

Adaptive Robust Traffic Engineering in Software Defined Networks

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Abstract—One of the key advantages of Software-Defined Networks (SDN) is the opportunity to integrate traffic engineering modules able to optimize network configuration according to traffic. Ideally, the network should be dynamically reconfigured as traffic evolves, so as to achieve remarkable gains in the efficient use of resources with respect to traditional static approaches. Unfortunately, reconfigurations cannot be too frequent due to a number of reasons related to route stability, forwarding rules instantiation, individual flows dynamics, traffic monitoring overhead, etc.

In this paper, we focus on the fundamental problem of deciding whether, when and how to reconfigure the network during traffic evolution. We propose a new approach to cluster relevant points in the multi-dimensional traffic space taking into account similarities in optimal routing and not only in traffic values. Moreover, to provide more flexibility to the decisions on when to apply a reconfiguration, we allow some overlap between clusters that can guarantee a good-quality routing regardless of the transition instant.

We compare our algorithm with state-of-the-art approaches in realistic network scenarios. Results show that our method significantly reduces the number of reconfigurations with a negligible deviation of the network performance with respect to the continuous update of the network configuration.

I. INTRODUCTION

Traffic Engineering (TE) [1] plays a crucial role for service providers since it permits to optimize network performance, reduce operational costs, and load balance the utilization of network resources. However, the dynamic nature of the traffic due to ordinary daily fluctuations and unpredictable events stirs up the trade-off between optimality of the routing configuration and network reconfiguration rate. The traditional approach of service providers is to optimize the routing considering the "worst case" traffic condition so as to rarely reconfigure the network. The resulting overprovisioning leads to the underutilization of network resources.

Software-Defined Networks (SDNs) [2] provide the needed flexibility to update more frequently TE policies. Having a global view of the network status, SDN controllers can integrate TE algorithms [3]–[5] to continuously optimize the network with an online twist. As the system evolves, new configurations are applied to the network equipment to optimize network performance. However, sudden and unpredictable system changes, like traffic variations, network failures, and the uncontrolled rate of change, still pose a major challenge for these methods.

The solutions that have been devised to cope with traffic variations can be broadly classified into three main classes: *dynamic TE*, *static TE*, and *semi-static TE*. While different in the way they calculate network configurations, all techniques require the use of Traffic Matrices (TMs) periodically collected by a network monitoring tool. *Dynamic TE*, like [3], [4], [6], [7], uses such information to predict the next system state and compute the corresponding optimal routing configuration using linear programming [8] or fast approximation algorithms [9]. The accuracy of the prediction highly affects the optimality of the computed solution while frequent network reconfigurations result in control plane congestion due to the low speed of flow programming [4] in hardware. In contrast, *static TE*, such as *oblivious routing* [10] and robust routing [11]–[13], monitors TMs over a long period of time and computes the TE configuration that minimizes the worst deviation with respect to the sequence of all optimal configurations. This class of TE policies keeps the network configuration stable, but it inevitably suffers from low optimality during most of the operational time.

Semi-static TE approaches such as [14], [15] combine both static and dynamic TE to approximate the optimal sequence of configurations with a limited set of routing solutions computed over clusters of TMs. Clusters of TMs are formed either by statically dividing time in different intervals or by finding similarities in the traffic domain. However, the arbitrary splitting of the time domain results in significant performance loss when sharp traffic variations are temporally close. Similarly, using the same routing configuration for TMs that are close in the traffic domain (i.e., their entries have the same magnitude) but far in the time domain can lead to frequent network reconfigurations. More importantly, the controller needs to decide whether and when to reconfigure. Transitory traffic fluctuations should be ignored to avoid system oscillations and the network should be reconfigured only when it is evolving towards a new state.

In this paper, we study the fundamental problem faced by SDN controllers of deciding whether, when and how to reconfigure the network after a traffic evolution. To provide an answer we study and address the problem of building a set of robust routing configurations associated to clusters of TMs that overlaps in time, traffic and routing domains. Time overlap refers to the amount of time we are able to use a routing configuration even for TMs that are outside the associated

cluster with minimal efficiency degradation. Traffic overlap denotes the similarity in the traffic space of TMs within the same cluster, whereas routing overlap indicates how similar routing configurations associated to two different clusters are.

Given the interplay between TM clusters and routing solutions, we decouple the problem into two subproblems, namely TM clustering and robust routing. To this aim, we propose Clustered Robust Routing (CRR), an iterative algorithm that achieves three objectives: 1) covering the entire TM space so that a feasible routing configuration is available for any traffic condition, 2) reducing the number of routing changes by creating a small set of robust routing configurations that can be used for a minimum duration each time one of them is applied, and 3) maintaining a minimum time overlap between adjacent clusters that can be exploited to decide whether to reconfigure the network. We analyze our algorithm on a realistic network scenario and compare its performance against state of the art approaches of the three TE classes discussed above.

This paper is structured as follows: Section II presents the related work. Section III describes the system model and the assumptions we made in the formulation of our problem. Section IV presents the algorithm to build clustered robust configurations considering the time continuum, the traffic space and routing similarities. Numerical results are discussed in Section V. Finally, concluding remarks are presented in Section VI.

