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A Novel Approach for Capacitated Vehicle Routing Using the Invasive Weed Optimization Algorithm

M. Foroutan Naddafi[1,*]

[1] Department of Civil Engineering, National University of Technical and Vocational Education, Tehran, Iran

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ABSTRACT

Routing is a fundamental challenge in civil engineering, with direct implications for the design, planning, and construction of transportation infrastructure such as roads, railways, and urban transit systems. Among various routing-related problems, the Vehicle Routing Problem (VRP) has attracted considerable attention due to its broad applicability in logistics, supply chain management, and service delivery. In the capacitated variant of the VRP (CVRP), each vehicle in the fleet is constrained by a fixed carrying capacity, making the task of determining optimal routes even more complex. Given the combinatorial nature of CVRP, the number of feasible routing configurations grows exponentially with the problem size, which necessitates the use of advanced metaheuristic algorithms capable of efficiently exploring the solution space. This study presents a novel CVRP-solving framework based on the Invasive Weed Optimization (IWO) algorithm, leveraging its strong global search ability, adaptability, and robustness in high-dimensional optimization problems. The proposed method is implemented in MATLAB, and its performance is benchmarked against several well-established optimization approaches. Simulation results reveal that the IWO-based method achieves lower total operational costs and faster convergence rates, demonstrating its potential as a practical decision-support tool for large-scale routing applications in transportation and civil engineering projects.

1. INTRODUCTION

Routing strategies play a pivotal role in civil engineering, serving as a cornerstone for the efficient planning, design, and management of contemporary infrastructure. By intelligently determining optimal paths, these methods contribute to enhanced operational efficiency, improved safety standards, and greater sustainability across construction and transportation projects. Beyond reducing costs, effective routing supports the structural durability of infrastructure, particularly in geologically complex or environmentally sensitive areas such as earthquake-prone zones and protected ecosystems. The multifaceted importance of routing in civil engineering can be understood across the following key areas [1–5]:

1.1. Cost Efficiency and Resource Management

[*] Corresponding Author: mforoutannaddafi@tvu.ac.ir
Department of Civil Engineering, National University of Technical and Vocational Education, Tehran, Iran

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Optimized routing substantially lowers expenses related to material handling and workforce deployment by selecting the most effective routes for project implementation. Cutting-edge tools such as Geographic Information Systems (GIS) and heuristic-based algorithms enable civil engineers to minimize logistical complexity while ensuring optimal utilization of resources [6].

1.2. Risk Assessment and Safety Improvement

Comprehensive route planning aids in identifying potential hazards like landslide zones or unstable geological formations allowing for timely preventive interventions. This is especially vital for critical infrastructure including tunnels, bridges, and transport corridors, where safety and structural soundness are directly interlinked [7].

1.3. Ecological Impact Minimization

Environmentally responsible routing incorporates tools that evaluate potential disruptions to ecosystems, thereby supporting the development of infrastructure with reduced ecological footprints. Methods like Environmental Impact Assessment (EIA) and Life Cycle Assessment (LCA) are often embedded into modern routing frameworks to align engineering practices with environmental conservation goals [8].

1.4. Intelligent and Data-Informed Routing

The integration of advanced technologies such as artificial intelligence (AI), machine learning (ML), and big data analytics has transformed traditional routing processes. These innovations empower engineers to conduct predictive simulations and leverage real-time datasets, enabling dynamic and highly accurate path selection under varying operational conditions [9].

1.5. Strategic Urban Growth and Mobility Planning

Modern routing tools are instrumental in anticipating urban sprawl, demographic changes, and evolving traffic patterns. This foresight facilitates the design of scalable infrastructure networks that support sustainable urban development. As part of smart city initiatives, adaptive routing algorithms are increasingly used to manage future transportation needs with precision and efficiency [10].

1.6. Research Focus and Paper Structure

This study introduces an innovative approach to the Vehicle Routing Problem (VRP), emphasizing cost reduction through advanced optimization techniques. The remainder of the paper is organized as follows:

- **Section 2:** A critical review of existing routing methodologies and their limitations.
- **Section 3:** Presentation of the proposed routing algorithm, detailing its theoretical framework.
- **Section 4:** Performance evaluation using simulation-based experiments and comparative analysis with benchmark methods.
- **Section 5:** Conclusions and recommendations for future research directions.

