Hybrid Beamforming using Machine Learning

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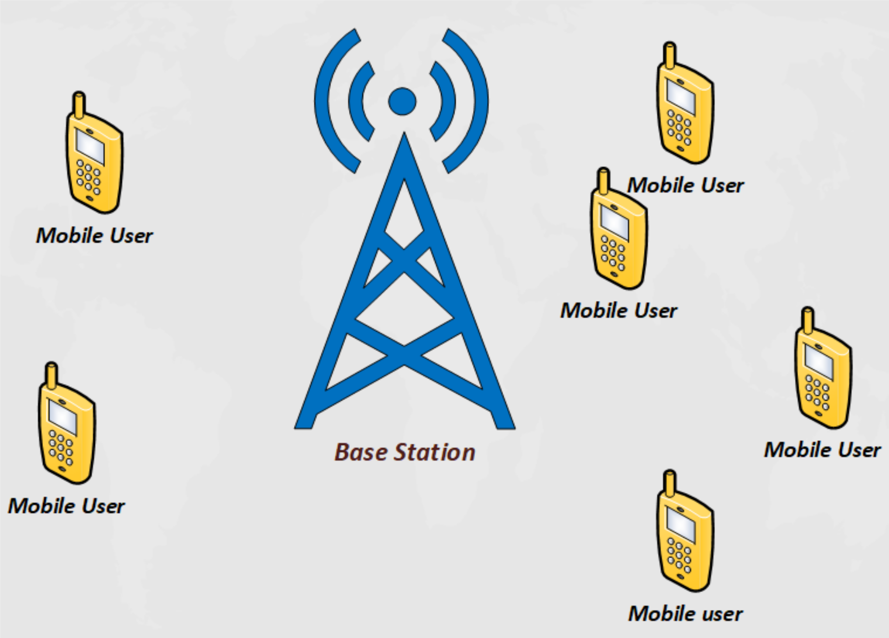
CELLULAR COMMUNICATIONS

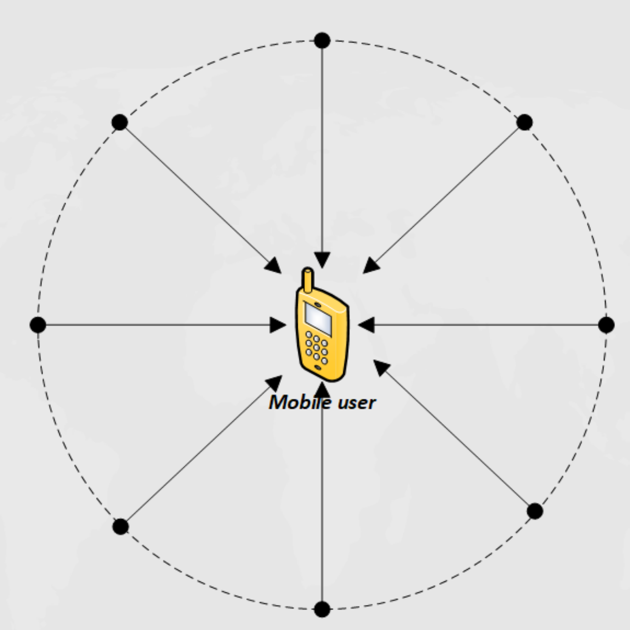
- What comprises a cellular system?
  - Base stations
  - Users
- Any user willing to communicate to another locates the nearest base station which connects it to the other user.
- Communication happens via the base stations.
- Focus: link between users and the base station.



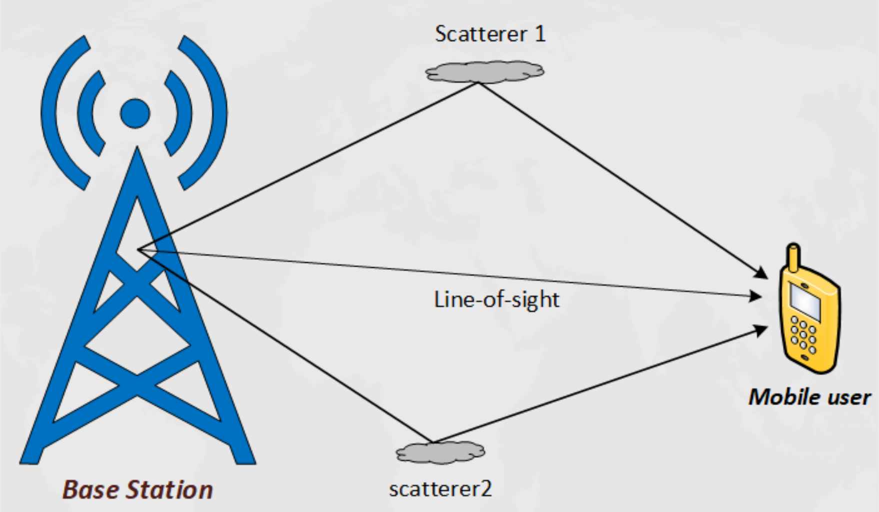
OMNIDIRECTIONAL AND DIRECTIONAL COMMUNICATIONS

- Communication using 4G spectrum exploits both non-directional and directional techniques.

OMNIDIRECTIONAL COMMUNICATION



DIRECTIONAL COMMUNICATION

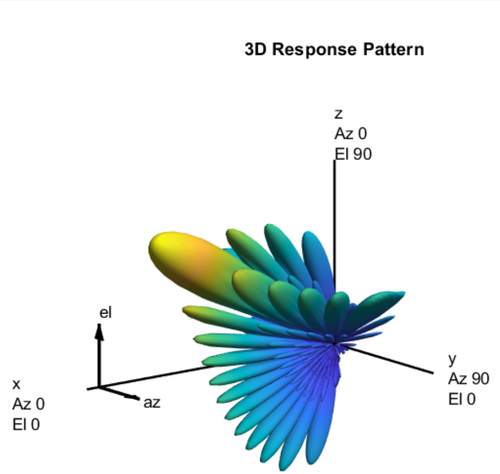


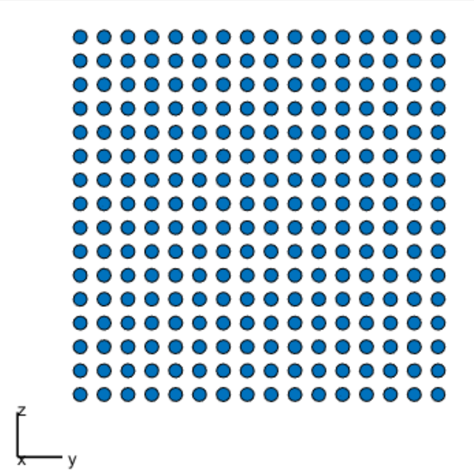
DIRECTIONAL COMMUNICATIONS

- 5G targets multi-Gbps data rates; 4G bandwidths aren't enough.
- Millimeter-wave frequencies (30-300GHz) are being adopted to achieve these data rates.
- High attenuation at these frequencies; non-directional communication not a feasible choice.
- What is possible?
  - Directional communications using massive-MIMO systems or **beamforming**.
- **massive-MIMO: high-dimensional arrays**
- Beamforming is used to direct signals from

  multiple antennas in desired directions.
- **Beamforming increases transmit power in intended**

