Distributed Timeslot Allocation in mMTC Network by Magnitude-Sensitive Bayesian Attractor Model

Tatsuya Otoshi, Masayuki Murata,

Hideyuki Shimonishi, Tetsuya Shimonkawa

Osaka University, Japan

5G Network and Timeslot Allocation Challenges

- 5G
  - Expanding coverage areas and simultaneous communication qualities
  - Three communication types: eMBB, URLLC, and mMTC
- Time slot allocation
  - Time slot allocation essential for satisfying different requirements
  - Random access: autonomous time slot selection by terminals
- Challenges
  - Challenges in mMTC: collision avoidance and limited information
  - Previous Approaches: sparing transmission and reinforcement learning (limitations)

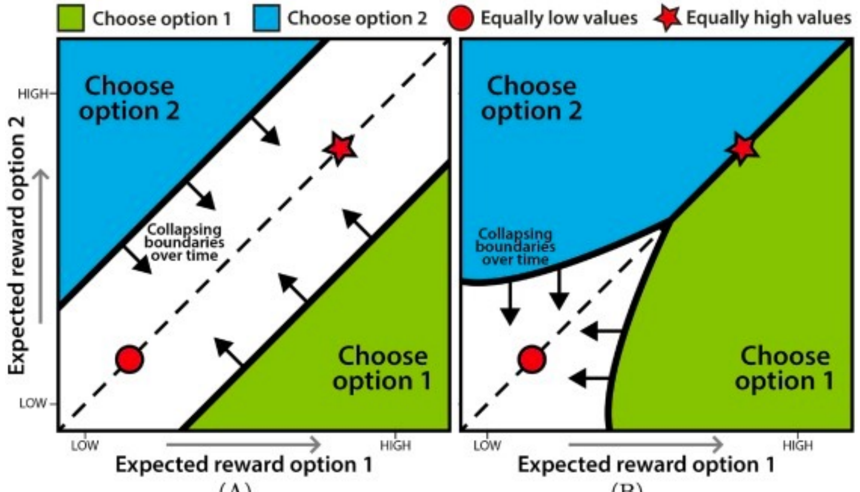
Approach

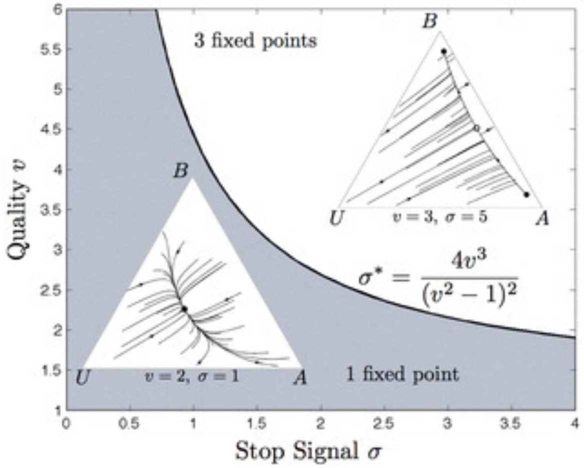
- Proposed scheme inspired by human decision-making property
  - BAM: decision model applied to network control problems
  - Magnitude sensitivity: tendency to make choices based on the sum of the values of alternatives
- Compatible with consensus building in group decision-making
  - Proposed method uses extended model of value-based BAM for autonomous decentralized timeslot allocation
  - Devices independently determine timeslot and consider the option of waiting for transmission based on magnitude sensitivity

Magnitude Sensitivity

[1] Pirrone, Angelo, et al. "Magnitude-sensitivity: rethinking decision-making." *Trends in cognitive sciences* 26.1 (2022): 66-80.
[2] Pais, Darren, et al. "A mechanism for value-sensitive decision-making." *PloS one* 8.9 (2013): e73216.

- Overview
  - Magnitude sensitivity refers to the tendency to make choices based on the sum of the values of alternatives.
  - When alternatives have high magnitude, accuracy is sacrificed to speed up the decision-making process.
- Advantages
  - It allows waiting for a better choice in the future when alternatives have low magnitude.
  - Magnitude sensitivity plays an important role in consensus building in group decision-making.

