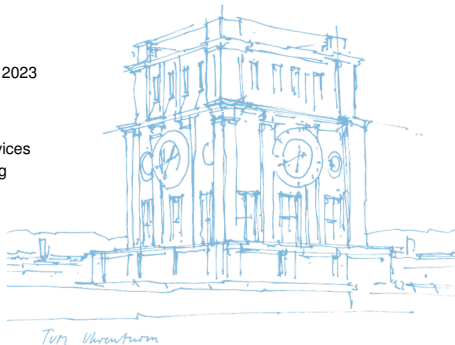


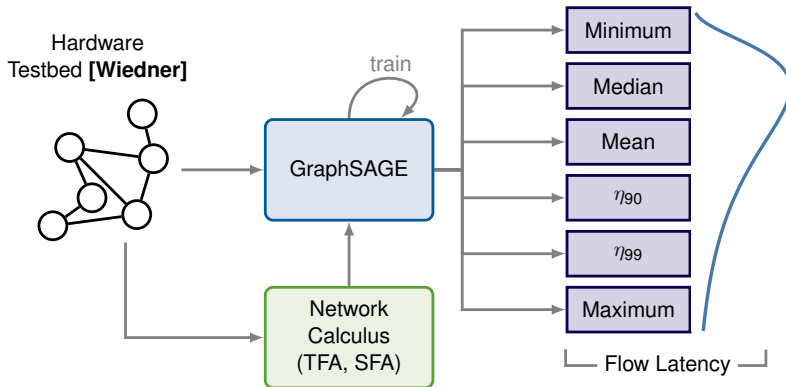
Predicting Latency Quantiles using Network Calculus-assisted GNNs

Max Helm, Georg Carle

2nd Graph Neural Networking Workshop 2023
December 8, 2023, Paris

Chair of Network Architectures and Services
Department of Computer Engineering
Technical University of Munich





[Wiedner] Wiedner, Florian, et al. "HVNet: Hardware-Assisted Virtual Networking on a Single Physical Host." IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE, 2022.

What? Why?

Questions to Answer

How well can we predict latency quantiles in a hardware setup?

Can Network Calculus bounds improve prediction performance?

Work	Year	GNN	Formal Method as Input	Data Source	Prediction Target
Rusek et al.	2020	✓	✗	Simulation	Normal, (gamma) distribution
Ferriol-Galmés et al.	2022	✓	✗	Simulation	Mean
Wang et al.	2022	✓	✗	Simulation	Mean per timestep
Yang et al.	2022	✓	✗	Simulation	Distribution (mean, η_{99} reported)
Zhang et al.	2023	✓	✓	Simulation	Mean
Suárez-Varela et al.	2023	✓	✗	Hardware Testbed	Mean
This Work	2023	✓	✓	Hardware Testbed	Mean + Quantiles

[Rusek] Rusek, Krzysztof, et al. "Routenet: Leveraging graph neural networks for network modeling and optimization in sdn." IEEE Journal on Selected Areas in Communications 38.10 (2020): 2260-2270.

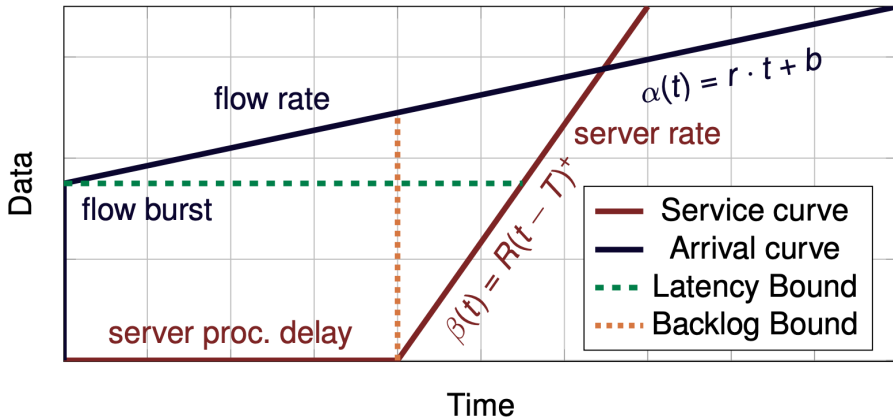
[Ferriol-Galmés] Miquel Ferriol-Galmes, Krzysztof Rusek, Jose Suarez-Varela, Shihan Xiao, Xiang Shi, Xiang Cheng, Bo Wu, Pere Barlet-Ros, and Albert Cabellos-Aparicio. 2022. Routenet-Erlang: A Graph Neural Network for Network Performance Evaluation. In IEEE INFOCOM 2022-IEEE Conference on Computer Communications. IEEE, 2018–2027.

