Conformal Prediction for Reliable Handover Under Distribution Shift

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***Abstract*—ML handover prediction is accurate in-distribution but fragile under shift. We evaluate conformal prediction (CP) for 5G handover under synthetic and real-world drift. We compare static CP, Adaptive Conformal Inference (ACI), weighted CP, and a confidence-gated triggered ACI against Top-k and a 3dB hysteresis baseline. On in-distribution synthetic data, static CP reaches 90.2% coverage with set size 2.46. Under speed and noise shifts, weighted CP reaches 91.1% in the speed-shift case. Under severe shadow shift, static CP drops to 69.2% while ACI restores 88.8% at larger sets (6.00). In regime-switch streams, ACI stabilizes rolling coverage near the 90% target. ACI step-size sweep shows $\gamma = 0.002$–0.005 gives the best reliability-overhead tradeoff in our setup. On Irish 5G driving traces with speed-split drift, static CP reaches 76.2% coverage (size 4.49), weighted CP 73.8% (size 4.07), and ACI 88.4% (size 15.4). Results show reliability under shift needs adaptive conformal control, not static calibration alone.**

I. Introduction

Predictive handover reduces latency but can fail badly when radio conditions shift. Traditional 3GPP handover logic relies on hysteresis events [2], [3]. ML-based handover prediction improves point accuracy but provides no risk control when distribution changes [4], [12]. In production, that gap maps directly to radio link failure risk.

Conformal prediction (CP) gives finite-sample marginal coverage guarantees [5], [6]. Recent wireless CP work focuses on demodulation, channel tasks, and beam selection [7]–[9], while handover under distribution shift is still underexplored. This paper targets that gap.

Contributions.

1) We benchmark handover reliability under four synthetic shifts plus a regime-switch stream.
2) We compare static CP, ACI [10], weighted CP, and confidence-gated triggered ACI under the same base predictor and KPI mapping.
3) We validate on Irish 5G driving traces with source-target speed split.
4) We provide budget-aware reproducible runs (local-first, capped overflow policy) and release all generated artifacts.

II. Related Work

ML handover methods span supervised and reinforcement-learning policies [4], [12]. CP in wireless has shown value for calibration and reliability [9]. CP for beam selection shows strong reliability-efficiency tradeoffs [7], [8]. The missing piece is handover under shift: static calibration can fail as mobility, shadowing, and measurement noise drift over time.

III. System and Methods

A. Handover Prediction Setup

At time t, the model predicts future best cell $y_t = \arg\max_k \mathrm{RSRP}_k(t+H)$ using input

$$\mathbf{x}_t = [\mathrm{RSRP}_1, \ldots, \mathrm{RSRP}_K, \mathbf{e}_{c_t}, v_t]. \tag{1}$$

We use an MLP classifier and softmax scores $\hat{p}(y \mid \mathbf{x})$.

B. Baselines and Conformal Variants

3dB baseline: handover if best neighbor exceeds serving by 3dB.

Static CP:

$$\mathcal{C}(\mathbf{x}) = \{y : \hat{p}(y \mid \mathbf{x}) \geq 1 - \hat{q}\}, \tag{2}$$

with $\hat{q}$ calibrated on held-out source calibration data.

ACI: online update of effective miscoverage level to track sequential drift [10].

Weighted CP: source calibration scores reweighted by estimated density ratio $w(\mathbf{x}) \propto p_T(\mathbf{x})/p_S(\mathbf{x})$ using a source-vs-target logistic discriminator.

Triggered ACI: confidence-gated mixture that uses static CP on high-confidence samples and ACI sets on low-confidence samples (threshold from source calibration confidence quantile).

C. System KPI Mapping

Coverage maps to handover success with bounded miss risk. Set size maps to measurement overhead. Undercoverage maps to RLF proxy. Serving-cell retention in small sets acts as implicit hysteresis and affects ping-pong rate.

IV. Experimental Setup

A. Synthetic Shift Benchmark

Source setting: medium scenario (4×4 cells, $\sigma = 6$ dB shadowing, measurement noise 4 dB, speed 1–30 m/s, horizon $H = 10$). We train on source and calibrate on source only.

Target shifts:

1) IID (same as source)
2) Speed shift (20–50 m/s)
3) Measurement-noise shift (8 dB)
4) Shadow shift ($\sigma = 10$ dB)
5) Regime switch (source-like first half, harsh second half)

Each result is mean±std across 5 seeds (42,123,456,789,1011), 600 trajectories/seed, 20 epochs.

