Department of Computer Engineering & Informatics

Laboratory for Signal Processing and Communications

Wireless and Mobile Communications

Key Technologies: Selected topics

Machine Learning & Comm. / Federated & Distributed Learning / RIS / Cell-free

Presentation outline

- Machine learning and communications
- Signal Processing and Machine Learning over networks
  - The cases of federated and fully distributed learning
- Reconfigurable intelligent surfaces
- Coordinated MultiPoint transmissions

Machine learning and communications (1/6)

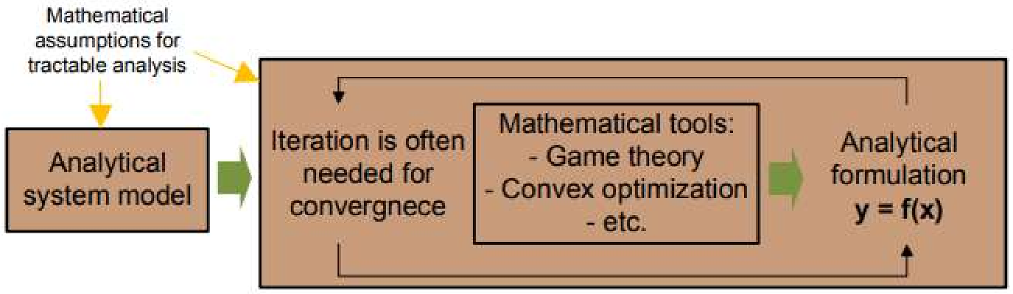
- Machine learning (ML) is penetrating every facet of our lives.
  - This has been enabled due to many recent advances in processing speed, data acquisition, and storage
- Wireless communications is another success story – ubiquitous in our lives, from handheld devices to wearables, smart homes, and automobiles.
- In recent years, there is intensive research activity in exploiting ML tools for various wireless communication problems.
- Moreover, designing physical layer techniques to enable distributed ML at the wireless network edge are also currently being intensively studied.
  - ➢ This further emphasizes the need to understand and connect ML with fundamental concepts in wireless communications

Machine learning for communications (2/6)

- Moreover, modern wireless communication systems are getting more complicated. For example, they will support (massive) machine-type transmissions with a large number of participating devices
- This scenario raises several challenges like communication overheads, scalability and latency issues as well as privacy considerations
- Signal processing and machine learning (SP&ML) is “moving” towards the edge of the network (Edge-SP&ML) in distributed architectures to address these challenges
- A combined expertise at the intersection of signal processing, machine learning and wireless communications is an enabler to effectively address many of the challenges in Edge-SP&ML

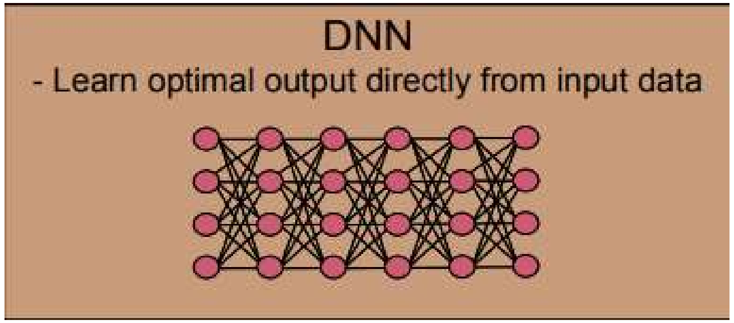
Machine learning for communications (3/6)

- The conventional approach for designing wireless communications systems, is model-based
  - The transmitter and the receiver follow a modular design
    - At the TX side: source and channel coders, modulator, beamformer, etc.
    - At the RX side: corresponding equalizers, decoders, etc.
  - There is a channel model that is adopted, impacting the design of signal processing algorithms at the PHY
- Each module (block) of the TX/RX uses the following methodology for describing its functionality (captured by $f(\cdot)$)



Machine learning for communications (4/6)

- The ML approach for designing wireless communications systems, is data-driven and is utilized via the following lines
  - The functionality of a particular module is captured by an ML model (e.g., CNN, LSTM, etc.) that approximates $f(\cdot)$
  - A series of modules or the whole TX-Channel-RX chain is modelled by an ML model
- It requires (as expected) a rich and representative dataset of the underlying communication scenario
- It drops assumptions and captures complicated aspects of the system that are not easily (or cannot be) modelled



