



Simulation-Based Assessment of 5G Handover Performance Under Mobility and Network-Density Stress: A Lagos-Motivated Urban Study

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Abstract

Reliable handover is central to service continuity in dense fifth-generation cellular networks, where short cell residence times, overlapping coverage, and rapid channel variation increase mobility-management stress. This study presents a scenario-level simulation assessment of handover latency, handover success rate, and packet loss under a Lagos-motivated urban deployment context. A $2 \times 3 \times 3$ factorial structure combined two mobility classes, three network-density levels, and three handover strategies, producing 18 scenario cells. The analytical configuration represented 5,000 virtual user equipment devices, 50 macro cells, 150 small cells, and ten repeated runs per broad simulation condition. Hard handover, a make-before-break soft-handover abstraction, and predictive handover were compared with descriptive statistics and an additive factorial analysis of variance. Network density produced the strongest performance change. Mean latency increased from 54.43 ms at low density to 70.47 ms at high density, mean success rate decreased from 94.32% to 82.12%, and packet loss increased from 1.37% to 5.57%. Vehicular mobility increased mean latency by 2.83 ms and packet loss by 1.05 percentage points relative to pedestrian mobility, while success rate decreased by 2.58 percentage points. Predictive handover recorded the most favorable overall means, with 61.59 ms latency, 88.40% success, and 3.22% packet loss, although the algorithm main effect was not statistically significant after density and mobility were controlled. The results show that density-aware cell planning and mobility-sensitive parameter adaptation are more influential than selecting one fixed handover method. Predictive and adaptive strategies should therefore operate within a context-responsive policy that adjusts hysteresis, time-to-trigger, and target-cell preparation to local density and movement conditions.

Keywords: *5G New Radio, handover, mobility management, network density, predictive handover, latency, packet loss, Lagos*

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1. Introduction

Fifth-generation cellular systems extend mobile broadband into a programmable radio-access infrastructure intended to support enhanced mobile

broadband, ultra-reliable low-latency communication, and massive machine-type communication. The 3GPP New Radio architecture defines the radio-access functions and procedures, while the IMT-2020 framework specifies performance expectations for data rate, latency, mobility, connection density, and reliability [1], [2]. These requirements place mobility management at the centre of end-to-end quality of service because a user must retain an active session while radio conditions and serving cells change. Handover transfers an active user-equipment connection from a serving cell to a target cell. The process involves measurement reporting, trigger evaluation, target selection, resource preparation, path switching, and release of the previous radio context. Dense heterogeneous deployments make these steps more difficult because macro cells, small cells, directional beams, high-frequency links, and overlapping coverage zones create frequent cell-boundary crossings and more candidate targets [3]-[8]. Poorly configured handover control produces late handovers, early handovers, radio-link failure, ping-pong events, excessive signalling, packet loss, and service interruption.

Lagos provides a relevant urban motivation for this analysis because dense residential districts, commercial activity, major transport corridors, building blockage, and high mobile-traffic demand create a demanding environment for cell planning and mobility control. Nigeria has continued to expand telecommunications infrastructure, which strengthens the need for evidence-based radio planning and performance evaluation before network-wide parameter changes are deployed [9].

The present study does not claim to reproduce live operator measurements from Lagos. Instead, Lagos serves as a realistic planning context for a controlled simulation matrix. Current handover research has moved from fixed received-signal thresholds toward adaptive hysteresis, adaptive time-to-trigger, conditional handover, reinforcement learning, Bayesian optimization, and movement prediction [10]-[21]. These methods seek to anticipate degradation and prepare target resources before the serving link becomes unreliable. Their reported benefits depend on prediction accuracy, measurement quality, traffic state, propagation conditions, and model generalization. A predictive method that performs well in one scenario may therefore lose its advantage when density or mobility changes.

A second challenge concerns evaluation practice. Many algorithm studies emphasize a single indicator, such as handover failure or ping-pong rate. Operational decisions require a joint view of interruption time, successful completion, and packet delivery. A third challenge concerns statistical consistency. Simulation conclusions should follow the underlying scenario data, and aggregate claims should not conceal cases where a baseline method performs better. These concerns motivate a joint and transparent assessment of latency, success rate, and packet loss.

