When Learning Meets the Channel: Edge AI through Split and Semantic Design
Part II

Vukan Ninković

October 28, 2025

Overview

1. Introduction & Motivation

2. Background & System Model

3. Vanilla Approach – Does It Work?

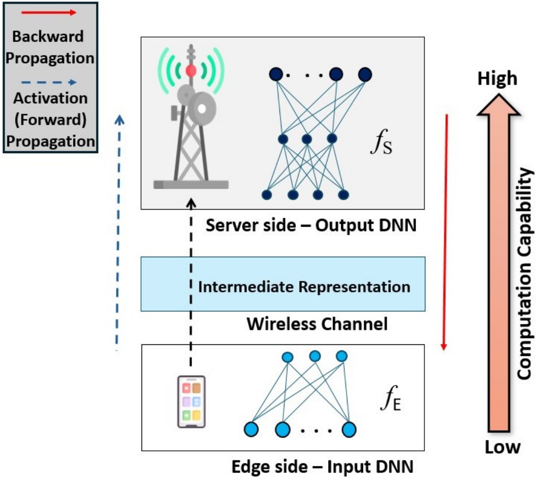
4. Extension 1 – Are All Symbols Equally Important?

5. Extension 2 – Semantic & AE-PHY
in UAV-Assisted IoT

6. Discussion

Introduction & Motivation

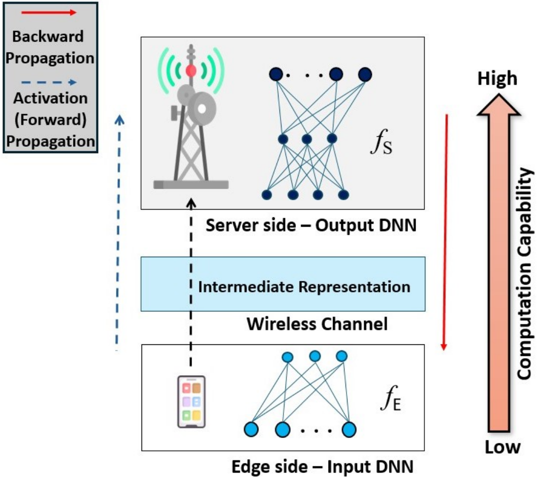
(Quick) Recap



Backward Propagation
Activation (Forward) Propagation
f_S
Server side – Output DNN
Intermediate Representation
Wireless Channel
f_E
Edge side – Input DNN
High
Computation Capability
Low

(Quick) Recap

- **Focus:** Communications for AI-driven systems.



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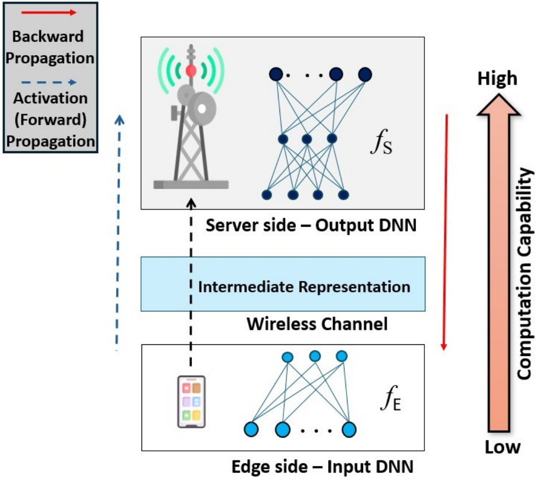
  - Promising performances in controlled settings.



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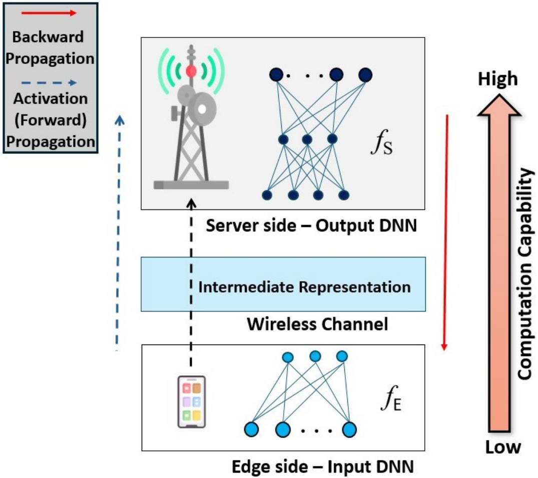

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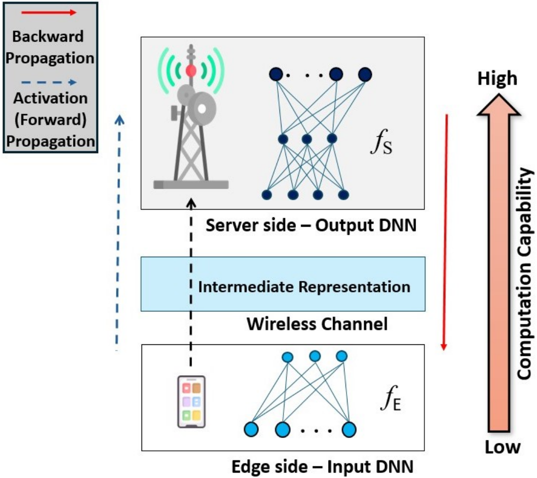
- **Challenges:**
  - Channel-coded latent transmission?
  - Max-info latent under bandwidth constraints?



