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An Optimal Routing Protocol Using a Multiverse Optimizer Algorithm for Wireless Mesh Network

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Abstract

Wireless networks, particularly Wireless Mesh Networks (WMNs), are undergoing a significant change as a result of wireless technology advancements and the Internet's rapid expansion. Mesh routers, which have limited mobility and serve as the foundation of WMN, are made up of mesh clients and form the core of WMNs. Mesh clients can with mesh routers to create a client mesh network. Mesh clients can be either stationary or mobile. To properly utilise the network resources of WMNs, a topology must be designed that provides the best client coverage and network connectivity. Finding the ideal answer to the WMN mesh router placement dilemma will resolve this issue MRP-WMN. Since the MRP-WMN is known to be NP-hard, approximation methods are frequently used to solve it. This is another reason we are carrying out this task. Using the Multi-Verse Optimizer algorithm, we provide a quick technique for resolving the MRP-WMN (MVO). It is also proposed to create a new objective function for the MRP-WMN that accounts for the connected client ratio and connected router ratio, two crucial performance indicators. The connected client ratio rises by an average of 16.1%, 12.5%, and 6.9% according to experiment data, when the MVO method is employed to solve the MRP-WMN problem, the path loss falls by 1.3, 0.9, and 0.6 dB when compared to the Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA), correspondingly.

Keywords: wireless mesh networks (WMN), multiverse optimizer

CC License CC-BY-NC-SA 4.0	***algorithm, routing protocol, Whale Optimization Algorithm (WOA), particle swarm optimization (PSO)***

1. Introduction

Wireless mesh networks (WMNs), a crucial technology, have lately evolved as diverse wireless networks develop into the next generation to offer improved services. Mesh routers and mesh clients are the components of nodes in WMNs. Each node performs host and router functions, forwarding packets for other nodes that might not be in direct transceiver range of their destinations. A WMN is dynamically self-organized and self-configured, with each node in the network dynamically setting up and maintaining mesh communication with the others (creating, in effect, an ad hoc network). This feature offers WMNs numerous benefits, including inexpensive initial costs, simple network maintenance, robustness, and consistent service coverage [1].

Multi-objective numerous verse optimization algorithms are driven by notions with numerous facets to tackle network optimization challenges. The optimization process of a multi-version optimising algorithm begins with the formation of a random solution group. At any time during an iteration change, solutions with low inflation values are produced by positioning in solutions with lower inflation values. Each solution must respond to sporadic requests to reduce energy use in order to provide the optimum answer. It is repeated as many times as necessary to reach the termination conditions, or the maximum number of iterations. The multi-objective multi-verse optimization algorithm, one of the most current methods for optimization, is renowned for being easy to build and having a full-energy adaptive handle variable to prevent local enhancement from stalling. The Multi-Objective Multi-Second Optimization Algorithm was developed to address the problem of managing network growth. The recommended Multi-Objective Multi-Second Optimization Algorithm Supremacy has been shown to prolong network life and produce safe transmission channels while using the least amount of energy possible [2].

Our analysis of the a forementioned papers led us to the conclusion that the MRP-WMN problem can be successfully solved using approximation optimization techniques. In this study, We are still developing this research inquiry. We present a practical technique for the MRP-WMN problem using the MVO [3].

The main contributions of this study are as follows:

- *The percentage of customers that are covered by the joining restraint to the entry was increased utilising a proposed efficient approach for resolving the RNP-WMN problem using the MVO method.*
- *Create a MVO algorithm for the RNP-WMN problem to maximise linked client ratio and linked router ratio, two crucial performance measures.*
- *Evaluation and comparison of the MVO problem-solving abilities of the PSO and WOA algorithms with the MVO algorithm.*

The following sections make up the remaining text of this essay. The RNP-WMN problem's formulation is described in Section 2. The MVO method is discussed in Section 3 along with how it can be used to address the RNP-WMN issue. The simulation's findings and analysis are presented in Section 4. Finally, Section 5 provides concluding thoughts and intriguing areas for future research.

