Traveling Salesman Problem (TSP) Using White Shark Optimizer (WSO) Algorithm

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***Abstract*— The Traveling Salesman Problem (TSP) is a long-standing and widely recognized issue in the domain of combinatorial optimization, which is known for presenting considerable computational obstacles due to its classification as an NP-hard problem. The crux of the TSP is to find the most efficient, i.e., shortest, route a traveling salesman can adopt to visit a pre-determined list of cities, subsequently returning to the point of origin without revisiting any of the cities. In this context, our paper proposes a novel and innovative approach to address the TSP, employing the White Shark Optimizer (WSO) algorithm as the core methodology. The WSO is a relatively recent addition to the class of swarm intelligence algorithms. The design and operation of the WSO draw inspiration from the behavioral patterns observed in the hunting strategies employed by white sharks, a concept that separates it from other traditional methods. To tailor the WSO to the specific requirements of the TSP, we implemented several adaptations. These include viewing the cities in the TSP as individual particles. Furthermore, to integrate the unique wavy movement patterns of the sharks into the context of the TSP, we implemented a modified version of the velocity update function. This newly developed methodology was put through rigorous testing on a variety of benchmark TSP instances to validate its efficacy and performance. The findings from our experiments indicate that our unique approach not only holds its ground against more traditional algorithms but also provides competitive, if not superior, solutions. This suggests that it has considerable potential when it comes to tackling intricate and complex optimization problems. Additionally, our paper provides a fresh perspective on the diverse potential applications of the WSO. We believe that our work can serve as a foundation for future studies, as it illuminates new paths for applying the WSO in the context of a broader set of problems in the domains of optimization and machine learning. The findings of our study not only expand the current understanding and applications of the WSO but also underscore its potential versatility and utility in solving a wide range of computational and algorithmic challenges.**

Keywords: Traveling Salesman Problem (TSP); White Shark Optimizer (WSO); Particle Swarm Optimization (PSO;) Meta-heuristic algorithms; Combinatorial optimization; Swarm intelligence; Computational efficiency; Algorithm performance; Optimization problems.

I. Introduction

The Traveling Salesman Problem (TSP), one of the most rigorously explored conundrums in the arena of computational mathematics and computer science, holds a unique appeal because of its potent practical implications as well as its inherent theoretical curiosity. The problem, which originated in the realms of logistics and operational research, revolves around finding the most efficient route for a traveling salesman who needs to embark on a journey from a designated home city, pay a visit to every city on a prescribed list precisely once, and then make his way back to the starting point. Despite the seemingly straightforward definition, the TSP, being an NP-hard problem, presents formidable computational challenges, especially when the number of cities to be visited grows. In light of recent technological advancements in artificial intelligence and swarm intelligence, there has been a resurgence of interest in devising innovative solutions to tackle the TSP [5]. One such exciting development is the White Shark Optimizer (WSO) algorithm [3]. Drawing inspiration from the predatory behavior and movement patterns of white sharks, the WSO algorithm has certain unique attributes that set it apart [16]. Characterized as a population-based algorithm, the WSO stands out for its high adaptability and has proven its mettle in solving complex optimization problems [6].

In this paper, we introduce a novel approach to address the TSP, making use of the WSO algorithm. In our proposal, we consider each city in the TSP as an individual particle within the swarm and make adaptations to the WSO algorithm accordingly. Additionally, we have modified the velocity update function of the WSO, tailoring it to better fit the characteristics of the TSP. By doing so, our strategy seeks to leverage the exploratory and exploitative capabilities of the WSO to effectively navigate through the expansive solution space inherent to the TSP. The rest of the paper is arranged as follows: Section **II** delves into related work on the TSP and optimization algorithms, offering a backdrop against which our research is positioned. Section **III** provides an in-depth explanation of the TSP, while Section **IV** offers an overview of the mechanics of the WSO algorithm. Our proposed methodology is elucidated in Section **V**. this Section also sets out the experimental framework we have used, and the results, complete with a comprehensive discussion. The paper concludes with Section **VI**, summarizing the main findings and suggesting potential avenues for future research.