2. REVIEW OF EXISTING METHODS

The Capacitated Vehicle Routing Problem (CVRP) is a well-studied area within operations research and logistics, focusing on optimizing vehicle routes for goods delivery while adhering to specific capacity constraints. The NP-hard nature of the CVRP has spurred extensive research into heuristic and exact algorithms aimed at finding efficient solutions. Recent advancements, particularly in optimization techniques such as the Invasive Weed Optimization (IWO) algorithm, have shown considerable promise in tackling the challenges posed by the CVRP.

The CVRP seeks to determine the optimal set of routes for a fleet of vehicles to deliver goods to a predetermined set of customers while meeting both vehicle capacity and customer demand constraints. This problem has been approached through various algorithmic frameworks. For instance, Baldacci et al. [11] provided a comprehensive overview of exact algorithms for solving the CVRP under capacity and time window constraints, highlighting the complexity and computational challenges associated with the problem.

Metaheuristic algorithms have become increasingly popular for solving the CVRP due to their flexibility and effectiveness. According to Elshaer and Awad [12], various metaheuristic algorithms, such as genetic algorithms, simulated annealing, and particle swarm optimization, have been rigorously explored in the context of CVRP. These techniques leverage heuristic methods to explore the solution space, balancing exploration and exploitation effectively.

The introduction of the IWO algorithm, inspired by the growth pattern of invasive weeds, has further enhanced the performance of metaheuristic approaches. Movassagh et al. [13] demonstrated the integration of the IWO algorithm with differential evolutionary models, showcasing its application in artificial neural networks. This hybridization has been found to improve solution quality and convergence speed in various optimization scenarios, including the CVRP.

Recent studies have begun to explore hybrid approaches that combine IWO with other optimization techniques. For example, Pasha et al. [14] implemented exact and metaheuristic algorithms in multi-objective settings for the CVRP, emphasizing the benefits of hybrid strategies in addressing complex routing scenarios. Furthermore, the application of quantum computing in CVRP, as discussed by Feld et al. [15], introduces a novel paradigm for solving routing problems through quantum annealers, although challenges in mapping the CVRP onto these frameworks remain [16].

Additionally, the emergence of deep reinforcement learning techniques has started to reshape the landscape of vehicle routing solutions. Li et al. [17] explored the use of deep reinforcement learning in solving the heterogeneous CVRP, revealing a significant potential for these methods to learn optimal routing patterns from historical data. This approach not only enhances computational efficiency but also improves solution accuracy.

Despite the advancements in algorithms and hybrid approaches, several knowledge gaps remain in the field of CVRP research. For instance, while metaheuristic algorithms have proven effective, their performance varies significantly based on problem instances and constraints. Future research could focus on developing adaptive algorithms that dynamically adjust their parameters based on the specific characteristics of the problem instance being addressed [18].

Moreover, the integration of sustainability considerations in vehicle routing is gaining traction, particularly in the context of electric vehicles. Hannan et al. [19] examined the application of particle swarm optimization in scheduled solid waste collection, underscoring the importance of incorporating environmental impacts into routing solutions. Future studies should prioritize developing innovative routing solutions that align with sustainable logistics practices.

Finally, exploring the potential of combining IWO with emerging technologies such as machine learning and quantum computing could open new avenues for solving the CVRP. The ongoing evolution of optimization techniques, coupled with the increasing complexity of logistics challenges, necessitates continuous exploration and innovation in this field [20].

Research into the Capacitated Vehicle Routing Problem and its variants, particularly through the lens of the Invasive Weed Optimization algorithm, highlights the dynamic and evolving nature of this field. With ongoing advancements in algorithmic strategies and a growing emphasis on sustainability, the future of CVRP research holds considerable promise, paving the way for more efficient and effective routing solutions.

3. PROPOSED METHOD

The Invasive Weed Optimization (IWO) algorithm is a population-based metaheuristic designed to solve complex optimization problems. Inspired by the natural behavior of weeds and their competition for limited resources, this algorithm has demonstrated high efficiency in tackling high-dimensional and nonlinear problems [11–13]. This section introduces the core principles of the IWO algorithm and subsequently presents a routing model based on its application.

