SmartAlaska: Can Smart Cities Deliver During Earthquakes?

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***Abstract*—Smart cities promise efficiency, sustainability, and more critically resilience during disasters. This paper introduces SmartAlaska, the first framework to couple real seismic signals with network-level resilience modeling in a 6G smart city context. Using real earthquake data from the Alaska Earthquake Center, the study models an integrated IoT–edge–fog architecture to evaluate alert timeliness, latency, coverage, and survivability under varying network densities and seismic intensities. Results show that optimized microcell deployment (130–150/km²) achieves sub-10 ms latency and sub-second alert dissemination, even under high seismic load. More than 85% of nodes remain operational during strong shaking, and system uptime reaches 90% within milliseconds. These findings demonstrate that well-parameterized edge–fog cloud architectures can significantly reduce notification delays and maintain service continuity under extreme conditions, offering a practical pathway toward resilient, life-saving smart city design in earthquake-prone regions.**

***Index Terms*—Smart Cities, 6G Networks, Edge Computing, Disaster Management, Earthquake Early Warning**

I. Introduction and Motivation

Natural disasters have long challenged human societies, but earthquakes remain among the most unpredictable and destructive. Their sudden onset allows only seconds for life-saving action. On November 30, 2018, a magnitude 7.1 earthquake struck near Anchorage, Alaska, shaking the city within seconds and damaging roads, bridges, and communication systems. Despite the region's advanced monitoring network, most residents received little or no warning. This tragic gap between detection and dissemination underscores a critical question: Can the next generation of smart city networks deliver real-time protection when it matters most?

The emergence of microcell based 6G-enabled Internet of Things (IoT) and edge–fog architectures has the potential to transform this challenge [1]. By fusing ultra-reliable low-latency communication (URLLC), integrated sensing, and distributed intelligence, cities can evolve from passive observers to proactive responders capable of detecting, predicting, and reacting within milliseconds. Yet, while research on smart cities has expanded rapidly, most frameworks emphasize efficiency, sustainability, and automation rather than emergency responsiveness. Few studies have explored how a city's digital nervous system behaves when disaster physically disrupts the very infrastructure it depends on.

Traditional Earthquake Early Warning Systems (EEWS) [2] detect the initial, low-energy P-waves and issue alerts before the destructive S-waves arrive [3]. Systems such as Japan's JMA [1], and the U.S. ShakeAlert system[2] exemplify this approach. However, their effectiveness remains limited by sparse sensor density, centralized data processing, and multi-second latencies [4]. Near epicenters, these delays can prove catastrophic. Moreover, EEWSs typically lacks the ability to generate localized, autonomous responses. Smart cities, powered by Information and Communication Technology (ICT), IoT, and Artificial Intelligence (AI), can help bridge this gap [5]. By leveraging edge–fog computing and predictive analytics, they can support real-time hazard awareness and autonomous infrastructure management [6]. The expansion of the U.S. Geological Survey's ShakeAlert in Alaska highlights this ongoing shift toward sensor-rich, intelligent disaster response [7]. For these systems to be effective in earthquake-prone regions, they must operate on URLLC networks resilient to environmental disruption capabilities that emerging 6G networks are uniquely positioned to deliver through Integrated Sensing and adaptive microcell topologies [8].

Given the growing frequency and impact of seismic events, it is essential to rethink disaster preparedness through a technological lens. Although 6G and smart city paradigms are often associated with efficiency, automation, and connectivity [9], their true potential lies in resilience, the ability to maintain life-critical functions when the environment itself fails. Yet, current designs lack validated models and experimental evidence for earthquake-prone regions. The end-to-end orchestration of seismic sensing, alert generation, network adaptation, and infrastructure resilience remains largely conceptual. This motivates the need for frameworks grounded in real seismic data to derive practical design guidelines and evaluate how 6G architectures can sustain operation under stress.