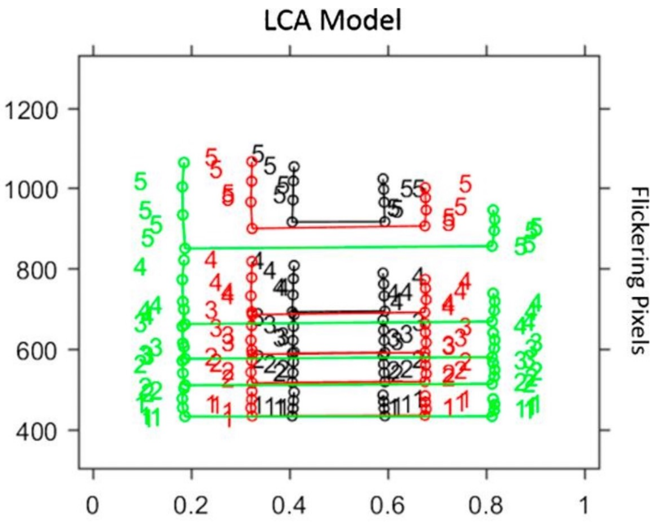




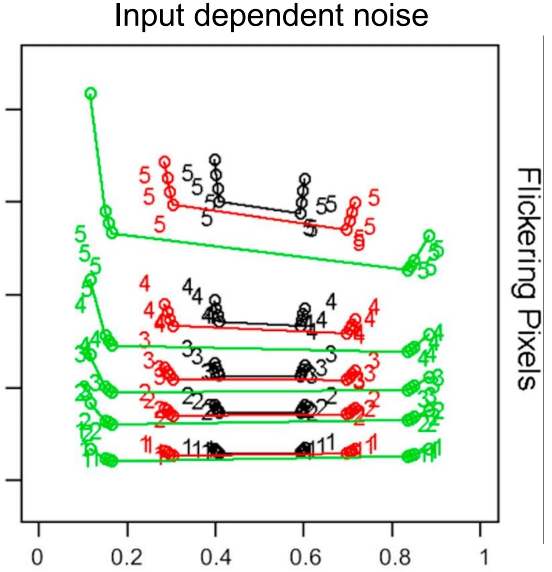
Magnitude Sensitive Models

- Leaky Competing Accumulator (LCA)
  - Drift term depends on the value
  - $z_{t+1}[i] = (1-\gamma)z_t[i] - \beta\sum_{j\neq i} z_t[j] + u_t[i]$

- Input Dependent Noise (IDN)
  - Noise term depends on the value
  - $z_{t+1}[i] = z_t[i] + \frac{u_t[i]}{\lambda+\sum u[i]} + \sqrt{(\sigma^2 + \pi u_t^2[i])}\epsilon_t[i]$
  - $\epsilon_t \sim N(0,1)$



z: state
u: value
ϵ: noise



[3] Teodorescu, Andrei R., Rani Moran, and Marius Usher. "Absolutely relative or relatively absolute: violations of value invariance in human decision making." *Psychonomic bulletin & review* 23.1 (2016): 22-38.

[4] Ratcliff, Roger, Chelsea Voskuilen, and Andrei Teodorescu. "Modeling 2-alternative forced-choice tasks: Accounting for both magnitude and difference effects." Cognitive psychology 103 (2018): 1-22.

Bayesian Attractor Model (BAM)

- Original BAM
  - Involves Bayesian updating based on observed values
  - Uses attractors and representative values
  - Generative model equations:
    - $z_t = f(z_{t-1}) + qw_t$
    - $x_t = (\mu_1, \cdots, \mu_K)\sigma(z_t) + sv_t$

z: state
x: observation
μ_i: representative value
v, w: noise
q, s: dynamic-, sensory uncertainty
u_{max}: maximum value

- Value-Based BAM
  - Observed and representative values changed to values of alternatives
  - Value estimation obtained through reward feedback information
  - Finds highest-value alternative using recognition scheme
  - Representative values:
    - $\mu_i = (0, \cdots, u_{max}, \cdots, 0)$

BAM with magnitude sensitivity

- Changing sensory uncertainty with value (BAM-LCA)
  - State update with observation
    - $\hat{z}_t - \hat{z}_{t-1} = \frac{\hat{P}_{zx}}{\hat{P}_{xx} + \frac{s}{u_t} I}(x_t - \hat{x}_t)$

