Practical Energy Optimization for Heterogeneous Mobile Networks via Digital Twins

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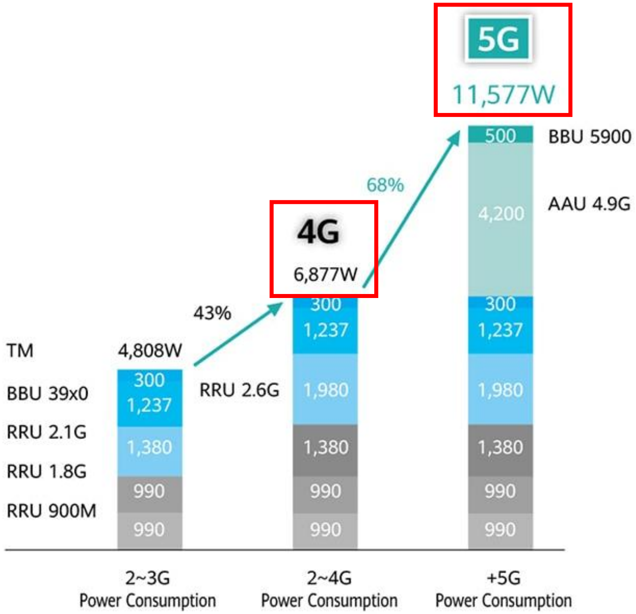

Typical maximum power consumption of a single base station[1].

[1] D. Chen, "5G Power: Creating a green grid that slashes costs, emissions & energy use," HuaweiTech, no. 89, Jul. 2020. [Online]. Available: https://www.huawei.com/en/huaweitech/publication/89/5g-power-green-grid-slashes-costs-emissions-energy-use.

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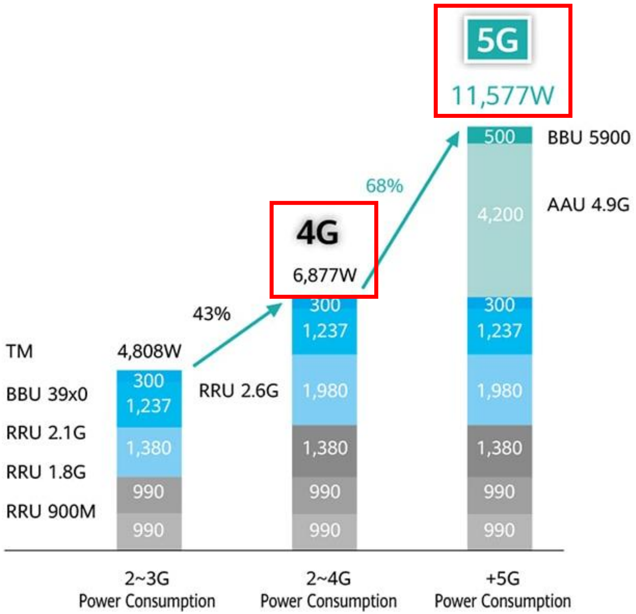

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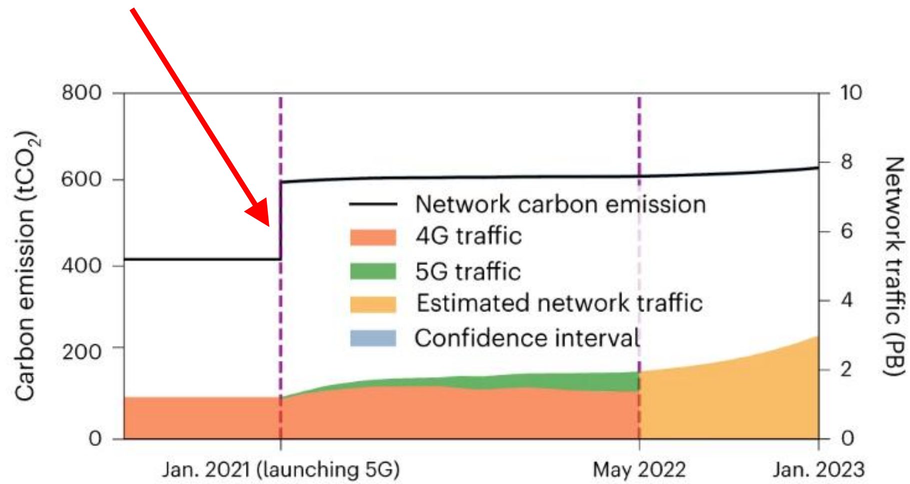

Launching 5G led to a sharp increase in carbon emissions[2].

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[2] Li, Tong, et al. "Carbon emissions of 5G mobile networks in China." Nature Sustainability 6.12 (2023): 1620-1631.

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- Mobile network energy consumption has become a pressing sustainability concern.
- Cell shutdown offers much saving potential by deactivating an entire cell[1].