3.1. Invasive Weed Optimization Algorithm

The IWO algorithm is fundamentally modeled on ecological processes and the competitive behavior of invasive weeds. In nature, weeds grow rapidly, exploit available resources efficiently, and dominate space by outcompeting other plants. These behaviors are translated into algorithmic procedures representing natural selection and competition mechanisms. The IWO algorithm follows several key steps:

- **Population Initialization:**
  An initial population of weeds (seeds) is randomly distributed across the search space. These represent candidate solutions to the optimization problem.

- **Fitness Evaluation:**
  Each weed is evaluated using an objective function that reflects the quality or fitness of the solution it represents.

- **Selection of Superior Individuals:**
  Based on fitness values, the algorithm selects superior weeds. Weeds with higher performance are given more opportunities to propagate in the next generation.

- **Reproduction and Propagation:**
  Selected weeds undergo a reproduction process, producing new weeds (offspring). The number of offspring and their distribution may be influenced by the fitness of the parent, with high-performing weeds generating more offspring.

- **Competition:**
  Newly generated weeds compete with existing individuals for limited resources. Weeds with lower fitness are gradually eliminated, ensuring that resources are allocated more effectively to stronger individuals.

- **Iteration:**
  The above steps are repeated iteratively until a stopping criterion is met such as reaching a maximum number of generations or achieving a defined level of convergence.

A flowchart illustrating the procedural steps of the IWO algorithm is presented in Figure 1.

The Invasive Weed Optimization (IWO) algorithm offers several notable advantages that make it highly effective in solving complex optimization problems:

- **Simplicity:**

Compared to other metaheuristic algorithms, IWO is relatively straightforward and easy to implement.

- **Adaptability:**

The algorithm demonstrates strong adaptability across a wide range of optimization problems and varying conditions.

- **Competitive Performance:**

IWO often yields results that are comparable to or better than those obtained by other established optimization algorithms in many benchmark problems.

The IWO algorithm has been successfully applied in various domains, including but not limited to:

- Engineering Design Optimization
- Resource Management Problems
- Computer Network Optimization
- Machine Learning and Data Mining Tasks

Fig. 1. Flowchart of the Invasive Weed Optimization (IWO) Algorithm

3.2. Problem Modelling

The Traveling Salesman Problem (TSP) is one of the most well-known and classical problems in optimization and graph theory. The primary objective of TSP is to determine the shortest possible route for a salesman who must visit a specified set of cities and ultimately return to the starting city [21-23]. The detailed aspects of the TSP are outlined as follows:

3.2.1. Problem Definition

In the TSP, a salesman must start from a specific city, visit all other cities exactly once, and return to the origin city. The goal is to minimize the total travel distance.

3.2.2. Inputs and Outputs

- **Input:** A set of cities and the distances or travel costs between them (typically represented as a distance or cost matrix).

- **Output:** The shortest possible route (tour) that includes all cities and returns to the starting city.

3.2.3. Applications

The TSP has widespread applications in various domains, including:

- **Goods Delivery:** Route planning for delivering products to customers.
- **Manufacturing and Production:** Optimizing the sequence of machines in production lines.
- **Network Management:** Routing optimization in transportation and communication networks.
- **Data Analysis:** Addressing clustering and data grouping problems.

3.2.4. Complexity

The TSP is classified as an NP-hard problem, meaning there is no known efficient algorithm that can solve all instances of the problem optimally in polynomial time.

While exact algorithms such as combinatorial methods or linear programming are feasible for small-scale instances, metaheuristic and approximation algorithms are required for large-scale problems due to their computational complexity.

Numerous studies and optimization algorithms have been developed to address the TSP, and the field continues to evolve. Despite its challenges, solving the TSP effectively can significantly reduce time and cost in real-world projects. TSP remains a central problem in graph theory and optimization, and research in this area is still vibrant in both mathematics and computer science.

4. SIMULATION RESULTS

The proposed method and benchmark method were implemented using MATLAB software developed by MathWorks Inc. The computational experiments were conducted on a system equipped with an Intel(R) Core(TM) i5-4460 CPU @ 3.2 GHz and 16 GB RAM.

The parameters for the Invasive Weed Optimization (IWO) algorithm were set as follows:

4.1. Simulation Results (Continued)

Table 1 outlines the key parameter settings used for the Invasive Weed Optimization (IWO) algorithm.

