

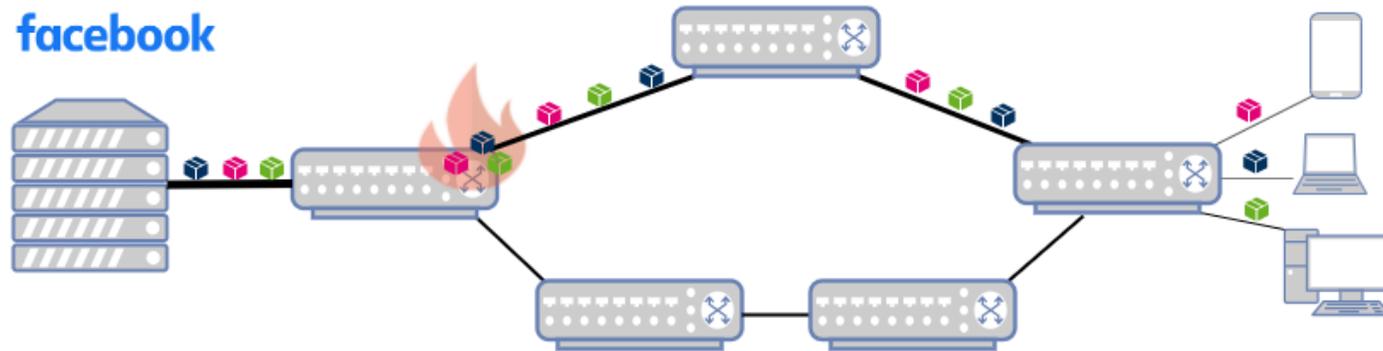
Peter Sossalla

Investigation of Reinforcement Learning Strategies for Routing in Software-Defined Networks

Diploma Thesis

7.11.2019

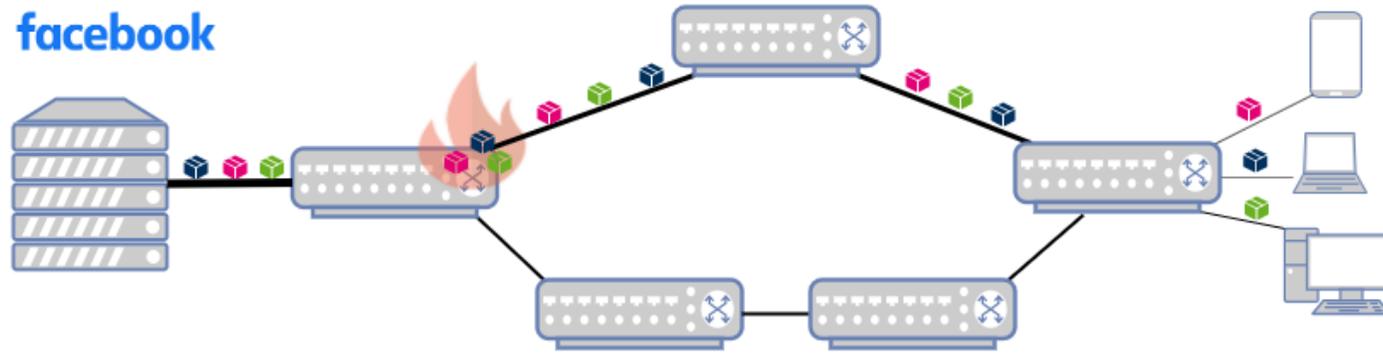
Motivation



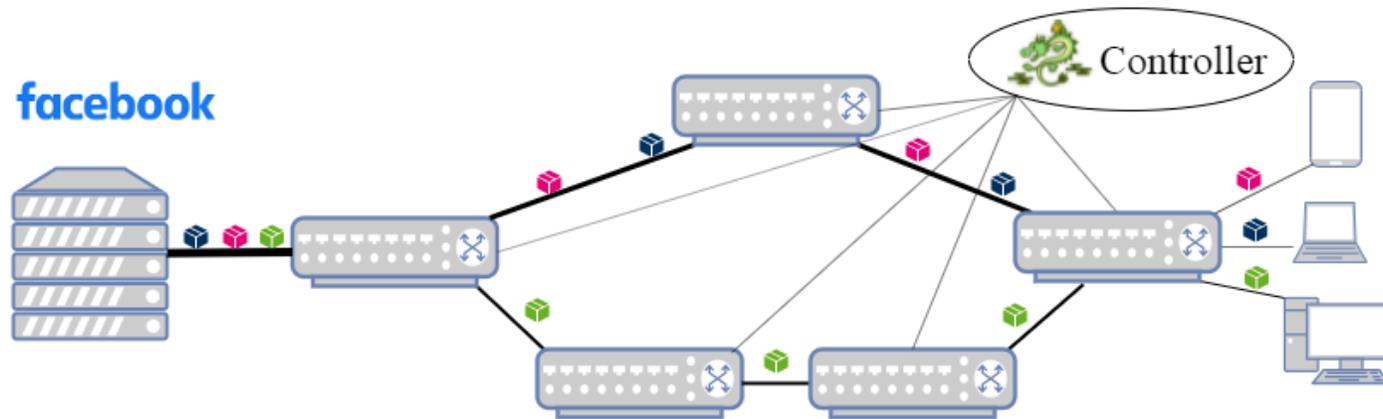
- Problem: rising and varying traffic demand
- Objective: deliver traffic with the best possible performance
- SPF does not consider demand, other paths or the influence of its routing decisions
- Overprovisioning → higher costs
- Enterprises such as Facebook use Software-Defined Networking (SDN)

Motivation

facebook



facebook



Reinforcement Learning

Agent interacts with the environment

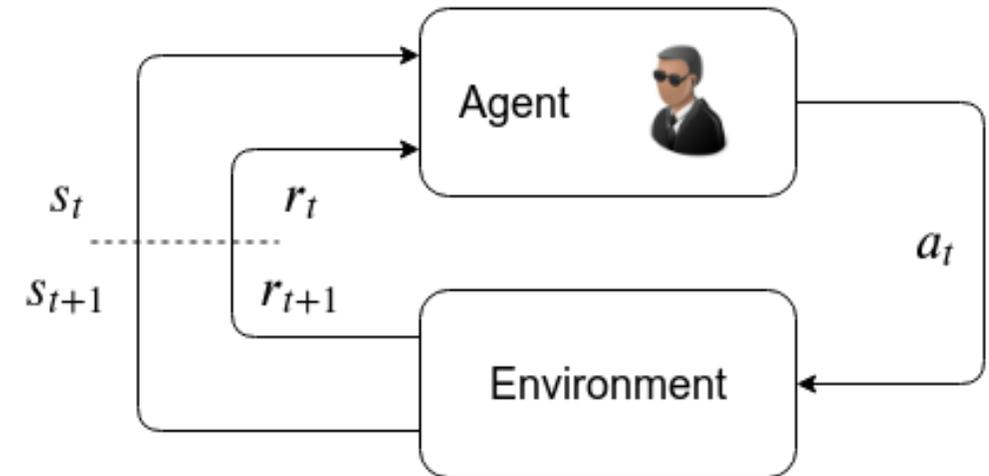
State s , Action a , Reward r

Q-value $Q(s, a)$ – Quality of action a in state s

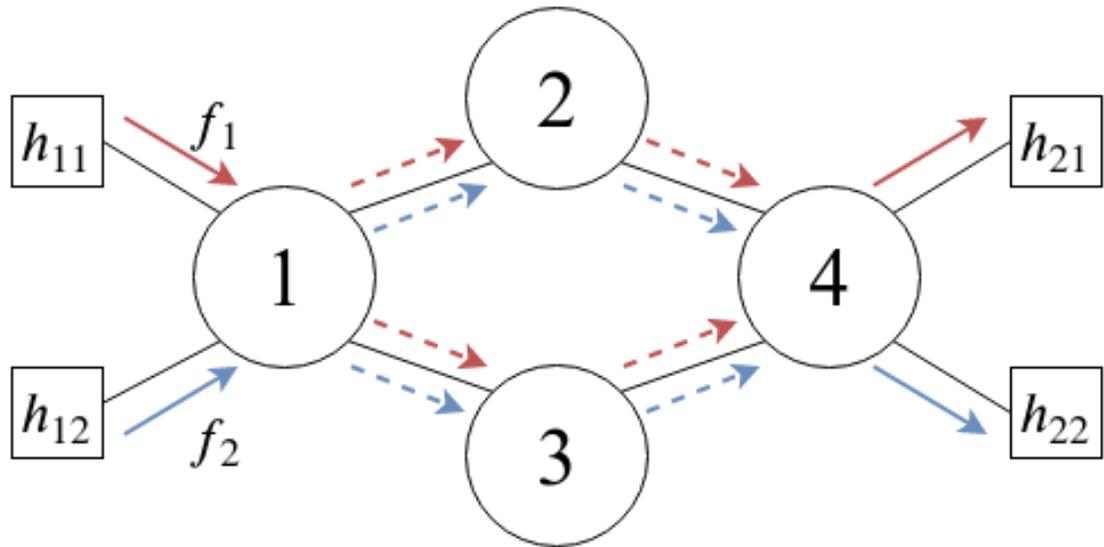
Q-learning for determining $Q(s, a)$

Q-table:

$Q(s, a)$	a_1	a_2
s_1	$Q(s_1, a_1)$	$Q(s_1, a_2)$
s_2	$Q(s_2, a_1)$	$Q(s_2, a_2)$



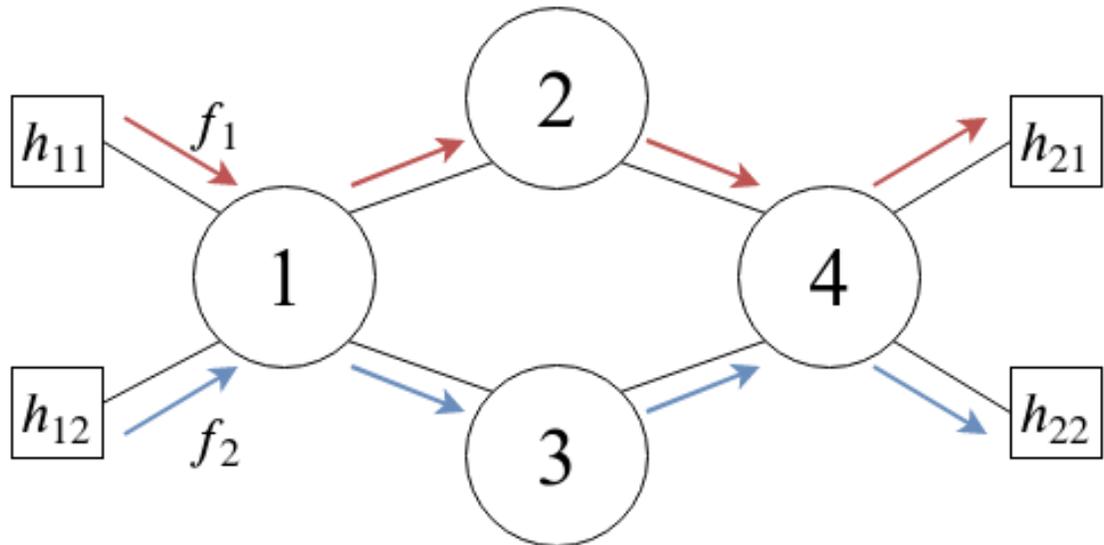
Implementation - States



Flow: [Path]

$f_1: [1,2,4]$ $f_2: [1,2,4]$	$f_1: [1,3,4]$ $f_2: [1,2,4]$
$f_1: [1,2,4]$ $f_2: [1,3,4]$	$f_1: [1,3,4]$ $f_2: [1,3,4]$

Implementation - Actions

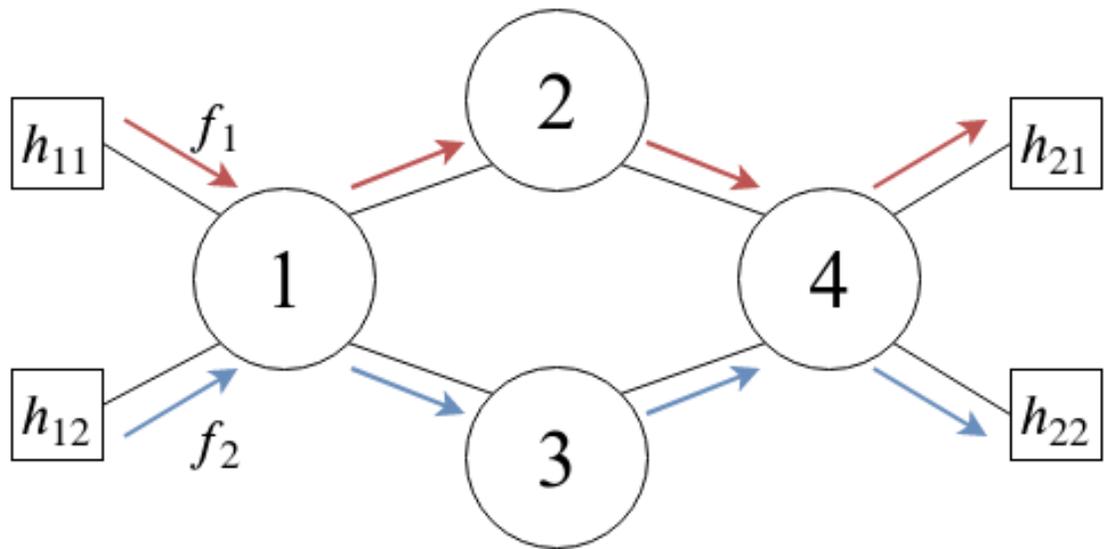


Flow: [Path]

$f_1: [1,2,4]$ $f_2: [1,2,4]$	$f_1: [1,3,4]$ $f_2: [1,2,4]$
$f_1: [1,2,4]$ $f_2: [1,3,4]$	$f_1: [1,3,4]$ $f_2: [1,3,4]$

A blue arrow points from the bottom-left cell to the top-left cell. A red oval highlights the bottom-left cell, with a blue arrow pointing from it to the bottom-right cell.

