# Intelligent Network Control with Human Experts in the Loop

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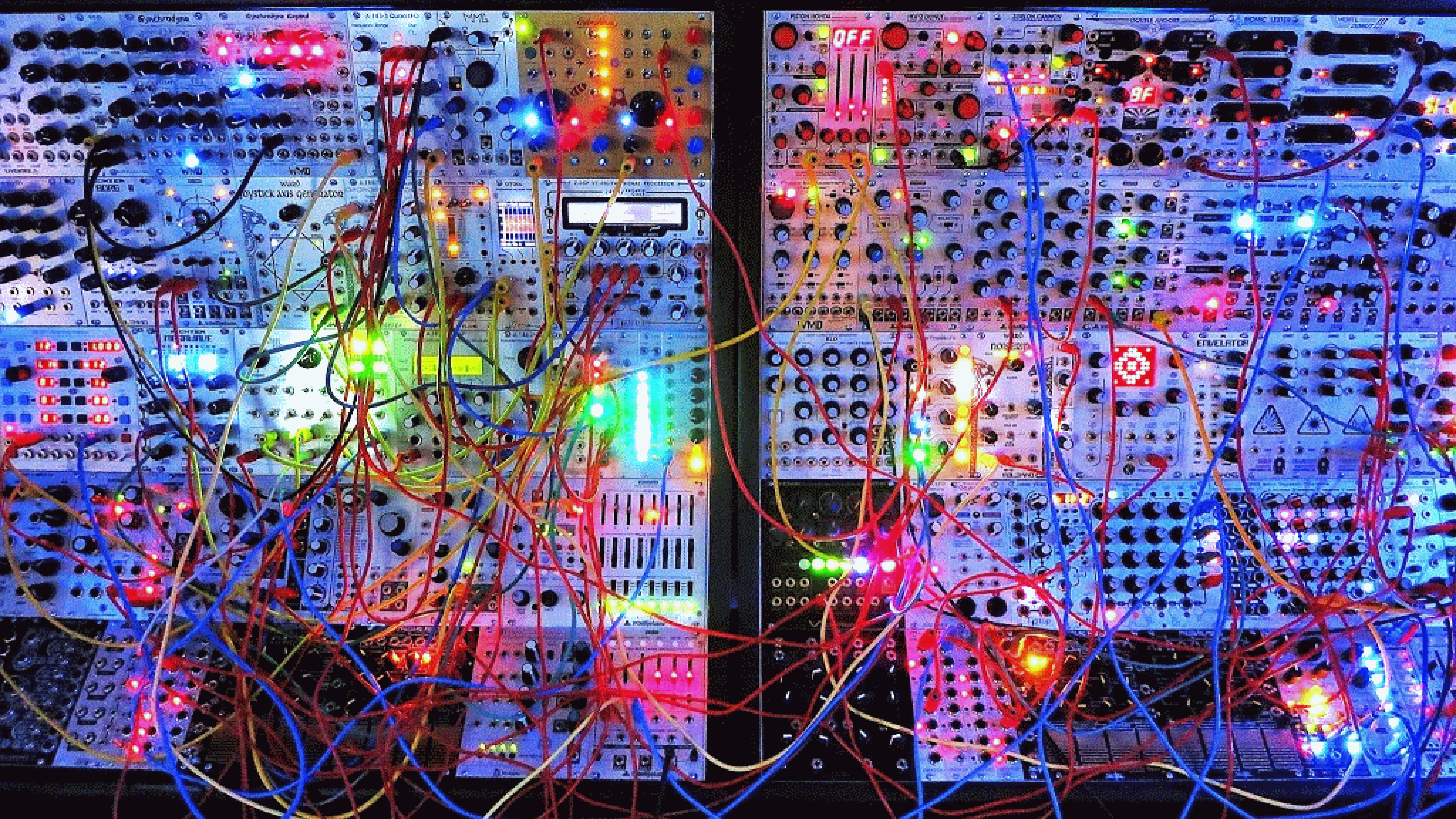
# Fact: Future networks need automation

**7-fold increase** in number of 5G connections by 2025 [CCS Insights]

5G needs to **co-exist with 4G/3G/etc.** → operation challenges

**New services** with very different requirements: low latency (AR/VR), ultra reliability (automotive IoT)


OFF
9F
WMD
Joystick axis generation
ENVELATOR

# Problems with traditional optimisation approaches

- Hard to find optimal point of operation in a **timely manner**
- **Multiple goals** to be fulfilled at the same time
- Even hard to know what an optimum looks like
- Network **environment changes** continuously
- Too **many ‘knobs’** to tweak

