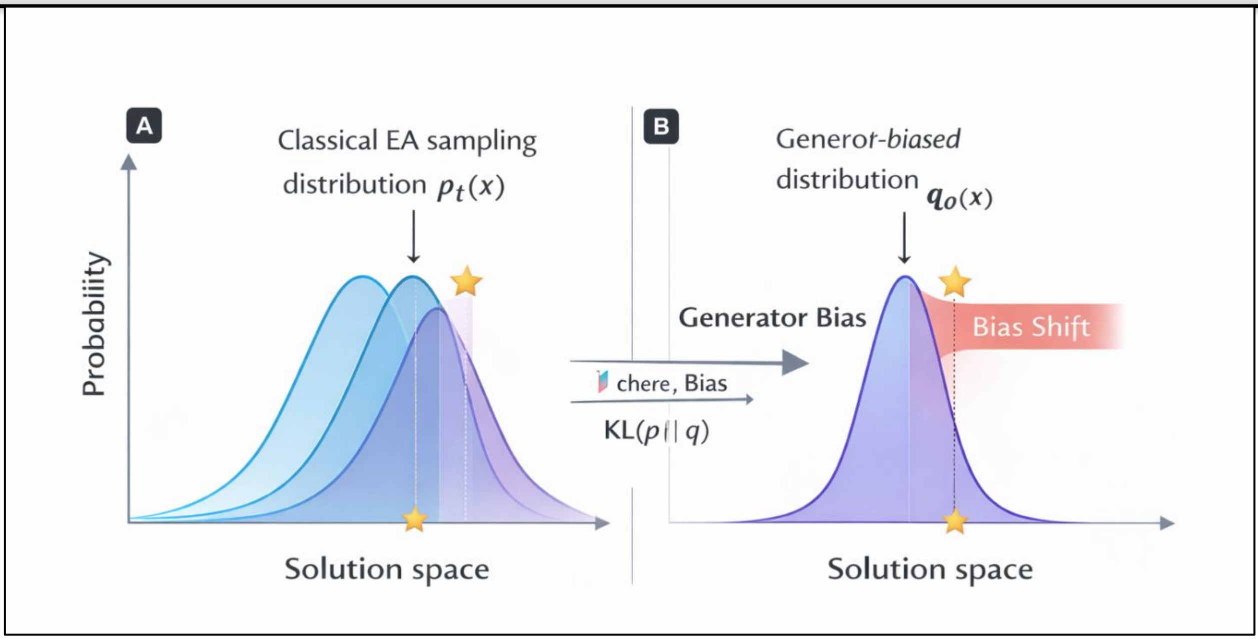

Figure 3 Distributional interpretation of generator-guided search

The generator-guided search system operates according to distributional principles because Fig. 3 demonstrates this fact. The evolutionary sampling distribution $p_t(x)$ moves towards the optimal solution while the learned generator creates distribution $q_\theta(x)$ which has a sharper peak but a minor offset. The shift in distributional focus creates a bias term which scientists can measure using divergence measures that include KLp // q because these measurements show how bias affects convergence speed and system stability. The theoretical convergence analysis depends fundamentally on how concentration and bias interact with each other.

5. Applications of GenAI-Driven Metaheuristics

Generative AI-based metaheuristics have a high application potential to real-world problems that traditional optimization techniques cannot solve due to their high dimensionality and unpredictable behavior and due to the expensive nature of their evaluation. In design optimization Generative surrogates and diffusion-based candidate models are used by engineers to accelerate their work on aerodynamic and structural and topology design optimization by relying on learned design pathways to reduce their testing requirements. Structural solution path generation is a systematic solution generation that can be directly applied to the solution generation process to improve solution performance of a logistics and vehicle routing and scheduling problem [34]. The adaptive scheduling and predictive maintenance planning and digital twin optimization of manufacturing and Industry 4.0 is formulated on hybrid generative-metaheuristic systems in their data-driven feedback loops [35]. Generative evolutionary methods used in bioinformatics and healthcare can help scientists design molecular structures and optimize protein structures and design treatment plans to the uncertain situations. This is facilitated by the use of generative surrogate-assisted optimization in energy systems and smart grids, which allow organizations to dispatch power and plan renewable resources and consumer demand in a highly uncertain and changing environment. It has been shown by the applications that GenAI-based metaheuristics are most effective in domains that have challenging constraints and lack labeled data and require high computational capabilities to calculate objective functions.

