https://doi.org/10.22581/muet1982.2203.08

2022, 41(3) 85-93

Statistical model and forecasting of bandwidth requirements on aggregating nodes of FTTX network using Monte Carlo computations for different demographic segments

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Received: 28 July 2021, Accepted: 05 February 2022, Published: 01 July 2022

KEYWORDS

FTTX

Peak Hour

Statistical Model

Link Capacity

Bandwidth Forecasting

Monte Carlo Computation

ABSTRACT

Telecom service providers are on a relentless task of development and upgradation of their networks to support increasing requirements of internet users. FTTX landline connections serves multiple users connected on a single line hence need more robust and high data rate capabilities. In FTTX network, link capacity allocation for a service node to aggregating node requires statistical study of usage patterns of customers of the service areas. Different service areas have different usage patterns hence their statistical distributions are different. In this article we have acquired a yearlong data of peak hour utilizations from customers of the largest FTTX service provider in Pakistan to develop a statistical model. We developed an empirical distribution of peak hours of the customers mapped on day clock. This distribution has been used in Monte Carlo computation to find maximum data rate requirements on aggregation nodes in comparison to subscribed data rates of all users on a service node. Further a forecasting model has been used to predict the growth in subscriber demands in different demographic segments for coming years. A combination of maximum possible data rate requirement at aggregation node and forecasted subscriber data rates led to develop a forecast of data rate requirement for next five years in different demographic segments.

1. Introduction

There are continuous developments in Information and Communications Technologies (ICT) which in turn improves many aspects of our lives. ICT developments has elevated human life style in business, entertainment, education and many other social domains. Many new knowledge areas such as e-commerce, telemarketing, remote education, social engineering and others have emerged due to ICT products and infrastructure. We can broadly bifurcate ICT developments in services and networks. The services are developed in form of software applications or hardware with targeted utilities. To make these applications viable, a telecom infrastructure is the second major category of ICT domain. Over the period of last three decades, we have observed an exponential growth in development of versatile applications, platforms and hardware [1]. This growth is mainly due to open-source platforms, hand held devices and their independence from underlying telecom network [2]. Telecom service providers follow this trend of growth in services and applications to update their telecom network for better performance of these applications for their subscribers [3]. This continuous pursuit of telecom operators has lead us to witness voice-oriented circuit switched networks transformed into modern data oriented packet switched networks in recent decades. These underlying telecom service provider networks are broadly classified in wireless or cellular operators and landline operators. Although the very concepts described in this article are applicable theoretically to both types of networks, it primarily considers landline networks as a case under discussion

Development and upgradation of telecom service provider network include the appropriate uplifting of their core and access networks to meet the increasing data rate requirements by their users. In earlier period of telephony, access network for fixed line telecom network was based on legacy copper network comprising one twister pair for each user. Initial development in data services for landline users emerged in form of dial up services by different Internet Service Providers (ISP) who engaged the twisted pair by establishing a one-to-one connection between modems at user end and the ISP. The data services from dialup modems were limited to few Kbps. By the advent of fixed line broadband services which not only promised improved internet speed on the scale of Mbps for a user but also improved access network utilization factor by multiplexing data and basic voice services on same twisted pair [4].

In recent past, usage of internet by cell phone applications and domestic internet applications mainly dominated by videos on demand (VoD), Internet Protocol Tele Vision (IPTV) and interactive game consoles has increased. On a land line internet connections at a user premises, Wi-Fi routers serve all internet users in a household either for their hand held devices or other internet services platforms. This formation of using landline internet service in a customer premises is a preferred choice due to better service performance and more economical data usage as compared to equivalent services offered by cellular data service providers [5]. The increasing demand of high data rates on landline access networks leads to add optical fibre in last mile hence introducing Fibre to The different premises (FTTX), a new class of access networks which use high bandwidth capacity of optical fibres to enable access links for ultimate speed [6]. FTTX includes different versions based on the reach of optical medium from telecom service node to customer geography which are fibre to the home (FTTH), fibre to the curb (FTTC) and fibre to the building (FTTB). In FTTH networks, optical fibre is used from telecom facility to customer premises hence alleviating the copper altogether from access network. This type of fibre based access networks has highest bandwidth potential. In some geographic areas, existing copper network and bandwidth requirements from the residents of the area are assessed to have a limited deployment of optical fibre. Optical fibre is laid from telecom facility to an appropriate location in the target area. Customer premises is accessed through existing copper network from active components installed at the location where optical fibre has been extended. This version of fibre based access network is called FTTC. In buildings with existing wiring of coaxial cable or twisted pair cable for its residents, Optical fibre is extended from main telecom facility to the building service rooms. From service room to each customer premises, existing copper network is utilized. This version is called FTTB. In this article, we will address all these versions and use the notation of FTTX for fibre based access networks.