II. RELATED WORK

The simplicity of controlling SDNs has brought back to light problems like mitigating and scheduling network reconfigurations [16], [17], since service providers are concerned about possible network outages caused by failures of route updates or sudden traffic changes. The networking research community has developed three classes of techniques to handle traffic change: (i) *dynamic TE*, which reconfigures the network each time a new event occurs, (ii) *static TE*, which uses a single precomputed configuration that minimizes the worst deviation to the optimum, and (iii) *semi-static TE*, which reconfigures the network at predefined time instants (e.g., twice per day at noon and midnight) to further improve network performance. Examples of *dynamic TE* includes methods like [3], [4], [6], [7], where sophisticated techniques are used to compute the best network configuration any time the traffic changes. However, reconfiguring the network too frequently can affect its stability, since programming hardware equipment with new flow rules can take longer than the reconfiguration period [4], thus causing the overflow of flow rules. Methods that reduce this burden have been proposed by prioritizing [18] or pre-filtering [19] network updates. Nonetheless, the computation of each routing solution is not robust against prediction errors on the next TM.

One of the first techniques of *static TE* is oblivious routing [10], [20], and its recent extension called *valiant routing* [21], which randomly selects paths to connect source-destination pairs using a small subset of preselected intermediate nodes. Being totally oblivious to any traffic information, oblivious routing shows high performance loss as

the network size grows. Exploring a partial knowledge of the traffic can reduce the performance loss. For example, COPE [13] considers only the most likely TMs for computing the optimal configuration and add a penalty term to avoid large deviation for less probable TMs. The technique proposed in [22] expands the most likely polytope by including TMs of normal operations in the direction of a predicted anomaly. The method proposed in [11] introduces different models for traffic uncertainty by expressing the maximum load that can be expected over a link in the pipe model or an upper bound on the traffic originating from a source node and directed to a destination node in the hose model.

Semi-static TE [14], [15], [23] provides a limited set of routing configurations with guaranteed performance loss. These works divide the TM polytope in two subsets according to the time dimension and compute a robust routing for each subset. While representing a first attempt to split the TM domain in multiple parts, these works present several limitations: (i) the slicing direction is arbitrary, (ii) the number of created subsets is limited, and (iii) the partition is performed either in the traffic domain or in the time domain.

Although semi-static TE approaches have the potential to optimize network performance using a limited set of routing configurations, traffic, time, and routing spaces/dimensions should be jointly considered when building clusters in order to avoid oscillations between routing configurations when TMs are close in the traffic space but far in the time dimension. Furthermore, clusters should not be sharply separated, since instantaneous routing changes are impossible even in SDNs. This work is a first attempt to address these problems and decide the best trade-off between reconfiguration rate and optimality of routing.

III. SYSTEM MODEL

In this section, we present the traffic and routing system models that we consider in the design of our CRR algorithm.

We consider a system composed of two main stages: (i) a cluster-maintenance stage where we group TMs into clusters and compute robust routing configurations over these clusters, and (ii) a cluster-activation stage where we track the traffic evolution and reconfigure the network accordingly. The target is to minimize the Maximum Link Utilization (MLU) over time, which is motivated in the domain of datacenter interconnection and enterprise networks, where the goal is to minimize the network congestion.

We model the network infrastructure as an undirected graph $G = (\mathcal{N}, \mathcal{L})$, where \mathcal{N} represents the set of network nodes and \mathcal{L} models the set of links $e = (i, j)$, connecting network nodes $i, j \in \mathcal{N}$. Each link $e \in \mathcal{L}$ has a limited capacity c_{ij} that represents the maximum amount of traffic that the link can transmit. The set of active demands, also known as Origin-Destination (OD) flows, that need to be routed through the network, is represented as a Traffic Matrix (TM): a $|\mathcal{N}| \times |\mathcal{N}|$ matrix $T = [t_{ij}]$ where each element t_{ij} denotes the amount of traffic transmitted from source node i to destination node j . Since the traffic evolves over time, we consider a dynamic TM

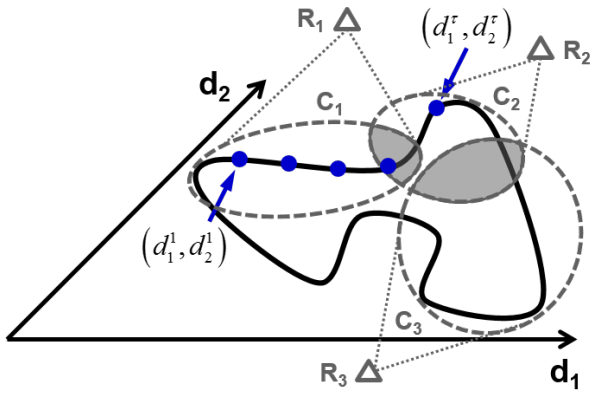


Fig. 1: Clustering of TMs. The solid black line represents the evolution of the two OD flows in the TM. Each blue point represents a sampled TM. Dashed ellipsoids denote the clusters of TMs, whereas triangles identify the corresponding routing configurations.

$T(\tau) = [t_{ij}^\tau]$, where τ denotes the time dimension. We assume that time is discretized and we have M samples of the TM (i.e., $\tau = 1, \dots, M$). To simplify the notation, TM are usually represented as a $|\mathcal{N}|^2 \times 1$ demand vector $D(\tau) = [d_h^\tau]$ where each element d_h^τ unequivocally corresponds to an element t_{ij}^τ of the TM.

