

Rethinking Failure-Tolerant Traffic Engineering with Demand Prediction

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Wide-Area Network (WAN)

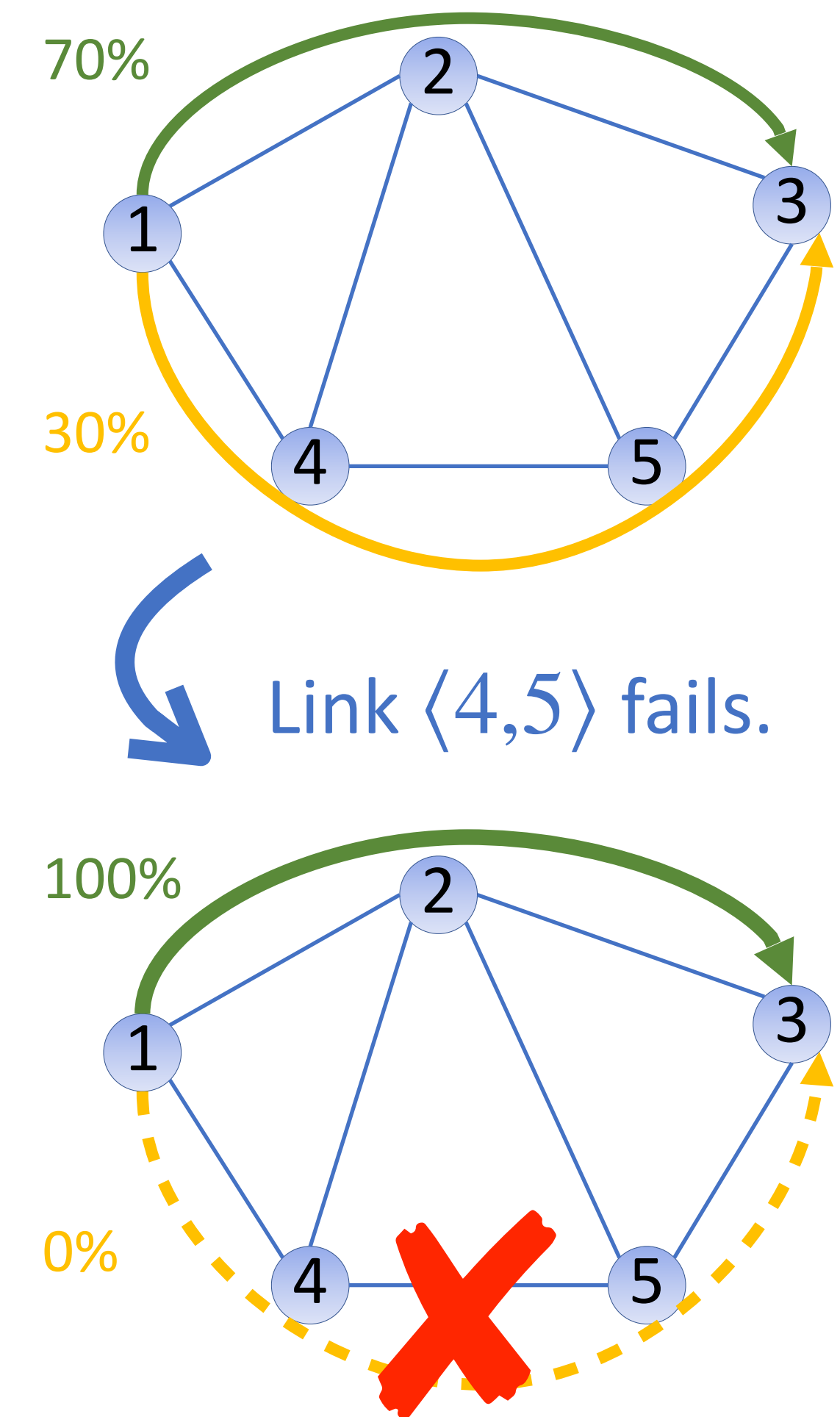


- An essential infrastructure
 - ✓ Connect vast areas
 - ✓ Carry various cloud services
 - ✓ ...
- Failures are common
 - ✓ Fiber cuts
 - ✓ Power outages
 - ✓ Hurricanes
 - ✓ Misconfigurations
 - ✓ ...