$$z_{t+1}[i] = (1-\gamma) z_t[i] - \beta \sum_{j \neq i} z_t[j] + u_t[i]$$

LCA

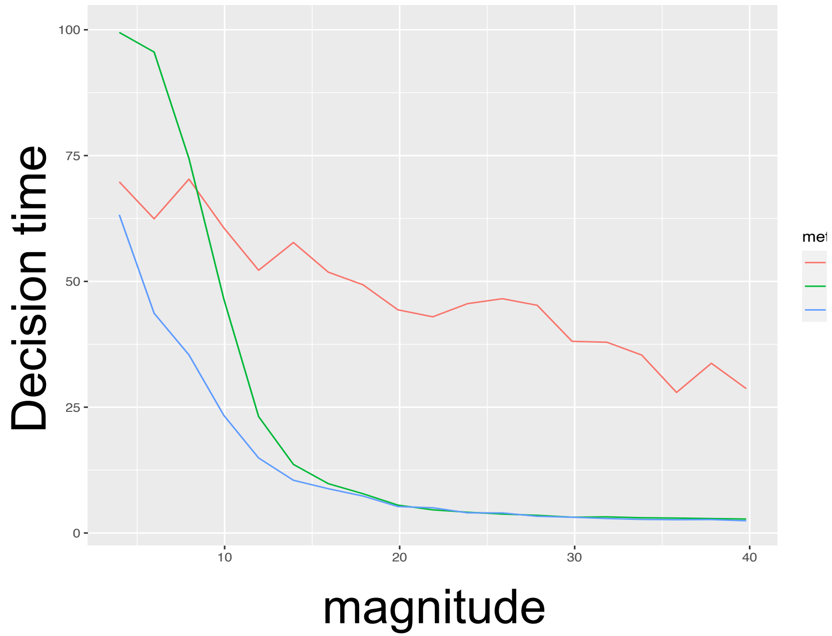
- Changing dynamic uncertainty with value (BAM-IDN)
  - Generative model of state
    - $z_t = f(z_{t-1}) + q\, \mathrm{w_t}$
    - $q \sim \Gamma(k, \theta), E[q] = \sqrt{q^2 + \pi u_t^2}$

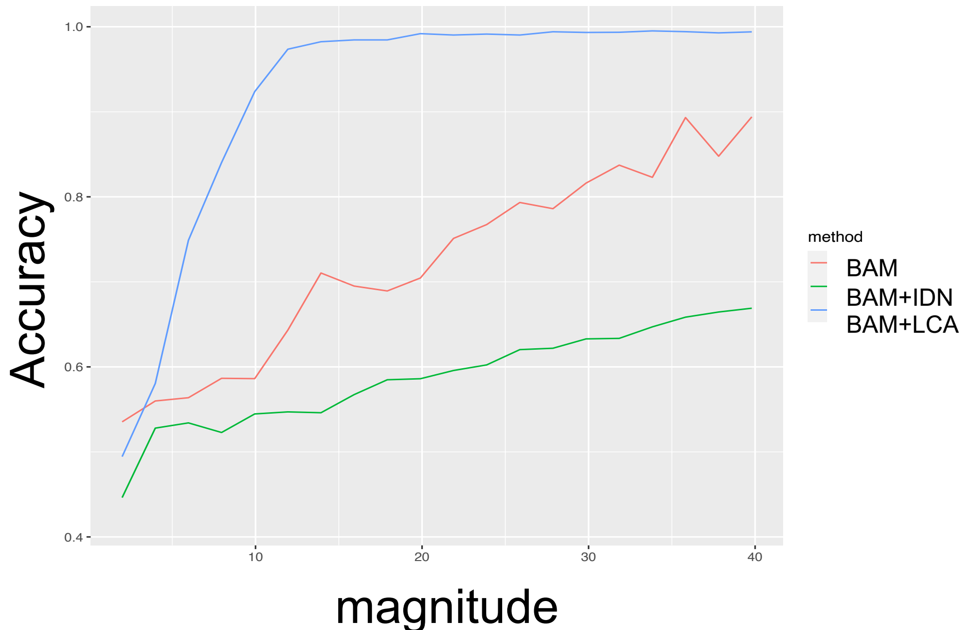
$$z_{t+1}[i] = z_t[i] + \frac{\mathrm{u_t}[i]}{\lambda + \sum u[i]} + \sqrt{(\sigma^2 + \pi u_t^2[i])\epsilon_t[i]}$$

IDN

Magnitude Sensitivity of Proposed Model

- All models show magnitude sensitivity:
  - Decision-making speed increases with the magnitude
- Accuracy also improves with increasing magnitude:
  - Earlier decisions result in more correct answers
- BAM-LCA has better decision time and accuracy compared to other models





System Model of Timeslot Allocation

- Resources
  - A subframe has K timeslots.
- Devices
  - Assumes a continuous packet generation model, more compatible with mMTC use cases (e.g., sensor networks).
  - N devices send data to the base station
- Base station
  - Successful transmission: only one device sends a packet per timeslot; collision occurs if multiple devices transmit simultaneously.
  - Broadcast feedback: the congestion level

[4] Sun, Yao, et al. "Service provisioning framework for RAN slicing: user admissibility, slice association and bandwidth allocation." IEEE Transactions on Mobile Computing 20.12 (2020): 3409-3422.
[5] Silva, Giovanni Maciel Ferreira, and Taufik Abrão. "Throughput and latency in the distributed Q-learning random access mMTC networks." Computer Networks 206 (2022): 108787.

