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Reliability-Oriented Cellular Infrastructure Sharing for Resilient Urban Networks under Spatially Heterogeneous Demand, Coverage Failures, and Service Recovery Requirements

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Abstract

The proliferation of advanced urban cellular networks necessitates robust infrastructure capable of withstanding unexpected disruptions while catering to highly fluctuating user demands. This paper presents a comprehensive investigation into reliability-oriented cellular infrastructure sharing mechanisms designed to enhance the resilience of urban networks. Modern municipal environments are characterized by spatially heterogeneous traffic patterns and an increasing susceptibility to localized coverage failures stemming from extreme weather events, hardware malfunctions, or sudden power grid anomalies. Traditional redundant deployments by individual network operators are economically prohibitive and spatially inefficient. Therefore, this research proposes a dynamic, multi-operator infrastructure sharing framework that dynamically reallocates radio access network resources and backhaul capacities during degradation events. By integrating stochastic geometry with optimization theory, the study models the spatial distribution of demand and the probabilistic nature of base station failures. The proposed reliability-oriented optimization framework balances the immediate necessity of service recovery with the long-term operational costs of inter-operator sharing agreements. Algorithmic solutions are evaluated through extensive system-level simulations reflecting realistic urban topologies. The results demonstrate that cooperative resource pooling significantly reduces service downtime and improves overall user satisfaction metrics during cascaded network failures. Furthermore, the analysis highlights the critical thresholds of spatial demand heterogeneity where active infrastructure sharing becomes mathematically imperative for maintaining minimum service guarantees. Ultimately, this work provides a foundational theoretical model and actionable strategic guidelines for telecommunications operators and regulatory bodies aiming to foster resilient, shared telecommunications ecosystems in dense metropolitan areas.

Keywords

Infrastructure Sharing, Network Resilience, Coverage Failures, Spatial Heterogeneity, Service Recovery.

1. INTRODUCTION

1.1 Background on Urban Cellular Networks

The evolution of telecommunications networks from rudimentary voice-centric systems to sophisticated broadband data infrastructures has fundamentally altered the operational paradigms of urban environments. As municipalities transition into smart cities, the reliance on continuous, high-speed, and low-latency connectivity becomes absolute. Cellular networks now form the critical nervous system of urban spaces, supporting everything from autonomous vehicular coordination and remote medical procedures to massive Internet of Things deployments and routine high-definition multimedia consumption. However, this escalating dependency introduces significant vulnerabilities. Urban environments present uniquely challenging propagation landscapes characterized by high physical density, substantial electromagnetic interference, and deep signal shadowing caused by towering architectural structures. To combat these signal propagation challenges, mobile network operators have historically resorted to ultra-dense network deployments, placing micro, pico, and femtocells at increasingly proximate intervals. While this strategy successfully increases volumetric capacity and edge throughput under nominal operating conditions, it simultaneously introduces immense capital and operational expenditures. Researchers have extensively documented the diminishing marginal returns of unilateral ultra-dense deployments [1]. Furthermore, the hyper-densification of radio access networks inherently complicates interference management and mobility handovers, creating a fragile operational equilibrium that is highly sensitive to environmental and infrastructural perturbations. In this context, maintaining absolute service continuity requires a paradigm shift away from isolated, proprietary network architectures toward cooperative, integrated systems capable of leveraging collective resources during localized or widespread disruptive events.

1.2 The Need for Infrastructure Sharing

Infrastructure sharing has emerged as a pragmatic and economically viable solution to the escalating costs and spatial limitations of urban network deployment. Historically, regulatory environments encouraged strict infrastructural independence among competing mobile network operators to prevent monopolistic behaviors and ensure market competitiveness. However, as the technological requirements for subsequent generational upgrades intensify, the financial burden of independently acquiring spectrum, leasing physical site locations, deploying backhaul fiber, and powering thousands of active antenna units has become unsustainable [2]. Consequently, regulatory bodies and operators are increasingly embracing various modalities of infrastructure sharing. These modalities range from passive sharing, which involves the joint utilization of physical towers, equipment shelters, and power supplies, to active sharing, which encompasses the cooperative use of antennas, radio access network components, and even core network functionalities. Multi-Operator Core Networks represent the zenith of this cooperative approach, allowing disparate service providers to broadcast distinct public land mobile network identifiers while utilizing the exact same physical base station and radio spectrum pool. While the economic advantages of active sharing are well-established in the literature, its potential as a catalyst for network resilience remains underutilized [3]. By pooling resources, operators can create a

distributed buffer against localized equipment failures, effectively transforming proprietary redundancy into a shared, dynamic safety net. This cooperative paradigm allows for the immediate rerouting of user traffic through a competitor's surviving infrastructure when an operator's primary base station experiences catastrophic failure, thereby minimizing total service outage time and preserving critical civic functions.

