Metro-Flow Traffic Modelling for Cognitive Adaptation of Core Virtual Network Topologies

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ABSTRACT
A successful use case of cognitive networking consists in the reconfiguration of core virtual network topologies (VNTs) based on traffic predictive models obtained by applying data analytics to monitored traffic data. This use case entails long times (several days) to collect enough traffic monitoring samples data at core nodes to allow traffic modelling algorithms (usually at the core controller) to produce accurate models. Notwithstanding, that requirement could not be achieved in the case that metro controllers re-route metro-flows for metro-scope re-optimization purposes. In that case, some metro-flows suddenly change its node entering the core VNT, which drastically impacts on core traffic behaviour. In this paper, we present core-flow traffic models based on the aggregation of metro-flow traffic models. We consider that metro controllers generate traffic models based on monitoring the traffic of the metro-flows and those models are available in a shared repository for the core controller to access them. Moreover, the announcement of metro-flows re-routing from metro controllers to the core controller is assumed to allow fast core-flows models adaptation. Such aggregated models are then used to generate inputs for cognitive core VNT re-optimization purposes.
Keywords: network traffic modelling, metro networks, core networks, virtual network topology reconfiguration.

1. INTRODUCTION

Next-generation internet services such as live TV and video on demand require high bandwidth and ultra-low latency. The ever-increasing volume, dynamicity and stringent requirements of these services' demands are generating new challenges to nowadays telecom networks. To decrease expenses, service-layer content providers are delivering their content near the end users, thus allowing low latency and tailored content delivery. Consequently, unseen metro and even core traffic dynamicity is arising with changes in the volume and direction of the traffic along the day.

A tremendous effort to efficiently manage networks is currently ongoing towards the realisation of 5G networks. This translates in looking for network architectures supporting dynamic resource allocation, fulfilling stringent service requirements and minimising the total cost of ownership. In this regard, *in-operation network planning* was recently proven to successfully support various network reconfiguration use cases in prospective scenarios [1]. Nevertheless, additional research to extend in-operation planning capabilities from typical reactive optimization schemes to proactive predictive schemes based on the analysis of monitoring data is required.

In [2], a procedure to allow network traffic flow modelling, from monitoring and data transformation to the estimation of a predictive traffic model based on this data, is proposed. Specifically, a cognitive approach to periodically adapt the core virtual network topology (VNT) to current and expected maximum traffic, using predicted traffic matrices based on origin-destination (OD) predictive models, is presented. This optimization approach, named VENTURE, is efficiently solved using dedicated heuristic algorithms and evaluated under dynamic traffic network scenarios. By using this approach, the VNT can be proactively adapted for the predicted near future traffic conditions.

However, the efficiency of that proposal strongly depends on accurate predictions, which entails long monitoring data collection times (i.e., several weeks) to collect enough data to produce highly accurate traffic models. That requirement cannot be achieved in the case that metro controllers re-route the traffic exchanged between metro areas (metro-flows) for metro-scope re-optimization purposes. In this situation, some metro-flows first entering the core VNT through origin node are re-routed in the metro segment and enter the core through a different node. When such re-routing occurs, the OD traffic patterns in the core change thus triggering a model re-estimation based on new monitored data. Depending on the frequency of such re-routings, re-estimation might not be even possible.

In this paper, we focus on the approach presented in [3] to create OD traffic models based on the aggregation of metro-flow traffic models. We assume that metro controllers are able to estimate traffic models based on monitoring metro-flow traffic and those models are available in a shared repository for the core controller to access them. In addition, we assume that metro controllers announce metro-flows re-routing to the core controller, when their core entrance node changes. Based on the aggregated model, we can predict future traffic for the OD pairs and use it as input for core VNT re-optimization purposes. Next sections are devoted to present the proposed metro-flow based OD pair modelling procedure and to numerically evaluate its accuracy to predict maximum OD pair traffic, which is the required traffic forecast for the VENTURE problem.

2. FLOW TRAFFIC PREDICTION UNDER CHANGING TRAFFIC

Modelling core OD and metro-flow traffic independently at each network segment can lead to degraded performance in the quality of the predictive models after metro-flow rerouting. OD pairs might aggregate many metro-flows and hence, reroute some of the metro-flows in the metro areas might change the aggregated traffic pattern of some ODs in the core network. For illustrative purposes, Fig. 1 presents an example of a metro-flow (*mf1*) originated at some metro network and routed toward datacenter DC2 through the core VNT. The metro-flow is encapsulated in a MPLS Label Switched Path (LSP) and routed through the VNT. Initially, the LSP enters the core VNT through ingress node R2 toward egress node R3, so it is aggregated into core OD pair R2→R3. Due to metro re-optimisation, the metro controller reroutes the metro-flow LSP so that to enter the core VNT through edge node R1, being aggregated into core OD pair R1→R3. As a result, the traffic profiles of both OD pairs (R1→R3 and R2→R3) have now changed.

