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BLACK WIDOW'S NEW APPROACH TO TACKLE THE TRAVELING SALESMAN PROBLEM

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ABSTRACT

This article explores the application of the Black Widow algorithm, a metaheuristic algorithm inspired by nature, to solve the classic Traveling Salesman Problem (TSP). The Black Widow algorithm is inspired by the predatory behavior of black widow spiders and uses a novel approach to guide the search for the best solution. We discuss the implementation of the algorithm and its effectiveness in handling NP-hard TSP. Through rigorous experiments and comparative analysis, we demonstrate that the algorithm can effectively navigate the solution space and produce promising results in terms of solution quality and computational efficiency. This research contributes to the continuous development of optimization algorithms and provides an opportunity to further explore bionic technology to solve combinatorial optimization problems. The effectiveness of the BWO algorithm in finding optimum solutions to the benchmark functions is tested over 51 different benchmark functions. The findings show that the suggested approach outperforms previous algorithms in several ways.

Keywords: *Traveling Salesman Problem, Black Widow Optimization, Combinatorial Optimization Problem, Black Widow Spiders.*

1. INTRODUCTION

The complexity of problems that occur in the real world has grown over the last several years, which has led to a rise in the need for efficient meta-heuristic approaches. Metaheuristic approaches have become more popular since they are both powerful and easy to use. Kumar et al. [1] state that these methods are used to solve NP problems [2] and practical engineering issues by quickly identifying the most promising solutions to them. These algorithms are utilized in a broad range of contexts, from economics to planning holidays to scheduling flights. They are not limited to the world of computer science or other engineering. Many fields in industry and academia make use of meta-heuristic algorithms. These algorithms can escape from confined regions with optimal solutions. The recent methods for optimally solving the Traveling Salesman Problem (TSP) [3] have direct practical applications [4,5].

Recently, because of the increasing complexity of issues originating in the real world, there has been an increase in the need for effective meta-heuristic methodologies. The widespread use of metaheuristic approaches may be attributed to their great efficiency and low implementation complexity. These techniques are used to find possible optimum solutions to NP problems, which arise in practical engineering applications, in a reasonable amount of time [1]. These algorithms are widely used in many fields outside of computer and other engineering, including economics, vacation planning, and many more. The capacity of meta-heuristic algorithms to break out of local optimums has led to their use in many kinds of business and research.

Meta-heuristic approaches may be broken down into physical, swarm, and evolutionary categories. Rules from the physical world, including those governing inertia force, gravitational force, electromagnetic force, and so on, serve as the foundation for physical-based algorithms. This group includes "Gravitational Search Algorithm (GSA)" [6], "Simulated Annealing (SA)" [7], "Big-Bang BigCrunch (BBBC)" [8], "Charged System Search (CSS)" [5], "Galaxy-based Search Algorithm (GbSA)" [9], and "Black Hole (BH)" [10] algorithms. Algorithms in the second category, called swarm-based, take cues from how social organisms interact with one another and their surroundings. The category includes some of the most popular algorithms, such as Particle Swarm Optimization [11], Wolf pack search algorithm [12], Bee Collecting Pollen Algorithm [13], Dolphin Partner [14], Cuckoo Search [15], Firefly Algorithm[16],

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The most recent category of algorithms draws their primary motivation from natural phenomena and the processes of biological evolution, such as “selection”, “reproduction”, “combination”, and “mutation”. These algorithms are based on Darwin's theory of natural selection, which is also referred to as "descent with modification". This refers to the concept that different species change through time and gives rise to new species [17]. The primary heritable characteristics of a species that are beneficial to the species' ability to live and reproduce eventually become more prevalent within a population because of the process of natural selection. The principle of natural selection has served as a source of motivation for almost all the evolutionary algorithms. However, there is significant flexibility in how this notion is depicted in any of these formats. Each algorithm mimics a distinct animal or human behavior to evolve and create offspring, and these differences are the consequence. The goal of evolutionary algorithms is to find the fit solution among a population of candidates by simulating the effects of natural selection on the candidates. These algorithms optimize based on a random process. The optimization procedure begins with a randomly generated seed population, which is then subject to modification throughout a predetermined number of generations. Almost all population-based algorithms can be reduced to this fundamental framework. Each algorithm is unique because it uses a different strategy for duplicating, relocating, and developing the answers it finds. It is generally agreed that the Genetic Algorithm (GA) [18] is among the most important evolutionary-based algorithms. Most evolutionary or population-based algorithms are somewhat like GA; some academics even refer to them as "Genetic-type algorithms" to distinguish them from GA. The algorithms in this set are inspired by others, such as the Evolution Strategy (ES) [19], the Forest optimization algorithm [20], and so on.