Cluster maintenance. Fig. 1 graphically illustrates the time evolution of a TM composed by only two demands, d_1 and d_2 . The solid line represents the continuous evolution of the TM, whereas solid dots corresponds to periodic samples measured by a traffic monitoring system. As illustrated in the figure, an offline stage splits the TM domain into N clusters, denoted as C_i , and computes for each subset of TMs a routing configuration R_i , which is robust against any possible traffic variation within the cluster C_i . To avoid oscillations between routing configurations, a cluster C_i is built with a minimum time length L that results in a minimum utilization of the same routing configuration C_i . Furthermore, a temporal overlap O (the gray intersection in Fig. 1) is imposed between two adjacent clusters C_i and C_j to guarantee the feasibility of the corresponding robust routing configurations R_i and R_j outside their clusters. The overlap O provides further robustness against inaccurate cluster transition and can potentially leave some time to the real-time SDN controller decision on whether to reconfigure the network.

Cluster activation. The different precomputed routing configurations are then activated by the SDN controller which follows the evolution of the traffic matrix. By receiving an estimate of actual traffic conditions (and possibly a short term prediction) from the monitoring system, it can even decide whether to fetch and activate a better robust routing configuration in switches.

Clearly, the performance of this approach depends on the size and the number of clusters. Many small clusters result in a high reconfiguration frequency, which may harms the network behavior itself. In contrast, too few clusters will provide a low gain over static-TE solutions (e.g., oblivious routing). This approach will always lead to a better performance than the

Parameter	Description
\mathcal{N}	Nodes (network devices).
\mathcal{L}	Edges (network links).
c_{ij}	edge capacity (in capacity units) $(i, j) \in \mathcal{L}$.
d_h^τ	rate of OD demand d measured at time τ .
N	number of robust routing configurations.
M	number of traffic matrices.
L	minimum holding time of a routing configuration.
O	temporal overlap between two adjacent clusters.

TABLE I: Input parameters of our CRR algorithm.

single-design case, because the network is no longer forced to always support the worst-case traffic demand. Indeed, the correct solution will be applied when the corresponding worst-case (among the possibly many that lie in different regions) appears.

Furthermore, a sharp boundary between clusters that are adjacent in the time domain requires an instantaneous reconfiguration of the network. For a smooth network reconfiguration when the TM enters into a new cluster, we compute clusters with a minimum time overlap, represented by the intersection of two clusters in Fig. 1.

In the next section, we show how our algorithm, Clustered Robust Routing (CRR), solves the problem of achieving a good trade-off between routing stability and optimality by maintaining a set of routing configurations for overlapping clusters of similar traffic matrices.

Table I summarizes the notation used throughout the paper.

IV. CLUSTERED ROBUST ROUTING

The CRR algorithm is implemented as a module of the network controller. It takes as input a set of TMs representative of the period in which robust routing configurations should be designed. These TMs can be obtained in several ways: they can be measurements from past network conditions, or the outcome of a TM prediction module, or even synthetically generated. For the sake of clarity, we neglect the effect of prediction errors in the description of the algorithm, however, we investigate the impact of inaccurate TMs within numerical results. The impact is indeed rather limited for realistic error values because the clustering generates intrinsically robust solutions. Each TM describes the expected traffic conditions at specific time instants. Therefore, TMs can be temporally ordered and the set of TM IDs can be used as time axis. The result of the algorithm is a set of Routing Configurations (RCs, denoted as R_i in Fig. 1) and the corresponding clusters of TMs (C_i in Fig. 1). Each RC will be activated in the network as soon as the traffic enters the corresponding cluster.

A. Requirements for CRR

The CRR algorithm, shown in Fig. 3, consists in an iterative clustering and routing process relying on four main points:

a) *Routing-based clustering:* A TM clustering approach based on the similarity among the OD demands of each TM can be highly inefficient. Indeed, since network's links have limited capacity, good quality routes can substantially differ for TMs with similar demands. Since the way traffic

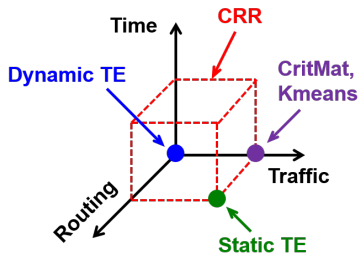


Fig. 2: Dimensions considered for the clustering of Traffic Matrices and computation of routing configurations. The traffic dimension is in reality multidimensional (one dimension for each OD flow).

is balanced over the network is not captured by the unique RC used to route the TM cluster, which is based on demand values, it may lead to high congestion for some TMs.

Things do not improve even if TMs with similar optimum routing are grouped together to generate a good unique cluster RC. Indeed, as we will show in Sec.V, this does not provide the best results. Due to scenario symmetries, different RCs can provide the same congestion, therefore clustering on the mere basis of RC topology can be largely suboptimal. Indeed, since the number of desired clusters in a solution is usually limited, this approach may waste clusters to separate TMs with different optimum routings, which could be equivalently well routed by another unique RC.

In order to better include the routing effects in the cluster selection, we need to consider the ultimate effect of the routing, that is the network congestion resulting from applying a given RC to a given TM. Only TMs that are characterized by a small congestion with the same RC must be grouped together into the cluster associated to the specific RC.

b) In-cluster robust routing: Although clustering is based on routing (i.e., it groups TMs having a similar congestion with a specific RC), the RC design cannot be strongly customized on a specific TM. Indeed, in practice we have to deal with deviation from the TM input set caused by imperfect measurements/predictions or even traffic anomalies. Therefore, we need a robust routing solution to cope with the demand uncertainty of the clustered TMs.