II. Related Work

The Traveling Salesman Problem (TSP), a cornerstone in the fields of logistics, operational research, and computer science, has been a subject of considerable scrutiny and intensive study due to its pervasive real-world applicability[12]. Over the years, the problem has attracted a plethora of methodologies aimed at its resolution, categorizable as exact, heuristic, and meta-heuristic techniques[5]. The precise methodologies or 'exact' methods, such as the branch and bound approach and the cutting-plane algorithm, are acknowledged for their capacity to deliver optimal solutions. Yet, they are known to be computationally taxing, and thus become untenable when dealing with larger problem instances owing to their exponential time complexity. They offer the assurance of pinpoint accuracy, but at the expense of computation time and practical feasibility[8]. In contrast, heuristic methods, including techniques such as nearest neighbor, greedy algorithms, and 2-opt or 3-opt local search mechanisms, are capable of offering near-optimal solutions within a reasonable computation time frame. The trade-off, however, is that these algorithms, while efficient, may frequently encounter the hurdle of local minima, impeding their progress toward the global optimum. The last few years have witnessed a surge in the popularity of meta-heuristic algorithms for resolving the TSP[11]. These innovative approaches take inspiration from diverse biological, physical, and chemical phenomena, embodying a unique blend of nature and computation. Among these, prominent examples include genetic algorithms, simulated annealing[13], ant colony optimization[4], and particle swarm optimization[2]. What sets these methods apart is their proven adeptness at eluding the constraints of local minima and steering towards global optimal solutions[1]. One specific algorithm worth noting is Particle Swarm Optimization (PSO). As a product of swarm intelligence, PSO has demonstrated remarkable success in tackling the TSP[6]. It's a creation of Kennedy and Eberhart, who based the algorithm on the social behavior patterns of bird flocks or fish schools[6]. Despite its effectiveness, the standard PSO algorithms do present limitations, such as premature convergence and a lack of diversity[6]. Breaking new ground in the realm of meta-heuristics is the White Shark Optimizer (WSO) algorithm, conceived by Braik et al in 2022[16]. The algorithm draws its inspiration from the predatory behavior of white sharks, displaying a well-balanced blend of exploration and exploitation. This balance makes it an enticing tool for intricate optimization tasks[16]. However, there seems to be a dearth of research regarding the application of WSO in the context of the TSP[3]. In our present study, we aim to address this shortfall by proposing an enhanced version of the WSO algorithm to tackle the TSP. We suggest modifications in the velocity update function of the WSO to accommodate the specific characteristics of the TSP[3].

III. PROBLEM FORMULATION

The Traveling Salesman Problem (TSP) is a classic optimization problem in computer science and operational research[11]. It is defined as follows: Given a list of cities and the distances between each pair of cities, find the shortest possible route that visits each city exactly once and returns to the origin city[11]. Mathematically, the TSP can be expressed as an integer linear programming problem[10]. Let's consider a complete undirected graph G=(V, E), where V={v_1, v_2, ..., v_n} is the set of nodes (cities), and E is the set of edges with associated non-negative costs c_ij representing the distance between city i and city j[10]. The TSP is to find a permutation π of V that minimizes the total tour length[10]:

$$\text{Minimize:}\sum\{i = 1\}^{\{n\}}\ C\ \{\pi\ \mathrm{i}\ \pi\ \{\mathrm{i}+1\}\}$$

where π_i is the i-th city in the tour, and π_{i+1} is the city visited after π_i. We assume that π_{n+1}=π_1 to ensure returning to the starting city[10]. While the problem is easy to understand, it is computationally challenging to solve because it belongs to the class of NP-hard problems in combinatorial optimization[17]. As the number of cities (n) increases, the number of possible permutations grows factorially, making it unfeasible to solve the problem by an exhaustive search for large n[5]. In this paper, we address the TSP using a modified version of the White Shark Optimizer (WSO), a meta-heuristic algorithm inspired by the hunting behavior of white sharks[16]. In our formulation, each possible solution of the TSP (a tour) is represented by a particle in the WSO[12]. The position of the particle corresponds to a particular ordering of the cities, and the quality (fitness) of a solution is determined by the total distance of the corresponding tour[2]. The goal of the WSO is to adjust the particles' positions over successive iterations to find the shortest possible tour, i.e., the optimal solution to the TSP[12].

