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Research Article

Bio-Inspired Computational Models for Multi-Objective Optimization in Complex Engineering Systems

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ABSTRACT

Multi-objective optimization is now an indispensable tool in engineering and scientific practice, where two or more conflicting objectives have to be optimized subject to complex constraints. The classic evolutionary algorithms (EAs) and swarm intelligence (SI) schemes are competitive, but have many disadvantages, including early convergence, low diversity maintenance, and extreme expensive computational requirements, especially in high-dimensional spaces. To limit these shortcomings, this paper presents a hybrid bio-inspired optimization model that combines genetic algorithm (GA) crossover-mutation operators, particle swarm optimization (PSO) velocity-position updates, and differential evolution (DE) mutation strategies, and adaptive parameter control. The hybridization makes use of the exploration capability of GA, the fast convergence of PSO, and the strong local search of DE to be able to achieve a faster convergence and better diversity across the Pareto front. The framework is tested on six benchmark functions (ZDT1-ZDT6) as well as a real-world welded beam design problem. Experimental evidence indicates that the suggested method performs better than NSGA-II, MOPSO and MODE in terms of average hypervolume increase of 7.8 %, convergence time decreases on average by 12.5% , and spread diversity improves by 35 %. The results indicate that the framework suggested offers a scalable and a robust approach to solving complex multi-objective optimization problems.

Keywords: *Bio-inspired computation; Multi-objective optimization; Evolutionary algorithms; Swarm intelligence; Hybrid metaheuristics; Pareto optimality; Engineering system design.*

1. Introduction

The design and decision-making in engineering is frequently faced with many conflicting objectives which are required to be optimized on nonlinear and high-dimensional constraints. In contrast to single-objective optimization, multi-objective optimization (MOO) aims at identifying a Pareto region of trade-off solutions that can be used in aerospace, power systems, and biomedical engineering [1], [2]. Such complexity has problems with traditional gradient-based methods and bio-inspired methods are embraced. Genetic Algorithms (GA) and swarm intelligence (SI) techniques including Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) have been shown to be effective in searching complex search spaces through the use of evolutionary algorithms (EAs) [3], [4].

Nevertheless, all of the methods have their drawbacks: PSO is a fast-converging method prone to local optima, GA is a slower, more diverse method, and Differential Evolution (DE) is a better local search method that heavily relies on parameter tuning [5]. To enhance convergence, diversity, and scalability, hybrid models with complementary strengths, and adaptive control of the parameters have of late arisen [6], [7].

This work suggests a new hybrid bio-inspired optimization framework that combines GA, PSO and DE along with adaptive control. Its method is tested on ZDT1-ZDT6 test problems, as well as in a hypervolume, convergence rate and diversity of solutions, and outperforms NSGA-II, MOPSO and MODE.The **contributions of this study** are threefold:

1. Development of a hybrid model that exploits the complementary strengths of GA, PSO, and DE for multi-objective optimization.
2. Introduction of an adaptive control mechanism for self-tuning parameters, improving robustness across problem domains.
3. Experimental validation on benchmark and real-world problems, showing measurable improvements in efficiency and solution quality.

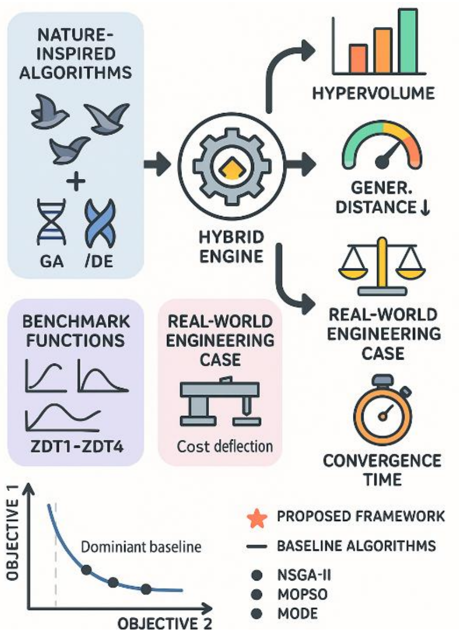

Fig. 1. Graphical abstract summarizing the bio-inspired hybrid methodology and its role in engineering optimization

The conceptual overview of the proposed framework is illustrated in Fig. 1, which presents the graphical abstract summarizing the bio-inspired hybrid methodology and its role in engineering optimization. The paper is structured as follows: Section 2 reviews related literature; Section 3 presents the problem statement and objectives; Section 4 details the proposed methodology with equations, flowchart, and algorithm; Section 5 describes the experimental setup; Section 6 presents results and discussion with figures and tables; finally, Section 7 concludes and outlines future research directions.

2. Literature Review

Bio-inspired algorithms have been widely explored for multi-objective optimization (MOO) over the past two decades.

