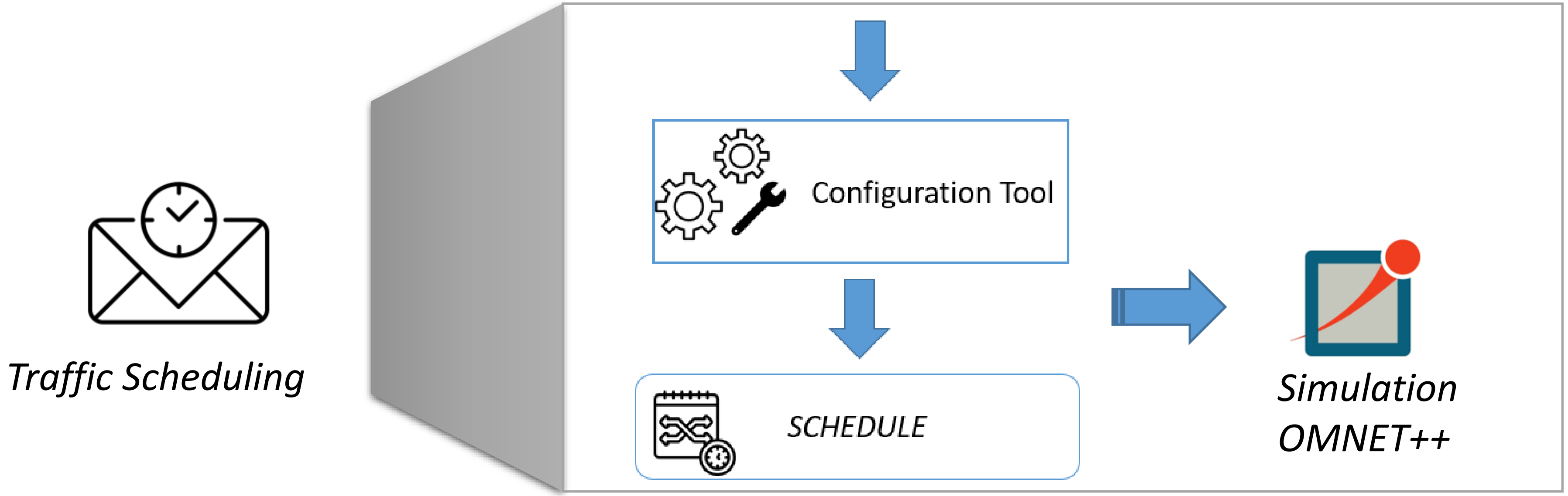
Time Sensitive Network | *Traffic Scheduling & Routing*

Title



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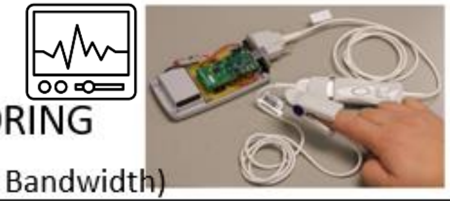
Agenda

Introduction | **Traffic Scheduling** | **Results** | **Next Steps**

Source: All Icons courtesy: https://thenounproject.com/

Motivation| *Internet of Medical Things*

ICU – TELEMONITORING



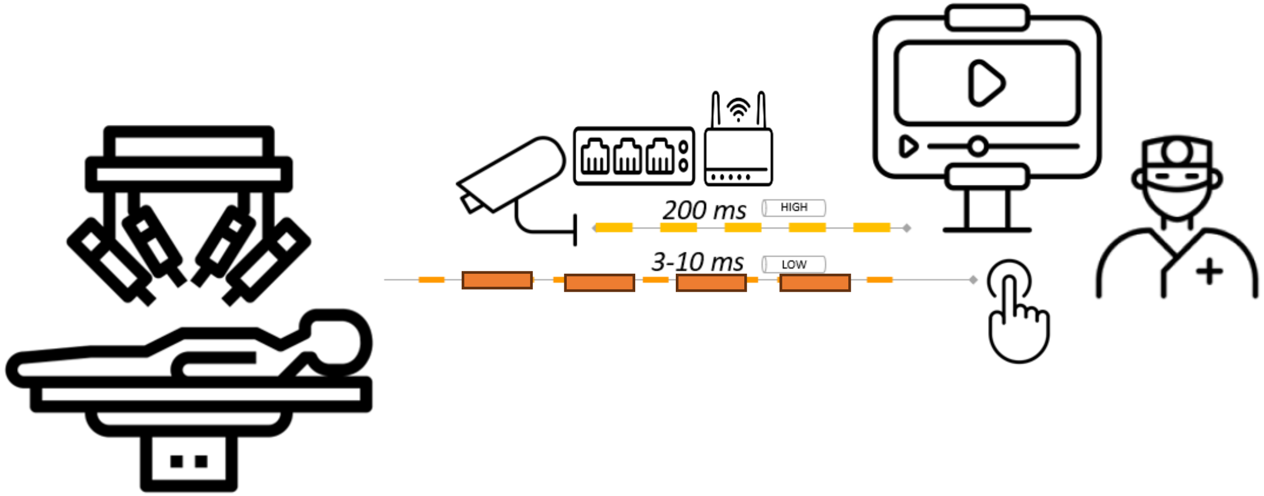
VITALS < 250 ms (Low Bandwidth)

TELE SURGERY

VIDEO - < 200 ms (High Bandwidth)
VITALS < 250 ms (Low Bandwidth)

OUT PATIENT CONSULTATION

Best Effort



Remote surgery, for instance, expects a latency guarantee of 200ms. Tactile feedback expects 10ms latency guarantee.

