Backhauling-as-a-Service (BHaaS) for 5G Optical Sliced Networks: An Optimized TCO Approach

Nassim Haddaji, Abdolkhalegh Bayati, Kim-Khoa Nguyen, and Mohamed Cheriet

***Abstract*—Due to their initial over-estimation of demand, many network operators are over-provisioning their infrastructure. Over-designed networks vastly increase operational costs without generating expected revenues. In particular, high density cell architecture in future 5G networks will face big technical and financial challenges due to avalanche of traffic volume and massive growth in connected devices. Planning scalable 5G Mobile Back-Haul (MBH) transport networks becomes one of the most challenging issues. However, existing planning solutions are no longer appropriate for coming 5G requirements. New 5G MBH architecture emphasizes on multi-tenancy and network slicing which requires new methods to optimize MBH Planning resource utilization. In this paper, we introduce an algorithm based on a stochastic geometry model (Voronoi Tessellation) to define backhauling zones within a geographical area and optimize their estimated traffic demands and MBH resources. Then, we propose a novel method called BackHauling-as-a-Service (BHaaS) for network planning and Total Cost of Ownership (TCO) analysis based on "You-pay-only-for-what-you-use" approach. Finally, we enhanced BHaaS performance by introducing a more service-aware method called Traffic-Profile-as-a-Service (TPaaS) to further drive down the costs based on yearly activated traffic profiles. Results show BHaaS and TPaaS may control and enhance 22% of the project benefit compared to traditional TCO model.**

***Index Terms*—5G, Optical Mobile Backhaul, Voronoi, BHaaS, TPaaS, CAPEX, OPEX, TCO, ROI, Traffic Profiles.**

I. Introduction

THE coming 5^{th} generation of mobile networks expected in 2020 is bringing new challenges to network architecture of Mobile Network Operators (MNO). Future 5G technology is more service aware offering applications with very strict requirements. An exponential growth in traffic demand and the number of connected devices is leading to high network costs and scalability challenges. Small cell technology is emerging with a very high density (may reach up to 1500 cells per km2 in coming years including femtocells as highlighted by [1]). MNOs started re-thinking the architecture of their networks in order to connect the increasing number of small cells while keeping the costs as low as possible [2].

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Coming 5G technology is bringing new requirements that will drive the transformation of the entire network from last-mile and access layers, to backhaul and aggregation and up to core and control layers. Together with front-hauling, Mobile BackHaul network (MBH) represents main challenges (33% of the entire 5G challenges as per [3]). Due to high cost of implementation, expansions and operations, MBH is contributing more than 50% to future small cell networks expenditures [4]. More efficient and innovative planning and design tools are required to control the costs of deploying new MBH projects as well as expanding already existing networks. Total Cost of Ownership (TCO) analysis is a critical step in the planning and validation of entire project life-cycle expenses. It allows making optimal decisions for acquiring, deploying, activating and operating of intended assets and infrastructure resources. TCO is calculated by adding initial CAPEX (CAPital EXpenditure) to five years OPEX (OPeration EXpenditure) based on published prices from the industry. Several solutions are being investigated to reduce new 5G MBH TCO. They either try to adapt and take advantages of traditional transport networks (e.g. microwave, copper and optical fiber) or to evolve into new introduced software-based technologies that may drop costs of network deployment [5] [6].

Wireless technologies like massive MIMO (Multi-Input-Multi-Output) antenna, visible light communication and millimeter-Wave (mmW) are actual technologies that will be adopted in 5G MBH, although some of these solutions are preferred in rural areas. For many operators, optical fiber technology remains preferable solution for 5G MBH thanks to its unlimited capacities, long reach, high performance and low latency. Particularly, Passive Optical Network (PON) technology and its variants are emerging as a low-cost MBH solution [7]. Among current optical technologies, like tree, mesh, and ring, optical rings are preferable choice for long distance MBH thanks to high reliability and scalability for big networks [10]. Optimal planning of optical MBH networks is a high complexity problem due to very high density and random architecture of 5G networks as well as the variety of 5G traffic profiles [11]. Massive expansions and replacing existing microwave links by fiber are very costly solutions. Excessive procurement of unused devices, modules and interfaces shall be avoided unless imminent activation is required. Uncontrolled deployment, expansion and operation costs of such huge MBH raises initial costs and long-term TCO. This may result in bottlenecks that affect network scalability and reliability [1]. Thus, efficient planning of scalable and profitable MBH is required. Innovative MBH solutions and more accurate estimations of CAPEX and OPEX are substantial to optimize network TCO and improve its scalability.

In this paper, we propose a novel TCO analysis method that can be implemented as a decision-helping module within optical MBH network planning tools to optimize MBH resource distribution and activation time over project lifetime based on estimated traffic demand and generated revenues. Our main contributions are following:

1) A comprehensive CAPEX and OPEX calculation model for optical MBH networks.
2) A novel TCO analysis BackHauling-as-a-Service (BHaaS) method based on ”You-pay-only-for-what-you-use” to optimize yearly planned installation and activation of resources based on estimated traffic demands and generated revenues.
3) An advanced Traffic-Profile-as-a-Service (TPaaS) method that further optimizes TCO based on planned activation time and costs of traffic profiles.
4) A novel algorithm based on Voronoi Tessellation stochastic geometry algorithm to define backhauling zones within a geographical area and optimize their estimated traffic demands.

The remainder of the paper is organized as follows. The related work on 5G MBH cost optimization is reviewed in Section II. Problem statement and research framework are defined in Section III. Proposed solutions including TCO formulation, BHaaS and TPaaS models and a Voronoi based algorithm are presented in Section IV. Performance evaluation is presented in Section V. Finally, we conclude the paper and present future work.

II. Related work

A. 5G MBH Solutions: TCO approach

Several technologies and techniques are proposed in the literature to plan efficient 5G MBH with reduced long-term TCO [13]. Fig. 1 summarizes wireline approaches discussed in this section. [14] and [15] emphasize on the novel concept of Crosshaul (Xhaul) as a cost-effective architecture. Xhaul architecture is defined by integrating 5G backhaul and fronthaul transport networks for flexible and heterogeneous transmission links. Different network architecture (tree, ring, etc) are integrated in a unified Xhaul packet Forwarding Element (XFE) and controlled by a central processing unit to reduce CAPEX and OPEX. [16] proposes a TCO comparison between wireless and fiber technologies in 5G fronthaul and backhaul solutions which shows that fiber is more cost effective than wireless in high density areas (less than 1 km spacing distance between adjacent eNodeBs).

From evolving fiber solutions perspective, [7] discusses advantages of PON technology in reducing up to 60% of 5G MBH cost. Traffic is collected by Edge Transport Nodes (ETN) and forwarded to Aggregation Transport Nodes (ATN) using the optimized fiber routes, locations of splitters, and number of ports. [9] adopts spectral-efficient OFDM (Orthogonal Frequency Division Multiplexing) modulation technique and proposes an Optical Distribution Network (ODN) sharing scheme based on existing PON infrastructure to avoid deploying new fiber cables. [8] applies K-means clustering and a multi-stage access nodes strategy with shared cable ducts and introduces a cost-effective solution based on TWDM-PON (Time and Wavelength Division Multiplexed PON) to optimize cost of dense 5G MBH. These solutions assume all OLTs covering the whole geographical area are co-located in a single Central Office (CO). Several cost modeling and optimization methods have been presented for optical network TCO analysis. [17] proposes CAPEX and OPEX cost modeling and a MILP (Mixed Integer Linear Programming) optimization method for large scale mesh networks based on column generation techniques and a rounding off heuristic. [18] introduces a comprehensive TCO evaluation model for small cells MBH by identifying critical cost drivers affecting CAPEX and OPEX. [19] proposes a MILP model to minimize CAPEX for multi-chassis routers and multi-rate line cards in IP over optical networks. Their proposed optimization is limited to initial (day one) CAPEX calculation while OPEX was not considered.

