Spatiotemporal Characterization of Campus Wi-Fi Activity during the Iberian Peninsula Blackout

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***Abstract*—On April 28, 2025, the Iberian Peninsula experienced its most severe electrical grid failure on record, causing widespread disruption across Spain, Portugal, and Andorra. While mobile networks collapsed, the Universidad Carlos III de Madrid maintained Wi-Fi connectivity through backup generators, providing a unique opportunity to study human behavior during a large-scale infrastructure failure. We analyze RADIUS authentication logs from the campus `eduroam` network, covering 2,819 users and 310 access points throughout the blackout event. Our analysis reveals three key findings. First, Wi-Fi occupancy spiked immediately after the outage as users migrated from failed mobile networks, followed by a gradual decline during the campus evacuation. Second, users redistributed spatially, shifting from interior spaces toward exterior areas, while cafeterias served as gathering points during the initial hours of the emergency. Third, the blackout led to increased network usage per user, transmitting more data per hour than under normal conditions. These findings demonstrate the value of Wi-Fi sensing data for understanding collective behavior during emergencies and provide insights for designing resilient campus communication infrastructure.**

***Index Terms*—WiFi-based occupancy, human mobility, blackout, eduroam, building occupancy monitoring.**

I. Introduction

Large-scale power outages represent critical stress tests for modern infrastructure and human behavior, yet opportunities to study their effects through fine-grained digital traces remain rare. On April 28, 2025, the Iberian Peninsula experienced its most severe electrical grid failure on record, affecting Spain, Portugal, and Andorra, and disrupting the daily routines of millions of people. While mobile networks collapsed across the region, the Universidad Carlos III de Madrid (UC3M)[1] maintained Wi-Fi connectivity through backup generators, creating a unique natural experiment to observe how campus populations adapt their spatial behavior and network usage under extreme conditions.

Understanding human mobility and network activity during emergencies has significant implications for crisis management, infrastructure resilience planning, and the design of communication systems that must operate when conventional networks fail. Previous research has leveraged Wi-Fi sensing data to study building occupancy and mobility patterns during events such as the COVID-19 pandemic [1], [2], demonstrating the value of network logs as proxies for physical presence. However, studies examining user behavior during sudden, large-scale infrastructure failures remain scarce, primarily because such events are unpredictable and rarely coincide with operational monitoring systems.

In this paper, we present a spatiotemporal analysis of campus Wi-Fi activity during the April 2025 blackout, leveraging RADIUS authentication logs from the `eduroam` network covering over 8,000 users and 310 access points. Our analysis addresses three key questions: (i) How did overall campus occupancy evolve during the blackout compared to normal operating conditions? (ii) Did users exhibit different spatial distributions across interior, exterior, and cafeteria zones? (iii) How did per user network usage intensity change when Wi-Fi became the sole connectivity option?

Our main contributions are as follows:

- We develop a methodology to identify representative mobile devices per user, enabling accurate occupancy estimation from multi-device datasets.
- We characterize the temporal evolution of campus presence, revealing an immediate spike in Wi-Fi connections following the outage as users migrated from failed mobile networks, followed by a gradual evacuation.
- We analyze spatial redistribution patterns, finding that users shifted toward outdoor areas and that cafeterias served as gathering points during the initial hours.
- We examine network traffic intensity, showing that users transmitted more data per hour during the blackout compared to typical days.

The remainder of this paper is organized as follows. Section II discusses related work, Section III provides background on the blackout event, describes the campus and dataset, and details our preprocessing approach. Section IV presents our analysis of user occupancy and mobility patterns. Section V examines network traffic characteristics, and Section VI concludes with a summary and directions for future research.

II. Related work

Previous studies have analyzed user behavior under extreme or unusual conditions. Among others, [3] analyzes the social response in Spain during blackout, but using a survey among

[1] https://www.uc3m.es/life-on-campus/campuses-plans/leganes

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users to evaluate the emotional impact in different social groups. Other studies use Wi-Fi data as a source of information for user mobility, such as [2], using Wi-Fi data for campus users to evaluate the probability of crowding and the risk of contagion at different stages of the COVID-19 lockdown, or [1], which analyzes the impact of COVID-19 Control Policies on Campus Occupancy and Mobility via Wi-Fi sensing.

Wi-Fi sensing has also been used to track users to manage/allocate spaces (e.g., classes on campus [4] contrasting it with other techniques, and resulting reliable and less resource expensive), or to drive Heating, Ventilation and Air-Conditioning (HVAC) systems operations (e.g., [5] and [6]), resulting in a reliable estimation of real-time occupancy counts.

Nevertheless, to the best of our knowledge, this study represents the first attempt of using Wi-Fi sensing to analyze the behavior of users in a blackout event, allowing to evaluate mass reaction to emergencies in public buildings and areas, on the basis of objective measurements, and to provide insights for the design of infrastructures and reaction protocols.

III. Background

A. The Blackout

On April 28, 2025, Spain experienced its most severe electrical failure on record, also affecting Portugal, Andorra, and parts of southern France. The outage caused widespread disruption to residential users, industrial activity, and transportation networks, making it one of the most significant recent power disruptions in Europe [7].

