Clustering-based dynamic bandwidth allocation for point-to-multipoint coherent optics

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Abstract: This article introduces a modified version of clustering techniques that can be applied in traffic aggregation for point-to-multipoint optical network architectures employing digital subcarrier multiplexing. The algorithm dynamically assigns individual subcarriers to nodes with uncorrelated traffic profiles.

1. Introduction

Recently, point-to-multipoint (P2MP) coherent optics – using digital subcarrier multiplexing (DSCM) [1] – is gaining a momentum among telecommunication operators as a technology that can potentially provide broadband connectivity with reduced costs, both in the aggregation and metro segments [2], but also in access or for the support of 5G mobile networks [3, 4]. Such P2MP technologies use DSCM to split the bandwidth into multiple Nyquist subcarriers (SCs) at a lower symbol rate. Each individual SC can be treated independently of all others, including modulation, management, aggregation, etc., and thus can be routed to different destinations, allowing a greater degree of flexibility with respect to classical fixed point-to-point (P2P) transceivers. In the case of 400 Gb/s DSCM, $m = 16$ SCs at 25 Gb/s, can be dynamically be shared / aggregated among nodes, e.g., in a passive filterless topology. In Fig. 1 we report the use case of SCs reconfigured over time: in Fig. 1(a) business end-users might demand high capacity (75G and 100G) during the day; while decreasing it over night (Fig. 1(b)). Similarly, residential ones might need low bandwidth during the day (25G), and increase it over the late hours (75G). Thanks to inherent flexibility of P2MP DSCM-based transceivers, the 16×25G-channels can be assigned to clients dynamically, moving channels from one client to another according to traffic demand [1]. This allows us to provide extra resources an end-user during his peak hour, and re-assigning that extra capacity to other clients whose peak hours occur later on.

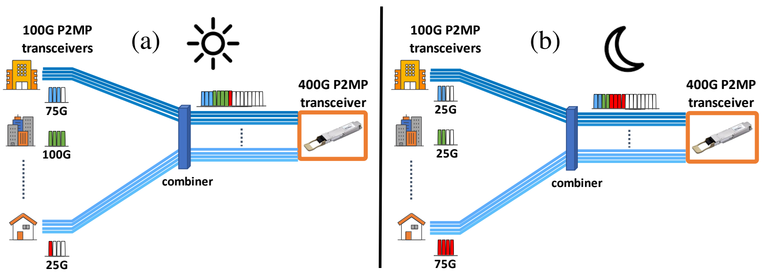

Fig. 1: Considered scenarios (a) morning–afternoon; (b) evening–afternoon.

In this article, we propose using unsupervised machine learning (ML) techniques (i.e. clustering) to efficiently aggregate nodes into clusters where the peak times of such nodes are uncorrelated, on attempts to maximize bandwidth use.

2. Finding groups of uncorrelated traffic sources

Clustering is a well-known unsupervised ML method for grouping elements based on a similarity or distance metric. It is used to reveal subgroups of similar structure within a set of unlabeled data, where each individual cluster has some homogeneity compared to the rest of the data. Most common distance metrics used in clustering techniques include cosine similarity, Euclidean, and Hamming distance.

In our case, we shall use correlation between daily profile traffic patterns as a distance metric, where two nodes with uncorrelated traffic patterns will be considered short-distance, while nodes with correlated peak times shall be avoided. In other words: $d(v_i, v_j) = \frac{1+cor(t_i,t_j)}{2}$ with $i \neq j$, where the minimum distance between nodes v_i and v_j (null distance) occurs when their traffic patterns are totally uncorrelated ($cor(t_i,t_j) = -1$) and the maximum distance (distance = 1) occurs when their traffic profiles are totally correlated ($cor(t_i, t_j) = 1$). Here, the traffic pattern t_i for node v_i is a 1×24 row vector whose elements represent the hourly traffic volume offered at each time of the day. Fig. 2(a) shows two examples of traffic profiles for business (red) and residential nodes (blue) as obtained from [5].