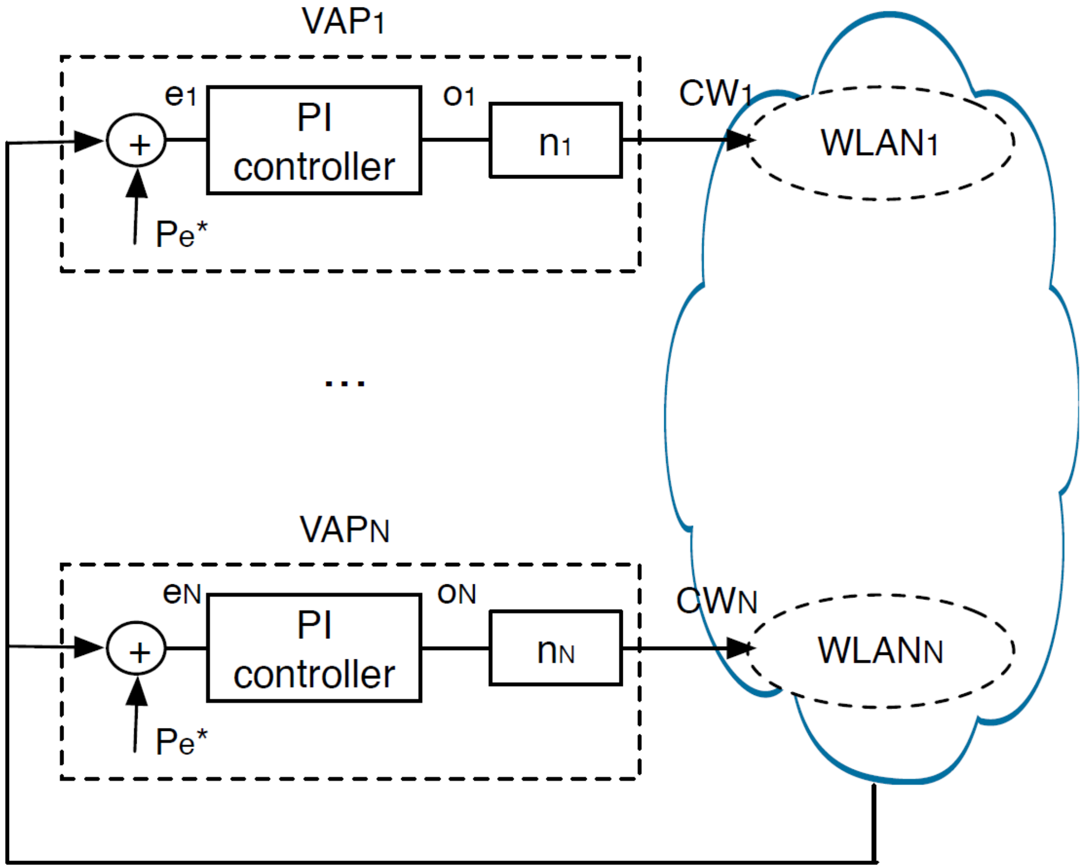
# Surely seen this before, right?

**Example:** Optimising throughput of virtualised Wi-Fi using control theory

- Optimal operation characterised by an invariant signal – empty slot probability

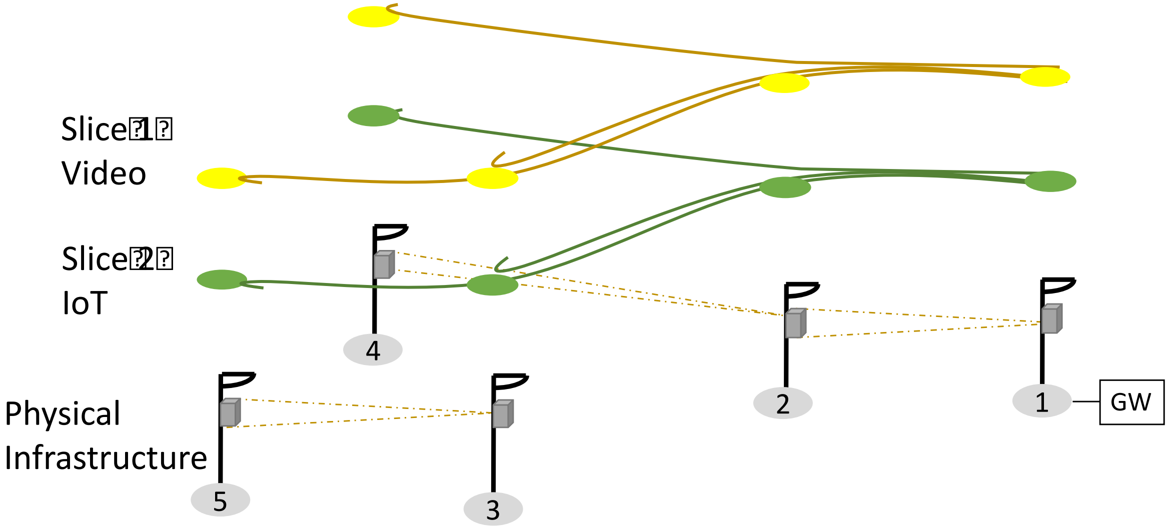
$$P_e^* \approx e^{-\sqrt{\frac{2T_e}{T_o}}}$$