While upgrading their access and core networks, telecom service providers have an important challenge to optimize cost of upgradation. Deployment of new infrastructure and allocation of capacity resources in network are directly related to economic feasibility and consequently impact the business model of the telecom company. One cannot apply a generous amount of resources without careful assessment of current and futuristic demand in the service area [7]. Our analysis in this article will provide a better techno economic model for telecom service providers for expansion of their networks.

A high level schematic diagram of FTTX network is shown in Fig. 1. Here a serving node which is Multi Service Access Gateway (MSAG) in case of FTTC and Optical Line Terminal (OLT) for FTTH is providing access to customer premises through Optical Distribution Network (ODN). Multiple Service Nodes are then converged on an aggregation node which is connected to core internet infrastructure of telecom network. These serving nodes handle the traffic of all subscribed customers and connect to internet through aggregation nodes. Estimation and forecast of data rate requirements for the aggregation link is the main focus of this article.

Network design is a deterministic problem whereas traffic generation and data rate requirements by subscribers are stochastic in nature. Customers on FTTX networks buy a subscription of a particular data rate from service provider as per their needs. Usually, this subscription is based upon maximum data rate requirement of the customer. Applying linear formulations with respect to number of customers on a service node and their subscribed data may lead to unrealistic aggregation assessments. Consequently under-estimations may lead to service issues while over-estimations may cause over investment on the network. It has been observed that actual usage varies throughout the day and this actual data requirement is less than the subscribed data rate. To start our analysis from usage pattern of customers, here we define peak hour (PH) for a particular user. Peak Hour is an hour, out of twenty four hours of the day when the user avails maximum data rate. Every user has a unique pattern of usage; therefore, the peak hour of all subscribed customers to a service node, MSAG or OLT, has been considered as independently distributed on the time span of a day. This stochastic behaviour of peak hour of an individual customer and joint distribution of peak hours of all customers connected on the same access network lead to the problem scenario for estimating the maximum data rate requirements at aggregation link with its probability measures.