Implementation - Actions

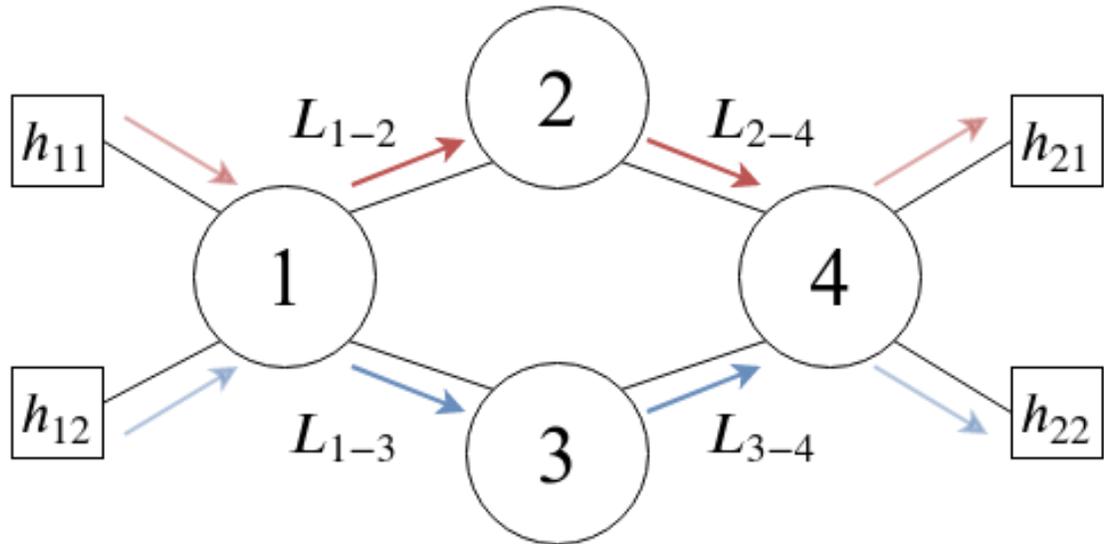


Flow: [Path]

$f_1: [1,2,4]$ $f_2: [1,2,4]$	$f_1: [1,3,4]$ $f_2: [1,2,4]$
$f_1: [1,2,4]$ $f_2: [1,3,4]$	$f_1: [1,3,4]$ $f_2: [1,3,4]$

Additionally "No Transition" action

Implementation - Reward



Latencies determined by measurements:

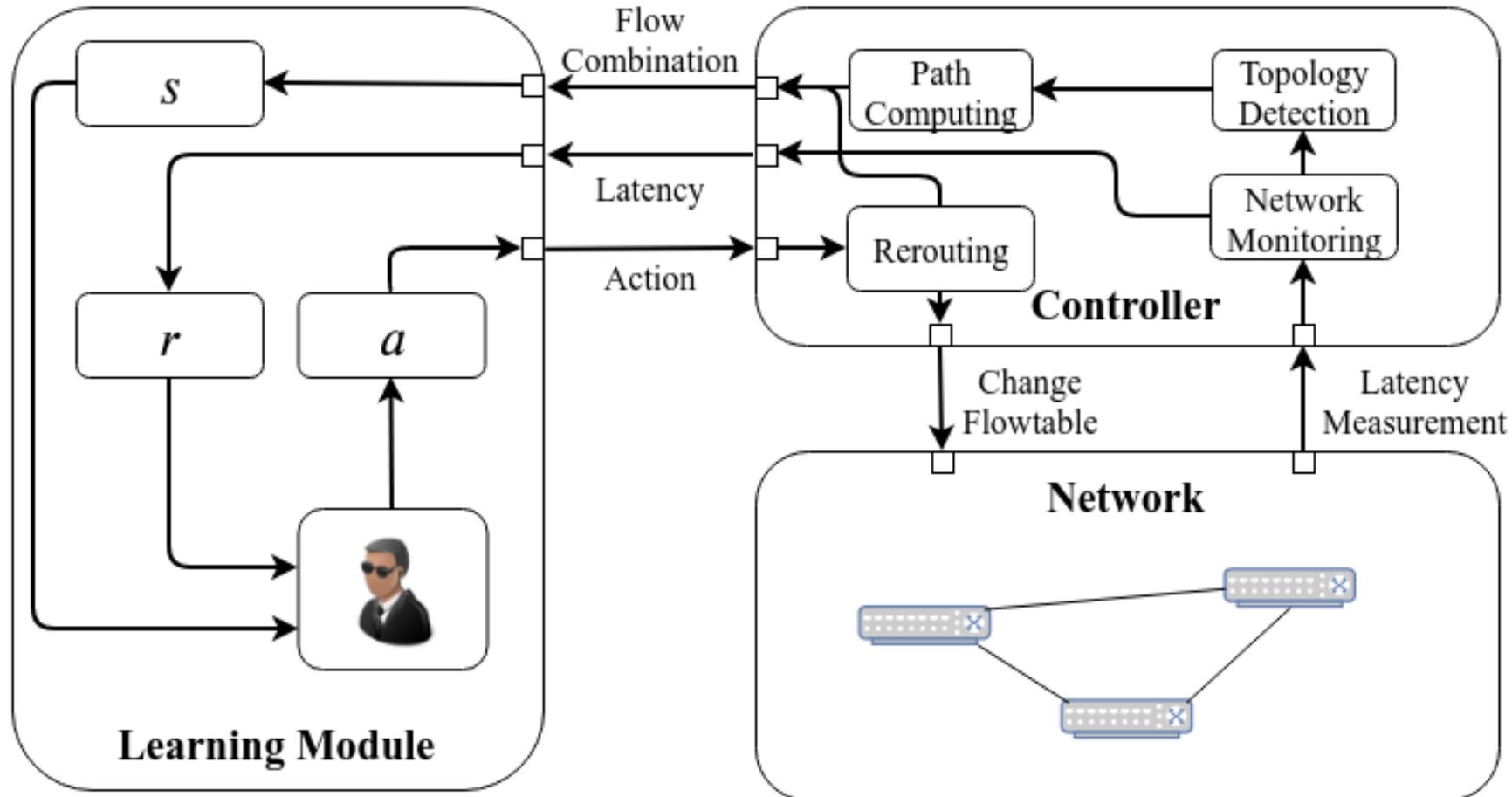
$$L(f_1) = L_{1-2} + L_{2-4}$$

$$L(f_2) = L_{1-3} + L_{3-4}$$

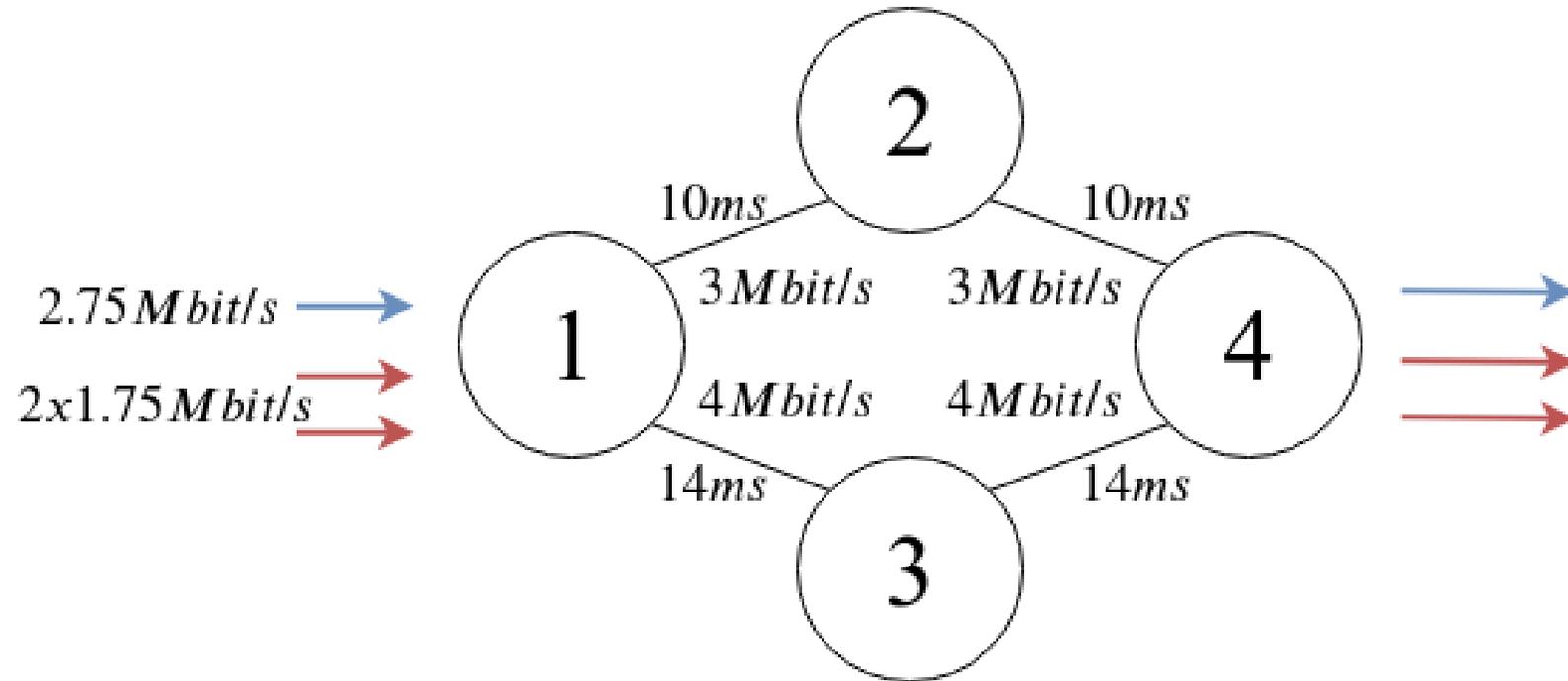
Reward: Root mean square of latencies

$$r = -\sqrt{\frac{L(f_1)^2 + L(f_2)^2}{2}}$$

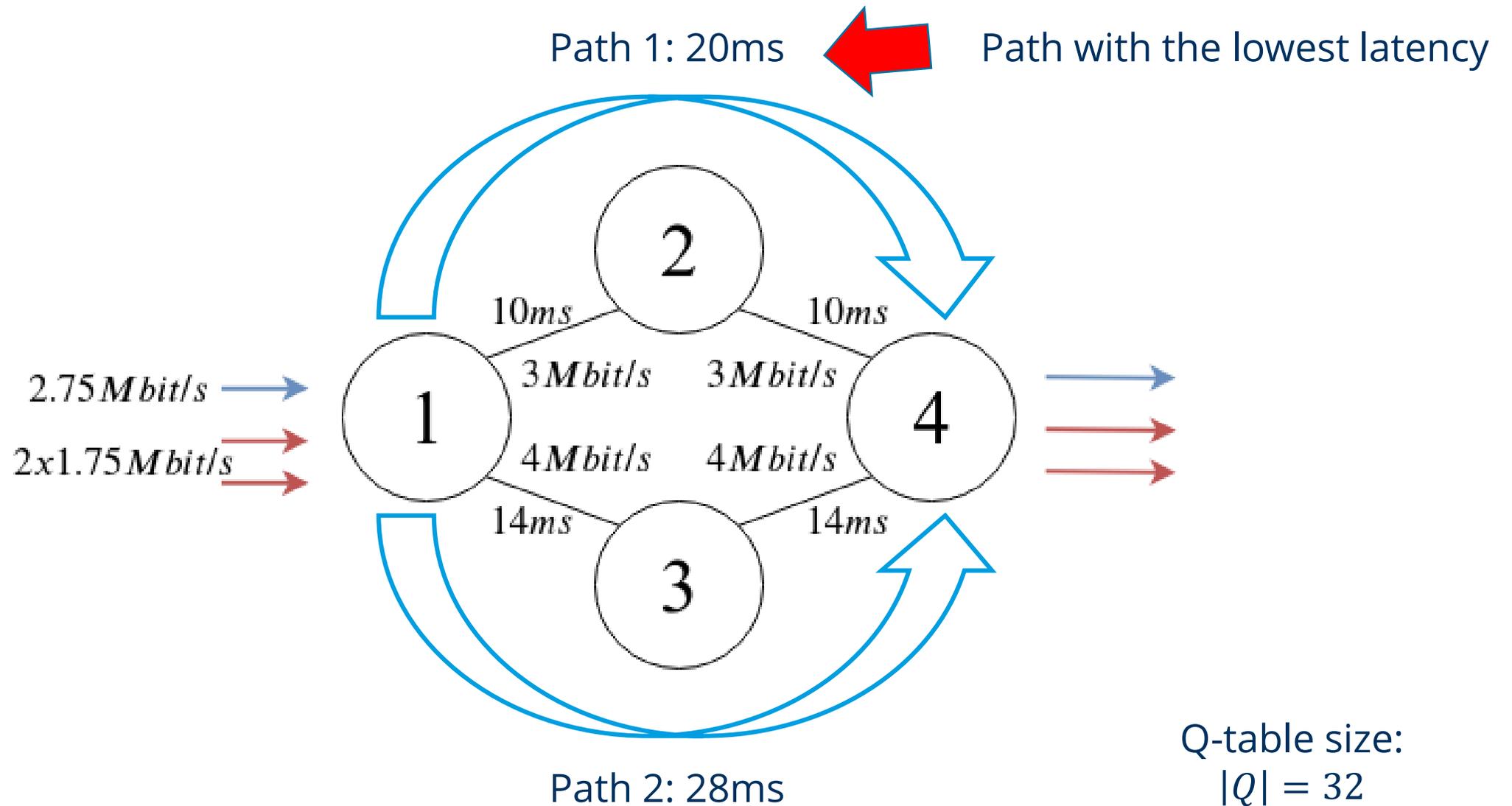
Implementation - System



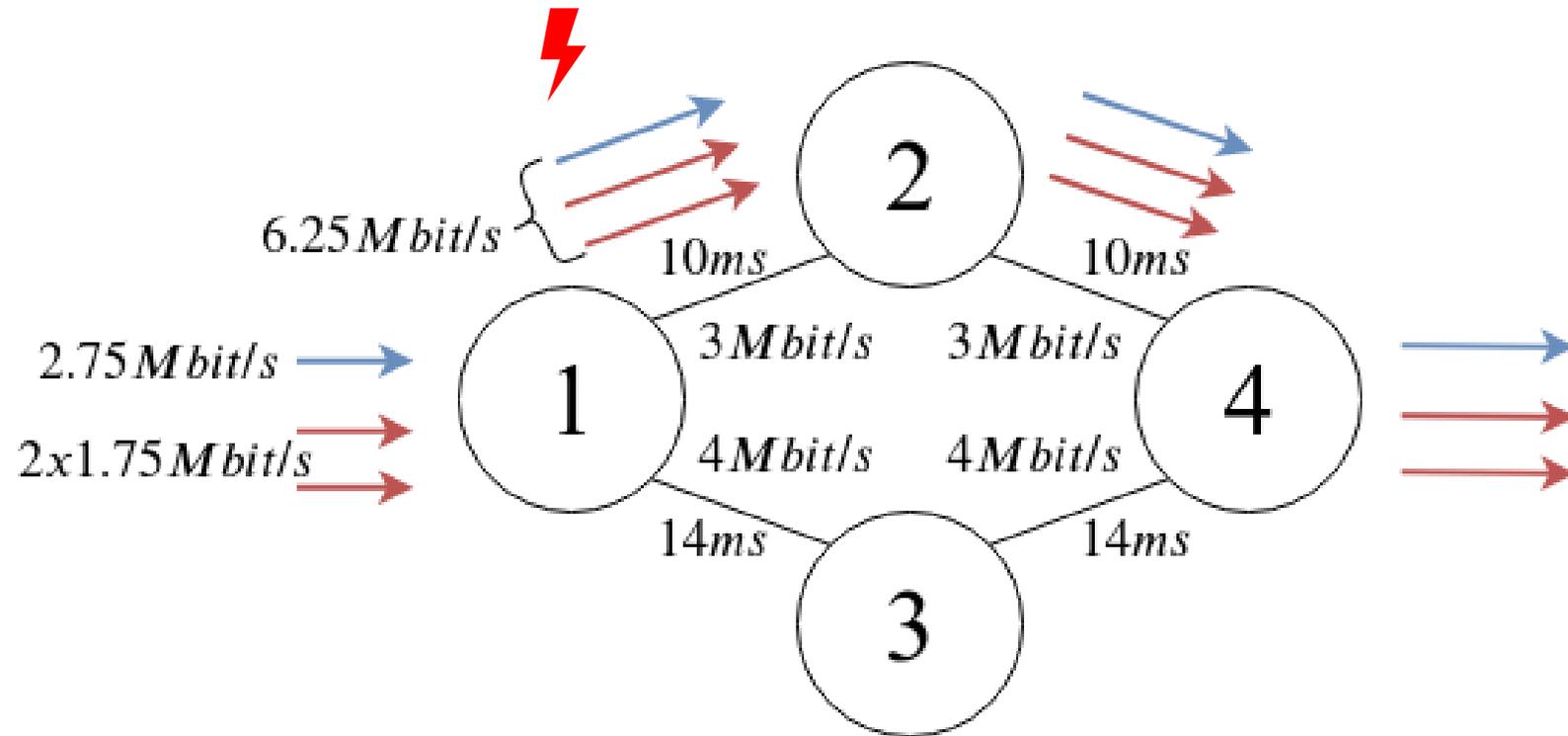
Evaluation - Topology



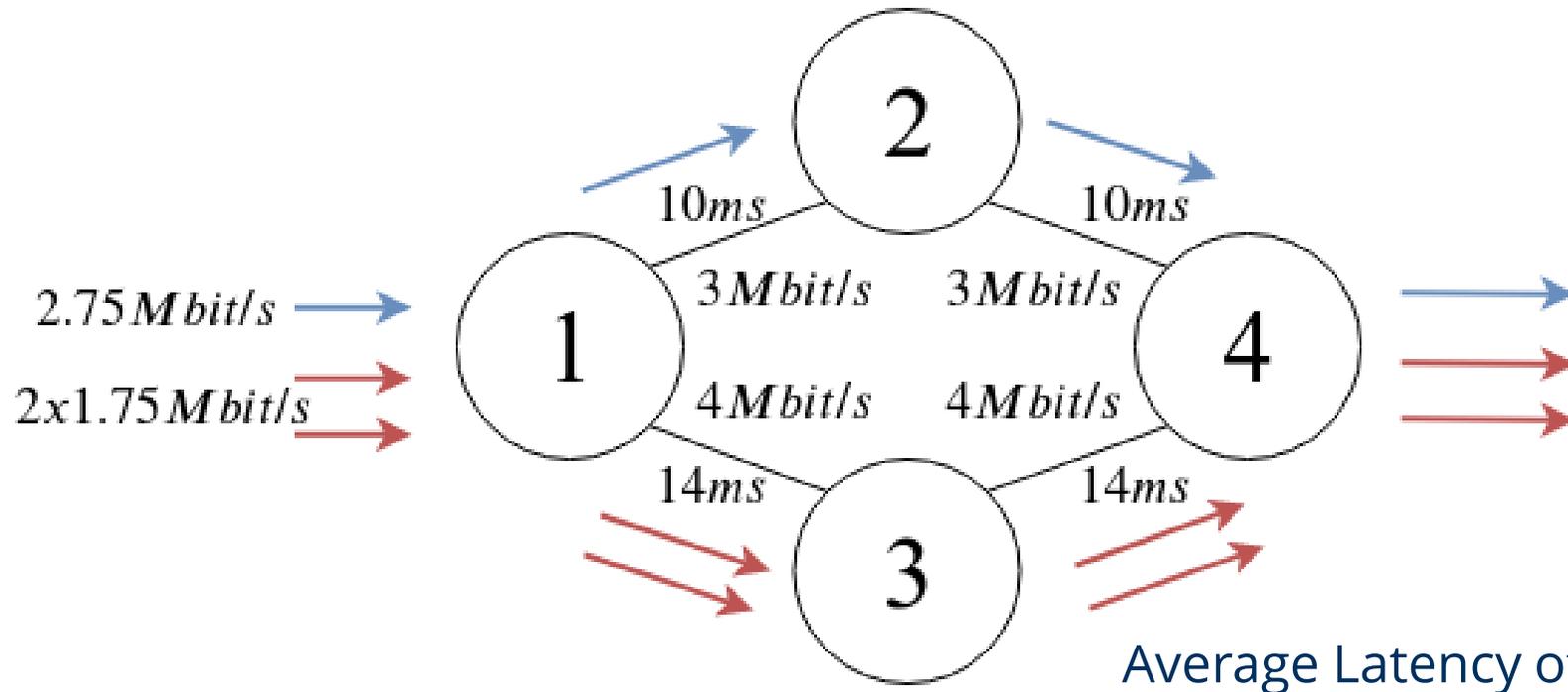
Evaluation - Topology



Evaluation – Topology (SPF)



Evaluation – Topology (Optimal)

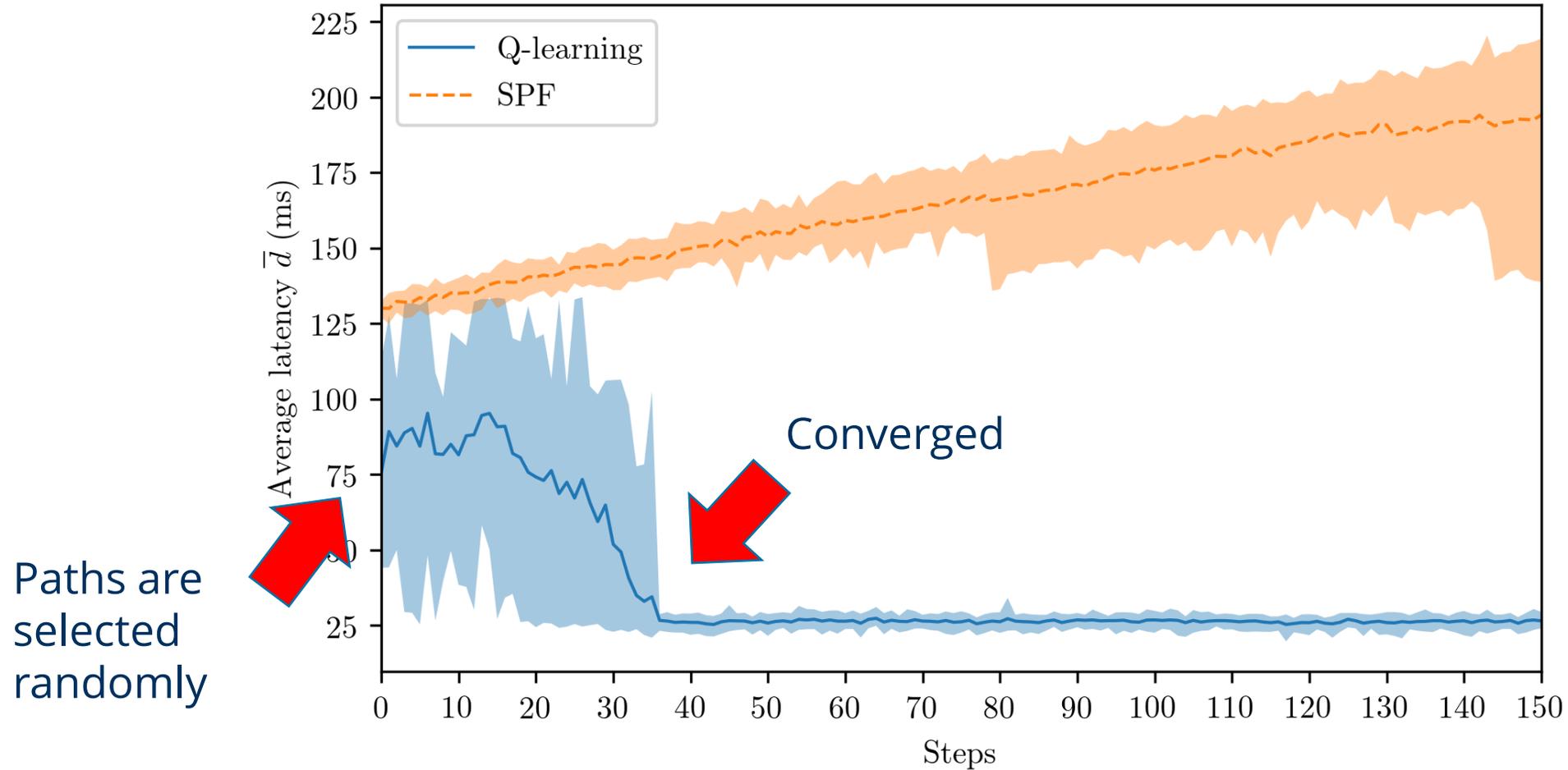


Average Latency of the flows:

$$\bar{d} = \frac{20 \text{ ms} + 2 \cdot 28 \text{ ms}}{3} = 25.3 \text{ ms}$$

Evaluation - Learning

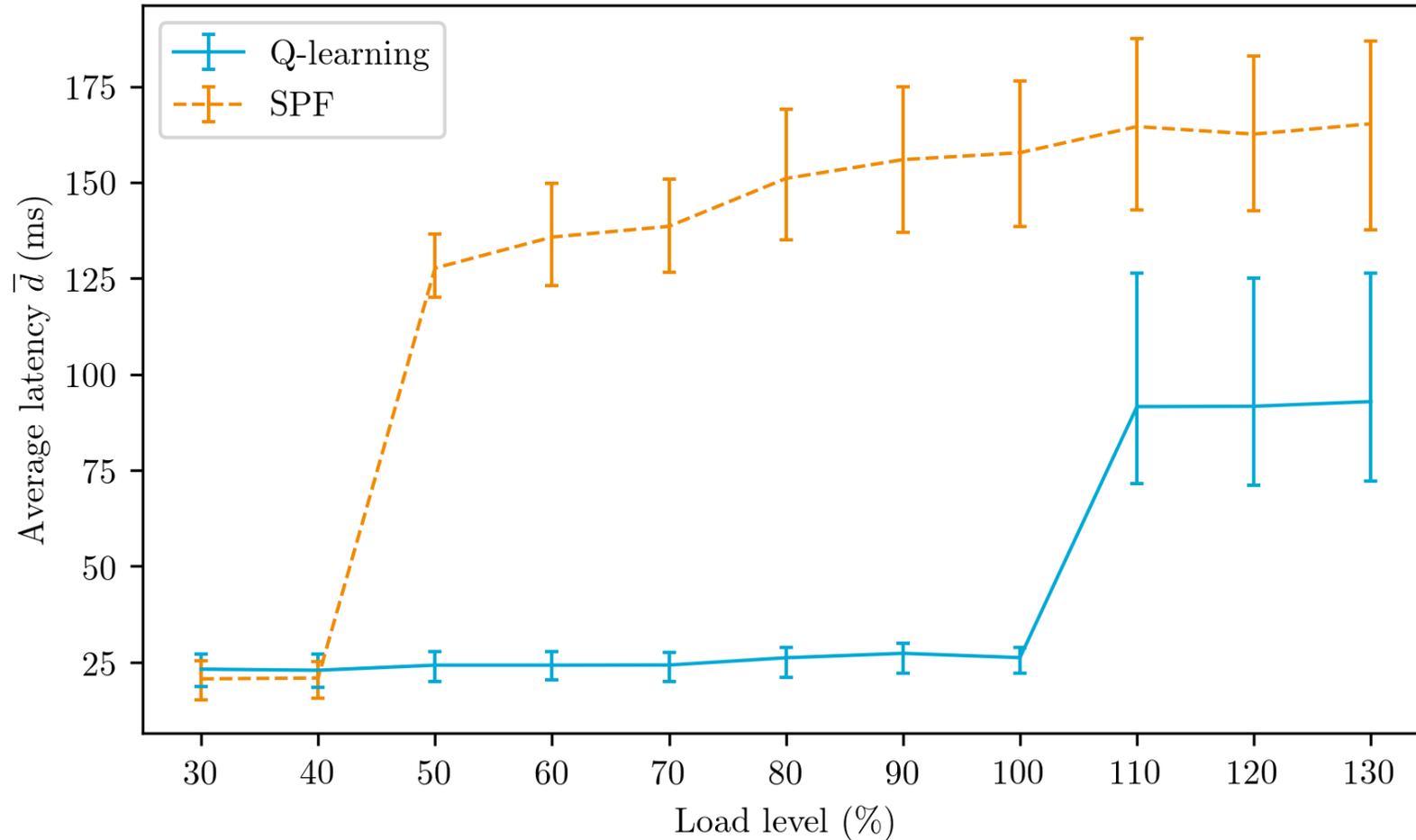
Average latency \bar{d} over steps



Evaluation - Load Level

How does the system perform for different loads?