Nevertheless, cost calculation models in prior work are driven by initial estimated hardware quantity and prices. Costs of basic equipment and related modules (subrack, management and power modules, switching fabric, user interfaces, etc) are all considered in the initial cost calculation even before they actually carry traffic and generate revenue. Their TCO models do not scale with the growth of service and generated ROI (Return On Investment). Continuous expansion of MBH physical networks based on current cost models will drastically increase network TCO for future very high density 5G networks. Innovative planning tools based on dynamic activation, pay-as-you-grow pricing and yearly distribution of traffic demand need to be developed to avoid over-provisioning infrastructure. This will help split project costs over several years and avoid high kick-off project budgets. Moreover, costs of various service-aware traffic profiles have to be taken into account according to different end-user Service Level Agreements (SLA) and generated revenues.

B. Multi-tenancy and Network slicing in 5G MBH

Multi-tenancy and network slicing are novel approaches to offer service-aware and cost-efficient 5G networks. [20] emphasizes on the importance of integrating recent SDN (Software Defined Networking) and NFV (Network Function Virtualization) concepts in optimizing 5G MBH resources and saving up to 14% of CAPEX. [6] presents infrastructure multi-tenancy within 5G SESAME project by sharing the physical resources among various MNOs, service providers and Over-the-Top (OTT) users. [15] presents a network slicing solution based on dynamic partitioning and sharing physical resources among several virtual networks. [21] introduces the concept of hierarchical Network Slicing as a Service (NSaaS) where customized end-to-end network slices are offered to MNOs as a service with enhanced slice management and quality assurance mechanisms. [23] discusses requirements of coming applications and services in 5G era and propose a

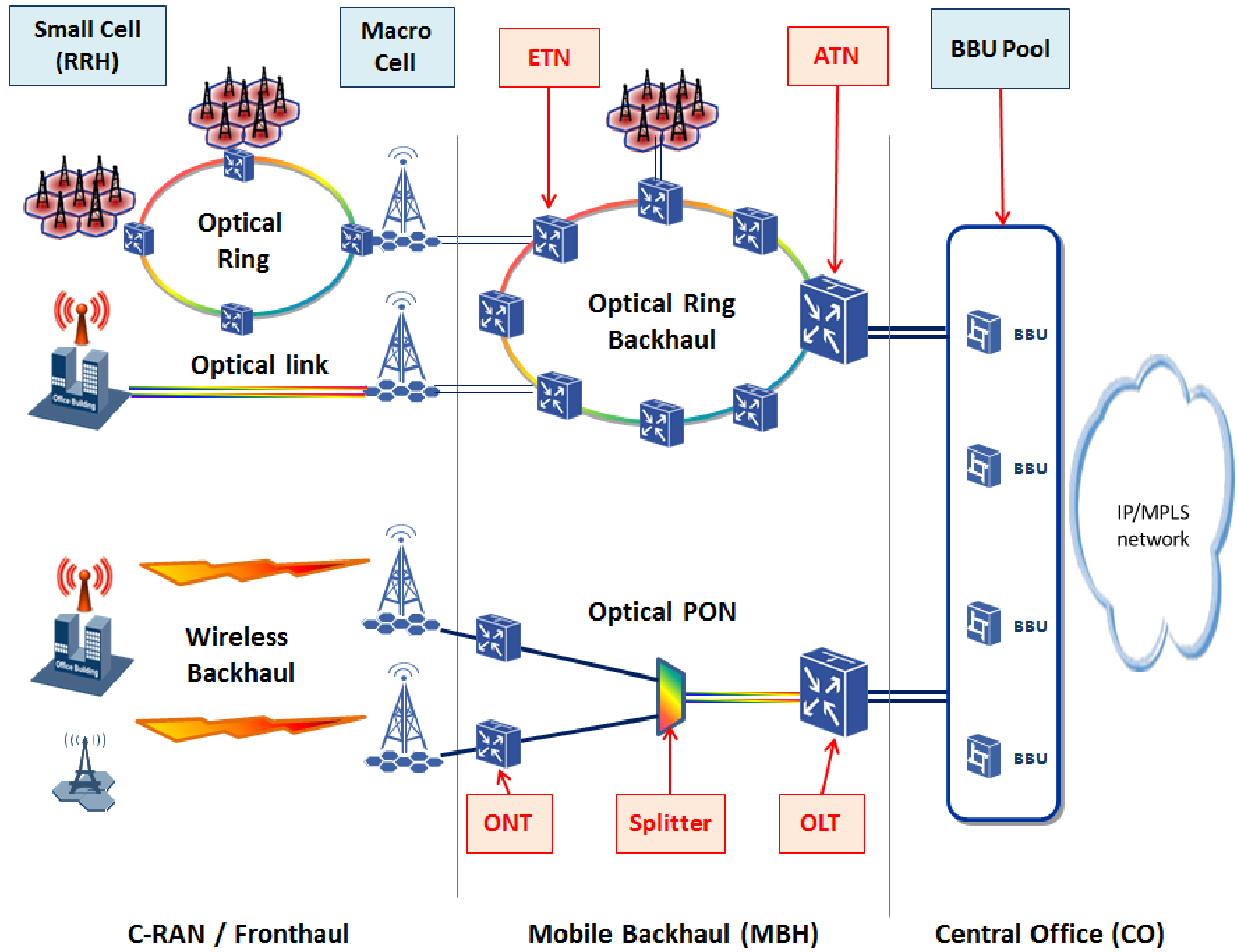

Fig. 1: Crosshaul network architecture (Fronthaul + Backhaul) for future 5G mobile networks.
ETN : Edge Transport Node, ATN : Aggregation Transport Node

new mechanism for multiple slicing based on required service type. [22] defines six unique traffic profiles based on NetFlow, cluster analysis and users application usage trends for future networks monitoring, policy enhancement and anomaly detection. Nevertheless, these solutions are not considered in TCO analysis. They rather rely on deterministic connectivities with static resource allocations and service-agnostic pipes. Resources are transparently allocated regardless of service SLAs and revenues. The pricing of traffic profiles is not considered in the costs of user interfaces and results in unfairness in TCO calculation. A wiser and more adaptive service-aware resource activation should be defined to reduce CAPEX and OPEX and enhance 5G network scalability.

III. Problem Statement and System Definition

In this paper, we consider the scenario in which a Telecom Service Provider (TSP) is planning an optical transport network to offer MBH connectivity services to a number of MNOs by leasing separate network slices. The goal is to minimize the costs of acquisition and deployment of the new MBH network, both in terms of CAPEX and OPEX, and maximize revenues (ROI). This will be achieved through TCO analysis which results in an optimized plan for demand distribution over time. We defined in a previous work [12] a traditional TCO calculation model used by current TSPs to estimate CAPEX and 5-years OPEX of the optical MBH. Proposed BHaaS and TPaaS models in this paper calculate optimal costs ahead of the network installation phase. Traffic demand is specified by the customers for the total project lifetime (for instance, 5 years). This demand cannot be reduced. However, it can be estimated more precisely through an efficient partition of backhauling zones defined by the location of the ATNs. The proposed models distribute this demand over project years to optimize the total cost. No network element is installed but only planned in this TCO analysis phase. CAPEX and OPEX of these elements will be added to their total cost of activation when they are really selected by BHaaS/TPaaS to be provisioned. The models result in no pre-installed device which is not yet active. User traffic demand which does not generate immediate revenue will be postponed later to a subsequent year when its ARPU (Average Revenue Per User) becomes positive.

ATNs are usually co-located within COs with mobile controllers (BSC, RNC, MME/SGW and coming 5G BBU pools) [11]. The number and locations of COs are given by TSP. Traffic demand is collected from small cell towers by ETNs and aggregated in dual-homed ATNs. Input parameters and decision variables are respectively detailed in Tables I and II. ATN and ETN CAPEX includes basic hardware cost (chassis, switching, power and management modules, deployment fees, etc) while their OPEX includes basic operation costs (RTU Right-to-Use and licensing keys, spare parts and warranty, managed services and maintenance costs, etc). TSPs usually plan and build required fiber cables prior to equipment installation phase. Whenever required, newly installed hardware equipment are connected to free pairs of fiber within shared fiber cables (for instance, 144 pairs of fiber per each cable) [7].

We focus first on ring-based optical MBH use case presented in Fig. 2 as a more reliable and scalable solution for long distance optical networks then we validate our work on low-cost PON-based networks. The proposed TCO model is applied for PON networks by substituting ATNs by OLTs and ETNs by ONTs as shown in Fig. 1 and in Section III-A.