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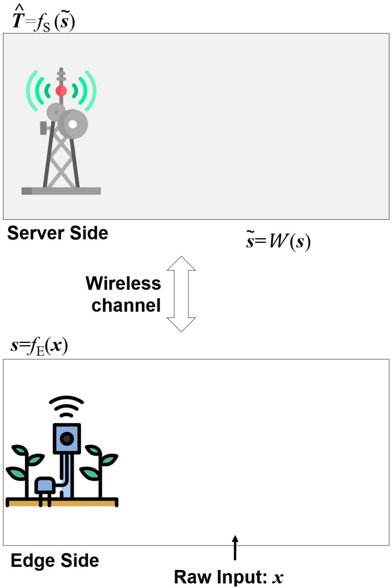
- **Semantic communication:** Send only information necessary for the task.
- **Solution:** Synergy of SL, AE–based PHY layer design and semantic communication:
  - Semantic- and channel-aware learning architecture for IoT edge-to-cloud forecasting.

Background & System Model

System Overview



System Overview

$$\boldsymbol{s} = f_{\mathrm{E}}(\boldsymbol{x})$$

$$f_{\mathrm{E}} : \mathbb{R}^N \to \mathbb{R}^n, \quad n < N$$

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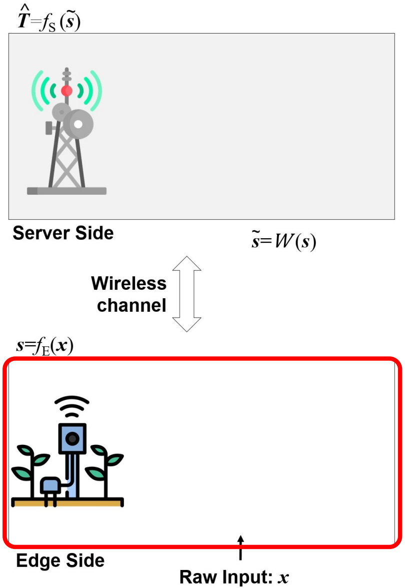

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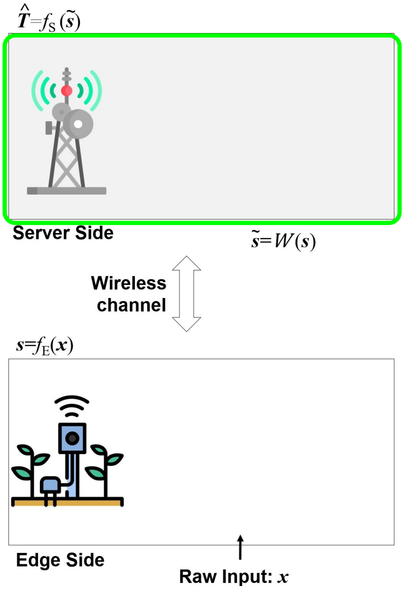

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Compact and informative representation?

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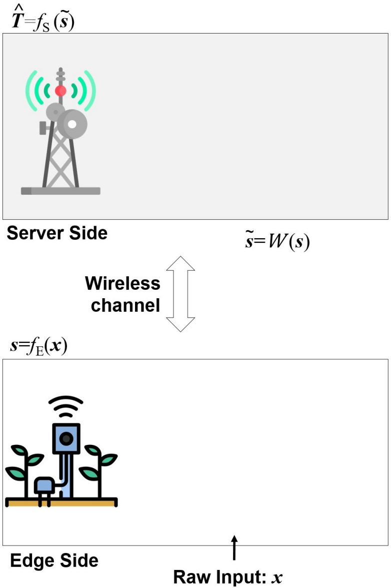