- Proportional-integrator controllers adjusting contention windows for each virtual access point (VAP)
- Settings propagated with every beacon (100ms)



A. Banchs, P. Serrano, P. Patras, M. Natkaniec, "Providing Throughput and Fairness Guarantees in Virtualized WLANs through Control Theory", ACM/Springer MONET, 2012

# Complexity of multi-service mobile networks



## Problem: Maximise the utility of sliced backhaul networks

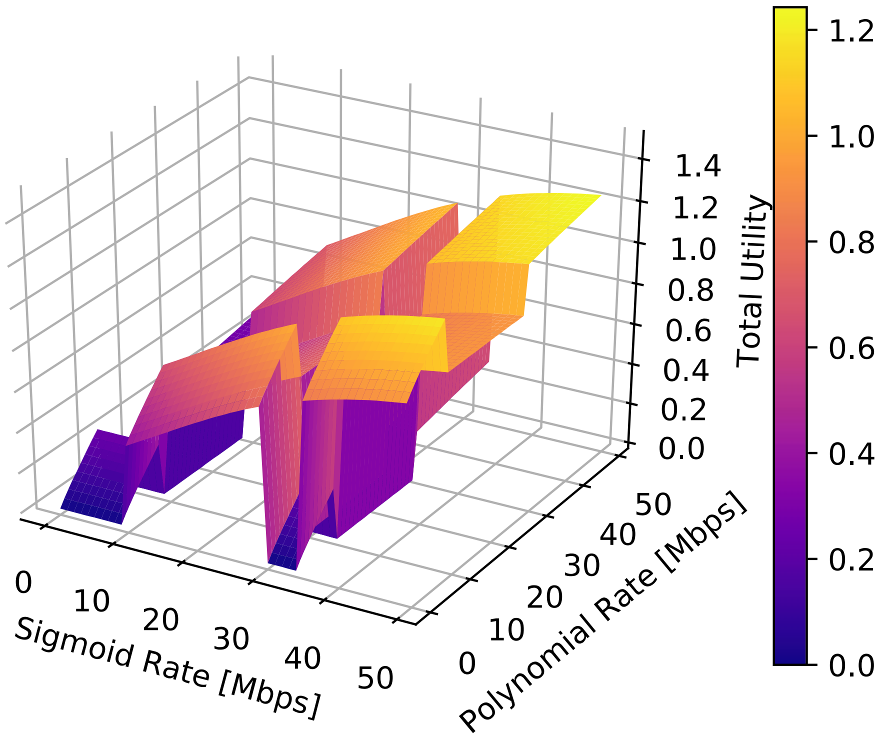
- Allocate rates $r_{i,j}$ to flows $f_{i,j}$
- to meet **service requirements** and
- to maximise **resource utilitsation**

$$\arg\max \sum U_i(r_{i,j})$$

where $U_i$ is polynomial/sigmoid/etc.