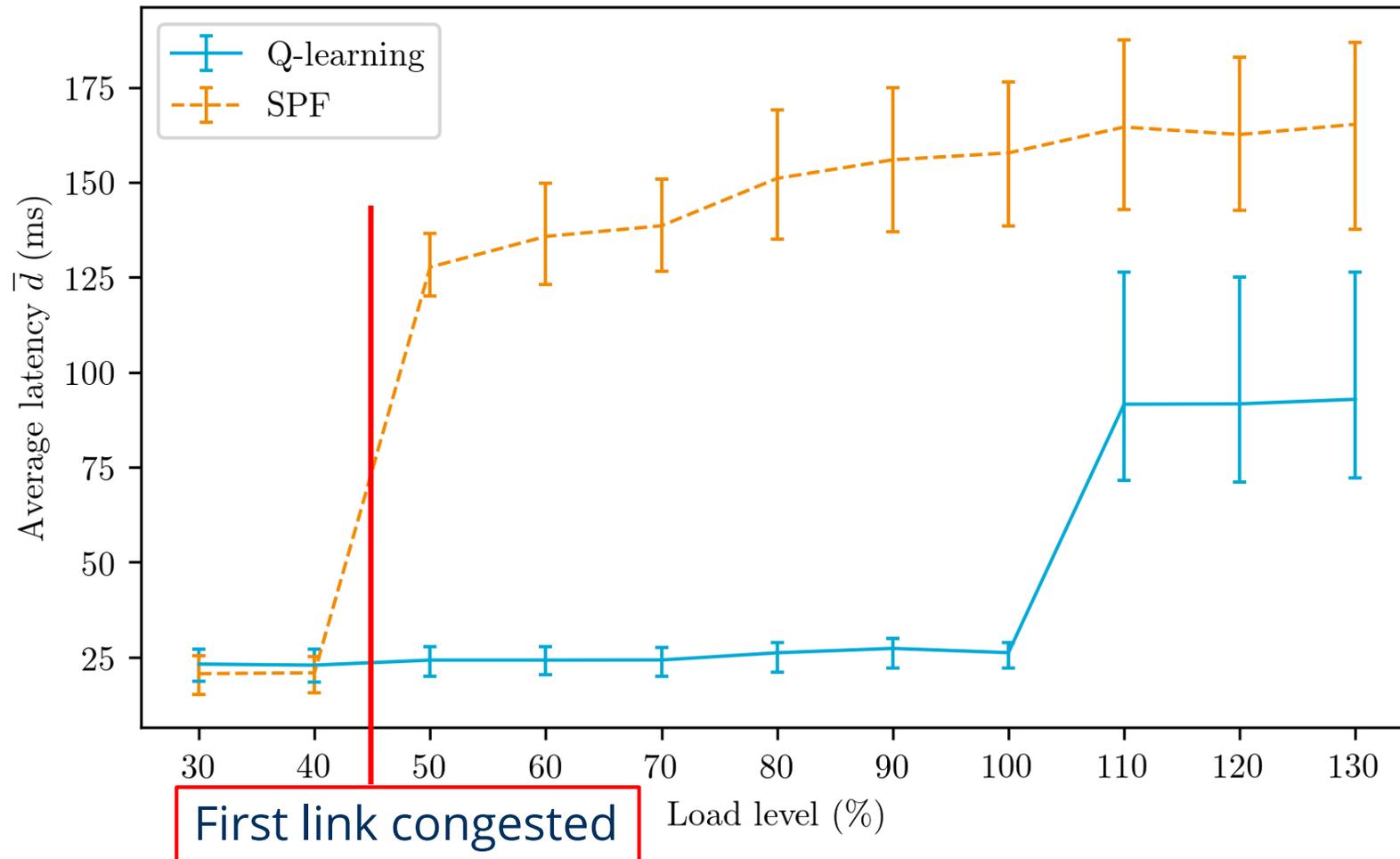
Average latency \bar{d} over load levels



Evaluation - Load Level

How does the system perform for different loads?

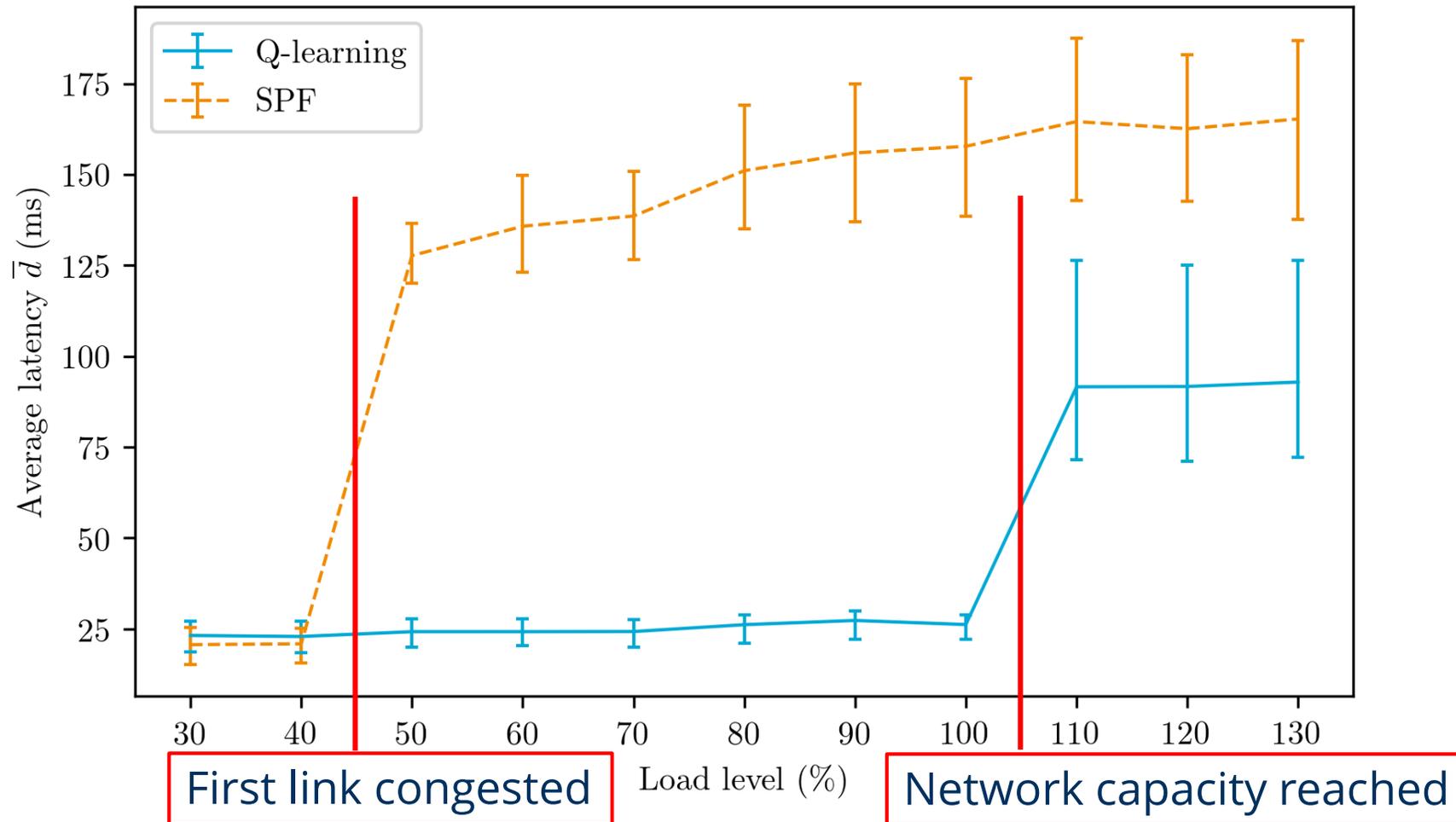
Average latency \bar{d} over load levels



Evaluation - Load Level

How does the system perform for different loads?

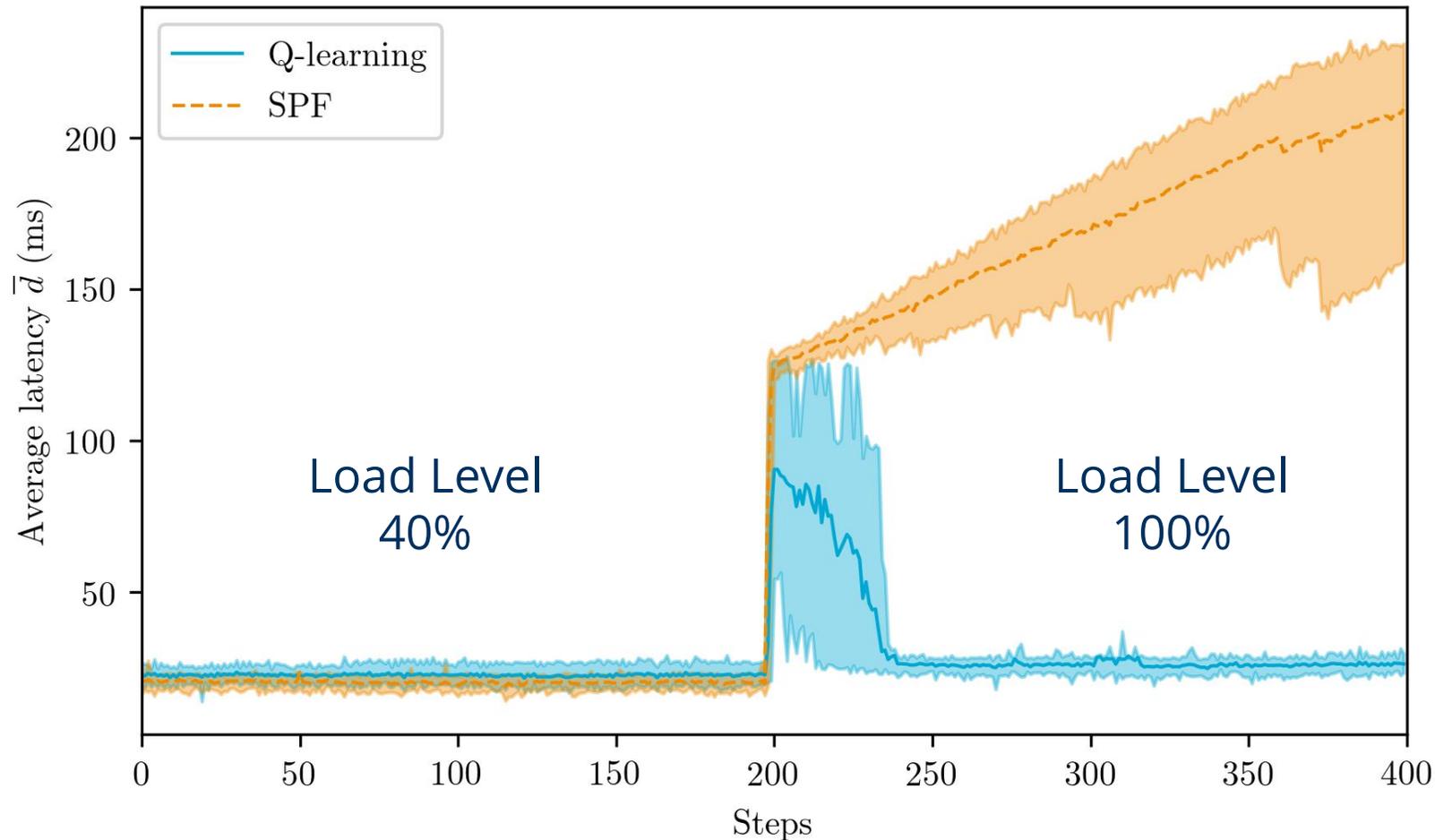
Average latency \bar{d} over load levels