	DTX / Channel Shutdown	Cell Shutdown	Deep Sleep
Time Scale	Sub-ms	Minutes – 1 Hour	Hours+ (Stable Periods)
Energy Saving Gain	Low–Moderate	High	Very High
Wake-up Cost	Low	Moderate	High
Scenario	All Day	All Day	Night Period

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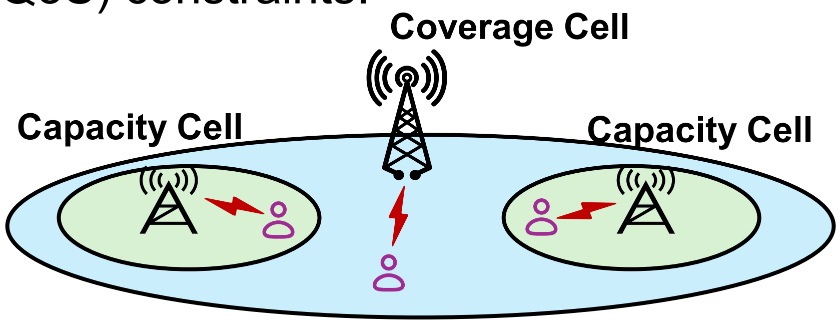

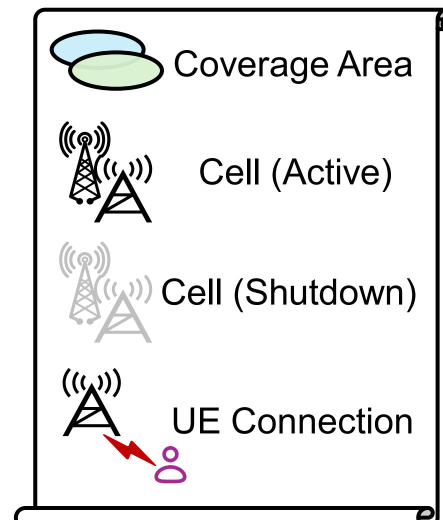

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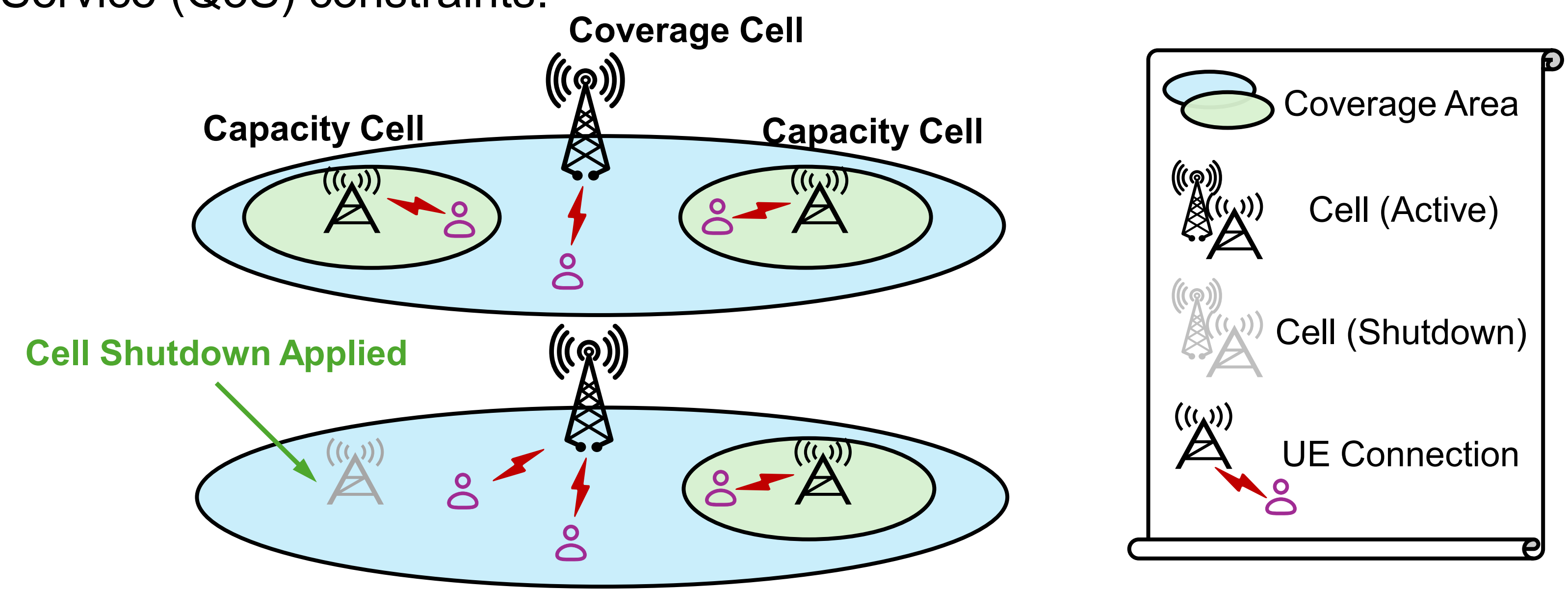