This article makes four contributions:

1. It presents a complete $2 \times 3 \times 3$ scenario matrix that isolates mobility class, network density, and handover strategy within one evaluation structure.

2. It evaluates three operational indicators together, namely handover latency, handover success rate, and packet loss.
3. It recomputes descriptive statistics, ANOVA results, model fit, and partial eta-squared effect sizes from the scenario-level dataset.
4. It translates the statistical patterns into engineering recommendations for cell planning, handover parameter control, predictive preparation, and field validation.

The remainder of the article is organized as follows. Section 2 reviews the technical basis and recent research. Section 3 presents the simulation design, mathematical definitions, and statistical method. Section 4 reports the results. Section 5 discusses engineering implications and study limitations. Section 6 concludes the study.

2. Technical Background and Related Work

2.1 Handover control in 5G networks

Connected-mode mobility in 5G NR relies on radio measurements and network-controlled decisions. The user equipment measures serving and neighbouring cells through indicators such as reference-signal received power, reference-signal received quality, and signal-to-interference-plus-noise ratio. Reports are filtered and compared with configured offsets, hysteresis, and time-to-trigger values. A small hysteresis or short time-to-trigger improves responsiveness but increases the probability of unnecessary handovers. A large hysteresis or long time-to-trigger stabilizes cell

association but raises the risk of late handover and radio-link failure [5], [12], [13].

Hard handover follows a break-before-make sequence. Resource use is limited because the old link is released before the new link becomes active, but the transition is sensitive to preparation and interruption delay. The source dataset also contains a soft-handover category. Classic soft handover is associated with code-division systems rather than standard 5G NR operation. In this article, the label is retained only as a make-before-break abstraction representing temporary overlapping connectivity, dual connectivity, or conditional preparation. Predictive handover represents anticipatory target preparation based on movement or radio trends. The dataset does not identify one specific machine-learning architecture, so predictive handover is assessed as an algorithm class rather than a validated implementation of a named model.

2.2 Mobility and network-density stress

Network densification reduces the average distance between users and access points and improves spatial reuse. The same change creates more cell edges, more overlapping coverage, and a larger target-cell set. Mobility management must then handle frequent measurements, short residence times, and increased signalling. Surveys of heterogeneous and ultra-dense networks identify cell association, interference, ping-pong control, and mobility robustness as recurring issues [6]-[8], [11], [12].

Mobility speed interacts with cell size. A pedestrian user normally remains within a cell longer than a

vehicular user. The longer dwell time permits more stable filtering and target preparation. A vehicular user traversing small cells experiences faster channel variation and a narrower decision window. Adaptive time-to-trigger and hysteresis methods address this problem by changing handover sensitivity with speed and radio context [13], [15].

2.3 Predictive and learning-based approaches

Machine-learning research frames handover as a sequential decision and prediction problem. Supervised models estimate target-cell quality or handover failure probability. Reinforcement-learning methods optimize policies through reward functions that combine signal quality, handover cost, packet loss, and load. Bayesian optimization tunes handover control parameters with fewer trials than exhaustive search. Deep-learning approaches use temporal measurements, trajectories, or blockage information to predict future serving conditions [10], [14]-[21].

The main limitation of predictive control is dependence on reliable inputs. Location error, sparse training data, changing traffic patterns, and non-stationary propagation reduce prediction accuracy. Predictive preparation also consumes resources when a forecasted target is not used. Comparative evaluation should therefore report both average gains and scenario-level exceptions.

2.4 Simulation platforms and research gap

System-level tools such as Simu5G and 5G-LENA support repeatable evaluation of mobility, radio resources, interference, and protocol behaviour

[22]-[27]. They permit controlled experiments without disrupting a production network. Site-specific simulation and ray-tracing integration provide a further route toward realistic urban propagation, while O-RAN controllers create a path for adaptive policies to move from offline analysis into near-real-time network control [28]. The gap addressed here is narrower and practical. Localized African urban evidence is limited, joint treatment of latency, success rate, and packet loss is uncommon, and scenario-level data are often summarized without effect-size interpretation. The present article uses a Lagos-motivated context, retains the complete 18-cell dataset, and distinguishes aggregate ranking from universal superiority.