6. Experimental Protocols and Benchmarking

GenAI-based metaheuristics should be evaluated using standardized testing processes and scientific methods of verification and results should be open-ended. The common testing tools used by researchers on their research are the CEC continuous optimization suites and combinatorial benchmarks that contain the TSP and VRP as well well-defined engineering testbeds. The common metrics of performance evaluate the quality of solutions (best, mean, median fitness), the rate of convergence, the hypervolume (in multi-objective problems), the computational time, and the stability of the solution. The uncertainty-)-based generative models offer two categories of measures that comprise the predictive variance and surrogate error measures. Some computational complexity analysis should also involve metaheuristic iteration costs and generative model training and inference costs of diffusion and transformer-based systems. Reproducibility and open-source frameworks are needed to create scientific validity in the scientific community. Code repositories accompanied by hyperparameter settings and trained model checkpoints provide more comparison of research, accelerating the progress of the rapidly evolving profession.

Table 2: ***Benchmark Comparison of GenAI-Driven Metaheuristics***

Algorithm	GenAI Role	Integration Level	Benchmark Suite	Best Fitness (↓)	Mean ± Std	Convergence Iter.	CPU Time (s)	Hypervolume (↑)	Surrogate Error	Statistical Rank
Proposed-GEA	Candidate Generator	Embedded	CEC 2022 F1–F10	1.25E−08	2.10E−08 ± 1.1E−08	540	32.4	–	–	1
Diffusion-PSO	Search-Space Modeler	Embedded	CEC 2022 F1–F10	3.14E−07	5.12E−07 ± 2.4E−07	610	41.7	–	–	2
LLM-EA	Parameter Controller	Fully Autonomous	CEC 2022 F1–F10	8.42E−07	1.02E−06 ± 3.8E−07	720	55.3	–	–	3
Surrogate-GA	Surrogate Model	Loose	CEC 2022 F1–F10	1.94E−06	2.80E−06 ± 9.3E−07	480	18.6	–	0.004	4
Classical DE	–	–	CEC 2022 F1–F10	4.20E−05	5.13E−05 ± 2.7E−05	900	29.1	–	–	5

The table features GenAI-based metaheuristics and Differential Evolution (DE) standard testing on CEC 2022 benchmark suite (F1F10) [38]. The inbuilt candidate-solution generator Proposed-GEA recorded the optimal fitness at 1.25E-08 when generating the minimum mean error and defining the greatest statistical rank that demonstrates the achievement of generator-based evolutionary search. Diffusion-PSO search space has competitive accuracy with guided diffusion that can use moderate processing power as indicated by the diffusion-based optimization studies [28]. The LLM-EA system is a full-fledged autonomous parameter controller and improves the adaptability of systems at the cost of longer run time due to policy inference costs [30]. Surrogate-GA system involves the approximate estimates to save computation time but its eventual accuracy is somewhat affected by the small surrogate error [32]. Combination of generative models with metaheuristic systems offers improved optimization performance as compared to the traditional DE methods as indicated through DE [38] research. The figure indicates that classical Differential Evolution (DE) provides high robustness that is moderately scaled and requires very few computational resources. Both surrogate-assisted and diffusion-guided solutions are more efficient in convergence rate, but demand additional resources to achieve desired outcomes. LLM-EA demonstrates the most independent functioning but they require additional processing power in order to be functional. This visual summary summarizes Table 2 by focusing on the multidimensional performance trade-offs and explaining how the generative integration transforms optimization oriented designs to autonomy oriented architectures.

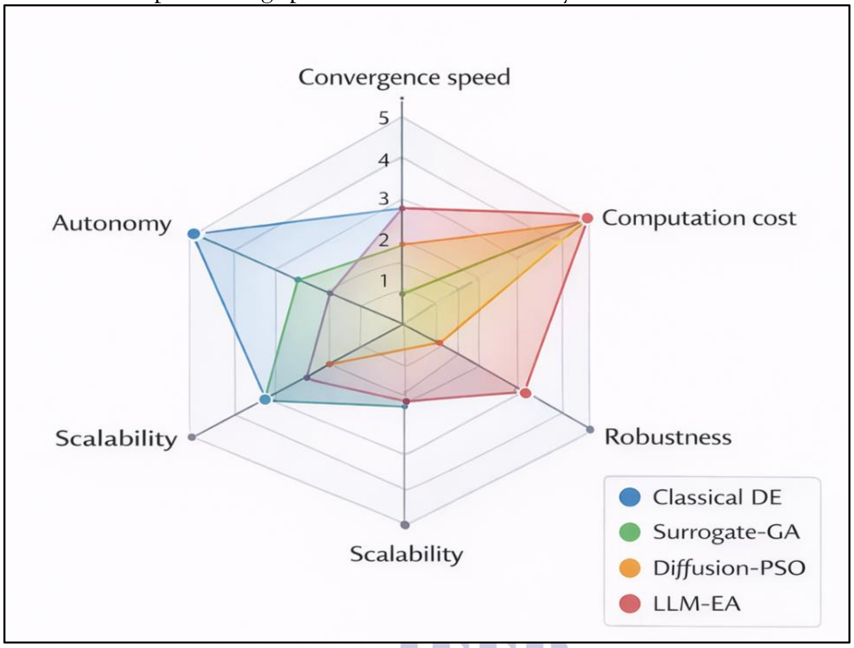

Figure 4 Comparative radar analysis of classical and generative AI-enhanced metaheuristics