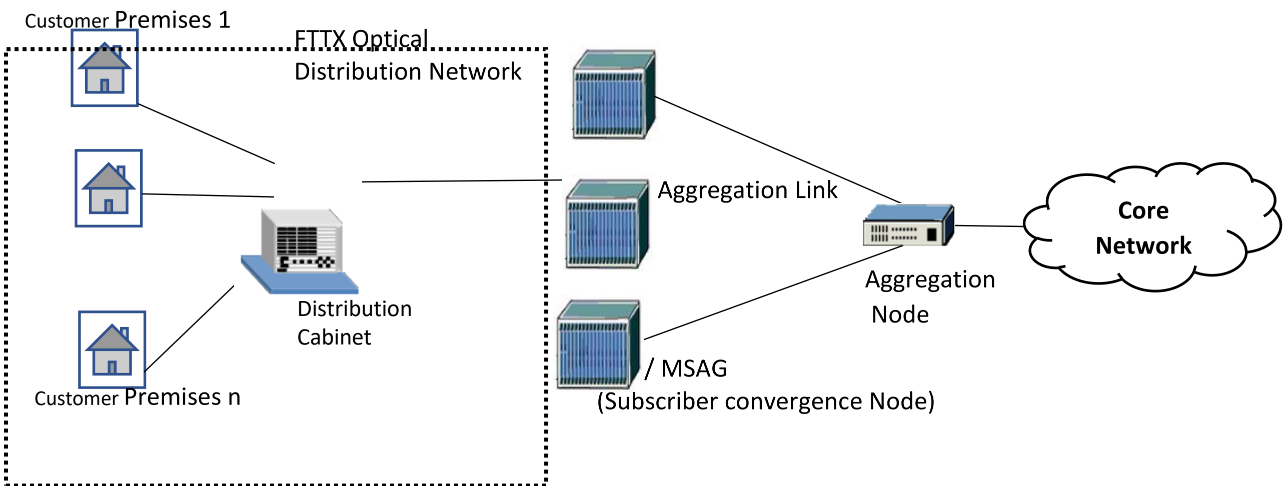

Fig. 1. High level network diagram indicating aggregation link in FTTX network

Besides pursuing for the statistical distributions and their converged impact, there is another interesting dimension of different distributions for different demographic regions. The traffic and data rate requirements from users varies due to economic conditions, social development and habits of residents of a service area [8]. Therefore, demographic based study of bandwidth requirements on aggregation links in FTTX network is valuable for telecom service providers to make customized network roll outs with better cost factors.

The demographic based traffic forecasting model has been discussed in our previous work [9] that describe the bandwidth requirement growth pattern. That study focused to suggest appropriate deployment or upgradation strategy of FTTX network for different demographic segments.

After presenting necessary background of FTTX based access networks and describing the problem statement, rest of the article is arranged in following sections. Relevant literature and other reported efforts has been compiled in section 2. In section 3, we discuss statistical inference from actual data acquired from largest FTTX service provider in Pakistan. Based upon statistical distribution in section 3, Monte-Carlo computation has been performed in section 4 to find a probability model which determines likelihood of maximum data rate requirements on aggregation link. These findings are applied to a forecasting model to make a reasonable prediction about bandwidth requirements on aggregation link for next five years. Finally, section 6 concludes the article with key findings and directions to pursue in future.

2. Literature Survey and Reported Works

Traffic modelling in data networks has been attempted by many researchers in different application scenarios. A large quantum of reported literature covers the statistics of packet arrivals at router ports [10-12]. Such works use Erlang models for data packets to establish a relationship of packet arrivals, delay and loss of packets with processing capacity of the serving nodes. Erlang loss and Erlang delay formulas have been used to model internet traffic at packet levels. These works did not address the particular situation of network scenario mentioned in our problem statement.

Data of access network utilization in peak and nonpeak hours has been collected from different ISPs in North America to develop a model for price variations to broadband users [13]. This work sets similar grounds for developing a model of customer's utilization as we have adopted but differs by setting its relationship to suggest variable prices of subscriptions. In contrast, we have linked the statistics of customer's usage to aggregation link hence addressed network design issues. Another relevant effort described a method of extrapolation of customer demands on a day scale to observe the random variations of data rate of an individual customer [14]. Data of federal communication commission for measuring broad band project has been processed to find the reliability of broadband service due to changing behaviours of broadband traffic [15]. This work develop a statistical study for subscribers at a service node but did not relate to the impact on aggregation link.

In a Japanese study [16], impact of growth in different access network technologies on internet back bone has been explored. This is an analysis which shows historical trends of access network technologies on core network. It neither discuss any model to set the relationship of recorded data nor tried to predict any future requirements. A techno-economic analysis has been reported for hybrid access networks [17]. Authors presented a techno economic comparison of different access techniques and predicted the growth in different segments based on their economic variables.

In another relevant article [18], they approached the problem of aggregation nodes by having a user data rate model. Their model is assuming dominant data streams such as videos by individual users as Poisson process. They contended with major data streams and ignored the impact of low data applications at individual customers.

There are some articles [19-20] which reported the use of deep learning techniques for prediction of traffic on telecom networks. Deep learning techniques use a large set of historic data for prediction. These articles mainly predict the network traffic on continuous time scale. These techniques have not been supported for prediction and planning of telecom networks for years. To predict for longer periods of time, some evolving factors and technology break through need to be incorporated and some outliers in history need to be adjusted. In our work, we developed model to incorporate the statistics of technological and social developments. Statistical model gives us better insight for predictions.

In comparison to reported works in this domain, we have approached the problem in a different way. We used actual data of a year to establish a statistical pattern of a customer's usage and a joint statistical model of all customers on a service node. We linked these statistical models to the probability model of data rate requirement on aggregation link in different hours of the day. The same procedure repeated for different demographic areas. In succeeding sections we describe the procedure in details.

