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User Scheduling in Integrated Satellite-HAPS-Ground Networks Using Ensembling Deep Neural Networks

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Outline

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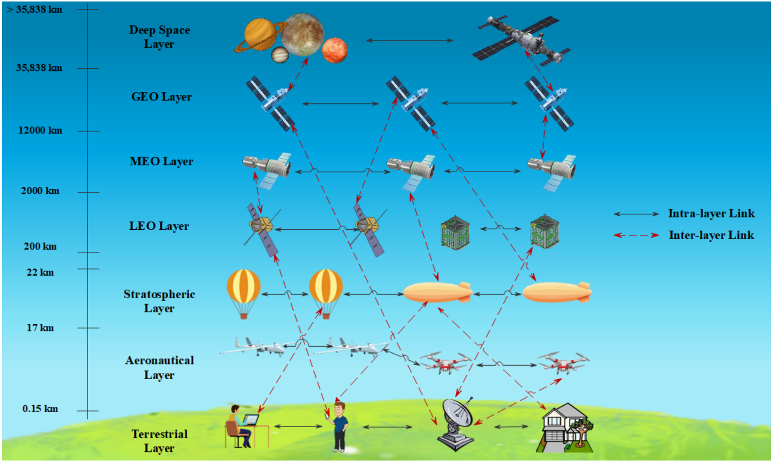
1. Motivation
2. System Model and Problem Formulation
3. Proposed Solution
   - Ensembling Deep Neural Networks
4. Simulation Results
5. Conclusions

Integrated Satellite-Air-Ground Networks

- 6G KVIs: Seamless, sustainable, resilient, digital inclusion.



N.Saeed, H.Almorad, H.Dahrouj, T.Y.Al-Naffouri, J.Shamma and M.-S.Alouini, "Point-to-Point Communication in Integrated Satellite-Aerial 6G Networks: State-of-the-Art and Future Challenges", in IEEE OJCOMS, Jun. 2021.

Integrated Satellite-HAPS-Ground Networks

- Current terrestrial communication infrastructure cannot empower the sixth generation of communication networks (6G).
  1. Terrestrial densified networks cannot cover extreme areas.
  2. Ultra-dense networks often prove to be interference-exacerbated.
- Space-air-ground network can
  1. Provide seamless, sustainable connectivity to extreme areas.
  2. Achieve the global digital inclusion needed in 6G systems.
  3. Provide connectivity from the sky.
  4. Democratize digital services.

Machine Learning for Space-Air-Ground Networks

- Space-air-ground networks are heterogeneous and complex.
  1. Consist of interconnecting segments (i.e., satellite segment, air segment, and ground segment).
  2. Optimization problems across the different layers are challenging.
- Machine learning is efficient for optimizing wireless systems.
  1. Accurate communication model is difficult to obtain.
  2. Traditional algorithms exhibit high computational complexity.
  3. Optimization problem is complex.

Our Work Contributions

1. Deep neural network is proposed to solve the user scheduling problem in a satellite-HAPS-ground network.
2. Ensembling deep neural networks are adopted to further improve system performance.
3. Simulations highlight the numerical prospects of the proposed solution.

Previous Works

This work is related to user scheduling and machine learning:

- User scheduling in typical terrestrial communication network:
  - Kaushik et al. (ICCW'21).
  - User-Association which can be formulated as generalized assignment problems is solved by deep neural network.
  - Interference between BSs is not considered.
- Resource management in device-to-device (D2D):
  - Cui et al. (JSAC'19) and Liang et al. (TWC'20).
  - Spatial convolutional filters + ensembling deep neural network.
  - Connectivity is limited to D2D.

Outline

Network Configuration

- Integrated satellite-HAPS-ground: one satellite, one HAPS, N_B ground BSs and N_U users.
- The satellite and HAPS are connected via FSO, and each user is served by either one of the BSs or by the HAPS via RF links.

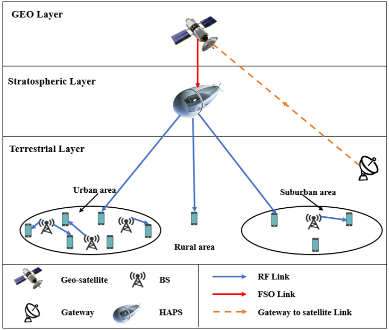


Figure: System model.

Rate Expression

- The rate of user j, once served by BS i:

$$R_{ij}^{Ground\_BS} = \beta \log_2 \left(1 + \frac{|\mathbf{h}_{ij}^{H} \mathbf{w}_{ij}|^2}{\sum_{u=1, u \neq j}^{N_U} \sum_{b=0}^{N_B} \gamma_{bu} \alpha_{bu} |\mathbf{h}_{bj}^{H} \mathbf{w}_{bu}|^2 + \sigma^2} \right), \quad (1)$$

- The achievable rate of user j served by the HAPS via the RF link:

$$R_{0j}^{HAPS\_RF} = \beta \log_2 \left(1 + \frac{|\mathbf{h}_{0j}^{H} \mathbf{w}_{0j}|^2}{\sum_{u=1, u \neq j}^{N_U} \sum_{b=0}^{N_B} \gamma_{bu} \alpha_{bu} |\mathbf{h}_{bj}^{H} \mathbf{w}_{bu}|^2 + \sigma^2} \right). \quad (2)$$

$$R_{0j}^{HAPS} = \min\{R_{0j}^{HAPS\_RF}, R_{FSO}\}, \quad (3)$$

- Scheduling: User to geo-satellite via the HAPS, or user to BS, i.e., $\alpha_{ij} \in \{0, 1\}$.