Wireless and Ethernet technologies have powered the communication requirements of a variety of applications thus playing a significant role in Internet of Things (IoT).

Internet Protocol (IP) based traffic provides best effort.

A deterministic communication system is necessary to serve the Quality of Services (QoS) to ensure medical professional experience.

Introduction| *Time Sensitive Networking -Architecture*

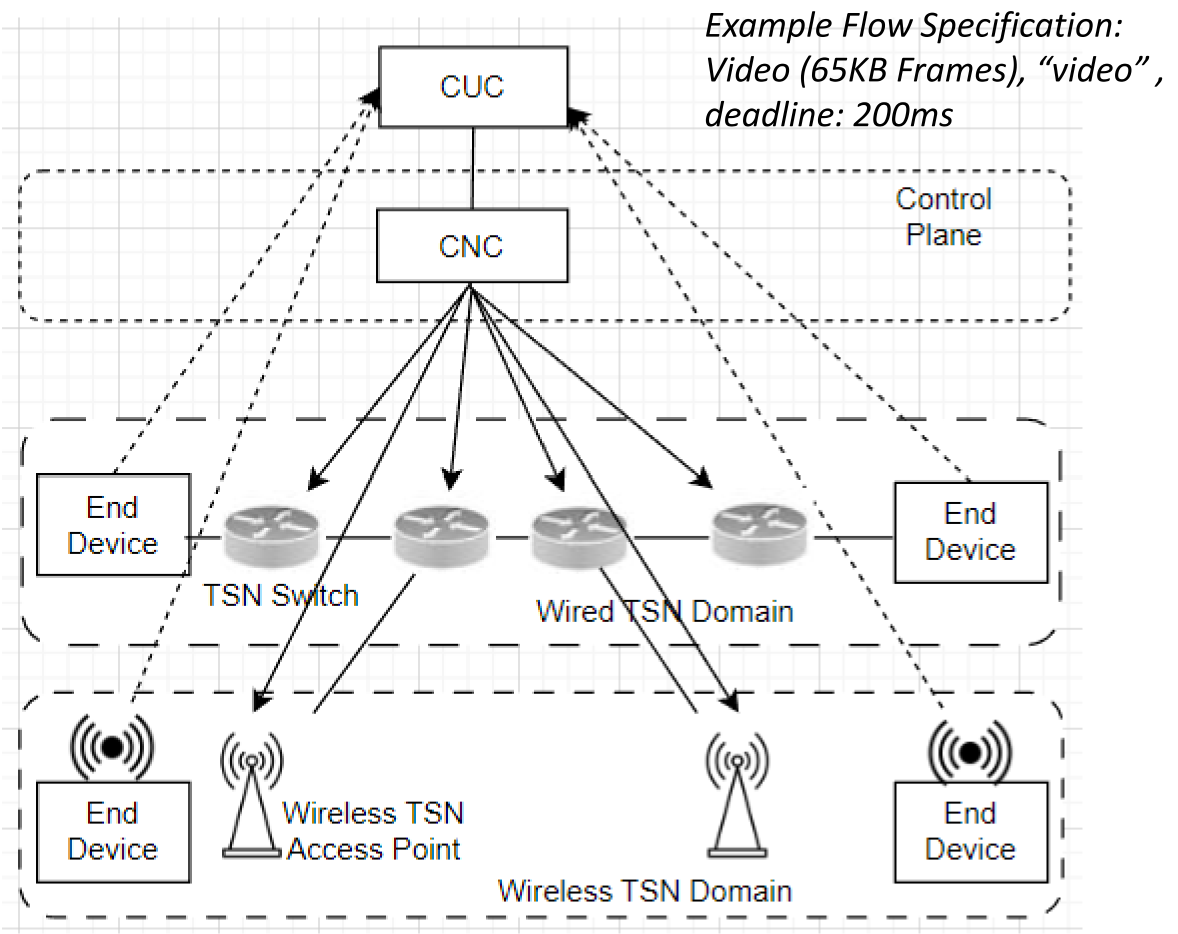
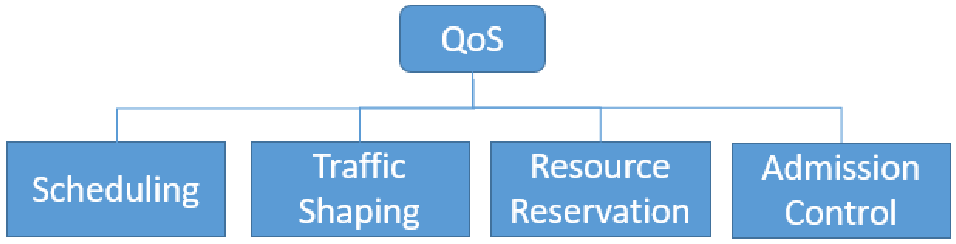
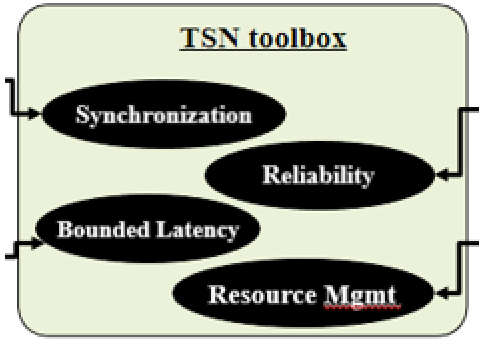


