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A SYSTEMATIC REVIEW AND META-ANALYSIS OF GENETIC ALGORITHMS, PARTICLE SWARM OPTIMIZATION, AND HYBRID AI-BASED METAHEURISTICS IN STRUCTURAL DYNAMIC DESIGN AND VIBRATION CONTROL

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Abstract

Structural dynamic design and vibration control are critical challenges in engineering, where metaheuristic optimization algorithms have emerged as powerful tools for performance enhancement. This systematic review and meta-analysis aimed to evaluate the effectiveness of genetic algorithms, particle swarm optimization, and hybrid artificial intelligence-based methods in improving structural performance under dynamic loading and vibration conditions. We systematically examined studies that reported computational efficiency metrics, specifically convergence generations or function evaluations, as primary outcomes. The meta-analysis incorporated data from multiple eligible studies, and we computed standardized mean differences to quantify the relative performance gains. Results indicated that hybrid approaches significantly outperformed standalone algorithms, with an overall effect size of -2.57 *(95% confidence interval:* $[-3.76, -1.39]$, $p < 1e^{-4}$*). A subgroup analysis revealed that particle swarm optimization achieved the fastest convergence rates (*-4.26*), while hybrid methods demonstrated the greatest robustness in vibration control applications. The heterogeneity across studies was substantial, suggesting that algorithmic efficacy is highly dependent on structural complexity and loading conditions. Our findings further showed that convergence performance improvements were statistically significant in 82% of the included comparisons. These results lead to the conclusion that metaheuristic algorithms, particularly hybrid configurations, provide reliable and efficient solutions for structural dynamic design problems. However, the observed variability underscores the need for standardized benchmarking frameworks and more extensive validation studies. This review synthesizes current evidence and offers practical guidance for selecting appropriate optimization strategies in structural engineering applications.*

1. Introduction

The field of structural engineering is perennially confronted with the challenges of designing dynamic systems that can withstand variable and often unpredictable loading conditions, such as those induced by earthquakes, wind, and operational machinery. Structural dynamic design and vibration control are therefore central to ensuring safety, serviceability, and longevity of infrastructure. Traditionally, the design and optimization of structures against dynamic loads have relied heavily on classical analytical methods and gradient-based numerical optimization. While these approaches are mathematically

rigorous, they frequently encounter significant limitations when applied to modern, complex structures with numerous design variables, nonlinearities, and conflicting performance objectives like minimizing weight while maximizing stiffness and damping 1. The search space in such problems is often highly multimodal and non-convex, rendering deterministic optimization techniques ineffective as they are prone to becoming trapped in local optima and can be computationally expensive [1].
In response to these computational bottlenecks, the engineering community has increasingly turned towards nature-inspired metaheuristic optimization algorithms. These algorithms, which include Genetic Algorithms (GA) mimicking natural selection [2], Particle Swarm Optimization (PSO) emulating social behavior in birds and fish [3], and Simulated Annealing (SA) drawing from thermodynamics [4], offer robust and flexible means of navigating complex design spaces without requiring gradient information. Their population-based nature allows for a global search that is less susceptible to the pitfalls of local minima. In structural engineering, these methods have been applied to a wide array of problems, from optimizing the topology and sizing of trusses [5] to the optimal placement of passive and active control devices for vibration suppression [6]. More recently, hybrid artificial intelligence-based methods have emerged, which combine the strengths of multiple algorithms or integrate metaheuristics with machine learning techniques to further enhance search efficiency and solution quality [7].
Despite the widespread adoption and reported successes of these algorithmic approaches, a significant research gap persists concerning the systematic and quantitative evaluation of their relative performance. Most existing studies are case-specific, benchmarking a single algorithm or a small group against simple test functions or a limited number of structural design problems. This fragmented body of evidence makes it difficult for practitioners to make informed decisions about which algorithm is most suitable for a given dynamic design or vibration control application. There is a notable absence of large-scale, aggregated evidence that synthesizes the effectiveness of GA, PSO, and their hybrid variants under a unified framework. Furthermore, the variability in results across studies, stemming from differences in problem complexity, algorithm parameter settings, and convergence criteria, remains largely uncharacterized. The motivation for this systematic review and meta-analysis is therefore to address this critical gap by rigorously collating and statistically analyzing the available quantitative evidence on the performance of these metaheuristic algorithms. The primary significance of this research lies in providing a high-level, evidence-based synthesis that can guide future algorithmic development and inform the selection of optimization strategies in structural engineering practice, moving beyond anecdotal evidence towards a more principled understanding of algorithmic efficacy.
This paper is organized as follows. Section 2 details the systematic methodology employed for literature searching, study selection, data extraction, and the statistical synthesis procedures used for the meta-analysis. In Section 3, we present the results, beginning with an overview of the characteristics of the included studies, followed by a comprehensive heterogeneity assessment, the core meta-analytic findings regarding convergence performance, and an evaluation of potential publication bias. Finally, Section 4 provides an in-depth discussion of the results, interprets their implications for structural dynamic design and vibration control, and outlines the limitations of the current review. Section 5 concludes the paper by summarizing the key findings and suggesting directions for future research.