Evaluation – Load Change

Average latency \bar{d} over steps for load change

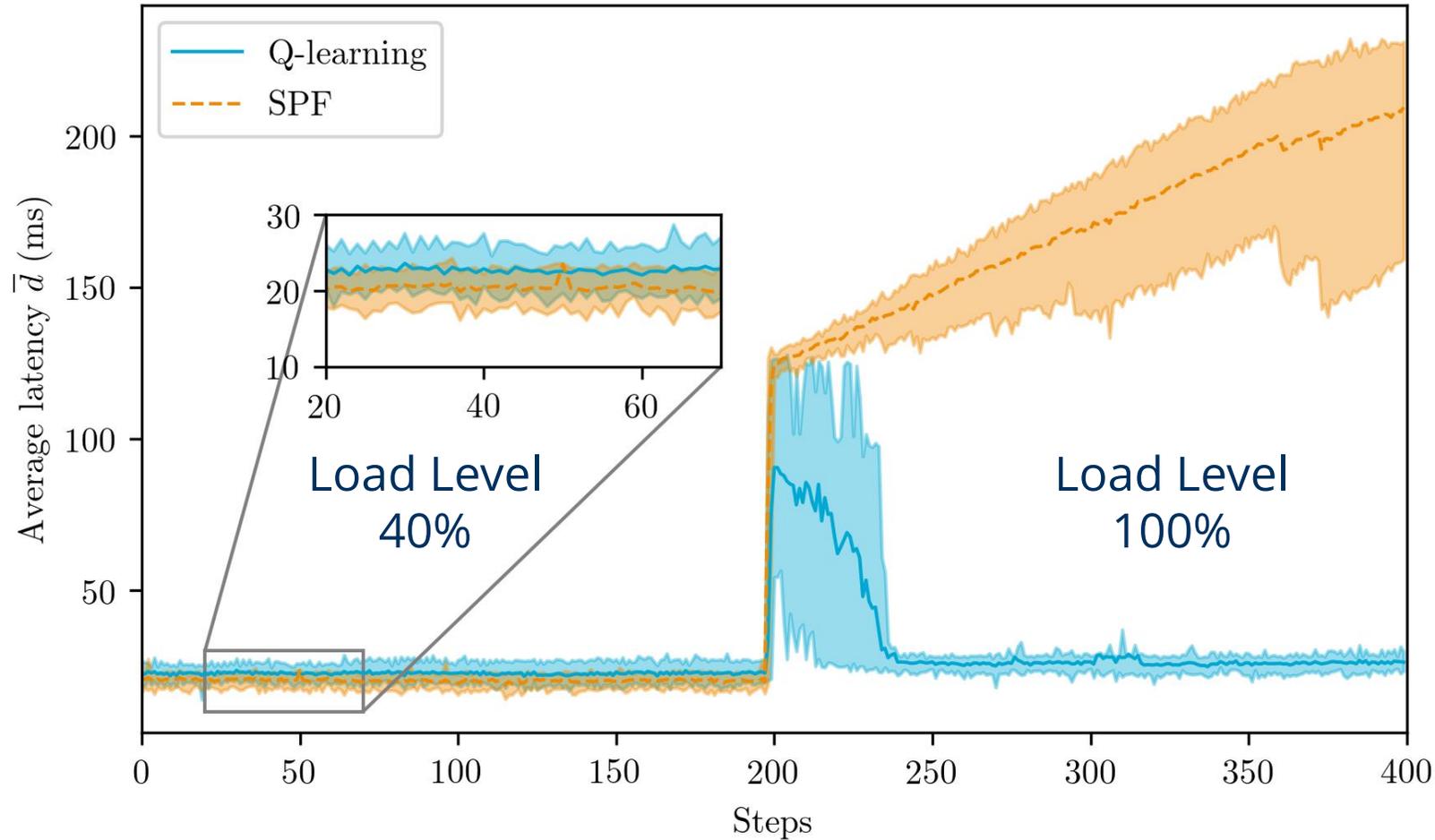
How does the system perform in a dynamic load change?



Appendix - Load Change

Average latency \bar{d} over steps for load change

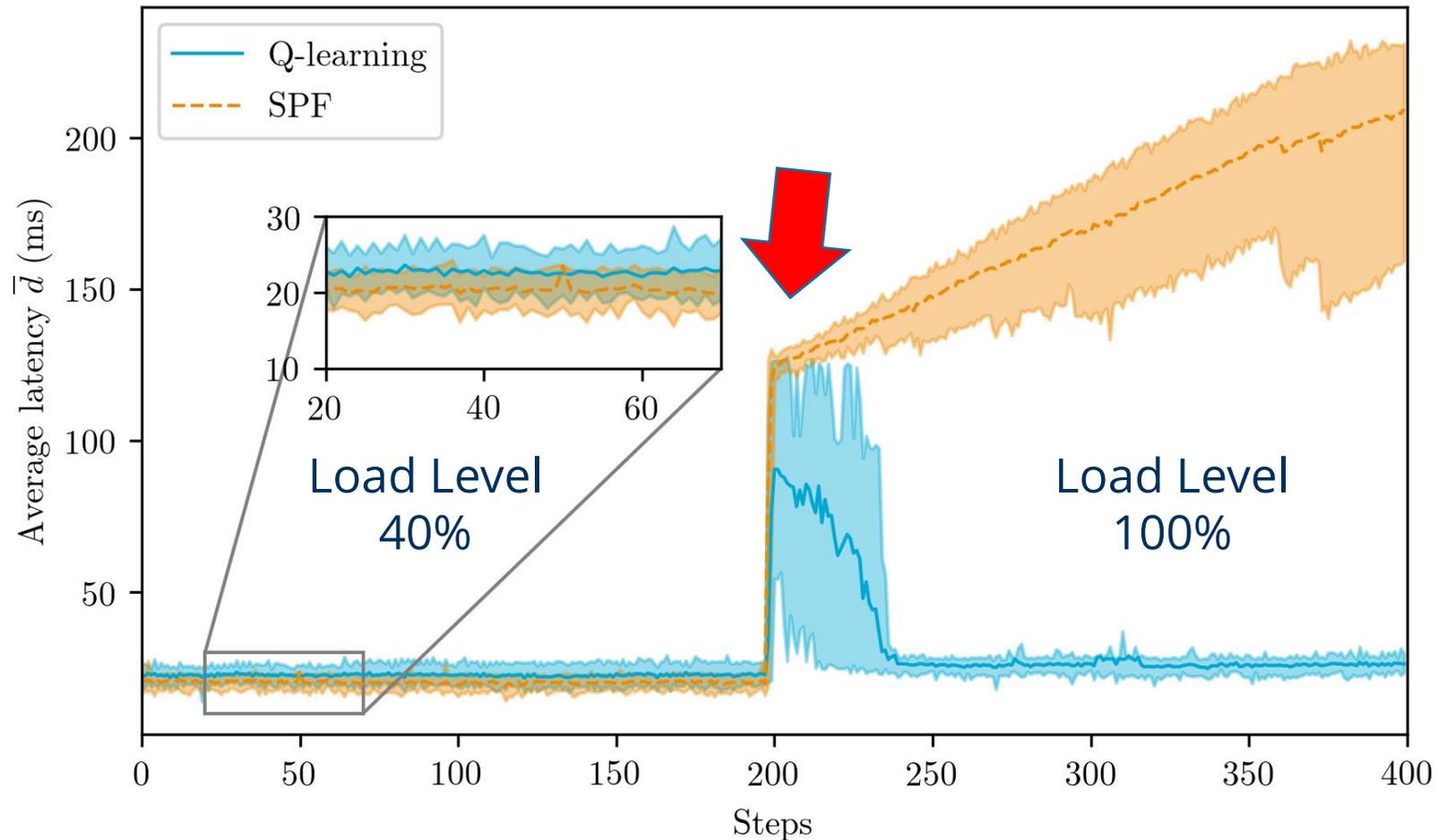
How does the system perform in a dynamic load change?



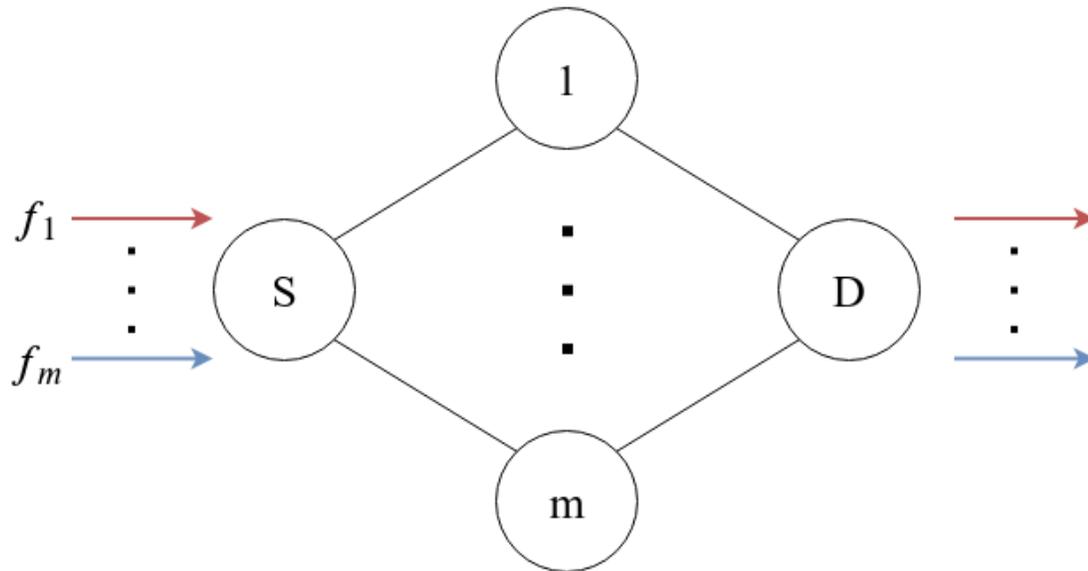
Appendix - Load Change

Average latency \bar{d} over steps for load change

How does the system perform in a dynamic load change?



Evaluation – Scalability



Scalability level m - Number of flows and intermediate switches

Equal path latencies

Single uncongested routing state

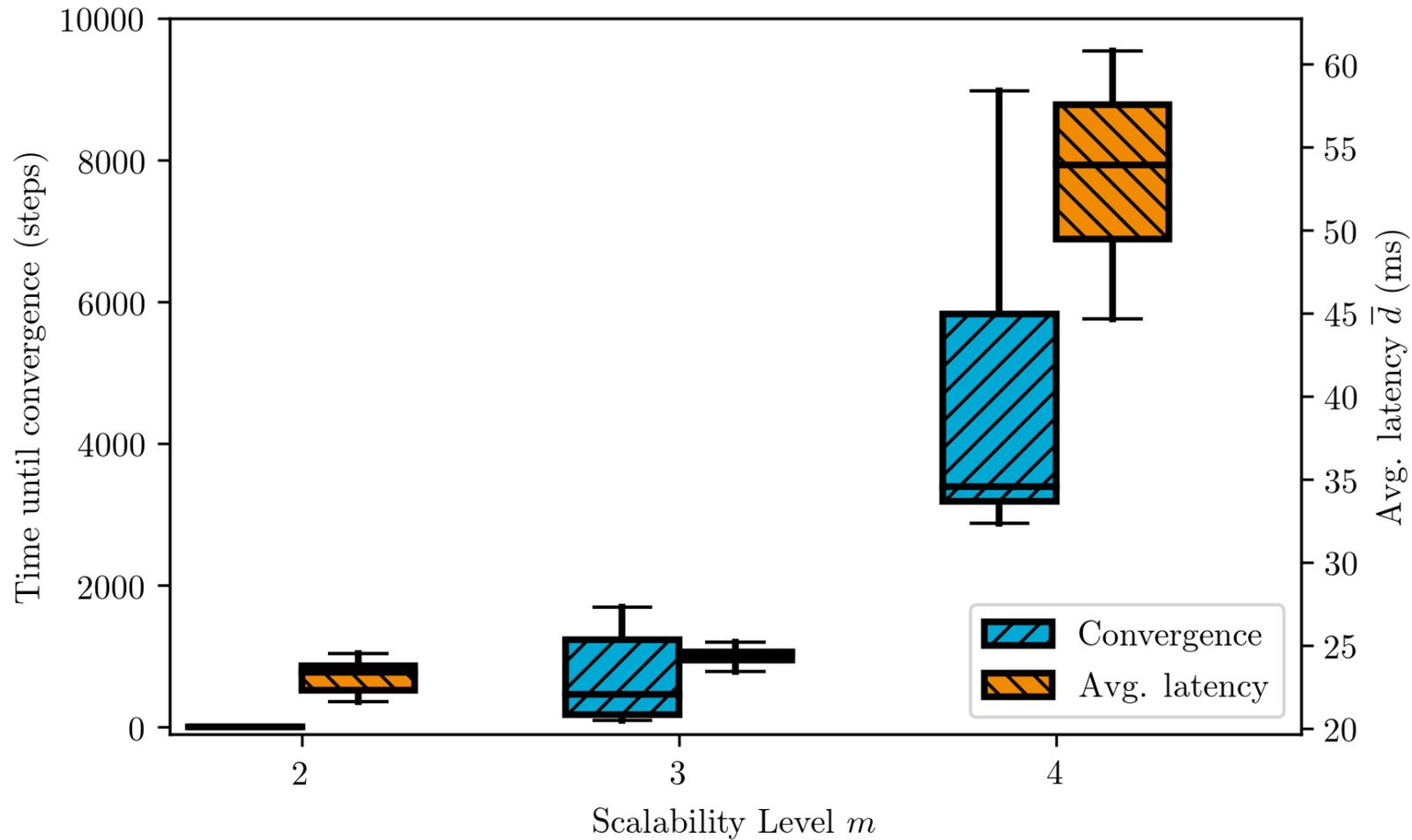
Q-table entries:

$$|Q| = m^m \cdot (m \cdot (m - 1) + 1)$$

→ Number of entries scales exponentially

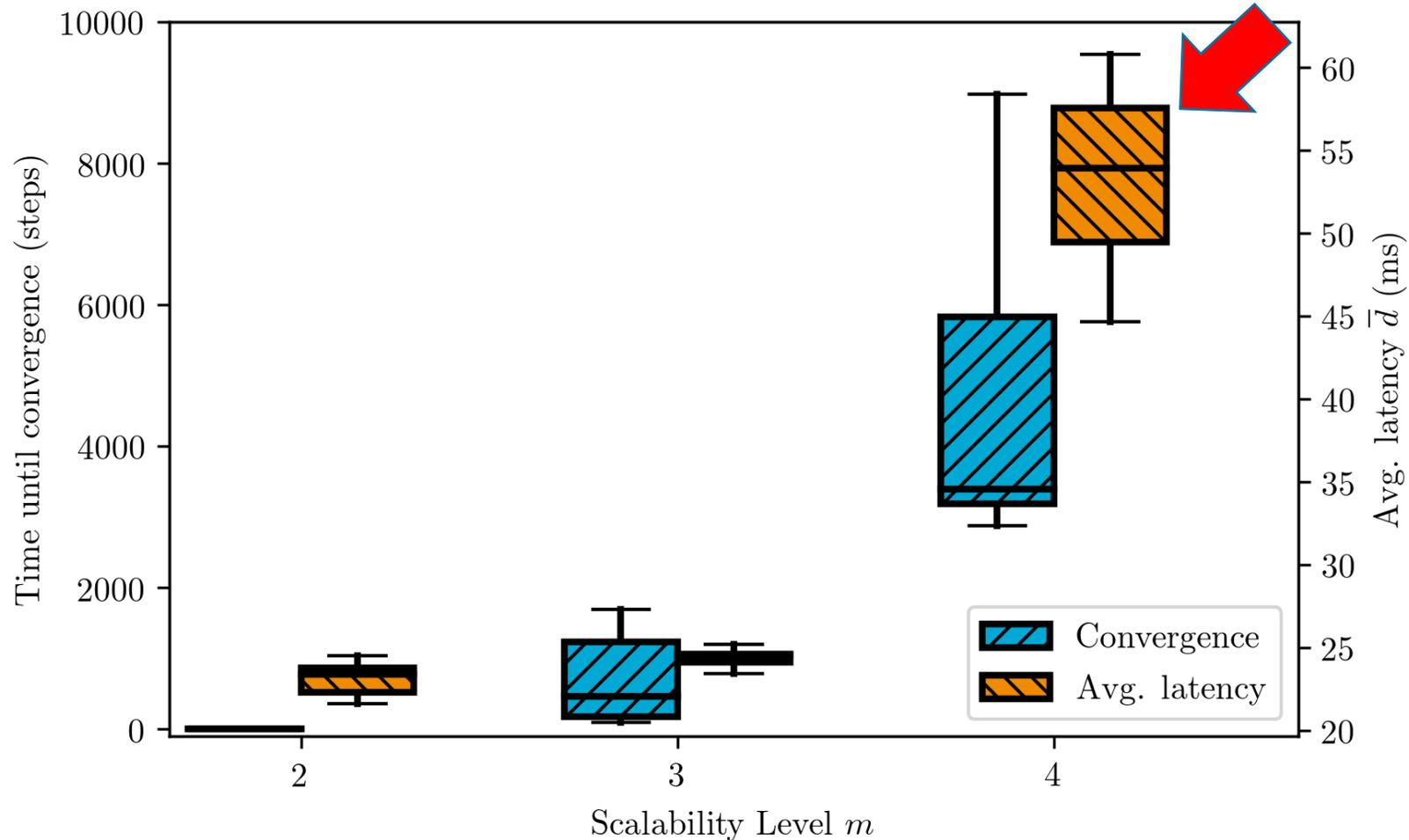
Evaluation - Scalability

Steps and average latency \bar{d} for different m



Evaluation - Scalability

Steps and average latency \bar{d} for different m Local minimum



Contribution

- Developed latency optimization with Reinforcement Learning
- Framework
 - Capable of latency measurement and dynamic routing
 - Adapts on changes of network loads
 - Can be used for hardware switches
 - Easily expandable or modifiable for further research
- Evaluated in an emulated environment with Mininet

Further Research Questions

- Scalability:
 - Limitation
 - Generalization
 - Bandwidth in state space
- Reward modification → different performance objectives
- Real network topologies
- Hardware switches

Thank you for your attention

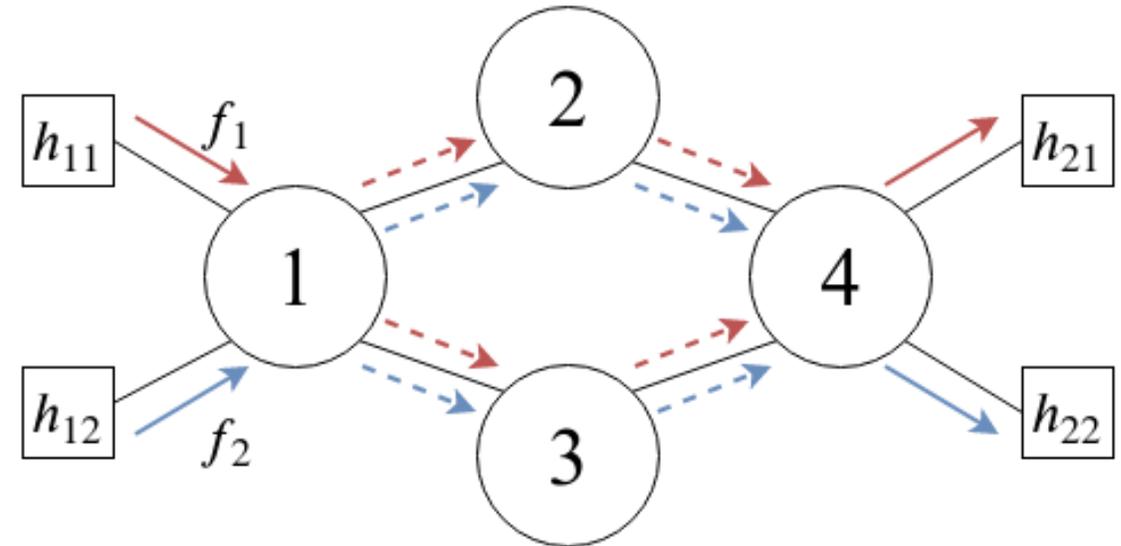
Appendix - Q-table

Number of actions:

$$|S| = \prod_{f \in F} |P(f)|$$

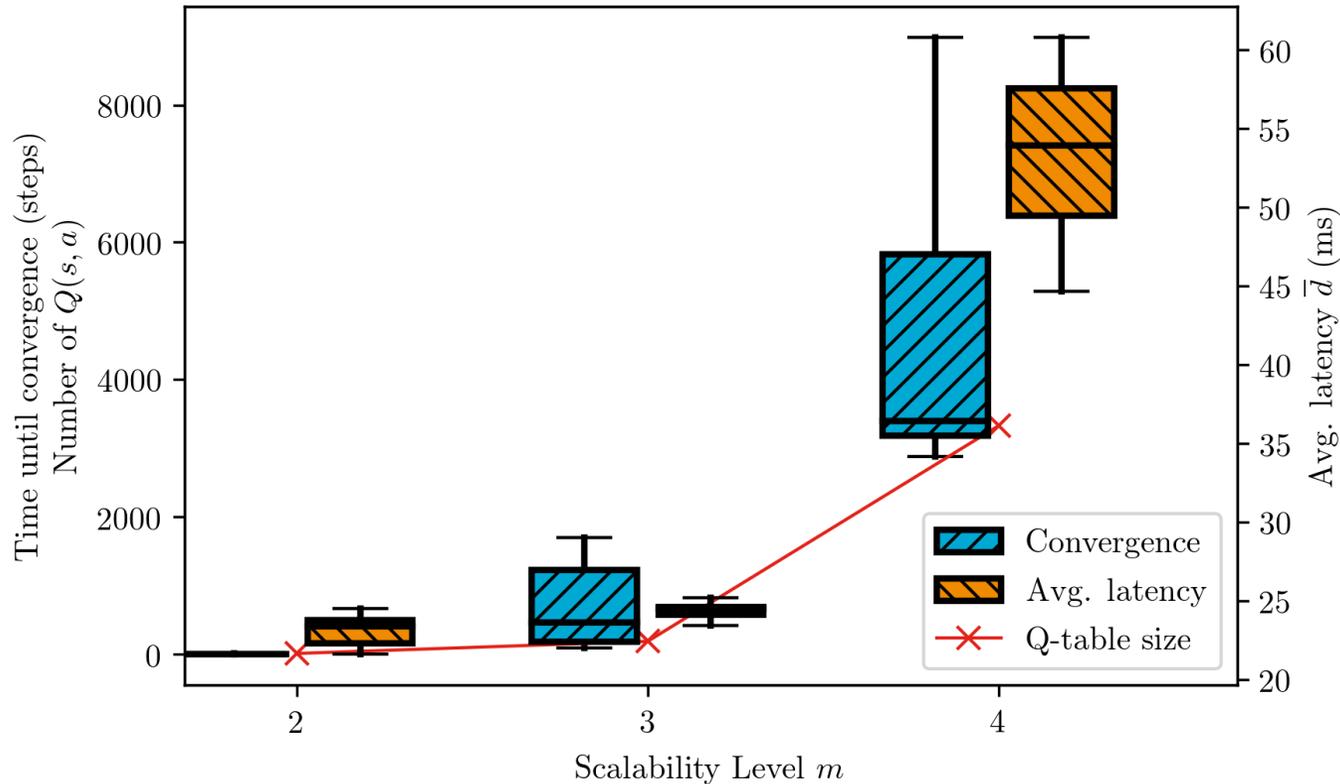
$$|A(s)| = \sum_{f \in F} (|P(f)| - 1) + 1$$

$$\begin{aligned} |Q| &= \prod_{f \in F} |P(f)| \left(\sum_{f \in F} (|P(f)| - 1) + 1 \right) \\ &= (2 \cdot 2) \cdot (2 \cdot (2 - 1) + 1) = 12 \end{aligned}$$



Appendix - Scalability

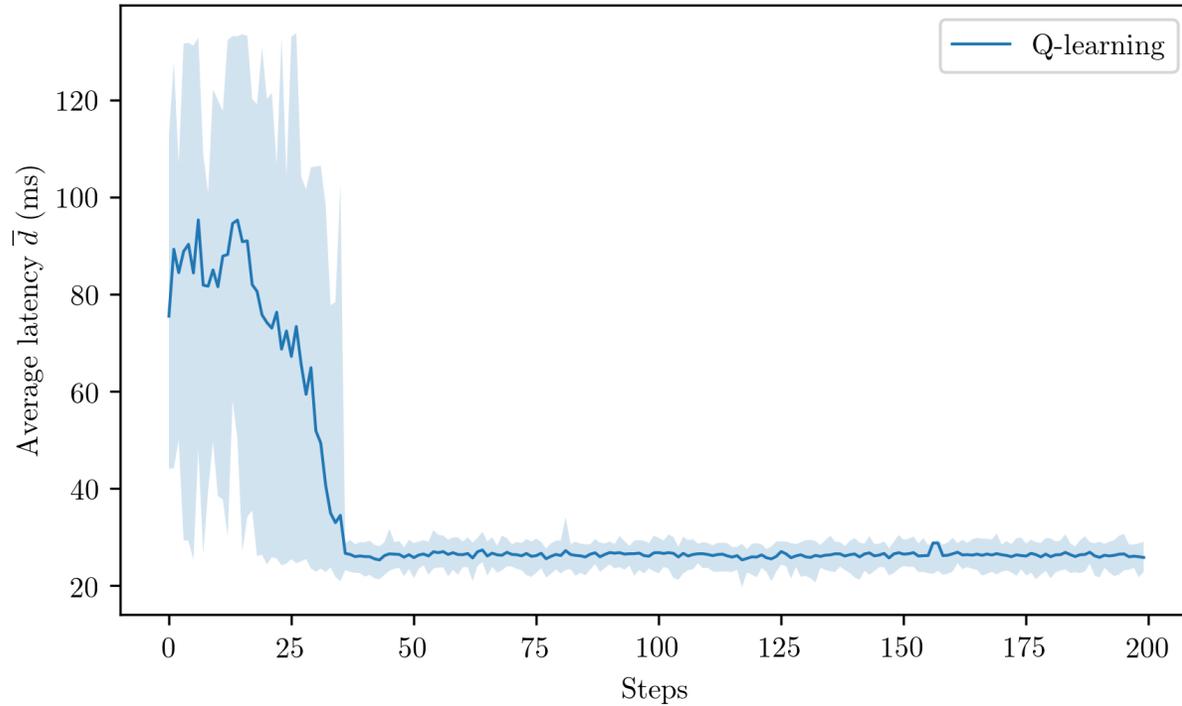
Convergence and \bar{d} for different m



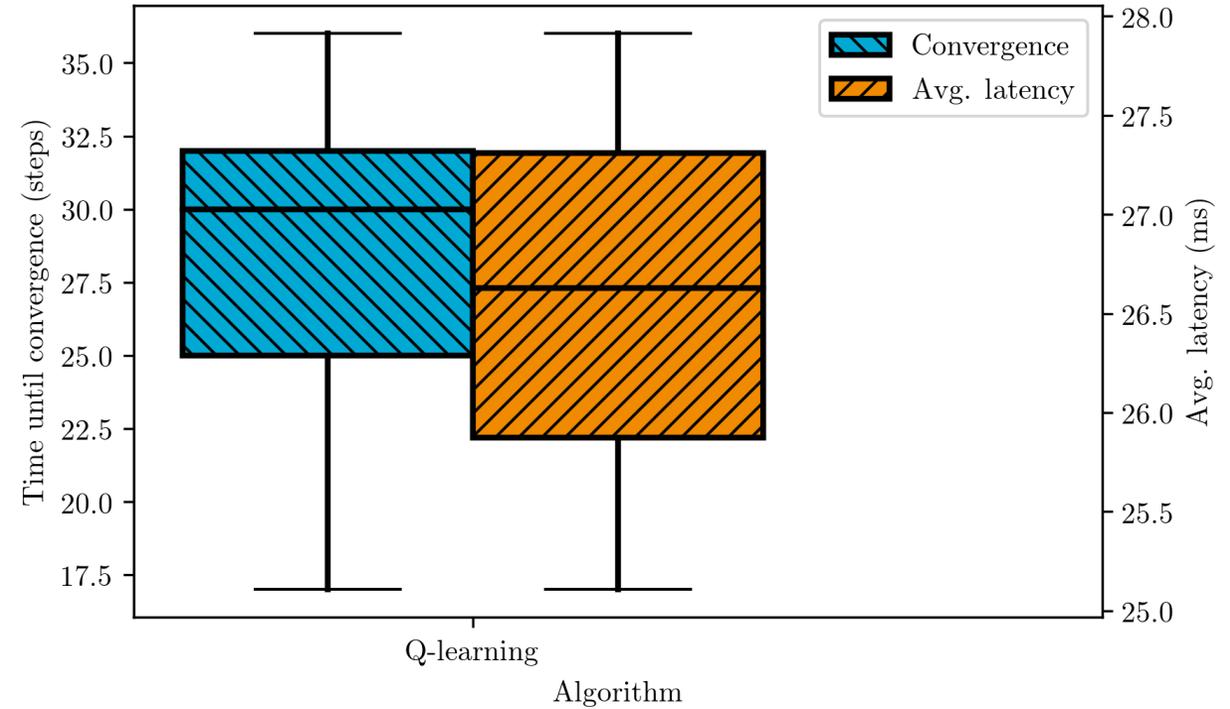
Level m	Q-table entries	Median Convergence steps
2	12	6.00
3	189	468.50
4	3328	3396.00

