Applications of Machine Learning in Wireless Communications: Deploytment, Challenges, and Applications

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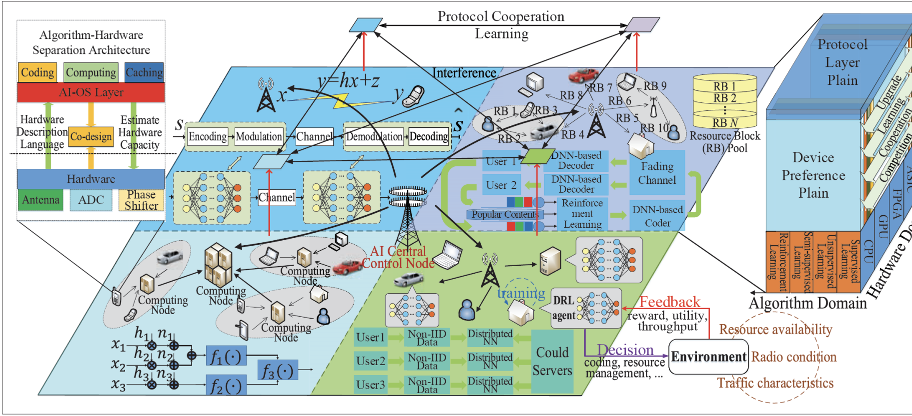
Overview

1. Deployment
   - Distribution of Network Intelligence
   - ML based Air interface
2. AI Integration: Key areas
3. Application of AI in Wireless Networks
   - AI for Physical layer
   - AI for Resource allocation
   - AI for Mobility management
   - AI for Wireless Security and Localization
4. Examples
   - Autoencoder
   - Scheduling

Motivation

- Wireless Network must support flexible data piplines for real-time decision making
- Must be AI-centric: instead of transporting user data support exchange of data, models, insights algorithms
- AI agent responsible for inclusion of data
- 5G→6G: SDR→ CogRadio→IntelRadio
- 5G→ 6G: Learning→ Deep Leaning → Federated Learning
- High degree of heterogeneity in many aspects
- Need of intelligent use of communications, control, storage resources from edge to the core
- Data driven network planning and operation

ML basel Air interface, Cont'd



6G architecture (Fig 2 in [Letaief19])

Comparison of Radio Technologies: SDR, CR, IR

	SDR (3/4G)	CR (4/5G	IR (6G)
Frequency band	Fixed	Adapt to Environment	Adapt to Env'nt and Hardware
Spectrum Sharing	Fixed	Opportunistic	AI-enabled
Hardware capability	Pre-claimed	Pre-claimed	Online estimated
Hardware upgrade	No	No	Yes
PHY Tx/Rx	Mod/Cod/ Det/Est	Mod/Cod/ Det/Est	Deep neural net
MA	Predetermined	Sensing-based	Distributed ML
Protocol L3	Fixed	Fixed	Self-upgradable
Main apps	Voice,data	Multimedia, data	AI, In network Computation

Table: Table 1 in [Letaief19]

Distribution of Network Intelligence

Feature: The network must no longer be built to transport *user-data only* but rather designed to support *exchange of data, models, and insights*, and it is the responsibility of the AI agents to include any necessary user data.
Goal: To integrate intelligent functions across the wireless infrastructure, cloud, and end-user devices with the lower-layer learning agents targeting local optimization functions while higher-level cognitive agents pursuing global objectives and system-wide awareness.

- **Autonomous** node-level AI: self-contained proplems at a node/device; no data transfer
- **Localized AI** single domain network: data tfansfer within network; geographical localization
- **Global AI** centralized entity: global knowledge, collects data and knowledge from multiple domains

Benefits and challenges at different levels of AI localization

	Autonomous AI node level AI	**Localized AI**	**Global AI**
Benefits	Ensures privacy Less delay No data overhead	Data shared across domains Favourable for power limited devices	Global optima
Chalenges	Local optima Device power and memory limitation Computational limits	Security/privacy in data sharing Data overhead Time delays	Deployment issue Data trasnfer cost Training complexity

Table: Table 1 in [Chalitta19arXiv]