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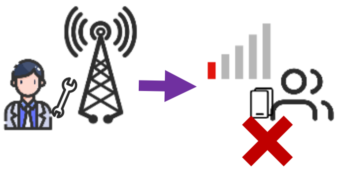
Challenges

- Optimizing cell shutdown policies in real-world networks is challenging:
  - **High-fidelity Network Modeling**:
    - Live trial is risky.
    - Complex network dynamics.



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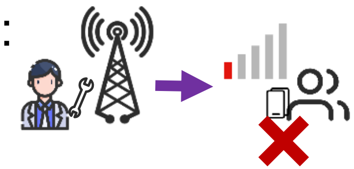
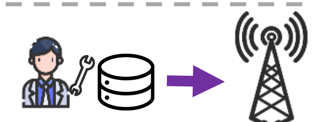


    - Live trial is risky.
    - Complex network dynamics.
  - **Optimization vs. Deployment Compatibility**:
    - Binary optimization: optimizable, but not deployable.
    - Threshold-based policy: deployable, but hard to optimize.

Binary Optimization:

Directly set status of cell i at time t: $x_i^t = 0$ (off) / 1 (on)

Threshold-based policy:



1) Set time-invariant threshold: θ
2) Collect traffic data of cell i at time t: l_i^t
3) $$x_i^t = \begin{cases} 0 \text{ (off)}, & \text{if } l_i^t < \theta \\ 1 \text{ (on)}, & \text{else} \end{cases}$$

Contributions

- We propose a digital twin empowered practical framework for energy optimization in heterogeneous mobile networks, addressing the challenges.
  - Optimize policies in digital twin.
  - Use reinforcement learning (RL) to optimize cell status.
  - Map status optimization into threshold-based policy
- We collect a large-scale dataset (over 14,000 base stations) from a real-world mobile network in China to evaluate our framework. Our framework achieves 3× energy savings of the strongest baseline while minimizing the impact on QoS.
- We deploy and validate our framework in three live networks. The cell shutdown policies generated by our framework consistently prove effective, delivering over 10% energy efficiency improvement across both 4G and 5G networks.

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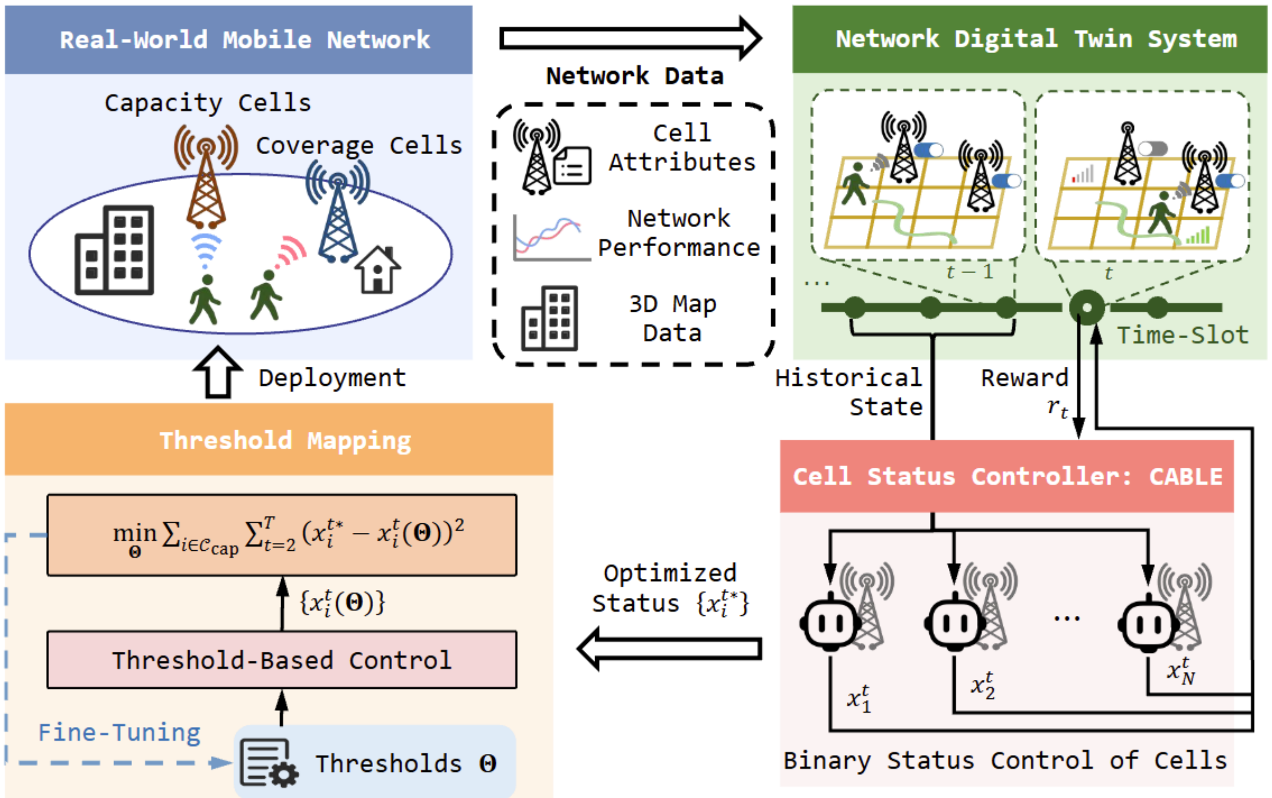
- Our solution: a digital twin empowered practical framework for energy optimization in heterogeneous mobile networks.