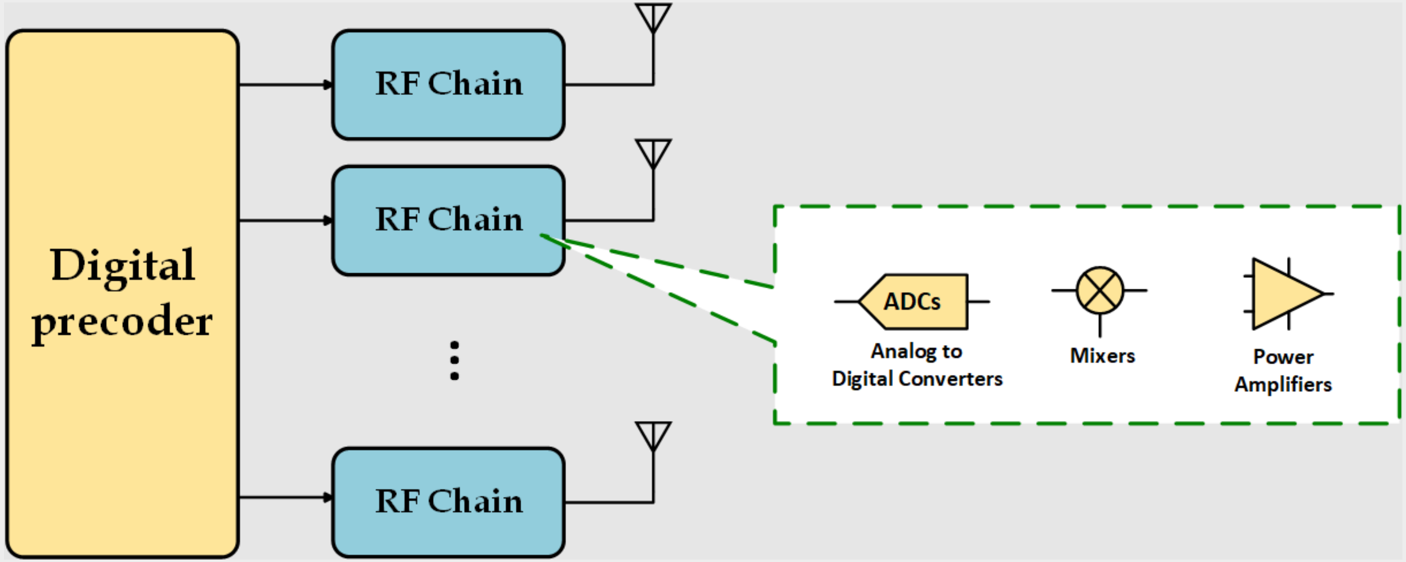
  directions; increases communication range.





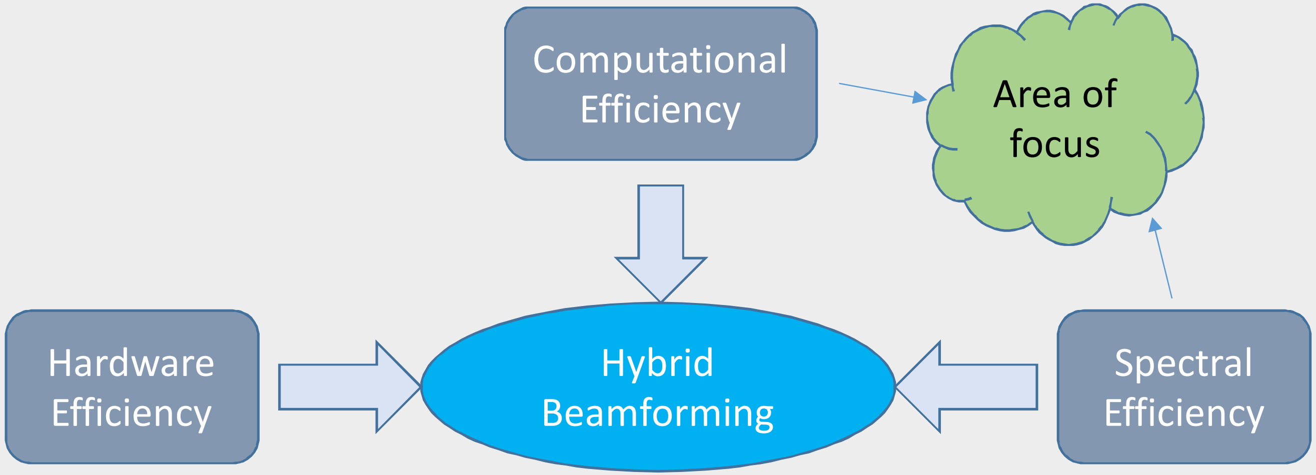
DIGITAL BEAMFORMING

- Conventionally, beamforming is done digitally at baseband.
- This requires analog signals received at antenna terminals to be converted to digital data.
- Each antenna is fitted with an RF chain for this purpose.

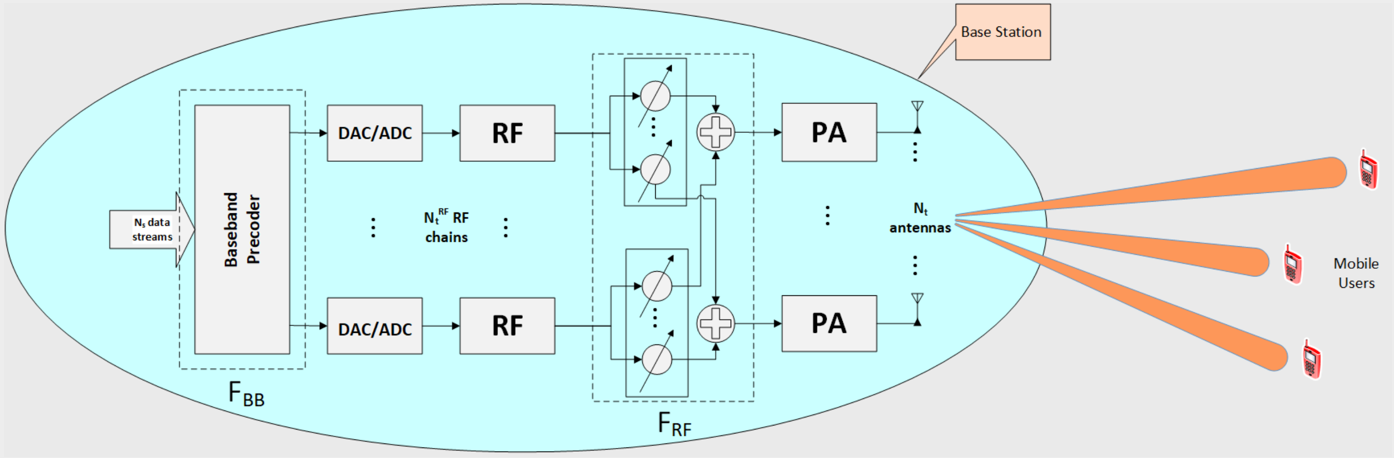


HYBRID BEAMFORMING & MILLIMETER-WAVE

- To lower the number of RF chains, **hybrid beamforming** is implemented whereby **each RF chain is connected to a multitude of antenna elements via RF phase shifters**.
- The design of an efficient hybrid beamforming system revolves around three important aspects
  - ➢ **Hardware efficiency** (associated cost and power) of the required hardware at mmWave frequencies
  - ➢ **Computational Efficiency** of the beamforming algorithm
  - ➢ **Spectral Efficiency** achieved by the system