[Wang] Mowei Wang, Linbo Hui, Yong Cui, Ru Liang, and Zhenhua Liu. 2022. xNet: Improving Expressiveness and Granularity for Network Modeling with Graph Neural Networks. In IEEE INFOCOM 2022 - IEEE Conference on Computer Communications. 2028–2037.

[Yang] QingqingYang, XiPeng, LiChen, LibinLiu, JingzeZhang, HongXu, Baochun Li, and Gong Zhang. 2022. DeepQueueNet: Towards Scalable and Generalized Network Performance Estimation with Packet-level Visibility. In Proceedings of the ACM SIGCOMM 2022 Conference. 441–457.

[Zhang] LianmingZhang, BenleYin, QianWang, and PingpingDong. 2023. GraphNeural Network-based Delay Prediction Model Enhanced by Network Calculus. In 2023 IFIP Networking Conference (IFIP Networking). IEEE, 1–7.

[Suárez-Varela] Jose Suarez-Varela et al. 2021. The graph neural networking challenge: a world- wide competition for education in AI/ML for networks. ACM SIGCOMM Computer Communication Review 51, 3 (2021), 9–16.



Total Flow Analysis [Bondorf]:

$$D_{s_i} = \begin{cases} h(\alpha_{s_i}, \beta_{s_i}) & \text{if } |F(s_i)| = 1 \text{ (FIFO per } \mu\text{Flow)} \\ bp(\alpha_{s_i}, \beta_{s_i}) & \text{otherwise} \end{cases}$$

$$D_{P(\text{foi})}^{\text{TFA}} = \sum_{s_i \in P(\text{foi})} D_{s_i}$$

- Aggregate flows
- Calculate latency bound per hop
- Sum up bounds along flow path

Separate Flow Analysis [Bondorf]:

$$\beta_{s_i}^{\text{l.o.foi}} = \beta_{s_i} \ominus \alpha_{s_i}^{x(\text{foi})}, \quad \beta_{P(\text{foi})}^{\text{l.o.SFAfoi}} = \bigotimes_{s_i \in P(\text{foi})} \beta_{s_i}^{\text{l.o.foi}}.$$

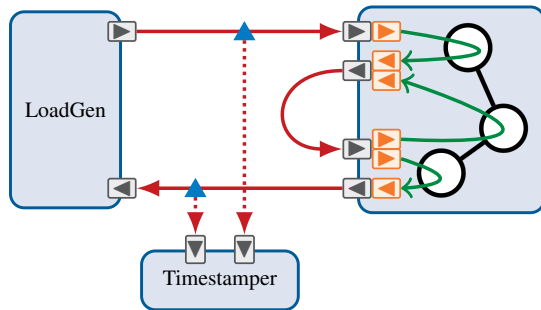
$$D^{\text{foi}} = h(\alpha^{\text{foi}}, \beta_{P(\text{foi})}^{\text{l.o.SFAfoi}}),$$

- Calculate left-over service curve per hop
- Convolute left-over service curves along the path
- Calculate latency bound

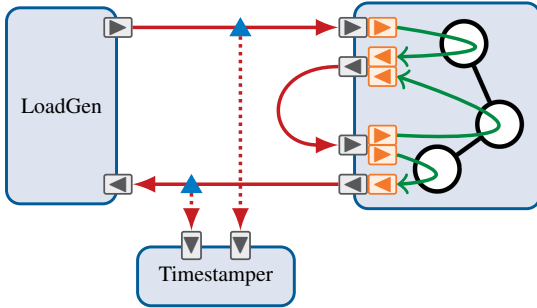
[Bondorf] Bondorf, Steffen. Worst-Case Performance Analysis of Feed-Forward Networks—An Efficient and Accurate Network Calculus. Diss. Technische Universität Kaiserslautern, 2016.