The Black Widow Optimization (BWO) algorithm was developed by Hayyolalam and Kazem in the year 2020 [21]. It is a ground-breaking, intelligent optimization method that was motivated by the peculiar black widow spider mating rituals. It offers considerable advantages in several areas, including early convergence and obtaining improved outcomes when evaluated against several benchmark functions. To identify which thresholds, provide the best results, an image segmentation problem was solved using the BWO method [22]. The statistical analysis of the BWO-based technique, in contrast to the other approaches, makes it abundantly evident that it can provide reliable and effective results. The BWO algorithm has been found to be extremely successful at solving optimization problems, although there are still several ways that the method's efficiency might be improved…

1.1 Travel Salesman Problem

A traveling salesman wants to make sure he stops in each of a group of towns precisely once, and he wants to do it both when he leaves and when he returns to his hometown. Finding the quickest and most direct route to his destination is one of his challenges. The traveling salesman problem, sometimes known as TSP for short, is a model problem in several subfields of mathematics, computer science, and operations research. In 1954, Dantzig, Fulkerson, and Johnson were the first people to design heuristics for the TSP and apply them to solve actual problem cases. Heuristics, linear programming, and branch and bound are still the primary components of today's most effective methods for difficult combinatorial optimization problems. These techniques were initially established for the TSP. G = (V, E) is a graph representation of the issue, where V is the set of n cities and E is the set of roads that completely link all of them. Each route (i,j) has a cost d_{ij} (the cost is the distance between the cities i and j), thus we correlate the graph with a matrix of distances X : (x_{ij}) (1 i n) & (1 j n) . The cost of each path (i,j) is the distance that separates the towns i and j. Using the following equation, the challenge is to reduce the cost of the circuit as much as possible.

$$\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} \quad (1)$$

The TSP continues to pose a formidable challenge across various domains. Our contribution introduces the Black Widow Optimization metaheuristic as a pioneering approach to solving the Traveling Salesman Problem. This novel approach harnesses the predatory behaviors of black widow spiders, offering a fresh perspective on solving complex routing and optimization conundrums.

BWO orchestrates an intricate dance of exploration and exploitation, akin to a spider weaving an intricate web. This unique perspective introduces a biology-inspired paradigm that combines optimization with the cunning strategies of these spiders. The algorithm starts by initializing a group of "spiders" (potential solutions) that mimic the spider's web-building process. Solutions are presented as paths, with cities as nodes. BWO continues to develop these pathways through

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iterative optimization, gradually weaving a carpet of potential solutions to spider webs. Incorporating the concept of widow-orphan interactions, BWO performs a dynamic selection process to refine the solution. Widows, representing good solutions, capture orphans (not-so-good solutions) and influence their paths. This interactive process mirrors the behavior of spiders exploiting successful strategies and modifying tactics of less successful opponents. In our contribution we use BWO for exploration phase and 2-opt for exploitation to improve the solution find by BWO algorithm.We present in this paper a fresh paradigm that showcases competitive results using a set of Benchmark instances, innovative optimization dynamics, and the potential for interdisciplinary synergy. Our work not only advances the field of metaheuristics but also illuminates the possibilities that arise when optimization algorithms embrace the intricacies of the natural world.

The Traveling Salesman Problem has long been the focus of combinatorial optimization, with many algorithms proposed to find the optimal solution. Traditional approaches face the challenge of efficiently exploring large solution spaces, which often leads to suboptimal results. A comprehensive literature review shows that existing metaheuristics, while effective, may suffer from scalability and convergence issues.

