International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

Achieving Optimal Scalability Network and Deployment Cost, and Improving Network Performance Based on Traffic Prediction in FiWi Network

Manjula Girish Emmi[1*], Nagaraju C.[2]

Submitted: 12/10/2023 **Revised**: 13/12/2023 **Accepted**: 21/12/2023

Abstract: The Fibre Wireless (FiWi) access network is a next generation (NG) access network that is designed for high data rate, broadband multiple services, scalable bandwidth, and flexible communication. The reason for the increased demand for bandwidth is due to applications that are being implemented by services such as smart grid (SG), smart cities (SC), and the Internet of Things. As a result, issues related to the planning and scalability of the communications infrastructure has become the focus of interest. Thus, there is need for designing cost-effective large–scale FiWi networks considering the rise in user groups demand for more bandwidth. This paper proposes two optimization algorithms to provide cost-effective scalability and network performance based on dynamic resource allocation for FiWi network.

Keywords: *Architecture, Fiber Wireless, Networks, Optical Network*

1. Introduction

The applications that are being implemented by services provided from smart grid (SG), smart cities (SC), and the Internet of Things (IoT) [1] require high bandwidth capability. Thus, deploying cost-effective scalable FiWi networks is utmost important. Optical and wireless access networks are two promising broad-band access technologies for high-capacity access networks and provide different levels of bandwidth [2–4]. FiWi network combines benefits of the high bandwidth capability of an optical access network with the simplicity of a wireless access network. Optical network acts as the backbone network of FiWi network providing downstream and upstream communication among end- users through Optical Network Unit (ONU) or Access Points (AP) as shown in figure 1. Access network is a part of communication network which delivers different data from the central office to multiple end-users making it a promising network structure for 5G communication’s "last mile" access [5-6].

This increasing demand for high capacity Internet is a requirement in many areas, such as resource and product management [7-9]. Although optical networks can transmit information at a high capacity, the low flexibility is the big problem in these networks that makes them inaccessible to the condition and users [10, 11]. Wireless networks, on the other hand, provide great flexibility in mobility and are useful in most situations. However, they are not suitable for data transmission over a high bandwidth environment [12,13]. Although high bandwidth wireless networks can be created, it is extremely far less than optical fibre networks [14]. Thus, a major challenge in designing future telecommunication networks involves dealing with growing user requirements for high bandwidth and network flexibility. The concerns can be effectively addressed using fibre-optic technologies over wireless networks.

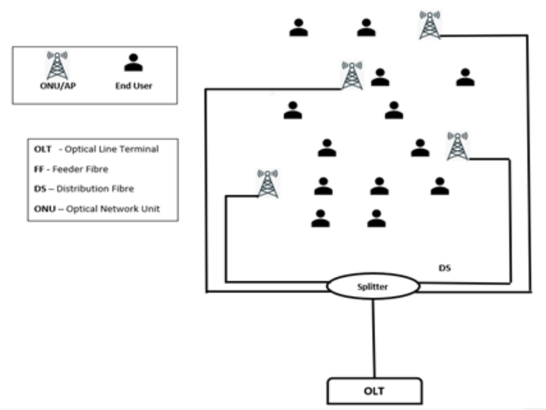

Fig 1 FiWi network structure

The IoT has emerged as a technology for information transmission and worldwide connectivity among all devices and things such as smartphones, smart TVs, medical equipment, and home appliances [15–17]. Its rapid progress over the past decade has made it an integral part of our everyday lives based on some new models and platforms such as blockchain [18-20]. Interconnected things are moving into our lives as the Internet evolves from P2P networking to social Internet and clouds [21–23]. Because of their application in large projects that require high

[1] *Department of Electronics & Communications, RN Shetty Polytechnic, Belagavi-590010.India*
[2] *Department of Electronics & Communications Engineering, The National Institute of Engineering, Mysuru - 570008, India*
Corresponding Author Email: author@email.com

bandwidth, IoT FiWi networks require bandwidth control, data transmission control, and routing control. Integration of IoT with FiWi involves two major challenges: Firstly, In order to understand the ubiquitous coverage required by IoT, it is required to redesign the network architectures for better scalability in FiWi integration. Secondly, given the diversity of connected devices in IoT and their various quality of service (QoS) requirements, another challenge is to design flexible and efficient QoS assurance schemes at the network level.

The scalability of FiWi networks refers to the capacity of a network or its potential to support increasing reach and number of users. The scalability of FiWi networks has been extensively investigated in the context of Passive Optical Networks (PONs) with special focus on LR-PON and its multithread polling-based DBA mechanisms. Horizontal scalability refers to the growth of the FiWi network over time and in conformity with the evolution and growth of users. This type of scalability involves a process that changes, evolves, and adapts automatically over time according to the addition of hardware such as base stations and fibre optic links. It does not examine the behaviour of the process in a single instant of time. It also does not guarantee capacity or capacity can be very limited. This capacity can be addressed by vertical scalability whose objective is to increase capacity without increasing the deployment cost of the communications infrastructure.

