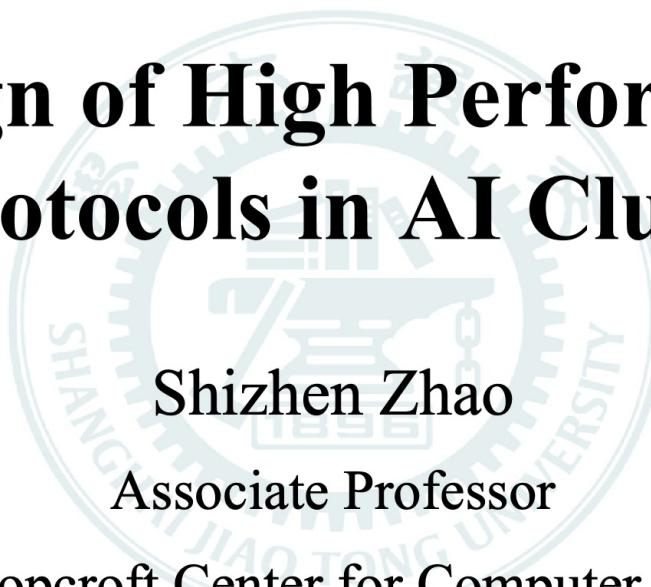


On the Design of High Performance Routing Protocols in AI Clusters



Shizhen Zhao

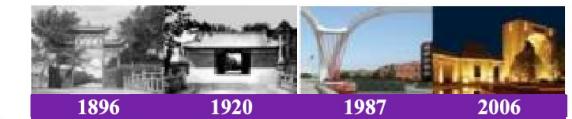
Associate Professor

John Hopcroft Center for Computer Science

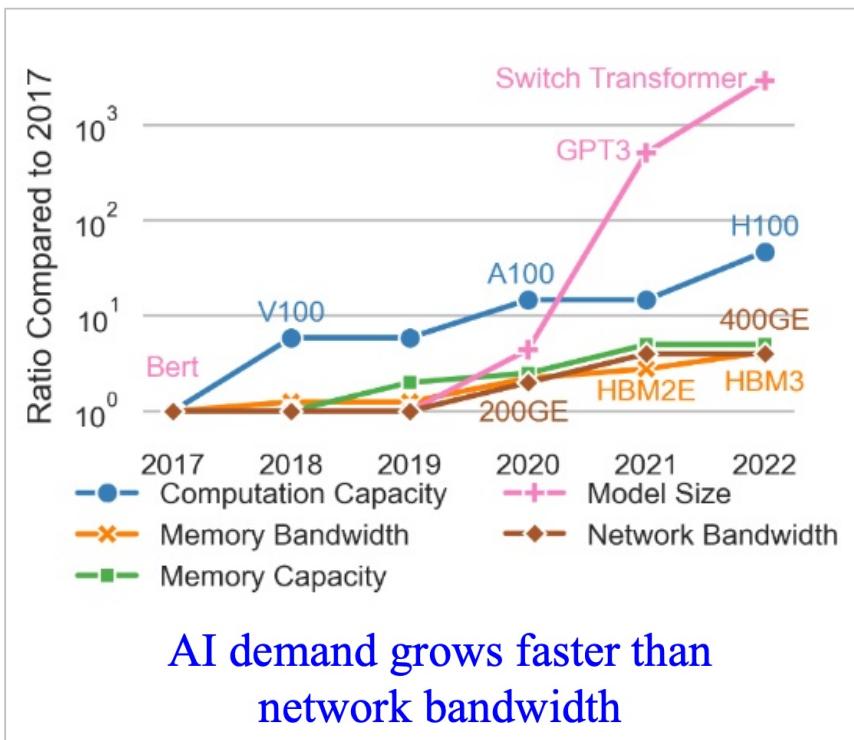
Shanghai Jiao Tong University



Background



AI traffic is growing faster than network bandwidth, and exhibit distinctive characteristics from traditional DCN traffic. Building a network specific for AI is crucial.



Collectives	Model Dist. purpose	Traffic pattern	Network congestion	GPU Msg (MB)	NIC Msg (KB)	Flow entropy per NIC	Topology need
AlltoAll(v)	Embedding distribution	full mesh with imbalanced traffic	N-to-N with possible incast	1	128	$\log(M * N)$	Full bisection bandwidth
AllReduce	DDP	Tree or Ring	2-to-1 incast for Tree	4 (Tree) 1 (Ring)	512	$\log(M)$	Tolerate over-subscription
AllGather	FSDP	Ring	1-to-1 low congestion	1	512	$\log(M)$	Tolerate over-subscription
ReduceScatter	FSDP	Ring	1-to-1 low congestion	1	512	$\log(M)$	Tolerate over-subscription

Characteristics of AI Workload:

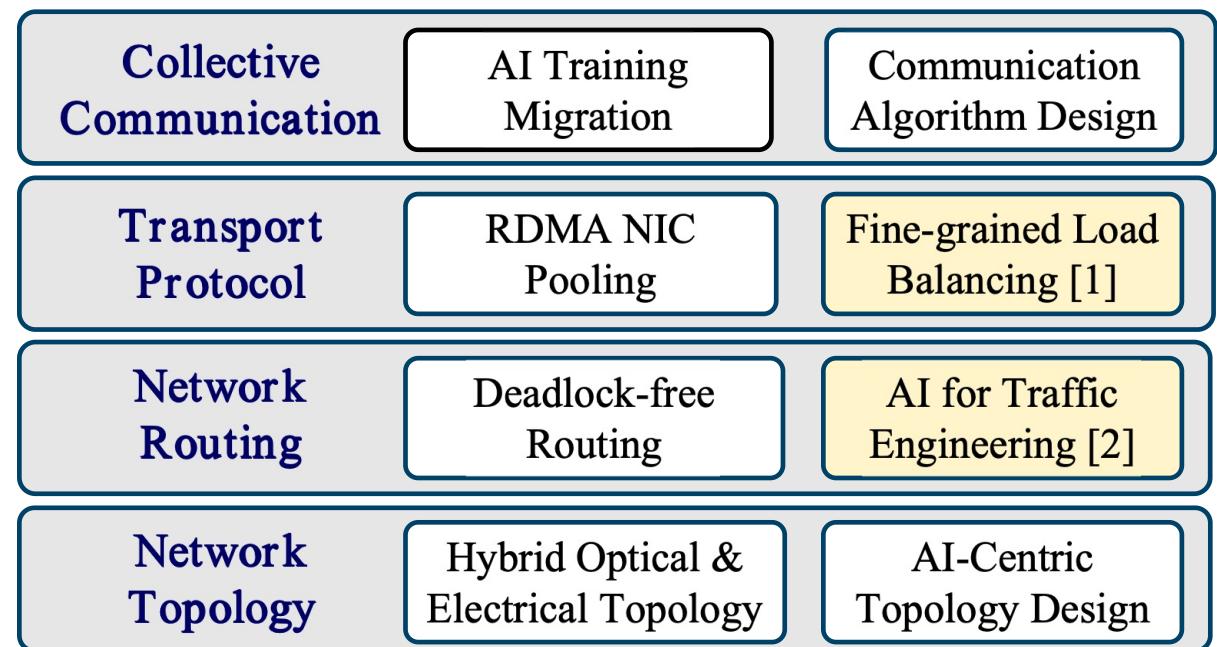
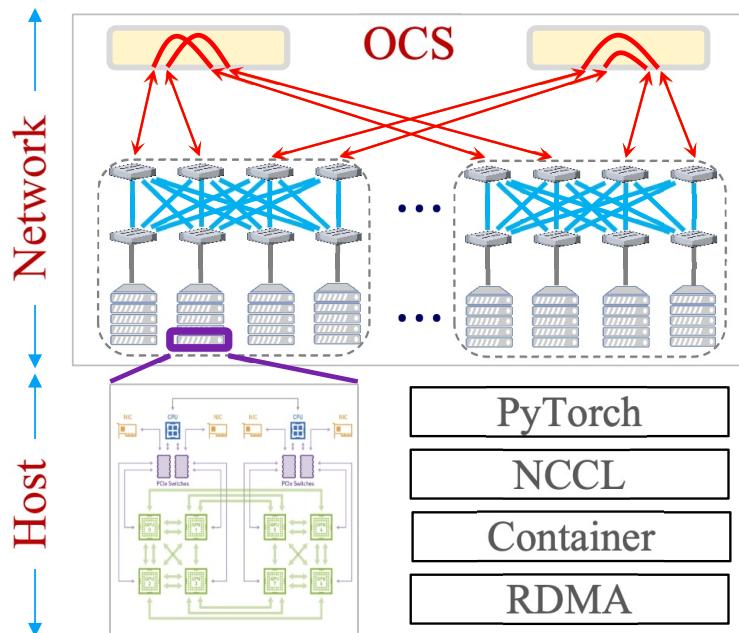
1. Predictable, alltoall may exhibit uncertainty.
2. Collective communication, traffic bursts together.
3. Low entropy, ECMP leads to load imbalance.
4. Delay sensitive, prone to long delay tail.



Buiding a Network for AI



We build hybrid optical & electrical networks for AI, which requires cross-layer optimization for topology, routing, transport protocol, collective communication, etc.



[1] Weihao Jiang, Wenli Xiao, Yuqing Yang, Peirui Cao, **Shizhen Zhao**, "Orderlock: A New Type of Deadlock and its Implications on High Performance Network Protocol Design," in SIGCOMM, 2025.

[2] Ximeng Liu, **Shizhen Zhao**, etc., "FIGRET: Fine-Grained Robustness-Enhanced Traffic Engineering," in SIGCOMM, 2024.



Fine-Grained Load Balancing



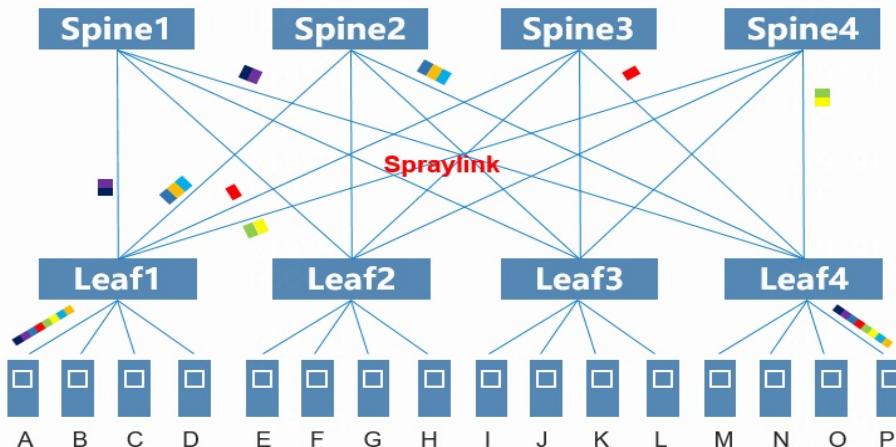
Orderlock: A New Type of Deadlock and its Implications on
High Performance Network Protocol Design
[SIGCOMM 2025]



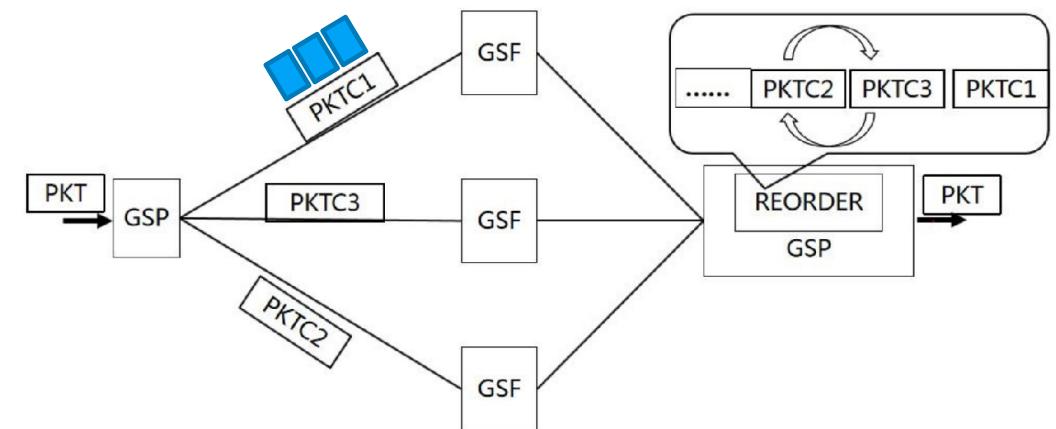
Fine-grained LB for AI Workload



AI workload requires fine-grained load balancing to fully utilize network bandwidth, due to its low entropy. Fine-grained load balancing may cause packet disordering.