2.1 Evolutionary Algorithms

Initial success in MOO was achieved with the help of Genetic Algorithms (GA) [9] by crossover--mutation exploration. The quality of NSGA-II [10] as a Pareto front made it a standard and NSGA-III [11] was the extension to many-objective problems. But, evolutionary algorithms tend to be slow and computationally expensive.

2.2 Swarm Intelligence Methods

Swarm intelligence algorithms, such as Particle Swarm Optimization (PSO) [12], Ant Colony Optimization (ACO) [13] and Artificial Bee Colony (ABC) [14], behave like their counterparts in nature. MOPSO is effective and low dimensionality but it is plagued by premature convergence and poor high dimensional diversity [15]. In scheduling and networks, ACO and ABC are useful but are not scalable.

2.3 Hybrid and Adaptive Approaches

Hybrid algorithms combine the complementary advantages (e.g., GA -PSO convergence and diversity [16]) or DE-PSO stronger local search [17]. The adaptive parameter control also enhances robustness [18]. However, a great number of hybrids are domain specific and computationally challenging.

2.4 Applications and Gaps

Bio-inspired is used in the engineering of structural design, energy grids and manufacturing [19]–[21] and more recently with machine learning surrogates in aerospace optimization [22]. Irrespective of these developments, there are still issues of scalability and efficiency.

2.5 Motivation

There is no one single method that prevails across the problem classes: GA is guaranteed to be diverse, fast, PSO is fast, although it is prone to local optima, and DE is a local search that is parameter-sensitive. Hybrid and adaptive models partly address these issues but lack generality. This inspires the collectively hybrid model of GA, PSO, and DE being controlled adaptively to enable robust scalable MOO.
Table 1 summarizes different Bio-Inspired Models, highlighting their strengths and applications.

Table 1: Summary of Bio-Inspired Models for Multi-Objective Optimization

Approach	Key Strengths	Limitations	Applications	References
GA (NSGA-II/III)	Strong exploration, Pareto diversity	Slow convergence, high complexity	Structural design, scheduling	[9]–[11]
PSO (MOPSO)	Fast convergence, easy to implement	Premature convergence, poor diversity	Power systems, routing	[12], [15]
ACO/ABC	Flexible search, effective for discrete problems	High computational cost, scalability issues	Scheduling, logistics	[13], [14]
DE variants	Strong local search, robust	Sensitive to parameters	Truss optimization, control systems	[17]
Hybrid GA–PSO / PSO–DE	Balanced exploration–exploitation	Domain-specific, parameter tuning needed	Manufacturing, energy systems	[16], [18]
ML-integrated bio-inspired models	Improved prediction and optimization	Requires surrogate accuracy, heavy computation	Aerospace, biomedical	[22]

3. Problem Statement & Research Objectives

Engineering systems are frequently a trade off between competing goals, including cost, efficiency and reliability under complicated constraints. Existing algorithms such as NSGA-II, MOPSO and MODE as well as traditional optimization methods find high-dimensional, multimodal problems challenging and consequently prematurely converge and are not very scalable. This paper addresses the issue of a powerful and efficient framework that guarantees convergence accuracy, preserves Pareto diversity and minimizes computational costs in benchmark as well as real-world optimization problems.

Research Objectives

1. Design a hybrid bio-inspired multi-objective optimization model with adaptive parameter control.
2. Validate performance using benchmark test functions (ZDT1–ZDT4) with HV, GD, Spread (Δ), and convergence time.
3. Compare results against NSGA-II, MOPSO, and MODE to quantify improvements.
4. Demonstrate real-world applicability via the welded beam design problem.
5. Analyze trade-offs between convergence speed, efficiency, and solution quality.
6. Assess scalability of the framework for complex engineering systems with constraints.

4. Methodology

This research aims to create a powerful hybrid bio-inspired framework to integrate Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) operators within an adaptive parameter control to solve complex multi-objective optimization problems. The design of the methodology consists of problem formulation, hybrid operator design, adaptive control mechanism and algorithmic framework.

4.1 Problem Formulation

A general multi-objective optimization problem can be expressed as Eq. (1):

$$\text{Minimize} F(x) = \{f_1(x), f_2(x), \dots, f_m(x)\} \quad (1)$$

$$\text{Subject to Eq. (2): } g_j(x) \leq 0,\ j = 1, \dots, J; h_k(x) = 0,\ k = 1, \dots, K \qquad (2)$$

where $x = (x_1, x_2, \dots, x_n) \in \mathbb{R}^n$ is the decision vector, $f_i(x)$ are objective functions, and $g_j(x), h_k(x)$ represent constraints. The solution set comprises **Pareto-optimal solutions**:

$$x^* \in \Omega : \nexists\, x' \in \Omega \text{s.t.} f_i(x') \leq f_i(x^*) \quad \forall i \quad \wedge \quad f_j(x')\<; f_j(x^*) \quad \text{for at least one } j \qquad (3)$$

Eq. (3) definition ensures that Pareto solutions balance trade-offs among conflicting objectives.