Architecture and Training Challenges

- Resource shortage and negotiating of resources
- How to distribute the models and knowledge bases over the devices
- Centralized or distributed learning?
- Offline or online learning?
- How to represent and prepare data for fast consuption by algorithms
- Short-time vs Long-time scale applications

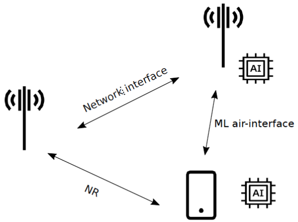
Possible training strategies: distributed ML (*i.e.* federated learning)

ML Air interface

Air interface: combination of parameters of wireless link, such as power, modulation, coding, pilots, ARQ, *etc* to facilitate wireless data transfer between two nodes.
Goals: provide effcient data transmission, low energy consupmtion, acceptable delay, proper control signalling.

ML/AI suitability ML is well adapted to optimize efficiency of transmission (modulation, coding, transmit power) since lots of data being transmitted and received
ML/AI challenges Situation awarness, control channel training (no data transmitted, received)
ML/AI initial deployment Mixed with 4G assisted and 5G NR technologies, focus on efficiency of data transfer

ML basel Air interface, Cont'd



ML air Interface supported by control plane through other network 4G/5G (Fig 1 in [Chalitta19arXiv])

Human designed RAT can be used to train ML autoencoder with indicating what bits are to be expected at the receiver and feeback losses.

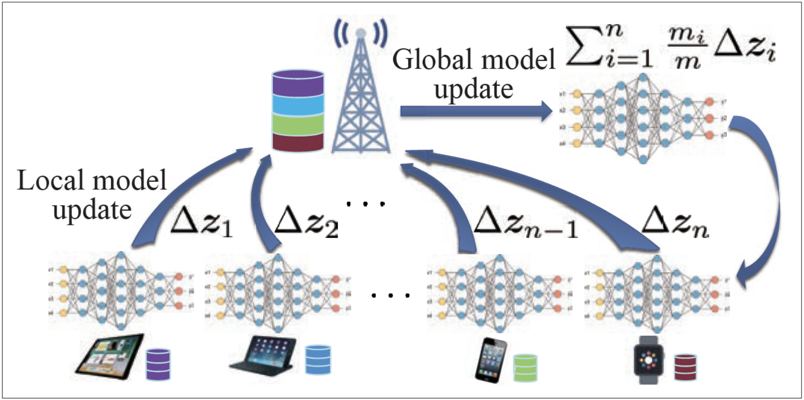
AI-enabled technologies for 6G

1. **Big Data Analytics**
2. **Closed Loop Optimization**
3. **Intelligent Wireless Comm**

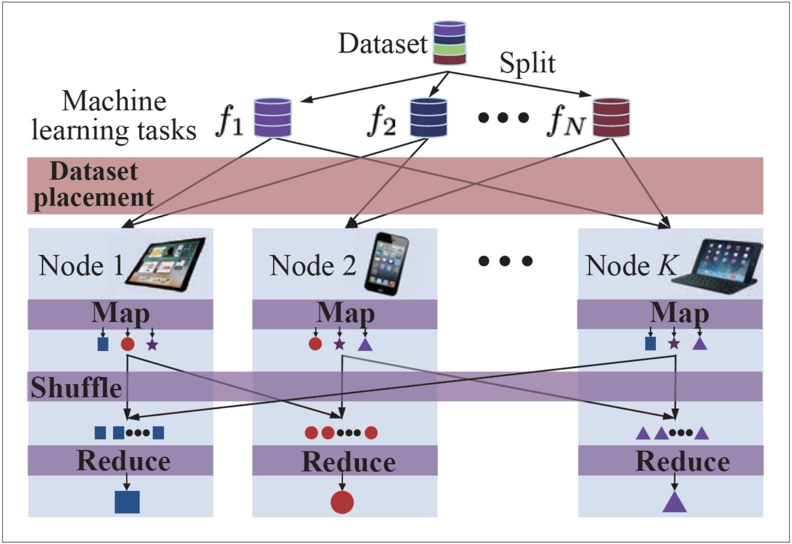
6G for AI applications

1. **Trends and challenges**
2. **Comm for distributed learning: training** Federated Training
3. **Comm for distributed learning: inference** Wireless MapReduce