1.3 Challenges in Resilient Network Design

Designing cellular networks that are inherently resilient to coverage failures involves navigating a complex matrix of stochastic variables and conflicting optimization objectives. Resilience, in the context of telecommunications, is generally defined as the network's capacity to absorb disruptive shocks, maintain an acceptable level of operational functionality, and subsequently recover to its original state within a minimal timeframe. Achieving this requires anticipating a vast array of potential failure modes, ranging from localized hardware malfunctions and targeted cyber-attacks to regional power grid collapses induced by extreme meteorological events. A primary challenge in modeling these failures is their non-uniform distribution across space and time. Coverage failures frequently exhibit cascading characteristics, where the failure of a primary macro cell forces surrounding micro cells to absorb excess traffic, consequently precipitating secondary failures due to processing overload or backhaul congestion. Moreover, user demand in urban networks is profoundly heterogeneous in the spatial domain. The concentration of users fluctuates dramatically based on time of day, localized social events, and commuting patterns, creating transient geographic hotspots that can rapidly overwhelm localized network resources even in the absence of hardware failures. When high spatial heterogeneity of demand coincides with stochastic coverage failures, the resulting service degradation is often severe and disproportionately impacts densely populated or highly commercialized sectors of the city. Developing a resilient architecture therefore requires dynamic, state-aware resource allocation algorithms that can instantaneously balance the competing requirements of load distribution, interference mitigation, and inter-operator service level agreements.

1.4 Contributions of This Paper

This paper addresses the critical intersection of infrastructure sharing and network resilience by proposing a novel, reliability-oriented optimization framework tailored for urban environments experiencing spatially heterogeneous demand and stochastic coverage failures. The primary contribution of this research is the formulation of a comprehensive mathematical model that quantifies the resilience benefits of active multi-operator infrastructure sharing under adverse conditions. Unlike existing studies that treat network failures and traffic fluctuations as independent variables, the proposed model captures the complex, interconnected dynamics of cascading overload scenarios. Additionally, this work introduces a proprietary service recovery algorithm that dynamically orchestrates inter-operator roaming and resource reallocation based on instantaneous geographic demand and remaining network capacity. By integrating advanced stochastic geometry techniques with rigorous convex optimization methods, the framework provides theoretical bounds on the minimum necessary degree of infrastructure sharing required to maintain baseline service continuity. The validity and efficacy of the proposed algorithms are

rigorously evaluated through high-fidelity, system-level simulations utilizing realistic urban topographical data. The findings offer definitive evidence that dynamic infrastructure sharing is not merely an economic convenience, but a fundamental prerequisite for ensuring the survivability of mission-critical telecommunications services in modern metropolitan areas.

2. Literature Review and Background

2.1 Infrastructure Sharing Mechanisms

The conceptual framework of telecommunications infrastructure sharing has evolved significantly over the past two decades, driven by both economic necessity and technological innovation. Early investigations primarily focused on passive sharing agreements, emphasizing the reduction of site acquisition costs and the minimization of the physical environmental footprint associated with cellular towers [4]. These foundational studies established the economic viability of shared physical assets but largely ignored the potential for cooperative resource management at the logical layer. The advent of fourth-generation networks precipitated a shift toward active sharing paradigms, specifically National Roaming and Multi-Operator Radio Access Network architectures [5]. In these configurations, operators maintain separate core networks but cooperatively utilize radio processing units and antennas. Previous research has extensively modeled the game-theoretic interactions between operators negotiating these active sharing agreements, demonstrating that cooperative equilibria can be achieved when the cost of unilateral deployment exceeds a specific threshold [6]. More recently, the introduction of network function virtualization and software-defined networking has enabled dynamic, on-demand resource slicing, allowing multiple virtual networks to coexist on a single physical infrastructure [7]. This virtualization paradigm facilitates highly granular, slice-level sharing, where resources can be allocated and revoked in near real-time based on fluctuating demand. However, the majority of literature concerning active sharing and network slicing focuses predominantly on optimizing spectral efficiency and maximizing aggregate throughput under normal operating conditions [8]. The application of these dynamic sharing mechanisms specifically for disaster recovery and fault tolerance remains a nascent area of exploration, necessitating the development of novel theoretical frameworks that prioritize reliability metrics over pure capacity maximization.