A. *Proposed Backhauling-as-a-Service (BHaaS) method*

[1] introduced the concept of Backhaul-as-a-Service (BHaaS) as a consolidated vision for self-optimized 5G backhaul. Recent backhaul technologies are combined under the holistic control and coordination of centralized SDN intelligence. Real-time network data is dynamically retrieved from multiple MNO networks and adapted actions are pushed to underneath network infrastructure. Massive devices, modules and interfaces (ports) are often running in several TSP networks without carrying traffic. They are usually deployed since day one (as initial CAPEX) and continue consuming space, power and maintenance fees (OPEX) without generating any revenue. We propose a Backhauling-as-a-Service (BHaaS) cost modeling method to optimize the network TCO and improve the project benefit. BHaaS is based on You-pay-only-for-what-you-use approach to help TSP analyze and validate, among others, his financial capability to build, operate and serve his customers within his limited budget (defined as a constraint in the optimization model). TCO and ROI are optimized for every year of the project runtime based on estimated Total Traffic Demand (TTD), hardware manufacturers yearly UPLs (User Price Lists) and yearly maximum assigned budget. The proposed model plans *a priori* the optimal time when equipment has to be purchased and activated to afford demand. No cost is registered until the moment when the equipment is actually acquired and activated. Installation cost will be added to the total cost of activation. BHaaS distributes the deployment time of devices on yearly basis based on TCO and ROI optimization. If a resource cannot improve TCO, then BHaaS will postpone its activation to future date after the first year to maximize the benefits. In any case, the total demand will be completely afforded when the project ends. As a result, BHaaS concept helps TSPs to:

- define the optimal time to kick-off the MBH project and when to purchase, commission and activate devices to fully satisfy traffic demand.
- prioritize traffic demands that actually generate revenues. Best-effort traffic with low income may be postponed to next year.
- avoid over-designed and unnecessary activated resources.
- optimize kick-off budget in the first year by fairly distributing the total project budget over all project implementation years.

B. *Proposed Traffic-Profile-as-a-Service (TPaaS) method*

In prior network TCO analysis, only hardware costs of ETN devices, modules and interfaces are taken into account. No service cost is considerd whether they carry low-cost best-effort or expensive critical traffic. Their CAPEX and OPEX are not proportional to carried service, SLAs and generated revenues. On the other hand, 5G multi-tenancy and network slicing architecture is more service-driven and shared by several tenants. The price of various service types with different traffic profiles should be defined accordingly. Thus, we introduce the concept of Traffic-Profile-as-a-Service (TPaaS) to improve the precision of the previous BHaaS method by separately and properly pricing each traffic profile based on its policies and Class-of-Service (CoS). In our model, only activated Priced Traffic Profiles (PTP) within ETN interfaces (point of attachment) are considered in the TCO and ROI calculation. If no PTP is activated in an ETN interface, then the entire interface is idle and thus excluded from the total TCO calculation. Similarily, if no interface is activated in ETN module, the entire module is not considered. TPaaS concept offers various benefits:

- Costs of each slice of shared infrastructure is specified for available PTPs.
- Long-term network TCO is optimized for multi-tenant 5G networks.
- Beyond simple connectivity, traffic profiles within TPaaS offer new types of services and define new revenue generation models.

We apply TPaaS on a PON-based MBH network using the same N_{TD} and TTD. Splitters cost is inclusive in the CAPEX of corresponding interfaces in the OLT. As ONT has no subrack or modules, the number of its module is 1 ($N^E_{mod} = 1$). Splitting ratio (e.g. 1:16, 1:32 or 1:64) is required in PON point-to-multi-point architecture and is equal to the number of ONTs per each OLT interface ($N^E_{sub} =$ 32 in our use case). The PON link between the OLT and the outdoor splitter cabinet is also protected by a redundant OLT interface (see Fig. 1). Thus, both PON and ring-based networks require a pair of interfaces in the ATN (or OLT) towards the access network.

IV. Cost modeling

Let:

T = {ETN, ATN} : Transport nodes ETNs and ATNs

C = {subrack, module, interface, fiber} : Components inside each transport node $t \in T$

TABLE I: Decision Variables

Name	Description
TCO	Optimal amount of TCO
ROI (YROI)	(Yearly) Return-On-Investment
$CX[y]$	CAPEX in year y (Vector of Integers)
$OX[y]$	OPEX in year y (Vector of Integers)
P_{TD}	Satisfaction of Traf. Demand (Matrix of Booleans)
P_c^t	Activation of $c \in C$ within $t \in T$ (Binary)

TABLE II: Problem parameters

Name	Description
PB_{Max}	Maximum project budget
Y	MBH project runtime in Years
$ARPU_x$	Average Revenue Per User x
N_{TD}	Traffic demand per ETN module
N_{TP}	Traffic profiles per ETN module
TTD	Total traffic demand in entire network
$tp, \quad tp \in TP$	Traffic profile
$\varepsilon_{CX}[y], \ \varepsilon_{OX}[y]$	All-in-one volume discount in year y
$CX_c^A, \ CX_c^E$	CAPEX for Component $c \in C$
$OX_c^A, \ OX_c^E$	OPEX for Component $c \in C$
N_c^A	Total number of Comp. c in all ATNs
N_c^E	Total number of Comp. c in all ETNs
C_{sub}^A (Voi, size: N_{sub}^A)	Bind subrack to ATN
C_{mod}^A (Voi, size: N_{mod}^A)	Bind module to subrack in ATN
C_{inf}^A (Voi, size: N_{inf}^A)	Bind interface to module in ATN
C_{sub}^E (Voi, size: N_{sub}^E)	Bind subrack to ETN
C_{mod}^E (Voi, size: N_{mod}^E)	Bind module to subrack in ETN
C_{TD}^E (Voi, size: N_{TD})	Bind T.D. to module in ETN

A. *Traditional TCO cost model,*

Traditional TCO analysis of MBH projects usually calculates entire hardware infrastructure required to afford traffic demand for a number of years Y (in general, 5 years) [12].

$$\begin{aligned} TCO[Y] &= \sum_{y \in Y} (CX[y] + OX[y]) \\ &= \sum_{y \in Y} \sum_{t \in T} \sum_{c \in C} \ (CX_c^t[y] + OX_c^t[y]) \end{aligned} \tag{1}$$

Subject to:

$$0 \leq TCO[y] \leq TCO_{Max}[y], \qquad \forall y \in Y \tag{2}$$

$$TCO[Y] \leq PB_{Max}, \tag{3}$$

Eqs. (1) calculates the TCO for the project lifetime (Y) by adding deployment and operating costs of all estimated transport nodes $t \in T$ and related components $c \in C$. Eq. (2) states that the TCO is limited in each year while Eq. (3) states that the total project budget is bounded.

B. *Proposed BHaaS cost model*

The objective of proposed BHaaS cost model is formulated in Eq. (4) to minimize the entire project cost TCO versus ROI (i.e. maximize the project benefit):

$$minimize \ (TCO[Y] - ROI[Y]) \tag{4}$$

where:

$$ROI[Y] = \sum_{y \in Y} YROI[y] = \sum_{y \in Y} \left(\sum_{d=1}^{N_{TD}} P_{TD}[d, y] * ARPU_{STD} \right) \tag{5}$$

Subject to:

$$CX[y] + OX[y] \leq TCO_{MAX}[y] \ , \quad \forall y \in Y \tag{6}$$

$$CX[y] = \varepsilon_{CX}[y] * \sum_{t \in T} CX[t, y] \ , \quad \forall y \in Y \tag{7}$$

$$OX[y] = \varepsilon_{OX}[y] * \sum_{t \in T} OX[t, y] \ , \quad \forall y \in Y \tag{8}$$

$$\begin{aligned} &CX[t, y] = \\ &\sum_{c \in C} \left([1 - \phi(t, c, y)] * \sum_{n=1}^{N_c^t} \psi(t, c, y) * [1 + \delta(t, c, y)] * CX_c^t[y] \right) \\ &\qquad + \sum_{n=1}^{N_{inf}^t} \psi(t, inf, y) * CX_{fiber}^t[y] \end{aligned} \tag{9}$$

$$\begin{aligned} &OX[t, y] = \\ &\sum_{c \in C} \left([1 - \phi(t, c, y)] * \sum_{n=1}^{N_c^t} P_c^t[y, n] * [1 + \delta(t, c, y)] * OX_c^t[y] \right) \end{aligned} \tag{10}$$

where:

$$\psi(t, c, y) = P_c^t[y, n] - P_c^t[y-1, n], \qquad \forall \ n = 1.. \ N_c^t \tag{11}$$

Eqs. (1) and (5) respectively calculate TCO and ROI for the project lifetime (Y). Eq. (6) states that TCO is limited in each year. Eq. (7) and (8) respectively calculate CAPEX and OPEX for each year $y \in Y$ for all transport nodes $t \in T$. The factors $\varepsilon_{CX}[y]$ and $\varepsilon_{OX}[y]$ represent yearly offered **all-in-one volume discounts** that TSP can benefit for each ordering year (y) regardless of ordered quantities.