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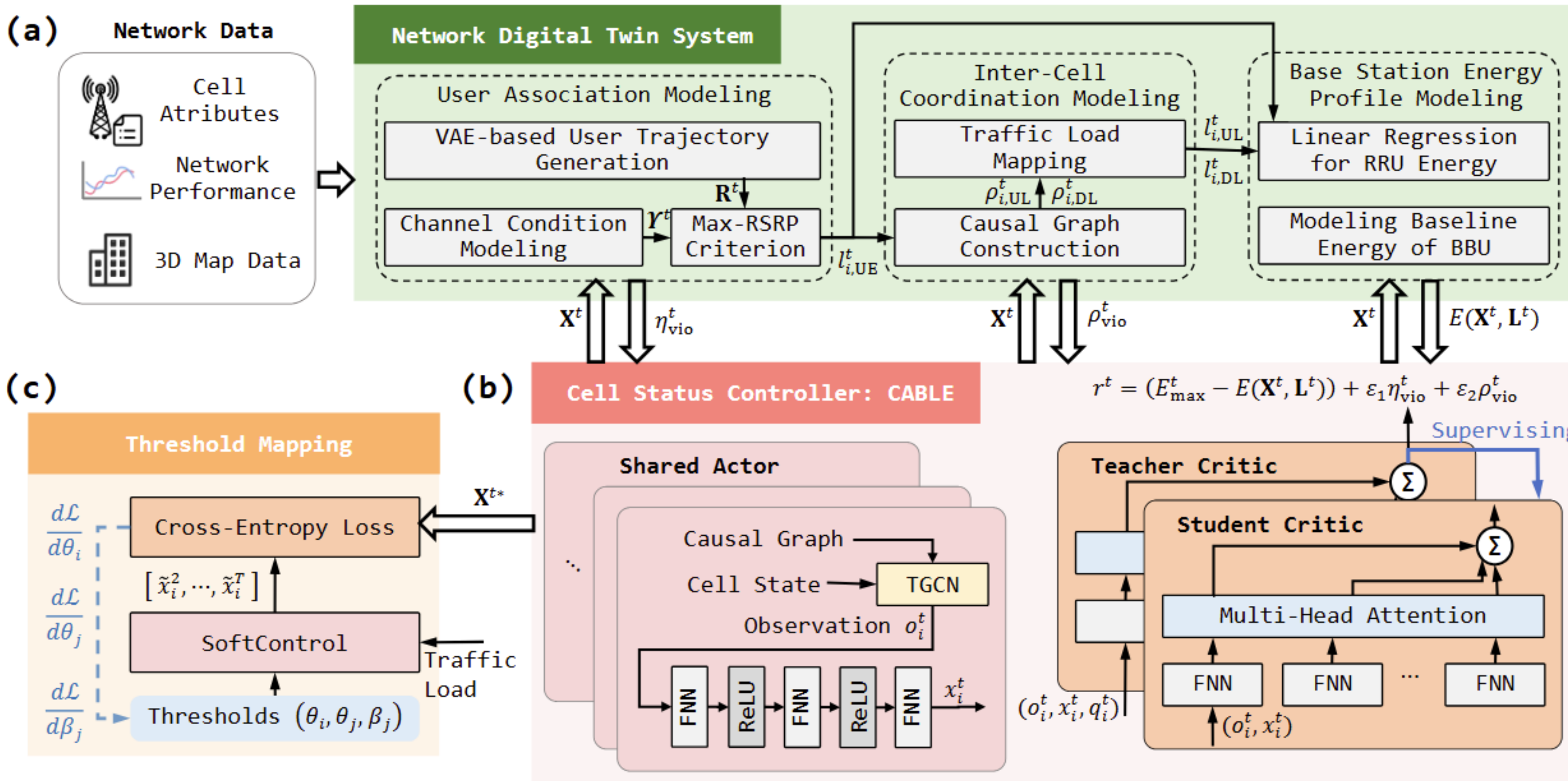
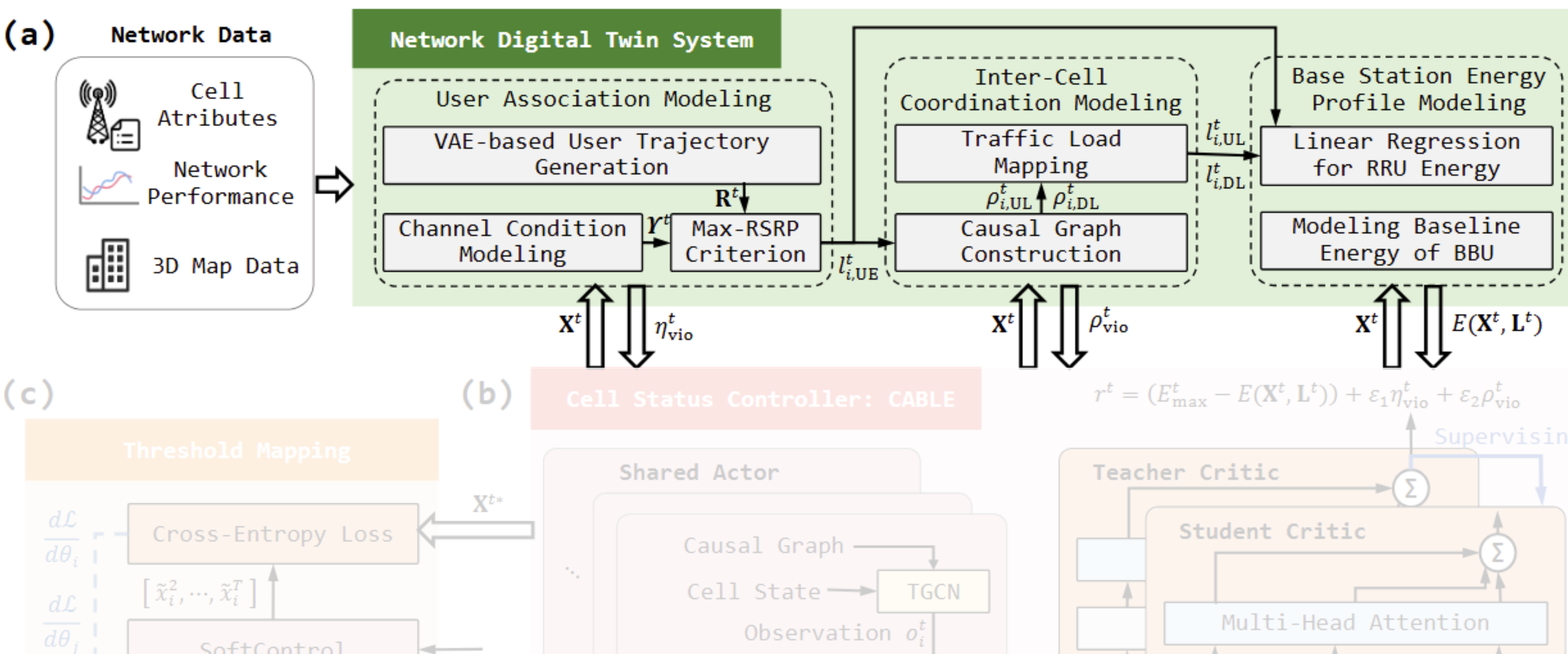