Machine learning for communications (5/6)

- As an example, let us see the problem of deep-learning-aided coordinated beamforming
- Multiple Base Stations (BS) align their transmissions for serving a particular user
- Conventionally, this can be accomplished as
  - The user transmits pilot signals and the BSs estimate the involved channels
  - This information is used either individually or collaboratively to select appropriate beamforming vectors for each BS
  - Increased overhead during transmission especially when multiple antennas are employed.

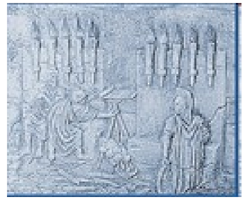
Machine learning for communications (6/6)

- For the same problem, using deep learning models, the following steps can be employed
  - Before rolling out the wireless communication system, model training is performed to get the desired models
  - The models select the appropriate beamforming vectors directly from the transmitted signals in a blind manner without a-priori known information
- The communication overhead is minimized; however, it is difficult to capture a representative dataset for training purposes
- It has been demonstrated that novel CNN and LSTM-based models may exploit inherent time and frequency correlations of OFDM signals (96% of peak performance achieved with only 18% of training data for the best model)[1]

[1] I. Nikas, C. Mavrokefalidis, K. Berberidis, "Efficient Deep Model Training for Coordinated Beam-Forming in mmWave Communications", in proc. of IWSSIP'22

SP&ML over networks - Motivation (1/10)

- In many cases, immense amounts of data are available, but at different spatial locations. Exchanging data can be prohibitive because of
  - Inefficient communication resources
  - Privacy considerations
- OR different nodes (spread in space) observe the same phenomenon
- OR they observe different views of the same phenomenon
- OR several subsets of nodes observe different phenomena
- We would like to establish a cooperation between the nodes so as to Estimate/Detect/Learn using all that data



SP&ML over networks - Formulation (2/10)

- Let us assume that there are K agents with sensing, processing, and communication capabilities and a common task.

- The agents may or may not collaborate with each other. In the former case, there can be an underlying communication topology and let N_k denote the neighborhood of agent k

- All agents aim to estimate / detect / learn a common unknown variable w using a-priori known information (e.g., statistical models in the form of probability density functions, available local data, etc.)

SP&ML over networks - Formulation (3/10)

- This is accomplished by minimizing a local cost-function $f_k(w)$
  - This cost-function can be (non)-convex
  - The minimization problem may incorporate constraints (in the form of regularizers or otherwise)

- In our discussion, the so-called global cost function is also relevant, denoted as

$$w^o = argmin_w \sum_k f_k(w)$$

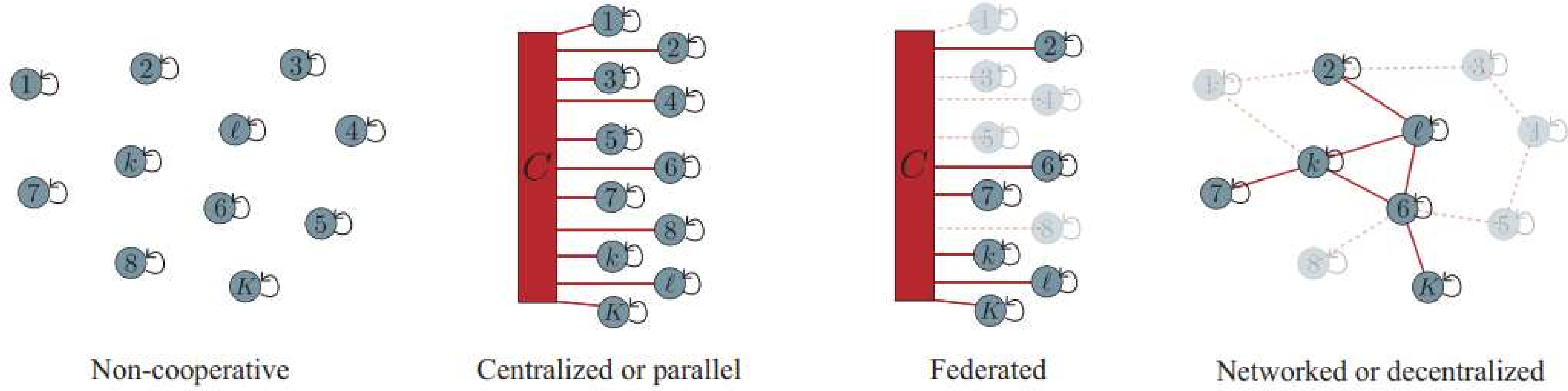
SP&ML over networks - Examples (4/10)