In this paper we assume the architecture given in figure 1 and present optimal scalability methods to achieve trade-off between network scalability and deployment cost. Section 2 presents a brief review on related work, sections 3 provide a methodical model for the problem, in the sections 4 and 5 we propose two network scalability methods for FiWi network, section 6 describes traffic a prediction model used to improve network performance of FiWi network, results and discussions are presented in section 7 and section 8 concludes the paper.

2. Related Work

A number of studies have focused on the electric energy reserves where the information of the data measured by leased secondary can be sent at the lowest possible price. Both cost of energy and communications are reduced by formulating a problem called cost minimization for meter data collections [24]. The authors proposed an optimal solution for the cost minimization in the selection of communication channels and a scheme for the energy delivery.

Based on the ECOSYS methodology and techno economic tool, authors in [25] presented commercial perspectives of time division multiplexing (TDM) and wavelength-division multiplexing (WDM) of PON architectures for Fibre-To-The-Home (FTTH) under different deployment conditions. Authors in [26] investigated system-of systems approach for WDM and TDM telecommunication networks for Fibre to the Home (FTTH). The work focused on the impact of adopting different deployment strategies or delaying implementations. A comprehensive methodology is applied to selected cases by the authors in [27,28] for evaluating the total cost of ownership of migration to next-generation optical access networks. The authors provided a detailed view of all the costs involved in migration.

The authors in [29] present real options theory basic concepts and provide a practical methodology to apply real options to realistic business cases in telecommunications. The reference [30] evaluates cost-benefit analysis for the deployment of a dark-fibre point-to-point infrastructure. It is revealed that it is necessary to investigate estimation methods used to evaluate the economic risk of dark fibre deployment in different environments. Moreover, the open access must be diversified in addition to quantifying installation and operation of an open access network [31].

Authors in [32–34], presented a new multi-stratum resources optimization architecture. This architecture designed to be software-defined networking to support multi-dimensional resource integration with radio over fibre networks. In order to effectively to improve radio coverage and meet the services requirement quality, the proposed architecture is designed to globally optimize radio frequency, optical spectrum, and baseband unit processing resources

3. Problem Formulation

Given a set of ONUs and a set of users requiring FiWi network services, the objective is to deploy a network that has minimum deployment cost and optimal scalability. More specifically, let $D = \{D_1, D_2, \dots, D_d\}$ be the set of d deployments created from the given set of ONUs and a set of end users $E = \{e_1, e_{2,\dots,} e_n\}$. Each deployment has its set of ONUs to provide network services their associated users. We assume that ONUs have overlapping users. We define the term scalability effectiveness (S) of a deployment as ability to network provide its services to the maximum user in E at the lowest deployment cost. We use U to denote the total number users in a particular FiWi deployment. The objective is to deploy new network with D_{new} from D such that.

$$U(D_{new}) = |E| \text{ and } S(D_{new}) \text{ is optimal} \tag{1}$$

We also define the second variation of the problem, where we assume that the network to be deployed has a constraint C_{dc} on the deployment cost. Let C denote deployment cost of a deployment. The objective is then to deploy a network D_{new} from D such that

$$C(D_{new}) \leq C_{dc} \text{ and } S(D_{new}) \text{ is optimal} \tag{2}$$

4. Optimal Scalability with Minimized Fiwi Deployment Cost.

Assuming the FiWi architecture presented in the Fig. 1, in which an end user is in the coverage of multiple ONUs/APs, we present a greedy algorithm [35], which achieves optimal scalability while minimizing network deployment cost to. We repeat the notations used in our problem formulation with , where $D = \{D_1, D_{2,\ldots,} D_d\}$ are the deployments with each deployment $D_i = \{o_1, o_2, \ldots, o_m\}$ containing m number of ONUs, and $E = \{e_1, e_2, \ldots, e_n\}$ be the n number of end users located in an area where network service is to be provide with better scalability effectiveness. Let U denote that number of users using the service from a deployment or an ONU in that deployment. Similarly, C denotes deployment cost of a network deployment or an ONU.

