

Route optimization in Software Defined Network for Reliable data delivery using Sail fish optimizer, Wild Geese optimizer and Aquila optimizer

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ARTICLE INFO

Received: 16 Dec 2024

Revised: 12 Feb 2025

Accepted: 24 Feb 2025

ABSTRACT

The reliability of data delivery in Software-Defined Networks (SDN) is essential, particularly for real-time and large-scale applications. This research compares and contrasts three meta-heuristic algorithms for route optimization in an SDN environment: Sailfish Optimization (SFO), Aquila Optimization (AO), and Wild Geese Optimization (WGO). SFO uses the cooperative hunting behaviors of sailfish and aims to balance exploration and exploitation phases for determining optimal paths for multipath routing. WGO draws inspiration from the migrating geese that utilize their collective intelligence for obtaining the stability of paths. WGO aims to handle route congestions and ensure the stability of the routes. On the other hand, AO is inspired by the hunting behavior of the bird known as Aquila. AO achieves a balance between the exploration and exploitation phases because of its dynamic search process such that it enhances network efficiency through route optimization. Our study performs simulations process using Mininet simulator. The simulation test and compare alternatives based on key factors such as throughput, bandwidth utilization, delay, and computation time. The assessment result indicates that WGO outperforms both SFO and AO with a throughput of 272.11 Gbps, latency of 0.42 ms, processing time of 2.96 sec, and bandwidth use of 29.19 mbps. The simulation provides that WGO achieves better throughput and bandwidth utilization with reduced delay and computation time with regard to route optimization in an SDN environment. The paper also gives valuable understanding towards selecting the best meta-heuristic optimization algorithm that is suitable for robust and effective multipath routing in SDN and enhances SDN performance and its reliability.

Keywords: SFO, WGO, AO, Reliability, SDN, route optimization

INTRODUCTION

Software-Defined Networking (SDN) is a paradigm that has revolutionized networking by decoupling the data and control planes to allow for centralized control and dynamic network optimization (Pavithra et al., 2023). Centralization and programmability in SDN provides better network management. However, one of the critical challenges in SDN is optimizing routing to ensure reliable data delivery. Reliability of data delivery is very fundamental in the sustenance of network performance, particularly in dynamic and large-scale scenarios. Route optimization in SDNs determines reliable data transmission, minimal latency, and optimal use of resources with load balancing (Akbar Neghabi et al.,

2019). Multipath routing is widely used as a beneficial mechanism to increase reliability by dispersing data across available paths, so that congestion and fault tolerance are both improved. Optimizing multipath selection to improve throughput, reduce delay, and decrease computation time is still an intricate issue that demands intelligent optimization mechanisms. SDN based multipath routing also improves the resilience of wireless sensor network as stated in (Aljohani & Alenazi, 2021). Meta-heuristic algorithms have obtained eminence as an effective tools to address these challenges due to their capacity to find near-optimal solutions in complex, dynamic environments. For high-dimensional problems, population-based approaches yield effective search results (Mahajan et al., 2022). This paper explores the role of three different meta-heuristic algorithms in route optimization for SDN. Meta-heuristic algorithms like the Sailfish Optimizer, Wild Geese Optimizer, and Aquila Optimizer have garnered attention due to their ability to effectively tackle complex optimization problems. SDNs Route optimization in SDNs is selected, based on bandwidth, latency, network congestion, and the suitable channels for data flow. Many standard approaches struggle with scalability and fluctuating network conditions. Meta-heuristic optimization techniques are useful for finding the best way to solve a problem by intelligently exploring possible routes. This work investigates and compares three nature-inspired meta-heuristic algorithms—Sailfish Optimizer (SFO), Wild Geese Algorithm (WGA), and Aquila Optimizer (AO)—to optimize multipath routing in SDN. SFO simulates the hunting style of sailfish to balance exploitation and exploration in path selection and effectively choose routes. WGA simulates cooperative bird flight patterns among migrating geese, taking advantage of leader-switching schemes to enhance convergence in discovering the best paths. AO imitates eagle hunting strategies which is based on Aquila's prey grabbing behaviour that dynamically adapts to search behaviour in order to maximize routing efficiency (Sasmal et al., 2023).