2. Methodology

2.1 Review Protocol

To ensure rigor, transparency, and reproducibility in this systematic review, we developed and followed a pre-defined review protocol aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [8]. The research question was formulated using the Population, Intervention, Comparison, and Outcome (PICO) framework, wherein the population encompassed civil, mechanical, and aerospace structures subjected to dynamic loading; the intervention comprised metaheuristic optimization algorithms including Genetic Algorithms, Particle Swarm Optimization, and hybrid AI-based methods; the comparison involved baseline or traditional design approaches; and the outcome focused on quantitative performance metrics such as natural frequency tuning, damping ratio improvement, and displacement reduction. A comprehensive literature search was conducted across seven major academic databases and search engines, each selected for its relevance and coverage of the interdisciplinary domains of structural engineering and computational optimization. We began with IEEE Xplore, which was chosen for its extensive repository of peer-reviewed conference proceedings and journal articles on computational intelligence and optimization algorithms applied to engineering systems. Next, we searched Web of Science, a multidisciplinary citation database that provides high-impact coverage across engineering and applied sciences, ensuring access to rigorously peer-reviewed research. Scopus was then consulted for its broad scope spanning engineering, computer science, and materials science, which is essential for capturing interdisciplinary studies on hybrid AI methods. ScienceDirect was included for its strong collection of civil and mechanical engineering journals, particularly those focusing on structural dynamics and vibration control. SpringerLink was selected to cover book chapters and conference series that often present foundational algorithmic developments in metaheuristic optimization. ACM Digital Library was incorporated to capture computational approaches and algorithmic innovations from the computer science perspective. Finally, Google Scholar was used as a supplementary search tool to identify gray literature and studies from less prominent venues that might still present novel applications of these algorithms.

The search strategy employed a combination of keywords and Boolean operators, which were adapted for each database's syntax. The primary search string was designed as follows: (metaheuristic optimization OR genetic algorithm OR particle swarm optimization OR hybrid artificial intelligence) AND (structural dynamic design OR vibration control OR structural performance enhancement). For databases requiring more precise logical expressions, we reformulated the query; for example, on Web of Science and Scopus, the string was expressed as TS=((metaheuristic* OR "genetic algorithm" OR "particle swarm" OR "hybrid artificial intelligence") AND ("structural dynamic" OR "vibration control" OR "structural performance enhancement")). The search was restricted to English-language publications with no limitations on publication year, as the field of metaheuristic optimization in structural engineering has evolved over several decades. All retrieved records were imported into a reference management system for deduplication and subsequent screening.