Problem: Network Failure

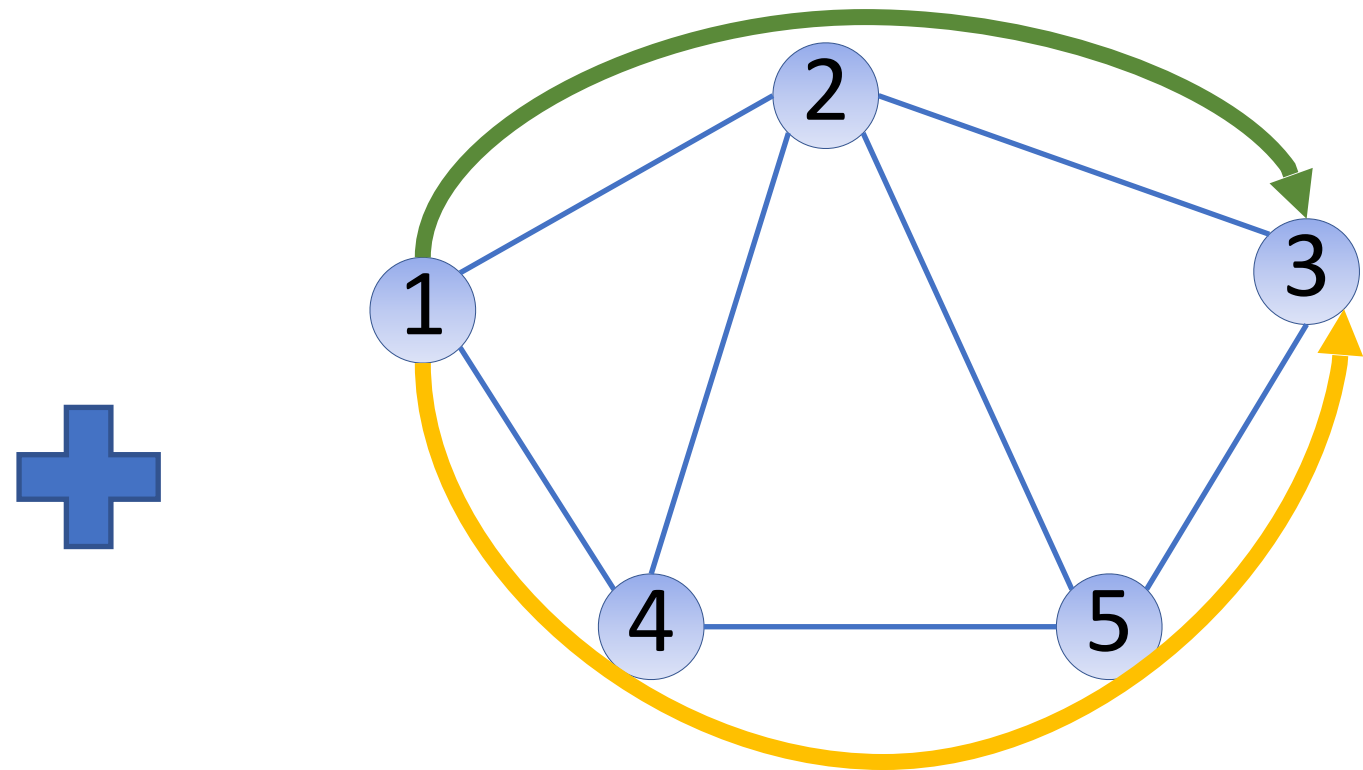
- Unpredictable
 - The unpredictable nature of infrastructure or operational failures is inherent in the networking system.
- Severe impact
 - Congestion, packet loss, long latency, availability drop, etc.
- **How to handle the unpredictable network failures?**
 1. **Data plane:** Fast rerouting (R3@SIGCOMM'10)
 2. **Control Plane:** *Proactively* handle common failure scenarios before accidents happen (FFC@SIGCOMM'14)