3. Data Acquisition and Statistical Model

The problem explained in previous section has been validated with real time observations recorded on an FTTX network for one of the largest FTTX service provider in Pakistan. We have selected service nodes from a variety of demographic areas ranging from high traffic generating urban areas to low traffic generating rural areas. Each demographic area has different pattern of usage based upon their culture, habits and economic conditions. On a specific urban NE, a comparison of subscribed data rate with the aggregated data rate on the year scale is shown in Fig. 2

The gap between subscribed data rates and actual data rates is due to distributed peak hours of served subscribers from this network element. This leads to analysis of distribution of traffic patterns of individual subscribers to find rational requirement of data rate to connect this service node to aggregation node via aggregation link. Therefore, the usage patterns of individual customers for a yearlong period has been acquired. We have studied that all subscribed users with different subscriptions have different trends of peak hours. Hence their aggregated traffic on node is not simply a linear combination of individual subscriptions rather it's a statistical distribution addressing the probability of customers sharing the same peak hour in a day.

So, first objective was to observe the usage patterns of each individual subscriber to evaluate peak hour. Peak hour of a landline customer premises is a random observation; therefore, we acquired data of subscribed customers on a particular Service Node elapsed over 365 days.

Ideally a user can have its peak traffic generation in any hour of the day, developing a uniform statistical distribution. However this imagination is not practical as there are always trends of peak traffic generation based upon habits common in a particular demography. Besides a large quantum of data, qualitative analysis by experts and officials supervising the services in the area has been accounted for to develop a realistic pattern of peak hour distribution amongst subscribed users [22].

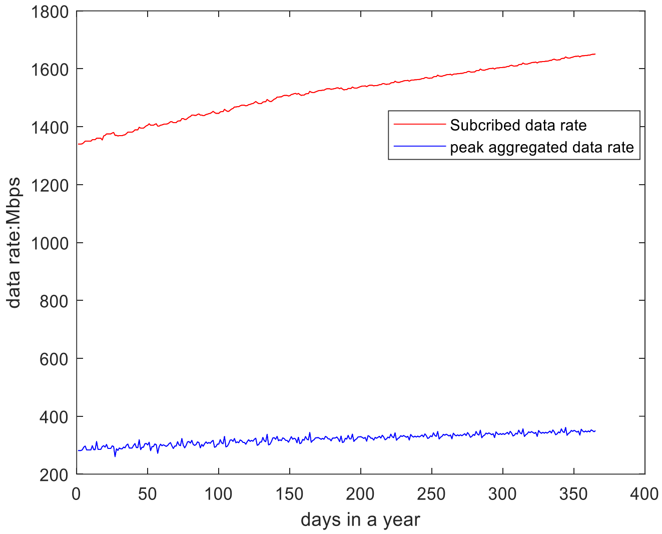

Fig. 2. Comparison of acquired peak hour data rate on aggregation node and subscribed data (for 365 days)

This set of data is sufficient to establish a reliable statistical inference for determination of peak hour of a customer. The notation H_{c1x} represents observed peak hour of customer $c1$ out of 24 hours in some day x from 365 days of observation period. To make a general formulation, sample size is represented by n which is 365 in our case. Eq. 1 computes the sample mean of data and PH_{c1}represent peak hour of customer $c1$.

$$PH_{c1} = \frac{H_{c11}+H_{c12}+H_{c13}+\cdots+H_{c1n}}{n} \quad (1)$$

Different service nodes are serving variable number of subscribers which keep on changing due to commercial reasons throughout any observation period. We targeted five different social segments hence chose multiple service nodes from each target social segment. For example three MSAGs/OLTs from high end urban areas. Collectively 1000 customers from each social segment has been processed to develop an empirical distribution in terms of percentage of customer sharing their peak hour in a particular day hour. This distribution has been considered as an empirical distribution of a random observation h and can be described as probability of a customer having its peak hour in h hour of day clock.

This results presented in this section has been developed for an urban service area with average traffic generation pattern as an example. This analysis and technique was extended to other demographic segments for their relevant distributions and computations for development of required information for forecasting model.