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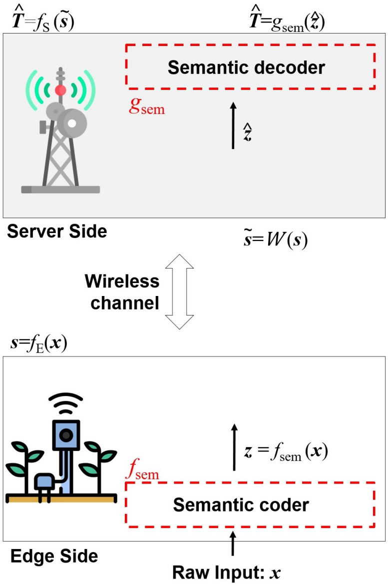

Semantic Communication

- Redefines objectives of communication systems:
  - **Focus:** From signal–level accuracy to the successful completion of different tasks.
  - Instead to recover the input ($\boldsymbol{x}$), task-relevant output is approximated ($\hat{T}(\boldsymbol{x})$).
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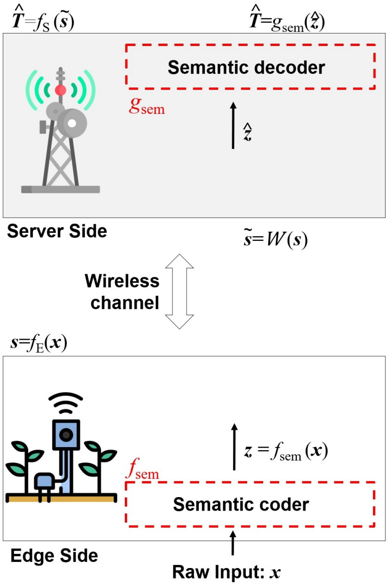

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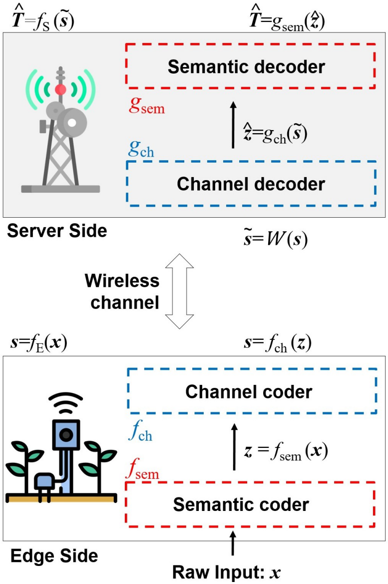

AE-Based PHY Modeling

- Flexible framework for designing the PHY layer as a differentiable neural network:
  - Separate modulation and coding blocks $\rightarrow$ Single end-to- end trainable system[1].
- f_{ch} and g_{ch} realized as symmetric AE neural network:
  - Semantic representation $\boldsymbol{z} \in \mathbb{R}^K \rightarrow$ Transmitted signal $\boldsymbol{s} \in \mathbb{R}^n$

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- Redefinition of the original training procedure - MSE loss:

$$\mathcal{L}_{\mathrm{AE}} = \sum_{k \in K} \|\hat{z}_k - z_k\|^2 \tag{2}$$

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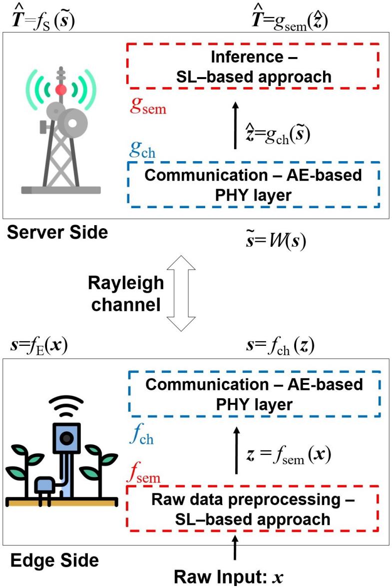

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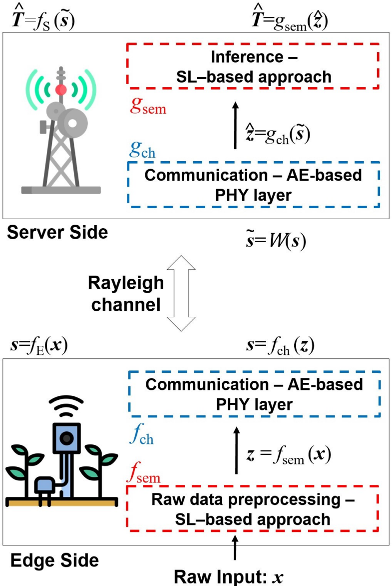

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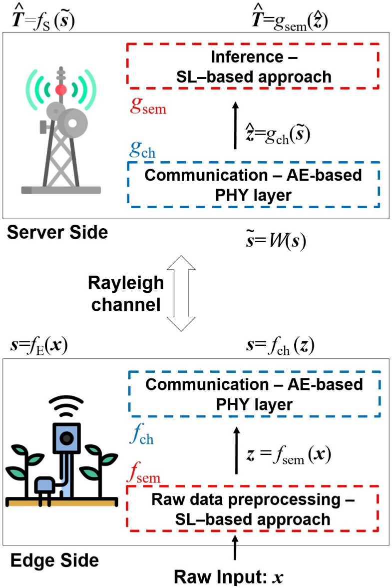