There are several approaches to robust routing in literature. The most straightforward solution is to consider the convex hull of all the discrete TMs and design the routing for the worst case in this continuous set. However, this approach has a number of drawbacks as the outcome may be strongly affected by a particular combination of demands that can be very rare in practice, thus producing an excessively conservative RC. In addition, the optimization process can be quite complicated [20], [24]. Since we assume a set of representative TM to be available, which represent the most likely or most important network conditions for the routing optimization process, we prefer to rely on a discrete space and adopt a multi-TM robust optimization approach, like those in [25]. A possible alternative when significant anomalies come into play is the approach presented in [13], in which the optimization process still focuses on the set of most representative TMs, while a

bounded penalty gap is guaranteed over the remaining traffic domain, thus also in case of anomalies. However, a complete analysis of the anomaly management is out of the scope of this paper.

c) Routing configuration holding time: Although SDN provides flexible and efficient tools to dynamically change network routes, we must pay attention not to change the network configuration too rapidly, entailing route flapping problems. Therefore, the CRR algorithm includes for each activated RC a minimum holding time before reconfiguring. If the set of considered TMs is a uniform sampling of the expected traffic conditions, the minimum holding time is equivalently described by a minimum number of consecutive TMs in each cluster.

This feature brings in a new dimension in the clustering problem by adding the time dimension together with routing and traffic. Figure 2 illustrates graphically the design space of our algorithm and how the other approaches locate with respect to our proposal. Exploiting the time continuum, as well as the traffic and routing, it allows to improve the network performance and at the same time to reduce the number of network reconfigurations.

d) Adjacent clusters overlap: The transition of traffic conditions from those described by the current cluster to those of a new cluster must be carefully addressed to maintain a good routing quality. Although the technical route update process has been thoroughly studied and several SDN-based consistent update schemes are available [26], [27], a further fundamental issue is to decide when this update should occur. Different algorithms can be implemented to decide the best switching point depending on the past, current and predicted traffic behavior, considering anticipatory networking aspects as well. However, the common aspect among them will be an unavoidable uncertainty about the time to switch. Therefore, considering an overlap among adjacent clusters is important, because it guarantees a graceful transition between them. This means that RCs of adjacent clusters will be reasonably good with the TMs that are expected to be close to a route transition. This helps algorithms not to be too much penalized from suboptimal decisions.

Besides making reconfigurations robust to prediction errors, the time overlap facilitates the network reaction to traffic changes. SDN switches can store several RCs, the active one and a set of RCs potentially useful in the immediate future, according to traffic predictions. The time overlap allows to pre-fetch next RCs before reaching the cluster boundary, and thus, to anticipate reconfigurations (e.g., using TimeFlip [28]).

B. CRR design

In light of the above points, the problem we want to solve is to find the best assignment of M TMs to N robust RCs in order to find N TM clusters having a minimum length of L TMs and an overlap O . Moreover, since TMs' IDs are temporally ordered, the solution also provides the best expected cluster transition instants.

Note that the members of a cluster are required as input of the in-cluster robust routing, which, in turn is required to drive

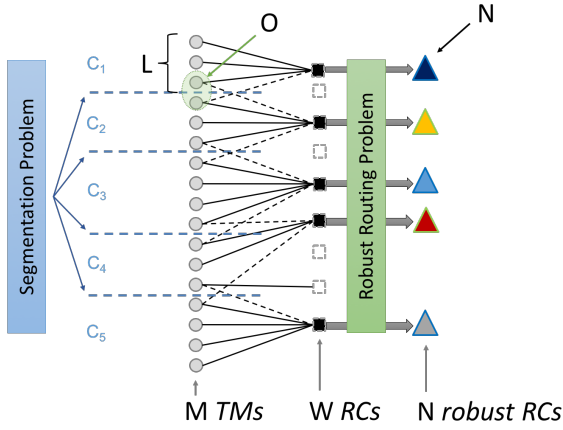


Fig. 3: High-level view of the proposed CRR algorithm.

the TM clusters formation, through the estimated congestion. Therefore, this two aspects must be jointly addressed to obtain an optimal solution. Unfortunately, the problem is strongly combinatorial and a joint optimization model has revealed to be very hard to solve. State-of-the-art integer programming solvers, like Gurobi Solver¹ or IBM CPLEX², could not provide a solution in reasonable times: small instances of tens of TMs require several days to get the optimum.

The hardness of the joint problem calls for the development of a heuristic approach to split the overall complexity in more affordable subproblems. In this perspective, we propose the two-step Clustered Robust Routing (CRR) algorithm represented in Fig. 3. In the first step, a *Segmentation Problem* is solved: the best assignment of M TMs to N out of W given RCs is computed, considering the minimum holding time constraint and the overlap. In the second step, a *Robust Routing Problem* is computed for each of the N clusters, in order to create new RCs better customized for the selected TMs. The new RCs are introduced in the set of available RCs to the Segmentation Problem and the two steps are repeated for a given number of iterations.

C. STEP 1 - Segmentation Problem

The Segmentation Problem takes in input a set of TMs $\mathcal{T} = T(1), \dots, T(M)$ and a set of RCs $\mathcal{R} = R_1, \dots, R_W$. Its goal is to assign each TM $T(i)$ to a RC R_j such that the overall association cost δ_{ij} is minimized and the number of used RCs is not larger than N . The cost δ_{ij} can be precomputed and corresponds to the network Maximum Link Utilization (MLU)³ when TM $T(i)$ is routed through RC R_j . This creates a set of N TM clusters and RCs to manage the routing during the considered time period.