Each user is assumed to have the ability to utilize the services offered through multiple ONUs. We assume that each ONU $o_j \in D_i,\ 1 \le i \le d,\ 1 \le j \le m,$ is deployed with minimum deployment cost, which is calculated according to Eq. (3)

$$C(o_j) = \sum_{l=1}^{|o_j|} \sqrt{(x(l) - x(o_j))^2 + (y(l) - y(o_j))^2} \qquad (3)$$

Where $(x(l), y(l))$ is the position of a wireless router associated with that ONU and $(x(o_j)$, $y(o_j)$ is the position of i^{th} ONU. The overall deployment cost of network and the average network deployment are expressed as shown in Eq. (4) and Eq. (5) respectively

$$C(D_i) = \sum_{j=1}^{m} C(o_j) \qquad (4)$$

$$C_{avg}(D_i) = \frac{C(D_i)}{m} \qquad (5)$$

To find a D_{new} from each $D_i \in D$, The algorithm operates in an iterative manner calculating at each step the scalability effectiveness of each ONUs according to Eq(6)

$$S(o_j) = \frac{C\,(o_j)}{|E(o_j) - E(D_{new})|},\ \ if\ \ |E(o_j) - E(D_{new})| > 0$$

and

$$S(o_j) = nil,\ \ if\ |E(o_j) - E(D_{new})| = 0$$

$$\text{and} \quad 1 \le j \le m \qquad (6)$$

Next, the algorithm chooses to include in D_{new} the ONU according to Eq. (7)

$$D_{new} = D_{new} \cup \{o_j\},$$

$$where\ S\,(o_j) = Min\{S(o_1), \ldots, S(o_m)\} \qquad (7)$$

The algorithm stops iterating when $U(D_{new}) = \ |E|$

4.1. The Algorithm

Algorithm 1 shows the steps required to create a deployment network that minimizes deployment cost and maximizes scalability of the network.

Algorithm 1

Input: $D_i = \{o_1, o_2, \ldots, o_m\}$ (Initial ONUs in a i^{th} deployment.

$E = \{e_1, e_2, \ldots, e_n\}$ (Each user attached with one or more ONUs)

Output: $D_{new} = \{o_1, o_2, \ldots, o_k\},\ k \le m$ are the new ONUs that minimizes FiWi deployment cost and provides optimal scalability

Begin:

Step1: $D_{new} = \{\}$

Step2: For each $o_j \in D_i\ 1 \le i \le d,\ 1 \le j \le m,$ calculate scalability effectiveness using Eq. (6).

Let o_j be the ONU with minimum scalability effectiveness.

Step3: $O_{new} = O_{new} \cup \{o_j\}$

$O = O - \{o_j\}$

if $U(O_{new}) == |E|$ then *exit*

Go To Step 2
End

4.2. Analysis of the algorithm

We prove that Algorithm 1 gives an approximate solution for the overall deployment cost but achieves optimal scalability. Let OPT be the optimal deployment cost of the network. There n number of users in the network. Assume that $(k-1)$ users have been added to network before an iteration of the Algorithm 1. Then the cost of adding k^{th} user to the network$\le OPT/(n-k+1)$. Thus

Cost of the Algorithm 1 $<= \left(\frac{OPT}{n} + \frac{OPT}{n-1} + \ \ldots\ + \frac{OPT}{1}\right)$

$<= OPT\left(\frac{1}{n} + \frac{1}{n-1} + \ \ldots\ + \frac{1}{2} + 1\right)$

$<= OPT(logn)$

Therefore, algorithm yields an approximate FiWi deployment cost while providing optimal scalability.

5. Optimal Scalability with Constrained Fiwi Deployment Cost

This problem seeks to maximize FiWi scalability in an area where FiWi deployment cost or budget is constrained or known in advance. We use the same notations that we used in section 5. In addition to these notations, we define C_{dc} as the FiWi deployment cost known in advance. We present a dynamic algorithm [36] to find maximum network whose deployment cost does not exceed C_{dc}. Thus, the scalability effectiveness V for the first i ONUs in a deployment with $C_{dc}(i)$ as the deployment cost constraint for this instance is given in Eq. (9).

$$V(i, C_{dc}(i)) = \begin{cases} \max\left(V(i-1, C_{dc}(i)), E(o_i) + V(i-1, (i) - C(o_i)\right) & if\, C_{dc}(i) - C(o_i) \geq 0 \\ V(i-1, C_{dc}(i)) & if\ C_{dc}(i) - C(o_i) < 0 \end{cases}$$

(8)

Algorithm 2

Input: $D_i = \{o_1, o_2, \ldots, o_m\}$ (Initial ONUs)

$E = \{e_1, e_2, \ldots, e_n\}$ (Each user attached to one or more ONUs)

Output: $D_{new} = \{o_1, o_2, \ldots, o_k\},\ k \leq m$ are the set of new ONUs that provides the optimal scalability for the FiWi Network with deployment cost constraintC_{dc}.