Fig 1. TSN Architecture Overview





802.1Qbu – Frame Pre-emption
802.1AS-Rev – Timing and Synchronization – Revision

802.1Qcc – Stream Reservation Protocol (SRP) Enhancements & Performance Improvements and TSN configuration

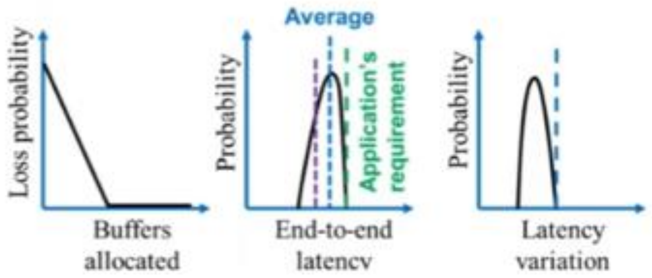
802.1Qbv – Enhancements for Scheduled Traffic (TAS)
802.1Qcr – Asynchronous Traffic Shaping (ATS)

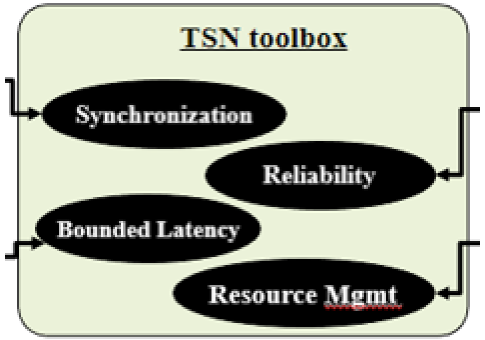
802.1CB – Frame Replication and Elimination for Reliability

Introduction| *Time Sensitive Networking Standards*

SHAPING

'Deterministic' Service:
- Zero congestion loss (not zero BER loss)
- Bounded latency, no tails (upper bound, meaning Average is likely higher than for Traditional Service)
- The right packet within the right time-slot
- Efficiency may suffer (overprovisioning) for other traffic





TSN Device

TSN Switch

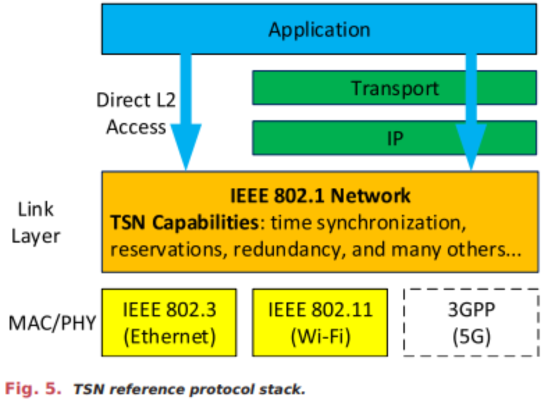
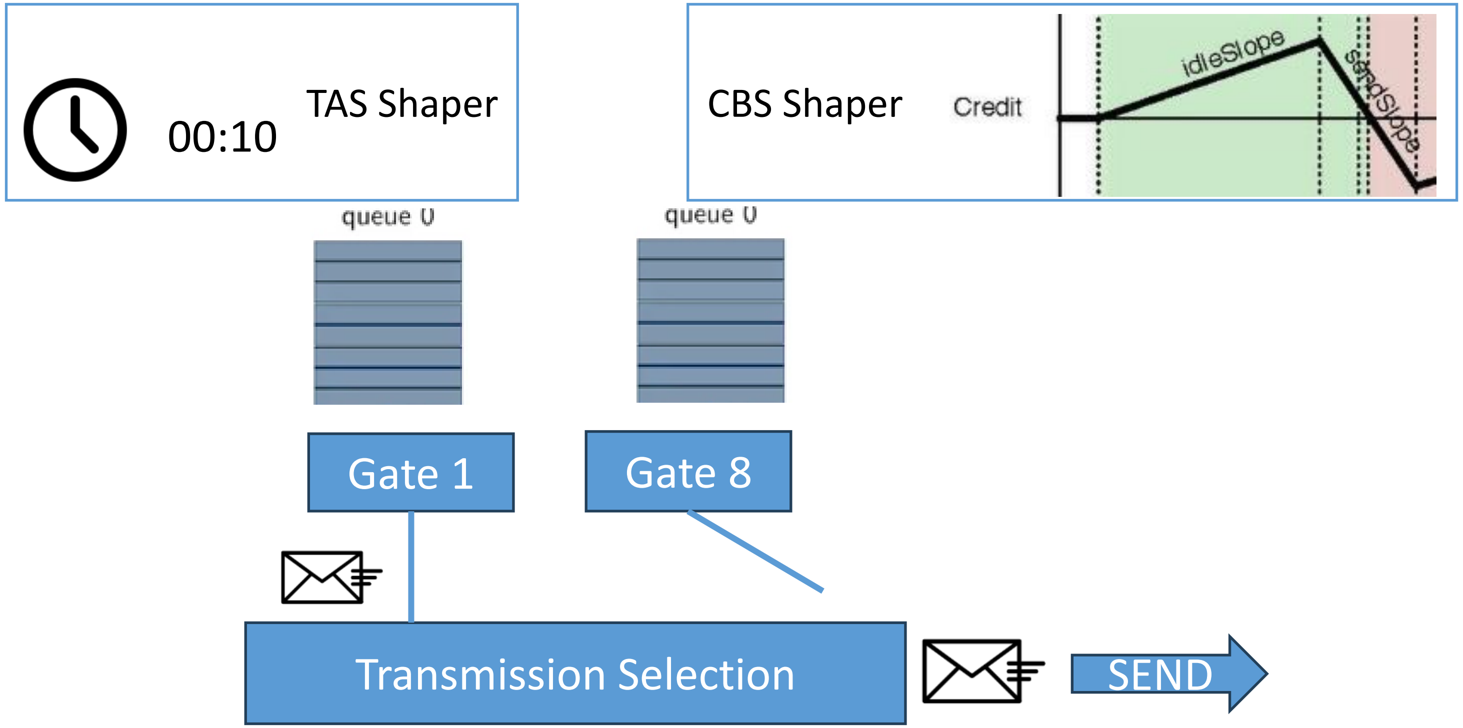