Figure 2 illustrates the traffic profile change in OD R2→R3. Before the rerouting event, the predictive core OD model perfectly fits the actual traffic; once metro-flow LSP *mf1* has been rerouted, the OD traffic profile changes and the corresponding predictive model becomes obsolete, thus triggering a re-estimation based on new monitoring data. Note that the difference between the actual traffic volume and the obsolete prediction can be mistakenly confused with an OD traffic anomaly [1], which would trigger unnecessary network reconfiguration. During this re-estimation process, the VENTURE algorithm will not be available for execution.

Alternatively, OD traffic can be predicted by considering its relationship with metro-flow traffic. Effectively, by aggregating the traffic models of those metro-flows being routed through each core OD pair, we can produce new, updated OD traffic models. Immediately after the rerouting event, the obsolete model for ODs R1→R3 and R2→R3 are replaced by new ones based on the aggregation of metro-flows predictive models. Figure 2 shows how the aggregation of metro-flow traffic predictions perfectly fits the new OD traffic pattern without the need of restarting the monitoring and estimation process from scratch. By following this approach, network operator can keep the predictive capabilities, provided that some coordination between metro and core segments exist.

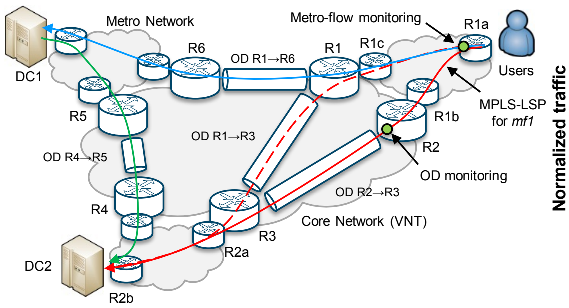


Figure 1. OD traffic change.

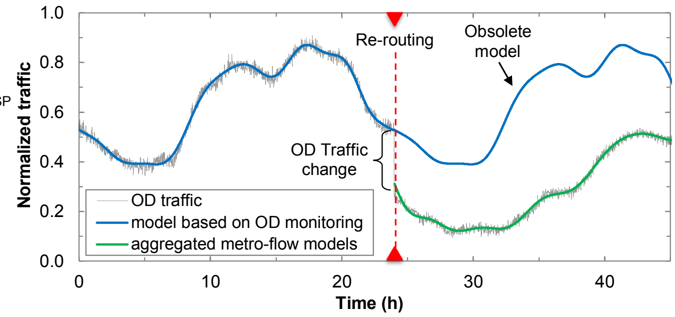
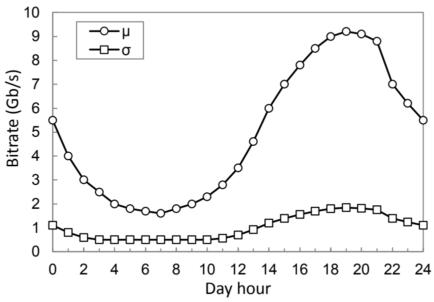


Figure 2. Example of obsolete model.

3. METRO-FLOW BASED OD PAIR TRAFFIC MODELLING

Let us consider a metro-flow f and the set Y_f containing all the data collected from f at the same relative time across m consecutive periods. Given a core OD pair od, we can consider the previous sets for all its metro-flows $F(od) = \{f_1, \ldots f_n\}$ and for itself, denoting the latter as Y_{OD}. It can be mathematically proven that the maximum value attained in Y_{OD} is upper bounded by the sum of the maximum values attained in each Y_f. In other words, that the sum of the maximum metro-flow bitrate always overestimates the maximum OD bitrate. As a result, solving the VENTURE problem based on large traffic overestimation would entail overprovisioning, thus removing the efficiency of the algorithm. Therefore, we need to devise a traffic model aggregation procedure that allows predicting the maximum OD bitrate accurately.

Instead, for a particular core OD pair od let us assume that predictive models for the mean (μ_f) and the variance (σ^2_f) are available for each metro-flow f in $F(od)$. Each metro-flow model consists of two piece-wise linear functions of a certain number of segments, each identified by an intercept a equal to the empirical value at the starting of the segment and a slope b computed from the values at both edges and the segment length (Fig. 3).



	μ		σ	
Segment	*a*	*b*	*a*	*b*
[0,1)	5,5	-1,5	1.1	-0.3
[1,2)	4	-1	0.8	-0.2
…	…	…	…	…
[14,15)	6	1	1.2	0.2
…	…	…	…	…
[23,24)	6.2	-0.8	1.2	-0.1

Figure 3. Example of a metro-flow piece-wise linear model.