Eqs. (9) and (10) respectively calculate the costs of each transport nodes $t \in T$ by considering CAPEX and OPEX of each individual activated component $c \in C$ inside the transport node $t \in T$. The function $\phi(t, c, y)$ represents the **incremental quantity discount (IQD)** which is the discount TSPs can benefit from high quantity in equipment orders and resulting from the delay of the investment. It is a given function of the estimated quantity ($\sum_{n=1}^{N_c^t} \ P_c^t[y, n]$) to be ordered for different types of components $c \in C$, within transport nodes $t \in T$ in each year y. In reality, the function ϕ can be a complex multi-level function [28]. The function $\psi(t, c, y)$ defined in Eq. (11) ensures that TSP pays CAPEX calculated in Eq. (9) for each component $c \in C$ only once (when activated). Contrariwise,

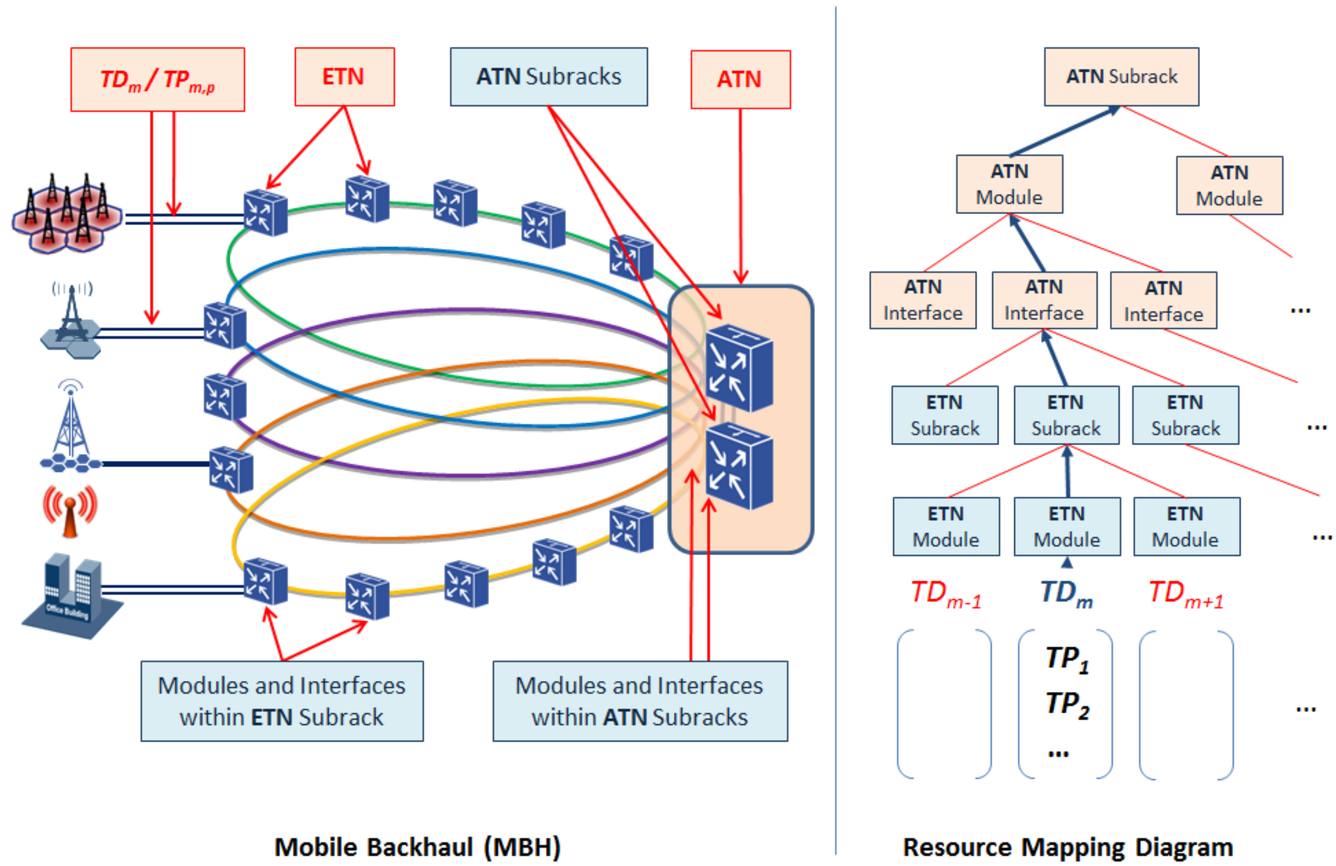

Fig. 2: MBH resource assignment and mapping diagram
TD_m : Traffic Demand for ETN Module m, $TP_{m,p}$: Traffic Profile p activated in module m

Eq. (10) shows that OPEX is paid every year after activation. The function $\delta(t,c,y)$ in Eqs. (9) and (10) represents the yearly increased costs for various components $c \in C$ due to the incremental approach in deploying the equipment [13]. In fact, this incremental approach may cause some increased costs related to the installation and configuration of equipment (due to inflation, logistics, manpower, etc) compared to the case that all the equipment (or most of it) is installed at once. The cost of digging and deploying fiber cables is usually shared by users. The cost of a single pair of fibers within the deployed cable is inclusive in the cost of connected ATN interfaces and is modeled by $CX^t_{fiber}[y]$ in Eq. (9). On the other hand, since the costs of ETN interfaces are negligible regarding ETN module and ATN interface, we neglect these costs in our calculations and assume they are inclusive in ETN module costs.

Control parameters:

In order to control deployment and activation of subracks, modules and interfaces for ATNs and ETNs as defined in the Resource Mapping Diagram (Fig. 2). We define following control parameters. A subrack s is activated in year y, if and only if at least one of its module m is activated in this year. If no module is active, the subrack s is considered idle therefore the subrack cost is not considered in TCO calculation. Same calculation is applied for the modules, interfaces and traffic demands.

$$P^A_{sub}[s,y] = \begin{cases} 1, \text{if } \sum_{m=1}^{N^A_{mod}} P^A_{mod}[m,y] \geq 1, \ \forall m, C^A_{mod}[m] = s \\ 0, \ \ \text{otherwise} \end{cases} \quad (12)$$

$$P^E_{sub}[s,y] = \begin{cases} 1, \text{if } \sum_{m=1}^{N^E_{mod}} P^E_{mod}[m,y] \geq 1, \ \forall m, C^E_{mod}[m] = s \\ 0, \ \ \text{otherwise} \end{cases} \quad (13)$$

$$P^A_{mod}[m,y] = \begin{cases} 1, \text{if } \sum_{i=1}^{N^A_{inf}} P^A_{inf}[i,y] \geq 1, \ \forall i, C^A_{inf}[i] = m \\ 0, \ \ \text{otherwise} \end{cases} \quad (14)$$

$$P^E_{mod}[m,y] = \begin{cases} 1, \text{if } \sum_{d=1}^{N_{TD}} P_{TD}[d,y] \geq 1, \ \forall i, C_{TD}[d] = m \\ 0, \ \ \text{otherwise} \end{cases} \quad (15)$$

$$P^A_{inf}[i,y] = \begin{cases} 1, \text{if } \sum_{s=1}^{N^E_{sub}} P^E_{sub}[s,y] \geq 1, \ \forall i, C^E_{sub}[s] = i \\ 0, \ \ \text{otherwise} \end{cases} \quad (16)$$

$$P^E_{mod}[m,y] - P^E_{mod}[m,y-1] \geq 0, \quad \forall i,y \quad (17)$$

$$P_{TD}[d,y] - P_{TD}[d,y-1] \geq 0, \quad \forall d,y \quad (18)$$

TABLE III: Average distance between eNodeBs [16]

Zone type	Ave. distance S_a	Typical value
Very dense urban zones (5G)	$S_a \leq 0.5\ km$	250 m
Dense urban zones	$0.5\ km \leq S_a \leq 1\ km$	750 m
Urban zones	$1\ km \leq S_a \leq 2.5\ km$	1750 m
Semi-urban or rural zones	$2.5\ km \leq S_a$	2500 m

$$\sum_{y \in Y} P_{TD}[d,y] \geq 1, \quad \forall d \tag{19}$$

Eqs. (17) and (18) state that if an ETN module (or a traffic demand) is activated within year y, it will remain activate in the following years. This constraint allows network evolution in one direction. We do not consider the exceptional cases where an activate ETN module is deactivated in following years.