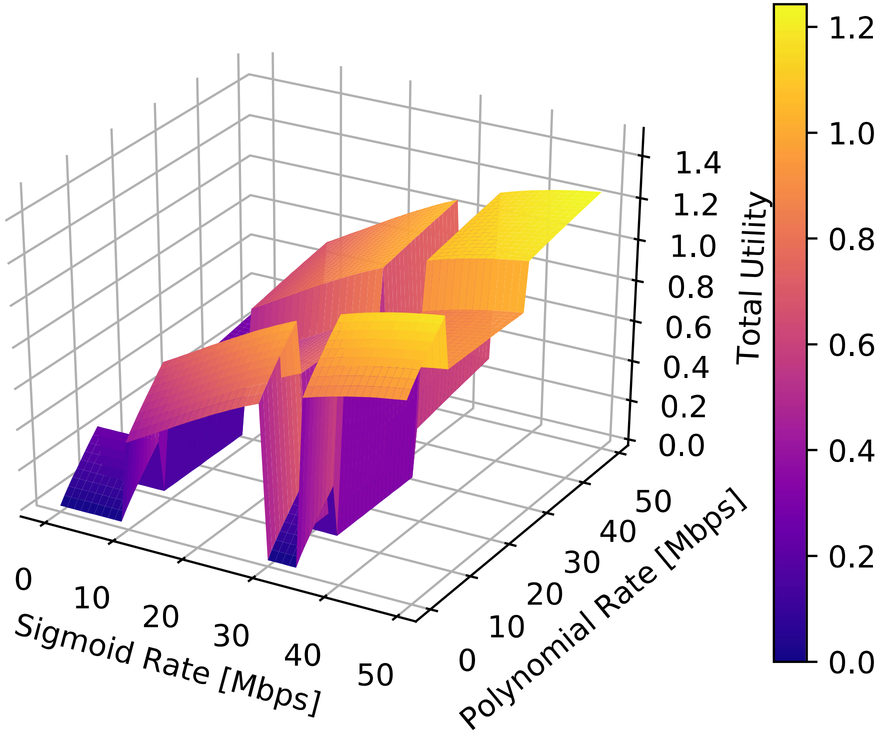
R. Li, C. Zhang, P. Cao, P. Patras, J. S. Thompson, "DELMU: A Deep Learning Approach to Maximising the Utility of Virtualised Millimetre-Wave Backhauls", MLN 2018

# Complexity of multi-service mobile networks



- High-dimensional problem, highly non-convex
- Global search is time consuming
- Heuristic methods can solve but sub-optimal

# The power of deep learning



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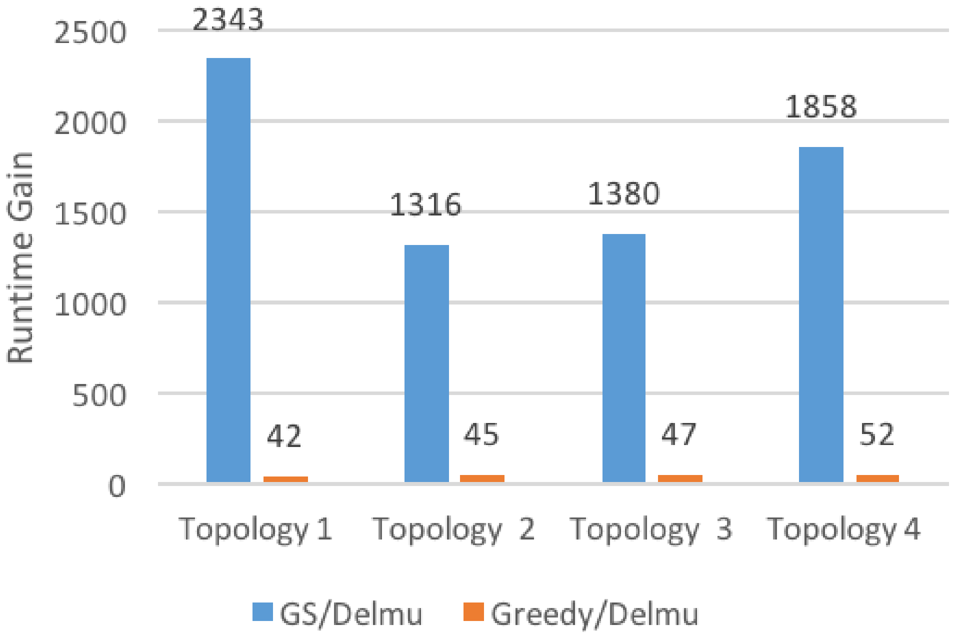
## Deep Learning