3. Simulation scenario

In Fig. 2(a), the traffic peak of the business profile results being during the morning hours (between 10 am and 3 pm); while the residential profile reports a peak mostly in the evening (between 6 pm and 11 pm), having peak-to-average ratios of 2.47 and 2.54 respectively. Following this pattern, we have simulated 50 nodes of each profile with uniformly distributed random peak values $U(10, 100)$ Gb/s plus a percentage of random noise to create a diverse dataset with different traffic profiles and demand volumes. Fig. 2 (b) shows a heatmap with the correlation and clustering of the resulting dataset.

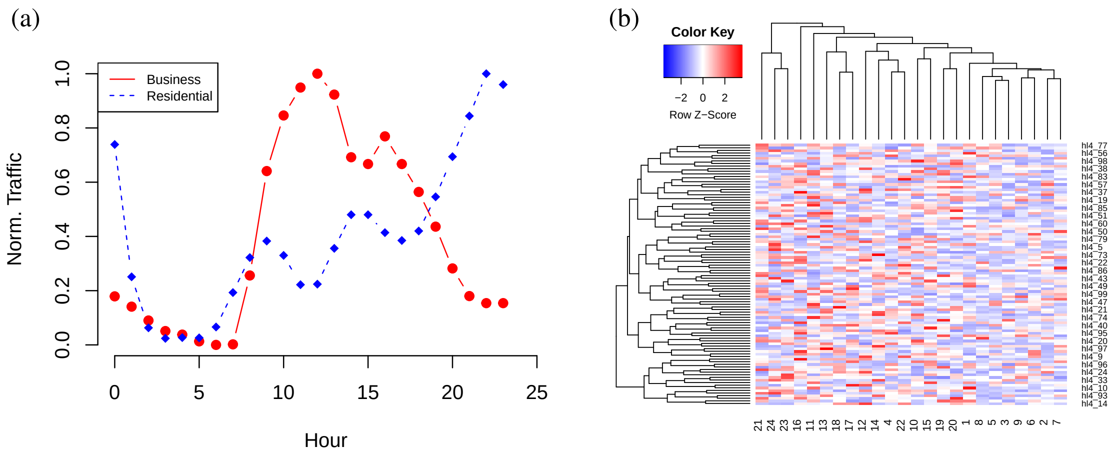

Fig. 2: (a) Normalised traffic profiles for business and residential nodes [5]; (b) Traffic correlation heatmap between nodes.

Selecting the optimal groups/clusters whose sum is below 16×25G SCs can be thought of as an extension of the classical bin-packing/Knapsack problem, which is known to be NP-complete. Instead, we use the clustering technique defined in Sec. 2 to find groups of uncorrelated traffic profiles, while satisfying that the number of SCs demanded is always below 16 during the whole day.

In this particular example, the clustering algorithm creates 20 clusters out of 100 nodes. Table 1 shows an example of cluster. As shown, the demands for 25G SCs vary greatly from one hour to the next, highlighting the benefits of having dynamic bandwidth allocation of 25G modules over different times. For example, in this cluster, at hour h12 (i.e. 12 noon), node 21 needs to jump from 4 SCs up to 7, while node 54 can reduce one of them (from 4 to 3). Similarly, at hour h14 (2pm), node 21 only needs 3 while node 54 needs to grow from 3 to 7.

Table 1: Example from cluster no. 4.

	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	h12	h13	h14	h15	h16	h17	h18	h19	h20	h21	h22	h23	h24
Node 21	3	3	1	6	1	5	2	1	1	1	1	4	7	3	1	6	4	4	6	6	1	5	1	2
Node 42	1	1	3	1	1	2	3	1	4	4	2	1	1	1	2	1	3	1	1	1	3	2	3	3
Node 54	3	1	1	4	2	1	4	2	1	6	3	4	3	7	3	3	1	2	3	3	4	4	2	2
Node 1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	2	1
Node 37	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Sum	9	7	8	13	6	10	11	6	8	13	8	11	13	13	8	12	10	9	13	12	10	13	9	9

Fig. 3 shows four different clusters where individual traffic demands are depicted in blue, and the total aggregated one is shown in red. As shown, the uncorrelated nature of individual flows is leveraged to hit (or nearly hit) the maximum number of SCs at different times of the day.

