REPETITA: Repeatable Experiments for Performance Evaluation of Traffic-Engineering Algorithms

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ABSTRACT

In this paper, we propose a pragmatic approach to improve reproducibility of experimental analyses of traffic engineering (TE) algorithms, whose implementation, evaluation and comparison are currently hard to replicate. Our envisioned goal is to enable universally-checkable experiments of existing and future TE algorithms.

We describe the design and implementation of REPETITA, a software framework that implements common TE functions, automates experimental setup, and eases comparisons (in terms of solution quality, execution time, etc.) of TE algorithms. In its current version, REPETITA includes (i) a dataset for repeatable experiments, consisting of more than 250 real network topologies with complete bandwidth and delay information as well as associated traffic matrices; and (ii) the implementation of state-of-the-art algorithms for intra-domain TE with IGP weight tweaking and Segment Routing optimization.

We publicly release our REPETITA implementation, hoping that the community will consider it as a demonstration of feasibility, an incentive and an initial code basis for improving experiment reproducibility: Its plugin-oriented architecture indeed makes REPETITA easy to extend with new datasets, algorithms, TE primitives and analyses. We therefore invite the research community to use and contribute to our released code and dataset.

1. INTRODUCTION

Reproducibility is a cornerstone of the scientific method, and a strongly desirable principle for any exact-science discipline – computer science included. By enabling third parties to check experimental results, it indeed ensures the validity of published contributions and stimulates new ones, ultimately providing a better, community-shared understanding of the state of the art.

Unfortunately, reproducibility of research in networking exhibits huge room for improvement. Despite recent enablers of reproducibility like network simulators [1], virtualization tools [2] and testbeds [3], articles still often come with a rough description of the performed experiments, and limited or no support (code, dataset, etc.) to reproduce the presented evaluation. As a consequence, reviewers have to believe the claimed results. Also, researchers willing to compare new proposals with the state of the art must re-implement technical contributions (to the best of their understanding) and re-create experiments from scratch: As confirmed by the few initiatives on reproducing research results like the Stanford CS244 course [4], this is a challenging, time-consuming task, that further provides no guarantees of achieving a fair comparison against the original proposal.

We believe that the networking community should find more effective ways to ease support for reproducibility, at least for a significant part of the experiments in every publication.

Of course, achieving reproducibility is not straightforward. In this work, we focus on traffic engineering (TE). For TE, a primary challenge consists in having access to both experimental settings, evaluation datasets, and evaluated algorithms, which unfortunately is costly if not impossible. The original experimental setting is generally hard to re-create: for example, testing infrastructures (e.g., servers, network equipment and software) are often not shared among researchers, may not be affordable for all research institutes, and tend to quickly become unsupported over time (e.g., because of new software releases). Also, evaluations on real, production-network data involve privacy concerns, as they contain sensitive information that can rarely be disclosed. Finally, releasing code (e.g., for algorithms, system prototypes, etc.) implies a significant effort that often comes with little benefits for authors.

We propose an approach based on repeatability, a looser form of reproducibility focused on reproducing a given set of experiments in a local setting (e.g., on a different server with respect to the one used in the original papers). By itself, repeatability avoids the main roadblocks deriving from rebuilding the original experimental setting.

To tackle the other challenges, we argue for more effective practices and tools that facilitate repeatability. As a concrete step in this direction, we publicly release1 REPETITA, a software platform that we have also used to develop our own research contributions [5]. REPETITA eases repeatable evaluation of TE algorithms: It automates most of the technical operations involved (topology pre-processing, evaluation setup, analyses, etc.) and enables users to run experiments on more than 250 topologies (with 5 synthetic traffic matrices each) with a single command-line instruction.

Admittedly, REPETITA is not a silver bullet for any possible evaluation on TE. Its dataset can be improved by adding more (e.g., different types and more updated) real topologies of networks, as well as real traffic data. The implemented algorithms mainly focus on optimization with two basic primitives (IGP and Segment Routing) – even if the configuration of explicit paths, like MPLS tunnels and

1see https://github.com/svissicchio/Repetita
OpenFlow-installed paths, is also supported. The evaluation metrics are far from covering the full spectrum of possible evaluations: they mainly focus on bandwidth optimization (e.g., in contrast with recent TE systems like [6, 7]). Even the type of possible experiments is limited, as it restricts to the static optimization of forwarding paths, with no knowledge of transient states and system dynamics.