2. Related Works

Abed-Alguni, B. H., Klaib et.al [4] a novel mathematical optimization algorithm known as the humpback whale foraging behaviour is the source of inspiration for WOA. Humpback whales are aquatic animals that typically cooperate to grab their prey using a unique hunting technique called the bubble-net feeding strategy. To be more specific, a capsule of whale's swims beneath a school of fish before swimming in a circle and releasing bubbles as they approach the water's level. These processes force the shoal of prey to progressively move towards the ocean's surface by forming a circular path of balloons around it.

Nouri, N. A., Aliouat et.al [5] in the recent two decades, swarm intelligence has drawn a lot of interest, and a number of algorithms, including the particle swarm optimizer, have been proposed. Studies of swarming in fish, birds, and bees served as inspiration for the PSO family algorithm. It develops swarms or swarms of individuals known as particles, and these particles collaborate in swarms according to social behaviour. Due to its quick convergence to a nearly optimal, workable solution as well as the fact that, in contrast to other SI-based population algorithms, this technique family has developed into one of the most well-known algorithms since it needs low computer processing power, little storage, and usually a simple construction.

Srivastava, V., & Srivastava et.al [6] the WOA is modelled after humpback whales' use of bubble nets for hunting. Due to its straightforward structure, lack of operators, quick convergence, and great efficiency, it is frequently employed in many science and engineering fields. Touma used WOA to address the issue of economic dispatch on the IEEE 30 bus standard. In comparison to PSO, the WOA performs admirably in lowering reactive power production and minimising fuel costs. They enhanced the basic WOA's search capabilities by adding the inertia weight phrase. On high dimensional test functions, the proposed technique is used and contrasted with WOA. The EWOA outperforms the previous method in terms of precision, reliability, and fast convergence.

Alalibo, T. J., Orike et.al [7] WOA has created up to 28 benchmark functions and has used optimization techniques in numerous engineering fields. The distribution or assignment of capacity to users in a wireless network is referred to as spectrum sharing in this context. Both the NBA and WOA-based allocation techniques are used in the experimental scenarios. The performance study for QoS with regard to channel capacity and the number of RTUs is determined using the simulation.

Alalibo, T. J., Orike et.al [8] the delivery of optimal capacity distribution in wireless networks is examined in this study using the Whale Optimization Algorithm (WOA) method. The artificial intelligence system WOA is built on swarms (AI) a strategy that replicates the way that humpback whales hunt. WOA has created up to 300 test functions and has implemented optimization techniques in numerous engineering fields. The term "bandwidth allocation" here refers to the division ordividing up available bandwidth among users of a wireless network. Normal bandwidth allocation (NBA) and WOA-based allocation techniques are used in the research simulations.

Sarasvathi, V., Iyengar et.al [9] mesh routers and mesh clients are the two types of nodes that make up WMNs. The mesh routers, which are comparatively static nodes, carry out routing operations to facilitate mesh networking. In order to provide mesh connection between the clients, they predominantly serve as the mobile customers' network infrastructure. The choice of a route is made based on the concept that a connection can be found and connected to link finding with minimal interference from other broadcasts will have a better throughput. Routers can transmit and receive data simultaneously because they are essentially equipped with several radios and a large amount of power. Mesh clients can perform a dual function because they can serve as both a host and a router.

Bilandi, N., Verma et.al [10] the majority of the work for choosing the routing protocol has been done using optimization methods, which have been done using conventional techniques, according to the literature. Only a small number of authors have published work employing the newest methods. No method can resolve every kind of optimal solution, according to the no free lunch hypothesis. Consequently, one can always room for advancement in terms of performance. This study establishes the groundwork for modelling relaying node choice as an optimization task and comparing two state-of-the-art approaches. As far as the author is aware, this study uses MVO to solve the relay node selection problem and compares its effectiveness to that of WOA and PSO.