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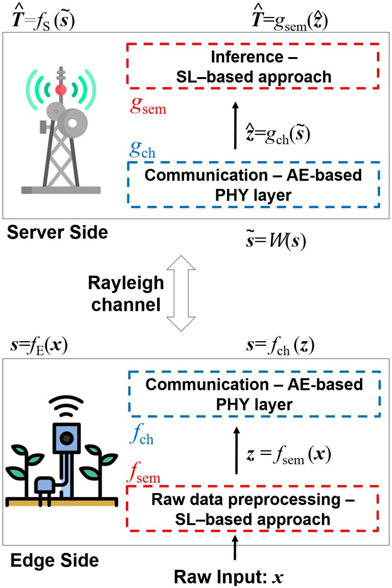

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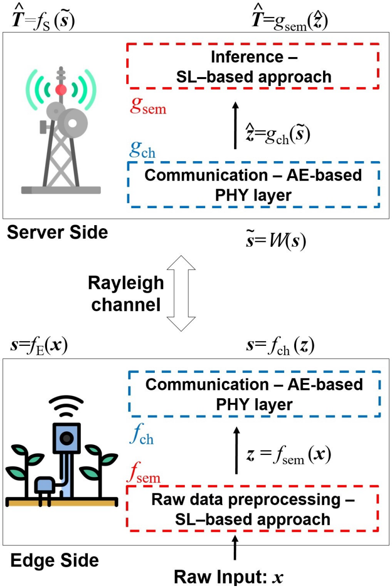

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- Overall inference system:

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- All components of the system - $f_{\text{sem}}, f_{\text{ch}}, g_{\text{ch}}, g_{\text{sem}}$:
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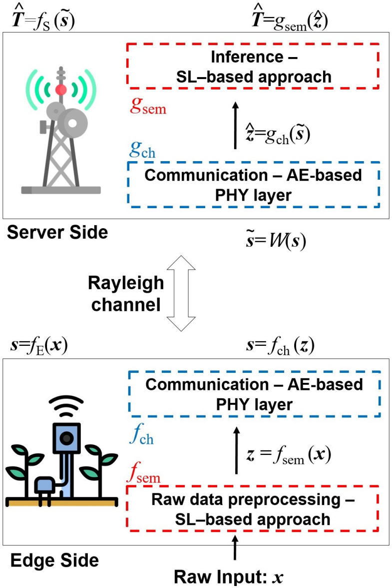

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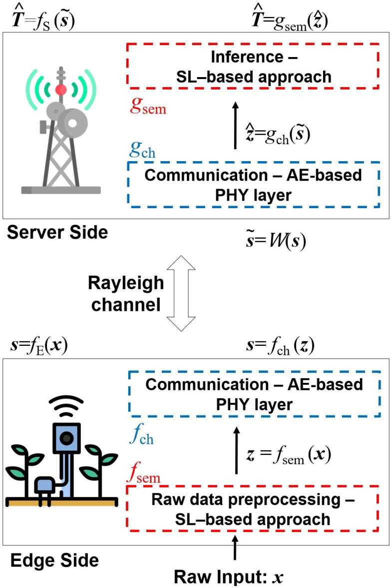

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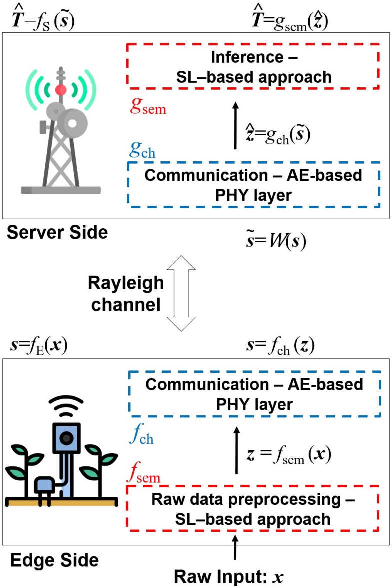
- **Goal:** Balance between semantic fidelity, channel resilience, and task reliability.



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Vanilla Approach – Does It Work?