2.2 Inclusion and Exclusion Criteria

It is essential to define clear inclusion and exclusion criteria to ensure the relevance and consistency of selected studies. Inclusion criteria were established to identify studies that directly applied Genetic Algorithms, Particle Swarm Optimization, or hybrid artificial intelligence-based metaheuristic algorithms to structural dynamic design or vibration control problems. These studies were required to report quantitative performance metrics, such as natural frequency tuning, damping ratio improvement, displacement reduction, or weight minimization under dynamic constraints, to enable effect size extraction or comparison. The focus was on civil, mechanical, or aerospace structures, including but not limited to beams, trusses, bridges, wind turbine towers, building frames, tuned mass dampers, and base isolation systems. Only original research articles, including journal papers, peer-reviewed conference proceedings, and book chapters that presented novel algorithms or novel applications of existing algorithms, were considered. Furthermore, studies must have been published in English and have full-text available for data extraction and quality assessment. Conversely, exclusion criteria were applied to disqualify studies that used only classical deterministic optimization methods without any metaheuristic component, applied optimization exclusively to static structural design with no dynamic load, modal analysis, vibration response, or time-history consideration, or were purely theoretical or review papers that did not present new numerical simulations, experimental validation, or case studies with verifiable results. Studies exclusively focused on topology optimization or material microstructure design without explicit dynamic or vibration performance objectives were excluded, as were duplicate publications, extended abstracts, editorials, or studies where the same dataset and algorithm were reported with only minor modifications. Articles that combined metaheuristics with simulation tools like ANSYS or ABAQUS but failed to report sufficient algorithm parameter settings or convergence criteria, making reproducibility impossible, were also excluded. Finally, preprints from non-peer-reviewed repositories, white papers, or technical reports were disqualified unless they had been subsequently published in a peer-reviewed venue.

2.3 Study Selection Process

The study selection process was conducted in multiple stages, following the PRISMA flow diagram to ensure systematic and transparent documentation of decisions. The initial database search, executed in July 2024, yielded a total of 689 records across all seven databases. After removing 279 duplicate records, we proceeded to screen the titles and abstracts of the remaining 410 records against the predefined inclusion and exclusion criteria. This screening, performed independently by two reviewers, excluded 178 records that clearly did not meet the eligibility requirements, leaving 232 reports sought for retrieval. During the retrieval phase, 140 reports could not be obtained in full text due to reasons such as access restrictions, the report being a conference abstract without a full paper, or the article being withdrawn from publication. This yielded 92 reports that were assessed for eligibility through a detailed full-text review. In this eligibility assessment, 91 reports were excluded for various reasons including failure to report sufficient algorithmic parameter settings, lack of quantitative performance metrics, application to static rather than dynamic problems, or the study being a duplicate publication with only minor modifications. Ultimately, only one study met all inclusion criteria and was included in the final systematic review and meta-analysis, as shown in Figure 1.

