WiP: TWINERGY – Towards Deployable Cell Shutdown with Network Digital Twins

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Abstract

Cell shutdown is a critical mechanism for reducing mobile network energy consumption, but optimizing it remains difficult in practice. Live trial-and-error can overload cells and degrade service; currently deployed threshold-based policies are interpretable but hard to optimize at scale. This paper presents Twinergy, which searches for safe binary shutdown decisions in a high-fidelity network digital twin and maps them into thresholds for currently deployed threshold-based policies. Twinergy combines a data- and knowledge-driven digital twin, scalable multi-agent reinforcement learning (RL), and differentiable threshold mapping. Twinergy saves 26.0%/12.4% energy on real-world 4G/5G network data with 14,349 base stations. Live trials show up to 13.07%/12.20% energy-efficiency gains with no user-experience degradation.

CCS Concepts

• **Networks** → **Mobile networks**; **Network management**.

Keywords

Mobile networks, network digital twins, energy efficiency, cell shutdown

1 Introduction

Mobile networks are critical infrastructure, but their energy footprint is increasingly difficult to ignore. The radio access network accounts for a dominant share of this footprint [3]. Among practical energy-saving mechanisms, we focus on *cell shutdown*: in heterogeneous 4G/5G deployments, low-frequency coverage cells remain active while high-frequency capacity cells can be switched off and offload traffic to neighbors. It offers large savings at practical intervals. Currently deployed threshold-based policies implement cell shutdown using time-invariant traffic-load thresholds [4, 8]. These thresholds cover indicators such as Physical Resource Block (PRB) usage and connected-user count, and logical rules trigger switch-off and wake-up events. This design is easy to inspect and configure, but static thresholds must be carefully tuned to avoid unsafe offloading.

Optimizing cell shutdown in mobile networks faces two challenges. **First, live trial-and-error is unsafe.** A poor shutdown decision can disconnect users, overload compensation cells, or degrade user experience, so policies need pre-deployment training and evaluation. However, conventional analytical models and discrete-event simulators either simplify radio dynamics or scale poorly. This motivates a high-fidelity network digital twin (NDT) for safe virtual evaluation of connectivity, overload, and energy.

Second, tractability conflicts with deployability. Operators typically rely on threshold-based policies, in which multiple traffic indicators are compared against cell-specific activation and deactivation thresholds to determine each cell's on/off status. This formulation induces a coupled and high-dimensional search space [6]. In contrast, directly optimizing the binary on/off cell status is more tractable and is widely adopted in prior cell-shutdown studies [7]. However, such binary decisions cannot be directly implemented in existing operational systems. A key issue is therefore to translate optimized binary decisions into deployable threshold-based policies.

To address these challenges, we propose Twinergy [5], a digital twin-empowered framework for deployable cell shutdown. To support safe evaluation, Twinergy builds an NDT that fuses operator data with radio-domain knowledge: data-driven user distributions and Third Generation Partnership Project (3GPP) propagation models [1] estimate connectivity, learned coordination dependencies capture offloading, and cell-specific energy profiles fit operational measurements. The NDT provides connectivity, traffic-overload, and energy feedback for safe virtual exploration. For deployability, Twinergy separates policy optimization into a *decision stage* and a *deployment stage*. The decision stage uses Cable, a scalable multi-agent RL controller with a shared actor for large-scale binary on/off control and a credit-guided critic for coordinating neighboring agents. The deployment stage uses SoftControl, a differentiable surrogate for the non-differentiable rules in threshold-based policies, to calibrate optimized binary decisions into heterogeneous thresholds.



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Evaluation results show the promise of this direction. In an NDT built from dataset of 14,349 real-world base stations, TWINERGY achieves 26.0% and 12.4% energy savings for 4G and 5G networks, respectively, with low connection drop and traffic overload. Live trials in three trials show up to 13.07% and 12.20% energy-efficiency gains with no user-experience degradation. We next plan to use post-deployment feedback to calibrate the NDT toward a real-sim-real loop.

2 Problem Statement and Challenges

We consider a heterogeneous network with coverage cells and capacity cells. At interval t, each capacity cell i has status $x_i^t \in \{0, 1\}$, where $x_i^t = 0$ denotes shutdown. Shutting down a cell requires offloading associated users and traffic to neighboring active cells. The objective is to choose the capacity-cell status $\{x_i^t\}$ to reduce energy while keeping all users connected and avoiding traffic overload after offloading. To solve this problem, we must address the following three design challenges.