Fig 2. TSN Stack view



RESERVATION

Reserve – Steam Reservation Protocol

Gate Open

Introduction| *Problem Statement*

Table 2. WiFi 7 low-latency use cases.

Sector and Use Case	Requirements		
	Latency (ms)	Reliability (%)	Throughput (Mbps)
Health care			
Telediagnosis, telemonitoring, and telerehabilitation	50–200	>99.9	0.5–5
Telesurgery	1–10	>99.9999	~10
Exoskeletons and prosthetic hands	5–20	>99.999	0.2–1

On the wireless Time Sensitivity is a bigger challenge. Avnu alliance (Intel) is working in the direction.

Wireless Challenges

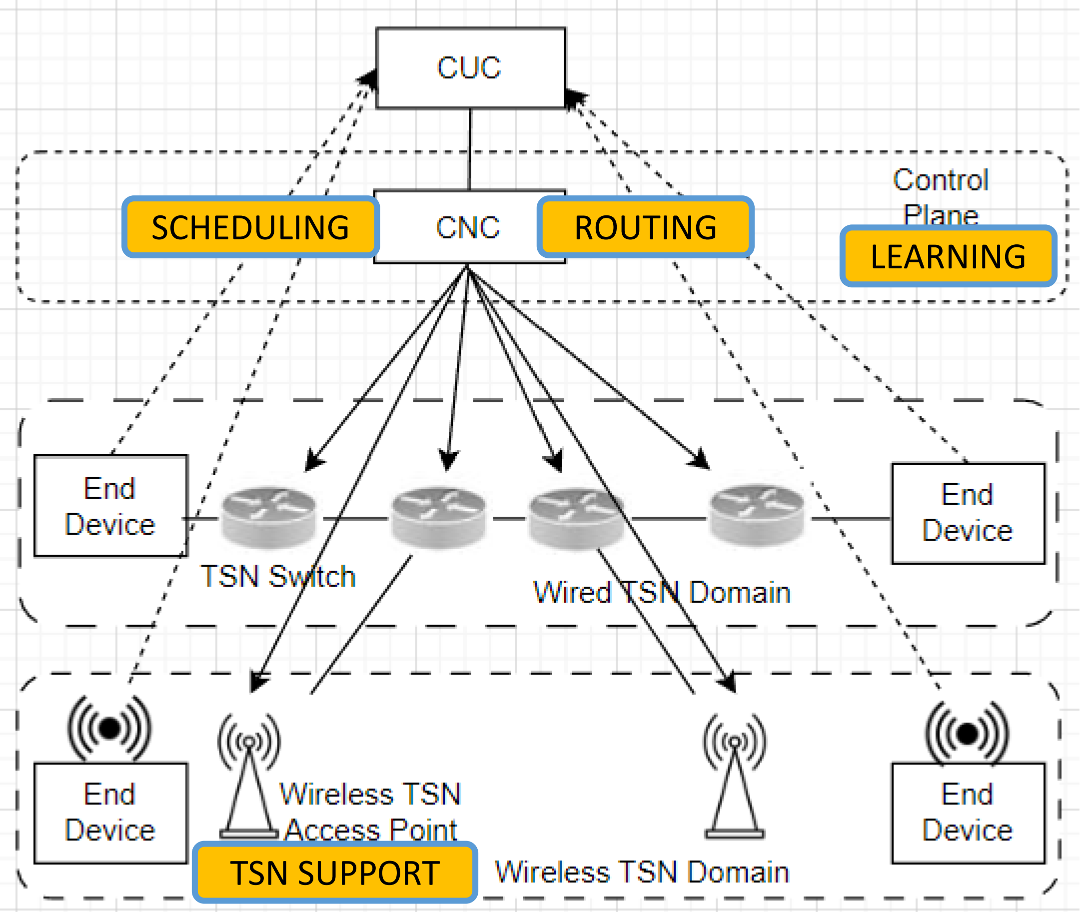
1. *Access Points today don't have support for Time Sensitivity*
2. *Variability and wireless Capacity*
3. *Wireless link and Packet Error Rate (PER) issues*

Research Problem

*For a set of requests with Mixed priorities, what should be the joint Scheduling and Routing strategy in order to minimize the cost associated with violation of the End-to-End Delay requirement? **(Scheduling and Routing)***

Challenges

1. *Mixed Flow scenario consisting of Video for RT Surgery, vital signs, best effort involves combinatorial strategies*
2. *End to End Delay Guarantee in Integrated Wired and Wireless Integration*