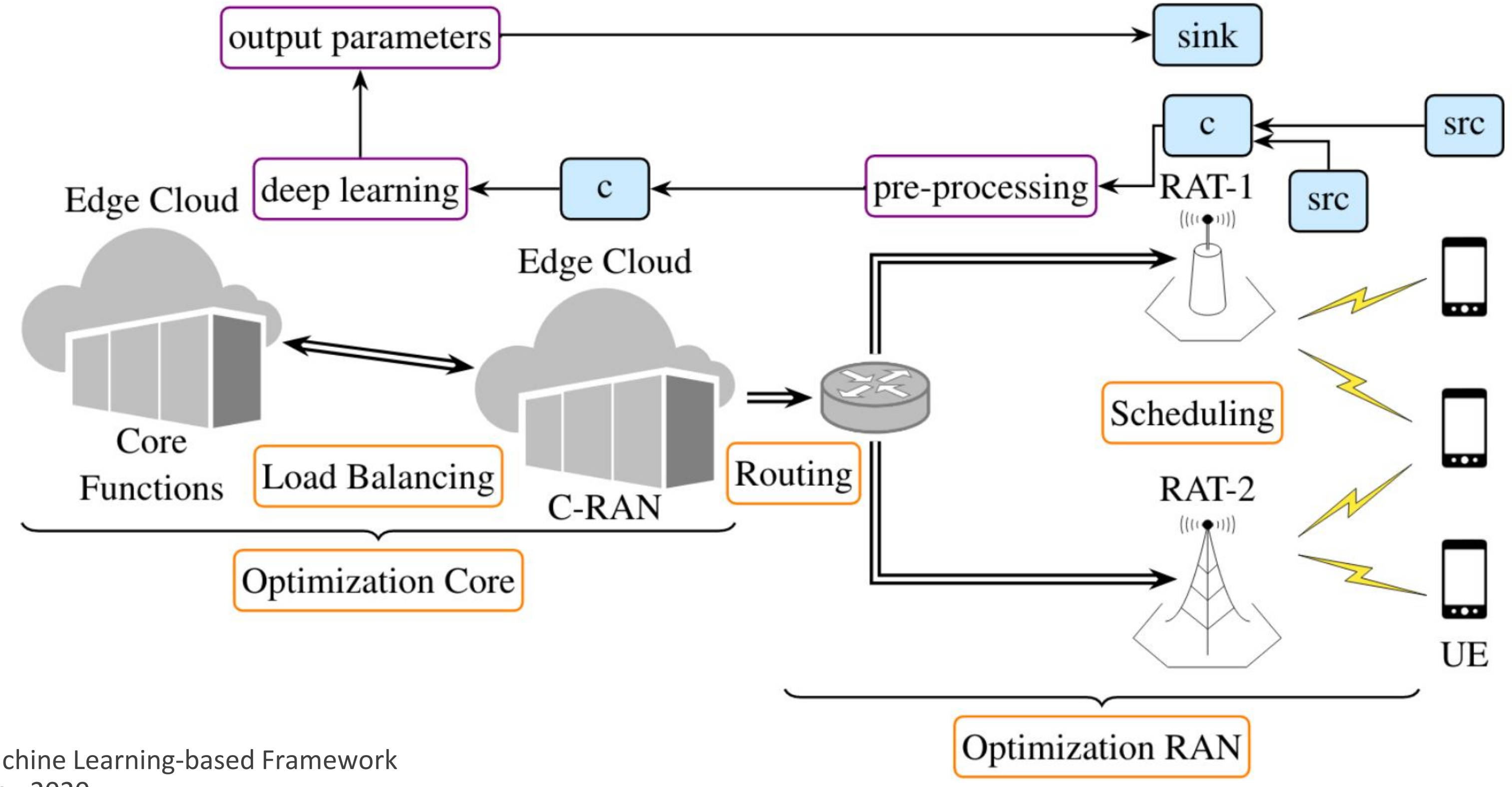
- Inference >2,300x faster than Global Search, 42x faster than Greedy heuristic
- Within 5% if the global optimum