Failure-Tolerant Traffic Engineering

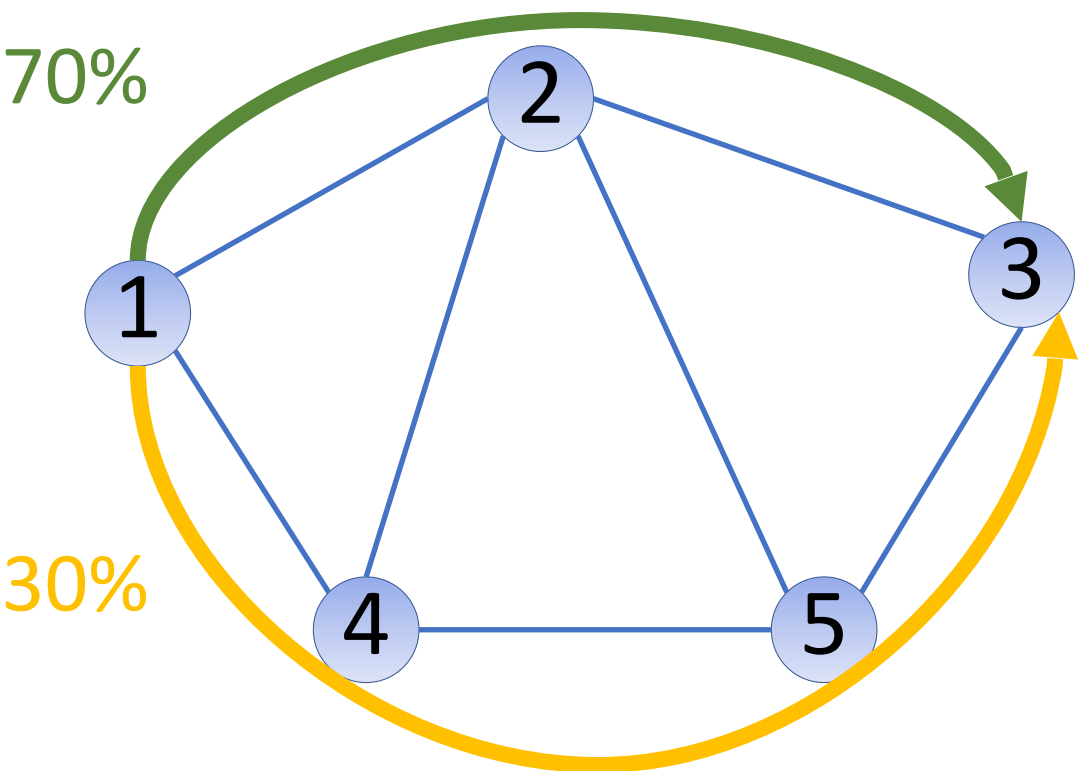
	1	2	3	...	N
1	0	10	3	...	13
2	12	0	5	...	0
3	20	0	0	...	32
...	0	...
N	12	0	50	...	0

Demand matrix

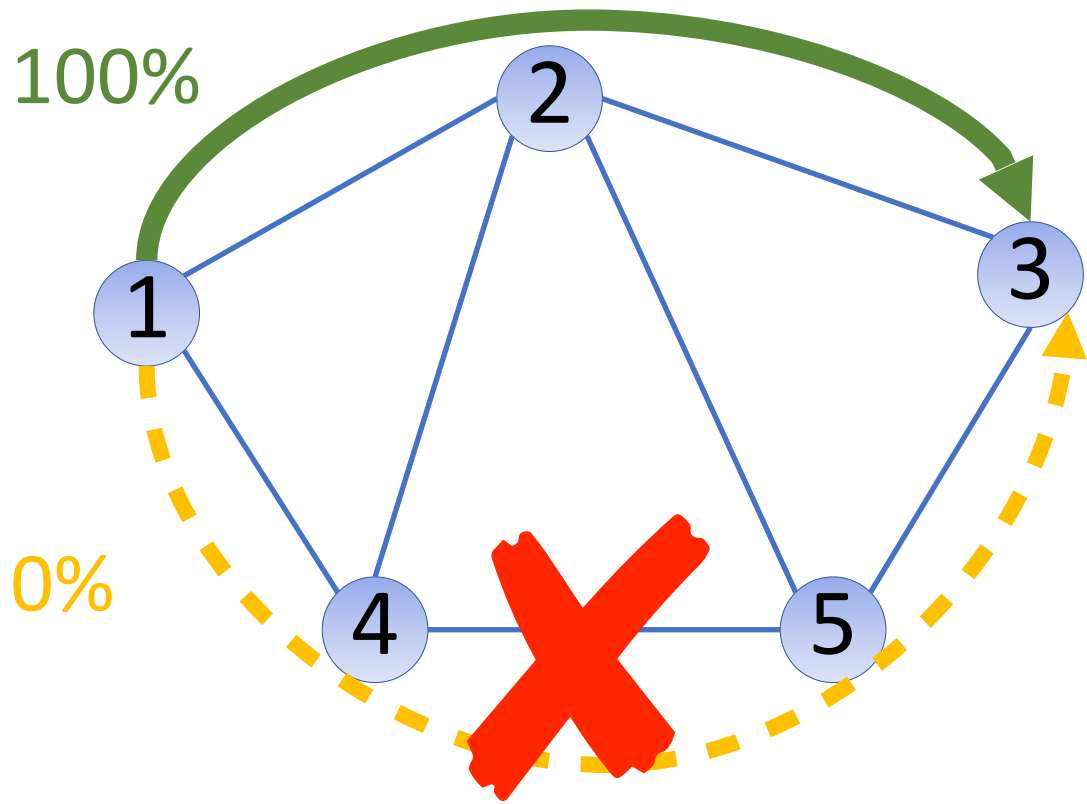


Topology & failure scenarios ...