C. Proposed TPaaS cost model

TPaaS cost optimization model enhances the BHaaS cost model given in Eqs. (4) to (19). It adapts the ARPU generated by each STD ($ARPU_{STD}$) according to different tenant service types and related PTP prices ($ARPU_{PTP}[ptp]$):

$$YROI[y] = \sum_{ptp=1}^{N_{PTP}} P_{PTP}[ptp,y] \ * \ ARPU_{PTP}[ptp] \quad \forall y \tag{20}$$

Subject to:

$$P_{PTP}[p,y] - P_{PTP}[p,y-1] \geq 0, \quad \forall p,y \tag{21}$$

$$\sum_{y \in Y} P_{PTP}[p,y] \geq 1, \quad \forall p \tag{22}$$

D. MBH survey algorithm for stochastic aggregation zones,

The BHaaS/TPaaS optimization algorithm accepts a matrix of traffic demand as input. Although in reality this matrix is provided by MNOs to the TSP, several demand prediction methods can be used to generate this matrix based on current demand (like time-series, gaussian, etc) [27]. The total numbers of subracks (N^A_{sub}, N^E_{sub}), modules (N^A_{mod}, N^E_{mod}) and interfaces (N^A_{inf}) in Table II are also required as input parameters for BHaaS and TPaaS optimization algorithm. They have to be estimated for each zone because each zone has different small cell densities. A detailed survey is usually done by TSP/MNOs (as part of the MBH network planning phase) in order to estimate the number of backhauling zones $a \in A$ within the MBH network, the cell density (D_a) for each backhauling zone and thus, the number of connection demands (CD_a) to connect each mobile tower to the corresponding ETN. The cell density (D_a) is defined by the number and average spacing distance (S_a) between adjacent mobile towers collecting end-users traffic. It is depending on the total number of estimated end-users and corresponding average bandwidth consumption in that zone. An example of average spacing distances (S_a) between cells is given in Table III. Given the number of ATNs geographically defined within *City*, we design a survey algorithm to define optimal distribution of backhauling zones by minimizing connecting distances between each ETN and its nearest ATN. Traffic demand of each zone is estimated based on calculated area and small cell densities. Algorithm 1 is based on a short-distance stochastic geometry model called Voronoi Tessellation algorithm [25]. It takes as input an area *City* to be fully covered by 5G small cells and a number of given ATNs. The algorithm returns a list of MBH zones (Z) aggregated by each ATN and a list of related calculated areas (R). The output of Algorithm 1 (R_a) will be combined with (S_a) to determine the connection demand (CD_a) and also the total traffic demand (TTD_a). Table IV presents an example of Sa definition and Da estimation. Once the areas and zones have been identified, the cell density (D), connection demand (CD) and TDD matrix are calculated as follows:

Algorithm 1 (MBH Survey Algorithm): Voronoi diagram and area calculation for optimal distribution of backhauling zones

Input: $ATN = \{ATN_a;\ a \in A\}$: list of ATNs geographically distributed
$C = \{(x_a, y_a);\ a \in A\}$: list of coordinates of ATNs
\# *Voronoi* : voronoi tessellation returning the zones from the list ATN
\# *Area* : Function computing the areas (in Pixels) of each zone given by *Voronoi*
Output: $Z = \{Z_a;\ a \in A\}$: list of zones given by *Voronoi*
$R = \{R_a;\ a \in A\}$: list of Areas of the zones in Z

```
Begin
Z = Voronoi(C)
R = Area(Z)
End
```

$$D_a = ROUNDUP\ (\frac{1000}{S_a})^2 \qquad \forall a \in A \tag{23}$$

$$CD_a = D_a * R_a \qquad \forall a \in A \tag{24}$$

$$TTD_a = CD_a * TD_a \qquad \forall a \in A \tag{25}$$

TTD is estimated based on calculated zone areas and related cell densities. The number of ETN/ATN subracks, modules and interfaces used as input parameters to resolve both BHaaS and TPaaS optimization problems can be estimated accordingly.

V. Results and Discussion

A. Traffic demand forecasting using MBH survey algorithm

The architecture of recent cities is often based on Manhattan model where different zones Z_a have equal area R^{eq}_a ($a \in A$). We compare connection demand CD_a calculated by Algorithm 1 to connection demand CD^{eq}_a calculated using Manhattan model where all aggregation zones have an equal and unified area R^{eq}_a calculated by Eq. (26).

$$R^{eq}_a = \frac{Total\ area\ of\ City}{Total\ number\ of\ aggregation\ zones}, \quad \forall a \in A \tag{26}$$

We consider as an example the Montreal island (Canada) with 8 geographically distributed ATNs and their coordinates as

TABLE IV: Number of Towers per Aggregation areas

Z_a	S_a	$D_a = D_a^{eq}$	$R_a(Km^2)$	CD_a	R_a^{eq}	CD_a^{eq}
Z_1	500	4	106,405	426	55,26	221
Z_2	300	12	41,755	501	55,26	663
Z_3	250	4	165,248	660	55,26	221
Z_4	300	12	63,178	758	55,26	663
Z_5	200	25	25,39	635	55,26	1382
Z_6	100	100	5,155	516	55,26	5526
Z_7	150	50	16,908	845	55,26	2763
Z_8	150	50	18,018	901	55,26	2763
Total	N.A	N.A	442,057	**5242**	442.08	**14202**

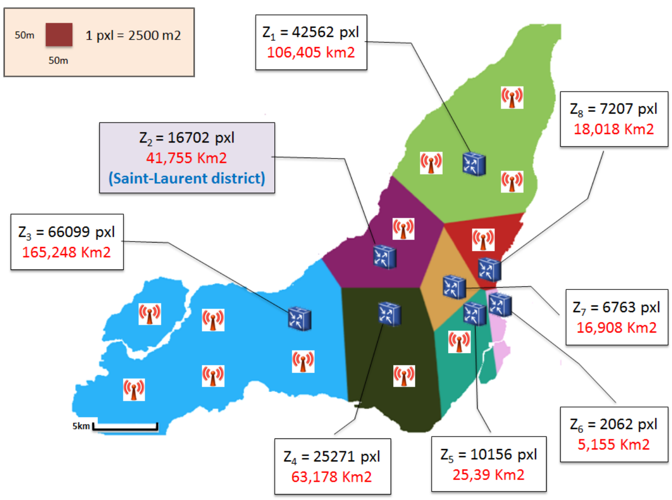

Fig. 3: Aggregation areas defined by Voronoi Tessellation algorithm (Montreal island use case)