This research evaluates and compares the performance of the three optimizers in SDN-based multipath routing by considering metrics such as throughput, delay, bandwidth utilization, and computation time. The result highlights the choice of the most appropriate optimization algorithm that can be used in SDN-based multipath routing applications for enhancing network performance and scalability. Meta-heuristic optimization algorithms are extensively applied to solve complicated optimization problems by imitating natural phenomena. The study provides a mathematical model for each of the three meta-heuristic optimization techniques with a comparative assessment done between them on the basis of metrics defined in the section below. The paper also conducts a simulation using a simple topology created in the Mininet simulator. We train the model using SFO, AO, and WGO. The result is shown with respect to throughput, delay, computation time, and bandwidth utilization.

Key Contribution of the paper is highlighted as below:

- To the best of my knowledge there have been no study related to the optimizer discussed in the paper in the field of SDN for multipath routing.
- Evaluates the performance of wild geese optimizer, Aquila optimizer and sail fish optimizer for multipath routing of data in Software defined network.

OBJECTIVES

The major objective of this work is to study the optimizer and discussed the usage of it in the field of SDN for multipath routing. It also aims at evaluating the performance of wild geese optimizer, Aquila optimizer and sail fish optimizer for multipath routing of data in Software defined network.

LITERATURE REVIEW

Route optimization in SDN is very important for enabling reliability in end-to-end delivery of data. Because of their propensity to resolve intricate optimization issues, meta-heuristic algorithms have

drawn a lot of interest in this area. Various researchers have explored meta-heuristic algorithm for route optimization in SDN with an emphasis on reliability, scalability and efficiency. (Chen et al., 2024) propose a method known as the African Vulture Routing Optimization (AVRO) algorithm. It is a population-based meta-heuristic algorithm. The method provides a faster convergence rate and the capability to obtain global optimization. The proposed method has better network performance than traditional routing algorithms and deep learning models for route optimization, as shown by the experiments. It indicates that the method has the highest fitness value with an increase in bandwidth utilization and improved load balancing. However, the experimental conduction could be done using more realistic simulators like Mininet and floodlight controllers. The network performance can improve more by applying heuristic algorithms with deep learning models. (Kamboj et al., 2023) develops QoS-aware dynamic multipath routing using an integer linear program (ILP) and a greedy heuristic approach. It considers three stages: splitting of incoming flows, determining minimum costs for routing, and flow reordering so as to obtain multiple paths. The approach achieves higher throughput for improved QoS compared to all other benchmark schemes. Despite the approach providing improved QoS, the work assumes that flow can be split without any overhead, but in many practical implications, this method may be less effective. (Tache (Ungureanu) et al., 2024) performs a thorough discussion on various heuristic optimization techniques for routing, balancing load, traffic optimization and minimizing delay and latency in SDN. This study highlights the necessity of heuristic and artificial learning approaches in SDN environment. However, there still exists open challenges in SDN so as to ensure network resilience and robustness along with its scalability and reliability. (Jayaprakash & Devi Priya, n.d.) proposes Lion optimization algorithm (LOA). It aims to find the best route for routing data packets between the hosts. This will effectively reduce packet loss and improves response time. The experiment is performed in SDN environment using OpenFlow in NS2 simulator. The method effectively obtained result in terms of decrease rate in packet loss, increase throughput and packet delivery ratio. However, in future the work may refine the result more even in various network scenarios and compare them with other meta heuristic algorithm so as to identify best and effective meta heuristic algorithm for route optimization. The scalability of the proposed work also needs to be tested. (Hu et al., 2023) performs its study on routing strategy using meta heuristic algorithm in order to optimize service function chain (SFC) routing. The method uses particle swarm optimization algorithm to adapt to dynamic nature of SDN topology to improve convergence rate. It then uses genetic algorithm to find the best or optimal path. It performs simulation process to obtain a result with improve link utilization, reduce routing time in large network topology and improved SFC routing. But the work has no discussion on multi path routing optimization while considering link utilization only for determining best path. (Abbas El-Hefnawy et al., 2022) develops a hybrid meta-heuristic algorithm that uses ant colony optimization algorithm with box covering and k means clustering method. The major goal of this work is to overcome time and space complexity for dynamic route optimization with reduced network congestion, delay and execution time with rate of packet loss.