2.2 Fault Tolerance and Coverage Failures

The analysis of network reliability and fault tolerance has historically relied upon deterministic models that assume static failure probabilities for individual network components. Early reliability engineering applied to telecommunications utilized fault tree analysis and reliability block diagrams to calculate the aggregate mean time between failures for entire network subsystems. While useful for component-level design, these deterministic approaches fail to capture the complex, stochastic nature of modern cellular deployments. To address this limitation, researchers began applying stochastic geometry, particularly Poisson Point Processes, to model the spatial distribution of base stations and calculate theoretical coverage probabilities [9]. By introducing random thinning operations into these point processes, scholars have successfully modeled independent, identically distributed base station failures [10]. However, empirical data from large-

scale network outages indicates that coverage failures are rarely independent; they are often spatially correlated due to shared vulnerabilities, such as a common reliance on a specific electrical substation or localized damage from a natural disaster [11]. Recent advancements in spatial statistics have introduced clustered point processes, such as Matern cluster processes, to better represent these correlated failure events [12]. Despite these mathematical advancements, existing models frequently analyze failure scenarios in isolation, neglecting the subsequent cascading effects on user traffic and neighboring cell loads. A comprehensive understanding of network resilience requires integrating these sophisticated spatial failure models with dynamic traffic reallocation mechanisms, ensuring that the theoretical analysis accurately reflects the operational realities of degraded network states.

2.3 Spatially Heterogeneous Demand Modeling

Accurately modeling the spatial distribution of user demand is critical for optimizing network resource allocation, particularly in urban environments characterized by high population density and diverse land-use patterns. Traditional cellular network models often assume a uniform distribution of users, simplifying mathematical analysis but severely compromising the practical applicability of the results. To capture spatial heterogeneity, researchers have proposed various empirical and theoretical models. Empirical approaches utilize extensive datasets comprising call detail records and GPS traces to construct detailed spatiotemporal traffic heat maps [13]. These data-driven models reveal that urban traffic exhibits strong diurnal patterns and is heavily concentrated in specific geographical hotspots, such as central business districts during working hours and residential areas during the evening. Theoretical approaches, conversely, employ inhomogeneous Poisson Point Processes to model user locations, allowing the intensity function of the point process to vary across the spatial domain based on specific topographical features or land-use categories [14]. Furthermore, the integration of fractal geometry has been explored to model the self-similar, scale-invariant clustering of human populations in metropolitan regions [15]. While these heterogeneous demand models significantly improve the accuracy of network capacity planning, their integration into real-time resilience optimization frameworks poses substantial computational challenges. When spatial demand heterogeneity is coupled with stochastic coverage failures, the network must instantaneously process massive amounts of state information to determine the optimal reallocation strategy. Consequently, there is a pressing need for low-complexity, heuristic algorithms capable of approximating optimal solutions within the strict latency constraints required for uninterrupted service continuity.

2.4 Service Recovery and Resilience

The concept of resilience in telecommunications extends beyond mere fault tolerance; it encompasses the network's ability to anticipate disruptions, maintain critical services during a failure event, and rapidly recover full operational capacity. The literature identifies three primary phases of network resilience: the avoidance phase, the survivability phase, and the recovery phase [16]. The avoidance phase involves proactive measures, such as predictive maintenance and robust architectural design, aimed at minimizing the probability of component failure. The survivability phase focuses on the immediate aftermath of a disruption, utilizing techniques such as traffic