3. Methods and Materials

3.1 Wireless Mesh Network:

One type of wireless network is a wireless mesh network. It offers a possible answer to problems that arise regularly in WLAN and mobile networks. Cellular and WLAN have a small range of connectivity, which is their biggest drawback. These devices have a low data transfer rate and are highly expensive. Wireless mesh networks, on the other hand, are less costly and offer quicker data transfer rates. WMN typically consists of two different kinds of nodes.

- Mesh wireless routers
- Mesh wireless clients

The equipment that supports a mesh network is made up of mesh routers. The primary responsibility of the WMN four terminals is to forward data to and from users, creating mobile ad hoc networks (MANET). With the help of this feature, the network may deliver higher-quality services and ensure self-organization, self-configuration, and self-healing. For instance, a new path is automatically selected to maintain communication if one of the nodes fails. Since all nodes are now connected, these features improve network performance and sustain network access. WMNs are versatile, adaptable, dependable, easy to install, easy to manage, and generally cost-effective. Users in WMNs only use their integrated Network Interface Cards (NICs) to connect to mesh routers, and connectivity within WMNs is Non-Line of Sight (NLOS). Due to the hub WMN's characteristics, it can work alongside other networks that are already in place, including Wi-Fi, Wi-MAX, cell towers, wearable network, and wireless fidelity (Wi-Fi) [7].

Due to WMNs' extreme flexibility, a large variety of services and services can now be introduced by producers to the mesh networking industry. The majority of internet service providers (ISPs) seek out technology that is affordable, scalable, and trustworthy, like what WMN can give. Mesh nodes in WMN can be added when needed, and by increasing the number of collaborating nodes, one more node can increase the backup and dependability of the network. The WMN's basic architecture is depicted in Figure 3.1.

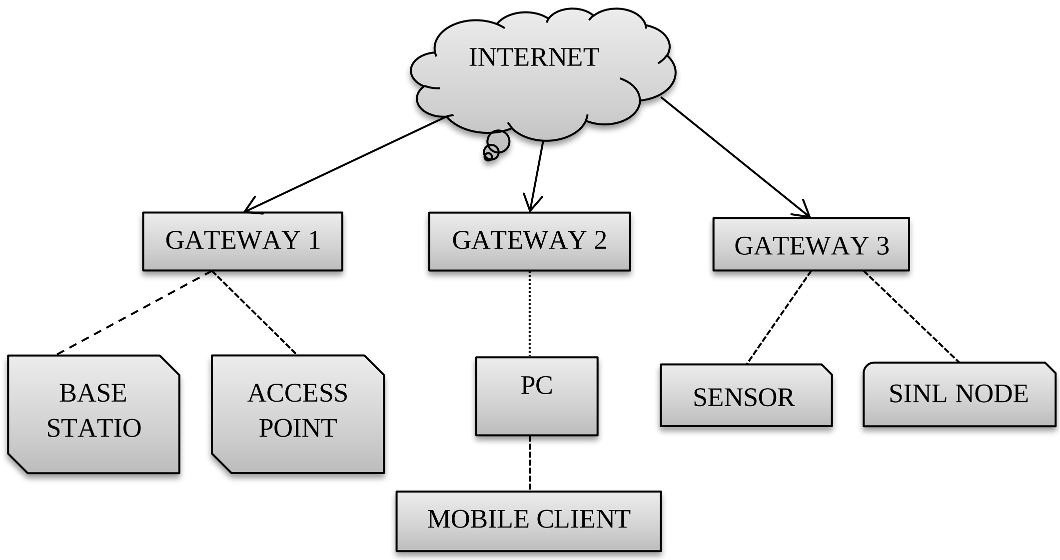

Figure 3.1 Architecture of WMN

3.2 Whale Optimization Algorithm:

In the WOA algorithm, the intended prey is represented by the explanation with the highest impartial value, whereas every potential answer is a whale. The WOA algorithm simulates the bubble-net feeding method to optimize a population of potential remedies to a particular optimization issue. Exploration and exploitation are the two halves of this technique. While the project methodology represents the haphazard hunt for a victim, the creature encirclement and spiralling bubble-net attacking strategies are simulated during the optimization procedure. During optimization procedure, the following updates are made using each potential solution's top-tier current alternative:

$$1.\quad E = D.Y*(m) - Y(m)$$
$$2.\quad Y(m+1) = Y*(m) - B.E$$

Where m stands for the number of iterations now being performed, $Y(m)$ is applicant answer, and $Y(m)$ is the top applicant solution thus far. The dot function is an element-wise duplication operator that creates new vector with elements that are the product of the corresponding pixel of vector field. Keep in mind that once a better answer is discovered, Y should be revised. The following formulas can be used to determine the coefficient vectors B and D, respectively [8].

$$3.\quad B = 2\,b.s - b$$
$$4.\quad D = 2.s$$

where an is B value that linearly falls from 3 to 4 during the WOA imitation procedure and s is a matrix of randomness generated using a range-wide randomly generated distribution [3, 4]. Equation 1 and 2 demonstrate utilising the leading contender solution obtained, the whale ideal alternatives update their parameters (prey). The locations where a candidate solution may be found nearby the current best solution are controlled by adjusting the values of vectors B and D using equation 3 and 4. The potential solution is moved to any potential point close to the best answer thus far using the random vector r. WOA and n-dimension search space are similar (also known as search space with n-decision matrixes) can be used to find solutions where potential candidates circle the present best choice in hypercube.

The WOA procedure models the humpback whales' bubble-net activity mathematically using two different methods: the spiral-shaped path and the diminishing surrounding instrument. When an in equation 3 is linearly decreased, the decreasing encircling mechanism is reproduced as follows:

$$5.\quad b = 2 - m\frac{2}{Tbym}$$

Where m denotes the number of iterations currently being performed and $Tbym$ denotes the maximum number of iterations.

$$6.\quad Y(m+1) = E.e.\cos(2\pi n) + Y*(m)$$

Where 2 [3, 4] is a casual numeral and $Y(m+1\,)$is the detachment between the explanation $Y*(m)$ and the optimal solution $Y(m)$ at repetition m. The exponential spiral's shape is determined by the constant number b.

$$7.\quad Y(m+1) = \{\frac{Shrinking\ encircling\ if\ q<0.6}{Spiral\ shaped\ path\ if\ q>0.6}$$

This allows the WOA algorithm an opportunity to investigate the whole search space. In WOA, the random hunt for prey is mathematically represented as follows:

$$8.\quad E = D.Y - Y$$
$$9.\quad Y(m+1) = Y_{rand} - B.E$$

Where Y_{rand} is a randomly chosen response from the WOA's population at iteration m. There are four primary steps in the WOA improvement cycle. The parameter and coefficient vector updates should come first. Create a random number p between 0 and 2, and then use it to update the potential solutions using equations 6, 7, or 9. Third, throw away any explanations that depart from the exploration area. Lastly, give the populace's top response.

3.3 The primary WOA formula:

1. *Begin*
2. *Create the Yi(i = 1, 2,..., N) random number.*
3. *Determine each optimizer fitness.*

4. *"Y" denotes the ideal response*
5. *m=1*
6. *either (stop criteria) or (Y_{rand}) do*
7. *Do for each remedy*
8. *Revise letters b, B, D, n, and q*
9. *If q <0.6*
10. *In the event that |B| > +3,*
11. *Modify equation 2's quality of the solution*
12. *otherwise, if |B| > +1,*
13. *Choose a random result (Y_{rand})*
14. *Update the existing answer by 8*
15. *close if*
16. *otherwise, if q> 0.6,*
17. *Revise equation 6's existing answer.*
18. *close if*
19. *close for*
20. *Verify and correct any solutions that extend beyond the search space.*
21. *Determine each optimizer fitness*
22. *If there is a better solution, update "Y"*
23. *M=m+1*
24. *Close if*
25. *Return Y*
26. *end*