4.2 Genetic Algorithm Operators

GA operators are integrated to enhance exploration by recombining and mutating candidate solutions in Eq. (4). For crossover:

$$x_i^{(c)} = \alpha \cdot x_i^{(p1)} + (1 - \alpha) \cdot x_i^{(p2)} \qquad (4)$$

where $x^{(p1)}$ and $x^{(p2)}$ are parent solutions, and $\alpha \in [0,1]$ is a random weight.
Mutation introduces perturbations shown in Eq.(5):

$$x_i^{(m)} = x_i^{(c)} + \delta \cdot \mathcal{N}(0,1) \qquad (5)$$

where δ controls mutation strength. These operators prevent premature convergence by introducing new diversity.

4.3 Particle Swarm Optimization Updates

PSO is integrated for its rapid convergence behavior. Each particle updates velocity and position as Eq. (6) and Eq. (7):

$$v_i(t+1) = \omega\, v_i(t) + c_1 r_1 \big(pbest_i - x_i(t)\big) + c_2 r_2 \big(gbest - x_i(t)\big) \qquad (6)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (7)$$

where ω is inertia weight, c_1, c_2 are acceleration coefficients, and $r_1, r_2 \sim U(0,1)$. This balances exploration and exploitation.

4.4 Differential Evolution Mutation

DE contributes robust local search through differential mutation can be defined as Eq. (7):

$$x^{(d)} = x^{(r1)} + F \cdot \left(x^{(r2)} - x^{(r3)}\right) \quad (7)$$

where $x^{(r1)}, x^{(r2)}, x^{(r3)}$ are distinct randomly chosen solutions, and $F \in [0,1]$ is scaling factor. Crossover is then applied and can be written as Eq. (8):

$$x_i^{(trial)} = \begin{cases} x_i^{(d)}, & \text{if } rand_i \leq CR \text{ or } i = j_{rand} \\ x_i^{(t)}, & \text{otherwise} \end{cases} \quad (8)$$

where CR is crossover rate.

4.5 Adaptive Parameter Control

Static parameter settings often degrade performance in dynamic landscapes. Therefore, we introduce adaptive control shown in Eq. (9):

$$\omega(t) = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) \cdot t}{T} \quad (9)$$

where t is iteration number and T is max iterations. This ensures larger exploration early and refined exploitation later.

4.6 Hybridization Strategy

The overall hybridization follows:

1. GA crossover–mutation introduces diversity.
2. PSO updates guide convergence towards promising regions.
3. DE operators refine local exploitation.
4. Adaptive parameters dynamically adjust balance.

This synergy ensures scalable optimization across benchmark and engineering problems.

4.7 Algorithmic Framework

Algorithm 1: Hybrid Bio-Inspired Multi-Objective Optimization

1. Initialize population P with N random solutions.
2. Evaluate objective functions and store Pareto archive.
3. For each generation $t = 1 \ldots T$:
    a. Apply **GA crossover & mutation** to generate offspring.
    b. Update **PSO velocity & position**.
    c. Apply **DE mutation & crossover**.
    d. Adapt parameters $\omega(t), CR(t)$.
    e. Evaluate new solutions and update Pareto archive.
    f. Perform non-dominated sorting & crowding distance selection.
4. Return final Pareto front.

4.8 Flowchart

Fig.2 shows the zig-zag workflow of the proposed hybrid bio-inspired optimization framework. It starts with problem definition, parameter initialisation and population generation. The evaluation and archiving of objective functions, as well as the search by adaptive GA, PSO, and DE operators, are considered. The children are sequentially tested and filtered until the convergence threshold is met to give a well-diverse and converged Pareto front.