A HYBRID BEAMFORMING SYSTEM



- F_{BB} - Baseband Precoder
- F_{RF} - RF Precoder
- PA – Power Amplifier
- ADC – Analog to Digital Converter
- DAC – Analog to Digital Converter

High mobility in mmWave systems → fast variations in channel state → frequent beam scanning

leads to large control signaling overheads due to large number of beams

an intelligent system/agent needs to be in place to track the random channel variations so that frequent beam scanning may be avoided

CONVENTIONAL APPROACH

- Currently deployed 5G systems uses a static policy.
- Involves a beam scanning process scheduled every T seconds; T varies between 20ms to 160ms.

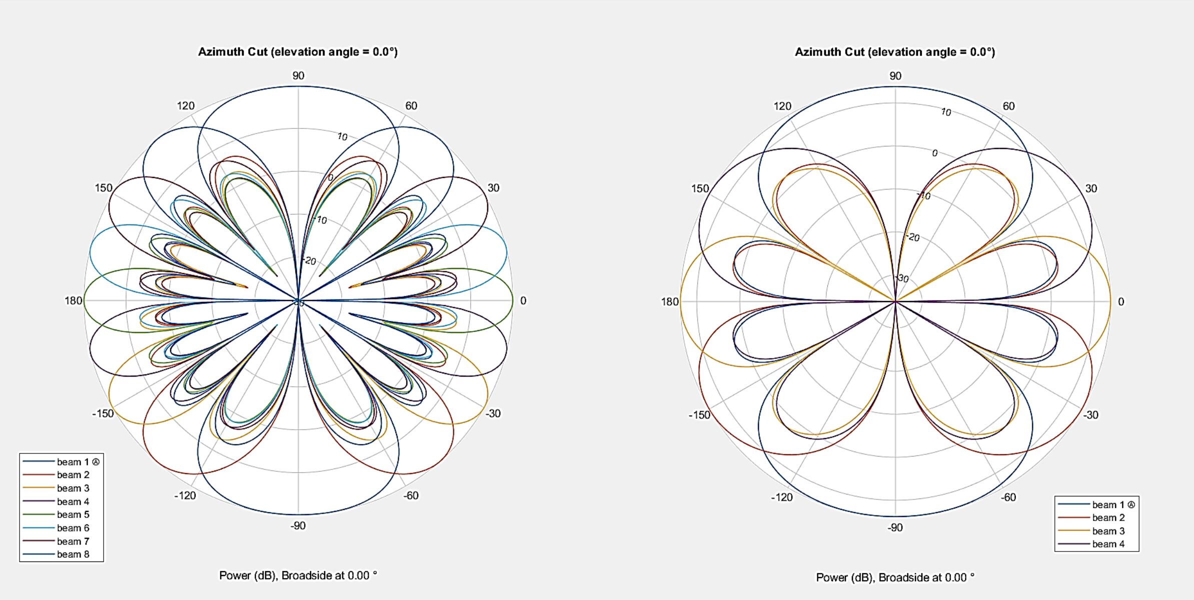
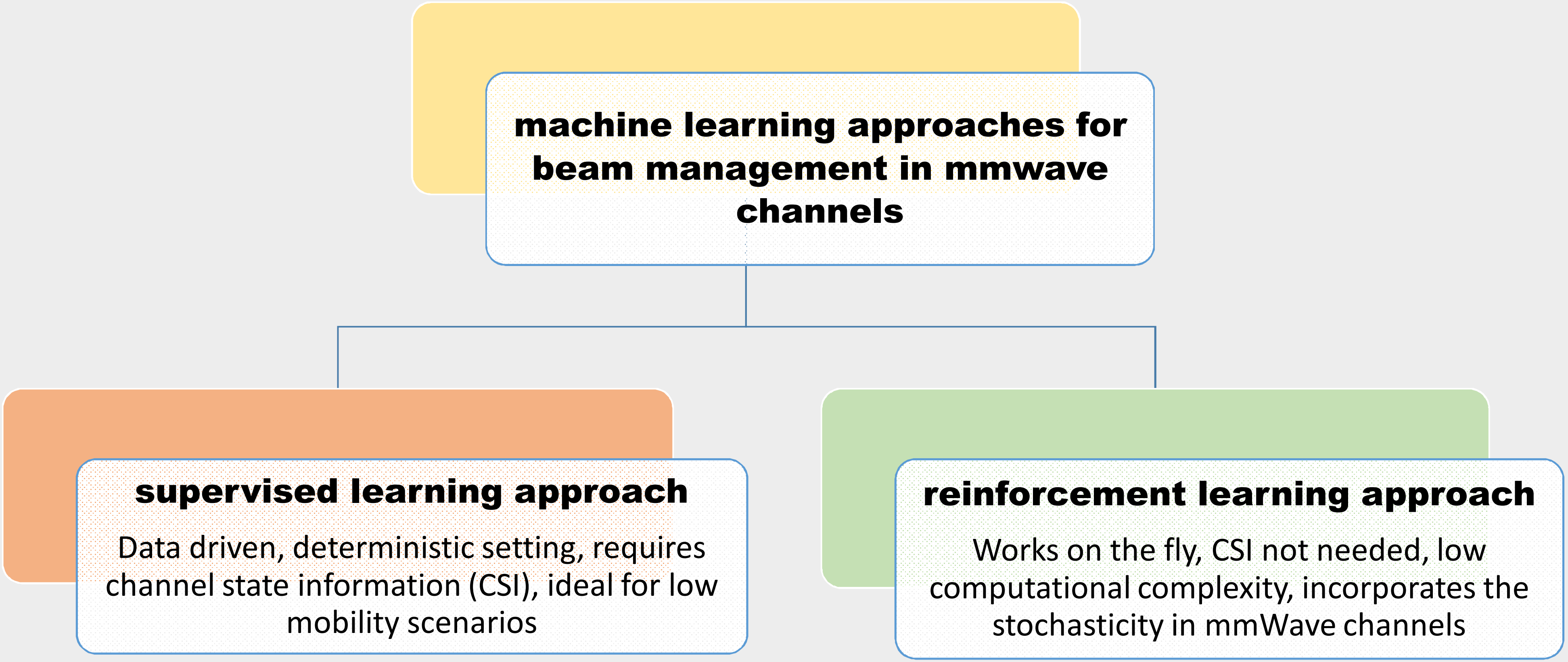