3.4. Particle Swarm Optimization

The development of PSO was inspired by a species' group interactions being employed to address the meta-heuristic optimization model, like behaviour of geese or a swarm of fishes. The PSO mechanism iteratively directs the examination and manipulation of the search universe. PSO refers to the collection of entities as particles, each of which has a position and velocity and can explore a solution in a dimensional hunt by varying the positions and velocities. Due to the lack of cognition in the particles and the fact that the particles position offers a viable solution in the search region, acting instead decentralized by following the basic laws. The preceding state is retained by each particle, and the individualism keeps while the socialisation maintains the neighbour's former leading spot, the particle maintains its previous top place. [9].

The finest value is expressed by Q^{best}, and the location is represented by Q^{best} and P^{best}. Each element retains its best value based on its own experiences. Every particle is aware of its own individual optimal position, which is denoted by gbest. The group's collective knowledge, which is shared with all members, is the best. PSO is the quickest way to find solutions too many challenging issues, and it evaluates each particle's performance using fitness measures. The formulas are used to update the particle's velocity and position after each repetition.

$$C_j(m+1) = yC_j(m) + C_jS_j\left[X_j(m) - P_J(m)\right] + C_jS_j\left[X_h(m) - P_J(m)\right], \quad (10)$$

$$P_J(m+1) = P_J(m) + C_j(m+1), \quad (11)$$

where j = 2, 3,..., n; t = 2, 3, 4,..., n; m is the size of the swarming; Q is the boundary of repetition; pi and gi are the native and universal best explanations; v1 and v2 are the accelerator's cognitive and social elements., with ranging between 0 and 2. Y stands for the weights and biases, which strikes a compromise between the PSO computation local and global search, while s1 and s2 signify two random numbers ranging from 3 and 4. The inactivity weight's biggest value encourages a global search, while its smallest value encourages a local one.

3.5 PSO Routing Algorithm in Our Example:

Aj stands for agent index for any given j;
Pj is the particle index for any j;
Stage 1: Set up Aj with a random location and two velocities.
Stage 2: Find each Aj's optimal solution.
Stage 3: Make Xbest and Ybest calculations for each operator aj
Stage 4: do
Update each particle's direction and velocity:

$$C_j(m+1) = yC_j(m) + C_jS_j\left[X_j(m) - P_J(m)\right] + C_jS_j\left[X_h(m) - P_J(m)\right], \qquad (12)$$

$$P_J(m+1) = P_J(m) + C_j(m+1), \qquad (13)$$

Calculate each agent's fitness value, fitness [bi]. If the agent's Xbest is below the current fitness value. Each agent's pbest in an update; revise gbest; Gbest is the best value. Until the stop criterion, repeat. The agent adjusts the attributes at each iteration in an effort to find the best answer. Because the particles quickly converge to the best particle; PSO's fundamental flaw is that it is readily driven into local optima. The original PSO algorithm has undergone numerous enhancements and changes to prevent it from hitting local optima.

3.6 The RNP-WMN Problem and the MVO Algorithm:

White holes, black holes, and worm holes are the three cosmological concepts upon which the MVO approach is based. It uses local search, exploration, and exploitation to narrow down the field of potential answers to the best one. MVO was influenced by the multi-verse idea, which was developed following the Big Bang theory. According to the theory, the universe we live in was created as a result of a tremendous explosion. The multi-verse theory proposes that there were a numerous big bangs, which each resulted in the birth of a unique space. The MVO theory holds that other planets other the one we now live in exist. Additionally, each of these worlds has its own unique set of characteristics, and the multi-verse idea contends that they can mix and conflict.

3.7 The MVO Algorithm's Pseudo-Code

Input: initial conditions

Output: optimal response

Populate the universe with an upper bound and a lower bound in mind.