Nevertheless, we believe that no repeatability-oriented approach can be successful if it does not involve a community effort and commitment. We designed and implemented REPETITA to be extendable, so that it can support the creation of benchmarks for TE algorithms, ideally merging contributions from the wide research and operator communities; (iii) reviewers and external readers to check evaluation results; and (iv) stimulate approaches that support repeatable evaluations of research contributions in other areas.

In the following, we describe how REPETITA fills a gap in the state of the art (§2), how it is designed (§3) and implemented (§4), and how it can be used for both repeating experiments and facilitating new insightful analyses (§5).

2. WHAT DO WE LACK?

Many networking contributions are hard to reproduce. Position papers [8], methodologies [9] and repositories of data [10, 11] have been published to facilitate experiment reproducibility in several areas of computer science.

In our experience, however, most networking contributions are hard to reproduce and fairly compare against. For instance, the majority of papers on wide-area traffic engineering (from earlier on IGP weight optimization [12] to more recent approaches based on MPLS [13, 14], SDN [6, 7] and SR [15]) present experiments made with proprietary code, often on a restricted dataset of private networks.

The networking community is pushing towards open-source code. Software Defined Networking (SDN) originated from the definition of OpenFlow [16], an open-source interface to network devices. Consistently, many SDN proposals, from projects about SDN programming languages (e.g., [17]) to those on network controllers (e.g., [18]), have publicly released the produced code – an encouraging step towards reproducibility. A few recent works also consider the problem of fairly comparing open-source proposals. Prominently, they focus on tools to benchmark SDN controllers (e.g., [19, 20]) and OpenFlow switches (e.g., [21]), under specific network conditions or workloads. While close in spirit with those contributions, this paper has a different scope (traffic engineering), that also comes with its own challenges like working around confidentiality of data (network topologies, traffic matrices, etc.) used in experiments.

We still miss approaches and tools that make reproducibility easy. The literature describes a plethora of tools that potentially enable repeatability, including simulators (e.g., [1]), emulation platforms (e.g., [2]) and testbeds (e.g., [3]). They provide the low-level means to perform network experiments at scale, but everything else (network setup, approaches to be evaluated, experimental configuration, etc.) must be added on top of them. As such, those tools make repeatability just possible.

We however believe that the networking community still lacks proven methodologies, tools and practices that make reproducibility not only possible, but also easy and affordable for researchers (and reviewers).

For example, a past proposal to enable TE experiments in non-SDN networks is TOTEM [22]. TOTEM defines a set of TE algorithms, but no standard experiment or analysis on them. Further, the code is not maintained since years. Hence, newer algorithms and support for cutting-edge technologies (from OpenFlow to Segment Routing) are not implemented. Even worse, it is unclear how to support such algorithms and technologies in TOTEM, since the tool is mainly a collection of heterogeneous scripts only sharing input and output format. By releasing an extendable platform that includes recent TE approaches and automates all the main operations to run repeatable experiments, we hope to overcome the difficulties of tools like TOTEM and provide immediate incentives for reproducibility in the TE field.

3. REPEATABILITY MADE SIMPLER

In this section, we overview REPETITA. We describe its design (§3.1), workflow (§3.2), and key benefits (§3.3).

3.1 Designing REPETITA

As shown in Figure 1, REPETITA design is based on modeling and separating three main concepts: settings, solvers, and scenarios. Altogether, they define the experiments and analyses that are performed in a run of REPETITA.

Settings. A setting represents the problem instance considered in an experiment. It therefore groups all the input data needed to run an experiment. In the TE case, settings include topologies, traffic matrices, and routing configurations. A topology represents a network and contains all its characteristics that are relevant for traffic engineering. We identify nodes, links, link capacities and delays as a basic set of such characteristics. A traffic matrix encompasses data (sources, destinations and volumes) about traffic flows assumed to traverse the network in a given experiment. A routing configuration contains additional infor-
ation to compute forwarding paths on the given topology and traffic matrix. Primarily, it includes link weights for shortest-path computations done by current intra-domain routing protocols (called IGPs). Also, it encompasses other protocol-specific configurations, like Segment Routing settings as well as explicit paths reflecting configured MPLS tunnels or OpenFlow rules.

