Formal Verification for Deep Learning-based Mobile Network Traffic Prediction

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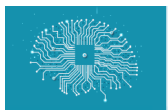

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Agenda

1. Introduction
2. Preliminaries
3. Proposed Verification Framework
4. Evaluation Results
5. Conclusion

Agenda

DL-based Network Traffic Prediction

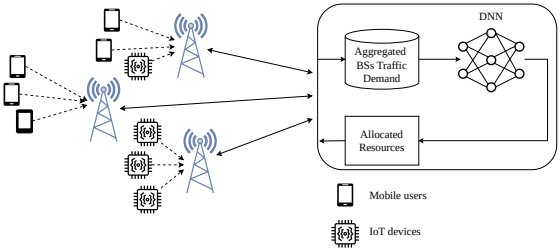

Figure: Deep learning (DL)-based network traffic prediction (NTP).

Pipeline description

- **Input:** historical traffic snapshots (*e.g.*, matrix/tensor of user demands at each base station)
- **DNN:** maps input $\rightarrow$ future demands
- **Application:** proactive link capacity provisioning, routing, traffic engineering

Can We Trust DL in Mission-Critical Tasks?

Autonomous Driving
Aircraft Autopiloting

Medical Equipments
AI-based Diagnosis

Security/Surveillance
Systems

[1]

[1] H. Zhang et al., *Formal verification of deep neural networks: Theory and practice*, Accessed: 2025-07-21, 2022. [Online]. Available: https://neural-network-verification.com/.

Solution – Related works

Adversarial Attacks on DL-based NTP

- Adversaries infiltrate smartphones or IoT devices
- Orchestrate botnets to inject minimal traffic
- Corrupting the DNN's capacity provisioning while evading anomaly detection

Existing Solutions – xAI

- xAI methods (e.g. GCAM, LRP)
- Identify input features and base stations susceptible to traffic-injection attacks;
- Inform adversarial training.

[a]

[a] S. M. Gholian et al., "Deexp: Revealing model vulnerabilities for spatio-temporal mobile traffic forecasting with explainable ai," *IEEE Transactions on Mobile Computing*, 2025.

Solution – NNV

Problem with non-certifying defense

- Non-certifying defense mechanisms are circumvented by stronger attack strategies
- Part of an ongoing arms race.

[a]

[a] A. Athalye et al., "Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples," in *International conference on machine learning*, PMLR, 2018, pp. 274–283.

Our Solution – NNV

- Neural networks verification (NNV) tools (e.g. NeuralSat, Reluplex, certified training)
- Provide provable guarantees that deep neural networks (DNN) remains resilient to attacks for all inputs within specified bounds.
- Complements explainable AI (xAI) and adversarial training
- Establishing DNN robustness through rigorous mathematical proofs

[a]

[a] H. Duong et al., "Neuralsat: A high-performance verification tool for deep neural networks," in *Computer Aided Verification*, Cham: Springer Nature Switzerland, 2025, pp. 409–423.

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System Model

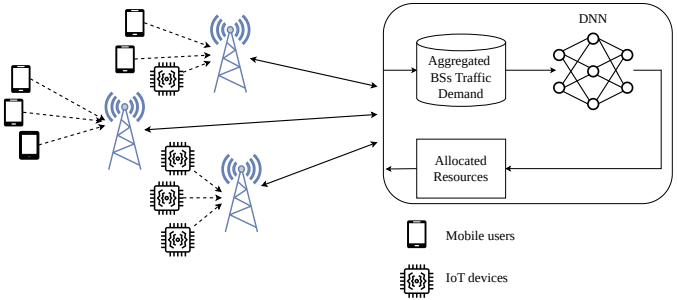

Figure: System model of DL-based NTP.

- A DNN is trained to forecast traffic at time t from T historical traffic snapshots $\delta^s(t-T), \ldots, \delta^s(t-1)$ (traffic demands at all base stations per slice s).
- **Input:** historical snapshots $\rightarrow$ 3D tensor (spatiotemporal).
- **Architecture:** encoder (3D-CNN) + decoder (MLP).
- **Output:** capacity forecast $c^s(t) = \{c_s^1(t), \ldots, c_s^M(t)\}$ at each base station
- M — number of base stations per slide s.

