TWO NATURE- INSPIRED ALGORITHMS IN FI-WI USING OPTIMAL ONU PLACEMENT AND TRAFFIC PREDICTION BASED ON NEURAL NETWORK

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Abstract : Fibre Wireless (Fi-Wi) access technology integrates the existing broadband access technology and wireless access technology to fulfil the users' demand for better Internet speed in "anytime anywhere" approach and cost-efficient manner. It is designed to make the best use of their advantages in terms of vast bandwidth, mobility, and cost effectiveness. However, there remain there remain several open and challenging issues that require concentrated research efforts to build such an access technology. ONU placement problem is one amongthese issues as ONU placement in Fi-Wi plays a critical role in overall network deployment cost and resource optimization. Server methods using nature-inspired algorithms have been proposed in literature to find optimumONU placement. We also implement a dynamic resource allocation based on a traffic perdition algorithm to improve network performance during a rapid traffic spike in the optical network. In this paper, we present performance analysis of the two nature-inspired algorithms by considering different of scenarios for ONUs and wireless routers in a FiWi network. We also compare present throughput gain for the algorithms when dynamic resource allocation is used under varied ONU and router deployment.

Keywords: *Fiber Wireless, Networks,* Optic, Architecture

1 Introduction

Optical fibre technology, in contrast to other wired access technologies such as Cable Modem (CM)[1] and Digital Subscriber Line (DSL) provides larger bandwidth capacity, better tolerance to interference and lower signal loss. However, it lacks the support for "anytime anywhere" access and involves huge deployment cost. On other hand, wireless access technology delivers "anytime anywhere" access, reduced cost, enhanced coverage, better fault tolerance, and easy deployment [2]. However, its bandwidth constraint due to spectrum scarcity makes it unsuitable for transmission of large volumes of data. Fi-Wi [3-5] is a hybrid fibre-wireless access network that combines technological merits of optical fibre and wireless access technologies to fulfil the users' demand for better Internet speed in "anytime anywhere" and cost-efficient manner. The technology has also been named as Optical and Wireless Access Network (OWAN) [6] or Wireless and Optical Broadband Access Network (WOBAN) [7]. Thus, the aim of Fi-Wi network is to provide the customers with higher bandwidth capacity and improved flexibility in network access resulting in better Quality of Service (QoS) and better Quality of Experience (QoE) [8-10].

However, several critical parameters must be tackled to design such a composite mix of access technology with technological merits of fibre-based Passive Optical Network (PON) technology and the wireless technology. Optical Network Unit (ONU) placement, survivability [11], energy savings, Quality of Service (QoS), flow and congestion control, delay and throughput gain are some of the interesting challenges and open issues in FiWi access technology. Several research studies in literature have proposed a wide range of algorithms to tackle these parameters to enhance the performance of Fi-Wi access technology. ONU placement one of critical parameters, which affects network deployment cost an hence its overall performance. ONU is a key component in Fi-Wi network because it interfaces with wireless access technology. Thus, placement of ONUs in the network plays a critical role in improving the Internet speed for users. Figure 1 depicts different components andtheir placements in Fi-Wi network to facilitate users for upstream and downstream communication.