Solvers. A solver is an object under test. In our case, a solver is a TE algorithm that given a setting, updates the routing configuration inside the setting for the corresponding topology and traffic matrix. This computation typically aims at optimizing network performance, e.g., maximizing bandwidth, avoiding congestion or reducing delay. Solvers are pieces of code that are either standalone or integrated in REPETITA. In the latter case, REPETITA offers TE libraries implementing building blocks like computation of IGP shortest paths, and the calculation of link utilizations induced by a given routing configuration.

Scenarios. A scenario models the dimensions along which the output of different solvers is analyzed. In other words, scenarios define analyses of interest for REPETITA users, and provide automated support to perform such analyses. For example, a scenario can define how good a TE algorithm (solver) is at optimizing bandwidth on a given network and traffic matrix (setting). In this sense, scenarios implement the abstractions (i.e., the evaluation metrics) that ensure comparability between different solvers.

We believe that REPETITA architecture can fit a broader class of networking problems, as for example congestion control (where solvers are congestion control schemes, settings encompass traffic rates and network conditions, and scenarios evaluate performance metrics as throughput) and security (where solvers are defense techniques, settings models networks, targets and attacks, and scenarios quantify success rate of solvers as well as consumed resources and time).

3.2 Running REPETITA

REPETITA provides the software infrastructure that links together the building blocks discussed in §3.1.

We now list the steps sequentially performed by REPETITA to carry out a (repeatable) experiment. Note that the framework also provides direct access to the functions used in those steps, hence it can be used as a software library (e.g., to solve multi-commodity flow problems) and calculate lower bounds for any TE algorithm.

The first step consists in processing the input. REPETITA parses topology and demands files using custom parsers: Those parsers create setting objects from files of tabular format, where every line describes an attribute (e.g., IGP weight, traffic volume, etc.) of a network element (node, link or demand). Once such files are parsed, REPETITA instantiates solvers and scenarios required in the experiments to be performed.

Scenarios are then asked to run. For the simplest possible scenario, this method call translates into passing the configured setting to the solver stored in the scenario, and reporting the differences (e.g., in terms of maximum link utilization) between the routing configuration before and after the solver’s optimization. More advanced scenarios can also modify the original settings or create new ones. For example, consider a scenario that requires to evaluate what happens in the case of any single link failure (like the robustness analysis described in §4.3). Such a scenario instantiates many new settings, each corresponding to a single link failure on the initial topology – and runs the configured solver on all the new settings.

Scenarios also implement two key functions. First, they enforce that every solver’s execution terminates after a (potentially infinite) time bound, e.g., stopping it after the given time bound and extracting the best routing configuration computed by the solver so far. Second, scenarios process the routing configurations returned by the solvers. Namely, they translate each of those configurations into paths, map the input traffic matrix to the computed paths, and evaluate metrics like link utilization or routing overhead. Such a translation leverages functions implemented in the REPETITA TE libraries, for independence from solver implementations.

Results of scenarios’ post-processing are finally reported on the screen (by default) or on a pre-configured output file.

3.3 Benefiting from REPETITA Design

REPETITA is designed to achieve usability and extensibility. Technical documentation, instructions to run experiments and examples to add new solvers are provided at https://github.com/svissicchio/Repetita.

REPETITA is easy to use. Users can run the implemented solvers on supported settings and scenarios by executing the framework from the command line. The following working example instructs REPETITA to run a solver called defoCP, once, for 1 second, on the Abilene network.

A few more CLI options enable users to adjust parameters like the output file name (REPETITA results are printed to the CLI standard output by default).

REPETITA is easy to run on already implemented solvers. For ease of adoption, we do not require solvers to be implemented within our framework. In contrast, our framework can run external solvers (written in any programming language) as long as they are packaged as executables that take as input a network and a traffic matrix. To add such solvers, it is sufficient to specify information about them in a textual file (i.e., external_solvers/solverspecs.txt) inside the REPETITA directory. Figure 2 reports a snippet of such file, displaying the description of an example solver (getRandomPaths.py) written in Python. As shown in the figure, limited information must be specified: general data like the name (to refer the solver within REPETITA) and the optimization objective; specification of the CLI commands to run the executable and extract the time taken by its last run; a description on how to interpret the output of the executable. More details on the file format are provided in the file itself.