In a final test, we have compared the amount of P2MP tree topologies of our clustering-based algorithm against different allocation of nodes into trees for a set of 1,000 nodes: (i) Our P2MP clustering algorithm outputs 234 clusters or P2MP tree topologies; (ii) A Random Fit (or dummy) algorithm clusters nodes into 263 P2MP tree topologies; (iii) The Smallest-Flow First Fit aggregates nodes into 259 P2MP tree topologies; and (iv) The Largest-Flow First Fit creates 261 P2MP tree topologies. As shown, our P2MP clustering algorithm based on decorrelated

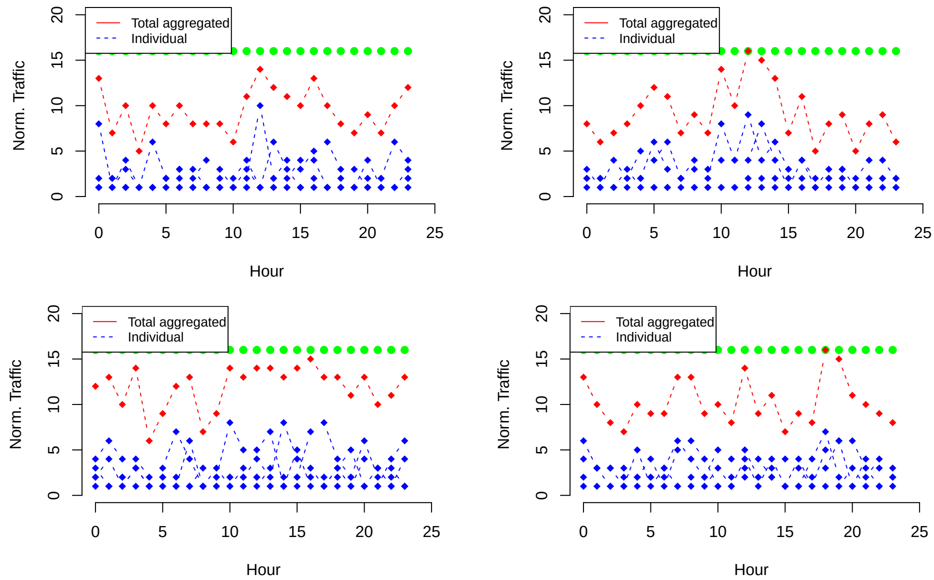

Fig. 3: Clusters no. 1, 2, 3 and 18.

traffic profiles reduces the number of P2MP tree topologies in at least 25 trees compared with the best case (Smallest-Flow First Fit), i.e more than 10% equipment savings. All the code with the algorithm and experiments of this paper can be found in our github repository [6].

Finally, if we dimension all nodes with P2P transceivers, the 1,000 nodes require: 430 pairs of 100G P2P transceivers, 459 pairs of 200G P2P transceivers and 111 pairs of 400G transceivers. It is worth noticing that our P2MP clustering algorithms reduces this to 239 400G P2MP transceivers on one side of the tree and 1,000 P2MP transceivers on the client side (i.e., 2,000 P2P vs 1,239 P2MP transceivers). This test can be found also in the Github code.

4. Conclusions

In this article, we show the applicability of Machine-Learning based clustering techniques to find groups of nodes whose aggregated traffic demands is best suitable for $m\times 25$ Gb/s P2MP topologies featuring DSCM. We observe more than 10% reduction in transceivers when compared to other P2MP strategies and large cost savings with respect to classical P2P architectures.

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