C1: High-fidelity policy evaluation. An NDT is needed to predict critical shutdown consequences: user association, traffic offloading, and energy consumption. These signals must be modeled jointly: a decision is useful only if it saves energy without user disconnections or traffic overload.

C2: Scalable shutdown optimization. The framework must optimize many coupled binary cell statuses. A cell's shutdown changes neighboring loads and feasible actions, so the optimizer must scale beyond centralized joint actions while capturing inter-cell offloading effects.

C3: Deployment alignment. The framework must convert optimized statuses into thresholds of currently deployed policies. This requires handling non-differentiable rules in threshold-based policies and recovering heterogeneous thresholds that match binary targets.

3 TWINERGY Design

TWINERGY follows a decision-to-deployment workflow, as shown in Fig. 1. The NDT addresses C1 by providing safe, high-fidelity policy evaluation. CABLE addresses C2 by learning scalable binary decisions in the NDT. Threshold mapping addresses C3 by translating these decisions into thresholds used by currently deployed threshold-based policies.

3.1 NDT for Safe Policy Evaluation

The NDT is a data- and knowledge-driven architecture. Operator measurements provide traffic, user count, and energy data; knowledge-based models constrain how the network should evolve after shutdown decisions. This targets C1: TWINERGY evaluates policies in a virtual environment.

User connectivity. The twin combines user distribution modeling with 3GPP path-loss models and max Reference

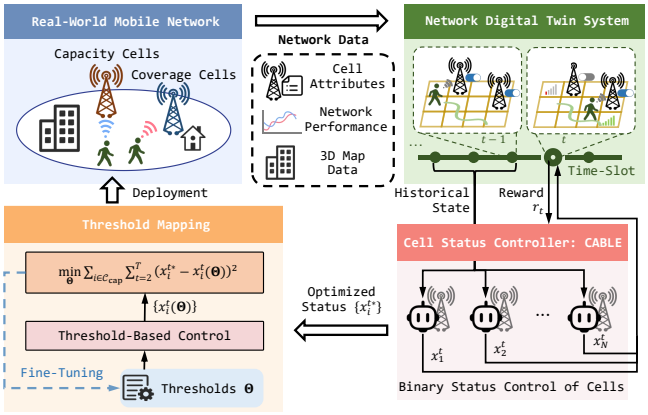


Figure 1: Overview of the TWINERGY workflow.

Signal Received Power (RSRP) association [1]. Given a candidate cell status, it recomputes which active cell can serve each user.

Cell collaboration. The twin models offloading by combining spatial neighbor relations with causality-based inter-cell dependencies. When a cell is off, the twin calculates traffic redistribution and checks overload.

Energy profile. The twin fits cell-specific energy profiles from operational data, estimating active-cell energy from Physical Resource Block (PRB) usage and user count. Together, these models expose the feedback needed by the controller: energy saving, connection loss, and traffic overload.

3.2 CABLE for Binary Status Control

CABLE optimizes binary cell status through multi-agent RL. Each capacity cell is an agent, but all agents share one actor network that maps local NDT observations to on/off decisions. This shared actor enables scalable control as the policy dimension is independent from cell count, while execution remains local.

Cell shutdown control is cooperative. One cell's decision changes the feasibility of its neighbors, and a locally safe action can become harmful when combined with nearby shutdowns. CABLE therefore uses a credit-guided critic during training. The critic incorporates local credit signals, including saved energy, connection loss, and overload around each cell, so that the shared actor learns coordinated actions rather than independent greedy shutdowns. Thus, CABLE addresses C2 while preserving network-level constraints.

3.3 SoftControl for Deployment Alignment

The binary policy learned by CABLE is useful for optimization, but deployed cell shutdown still relies on threshold-based policies. SoftControl bridges this gap by approximating the non-differentiable rules in threshold-based policies with a differentiable surrogate. For an active capacity cell i paired

Table 1: Cell shutdown optimization results in the NDT.

Method	4G ES (%)	5G ES (%)	Conn. Drop (ppm)	4G TOL (ppm)	5G TOL (ppm)
CHP	6.6	5.8	**30**	297	98
Heuristic	8.7	11.2	99	198	138
RL-based	11.8	11.3	34	144	132
TWINERGY	**26.0**	**12.4**	31	**127**	**0**

with coverage cell j, we define the surrogate for its binary status as $\tilde{x}_i^t = 1 - Q(\sigma_k(\theta_i - \ell_i^t))Q(\sigma_k(\theta_j - \ell_j^t))$, where ℓ denotes load, θ denotes switch-off thresholds, σ_k is a steep sigmoid, and Q multiplies vector elements. A symmetric soft wake-up rule uses the coverage-cell wake-up threshold β_j when the capacity cell is already off.

