Presentation On

NETWORK SLICING

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Course: Introduction to Machine Learning

Presented to

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Paper Title

ECP: Error-Aware, Cost-Effective and Proactive Network Slicing Framework

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Date of publication 17 April 2024; date of current version 3 May 2024

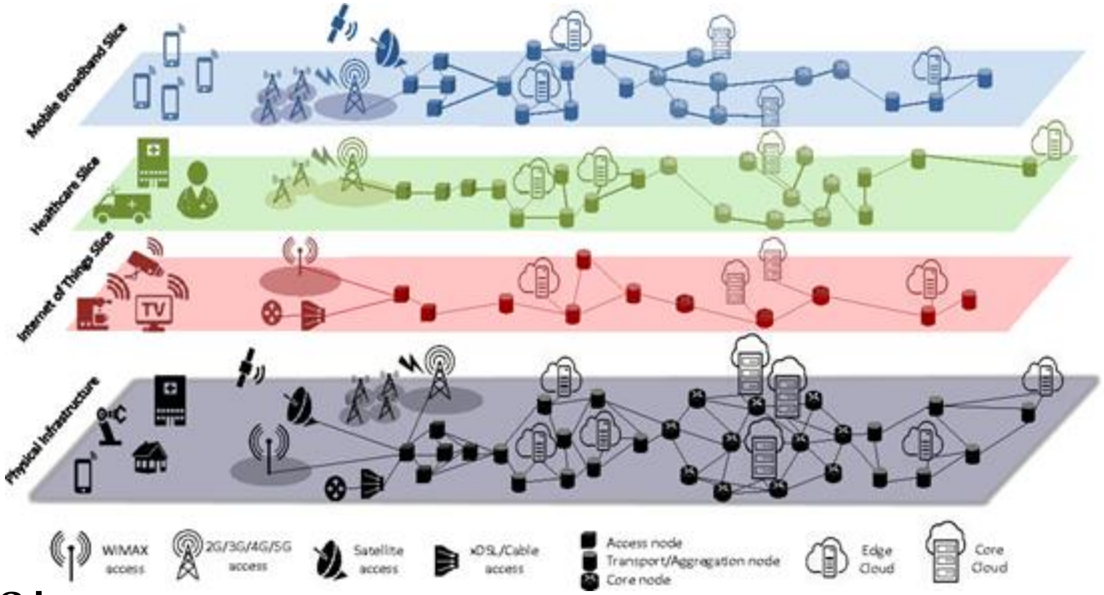
Presentation Outline

- Introduction
- Objective
- System Architecture
- Methodology
- Problem Formulation
- Algorithm Analysis
- Simulation Results
- Conclusion

Introduction

The **5G network revolution** has introduced unprecedented connectivity and performance, enabling critical applications like:

- **Healthcare**: Remote surgeries and real-time monitoring.
- **Autonomous Systems**: Self-driving cars and drones.
- **IoT Expansion**: Smart cities and industrial automation.



Objectives

- ✓ Proactively predicts network slice loads.
- ✓ Corrects prediction errors.
- ✓ Minimizes costs while meeting service KPIs.
- ✓ Diverse Key Performance Indicators (KPIs).
- ✓ Cost variations and over/under-provisioning.
- ✓ Efficient resource allocation is critical for quality service.