Method

(a) Data- and knowledge-driven high-fidelity **Network Digital Twin System**.

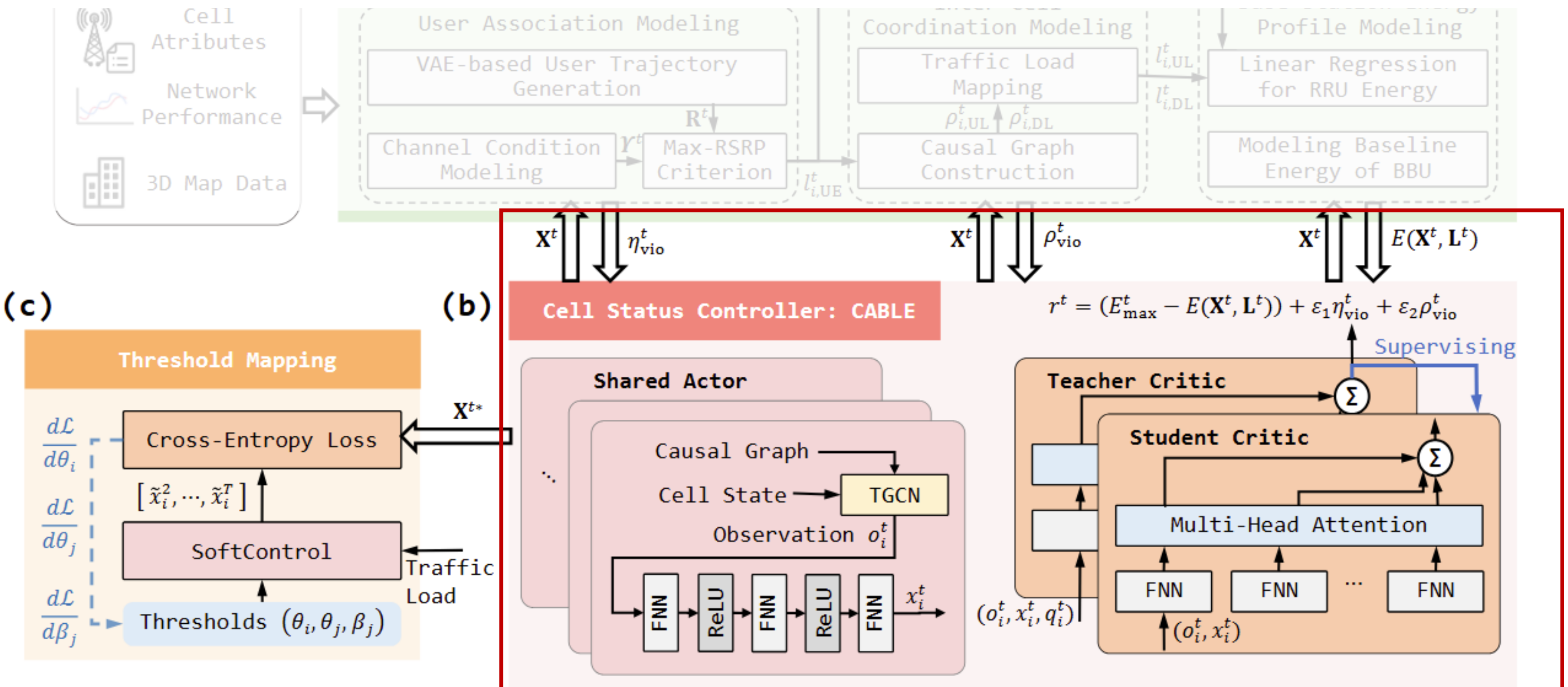
- VAE modeling UE Mobility +3GPP analytical model for Channel Condition.