Objective

Maximize the system's sum-rate, which consists of:

- Rate of user served by ground BS.
- Rate of user served by HAPS subject to backhaul capacity constraints:

$$R = \sum_{j=1}^{N_U} \left(\sum_{i=1}^{N_B} \gamma_{ij} \alpha_{ij} R_{ij}^{Ground\_BS} + \gamma_{0j} \alpha_{0j} R_{0j}^{HAPS} \right) \quad (4)$$

Constraints

- Payload constraints:

$$\sum_{j=1}^{N_U} \gamma_{ij}\alpha_{ij} \leq M_i, \; \forall i \in \mathcal{B}, \tag{5}$$

$$\sum_{i=0}^{N_B} \gamma_{ij}\alpha_{ij} \leq 1, \; \forall j \in \mathcal{U}, \tag{6}$$

- Fairness constraint:

$$\sum_{i=0}^{N_B} \sum_{j=1}^{N_U} \gamma_{ij}\alpha_{ij} \geq K, \tag{7}$$

- Binary variable constraint:

$$\alpha_{ij} \in \{0, 1\}, \; \forall i \in \mathcal{B}, \forall j \in \mathcal{U}, \tag{8}$$

- Power constraint:

$$\sum_{j=1}^{N_U} \gamma_{ij}\alpha_{ij}\mathbf{w}_{ij}^H \mathbf{w}_{ij} \leq P_i^{max}, \; \forall i \in \mathcal{B}. \tag{9}$$

Problem Formulation

$$\max_{\alpha_{\mathbf{ij}}} \quad \sum_{j=1}^{N_U} \left(\sum_{i=1}^{N_B} \gamma_{ij}\alpha_{ij}R_{ij}^{Ground\_BS} + \gamma_{0j}\alpha_{0j}R_{0j}^{HAPS} \right) \tag{10}$$

$$\text{subject to} \quad \text{Constraints } (3), (5),\ (6),\ (7),\ (8),\ \text{and } (9)$$

- It is non-convex and discrete $\Rightarrow$ hard to solve.

Outline

Learn to Optimize

- Supervised learning: using ILP-GAP to generate labeled training data.
  - A massive amount of training data is computationally intensive.
  - Supervised learning strongly depends on the original algorithm.
- Unsupervised learning: excavating models from unlabeled data.
  - Objective function is used as the loss function.
  - Using specific penalty terms to account for the constraints.
  - Ensembling learning is adopted to improve the optimality search.
- Supervised learning is akin to a redesign of existing traditional methods
- Adopt unsupervised learning to address the user scheduling dilemma.

Loss Function

Using an online optimization approach, the maximization problem (10) can be recast as a minimization of the following loss function:

$$L = \mathbb{E}[-R(\mathbf{H}, \gamma, \boldsymbol{\theta}) + (\sum_{j=1}^{N_U} \mu_j C_{1,j}) + (\sum_{i=0}^{N_B} \lambda_i C_{2,i}) + (\sum_{i=0}^{N_B} \delta_i C_{3,i}) + \rho C_4], \quad \text{(11a)}$$

where

$$C_{1,j} = ReLU(\sum_{i=0}^{N_B} \gamma_{ij}\alpha_{ij} - 1), \quad \text{(11b)}$$

$$C_{2,i} = ReLU(\sum_{j=1}^{N_U} \gamma_{ij}\alpha_{ij} - M_i), \quad \text{(11c)}$$

$$C_{3,i} = ReLU(\sum_{j=1}^{N_U} \gamma_{ij}\alpha_{ij}\mathbf{w}_{ij}^H \mathbf{w}_{ij} - P_i^{max}), \quad \text{(11d)}$$

$$C_4 = ReLU(K - \sum_{i=0}^{N_B} \sum_{j=1}^{N_U} \gamma_{ij}\alpha_{ij}), \quad \text{(11e)}$$

Deep Neural Network Structure

- the neural network consists of 2 hidden layers which have $ReLU$ activation functions and adopts batch normalization.