Appendix - Learning

Average latency \bar{d} over steps



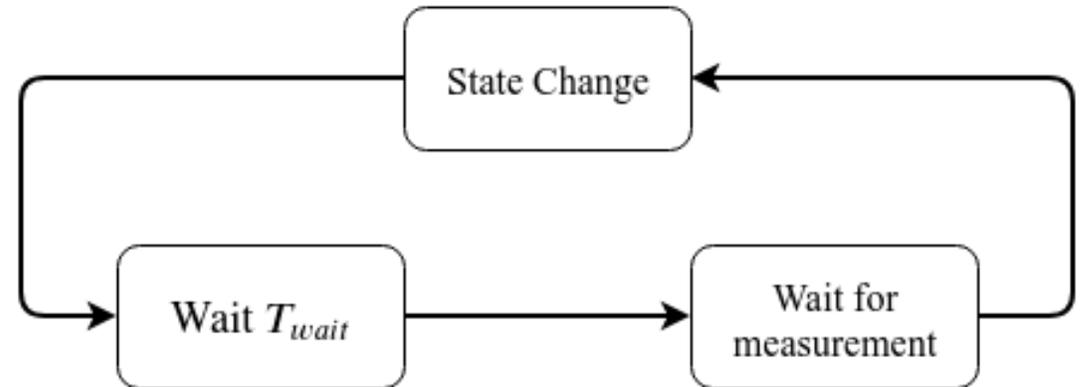
Steps and average latency



Appendix - Time and Steps

After state change a time is waited to ensure that stationary state reached (queues were emptied or filled)

Then it is waited until all latencies were measured successfully, because the measurement packets could be dropped due to congestion



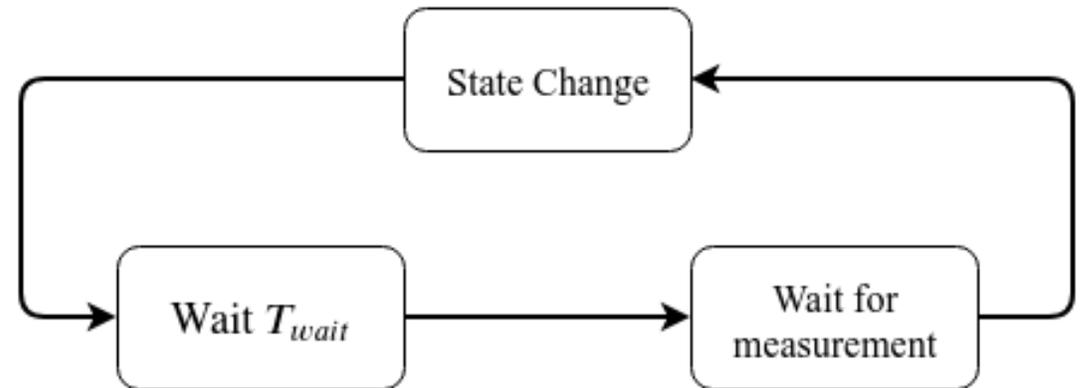
Appendix - Time and Steps

$$p(\text{dropped}) = \begin{cases} 1 - \frac{C(l)}{b^f(l)}, & b^f(l) > C(l) \\ 0, & \text{otherwise} \end{cases}$$

$$r_{\text{empty}} = \frac{b_{\text{diff}}}{k_{\text{UDP}}} = \frac{0.25 \text{ Mbit/s}}{1512 \text{ byte} * 8 \text{ bit/byte}} = 21.67 \text{ Hz}$$

$$T_{\text{empty}} = \frac{K}{r_{\text{empty}}} = \frac{30}{21.67} \text{ s} = 1.38 \text{ s}$$

$$T_{\text{delay}} = \frac{K * k_{\text{UDP}}}{C(l)} = 115.54 \text{ ms}$$

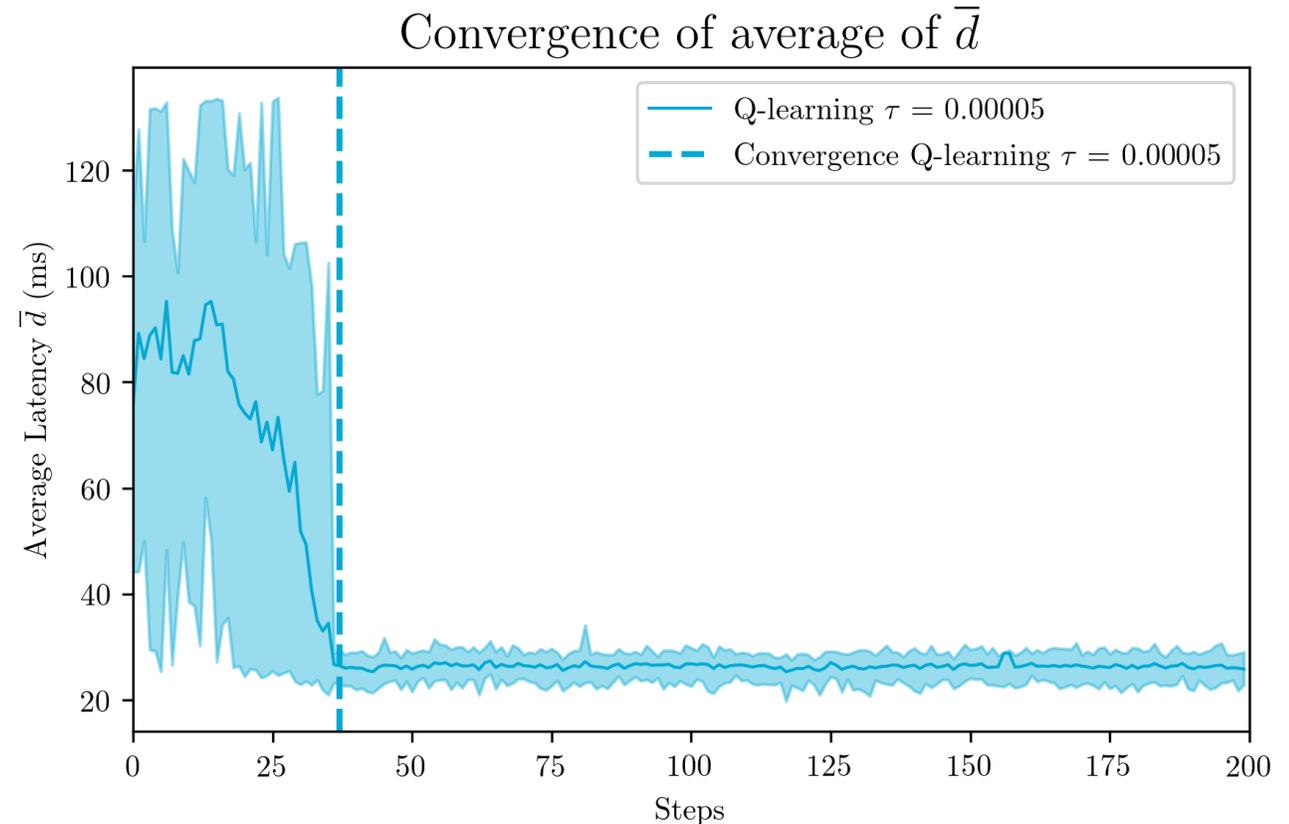


Appendix – Convergence Criterion

Moving average with N=40

$$|\bar{d}(t) - \bar{d}_c| < \epsilon$$

Smallest t_c with a value \bar{d}_c in which all following values $\bar{d}(t)$ are within the range



Appendix – Exploration vs. Exploitation

Exploitation: selecting the most promising action

Exploration: Probing another candidate action

Softmax:

$$a = \max_{a \in A(s)} \frac{\exp(Q(s, a)/\tau)}{\sum_{b \in A(s)} \exp(Q(s, b)/\tau)}$$

Modified Softmax:

$$a = \max_{a \in A(s)} \frac{\exp(-1/(\tau Q(s, a)))}{\sum_{b \in A(s)} \exp(-1/(\tau Q(s, b)))}$$

Maps Q-values to selection probabilities

Appendix – Exploration vs. Exploitation

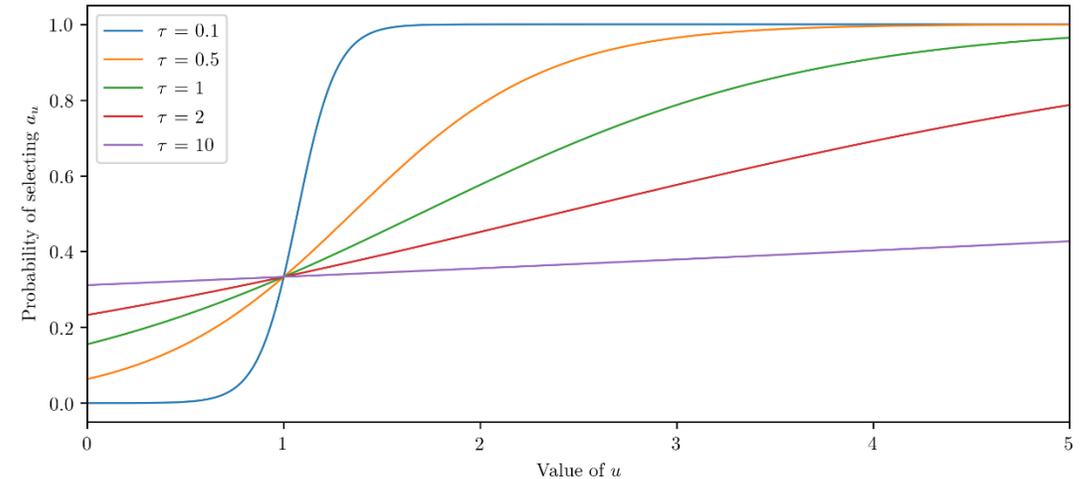
Softmax:

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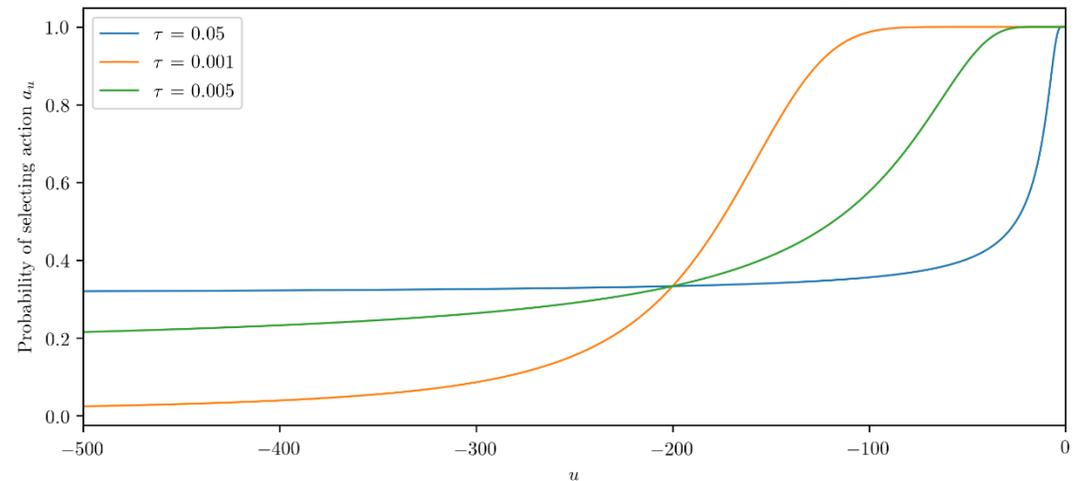
Modified Softmax:

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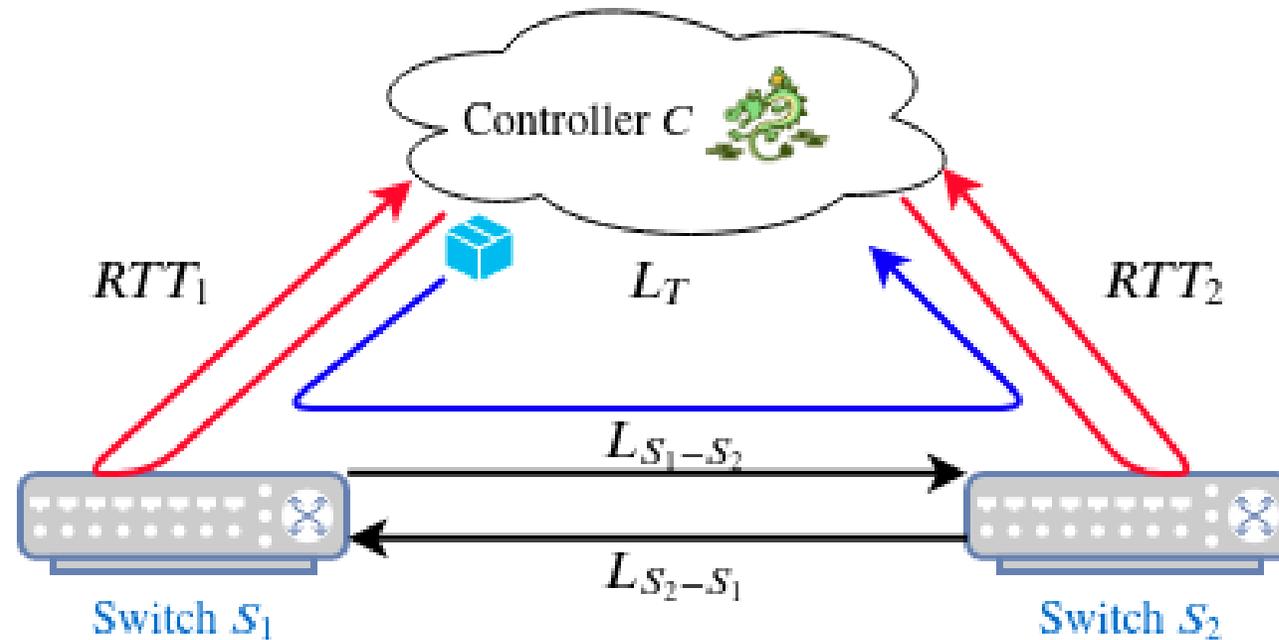
Action selection probabilities using Softmax for $u[a_u, 200, 200]$