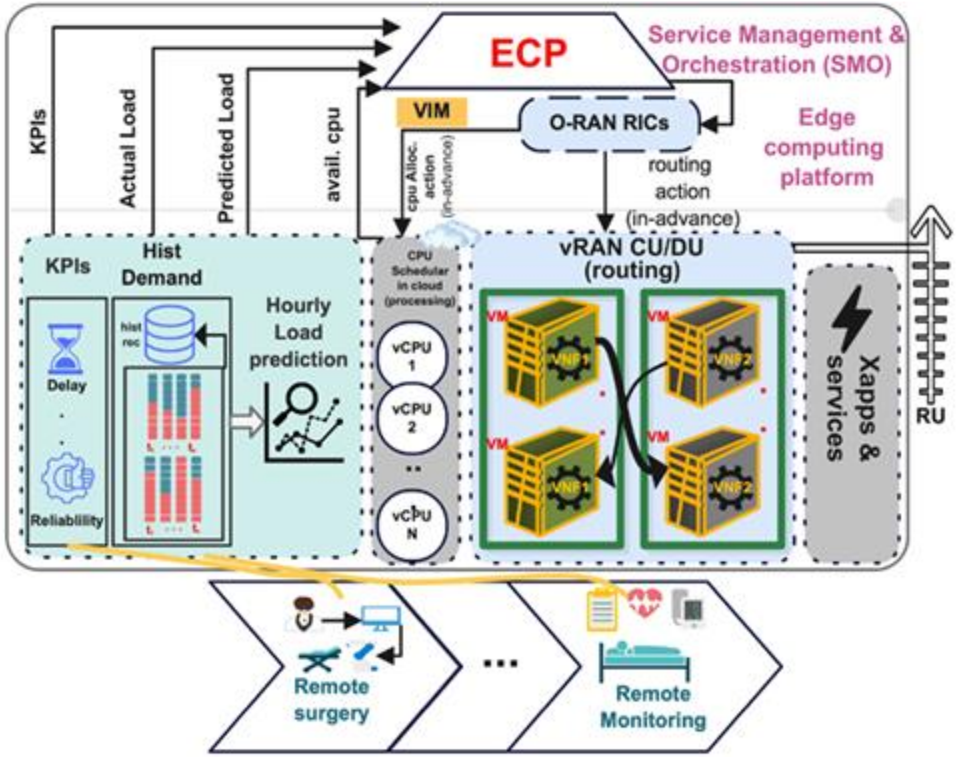
ECP Framework

- **Two-Phase Approach**:
  - **Prediction Phase**:
    - Historical load data analyzed using AI-based models.
    - Predicts service loads and KPI requirements.
  - **Optimization Phase**:
    - DRL agent corrects prediction errors.
    - Allocates resources to minimize costs and ensure QoS.

System Architecture

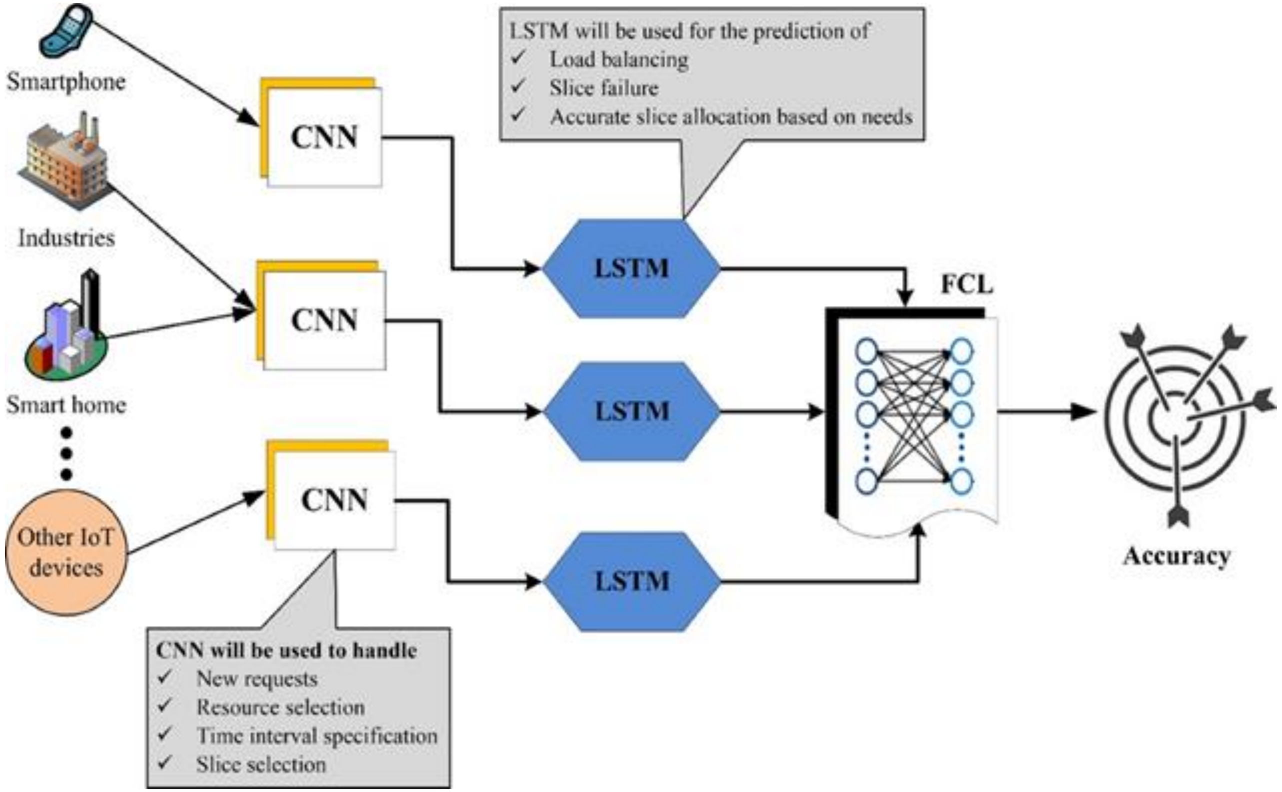
System model within the Open RAN 5G architecture

- Virtual Control Unit (vCU) and Distributed Unit (vDU).
- DRL agent for dynamic slice optimization.