Given these challenges, there is an urgent need to explore and apply innovative metaheuristics. The Black Widow algorithm, inspired by the predatory behavior of black widow spiders, is a promising candidate. The literature highlights the algorithm's unique mechanisms for solution exploration and development and demonstrates potential advantages over traditional methods.

This work aims to address the limitations identified in current problem tsp solving approaches by leveraging the Black Widow Algorithm. Through a critical examination of existing literature, we aim to justify the necessity of adopting this novel metaheuristic for TSP, anticipating improved solution quality, convergence speed, and scalability in comparison to established methods.

The rest of this paper is organized as follows: Section 2 presents the Black widow optimization Algorithm Problem. The following section briefly describes a differential mutation and selection algorithm for the Adaptive Black Widow Optimization. Section 4 provides a description of our Adapted method BWO to solve TSP. The following paragraph presents the results obtained after its application on the Travelling Salesman Problem, the comparison of the proposed algorithm with other known metaheuristics is the subject of section 6, we will end with a conclusion and a summary of this work.

2. BLACKWIDOW OPTIMIZATION ALGORITHM

The black widow spider is a species of spider that is about the size of a dime and belongs to the family Orygiidae. It is most often found in the nations of Europe that are located near the Mediterranean Sea. Spider webs are the primary habitat of female spiders, where they spend most of their lives eating, mating, and hatching their young. When the female widow wants to have children, she secretes a pheromone-like substance someplace in the web to attract the attention of the male. By reducing the size of the web, the first male to join a female's web makes the female's web less appealing to competitors. After mating, the female will consume the male and take her eggs to her egg sock to hatch. Cannibalism among the young occurs shortly after they have hatched out of their eggs. The powerful widow might swallow the vulnerable, and the offspring could even end up eating their own mother if they remain in their mother's web for an extended amount of time. By implementing the black widow spider's behavior as a mathematical model, Hayyolalam and Kazem developed the Black Widow Optimization algorithm in the year 2020. To solve the optimization problem, the algorithm models the reproduction and growth of a spider population, considering both large-scale and minute-scale factors. The principles of survival of the fittest and dominance of the fittest are fundamental to Darwin's evolutionary theory. Black widow spiders' behavior, which involves both reproduction and cannibalism, is a macrocosmic reflection of these ideas. The mutation that has happened in spider populations, on the other hand, is an example of genetic engineering at the molecular level. The spider population may grow more competitive with time [18] due to the species' peculiar reproductive and developmental processes.

2.1 Initialization

A population of spiders is represented by N widows, denoted as X_1, X_2, ..., Xn. D represents the dimensionality of an optimization problem. Each widow in the population, represented by Xi, undergoes initialization according to :

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$$x_{i,j} = l_j + \text{rand}(0,1).(u_j - l_j), 1 \leq j \leq D \quad (2)$$

This equation governs the initialization process of each element within an individual. It takes into consideration "The Lower Bound" (LB) And "Upper Bound" (UB) values associated with the variables in the optimization model.

2.2 Procreate

Black widows have a peculiar mating ritual that produces offspring. Mating begins with a random selection of female and male spiders from the population depending on their procreation rate (Pp). Eq. (3) yields the offspring.

$$\begin{cases} Y_i = \alpha X_i + (1-\alpha)X_j \\ Y_j = \alpha X_j + (1-\alpha)X'_i \end{cases} \quad (3)$$

The stage encompasses all three types of cannibalism: "sexual cannibalism", "cannibalism between siblings", and "cannibalism between children and their mother". It is possible to maintain a population of exceptional individuals by culling out the less robust spiders.

Sexual Cannibalism: During or after the mating process, the female black widow will consume her spouse. Only the female spiders that manage to stay alive are passed on to the following generation.

Sibling Cannibalism: When there are insufficient food supplies or natural predators, stronger spiders will consume their younger siblings. The strength of a spider may be understood to be equivalent to its worth as a fitness resource. The amount of people that make it through this algorithm is based on the cannibalism rating, often known as CR.