DNN architecture — DeepCog

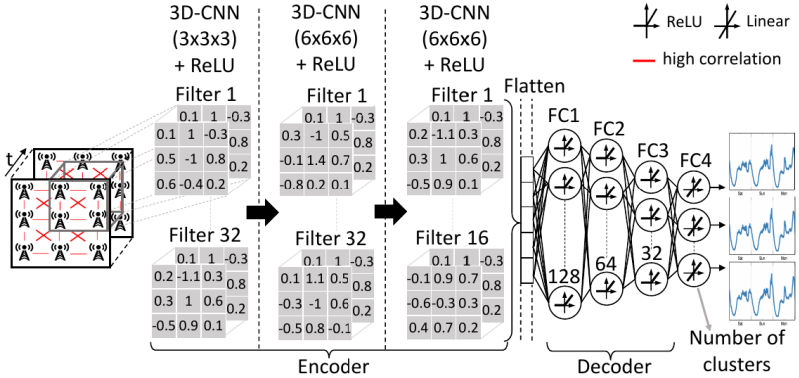

Figure: DeepCog[2] model based on 3D Conv.

[2] D. Bega et al., "Deepcog: Cognitive network management in sliced 5g networks with deep learning," in *IEEE INFOCOM 2019-IEEE conference on computer communications*, IEEE, 2019, pp. 280–288.

Threat Model

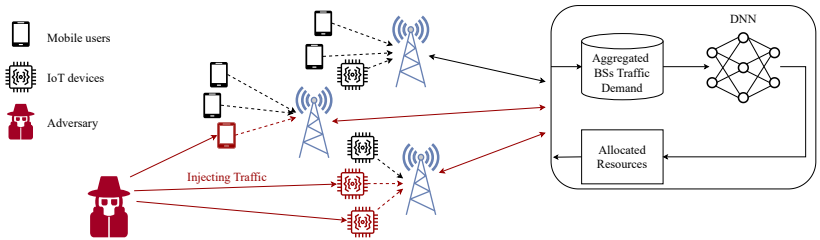

Figure: Threat model of DL-based NTP.

- Adversary controls compromised devices (*e.g.*, IoT, smartphones) that inject traffic into the network (Mirai-style).
- Goal: the DNN over-/under-provisioning → wasteful/service degradation.
- Injection is minimal to avoid detection and stay within data limits.

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Local Robustness Properties for DL-based NTP

Input property ϕ_{in}

Encodes *permitted adversarial traffic injection* as a hyperrectangle.

- Perturbation $\eta \in [\eta_L, \eta_U]$ (same dim as traffic snapshot $\delta^s(t)$).
- Adversarial input: $\delta'^s(t) = \delta^s(t) + \eta$.
- ϕ_{in} constrains perturbed traffic to $[\delta^s(t) + \eta_L, \delta^s(t) + \eta_U]$ so verification covers all injection scenarios within bounds.

Output property ϕ_{out}

Constrain forecast vs. actual demand $d_s^j(t)$ (tolerance ζ):

- **Overprovisioning:** $\neg(c_s^j(t) \geq (1+\zeta)\, d_s^j(t))$.
- **Underprovisioning:** $\neg(c_s^j(t) \leq (1-\zeta)\, d_s^j(t))$.

SoTA DNN Verifiers

NeuralSAT

Leverage SOTA DNN verifier used as a black-box; top-performing in Verification of Neural Networks Competition (VNNCOMP).

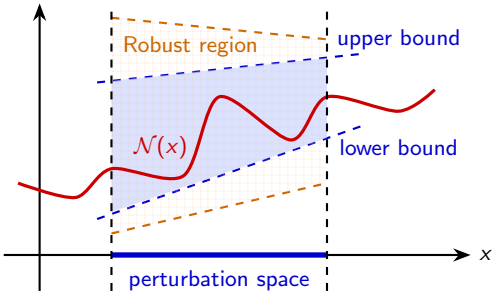

Figure: NNV propagates continuous intervals

Verification outcome

$\text{NEURALSAT}(\phi_{in}, \phi_{out}, \mathcal{N}(x)) \rightarrow$ outcomes:

- **SAT:** exists adversarial input in $[\eta_L, \eta_U]$ violating $\phi_{out} \Rightarrow$ vulnerable
- **UNSAT:** no such input $\Rightarrow$ proven robust
- **TIMEOUT:** DNN verifier unable to solve the instance within the time limit