Table 1. Parameter Settings of the Invasive Weed Optimization (IWO) Algorithm

Parameter	Value
N_{weed} (Initial Population Size)	50
MaxIt (Maximum Iterations)	1000
P_{max} (Maximum Number of Plants)	50
S_{max} (Maximum Number of Seeds per Plant)	10
S_{min} (Minimum Number of Seeds per Plant)	1
$\delta_{initial}$ (Initial Standard Deviation)	0.3
δ_{final} (Final Standard Deviation)	0.001
pow (Nonlinear Exponent for Standard Deviation Reduction)	3

These parameter values were selected to create a balance between the convergence speed and the solution accuracy of the algorithm.

A sample solution of the Traveling Salesman Problem (TSP) corresponding to Figure 2 is illustrated using the proposed method in Figure 3, and the optimization convergence trend for this example is depicted in Figure 4.

Similarly, a sample solution of the Multiple Traveling Salesmen Problem (MTSP) corresponding to Figure 5 is presented using the proposed approach in Figure 6, and the convergence process for this problem is shown in Figure 7. These parameters were selected in a manner that strikes a balance between the speed and accuracy of the algorithm. An example of solving the TSP (Traveling Salesman Problem), corresponding to Figure 2, is illustrated using the proposed method in Figure 3. The optimization process is depicted in Figure 4. Similarly, an example of solving the MTSP (Multiple Traveling Salesmen Problem), corresponding to Figure 5, is presented using the proposed method in Figure 6. The optimization process for this case is illustrated in Figure 7.

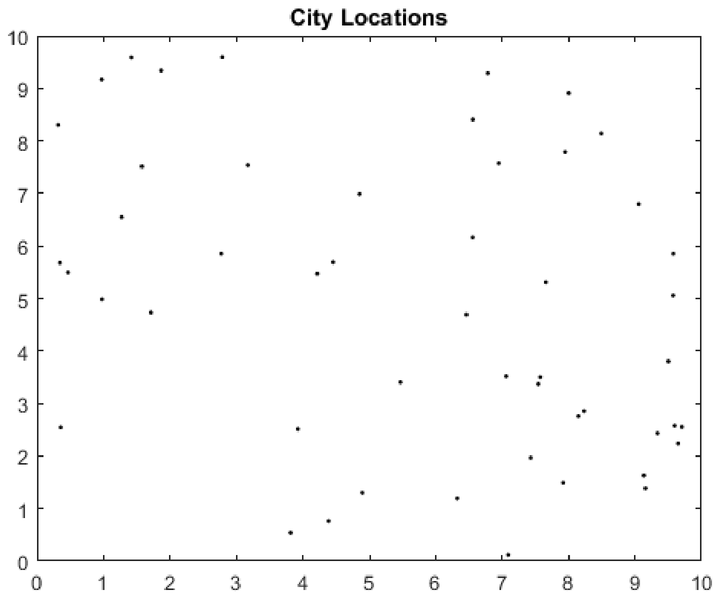

Fig. 2. City locations in the TSP instance.

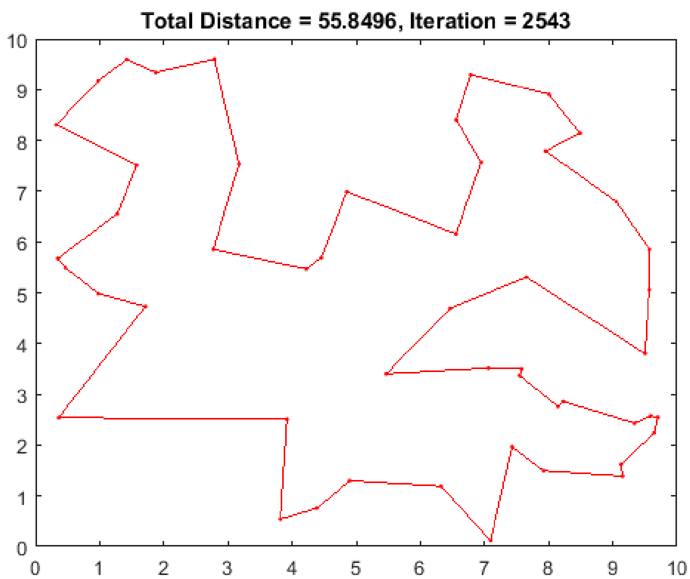

Fig. 3. Proposed solution for the TSP.