- In automotive domain, connected and autonomous vehicles may collaborate
  - They employ cameras, LiDAR, GPS and other sensors
  - They aim for, e.g., (a) vehicle and pedestrian recognition and (b) improving they localization information (positioning of themselves and the surrounding vehicles)
  - They use, for example, data-driven models (e.g., CNN-based, Transformer-based, etc.)
- In wireless communications, devices may collaborate
  - They sense for transmitting signals in spectral bands of interest
  - They aim for detecting spectral gaps to utilize them for their transmissions (Cognitive Radio Networks)
  - They use detection theory (if signal models are available) or data-driven models (e.g., CNNs)

SP&ML over networks - Examples (5/10)

- In the environmental domain, devices in an IoT network may collaborate towards a common task:
  - The devices sense the temperature and / or other environmental quantitates in an area of interest
  - They aim for forecasting future values in the short or long term
  - To this end, model-based linear predictors or data-driven models can be used (e.g., LSTMs)
- In smart-grids, end-users (namely, consumers) may collaborate:
  - They employ smart meters for measuring the power consumptions of houses / devices
  - The aim is to, e.g., forecast future consumption requirements for driving demand-response services or employ energy disaggregation for extracting consumption information of individual devices
  - To this end, again data-driven models can be learned and employed (e.g., dictionaries per device, LSTMs, etc.).

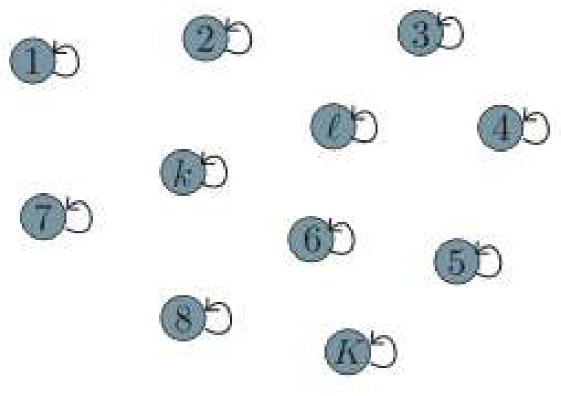
SP&ML over networks - Topologies (6/10)



- In non-cooperative topologies, each agent operates individually
- In centralized or parallel topologies or federated, local processing is employed by agents, while sending only local inferences to the fusion center C
- In networked or decentralized topologies, all participating entities are peers and collaborate for a common task

[1]Vlaski et al., "Networked Signal and Information Processing: Learning by multiagent systems", IEEE Signal Processing Magazine, 2023

SP&ML over networks – The non-cooperative case (7/10)



Non-cooperative

■ Here, each agent operates in a stand-alone fashion and solves a minimization problem with respect to its local cost-function $f_k(w)$ using, e.g., gradient descent:

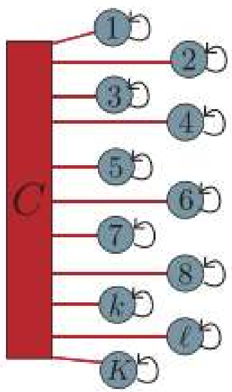
$$w_{k,i+1} = \mathrm{w}_{k,i} - \mu \nabla f_k(w_{k,i})$$

■ In case, the true gradient is not known, the estimation is used. In this case, the stochastic gradient descent iterations are employed.