To address this challenge, we introduce SmartAlaska, a simulation-based framework that evaluates the resilience of 6G-enabled smart city infrastructures under seismic stress. When the 2018 Anchorage earthquake struck, 300,000 residents had less than 15 seconds of warning. SmartAlaska explores how future 6G cities could extend that window and save lives. Using real ground-motion data from the Alaska Earthquake Center, SmartAlaska models a three-tier IoT–edge-fog cloud architecture to analyze end-to-end alert dissemination, node survivability, and system uptime during dynamic earthquake scenarios. The magnitude 7.3 earthquake

[1] https://www.jma.go.jp/jma/en/Activities/eew.html
[2] https://www.shakealert.org/

that struck off Alaska's Aleutian Islands in July 2025 further underscores the region's vulnerability and its value as a testbed for next-generation urban resilience frameworks [4].

Building upon the standardized MES6 evaluation framework [10], SmartAlaska quantifies system performance across four key dimensions *speediness, reliability, resilience, and scalability*. This study makes the following contributions:

- Introduces a novel multi-layer 6G smart city simulation using real seismic data for event-driven stress testing.
- Defines cross-layer Key Performance Indicators (KPIs) that jointly capture latency, packet delivery ratio (PDR), dissemination delay, survival ratio, and system uptime.
- Analyzes how microcell density, IoT device scaling, and edge/fog coordination influence low-latency, fault-tolerant operation during seismic disruption.
- Provides practical design guidelines for 6G-enabled smart cities in earthquake-prone regions, emphasizing proactive density tuning and redundancy.

Our results demonstrate that sub-10 ms latency and sub-second alert dissemination are achievable even under large-scale seismic disruption, with over 85% of nodes remaining operational. SmartAlaska provides an early blueprint for 6G-based urban infrastructures capable of emergency endurance.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the experimental design and simulation setup. Section IV discusses performance evaluation. Finally, Section VI concludes the paper and outlines future research directions.

II. Related Work and Background

A. Background

The 6G vision emphasizes ubiquitous, ultra-reliable, and extremely low-latency connectivity, with end-to-end intelligence and pervasive connectivity as its central goal [11]. Research highlights real-time sensing, analytics, and emergency services as key application domains, which directly align with the need for instantaneous sensing–actuation loops in seismic response [12]. In the context of smart cities, researchers have reviewed IoT features, architectures, and protocols, and identified open challenges that directly affect public-safety applications [5]. One example is a real-time IoT-based public-safety alert and response system that integrates heterogeneous sensors with edge nodes and cloud back-ends, achieving low-latency detection and rapid dissemination, an approach well suited for earthquake notifications [6]. On the software side, digital twin (DT) infrastructures are emerging as powerful tools that combine IoT data with predictive models to support urban decision-making [13]. Likewise, studies on fog and edge computing show that combining cloud and fog resources is necessary to meet the strict real-time requirements of sub-second alerts and closed-loop control [14]

B. Related Work

Several researchers have addressed earthquake response with technology-driven solutions starting with novel design of a city–county earthquake emergency platform [15]. Evacuation planning and emergency responses developments from using crowd data, integrating geospatial sensor webs and applying lessons from Great East Japan Earthquake also are proposed [16]. Predictive analytics are increasingly being applied to seismic risk [4]. Also, researchers aims to predict soil liquefaction using machine learning [17]. Collectively, these studies highlight significant progress in earthquake management, but they also point to the need for integrated frameworks that connect detection, prediction, and response across the entire smart-city ecosystem. Building disaster-resilient cities requires both technological innovation and coordinated planning. Repurposing existing smart city infrastructure to support disaster recovery and give responders better real-time visibility in the immediate aftermath of a disruptive event [18]. Use of ISAC, outlining requirements and challenges, optimizing city-scale early warning and notification systems is also explored [19].

While disaster resilience is a common goal in smart city visions and 6G networks are recognized as key enablers, existing work lacks a fully integrated, simulated earthquake-response testbed, an area directly addressed by SmartAlaska.