This distribution in Fig. 3 indicates that percentage of users having their peak hour in certain part of the day. Due to urban sample, it shows two peaks indicating mid-day traffic due to official usage and later in night due to domestic internet usage. Subsequent to this measured distribution of hitting peak hours, we further measured the traffic converging on aggregating node for the whole span of the day from this particular service node. It is notable that for any particular hour, traffic from peak hitting users along with all other users contribute to develop the aggregated traffic on converging NE. This behaviour of convergence in terms of megabits per second and in comparison with total subscribed traffic has been shown in Fig. 4. The empirical distribution in Fig. 3 sets a basic format to launch Monte Carlo computations.

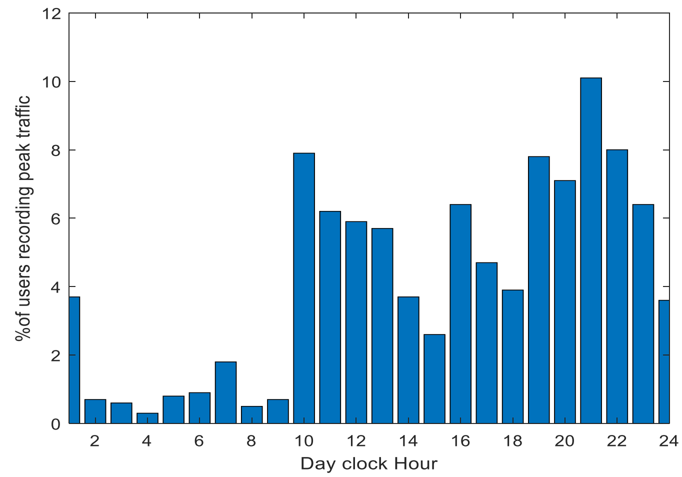

Fig. 3. Distribution of peak hours of subscribed users in urban area

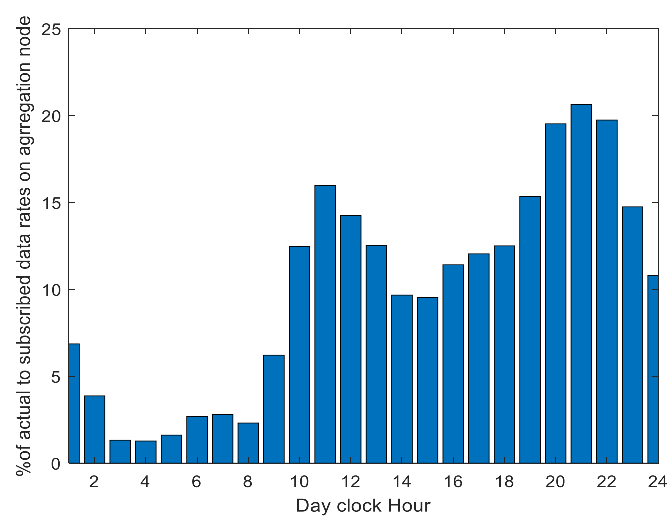

Fig. 4. Percentage of observed data rates to subscribed data rates on aggregation link on clock Hours

Fig. 5 describes the procedure in a flow chart from acquisition of data to develop an empirical distribution. This distribution is simulated for a large set of iterations to extract the maximum number of users having their peak hours statistically possible for any hour of day clock. This maximum number leads us to compute maximum data rate requirement on aggregation link. Same procedure would be repeated for different demographic sections.

4. Monte Carlo Computations

At this stage we defined a random variable, *r* representing the number of hours where more than 5% of customers render their peak data rate to assess the probability of having common peak hours on a service node. For this purpose a Monte Carlo computation technique has been performed for 400 customers in urban area. This number of 400 has been adopted due to most commonly deployed capacity of NEs. The empirical formulation of observed distribution in Fig. 3 has been iterated for 100,000 times to seek a large number of varying realizations.