REPETITA is easy to extend. Its architecture supports separate evolution (e.g., modification or replacement) of the dataset, the solvers and the evaluation analyses. Topologies and traffic data are controlled with a command-line parameter, that specifies the directory containing them. Additional
analyses can be implemented by defining new scenario objects in the REPETITA code. Beyond using external solvers, new algorithms can also be integrated within the framework. Two options are viable, as detailed on the REPETITA Web page. The first option is to re-implement the original solver using the REPETITA TE libraries, as we did for our 156-line long implementation of the IGP weight optimization heuristic based on [12]. A more lightweight alternative consists in adding the new solvers, unmodified, along with solver-specific wrappers, i.e., software objects that convert input and output of method calls between the framework and the original solver. We used the latter option to support the original DEFO solver [24] (in Scala) in our current REPETITA implementation.

4. REPEAT, FOR REAL!

We now describe settings (§4.1), solvers (§4.2) and scenarios (§4.3) supported by our Java-based implementation.

4.1 Topologies and Traffic Matrices

We first detail how settings are built, and why.

We collected realistic topologies used in the evaluation of previous TE papers. We relied on 3 public data sources: the Rocketfuel project [25], the synthetic topologies used in DEFO [24], and the Internet Topology Zoo [26]. The former two sources provide a limited number of topologies, either inferred from Internet measurements (Rocketfuel) or artificially generated to stress-test algorithm scalability (DEFO). Internet Topology Zoo gathers real topologies (often WANs) as reported by official Web sites of commercial companies.

We post-processed the available topologies to have a complete dataset. Original topologies in the Internet Topology Zoo dataset were incomplete in several cases. We completed them as follows. First, we kept only the largest connected component of any disconnected topology. Second, for topologies where no link capacity is specified, we set the same value on all links. Third, when capacity information are specified only for a subset of network links, we set the capacity of any link with missing capacity as equal to the average capacity across all links. Further, we normalized link capacities to avoid too large variations (e.g., Kbps access links versus Gbps core links) leading to unavoidable traffic bottlenecks on which all TE algorithms would perform equally bad. In particular, we impose that the value of any link capacity is not less than 1/20-th of the largest link capacity in the topology.

We considered 3 heuristics to assign IGP weights. Intra-domain routing protocols (i.e., IGPs) are based on shortest-path computation. We therefore need IGP weights of all the links in every topology to compute pre- and post-TE paths. Unfortunately, the Internet Topology Zoo dataset does not contain this information. Our framework implementation then uses 3 standard heuristic assignments of IGP weights. The first heuristic assigns unary weight to all links: It is motivated by simplicity, and by the intuition that unitary weights may provide the most flexibility for protocols built on top of IGP (like Segment Routing [24]). The second heuristic sets IGP weights as inversely proportional to link capacities, i.e., reflecting a default that has been classically adopted by vendors. The third option is to consider weights optimized for a given traffic matrix, i.e., according to our IGP-WO solver (see §4.2).

We synthesized traffic matrices. We adopted a randomized gravity model that has been shown to generate realistic traffic matrices [27] and is often used to evaluate TE algorithms ([14],[24],...). We generated 5 traffic matrices per topology to have some diversity while keeping the dataset manageable. We scaled the traffic matrices so that the maximally utilized link is loaded at 90% of its capacity in the optimal solution of the corresponding multi-commodity flow problem (using the REPETITA LP described in §4.2). The maximal link utilization is thus larger or equal than 90% in any real TE solution. We are well aware that operators (especially in WANs) do not typically run production networks at a so high utilization rate. However, we applied this scaling factor to build cases where very effective bandwidth-optimizing TE algorithms are absolutely needed – cases for which recent TE approaches in private networks even argue [6, 7]. To match more common settings, traffic-matrix values can be divided by a constant factor (e.g., 3 for an optimal maximum link utilization of 30%).