Figure: a beam scan determines the best transmitter (left) and receiver (right) beams so as to maximize spectral efficiency

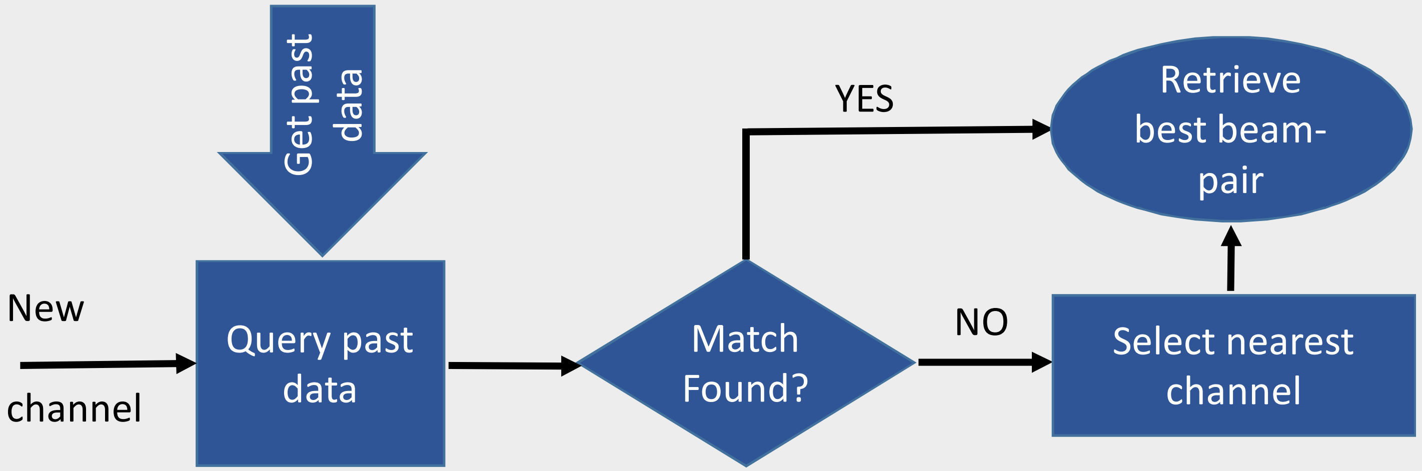
- A beam scan translates to an **exhaustive search over all transmitter(tx)-receiver(rx) beams** to select beams with good alignment.
- **High computational complexity and high signaling overhead.**

BEAM MANAGEMENT AND AI



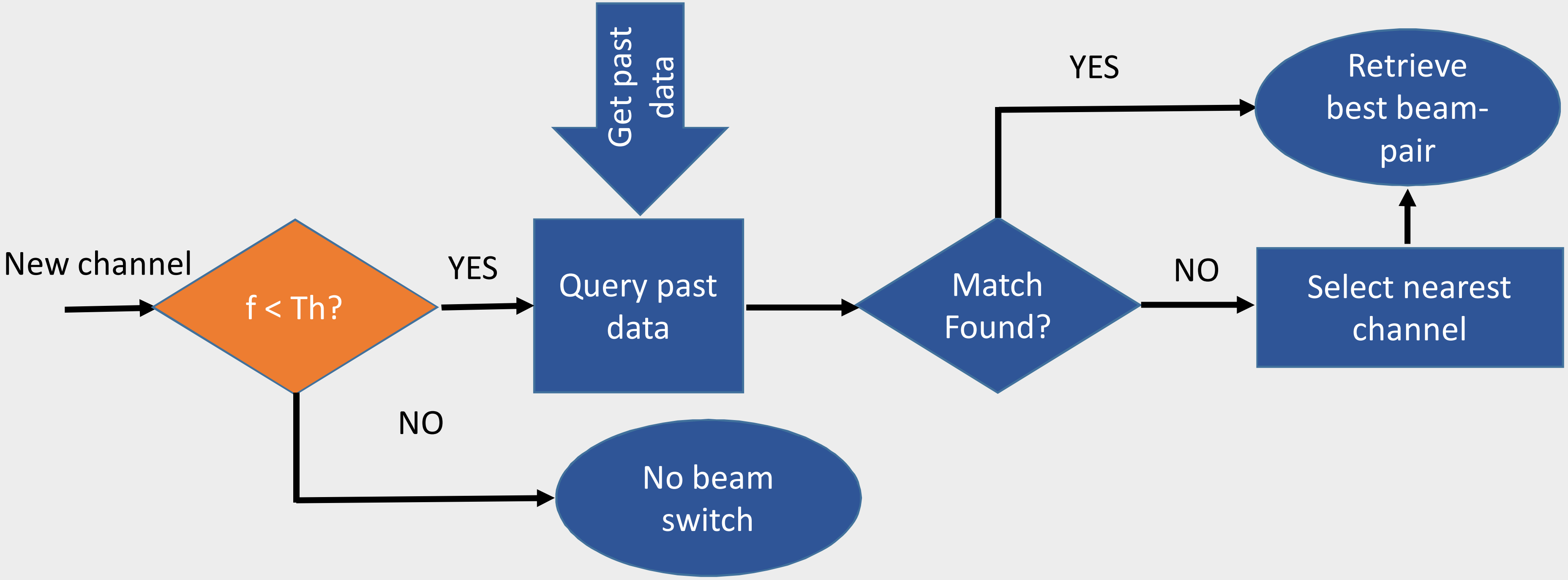
SUPERVISED LEARNING APPROACH

- Involves a training phase to generate a look-up table to select beams given a particular channel state.
- **Removes the need for an exhaustive search across all beams.**
- **Does not require a singular-valued decomposition (SVD) of the channel matrix to determine the precoders.**



LOW OVERHEAD BEAM SWITCHING ALGORITHM

- **Proposed Algorithm: low-overhead Beam Switching Algorithm (LO-BSA).**
- **Reduces computational complexity by controlling the number of beam switches.**
- **The parameter f represents the percentage of times the algorithm opts for a beam change.**
- $0 < Th < 1$ **is a pre-set value.**



