Cache-Aided NOMA for 6G Networks

Predictive Cache Placement and Performance Evaluation

PROJECT SYNOPSIS

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Contents

1 Abstract

This project investigates a Cache-Aided Non-Orthogonal Multiple Access (NOMA) framework for next-generation (6G) wireless networks with an emphasis on predictive cache placement. We propose a simulation-based study that integrates NOMA physical-layer modeling with edge caching strategies. A machine-learning based predictor will forecast file popularity and guide cache placement at base stations and edge nodes. The project evaluates performance on key metrics including cache hit ratio, average access time, system sum-rate, and outage probability for cell-edge users; comparisons will be made against standard caching policies. Optional relay-assisted schemes will be modeled to examine improvements for far users. Expected outcomes include quantified gains from prediction-driven caching under varying cache sizes, user densities, and channel conditions, accompanied by recommendations for practical cache placement strategies in cache-aided NOMA systems.

2 Introduction

The evolution toward 5G/6G demands extremely low latency, high spectral efficiency and massive connectivity. Two complementary techniques proposed to meet these requirements are edge caching and Non-Orthogonal Multiple Access (NOMA). Edge caching reduces backhaul load and access latency by placing popular content closer to users, while NOMA improves spectral efficiency by enabling multiple users to share the same time–frequency resources via power-domain multiplexing and SIC. The joint paradigm, *cache-aided NOMA*, aims to combine benefits from both approaches and has been surveyed and motivated in recent literature.

3 Literature Review

In early empirical work Foundational developments in caching and NOMA demonstrated that content popularity often follows Zipf-like distributions, a baseline model commonly used for cache-placement analysis [3]. Architectures that push content closer to users—such as *femtocaching* and helper/D2D caches—were proposed to exploit spatial locality and reduce core network load [9, 11]. A major theoretical advance was the coded-caching framework which revealed multicast opportunities and global caching gains under coordinated placement [14]. In parallel, NOMA matured as a key PHY/MAC technique for 5G with detailed treatments of power allocation, SIC decoding, and practical challenges [6, 7].

In convergence of caching and NOMA (recent advances), the interplay between caching and NOMA has been explored from analytical, stochastic-geometry and optimization perspectives. Stochastic-geometry based analyses model cache-enabled NOMA networks to estimate coverage and rate metrics [15], while joint optimization works consider cache placement together with power allocation to maximize throughput or minimize latency [4, 10]. Surveys summarizing the state-of-the-art in cache-aided NOMA highlight key performance indicators, promising application scenarios (edge/MEC, UAVs, D2D) and open challenges [2]. On the prediction side, machine-learning approaches—ranging from statistical predictors to LSTM and deep-RL methods—have been proposed to adapt placement to temporal popularity changes [8, 12, 5].

For relay-assisted and coverage-extension works to improve cell-edge performance in NOMA systems, cooperative and relay-assisted designs (including partial decode-and-forward and UAV relays) have been investigated. Relay-assisted NOMA can reduce outage for far users under specific conditions, at the cost of additional coordination and latency [1, 13].

In Critical appraisal — the strengths and limitations are as: Coded caching offers provable multicast and peak-rate reduction gains under coordinated placement [14]. NOMA increases spectral efficiency with flexible power allocation and SIC-based decoding [6, 7]. ML-driven prediction improves cache-hit rates by adapting to temporal popularity shifts in realistic workloads [8, 12, 5].

In Limitations and research gaps: Many theoretical analyses assume ideal links or perfect SIC, which neglects residual interference and CSI estimation errors that degrade practical performance [6, 7]. Joint optimization of long-term cache placement and short-term NOMA power allocation is computationally heavy; practical heuristics are still required [4]. Existing studies often lack comprehensive simulation under realistic wireless channel models (fading, mobility) and hardware impairments — a gap noted in recent surveys [2, 10]. ML-based cache predictors deliver gains but rely on sufficient historical data and careful feature design; privacy and trace availability remain practical constraints [5, 8].

Given the limitations above, a simulation-oriented study that integrates lightweight ML predictors with PHY-level NOMA modeling (including imperfect SIC and optional relay-assisted delivery) is necessary to evaluate practical trade-offs between cache-hit improvements and user outage under realistic operating conditions [2, 4].