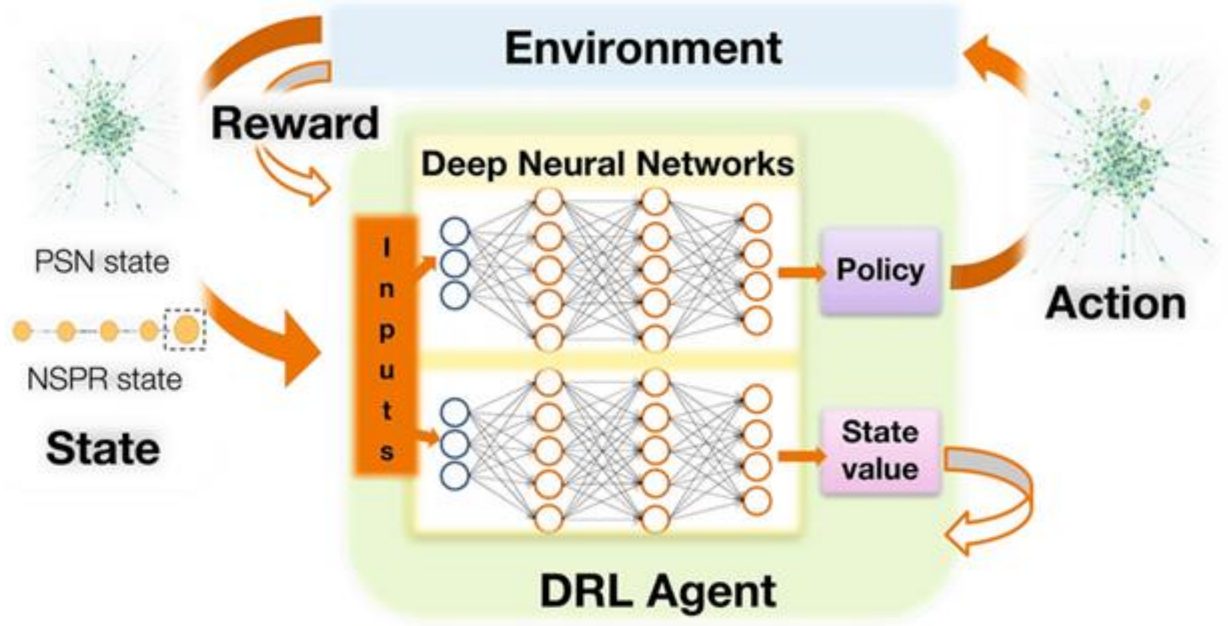
Methodology

- **Phase 1: Predictive Model**:
  - Uses historical data for load forecasting.
  - Models tested: ARIMA, SARIMA, LSTM, etc.



Methodology

- **Phase 2: Network Slice Optimization**:
    - DRL-based allocation.
    - Objectives: Minimize costs, correct prediction errors, and meet KPIs.
    - DRL was used to ensure the optimal choice of paths and resources.



Ecp Algorithm

Input

- **Simulation Parameters**:
  - Episode Counter (**Ecounter**) and Maximum Episodes (**Emax**).
  - Buffer Size (**Bsize**) and Allocation Map (**M**).
  - Simulation Hours Per Day (**hcount**).
- **Service Data**:
  - Hourly Forecasts for all services (**σs**) and actual loads (**σ*s**).

Output

- Optimized resource allocation map (**M**).
- Metrics for cost efficiency, resource utilization, and adherence to service demands.