Optimize a global objective



TE configuration



Rerouting

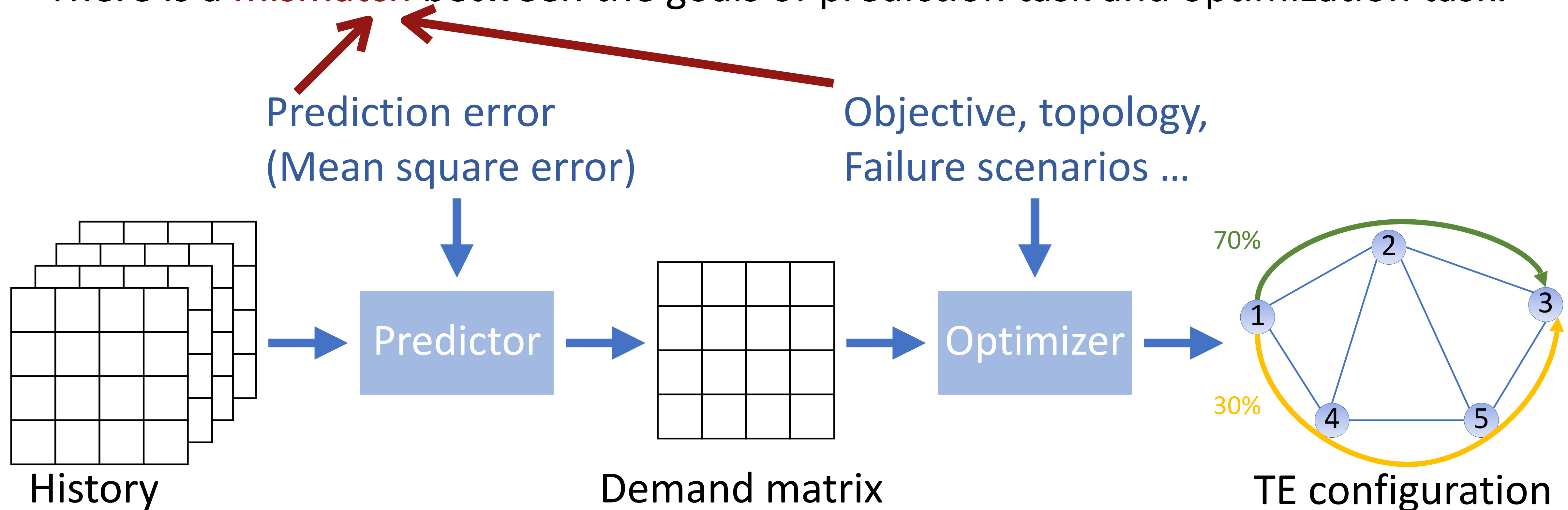
1. First, predict the demand matrix, i.e., the traffic demands of all node pairs.
2. Second, optimize the network risk, e.g., demand loss and availability.
3. Third, reroute upon detecting network failures.

Examples:

FFC@SIGCOMM'14,
TEAVAR@SIGCOMM'19,
ARROW@SIGCOMM'21

Challenge: Demand Uncertainty

- However, a certain degree of unpredictability remains in customer-facing traffic demands.
- There is a **mismatch** between the goals of prediction task and optimization task.