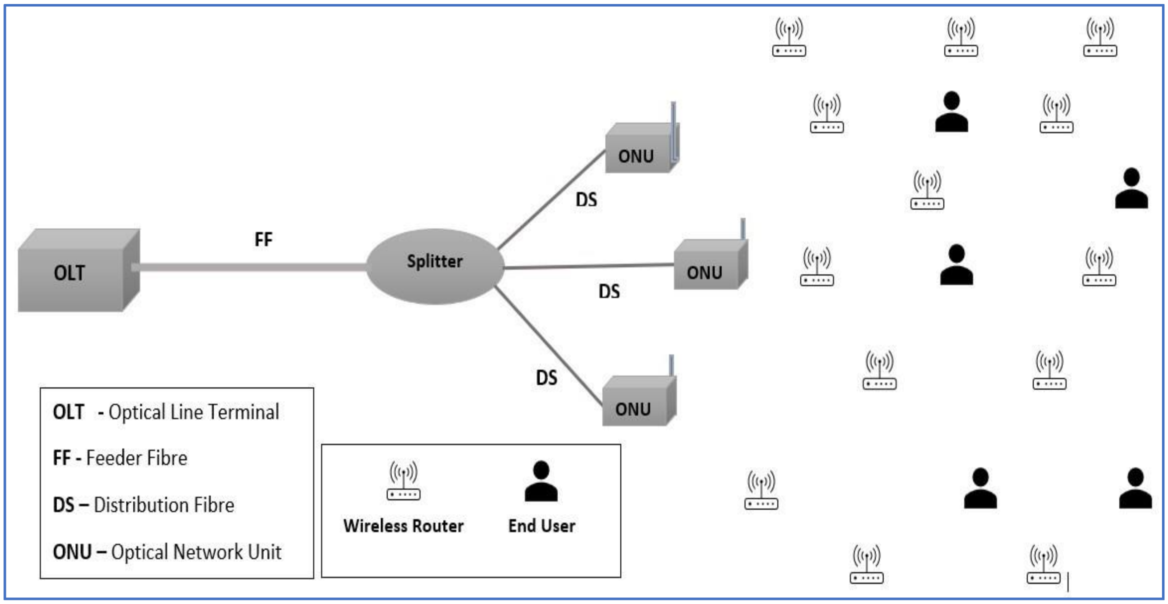

Figure 1. The architecture of Fi-Wi Network

ONUs are the interfaces that perform signal translation between Optical fibre communication technology (back-end) and Wireless communication technology (front-end). That is, it translates signal for upstream communication from wireless network to optical network and for downstream communication from optical network to wireless network. Upstream communication is facilitated by sending the user data to nearby wireless routers that in turn forward to their primary ONU. The primary ONU does the signal translation and upstreaming of the signal to Optimal Line Terminal (OLT). Downstream communication requires the reverse mechanism of this process.

It is important to find optimal ONU placement in FiWi network as arbitrary ONU placement severely affects network deployment cost and performance. In this paper, we present performance analysis of some of well- known optimization algorithms in terms of their capability to minimize network deployment cost. Section 2 presents a brief review of the existing methods in literature. Section 2 presents a mathematical model for the problem. Sections 3 and 4 explains two prominent nature-inspired algorithms namely Moth Flame Optimizationand Whale Optimization algorithms, which are used for the performance analysis study in this paper. Finally, section 5 presents analysis and discussion of the results obtained for different ONU placements. Finally, section6 concludes the paper.

2 Related Work

FiWi technology combines the existing passive optical network communication technology as the back-end and the widely used Wi-Fi communication technology as the front-end to fulfil the requirement of better internet speed in “anytime anywhere” and cost-efficient manner. Wide range of algorithms have been proposed and studied to tackle parameters such as QoS, delay, throughput gain, ONU placement, routing, energy saving, survivability etc. ONU/gateways placement is one of the critical parameters that is extensively studied asit is shown to have influence on FiWi network performance. Optimal ONU/gateways deployment is important form the viewpoint of cost and resource optimization. This sections briefly presents various algorithms proposedfor the optimization of ONUs position in FiWi network.

The authors in [12] studied various ONU placement by comparing random and deterministic ONU placement using Greedy algorithm. A heuristic based Tabu Search is used in [13] for ONU deployment to enhance overall network throughput. Considering peer-to-peer communication, authors in [14,15] presented a load balance ONU placement (LBOP) algorithm that works in two stages. The first stage deploys minimum number of ONUs considering hop number as the constraint. The second stage addresses the problem of load balancing among deployed ONUs to satisfy the constraint of load balancing. A genetic-based hybrid algorithm for optimal ONU deployment is proposed by the authors in [16]. This algorithm aims to provide an efficient ONU placement solution in terms of overall network deployment cost.