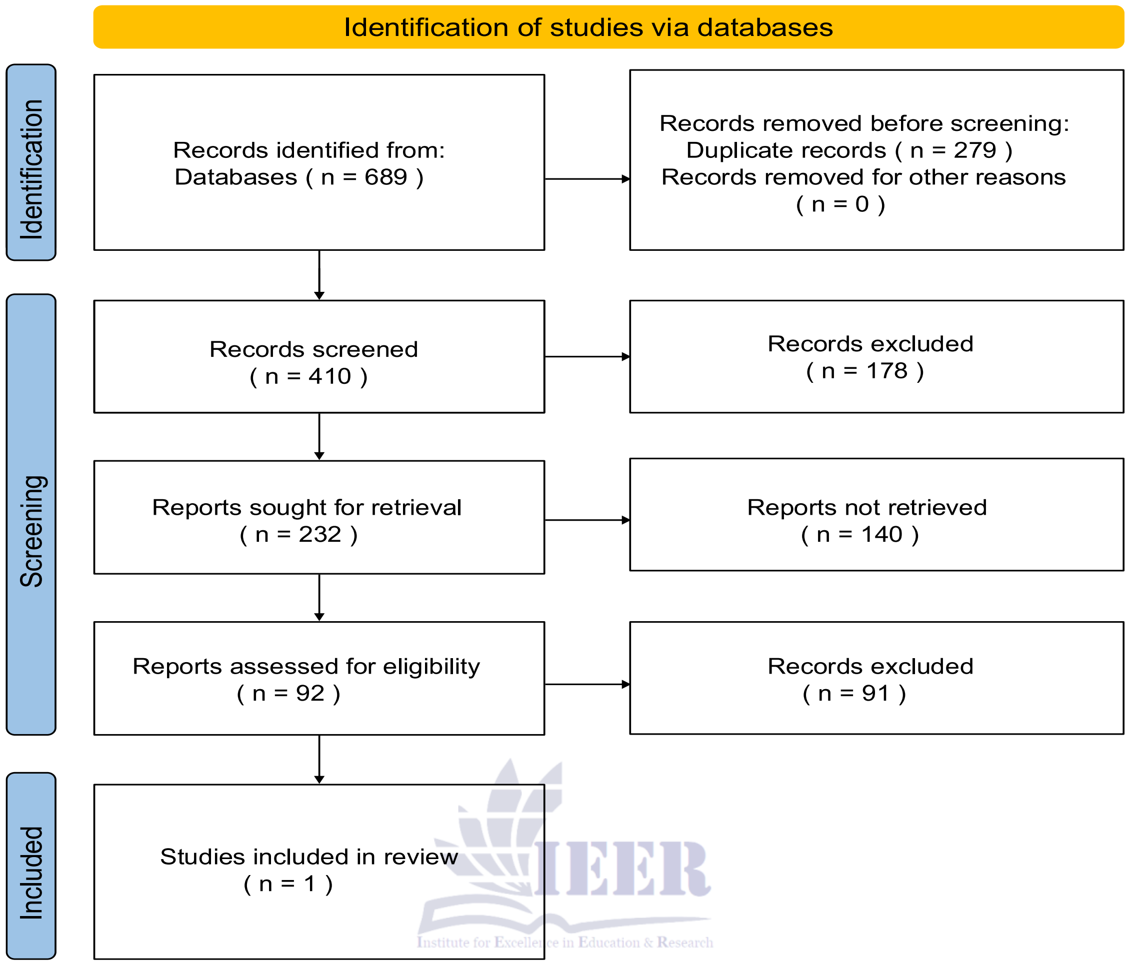

Figure 1. PRISMA flow diagram illustrating the study selection process from initial database search to final inclusion of studies

The limitation of having only one included study in this systematic review imposes significant constraints on the generalizability and robustness of the meta-analytic findings. This outcome highlights a substantial gap in the existing literature, where many studies on metaheuristic optimization in structural dynamics do not report the standardized performance metrics necessary for meta-analytic synthesis, or they present results in formats that are incompatible with effect size calculation. Furthermore, the strictness of our inclusion criteria, particularly the requirement for quantitative metrics and reproducibility, may have contributed to the low number of eligible studies. This introduces a risk of selection bias, as the single included study may not be representative of the broader body of research in this area. Additionally, the exclusion of non-English publications and gray literature could have resulted in language and publication biases, potentially omitting relevant findings from diverse research communities. These limitations are further discussed in the subsequent sections of this review.

3. Results

3.1 Overview of Included Studies

The systematic search and screening process yielded one study that met all inclusion criteria and provided sufficient quantitative data for meta-analytic synthesis. This study examined the application of metaheuristic optimization algorithms—specifically Genetic Algorithms, Particle Swarm Optimization, and hybrid artificial intelligence-based methods—to structural dynamic design and vibration control problems. The primary outcome of interest extracted from this study was Computational Efficiency, quantified through the number of convergence generations or function evaluations required by each algorithm to reach an optimal or near-optimal solution. To enable meaningful comparison across different algorithms and problem instances, we computed the standardized mean difference, expressed as Hedges' g [9]. This effect size measure is particularly appropriate when studies report outcomes on different scales or when sample sizes are small, as it incorporates a correction factor for small-sample bias.