Federated Learning



Distributed Inference



AI Integration: Key areas

- Data Acquisition
- Data Security and Integrity
- Confidetial computing
- Efficient AI implementation
- Reinforcement learning in cell networks
- Efficient training process
- AI alignment
- Active learning
- Explainable AI
- Real time intelligence

Background and Motivation

- Use: context information prediction, network changes adaptation, proactive radio resource management
- AI based solutions will be introduced along short/long term tracks
- **Short term** targets separate blocks (, modulation scheduler, mobility management, *etc.*)
- **Long term** cross-layer optimization based on QoE metrics, end-to-end performance, violation of OSI stack, full ML Air interface
- Importance of efficient UE measurements reporting procedures

AI for Physical layer

- ML based modulations (precoder+OFDM)
- pilotless demodulation schemes
- Intelligent Surfaces (IS) control
- fast changes detection

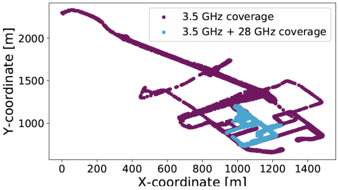
AI for resource allocation

- Generally NP–hard
- ML may provide useful heuristic instead of exact solutions
- Beam alignment
- Scheduling
- Beamforming

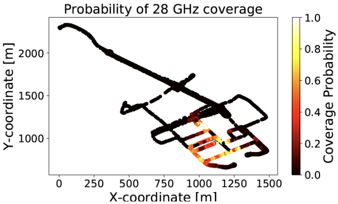
AI for Mobility management

- Use 6 GHz and above range in NR cause huge measurement overhead
- Leverage predictive power of ML for tracking and prediction
- Use lower frequency coverage measurements to predict high frequency coverage
- Multimode positioning and localization/location estimation
- Scene dependent representation of information

Example of coverage prediction



(i)



(ii)

Multiple frequency coverage map and coverage prediction using lover freqencies (Fig 4 in [Chalitta19arXiv])

AI for Wireless Security

Leverage ML classification potentian for the following tasks

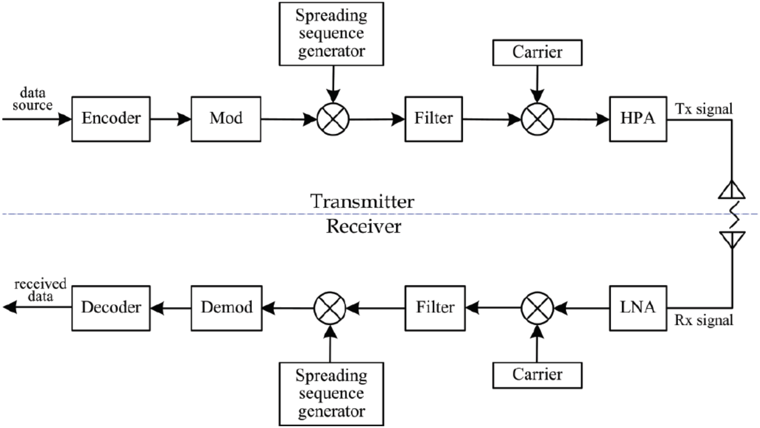
- False base station identification
- Rogue drone detection
- Rogue messaging
- Attack detection

Machine Learning Based Featureless Signalling [Shakeel18milcom]

Any features can be used by unintended receiver to detect or even decode the message. Ideal **Jamming-Resilient (JR)** signalling/**Low Probability Detection (LPD)** must satisfy the following principles