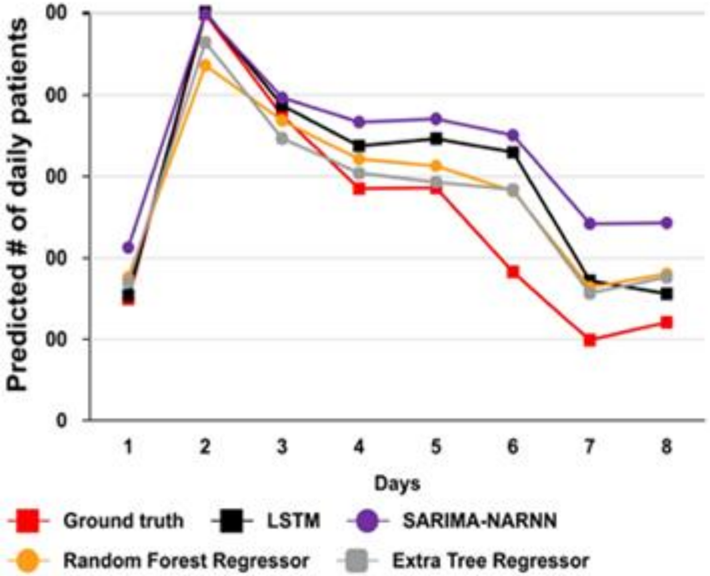
Main Loop

1. **Reinitialize Environment**: Prepare for a new episode.
2. **Iterate Through Days and Hours**:
   1. Form **state (St)** using:
      1. Current day/hour (**dcurr**, **hcurr**).
      2. Hourly service forecasts (**σs**).
   2. Feed **St** to the PPO agent to select action (**at**) for each service.
   3. Save paths and intermediary nodes in **M.**
3. **Resource Allocation**:
   1. **Link Bandwidth Adjustment**: Split equally among demanding services if links exceed capacity.
   2. **Node Resource Adjustment**: Proportionally share resources for over-utilized nodes.
4. **Execute Action**:
   1. Apply action (**at**) and transfer data using updated map **M.**
   2. Calculate **reward (rt+1)** based on performance.
   3. Save the trajectory (**st, at, rt+1, st+1**) in the buffer (**B**).

Training Phase

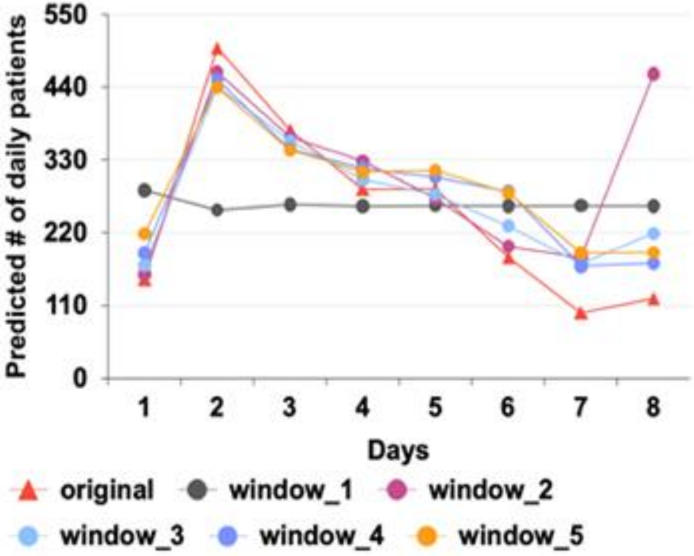
5. **Batch Processing**: For each mini-batch in buffer (**B**):
   5. Compute **Rewards-to-Go (R̂t)** and **Advantage Estimates (Ât)**.
   6. Update the PPO's Actor and Critic Neural Networks.
6. **Increment Episode Counter**: Continue until **Ecounter** equals **Emax**.

Simulation Results



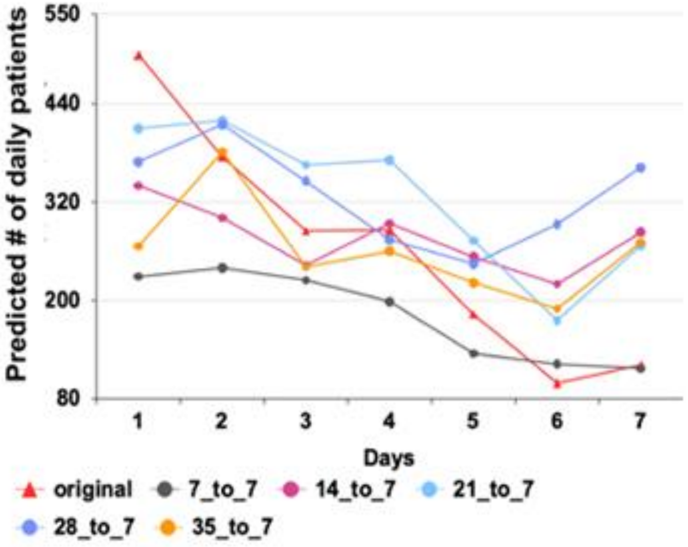
(a) Set 1 performance

The prediction of classical machine learning algorithms



(b) Set 2 performance

The effect of different window sizes of the LSTM model on the prediction



(c) Set 3 performance

Changing input length affects the prediction output.

Conclusion

- ✓ First to integrate dynamic load prediction, error correction, and end-to-end slice optimization.
- ✓ Effectively balances cost reduction with minimal resource over-provisioning.
- ✓ 37-51% cost savings compared to static and reactive allocation methods.
- ✓ The framework ensures high-quality service delivery.

Overall Conclusion

- ✓ Resource allocation Optimized in end-to-end network slicing under demand.
- ✓ It ensures high-quality service delivery while minimizing costs.
- ✓ Maximize utility in end-to-end network slicing using AI.
- ✓ Improved healthcare service delivery.
- ✓ The framework ensures high-quality service delivery.
- ✓ Establish sustainable economic models for network operators.
- ✓ Allocates resources to minimize costs and ensure QoS.

Thank You