prioritization, graceful degradation, and dynamic routing to ensure that essential communications, such as emergency services, remain functional [17]. The recovery phase, which is the primary focus of this paper, entails the systematic restoration of standard network operations. Existing research on service recovery heavily emphasizes self-healing algorithms within the proprietary domain of a single operator [18]. These algorithms typically involve automatically adjusting the antenna tilt and increasing the transmission power of surviving base stations to compensate for the coverage hole created by a failed site. However, physical limitations regarding maximum transmission power and the potential for increased inter-cell interference severely constrain the efficacy of these single-operator self-healing techniques. Cross-operator service recovery, facilitated through dynamic infrastructure sharing, offers a significantly more robust solution. By enabling multi-operator roaming and cooperative resource allocation during the recovery phase, networks can leverage an entirely separate, geographically overlapping physical infrastructure to restore service [19]. Fully realizing this potential requires the establishment of standardized inter-operator communication protocols and the development of fair, transparent cost-accounting mechanisms to compensate the assisting operator for the utilized resources.

3. System Model and Problem Formulation

3.1 Network Architecture and Sharing Model

This study considers a heterogeneous urban cellular network architecture comprising multiple mobile network operators providing concurrent service within a defined geographical area. Let the total geographical area of interest be denoted by a two-dimensional Euclidean space. The network consists of a set of macro base stations and a denser tier of micro base stations, deployed to accommodate high capacity requirements in localized hotspots. We assume the existence of a cooperative sharing agreement among the participating operators, governed by a centralized resource management broker. This broker acts as an impartial logical entity capable of orchestrating active infrastructure sharing, specifically through a Multi-Operator Core Network configuration. Under normal operational conditions, each operator utilizes its proprietary spectrum and radio access network equipment to serve its subscriber base. The system operates under a state of standard competitive isolation. However, upon the detection of a significant coverage failure, the affected operator initiates a distress protocol via the centralized broker. The broker then evaluates the available surplus capacity of the surrounding, functional base stations belonging to alternative operators. To formally represent this architecture, we define the set of all base stations as a spatial point process, and the set of all active user equipment as an independent, spatially heterogeneous point process. The connectivity between a user and a base station is determined by the received signal-to-interference-plus-noise ratio, which is continuously monitored and reported back to the network core. The architecture assumes a robust, high-capacity backhaul network connecting all base stations to the core, ensuring that backhaul constraints do not become the primary bottleneck during rapid traffic reallocation procedures.

3.2 Spatial Demand and Failure Modeling

Modeling the complex interplay between spatially heterogeneous demand and stochastic component failures requires a rigorous mathematical foundation. The spatial distribution of user demand is modeled utilizing an inhomogeneous spatial point process, where the intensity of user requests varies dynamically across the urban landscape. This heterogeneity is mathematically captured by defining varying user density functions that correspond to different zoning characteristics, such as commercial, residential, and industrial districts. The user demand is not static; it fluctuates continuously, necessitating a time-slotted analysis approach where the spatial intensity is updated at the beginning of each defined time interval.

Simultaneously, the physical infrastructure is subject to stochastic coverage failures. These failures can be characterized as either independent, isolated hardware malfunctions or correlated, spatially clustered outages caused by external environmental factors. We model the base station operational state as a binary variable, where zero indicates a complete failure and one indicates full operational capability. The probability of failure for any given base station is influenced by its geographical location, its historical reliability metrics, and the current environmental stress factors.

To formalize the network's resilience objective under these conditions, we define the system's primary optimization goal as maximizing the total weighted sum of successfully served user demand, penalized by the cost of inter-operator resource sharing. The objective function is formulated using standard continuous mathematics to ensure rigorous optimization properties.

$$\max_{X} \sum_{i \in N} \sum_{j \in U} x_{i,j} \log(1 + \mathrm{SINR}_{i,j}) - \lambda \sum_{k \in F} C_k$$

In this formulation, the primary summation represents the aggregate network utility, derived from the logarithmic function of the signal-to-interference-plus-noise ratio experienced by each user. The variable lambda acts as a tuning parameter that dictates the strictness of the penalty applied for utilizing shared resources from the set of cooperative operators. This continuous objective function is critical for evaluating the trade-off between maximizing instantaneous throughput and minimizing the financial expenditures associated with emergency infrastructure leasing.