Measurements

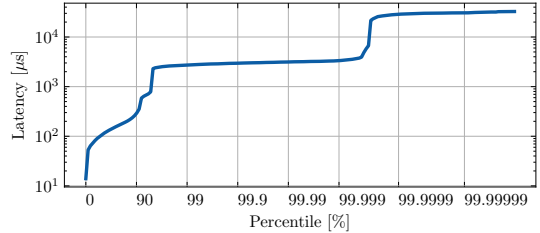
Setup [Gallenmüller], [Wiedner]:



Setup [Gallenmüller], [Wiedner]:



Results [Wiedner]:



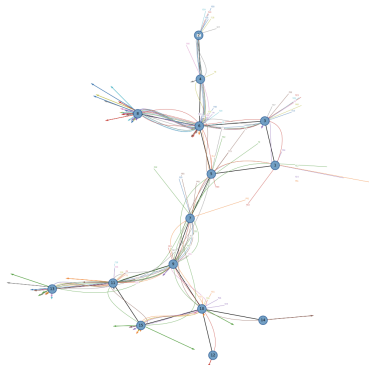
- Measured 14 billion latency values

[Gallenmüller] Gallenmüller, Sebastian, et al. "How Low Can You Go? A Limbo Dance for Low-Latency Network Functions." Journal of Network and Systems Management 31.1 (2023): 20.

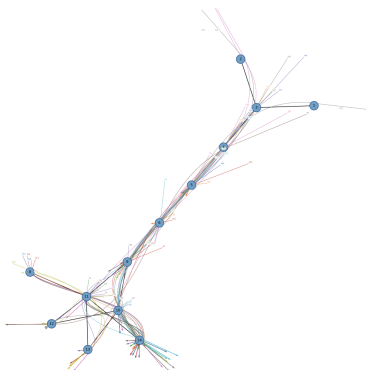
[Wiedner] Wiedner, Florian, et al. "HVNet: Hardware-Assisted Virtual Networking on a Single Physical Host." IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE, 2022.