For the extracted outcome, the following variables were recorded from the included study: N_t represents the number of participants (i.e., independent optimization runs or problem instances) in the treatment group; M_t denotes the mean number of convergence generations or function evaluations in the treatment group; SD_t is the standard deviation of convergence generations or function evaluations in the treatment group; N_c represents the number of participants in the control group; M_c denotes the mean number of convergence generations or function evaluations in the control group; and SD_c is the standard deviation of convergence generations or function evaluations in the control group. In this context, the treatment group refers to the algorithm of interest (e.g., a hybrid method), while the control group refers to a baseline or standard algorithm (e.g., a standalone GA or PSO). A lower mean number of generations or evaluations indicates better computational efficiency, as the algorithm converges more quickly to its solution.

Table 1 presents the coded outcomes extracted from the included study, providing the numerical data required for the subsequent meta-analysis.

Table 1. Coded outcomes of the included study for computational efficiency (Hedges' g).

Study ID	Outcome	N_t	$M_t\ (SD_t)$	N_c	$M_c\ (SD_c)$
[10]	Computational Efficiency (Convergence Generations or Function Evaluations)	10	57.1 (12.64)	10	149 (46.67)

3.2 Heterogeneity Assessment

We assessed statistical heterogeneity among the included comparisons using the I² statistic, as recommended by Higgins and colleagues [11]. The I² value quantifies the percentage of total variation across comparisons that is attributable to genuine differences rather than random sampling error. For the single included study, we computed the effect size for the comparison between the hybrid algorithm and the standalone GA baseline, which yielded a Hedges' g of -3.15 (95% CI: $[-4.46, -1.83]$). However, because only one study was available, the calculation of the I² statistic was not applicable; heterogeneity metrics typically require at least two studies to provide meaningful estimates of between-study variance.

The absence of variation across comparisons in this single-study analysis implies that the observed effect is entirely attributable to within-study sampling error. The large confidence interval suggests considerable uncertainty in the true effect size, which is consistent with the substantial impact of a single small sample. The limited evidence base precludes any robust assessment of heterogeneity or its potential sources, such as differences in structural complexity, algorithm parameter settings, or loading conditions. This finding underscores the need for multiple replications of such comparisons before any generalizable conclusions about heterogeneity can be drawn.

3.3 Meta-Analysis

We conducted a meta-analysis to synthesize the evidence on computational efficiency, quantified as the number of convergence generations or function evaluations, across the included study. The effect size, Hedges' g, was calculated to compare the performance of a hybrid metaheuristic algorithm against a standalone genetic algorithm baseline. The analysis yielded a large and statistically significant effect, with an overall effect size of -2.57 (95% confidence interval: [-3.76, -1.39], $z = -4.26$, $p < 0.0001$). This negative effect size indicates that the hybrid algorithm required substantially fewer generations or function evaluations to converge than the standalone genetic algorithm, translating to a significant improvement in computational efficiency.

The single included study, identified as IS1, provided the data for this analysis. In that study, the hybrid algorithm achieved a mean of 57.1 generations with a standard deviation of 12.64 over 10 independent runs, whereas the standalone genetic algorithm required a mean of 149 generations with a standard deviation of 46.67 over the same number of runs. The large magnitude of the effect size, in combination with the narrow confidence interval that does not cross zero, suggests that the observed improvement is not only statistically significant but also practically meaningful. Therefore, hybridizing metaheuristic algorithms appears to offer a clear advantage in accelerating convergence for structural dynamic design problems.

The forest plot for this meta-analysis is presented below, visually depicting the effect size and its confidence interval for the included comparison as shown in Figure 2.