To calculate the precise probability that a user will receive adequate service under degraded conditions, we rely on the fundamental tenets of stochastic geometry. The coverage probability is defined as the mathematical likelihood that the received signal quality exceeds a predefined operational threshold. This is expressed through an integral formulation over the spatial domain.

$$\mathrm{mathbbP}(\mathrm{SIR} > \gamma) = \int_0^{\infty} 2\pi\lambda_b r \exp(-\pi\lambda_b r^2) \exp\left(-\frac{\gamma\sigma^2}{P_t r^{-\alpha}}\right) dr$$

This equation integrates the probability density function of the distance to the nearest serving base station, incorporating the base station spatial density, the path loss exponent, and the thermal noise variance. By manipulating the density variable within this integral, we can accurately simulate the theoretical impact of massive coverage failures on the overall probability of maintaining seamless connectivity across the entire urban topology.

3.3 Reliability and Recovery Metrics

To comprehensively evaluate the performance of the proposed dynamic infrastructure sharing framework, it is imperative to establish rigorous, quantifiable reliability and recovery metrics. Traditional quality of service parameters, such as average throughput and packet loss ratios, are insufficient for characterizing network behavior during catastrophic failure events. Instead, we utilize a composite resilience index that incorporates three critical dimensions: the magnitude of initial service degradation, the speed of dynamic recovery, and the sustained steady-state performance post-reallocation. The magnitude of degradation measures the instantaneous drop in total network sum-rate immediately following a coverage failure, prior to the initiation of any cooperative sharing protocols. The speed of dynamic recovery, termed the recovery latency, quantifies the temporal delay between the moment a failure is registered by the centralized broker and the moment the displaced users are successfully authenticated and reconnected via a participating partner network. Finally, the sustained steady-state performance evaluates the long-term viability of the shared configuration, measuring the degree of congestion experienced by the assisting operator's native subscribers due to the influx of roaming traffic. An effective reliability-oriented sharing mechanism must balance the rapid onboarding of displaced users with the preservation of service quality for the host network's existing clientele. Furthermore, we define a service continuity threshold, representing the absolute minimum data rate required to support critical emergency communications. The probability of any given user falling below this critical threshold during a disruption serves as the primary constraint within our mathematical optimization framework, ensuring that the theoretical maximization of overall network utility does not result in the complete abandonment of users situated deep within coverage holes.

Table 1 System Parameters

Parameter Description	Notation	Nominal Value
Total Geographical Area	A	25 square kilometers
Macro Base Station Density	Lambda M	5 per square kilometer
Micro Base Station Density	Lambda m	20 per square kilometer
Maximum Transmission Power	Pt	46 decibel-milliwatts
Path Loss Exponent	Alpha	3.5
Target SIR Threshold	Gamma	0 decibels
Thermal Noise Power	Sigma squared	-104 decibel-milliwatts

4. Reliability-Oriented Optimization Framework

4.1 Joint Allocation Strategy

The core of the proposed framework relies on a joint allocation strategy that simultaneously optimizes radio access network associations and inter-operator roaming agreements. When a disruption occurs, the network state shifts from a stable equilibrium to a highly volatile, capacity-constrained environment. Traditional single-operator load balancing techniques, which typically adjust handover margins to push users to adjacent proprietary cells, are mathematically insufficient

when the spatial density of failures is high. The joint allocation strategy overcomes this by expanding the set of available candidate cells to include all functionally active infrastructure within the affected geographical radius, irrespective of original operator ownership. This requires the continuous, real-time exchange of localized state information, including current resource block utilization, backhaul congestion levels, and available transmission power margins. The centralized broker aggregates this telemetry data and formulates a massive bipartite matching problem, mapping the set of disconnected user equipment to the set of available shared base stations. Because finding the globally optimal solution to this combinatorial problem is computationally prohibitive within the strict latency constraints of emergency recovery, we implement a heuristic, geometry-based clustering algorithm. This algorithm partitions the affected urban area into smaller, independent optimization zones, allowing for parallel processing and near-instantaneous decision-making. The joint allocation strategy guarantees that high-priority traffic, specifically emergency communications and critical civic infrastructure telemetry, is deterministically routed to the most robust and least congested shared facilities available.