Figure 1. Conceptual framework linking simulation inputs, handover control, performance indicators, and engineering decisions.

Figure 1 shows the analytical chain used in the study. Mobility, density, and algorithm type enter the handover-control abstraction as independent scenario factors. The control process produces latency, success rate, and packet-loss outcomes. These outcomes do not represent isolated statistics. Together, they indicate whether the network completes a transition quickly, retains session continuity, and preserves data delivery. The final block links measurement to engineering action, including cell-layout review, hysteresis adjustment, time-to-trigger adjustment, and predictive target preparation.

3. Materials and Methods

3.1 Research design and study context

The study used a quantitative simulation-based design. The independent factors were mobility class, network density, and handover strategy. The dependent variables were handover latency, handover success rate, and packet loss. Lagos was used as an urban planning context rather than a field-measurement site. No personal data, subscriber identifiers, or human participants were involved. The source configuration reported 5,000 virtual user-equipment devices, 50 macro cells, 150 small cells, and ten repeated runs per broad simulation condition. The available analytical dataset contains 18 scenario-level values, one for each combination of two mobility classes, three density classes, and three algorithms. The run-level observations were not included in the source file. The descriptive and inferential analyses in this article therefore treat the 18 scenario values as the unit of analysis.

Table 1. Simulation design and analytical assumptions

Element	Configuration	Engineering interpretation
Study context	Lagos-motivated dense urban setting	Context for planning. It is not a live operator drive test.
Factorial structure	2 mobility × 3 density × 3 algorithm levels	Eighteen scenario cells permit balanced main-effect comparison.
Mobility classes	Pedestrian and vehicular	Categorical speed classes. Exact speed traces were not supplied.
Density classes	Low, medium, and high	Relative deployment stress. Exact site area and inter-site distance were not supplied.
Handover strategies	Hard HO, soft-HO abstraction, predictive HO	Baseline, overlapping-connectivity abstraction, and anticipatory preparation.

Virtual user equipment	5,000	Represents a high-load urban population in the simulation configuration.
Radio sites	50 macro cells and 150 small cells	Represents heterogeneous network densification.
Replications	10 per broad simulation condition	Reported in the source configuration. Run-level outputs were unavailable.
Analytical observations	18 scenario-level values	One latency, success, and packet-loss value for each factor combination.
Primary outputs	Latency, success rate, packet loss	Joint indicators of transition speed, continuity, and data delivery.

Table 1 separates reported configuration values from analytical assumptions. The distinction is important. The cell counts and virtual-user count describe the intended scale, while the statistical dataset contains aggregated scenario outputs. Exact mobility speeds, radio frequencies, bandwidth, scheduler, propagation model, and inter-site distances were not reported. The findings therefore support comparative scenario analysis rather than protocol conformance or site-specific dimensioning.

3.2 Handover decision abstraction

A generic A3-style decision condition provides the engineering interpretation of the handover trigger. A target cell becomes eligible when its filtered measurement exceeds the serving-cell measurement by the configured margin for at least the time-to-trigger interval.

$$M_t(t) - M_s(t) > H + O, \text{ for a duration } \geq T_TTT \tag{1}$$

In Equation (1), $M_t(t)$ is the filtered target-cell measurement, $M_s(t)$ is the serving-cell

measurement, H is the hysteresis margin, O is the effective offset, and T_TTT is the time-to-trigger. Increasing H or T_TTT suppresses rapid switching but delays handover. Decreasing either term accelerates response but raises ping-pong risk. The source dataset does not contain the underlying measurement traces, so Equation (1) explains the control principle rather than a directly fitted model.

Hard handover was represented as break-before-make execution. The soft-handover class represented overlapping connectivity and smoother transfer. Predictive handover represented early target preparation based on anticipated movement or radio degradation. All three strategies were evaluated under the same mobility and density cells.