Begin:

Step 1: for $i = 0$ to C_{dc} do $(0, i) = 0$

Step 2: for $i = 1$ to m do $(i, 0) = 0$

for $j = 1$ to C_{dc} do if $C(o_j) \leq j$ then

Compute $V(i, C_{dc}(i))$ using the max function defined in Eq. (8).

Else

$V(i, C_{dc}(i)) = V(i-1, C_{dc}(i))$

Step 3: $i = m,\ j = C_{dc}$

Step 4: if $V(i, j) > V(i-1, j)$ then $O_{new} = O_{new} \cup \{o_i\}$

$j = j - C(o_i)$

Step 5:$i = i - 1$ if $i > 0$ then Go To Step 4

End

It is obvious that the algorithm runs in $\theta(m \cdot C_{dc})$ as the storage S has $(m+1) \cdot (C_{dc}+1)$ entries.

Algorithm 2 uses Eq. (8) to present the steps required deploy the FiWi network that achieves optimal scalability for the known deployment costC_{dc}.

6. Network Performance and Resource Utilization Improvement

The future optical networks must boost their channel capacity due to the estimated exertional traffic growth. As opposed to fixed-grid spectrum allocation limit of conventional Wavelength Division Multiplexing (WDM) networks, Elastic Optical Networks (EONs) allocate appropriate-sized, optical bandwidth to an end-to end optical path. That is, EONs expand an optical Path based on traffic volume. However, without intelligent decision-making abilities of existing EONs cannot realize dynamic resource allocation. Considering peak loads for resource allocation usually leads to under-utilization and wastage of resource and increases operating expenses. Therefore, dynamic adjustment of network resources based on accurate traffic prediction in EONs is of great important to improve network performance and resource utilization.

To model traffic dynamics as an information dissemination process, researchers proposed Graph Convolution Network (GCN). GCN operates directly on a graph structure. Recent studies exploited it to capture spatial dependency in network traffic. Furthermore, its integration with Recurrent Neural Network (RNN) or Convolutional Neural Network (CNN) has shown to be very effective in taking the full advantage spatial and temporal features. The authors in [37] considered latent spatial and temporal dependency among optical network nodes and proposed GCN with the gated recurrent unit (GRU) to study the pair-wise spatial correlations between optical network nodes using a directed graph. Nodes of the graph are the switch traffic and edge weights denote the connections among the nodes. In this paper, we use GCN-GRU model to improve network performance and resource utilization based on accurate traffic prediction in optical network. This uses GCN-GRU model to improve FiWi network performance through better resource utilization.

Fig. 2 shows the components and the steps of the GCN-GRU model. As shown in the Figure, the model comprises three layers namely, a GCN layer, a GRU layer, and an output layer sequentially. GRU captures trends in traffic through time steps simultaneously. That is, it can capture spatiotemporal dependencies among time series and apply to various multiple-nodes time series prediction tasks. With help of back propagation through time, the model maximizes the likelihood of generating the target future time series to train the entire framework. With spatial and temporal dependency modelling, model has found to consistently achieve satisfactory accuracy when evaluated on various real-time traffic load.

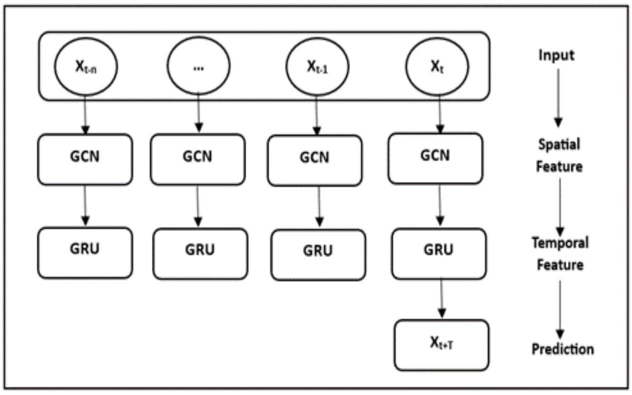

Fig 2. Working of GCN-GRU model

7. Results and Discussion

We consider the initial FiWi network with randomly deployed nodes (users) in 1000 × 10000 sq. meter area. From the given set of ONUs and end users, we randomly deploy FiWi networks each with minimum deployment cost which is calculated as explained in [*]. It is also assumed that ONUs includes overlapping users in the network. We apply Algorithm 1 to each network to create a new network deployment that has the optimal scalability and minimized deployment cost; that is, the deployment for the resulting network is minimized as much as possible with respect to the initial deployment cost. The algorithm does this by finding scalability effectiveness of each ONU and selects the with minimum scalability effectiveness. We monitor behaviour of the algorithm by deploying networks of different sizes.