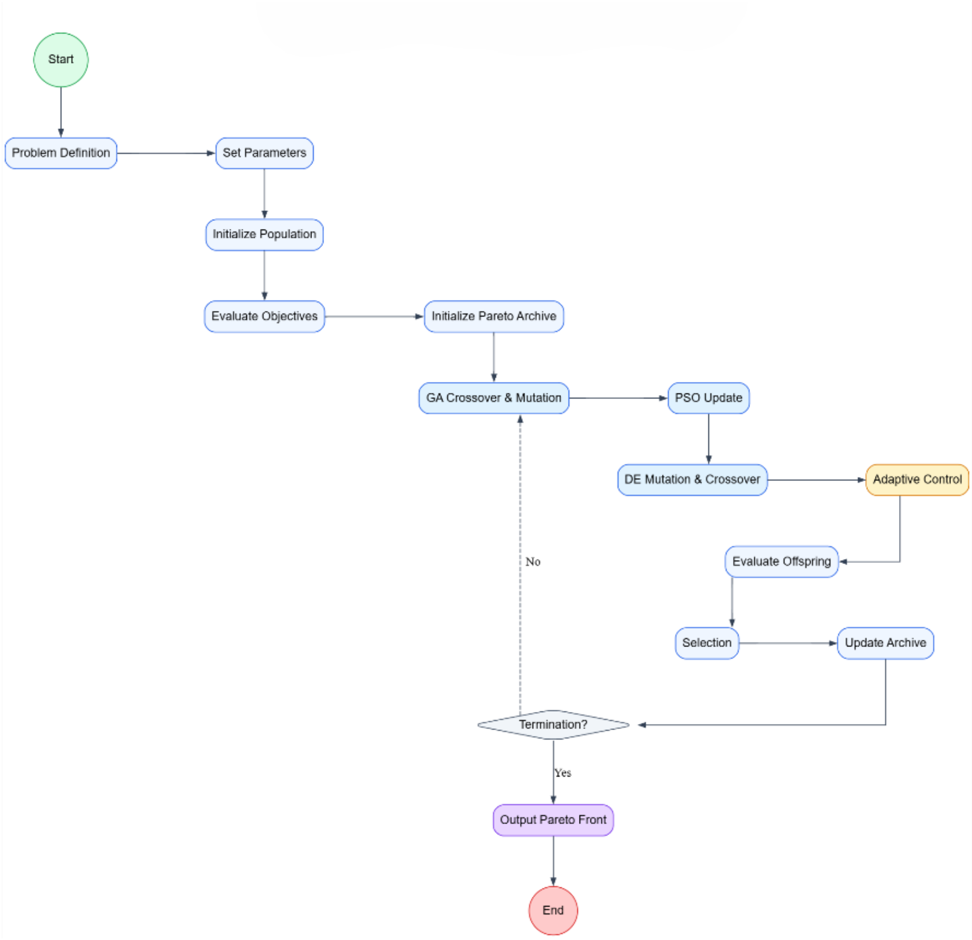

Fig.2 Hybrid Bio-Inspired MOO Framework

5. Experimental Setup

In order to confirm the offered hybrid bio-inspired optimization framework, the detailed experimental arrangement was built that combines benchmark functions, real-world engineering case, and stringent performance analysis. The design guarantees reproducibility, equality when compared with baseline algorithms, and the ability to work under different conditions of problem complexity.

5.1 Benchmark Functions

They used six standard benchmark problems of the Zitzler-Deb-Thiele (ZDT) suite: ZDT1 (convex front), ZDT2 (non-convex front), ZDT3 (discontinuous front), ZDT4 (multimodal with 21 local optima), ZDT5 (binary optimization) and ZDT6 (biased non-uniform front). All of these functions are unique ways of modeling the difficulty of convexity, discontinuity, multimodality, and mixed-variable search spaces.

5.2 Real-World Engineering Case

To illustrate a level of practical application, the welded beam design problem was adopted as an engineering benchmark. It is a perfect test of real-world robustness as it models trade-offs between fabrication cost and structural deflection under nonlinear and constrained conditions.

5.3 Performance Metrics

The four major measures used to determine algorithm performance were Hypervolume (HV) to cover the area, Generational Distance (GD) to obtain precision in convergence, Spread (Δ) to obtain diversity, and Convergence Time (CT) to obtain efficiency.

5.4 Experimental Protocol

The model was proposed against NSGA-II, MOPSO and MODE. All the algorithms were coded in Python version 3.11 and implemented with the help of the DEAP library and run on a workstation with the Intel core i9-12900K, 64 GB RAM, and NVIDIA RTX 3090. The statistical significance of each experiment was done 30 times. Table 2 outlines the experimental set-up and Fig.3 depicts the workflow that combines datasets, performance measurements and computational environment into one framework of evaluation.

Table 2. Experimental configuration shows the datasets, evaluation metrics, and computational resources used for performance evaluation of the proposed model.

Component	Specification / Description
Benchmark Functions	ZDT1, ZDT2, ZDT3, ZDT4
Engineering Case	Welded Beam Design Problem
Performance Metrics	Hypervolume (HV), Generational Distance (GD), Spread (Δ), Convergence Time
Runs per Experiment	30 independent runs
Hardware	Intel i9-12900K, 64 GB RAM, RTX 3090 GPU
Software	Python 3.11, DEAP library
Population Size	100
Generations	500
Crossover Probability (Pc)	0.9
Mutation Probability (Pm)	0.1