UEC (Ultra Ethernet Consortium)
performs packet-level load balancing



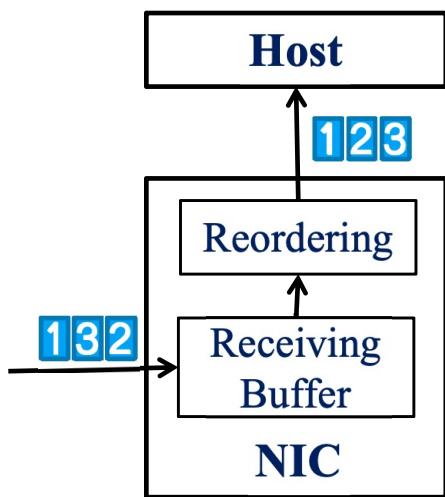
China Mobile's GSE performs packet
container level load balancing



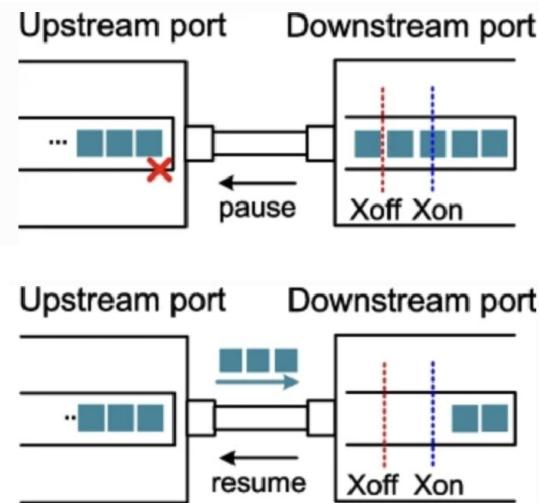
Desirable Features for AI Networks



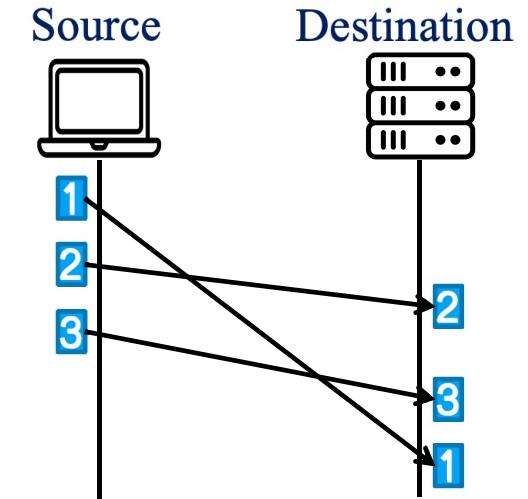
In-order delivery (I), Lossless Transmission (L) and Out-of-order Capability (O) are three important features for AI workloads to fully utilize network bandwidth.



In-order Delivery (I)



Lossless Transmission (L)



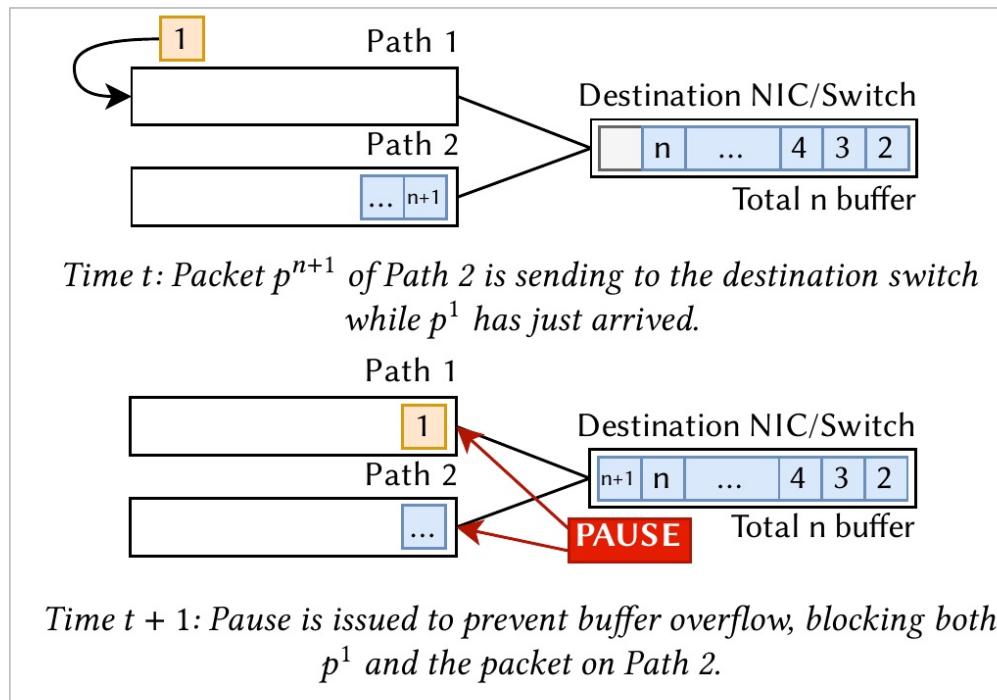
Out-of-order Capability (O)



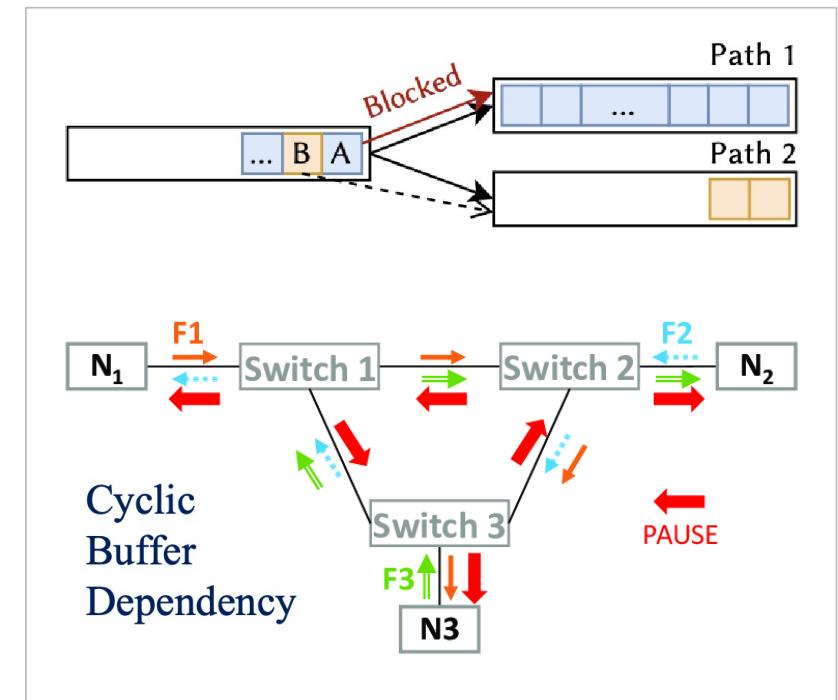
ILO Triggers Orderlock



Simultaneously achieving In-order delivery, Lossless Transmission and Out-of-order Capability triggers Orderlock, which is different from HLB and PFC deadlock.