III. SmartAlaska: Experiment Design

A. Smart City Network Architecture

Following a M6SET, a standard topology framework reported in a recent work (See [10]), the SmartAlaska models a 6G-enabled smart city network with five interconnected layers with their design profiles (Figure 1): Zone, Microcell, Edge, Aggregation/Backhaul, and Fog Cloud as below:

- Zone Layer: IoT sensors monitor seismic, structural, and environmental parameters.
- Microcell (6G) Layer: Connects hundreds of IoT nodes; operates in mmWave/sub-THz for ultra-low latency. Each zone is served by atleast one microcell.
- Edge Layer: Performs AI-based seismic event validation and alert broadcasting within milliseconds. Each zone has atleast one edge device.
- Aggregation Layer: Ensures redundant, QoS-aware data transport between edges and fogs.
- Fog Layer: Coordinates multi-city/zone resource allocation and large-scale situational awareness.

B. Key Performance Indicators (KPIs)

To enable a holistic evaluation of SmartAlaska's microcell-enabled edge–fog–IoT architecture [10], the following KPIs are selected to provide complementary insights. Timeliness and latency capture speediness; coverage and PDR represent reliability; survival ratio and uptime quantify resilience; while energy and throughput characterize scalability. All metrics are averaged over multiple simulation runs.

- Alert Timeliness (Lead Time): Measures how early each IoT node receives an ALERT relative to the theoretical arrival of seismic waves (P, S, or Surface).

$$\mathrm{Lead}_i^{(X)} = t_X - t_{\mathrm{alert},i}, \quad t_X = \frac{d_i}{V_X}$$

$$d_i = \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2}$$

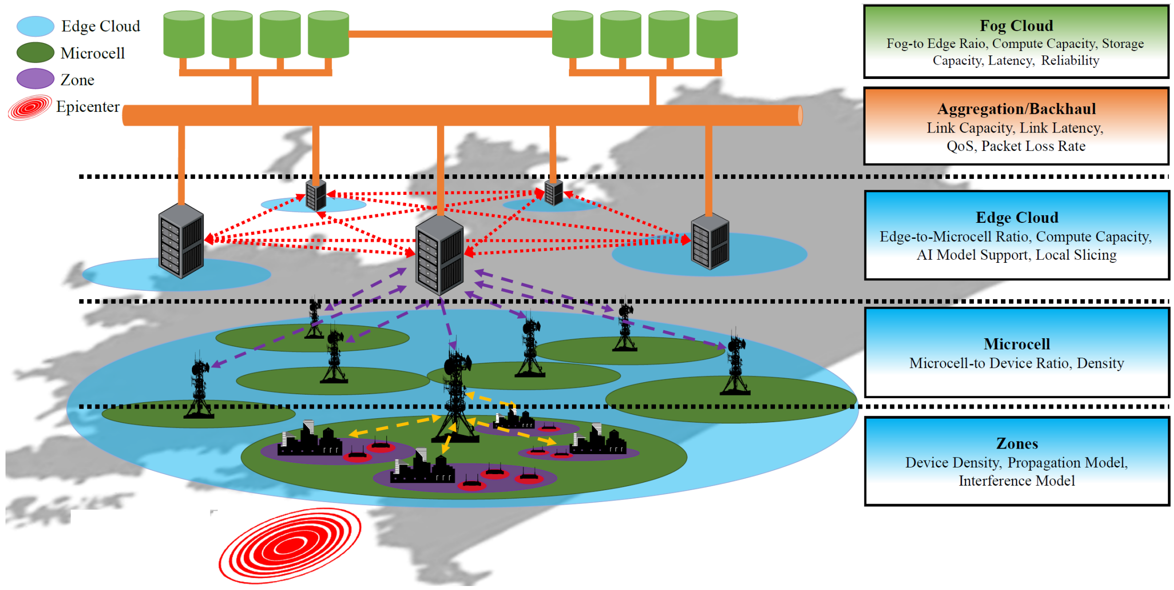


Fig. 1: SmartAlaska Framework: 6G-Enabled iot-edge-fog Smart City architecture. Arrows represent communication links.

A positive value indicates that the alert was received before the wave arrival.

- End-to-End Latency (E2E): Represents the total time elapsed between DETECT generation and ALERT reception.

$$\text{E2E Latency} = \frac{1}{N}\sum_{i=1}^{N}(t_{\text{receive},i} - t_{\text{send},i})$$

Lower latency indicates faster response within URLLC targets.