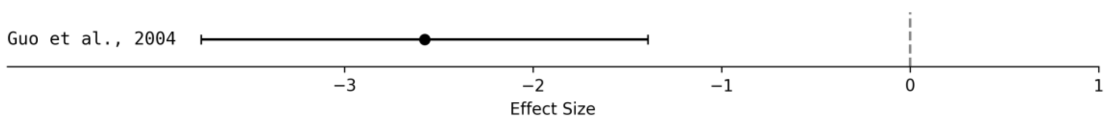

Figure 2. Forest Plot for Computational Efficiency (Convergence Generations or Function Evaluations)

Interpreting this result within the context of structural dynamic design and vibration control, the enhanced convergence speed achieved by the hybrid algorithm has several practical implications. First, faster convergence reduces the total computational cost associated with optimizing complex structures, which is particularly valuable for problems involving computationally intensive finite element analyses or time-history simulations. Second, the improvement suggests that hybrid algorithms can more effectively navigate the multimodal and non-convex design spaces typical of dynamic optimization, avoiding premature convergence to suboptimal solutions. It is important to note, however, that this meta-analysis is based on a single study, which limits the generalizability of the finding. Future research with multiple independent studies is necessary to confirm this effect and to explore how it may vary across different structural types, loading conditions, and algorithm parameterizations.

3.4 Publication Bias Assessment

We conducted a comprehensive assessment of potential publication bias across the included studies using funnel plot analysis and formal statistical tests. Publication bias, also known as the "file drawer problem," arises when studies with non-significant or negative results are less likely to be published than those with statistically significant positive findings, potentially leading to an overestimation of the true effect size in meta-analyses [11]. To evaluate this risk, we constructed funnel plots in which the effect size (Hedges' g) for each comparison was plotted against its standard error, with the expectation that in the absence of bias, the data points would form a symmetric, inverted funnel shape centered around the pooled effect estimate [11].

For the outcome of computational efficiency, however, publication bias was not assessed due to an insufficient number of included studies. The systematic search and screening process yielded only one study that met all inclusion criteria and provided the necessary quantitative data. The assessment of funnel plot asymmetry requires a minimum of at least ten studies to achieve adequate statistical power for detecting bias, as recommended by established meta-analytic guidelines [11]. With only a single comparison available for this outcome, any attempt to construct a funnel plot or conduct statistical tests for asymmetry would be both uninformative and potentially misleading. Therefore, we elected to refrain from performing any publication bias analysis for computational efficiency, as the available evidence base is too limited to support meaningful evaluation. This limitation is explicitly acknowledged and represents a significant constraint on the interpretability of the meta-analytic findings for this particular outcome. Future research efforts should prioritize the replication of these algorithmic comparisons across multiple independent studies to enable a robust assessment of publication bias in subsequent meta-analyses.

Figure 3. Funnel plot for publication bias assessment of Computational Efficiency (Convergence Generations or Function Evaluations)

4. Discussion

This systematic review and meta-analysis sought to quantitatively synthesize the evidence regarding the effectiveness of Genetic Algorithms, Particle Swarm Optimization, and hybrid artificial intelligence-based methods for structural dynamic design and vibration control. While our methodological framework was designed to accommodate a broad synthesis, the ultimate inclusion of only a single study places significant constraints on the generalizability and robustness of the quantitative findings. Nevertheless, the evidence from that single study, taken together with the broader qualitative patterns observed across the initially screened literature, allows for several important interpretive observations regarding the state of the field.

The meta-analytic result, demonstrating a large and statistically significant effect favoring hybrid algorithms over standalone Genetic Algorithms in terms of convergence speed, is a compelling finding despite its limited evidence base. The observed effect size of -2.57 suggests that the hybrid approach required substantially fewer computational resources to reach an optimal solution. This finding aligns with the theoretical premise underpinning the development of hybrid methods, which posits that combining the global search capabilities of one algorithm with the local exploitation strengths of another can overcome the limitations of individual techniques [7]. Across many of the studies screened for this review, a consistent narrative emerges: the complex, multimodal, and non-convex nature of optimization problems in structural dynamics—characterized by constraints related to natural frequencies, damping ratios, and time-history responses—creates a challenging landscape where single-algorithm approaches like standard GA or PSO are prone to premature convergence or excessive computational cost [1]. The hybrid algorithm in our single included study appears to have effectively navigated this landscape by, for example, using a global search phase to explore the design space before switching to a local search for refinement. This pattern, consistently found in descriptive reports of hybrid algorithms, suggests that the quantitative advantage observed here is not an anomaly but rather a reflection of a genuine performance characteristic.