As mentioned in the problem, we create $D = \{D_1, D_2, \dots, D_d\}$ containing a set of d different deployment from the given ONUs and end users in E. As before, we use C to denote cost for a deployment, and S denote the scalability effectiveness. Let N be the number of ONUs in the resulting deployment. For Algorithm 1, we measure the total scalability effectiveness of the resulting deployment according Eq. (9). The smaller this value the better the network deployment cost.

$$S(D_{new}) = \sum_{i=1}^{k} S(o_i)\,, o_i \in D_{new} \text{ and } k = |D_{new}| \quad (9)$$

Algorithm 2 aims to find optimal scalability with the known deployment cost. This is useful in a region that has restricted infrastructure cost and requires the network service to be exposed to the maximum users. Scalability effectiveness here indicates the ability to provide network services to the maximum users in the region, where the maximum deployment cost in known. In this case, we first measure network deployment cost constraint (C_{dc}) as 75% of average of total cost of all deployments which is given by the Eq. (10). The scalability effectiveness (S) is calculated as the ratio of C_{dc} to the total number of users in the network as shown in Eq (11). For the convenient of measuring scalability effectiveness, it is assumed that each user is associated with a single ONU in each deployment. SD denotes the scalability difference of scalability effectiveness of a deployment and resulting deployment. Smaller this value better the scalability of the resulting deployment.

$$C_{dc} = \left(\frac{\sum_{i=1}^{d} C(D_i)}{d}\right) \times 0.75 \quad (10)$$

$$S = \frac{C_{dc}}{NS},\ NS = network\ size \quad (11)$$

The Table 1 shows the simulation parameters used to monitor the behaviour of the two algorithms. Table 2 shows the results obtained from Algorithm 1 for network containing 100 users. We run the algorithm for five different network each deployed with 10 ONUs as shown in the Table 2. We use D_{new}^{i} to denote the resulting deployment from the deploymentD_i. The resulting network from the deployment D_5 has the best scalability effectiveness, which means that the deployment can provide network services to all users at the lowest cost possible and has requires only 50% of the total ONUs be installed to achieve this. For D_1 and D_4 , any one of the resulting deployments be considered for deployment as their final deployment cost is the same, although they have different S values. The deployment D_2 has the highest resulting deployment cost with its S being maximum of all. It is obvious from the table that given network with its deployment cost, S value is directly proportional to its resulting deployment cost.

Table 1. Simulation parameters

Parameter	Value
Network area	1000×1000 sq. meter
Network size	100, 200
No. of ONUs for a deployment	10
Number of randomizations	25
Deployment cost constraint	C_{dc}
Number of deployments	5

Table 2. Results of Algorithm 1 for network size=100

D	$C_{avg}\ (D_i)$	$C_{avg}(D_{new}^{i})$	$N(D_{new}^{i})$	$S(D_{new}^{i})$
D_1	195	190	7	167.7
D_2	228	220	7	215.6
D_3	219	212	7	185.4
D_4	206	190	7	161.7
D_5	214	182	5	63.3

Table 3. Shows the results obtained from deployments where the network size is 200 and has the same number of initial ONUs as before. Although the deploymentsD_2 , D_4 and D_5 have the same number of OUNUs with D_2 being the deployment with lowest S values, we choose to consider D_5 because of its resulting deployment cost compared to the initial deployment cost. Similarly, it is very clear from the table that between D_2 andD_4, D_4 is to be preferred considering the extent to which the original cost is reduced. In the case of D_1 andD_3 , scalability is achieved with 8 ONUs for D_1 and its resulting network has better deployment cost thanD_3 . Thus, we choose to use the resulting deployment fromD_1.

Table 3. Results of Algorithm 1 for network size=200

D	$C_{avg}\ (D_i)$	$C_{avg}(D_{new}^i)$	$N(D_{new}^i)$	$S(D_{new}^i)$
D_1	223	218	8	85.1
D_2	241	230	7	72.2
D_3	228	222	9	123.7
D_4	227	213	7	79.9
D_5	210	191	7	75.1

Table 4. Performance of Algorithm 2 for $NS = 100$ and $C_{dc} = 1167$

$\boldsymbol{D}$	$\boldsymbol{C(D_i)}$	$\boldsymbol{N(D_{new}^i)}$	$\boldsymbol{C(D_{new}^i)}$	$\boldsymbol{S(D_i)}$	$\boldsymbol{S(D_{new}^i)}$	$\boldsymbol{S_d}$
D_1	1263	5	1076	11.67	13.58	-1.90
D_2	1471	5	1083	11.67	14.97	-3.29
D_3	1529	6	1136	11.67	13.58	-1.90
D_4	1777	5	1067	11.67	15.99	-4.32
D_5	1743	7	1166	11.67	15.56	-3.89

Table 4. shows results obtained from the Algorithm 2 for a network of size 200 with different deployments. We keep the same number of ONUs for each deployment as before. In table 4. and table 5. $C(D_i)$ and $C(D_{new})$ indicate the total deployment cost of D_i and the resulting deployment from D_i . $S(D_i)$ and $S(D_{new}^i)$ is the scalability effectiveness of D_i and the resulting deployments from D_i , whose values are computes using Eq. (11). Note that $S(D_i)$ is the same for all deployments as shown in the table 4., since the network size remains the same for all deployments. S_d is the new difference between $S(D_i)$ and $S(D_{new}^i)$. That is, $S_d = S(D_i) - S(D_{new}^i)$. Deployment cost constraint $C_{dc} = 1167$ is calculated using Eq. (10).