- Dissemination Delay (Δ_{diss}): Quantifies synchronization efficiency across IoTs by measuring the temporal gap between the first and last ALERT receptions.

$$\Delta_{\text{diss}} = \max_i(t_i^{(1)}) - \min_i(t_i^{(1)})$$

- Coverage Ratio (C): Fraction of IoT nodes that successfully receive at least one ALERT, indicating completeness of city-wide dissemination.

$$C = 100 \times \frac{|\{i : r_i \geq 1\}|}{N} \quad [\%]$$

- Packet Delivery Ratio (PDR): Ratio of total ALERT packets received to those transmitted by the edge. Reflects communication reliability pre- and post-disaster.

$$\text{PDR} = \frac{R_{\text{IoT}}}{T_{\text{Edge}}}$$

- ALERT Throughput (T): Measures dissemination capacity as the number of ALERT packets delivered per second within an observation window W.

$$T = \frac{A}{W} \quad [\text{alerts/s}]$$

- Survival Ratio (S): Fraction of devices or microcells that remain operational under increasing seismic intensity, indicating system resilience.

$$S = 100 \times \frac{|\mathcal{S}|}{N_{\text{initial}}} \quad [\%]$$

- System Uptime ($U(\tau)$): Cumulative percentage of IoTs that have received at least one ALERT within τ seconds after the first broadcast.

$$U(\tau) = 100 \times \frac{|\{i : t_i^{(1)} - t_0 \leq \tau\}|}{N} \quad [\%]$$

- Cumulative Failures ($F(\tau)$): Total number of node or AP failures over time, representing degradation and recovery behavior.

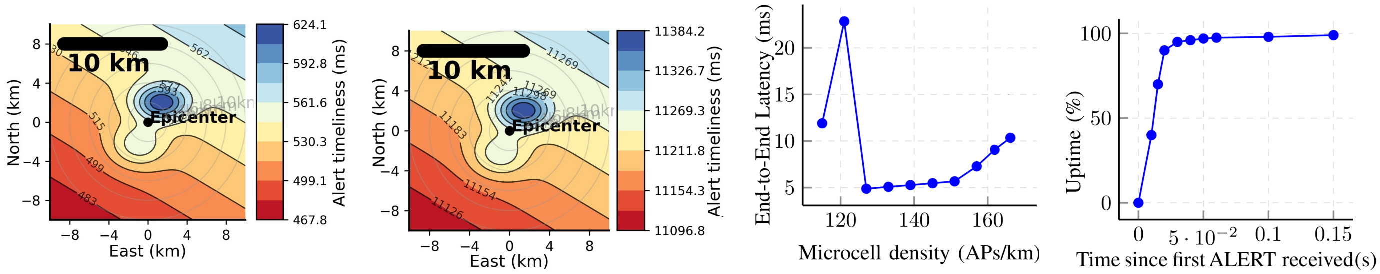
$$F(\tau) = N_{\text{total}} - N_{\text{alive}}(\tau)$$

- Energy per Event (E_{event}): Average energy consumed by an IoT node to sense, process, and transmit one ALERT event.

$$E_{\text{event}} = \frac{1}{N}\sum_{i=1}^{N}(P_i \times t_{\text{active},i}) \quad [\text{mJ/event}]$$

C. Network and Earthquake Dynamics

In the simulation, each IoT node continuously senses ground motion and sends a DETECT message to its assigned edge cloud upon seismic activity. The first detection triggers the edge to broadcast ALERT messages to all connected nodes. Each IoT records message arrivals and timestamps for latency and reliability analysis. Seismic P, S, and surface waves are modeled with realistic propagation speeds and time-stamped origins to emulate wave travel across city zones. A failure module progressively disables IoT nodes and access points



(a) (b) (c) (d)

Fig. 2: Speediness Metrics: (a,b) ALERT Timeliness for P and S waves, (c) End-to-End latency vs Microcell density, and (d) Cumulative System Uptime (% of IoTs with receipt $\geqslant 1$) vs Time.

when local intensity exceeds thresholds, simulating infrastructure damage. Nodes near the epicenter detect events first, initiating cascading alerts across the network. The edge validates detections, confirms the event, and multicasts alerts to IoTs, emergency services, and control systems while forwarding summaries to the fog layer for regional aggregation and inter-zone coordination, enabling early inland warnings.