# Deploying AI in mobile networks

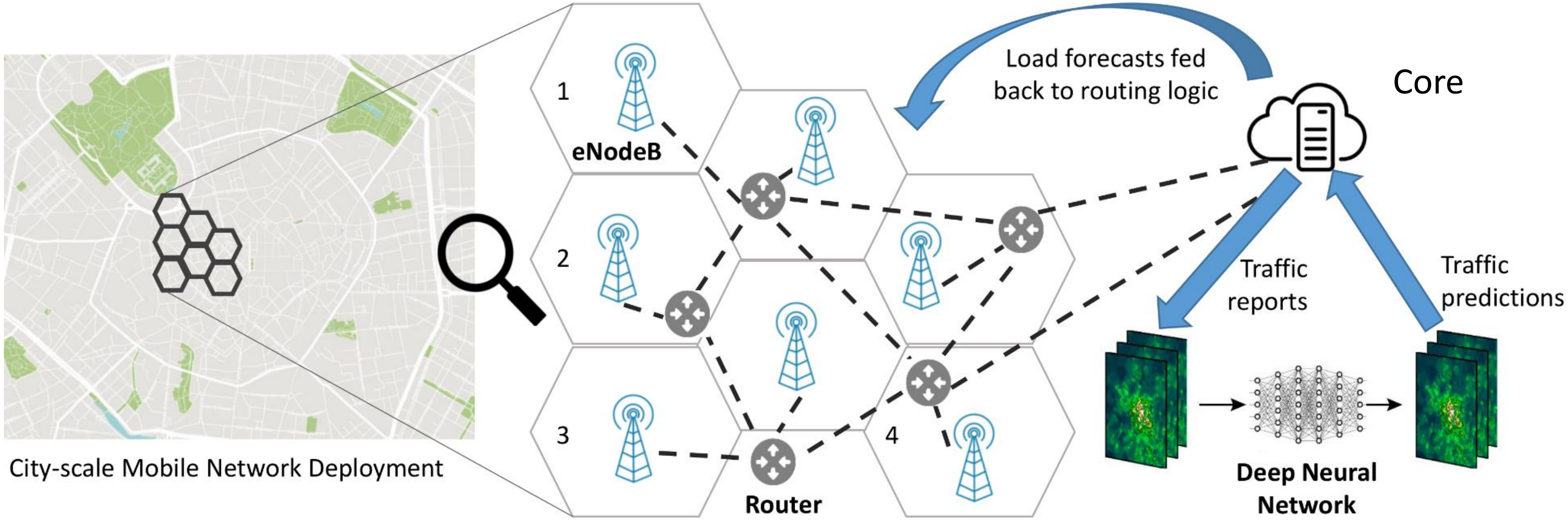
Follow ITU-T Y.3172 (Architectural framework for machine learning in future networks including IMT-2020)

- Fuel existing network control mechanisms with AI-driven analytics
- No need to design problem-specific ML algorithms

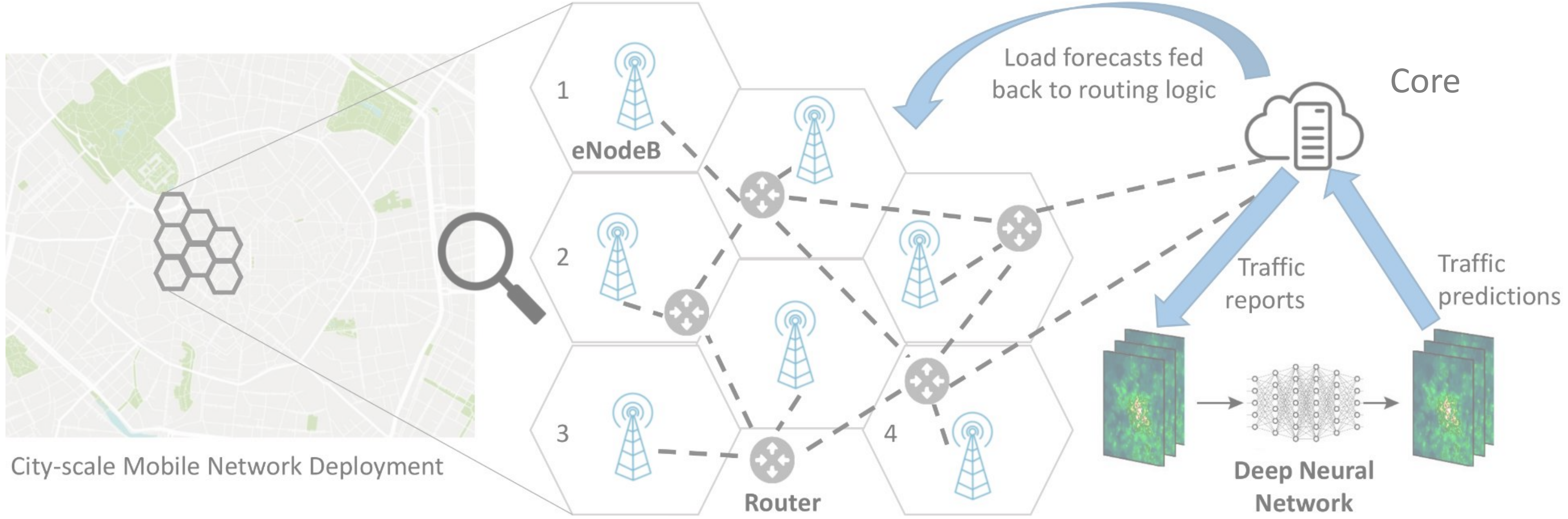


C. Fiandrino, C. Zhang, P. Patras, A. Banchs, and J. Widmer, "A Machine Learning-based Framework for Optimizing the Operation of Future Networks," IEEE Com. Mag., 2020.