Routes optimization in SDN for reliable data delivery can be affectively obtained using various meta-heuristic algorithm. Various meta heuristic algorithms have been proposed and tested with their own unique methods, process and their performance metrics for network performance evaluation. However, some algorithm offers scalability over reliability, while others offer robustness over traditional routing methods, wherein they suffer from local optima and slow convergence rate. They also have very few study that basis their study on multi path routing for dynamic routing in SDN. Therefore, this paper offers three unique meta-heuristic algorithm applied on a network traffic, such that their performance is evaluated in terms of throughput, delay, computation time and bandwidth utilization so as to provision quality of service in SDN environment.

METHODS AND SYSTEM MODEL

Meta-heuristic algorithm are the efficient means for obtaining route optimization in dynamic SDN environment. The system model uses the traffic generated using Mininet simulator with OpenFlow

protocol and Ryu controller. The model works based on the traffic types determining congestion in the routes. Three different algorithms are applied in the similar scenario and a result is obtained so as to identify the best routing algorithm for reliably delivering data in SDN. The three meta-heuristic algorithm are Sail Fish optimization, Wild Geese optimization and Aquila optimization algorithm. SFO is the Sailfish Optimizer, inspired by sailfish hunting behavior. It finds optimum answers by balancing exploitation with discovery. SDNs have applied SFO to reduce delays and boost throughput, thereby optimizing the routing paths (Shadravan et al., 2019). WGO, replicates the migratory pattern of wild geese. The Wild Geese Optimizer (WGO) utilizes a leader-follower strategy to optimize the search space. SDNs have implemented WGO to optimize routing by focusing on energy economy and load balancing. Its ability to control multiple-objective optimization equips it for demanding network contexts. AO The basis of the Aquila Optimizer is hunting methods of the Aquila bird. It combines exact exploitation with rapid investigation to get optimum answers. SDNs have applied AO to enhance network resilience and minimize packet loss, thereby optimizing routing paths. Over many network topologies, its performance has been validated (Abualigah et al., 2021). AO reduces packet loss and shows higher performance-enhancing network dependability.

The comparative study of these algorithm emphasizes variations in their performance on throughput, delay, computational time and bandwidth utilization. These parameters aims towards achieving reliability in data delivery. A system model or methodology used in the proposed work is given in Fig 1.