D. Simulation Set-up

Our simulation setup follows below:

- Platform: OMNeT++ 5.7.1 with INET 4.
- Area: 10x10 km grid; 1 microcell per 500–1500 IoTs.
- Seismic Model[3]: P-wave (6.5 km/s), S-wave (3.6 km/s), surface-wave (3.2 km/s).
- Scenario: Offshore quake near southern Alaska, square ; edge cloud detects, validates, and disseminates alerts; fog synchronizes inter-city alerts.
- Hardware: 32-core CPU, 256 GB RAM.

IV. Performance Evaluation

To demonstrate SmartAlaska's effectiveness in delivering earthquake alerts across a large urban IoT network, this section evaluates the system along four key dimensions: speediness, reliability, resilience, and scalability.

A. Speediness

Speediness measures how quickly SmartAlaska can detect, send, and spread alerts through the whole network. Figure 2 gives a summary of the main timing related metrics like alert timeliness, latency, dissemination delay, and uptime.

The timeliness heatmaps (Fig. 2a,b) show how early SmartAlaska sends alerts before the P- and S-wave reach sensors. About 85% of IoT nodes get the alert before any destructive wave, and the system usually gives a sub-second warning during the P-wave phase (around 480–620 ms lead time). Latency (Fig. 2c) drops fast as AP density increases, reaching around 4–6 ms when there are 130–150 APs per km^2, which fits well with 6G URLLC goals. Dissemination delay stays below one second across the map, proving the alerts are synchronized citywide. System uptime (Fig. 2d) crosses 90% within just a few milliseconds, showing near instant alert spread once the first broadcast starts.

B. Reliability

Reliability checks how consistent the alerts are under both normal and stressed network loads. Figure 3 shows the packet delivery ratio (PDR) and throughput when the number of microcells and IoT devices changes.

As seen in Fig. 3a, PDR goes up with more APs and levels out around 35–39 alerts per device even after disasters, mainly because of redundant edge rebroadcasting. In Fig. 3b, when IoT density increases, PDR drops a bit due to channel contention, but SmartAlaska's fog coordination helps reduce packet loss. The throughput curve (Fig. 3c) also grows with AP density, showing better bandwidth use and stable delivery under high load. Overall, coverage stays close to 100% even at large device counts (5,000–50,000), which means the alert system remains highly reliable across the whole city.

C. Resilience

Resilience focuses on how well SmartAlaska keeps running during disasters when parts of the system fail. Figure 4 combines survival rates and latency recovery data.

From Fig. 4a, even under strong seismic intensity, about 85–90% of IoT devices keep working. The survival trends in Fig. 4b show that APs drop to around 85% over time, mostly because of modeled structural failures. The cumulative failures (Fig. 4c) spike around 24 s, which is when the S-wave hits hardest, but fog coordination keeps most of the network alive. Latency recovery (Fig. 4d) shows quick rebound, after short spikes near 40 ms, the delay returns to below 10 ms, proving strong failover and rerouting ability.

D. Scalability

Scalability looks at how SmartAlaska performs as the number of devices and access points increases. Figure 5 compares latency, dissemination delay, and PDR as the network scales.

Latency in Fig. 5a slowly rises after around 12,000 devices/km^2, marking a limit where sub-10 ms response time can still be kept. Dissemination delay (Fig. 5b) stays under one second even when AP density goes up, showing that alert broadcasting stays well synchronized.