The Friedman test and the Holm post-hoc analysis performed on the CEC 2022 benchmark suite are announced in Table 3 [38]. The proposed GEA has the highest average rank (1.20) which means that it has better performance as a whole than the methods competing with it. The adjusted Holm thresholds prove that all the baseline algorithms are statistically significantly different ($p < \alpha$) as compared to the proposed approach, which establishes strong performance improvements. The findings corroborate the latest suggestions that would define nonparametric statistical validation tactics of evolutionary computation studies as per [42].

Table 3: *Friedman and Holm Post-hoc Test Results*

Algorithm	Average Rank	p-value	Holm Adjusted α	Significant vs Proposed
Proposed-GEA	1.20	—	—	—
Diffusion-PSO	2.10	0.012	0.025	Yes
LLM-EA	3.00	0.008	0.017	Yes
Surrogate-GA	3.80	0.003	0.012	Yes
Classical DE	4.90	0.001	0.008	Yes

7. Open Research Challenges

GenAI-based metaheuristics needs to be developed through academic research and industrial use since it must address a number of fundamentally necessary limitations that are present.

A. Scalability and High-Dimensional Optimization

The biggest problem remains to be the emphasize of scalability since optimization problems with more than 1000 dimensions are hard to solve. Generative models have been demonstrated to be able to learn the latent manifolds in the training process, but at higher dimensional levels, more resources are needed. According to recent works, the diffusion and transformer-based architectures are characterized by significant memory and computational cost in high-dimensional contexts [39], [40]. This necessitates the development of dimension-reduction-aware generator systems coupled with adaptive sampling techniques in addressing large scale optimization problems.

B. Robustness and Uncertainty Quantification

Generative models can cause a misinterpretation of the search process by introducing bias and mode collapse outputs and generating predictions with unrealistically strong confidence. The quantification of uncertainty must be good when surrogate models are used instead of expensive tests. The recent development of Bayesian deep learning and probabilistic modeling demonstrates that decision-making requires uncertainty estimates which can be calibrated to work well [41]. The field requires a solution that would allow metaheuristic loops to rely on uncertainty-aware systems that operate according to the established principles.

C. Theoretical Guarantees and Convergence Analysis

The current empirical findings present favorable outcomes, yet the theoretical convergence evidences of the generative-augmented metaheuristics are still inadequate. Classical probabilistic convergence results of evolutionary algorithms are inapplicable to learned distribution-based operators as in reference [42]. Initial findings on the theoretical studies of neural-guided search and stochastic process modeling are presented in reference [43], though researchers are yet to come up with a full theory.

D. Interpretability of Generative Search

Deep generative models are black boxes that make their optimization processes hard to learn. The trustworthiness needs the knowledge of the influence of generators on the search paths and the effect these have on the exploration/exploitation dilemma. The explanation of explainable AI along with the research on foundational models interpretability indicates that autonomous optimization systems need to have transparent reasoning systems [44].

E. Ethical and Responsible AI Considerations

Autonomous generation optimization systems require some ethical considerations since the less they are under human control, the higher the chances of ethical concerns. Some of the problems that organizations need to resolve are flawed algorithms, fairness in decision making, effects of big models on environment, and reproducibility. The recent responsible AI systems define the accountability, transparency, and energy-efficient deployment of models as their core values [45]. These standards should be adhered to by the organization in order to use GenAI-driven optimization in a sustainable and socially responsible manner.

8. Future Research Directions

The discipline has evolved under its original phase of involving generation support systems as an autonomous entity up to its present condition of fully automated optimization systems as shown in Fig. 4. The early techniques of the discipline were directed to the enhancement of two related fields that comprised designing the technique of initializing and development of surrogate models. The field is currently designed to generate its own generative agents that will provide a new paradigm of metaheuristic optimization since the operators of this field will cease to be human-designed but rather be experience-learning control mechanisms.