The most acceptable resulting deployment out of five deployments can be decided by looking at the value of S_d. The objective of the algorithm is to achieve a value for S_d that is closer to 0. In other words, maximizing the value of S_d means that maximizing the number of users to have network services within a known network deployment cost. Thus, the resulting deployments D_{new}^1 and D_{new}^3 should be considered as they have the best scalability effectiveness for the given set of deployments. However, the deployment cost of the D_{new}^1 is considerably lower than the deployment cost of the D_{new}^3 . Thus, D_{new}^1 is preferred to D_{new}^3 when we consider the cost minimization. The deployment D_{new}^4 has the worst scalability effectiveness although its deployment cost is notably smaller as compared with $\boldsymbol{C_{dc}}$ and it is the least among all deployment cost. This means that at this cost it can provide network services to the least numbers of end users.

Table 5. shows scalability effectiveness values for deployments with network size 100 and the deployment constraint$C_{dc} = 1317$. The deployment D_{new}^1 achieves the maximum scalability effectiveness at the cost of 1214, which makes it most preferred network deployment to offer network services to its users. The deployment D_{new}^4 achieves the lowest deployment cost; however, at this cost it can provide network services to the least number of users as compared with other deployments.

Table 5. Performance of Algorithm 2 for $NS = 200$ and $C_{dc} = 1317$

$\boldsymbol{D}$	$\boldsymbol{C(D_i)}$	$\boldsymbol{N(D_{new}^i)}$	$\boldsymbol{C(D_{new}^i)}$	$\boldsymbol{S(D_i)}$	$\boldsymbol{S(D_{new}^i)}$	$\boldsymbol{S_d}$
D_1	1428	5	1214	6.59	7.36	-0.77
D_2	1637	5	1136	6.59	8.18	-1.60
D_3	1784	6	1272	6.59	8.39	-1.80
D_4	1918	6	1124	6.59	9.35	-2.76
D_5	2018	6	1270	6.59	9.09	-2.50

As mentioned previously, to improve network performance during peak loads and reduce operating expenses in FiWi network, we use GCN-GRU model to predict spikes in the traffic to achieve efficient resource utilization. We consider the best network selected using Algorithm 1 and use GCN-GRU to improve its performance under burst traffic. We use ns2 simulator to generate burst traffic and analyse throughput analysis to understand the ability of the network to operate under large spike in traffic followed by a small decline and then a additional, higher-traffic burst. Table 6 shows the simulation parameters for this experimental setup.

Table 6. Simulation Parameters

Parameter	Value
Network Size	1000×1000 sq. meter
Number of wireless routers	100
Packet size	100KB
Burst Time	2s
Idle Time	1s
Data rate	100 to 500Kbps
Number of randomizations	25

Burst times and idle times mentioned in the table are taken from exponential distributions. We measure the percentage of data received by all users in the network every 60secs for different data transmission rates. We call this measure utility of the network as shown in the Fig. 3.

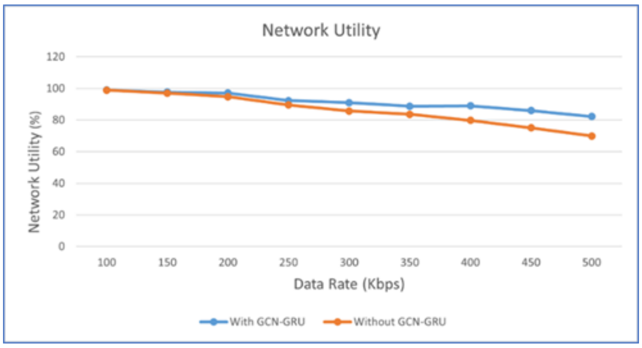

Fig 3. Network Utility for peak loads.