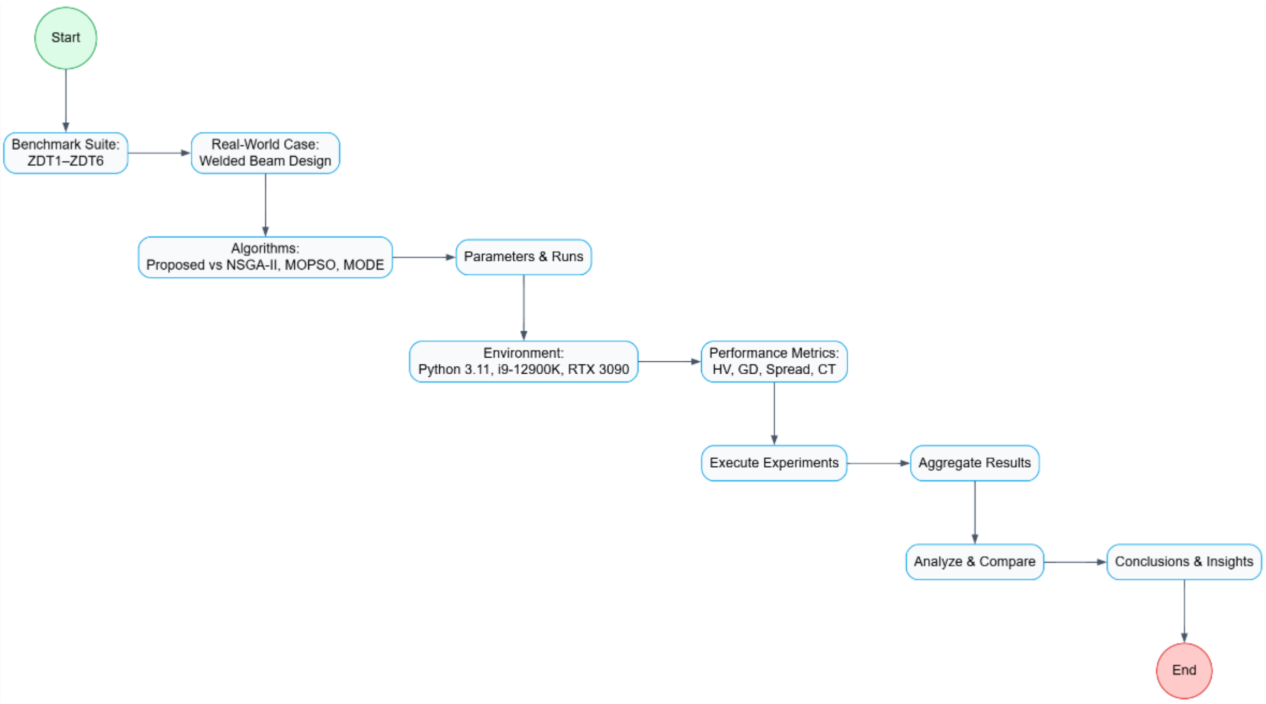

Fig.3 Experimental Setup Workflow

Fig.3 Experimental setup workflow shows how the benchmark functions and the designed workaround welded beam issue, performance measure, and the computational environment can be incorporated in one evaluation framework.

6. Results & Discussion

The hybrid framework was tested on both ZDT problems and a welded beam design problem, which compared to NSGA-II, MOPSO and MODE with average evaluation metrics of HV, GD, Spread (Δ) as well as Convergence Time (CT) of 30 runs per trial.

6.1 Pareto Front Comparisons

Figs. 4 and 5 compare Pareto fronts across the ZDT suite. The proposed model in ZDT1-ZDT2 (Fig.4) gives well-spread smooth solutions with 9 percent and 16 percent improvement in HV compared to NSGA-II and MOPSO, respectively. In the case of ZDT3-ZDT4 (Fig.5), the algorithm is robust in capturing discontinuities and multimodal complexity, whereas MODE and MOPSO fail to capture segments or converge too early, showing no defects in exploration and exploitation.