3.3 Performance metrics

$$L_{HO} = t_{complete} - t_{trigger} \quad (2)$$

Equation (2) defines handover latency as the elapsed time from the trigger instant to completion. Lower values indicate faster transition and a smaller interruption window.

$$HSR = \left(\frac{N_{success}}{N_{attempts}}\right) \times 100\% \quad (3)$$

Equation (3) defines handover success rate. N_success is the number of completed handovers and N_attempts is the number of initiated handovers. Higher values indicate stronger session continuity.

$$PLR = \left(\frac{N_{lost}}{N_{transmitted}}\right) \times 100\% \quad (4)$$

Equation (4) defines packet-loss rate. N_lost is the

number of packets not delivered during the observation interval and N_transmitted is the total transmitted packet count. Lower values indicate more reliable data delivery.

$$\bar{x} = \left(\frac{1}{n}\right) \sum_{i=1}^n x_i \quad (5)$$

Equation (5) gives the arithmetic mean used to summarize each algorithm, mobility class, and density level. The mean is an aggregate indicator and does not identify the best method in every individual scenario.

$$s = \sqrt{\left[\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{(n - 1)}\right]} \quad (6)$$

Equation (6) gives the sample standard deviation. A larger value indicates stronger variation across the six mobility-density combinations evaluated for each algorithm.

Table 2. Performance metrics, equations, and optimization direction

Metric	Equation	Unit	Preferred direction	Operational meaning
Handover latency	Equation (2)	Ms	Lower	Transition speed and interruption exposure.
Handover success rate	Equation (3)	%	Higher	Probability of completing the mobility procedure.
Packet loss rate	Equation (4)	%	Lower	Data-delivery reliability during mobility.
Arithmetic mean	Equation (5)	Metric unit	Context dependent	Average performance within a factor level.
Standard deviation	Equation (6)	Metric unit	Lower for stability	Dispersion across scenarios.

Table 2 clarifies why no single indicator should determine algorithm selection. A low-latency

method may still lose packets or fail to complete some transitions. The preferred handover policy should therefore minimize Equations (2) and (4) while maximizing Equation (3). Standard deviation adds a stability perspective because an algorithm with a strong mean and large variation may be difficult to tune across a heterogeneous city.

3.4 Statistical model

An additive factorial model was fitted separately to latency, success rate, and packet loss. Interaction terms were not estimated because the dataset provides only one aggregated observation per complete factor combination. A saturated interaction model would leave no independent residual error.

$$Y_{ijk} = \mu + M_i + D_j + A_k + \varepsilon_{ijk} \quad (7)$$

Equation (7) expresses each outcome Y_{ijk} as the grand mean μ , the mobility effect M_i , the density effect D_j , the algorithm effect A_k , and residual error ε_{ijk} . The model estimates main effects after the other factors are controlled.

$$R^2 = 1 - \left(\frac{SS_{error}}{SS_{total}} \right) \quad (8)$$

Equation (8) reports the proportion of scenario-level variation explained by the additive model. A high R^2 indicates strong fit within the 18 observations. It does not establish external validity for a live network.

$$\eta_p^2 = \frac{SS_{effect}}{(SS_{effect} + SS_{error})} \quad (9)$$

Equation (9) gives partial eta-squared, an effect-size measure for each factor. It quantifies the share of the effect-plus-error variation associated with a factor after other main effects are included. Values are interpreted only within this scenario dataset. Descriptive statistics were calculated directly from the 18 rows. Type-II sums of squares were used because the design is balanced and the model includes only main effects. Statistical significance was assessed at $\alpha = 0.05$. Because the observations are scenario means rather than independent run-level measurements, the p-values are exploratory and should not be treated as population-level proof.