LOW OVERHEAD BEAM SWITCHING ALGORITHM

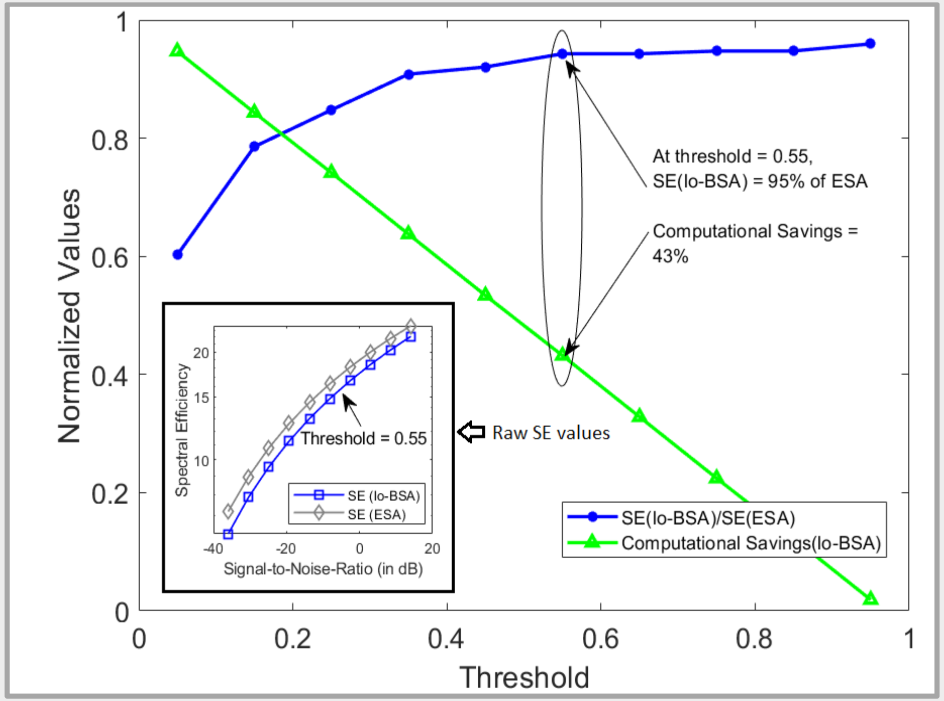
Algorithm 1 Low Overhead Beam-Switching Algorithm

procedure *Training*(V, $\mathcal{H}$, P, N_s, T)
  Initialize $Q(H_t, v) = 0\ \forall H_t \in \mathcal{H}, v \in V$ and $t \leftarrow 1$.
  while $t \leq T$ **do**
    Observe channel state H_t at time t.
    $Q(H_t, v) \leftarrow \eta, \forall v \in V$ where η is given by.
    $t \leftarrow t + 1$.
  end while
end procedure
procedure *RF_Pre_Sel*(Q, H, P, N_s, Th)
  Initialize threshold Th, c_i, n_i.
  if $c_i/n_i \leq Th$ **then**
    $c_i \leftarrow c_i + 1$, $n_i \leftarrow n_i + 1$.
    Observe current channel H.
    $\tilde{H} \leftarrow \operatorname{argmin}_{\bar{H} \in \mathcal{H}} \|\bar{H} - H\|_2$.
    $\{F_{RF}, W_{RF}\} \leftarrow \mathbf{v}$, where $\mathbf{v} = \operatorname*{argmax}_{v \in V} Q(\tilde{H}, v)$.
    $H = U\Sigma V^*$, $U = [U_1 U_2]$, $V = [V_1 V_2]$, where $U_1 \in \mathbb{C}^{N_r \times N_s}$ and $V_1 \in \mathbb{C}^{N_t \times N_s}$.
    $F_{opt} \leftarrow V_1$ and $W_{opt} \leftarrow U_1$.
    $i_{BB} \leftarrow (i_{RF}^H i_{RF})^{-1} i_{RF}^H i_{opt}$, $i \in \{F, W\}$.
    $i_{BB} \leftarrow \sqrt{N_s}(i_{BB}/\|i_{RF} i_{BB}\|_F)$.
    Save matrices F_{RF},F_{BB},W_{RF},W_{BB} in buffer.
    return F_{RF},F_{BB},W_{RF},W_{BB}.
  else
    load F_{RF},F_{BB},W_{RF},W_{BB} from buffer.
    $n_i \leftarrow n_i + 1$.
  end if
end procedure

- Norm-2 difference of current channel matrix and stored data is opted to determine the nearest channel.
- SVD is performed to determine the optimal beamforming vectors/precoders.
- For the single-user case considered in our simulations, these computations may be further avoided.
- For multiuser cases, the SVD calculations may be also exploited to compare a few singular vectors instead of a norm-2 difference.

PERFORMANCE COMPARISON (ESA VS LO-BSA)

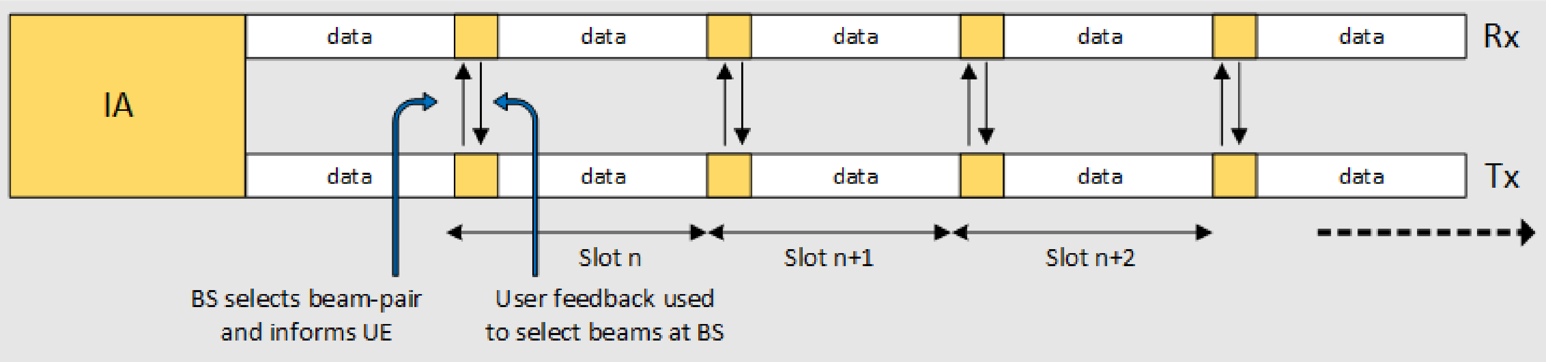
- ESA searches among the beam-pairs of tx and rx beams that are adjacent to the current beams.
- The number of computations/flops for ESA f_{ESA} is a constant; $f_{ESA} = 2817828$.
- The number of flops in LO_BSA is $f_{lo-BSA}(Th) \approx Th \times 2868412 + (1 - Th) \times 11$.
- Huge reduction in computational complexity
- marginal compromise in spectral efficiency.



flops: floating-point operations per second

REINFORCEMENT LEARNING APPROACH

- With no channel statistics available, the beam selection problem can be formulated as a Multi-Armed Bandit (MAB) problem.
- Each arm represents an action - a pair of transmitter and receiver beams.
- We propose a reinforcement learning (RL) algorithm to select the optimal beam-pair in the long run and avoid repeated beam-scanning.



- Thompson Sampling based algorithm: select the arms at discrete slots to maximize the spectral efficiency of the system.