Traffic Scheduling| *Methodology*

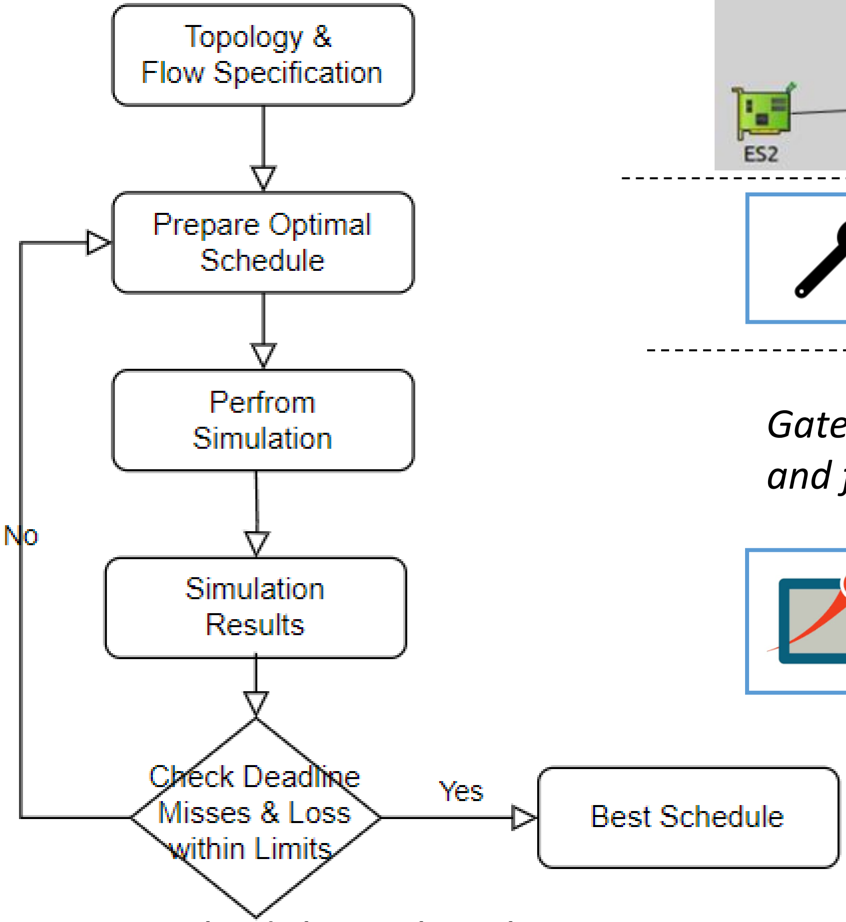
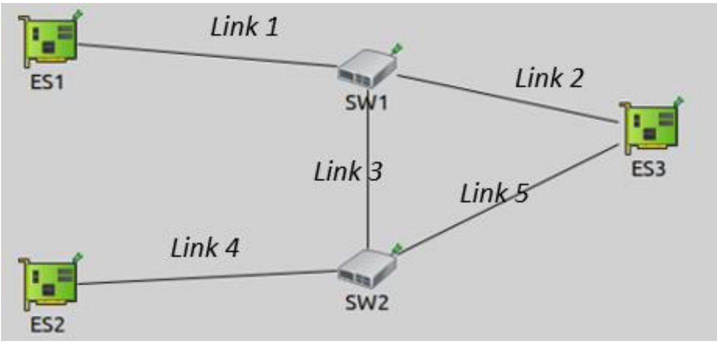


Fig 3. Methodology Flowchart



Link/Hop Flows	Link 1	Link 2	Link 3	Link 4	Link 5
Flow 1	1	2	-	-	-
Flow 2	1	-	2	-	3
Flow 3	-	-	-	1	2
Flow 4	-	3	2	1	-

Scheduling Tool

Using Reinforcement Learning

Gate Schedule for all routes and flows in the Network

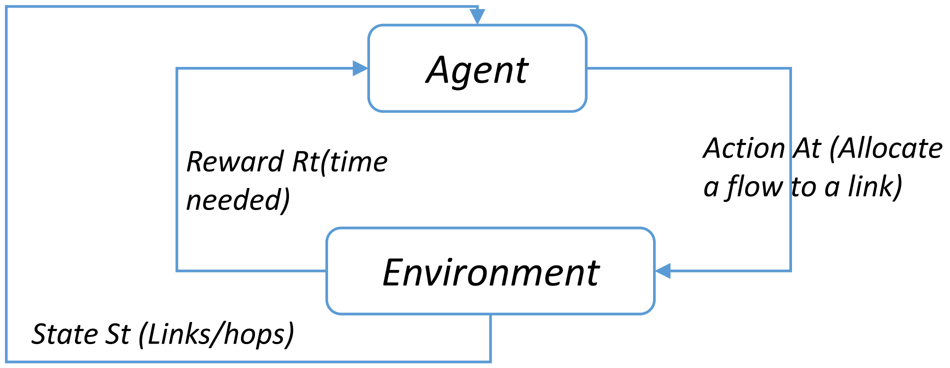
Link1: Flow1 {Start Time : 00:40 , End Time:00:60} Flow2 {Start Time : 00:70 , End Time:00:80}