We model the Segmentation Problem as an ILP model based on two sets on binary variables. Variables $x_{ij}, i \in \mathcal{T}, j \in \mathcal{R}$,

¹www.gurobi.com

²www.ibm.com/software/commerce/optimization/cplex-optimizer/

³Note that we decided to use MLU as it is a commonly used metric that directly expresses the network congestion, however the model is general enough to consider other types of metric

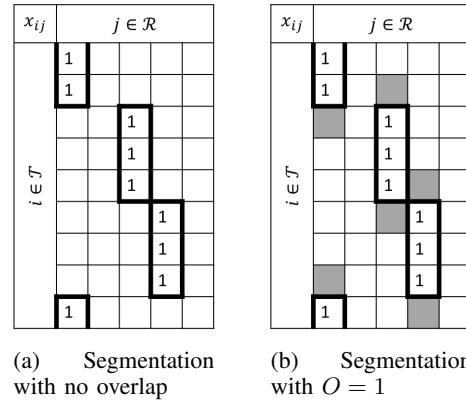


Fig. 4: Segmentation problem, x_{ij} matrix

setting the assignment of TM $T(i)$ to the cluster associated to RC R_j , and variables $z_j, j \in \mathcal{R}$, indicating with the value 1 that RC j is used to form a cluster. If we visualize the matrix corresponding to variables x_{ij} (see Fig. 4a), the solution of the problem is a set N row-sequences of 1's with minimum length L . These sequences must be unique when appearing in a column, and correspond to a set of TM clusters associated to RCs. In order to identify the beginning of each cluster, we rely on variables $y_{ij}, i \in \mathcal{T}, j \in \mathcal{R}$, forward differences of variables x_{ij} . When $y_{ij} = 1$, we can identify the initial TM of the cluster assigned to RC R_j : $T(i + 1)$. The problem is fully described by the following ILP model:

$$[\text{SP}] : \min. \sum_{i \in \mathcal{T}, j \in \mathcal{R}} x_{ij} \delta_{ij} \quad \text{s. t.:} \quad (1)$$

$$y_{ij} \geq x_{(i+1) \bmod \mathcal{T}, j} - x_{ij}, \quad \forall i \in \mathcal{T}, j \in \mathcal{R} \quad (2)$$

$$\sum_{i \in \mathcal{T}} y_{ij} \leq z_j, \quad \forall j \in \mathcal{R} \quad (3)$$

$$\sum_{i \in \mathcal{T}, j \in \mathcal{R}} y_{ij} \leq \sum_{j \in \mathcal{R}} z_j \quad (4)$$

$$\sum_{j \in \mathcal{R}} x_{ij} = 1, \quad \forall i \in \mathcal{T} \quad (5)$$

$$\sum_{i \in \mathcal{T}} x_{ij} \geq L \cdot z_j, \quad \forall j \in \mathcal{R} \quad (6)$$

$$\sum_{j \in \mathcal{R}} z_j \leq N \quad (7)$$

$$x_{ij}, y_{ij}, z_j \in \{0, 1\}, \quad \forall i \in \mathcal{T}, j \in \mathcal{R} \quad (8)$$

The objective function (1) minimizes the sum of the association costs. The first set of constraints (2)⁴ force variables y_{ij} to be 1 whenever the forward differences of variables x_{ij} are 1. Constraints (3) force the activation of the variable z_j , associated to RC R_j , if a non-null forward difference is present in column j , which means cluster C_j is considered in the solution. Constraint (4) states that the number of non-null forward differences in the matrix must not exceed the number of selected RCs. Therefore, together with constraints (3), this guarantees a unique cluster for each “active” column. The set

⁴The notation $(\cdot)_m$ indicates the modulo- m operator

of constraints (5) impose each TM $T(i)$ to be assigned to a unique RC, while constraints (6) force a minimum number of TMs associated to RC R_j , which, combined with the previous constraints imposing a unique and compact sequence of 1's within a column, correspond to constrain the minimum cluster length. Finally, constraint (7) states that no more than N clusters can be generated.

The set \mathcal{R} is initialized by considering W RCs obtained by the solution of the Robust Routing problem over W sequential groups of TMs spanning the entire set \mathcal{T} . At the end of each algorithm iteration, the computed RCs are included in this initial set, this provides \mathcal{R} with more refined RCs, which could be selected in the solution of the Segmentation Problem of the next iteration.

In order to consider an overlap between adjacent clusters, formulation **SP** must be amended to introduce the fact that up to O TMs beyond the boundaries of the clusters could be routed with the RC associated to the cluster. We model this by stating that each of the O TMs in overlap (grey cells in Fig. 4b) provides a congestion contribution δ_{ij} that is the average between the one of its associated cluster and the one of that in overlap⁵. The following constraints:

$$w_{ij} \geq x_{(i-1)|\mathcal{T}|j} - x_{ij}, \quad \forall i \in \mathcal{T}, j \in \mathcal{R} \quad (9)$$

$$\sum_{i \in \mathcal{T}} w_{ij} \leq z_j, \quad \forall j \in \mathcal{R} \quad (10)$$

$$\sum_{i \in \mathcal{T}, j \in \mathcal{R}} w_{ij} \leq \sum_{j \in \mathcal{R}} z_j \quad (11)$$

and a new objective function must be introduced in **SP**:

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{T}, j \in \mathcal{R}} x_{ij} \delta_{i,j} + \\ & \frac{1}{2} \sum_{i \in \mathcal{T}, j \in \mathcal{R}} y_{ij} \left(\sum_{(i-O < k \leq i)|\mathcal{T}|} \delta_{k,j} - \sum_{(i+1 \leq k \leq i+O)|\mathcal{T}|} \delta_{k,j} \right) + \\ & \frac{1}{2} \sum_{i \in \mathcal{T}, j \in \mathcal{R}} w_{ij} \left(\sum_{(i \leq k < i+O)|\mathcal{T}|} \delta_{k,j} - \sum_{(i-O \leq k < i)|\mathcal{T}|} \delta_{k,j} \right) \end{aligned} \quad (12)$$

Constraints (9)-(10) define variables w_{ij} as backward differences of x_{ij} . Interpreted as the end of the compact row-sequences of 1's in Fig. 4, w_{ij} must satisfy the same uniqueness requirements as y_{ij} . The new objective function (12) updates the association cost of TMs in overlap by removing half of the cost related to the associated cluster's RC and adding half of the cost towards the RC of the cluster in overlap.

D. STEP 2 - Robust Routing Problem

Once TMs have been clustered around an RC in STEP 1, STEP 2 computes a new robust RC R considering the TMs in the cluster. This will likely provide a better customized routing. In addition, being a robust routing, it makes CRR intrinsically robust against noisy TM measurements.

⁵The model can capture other assumptions by simply changing some of the coefficients in the formulation.

We compute R as robust RC that minimizes the MLU γ_{max} measured over network links, $(i, j) \in \mathcal{L}$, when the set of TMs in cluster C_c , denoted as \mathcal{T}_c , is routed via R . The TMs in \mathcal{T}_c are characterized by the same demand set \mathcal{H} , but different demand values, varying according to the traffic time evolution. We express the unique RC via flow variables f_{ij}^h , which indicate the amount of demand h flow of every TM in \mathcal{T}_c must be routed along the link (i, j) .

The ILP formulation of the Robust Routing Problem is:

$$[\mathbf{RR}] : \min. \gamma_{max} \quad \text{s. t.} \quad (13)$$

$$\sum_{(i,j) \in \mathcal{L}} f_{ij}^h - \sum_{(j,i) \in \mathcal{L}} f_{ji}^h = \begin{cases} 1 & \text{if } i = O_h \\ -1 & \text{if } i = D_h \\ 0 & \text{otherwise} \end{cases} \quad (14)$$

$$\forall i \in \mathcal{N}, h \in \mathcal{H} \quad (14)$$

$$\sum_{h \in \mathcal{H}} d_h^m \cdot f_{ij}^h \leq c_{ij}, \forall m \in \mathcal{T}_c, (i, j) \in \mathcal{L} \quad (15)$$

$$\gamma_{max} \geq \frac{\sum_{h \in \mathcal{H}} d_h^m f_{ij}^h}{c_{ij}}, \forall m \in \mathcal{T}_c, (i, j) \in \mathcal{L} \quad (16)$$

$$0 \leq f_{ij}^h \leq 1, \quad \forall h \in \mathcal{H}, (i, j) \in \mathcal{L} \quad (17)$$

Constraints (14) are standard flow conservation constraints for splittable routing⁶, with O_h and D_h , respectively, origin and destination of the OD demand h . Constraints (15) guarantee that the routing of each demand, with a request of d_h^m units of flow in TM $T(m)$, does not exceed the link capacity c_{ij} for any TM. Finally, constraints (16), together with the objective function, implement a min-max of the standard link utilization formulation at RHS of (16) over the TMs in \mathcal{T}_c .

V. NUMERICAL RESULTS

In order to assess the performance of the proposed algorithm, we consider a daily scenario in which we compare our CRR algorithm to different routing solutions within the Abilene Network [29], whose traffic requests are described by a set of TMs with granularity 5 minutes (288 TMs for the entire day). Abilene network was one of the first high-performance backbone networks, connecting 11 cities across United States. Nowadays, it is one of the very few real data sets in which network TMs and routing are public available. We imagine a scenario in which the optimization of clusters and RCs for the day after is run during the night, on the basis of daily TM predictions. Unless differently indicated, we average obtained results over a week and run the algorithm for 10 iterations. The CRR algorithm has been implemented in Python, using Gurobi Solver language interface.

A. Clustering approaches comparison

Fig. 5 shows the comparison of different clustering techniques, for the moment we do not consider the minimum cluster length constraint L and the overlap O . We measure

⁶We consider here a more general splittable routing because it can be easily implemented on SDN switches, however the model can be easily modified to consider unsplitable routing solutions as well.