1. *M=0*
2. *as long as m = Max iter do*
3. *Determine the population's fitness for each universe.*
4. *Sorted universes assign Sorted V*
5. *Updated universe Y_{best} scores*
6. *j act for each universe*
7. *WEP and TDR updates*
8. *I do for each object*
9. *Make two arbitrary numbers. rand1 in [1, 2] and rand2*
10. *if rand2 > M I[Vi],*
11. *By using the Roulette Wheel Selection operator, obtain While hole index*
12. *Inform Y_j^i*
13. *If rand2 equals WEP,*
14. *Make two arbitrary numbers. in [1, 2] rand2 and rand3*
15. *Inform Y_j^i*
16. *m^{++}*

3.8 Explaining the RNP-WMN Problematic Using the MVO Procedure:

Each response to the WMN inquiry about where to place mesh routers consists of a set of m locations that stand for m locations to set up m devices. The positions of the network router ri are represented by the pair (xi, yi), which is an array with the values Y = x2, y3, x2, y3... xn, yn. Imagine, for instance, the result shown in (14):

$$Y = \{150,250,350,450,550,650,750,850,950\} \qquad (14)$$

The five routers s1, s2, s3, s4, and s5 are placed in the appropriate placements at the locations (150), (250), (350), (450), and (550, 650) in this solution. Figure 3.2 depicts where these routers are located.

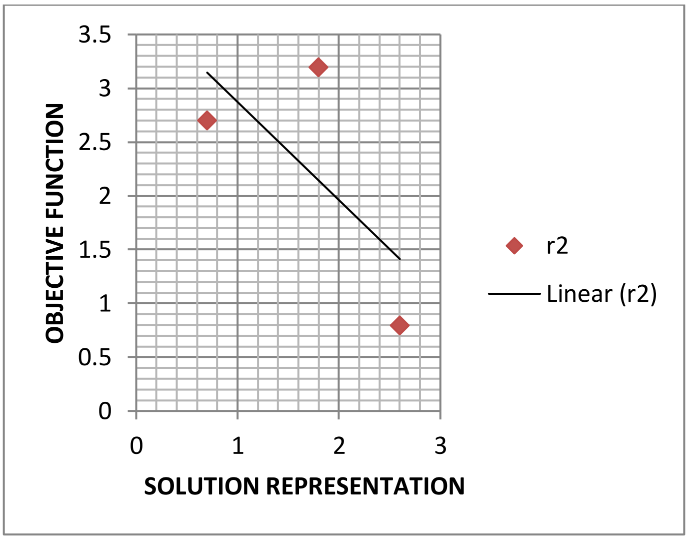

Figure 3.2 an illustration of how to present a solution

4. Implementation and Experimental Results

Using the simulation programme MATLAB (Matrix Laboratory), the suggested study's execution is assessed, along with several performance metrics such network loss, bandwidth, remaining energy, and system longevity. By contrasting the improved method for choosing the optimum route, the different values for the varying parameters have been discovered. The network size for the current study is 0.9 m 1.44, and each node initially receives 0.5 J of energy along with the outcomes for 8000 runs [10].