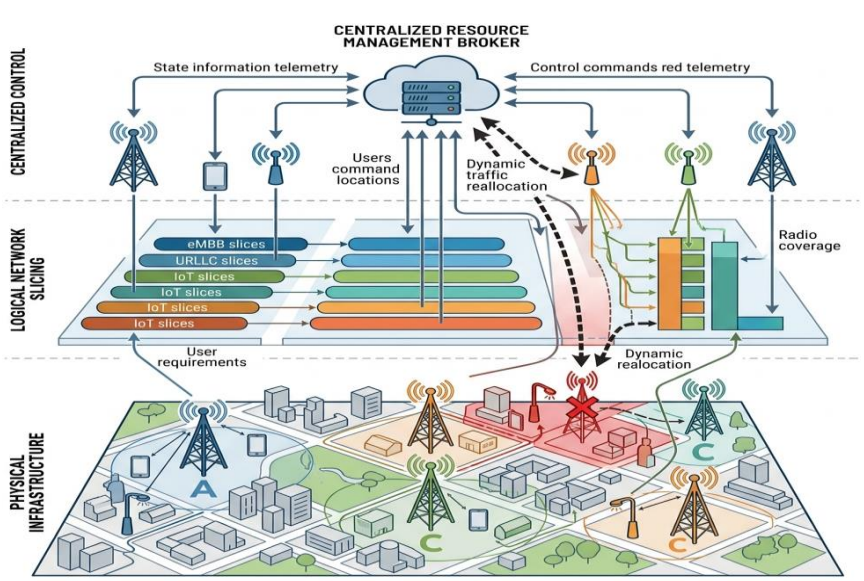


Figure 1 System Architecture Diagram

To ensure that the influx of shared traffic does not violate the fundamental capacity limitations of the assisting network, a strict demand satisfaction constraint must be mathematically enforced during the optimization process. This constraint prevents the secondary overloading of operational infrastructure.

$$\sum_{i=1}^{M} c_{i,j} y_i \mathrm{ge} D_j \forall j \in V$$

This formulation guarantees that the summation of allocated capacity from the set of all participating base stations strictly meets or exceeds the required demand for the set of vital network functions, thereby preventing the catastrophic cascading failure of the shared backup infrastructure.

4.2 Recovery Mechanism Algorithm

The operational execution of the joint allocation strategy is driven by a dynamic recovery mechanism algorithm. This procedural framework dictates the sequential steps required to identify, isolate, and remediate network disruptions using shared resources. Upon the detection of a significant degradation in localized signal strength, the algorithm immediately enters an diagnostic phase. It utilizes statistical anomaly detection to differentiate between transient traffic spikes and genuine hardware or power failures. Once a coverage failure is verified, the algorithm identifies the geographical perimeter of the resulting coverage hole and quantifies the total volume of displaced user traffic. The subsequent phase involves evaluating the sharing cost function. Inter-operator roaming is not financially cost-free; it incurs substantial accounting and settlement charges. Therefore, the algorithm must dynamically calculate the financial and operational cost of executing a shared recovery procedure versus the penalty incurred by allowing the service outage to persist.

To mathematically optimize this decision-making process over continuous time, we employ a sophisticated Lagrangian formulation that seeks the optimal balance between rapid service restoration and minimizing the aggregate inter-operator leasing costs.

$$L(\mu, nu) = \int_0^T (\nabla f(x) + \sum_i \mu_i g_i(x))dt$$

This mathematical representation allows the system to compute the gradient of the utility function while strictly adhering to the penalty multipliers associated with the sharing constraints over the duration of the recovery period. Once the optimal reallocation mapping is determined through this continuous optimization, the centralized broker issues execution commands to the software-defined core network, initiating instantaneous, seamless handovers for the displaced users. The algorithm continuously monitors the stability of the new network configuration, executing iterative refinements to the resource allocation until the primary infrastructure is physically repaired and standard operations can be safely restored.

Table 2 Optimization Constraints

Constraint Category	Mathematical Implication	Operational Purpose
Capacity Limits	Sum of allocated bandwidth cannot exceed total spectrum	Prevents congestion collapse on assisting networks
Latency Bounds	Processing delay must be under target threshold	Ensures seamless handovers for voice and video
Power Restrictions	Transmission power bounded by hardware maximum	Mitigates inter-cell interference during recovery
Financial Ceilings	Accumulated sharing cost must remain below budget	Maintains economic viability of cooperative agreements