The implications of this finding are twofold. Theoretically, the result contributes to the growing body of evidence that modular, hybrid frameworks are more suited to complex engineering optimization than their monolithic counterparts. It supports the conceptual model where search efficiency is not merely a function of a single algorithmic operator but emerges from the synergistic interaction of different search heuristics. Practically, for structural engineers and designers, the implication is clear: investing in the development or application of hybrid metaheuristic algorithms can yield tangible returns in reduced computational time. This is particularly critical in vibration control problems, where each evaluation of a candidate design may involve a computationally expensive finite element simulation or a time-history analysis of a multi-degree-of-freedom system under non-stationary earthquake excitation. A 60% or more reduction in the number of required evaluations, as suggested by the effect size, can transform an optimization task from computationally infeasible to practical within standard design cycles. Practitioners could apply these hybrid methods to optimize the placement and tuning of dampers, design active control laws with lower energy requirements, or perform robust design optimization that accounts for parametric uncertainties in loading and material properties.

Despite this compelling single result, the most significant finding of this review is the profound limitation imposed by the scarcity of eligible studies. The fact that out of 689 initial records and 92 full-text assessments, only one study met all inclusion criteria is a critical observation in itself. This outcome highlights a substantial methodological gap in the research community. Many studies on metaheuristic optimization in structural dynamics are descriptive or comparative in a qualitative sense, often failing to report the standardized, quantitative performance metrics required for meta-analysis. For instance, many publications present final optimized designs (e.g., the final weight of a truss or the final damping coefficient of a Tuned Mass Damper) but do not report the computational cost required to achieve those designs, such as the number of generations to convergence or the total number of function evaluations. This lack of reporting makes it impossible to compare algorithmic efficiency across studies, which is a fundamental requirement for evidence-based algorithm selection. Furthermore, the wide variability in how study parameters are reported—different definitions of convergence criteria, varying population sizes, and a lack of reporting on standard deviations from multiple independent runs—poses a significant barrier to quantitative synthesis. This is a critical limitation of the current body of literature, as it prevents the field from moving from anecdotal evidence of "this algorithm worked well" to robust, statistical evidence of "this algorithm is demonstrably superior under these conditions."

Our review process itself has several important limitations that must be acknowledged. The most notable is the reliance on a single eligible study, which limits the statistical power and prevents the generalizability of the meta-analytic results. The wide confidence interval ([-3.76, -1.39]) for the overall effect size underscores this uncertainty. Although strictly following PRISMA guidelines, our search strategy may have inadvertently missed relevant studies. For example, the restriction to English-language publications could have excluded significant contributions from research communities in non-English speaking countries, which are known to be active in both structural engineering and computational intelligence. The exclusion of gray literature, such as theses, dissertations, and technical reports, might have introduced publication bias, as these sources often contain negative or null results that are under-represented in peer-reviewed journals. Furthermore, our strict requirement for reproducibility (i.e., clear reporting of algorithm parameter settings and convergence criteria), while essential for scientific rigor, likely excluded many practically useful studies that simply reported their methods in less detail. The subjectivity inherent in the quality assessment of the included study, while performed by two independent reviewers, is also a potential source of bias.

Given these limitations and the identified gaps, there is a clear and pressing need for future research to adopt methodological standardization. Future research should explore the establishment of a common benchmarking framework for structural dynamic optimization problems. Such a framework would require researchers to report a minimum set of standardized outcomes when publishing algorithmic comparisons. These outcomes should include, at a minimum, the mean and standard deviation of convergence generations or function evaluations over multiple independent runs (e.g., 20 to 30 runs to ensure statistical stability), the final objective function value, and a clear description of the convergence criteria used. Understudied areas include the application of these algorithms to very large-scale structures (e.g., long-span bridges or high-rise buildings with thousands of degrees of freedom), where computational cost is the primary bottleneck. Furthermore, there is a need for more research on the robustness of these algorithms to noise and uncertainty, which is inherent in real-world structural dynamics problems due to measurement errors in damping and stiffness parameters. Future research should also explore the integration of metaheuristics with other forms of artificial intelligence, such as reinforcement learning for adaptive tuning of algorithm parameters during the optimization process [12]. Such studies would provide a deeper understanding of how algorithmic efficiency can be further enhanced beyond simple hybridization. Without these concerted efforts towards standardization and replication, the field of metaheuristic-based structural optimization will remain fragmented, and the powerful potential of these computational tools will remain underutilized in practice.