4.2 TE Algorithms

REPETITA includes a linear program that computes a baseline for bandwidth-optimization algorithms.

Linear Program (LP), solving the multi-commodity flow problem. The LP provides a theoretical lower bound for the classic TE goal of minimizing the maximum link utilization. It is indeed allowed to arbitrarily split traffic among any possible path, and ignores IGP weights. We used the LP for scaling the traffic matrices in our datasets (as just described), and as a baseline in our experiments (see §5). We report the LP formal definition in the Appendix.

In addition, REPETITA currently includes three solvers. To show the possibility to implement algorithms based on qualitatively-different primitives, we encoded a weight optimization algorithm as well as recent proposals based on the newer Segment Routing (SR) protocol. To ensure practicality of the implemented algorithms and apples-to-apples...
comparison, all the solvers assume that traffic is equally split among all the paths used from any traffic source to any destination – a feature called even load balancing.

**IGP Weight Optimization (IGP-WO), based on [12].** Given a traffic matrix and a topology, this algorithm runs a local search to find IGP weights that minimize the load on the maximally-utilized link. We implemented an approach based on [12] in 156 lines of code by leveraging REPETITA TE libraries (e.g., for shortest-path computation).

**Mixed Integer Linear Programming (MILP) optimization, inspired by [15].** We use standard optimization tools (i.e., the Gurobi optimizer\(^5\)) to solve mixed integer linear programs inspired by the first work on SR-based TE, from Bhatia et al. [15]. As in [15], our formulation admits that 2 IGP shortest paths are stitched together, sharing a common node or detour, thanks to SR. In contrast to [15], though, we removed the assumption that traffic flows could be split with arbitrary ratios at the network ingress – as none of the other algorithms relies on the same assumption. We also reduced the number of variables, using a modified node-link formulation [29], lowering the consumed memory. We detail our MILP model in the Appendix.

**Constraint Programming heuristics (DEFO), as proposed in [24].** DEFO [24] is a Constraint Programming heuristic designed to trade optimality for time efficiency and scalability. This algorithm is heuristic in two ways. First, it does not completely explore the solution space but iteratively samples it using a randomization technique called Large Neighborhood Search. Second, at every iteration, it greedily selects demands (from the biggest to the smallest) and an unconstrained number of detours per demand. We plugged DEFO in REPETITA by implementing a software wrapper for the original DEFO code, as described in §3.3.

### 4.3 Scenarios

**Max-congestion Analysis.** This scenario computes the maximum link utilization of paths returned by solvers. It therefore evaluates the quality of solutions found by input solvers with respect to a classic traffic-engineering goal (see, e.g., [12]), i.e., minimization of maximal link utilization.

**Overhead Analysis.** Primitives like segment routing enables more flexibility in the choice of forwarding paths at the cost of additional overhead (e.g., information added to packets and router configuration to implement detours). This scenario quantifies such overhead by keeping track of changed IGP weights, traffic demands re-routed with SR, and modified explicit paths.

**Robustness Analysis.** REPETITA finally allows users to evaluate the robustness of a TE configuration with respect to failures. For any given topology and routing configuration (returned by a solver), the robustness analysis scenario evaluates how the maximum link utilization changes after the failure of every link that does not disconnect the network. To this end, it recomputes the paths associated to the given routing configuration (e.g., IGP weights or SR paths) on all the topologies resulting from removing any single link from the original network.

\(^5\)see www.gurobi.com

### 5. REPETITA IUVANT\(^6\)

We ran our REPETITA implementation using a 40-core Intel(R) Xeon(R) 3.10GHz machine with 128GB memory. We limited multithreading of any given solver to 4 cores. The used JVM is OpenJDK version 1.8.0_91. Experimental results are summarized in the following.

**REPETITA eases reproduction of published evaluations.** We reproduced experiments described in [24], running each of them 20 times. Our results confirmed what reported in the original publication, with minimal differences (at most 3%) in the maximal link utilization that should be ascribed to the randomized nature of the DEFO algorithm.