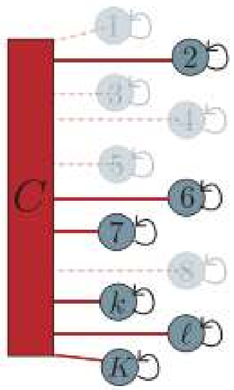
■ In the non-cooperative case, common knowledge cannot be exploited, and, in case, the local available dataset is not large enough, the minimization might lead to a poorly performing data-driven model.

[1]Vlaski et al., “Networked Signal and Information Processing: Learning by multiagent systems”, IEEE Signal Processing Magazine, 2023

SP&ML over networks – The centralized / federated case (8/10)



Centralized or parallel



Federated

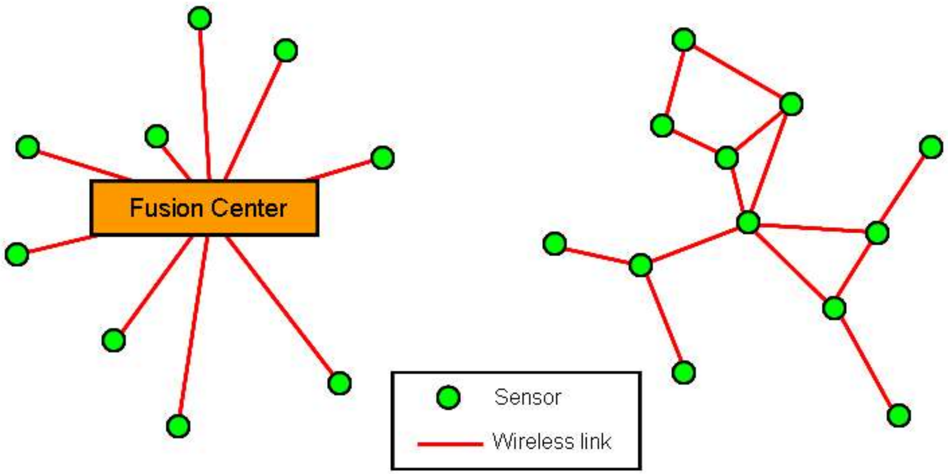
- Here, the minimization is performed following a two-step iterative procedure in order to guarantee a consensus among the agents.
- (Local step) In the first step, each agent performs local processing and forwards the results of the operation to a fusion center.
  - For example, stochastic gradient descent is used

$$w_{k,i+1} = \mathrm{w}_{k,i} - \mu \nabla f_k(w_{k,i})$$

- (Consensus step) In the second step, the fusion center aggregates the received results, namely, the w's using, for example, a mean rule, to get the new global model:

$$w_{i+1} = \frac{1}{K} \sum_{k=1}^{K} \mathrm{w}_{k,i}$$

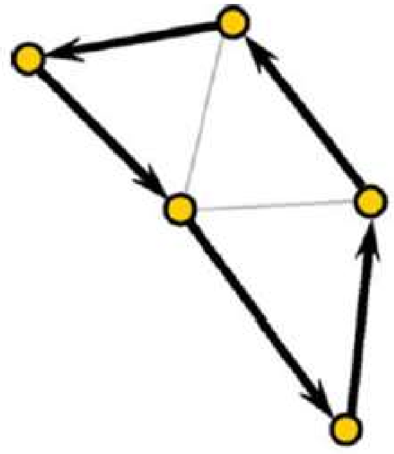
SP&ML over networks – The fully distributed case (9/10)



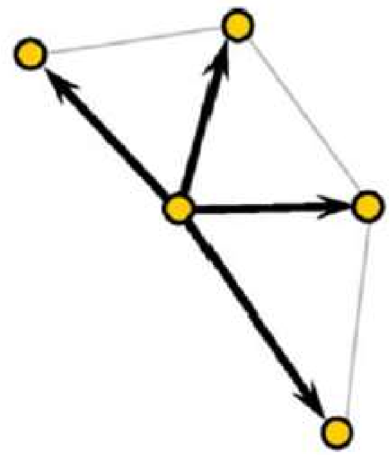
- Transmitting all data to a single location is costly
- Processing all data by a single processor is impractical
- Individual agents may not want to share sensitive/confidential local data

SP&ML over networks – The fully distributed case (10/10)