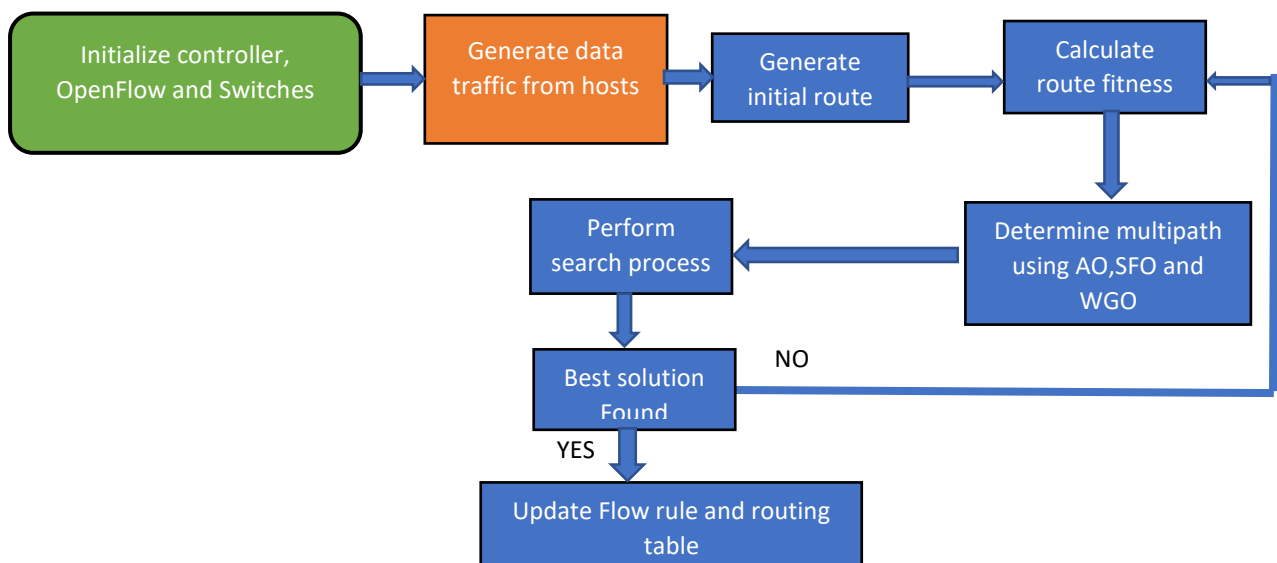


Fig 1. System model

Mathematical Formula for Sail fish optimizer (Shadravan et al., 2019)

Sail fish optimizer (SFO) is a nature-inspired population based meta-heuristics optimization algorithm. SFO is motivated by a collective hunting ability of sailfish. Sailfish is one of the fastest fish that hunts in a group and has a speed of around 100 km/h. The group hunting strategy used is the alternation of attack such that the hunter saves the energy while the prey is being injured by the predators. They do not directly capture the prey but with frequent attacks, more and more preys are hurt. They are like animals that hunts in packs.

Stages in SFO algorithm

- a) Initialization: candidate solution is sailfish and position of sailfish is the problem's variable and populations over solution space is generated randomly.

- b) Copying the unchanged best solution or position to next best solution calling it as an elite given as $X_{elite_SFO}^i$. The position of injured sardine is also saved in each iteration as $X_{injured_SR}^i$.
- c) Alternation of attacks: sailfish coordinates the attack alternatively. They chase the prey and adjust their position based on the hunter position. They perform attack alternation strategy while they hunt on groups. It provides exploration phase over a large search space. They attack in all directions while shrinking the search space consequently and updates the best possible solution.

At the i^{th} iteration, the best updated sailfish position is given as in equation Eq 1.

$$X_{SFO_new}^i = X_{elite_SFO}^i - \lambda_i \times \left(rand(0,1) \times \left(\frac{X_{elite_SFO}^i + X_{injured_SR}^i}{2} \right) - X_{SFO_old}^i \right) \quad \text{Eq 1}$$

- d) Prey hunting and catching: The prey or sardines are injured over many iterations. Eventually the sailfish hunts and catches the prey and updates the current best position of prey or sardines given by equation Eq2.

$$X_{Sar_new}^i = r \times (X_{elite_SFO}^i - X_{Sar_old}^i + PA) \quad \text{Eq 2}$$

At last stage the injured sardine is quickly captured. The position of sailfish is replaced with the current position of sardine given by equation eq3

$$X_{SFO}^i = X_{sar_curr}^i \text{ if } f(S_i) < f(SF_i) \quad \text{Eq 3}$$

Wherein the symbols are represented as below:

$X_{elite_SFO}^i$	Position of elite or fittest sailfish
$X_{injured_SR}^i$	Position of injured sardines with high fitness at ith iteration
$X_{SFO_new}^i$	Sailfish's new position
λ_i	Coefficient
$X_{SFO_old}^i$	Current sailfish position
$X_{Sar_new}^i$	Sardine's new position
r	Random number between 0 and 1
$X_{Sar_old}^i$	Current position of sardines
PA	Power attack at each iteration
X_{SFO}^i	Current position of sailfish at ith iteration
$X_{sar_curr}^i$	Current position of sardines at ith iteration

The algorithm guarantees search space exploration with random selection of selfish and sardines. It uses the population of sardine such that it avoids getting stucked at local optima. The method uses encircling strategy while sardines maneuverate around best solution promoting exploitation with increase in iteration. It updates the sardines position and explores position around sailfish. The algorithm 1 depicts the process.