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  - **Semantic part** - Two–layer LSTM network ($K = 10$ hidden states) followed by a FC layer:
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  - **Channel part** - Simple AE architecture (with symmetric FC layers):
    - f_{ch} and g_{ch} comprise a single hidden layer with 10 neurons.
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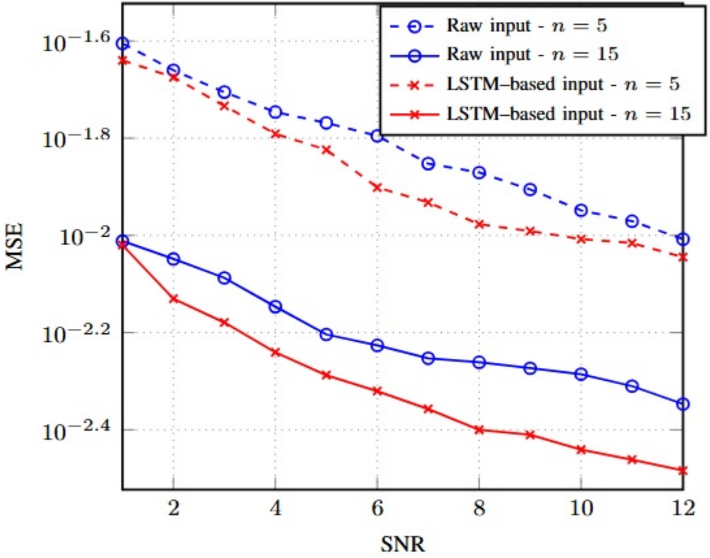
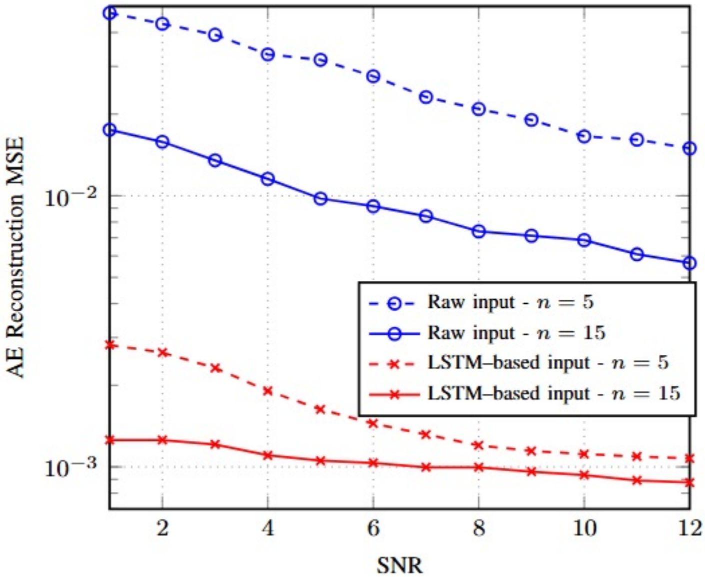
- Loss function:

$$\mathcal{L} = \underbrace{\mathcal{L}(T, \hat{T}(\boldsymbol{x}))}_{\text{Task Loss}} + \underbrace{\mathcal{L}_{\text{AE}}(\boldsymbol{z}, \hat{\boldsymbol{z}})}_{\text{AE Rec. Loss}} = \mathbb{E}\left[(\hat{T} - x_{t+1})^2\right] + \mathbb{E}\left[||\hat{\boldsymbol{z}} - \boldsymbol{z}||_2^2\right] \quad (4)$$

Performance Evaluation - Task MSE



Performance Evaluation - AE Reconstruction MSE



Extension 1 – Are All Symbols Equally Important?

Experimental Setup & Training procedure

- We reuse dataset and NN architecture from the vanilla approach.

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- **Solution:** AE-based unequal error protection (UEP) codes[2].
  - Not all parts of the message are equally protected.
  - Training procedure – composite loss function:

$$\mathcal{L}_{\mathrm{UEP}} = \lambda \sum_{k \in \mathcal{K}_{\mathrm{imp}}} \|\hat{z}_k - z_k\|^2 + (1-\lambda) \sum_{k \notin \mathcal{K}_{\mathrm{imp}}} \|\hat{z}_k - z_k\|^2, \tag{5}$$

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- $1 \geq \lambda > 0.5$ – weighting parameter (flexible trade-off between classes).

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- $1 \geq \lambda > 0.5$ – weighting parameter (flexible trade-off between classes).
- **Problem:** $\mathcal{K}_{\mathrm{imp}}$ is fixed in conventional UEP schemes, but in a dynamic IoT system symbol importance evolves over time.

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Training Procedure - Dynamic UEP

- **Proposed solution:**
  - Recall the IB principle:

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  - $f_\theta(\boldsymbol{z}, T(\boldsymbol{x}))$ - Neural discriminator implemented as a three-layer FC + ReLU network.
  - **Training batch:** Compute gradients of $\hat{I}(\boldsymbol{z}; T(\boldsymbol{x}))$ w.r.t. $\boldsymbol{z}$, select the L most task-relevant latent dimensions, and update the ranking dynamically.