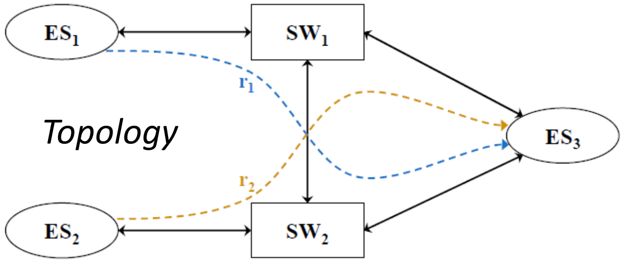
OMNET ++

Results & Analysis

Setup and Approach for Traffic Scheduling

Traffic Scheduling| *Markov Decision Process and Reward Design (RL)*





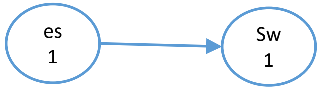
The State space consists of all Links {es1->sw1,es2->sw2, sw1->es3, sw2->es3, sw1->sw2}

The Action space consists of allocating Flow Fragments {allocate Flow1 Fragment1, allocate Flow2 Fragment2…}

State Space	Action Space	Reward Design

State Space

Set of Links (L1->Ln)



Action Space

Allocate flow fragments

Flow1 Fragment1 | Flow2 Fragment1

Reward Design

Regulated Reward:
Makespan /Max operation length
Negative Reward if the total time per flow > deadline

Fig 4. Modeling as Markov Decision Process and Reward Design

Traffic Scheduling| *Environment for Reinforcement Learning*

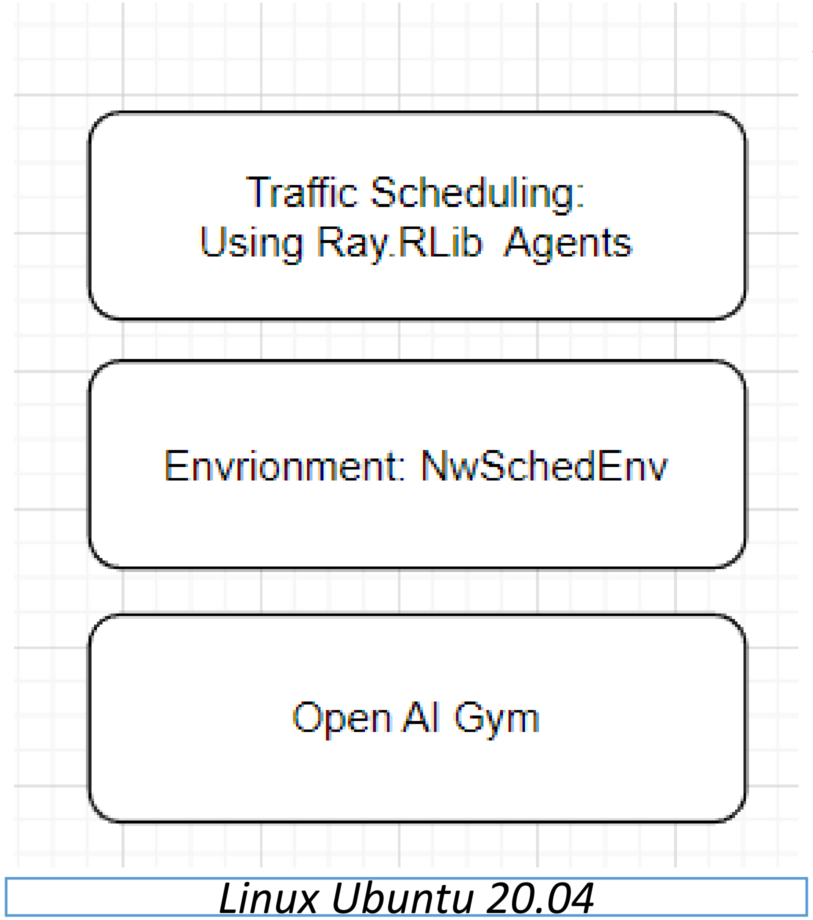


Fig 5. Environment

Algorithm: Proximal Policy Optimization

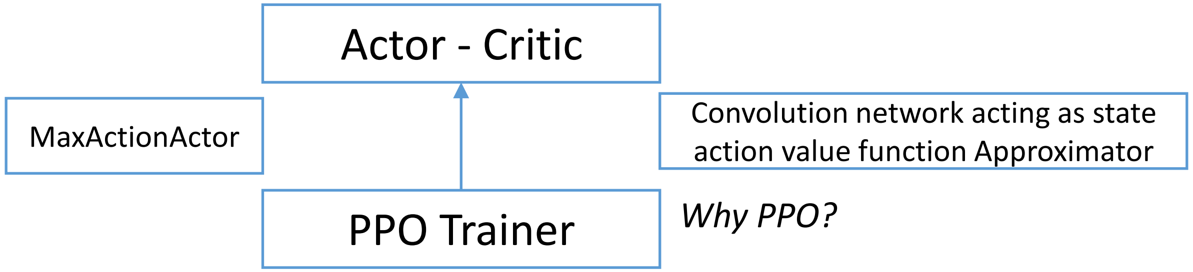


Fig 6. PPO details

Why PPO?