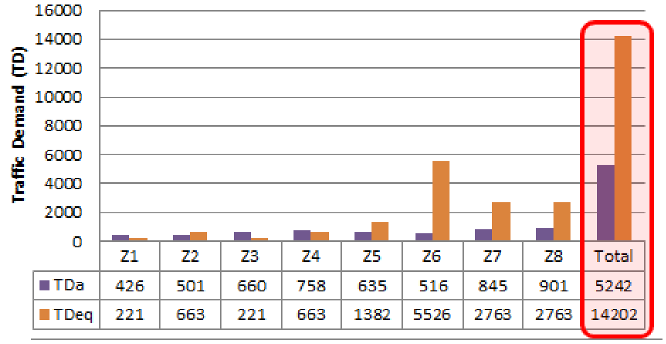

Fig. 4: Estimated traffic demand for various small cell density zones

TABLE V: Use case values

Parameter	Use case	Parameter	Use case
CX_{sub}^{A}	400.000 $	CX_{mod}^{A}	40.000 $
$CX_{inf}^{A} = CX_{fiber}^{A}$	2.000 $	CX_{sub}^{E}	80.000 $
CX_{mod}^{E}	20.000 $	CX_{inf}^{E}	2.000 $
OX_{sub}^{A}	200.000 $	OX_{mod}^{A}	20.000 $
OX_{inf}^{A}	2.000 $	OX_{sub}^{E}	40.000 $
OX_{mod}^{E}	10.000 $	OX_{inf}^{E}	1.000 $
N_{sub}^{A}	2	N_{mod}^{A}	4
N_{inf}^{A}	8	N_{sub}^{E}	8
N_{mod}^{E}	2	$\varepsilon_{CAPEX}[y]$, $\varepsilon_{OPEX}[y]$	5%
N_{TD}	2,4,6,8,10,12	$\phi[t,c,y]$, $\forall(t,c,y)$	y*10%
$ROI_{TPaaS}[tp]$	$2^{tp-1} * 1.200$ $	ROI_{BHaaS}	4800 $

input. Algorithm 1 calculates the optimal zone distribution and returns the list of zones and areas as detailed in Table IV and Fig. 3. Table IV presents also cell density D_a for each ATN zone (Eq. 23) and the number of connection demand CD_a (Eq. 24). Small cell densities ($D_a^{eq} = D_a$) remain the same for both calculations. As shown in Table IV and Fig. 4, traffic demand can be estimated more precisely using Algorithm 1. For example, our estimation of traffic demand is 63% lower than Manhattan model. In other words, over-provisioning is avoided. total estimated traffic demand for all MBH zones calculated by Algorithm 1 is optimized. Algorithm 1 performance increased when small cells are denser (e.g. higher than 10 cells per km2). Recall that 10 cell/km2 is the minimum density required by 5G RAN. Thus, MBH resources allocation is more efficient using Algorithm 1.

B. Comparing TPaas, BHaaS and Traditional TCO model

In the second experiment, we focus on Zone 2 (Saint-Laurent district) with $CD_{zone2} = 501$. The target is to plan a future MBH with optimized TCO. We consider the input values defined in Table II where the number of ETNs in Zone 2 is equal to 512 (= 2*4*8*8) ETNs. The number of ETNs providing 1+1 protected access connection is 1024 (= 512*2). We assume an average traffic demand of 6 TDs per each connection CD, the TTD for Zone 2 is: $TTD_{zone2} = CD_{zone2} * TD_{zone2} = 2*512*6 = 6144$. So, we use randomly generated traffic demand matrices as input to BHaaS optimization algorithm with TTD increasing from 1024 up to 6144 (= n * 1024). Three TCO calculation models are considered:

1) Traditional TCO cost model in Section IV-A
2) BHaaS cost model in Section IV-B.
3) TPaaS cost model in Section IV-C.

Fig. 5. (a) compares cumulative TCO and ROI of three models Traditional, BHaaS and TPaaS regarding the TTD. Since the Traditional TCO estimates the entire project requirements from the first year, it remains constant regardless of the evolution of TTD. On the other hand, BHaaS and TPaaS models are gradually optimizing TCO over years to satisfy TTD. Results show that TSP starts generating profits (the point where ROI exceeds TCO) when TTD reaches 7168 for BHaaS and 5120 for TPaaS. This suggests an advantage of TPaaS over BHaaS and traditional cost models. It is worth noting that Traditional TCO method does not allow to calculate ROI [12]. Fig. 5. (b) compares the yearly CAPEX and OPEX of the three models when TTD is is large (TTD = 6144). The colors in Fig. 5.(b) represent the different years from 1 to 5 as shown in the right side of the figure. Each year is represented by a different color. Traditional TCO counts all project CAPEX

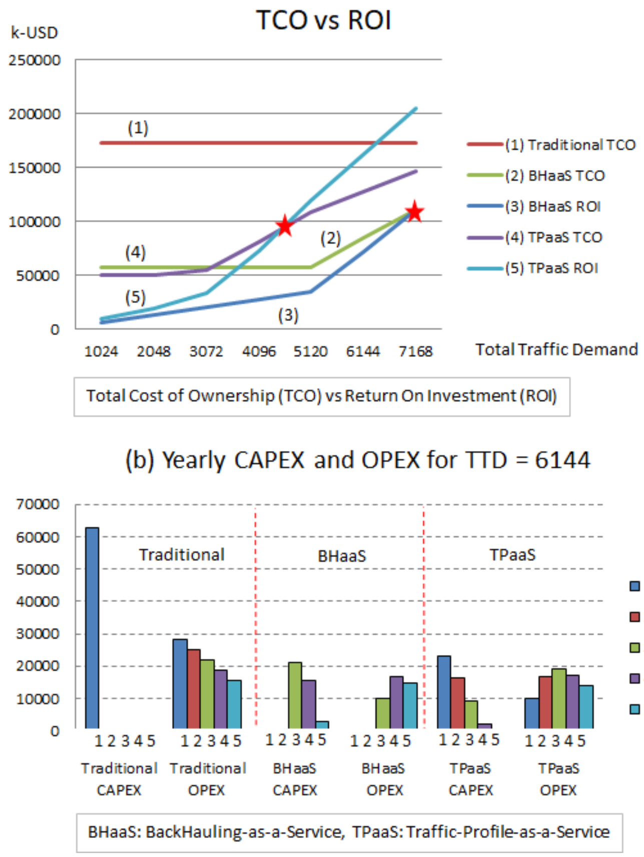

Fig. 5: Comparing TPaas, BHaaS and Traditional TCO

immediately since the first year which makes it very high and unaffordable by several TSPs. Since all commissioned resources are considered as active since first activation date, traditional OPEX starts always from the first year. Thus, TSP has to pay licenses, maintenance and warranty fees from the first year while their subracks, modules and interfaces are not yet carrying traffic and not generating any revenue. BHaaS allows TSP to postpone their acquisition of these resources to a future time. The algorithm calculates demand distribution since the first year of the project. However, it may decide to serve no demand in the first 2 years, as shown in Fig. 5. (b) because of no profit. No cost is registered until the moment when the equipment is actually deployed and activated. Installation cost will be added to the total cost of activation. In this case, demand will be afforded in the subsequent years. In other words, the project is not yet launched within this time, and there is no CAPEX. In any case, the total demand will be completely afforded when the project ends. On the other hand, TPaaS allows TSP to start the project immediately from the first year and then distribute the costs over the following years. TPaaS CAPEX decreases over the years until all TTD is satisfied. Yearly TPaaS OPEX increases slowly to the maximum value in the third year.

C. CAPEX and OPEX analysis using TPaaS

We apply our proposed model on two different MBH optical network architecture: PON and Ring and compare CAPEX and OPEX for every year (Fig. 6). Results in Fig. 6 (a) show that for very low TTD, no resource is activated by TPaaS until the fourth year for both technologies. This is explained by the fact that traffic demand is not yet high enough to generate profit. A suboptimal solution could be launching the project since the first year with a smaller number of subracks and modules within ATNs and ETNs. Fig. 6 (b) shows that for TDD = 2048, Ring resources remain inactivated for the first three years. However, PON resources are activated in the second year. This is because CAPEX and OPEX values are much cheaper for PON than Rings. Thus, the yearly accumulative demand will sooner be enough to afford the cost of PON than of Ring, and hence the project will start getting profits sooner. PON CAPEX drops in the third year because OLTs have been allocated in the first year although their components (modules, interfaces, splitters and ONTs) have not been filled. Additional OLTs will be required only in the fourth and fifth years. This is not an over-provisioning of resources because OLT is unsplittable. However, a virtual OLT architecture may help improve resource allocation which is subject to our future work. Fig. 6 (c) shows that TDD = 3072 is still too low for Ring to get revenue in the first two years. Fig. 6 (d) shows that with TDD = 4096, TPaaS will activate resources and consume CAPEX and OPEX in the second year for Ring. Similarly to PON in Fig. 6 (c), major Ring CAPEX is required to purchase ATNs. This cost drops in the third and fourth year because no more ATN is required until the fifth year. OPEX keeps consuming most of the network budget for following years. Fig. 6 (e) show that TDD = 5120 is the minimum demand required to kick-off the project since the first year for Ring. Fig. 6 (f) shows that for very high (TDD = 6144), CAPEX and OPEX of PON and Ring have almost the same behavior. Major CAPEX is spent in the first year to acquire ATNs and OLTs, which are not full of components until the fourth year. OPEX is increasing rapidly to reach its peak in the third year where the demand is highest. Then OPEX decreases thanks to yearly discount (input parameter $\varepsilon_{OPEX}[y]$ in Table II, in general 10% per year on all UPL items) offered by solution manufacturers to the TSP for both CAPEX and OPEX.