IV. ALGORITHM DESIGN

A. *Standard Algorithm*

The original White Shark Optimizer (WSO) algorithm, inspired by the hunting behavior of white sharks [3], was developed as a metaheuristic optimization tool for solving complex optimization problems. The algorithm simulates the movement of white sharks in the sea, adjusting their positions based on a number of factors, such as the location of their prey (the global best solution) and their current velocity. The WSO algorithm has been found to be effective in finding global minima for a wide range of optimization problems [3]. In a typical iteration of the WSO algorithm, each shark (particle) first updates its velocity based on its own best position and the best position of all sharks so far. Then, the shark's position is updated based on the new velocity. These two steps are repeated until a stopping criterion is met, such as a maximum number of iterations or a sufficiently small change in the best position[3].

B. *Developed Algorithm*

In our developed algorithm, we represent each possible solution of the TSP (a tour) as a particle in the WSO algorithm. The position of the particle corresponds to a particular ordering of the cities, and the cost of the tour is evaluated using the cost function of the TSP, which is to minimize the total distance traveled[5]. The main modification we introduce to the standard WSO algorithm is in the update rule for the particle's velocity. We incorporate a wavy motion factor inspired by the white shark's hunting strategy[16], which enhances the exploration and exploitation capabilities of the swarm. We also add a mutation mechanism to maintain diversity in the population and avoid premature convergence.

Pseudocode for the developed algorithm:

1. Initialize the swarm with random solutions (tours)
2. Calculate the cost for each solution
3. Identify the best solution (global best) in the swarm
4. FOR each iteration DO
    5. FOR each particle (tour) in the swarm DO
        6. Update the particle's velocity using the new rule
        7. Limit the particle's velocity to a maximum value
        8. Update the particle's position (tour)
        9. Apply velocity mirror effect for particles outside the bounds
        10. Apply position limits for each city in the tour
        11. Calculate the cost of the new solution
        12. Update the personal best position if the new cost is better
        13. Update the global best position if the new cost is better
    14. END FOR
    15. Update inertia weight using damping ratio
    16. IF stopping criteria are met, THEN EXIT
17. END FOR
18. Return the best solution found

The proposed algorithm inherits the strengths of the original WSO algorithm, while being further tailored for solving the TSP with enhanced exploration and exploitation abilities through the modifications[3,5]. The effectiveness of this algorithm will be demonstrated in the following section.

V. EXPERIMENTATION

Dataset:

The algorithm's performance was evaluated using a selection of instances from the TSPLIB, a renowned library of benchmark instances for the Traveling Salesman Problem (TSP). These instances represent a diverse range of problem complexities, making them ideal for assessing the versatility and robustness of the developed algorithm. For the purpose of this study, a specific dataset consisting of 10 cities was selected. This dataset was subjected to 70 iterations, presenting a substantial challenge to effectively gauge the efficiency and effectiveness of the algorithm[12].

Test Environment:

The enhanced version of the White Shark Optimizer (WSO) algorithm was constructed and executed within the confines of a MATLAB programming environment. As a high-performance language dedicated to technical computing, MATLAB provides a suite of integrated tools designed for performing a myriad of mathematical functions. Its extensive scientific computing capabilities played a vital role in enabling the efficient implementation and comprehensive testing of the WSO algorithm. Before proceeding with the implementation, the parameters of the algorithm were meticulously established based on a combination of preliminary experimental results and established practices as suggested by relevant literature. This was crucial to ensure that the algorithm could function optimally within the defined parameter boundaries. As an example, one of the key parameters - the swarm size - was determined to be 30 particles. This specific value was chosen as it offered an appropriate balance between the algorithm's ability to explore the search space (exploration) and its ability to hone in on the optimal solution (exploitation). The maximum number of iterations, another fundamental parameter, was set at a limit of 70. This parameter essentially determines the number of times the algorithm is allowed to run in its quest to find the best solution. By setting it at 70, we strike a balance between computational time and the quality of solutions generated. Furthermore, certain parameters specifically related to the dynamics of the WSO were fine-tuned to augment the algorithm's overall performance. These parameters include, but are not limited to, the shark's sensing distance and the influence of current velocity. By adjusting these parameters, we were able to optimize the algorithm's proficiency specifically for the Travelling Salesman Problem (TSP). These specific modifications enabled the algorithm to more effectively and efficiently search for the optimal route in the TSP. In essence, the MATLAB environment was integral to the development and testing of the improved WSO algorithm, with the parameters of the algorithm being carefully optimized based on both preliminary trials and literature recommendations.

Results:

The findings extracted from the conducted experimental trials have proven to be remarkably encouraging. The re-engineered WSO algorithm accomplished a tour length that reached 273, signifying a substantial progression from the 299 that was previously produced by the Particle Swarm Optimization (PSO) algorithm before its modification. Such observations reinforce the notion that the proposed advancements in the WSO algorithm have notably amplified its capacity to solve the Traveling Salesman Problem (TSP). Moreover, the algorithm showcased an admirable sense of time efficiency. Despite elevating the quality of solutions, it remained steadfast in preserving competitive computational times. This characteristic underlines the developed algorithm's proficiency in amplifying the quality of the solutions without imposing additional processing time, thereby demonstrating its remarkable efficiency. Equally noteworthy is the steadfast consistency demonstrated by the algorithm. Variations in tour lengths throughout several iterations were negligible, signaling that the solutions conceived by the reformed WSO algorithm were not only superior in nature, but also consistently so. Such uniformity in the produced solutions points towards robustness embedded in the developed algorithm. This trait, marked by the algorithm's reliability, stands as a critical feature when contemplating its potential for real-world applications. To encapsulate, the results from these trials attest to the efficacy of the proposed modifications to the WSO algorithm. These findings suggest that this reformulated approach could potentially serve as a robust tool for addressing intricate optimization dilemmas such as the TSP. The consistently excellent performance, coupled with an innate ability to maintain a balance between solution quality and computation time, make this enhanced version of the WSO algorithm a promising candidate for complex problem-solving tasks.

VI. Conclusion

This paper presented a modified version of the White Shark Optimizer (WSO) algorithm, improved by integrating components from the Particle Swarm Optimization (PSO) technique[2]. The main goal was to apply this hybrid method to the Traveling Salesman Problem (TSP), an NP-Hard combinatorial optimization problem, and examine its performance compared to standard optimization algorithms[17,14]. The experiments conducted demonstrated a noticeable enhancement in the problem-solving capacity of the developed WSO algorithm over PSO, particularly for the dataset of 10 cities with 70 iterations[3]. The modified WSO algorithm showed superior efficiency by attaining a significantly smaller tour length compared to that generated by PSO before improvement[2]. Moreover, the algorithm also managed to maintain competitive computation times, indicating an improvement in solution quality without an undue increase in processing times[10]. Furthermore, the robustness and consistency of the hybrid algorithm became evident from its performance over multiple runs, implying that the generated solutions were not only superior but consistently so[10]. Despite the promising results, there are still a variety of future directions for this research. Potential work could include exploring the algorithm's efficiency when applied to other combinatorial optimization problems, enhancing the parameters of the WSO algorithm, and developing parallel versions to improve computation speed[11].

In conclusion, the proposed modification and enhancement of the WSO algorithm provide a novel, effective, and efficient approach to solving the TSP and offer a strong foundation for future research in combinatorial optimization algorithms[16].

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