[3]https://earthquake.alaska.edu/

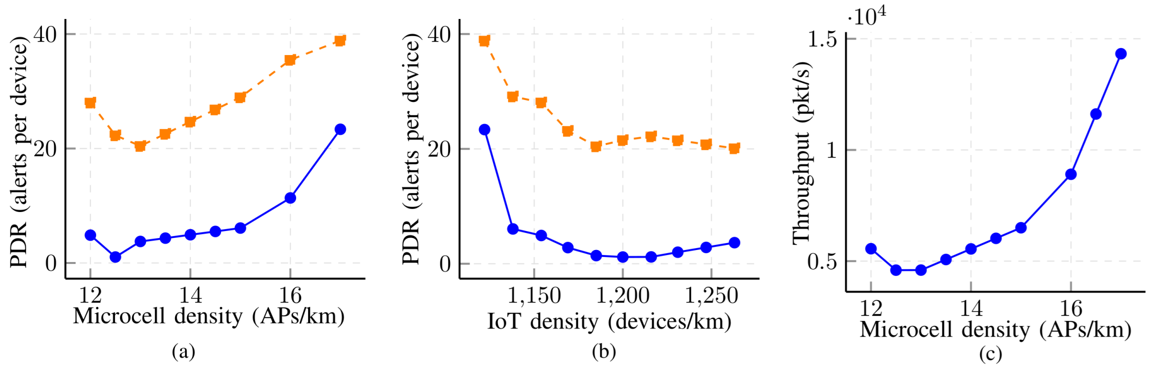


Fig. 3: Reliability Metrics: (a) PDR vs AP Density (Pre and Post failure), (b) PDR vs IoT Density (Pre and Post failure), and (c) ALERT Throughput vs AP Density.

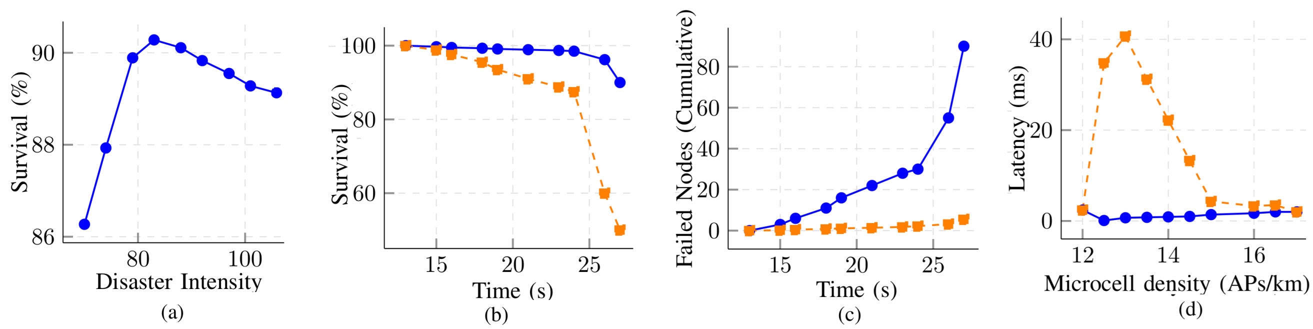


Fig. 4: Resilience Metrics: (a) Survival Ratio vs Disaster Intensity (Proxy: Max failed IoTs), (b) Survival Ratio Over Time (Pre and Post Failure), (c) Cumulative Failures over time (Pre and Post Failure), and (d) latency recovery vs AP density (Pre and Post Failure).