SFO Algorithm 1

Input: Random initialization of population of Selfish and sardine as candidate solutions

Output: Optimal solution or best sailfish

Elite position selection

Select the best position of sailfish in each iteration

$$X_{elite_SFO}^i$$

Save the position of injured sardines

$$X_{injured_SR}^i$$

While not reach maximum iteration do

For each sailfish

Find the best position of sailfish

End for

Compute power of attack and update sardine best position

Calculate fitness of sardines

if better solution found

Replace sailfish with injured sardine

Update best of sardine and selfish

End if

End while

Mathematical Formula for Aquila optimizer (AO)

AO is a meta-heuristic optimization algorithm that gets its inspiration from the hunting behaviour of a bird called as Aquila. The algorithm enhances its optimization efficiency by balancing exploration and exploitation phase. Moreover it has high convergence speed while sometimes can get stuck in local optima. AO simulates Aquila's behaviour during hunting, showing actions of each step of the hunt (Abualigah et al., 2021). The stages are divided into four steps (Abualigah et al., 2024).

- Search space selection using high soar with vertical stoop given by Eq 4
- Explores within diverge search space using contour flight with short glide attack given by Eq 5
- Enters exploitation phase where it converges search space using low flight with slow descent attack given by Eq 6, 7.
- Attacks and grabs the prey.

The four steps along with mathematical model are explained using 4 phases. They are:

Expanded Exploration : $X_1(t+1) = X_{best}(t) \times \left(1 - \frac{t}{T}\right) + XM(t) - (X_{best}(t) * rand)$ Eq 4

Narrowed Exploration : $X_2(t+1) = (X_{best}(t) \times Levy(D) + XR(t) + (y - x) * rand)$ Eq 5

Expanded Exploitation : $X_3(t+1) = (X_{best}(t) - XM(t)) \times \alpha - rand + ((UB - LB) \times rand + LB) \times \delta$ Eq 6

Narrowed Exploitation : $X_4(t+1) = QF \times X_{best}(t) - (G1 \times X(t) \times rand) - G2 \times Levy(D) + rand \times G1$ Eq 7

Wherein the symbols are represented as below:

X	Candidate solution
T	Max.no of iteration
rand	Random value between 0 and 1.
s	Constant value 0.01
UB and LB	Upper bound and lower bound
G1,G2	Denotes motions of AO
t	Current Iteration
XM(t)	Location mean value of current solution at t iteration.
Levy(D)	Levy flight distribution function
u and v	Random number between 0 and 1
Q	Quality function

Mathematical Formula for Wild Geese optimizer

WGO is also a meta-heuristic optimization algorithm like SFO. It is motivated from wild geese. It enables fault handling mechanism along with multipath routing mechanism. The mathematical formula is given in (Ghasemi et al., 2021). It consists of following stages with algorithm 2:

- a) Population generation: The population size= N , no. of the head geese= M . L is the initial radius size of migration group.
- b) Formation of migration groups: Migration groups is reestablished according to the position of the head geese and the members of each group are randomly distributed within the radius L with the head goose as the center
- c) Synchronized flight: It simulate the flight characteristics of wild geese, and the flight steps in the migration group members.
- d) Free foraging: Migration group members randomly explore according to the information of the head goose.
- e) Selection of head geese: The head geese must be replaced frequently to achieve high flight durability and the optimal individuals in each migration group will be selected as the head geese of the new generation after each location update

Algorithm Wild Geese Optimizer

Data: Initial population P , maximum number of iterations $maxIter$

Result: Optimal solution

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1 initialization while not reached maximum iteration do
2   for each goose in population  $P$  do
3     Perform local search to update goose's position
4   Update global best solution
5   Update population  $P$ 

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RESULTS AND DISCUSSION**Experimental Conduction**

Mininet experiment conduction using OpenFlow protocol, Ryu controller in pycharm for captured audio data. The data traffic is generated using iperf tool and TCP SYN flood. Flow statistics are collected every 30 secs. The network performance for SFO, WGO and AO is then determined using reliability metrics such as throughput, delay, computation time and bandwidth utilization. The result is obtained from the simulation process undergoing many rounds. This is discusses in Section 4.

This section shows the result obtained from Mininet simulation for SFO, WGO and AO. The metrics that determines network reliability are throughput, delay, computation time and bandwidth utilization.

