

Routing Optimization of QKD-Networks using Machine-Learning Based Prediction

Tim Johann¹, Daniel Giemsa², Sebastian Kühl¹, Annika Dochhan¹ and
Stephan Pachnicke¹

¹Lehrstuhl für Nachrichtenübertragungstechnik, Christian-Albrechts-Universität zu Kiel

²Deutsche Telekom Technik GmbH

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ML



1. Motivation
2. Meshed QKD-networks
3. ML-based prediction
4. Results
5. Conclusion



- Progress in quantum computing challenges the conventional cryptography

Why QKD?

- Information-theoretical security

Challenges:

- No quantum repeaters available → limited reach
 - How to realize meshed long-haul networks?
 - How to control the network/which information should be shared?
 - Limited keyrates
-
- Based on which rules should the routing take place?

➤ How to realize a QKD network in a German topology?

- Nobel-Germany topology
 - Extended with trusted nodes

Trusted Nodes (green):

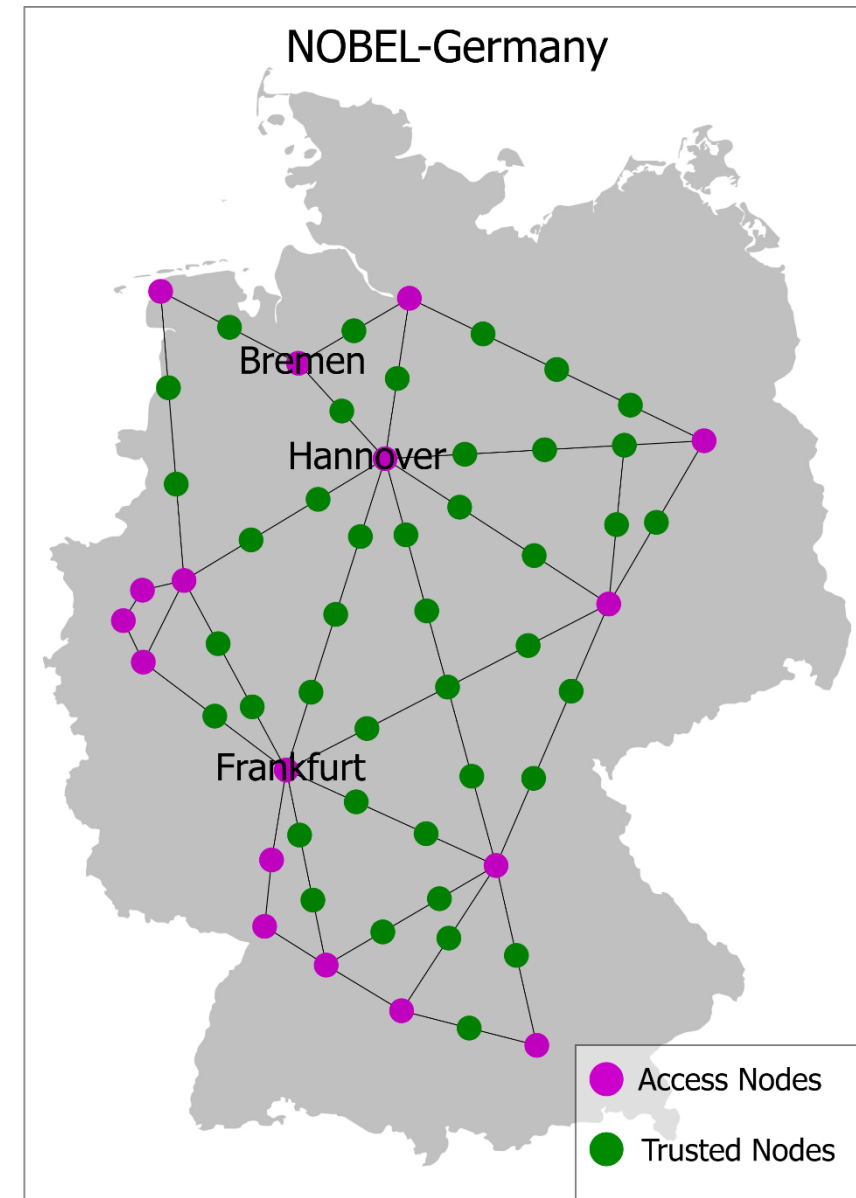
- Necessary due to reach limitations of QKD-devices
- Must be secured properly
- Placed equidistantly on the links