Value-based BAM for Timeslot Allocation

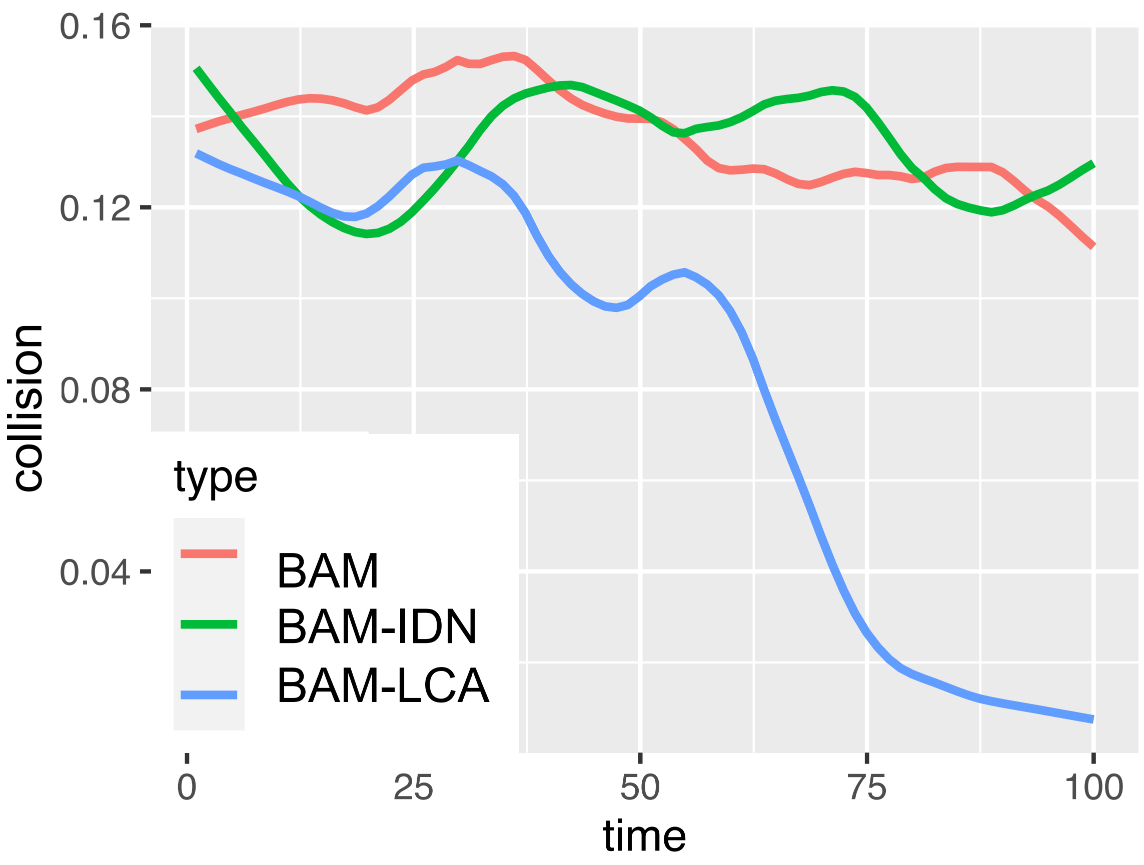
- Attractors
  - K attractors ($\phi_1, \cdot \cdot \cdot, \phi_K$) represent K timeslots in subframe
- Feedback information:
  - +1 for successful transmission
  - Negative value for collision, discretized by b bits of congestion
  - Time-smoothed value used for stable understanding of congestion
  - α = 0.3 (smoothing parameter)
- Decision-making:
  1. Maximum confidence selection if BAM's confidence levels ratio for top two choices exceeds threshold
  2. Select timeslot k if attractor ϕ_k is selected, transmit packet
  3. Wait for next subframe if no decision made in current subframe