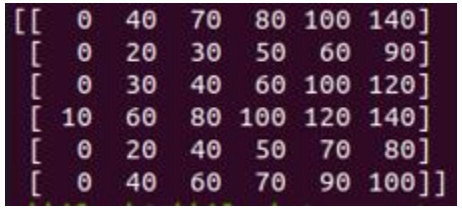
Uses SGD (less computation), doesn't go far, and stays in a clipped area to do policy optimization. Actor Critic methods suffer from policy crash (performance collapse)

Single Agent Problem

Steps:

1. *Created a new Environment in Open AI Gym and registered it*
2. *Using the Environment with the Model, different types of actors (MaxActionActor), PPO Trainer to Train using Tensorflow*

Traffic Scheduling| *Results - Schedule*



```
[[  0  40  70  80 100 140]
 [  0  20  30  50  60  90]
 [  0  30  40  60 100 120]
 [ 10  60  80 100 120 140]
 [  0  20  40  50  70  80]
 [  0  40  60  70  90 100]]
```

Fig 7. Resulting Schedule as array

Each array within represents each flow.
The numbers inside each flow array represent the start time of the flow fragment. The period/time for processing is provided as input

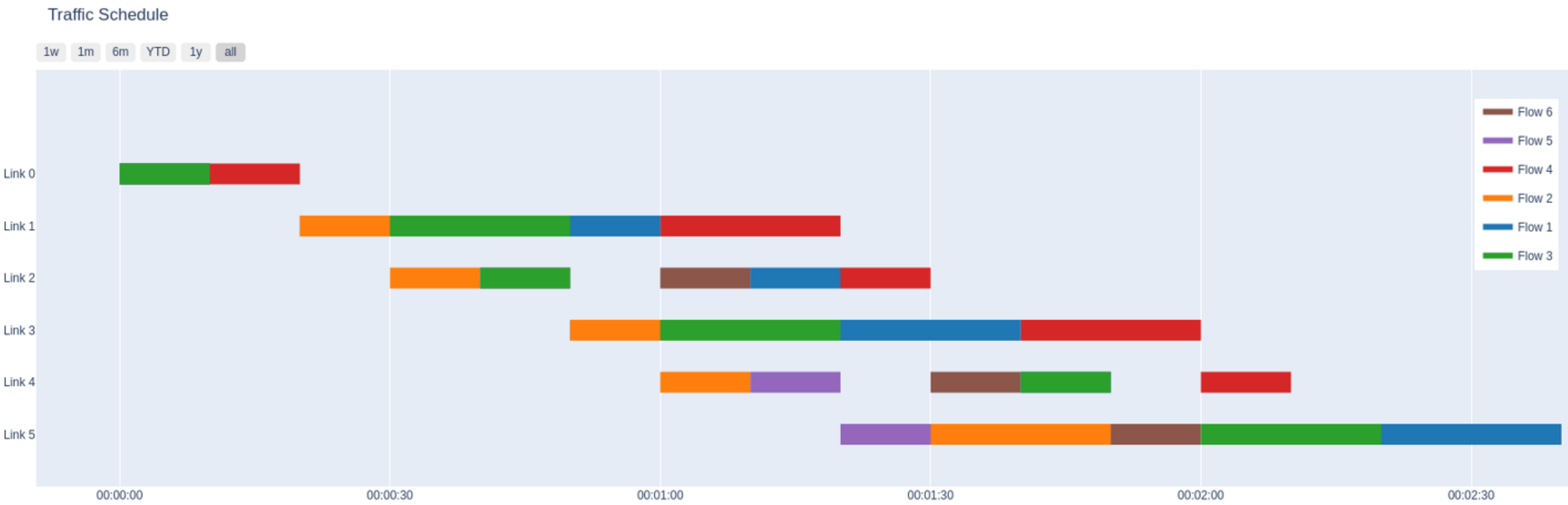


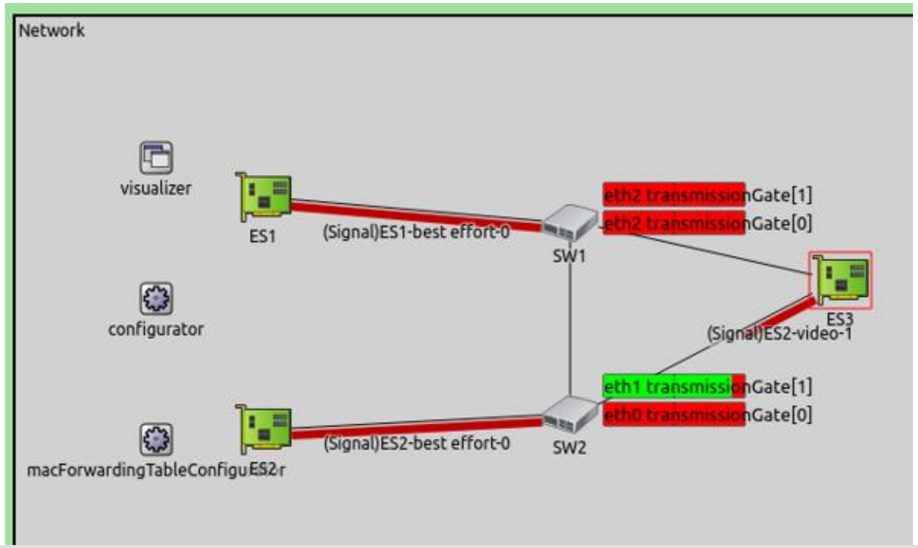
Fig 8. Resulting Schedule as Gannt Chart