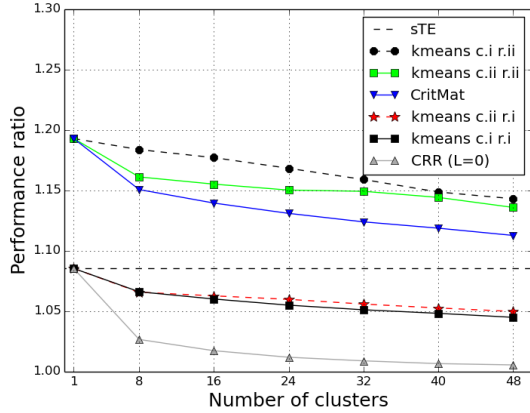


Fig. 5: Performance comparison of different TM clustering and robust routing approaches.

the performance in terms of ratio of TM-averaged network MLU with respect to the value achievable by routing each TM through its MLU-optimum routing, that is, by applying dynamic TE. On the x-axis, the number of generated clusters is shown. We tested our CRR algorithm against different alternative approaches:

- *sTE*: A static TE solution where a robust routing is computed over the entire TM set. The result is a single daily RC and no reconfiguration is required, like in the case of oblivious routing.
- *CritMat*: This approach, presented in [15], consists in clustering TMs according to dominating cluster heads, which are synthetic TMs including the maximum of each demand among the TMs grouped into the cluster. The RC associated to the cluster is the MLU-optimum routing for the cluster head.
- *K-means clustering*: Most of the TM clustering approaches in literature are based on a variant of the well-known k-means technique. We have applied four k-means versions considering all combinations of the following clustering domains (*c*) and in-cluster robust routing approaches (*r*): *c.i*) clustering in the TM domain (considering similarity among OD demand values) and *c.ii*) clustering in the best-routing domain (considering similarity among MLU-optimum routing for each TM); *ri*) robust routing applied as in formulation **RR**, *rii*) MLU-optimum routing applied to the dominating TM of each cluster.

We can note how the proposed CRR algorithm outperforms all other alternatives. The curves' trend shows that CritMat dominating TM appears to be over-conservative, as the resulting congestion is even worse than that of static TE. Indeed, the outcome RCs can address such a large set of potential TMs that their working points are largely suboptimal when RCs are applied to specific TMs. The k-means approaches show very different congestion levels. The type of applied in-cluster robust routing is the main performance driver: **RR** formulation provides remarkably better results than relying

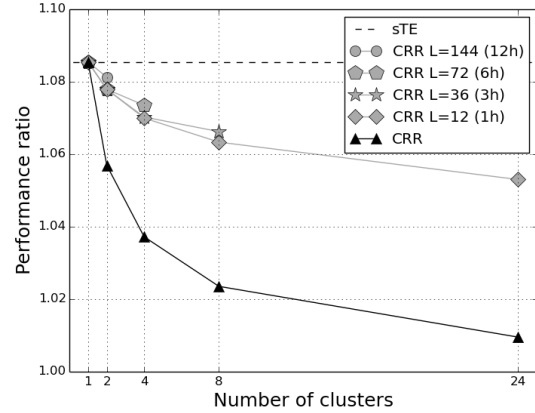


Fig. 6: Impact of different minimum cluster lengths on the CRR performance

on a dominating TM. The impact of the clustering approach, instead, is limited and its benefit depends on the type of robust routing strategy subsequently applied.

Except for *sTE*, however, all the aforementioned clustering approaches have no constraints on the number of reconfigurations per time interval the network can be subject to. CRR has been applied with $L = 0$, CritMat can be shown to produce many RC changes. Even k-means approaches, although fixing the number of potential clusters, thus RCs, do not limit how many times they repeat and do not prevent reconfiguration bursts, where several RCs change in a short time interval. Therefore, we need to explicitly provide a minimum cluster length guarantee to avoid route flapping problems, which, as we will see, comes at the cost of a small congestion increase. This guarantee results in a fixed number of transitions, each separated by the desired length L .

B. Impact of minimum cluster length and overlap

In Fig. 6, we assess the performance of CRR algorithm when the minimum cluster length constraint is activated with different values of L . The x-axis shows the number N of clusters in a day, while different curves represent different values of L . Note that the values of L and N are not independent, as N clusters are generated in one day, N cannot be larger than the ratio 24 hours / L (in hours). Therefore curves with larger L stops at smaller N values. We can see that the minimum length constraint impacts on the performance of the clustering algorithm. With realistic N values, the MLU performance ratio increases from values about 1.02 (still referring to dynamic TE) to values about 1.06. CRR with $N = 8$ and $L = 36$ results in keeping the same routing configuration for at least 3 consecutive hours and changing only 8 times the RC during the next day.

Focusing on $N = 8$, the congestion of CRR with a minimum length $L = 1h$ is 6.3% higher than that in dynamic TE, which is better than the performance of the closest alternatives with no time constraints, 6.5%, that of the TM-domain k-means clustering with robust routing shown in Fig. 5. Therefore, our proposal, besides guaranteeing strong

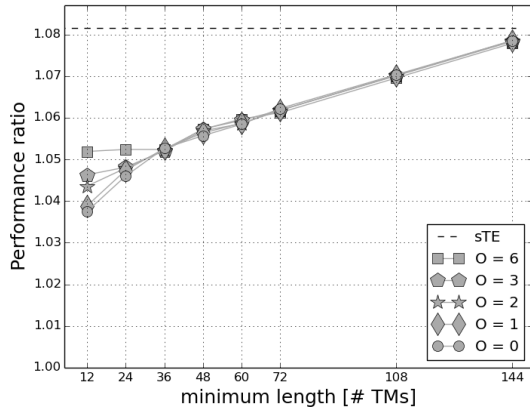


Fig. 7: Impact of different degrees of overlap on the CRR performance

bounds on the level of reconfiguration, allows to even decrease the network congestion. The quality of the clustering approach fully compensates the congestion increase caused by the minimum length constraint.