Simulated annealing algorithm [17] proposed by Sarkar et al involves five phases: Initialization, Perturbation, Cost calculation, Acceptance and Update. The first phase uses the greedy algorithm to deploy ONUs. Perturbation phase perturbs initial ONU positions and computes new positions for the ONUs, and Cost calculation phase calculates new cost with respect to old cost. The algorithm terminates when there is no update in cost improvement in the last phase. In [18] L agrangian relaxation method is used for ONU placement. The authors proposed a mixed integer programming (MIP) model for optimal placement of ONUs and base stations by considering several constraints such as base station and ONU installation, user and channel assignment, signal-quality and interference constraints. Authors in [19] proposed a method in which ONUs are initially placed at the center of the network grid and then ONUs positions are optimized by applying Teaching Learning Based Optimization (TLBO) algorithm.

Several of the authors used nature inspired algorithms to address the problem of finding optimal ONUs placements. A nature inspired algorithm called whale optimization algorithm (WOA) is used in [20] for ONU placement. WOA performs optimization based on the locations of local search agent and best search agent in the network. The authors considered energy optimization in FiWi network by minimizing average communication distance among wireless routers and ONUs using WOA algorithm. This algorithm was encouraged by the societal performance of Humpback Whale and its bubble net attacking strategy.

Moth Flame Optimization (MFO) algorithm [21] is another nature inspired algorithm that has been used in many diverse areas. Authors in [21,22] used Moth Flame Optimization (MFO) algorithm to lower the ONU deployment cost in FiWi network. MFO gives a cost function value which is lower than the existing algorithm, where cost function is formulated as a function of the distance between ONUs and wireless routers. Many diverseareas have used MFO algorithm in literature to solve optimization problems. For example, MFO algorithm as found its application in thermal power systems [23-25] to solve optimization problems such as optimizing fuzzy based proportional parameters, integral and derivative controllers, secondary controllers, and to solve constrainedoptimization problems. Authors in [26] used MFO algorithm to obtain optimized network delay and energy consumption for Open Shortest Path First (OSPF) routing algorithm. Other examples include precise and reliable estimation of annual electricity consumption [27], powerloss reduction and voltage profile improvement in the transmission line network [28], cost optimization of the software [29], feature selection strategy based on MFO algorithm [30] etc.

3 Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) is a population-based algorithm proposed by SeyedaliMirjalili and Andrew Lewis [31,32]. It simulates bubble-net feeding strategy of the humpback whales. The result obtained bythis algorithm on various mathematical and structural problems was much better than other existing algorithms. Furthermore, WOA has low number of parameters and lacks local optima entrapment in solving clustering problem. This makes it the right choice for optimized ONU deployment in FiWi network.

Optimization of ONU positions in WOA is based on computing the best search agent and local search agent in the network. The best search agent is the ONU whose average communication distance is minimum in the network and the ONU itself is the local search agent. The optimal position for each ONU in the network is computed according to the best search agent, which gives the minimum ONU deployment cost. To do this, wireless routers are randomly deployed in a network of $L \times L$ Sq-meters area. The first step involves finding initial deployment cost of each ONU for the initial placement of ONUs. ONUs are then placed in such manner that maximum users (wireless routers) can connect to present ONU. With each ONU, the wireless routers that are in the communication range of the ONU and which can communicate with it using limited hope are associated. Specifically, each ONU will include a subset of wireless routers according to Eq.(1),

$$O_i = \{R_j \mid H^{O_i}_{R_j} \le H\_Max\} \quad (1)$$

$$R = \bigcup_{i=1}^{|O|} O_i \quad (2)$$

Once each wireless router is associated with its neatest ONU, the initial deployment cost of each ONU is determined according to the Eq. (3)

$$Cost(O_i) = \sum_{j=1}^{|O_i|} \sqrt{(x_j - O_i x)^2 + (y_j - O_i y)^2} \tag{3}$$

where(x_j, y_j) is the position of R_j and $(O_i x, O_i y)$ is the position of i^{th} ONU. The overall deployment cost of ONUs is calculated as the average deployment cost of all ONUs as shown in Eq. (4).

$$Cost(O) = \frac{1}{|O|} \sum_{i=1}^{|O|} Cost(O_i) \tag{4}$$

In the next step the WO algorithm is applied to further minimize $Cost(O)$ by finding optimal ONU positions based on the locations of the best search agent. Optimal ONU positions are found using the following two approaches:

3.1 Encircling prey mechanism: This approach calculates optimal position ofi^{th} ONU according to Eq. (5),Eq. (6), Eq. (7) and Eq. (8)

$$P_1 = C_1 \times x_{bsa} - O_i x \tag{5}$$

$$P_2 = C_1 \times y_{bsa} - O_i y \tag{6}$$

$$O_i x_{new} = x_{bsa} - C_2 \times P_1 \tag{7}$$

$$O_i y_{new} = y_{bsa} - C_2 \times P_2 \tag{8}$$

where (x_{bsa}, y_{bsa}) is the position for the best search agent, C_1 and C_2 are the coefficient vectors and $(O_i x_{new}, O_i y_{new})$ is the new position for the ONU in question.

3.2 Spiral updating position: This approach calculates new position for ONUs based on constant defined by spiral shape as shown in the following equations.

$$D = x_{bsa} - O_i x \tag{9}$$

$$O_i x_{new} = De^{bl} cos2\pi l + x_{bsa} \tag{10}$$

$$O_i y_{new} = De^{bl} cos2\pi l + y_{bsa} \tag{11}$$

where D is defined as the distance of the best search agent to a local search agent, l is a random number between -1 to 1 and b is constant for defining of the logarithmic spiral,$(O_i x_{new}, O_i y_{new})$ indicates the new position for i^{th} ONU.

For a given ONU, each wireless router associated with it determines the area of that ONU. If $(O_i x_{new}, O_i y_{new})$ is within this area, then the ONU is relocated to this new position. Otherwise, the ONU retains the old position.

4 Moth-Frame Optimization Algorithm

Moth-Flame optimization (MFO) is a novel nature inspired optimization algorithm to determine the optimal positions of the multiple ONUs. The algorithm is inspired by the navigation method of moths in nature called transverse orientation. Moths they can fly in a straight line for a long distance by maintaining a constant angle with respect a bright celestial light such as moon. The difference in the angle between month the light source remains negligible even after travelling for such a long distance. However, when a much closer artificial light isencountered and is used for navigation, a noticeable change in the angle is observed after only short distance. The moth instinctively attempts to correct by turning toward the light causing the moth to come plummeting downward and turning the path to a spiral shape as it comes closer and closer to the light source. This behavior can be mathematically modelled and used to perform optimization. The statistical results obtained after comparing MFO with other well-known nature inspired optimization shows that MFO can provide much better results.

The optimization in MFO algorithm involves 5 steps as shown below:

a. Setting the initial conditions which include several candidate solutions, lower bound and upper bound of variables, dimension of the variables and number of iterations. In this model, the number of candidate solutions correspond to the number of moths and the positions of moths are represented by the variables.
b. Set the values for flames. Flames represent the best solutions obtained so far while the moths are the actual solutions. Each moth searches around a flame and updates its solution to a bettersolution if there is one. Thus, this mechanism leads always leads a moth to its best solution.
c. The i^{th}Moth updates its position with respect to thej^{th}flame using Eq. (12)

$$m_{\mathrm{i}} = S(m_{\mathrm{i}}, f_{\mathrm{j}}) \tag{12}$$

where S is the spiral function. The lower and upper bound of the function is considered by the moth to update its position. This function models the transverse orientation of moths on flames.

d. The initial position to start is the initial moth position and flame is the target position. Eachmoth uses a logarithmic spiral as the main update mechanism (Eq. (13)) to reach the target. InEq(13) d_{ij} denotes the distance from m_{i} to f_{j} as defined in Eq.(14), b defines the spiral shape and t is a random number in [-1,1]. The conditions for the algorithm state that the fluctuation range for the spiral should within the search space.

$$S(m_{\mathrm{i}}, f_{\mathrm{j}}) = d_{\mathrm{ij}} e^{\mathrm{bt}} \cos(2\pi t) + f_{\mathrm{j}} \tag{13}$$

$$d_{\mathrm{ij}} = |f_{\mathrm{j}} - m_{\mathrm{i}}| \tag{14}$$

A moth will be at the closet position to the flame when $= -1$, while $t = 1$ indicates the farthest distance from the flame. Thus, we can assume a hyper ellipse formation around the flame in all directions and next position of the month would be within the hyper ellipse. Therefore, the algorithm guarantees exploration and exploitation of the search space.