4 Problem Definition

Problem Statement: 6G networks demand ultra-low latency, high spectral efficiency, and massive connectivity. Cache-aided NOMA addresses these via edge caching and NOMA. Key challenges include proactive content placement, aligning caching with NOMA, and handling real-world impairments.

> **Core Problem:** *Design and evaluate a lightweight, prediction-driven cache placement strategy for cache-aided NOMA downlink to maximize cache-hit rate, reduce latency, and ensure acceptable edge user outage performance under realistic conditions.*

Primary Objective: Develop a Python simulation framework integrating NOMA and ML predictor-driven cache placement. Quantify benefits via cache-hit ratio, AAT, sum-rate, and outage probability.

Specific Objectives: Implement NOMA/channel models, baseline/predictor caching, and integrate caching with NOMA delivery (optional relay). Evaluate metrics across parameter sweeps. Produce analysis, visualizations, and recommendations.

5 Methodology and Planning of Work

Overview: This project’s methodology centers on designing and evaluating a cache-aided NOMA downlink system through a **Python-based simulation framework**. The core approach involves three phases:

- **Phase I: NOMA Physical-Layer Simulation:** Constructing a NOMA physical-layer simulator incorporating **Successive Interference Cancellation (SIC)**.
- **Phase II: Cache Implementation:** Implementing diverse cache placement policies, including a lightweight **Machine Learning (ML) prediction module** for proactive content placement.
- **Phase III: Controlled Experiments:** Conducting **controlled experiments** to meticulously measure key performance indicators such as **cache hit ratio**, **average access time (AAT)**, **system sum-rate**, and **outage probability** for edge users, under a range of varying parameters including cache size, Zipf skewness, SIC imperfection, and user density. The ML prediction models will utilize lightweight architectures like Decision Tree for baseline comparisons, with an optional Long Short-Term Memory (LSTM) network for capturing temporal sequence patterns.

6 Facilities Required for Proposed Work

Software:

- **Python 3.9+** with essential packages: ‘numpy‘, ‘scipy‘, ‘pandas‘, ‘matplotlib‘, ‘seaborn‘, ‘scikit-learn‘, ‘tensorflow‘, ‘simpy‘, ‘commpy‘.
- **Jupyter Notebook / JupyterLab** for experiments and plotting.
- **Git** for version control, hosted on GitHub/GitLab.
- **‘ns-3‘ or ‘OMNeT++‘** for packet-level simulation.

Data and Traces.

- **Synthetic Trace Generation:** Built-in Zipf-based request generator.
- **Public Traces:** Pre-processed MovieLens or CDN/public traces as popularity proxies.

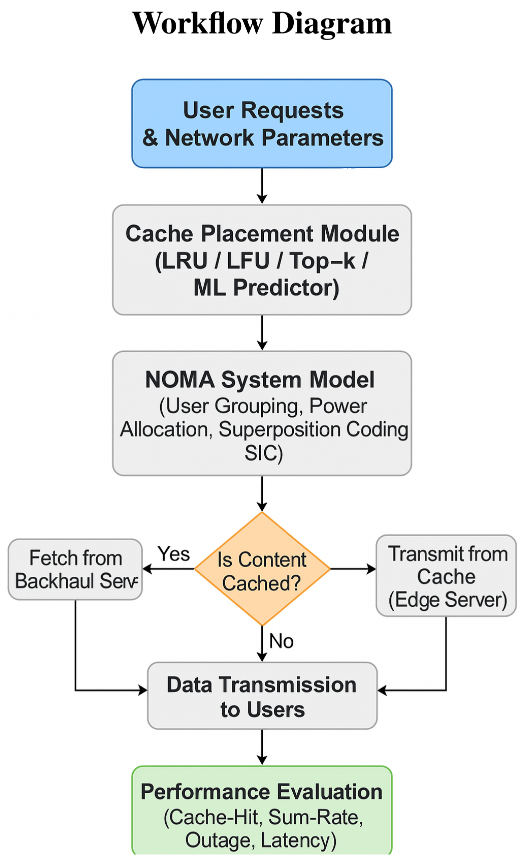

Figure 1: Cache-Aided NOMA Diagram

7 References

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