- Incremental:
  - Cyclic structure, each node knows its upstream and downstream neighbor
  - Each note sends its estimate to one neighbor
  - NP-hard problem
  - It may converge to the centralized solution

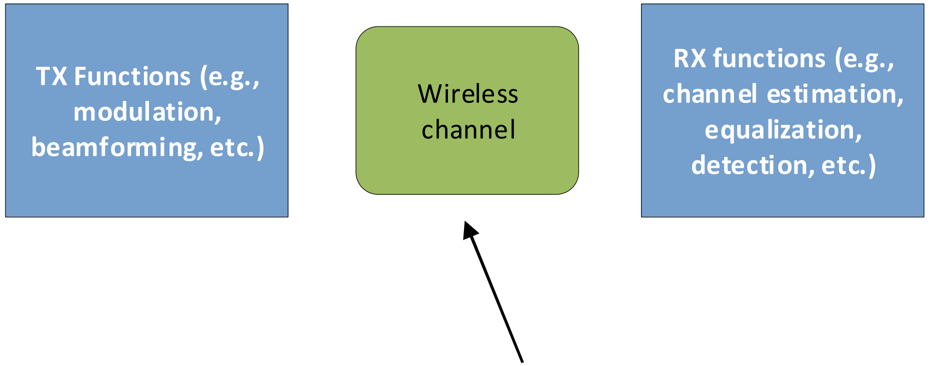


- Diffusion:
  - Each node communicates with (all) its neighbors
  - Communications cost is higher / More data to process
  - May even outperform the centralized solution
  - Higher reliability



Reconfigurable intelligent surfaces (1/3)

- Current wireless communication system designers focus their efforts on the functionality of the TX and RX devices
  - The wireless channel is uncontrollable and should be considered for efficient TX/RX operation using appropriate models, acquiring each impulse response, etc.



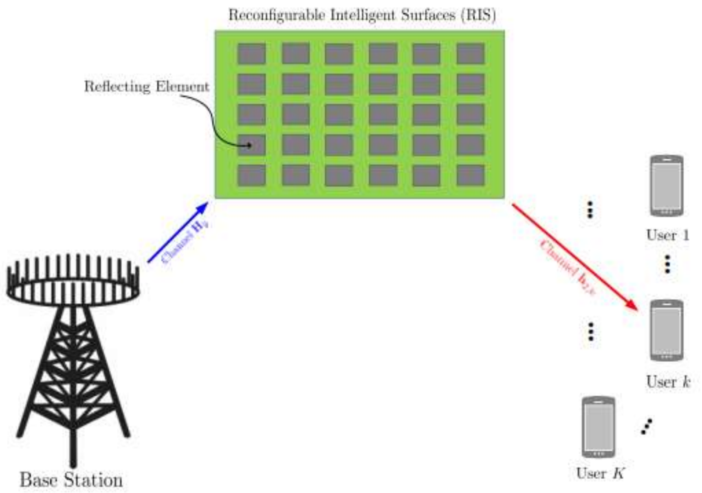
Given by nature. Something to be dealt with by the TX /RX functionalities

Reconfigurable intelligent surfaces (2/3)

- The designers of future wireless communication systems will be able to also control the wireless channels!!!
- The smart radio environment is currently under study
- A smart radio environment is a wireless environment that is turned into a smart reconfigurable space and that plays an active role in transferring and processing information
  - Namely, the wireless environment itself is turned into a software-reconfigurable entity
  - Its operation is optimized to enable uninterrupted connectivity, quality of service guarantee, etc.

Reconfigurable intelligent surfaces (3/3)