THOMPSON SAMPLING-BASED BEAM SELECTION

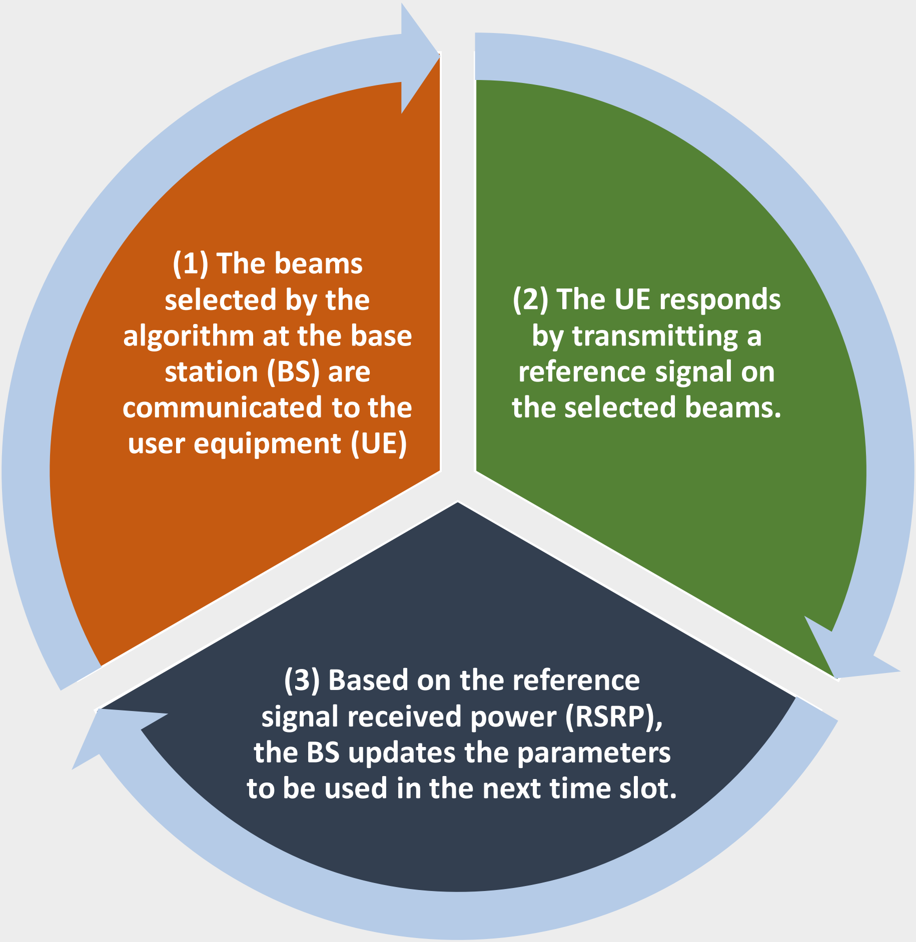


Fig: Summary of operations in a time slot

Algorithm 1 Thompson Sampling

for $t = 1, 2, ..., T$ **do**

  Step 1a. Sample each arm

  $\bar{s}_t \sim \mathcal{N}(\bar{\mu}_t, \bar{\sigma}_t)$.

  Step 1b. Select best arm

  $\beta \leftarrow \arg\max_{b \in \mathcal{B}} \bar{s}_t$.

  Step 2. Observe SNR r for β

  Step 3. Update $\mu_{t+1}(\beta), \sigma_{t+1}(\beta)$ using

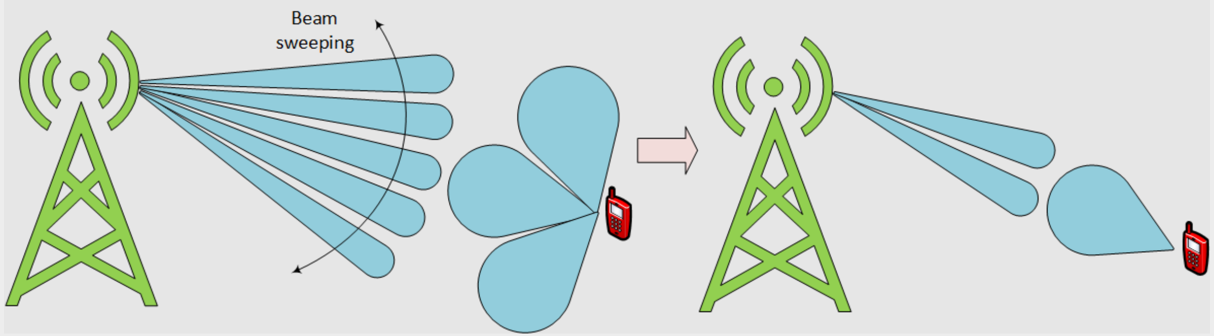
  $\mu_{t+1}(i) = \frac{r + \mu_t(i)/\sigma_t(i)}{1 + 1/\sigma_t(i)}$,

