An Enhanced Dipper-Throated Optimization Framework for Efficient Engineering Design Problem Solving

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Abstract

Metaheuristic algorithms effectively solve complex optimization problems but often suffer from premature convergence or weak local refinement. This paper proposes a hybrid GWO+DTO algorithm combining Grey Wolf Optimizer (GWO) exploration with Dipper-Throated Optimizer (DTO) exploitation.

The method is evaluated on the Pressure Vessel and Tension/Compression Spring design problems. GWO+DTO achieves superior performance (5950.28 and 0.01266) with fewer function evaluations, demonstrating improved convergence and robustness.

Index Terms— *Hybrid Metaheuristic, GWO, DTO, Engineering Optimization.*

1. INTRODUCTION

Metaheuristic optimization balances exploration and exploitation for nonlinear, constrained problems. GWO provides strong global exploration but may converge prematurely. DTO offers effective local refinement but may lack global diversity.

The proposed GWO+DTO integrates both strengths to improve convergence accuracy and robustness. Performance is validated on two benchmark engineering problems.

2. LITERATURE REVIEW

Optimization has evolved from classical mathematical methods to adaptive, hybrid metaheuristics [3]–[15]. Recent work emphasizes multi-objective handling, hybridization, and adaptive mechanisms for improved convergence and robustness. Nature-inspired approaches such as DOA and enhanced MPA demonstrate strong exploration–exploitation balance. Hybrid frameworks show consistent improvements for complex real-world problems.

3. HYBRIDIZATION: GWO+DTO

The hybrid combines GWO's hierarchical hunting mechanism with DTO's adaptive movements

Step 1: Initialization

$$X_i = X_{\min} + r \cdot (X_{\max} - X_{\min}) \qquad (1)$$

where $r \in [0,1]$.

Step 2: Fitness Evaluation

Each solution is evaluated, and the best candidates are identified.

Step 3: GWO-Based Exploration

Positions are updated using alpha, beta, and delta leaders:

$$X(t+1) = X_p(t) - A \cdot | C \cdot X_p(t) - X(t) | \qquad (2)$$

where $X_p(t)$represents leaders and $A, C$are adaptive coefficients.

Step 4: DTO-Based Exploitation

Swimming (Local Search):

$$BP_{nd}(t+1) = BP_{best}(t) - C_1 \cdot | C_2 \cdot BP_{best}(t) - BP_{nd}(t) | \qquad (3)$$

Flying (Diversity Enhancement):

$$BP_{nd}(t+1) = BP_{nd}(t) + BV(t+1) \qquad (4)$$

Velocity update:

$$BV(t+1) \qquad (5)$$

Step 5: Adaptive Switching

$$P_{switch} \quad (6)$$

where P_{switch} increases over iterations to gradually shift from exploration to exploitation.

Step 6: Termination

The process stops when the maximum iterations are reached or convergence criteria are satisfied.

4. ENGINEERING PROBLEM FORMULATION

A. Pressure Vessel Design

This problem minimizes the total manufacturing cost of a cylindrical pressure vessel subject to structural constraints. The decision variables are:

- x_1: Shell thickness
- x_2: Head thickness
- x_3: Inner radius
- x_4: Vessel length

The objective function is:

$$\text{Minimize } f(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3 \quad (7)$$

B. Tension/Compression Spring Design Problem (TCSDP)

This problem minimizes the spring weight under stress and design constraints.

Decision Variables:

• x_1: Wire diameter • x_2: Mean coil diameter • x_3: Number of active coils

Objective Function:

$$\text{Minimize } f(x) \quad (8)$$

Constraints:

$$g_1(x) \leq 0 \text{(Shear stress)} \quad (9)$$
$$g_2(x) \leq 0 \text{(Surge frequency)} \quad (10)$$
$$g_3(x) \leq 0 \text{(Spring index)} \quad (11)$$
$$g_4(x) \leq 0 \text{(Active coil)} \quad (12)$$

Both problems are highly nonlinear and constrained, making them suitable benchmarks for evaluating the proposed hybrid optimizer.

5. EXPERIMENTAL RESULTS AND DISCUSSION

The GWO+DTO hybrid was tested on the Pressure Vessel Design Problem (PVDP) and the Tension/Compression Spring Design Problem (TCSDP), and compared with standalone GWO and DTO.