Simulation Setting

- N devices occupy K timeslots simultaneously
  - $N = 10$
  - $K = 2^\mu$
  - $\mu=4$: numerology
- Base station provides feedback in b bits for congestion level
  - $b = 2$
- Performance metrics: collision
  - The ratio of the number of timeslots in which collisions occur out of K timeslots

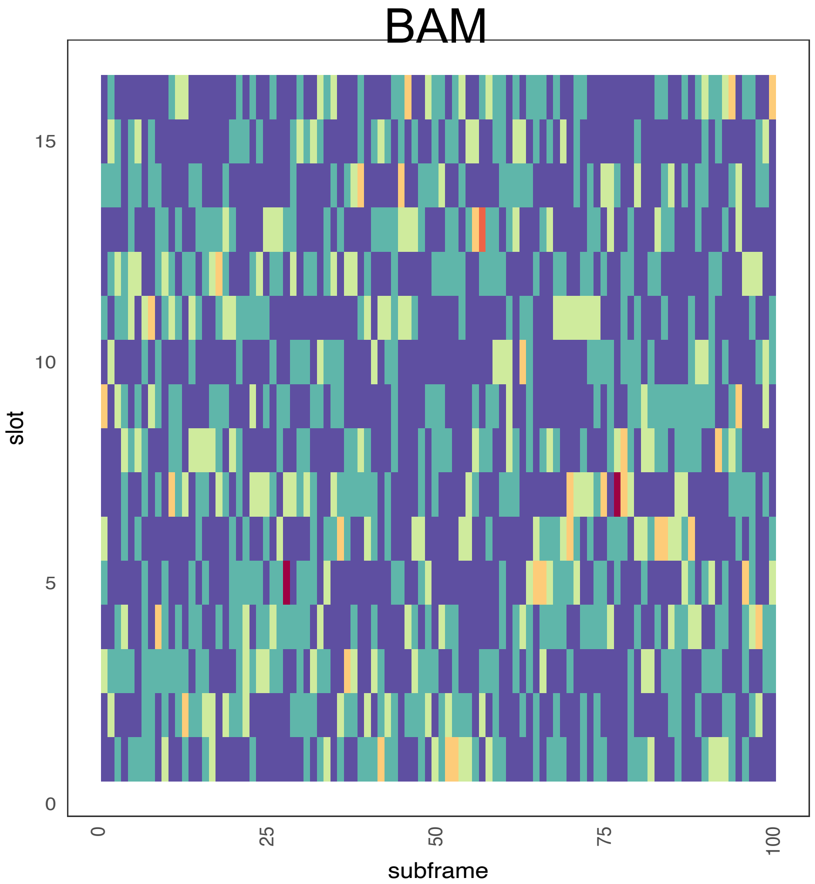
Result

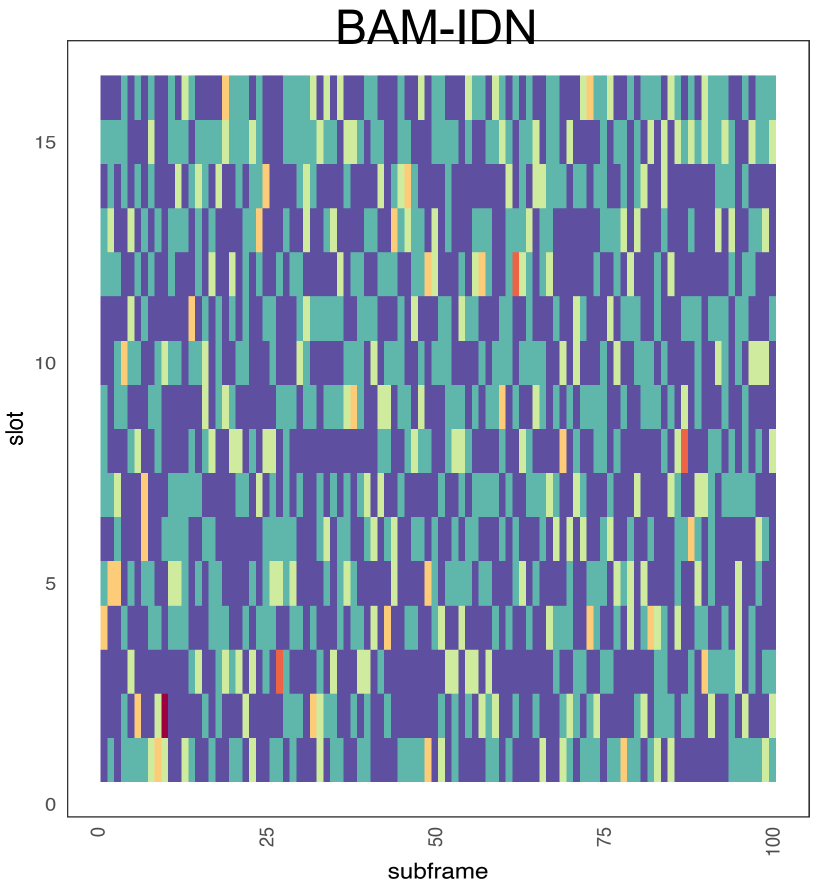
- BAM-LCA achieves collision avoidance
  - The greater the value, the stronger the decisive movement, and the more likely it is that the same terminals will segregate using the same timeslot.
- BAM is slowly declining, but not to the point of segregation of time slots.
- BAM-IDNs cannot segregate time slots due to the noise