4. Results

4.1 Scenario-level dataset

Table 3. Scenario-level handover performance dataset

Code	Mobility	Density	Algorithm	Latency (ms)	Success (%)	Packet loss (%)
P-L	Pedestrian	Low	Hard HO	52.48	94.72	1.32
P-L	Pedestrian	Low	Soft HO	57.62	94.53	0.88
P-L	Pedestrian	Low	Predictive HO	57.90	96.53	0.77
P-M	Pedestrian	Medium	Hard HO	62.71	89.07	2.77
P-M	Pedestrian	Medium	Soft HO	61.21	86.17	2.14
P-M	Pedestrian	Medium	Predictive HO	57.19	87.97	3.16
P-H	Pedestrian	High	Hard HO	65.46	82.18	5.73
P-H	Pedestrian	High	Soft HO	68.87	85.14	4.29
P-H	Pedestrian	High	Predictive HO	67.28	85.22	4.42
V-L	Vehicular	Low	Hard HO	56.88	90.80	1.85
V-L	Vehicular	Low	Soft HO	51.99	95.70	1.99

V-L	Vehicular	Low	Predictive HO	49.71	93.65	1.39
V-M	Vehicular	Medium	Hard HO	66.04	83.08	3.34
V-M	Vehicular	Medium	Soft HO	65.98	88.48	4.09
V-M	Vehicular	Medium	Predictive HO	64.42	86.40	3.26
V-H	Vehicular	High	Hard HO	71.40	81.08	6.53
V-H	Vehicular	High	Soft HO	76.72	78.47	6.16
V-H	Vehicular	High	Predictive HO	73.07	80.65	6.31

Table 3 preserves all 18 observations used in the analysis. The low-density rows show generally lower latency and packet loss, together with higher success. High-density vehicular scenarios form the most demanding operating region. The table also shows why aggregate ranking requires caution. Hard handover records the lowest latency in the pedestrian-low and both high-density scenarios. Soft handover records the lowest packet loss in several medium- and high-density scenarios. Predictive handover leads many low- and medium-density cases, but it does not dominate every cell.

Figure 2. Handover latency for hard, soft, and predictive handover across six mobility-density scenarios. P denotes pedestrian, V denotes vehicular, and L, M, and H denote low, medium, and high density.

Figure 2 shows a strong density gradient. Latency rises from the low-density categories toward the high-density categories for both mobility classes. Predictive handover has the lowest overall mean, but the scenario bars reveal exceptions. Hard handover produces the minimum latency in P-L, P-H, and V-H, while predictive handover leads P-M,

V-L, and V-M. Soft handover has the highest overall latency because its overlapping-connectivity abstraction introduces additional preparation or coordination cost in several cells.

Figure 3. Handover success rate across the six mobility-density scenarios.

Figure 3 shows that success rate declines as density increases. The pattern is clearer than the differences among algorithms. Predictive handover gives the highest success in P-L and P-H. Soft handover leads V-L and V-M. Hard handover leads P-M and V-H. The mixed pattern indicates interaction-like behaviour at the scenario level even though interactions cannot be estimated from the aggregated dataset. Network operators should not interpret the highest overall mean as proof of universal dominance.

Figure 4. Packet loss across the six mobility-density scenarios.

Figure 4 shows the largest relative degradation among the three indicators. Packet loss remains near 1% to 2% in low-density scenarios, increases to roughly 2% to 4% at medium density, and exceeds 4% in every high-density case. Predictive handover minimizes packet loss in P-L, V-L, and V-M. Soft handover leads P-M, P-H, and V-H. Hard handover does not produce the minimum packet loss in any scenario. This result suggests that overlapping or anticipatory preparation is more useful for packet continuity than a strict break-before-make baseline.

4.2 Performance by handover algorithm

Table 4. Descriptive performance by handover algorithm

Algorithm	Latency, mean ± SD (ms)	Success, mean ± SD (%)	Packet loss, mean ± SD (%)
Hard HO	62.50 ± 6.82	86.82 ± 5.51	3.59 ± 2.10
Soft HO	63.73 ± 8.74	88.08 ± 6.39	3.26 ± 1.93
Predictive HO	61.59 ± 8.32	88.40 ± 5.80	3.22 ± 2.02

Table 4 ranks predictive handover first on all three aggregate means. Relative to hard handover, predictive handover lowers mean latency by 0.90 ms, raises mean success by 1.58 percentage points, and lowers packet loss by 0.37 percentage points. The differences are modest compared with the density effect. Predictive and soft handover also have larger latency dispersion than hard handover, which reflects stronger scenario sensitivity. The algorithm means therefore support predictive handover as a preferred average strategy, not as a fixed rule for every operating condition.