An example of Orderlock



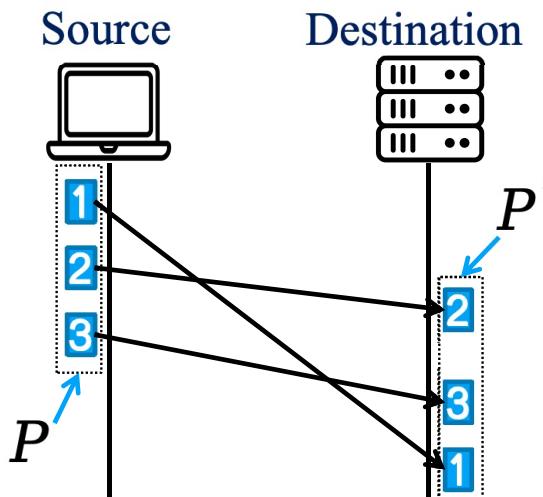
Orderlock is different from
HLB and PFC deadlock



Rigorous Definition of O



For each packet p , we define its out-of-order arrival index $OA(p)$ as the number of packets with larger index that arrives earlier than p . Then MOA characterizes the maximum out-of-order level of the arrival sequence P' . We use MOA to define O.



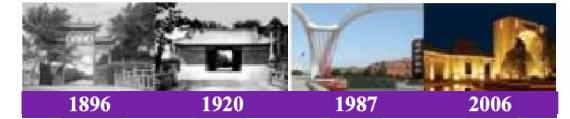
$$OA(p) := \|\{s \in P, \text{idx}_P(s) > \text{idx}_P(p) \text{ and } \text{idx}_{P'}(s) < \text{idx}_{P'}(p)\}\|$$
$$MOA := \max \{OA(p), \forall p \in P'\}$$

Out-of-order Capability

A network routing protocol is O if there exists P' such that its MOA is greater than or equal to the receiver's reordering limit.



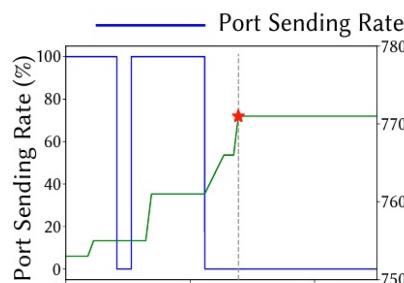
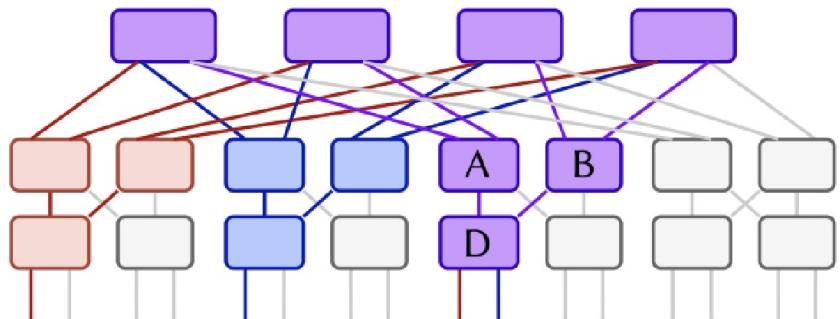
Triggering Frequency of Orderlock



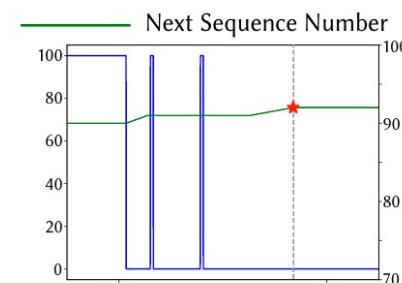
We test three O-policies. When combined with IL, all policies trigger orderlock even for a single flow. The triggering frequency increases as number of flows grows.

O-Policies

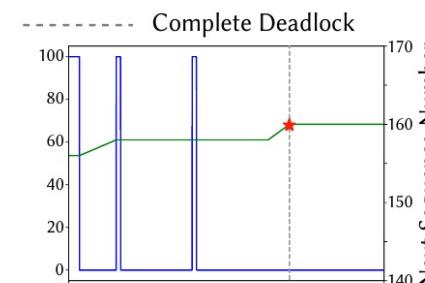
1. **Random:** randomly select a path for each packet at each switch;
2. **QDAPS:** chooses a port with slightly higher queue length to minimize out-of-order;
3. **Adaptive:** direct each packet to the port with the least queue length.



(a) Random



(b) QDAPS



(c) Adaptive

Table 1: Orderlock occurrence rate

Strategy	Number of Flow		
	250	500	750
Random	7.1%	58.1%	90.4%
QDAPS	25.3%	67.3%	91.5%
Adaptive	20.1%	60.3%	86.1%
No reorder	0	0	0

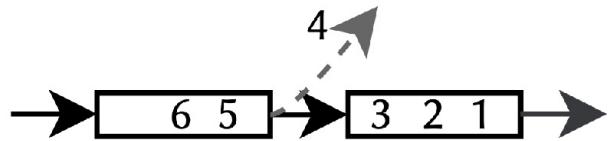


Increasing Reordering Buffer?

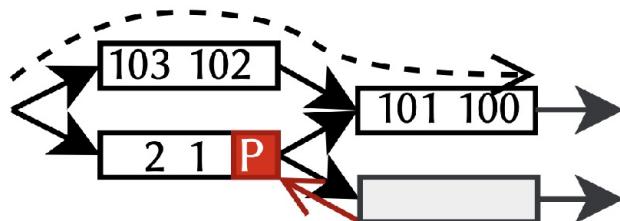


With packet spray and PFC, the on-the-fly packets of a flow can be far more than the bandwidth-delay product. Testbed experiments show that MOA and reordering buffer requirement of a flow grows with flow size.

Analysis

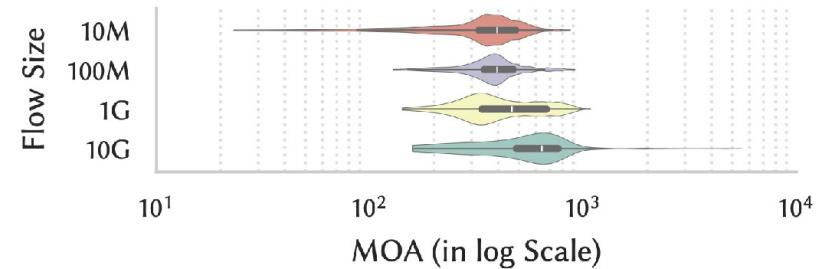


Without packet spray, BDP is enough



With packet spray, PFC increases MOA

Testbed Measurement



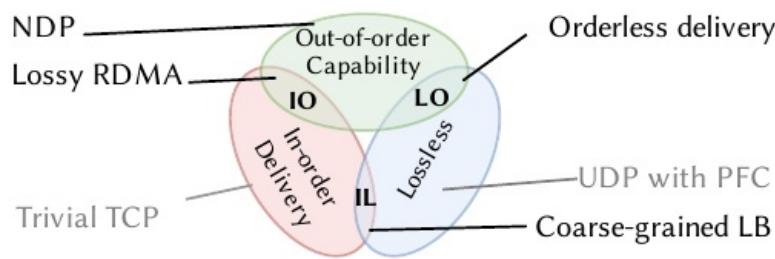
Buffer size (n)	Flow Size				
	1MB	10MB	100MB	1GB	10GB
64	7.1%	99.7%	100%	100%	100%
128	0	97.5%	100%	100%	100%
256	0	87.0%	93.4%	92.8%	92.8%
(Flow ECMP)	0	0	0	0	0



Avoid Order lock



We test 6 orderlock-free routing policies with AI collective communication workload.
LO-policies offer the best performance.