Measurements

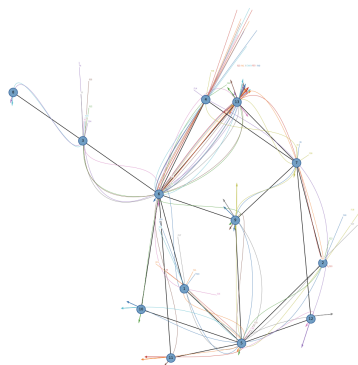
Example Network Topologies



(a) Network I

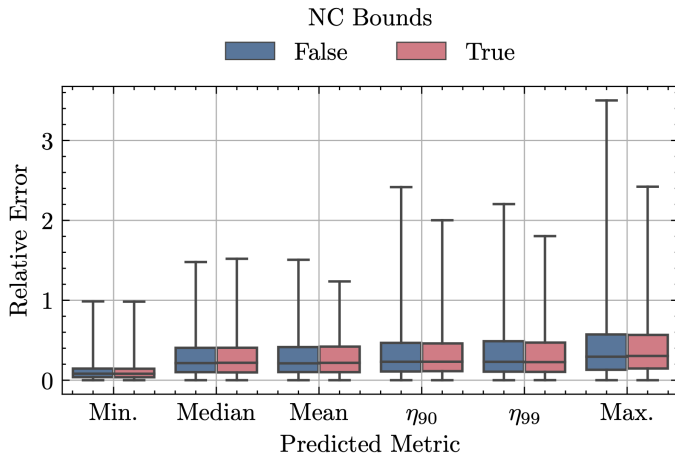


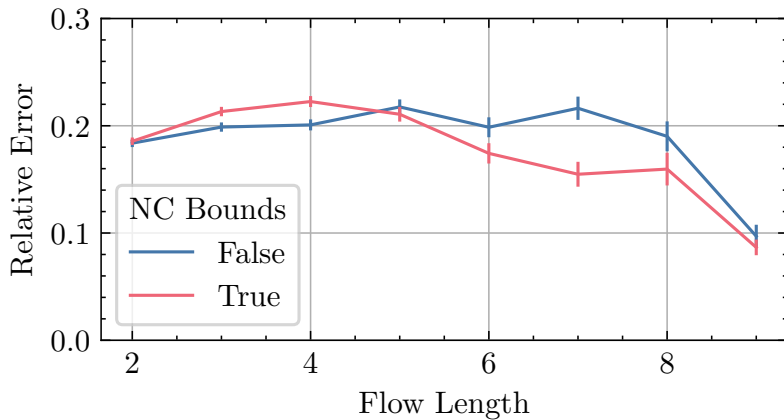
(b) Network II



(c) Network III

Measurements on 100 random, non-isomorph network topologies





Prediction Evaluation

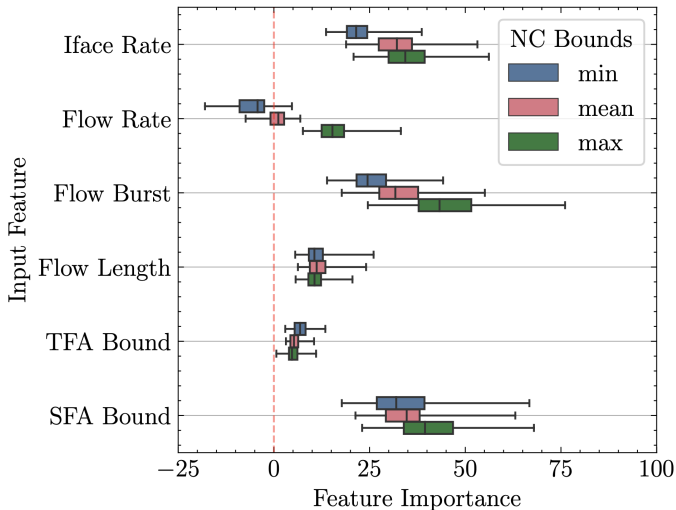
Importance of Network Calculus Results

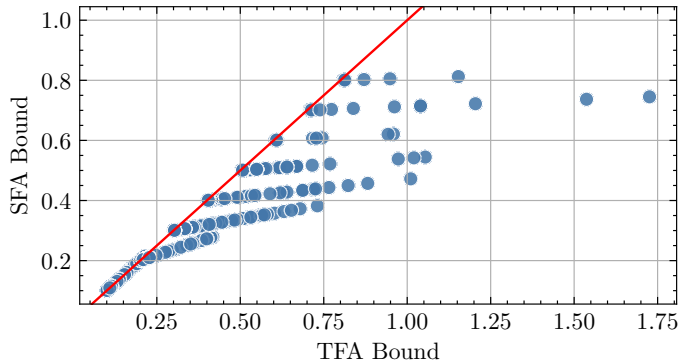
Network Calculus analysis methods:

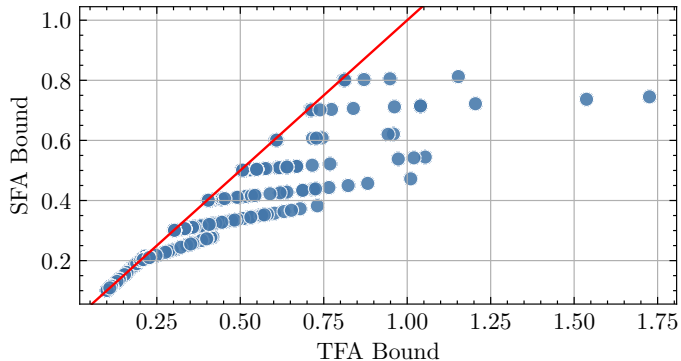
- Total Flow Analysis (**TFA**): Bounds on flow aggregates on per-hop basis
- Separate Flow Analysis (**SFA**): Bounds per flow using left-over service curves and service curve convolutions

Network Calculus analysis methods:

- Total Flow Analysis (**TFA**): Bounds on flow aggregates on per-hop basis
- Separate Flow Analysis (**SFA**): Bounds per flow using left-over service curves and service curve convolutions







- SFA bounds always as tight or tighter than TFA bounds
- TFA provides worse upper bounds

Data:

- Simple GNN for quantile point predictions
- Based on hardware measured latencies
- 100 different network topologies
- **Limitations:** queueing, network size, sample size

Paper:



Results:

- Network Calculus bounds reduce large prediction errors
- Network Calculus more useful for higher quantiles
- GNN is able to include bound tightness into decision making
- **Limitations:** GNN architecture, Network Calculus analysis methods

Data and Code:



Questions?: helm@net.in.tum.de