From the linearity of the expectation [5], the average OD traffic (μ_{od}) is equivalent to the sum of the metro-flow average traffic (eq. (1)). Regarding the OD pair variance (σ^2_{od}), it can be expressed as the summation of metro-flow variances if and only if variances are uncorrelated (eq. (2)). Correlation is commonly observed in the traffic and has been already studied in the literature [6]. Therefore, it would not be realistic to assume that the aggregated metro-flows have uncorrelated traffic if, for instance, they convey similar service traffic. When correlation is present between metro-flows, the expression of the OD variance becomes more complex since it additional nonzero co-variances between all pairs of aggregated flows needs to be added [5]. The bias introduced in the estimation of σ^2_{od} when covariance terms are excluded will be numerically evaluated in Section 4.

Table 1 presents the proposed algorithm to create or update core OD traffic models after a metro-flow rerouting event. It receives the set Q with all OD pairs, where each pair includes its model m and the set of aggregated metro-flows. First, the set of obsolete models is found by inspecting the current aggregation of the metro-flows (line 1 in Table 1). For each obsolete OD model, the type of the model determines whether it is a model estimated from core traffic monitoring (NEW_CORE) (lines 4-5), from metro traffic monitoring (NEW_METRO) (lines 6-7) or it is a model that needs to be updated (UPDATE) by including the new metro-flows entering the OD pair and excluding those ones leaving it from the prediction (lines 8-9). For the updating process, we can take advantage of the linearity of the mean and the variance in the aggregation to produce updates applying equations (3) and (4), only taking into account those metro-flows leaving/entering the core OD.

Finally, the algorithm returns the set of updated models (line 9). Note that the aggregation of μ and σ^2 models entails adding the metro-flows piece-wise linear functions. However, this is immediate from the linearity of these functions by simply adding the slopes and intercepts for each segment to obtain the aggregated piece-wise linear function for μ_{od} and σ^2_{od}. For the sake of simplicity, we assume that all aggregated models present the same period and number of segments. Otherwise, additional computation would be required to obtain the partitioning resulting from merging all the piecewise linear functions μ_f and σ^2_f using the least common multiple period.

Table 1. OD model update algorithm.

	INPUT $Q = \{<od, m, F(od)>\}$
	OUTPUT $S = \{<od, m'>\}$
1:	$Q_{obs} \leftarrow$ getObsoleteModels(Q)
2:	$S \leftarrow \emptyset$
3:	**for each** $q = <od, m, F(od)>$ **in** Q_{obs} **do**
4:	**if** type(m) = NEW_METRO **then**
5:	$m' \leftarrow m$
6:	**else if** type(m) = NEW_METRO **then**
7:	$m' \leftarrow$ newAggregate($F(od)$) (eqs. (1),(2))
8:	**else if** type(m) = UPDATE **then**
9:	$m' \leftarrow$ updateAggregate(m, $F(od)$) (eqs. (3),(4))
10:	$S \leftarrow S \cup \{<od, m'>\}$
11:	**return** S

$$\mu_{od}(t) = \sum_{f \in F(od)} \mu_f(t) \tag{1}$$

$$\sigma^2_{od}(t) = \sum_{f \in F(od)} \sigma^2_f(t) \tag{2}$$

$$\mu_{od}(t) += \sum_{f \in F_{IN}(od)} \mu_f(t) - \sum_{f \in F_{OUT}(od)} \mu_f(t) \tag{3}$$

$$\sigma^2_{od}(t) += \sum_{f \in F_{IN}(od)} \sigma^2_f(t) - \sum_{F_{OUT}(od)} \sigma^2_f(t) \tag{4}$$

$$\max_{od}(t) \approx \mu_{od}(t) + k\sqrt{\sigma^2_{od}(t)} \tag{5}$$

Let us now analyse the worst-case time complexity of the previous algorithm, assuming that all OD models need to be re-estimated ($|Q_{obs}| = |Q|$) with a maximum number of metro-flows $|F|$ for each re-estimation. Let us also assume that all aggregated models are of type NEW_CORE (i.e., built from scratch using eqs. (1) and (2)) being this the most time-consuming case. Then, the worst-time complexity is $O(|Q| \cdot |F| \cdot nSegm)$, where $nSegm$ is the number of segments in a piece-wise linear function.

Limiting the piece-wise linear model evaluation to the mean and the variance discards other interesting estimations such as the maximum bitrate. Although the algorithm does not directly provide this estimation, we can obtain it in a later stage by applying eq. (5). Thus, assuming normality, a reasonable estimation of the maximum can be achieved by k= 3; on the other hand, when normality assumption cannot be accepted, larger k, e.g. k = 6, can be setup according to Chebyshev theorem [5].