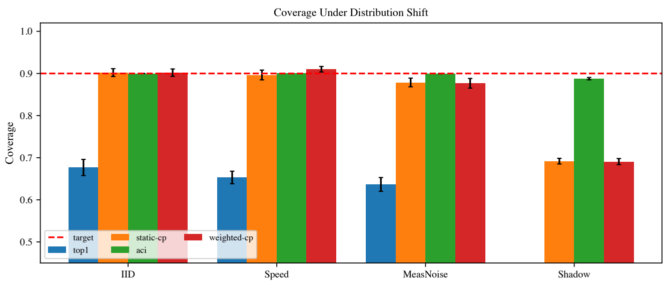

Fig. 1. Coverage across synthetic shifts. Static CP degrades under hard shift, ACI is most robust, weighted CP helps in moderate covariate shift.

TABLE I
SYNTHETIC SHIFT COVERAGE (MEAN ± STD)

Shift	3dB	Top-1	Top-3	Static CP	ACI
IID	$.64 \pm .02$	$.68 \pm .02$	$.91 \pm .01$	$.90 \pm .01$	$.90 \pm .00$
Speed	$.62 \pm .01$	$.65 \pm .02$	$.90 \pm .01$	$.90 \pm .01$	$.90 \pm .00$
MeasNoise	$.55 \pm .02$	$.64 \pm .02$	$.89 \pm .01$	$.88 \pm .01$	$.90 \pm .00$
Shadow	$.40 \pm .01$	$.43 \pm .01$	$.72 \pm .01$	$.69 \pm .01$	$.89 \pm .00$
Regime	$.49 \pm .02$	$.53 \pm .02$	$.79 \pm .01$	$.78 \pm .02$	$.89 \pm .00$

B. Real-World Drift Benchmark

Dataset: Irish 5G driving traces [13]. We split traces by average speed: lower-speed traces as source, higher-speed traces as target. Model trains and calibrates on source only, then evaluates on target.

V. RESULTS

A. Coverage Under Shift

Table I shows the main trend: static CP is reliable near source but degrades under strong shift (shadow, regime). ACI keeps coverage close to target by expanding sets online.

B. Tradeoff in Hard Shifts

Paired seed deltas confirm hard-shift reliability gains: ACI vs static is $+19.6$pp coverage on shadow shift (95% CI $[18.9, 20.2]$) and $+11.3$pp on regime switch (95% CI $[10.1, 12.6]$). Triggered ACI keeps most of that gain ($+15.2$pp shadow, $+9.0$pp regime) while reducing overhead versus full ACI by 5.81pp and 2.90pp, respectively.

C. Regime-Switch Stability

In regime-switch streams, static and weighted thresholds lag after the phase boundary. ACI adapts online and recovers target-level coverage.

D. ACI Step-Size Sensitivity

Figure 3 quantifies ACI sensitivity. In our regime-switch benchmark, small step sizes ($\gamma = 0.002$–0.005) achieve the highest coverage ($\approx 89.6\%$) with moderate set inflation, while larger values ($\gamma = 0.05$) reduce coverage to 87.3% but lower overhead. This supports tuning γ as a direct reliability-overhead control knob.

TABLE II
HARD-SHIFT KPI TRADEOFF (MEAN OVER 5 SEEDS)

Shift	Method	Coverage	Set Size	RLF Proxy	Overhead
Shadow	Static CP	.692	2.61	.306	.169
	ACI	**.888**	6.00	**.073**	.599
	Triggered ACI	.843	5.41	.121	.541
	Weighted CP	.691	2.60	.307	.168
Regime	Static CP	.780	2.60	.218	.167
	ACI	**.892**	4.50	**.084**	.415
	Triggered ACI	.869	4.23	.109	.386
	Weighted CP	.787	2.69	.210	.174

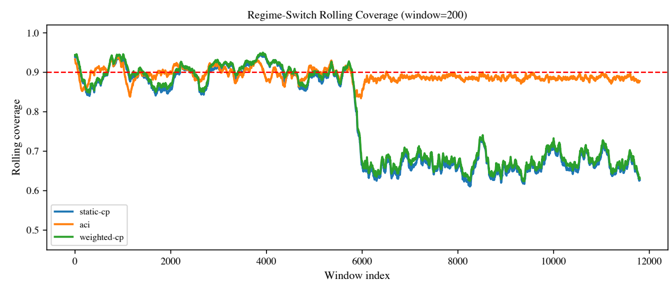

Fig. 2. Rolling coverage in regime-switch stream (window=200). ACI tracks the 90% target more closely than static and weighted CP.

