

# Switching Constrained Max-Weight Scheduling for Wireless Networks

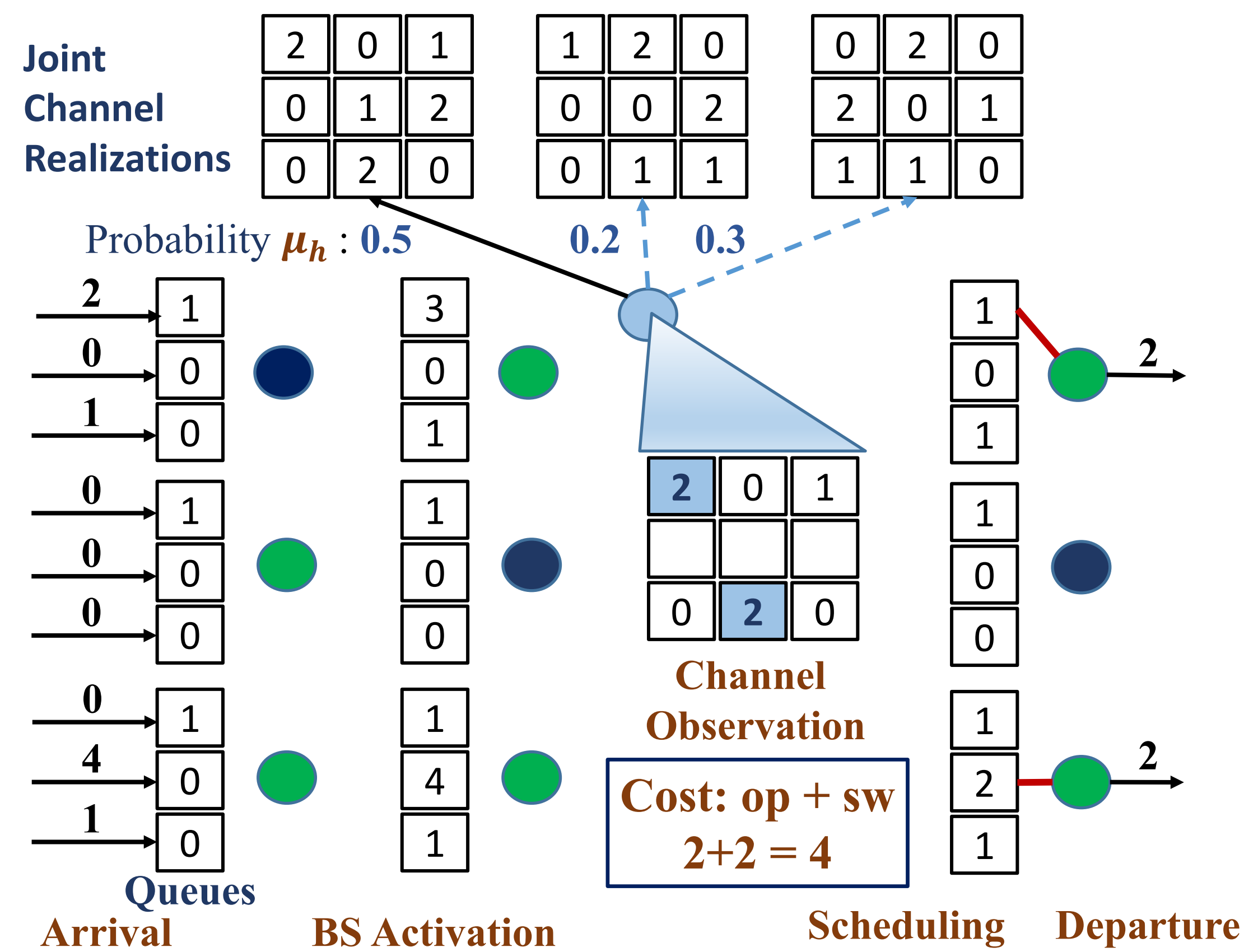
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## Dense Cellular Networks

- **Dense deployment** of base stations (BS) to support peak data traffic
- **Dynamic** activation and de-activation of BS to **optimize energy** usage
- **Fast activation** dynamics is **necessary** to maintain **data rate**
- **Fast activation** dynamics leads to **large switching overhead**, e.g. **hand-offs, state exchange** among BSs, and **BS start-up costs**