# Example: Proactive routing based on load forecasts


City-scale Mobile Network Deployment
1
eNodeB
2
3
4
Router
Load forecasts fed back to routing logic
Core
Traffic reports
Traffic predictions
Deep Neural Network

# Example: Proactive routing based on forecasts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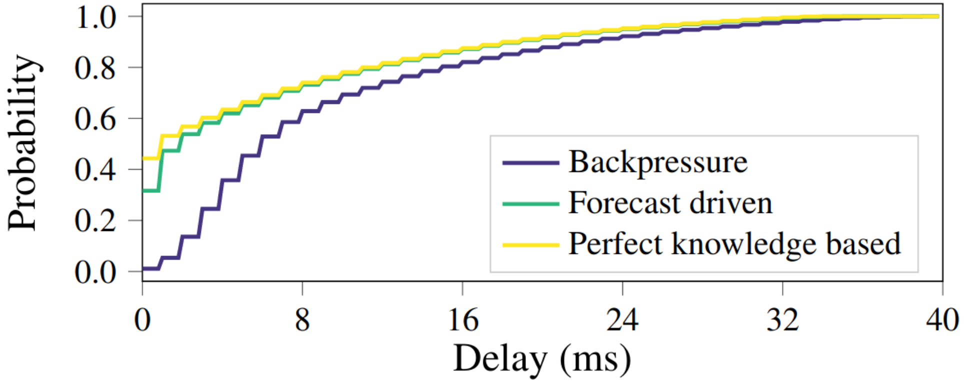
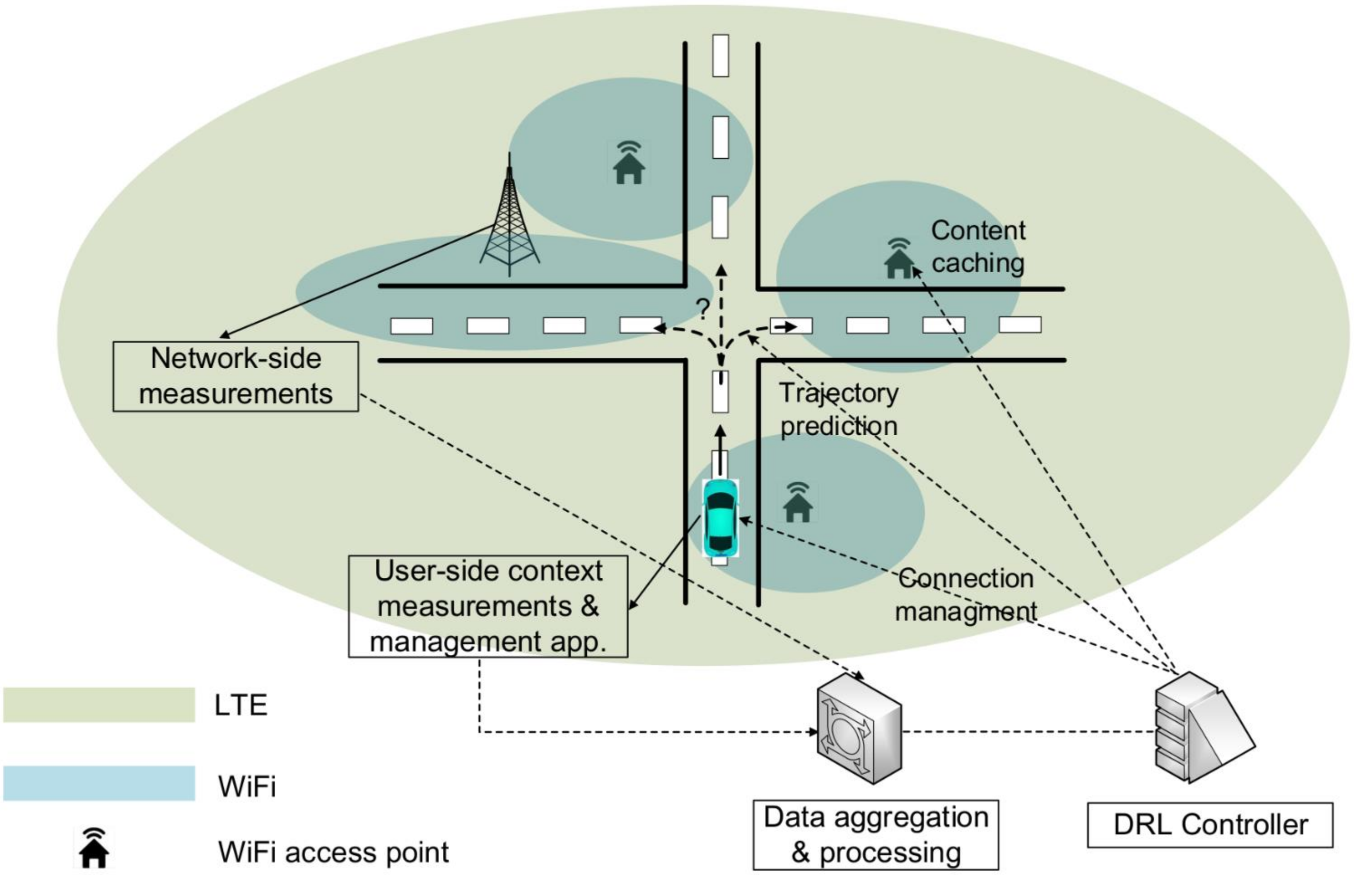