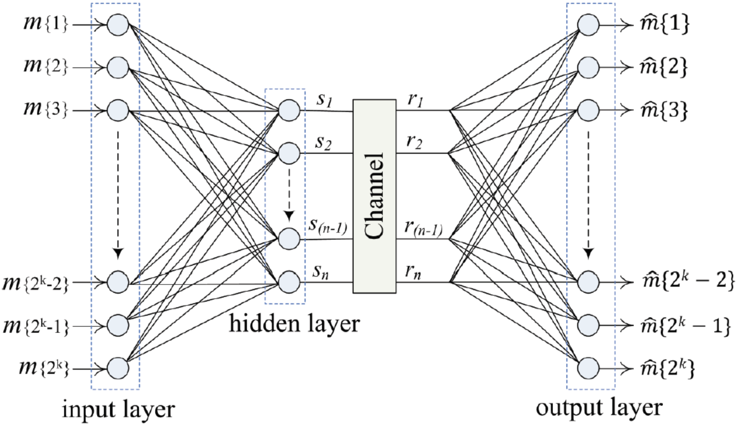
- Gaussianity (noise like) with minimum correlation
- Below noise floor (low power spectral density)
- Physical layer security
- Non-repetition
- Uncoordinated synchronization

Classical DSSS Receiver



(Fig 1 in [Shakeel18milcom])

ML DSSS Receiver



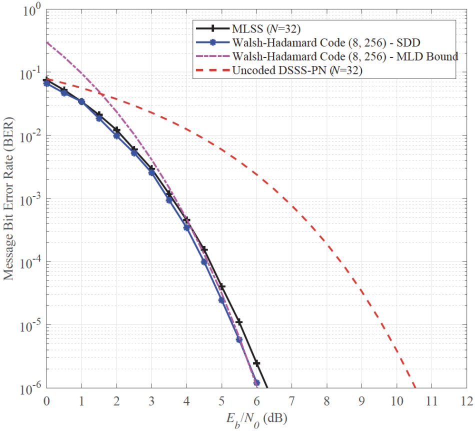
(Fig 1 in [Shakeel18milcom])

ML DSSS NN settings

Parameter	Setting
Training algorithm	One-step secant backpropagation
Number of hidden layers	1
Number of inputs- Input layer	256
Number of neurons - Hidden layers	256
Number of neurons - Output layers	256
Activation function - Hidden layer	Linear
Activation function - Output layer	Softmax
Loss function	Cross-entropy
Channel	AWGN
Trained SNR	∞
Number of trained weights	131584

Table: Table 1 in [Shakeel18milcom]

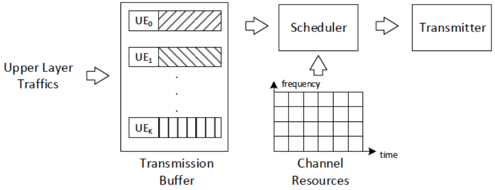
ML DSSS Receiver BER



Conlusions

- De-facto off-line training
- Channle is not realistic to allow off-line training but could be used to create a code book
- No noise considered in training
- Deep network will be required for longer messages

Buffer-Aware Wireless Scheduling [Xu19arXiv]



- System consists of K UE with packet arrival intensity λ
- Each moment of time B resource blocks are available
- N time transmission intervals are considered for planning
- Multi-objective optimization problem with three performance measures
    1. Jain's fairness index(JFI)
    2. System Throughput (THP)
    3. Packet drop rate

Schedulings, cont'd

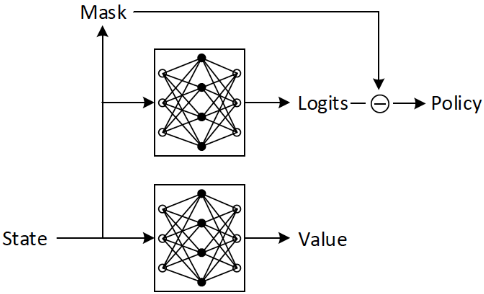
- Three objectives interrelated and cannot be optimized independently
- Pareto optimization results into a trade-off curve (Pareto Front)
- Full solution is computationally prohibitive, especially real time
- Genetic algorithms, Heuristics

Scheduling: Deep Reinforcement Learning appproach

- Model: Markov decision process (MDP): $\mathcal{S}, \mathcal{A}, R, r$
- State $\mathcal{S}$: containes all UE observations: rates, buffer state, etc
- Action $\mathcal{A}$: indicates which UE is selected for transmission
- Reward $r = \alpha THP + \beta JFI - \delta PDR$
- Actor-Critic (A2C) algorithm is used optimization (policy based Deep Reinforced Learning): directly parameterises policy $\pi_\theta(a|s)$
- Updates gradient descent of expected return

$$g = \nabla_\theta \mathcal{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right]$$