e. Based on the distance between moth and the flame calculate the moth positions using Eq (15). To address the issue of degrading exploitation of the promising solutions, an adaptive mechanism is used for the number of flames in MFO as shown in Eq(15).

$$n(f) = \lfloor (N - l * N - 1/T \rfloor \tag{15}$$

where is N maximum number of flames and $T$is the maximum number of iterations and l is the current numberof iterations.

In the next we apply WOA and MFO to calculate optimum ONU deployment cost.

5 Dynamic Resource Allocation Based on a Non-linear GCN-GAN Model

We use Graph Convolutional Network - Generative Adversarial Network (GCN-GAN) model [33] to predict unexpected rapid traffic spikes and use a resource provisioning algorithm to adjust resource allocation strategies.GCN-GAN predicts any burst events in the optical network model by training the network quickly and efficiently. The model divides the entire network into two parts; Generative network and Discriminative Network, The first part consists of GCN and GAN and is used to create burst traffic causing an increase RequestBlocking Probability (BP), which is defined as a ratio of rejected requests divided by all requests offered to the network. The other part includes a simple feedforward neural network that tries to predict the appearance of future rapid traffic spikes or burst events from the current state data so as to minimize BP by adjusting the network resource allocation. strategy. The figure 2 shows the schematic representation of GCN-GAN model.

In the Discriminative Network, GCN captures the topological structure characteristics or the network state at a ofeach single graph snapshot at specific time. Next, the GAN generates the predicted next state of the graph bydiscovering features information. While the discriminator predicts future network state, GAN will constructrealistic graph in the adversarial process. This process is repeated for every single network snapshot, during the entire simulation time.

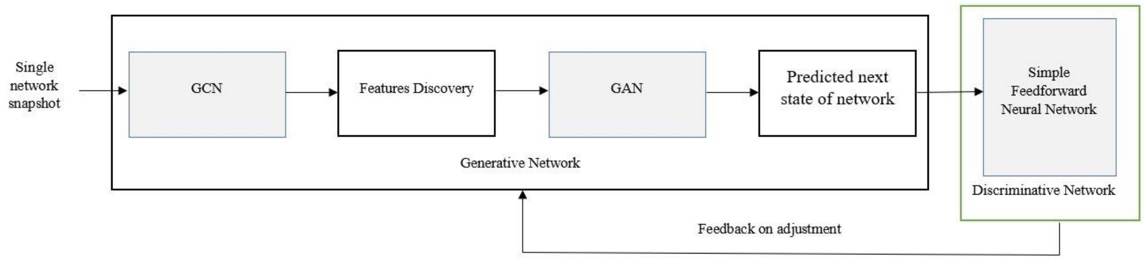

Figure 2. GCN-GAN schematic representation

6 Performance Analysis of WOA and MFO algorithms

In this section we present the experiment results of performance of WOA and MFO algorithms in terms of their ability to optimize ONU deployment cost.

6.1 Analysis of Network Deployment Cost

We consider FiWi network with 100 wireless routers randomly deployed in 1000×1000sq.meter area. We calculate the initial average deploy cost of i^{th} ONU and the initial deployment cost as given in Eq. (16), Eq. (17)and Eq. (18)

$$Cost(O_i) = \sum_{j=1}^{|O_i|} D_{r_j}^{O_i} \tag{16}$$

$$Avg\_Cost(O_i) = \frac{Cost(O_i)}{|O_i|} \tag{17}$$

$$Deployment\_Cost(Nw) = \sum_{i=1}^{|O|} \frac{Avg\_Cost(O_i)}{|O|} \tag{18}$$

Here $D_{r_j}^{O_i}$ is the Euclidean distance (Eq(19)) between j^{th} wireless router and its ONU.