Throughput: Throughput is determined by the amount of packet received with respect to packet send. It is maximization function. Table 1 and Fig 2, brings out a comparative value for throughput between SFO, WGO and AO with respect to 100 rounds of experiment. The average value for throughput is seen to be 228.71 for SFO, 241.02 for AO and 272.11 for WGO. This value indicates that WGO outperforms SFO and AO in terms of throughput.

Table 1. Throughput for SFO,WGO and AO			
Rounds	SFO	AO	WGO
10	140.0584	221.1694	291.0585
20	348.8657	317.9768	356.8658
30	169.9533	177.0643	223.9534

40	301.5887	294.6997	332.5888
50	154.8166	143.9276	155.8167
60	350.3595	335.4706	380.3596
70	130.9334	143.0444	167.9335
80	233.4005	262.5115	273.4006
90	158.8051	188.9161	210.8052
99	298.3546	325.4657	328.3547

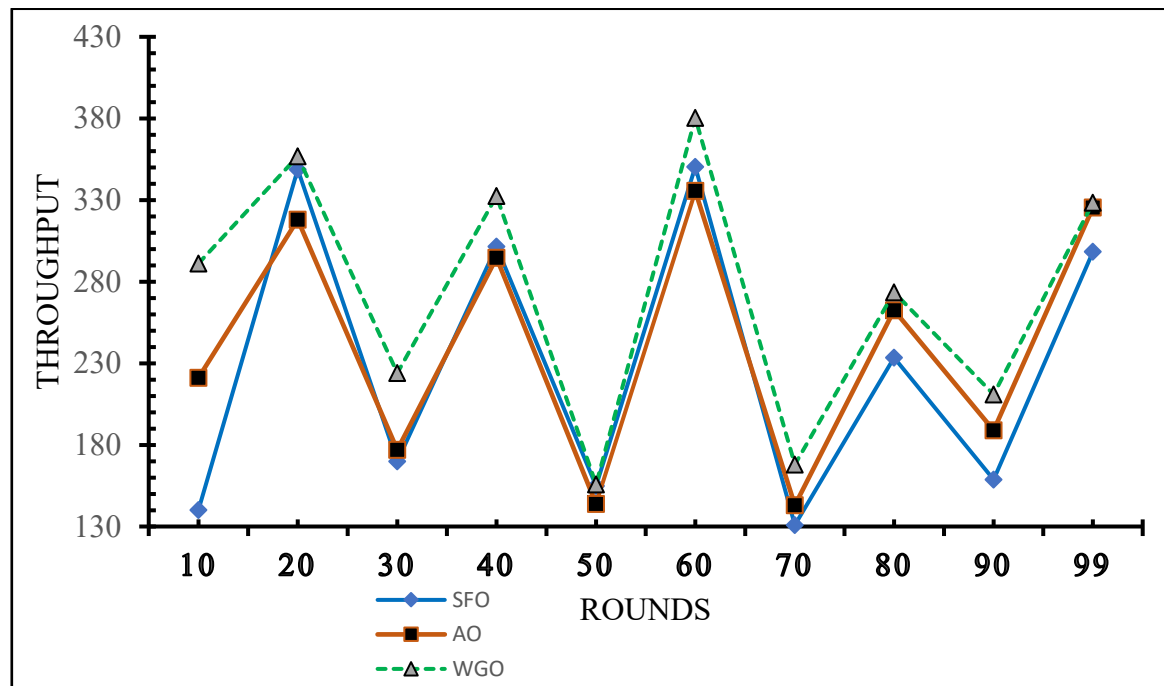


Fig 2. Throughput for SFO, WGO and AO

Delay: Delay is determined by calculating the amount of time taken by the packet to reach destination. It is minimization function. Table 2 and Fig 3 shows delay value obtained for SFO, WGO and AO for 100 rounds of simulation. The average value obtained indicates 0.501msec for SFO, 0.473msec for AO and 0.417msec for WGO. This shows that WGO performs better than SFO and AO.