Maternal and Off-Spring Cannibalism: There are young spiders that are so powerful that they can even devour their mother. If the parents are successful in producing a solution that has a high fitness value, eventually, the answer will grow up and replace its parent.

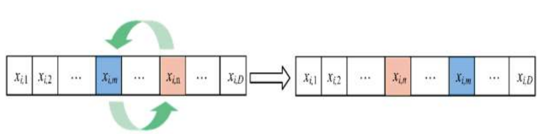

Figure 1 . Maternal And Off-Spring Cannibalism

3. A DIFFERENTIAL MUTATION AND SELECTION ALGORITHM FOR THE ADAPTIVE BWO

The BWO algorithm simulates the behavior of a colony of black widow spiders as it searches for and selects the best candidate from among all the candidates. Another advantage is that it is easy to understand and implement. Unfortunately, the convergence time and accuracy of the traditional BWO approach fall short when applied to practical optimization problems.

To that end, we propose "Adaptive Black Widow Optimization with Selection strategy and Differential mutation (SDABWO)" as a more refined variant of BWO to boost the algorithm's overall performance. The first factor that occurs is the traditional means of reproduction are discarded and replaced. The Differential Evolution (DE) algorithm's mutation operator is then employed to switch to a new mutational approach. Currently, an adaptive computation of three crucial parameters is taking place to eliminate the parameter impact .

3.1 Procedure for Choosing Potential Employees

The original BWO would choose a male widower at random when a woman was ready to have a family. To rephrase, the new approaches are created independently of the context of the older ones. On the other hand, in other optimization algorithms, such as the "Gray Wolf Optimization algorithm (GWO)", the "Particle Swarm Optimization algorithm (PSO)," and the "Whale Optimization Algorithm (WOA)," the new solutions will be closer to the optimal solution by either learning from exceptional individuals or by encircling the prey. These approaches are described in detail in the respective papers. New particles emerge in PSO because of a fusion of individual experience with that of the community [23]. Furthermore, GWO's wolf population is structured in a wide range of hierarchies. The remaining wolves allude to the information that the three healthiest wolves possess to keep themselves current [24]. Individuals in WOA may quickly arrive at the optimum option by modeling the behavior of the surrounding prey [25]. In other words, other classical algorithms provide innovative answers by thinking about the generation's underlying structural link. Therefore, using the structural information held by parents' spiders to produce superior offspring requires thorough analysis. The problems that arise from

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choosing a partner at random are shown in Fig. 2 The offspring may emerge in the region within the red circle rather than going closer to the best solution when the female selects the closer male on the same side as the optimal solution. In a manner analogous to the practice of inbreeding, the kids receive an excessive number of identical genes from their parents. This may result in the offspring being at a greater risk of having faulty genes than their parents were at the same age. In this scenario, many poor solutions are generated, which results in a slow convergence time and poor accuracy. As a result, a fresh approach has been suggested as a potential solution to the problem.