  $\sigma_{t+1}(i) = \frac{1}{1 + 1/\sigma_t(i)}$

end for

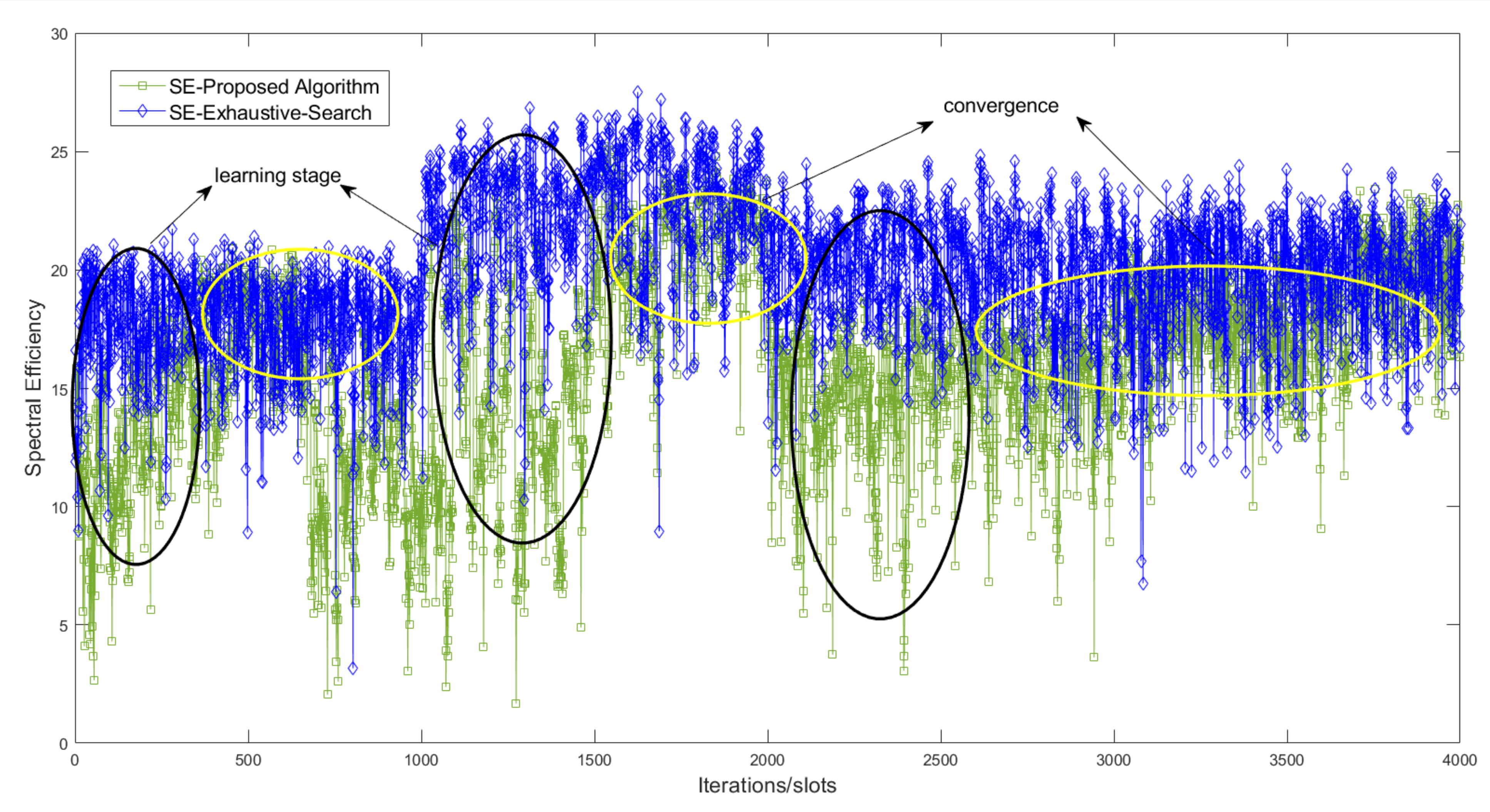
THOMPSON SAMPLING-BASED BEAM SELECTION

- **Performance may degrade due to temporal variations or when a mobile user moves out of coverage of the current beam.**
- **A beam-grouping based strategy is adopted to avoid beam failure and converge fast to the optimal action.**

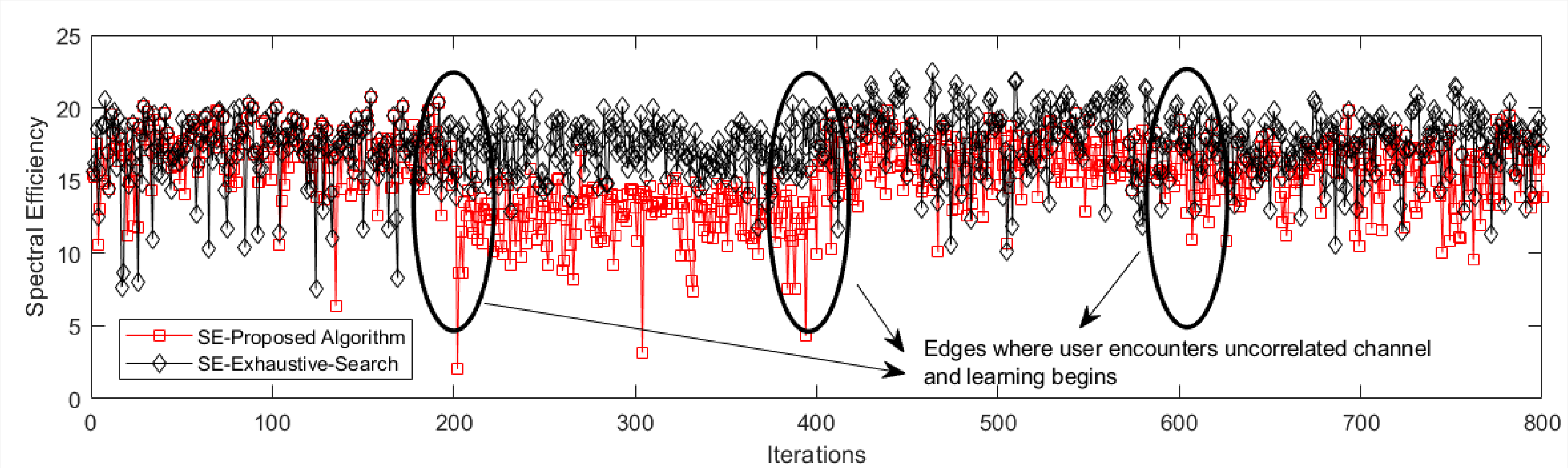


- **The performance of the modified TS algorithm is compared against an exhaustive search algorithm that determines the optimal action at each time-slot.**
- **The algorithm works with minimal control signaling while achieving a spectral efficiency comparable to that of the exhaustive search algorithm.**

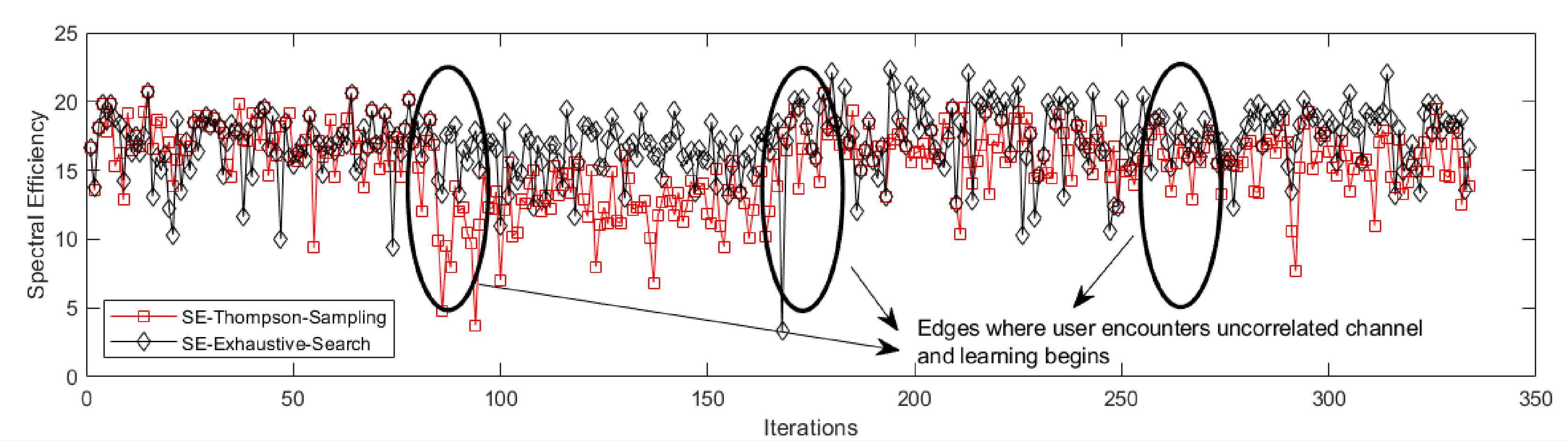
PERFORMANCE OF PROPOSED RL ALGORITHM



PERFORMANCE OF PROPOSED RL ALGORITHM (SLOT DURATION: 5MS)