Rounds	SFO	AO	WGO
10	0.534741	0.473074	0.409883
20	0.457581	0.442322	0.377752
30	0.48665	0.472299	0.4313
40	0.571836	0.584105	0.531641
50	0.4894	0.442627	0.415947
60	0.460631	0.409039	0.367283
70	0.539992	0.51678	0.487633
80	0.482456	0.460754	0.36315
90	0.435428	0.407674	0.356468
100	0.558114	0.521981	0.436972

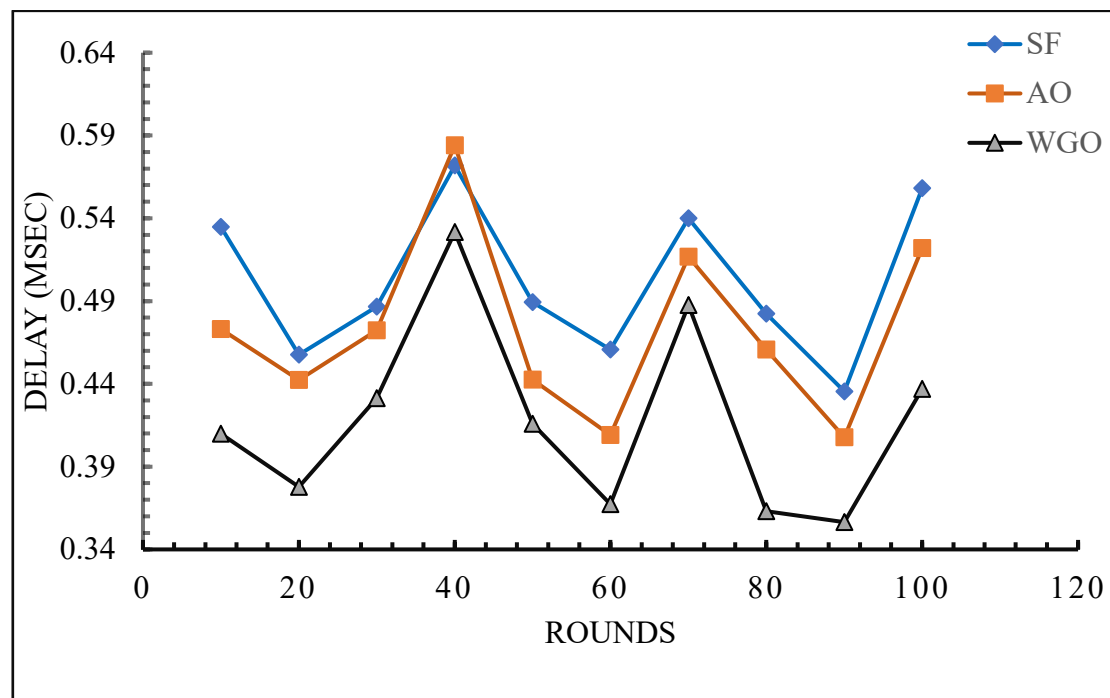


Fig 3. Delay for SFO, AO and WGO

Computational time: Time taken for the packet to travel from source to destination determines computational time. It is minimization function. Table 3 and Fig 4 determines computation time take by SFO, WGO and AO. The average value obtained are 9.34sec for SFO, 8.77 sec for AO and 7.96sec for WGO. This shows that WGO has lowest computation time.

Table 3. Computational time for SFO,WGO and AO			
Rounds	SFO	AO	WGO
10	7.33048	6.903775	6.090537
20	7.97797	7.328941	6.517295
30	8.221224	7.689307	6.910549
40	8.777056	8.092961	7.407883
50	9.320327	8.729097	7.818145
60	9.699276	9.057008	8.257131
70	9.931352	9.416432	8.720003
80	10.35184	9.809693	8.879451
90	10.64184	10.0009	9.164591
100	11.14988	10.71882	9.894906