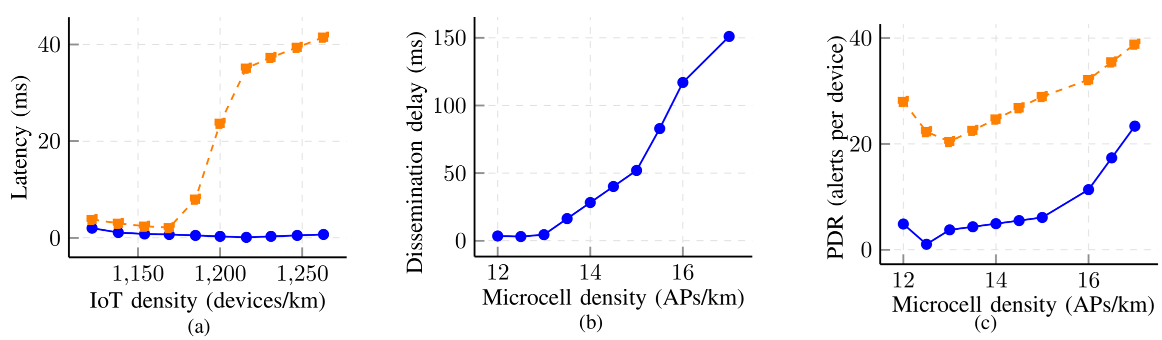


Fig. 5: Scalability Metrics: (a) Latency vs IoT Density (Pre and Post failure) , (b) Dissemination Delay vs AP Density, and (c) PDR vs AP Density (Pre and Post failure).

Lastly, Fig. 5c shows that PDR remains strong until roughly 150 AP/km^2, after which a little contention appears. Overall, these results show that SmartAlaska scales smoothly with bigger networks and denser deployments without losing real-time performance.

V. Discussion

SmartAlaska achieves a balanced mix of ultra-low latency, reliable communication, and adaptive resilience under both normal and earthquake conditions. Beyond demonstrating performance, the results highlight key design lessons for smart-city networks operating in disaster-prone regions.

SmartAlaska consistently provides sub-second early warnings before the arrival of P- and S-waves, confirming the benefit of its multi-tier, edge-triggered architecture. The end-to-end latency remains within 4–6 ms when the microcell density is between 130–150 AP/km^2, which appears to be the optimal range for real-time alert delivery. Below this range, sparse coverage increases delay; above it, interference and coordination overhead rise. These results show that dense but interference-controlled topologies are essential for fast and reliable early-warning systems. PDR and throughput remain high even when parts of the network fail. During earthquake disruptions, redundant edge and fog rebroadcasts preserve link reliability. The results also show that the microcell-to-device ratio directly affects alert consistency each access point should ideally serve fewer than about 12,000 IoT devices/km^2 to prevent congestion while maintaining 6G-level reliability. This supports geo-adaptive network planning, where denser AP layouts are deployed in structurally weak or high-risk areas.

Resilience indicators show that more than 85% of network elements stay functional during strong shaking, and latency quickly returns to normal after temporary failures. Cumulative failures rise gradually instead of cascading, confirming the self-healing behavior of the fog-coordinated topology. Latency stays below 10 ms up to around 12,000 IoT nodes/km^2, and dissemination delay scales sub-linearly with microcell density, indicating that SmartAlaska can scale to city levels without losing responsiveness. Above this density, contention begins to dominate, pointing to the need for microcell clustering and adaptive spectrum management in dense hazard zones.

SmartAlaska represents the first attempts to model an integrated early-warning system for smart cities under realistic seismic conditions. Many advanced components that could further enhance performance, such as AI-based routing, edge slicing, autonomous bandwidth allocation, and multi-fog coordination are not yet included in this study. Real-world deployment validation and integration with actual seismic and structural sensor data are also needed to strengthen the framework's applicability.

VI. Conclusion

The SmartAlaska study shows that smart city networks can indeed deliver when it matters most during major seismic events. By combining real earthquake data with a realistic multi-layer 6G IoT architecture, we demonstrated that alert latency, reliability, and survival can all be optimized through balanced microcell and device density. The results confirm that sub-second alerts are achievable when iot-microcell-edgefog coordination is used, latency remains below 10 ms under high device density, more than 85% of nodes survive strong shaking due to redundancy and adaptive rebroadcasting. These findings highlights the importance of density tuning, redundant edge connectivity, and AI-based resource allocation in designing urban infrastructures for disaster resilience.

It is essential to validate proposed framework with real-world testing with heterogeneous sensors and live seismic feeds. Future work includes integration of AI-driven predictive routing, real-time structural feedback, and cross-city fog coordination to handle cascading failures across regions. Prototype deployment plan and collaboration with local emergency centers are in works. As cities worldwide face increasing seismic risk, frameworks like SmartAlaska can bridge the gap between digital innovation and human safety.

Acknowledgment

The authors thank for the access and support for high-performance computing resources provided by Dr. Raj Kumar Vinnakota through the CMMS facility of Troy University.

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