$$D_{r_j}^{O_i} = \sqrt{(x_j - O_i x)^2 + (y_j - O_i y)^2} \tag{19}$$

We then apply WOA and MFO algorithm to find the optimal deployment cost.

$$Opt\_WOA\_Cost(Nw) = WOA(Deployment\_Cost(Nw))$$

$$Opt\_MFO\_Cost(Nw) = MFO(Deployment\_Cost(Nw))$$

We consider the following four cases to deploy four ONUs and calculate the initial ONU deployment cost:

1. Deploy the wireless routers and ONUs randomly in the network and calculate the initial average deploy cost based on nearest ONUs association of each wireless router. Thus, for this case $D_{r_j}^{O_i}$ in Eq() is the minimum of Euclidean distances between r_j and all ONUs.
2. We consider the same randomly wireless routers in the case 1 and place ONUs at the centroid of its associated wireless routers. That is, ONUs are deploy deterministically using the Eq (20)

$(O_i x \quad O_i y \ \_\_ \quad) = (1$

$\sum^{|0i|} x$, 1 $\sum^{|0i|}$ $y)$

(20)

i new, i new |0i| j=1 j |0i| j=1 j

where (x_j, y_j) is the coordinate of r_j of O_i

3. Divide the network onto virtual grids where each grid contains equal number of randomlydeployed wireless routers. We then randomly place one ONU in each of the virtual grids.
4. We consider the virtual grid created in the case 3 and place each ONUs at the center of its grid using Eq(21).

$(O\ x\ O\ y$) = ((0il+0ir) , (0it+0ib) (21)

(i new, i new 22)

where $O_i l$, $O_i r$, $O_i t$ and $O_i b$ are left, right, top and bottom boundaries of the grid of O_i.

We used NS2 simulator to obtain experimental results for the above four cases. Table.1 highlights simulation parameters used in the experiments. Simulation parameters for MFO are the same as the ones used in [22].

Table 1 : Simulation parameters used in the experiments

Parameter	Value
Network Size	1000 × 1000 sq. meter
Number of wireless routers	100
Number of ONUs	4
Number of randomizations	25
MFO -Number of Moths	100
MFO – Number of Iterations	5
MFO - Dimensions	6
MFO - Lower Bound	0,0,0,0,0,0
MFO - Upper Bound	1000,1000,1000,1000,1000,1000

Table 2. shows the initial and optimized ONU deployment cost for each of the aforementioned four cases. The ONU deployment cost is shown is in terms of average communication distance in meters between ONUs and their respective wireless routers. Initial deployment cost obtained in the experiment is an average of 125 simulation runs over different wireless router and ONU positions. Our experiment results indicate that MFO algorithm significantly improves network deployment cost as compared with WOA. This is due its capability balance to exploration and exploitation in the search space.

Table 2. presents an illustration of MFOs' ability to return lower value of cost function. Spiral updating positionfor WOA performs considerably better than Encircling Prey Mechanism. Thus, as we can see from the table there is slight improvement in deployment cost by MFO algorithm mover the deployment cost obtained with Encircling Prey Mechanism of WOA. For the same deployment cost, Table 3 presents comparisons of differentcases in terms of percentage improvement from the initial deployment by each algorithm.

Table 2. Deployment cost for each case.

Case	Initial Deployment Cost	WOA Cost (Encircling Prey Mechanism)	WOA Cost(Spiral Updating Position)	MFO Cost
1	284	268	262	260
2	352	304	285	274
3	191	181	177	176
4	187	178	175	172

Table 3. Percentage improvement in deployment cost

Case	Initial DeploymentCost	WOA Cost (EPM) % Improvement	WOA Cost(SUP) % Improvement	MFO Cost % Improvement
1	284	5.7%	7.7%	8.4%
2	352	13.6%	19.0%	22.1%
3	191	5.7%	7.3%	7.8%
4	187	4.8%	6.4%	8.0%

MFO algorithm shows a slight improvement in deployment cost over WOA- Spiral Updating Position method. Maximum improvement in deployment cost is shown by each algorithm is for case 2, where the ONUs are placed at the centroid of their respective regions. In this case MFO outperforms both Encircling Prey Mechanism and Spiral Updating Position. Case 4 yields the minimum initial deployment cost because the ONUsare placed at the center of their grids. For the same reason all methods have shown the minimum improvement in the value of cost function.