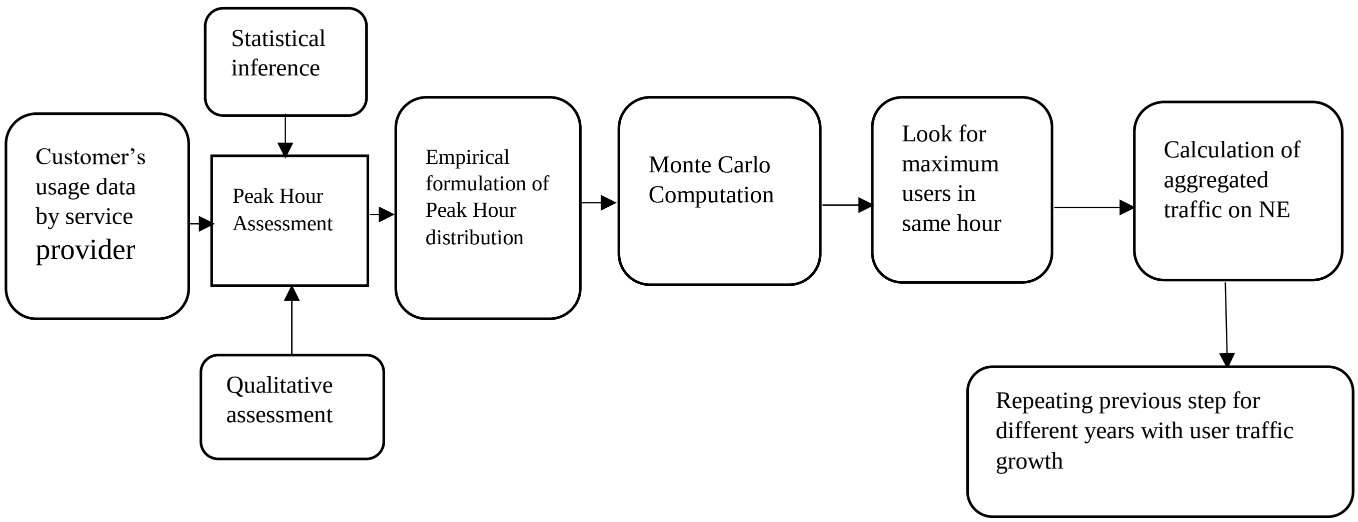

Fig. 5. Flow diagram for modelling and forecasting

This large number of realization has been processed to compute the value of *r* where more than 5% users generated their peak traffic. Moreover the probability distribution of 400 customers with threshold of 5% users or more hitting their peak in same hour has been computed and probability distribution has been shown in Fig. 6. The benchmark of 5% has been taken to account for maximum possibilities of spread of peak hours. This distribution indicates that probability of having more than 20 users hitting their peak in the same clock hour of the day is maximum for 8 different hour slots. It means we are observing 8 different hour slots where users are availing their maximum data rates. It's quite rational that larger the number of hour slots where users hitting their peak traffic, lesser would be aggregated peak traffic on converging node. We would select the minim number of hour slots which in turn correspond to least spread and more convergence of traffic. Therefore, 4 would be taken as number of hours where distribution has minimum probability. This would serve as highest data rate requirement case on convergence node.

Such cases collectively bear the probability of 0.54×10^{-3}. 54 realization amongst 100,000 iterations fall in this least probable category. To further sort out the maximum accumulation of users in any hour slot, 54 realizations were processed to find a realization where any one hour observe maximum number of users generating their peak traffic. One such realization has been presented in the Fig. 7. This is highly unlikely scenario as this bears the probability of 0.1×10^{-4}. So, we can safely adopt this case as maximum traffic requirement in any single hour of the day.

Here we observed that 95 out of 400 customers were sharing the peak load at 21st hour of the day. This observation leads us to estimate an aggregated data rate requirement for a least probable case where maximum possible number of users are generating their peak data. Given this information along with known set of subscribed data rates, we can compute the maximum data rate requirement at any busy hour on aggregated link. These computations have been performed in next section to a set of subscriber data rates available from a forecasting work.

5. Estimation and Forecasting of Maximum Data Rate on Aggregation Link

Based upon the analysis and finding about an hour where most of the users avail their maximum data rates, we can estimate the data rate requirement for aggregation link. To observe the implications of statistical distributions on various possible cases, we have considered an urban NE for different number of subscribers. Maximum subscription available for any user from that NE has been considered as reference variable to compute the aggregated requirement. This estimation has been presented in Fig. 8.