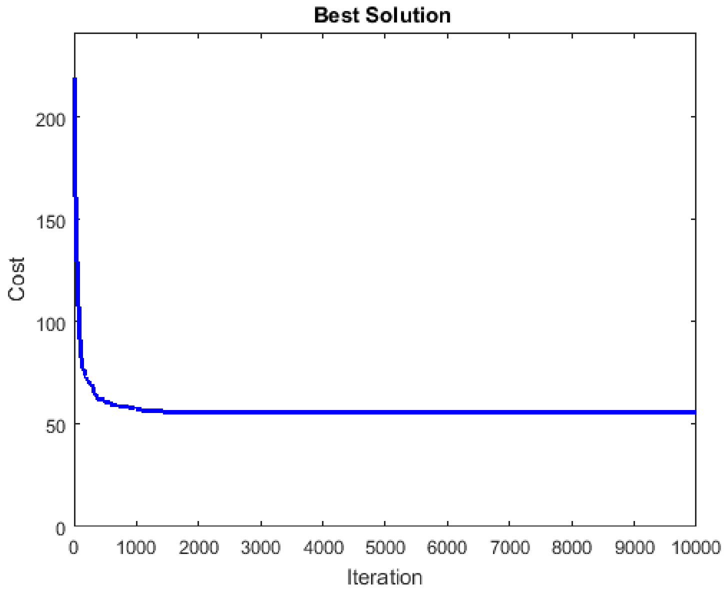

Fig. 4. Optimization process.

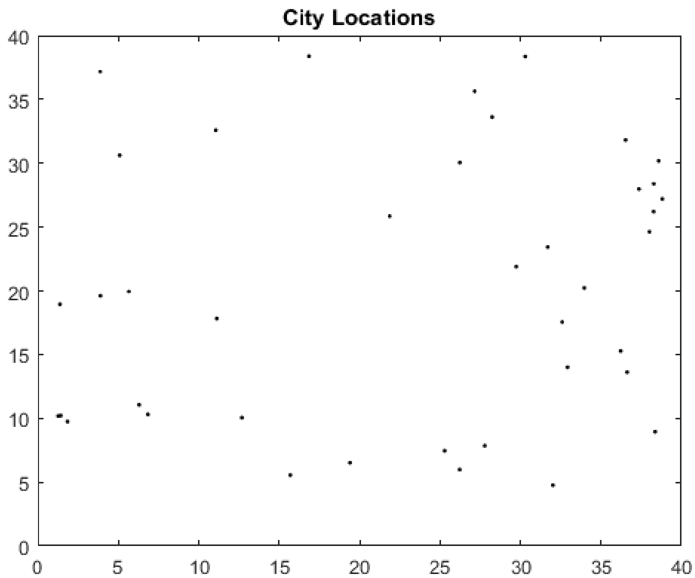

Fig. 5. City locations in the MTSP instance.

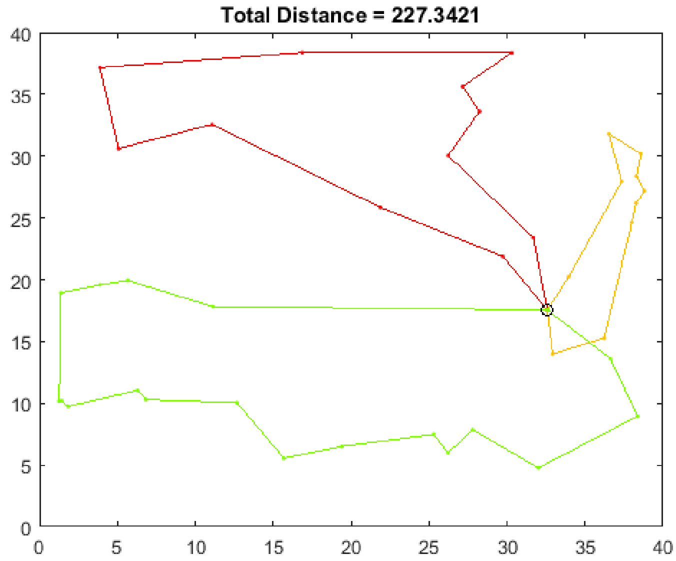

Fig. 6. Proposed solution for the MTSP.