In the Table 3 we compare overall ability cost improvement by MFO and WOA. Although the improvements byMFO are slightly better than WOA, in a network with many wireless routers MFO is a preferred scheme of ONU deployment.

Table 4 : Comparision of overall ability cost improvement by MFO and WOA

Case	WOA Cost % Improvement	MFO Cost % Improvement
1	1.8%	2.4%
2	1.2%	3.1%
3	1.3%	2.1%
4	1.1%	1.7%

6.2 Analysis of Throughput Gain

We also measured network throughput gain by the algorithms for the initial ad optimized ONU deployments in the aforementioned cases. Network throughput is calculated by dividing the total amount of data successfully delivered to their destinations by the total time the simulation is run. simulation. Specially, we measure the throughput in terms of number of bits delivered per second (kbps).

Table 5: Simulation parameters used for this analysis

Parameter	Value
Packet Size	512 bytes
Date Rate	4 packet/sec
Traffic Type	Constant Bit Rate

Max. Communication Range	50m
Simulation Length	150 seconds

Table 4 highlights the simulation parameters used for this analysis. Figure 3 shows throughput obtained for the initial wireless router and ONU deployment. Throughput calculated is an average of 125 simulation runs over different wireless router and ONU positions as before. Figure 4 shows throughput gain for the combined ONU positioned methods (Encircling Prey Mechanism and Spiral Updating Position) in WOA for each of the cases. Similarly Figure 5 shows throughput gain obtained when MFO used for the network deployment. We implemented GCN-GAN model to predict the rapid traffic spikes and adjusted resource provisioning strategies to improve network performance. Percentage throughputs gain by each algorithm is given in Table 5. As the table shows percentage throughput gain is the maximum for MFO in case 2 ,and it further improves the throughput gain obtained by the schemes. However, it is clear from the Figure 3 that under based wireless router and ONUs deployment MFO provides the best throughput gains for the users.