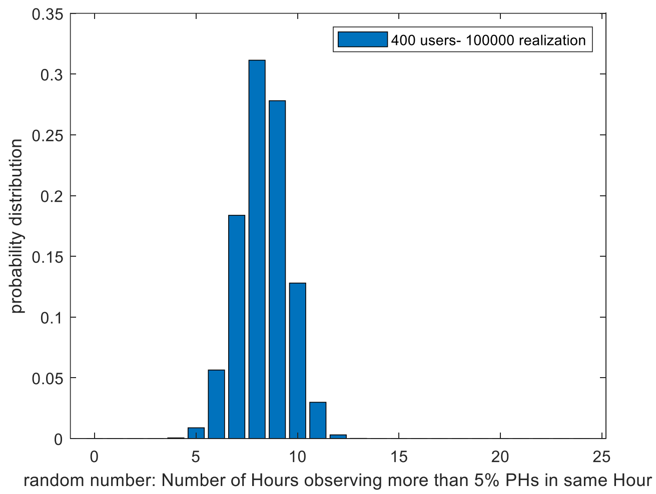

Fig. 6. Distribution of number of populated hours with 5% or more users having same peak hour

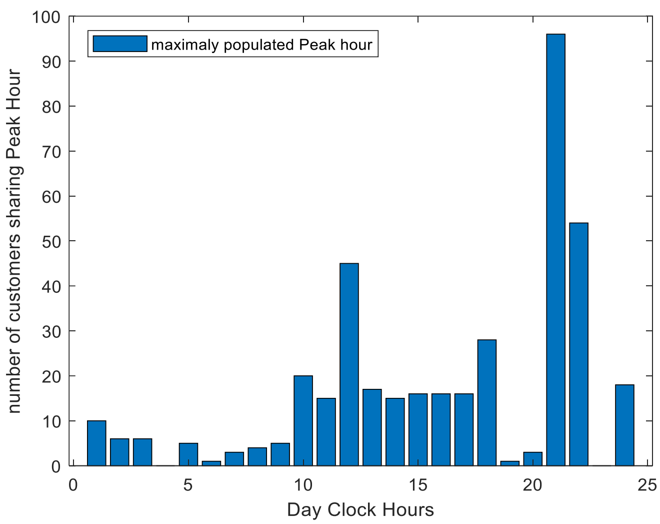

Fig. 7. Sample realization where maximum number of customers are sharing peak hour

A service node may serve variable number of customers. In estimation provided in Fig. 8, we have considered multiple cases of subscriber base from 200 to 500 customers. For each customer base, we have repeated the Monte Carlo computations to find the least probable but maximally availed hour from users for their maximum data rate usage. This analysis not only identified the hour slot when maximum requirement on aggregation link can be considered but also provided the number of users who are generating their maximum data rate usage. Now we can compute the aggregated requirement on the link with the help of these findings and maximum subscription rates available at any NE. Therefore, subscriptions rates has been considered as independent variable and range from 10 to 50 Mbps. It is quite evident that increase in subscriber base of service node will increase the aggregated link requirement, we have observed larger number of customers sharing the peak hour as the subscriber base increase. This observation relates to common behaviours of users from any particular service area. This has been reflected in increased slope of each graph in Fig. 8. The estimation in Fig. 8 is based upon the maximum subscription rates from service node. These subscriptions are subject to increasing demand by customers. When the subscription data rate increase, the aggregated data rate requirement also change. In succeeding paragraphs, we have used a forecasting model to observe the year by year estimation of data rate requirement on aggregation link.

In our earlier work [9], we have discussed in details about the factors affecting the growth in data rate requirements and presented a model to forecast the growth in requirements of landline users in five demographic sections ranging from high end urban areas to low end rural areas in Pakistan. The forecasting model has been conceived to help telecom service providers to wisely choose the areas where they can invest their valuable CAPEX to uplift their outdoor networks. This model accounted for demographic and technical evolutions in areas under study. On demographic side, average house hold population, growth in population in cities and rural areas, shift of age group patterns in urban and rural population of the country were accounted for the estimations. On technology side, growth in internet enabled devices per house hold, S curves for adoption of new services and devices [21] and technical developments alluring individual users to upgrade were considered on the basis of data from different reporting agencies. The forecasting model applied for five different demographic patterns to predict the demand of an average user in a particular demography. This forecasting model indicated a considerable increase in demand of data rate in urban high end areas whereas low end areas in both urban and rural sides are minimal on five years scale. An important outcome of forecasting model is to have data rates requirements of landline subscribers described in Mbps. These requirements can be considered as subscribed data rates in statistical model described in details in previous sections.