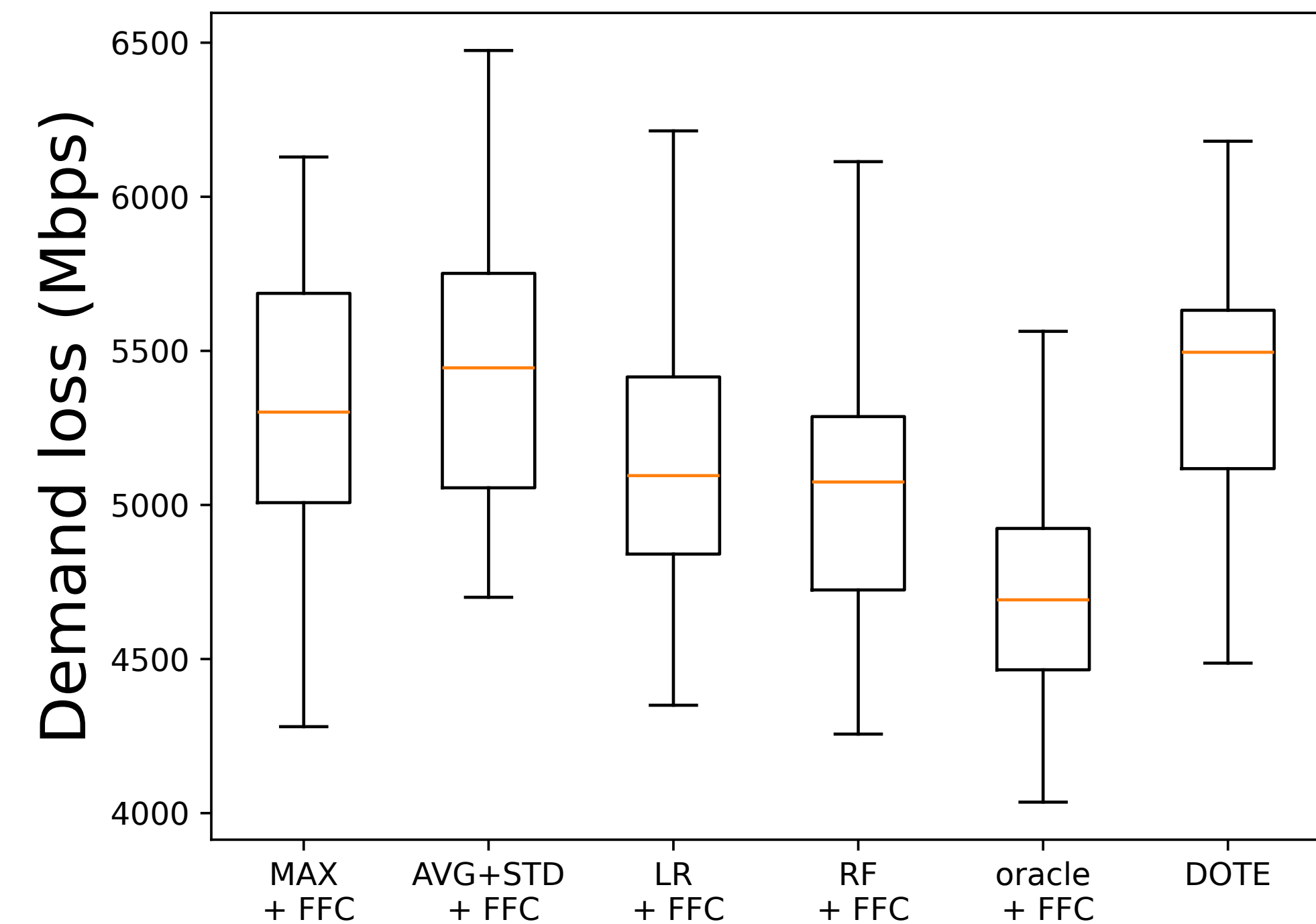


Motivation

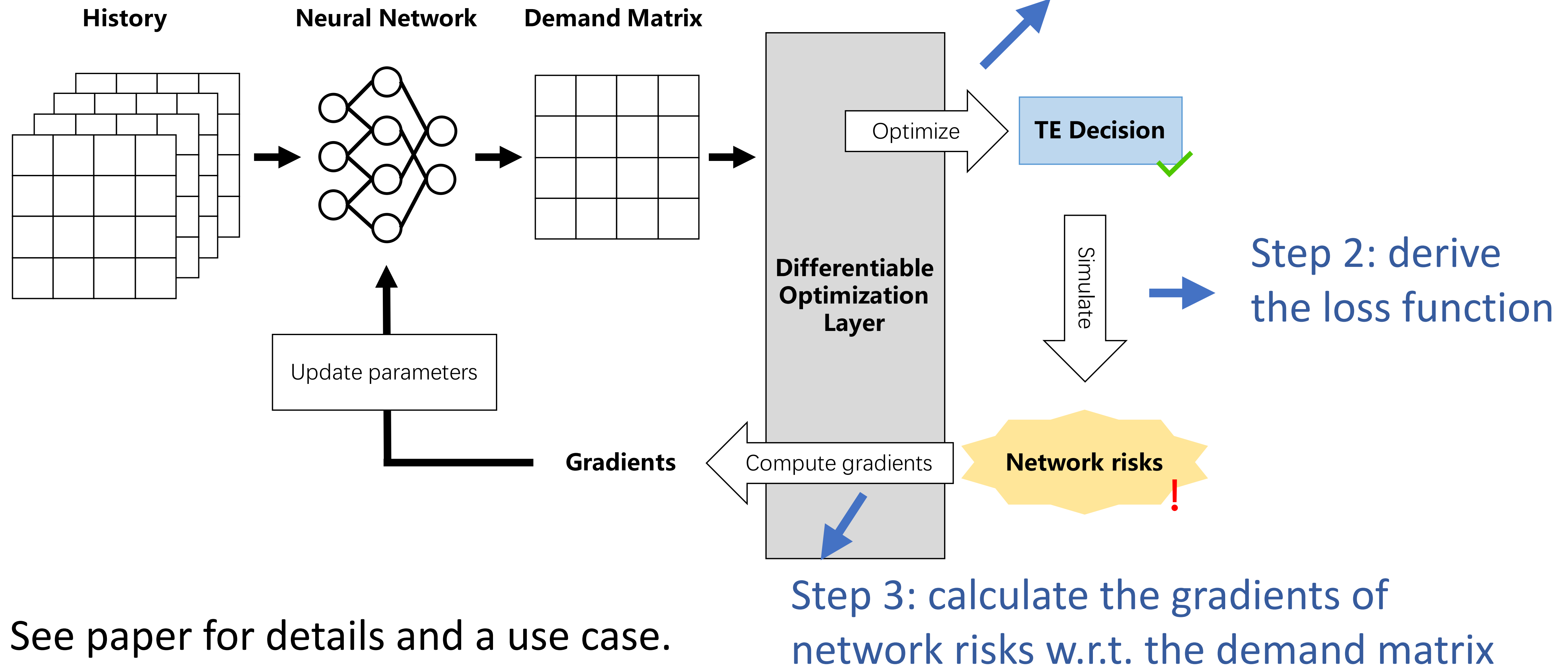
- We tested FFC combined with different prediction methods.
- Prediction Methods
 - MAX: the maximum value
 - AVG+STD: the mean plus two standard deviations
 - LR: linear regression
 - RF: random forest regression
 - Oracle: ground truth traffic demands