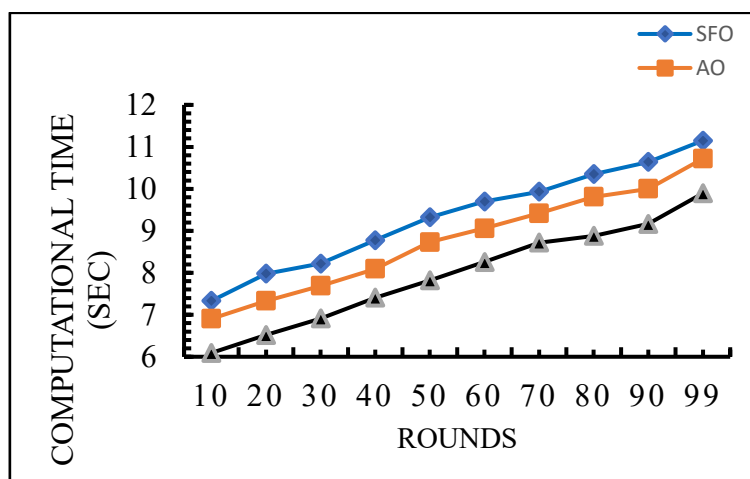


Fig 4. Computation time for SFO, WGO and AO

Bandwidth utilization in Mbps: Bandwidth utilization is a minimization function. It determines the utilization of bandwidth by SFO, WGO and AO in SDN environment for 100 rounds. It is shown in Table 4 and Fig 5. The average value obtained for bandwidth utilization for SFO is 33.16 mbps, 31.34 mbps for AO and 29.19 mbps doe WGO.

Rounds	SFO	AO	WGO
10	19.6478	18.09276	15.60817
20	22.61825	21.11887	18.67584
30	24.96433	23.10195	21.27407
40	28.42931	26.6418	24.6302
50	30.80487	28.79057	26.6132
60	34.41412	32.84668	30.59214
70	37.50252	35.66407	33.4375
80	41.2485	39.12864	37.37744
90	44.38829	42.28048	40.48124
99	47.60569	45.81472	43.21968

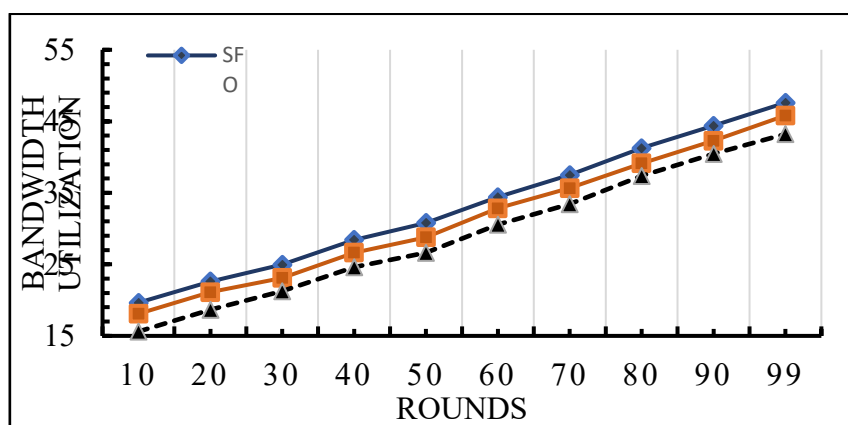


Fig 5. Bandwidth Utilization for SFO, WGO and AO

Comparative study between SFO, AO and WGO in terms of throughput, delay, computation time and bandwidth utilization.

The table 5 depicts the comparative values obtained for SFO, AO and WGO in SDN environment for multipath routing. It shows that WGO outperforms SFO and AO in terms of all the metrics considered.

Table 5. Comparison between SFO, AO and WGO based on QoS metrics				
Meta-heuristic algorithm	Throughput	Delay	Computation time	Bandwidth utilization
SFO	228.7136	0.501683	9.340125	33.16237
AO	241.0246	0.473066	8.774694	31.34806
WGO	272.1137	0.417803	7.966049	29.19095

CONCLUSION AND FUTURE WORK

In this work, we investigated route optimization in Software-Defined Networks (SDNs) using bio-inspired optimization algorithms: Aquila Optimizer (AO), Wild Geese Optimizer (WGO), and Sailfish Optimizer (SFO) to guarantee reliable data delivery. These techniques clearly solve the problems of dynamic routing, load balancing, and network congestion in SDNs. The simulation process determines the efficiency of these algorithms for multipath routing. The results obtained show that WGO outperforms SFO and AO with respect to minimizing delay, bandwidth utilization, and computational time while maximizing throughput. To further validate their scalability and dependability in real-world SDN systems, future studies should focus on hybrid approaches integrating these optimizers and testing them in broader, more complex network topologies.

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