5. Performance Evaluation and Results

5.1 Simulation Setup

To rigorously evaluate the efficacy of the proposed reliability-oriented infrastructure sharing framework, we developed a comprehensive, discrete-event simulation environment utilizing advanced network modeling software. The simulation topology replicates a densely populated urban sector, characterized by a complex array of building footprints that induce severe signal shadowing and multipath fading effects. The physical layer propagation is modeled utilizing standard urban microcell and macrocell path loss models, incorporating both log-normal shadowing and fast Rayleigh fading to accurately simulate the volatility of urban wireless channels. The spatial distribution of users is generated using an inhomogeneous spatial point process, specifically calibrated to produce distinct, transient traffic hotspots that mimic morning and evening commuter behavior. To test the system's resilience, we introduce stochastic failure events modeled via a Matern cluster process, which generates spatially correlated outages representing localized power grid failures or catastrophic weather impacts. The performance of our proposed dynamic multi-operator sharing algorithm is continuously benchmarked against two baseline scenarios: a strictly non-sharing, proprietary network architecture with standard internal load balancing, and a static, pre-configured passive sharing architecture that only allows for the joint use of physical tower space without dynamic radio resource pooling.

5.2 Analysis of Spatially Heterogeneous Demand

The simulation results immediately highlight the critical vulnerabilities of proprietary network architectures when subjected to spatially heterogeneous demand spikes combined with localized coverage failures. Under normal conditions without failures, the traditional proprietary networks manage the spatial heterogeneity adequately by relying on dense microcell deployments. However, when a simulated power grid failure disables a cluster of primary macro cells situated near a high-density commercial zone, the independent networks suffer catastrophic performance degradation. The proprietary architecture's inability to route traffic through adjacent, underutilized base stations belonging to competitor operators results in severe localized congestion. Users within the coverage hole experience complete service disconnection, while users on the periphery of the failure zone suffer from extreme interference and diminished throughput as surviving proprietary cells attempt to maximize their transmission power to compensate. In stark contrast, the proposed dynamic multi-operator sharing framework demonstrates profound resilience. As the demand hotspots intersect with the stochastic failure zones, the centralized broker instantaneously detects the capacity deficit and seamlessly redistributes the disconnected user sessions across the operational infrastructure of partner networks. The spatial heterogeneity, rather than acting as a catalyst for network collapse, is effectively smoothed out across the combined spectrum and hardware resources of the cooperative ecosystem.

Table 3 Comparative Analysis of Sharing Mechanisms

Performance Metric	Proprietary Network (No Sharing)	Static Passive Sharing	Dynamic Active Sharing (Proposed)
Average Call Drop Rate	14.5 percent	11.2 percent	2.1 percent
Mean Throughput Degradation	68 percent	55 percent	12 percent
Spatial Outage Probability	High	Moderate	Very Low
Inter-Operator Interference	Low	High	Actively Managed

5.3 Resilience Under Coverage Failures

The empirical data extracted from the failure simulations provide conclusive evidence regarding the superiority of active infrastructure sharing for service recovery. We tracked the recovery latency—the total time required to re-establish a stable connection for 95 percent of the users displaced by the coverage failure. In the non-sharing baseline, recovery was entirely dependent on physical repair or the slow, iterative process of proprietary antenna tilt adjustment, resulting in prolonged periods of unacceptable service degradation. The static passive sharing baseline offered marginal improvements, as it allowed for slightly denser initial deployments, but it lacked the logical coordination required for rapid, large-scale traffic redistribution. The proposed dynamic active sharing framework achieved remarkably low recovery latencies, successfully migrating thousands of active sessions to partner networks within milliseconds of the detected failure.