Training Procedure - Dynamic UEP

- **Proposed solution (continued)[3]:**

[3] V. Ninkovic, D. Vukobratovic, D. Miskovic, and C. Wang, "Adaptive Unequal Error Protection for Semantic Split Learning over Wireless Channels", submitted at *2026 IEEE ICC.*

Training Procedure - Dynamic UEP

- **Proposed solution (continued)**[3]**:**
  - AE reconstruction loss (Eq. 5) remains compound, with $\mathcal{K}_{\mathrm{imp}}$ ($|\mathcal{K}_{\mathrm{imp}}| = L$) determined adaptively.

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$$\mathcal{L} = \mathcal{L}_{\text{task}} + \mathcal{L}_{\text{UEP}} + \mathcal{L}_{\text{MI}}. \tag{8}$$

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  - $\mathcal{L}_{\mathsf{MI}}$ — negative DV bound (Eq. (7)) used to train f_θ:
    - Enables stable estimation of $I(\boldsymbol{z}; T(\boldsymbol{x}))$.
    - Allows reliable identification of $\mathcal{K}_{\mathrm{imp}}$.

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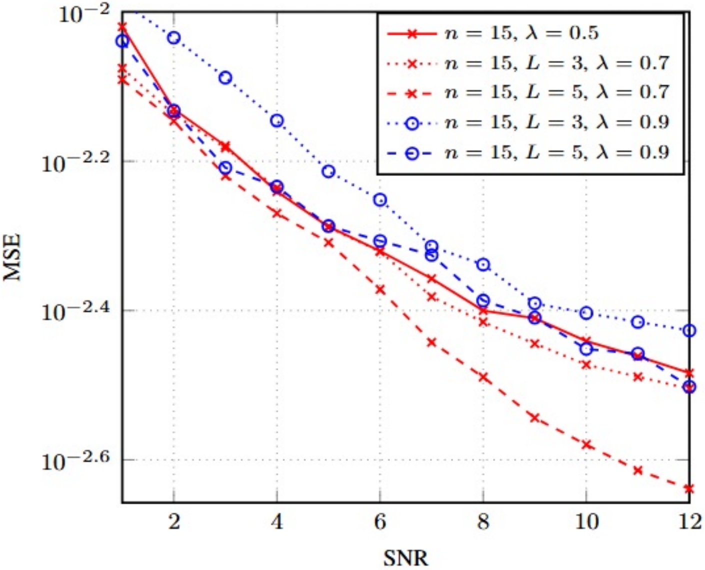
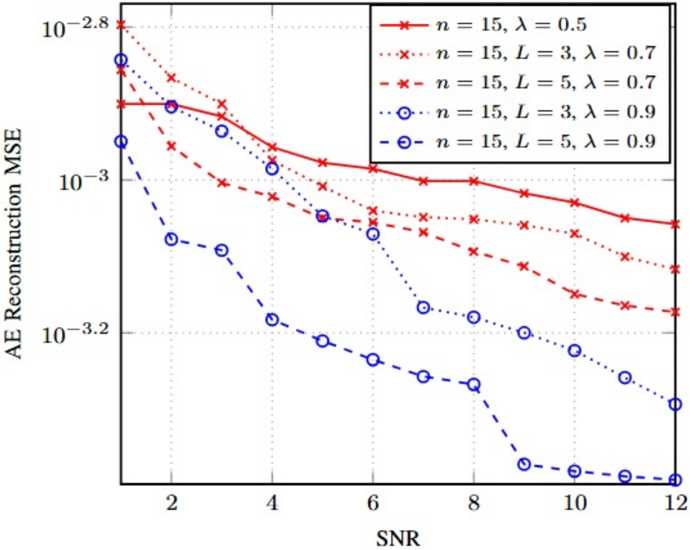
Impact of Dynamic UEP on Performance - Task MSE



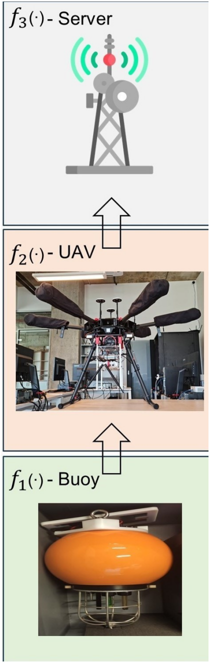
Impact of Dynamic UEP on Performance - AE Reconstruction MSE



Extension 2 – Semantic & AE-PHY in UAV-Assisted IoT

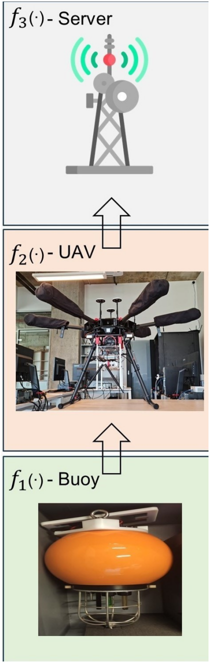
System Model

- Push toward real-world deployment.