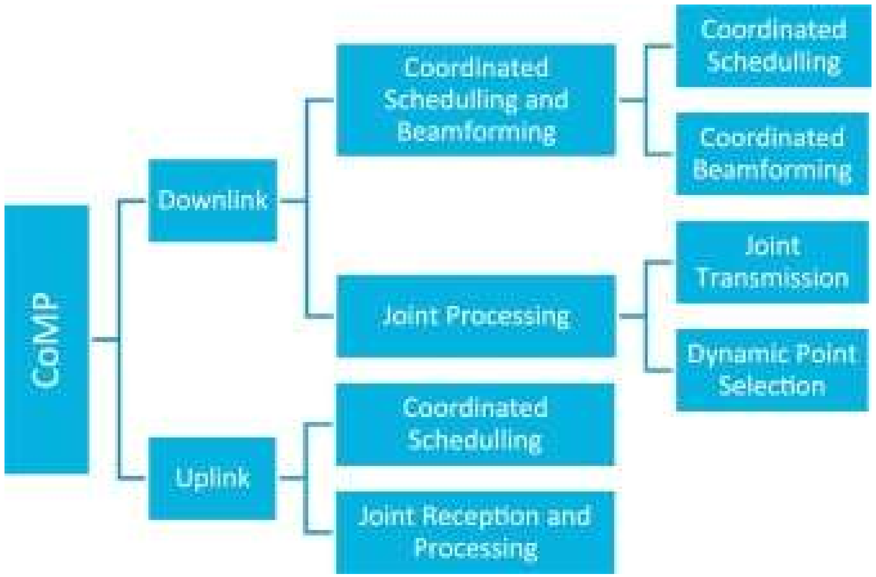
- An enabler for smart radio environments is the so-called Reconfigurable Intelligent Surface (RIS)
- RIS can be considered as an array of reconfigurable elements
  - Passive elements can reflect the incident signal with an appropriately controllable phase shift to coherently add at RX
  - Active elements can also amplify the reflected signals via amplifiers so as to compensate for the large path loss of RIS-aided links,
- RIS may achieve
  - high array gain, low cost, and
  - low power consumption,
  - high spectral efficiency

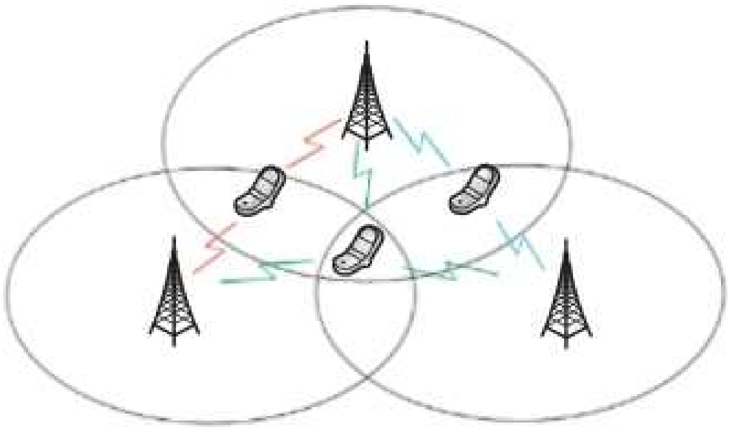


Coordinated MultiPoint transmissions (1/3)

■ Coordinated Multi-Point (CoMP) transmissions enhance throughput and coverage performance by reducing (or managing) interference, especially for cell-edge users.

■ Multiple BS stations either transmit to or receive from a single device by transmitting collaboratively coherent signals