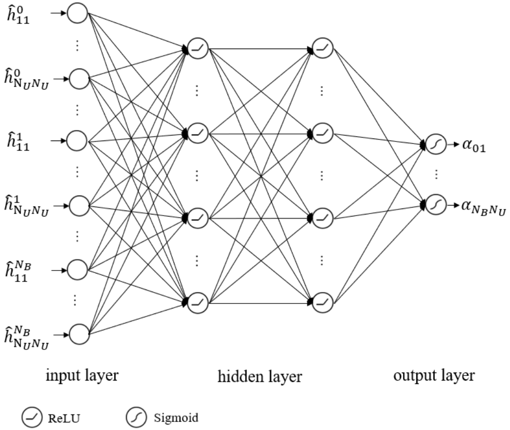


Figure: The structure of deep neural network (DNN).

Ensembling Deep Neural Networks

- Each of the ensembling of deep neural networks is trained with different training data and initialization methods.
- The best resulting solution is selected.

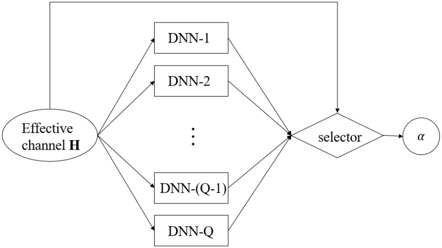


Figure: Model of ensembling deep neural networks.

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Simulation Model

Table: Simulation Parameters

Parameter Name	Parameter Value
The height of HAPS, z^{HAPS}	18 km
The height of geo-satellite, $z^{satellite}$	36000 km
Bandwidth of BSs, β	10 MHz
Central carry frequency, f_c	3 GHz
Rician factor, κ_{HAPS}	5
Noise power, N_0	-174 dBm/Hz
Ground base-station antenna, N_A^{BS}	1
HAPS antennas , N_A^{HAPS}	10
Maximum power of urban BS, $P_{BS}^{max\_urban}$	1 watt
Maximum power of suburban BS, $P_{BS}^{max\_suburban}$	2 watt
Maximum power of rural BS, $P_{BS}^{max\_rural}$	5 watt
Standard deviation of ground-level shadowing σ_a	5dB
Data availability γ_{ij}	1
The number of users N_U	20
The number of ground Bss N_B	10
The ensembling size Q	8
The minimum number of users to be served K	15

Sum-rate Versus the Maximum Power of HAPS

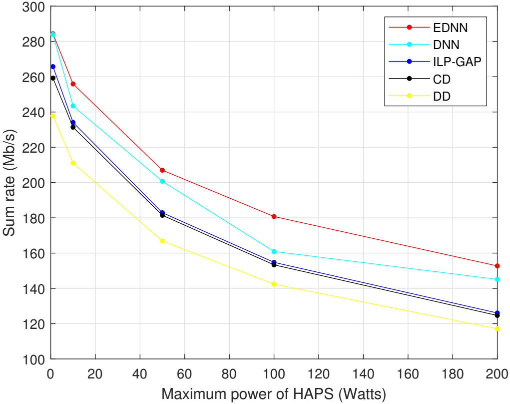

Figure: Sum-rate versus maximum power of HAPS.

Sum-rate Versus K Value

- The maximum power of HAPS is 200 Watt.

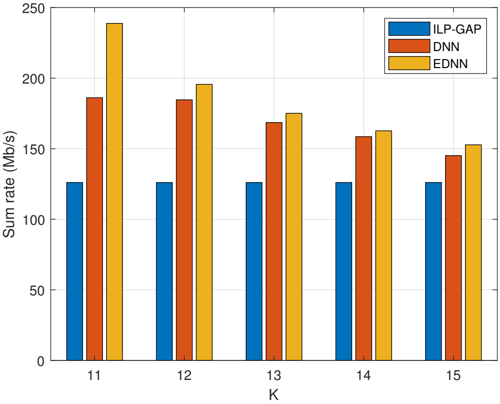

Figure: Sum-rate versus values of K.

Ensembling Size

- The maximum power of HAPS is 200 Watt and the K is set to be 15.

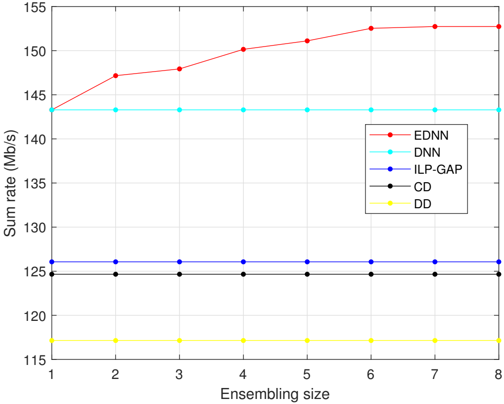

Figure: Sum-rate versus ensembling size.

Outline

Conclusions

- Integrated space-air-ground systems are expected to trigger a new era in physical layer.
- Developed and evaluated the benefits of optimized user scheduling in space-HAPS-ground networks.
- Proposed an ensembling deep neural network framework.
- Simulation results highlight the numerical prospects of the proposed solution in satisfying 6G ambitious objectives.
- A crisp illustration for connecting the unconnected and ultraconnecting the connected.

THANK YOU

More details can be found at

https://arxiv.org/abs/2205.13958

For more questions, please email

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