System Model

- Push toward real-world deployment.
- UAV-assisted IoT system:
  - UAV acts both as a relay and as part of the inference system.
  - Buoy $\rightarrow$ UAV $\rightarrow$ Server.



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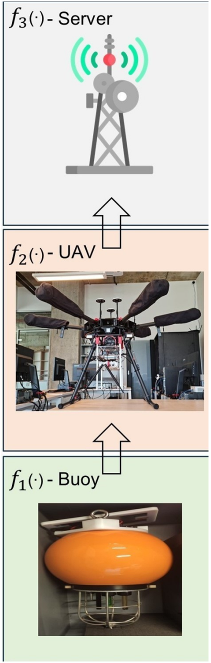
  - SL and semantic communications for information (pre)processing.
  - AE-based physical-layer/channel coding.
  - Early Exit mechanism.



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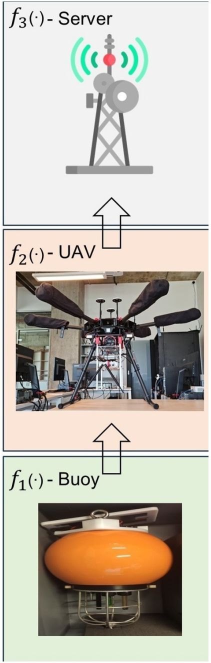
- Integration of multiple principles:
  - SL and semantic communications for information (pre)processing.
  - AE-based physical-layer/channel coding.
  - Early Exit mechanism.
- Three deployment scenarios:
  - Semantics processed at the server.
  - Semantics processed at the UAV.
  - Semantics processed at the edge (IoT device).



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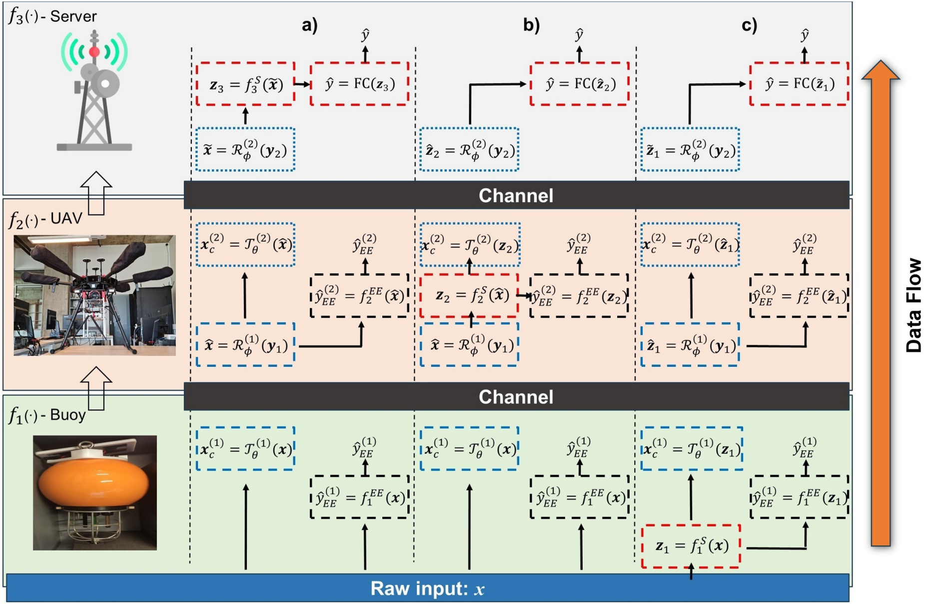
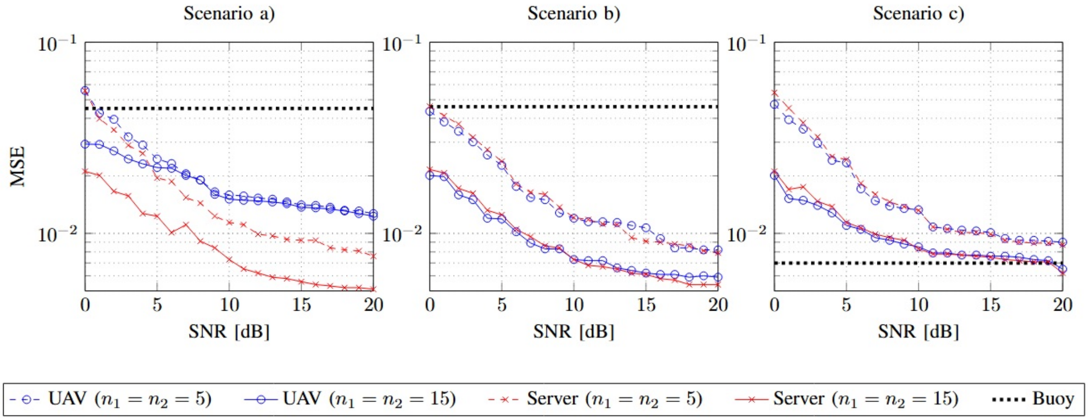