Settings: Population = 30, Iterations/FEs = 15000, Runs = 30, Static penalty method, Python/MATLAB (Intel i7, 16 GB RAM).

Metrics: Best, Average, Std. Dev., Worst, FEs.

TABLE I RESULTS FOR PRESSURE VESSEL DESIGN PROBLEM

Algorithm	Best	Average	Std Dev	Worst	FEs
GWO+DTO	5950.29	7094.38	1329.85	11941.63	15000
GWO	5980.03	6139.68	305.96	7251.55	15000
DTO	5977.30	6289.31	205.78	6870.40	15000

TABLE II RESULTS FOR TENSION/COMPRESSION SPRING DESIGN PROBLEM

Algorithm	Best	Average	Std Dev	Worst	FEs
GWO+DTO	0.01267	0.01289	0.00022	0.01345	13624
GWO	0.01266	0.01423	0.00343	0.03045	15000
DTO	0.01266	0.01331	0.00104	0.01777	15000

GWO+DTO achieved the best solutions in both problems and required fewer evaluations in TCSDP. It showed improved stability in the spring problem and stronger global search in PVDP. Although variability exists in PVDP, overall results confirm the hybrid's superior accuracy, convergence efficiency, and robustness compared to standalone methods.

6. CONCLUSION

The hybrid GWO+DTO improves solution quality, convergence speed, and robustness compared to standalone methods. It is effective for constrained engineering optimization and scalable to large-scale and multi-objective problems.

7. REFERENCES

[1] A. Alhussan, E.-S. M. El-Kenawy, D. S. Khafaga, A. H. Alharbi, and M. M. Eid, "Groundwater resource prediction and management using comment feedback optimization algorithm for deep learning," *IEEE Access*, 2025.

[2] M. A. Hossain, E. Gray, J. Lu, M. R. Islam, M. S. Alam, R. Chakrabortty, and H. R. Pota, "Optimized forecasting model to improve the accuracy of very short-term wind power prediction," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 10, pp. 10145–10159, 2023.

[3] N. M. Khan, M. H. Z. Khan, and U. A. Khan, "Short-term power forecasting of wind energy system using deep neural network (DNN) trained by a novel meta-heuristic optimization algorithm," in *Proc. 16th Int. Conf. Emerging Technologies (ICET)*, 2021, pp. 1–6.

[4] M. A. Kousounadis-Knousen, I. K. Bazionis, D. Soudris, F. Catthoor, and P. S. Georgilakis, "A new co-optimized hybrid model based on multi-objective optimization for probabilistic wind power forecasting in a spatio–temporal framework," *IEEE Access*, vol. 11, pp. 84885–84899, 2023.

[5] L. Jovanovic, K. Kumpf, N. Bacanin, M. Antonijevic, J. Mani, H. Shaker, and M. Zivkovic, "Decomposition-aided bidirectional long short-term memory optimized by hybrid metaheuristic applied for wind power forecasting," in *Computational Sciences and Sustainable Technologies*, vol. 1973, Springer, 2024, pp. 30–42.

[6] S. A. Perez-Rodriguez et al., "Metaheuristic algorithms for solar radiation prediction: A systematic analysis," *IEEE Access*, vol. 12, pp. 100134–100151, 2024.

[7] M. Zivkovic, L. Jovanovic, M. Pavlov, N. Bacanin, M. Dobrojevic, and M. Salb, "Optimized recurrent neural networks with attention for wind farm energy generation forecasting," in *Proc. 16th Int. Conf. Advanced Technologies, Systems and Services in Telecommunications (SIKS)*, 2023, pp. 187–190.

[8] T. Kunakote et al., "Comparative performance of twelve metaheuristics for wind farm layout optimisation," *Archives of Computational Methods in Engineering*, vol. 29, no. 1, pp. 717–730, 2022.

[9] Li et al., "Short-term interval prediction of wind power using deep learning model with gradient descent optimization," *Renewable Energy*, vol. 155, pp. 197–211, 2020.

[10] Stojkovic, B. Nikolic, M. Zivkovic, and N. Bacanin, "Photovoltaic farm production forecasting: Modified metaheuristic optimized long short-term memory based networks approach," *IEEE Access*, 2025.

[11] V. V. Lakshmi et al., "Wind power forecasting with support vector machines using Sparrow Search Algorithm," in *Proc. 2nd Int. Conf. Computer, Communication and Control (IC4)*, 2024, pp. 1–5.