8. Conclusion

Providing FiWi services to the maximum users in an area is as important as deployment that network at the minimum cost. We prefer to use the network that provides services to the maximum possible users at the lowest possible network cost. In this paper we proposed two algorithms address this important problem, where the first algorithm ensures providing services to every user at the minimum possible cost of network deployment. The second algorithm ensures that network deployment cost does not exceed a certain limit while focusing on providing services to the maximum users. The experimental results from Algorithm 1 show that the focus must be on reducing deployment cost as the maximum scalability is always ensured. In other words, we always prefer the deployment with lowest cost irrespective of its scalability values. In the case of Algorithm 2, results show that the focus must be on maximizing network service as resulting cost is bounded by certain upper limit on deployment cost; however when the deployment costs are equal, we must prefer the deployment that has maximum scalability effectiveness value.

References

[1] P. Branchi, I. Matías, and C. Fernández, "City & technology: An analysis matrix to serve citizens," in Int. Conf. on New Concepts in Smart Cities: Fostering Public and Private Alliances (SmartMILE), pp. 1–5, Dec. 2013.

[2] W. Shaw, S. Wong, N. Cheng, K. Balas, X. Zhu, M. Maier, L. Kazovsky, Hybrid architecture and integrated routing in a scalable optical-wireless access net-work, *J. Light wave Technol.* 25 (11) 3443–3451, (2007).

[3] C. Lim, A. Nirmalathas, M. Bakaul, P. Gamage, K. Lee, Y. Yang, D. Novak, R.Waterhouse, Fiber-wireless networks and subsystem technologies, *J. Light-wave Technol.* 28 (4) 390–405. (2010).

[4] A. Reaz, V. Ramamurthi, S.B. Sarkar, D.G. Mukherjee, Hybrid wireless-optical broadband access network (WOBAN): capacity enhancement for wireless access, in: *Proceedings of IEEE Global Telecommunication Conference*, 2008.

[5] U. R. Bhatt, A. Chhabra, and R. Upadhyay, "Fiber-wireless (Fi-Wi) architectural technologies: A survey," *in Int. Conf. on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, Mar. 2016, pp. 519–524.

[6] A. D. L. Oliva, X. C. Perez, A. Azcorra, A. D. Giglio, F. Cavaliere, D. Tiegelbekkers, J. Lessmann, T. Haustein, A. Mourad, and P. Iovanna, "Xhaul: Toward an integrated fronthaul/backhaul architecture in 5G networks," *IEEE Wireless Commun.*, vol. 22, no. 5, pp. 32–40, Oct. 2015.

[7] Qiao, H., Gan, C., Yan, Y., & Li, X. Tg-minimised bandwidth-allocated scheme for multi subsystem-based VPON in metro-access optical network. *IET Communications*, 13(9), 1192–1199 (2019).

[8] S. Vahdat, The role of IT-based technologies on the management of human resources in the COVID-19 era. Kybernetes (2020).

[9] Zhang, Z., Liu, S., & Niu, B. Coordination mechanism of dual-channel closed-loop supply chains considering product quality and return. *J Clean Prod*, 248, 119273 (2020)..

[10] Shao, Q., Zhao, Y., Chen, Y., & Gan, C. High-reliability grid architecture supporting discretionary and efficient communication between ONUs in metro-access optical network. *Int. J Commun Sys*, 32(14), e4086,(2019).

[11] Gong, C. S. A., Chang, C. H., & Tsou, Y. L. Fully integrated 2.45-GHz OOK receiver for wireless sensor networks. *Int. J Cir Theo Appl*, 44(11), 1926–1941(2016).

[12] Jiang, Q., Kumar, N., Ma, J., Shen, J., He, D., & Chilamkurti, N. A privacy-aware two-factor authentication protocol based on elliptic curve cryptography for wireless sensor networks. International *J Net Manage*, 27(3), e1937(2017).

[13] Roy, A., & Sarma, N. Multichannel ordered contention MAC protocol for underwater wireless sensor networks. *The Comp J*, 64(2), 185–194(2020).

[14] Sun, L., Li, C., Zhang, C., Liang, T., & Zhao, Z. The strain transfer mechanism of fiber Bragg grating sensor for extra-large strain monitoring. *Sensors*, 19(8), 1851(2019).

[15] Lv, Z., Qiao, L., & Song, H. Analysis of the security of internet of multimedia things. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 16(3), 1–16(2020).

[16] Lv, Z., Lou, R., Li, J., Singh, A. K., & Song, H. Big data analytics for 6G-enabled massive internet of things. *IEEE Inter Thing J*, 8(7), 5350–5359 (2021).

[17] Hajiheidari, S., Wakil, K., Badri, M., & Navimipour, N. J. Intrusion detection systems in the Internet of things: A comprehensive investigation. *Comp Net*, 160, 165–191(2019).

[18] Yu, Z., Song, L., Jiang, L., & Sharafi, O. K. Systematic literature review on the security challenges of blockchain in IoT-based smart cities. Kybernetes. (2021).