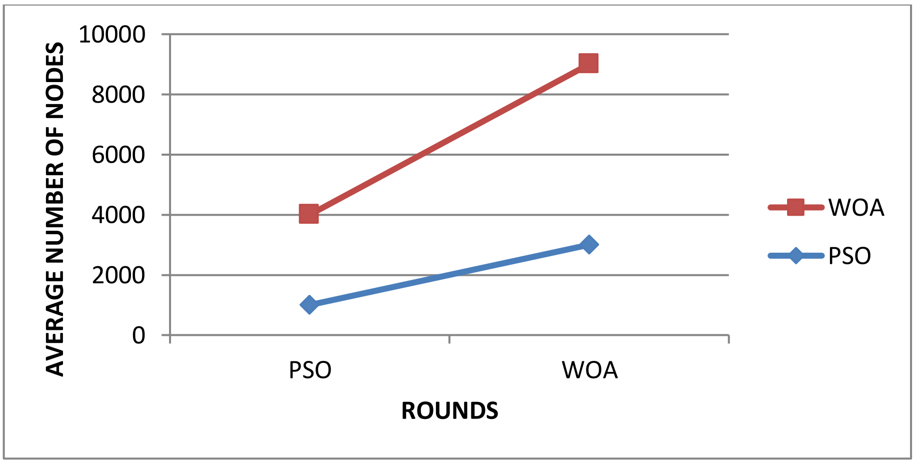

Figure 4.1 Network Lives for PSO and WOA

Table 1. The Comparison of Different PSO and WOA Parameters

Constraints	Algorithms	
	PSO	**WOA**
Network Lifetime	1400	4100
Throughput	7700	1710
Residual Energy	3000	9000
Path Loss	142	456

The hPSO-SA algorithm's capacity to look the remaining power at each sensor node during network operation is increased by the usage of a multichip telecommunications. Based on economic function, the energy consumption of a relaying sensor node is evaluated. Due to the heavy load on the sink in PSO and WOA, a few sensor nodes drain prematurely. In order to balance the load on the sensor nodes, WOA selects a different relay sensor node using multichip communication for every round. This finding shows that WOA has a maximum quantity rate, which is shown in Figure 4.1, and is also very energy-efficient [11].

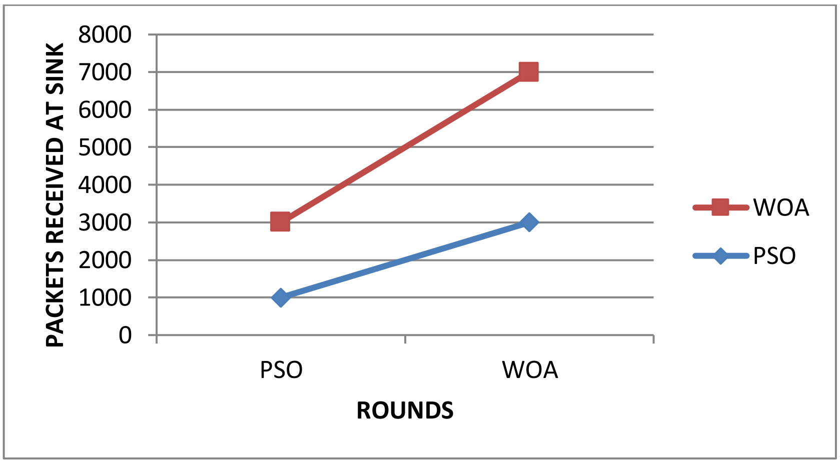

Figure 4.2 Flows for PSO and WOA

The network's lifetime is equal to the interval between the initial death node that increases to the network's stability period and the last dead node detected, and the retained customers is the interval between these two. The stability window for the two suggested techniques is displayed in Figure 4.2 and Table 1. The term "unbalanced period" refers to the interval between the death of the first and last sensor network. All of the algorithms are seen to function properly, but WOA's stability period is longer than PSO's. The graph makes it evident that the first node for the proposed WOA dies at round 3760 while the first node for the PSO dies at round 2500. When compared to PSO, the original node's lifetime with WOA is around 1.6 times longer, which is sufficient to uphold stable for a prolonged period of time.

Table 2. Performance Evaluation of Connected Clients' Number

EXAMPLES	m	AMOUNT OF CUSTOMERS	LINKED	LINKED CLIENTELES PROPORTION	
		PSO	**WOA**	**WOA**	**PSO**
Inst-1	5	20.1	32.3	45.3	55.3
Inst-2	10	21.2	33.4	46.2	56.9
Inst-3	15	23.4	35.6	47.5	54.3
Inst-4	20	25.9	32.6	46.2	57.8
Inst-5	25	27.5	38.9	41.2	56.3
Inst-6	30	26.9	39.6	49.6	59.3