## System Model

- **Downlink** time-slotted system consists of **N BSs** and **M users**
- **Queue**  $Q_{nm}(t)$  correspond to the queue for **(n,m)** BS-user pair
- An i.i.d. **joint arrival**  $A(t)$  ( $N \times M$ ) is realized:  $A_{nm}(t)$  packets for  $Q_{nm}$
- An i.i.d. **joint channel**  $H(t)$  ( $N \times M$ ) is realized: state  $h$  with prob.  $\mu_h$
- Two stages of decisions **Activation**, and **Scheduling** from active BSs
- **Step 1: Activate** a subset of BSs,  $J(t)$ , in timeslot  $t$
- **Step 2: Observe channel** from active BSs: row  $n$  of  $H(t)$  iff BS  $n$  is ON
- **Step 3: Schedule** an 'active BS'-user matching  $S(t)$  from  $S(J(t), H(t))$
- **Cost of operation + switching**:  $C(t) = |J(t)| + |J(t-1)\Delta J(t)|$
- **Departure**  $D(t)$ :  $D_{nm}(t) = H_{nm}(t)$  if (BS  $n$  is ON & serves User  $m$ ), o/w 0
- **Queue Update**:  $Q_{nm}(t+1) = (Q_{nm}(t) + A_{nm}(t) - D_{nm}(t))^+$

## BS Activation and Scheduling

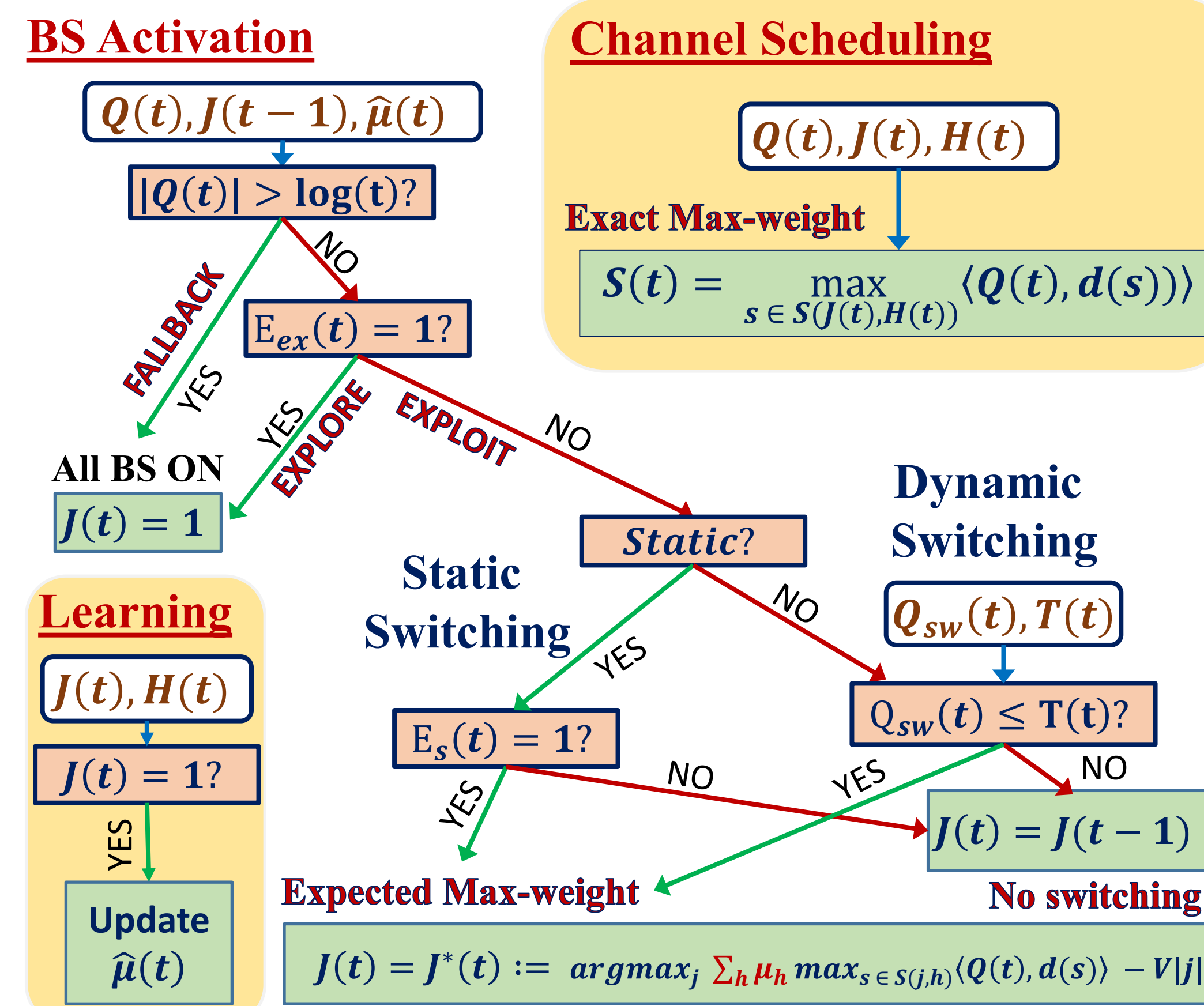
- **Two key decisions**: BS activation and Channel Scheduling
- **BS activation** is further split into two decisions
  - **When to switch?** Switch at a very slow rate (Constrained Switching)
  - **What to switch to?** Expected Max-weight with activation penalty
- **Channel state** is unknown before BS activation
  - **Exploration-exploitation** tradeoff in learning channel states
- **Channel Scheduling**: Exact max-weight with known channel state