SoftControl learns the switch-off and wake-up thresholds that best match CABLE's binary decisions by backpropagation, then executes the learned thresholds with the original rules in threshold-based policies. This addresses C3 by preserving binary-control gains while producing deployable heterogeneous thresholds.

4 Evaluation Results

We evaluate TWINERGY in an NDT built from one week of commercial-operator data in City A: 14,349 base stations with 30-minute logs, evaluated on 2,934 held-out base stations (7,185 4G and 4,261 5G cells). We also report three trials of live deployments in City B: rural nighttime, urban full-day, and dense 5G full-day trials.

Fidelity of Network Digital Twin. We validate the NDT on held-out cells using shutdown-relevant feedback signals. Median correlation reaches about 0.85/0.90 for 4G/5G user association and about 0.90/above 0.70 for 4G/5G DL PRB usage; energy modeling reaches mean R^2 scores of about 0.81/0.76 on 4G/5G RRUs. Compared with the strongest alternatives, user-association correlation improves by 0.1–0.2 over POI-based modeling, while DL PRB correlation is over 2× the flow-level baseline.

Evaluation in Network Digital Twin. We compare cell-shutdown optimization methods: Current Homogeneous Policy (CHP) that applies the same configuration to all capacity cells; Heuristic, a state-of-the-art threshold-tuning method [8]; and RL-based, a state-of-the-art end-to-end RL optimizer [2]. Table 1 reports energy saving (ES), connection drop, and traffic overload (TOL), with violations in parts per million (ppm). TWINERGY achieves the highest ES while keeping violations low. Compared with CHP, it increases 4G ES from 6.6% to 26.0% and 5G ES from 5.8% to 12.4%. Its connection drop remains close to baselines, while its TOL is lowest, including zero 5G TOL. Fig. 2 reports gains by network density, where N is the number of cells per unit area. Gains increase with density because denser deployments provide overlapping coverage. TWINERGY improves all 4G subnets; in 5G, one sparse subnet does not improve because limited overlap restricts constraint-feasible shutdowns.

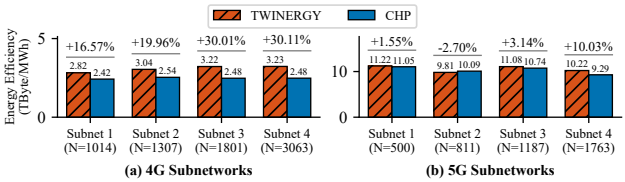


Figure 2: Energy-efficiency gain across subnets.

Table 2: Live deployment results relative to CHP. EE: energy-efficiency; Conn. Succ.: connection success; UL/DL Exp.: uplink/downlink experience.

Scenario	4G EE	5G EE	Conn. Succ.	UL Exp. Rate (Mbps)	DL Exp. Rate (Mbps)
Rural (Night)	2.266 (+13.07%)	6.414 (+3.71%)	96.01% (-0.10%)	7.85 (+1.68%)	148.59 (+1.09%)
Urban (All Day)	2.302 (+8.18%)	9.289 (+3.42%)	98.89% (+0.01%)	17.86 (+1.13%)	246.50 (+2.39%)
Dense 5G (All Day)	–	11.746 (+12.20%)	96.021% (+0.00%)	32.46 (+3.24%)	153.77 (+0.57%)

Live Real-World Deployment. Live trials shown in Table 2 is consistent with results of NDT. The dense 5G trial improves EE by 12.20%, matching the trend in Fig. 2. The urban trial has higher traffic demand and violation risk than the rural trial, yet TWINERGY preserves connection success and achieves stable EE gains of 8.18% and 3.42% for 4G and 5G, respectively. Experience-rate gains arise because CHP's homogeneous thresholds can ignore collaboration and over-shut low-load cells, while TWINERGY models collaboration in the NDT.

5 Conclusions and Future Work

This paper presents TWINERGY, a deployable cell-shutdown framework that combines an NDT for safe exploration, CABLE for scalable binary decisions, and SoftControl to align decisions with currently deployed threshold-based policies. NDT evaluation and live deployments show energy-efficiency gains while preserving connection success and user experience. Future work will test more scenarios and use post-deployment feedback for real-sim-real NDT calibration.

Acknowledgments

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