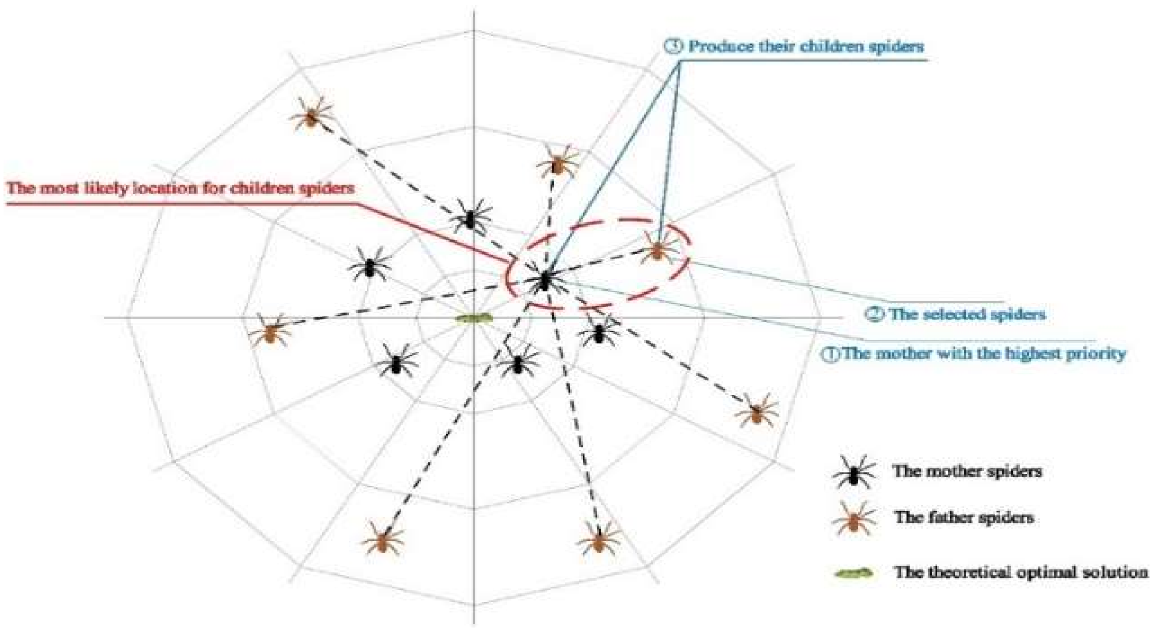

Figure 2. Choosing A Partner At Random

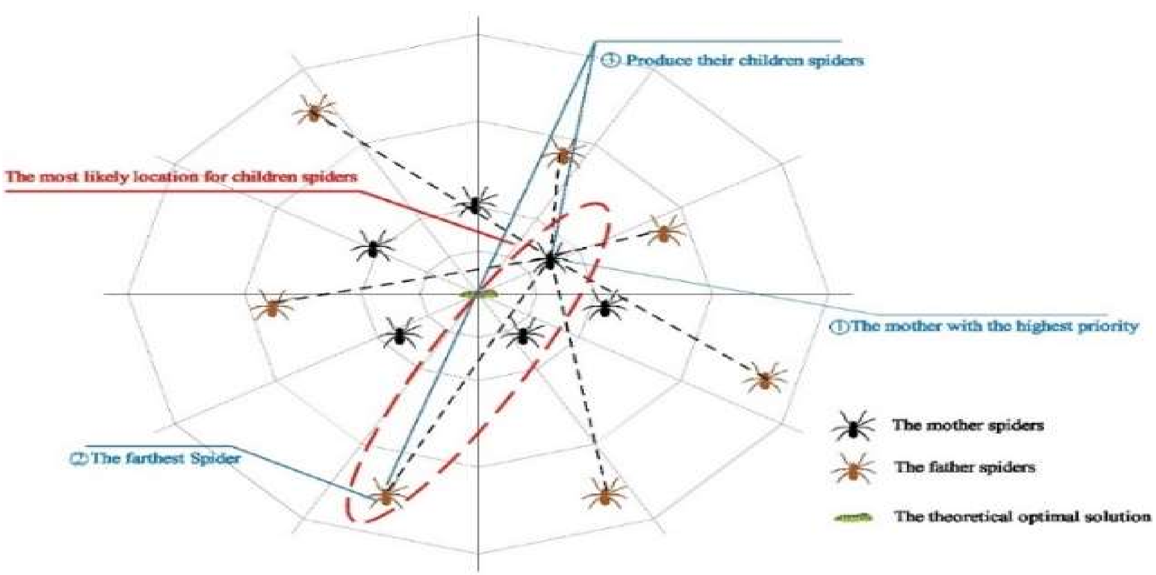

Figure 3. Choosing A Partner Using The New Method.

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4. ADAPTED BWO TO SOLVE TSP

In this adaptation, the Black widow Algorithms takes on a transformative role, employing it is predators to guide the search for optimal TSP solutions.This section presents an in-depth look at an innovative adaptation of the Black Widow algorithm to solve the famous problem , the traveling salesman problem. We elaborate on the rationale behind this fitting and show how algorithms can mimic spider behavior to systematically improve the exploration and exploitation of solution spaces. Through a series of controlled experiments and comparisons, we demonstrate that the algorithm is capable of generating near-optimal solutions for TSP instances of varying complexity.The pseudo code of the Black widow algorithm Fig.4 summarizes our proposed method to adapt BWO to solve the travelling salesman problem.