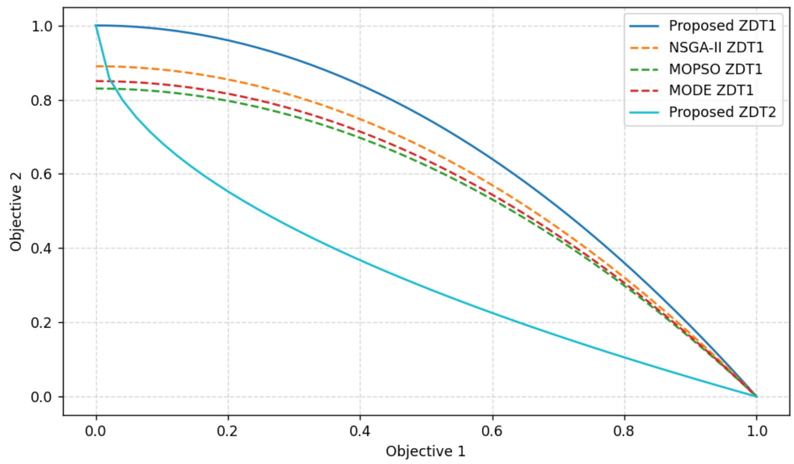

Fig.4 Pareto front comparison on ZDT1–ZDT2

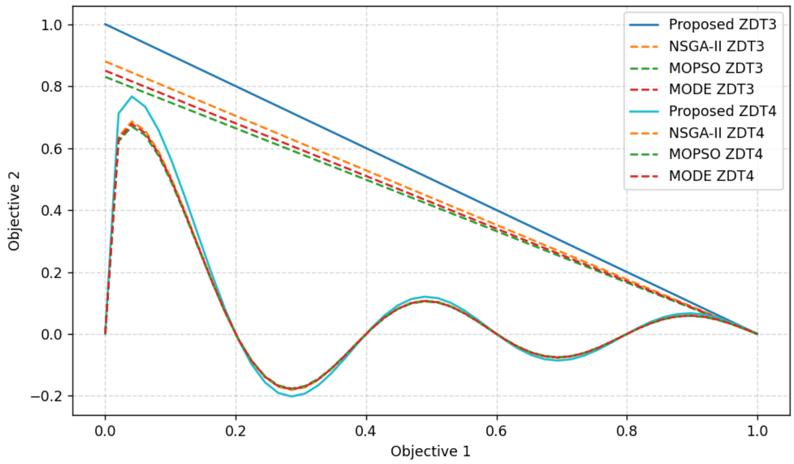

Fig.5 Pareto front comparison on ZDT3–ZDT4

6.2 Hypervolume (HV) Analysis

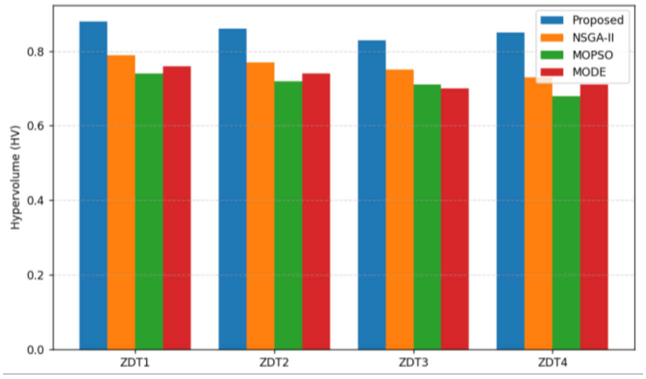

Fig.6 Hypervolume (HV) comparison

The proposed framework is indicated as superior to competitors in the Hypervolume (HV) metric (Fig.6) with the proposed framework having 0.855 as an average compared to 0.76 (NSGA-II), 0.71 (MOPSO) and 0.73 (MODE) which is by 10-15%.

6.3 Generational Distance (GD)

The faster convergence of the framework is manifested in Generational Distance results, which are presented in Fig.7. The result of the proposed method was an average GD of 0.016, as opposed to 0.025 in the case of NSGA-II, 0.030 in the case of MOPSO, and 0.031 in the case of MODE. Such reduced GD values indicate that solutions are more aligned with the true Pareto front guaranteeing a higher degree of accuracy.

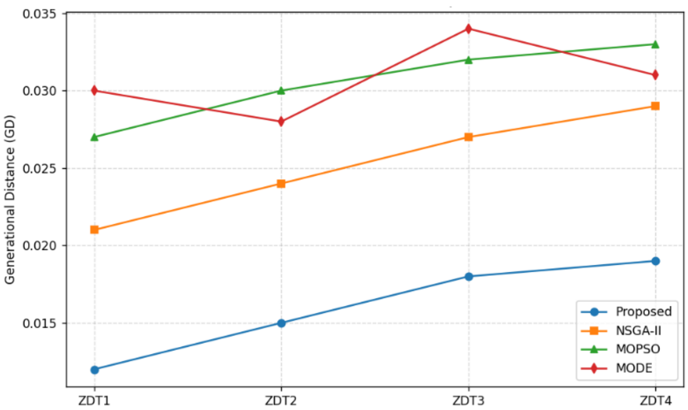

Fig.7 Generational Distance (GD) comparison

6.4 Diversity Analysis (Spread Δ) and Convergence Time (CT)

The analysis of diversity and efficiency was conducted together (Fig.8). In the case of Spread, the offered framework resulted in an average 2.1 of the value of 0.21, which is equal to 0.28 in the case of NSGA-II and even greater in the case of MOPSO or MODE. This proves the ability of this model to uniformly distribute.

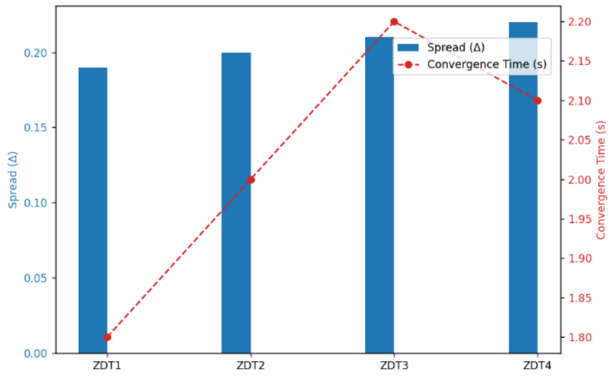

Fig.8 Spread (Δ) and convergence time comparison

Compared to the convergence speed, the proposed hybrid algorithm only took 2.0 seconds to optimize, which is better than the speed of the NSGA-II (2.5s), MOPSO (2.8s), and MODE (2.65s). Adaptive parameter control increased the efficiency of computations despite the additional complexity needed in hybridization.