Secret Keys:

- Limited keyrate
 - Precious resource
- One key to encrypt one GByte of data

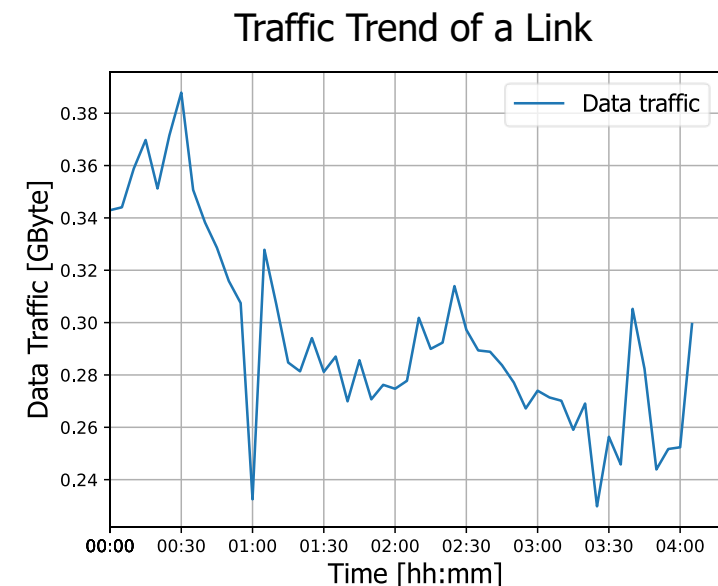
Keystores:

- One substore per link



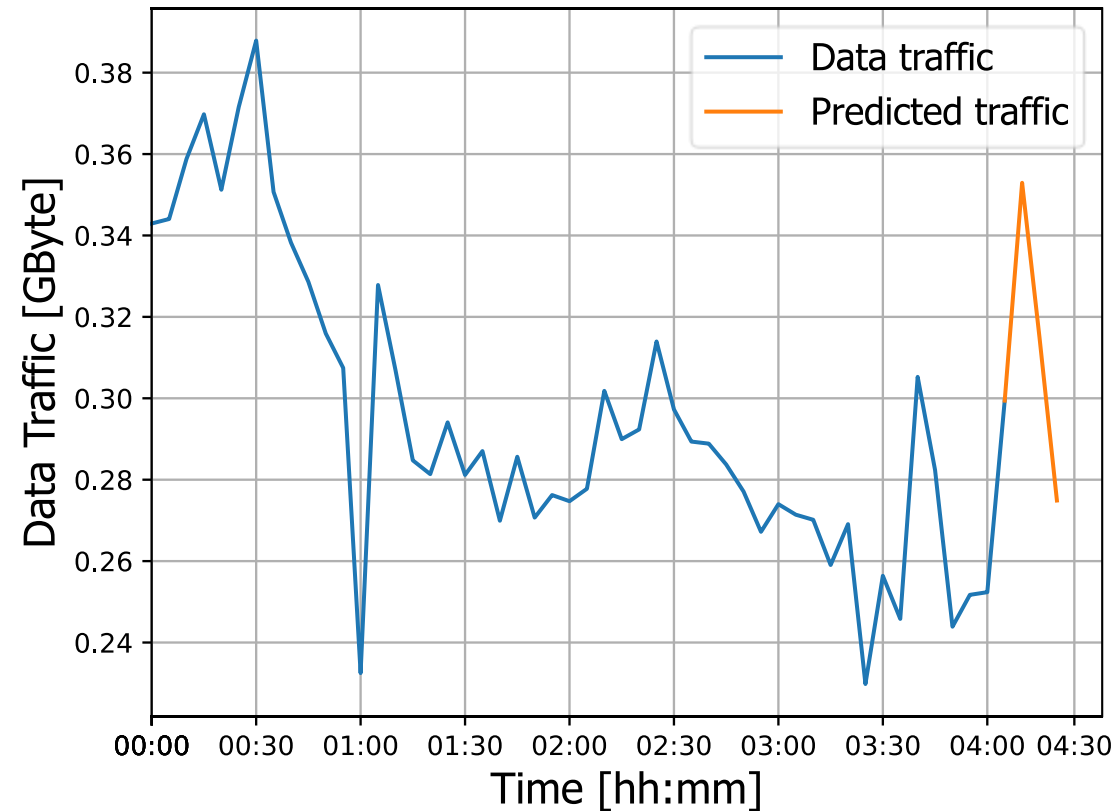
Challenges:

- Avoid keystores running empty
- What are the possibilities to route using limited information only?
 - Simple hop-count based algorithm (Dijkstra)
 - Include prediction of future key demands
- Past demand matrices can be used to predict the future data traffic
 - Information can be used to optimize weight of network edges
 - Machine Learning is used for prediction

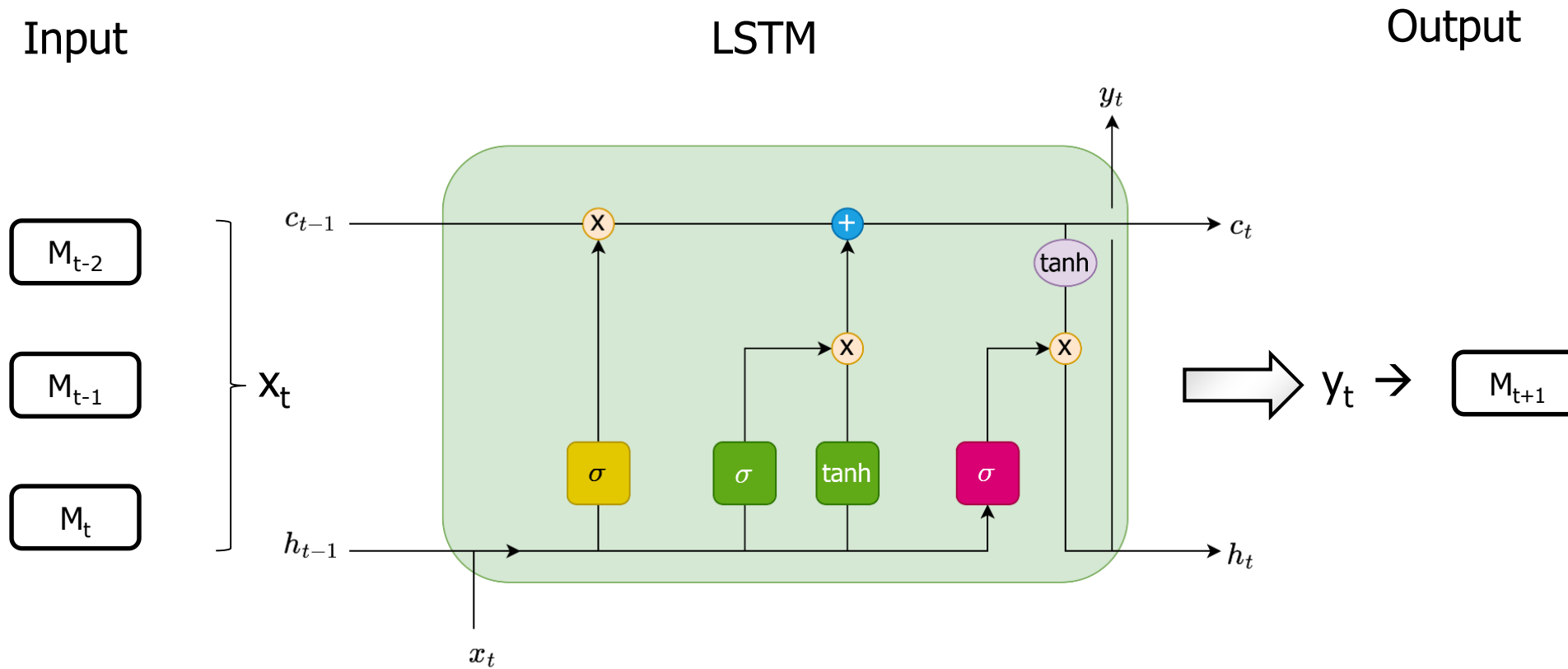


- Using prediction to proactively adapt edge weights
 - Execute Dijkstra based on these weights
 - ➔ Leads to more balanced usage of network and avoids keystores to run empty