In the rest of document, we will present the results find on an ensemble of TSPLIB [26] instances after the development of the algorithm using C++. These results will be compared by the results found by other Metaheuristic to know the advantages and limitations of our adaptation and try to improve it later.

```
Algorithm 1:
Input : Maximum number of iterations, stopping criterion, rate of mutation
Outpout : Near-optimal solution for the objective function.

// Initialize parameters
Set the number of the spiders
Set the maximum number of iterations
Define the stopping criterion
Set the rate of mutation
Set the number of reproduction n
Create the population of spiders randomly P1
while the termination conditions is not satisfied : do
    Calculate the total distance of the given path
    Select the best solution in population
    //Exploration Phase ( Black widow Algorithm)
    //Procreating and cannibalism
    For i=1 to n:
      Select two solutions from population as parents
      Generate D solutions ( Children )
      Destroy one of the solution ( father )
      Delete some of solutions using the cannibalism rate)
      Save the remain solution in other population P2
    End For
    // Mutation   Calculate number of mutation nm using the mutation rate
    For i=1 to nm:
      Select randomly solution from P1
       Mutate randomly one chromosome to generate a new solution and save it in
     other population P3
    End For
    Update P1 =P2+P3
    // Exploitation Phase ( 2-opt )
    Improve the solution of P1 by applying local search technique 2-opt to optimize
     the path
end While
Return the best solution from P1
```

Figure 4. Pseudo Code Of Black Widow Optimization Algorithm To Solve TSP

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In the following document, we will present the results find on an ensemble of TSPLIB [26] instances after the development of the algorithm using C++. These results will be compared by the results found by other Metaheuristic in order to know the advantages and limitations of our adaptation and try to improve it later .

5. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we present the experimental results obtained for applying our adaptation for TSP using Benchmark instances. Table 1 present the results found, here is the detail of each column. The first column is the name of the instance, the second field presents the best solution found in TSPLIB , the third column present the average of all solution found , then you find the deviation that is calculated using the Eq. (4) and finally we have the run time and the number of times the optimum was found.

$$DEV = \frac{Average\_optimum}{Optimum} \quad (4)$$

According to the result presented in Table 1, we can say that the results are conforms. After 30 independent test for each instance we had the optimum for most instance (16 from 18).We will compare the results obtained by BWO with other algorithm as well as , the Artificial Bee Colony-based Ant Colony System (ABC-ACS) [27] , Ant Colony System (ACS) [28].

Table 1: Experimental Results Of Bwo Algorithm

Instance	Optimum	AVG	Dev%	Time	C_{opt}
Berlin52	7542	7542	0	0,4	30/30
eil51	426	426	0	0,2	30/30
att48	10628	10628	0	0,6	30/30
bayg29	1610	1610	0	0,02	30/30
bays29	2020	2020	0	0,12	30/30
eil76	538	538	0	1,96	30/30
bier127	118282	118282	0	3,09	30/30
st70	675	675	0	0,99	30/30
gr21	2707	2707	0	1,67	30/30
gr24	1272	1272	0	0,35	30/30
Fri26	937	937	0	0,65	30/30
gr21	2707	2707	0	1,3	30/30
gr24	1272	1272	0	1,4	30/30
fri26	937	937	0	1,9	30/30
kroA100	21282	21282	0	3,5	30/30
eil101	629	629	0	1,32	30/30
a280	2579	2786	0,080	0,4	26/30
lin318	42029	43905	0,044	0,2	23/30

After the comparison in Table 2 we can conclude that BWO prove its effectiveness. we note that our results found after 30 executions.