Typical Routing Policies

IL: ECMP, Flowlet, Conweave, Credit-based FC

IO: IRN

O: NDP

LO: SRNIC

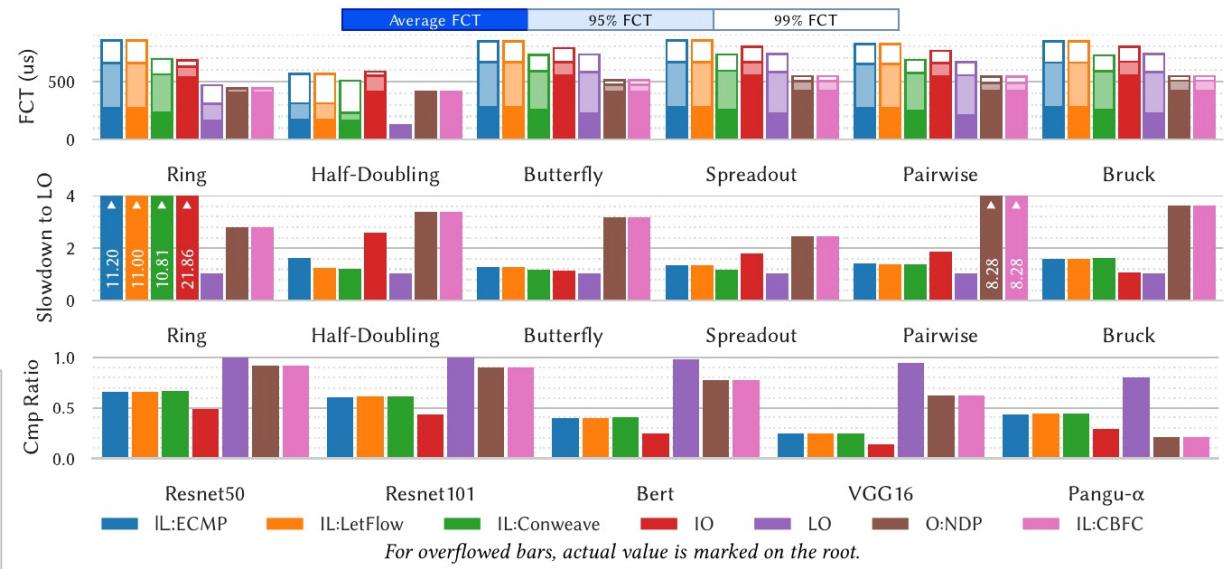


Figure 13: Performance comparison



Traffic Engineering



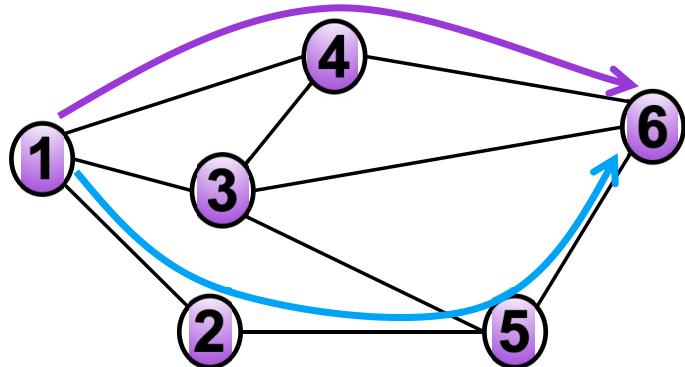
FIGRET: Fine-Grained Robustness-Enhanced
Traffic Engineering
[SIGCOMM 2024]



AI Workload Needs TE

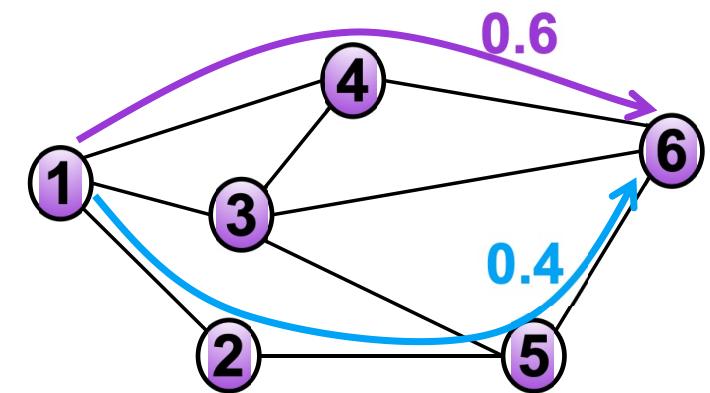


O-Policies performs fine-grained load balancing among multiple paths, but how to split the traffic?



$$\begin{bmatrix} 0 & 34 & \dots & 8 \\ 9 & 0 & \dots & 22 \\ \vdots & \vdots & 0 & \vdots \\ 11 & 10 & \dots & 0 \end{bmatrix}_{6 \times 6}$$

Traffic engineering calculates split ratios among all the paths based on user's traffic demand matrix.