[19] Li, B., Liang, R., Zhou, W., Yin, H., Gao, H., & Cai, K.. LBS meets blockchain: An efficient method with security preserving trust in SAGIN. *IEEE Inter Thing J* (2021).

[20] Sheng, H., et al. Near-online tracking with co-occurrence constraints in blockchain-based edge computing. *IEEE Inter Thing J*, 8(4), 2193–2207(2020).

[21] Sharma, G., & Kalra, S. A lightweight user authentication scheme for cloud-IoT based healthcare services. Iranian Journal of Science and Technology, *Trans Elec Engg*, 43(1), 619–636. (2019).

[22] Lv, Z., Qiao, L., Li, J., & Song, H. Deep-learning-enabled security issues in the internet of things. *IEEE Inter Thing J*, 8(12), 9531–9538(2020).

[23] Jahantigh, M. N., Rahmani, A. M., Navimirour, N. J., & Rezaee, A. J. I. C. Integration of internet of things and cloud computing: A systematic survey. *IET Commun*, 14(2), 165–176, (2019).

[24] P. Li, S. Guo, and Z. Cheng, "Joint optimization of electricity and communication cost for meter data collection in smart grid," *IEEE Trans. Emerging Top. Comput.*, vol. 1, no. 2, pp. 297–306, Dec. 2013.

[25] T. Rokkas, D. Katsianis, T. Kamalakis, and D. Varoutas, "Economics of time and wavelength domain multiplexed passive optical networks," *J. Opt. Commun. Netw.*, vol. 2, no. 12, pp. 1042–1051, Dec. 2010.

[26] R. Yu, Y. Zhang, and Y. Chen, "Hybrid spectrum access in cognitive neighborhood area networks in the smart grid," *in IEEE Wireless Communications and Networking Conf. (WCNC)*, pp. 1478–1483 Apr. 2012,.

[27] C. M. Machuca, M. Kind, K. Wang, K. Casier, M. Mahloo, and J. Chen, "Methodology for a cost evaluation of migration toward NGOA networks," *J. Opt. Commun. Netw*, vol. 5, no. 12, pp. 1456–1466, Dec. 2013.

[28] F. Phillipson, C. Smit-Rietveld, and P. Verhagen, "Fourth generation broadband delivered by hybrid FTTH solution—A techno-economic study," *J. Opt. Commun. Netw*, vol. 5, no. 11, pp. 1328–1342, Nov. 2013.

[29] M. Tahon, S. Verbrugge, P. J. Willis, P. Botham, D. Colle, M. Pickavet, and P. Demeester, "Real options in telecom infrastructure projects—A tutorial," *IEEE Commun. Surv. Tut*, vol. 16, no. 2, pp. 1157–1173, 2014.

[30] M. V. der Wee, S. Verbrugge, M. Tahon, D. Colle, and M. Pickavet, "Evaluation of the techno-economic viability of point-to-point dark fiber access infrastructure in Europe," *J. Opt. Commun. Netw*, vol. 6, no. 3, pp. 238–249, Mar. 2014.

[31] M. V. derWee, K. Casier, A. Dixit, B. Lannoo, S. Verbrugge, D. Colle, and M. Pickavet, "Techno-economic evaluation of open access on FTTH networks," *J. Opt. Commun. Netw*, vol. 7, no. 5, pp. 433–444, May 2015.

[32] H. Yang, J. Zhang, Y. Ji, Y. He, and Y. Lee, "Experimental demonstration of multi-dimensional resources integration for service provisioning in cloud radio over fiber network," *Sci. Rep*, vol. 6, 30678, July 2016.

[33] H. Yang, J. Zhang, Y. Ji, and Y. Lee, "C-ROFN: Multi-stratum resources optimization for cloud-based radio over optical fiber networks," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 118–125, Aug. 2016.

[34] H. Yang, Y. He, J. Zhang, Y. Ji, W. Bai, and Y. Lee, "Performance evaluation of multi-stratum resources optimization with network functions virtualization for cloud-based radio over optical fiber networks," *Opt. Express*, vol. 24, no. 8, pp. 8666–8678, Apr. 2016.

[35] Chandra Chekuri, "Approximation Algorithms: Covering Problems", https://courses.engr.illinois.edu/cs583/sp2018/Notes/covering.pdf, January 19 2018.

[36] P. Xiaohui and Z. Tao, "Comparison and Analysis of Algorithms for the 0/1 Knapsack Problem", *IOP Conf. Series: Journal of Physics: Conf. Series* 1069 (2018) 012024, doi :10.1088/1742-6596/1069/1/012024

[37] G. Yihan, W. Danshi, G. Luyao, Z. Min, "Optical Network Traffic Prediction Based on Graph Convolutional Neural Networks", *Opto-Electronics and Communications Conference (OECC)* , 2020.