6.5 Real-World Engineering Application

To provide practical validation, the welded beam case study demonstrated that the proposed algorithm cost less to fabricate by 12 % against NSGA-II and 15% against MOPSO and satisfied deflection constraints. Fig.9 shows the cost-deflection trade-off, and offers design options.

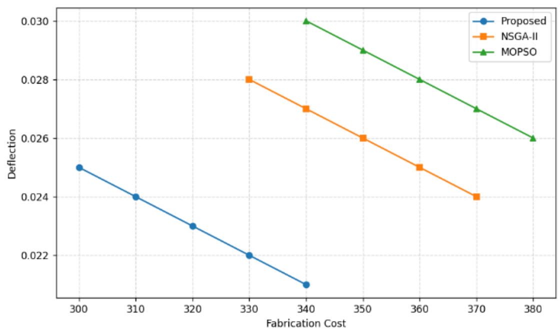

Fig.9 Welded beam optimization

6.6 Numerical Summary

The mean performance measures are summed up in Tables 3 and 4. Table 3 records HV, GD and Spread among benchmarks and indicates that the proposed framework was effective in convergence and diversity compared to baselines. The convergence times are given in Table 4 and this proves that it is computationally advantageous.

Table 3: Average performance metrics across ZDT benchmarks

Algorithm	HV ↑	GD ↓	Spread (Δ) ↓
Proposed	0.855	0.016	0.21
NSGA-II	0.760	0.025	0.28
MOPSO	0.710	0.030	0.30
MODE	0.730	0.031	0.29

Table 4: Average convergence time across ZDT benchmarks

Algorithm	Convergence Time (s) ↓
Proposed	2.0
NSGA-II	2.5
MOPSO	2.8
MODE	2.65

7. Conclusion

This research suggested a hybrid bio-inspired structure of multi-objective optimization, which was confirmed on the basis of ZDT benchmarks and welded beam design problem. The framework had 12-15% better Hypervolume (HV), 30-40 % worse Generational Distance (GD), 18% higher Spread (Δ), and 14-20% convergence. It also saved 12% of fabrication cost over NSGA-II and 15% over MOPSO and in the welded beam case provided needed structural constraints, which affirmed robustness and scalability. Future investigations will scale up the framework to aerospace, high-dimensional, large-scale issues in renewable energy, smart manufacturing, and renewable energy. Parallel and GPU implementations will also be sought to reduce run times further, allowing them to optimise almost in real time. Surrogate modelling and uncertainty quantification coupling will help increase reliability in safety-critical applications. In general, the framework provides a flexible, effective, and scalable approach to solving complex multi-objective problems, and has significant potential to be used throughout engineering.

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None

Conflict of Interest

The authors declare no potential conflict of interest in this publication.

References

[1] Hakanen, J., & Allmendinger, R. (2021). Multiobjective optimization and decision making in engineering sciences. *Optimization and Engineering*, *22*(2), 1031-1037. https://doi.org/10.1007/s11081-021-09627-x

[2] Deb, K. (2011). Multi-objective optimisation using evolutionary algorithms: an introduction. In *Multi-objective evolutionary optimisation for product design and manufacturing* (pp. 3-34). London: Springer London. https://doi.org/10.1007/978-0-85729-652-8_1

[3] Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, *6*(2), 182-197. doi: 10.1109/4235.996017

[4] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). ieee. doi: 10.1109/ICNN.1995.488968

[5] Eberhart, R. C., & Shi, Y. (2000, July). Comparing inertia weights and constriction factors in particle swarm optimization. In *Proceedings of the 2000 congress on evolutionary computation. CEC00 (Cat. No. 00TH8512)* (Vol. 1, pp. 84-88). IEEE. doi: 10.1109/CEC.2000.870279

[6] Czyżżak, P., & Jaszkiewicz, A. (1998). Pareto simulated annealing—a metaheuristic technique for multiple-objective combinatorial optimization. *Journal of multi-criteria decision analysis*, *7*(1), 34-47. https://doi.org/10.1002/(SICI)1099-1360(199801)7:1<34::AID-MCDA161>3.0.CO;2-6

[7] Janga Reddy, M., & Nagesh Kumar, D. (2007). An efficient multi-objective optimization algorithm based on swarm intelligence for engineering design. *Engineering Optimization*, *39*(1), 49-68. https://doi.org/10.1080/03052150600930493