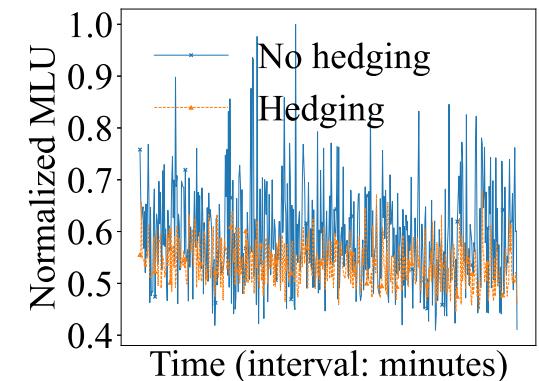
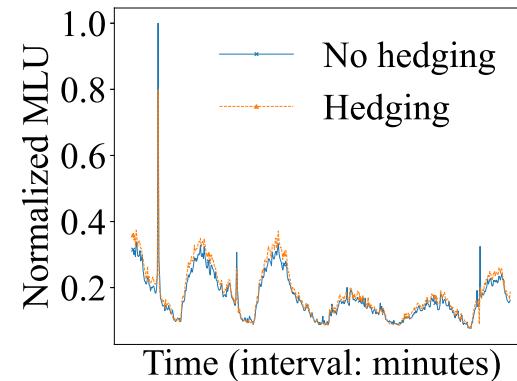
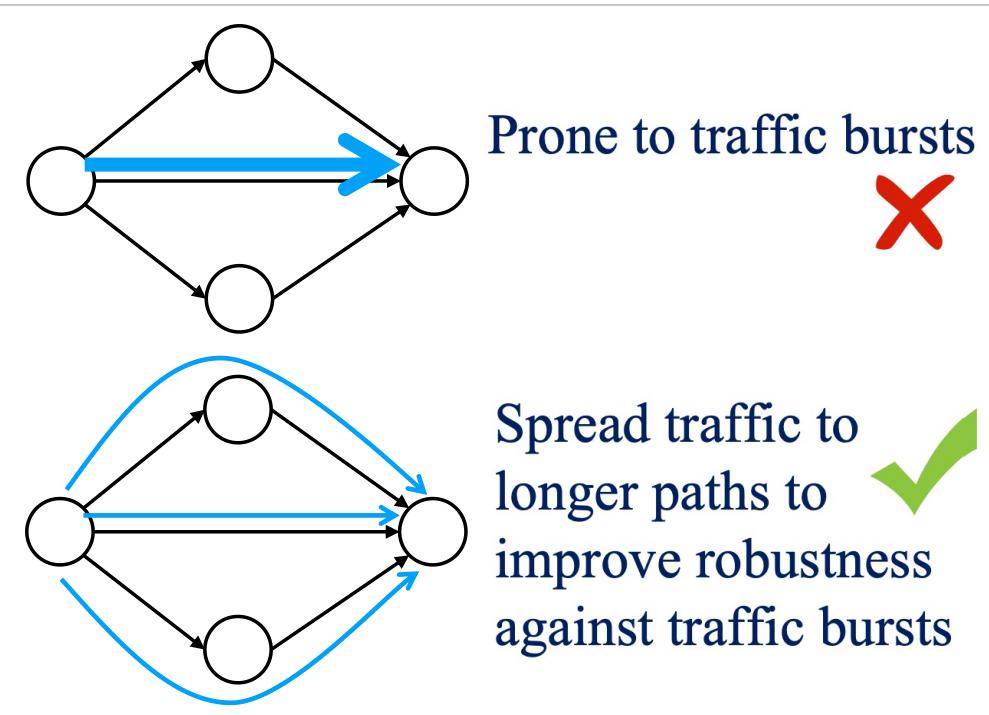




Handling Traffic Uncertainty in TE



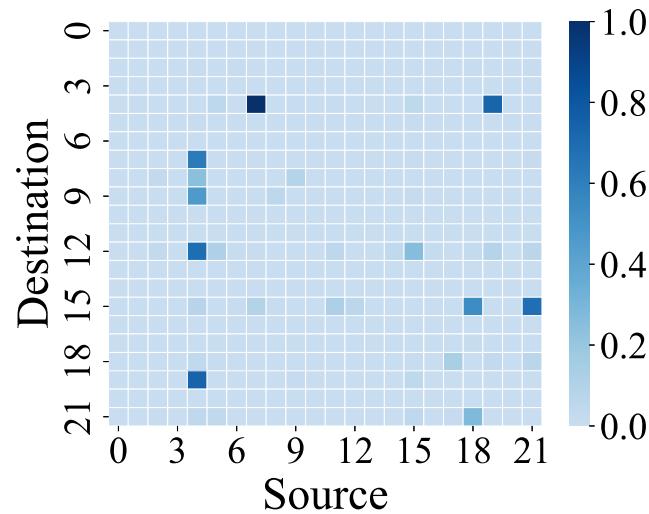
CHALLENGE: Network traffic matrix (TM) keeps changing. Even if we compute the optimal TE based on the current TM, TM may change at the next time instance. Note that calculating new TE solutions takes time.



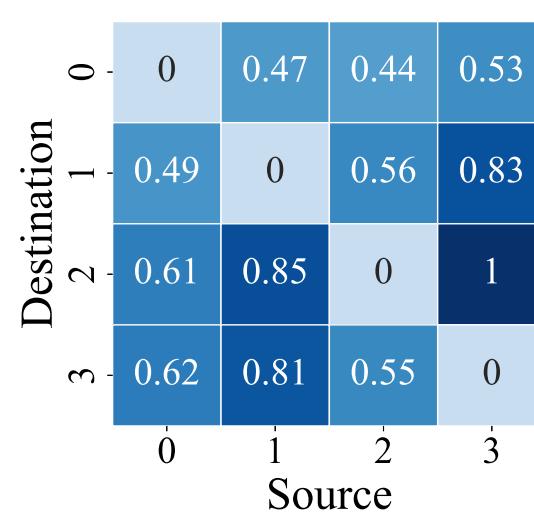
Traffic spreading (called hedging in Google) reduces MLU under traffic bursts, but increases average hop count.



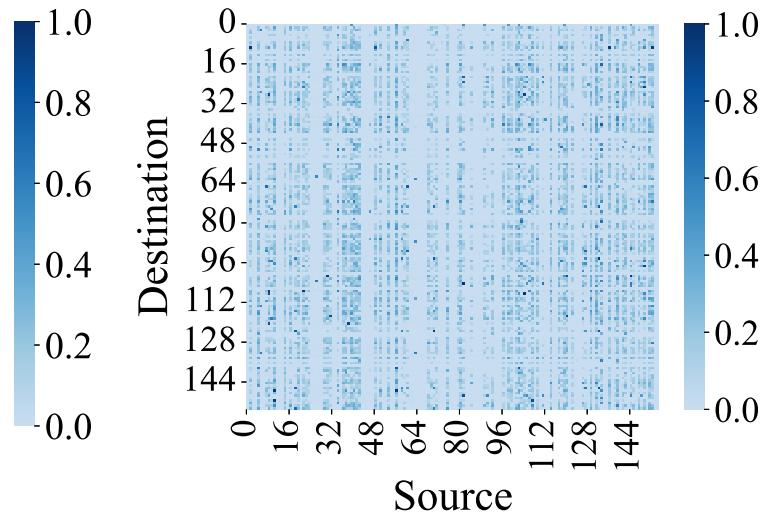
Diversity in Traffic Characteristics



GEANT, WAN



Meta, PoD-level DC



Meta, ToR-level DC

The variance of traffic demand by source and destination

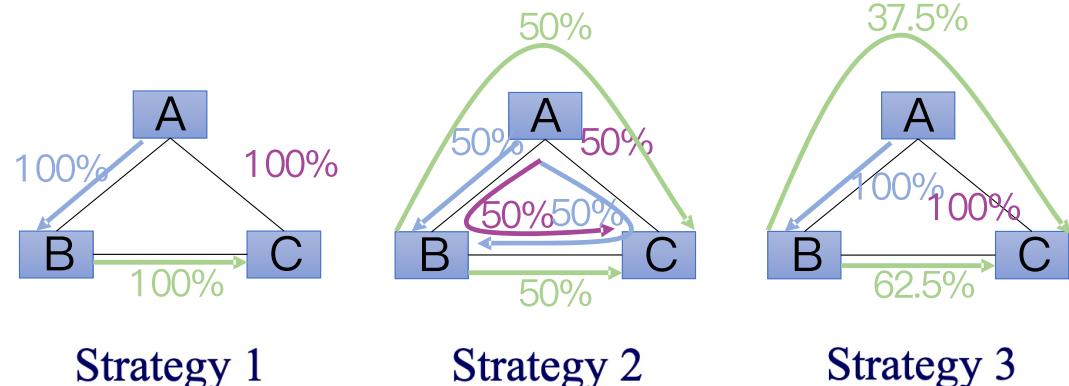


Key Insight



KEY IDEA: Treat different SD-pairs differently based on their likelyhood of burst.

