Communication and Learning in Dynamic Networks

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GTTI annual meeting, September 11, 2023
Introduction

- Modern networks are characterized by **heterogeneous** applications

- The **same architecture** must adapt to different scenarios in real time

- Network control is distributed among **multiple autonomous units**

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1. We need to estimate the overall network status
   → **Network Mapping**

2. We need to coordinate multiple control units
   → **Distributed Learning**

3. We need to balance resources among services
   → **Resource Allocation**
Network Mapping: Scenario

We consider a group of **autonomous nodes** that move in a 2D or 3D scenario. At each timeslot $t$, each node $n \in \mathcal{N}$:

- Uses local sensors to **observe** the environment and estimate its **own state**
- Spreads its state estimate according to some **communication** strategy
- Exploits the received information to **estimate** the overall **network state**
Network Mapping: Model

Each node $n \in \mathcal{N}$ is equipped with $|\mathcal{N}|$ **Unscented Kalman Filters (UKFs):**

- The node $n$ uses one UKF to compute the state estimate $\hat{s}_{n,n}(t)$
- It uses the other UKFs to compute the state estimates $\hat{s}_{n,k}(t), \forall k \in \mathcal{N}: k \neq n$

The **system performance** is given by:

$$\Omega = \frac{1}{|\mathcal{N}|} \sum_{n \in \mathcal{N}} (|\hat{s}_{n,n}(t) - s_n(t)| + \sum_{k \in \mathcal{N}, k \neq n} |\hat{s}_{n,k}(t) - s_k(t)|)$$
Network Mapping: Approach

Benchmark:
new communications are started according to the age of the information

New proposal:
new communications are started according to the urgency of the information

- Each node $n \in \mathcal{N}$ implements as additional UKF emulating the tracking process of the other nodes
We tune communication according to:

- Channel sensing
- State estimation

Network Mapping: Approach

We design two new models, named **CTRA+** and **3D-CTRA**, to operate in 3D scenarios.

- More advanced models lead to a higher communication overhead.

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Network Mapping: Results


- SF → Spreading Factor
- CS → Constant Speed
- CTRA → Constant Turn Rate and Acceleration
Distributed Learning: Scenario

We consider a group of autonomous nodes that move in a 2D scenario. At each timeslot $t$, each node $n \in \mathcal{N}$:

- Spreads local information according to some communication strategy
- Exploits the received information to estimate the overall network state
- Decides in which directions to move in order to reach a target location
Distributed Learning: Model

- Each node is controlled by a **Reinforcement Learning (RL)** agent computing its **policy** $\pi(\cdot): S \rightarrow A$

- At each **step** $t$, the agent observes the **state** $s_t \in S$, takes an **action** $a_t \in A$ and receives a **reward** $r_{t+1}$

- In our system, **multiple agents** interact with the **same environment**

**Performance** is given in terms of:

Success probability $P_{succ}$  Step per episode $N_{step}$
Distributed Learning: Approach

Centralized training:
all the nodes share their local experience with a central agent

Distributed implementation:
each node is controlled by a different instance of the central agent

➢ We can adapt the same system to new scenarios by the **Transfer Learning (TL)** paradigm
Distributed Learning: Results

Distributed Learning: Approach

Ideal scenario:
all the nodes observes the same system state

Benchmark scenario:
the communication policy is pre-determined

New proposal:
the communication policy is adapted to the control policy
Distributed Learning: Results

OC → Omniscient Communication
RC → Random Communication
CC → Closest Communication

DJCC → Distributed Joint Communication Control
CJCC → Centralized Joint Communication Control
Resource Allocation: Scenario

We consider a network with multiple traffic flows $\phi \in \Phi$ associated with specific slice classes $\sigma \in \Sigma$

- Flows contend for the same computational and communication resources
- Performance depends on both resource allocation and slice characteristics
Resource Allocation: Model

We associate each node $n \in \mathcal{N}$ and link $\ell \in \mathcal{L}$ with a **learning agent**. At each timeslot $t$:

- Each node $n \in \mathcal{N}$ allocate its **computational power**
- Each link $\ell \in \mathcal{L}$ allocates its **communication bandwidth**
- Each flow $\phi \in \Phi_\sigma$ computes its **performance** as $f_\sigma(\phi, t)$

The **system performance** is given by:

$$\Omega = \frac{1}{|\Phi|} \sum_{\sigma \in \Sigma} \sum_{\phi \in \Phi_\sigma} f_\sigma(\phi, t)$$
Resource Allocation: Approach

Centralized training:
we train a different agent for each resource type and slice class

Distributed implementation:
we implement a different agent for each network facility and traffic flow

Transfer Learning (TL) can be used to refine the learned policy during the testing phase!
Resource Allocation: Results


DRL \rightarrow Deep Reinforcement Learning
Resource Allocation: Approach

**Ideal scenario:**
Learning agents and network users exploit **dedicated** resources

**Real scenario:**
Learning agents and network users exploit **shared** resources

There is a **trade-off** between:

- Immediate performance
- Future adaptability
Resource Allocation: Results

\[ T_\rho \rightarrow \text{Percentage of training resources} \]

F. Mason, F. Chiariotti, and A. Zanella, “No Free Lunch: Balancing Learning and Exploitation at the Network Edge,” in IEEE International Conference on Communications, Seoul, South Korea, 2022
Conclusions

1. Networks require a more **flexible architecture** managed by multiple agents.

2. **Communication, control, and resource allocation** must be jointly optimized.

3. When **resources** are limited, **performance** is inversely proportional to **adaptability**.
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