- **Findings:** The demand loss of prediction-based methods is 5.77% greater than that of the ideal case.

Demand loss:

the greatest traffic loss when a component of network fails.

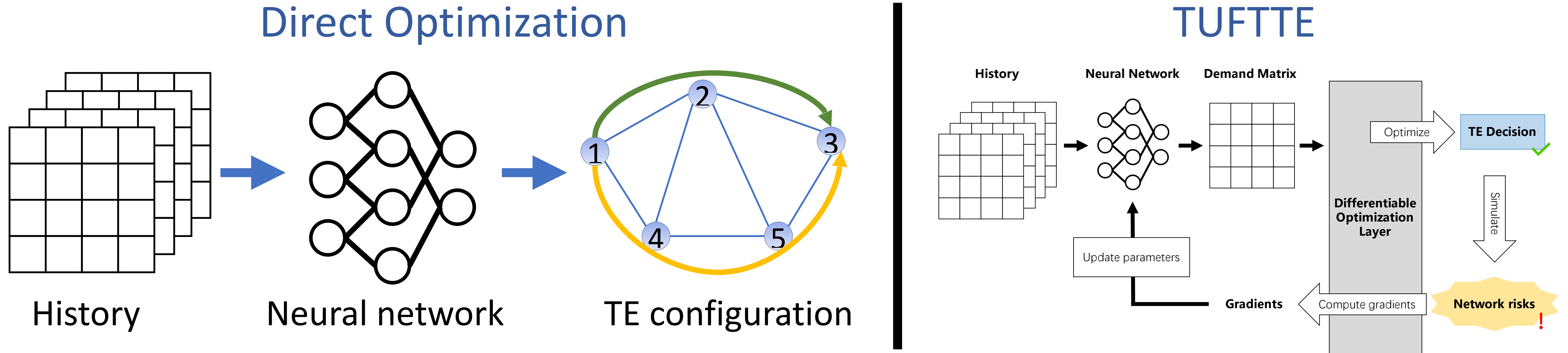


Our Solution: TUFTTE



- See paper for details and a use case.

Discussion: Why not Direct Optimization?