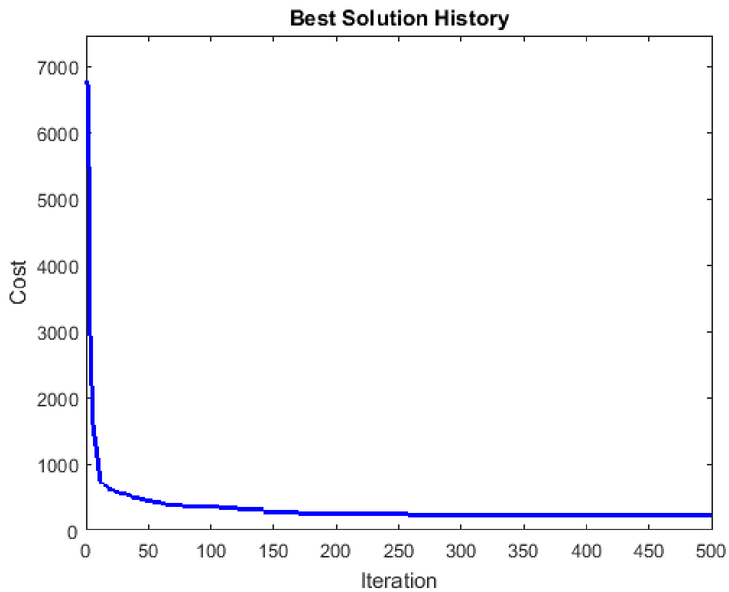

Fig. 7. Optimization process.

In this experiment, the Christofides benchmark dataset was used [21-23]. This dataset comprises 14 instances, labeled C1 to C14, in which the number of customers ranges from 50 to 199. The coordinates are given in Cartesian form and the distances are based on Euclidean metrics (see Table 2). The comparison results are presented in Table 3. These results demonstrate the superior performance of the proposed method.

Table 2. Christofides Test Dataset

Problem	Number of Customers	Number of Vehicles	Capacity	Maximum Tour Length	Service Time
C1	50	5	160	∞	–
C2	75	10	140	∞	–
C3	100	8	200	∞	–
C4	150	12	200	∞	–
C5	199	17	200	∞	–
C6	50	6	160	200	10
C7	75	11	140	160	10
C8	100	9	200	230	10
C9	150	14	200	200	10
C10	199	18	200	200	10
C11	120	7	200	∞	–
C12	100	10	200	∞	–
C13	120	11	200	720	50
C14	100	11	200	1040	90

Table 3. Comparison Results Between the Proposed Method and Existing Approaches

Instance	GA (Berger and Barkaoui, 2003)[24]		PSO (Ai, Kachitvichyanukul, 2009)[25]		Proposed	
	Fitness	Time	Fitness	Time	Fitness	Time
C1	524.81	213	524.81	–	520.7	**45**
C2	849.77	765	844.42	–	831.22	**159**
C3	840.72	1148	829.40	–	822.14	**230**
C4	1055.85	2475	1048.89	–	1024.08	**505**
C5	1378.73	3999	1323.89	–	1290.11	**799**
C6	560.29	217	555.43	–	550.31	**46.1**
C7	914.13	786	917.68	–	908.62	**157**
C8	872.82	1134	867.01	–	845.84	**236.8**
C9	1193.05	2258	1181.14	–	1152.24	**442.7**
C10	1483.06	3687	1428.46	–	1396.56	**750**
C11	1060.24	1633	1051.87	–	1040.11	**235**
C12	877.8	1160	819.56	–	819.52	**241**
C13	1562.25	1694	1546.20	–	1540.75	**332**
C14	872.34	1197	866.37	–	864.27	**249**

5. CONCLUSION

In this study, a novel vehicle routing method based on the Invasive Weed Optimization (IWO) algorithm was proposed. This algorithm, recognized for its suitability in solving high-dimensional optimization problems, has demonstrated superior performance compared to Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). As an emerging technique in the field of optimization, IWO has attracted the attention of researchers and engineers due to its simple structure and high efficiency. The simulations were carried out using MATLAB software. The obtained results confirm the superior performance of the proposed method in comparison with existing approaches.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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