**REPETITA enables new, large-scale comparisons, not provided in the original papers.** We compared MILP and DEFO performance on all the Internet Topology Zoo networks with link weights assigned as inverse of their capacity. We ran both solvers with two time limits (30 and 300 seconds), for a total of 5,200 experiments (1,300 settings per solver with a given time limit). This is an original head-to-head comparison between the two algorithms.

Those experiments are meant to be a demonstration of how our framework can be used to evaluate different TE algorithms according to several metrics. The evaluated solvers are indeed based on different principles: MILP looks for optimal solutions, DEFO trades optimality guarantees for speed and scalability. The following results quantify the tradeoffs achieved by those two algorithms.

First, we evaluated the quality of solutions returned by MILP and DEFO, as shown in Figure 3. In few cases (about 10%), both the solvers are quite far from the theoretical lower bound, likely because of intrinsic limitations of segment routing (e.g., SR cannot force traffic on any possible path) and the assumed flow unsplittability (for practicality). The remaining experiments highlight fundamental differences between the considered algorithms, mostly depending on the size of input topologies. For small and medium topologies (Figures 3a and 3b), both solvers are within 10% of the theoretical lower bound, most of the time. Nevertheless, MILP is closer to the theoretical optimum than DEFO, as expected since the latter implements a heuristic approach. For bigger topologies (Figure 3c), however, DEFO definitely outperforms MILP, as the latter often needs much more time to optimize SR paths. Also, the larger variation of results suggests that the allowed execution time is more critical for MILP than for DEFO, as the latter tends to converge faster to good TE solutions.

We also ran the overhead analysis for the two solvers. Table 1 stresses the huge difference between the high overhead needed by MILP (to reach optimal traffic spread), and the little one induced by DEFO (which moves far less flows).

- **Experiments** 25% Median 75% 95% 
- **MILP (30s)** 42.7% 56.6% 65.9% 75.2% 
- **MILP (5m)** 42.7% 56.9% 66.1% 75.2% 
- **DEFO (30s)** 1.1% 2.7% 6.1% 16.2% 
- **DEFO (5m)** 1.6% 4.2% 8.8% 20%

Table 1: Overhead comparison performed with REPETITA. The table reports the percentage of demands re-routed by MILP and DEFO, in the same experiments as in Figure 3.

\(^6\)Latin for “repeating does good”
REPETITA facilitates new analyses. We extended the comparison between MILP and DEFO with metrics not considered in previous papers. We ran the robustness analysis scenario to assert whether solutions computed with a congestion minimization focus are robust to failures. We provided MILP and DEFO with a 300s time limit, and collected their output for all topologies and one demand file per topology. The robustness analysis scenario then simulated single link failures and compared the maximum link utilization for each solution with their respective theoretical lower bound. On a total of 17, 144 possible link failures (across all networks), congestion appeared in 9, 489 cases for DEFO paths and in 11, 174 MILP cases. In contrast, REPETITA lower bound could not avoid congestion in only 3, 289 cases. This observation opens an interesting question on whether and to what extent SR can be used to optimize both link utilization during normal operation while simultaneously providing some guarantees in the case of failures.

REPETITA motivates new research questions, by showing the impact of TE algorithms in specific settings. In particular, our experiments highlight two aspects.

First, they confirm the potential relevance of TE algorithms whenever links are run at high utilization. For example, Figure 3c shows huge differences in the ability to quickly remove congestion (as for online TE) between two algorithms, despite relying on the same primitive (SR). This observation complements the more system-oriented perspective taken by recent works [6, 7], focused on how to robustly extract input data and try to enforce TE decisions.

Second, our experiments motivate questions about TE primitives and technologies. As an illustration, we compared results obtained by IGP-WO with those returned by our SR algorithms (keeping the best result between MILP and DEFO, for each experiment). Figure 4 summarizes such comparison, when all the solvers are run for 5 minutes per experiment, on all topologies with inverse-capacity link weight assignment. While SR enables a substantially better solution in 25% of the cases, solutions obtained by re-weighting links and using SR are quite similar from the congestion-avoidance perspective in most cases (within 1% in 57% of our experiments), with IGP-WO being even more effective than SR algorithms for about 7% of the settings. This raises questions about the real expressive power of segment routing, and its usefulness in (which) network setups.