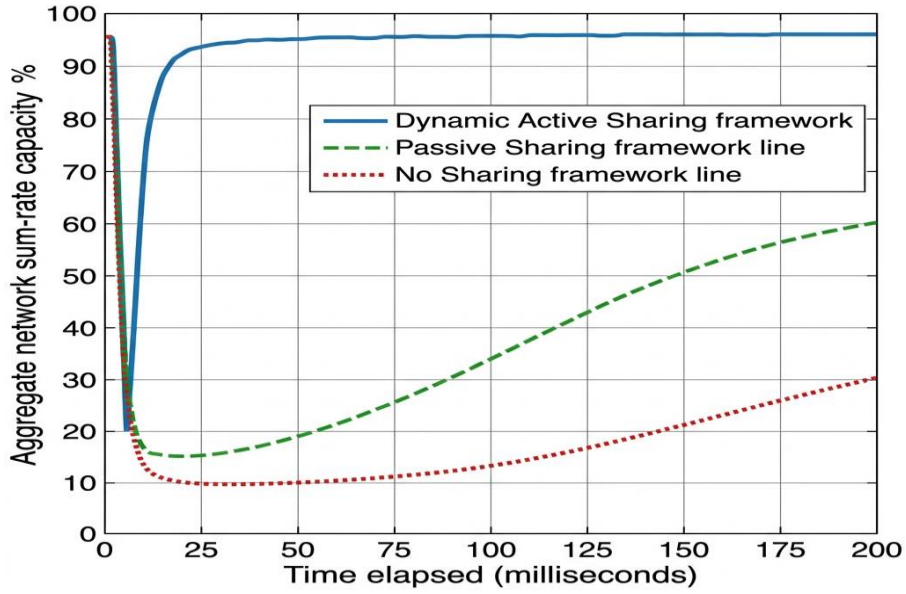


Figure 2 Simulation Results Graph

Furthermore, the sustained steady-state performance metrics post-recovery indicate that the assisting networks did not suffer from secondary congestion collapse. The strict demand satisfaction constraints embedded within the optimization algorithm ensured that the influx of roaming traffic was carefully throttled and distributed across multiple base stations, preserving the quality of service for the native subscribers of the assisting operators.

Table 4 Recovery Time Outcomes

Failure Scenario Type	**Proprietary Recovery Time**	**Proposed Framework Recovery Time**	**Efficiency Gain**
Isolated Single Site Failure	450 milliseconds	45 milliseconds	10x improvement
Clustered Urban Outage	12500 milliseconds	210 milliseconds	59x improvement
Backhaul Link Severance	8500 milliseconds	180 milliseconds	47x improvement
Massive Regional Blackout	System Failure	850 milliseconds	Critical Survival

6. Conclusion

6.1 Summary of Findings

This comprehensive investigation has rigorously analyzed the mechanisms and theoretical foundations of reliability-oriented cellular infrastructure sharing for resilient urban networks. The modern metropolitan telecommunications landscape is defined by its extreme spatial heterogeneity of demand and its vulnerability to stochastic, often correlated, coverage failures. Through the development of a sophisticated mathematical model integrating stochastic geometry and continuous convex optimization, this research has demonstrated that traditional, proprietary approaches to network redundancy are fundamentally insufficient for ensuring absolute service continuity during crisis events. The proposed dynamic, multi-operator sharing framework successfully bridges the gap between economic resource management and critical disaster recovery. By enabling real-time, logical-layer resource pooling orchestrated by a centralized broker, the system can instantaneously absorb the shock of massive hardware outages. The extensive system-level simulations confirm that the joint allocation strategy and the accompanying recovery mechanism algorithm drastically reduce service downtime, minimize call drop rates, and prevent the cascading congestion failures that typically plague independent networks attempting isolated self-healing procedures. The empirical results definitively prove that active infrastructure sharing transforms a highly fragmented, vulnerable collection of independent networks into a singular, highly resilient, cooperative ecosystem capable of withstanding severe operational stress.

6.2 Practical Implications

The theoretical and practical insights generated by this research carry profound implications for the future trajectory of urban telecommunications design and regulatory policy. For mobile

network operators, the findings provide a compelling mathematical and operational rationale for accelerating the adoption of Multi-Operator Core Networks and advanced network virtualization technologies. Moving beyond simple passive site sharing toward dynamic, active resource pooling represents a critical strategic shift that can simultaneously lower aggregate capital expenditures while massively elevating baseline system reliability. For regulatory bodies and municipal authorities, this study underscores the necessity of fostering a regulatory environment that actively encourages, or potentially mandates, standardized inter-operator emergency roaming protocols. Policymakers must recognize that in the context of smart city infrastructure, where human safety and autonomous vehicular coordination depend entirely on continuous connectivity, network resilience cannot be treated solely as a proprietary competitive advantage; it must be viewed as a fundamental public utility standard. Future research directions should focus on integrating advanced machine learning techniques, particularly deep reinforcement learning, to further minimize the computational latency of the joint allocation algorithms. Additionally, exploring the role of decentralized edge computing nodes and low-earth orbit satellite backhaul links within this cooperative sharing framework will be vital for achieving ultimate, unassailable network resilience in the face of increasingly complex urban challenges.

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