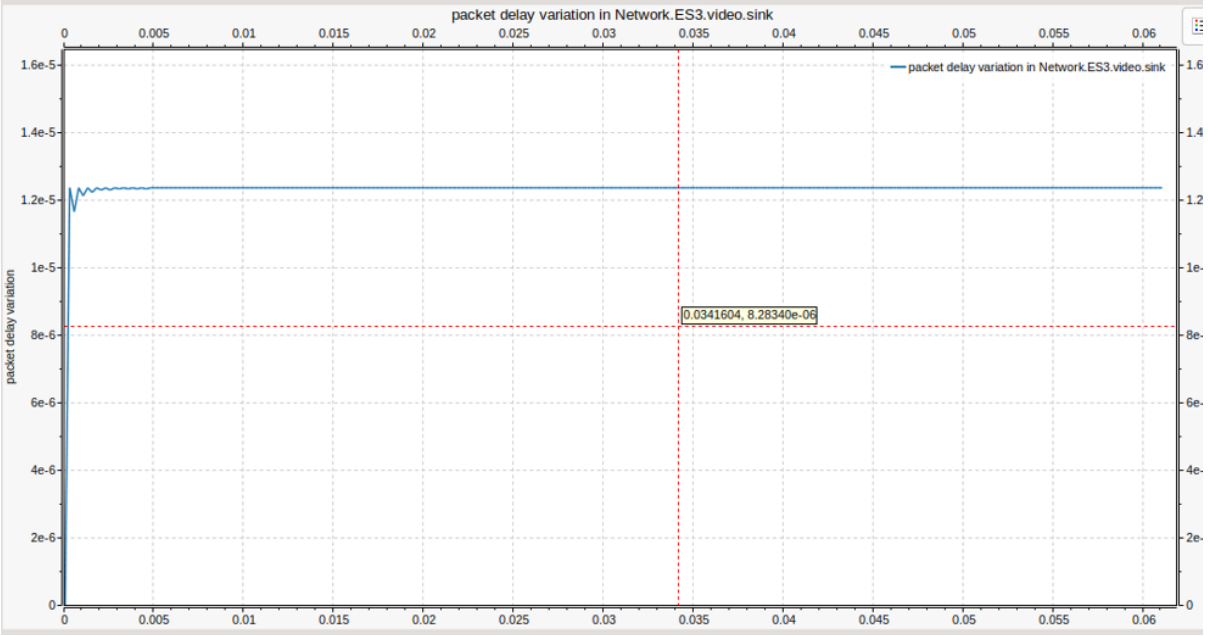
Resulting Schedule

Traffic Scheduling| *Results – Reinforcement Learning*

The result analysis in terms of convergence (sampling efficiency), stability

Fig 9: Reward Curve for Scheduling with deadline handing



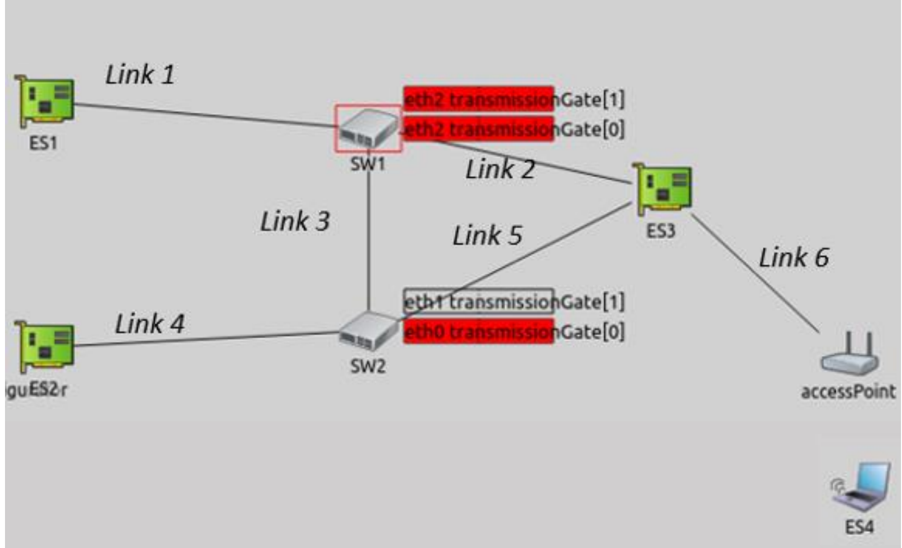


The optimum policy /here schedule is achieved in 68 episodes and then on it stays stable.

Simulation using OMNET++ provides input of having delay variation is within control. TSN Scheduling efficiency.

Traffic Scheduling | *Observations and Next Steps*

IoT networks require a certain level of dynamics which is possible to be provided by Deep Reinforcement Learning approaches. The makespans obtained using Policy Proximity Optimization is better than following approaches like genetic algorithms or QLearning.



Observations

Training takes time and memory using the neural networks and policy gradient. But within few episodes the approach is able to learn and stabilize. There are some losses and deadlines missed with the schedule prepared.

From the simulations we could identify that the schedule is feasible and also on using TSN Gate Schedule Configurator, the delay variation is within control or determinism is achieved over ethernet

Link/Hop Flows	Link 1	Link 2	Link 3	Link 4	Link 5	Link 6
Flow 1	1	2	-	-	-	-
Flow 2	1	-	2	-	3	-
Flow 3	-	-	-	1	2	-
Flow 4	-	3	2	1	-	-
Flow 5	-	-	-	1	2	3

Future Work

Wireless integration. Need to try with more scenarios and compare the results with complex networks to generate the feasible schedule. Also need to see how the feedback from simulation can be considered to improve the learning. Today the link processing time is coming as input, this can come from simulation.

Traffic Scheduling | *References*

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Thank you!