Taking the output of our model presented for statistical inference in section 3 and 4 to one step ahead for forecasting the link requirements in different demographic segments, we have used the forecasted data rate subscriptions for coming years as input. For each demographic section, forecasted data rates along with statistics of usage patterns of the same section combined together to assess the maximum data rate requirements on the aggregation links.

As every demographic section has different usage patterns hence develop different distribution of peak hours. The whole procedure described in previous section of Monte Carlo computation has been repeated for five different demographic sections for each year. This forecasting has been presented for five years. The year wise forecasts for peak requirements has been shown in Fig. 9

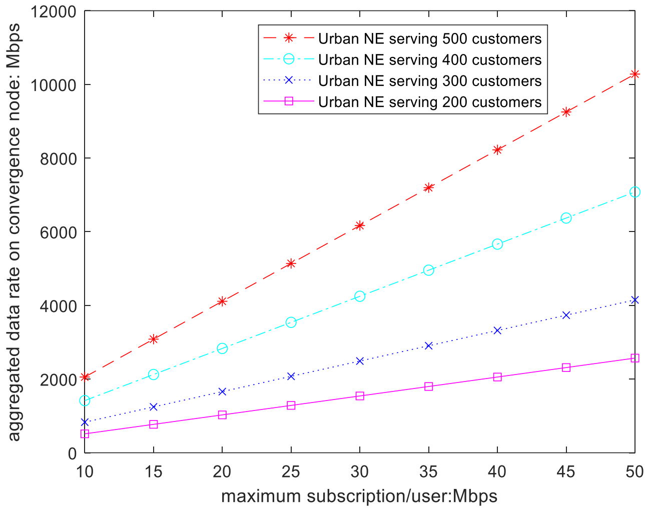

Fig. 8. Aggregated data rates on convergence node for an Urban NE serving different number of customers for different subscriptions

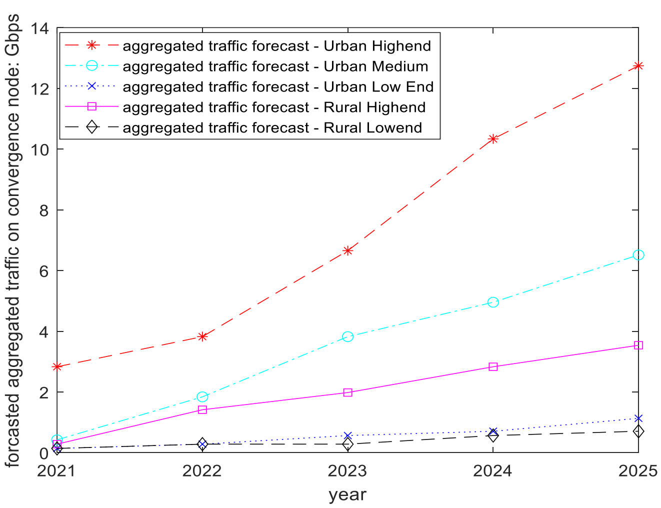

Fig. 9. Forecasting of bandwidth requirement growth for AGGREGATION Node on yearly scale for different demographic patterns

Five demographic sections comprise urban areas with higher data rate requirements, with medium end users and low end user areas. For Rural areas, two categories of higher end and lower end has been processed for this forecast.

The outcomes of this forecast is in form of data rate requirements on aggregate links in Gbps. This forecast can be used to suggest telecom operators how they can build and plan their networks from aggregation nodes to core networks according to statistics in different demographic sections for optimization of their network deployment resources.

6. Conclusion

The customer usage data of landline subscribers has been processed to extract statistical meanings. It has been observed that all users are not generating their maximum at same time. Their peak hours are randomly distributed. These distributions are different in different demographic segments hence network planning approaches vary in different areas. Another important outcome indicates that distribution of peak hours of users on a service node mainly determine the requirement of data rates on aggregation nodes. This work leads to a valuable approach for telecom service providers that deliberate efforts by intelligent tariff plans in different hours of the day can considerably improve the network efficiency.

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