D. TCO and ROI analysis using TPaaS

An objective of TCO analysis is to determine how soon the project is profitable. This can only be achieved by comparing project costs and revenues. Fig. 7 compares both values for PON and Ring.

1) Ring-based MBH networks: Fig. 7 (a), (b) and (c) show that for both Ring TCO and ROI are zero in the first three years when TTD $\leq$ 3072 because this demand is still too low. Starting from TTD = 4096 in Fig. 7 (d), TPaaS starts activating resources in the second year. ROI increases constantly but the project is not yet profitable since the revenue (ROI line) is still lower than the costs (TCO line). The project gets net profit when TTD = 5152 in Fig. 7 (e). ROI is steady when all demand are fully afforded in the fourth year. For higher traffic demand (TTD=6144) in Fig. 7 (f), the net profit is sooner obtained (in the second year).

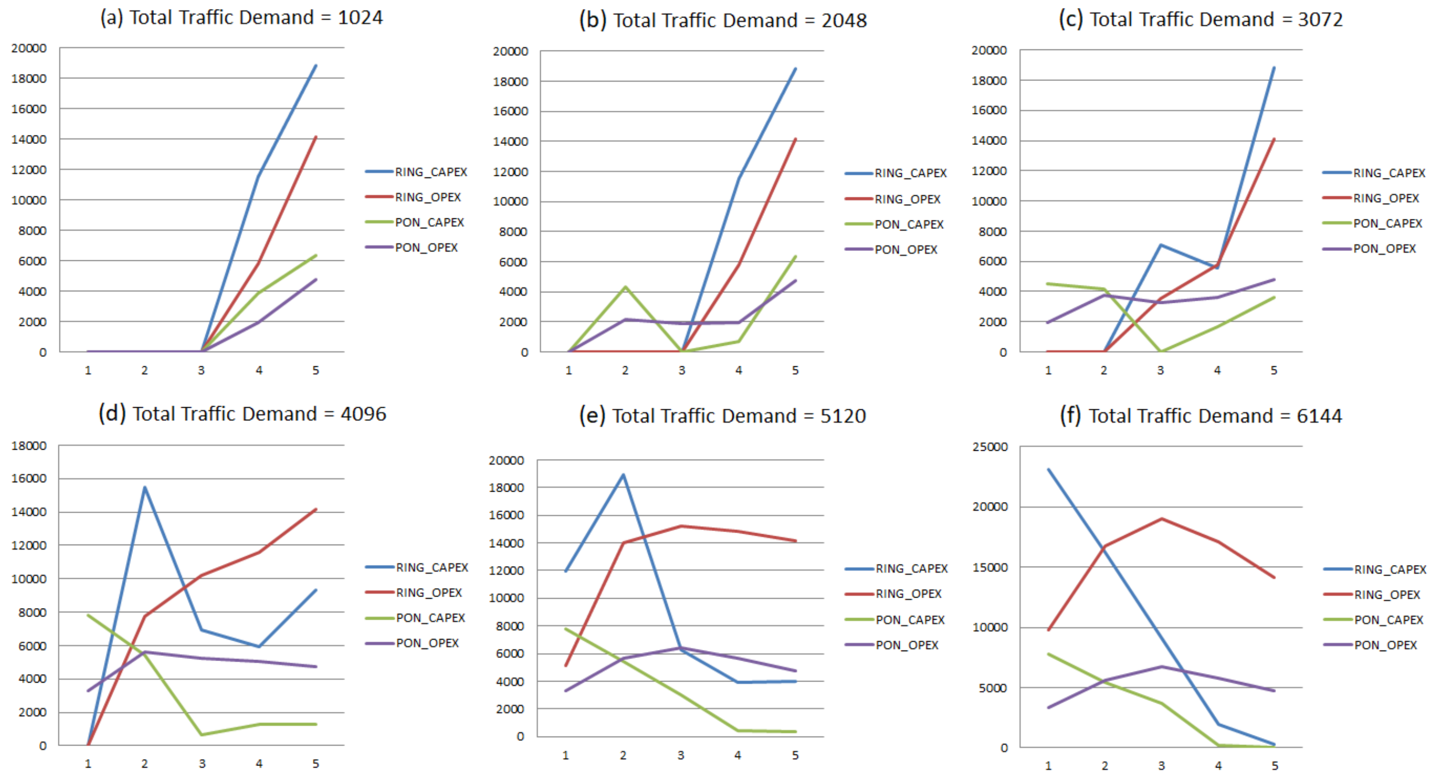

Fig. 6: CAPEX and OPEX yearly evolution for PON and Ring-based networks (using TPaaS)

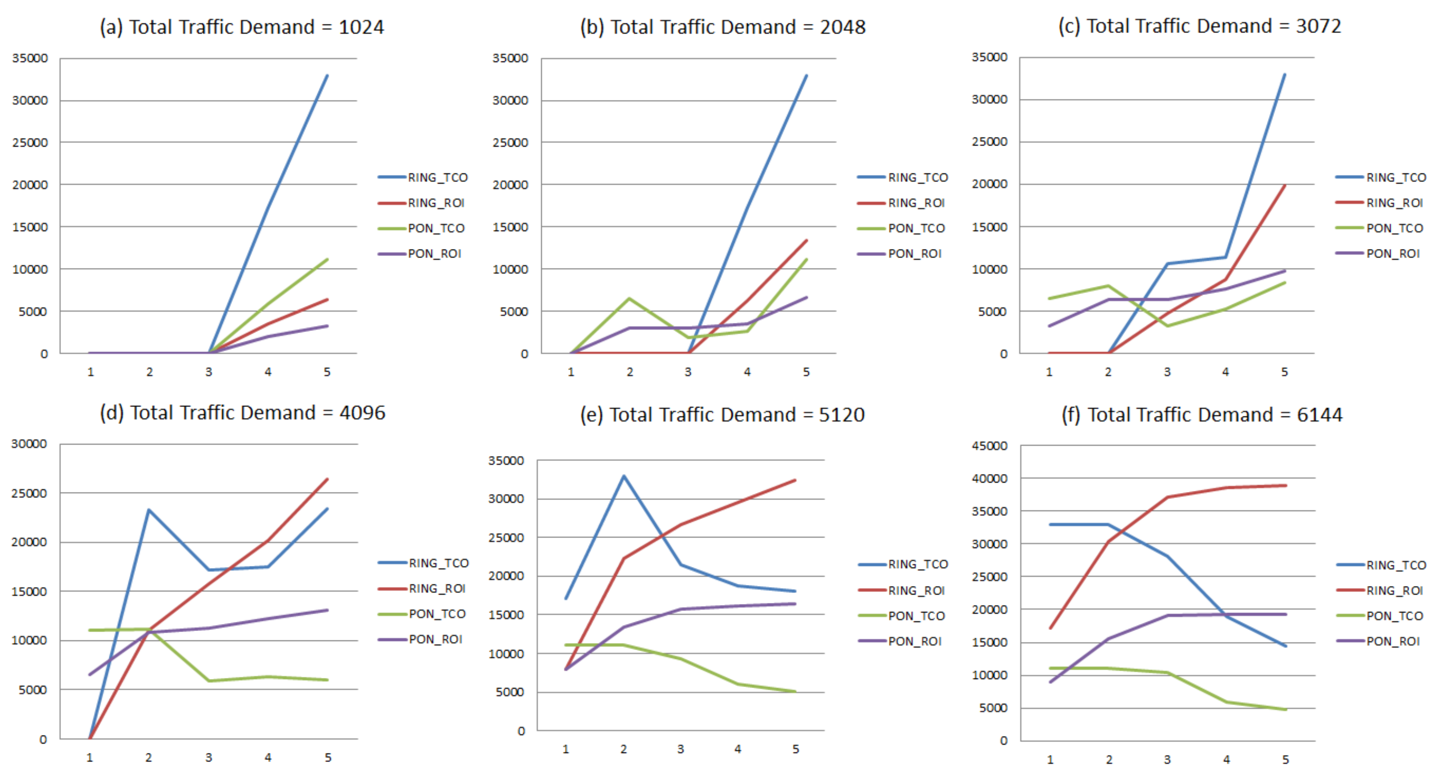

Fig. 7: TCO and ROI yearly evolution for PON and Ring-based networks (using TPaaS)