## Need for a New Approach

- **Greedy Optimization Techniques** (Primal-Dual, Drift+Penalty)
  - Frequent BS state change as switching cost is not optimized
- **Reinforcement learning with bounded queue length**
  - Prohibitive computation for large queue lengths
  - Complex packet drop vs optimality tradeoffs
- **Sticky BS selection using static-split rule + MW scheduling**
  - Large delay as BS selection is non-adaptive to queue lengths

## Learning Aided Switching and Scheduling (LASS)

- **Parameters**: Switching rate,  $\epsilon_s$  and Penalty scale,  $V$
- **Independent R.V.s**: Switch:  $E_s(t) \sim \text{Ber}(\epsilon_s)$ , Explore:  $E_{ex}(t) \sim \text{Ber}(\log(t)/t)$



## Dynamic Switching

- Uses two variables **Switch Counter**:  $T(t)$  and **Switch Queue**:  $Q_{sw}(t)$
- **Switch counter** keeps count of the time since  $J^*(t)$  is scheduled
- **Switch queue** counts the number of switching events that exceeds rate  $\epsilon_s$ 
  - Switch queue**:  $Q_{sw}(t+1) = (Q_{sw}(t) - E_s(t) + 1\{Q_{sw}(t) \leq T(t)\})^+$
  - Switch counter**:  $T(t+1) = 1\{J(t) = J^*(t)\}(1 + T(t))$

## Performance Guarantees

- Assumptions on **system parameters**
  - **Capacity gap**  $\epsilon_g > 0$ , and **bounded** arrivals and departures
  - **Optimal cost** of the system  $C_{avg}^*$  with **no switching constraints**
- **Algorithm parameters**: Switching rate,  $\epsilon_s$  and Penalty scale,  $V$
- **Performance metrics** of interest:
  - Time average of queue lengths:  $Q_{avg}$  and costs:  $C_{avg}$
  - Tail bounds for queue lengths:  $\mathbb{P}(|Q(t)| \geq x)$

- For **LASS with Static** switching and **LASS with Dynamic** switching

$$Q_{avg} \leq O\left(\frac{C_{avg}^*}{\epsilon_g} + V + \frac{NM}{\epsilon_g \epsilon_s}\right) \text{ and } C_{avg} \leq C_{avg}^* + O\left(\epsilon_s + \frac{NM}{V \epsilon_s}\right)$$

- For **LASS Static**:  $\mathbb{P}(|Q(t)| \geq x) \leq \exp(-\Theta(\epsilon_s \epsilon_g) x) + O\left(\frac{\log(t)}{t}\right)$

- For **LASS Dynamic**:  $\mathbb{P}(|Q(t)| \geq x) \leq \exp(-\Theta(\epsilon_g) x) + O\left(\frac{\log(t)}{t}\right)$

## Simulation Results

- Four algorithms are simulated for **8 Users** and **3 BSs** until convergence:
  - **DP**: Greedy Drift + Penalty
  - **LSG**: LASS Static with geometric inter arrival between  $E_s(t)$
  - **LSF**: LASS Static with fixed inter arrival between  $E_s(t)$
  - **LD**: LASS with Dynamic switching

- **First plot**:  $Q_{avg}$  of  $DP < LD < LSF < LSG$  ( $V = 100$ , load = 0.9)

- **Second plot**:  $C_{avg}$  of  $DP > LD \approx LSF \approx LSG$  ( $V = 100$ ,  $\epsilon_s = 0.1$ )

- **Third and Fourth plot**: Separation of queue length tail distribution