- Causal graph construction for Inter-Cell Coordination.
- Heterogeneous Energy Profiling for base stations.



Method

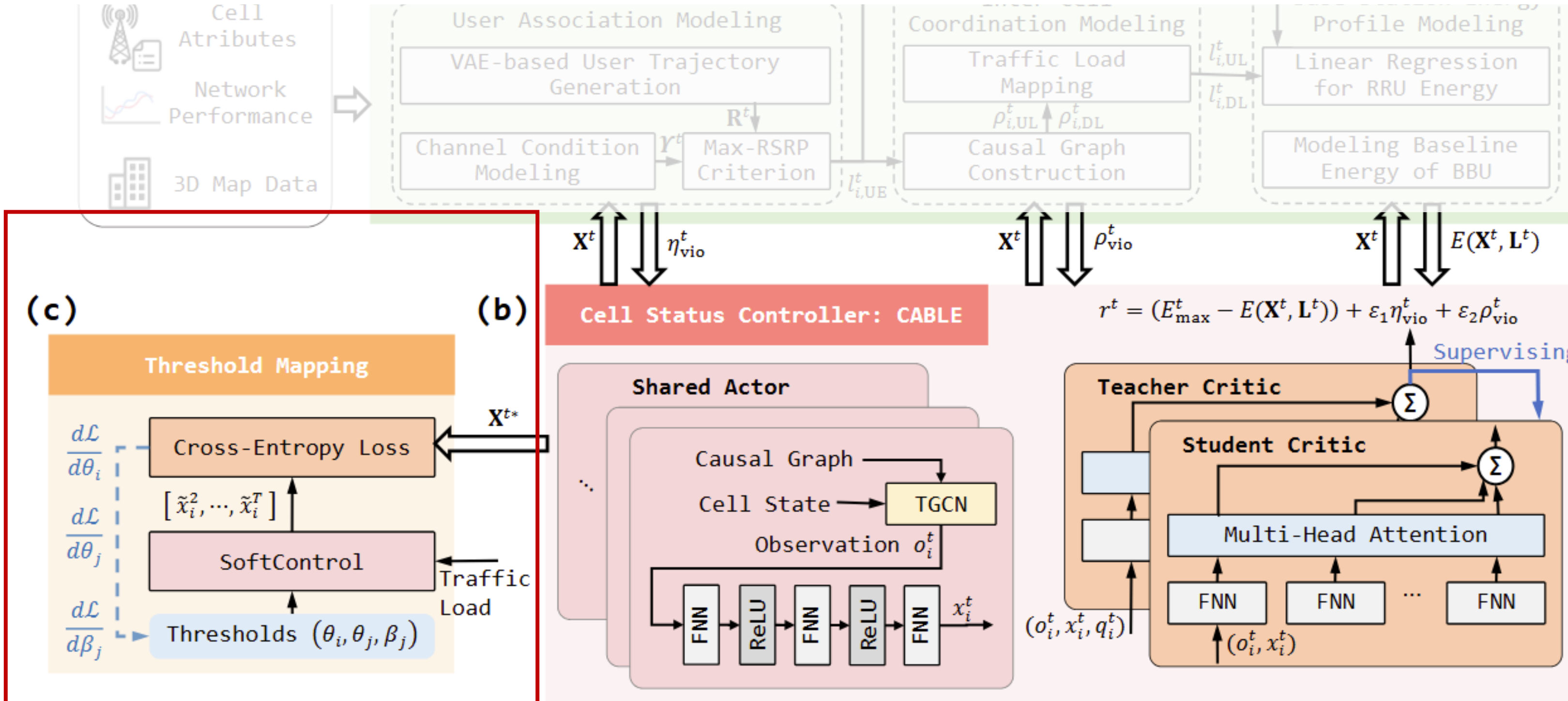
(b) Multi-agent RL for binary cell status optimization.