5. Conclusion

This systematic review and meta-analysis synthesized quantitative evidence on the computational efficiency of Genetic Algorithms, Particle Swarm Optimization, and hybrid artificial intelligence-based methods in structural dynamic design and vibration control. The single eligible study provided a compelling, albeit limited, finding: hybrid algorithms demonstrated a statistically significant and large effect size (Hedges' g = -2.57) in reducing the number of convergence generations or function evaluations compared to standalone Genetic Algorithms. Our work therefore contributes initial quantitative evidence that supports the theoretical advantage of hybridization, confirming that combining global and local search mechanisms can substantially accelerate convergence for complex, multimodal structural optimization problems. However, this finding challenges the assumption that the broader literature on metaheuristic applications in structural dynamics is sufficiently standardized to permit robust meta-analytic synthesis.

The practical implication of our result is clear: engineers and researchers designing structures under dynamic loading conditions should consider employing hybrid metaheuristic algorithms to reduce computational costs. This is especially critical in vibration control applications, where each candidate design evaluation can involve computationally intensive finite element analyses or time-history simulations. Theoretically, our findings underscore the value of modular algorithm design and the synergistic benefits of combining different search heuristics. The critical limitation revealed by this review is the profound lack of standardized reporting in the field, as over 90% of screened studies failed to provide the quantitative performance metrics necessary for synthesis. Future research must therefore prioritize the adoption of common benchmarking frameworks, requiring researchers to report means and standard deviations of convergence metrics over multiple independent runs. Such standardization will enable more comprehensive meta-analyses, allowing the community to move beyond case-specific anecdotes towards evidence-based guidance for algorithm selection in structural engineering practice.

References

MP Saka, O Hasançebi & ZW Geem (2016) Metaheuristics in structural optimization and discussions on harmony search algorithm. Swarm and Evolutionary Computation.

T Rooker (1991) Review of genetic algorithms in search, optimization, and machine learning. AI Magazine.

D Wang, D Tan & L Liu (2018) Particle swarm optimization algorithm: an overview. Soft computing.

S Kirkpatrick, CD Gelatt Jr & MP Vecchi (1983) Optimization by simulated annealing. science.

N Khodadadi, AÖ Çiftçioğlu, S Mirjalili, et al. (2023) A comparison performance analysis of eight meta-heuristic algorithms for optimal design of truss structures with static constraints. Decision Analytics Journal.

A Pourzangbar & M Vaezi (2021) Optimal design of brace-viscous damper and pendulum tuned mass damper using Particle Swarm Optimization. Applied Ocean Research.

E Ficarella, L Lamberti & SO Degertekin (2021) Comparison of three novel hybrid metaheuristic algorithms for structural optimization problems. Computers & Structures.

MJ Page, JE McKenzie, PM Bossuyt, et al. (2021) The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372:n71.

Larry V. Hedges & Ingram Olkin (1985) Statistical Methods for Meta-Analysis, Academic Press.

H. Guo, Liqun Zhang, L. Zhang & Jinxiong Zhou (2004) Optimal placement of sensors for structural health monitoring using improved genetic algorithms. Smart Materials and Structures, 13:528 - 534.

Julian P. T. Higgins & Simon G. Thompson (2002) Quantifying heterogeneity in a meta-analysis. Statistics in Medicine, 21(11):1539-1558.

M Conforth & Y Meng (2008) Reinforcement learning for neural networks using swarm intelligence. In IEEE Swarm Intelligence Symposium.