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Table 2: Performance Comparison

Instance	Optimum	Algorithm	Best solution	Worst solution	Avg Solution
Eil51	426	BWO	426	426	426
		ACS	426	430	427.43
		ABC-ACS	426	429	427.15
Eil76	538	BWO	538	538	538
		ACS	538	550	540.84
		ABC-ACS	538	549	540.21
kroA100	21282	BWO	21282	21282	21282
		ACS	21282	21881	21399.34
		ABC-ACS	22141	22381	22288.13
EIL101	629 629	BWO	629	629	629
		ACS	630	651	640.70
		ABC-ACS	629	650	635.72
lin318	42029	BWO	42029	44276	43905
		ACS	42943	44015	43532.71
		ABC-ACS	42591	43989	43501.42

6. CONCLUSION

In conclusion, this study introduces a novel approach The Black Widow Optimization to address the Traveling Salseman Problem , this method has proven to be a transformative endeavor. This novel metaheuristic, inspired by the predatory instinct of the black widow spider, shows remarkable effectiveness in the complex solution space of TSP. Through extensive experiments and analyses, our study confirms that this algorithm is able to provide the highest quality solutions while solving the computational challenges associated with traditional methods.

The adaptive nature of the Black Widow algorithm, which combines exploration and exploitation strategies, is a key factor in its success in optimizing TSP instances. Furthermore, our results show that this metaheuristic approach exhibits significant resilience when dealing with larger problem cases, highlighting its potential scalability.

By leveraging BWO we have demonstrated significant improvements in our test using set of Benchmark instance. Furthermore, the adaptability of our method to handle varying constraints and large datasets suggests its versatility across diverse industries .In summary , BWO approach presents a promising step forward in solving TSP and opens new avenues for optimization techniques in various domains . This study not only highlights the importance of bioinspired algorithms in optimization problems, but also positions the black widow algorithm as a valuable addition to the toolkit for solving complex combinatorial problems such as TSP. As we continue to explore and refine metaheuristic methods, the Black Widow algorithm becomes a promising avenue for future research and practical applications in various optimization fields. Overall, our research advances the understanding of innovative algorithmic solutions and their impact on solving real-world challenges. We can conclude that this method will solve a large number of combinatorial optimization problems and more complex real-world problems in the near future.

REFERENCES:

[1] Kumar, Vijay, Chhabra, Jitender Kumar, Kumar, Dinesh, 2014. Parameter adaptive harmony search algorithm for unimodal and multimodal optimization problems. J. Comput. Sci. 5 (2), 144–155.

[2] TSAI, Cheng-Hsiung, LIN, Yu-Da, YANG, Cheng-Hong, et al. A Biogeography-Based Optimization with a Greedy Randomized Adaptive Search Procedure and the 2-Opt Algorithm for the Traveling Salesman Problem. Sustainability, 2023, vol. 15, no 6, p. 5111.

[3] Baranidharan, B.; Meidute-Kavaliauskiene, I.; Mahapatra, G.S.; Činčikaitė, R. Assessing the Sustainability of the Prepandemic Impact on Fuzzy Traveling Sellers Problem with a New

Fermatean Fuzzy Scoring Function. Sustainability 2022, 14, 16560.

[4] Dell'Amico, M.; Montemanni, R.; Novellani, S. Exact models for the flying sidekick traveling salesman problem. Int. Trans. Oper. Res. 2022, 29, 1360–1393.

[5] Huerta, I.I.; Neira, D.A.; Ortega, D.A.; Varas, V.; Godoy, J.; Asín-Achá, R. Improving the state-of-the-art in the traveling salesman problem: An anytime automatic algorithm selection. Expert Syst. Appl. 2022, 187, 115948.

[6] Rashedi, Esmat, Nezamabadi-pour, Hossein, Saryazdi, Saeid, 2009. GSA: A gravitational search algorithm. Inform. Sci. 179 (13), 2232–2248, Retrieved (http://www. sciencedirect.com/science/article/pii/S0020025509001200).

[7] Kirkpatrick, Scott, Daniel Gelatt, C., Vecchi, Mario P., 1983. Optimization by simulated annealing. Science 220 (4598), 671–680.