4.3 Effects of mobility and network density

Table 5. Mean performance by mobility class

Mobility class	Mean latency (ms)	Mean success (%)	Mean packet loss (%)
Pedestrian	61.19	89.06	2.83
Vehicular	64.02	86.48	3.88

Table 5 isolates the mobility effect. Vehicular mobility increases mean latency from 61.19 ms to 64.02 ms, a 4.63% increase. Success rate decreases from 89.06% to 86.48%, while packet loss rises from 2.83% to 3.88%. The packet-loss increase is 37.05% relative to the pedestrian mean. The larger reliability penalty reflects shorter cell dwell time

and a narrower interval for measurement filtering, target preparation, and path switching.

Table 6. Mean performance by network-density level

Network density	Mean latency (ms)	Mean success (%)	Mean packet loss (%)
Low	54.43	94.32	1.37
Medium	62.93	86.86	3.13
High	70.47	82.12	5.57

Table 6 identifies density as the dominant stressor. From low to high density, mean latency increases by 16.04 ms, equal to 29.46%. Mean success decreases by 12.20 percentage points, equal to a 12.93% relative reduction. Mean packet loss increases by 4.21 percentage points, equal to a 307.80% relative increase. The packet-loss result is especially important because a small absolute baseline produces a large relative deterioration. Dense deployments therefore require more than added cells. They require coordination, interference control, target selection, and mobility-parameter tuning.

Figure 5. Mean handover latency by network density.

Figure 5 shows an almost linear increase in mean latency across the three density levels. The 8.50 ms rise from low to medium density is slightly larger than the 7.54 ms rise from medium to high density. This pattern is consistent with additional signalling, candidate evaluation, interference, and resource-preparation pressure as cell overlap increases.

Figure 6. Mean handover success rate by network density.

Figure 6 shows the opposite trend. Success rate drops sharply between low and medium density, then continues to decline at high density. The first step loses 7.46 percentage points and the second step loses 4.74 percentage points. The stronger initial decline suggests that the transition from sparse to moderately dense deployment introduces substantial mobility complexity before the highest-density state is reached.

Figure 7. Mean packet loss by network density.

Figure 7 shows accelerating packet-loss growth. The increase is 1.76 percentage points from low to medium density and 2.45 percentage points from medium to high density. The steeper second step indicates a compounding effect from interference, more frequent handovers, and shorter time available for stable packet forwarding.

4.4 Factor effects from analysis of variance

Table 7. Additive factorial ANOVA and partial eta-squared effect sizes

Outcome	Factor	df	F statistic	p value	Partial η^2	Model R^2
Latency	Mobility	1	2.849	0.1172	0.192	0.844
Latency	Network density	2	30.487	1.977e-05	0.836	0.844
Latency	Algorithm	2	0.545	0.5935	0.083	0.844
Success rate	Mobility	1	8.873	0.0115	0.425	0.924
Success rate	Network density	2	67.217	3.029e-07	0.918	0.924

Success rate	Algorithm	2	1.242	0.3234	0.172	0.924
Packet loss	Mobility	1	22.298	4.952e-04	0.650	0.957
Packet loss	Network density	2	120.613	1.132e-08	0.953	0.957
Packet loss	Algorithm	2	1.125	0.3567	0.158	0.957

Table 7 confirms the descriptive pattern. Network density is statistically significant for latency, success rate, and packet loss, with partial eta-squared values of 0.836, 0.918, and 0.953. Mobility is significant for success rate and packet loss, but not for latency at the 0.05 level. Algorithm type is not significant for any outcome after mobility and density are controlled. Model R^2 ranges from 0.844 to 0.957, which means the three main effects explain most of the variation within the 18 scenario values. These results should remain exploratory because the model uses aggregated scenario means.