H. Duong et al., "Neuralsat: A high-performance verification tool for deep neural networks," in *Computer Aided Verification*, Cham: Springer Nature Switzerland, 2025, pp. 409–423

Additional Conversion

Convert DL-based NTP to VNNCOMP-style inputs

1. 3DConv not supported by `NeuralSAT` → reimplement DeepCog as *two consecutive 2D* convolutional layers (no loss in forecast accuracy).
2. Export DeepCog to **ONNX**: open standard for interoperable DNN models; VNNCOMP uses ONNX for the network format[a].
3. Export ϕ_{in} (bounds $[\delta^s(t) + \eta_L, \delta^s(t) + \eta_U]$) and ϕ_{out} in **VNNLIB**: declarative format for input/output constraints in VNNCOMP.

[a] C. Brix et al., "The Fifth International Verification of Neural Networks Competition (VNN-COMP 2024): Summary and Results," *arXiv preprint arXiv:2412.19985*, 2024.

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Evaluation Setup

Dataset — Telecom Italia Milan 2014

- Publicly available mobile traffic data; 1,728 base stations.
- $\sim 7,000$ time steps, 50 days measurements, 10-minute granularity.
- *Internet activities* traffic demands [5].
- Spatial-temporal pattern well-suited for DeepCog-based traffic forecasting.

DNN Parameter — DeepCog

- 5×5 grid; $T = 10$ historical steps; each model forecasts capacity of the *central cell* only [2].
- $\alpha = 2$ (prioritize avoiding underprovisioning over overprovisioning) [5].
- Adam, learning rate 3×10^{-4}, 50 epochs; ReLU activation; 80:20 train-test split.
- Verify on perturbed data on test set, NeuralSAT timeout after 60s.

[a]

[a] Publicly available implementation at `https://github.com/thanhlexyz/nnv4ntp`

Robustness Analysis - Underestimation

	Percentage of injected traffic				
	+1%	+5%	+10%	+15%	+20%
$\zeta = 1\%$	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0
$\zeta = 5\%$	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0
$\zeta = 10\%$	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0

Table: Fraction of UNSAT, SAT, TIMEOUT for underestimation of user demand

Observations

- Verifier consistently SAT across all injection levels (+1%–+20%) and all ζ (1%, 5%, 10%).
- Despite α set to reduce underestimation, the model remains vulnerable on all properties.
- Adversary can easily induce capacity underestimation beyond $\zeta \Rightarrow$ DoS / QoS degradation.

Robustness Analysis - Overestimation

	Percentage of injected traffic				
	+1%	+5%	+10%	+15%	+20%
$\zeta = 1\%$	1.0/0.0/0.0	1.0/0.0/0.0	1.0/0.0/0.0	0.0/1.0/0.0	0.0/1.0/0.0
$\zeta = 5\%$	1.0/0.0/0.0	1.0/0.0/0.0	1.0/0.0/0.0	0.0/0.0/1.0	0.0/1.0/0.0
$\zeta = 10\%$	1.0/0.0/0.0	1.0/0.0/0.0	1.0/0.0/0.0	1.0/0.0/0.0	0.0/0.0/1.0

Table: Fraction of UNSAT, SAT, TIMEOUT for overestimation of user demand

Observations

- **Small injection** (+1%, +5%, +10%): `NeuralSAT` often `UNSAT` ⇒ *provably robust* against overprovisioning.
- **High injection** (+15%, +20%): more `SAT`/`TIMEOUT` ⇒ extreme perturbations can compromise robustness.
- Takeaway: asymmetric profile — resilient to overestimation under moderate η; highly vulnerable to underestimation.

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Concluding remarks

- **Contribution:** Formal verification framework for DL-based mobile traffic prediction → provable robustness against adversarial traffic injection.
- **Approach:** Input perturbations (hyperrectangle) + output properties (over/underprovisioning bounds) + trained DNN → `NeuralSAT` for sound guarantees.
- **Finding:** Asymmetric robustness on Telecom Italia Milan: resilient to overestimation under moderate perturbations; highly vulnerable to underestimation attacks.
- **Future work:** Broader evaluation (more datasets and models); verifier in the adversarial retraining loop.