Capacity	Demand	
	Normal	Burst
A↔B: 2	A→B: 1	A→B: 1
A↔C: 2	A→C: 1	A→C: 1
B↔C: 2	B→C: 1	B→C: 4



Only SD pair B→C may experience bursts.

	Normal performance	Burst
Strategy 1	0.5	2
Strategy 2	0.75	1.5
Strategy 3	0.6875	1.25

Strategy 3 achieves a better performance tradeoff



Burst-aware TE Formulation



KEY IDEA: Minimize the product of demand variance and maximum split ratio.

Original TE

$$\begin{aligned} \min_w \mu \\ \left\{ \begin{array}{l} w_{ij}^1 + w_{ij}^2 + \dots + w_{ij}^K = 1 \\ \forall \text{edge } l, \sum_{l \in P_{ij}^k} D_{ij} w_{ij}^k \leq \mu C_l \end{array} \right. \end{aligned}$$

Traffic of an SD pair on path p:
 $(D_{ij} + \delta_{ij}) \times w_{ij}^k$

Utilization of edge e on path p affected by the burst:
 $\delta_{ij} \times w_{ij}^k / C_l$

Many w_{ij}^k 's are 1.
Prone to traffic bursts

Burst-aware TE

$$\begin{aligned} \min_w \{ \mu + \alpha \sum_{ij} \text{Var}(D_{ij}) \times \max_k \{ w_{ij}^k \} \} \\ \left\{ \begin{array}{l} w_{ij}^1 + w_{ij}^2 + \dots + w_{ij}^K = 1 \\ \forall \text{edge } l, \sum_{l \in P_{ij}^k} D_{ij} w_{ij}^k \leq \mu C_l \end{array} \right. \end{aligned}$$

Flow burstiness
 $\text{Var}(D_{ij})$ increase

Weight bound
 $\max_k \{ w_{ij}^k \}$ decrease

Computational complexity
of burst-aware TE is high!



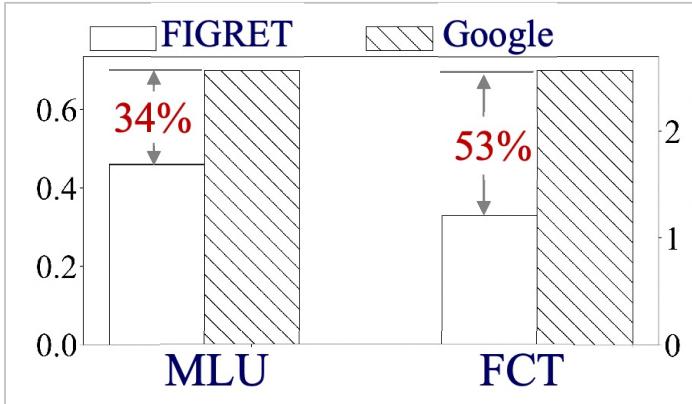
AI-aided TE Solver



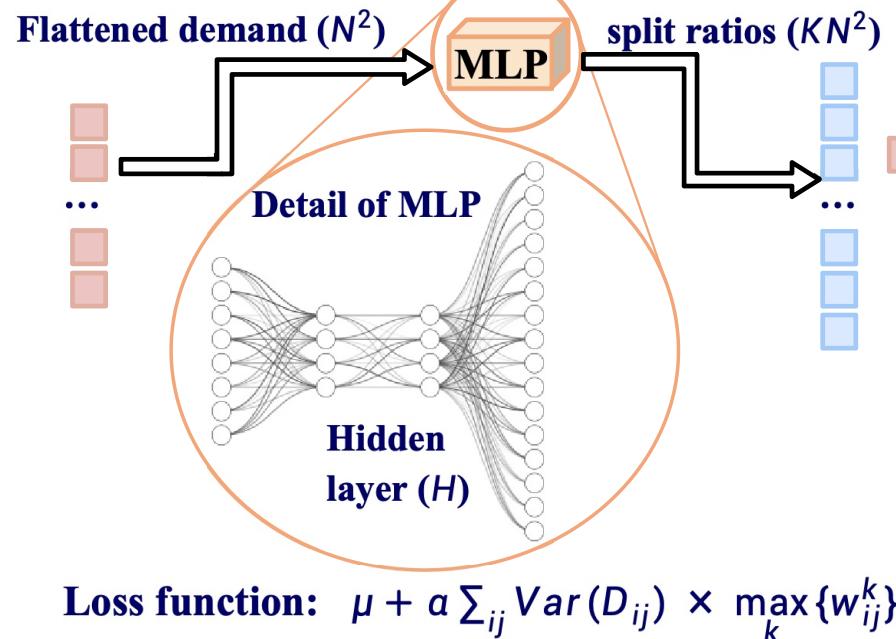
SOLUTION: Use deep learning to solve TE problems, speed up over 1000×.

Burst-aware TE

$$\min_w \{ \mu + a \sum_{ij} \text{Var}(D_{ij}) \times \max_k \{w_{ij}^k\} \}$$
$$\begin{cases} w_{ij}^1 + w_{ij}^2 + \dots + w_{ij}^K = 1 \\ \forall \text{edge } l, \sum_{l \in P_{ij}^k} D_{ij} w_{ij}^k \leq \mu C_l \end{cases}$$