- Causal graph-based local spatio-temporal feature extraction.
- Credit-guided critic network for explicit multi-agent collaboration modelling.



Method

- Deployable **Sim-to-Real** policy mapping.
  - SoftControl: differentiable surrogate for cell shutdown threshold policies.
  - Gradient-based threshold fine-tuning for deployable policy mapping.



Experimental Results

- Dataset: a large-scale mobile network dataset (July 2023)
  - Comprising **14,349 base stations** (8,000+ 4G, 5,000+ 5G)
  - **30-minute** network performance logs **in one week** + cell-level attributes
  - 2,934 base stations (20%) as test set for validation

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- Baselines:

	Binary Status Opt.	**Threshold Policy Opt.**
Current Deployed	- -	CHP
Heuristic Algorithm	REDEEM (2024 [1])	HHTP (2014 [2])
RL Algorithm	PPO4Param (2022 [3])	PPO- EPO (2025 [4]), DRAG (2019 [5])

[1] Ma, Yibo, et al. "Mitigating energy consumption in heterogeneous mobile networks through data-driven optimization." IEEE Transactions on Network and Service Management 21.4 (2024): 4369-4382.
[2] Yu, Guanding, Qimei Chen, and Rui Yin. "Dual-threshold sleep mode control scheme for small cells." IET communications 8.11 (2014): 2008-2016.
[3] Choi, Minsuk, et al. "Cell on/off parameter optimization for saving energy via reinforcement learning." 2021 IEEE Globecom Workshops. IEEE, 2021.
[4] Ntassah, Rawlings, Gian Michele Dell'Aera, and Fabrizio Granelli. "PPO-EPO: Energy and performance optimization for O-RAN using reinforcement learning." 2025 IEEE International Conference on Communications Workshops (ICC Workshops). IEEE, 2025.
[5] Ye, Junhong, and Ying-Jun Angela Zhang. "DRAG: Deep reinforcement learning based base station activation in heterogeneous networks." IEEE Transactions on Mobile Computing 19.9 (2019): 2076-2087.

Experimental Results

- Evaluation in Digital Twin:
  - Our framework achieves **SOTA** performance, without degrading user association or network performance.

- Conn. Drop: connection drop rate
- TOL: traffic overload
- ppm is parts per million

(a) Cell shutdown with binary status control.

Methods	4G Energy Saving (%)	5G Energy Saving (%)	Conn. Drop (ppm)	4G TOL (ppm)	5G TOL (ppm)
REDEEM	8.0	6.0	175	1392	57
DRAG	11.3	4.4	67	**166**	84
PPO-EPO	12.4	5.4	42	243	12
CABLE	**41.5** ↑3x	**19.3** ↑3x	**40**	180	**7**

(b) Cell shutdown with threshold-based policies.