[8] Kirkpatrick, Scott, Daniel Gelatt, C., Vecchi, Mario P., 1983. Optimization by simulated annealing. Science 220 (4598), 671–680.

[9] Shah-Hosseini, Hamed, 2011. Principal components analysis by the galaxy-based search algorithm: A novel metaheuristic for continuous optimisation. Int. J. Comput. Sci. Eng. 6 (1–2), 132–140.

[10] Hatamlou, Abdolreza, 2013. Black hole: A new heuristic optimization approach for data clustering. Inform. Sci. 222, 175–184.

[11] Poli, Riccardo, Kennedy, James, Blackwell, Tim, 2007. Particle swarm optimization. Swarm Intell. 1 (1), 33–57.

[12] Yang, Chenguang, Tu, Xuyan, Chen, Jie, 2007. Algorithm of Marriage in Honey Bees Optimization Based on the Wolf Pack Search, In: The 2007 International Conference on Intelligent Pervasive Computing (IPC 2007), pp. 462–67

[13] Lu, Xueyan, Zhou, Yongquan, 2008. A Novel Global Convergence Algorithm: Bee Collecting Pollen Algorithm, In: International Conference on Intelligent Computing, pp. 518–525.

[14] Shiqin, Yang, Jianjun, Jiang, Guangxing, Yan, 2009. A Dolphin Partner Optimization, In: 2009 WRI Global Congress on Intelligent Systems, Vol. 1, pp. 124–28.

[15] Yang, Xin-She, Deb, Suash, 2009. Cuckoo Search via L{é}vy Flights, In: 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), pp. 210–14.

[16] Yang, Xin-She, 2010a. Firefly Algorithm, Stochastic Test Functions and Design Optimisation. arXiv preprint arXiv:1003.1409

[17] Beddall, Barbara G., 1968. Wallace, darwin, and the theory of natural selection. J. Hist. Biol. 1 (2), 261–323.

[18] Holland, John H., 1975. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications To Biology, Control, and Artificial Intelligence.

[19] Beyer, Hans-Georg, Schwefel, Hans-Paul, 2002. Evolution strategies–A comprehensive introduction. Nat. Comput. 1 (1), 3–52.

[20] Ghaemi, Manizheh, Feizi-Derakhshi, Mohammad-Reza, 2014. Forest optimization algorithm. Expert Syst. Appl. 41 (15), 6676–6687.

[21] V. Hayyolalam, A.A. P. Kazem, Black Widow Optimization Algorithm: A novel meta-heuristic approach for solving engineering optimization problems, Eng. Appl. Artif. Intell. 87 (2020) 103249.

[22] E.H. Houssein, B.E-d. Helmy, D. Oliva, A.A. Elngar, H. Shaban, A novel Black Widow Optimization algorithm for multilevel thresholding image segmentation, Expert Syst. Appl. 167 (2021) 114159.

[23] D. Freitas, L.G. Lopes, F. Morgado-Dias, Particle Swarm Optimisation: A Historical Review Up to the Current Developments, Entropy. 22 (3) (2020) 362.

[24] N.M. Hatta, A.M. Zain, R. Sallehuddin, Z. Shayfull, Y. Yusoff, Recent studies on optimisation method of Grey Wolf Optimiser (GWO): a review (2014-2017), Artif. Intell. Rev. 52 (4) (2019) 2651-2683.

[25] H.M. Mohammed, S.U. Umar, T.A. Rashid, A Systematic and Meta-Analysis Survey of Whale Optimization Algorithm, Comput. Intel. Neurosc. 2019 (1) (2019) 8718571.

[26] Reinelt, G. (1991). TSPLIB—A traveling salesman problem library. ORSA Journal on Computing, 3, 376–384.

[27] Stodola, P., & Nohel, J. (2022). Adaptive Ant Colony Optimization with Node Clustering for the Multi-Depot Vehicle Routing Problem. IEEE Transactions on Evolutionary Computation.

[28] Stodola, P., & Nohel, J. (2022). Adaptive Ant Colony Optimization with Node Clustering for the Multi-Depot Vehicle Routing Problem. IEEE Transactions on Evolutionary Computation.