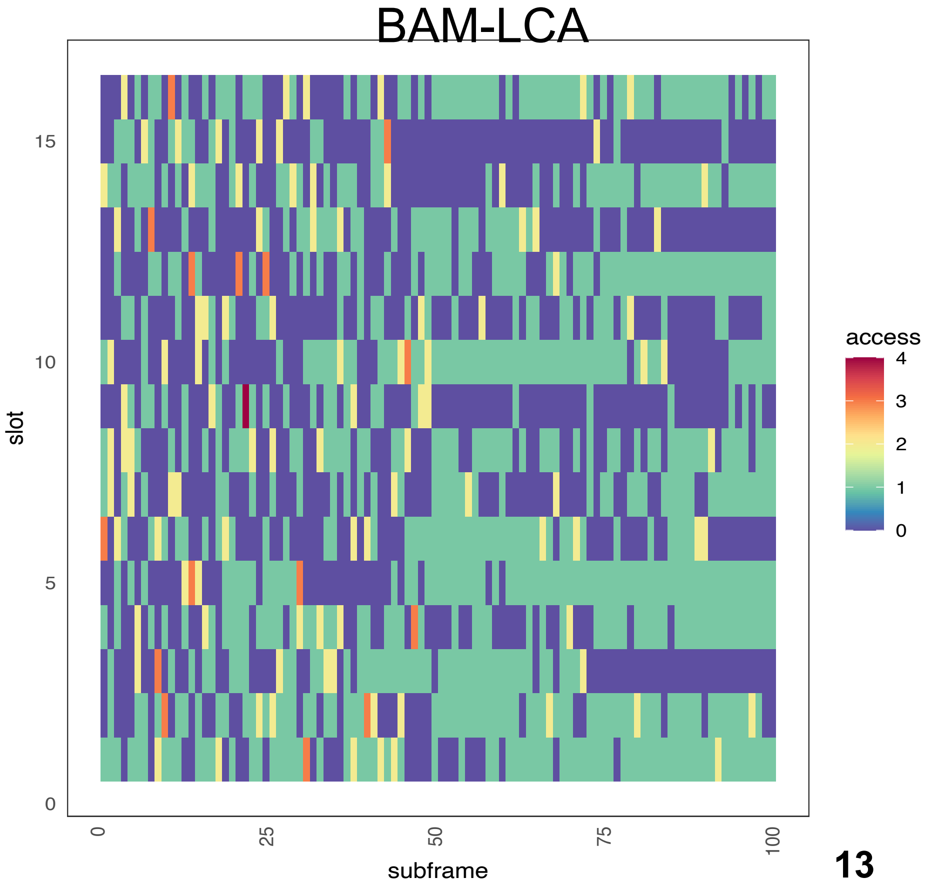


Timeslot access

- Heatmap of the number of access for each subframe x timeslot pair
- BAM+LCA tends to select similar time slots







Summary

- Summary
  - Magnitude-sensitive decision models applied for autonomous decentralized timeslot allocation in mMTC networks.
  - Proposed magnitude-sensitive BAM, BAM-LCA, and BAM-IDN as extensions of BAM.
  - Proposed method allows each device to autonomously select a suitable timeslot based on feedback reflecting timeslot congestion.
  - Simulation-based evaluation showed that BAM-LCA effectively avoids timeslot collisions compared to other methods.
- Future Work
  - Conduct comprehensive performance evaluations in various settings to assess the effectiveness of the proposed models.
  - Investigate strategies to dynamically adjust decision-making based on the number of devices present in the network.

Thank you for your attention

This work was supported by MIC under a grant entitled ”R&D of ICT Priority Technology (JPMI00316)”.