E. Real-World Drift Results

Trace-bootstrap on Irish confirms the reliability-cost pattern: ACI vs static gives $+12.2$pp coverage (95% CI $[5.7, 20.6]$) with $+10.90$ set size (95% CI $[4.22, 20.14]$), while triggered ACI gives $+5.9$pp coverage (95% CI $[2.0, 11.0]$) with $+5.50$ set size (95% CI $[1.46, 11.36]$). Triggered ACI versus full ACI loses 6.3pp coverage (95% CI $[-11.7, -2.3]$) but cuts set size by 5.40 (95% CI $[-11.91, -0.74]$).

VI. DISCUSSION

When to use which method. Static CP is a strong default in stable conditions. Weighted CP helps moderate covariate shift when target feature support overlaps source. ACI is the robust choice for severe sequential drift, with γ tuning used to set reliability-overhead preference. Triggered ACI is a middle point when overhead budget is tight.

System implications. Reliability gains translate to lower RLF proxy but require explicit overhead budgeting. A practical policy can use ACI in high-uncertainty periods and revert to static CP in stable periods.

Limitations. Synthetic channels still simplify real deployments. Irish traces have limited feature richness versus full network measurement reports. We evaluate offline; online deployment requires streaming integration and control-plane constraints.

VII. CONCLUSION

We presented a shift-focused handover reliability study with conformal prediction. Static CP works well in-distribution

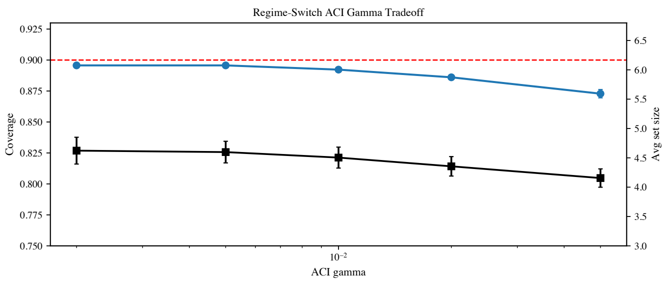

Fig. 3. Regime-switch ACI tradeoff over γ. Smaller γ improves coverage but increases set size and overhead.

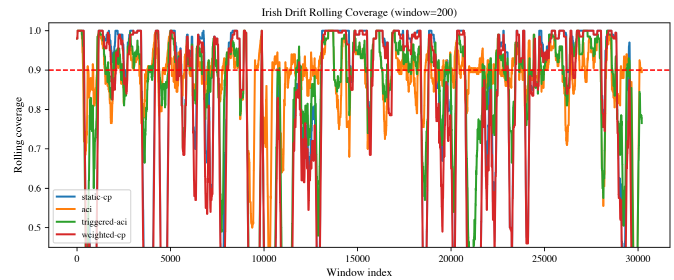

Fig. 4. Irish drift rolling coverage (window=200). ACI is most stable under source-target speed split.

TABLE III
IRISH 5G SPEED-SPLIT DRIFT RESULTS

Method	Coverage	Avg Size
Top-1	.315	1.00
Top-3	.649	3.00
Static CP	.762	4.49
ACI	**.884**	15.38
Triggered ACI	.821	9.99
Weighted CP	.738	4.07

TABLE A1
APPENDIX: CP VS ENSEMBLE (FROM V5 RUNS, 5 SEEDS)

	CP (1 model)		Ensemble (5 models)	
Scenario	Coverage	Size	Coverage	Size
Easy	.900	1.37	.900	1.38
Medium	.893	2.47	.898	2.57
Hard	.898	4.80	.903	5.05

but degrades in severe shift. ACI restores near-target coverage under shadow and regime-switch drift. Weighted CP improves moderate shifts with smaller set inflation than ACI. A confidence-gated triggered ACI recovers most hard-shift reliability gains with lower overhead than full ACI. On Irish real-world speed-split drift, ACI achieves the highest reliability. The core practical result is clear: robust handover reliability needs adaptive conformal control, not static calibration alone.

APPENDIX A
APPENDIX: ENSEMBLE AND LATENCY

Measured medium-scenario latency: calibration 0.08 ms, CP set construction $1.59\,\mu$s/sample, NN inference $0.50\,\mu$s/sample.

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