2) PON-based MBH networks: Fig. 7 (a) shows that TTD=1024 is too low traffic demand to kick-off the project even for PON. TPaaS activates PON resources at earliest in the second year when TTD = 2048 (Fig. 7 (b)). Fig. 7 (c) shows that for TTD=3072, PON is not profitable. PON profit starts since the second year for TTD=4096 (Fig. 7 (d)), which is earlier than Ring. Fig. 7 (e) and (f) show for TTD = 5120 and 6144, ROI is steady when traffic demand is peaked at the third year.

E. Satisfied traffic demand and activated resources

In this section, we analyze the impact of the TCO optimization using TPaaS on the evolution of the network infrastructure and related traffic engineering. Fig. 8. (a), (b) and (c) show respectively the yearly evolution of deployed rings, activated ETNs and Satisfied Traffic Demand (STD) when TDD increases from 1024 to 6144. Each ring is aggregated by two ATN interfaces hosted on two different ATN modules for redundancy reason. Subracks, modules, interfaces and traffic profiles are activated within each ATN and each ETN on yearly basis. Results show that the traffic demand is optimally satisfied over the years according to a non-linear model. The higher demand, the sooner Ring resources are activated (Fig. 8. (a)). This may result in over-provisioning of Rings in the first year of the project. A new ring is activated as soon as a single ETN is active. Thus, Fig. 8. (a)) shows that, for TDD = 6144, most of Rings are activated since the first year while activation of ETNs (Fig. 8. (b)) and STD (Fig. 8. (c)) still increase over years.

F. Calculation Runtime for various traffic demands

We used IBM ILOG CPLEX as a solver for our optimization models. Fig. 9 shows calculation time on Windows 7 HP machine with i7-4790 CPU @ 3.6 GHz and 8 GB RAM when TTD increases from 1024 to 6144. Execution time is very short for TTD $\leqslant$ 5120. Starting from TDD = 6144, calculation time increases rapidly. The graph shows also that TPaaS requires a shorter calculation time than BHaaS.

VI. Conclusion

In this paper, we presented an algorithm based on Voronoi Tessellation algorithm to define 5G backhauling zones and estimate more precisely traffic demand and MBH resources. Then, we proposed two new pay-as-you-grow concepts, respectively called BackHauling-as-a-Service (BHaaS) and Traffic-Profile-as-a-Service (TPaaS), to improve the performance and accuracy of network planning and TCO analysis for future 5G MBH networks. The proposed cost models optimize the distribution of CAPEX and OPEX of optical MBH over the project years regarding generated revenues. Results shows the efficiency of BHaaS and TPaaS compared with Traditional TCO model in estimating the entire TCO. In particular, results show benefits of using TPaaS cost model to quickly start generating net profit while satisfying traffic demands. It is worth noting that the TCO model proposed in this paper is rather appropriate for ”You-pay-only-for-what-you-use” business model. From a traditional TSP perspective, this model may have some shortcomings in losing potential customers. For example, customers with urgent demand may prefer a TSP that accepts initially high investment to immediately afford their demand, thus this later TSP may gain new customers. This issue will be addressed in our future work by an efficient demand prediction which takes into account market behaviors. We intent also to validate the proposed models on SDN/NFV based optical MBH networks and design a heuristic algorithm to reduce calculation time. A new TCO model for virtual resources will thus be taken into account.

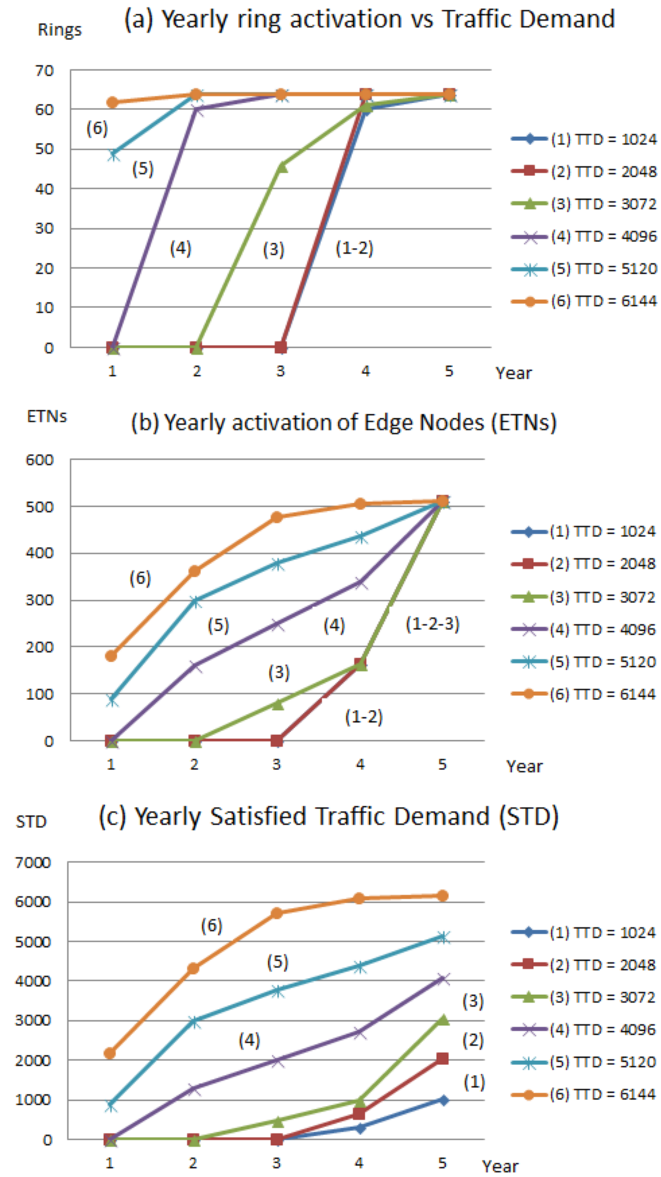

Fig. 8: Yearly evolution of new activated rings, Edge Nodes and Satisfied Traffic Demand for Ring-based networks (using TPaaS)

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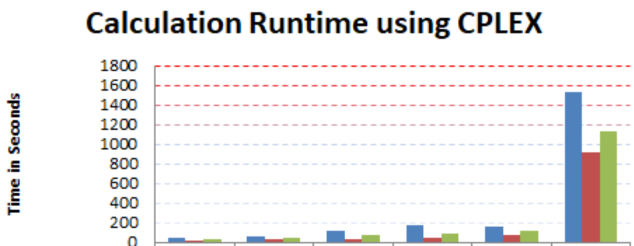

	TTD = 1024	TTD = 2048	TTD = 3072	TTD = 4096	TTD = 5120	TTD = 6144
BHaaS , ETN = 8	42	58	124	173	164	1526
TPaaS , ETN = 6	22	28	32	51	75	918
TPaaS , ETN = 8	27	45	73	83	122	1125

Fig. 9: Calculation runtime using CPLEX optimization tool for various traffic demands

Voronoi model. The view expressed in this article are those of the authors and do not reflect the official policy of Ciena.

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