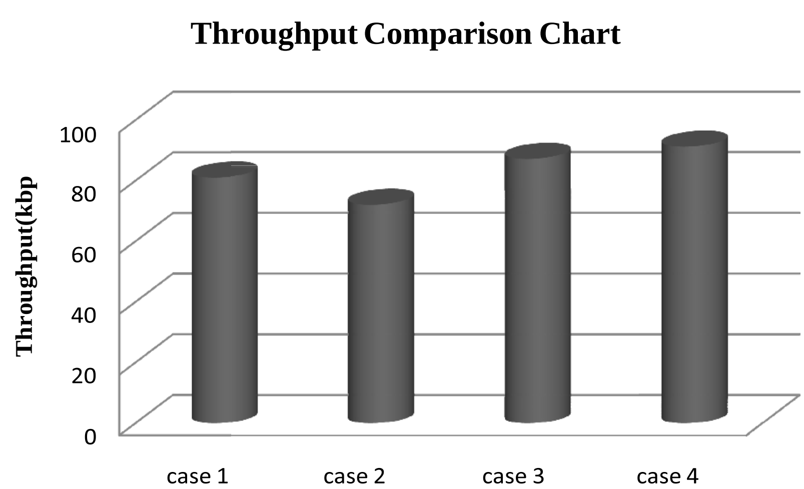

Figure 3. Throughput for the initial network deployment

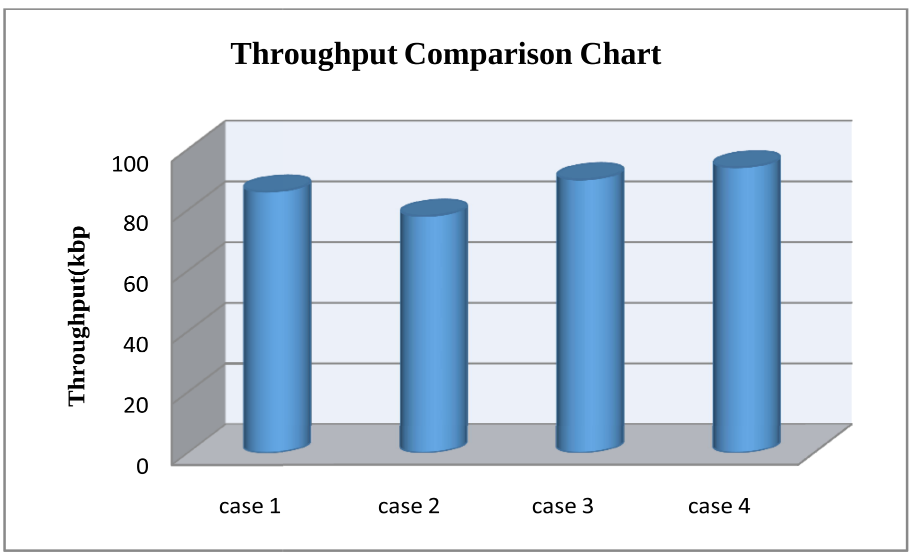

Figure 4. WOA throughput gain for the optimized network deployment

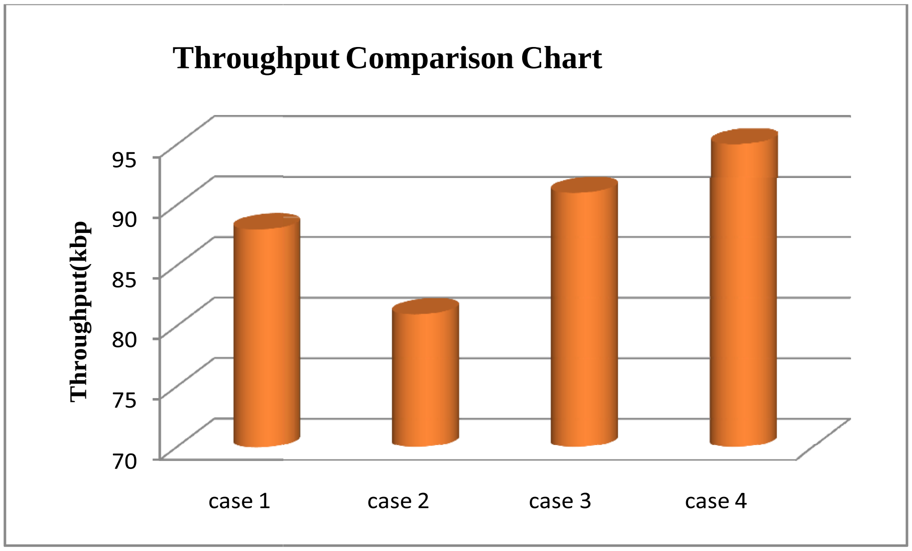

Figure 5. MFO throughput gain for the optimized network deployment

Table 6 percentage throughput gain

Case	WOA	MFO
1	6.1%	8.6%
2	8.3%	12.5%
3	3.4%	4.5%
4	3.2%	4.3%

6. Conclusion

In this paper we focused on the performance of two nature-inspired algorithms (WOA and MFO) in terms of their ability to optimize the FiWi network deployment cost. Determining Optimal ONU place ment in FiWi is a critical issue to minimization of deployment cost. In this regard, this paper attempts to evaluate of the aforementioned algorithms in terms of their ability to optimize FiWi deployment cost under four ONU placement scenarios. The results obtai ed show that both the algorithm performs well when the wireless routersand ONUs deployed under the scenario where the network is divided into equal grids. MFO in this case is the better choice since considerable i proves the deployment cost over WOA. The reason for MFOs'out performance is its ability to well balance between exploitation and exploration stages of the algorithms ascompared with WOA.

We also presented their performance in terms of throughput gain under the four cases. Throughput gains are comparatively better under grid-base network deployment of the routers and ONU as the communication distance considerably least as opposed to the other two deployment scenarios. In particular, MO has exhibited the finest throughput gain when ONU are placed at the center of the virtual grids as the deployment cost is optimal as compared to the other scenario.

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