In Fig. 7, we analyze the performance of the CRR algorithm varying the degree of overlap O . The figure shows on the x-axis the minimum length L imposed to the cluster, while different curves are plotted for some values of O . We can see the impact of the overlap is significant only for short clusters, while it becomes quickly negligible when the minimum cluster length increases. Moreover, note that each TM included in the overlap provides an overlap extension of 5 minutes on each side. Therefore, considering $O = 1, \dots, 6$ means applying transition periods from 10 minutes to 1 hour, which we believe could reasonably include the complete set of meaningful values in practice, in terms of both uncertainty on the transition point and time required to anticipate reconfigurations.

C. Impact of prediction error

In the previous sections, we have analyzed the performance of the CRR algorithm when the clustering and the related RCs are computed over a set of TMs and applied to the same set. This corresponds to assume perfect TM prediction and provide the potential performance achievable by the algorithm. In this

TABLE II: CRR performance when prediction error is considered. Results are expressed as percentage increase with respect to the ideal optimum routing.

α		$cluster.$				
		0	15	30	45	60
sTE		6.52	7.02	8.19	9.25	10.52
CRR	L=72	4.07	5.13	6.93	8.94	11.09
	L=60	4.04	5.23	7.24	9.44	11.19
	L=48	3.76	5.06	7.12	9.61	11.79
	L=36	3.17	4.55	6.74	9.04	11.33
	L=24	2.84	4.50	6.85	9.35	11.93
	L=12	2.06	4.29	7.04	10.08	12.28

section, we relax this assumption and analyze the impact of prediction errors.

In order to reproduce the effect of unideal predictions, we run the CRR algorithm over a noisy version of the daily set of TMs to compute clusters and RCs, then apply the RCs to the original set of TMs, which represent the real traffic behavior. Each noisy TM version has been obtained from the original one by adding a uniform relative error $[-\alpha, \alpha]$ % to every OD demand d_h^m . The results of these experiments are shown in Table II, where the performance achievable with different cluster lengths L and prediction errors α is reported. Similarly to previous analyses, the performance is computed as the percentage increase of the average network MLU with respect to the ideal case of applying dynamic TE in perfect prediction conditions.

We can clearly note that the performance of CRR is negatively impacted by the presence of prediction error, however the intrinsic robustness of the clustered approach limits the performance decrease. Even with large errors, the gap with respect to the ideal Dynamic TE is within 10-12%. The most interesting aspect to note is the parameters setting that provides the best performance, whose outcome is marked in bold in the table. The results show that the larger the error, the larger the clusters of the best solution. Indeed, when the quality of predicted TMs worsens, considering robust RCs computed over larger sets of TMs provides more robustness to any variation. A bigger variety of TMs included in the cluster used to generate a RC allows to better cope with traffic uncertainty. Taking this to extremes, when we have very low-quality predictions, no clustering can be helpful, because the representative set of TMs and the actual traffic will have little correlation. In these conditions, the Static TE approach, which builds a single RC considering all possible TMs in a day, is the best one can apply, as it generates the most robust RC. On the contrary, however, few and larger clusters lead to a bigger gap with respect to the dynamic TE, shown in Fig. 5 and 6, as the generated RCs are more conservative and far from being MLU-optimal for specific TMs. Therefore, a trade-off between cluster length and prediction accuracy exists. In case of good predictions, the size of the clusters drives the performance, vice versa, if predictions are affected by large errors, the impact of TM uncertainty completely overwhelms the effect of cluster sizes.

D. Open issues

This trade-off between cluster size and prediction accuracy opens a new technical challenge, which we cannot address in this paper, but appears to be a promising research direction. Thanks to the SDN paradigm, the controller can collect quasi-realtime measurements, predict the traffic evolution, and estimate a-posteriori the prediction error. It can act as an on-line mechanism able to anticipate the clusters that could be potentially visited in the near future and could provide the desired optimality gap with respect to an ideal congestion level. Moreover, the controller can prearrange a set of robust RCs derived from TM clusters, which, although referring to

the same TM centroid, are characterized by different sizes, i.e., robustness levels, so that the system can easily shift through different RCs when the prediction accuracy suddenly changes, as in case of anomalies. Accuracy changes can be detected by comparing link utilizations considered during the clusters' creation and those actually measured in the real network. Finally, clusters can be synthetically generated as well, in order to include potentially severe failures RCs must be robust against.

The SDN controller must play the main role in real-time managing the set of available RCs to orchestrate the routing of the entire SDN network over time by dispatching and activating the best RCs in each SDN switch. The design of the algorithm to select the type of generated RCs and the orchestration strategy is fundamental to provide performance optimality and full flexibility in front of traffic changes to advanced Software Defined Networks.

VI. CONCLUSION

In this paper we investigated how robust routing approaches can be made adaptive in the SDN context. Assuming the availability of traffic predictions, we designed an off-line method to split the traffic space into smaller partitions and build routing configurations that are robust against any real-time traffic variation within the partition.

The results showed that routing configurations based on TM clustering can achieve a performance very close to the optimal routing only if a good clustering domain is chosen. Our proposal based on the estimation of the congestion caused by the activation of a given routing outperforms the other candidate solutions. This good performance is also confirmed when the clustering is further constrained by technical and practical issues on the obtained routing configurations, which we considered in our approach.

Finally, we investigated the behavior of our solution when the accuracy of traffic predictions varies. It showed an interesting trade-off between cluster sizes and prediction errors that opens a new research direction for the orchestration of robust routing configurations over time in SDN.

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