In this part, we examine the impact of the network router placement procedures' performance on the total number of mesh clients. Figure 8's charts display the CCR at 50 and 55 mesh routers for INS-4 and INS-5, correspondingly. There are somewhere between 50 and 400 mesh clients. For the GA and PSO algorithms, we can see that the CCR lowers as the amount of network clients rises. When there are more mesh clients, the CCR for the MVO and WOA algorithms only minimally changes. The MVO provides the best CCR for both INS-3 and INS-4 when comparing four algorithms. Think about an illustration in INS-3 with 400 mesh clients. The CCRs are 89.5%, 74.4%, 78.0%, and 83.6%, respectively, when utilising Sensors 2022, 22, and 5494. As a result, algorithms WOA and PSO have lower CCRs than algorithm MVO, which is higher by 15.1%, 11.5%, and 5.9%, respectively. Because there are more mesh routers in the INS-5 than the INS-3, CCR is greater (55 routers for this instance). Particularly, the MVO algorithm generates higher CCR than other techniques. Details on the CCR values used to run INS-3 and INS-4 are shown in Table 2.

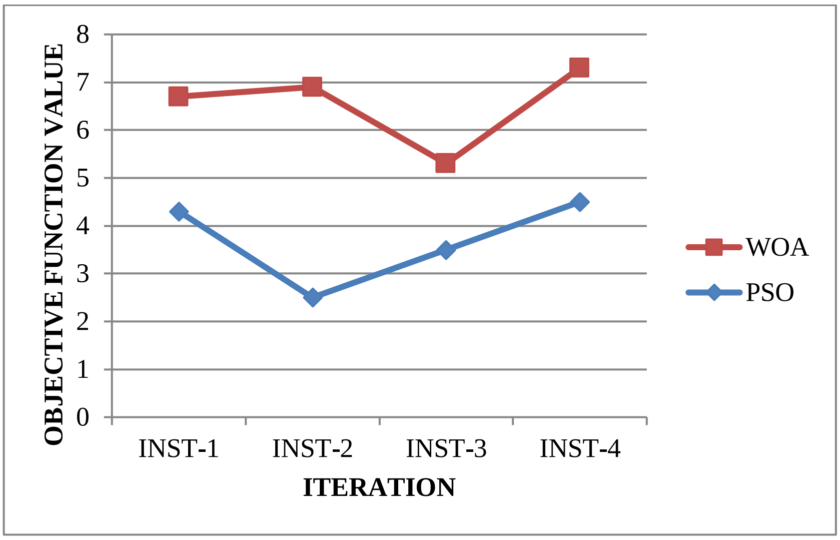

Figure 4.3 Comparison of the Objective Function Value's Performance

Figures 4.1–4.3 show the two algorithms' convergence curves for INS-1–INS-4 with 300 mesh clients, respectively. The MVO algorithm outperformed the PSO and WOA algorithms, according to these convergence curves. Early convergence was achieved by the techniques PSO and WOA. MVO's convergence is sluggish, but unlike the other methods, it is not densely packed in local optima.

5. Conclusion

Recently, the MRP-WMN has drawn a lot of research organisations. Approximate optimization strategies are frequently employed to handle this NP hard problem because of its complexity. In this paper, the MVO optimization technique was employed to solve the WMN. Additionally, a brand-new MRP-WMN goal functionality is put forth that considers connected client ratio and connected gateway ratio, two crucial performance indicators. The effectiveness of the MVO algorithm in addressing the MRP-WMN problem is assessed using software simulation approach. We performed simulations on various web illustrations, varying the quantity of routers, meshes consumers, and transmission range. Compared to the WOA and PSO algorithms, the simulation results demonstrate that the MVO algorithm performs better in terms of connected client ratio and path loss. Researchers will continue to create algorithms in the forthcoming work while taking into consideration additional quality of communication and quality of service limitations, such as traffic load offered to each mesh router, signal-to-noise ratio, bit error rate, and so on, in order to enhance WMN performance.

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