Traffic Trend of a Link



- Dynamic traffic data: 24 hours → 5 minute intervals → 288 demand matrices → 73,512 demands
- Routing optimization based on (hypothetical) perfect prediction of demand matrices
- LSTM prediction of demand matrices based optimized routing algorithm
- One request per second
- Constant key generation
- Filled keystores (100,000 keys for each link)



- Three historic matrices as input
- One-step ahead prediction

Legend:

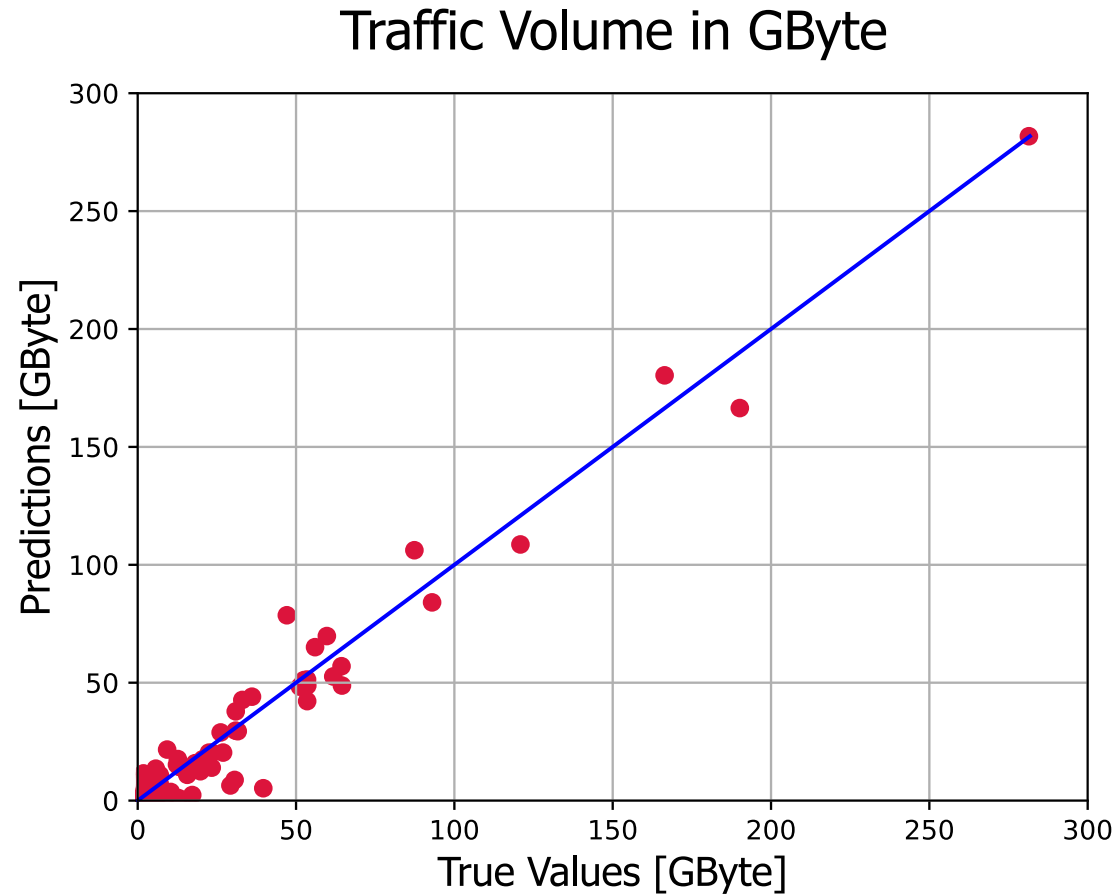
X_t = input

C_{t-1} = cell state

h_{t-1} = hidden state

Deviation between predictions and true values:

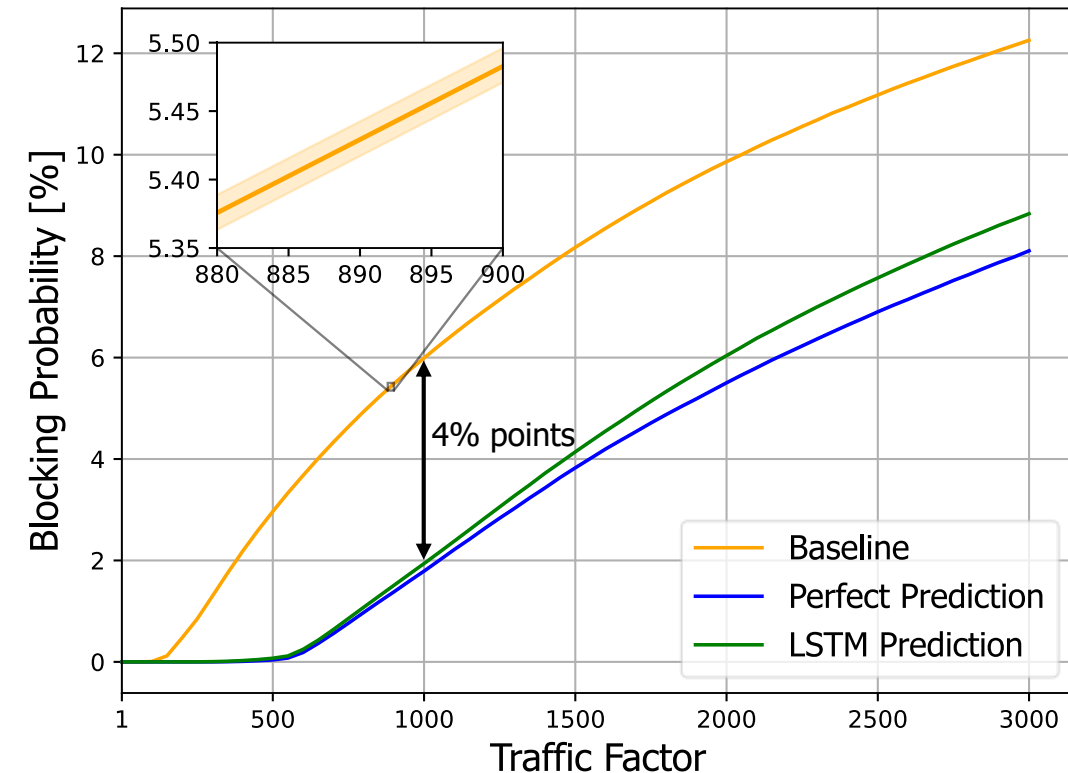
- Traffic matrices dominated by low volume demands



- Increasing traffic factor for scaling of demands

Main goal: Reduction of blocking probability

- Significantly better performance of prediction-based algorithms (up to 4 percentage points)
- Higher traffic load factor → higher deviation between LSTM and perfect prediction



Investigation of Keystore Filling Level

➤ Exemplary visualization of the keystore filling level for a traffic factor of 1000

Baseline:

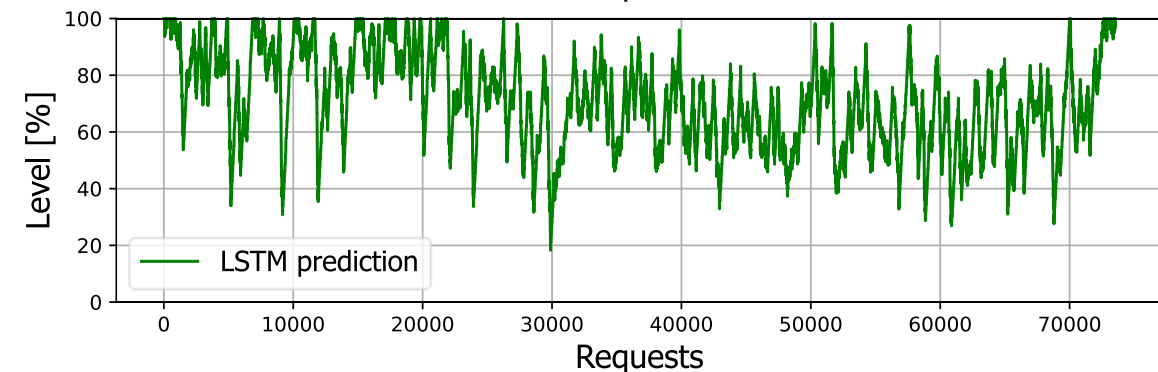
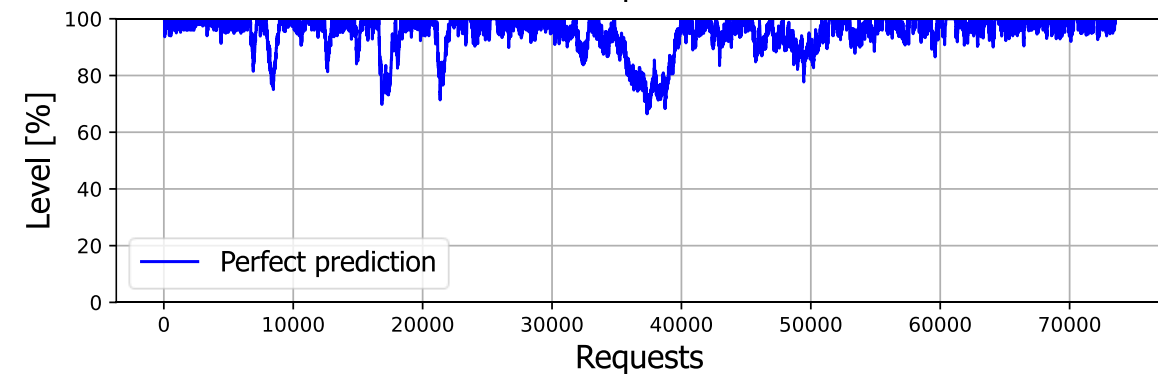
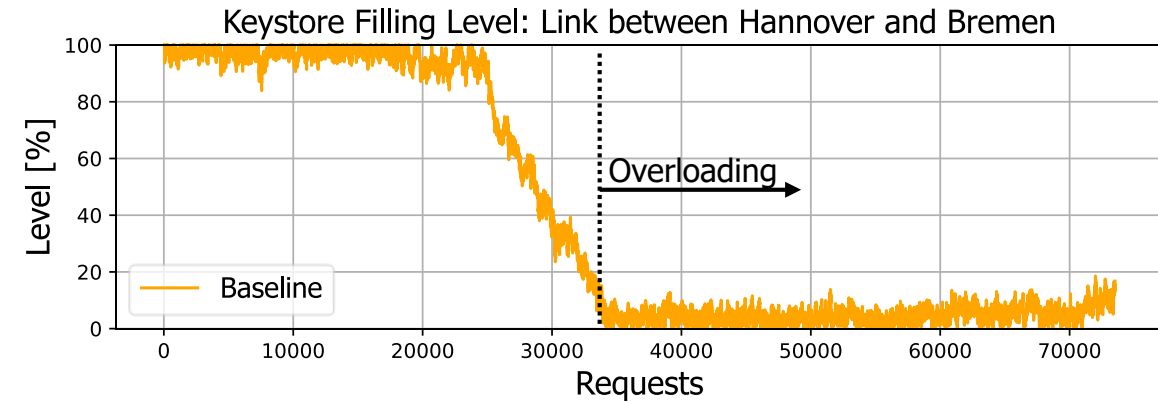
- Abrupt transition between „full“-state and a nearly empty keystore

(hypothetical) Perfect prediction:

- Keeps high level of remaining keys

LSTM prediction:

- Higher fluctuation
- No overloading

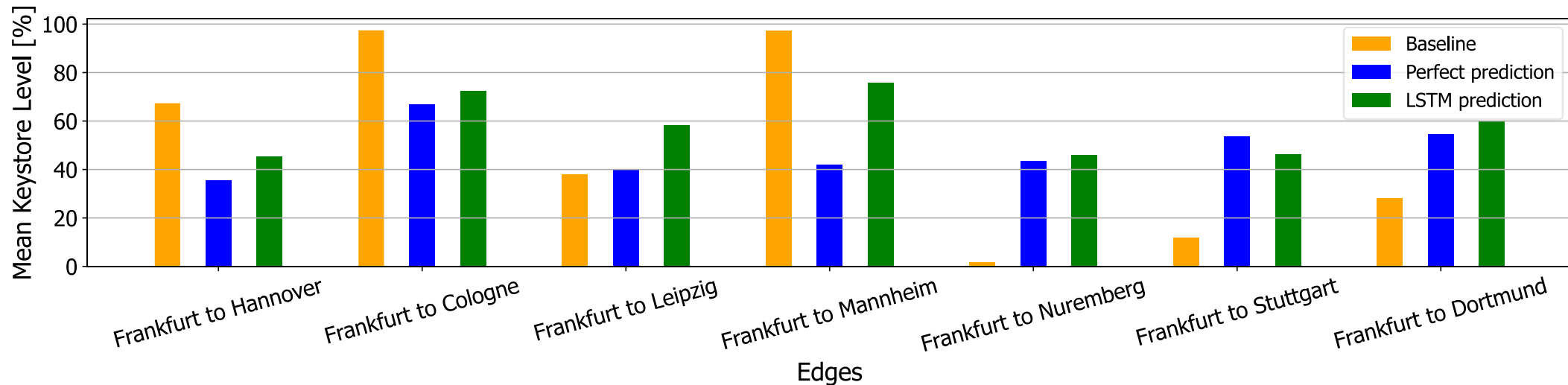
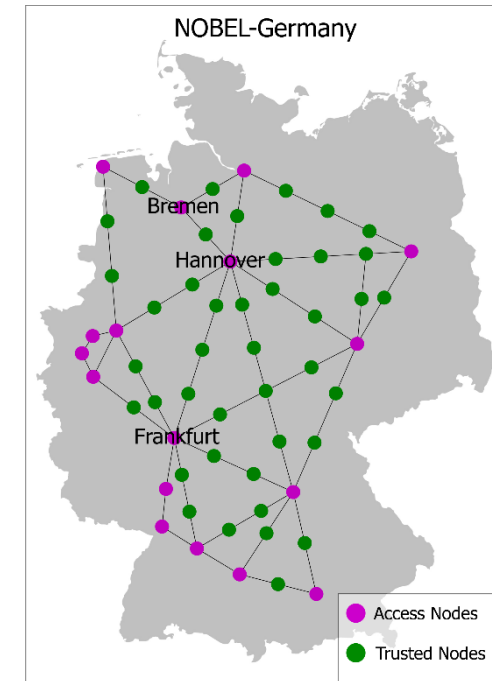


Investigation of Mean Keystore Level

➤ Frankfurt is one of the most heavily used nodes in the network

Results for a traffic factor of 1000:

- LSTM prediction enables more evenly distributed utilization
- Higher variance for the Baseline due hop-based approach
- (hypothetical) Perfect prediction performs similar to LSTM prediction



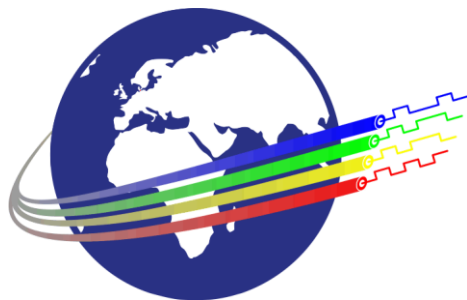
- Keystores running empty can be avoided by traffic prediction
- LSTM prediction performs better than hop-based routing
 - Blocking probability is reduced by up to 4 percentage points
 - Traffic load is distributed more evenly
- No sensitive information required

tim.johann@tf.uni-kiel.de

Acknowledgements:



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Thank you!