FIGRET

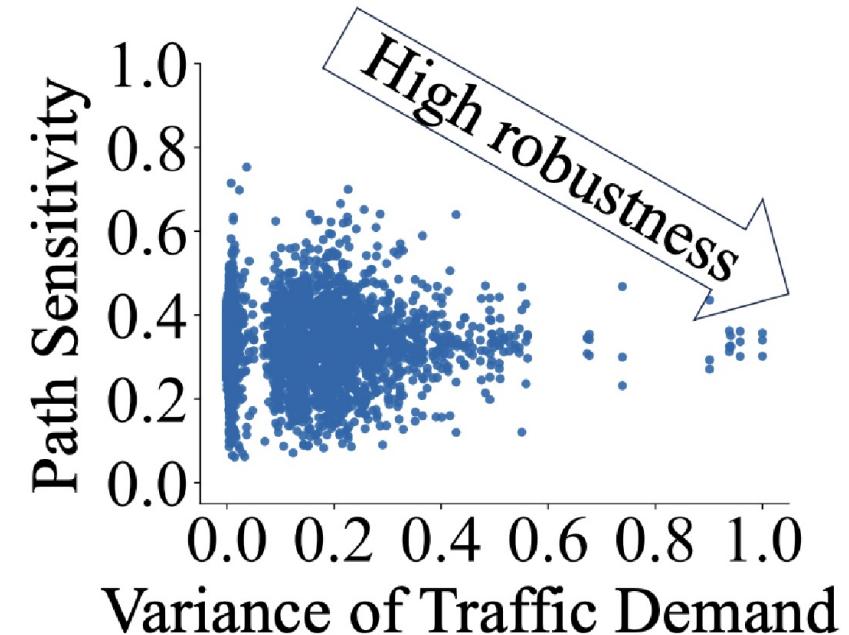
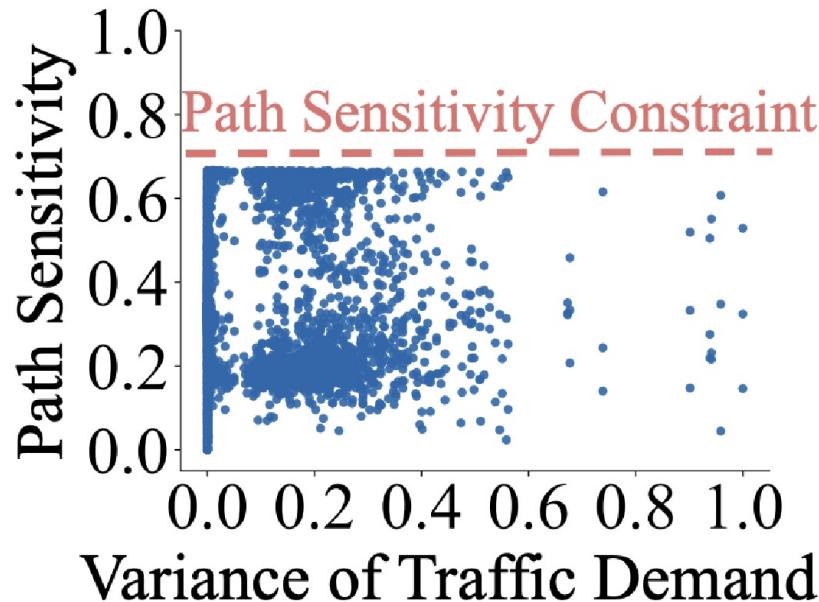




Why FIGRET Performs Better?



UNDERSTANDING: We plot (demand variance, demand split ratio) pairs, and find that FIGRET enforces lower demand split ratios for high variance demand.





New Opportunities of AI for TE



Handle Network Failures (APNet'25 [1]):

- Traditional failure-resilient TE has poor compatibility

Handle Network Dynamics (Arxiv'25 [2]):

- Retraining is costly when network changes

Joint Optimization of Collective Communication and Routing (Ongoing):

- Alltoally is bottleneck; existing CCL optimization algorithms are too slow

Close-loop Traffic Matrix Prediction for TE:

- Minimizing MSE may not be a good choice for TM prediction in TE

[1] Xiyuan Liu, Yang Liu, Jingyi Cheng, Ximeng Liu, Shizhen Zhao, "FauTE: Fault-tolerant Traffic Engineering in Data Center Network," in APNet, Shanghai, China, August, 2025

[2] Ximeng Liu, Shizhen Zhao, Xinbing Wang, "Geminet: Learning the Duality-based Iterative Process for Lightweight Traffic Engineering in Changing Topologies," available online: <https://arxiv.org/pdf/2506.23640v1.pdf>



Questions?

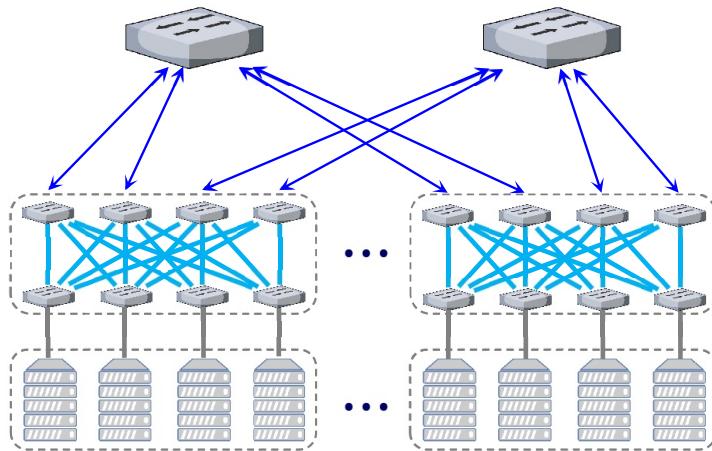




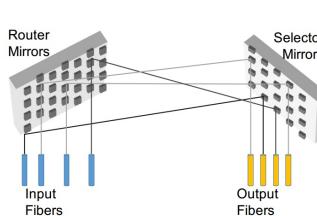
Electrical Core vs Optical Core



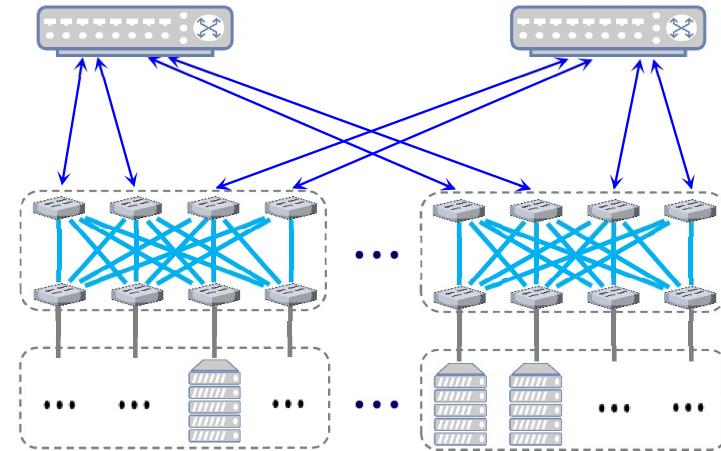
Electrical Packet Switches (EPS)



Replace the
core layer
EPSes by
OCSes



Optical Circuit Switches (OCS)



Broadcom Tomahawk 5 chip bandwidth 51.2T

Configuration: 800Gbps x 64 ports

3-layered FatTree: $2 \times 32^3 = 65536$ nodes

Configuration: 1.6Tbps x 32 ports

3-layered FatTree: $2 \times 16^3 = 8192$ nodes

OCS size: 256 speed agnostic ports

Broadcom Tomahawk 5 chip bandwidth 51.2T

Configuration: 800Gbps x 64 ports

Hybrid network: $256 \times 32^3 = 262144$ nodes

Configuration: 1.6Tbps x 32 ports

Hybrid network: $256 \times 16^2 = 65536$ nodes