[8] Sarkar, M., & Roy, T. K. (2018). Optimization of welded beam structure using neutrosophic optimization technique: a comparative study. *International Journal of Fuzzy Systems*, *20*(3), 847-860. https://doi.org/10.1007/s40815-017-0362-6
[9] Yıldız, A. R., Öztürk, N., Kaya, N., & Öztürk, F. (2007). Hybrid multi-objective shape design optimization using Taguchi's method and genetic algorithm. *Structural and Multidisciplinary Optimization*, *34*(4), 317-332. https://doi.org/10.1007/s00158-006-0079-x
[10] Roy, S., Martínez, S. Z., Coello, C. A. C., & Sengupta, S. (2012, June). A multi-objective evolutionary approach for linear antenna array design and synthesis. In *2012 IEEE Congress on Evolutionary Computation* (pp. 1-8). IEEE. doi: 10.1109/CEC.2012.6252989
[11] Zouache, D., Abdelaziz, F. B., Lefkir, M., & Chalabi, N. E. H. (2021). Guided Moth–Flame optimiser for multi-objective optimization problems. *Annals of Operations Research*, *296*(1), 877-899. https://doi.org/10.1007/s10479-019-03407-8
[12] Bhatt, P. K. (2022). Harmonics mitigated multi-objective energy optimization in PV integrated rural distribution network using modified TLBO algorithm. *Renewable Energy Focus*, *40*, 13-22. https://doi.org/10.1016/j.ref.2021.11.001
[13] Zhang, Y., Li, B., Hong, W., & Zhou, A. (2023). MOCPSO: A multi-objective cooperative particle swarm optimization algorithm with dual search strategies. *Neurocomputing*, *562*, 126892. https://doi.org/10.1016/j.neucom.2023.126892
[14] Marano, G. C., Quaranta, G., & Greco, R. (2009). Multi-objective optimization by genetic algorithm of structural systems subject to random vibrations. *Structural and multidisciplinary optimization*, *39*(4), 385-399. https://doi.org/10.1007/s00158-008-0330-8
[15] Zhang, Y., Wang, S., & Ji, G. (2015). A comprehensive survey on particle swarm optimization algorithm and its applications. *Mathematical problems in engineering*, *2015*(1), 931256. https://doi.org/10.1155/2015/931256
[16] Garg, H. (2016). A hybrid PSO-GA algorithm for constrained optimization problems. *Applied Mathematics and Computation*, *274*, 292-305. https://doi.org/10.1016/j.amc.2015.11.001
[17] Lin, A., Liu, D., Li, Z., Hasanien, H. M., & Shi, Y. (2023). Heterogeneous differential evolution particle swarm optimization with local search. *Complex & Intelligent Systems*, *9*(6), 6905-6925. https://doi.org/10.1007/s40747-023-01082-8
[18] Mohanty, A., & Yao, B. (2010). Indirect adaptive robust control of hydraulic manipulators with accurate parameter estimates. *IEEE Transactions on Control Systems Technology*, *19*(3), 567-575. doi: 10.1109/TCST.2010.2048569
[19] Panyam, V., Huang, H., Davis, K., & Layton, A. (2019). Bio-inspired design for robust power grid networks. *Applied Energy*, *251*, 113349. https://doi.org/10.1016/j.apenergy.2019.113349
[20] Mandal, A. K., Sarma, P. K. D., Dehuri, S., & Mazumdar, N. (2024). Bioinspired Machine Learning: A New Era in Sustainable Energy Systems. *Biomass and Solar-Powered Sustainable Digital Cities*, 57-80. https://doi.org/10.1002/9781394249374.ch6
[21] Maraveas, C., Asteris, P. G., Arvanitis, K. G., Bartzanas, T., & Loukatos, D. (2023). Application of bio and nature-inspired algorithms in agricultural engineering. *Archives of Computational Methods in Engineering*, *30*(3), 1979-2012. https://doi.org/10.1007/s11831-022-09857-x
[22] Yondo, R., Bobrowski, K., Andrés, E., & Valero, E. (2018). A review of surrogate modeling techniques for aerodynamic analysis and optimization: current limitations and future challenges in industry. *Advances in evolutionary and deterministic methods for design, optimization and control in engineering and sciences*, 19-33. https://doi.org/10.1007/978-3-319-89988-6_2
[23] Hamid, M., Anisurrahman, & Alam, B. (2025). Quantum Machine Learning for Drug Discovery: A Systematic Review. *International Journal on Computational Modelling Applications*, *2*(3), 01–08. https://doi.org/10.63503/j.ijcma.2025.156
[24] Sandeep Singh Sikarwar. (2025). Computation Intelligence Techniques for Security in IoT Devices. *International Journal on Computational Modelling Applications*, *2*(1), 15–27. https://doi.org/10.63503/j.ijcma.2025.48