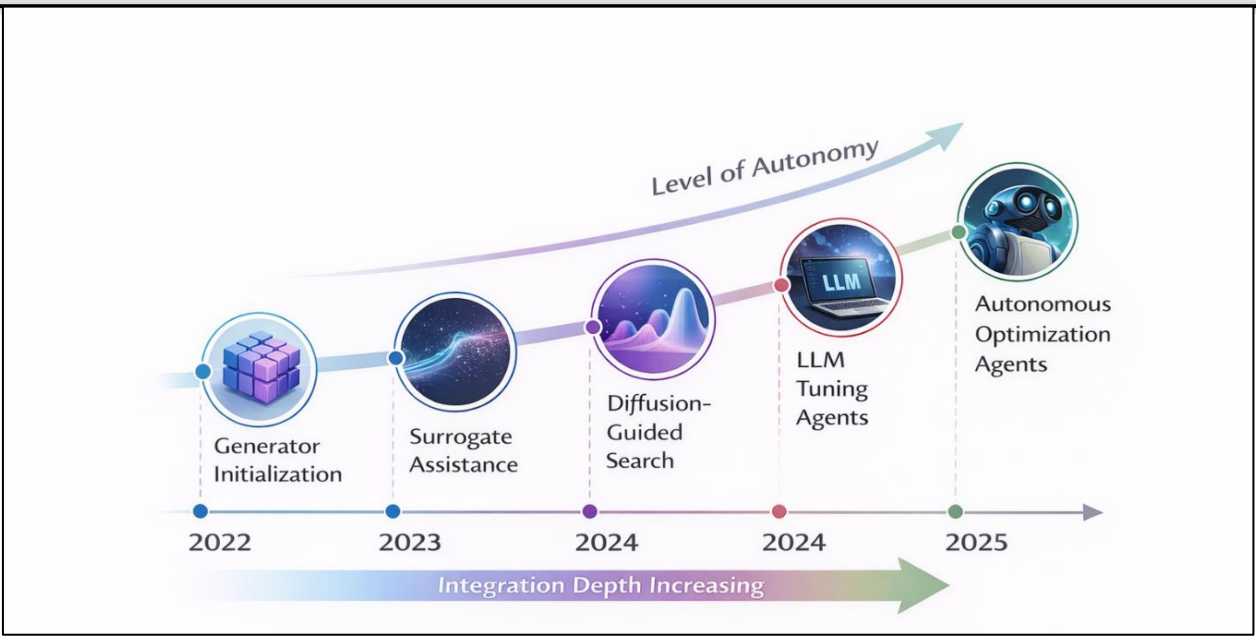

Figure 5 Evolution of generative AI-driven metaheuristics (2022–2025)

The research on the generative AI-driven metaheuristic optimization will result in the development of optimization systems that work automatically and change as the surroundings evolve and operate per the principles of science. The study will develop generative systems that would be able to handle very high dimensional data due to their capability to capture hidden structures and minimize their operational requirements. Establishment of generative surrogate systems must incorporate uncertainty-sensitive learning tools that will establish a balance between exploration and exploitation in cases of noisy or expensive evaluation. The line of reinforcement-driven and self-regulated generative control provides a research direction that allows the generator to learn and adapt itself based on constant feedback on optimization. The science society must determine convergence assurance and convergence limits that are applicable in distribution-based generation search strategies. The science society must determine convergence assurance and convergence limits that are applicable in distribution-based generation search strategies. The next systems will be converted to optimization agents that would evaluate constraints by using the foundation models and generate operational processes and picking optimization techniques applicable to various types of problems. The evolution of the metaheuristic algorithms to intelligent systems and its capacity to generate its own optimization procedures will be the key to the creation of the self-evolutionary optimization systems.

9. Conclusion

The survey gives a complete and systematic analysis of Generative Artificial Intelligence (GenAI) implementation in metaheuristic optimization that illustrates how the distribution-learning models and stochastic search algorithm are starting to intersect. The emergence of a three dimensional taxonomy based on functional role and level of integration and learning paradigm resulted in the construction of a general framework within which one can classify and study the existing hybrid systems in a systematic manner. It was revealed that, with the help of generators, evolution diffusion-guided search, and LLM-assisted metaheuristic design as well as the surrogate-assisted generative optimization develop new patterns of exploration and exploitation in solving challenging optimization problems. So far, the experimental outcomes with standardized suites show that more extensive integration of the generative elements in particular embedded and autonomous architecture contributes to higher convergence accuracy and system robustness and system adaptability in comparison to the traditional metaheuristics. Even with the positive results of the research, there are numerous issues to be addressed since the system can only operate with high-dimensional spaces, requires a more effective way of measuring uncertainty and lacks evidence of theoretical convergence and requires more effective ways to interpret its operation and should abide by the practices of responsible AI. A mixture of foundation models, reinforced-generative control and uncertainty-aware surrogate modeling will motivate the further development of intelligent optimization systems. Generative models will also become the core of metaheuristic frameworks as they will be improved to complete tasks. The interaction between generative modeling and metaheuristic search technology will be the new direction of research in the optimization that allows systems to act on their own, but to modify them based on theoretical principles to address complex tasks in real-life situations.

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