**3x lower median delay than that of reactive routing**
**Very close to ideal case with perfect knowledge**

# Full autonomy with deep reinforcement learning

- DRL agent learns from complex context (link qualities, user/app profiles, traffic load, mobility patterns, etc.) and
- interacts with changing environment via a control policy,
- aiming to maximise some reward (reduced latency, throughput gains, etc.)

Example: mobile connectivity management/content caching


Content caching
Network-side measurements
?
Trajectory prediction
User-side context measurements & management app.
Connection managment
LTE
WiFi
WiFi access point
Data aggregation & processing
DRL Controller

# Many challenges

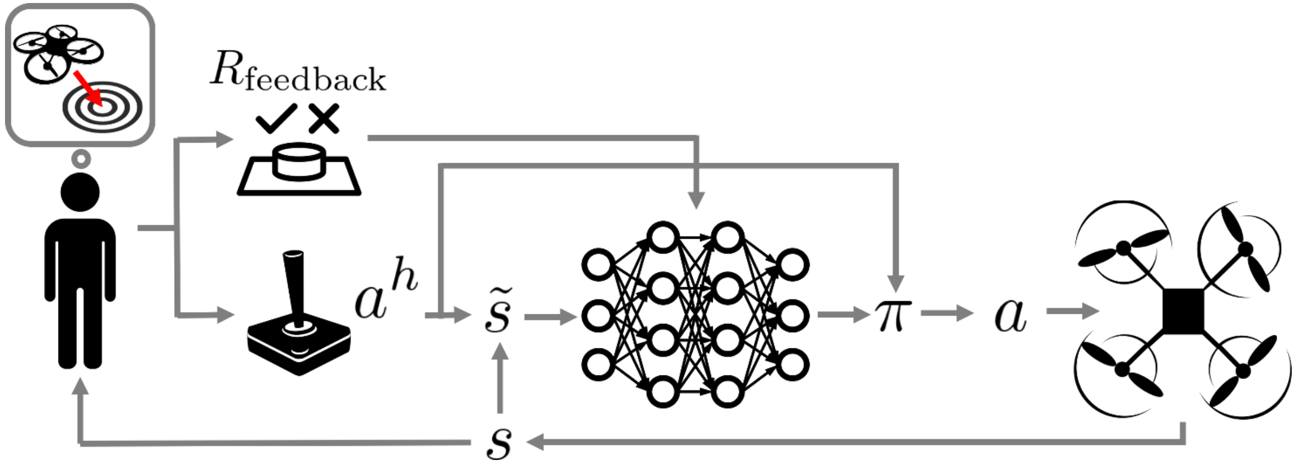
- Huge action/state spaces → neural network models take a lot of time to converge
- Difficult to model the environment (model free learning) → sample complexity
- New circumstances call for retraining

- Often missing the ‘bigger picture’

*“AI Camera Ruins Soccer Game For Fans After Mistaking Referee's Bald Head For Ball”*

# Wise to keep the human in the loop (shared autonomy)

- Already considered for robotic control



- Combine agent observations of the environment with user input
- Still need to pre-train agent in simulation to avoid user overload

S. Reddy, A. Dragan, S. Levine, “Shared Autonomy via Deep Reinforcement Learning”, arXiv, 2018.

# Towards autonomous networks

- No ‘one size fits all’ solution
- Take into account specifics of individual use cases
- Hierarchical approach to control (?), i.e. ask operator for assistance when confidence about decisions low
- How to do this in real-time (anticipate future state?)
- What about computation costs?