Figure 8. Partial eta-squared effect sizes for mobility, network density, and algorithm type.

Figure 8 provides a visual comparison of factor strength. Density dominates every metric, particularly packet loss and success rate. Mobility has its strongest influence on packet loss. Algorithm selection has the smallest effect across all outcomes. This result does not remove algorithm design from the engineering problem. It shows that algorithm gains depend on the surrounding density and mobility regime, so parameter adaptation and deployment context deserve priority.

4.5 Scenario-specific best performers

Table 8. Best-performing algorithm within each

mobility-density scenario

Scenario	Definition	Lowest latency	Highest success	Lowest packet loss
P-L	Pedestrian, low density	Hard HO	Predictive HO	Predictive HO
P-M	Pedestrian, medium density	Predictive HO	Hard HO	Soft HO
P-H	Pedestrian, high density	Hard HO	Predictive HO	Soft HO
V-L	Vehicular, low density	Predictive HO	Soft HO	Predictive HO
V-M	Vehicular, medium density	Predictive HO	Soft HO	Predictive HO
V-H	Vehicular, high density	Hard HO	Hard HO	Soft HO

Table 8 is the strongest evidence against a universal algorithm claim. Predictive handover wins the latency criterion in three scenarios, hard handover wins the other three, and soft handover wins none. Success-rate leadership is evenly distributed, with two scenarios for each algorithm. Packet-loss leadership is split between predictive and soft handover, with three scenarios each. A practical controller should therefore select or tune the handover policy according to the current density, mobility, and service objective.

5. Discussion

5.1 Network density as the primary performance driver

The dominant density effect agrees with the wider literature on heterogeneous and ultra-dense networks [5]-[8], [11], [12]. Added access points reduce average link distance but create more cell boundaries and overlapping candidate regions. Each

boundary increases measurement, signalling, and decision activity. When neighbouring cells use the same spectrum, inter-cell interference also affects the quality and stability of measurement reports. These mechanisms explain the simultaneous rise in latency and packet loss and the decline in success rate.

The engineering implication is that densification should include a mobility plan. Small-cell placement should avoid excessive overlap along transport corridors. Neighbour-relation tables should be pruned to remove weak or unnecessary candidates. Load and interference information should influence target selection. Conditional handover or preconfigured target sets may reduce preparation delay when several cells are plausible. Density zones also require separate parameter profiles rather than one network-wide hysteresis and time-to-trigger setting.

5.2 Mobility-sensitive reliability control

Vehicular mobility produces a larger penalty for success rate and packet loss than for latency. This distinction matters. The handover procedure may complete within a similar time interval, yet the faster user traverses the transition region before packet forwarding and radio conditions stabilize. Adaptive time-to-trigger and hysteresis methods address this problem by shortening the decision interval for fast users and increasing stability for slow users [13], [15]. Speed estimation, trajectory prediction, and road topology may further improve target preparation. The results support mobility-class profiles. Pedestrian users may use a longer

time-to-trigger to suppress ping-pong events. Vehicular users require earlier preparation, fewer weak candidates, and stronger path-switching coordination. The profiles should also depend on service type. Interactive video, telemedicine, connected vehicles, and industrial control place different weights on latency, packet loss, and interruption probability.

5.3 Role of predictive handover

Predictive handover produces the best aggregate means, which supports continued research into data-driven mobility management [10], [14]-[21]. Its average gain is modest, and the ANOVA does not identify a significant algorithm main effect. The scenario winners explain why. Prediction helps when movement or degradation is sufficiently regular, but hard or overlapping-connectivity methods lead some individual cells. Predictive control should therefore act as a context-dependent layer rather than a permanent replacement for every baseline procedure. A deployment-ready predictive controller requires confidence estimation and fallback logic. When prediction confidence is high, the network may prepare a target early. When confidence is low, the controller should revert to conventional measurement-based triggering. Resource reservations should expire quickly when a predicted target is not used. Model monitoring should detect drift caused by new traffic patterns, site changes, weather, blockage, or device behaviour.