- Direct optimization (DOTE@NSDI'23, FIGRET@SIGCOMM'24) leverages a neural network to decide the TE configuration, without predicting the traffic demands.
- However, the use of risk function $R(\mathbf{x}, D)$ for training results in an increase in the value of the output x_t , thereby exceeding the capacity of the edge.

$$R(\mathbf{x}, D) = \max_{s \in S} \sum_{(u,v) \in K} \max \{ d_{u,v} - \sum_{t \in T_{u,v}} \lambda_{t,s} x_t, 0 \} .$$

x_t : the amount of traffic loaded on tunnel t

Evaluation

- Datasets

- Abilene and GEANT from SNDlib [1]
- 3 days of traffic traces for training
- 1 day of traffic traces for testing

- Baselines

- Prediction-based methods: MaxMin (max-min fairness), MLU (maximum link utilization), FFC@SIGCOMM'14, TEAVAR@SIGCOMM'19
- Direct optimization: DOTE@NSDI'23

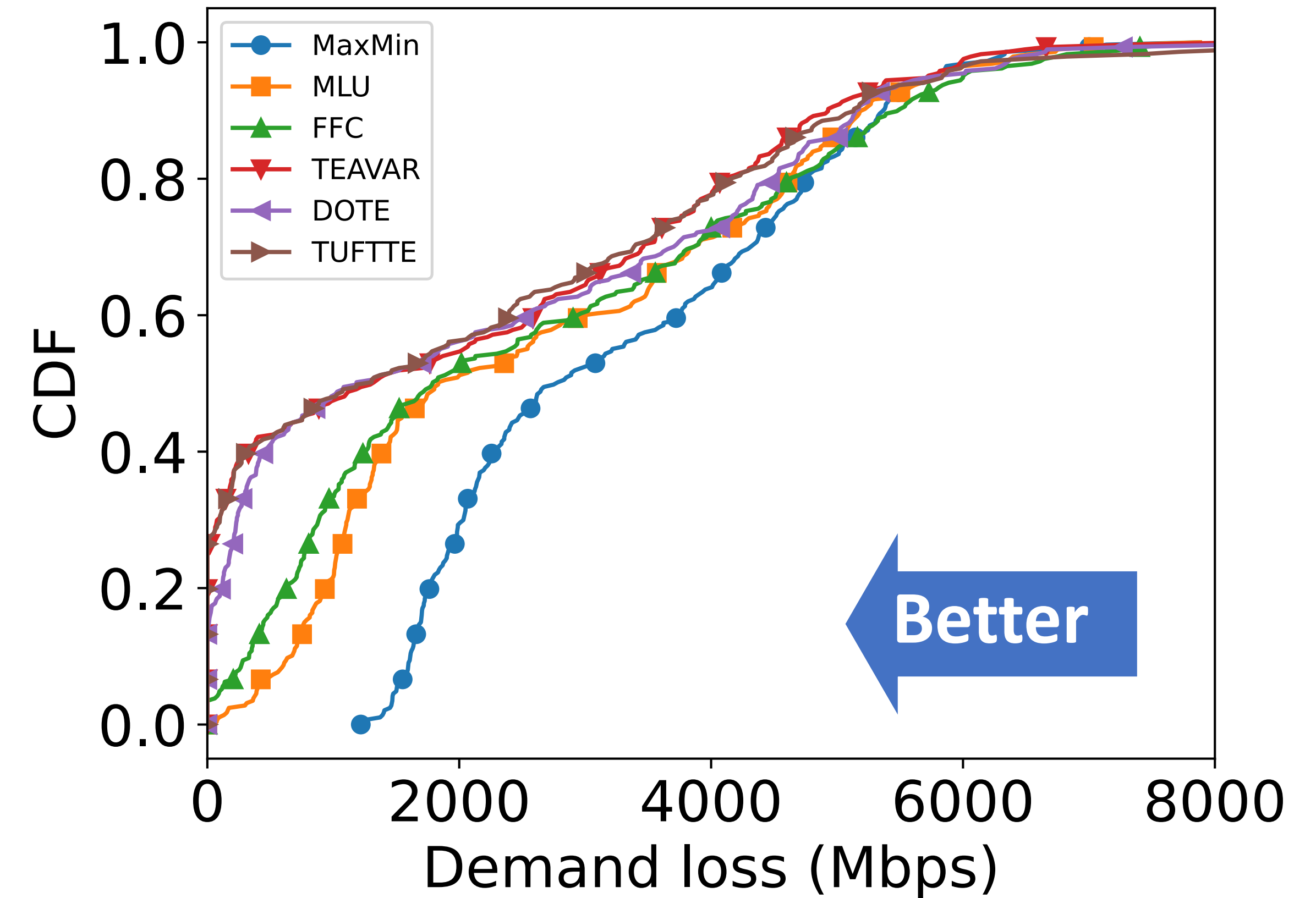
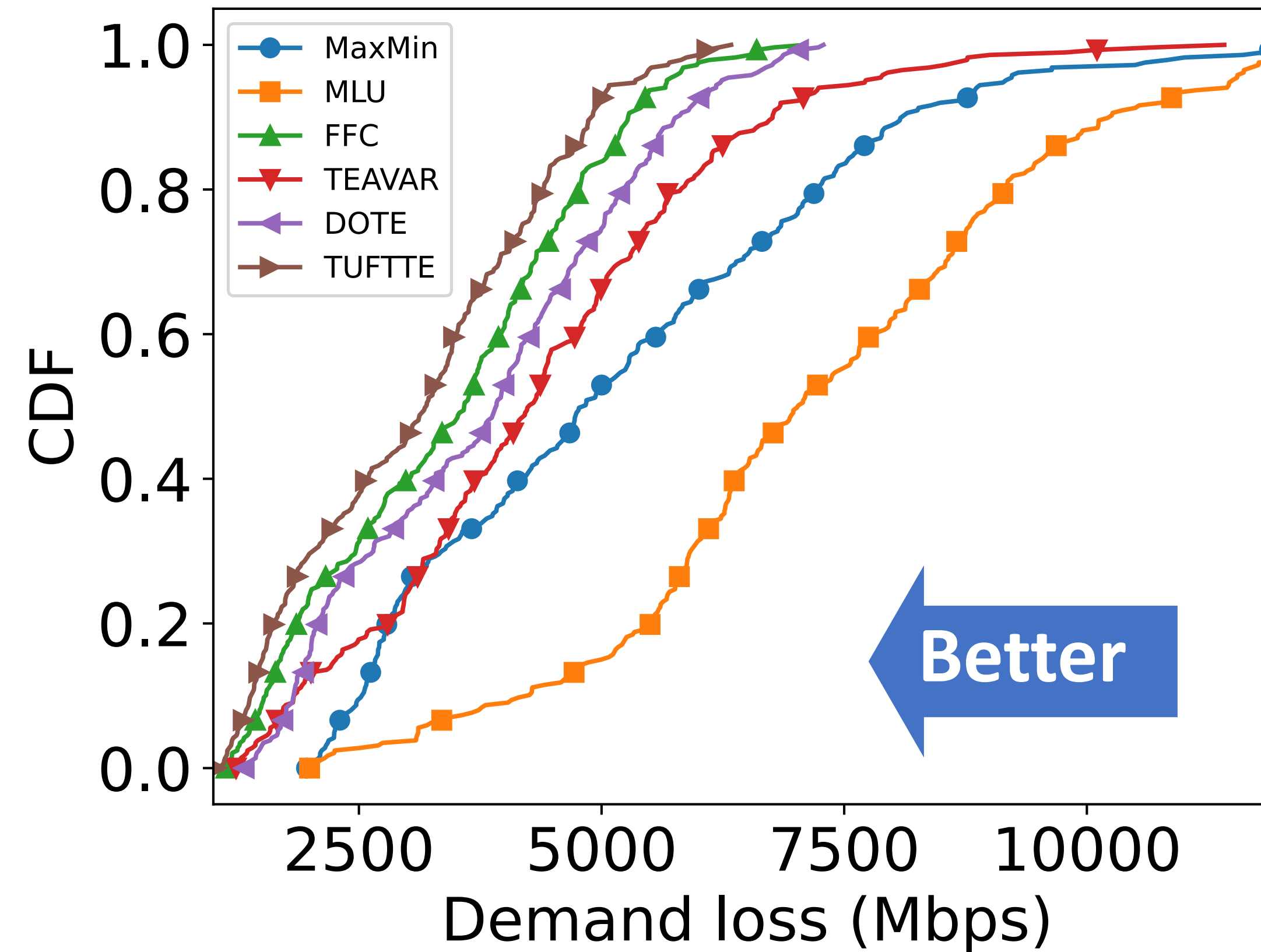
- Metric

- Demand loss risk: the greatest traffic loss across all failure scenarios.

Topology	# of nodes	# of links
Abilene	12	15
GEANT	22	36

[1] <https://sndlib.put.poznan.pl/home.action>

Main Result



- TUFTTE reduces the demand loss by an average of 11.59% on the GEANT topology compared to FFC.

Resilience to traffic fluctuations

- We increase the variation of traffic demands d by multiplying a noise, i.e., $d \leftarrow d(1 + \epsilon)$, where ϵ is sampled from a uniform distribution $[-c, c]$.
- The increment in demand loss is calculated based on running TUFTE with traffic demands without noise.

Noise c in traffic	FFC's increment on average	TUFTE's increment on average
10%	10.40%	1.03%
15%	11.62%	1.30%
20%	13.08%	2.69%
25%	14.36%	4.49%
30%	15.54%	6.42%

- **Summary:** The noise has a relatively small effect on the solution quality of TUFTE.

Thank you!

Code: <https://github.com/shijuzhao/tuftte>

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