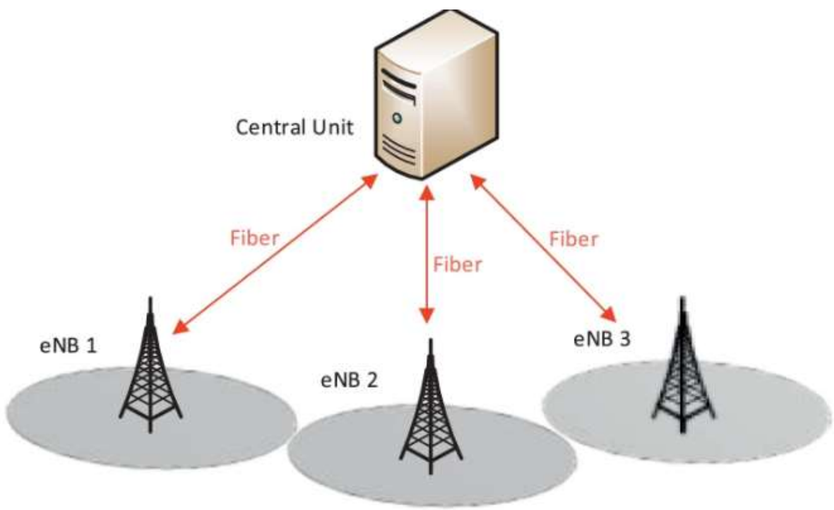




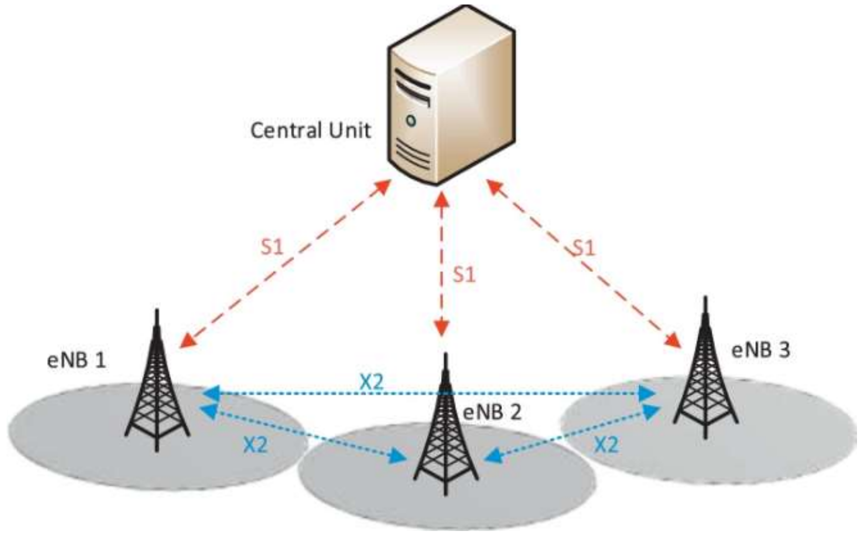
Coordinated MultiPoint transmissions (2/3)

■ In CoMP, BSs coordinate using, e.g., fiber links, either via the central unit or directly in a distributed fashion by exchanging CSI information.

Centralized CoMP

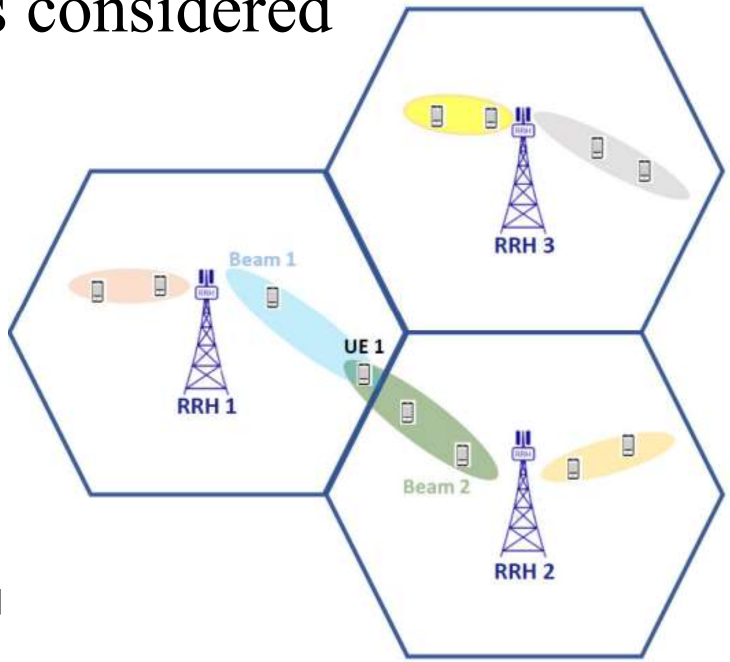


Distributed CoMP



Coordinated MultiPoint transmissions (3/3)

- As an example, cell-edge throughput improvement via CoMP in small cells is considered[1]
- To support many users in modern wireless systems, existing and new technologies need to coexist and share limited resources
- Assuming a group of small cells, clustering of BSs in COMP employing NOMA and beamforming is considered
- A coalition formation game is formulated for clustering the BSs for improving cell-edge user throughput without affecting the remaining users



[1]P Georgakopoulos et al., "Coalition Formation Games for Improved Cell-Edge User Service in Downlink NOMA and MU-MIMO Small Cell Systems", IEEE Access, 2021