Experimental Setup & Training Procedure

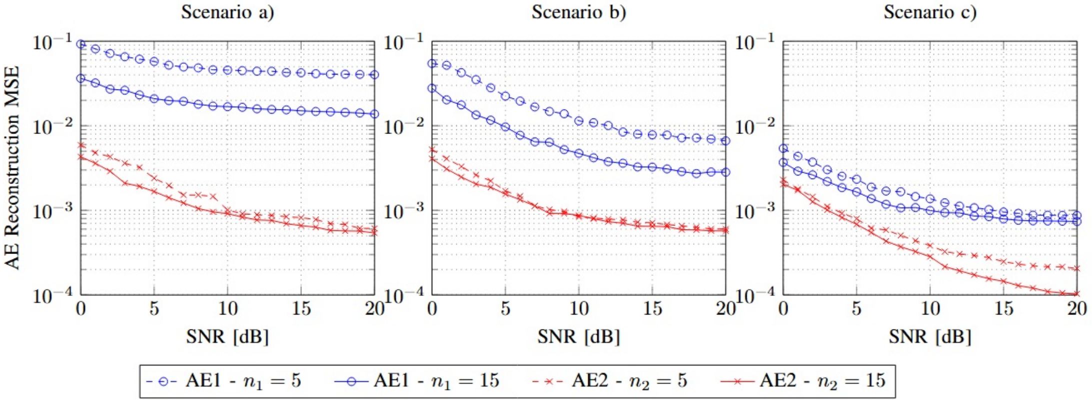
- Dataset: Pollution of the Danube river near Novi Sad.
  - 3,264 instances - Each instance represents a daily measurement from 2013 to 2022
  - Estimation of dissolved oxygen based on previous $N = 10$ days.
- Neural network architecture:
  - **Semantic part -** LSTM layer (with 10 hidden states) + FC layer:
    - Server side - Always FC layer.
    - LSTM layer position depends on implementation scenario.
  - **Channel part:**
    - Two AE modules (AE1 between buoy and UAV, AE2 between UAV and server).
    - Symmetric AE architecture with one hidden FC layer.
  - **Early Exit** - Additional FC layer.
- Loss function:

$$\mathcal{L} = \underbrace{\mathcal{L}_{\text{task}}}_{\text{Task loss}} + \underbrace{\mathcal{L}_{\text{EE}_1}}_{\text{EE at buoy}} + \underbrace{\mathcal{L}_{\text{EE}_2}}_{\text{EE at UAV}} + \underbrace{\mathcal{L}_{\mathrm{AE}_1}}_{\text{AE1 recon.}} + \underbrace{\mathcal{L}_{\mathrm{AE}_2}}_{\text{AE2 recon.}} \tag{9}$$

Performance Evaluation - Task MSE



Performance Evaluation - AE Reconstruction MSE[4]



[4] V. Ninkovic, R. S. Molina, et al. "Semantic IoT Framework for Environmental Monitoring: FPGA-Accelerated Distributed Learning at the Edge," manuscript in preparation

Discussion

Next Steps & Open Problems

- Step toward practical task-oriented IoT monitoring.
- Further move toward real-world implementation — FPGA deployment[5].

[5] Already implemented; details will be presented by Romina Soledad Molina

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  - Controlled lab environment as an initial stage.
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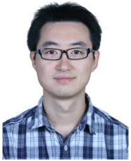
  - Real-world field deployment as the next step.
- Fits within the broader vision of 6G communication architectures.
- Next steps — multimodal data processing, multi-task learning, and adaptive prioritization across heterogeneous devices.

[5] Already implemented; details will be presented by Romina Soledad Molina

Acknowledgment[6]

Dejan Vukobratovic, PhD

Dragisa Miskovic, PhD



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[6]This work has received funding from: the Horizon 2020 grant agreement No 101086387 - REMARKABLE; the Serbian Ministry of Science, Technological Development and Innovation (No. 00101957 2025 13440 003 000 620 021) & Intergovernmental International Science and Technology Innovation Cooperation of National Key Research & Development Program of China under Grant 2024YFE0197400.

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Thank you for your attention!

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