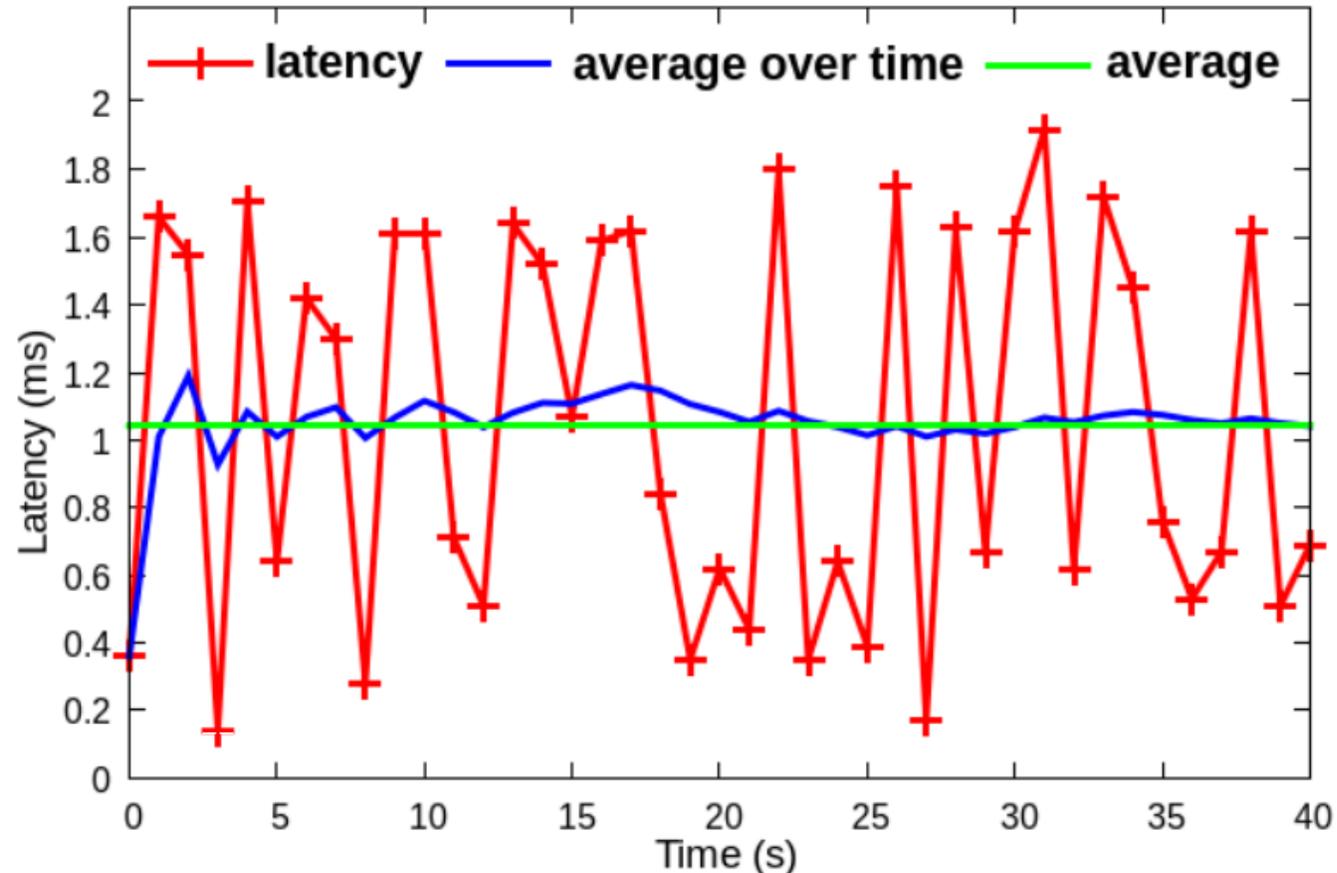
Action selection probabilities using the modified Softmax for $u[a_u, -200, -200]$



Appendix - Latency Measurement



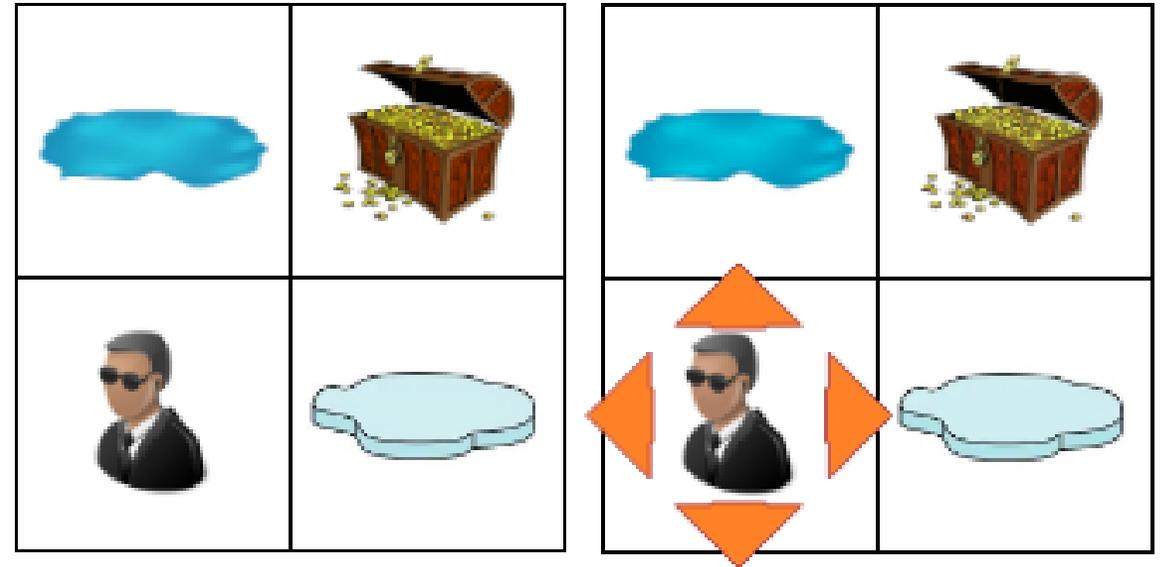
Appendix - Latency Measurement Uncertainty



K. Phemius and M. Bouet, "Monitoring latency with OpenFlow", 2013

Appendix - Q-learning

$$Q(s, a) = Q(s, a) * \alpha (r + \gamma \operatorname{argmax}_a Q(s', a) - Q(s, a))$$



Appendix - Routing

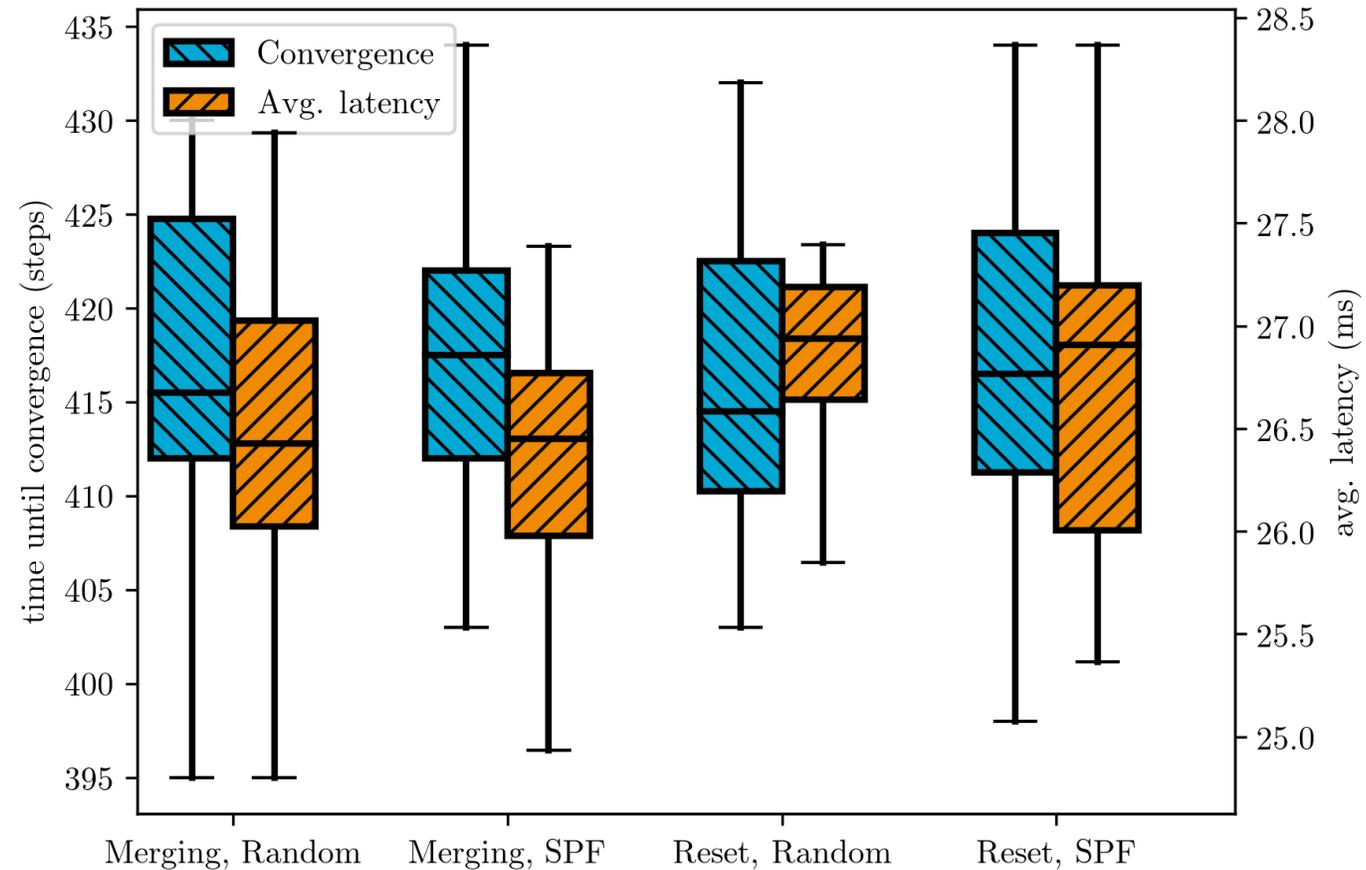
Algorithm 3 Path Search

```
1: function SEARCHINGPATHS(ADJACENCYMATRIX, SRC, DST)
2:   if src == dst then return src
3:   paths = []
4:   stack = [(src, [src])]
5:   while stack do
6:     (node, path) = stack.pop()
7:     neighbors = adjacencyMatrix[node]           ▷ All neighbors of vertex
8:     forwardNeighbors = SET(neighbors)-SET(path) ▷
Neighbors without origin path
9:     for next in forwardNeighbors do
10:      if next == dst then
11:        paths.append(path + [next])
12:      else
13:        stack.append((next, path + [next]))
14:      end if
15:    end for
16:  end while
17: end if
18:  return paths
19: end function
```

Algorithm 4 Rerouting

```
1: procedure ROUTEDEPLOYMENT(OLDPATH, NEWPATH, FLOWID)
2:   flowAddList ← [ ]           ▷ Switches in which flow table entries are added
3:   flowModList ← [ ]          ▷ Switches in which flow table entries are modified
4:   flowDelList ← [ ]         ▷ Switches in which flow tables entrie are deleted
5:   for index, switch in ENUMERATE(newPath) do
6:     if switch in oldPath then
7:       oldIndex ← GETINDEX(oldPath, switch)
8:       if oldPath[oldIndex-1] == newPath[index-1] then ▷ If same previous switch
9:         continue
10:      else
11:        if newPath[index-1] not in flowAddList then
12:          flowModList ← flowModList + newPath[index - 1]
13:        end if
14:      end if
15:    else
16:      flowAddList ← flowAddList + switch
17:      if newPath[index-1] not in flowAddList then
18:        flowModList ← flowModList + newPath[index - 1]
19:      end if
20:    end if
21:  end for
22:  for switch in flowAddList do           ▷ Adding flow table entries
23:    followingSwitch ← newPath[GETINDEX(newPath, switch) + 1]
24:    ADDFLOWSWITCH(switch, flowID, followingSwitch)
25:  end for
26:  for switch in REVERSED(flowModList) do   ▷ Modify flow table entries
27:    followingSwitch ← newPath[GETINDEX(newPath, switch) + 1]
28:    MODFLOWSWITCH(switch, flowID, followingSwitch)
29:  end for
30:  flowDelList ← SETDIFFERENCE(oldPath, newPath)
31:  for switch in flowDelList do           ▷ Delete flow table entries
32:    DELFLOWSWITCH(switch, flowID)
33:  end for
34: end procedure
```

Appendix – Joining flows



Different flow initializations and if Q-table is merged