5.4 Implications for Nigerian urban 5G planning

For Nigerian operators and radio-frequency

planners, the results prioritize four actions. First, classify cells by density and mobility exposure. Second, tune hysteresis and time-to-trigger by class. Third, evaluate packet continuity alongside average signal strength. Fourth, validate simulation outputs with drive tests and network counters before deployment. High-density transport corridors deserve separate analysis because they combine rapid movement, short residence time, traffic load, and severe propagation change.

O-RAN architectures provide a future implementation path for context-aware policies [28]. A near-real-time controller may collect measurements, infer mobility state, and recommend handover parameters. Such automation should remain bounded by safety limits, rollback rules, and continuous KPI monitoring. Offline simulation should be used to screen policies, while field trials should confirm performance under live radio and traffic conditions.

5.5 Study limitations

The study has six limitations. First, the dataset contains 18 aggregated scenario values rather than run-level outputs. Second, exact mobility speeds were not reported. Third, density classes were relative and lacked inter-site distance or geographic area. Fourth, the source did not specify frequency band, bandwidth, propagation model, scheduler, antenna pattern, traffic mix, or handover-control parameter values. Fifth, the predictive method was described as an algorithm class rather than a reproducible trained model. Sixth, Lagos provided contextual motivation without drive-test calibration.

These limitations restrict external validity. The results identify internally consistent comparative patterns, not absolute performance targets for a commercial network. Future work should publish configuration files, random seeds, per-run data, confidence intervals, interaction analyses, and code. Calibration with 5G-LENA, Simu5G, ray-tracing data, or operator counters would strengthen reproducibility and site-specific relevance [22]-[27], [29].

6. Conclusion and Recommendations

This study evaluated 5G handover performance across mobility, density, and algorithm conditions using 18 scenario-level observations. Network density was the principal driver of degradation. Moving from low to high density increased mean latency from 54.43 ms to 70.47 ms, reduced mean success rate from 94.32% to 82.12%, and increased packet loss from 1.37% to 5.57%. Vehicular mobility produced lower success and higher packet loss than pedestrian mobility. Predictive handover recorded the most favorable aggregate means, but the algorithm main effect was not significant and no method dominated every scenario. The central engineering conclusion is that handover performance depends more on operating context than on one fixed algorithm label. Dense urban networks should use density-aware cell planning, mobility-sensitive hysteresis and time-to-trigger profiles, context-aware target preparation, and packet-continuity monitoring. Predictive control should include confidence thresholds and fallback logic. Before operational deployment, the scenario findings should be validated with run-level

simulation, calibrated system-level tools, and live network measurements.

Table 9. Recommendations linked to the observed evidence

Stakeholder	Recommended action	Evidence from the study
Network operators	Deploy adaptive handover profiles by density and mobility class.	Density and mobility explained more variation than algorithm type.
RF planners	Review small-cell placement, overlap, and neighbour relations along transport corridors.	High-density scenarios had the highest latency and packet loss and the lowest success.
Optimization teams	Tune hysteresis, time-to-trigger, and target preparation jointly.	No single algorithm led every scenario and metric.
Data-science teams	Use confidence-aware prediction with fallback to measurement-based control.	Predictive handover led aggregate means but had scenario exceptions.
Researchers	Publish per-run data, full configurations, interaction models, and code.	The available dataset contained aggregated scenario values only.
Regulators and infrastructure planners	Support site coordination, fibre availability, and evidence-based urban deployment review.	Mobility performance depends on coordinated density and backhaul planning.

Table 9 converts the statistical results into stakeholder actions. The recommendations emphasize adaptive operation and validation rather than blanket replacement of one handover algorithm with another. They also separate radio-planning tasks from data-driven control tasks, which supports clearer responsibility during deployment and optimization.

Declarations

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Data availability: The complete scenario-level dataset used for the reported analysis is reproduced in Table 3. Run-level simulation outputs and source **Acknowledgement:** The author acknowledges the Department of Electrical/Electronic Engineering Technology, Federal Polytechnic Ohodo, for its academic environment and technical support.

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