Methods	4G Energy Saving (%)	5G Energy Saving (%)	Conn. Drop (ppm)	4G TOL (ppm)	5G TOL (ppm)
CHP	6.6	5.8	**30**	297	98
REDEEM w/ TM	6.9	4.1	149	697	12
DRAG w/ TM	7.8	2.7	47	**109**	37
PPO-EPO w/ TM	8.6	3.9	33	215	0
HHTP	8.7	11.2	99	198	138
PPO4Param	11.8	11.3	34	144	132
TWINERGY	**26.0** ↑2x	**12.4**	31	127	**0**

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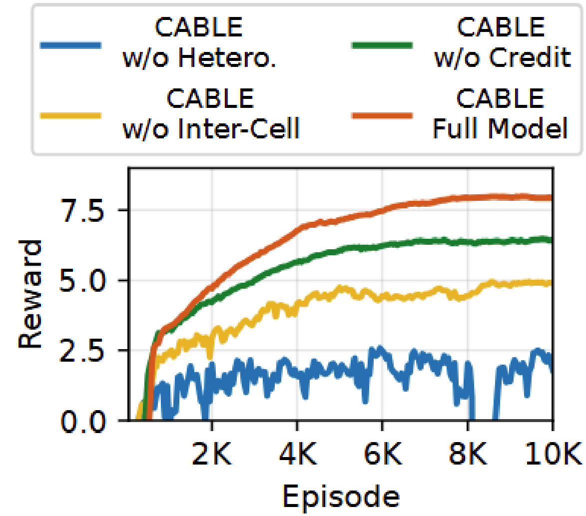
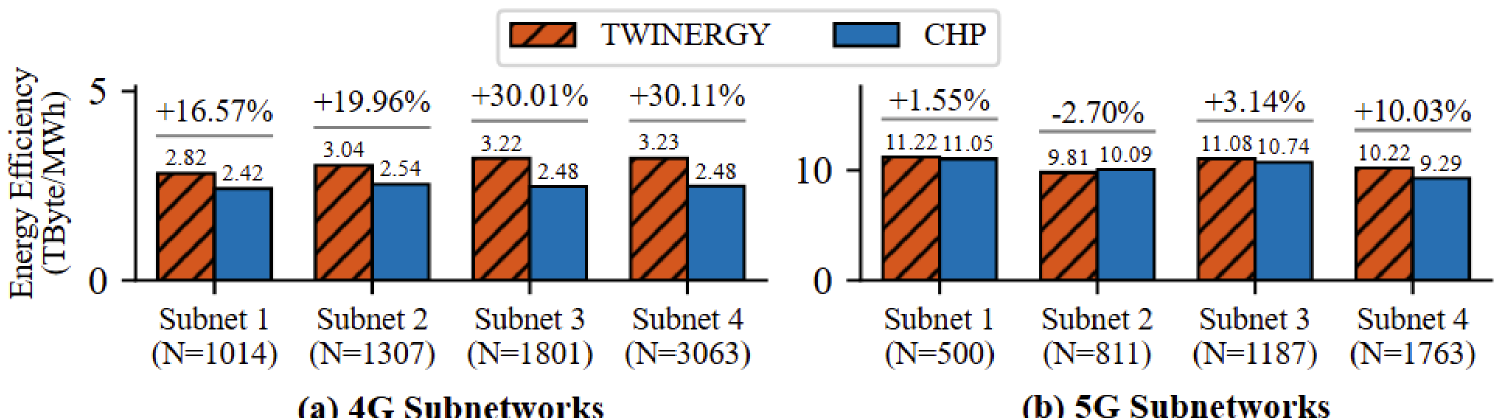
- Evaluation in Digital Twin:
  - Ablation studies demonstrate the contribution of each component.



  - Energy-saving experiments on subnetworks demonstrate **strong regional generalization capability** of our framework.



Experimental Results

□ Trials on real-world networks:

- **Network energy efficiency improvement in all trials.**
- Negligible impact on user connection and experience rate.

		4G EE (TByte/MWh)	5G EE (TByte/MWh)	Conn. Succ. Rate	UL User Exp. Rate (Mbps)	DL User Exp. Rate (Mbps)
Trial 1 (**Rural**, 25 cells)	CHP	2.004	6.184	96.11%	7.72	146.99
	TWINERGY	2.266 (+13.07%)	6.414 (+3.71%)	96.01% (-0.10%)	7.85 (+1.68%)	148.59 (+1.09%)
Trial 2 (**Urban**, 347 cells)	CHP	2.128	8.982	98.88%	17.66	240.75
	TWINERGY	2.302 (+8.18%)	9.289 (+3.42%)	98.89% (+0.01%)	17.86 (+1.13%)	246.50 (+2.39%)
Trial 3 (**Dense**, 3049 cells)	CHP	–	10.469	96.021%	31.44	152.90
	TWINERGY	–	11.746 (+12.20%)	96.021% (+0.00%)	32.46 (+3.24%)	153.77 (+0.57%)

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Conclusion

- We **propose a digital twin-driven framework for cell shutdown optimization**, enabling trial-and-error optimization of binary cell status and deployable policies through a Sim2Real mapping.
- We **collect a large-scale dataset (14,000+ base stations)** to develop and validate the framework, achieving significant energy savings (40+%) while preserving QoS.
- We **deploy the framework in three live networks**, achieving over 10% energy efficiency improvement across both 4G and 5G networks.