6. CONCLUSIONS

Repeatability of experiments is a key ingredient of science, and a largely-unfulfilled need in the networking community. This paper shows that we can overcome major obstacles to repeatability. Prominently, we can simplify the release of code in a way that allows repeatable evaluation and comparison with the state of the art. We presented REPETITA, a software framework that automates most of the experimental setup and evaluation process for traffic-engineering algorithms. To this end, REPETITA (i) includes a large and diversified input dataset, (ii) implements procedures (e.g., computation of shortest paths and traffic-to-path mapping), baselines (e.g., multi-commodity flow solutions) and cutting-edge algorithms for traffic engineering, and (iii) includes a pre-defined set of analyses tailored to traffic-engineering. Our experiments confirm the practicality of REPETITA for both repeating previous evaluations and performing new ones, that both deepen pros and cons of specific algorithms and open new research questions. We invite other researchers to join our effort, integrating our released code and proposing similar tools for other areas.

Our work also aims at raising a serious discussion on how to work around real-data confidentiality (e.g., for network topologies and traffic data). Our proposal is to lower the need for proprietary data rather than keep looking for a method to share them. We bootstrapped a repository that we envision to collect real or realistic network topologies for repeatable TE evaluations. While current topologies mainly refer to specific networks (Internet transit provider ones, at per-router level), we plan to further enrich our repository, possibly integrating feedback from operators and vendors.
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Appendix: REPETITA LP Models

We detail here the mathematical formulation of the Linear Program (LP) models used in REPETITA.

General notation. We use V and E to indicate the sets of nodes and links in the input network, respectively. We write c(e) for the capacity of edge e ∈ E, and Tij for the traffic volume from node i ∈ V to j ∈ V. Also, we use ecmpij to denote the load that shortest-path routing would generate on each link if a demand of 1 unit was routed from i to j. That is, ecmpij(e) is a fractional value in [0,1] when e is on a shortest path from i to j, 0 otherwise.

Linear Program for theoretical optimum computation. REPETITA solves the multi-commodity flow problem through a linear program (LP), to provide a baseline for TE algorithms (see §3.2) The mathematical formulation of such an LP follows: the first constraint ensures the flow conservation in any node i for the traffic destined to any node t, while the second constraint defines the maximum link utilization.

Variables:

- loadt(e) fraction of the load on edge e to destination t
- U maximum link utilization

Minimize U under:

∀t ∈ V, i,j ∈ E loadt(e) = ∑_{e ∈ Tij} loadt(e) = T_{it}
∀e ∈ E, i,j ∈ E loadt(e) ≤ c(e)U

Note that demands are aggregated by destination, which requires O(|V||E|) variables, rather than O(|V|^2|E|) as in per-demand models. This is enough to compute the maximum link utilization, but does not retain per-demand information (e.g., the fraction of link load due to each demand).

MILP SR model. REPETITA includes a mixed integer linear program inspired by [15] (see §4.2). This MILP assumes that demands can only be re-routed via at most one detour. This means that every path from any i to any j can be represented by a variable path_{kj} equal to ikj for some node k (possibly, k = j if there is no detour). We however reformulated the original model to have O(|V|^2|E|) variables rather than O(|V|^3|E|). To do so, we separately group the traffic before a detour (step1) and after it (step2).
Variables:
\( \text{path}_{ikj} = 1 \) iff \( \text{path}_{ij} = ikj \)

\( s_{ij}^{(1)} \)  traffic to send from i to j in step 1

\( s_{ij}^{(2)} \)  traffic to send from i to j in step 2

\( U \)  maximum link utilization

Minimize \( U \) under:

\( \forall i, j, k \in V \) \( \sum_k \text{path}_{ikj} = 1 \)

\( \forall i, k \in V \) \( s_{ik}^{(1)} = \sum_j T_{ij} \text{path}_{ikj} \)

\( \forall k, j \in V \) \( s_{kj}^{(2)} = \sum_i T_{ij} \text{path}_{ikj} \)

\( \forall e \in E \) \( \sum_{i,j} \text{ecmp}_{ij}(e)(s_{ij}^{(1)} + s_{ij}^{(2)}) \leq c(e) U \)

\( \forall i, j, k \in V \) \( \text{path}_{ikj} \in \{0, 1\} \)