DRL algorithm: cont'd



DRL algorithm: cont'd

Algorithm 1 A2C algorithm

Initialize all environments
Initialize actor network π_θ and critic network V_ϕ
Initialize experience buffer E
for iteration = 1, M **do**
  SAMPLE_BATCH(n, π_θ)
  Update discounted reward r_i for ith experience
  Policy objective $J_\theta = \sum_i (r_i - V_\phi(s_i)) \log \pi_\theta(a_i|s_i)$
  Entropy term $H_\theta = -\sum_i \pi_\theta(a_i|s_i) \log \pi_\theta(a_i|s_i)$
  MSE of value $L_\phi = \sum_i (r_i - V_\phi(s_i))^2$
  SGD with $G = -(\nabla_\theta J_\theta + \lambda_e \nabla_\theta H_\theta) + \lambda_v \nabla_\phi L_\phi$
end for
function SAMPLE_BATCH(n, π_θ)
  Clear E
  for t = 1, n **do**
    Observe s_t
    Choose action $a_t \sim \pi_\theta(s_t)$
    Take action a_t, observe s_{t+1} and r_t
    Store (s_t, a_t, r_t, s_{t+1}) into E
  end for
end function

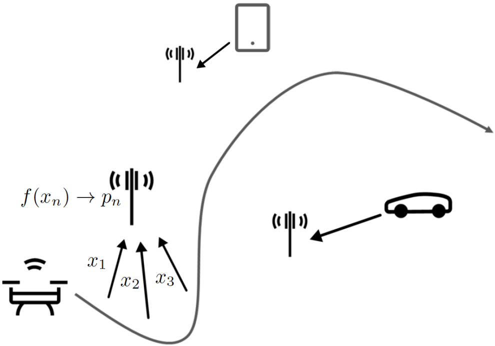
ML for Rogue Drone Detection [Ryden19WCNC]

Civilian use of drones (unmanned airial vehicles)

- Precision Agriculture
- Inspection and Monitoring
- Delivery
- Photography
- Mobile base stations, sidelobe BS enhancers and relays
- **Problem:** Rogue drones can pose as legitimate UE drones, especially drone with attached registered UE like a cell phone. may cause additional interference.

Problem statement

- Detect a UE which is unauthorized drone
- Use of service area handover triggering event A3 and radio measurement
- $f(x) \rightarrow p$: $f(\odot)$ is ML model, x UE reported measurement, p probability of being a drone



Contsructing the ML model

- Supervised learning
- Data is generated through 3GPP model simulations (training and test sets)
- Legitimate drones are labelled as such
- Mixture of drone and land mobile UE is used
- Feature metric: RSSI, RSSI-gap, RSSI-STD
- Logistic regression

$$p = \frac{1}{1 + \exp\left(-\alpha - \beta_1 x_1 - \cdots - \beta_n x_n\right)}$$

Results

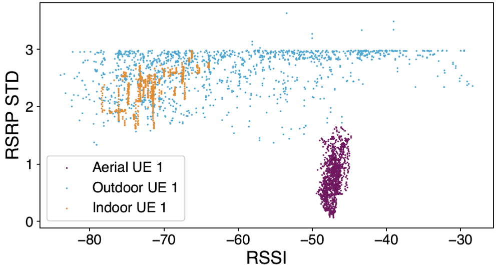
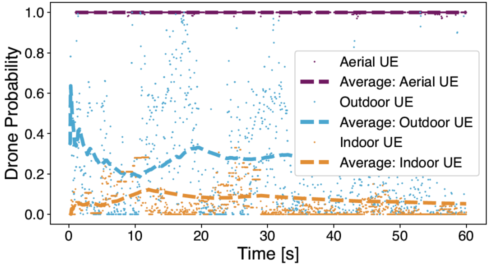


Fig. 4. {RSSI, RSRP-STD} samples for three UEs of different types



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