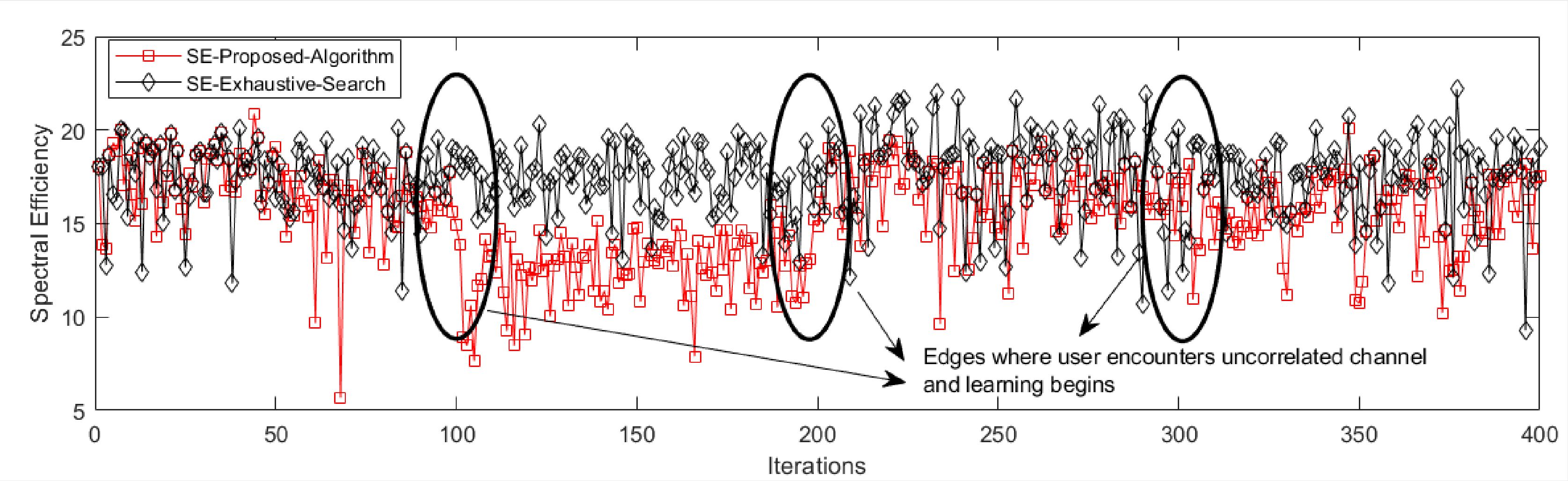


One time-slot/iteration = 5ms;
User velocity = 36 kmph;
Move Distance= 40 m;
Move Duration=4s

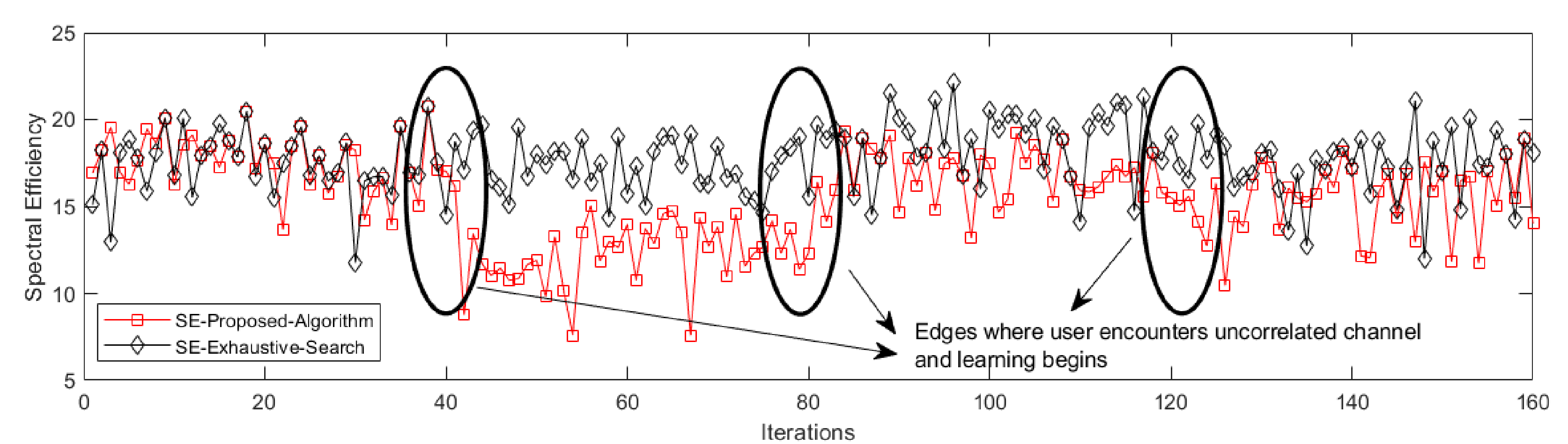


One time-slot/iteration = 5ms;
User velocity = 86 kmph;
Move Distance= 40 m;
Move Duration=1.665s

PERFORMANCE OF PROPOSED RL ALGORITHM (SLOT DURATION: 10MS)



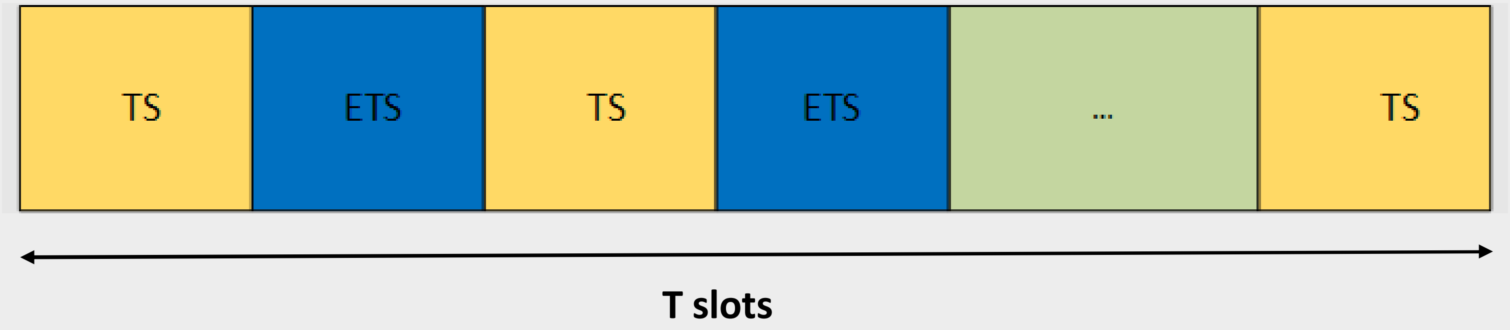
One time-slot/iteration = 10ms;
User velocity = 36 kmph;
Move Distance= 40 m;
Move Duration=4s



One time-slot/iteration = 10ms;
User velocity = 90 kmph;
Move Distance= 40 m;
Move Duration=1.6s

CONCLUSION

- The proposed algorithm runs two TS entities alternately to address the beam selection in changing channel conditions.



- This gives us a T-element policy consisting of arms a_t selected at time-slots $t = \{1, \dots, T\}$.
- Target: maximize T to prolong an additional IA procedure.

QUESTIONS?