4. NUMERICAL RESULTS

In this section, we evaluate the proposed approach to obtain OD core traffic models based on the aggregation of metro-flow traffic models. To that end, synthetic metro and core-flow monitoring data has been obtained following the approach in [7]. Two different traffic profiles has been considered: *i*) one representing the traffic aggregation of end users consuming high-bandwidth applications such as video-on-demand or live TV, with higher activity at evening hours (*Users*), and *ii*) one aggregating traffic between distributed datacenters as a consequence of connectivity services required for dynamic management activities (*DC*). An increasing number of *Users* and *DC* metro-flows were synthetically generated and aggregated into a single OD pair and monitored for 3 months. Piece-wise linear models for the maximum bitrate of every metro-flow and the aggregated OD pair were computed. As already anticipated, the simple addition of the maximum bitrate of each metro-flow overestimates the actual maximum predicted with the OD pair model, as illustrated in Fig. 4. Note that overestimation exceeds 100% when more than 500 *Users* metro-flows are aggregated. Hence, the need of using eq. (5) to provide an accurate OD maximum bitrate estimation as a function of metro-flows maximum estimations is highlighted.

Let us now evaluate the bias introduced in the estimation of σ^2_{od} (anticipated in Section 3) by running experiments where the maximum bitrate is predicted for a single OD pair aggregating *Users* metro-flows only, which leads to a large and positive covariance. Figure 5a shows the minimum value of k needed to predict the maximum bitrate below a given error, for a different number of aggregated metro-flows. A value of k close to 6 suffices to ensure an error below 2% for any number of aggregated metro-flows. On the contrary, we observe that the value of k cannot be bounded to ensure a prediction error close to 0%; in fact, the minimum value of k seems to increase with the number of aggregated metro-flows. Finally, we observe that a value of approximately $k = 5.75$ tightly bounds the prediction error below 1.6% for any number of aggregated metro-flows. For the particular case of 500 aggregated metro-flows, Fig. 5b illustrates the prediction error for as a function of k.

Finally, Fig. 6 illustrates the bitrate of an OD pair along the day mixing different metro-flow traffic profiles, as well as the predictions based on the proposed metro-flow model aggregation. Note that min and max models have been obtained for $k = 5$. As expected, because of traffic aggregation, the variability of OD traffic is much smaller than that of metro-flows.

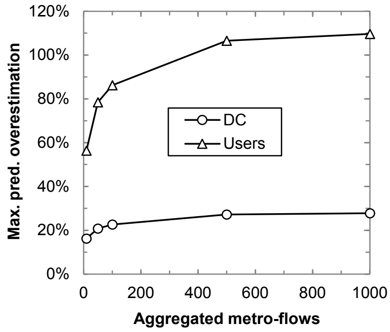


Figure 4. Overestimation analysis.

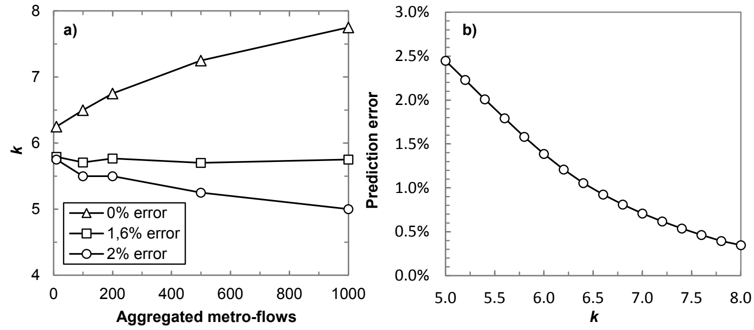


Figure 5. k parameter evaluation.

5. CONCLUSIONS

Aggregated metro-flow traffic predictive model is proposed to cope with OD traffic changes in the core as a result of uncoordinated metro-flow rerouting, where the predictive traffic models are used to reconfigure the core VNT. By conveniently aggregating metro-flows after they become rerouted, OD predictive models can be rebuilt fast to keep the predictive capabilities in the core.

To obtain quality metro-flow predictive models, an estimation procedure that allows obtaining models that can be aggregated and evaluated efficiently is presented. Results show predictions based on metro-flow model aggregation as accurate as those obtained by OD pair traffic models trained with OD monitoring data.

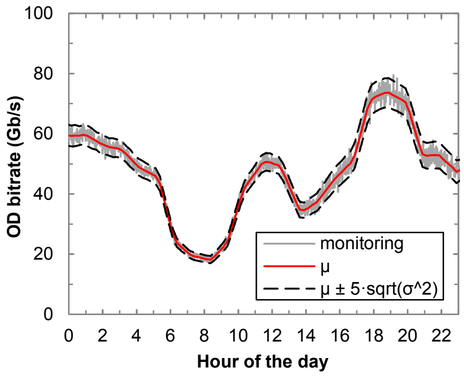


Figure 6. OD pair example.

ACKNOWLEDGEMENTS

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