

# Reliable Cache Control in Unreliable Edge Environments Using Reinforcement Learning

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## 1. INTRODUCTION

### Background and Problem Statement

- **Mobile Edge Caching (MEC)** places cache servers close to users to reduce latency and backhaul traffic.
- In practice, a large number of **edge servers (ESs)** are **low-cost and unreliable**, suffering from frequent failures.
- To improve reliability, **erasure coding** (e.g., Reed–Solomon / MDS codes) is applied by splitting contents into multiple chunks.
- A content can be successfully restored if at least **k chunks** are obtained from available ESs.

### Challenges

- Existing studies mainly assume:
  - Static content placement
  - Fixed caching policies
  - Known and stable environments
- In reality:
  - Content popularity changes dynamically
  - ES availability varies over time
  - Static cache control causes over-caching of popular contents and low diversity of chunks
  - → Dynamic cache control considering unreliability is required.

## 2. PROPOSED METHOD

### Placement method

We propose a **reinforcement learning (RL)–based cache control method** for unreliable edge environments using erasure coding. The cache insertion probability  $f_m$  for each content  $m$  is optimized dynamically. RL learns appropriate insertion actions based on observed system states.

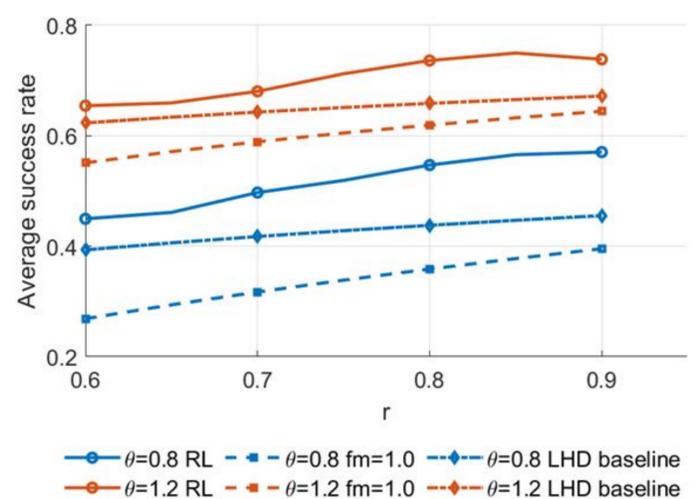
### Optimization methods

- Optimization methods such as HomoCP and reinforcement learning are used to optimize cache control parameters under unreliable edge environments.

## 3. EVALUATION

### Evaluation Metrics

- Average Successful Recovery Rate
  - Ratio of contents successfully restored using only chunks obtained from ESs
- Comparison with baseline methods:
  - Fixed insertion probability ( $f_m = 1.0$ )
  - **(RL)–based caching**
  - Leave-Hot-Down (LHD)



### Results

- The proposed method achieves:
  - Higher recovery success under dynamic environments
  - Better chunk diversity across ESs
- When ES availability is high:
  - Baseline methods suffer from over-concentration of popular contents
  - The proposed method avoids unnecessary redundancy
- The RL-based policy generalizes well to unseen environments without retraining

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