In a nutshell, the main sequence of events were as follows (all times are in CEST):

- The collapse began at 12:32:57 when a sequence of generation trips (2.2 GW) occurred in southern Spain.
- Following a number of subsequent events (frequency drops, load-shedding defense, disconnections), the commonly quoted "start time" for the blackout was 12:33.
- The security staff in the campus reported the outage across the entire campus at 12:35, determining that the issue was nationwide thanks to radio communications.
- Backup generators at the University were successfully activated immediately after the power outage, keeping essential internal systems such as air conditioning and Wi-Fi connectivity operating.
- At 15:30 the university started closing the library and enforced an evacuation of the buildings (one by one) in the Leganés campus. The campus was eventually closed, leaving only specific areas for circulation.
- Starting from 17:30, power was restored in central parts of Madrid, although the specific time depends on the area. In fact, at UC3M different buildings recovered their power at different times, experiencing some issues due to failures in the UPS (Uninterruptible Power Supply) of the DPC (Data Processing Center).
- At 22:45 the power was fully restored on the Leganés campus, while at 23:00 it was restored in all the University.
- The grid operator Red Eléctrica de España estimated that about 99% of demand was met by 07:00 on 29 April, with "full restoration" happening around 11:00 that morning.

B. Campus description

We rely on a dataset of all users connected to the `eduroam` network in the Leganés Campus of UC3M. The wireless network is provided by 310 APs distributed across seven buildings. Most of the buildings serve multiple purposes, which include classrooms, study areas, and offices. There is one library, one main cafeteria distributed in two floors (students and stuff), and a small cafeteria. Each AP provides coverage for approximately 250 m^2, while the entire campus spans approximately 80.000 m^2 .

We are provided the data by system administrators, which rely on a RADIUS system that logs device associations and re-associations to the APs. Before processing the data, we consulted the Data Protection Officer (DPO) at UC3M to ensure full compliance with ethical and legal requirements. The dataset was pseudonymized using MD5 hashing of user identifiers and MAC addresses. Access to the data was restricted to secure servers with user-based authentication and activity logs. In addition, the university provided public notice of data collection practices, including the right to access, modify, or delete personal data. Our team also formally committed not to attempt any form of re-identification.

C. Dataset

The dataset used in this work is derived from logs generated by the university Wi-Fi RADIUS authentication infrastructure, which records device associations. Thus, the `eduroam` SSID is broadcasted by the access points (APS) , which are managed by a central controller via CAPWAP [8]. The wireless network uses WPA2 enterprise and requires a database of authorized users, which could be either internal to the organization (i.e., UC3M) or external (from other entities). Every association or re-association with an AP triggers a message that is collected by a RADIUS server, allowing user mobility to be inferred from the sequence of access point connections [9]. Furthermore, with a periodicity of at most 15 minutes, the status of each device is updated into the server in case there was any change. In this way, in case a user abruptly disappears from the network, 15 minutes after its last activity it will be no longer reported in the server.

All events generated by the RADIUS server are stored and managed through a centralized logging infrastructure. The RADIUS database is periodically dumped into an Elastic-Logstash-Kibana (ELG) stack, which is used for network diagnose and anomaly detection. Each entry in the ELG database includes a timestamp, the user identity, the MAC address of the wireless client (all of which are pseudonymized for ethical and privacy considerations), the MAC address of the AP to which it is connected, a pseudonymized device identifier, and cumulative inbound and outbound traffic. System administrator provided us access to this database via an API.

1) Data Description: Based on the data provided by system administrators and described above, for our analysis, we selected a period from the previous academic year consisting of September 2024 until the day before the blackout in April 2025. This time window represents regular campus activity under normal operating conditions. It includes standard teaching weeks defined by the course schedule, as well as specific academic calendar events such as Winter holidays and Easter, which are taken into account when interpreting variations in occupancy levels.

From these records, we compute the number of distinct users and devices observed during the reference period and compare them with those recorded on the blackout day. Table I presents this comparison, providing a baseline to quantify the changes in network presence and connectivity associated with the extreme event.

	Semester	Blackout
Users	8,239	2,819
Devices	28,942	4,890

TABLE I
COMPARISON OF UNIQUE USERS AND DEVICES OBSERVED DURING THE SEMESTER AND DURING THE BLACKOUT DAY

2) Discretization: The recorded data consist of irregularly spaced events that describe changes in network association. The collected logs provide a fragmented view of user activity, as they register moments of connection change but not continuous presence. This results in data that are uneven in time and difficult to interpret directly when studying collective behavior or comparing activity across different periods.

To address these limitations, we discretized the data into intervals of one minute, generating a discrete time series of APs for each user. This temporal aggregation allows us to focus on global user behavior over short, uniform windows, facilitating the analysis of occupancy and mobility patterns at scale. Although we will lose some short transitions, it is a trade-off we accept in order to obtain a more manageable and interpretable dataset. Our main interest lies in where users spend the majority of their time, rather than in every short transition between APs, which are less relevant for our analysis. The resulting dataset simplifies user counting and analysis.

Discretization consists of dividing the timeline into one-minute intervals. When only a single AP is observed within a given minute, that AP is directly assigned to the interval, as illustrated in Figure 1 at 9:03. When a device connects to multiple APs within the same minute, the AP corresponding to the longest connection duration is selected, as occurs at 9:02. One example of a lost connection is the brief activity observed on AP2 in the first time slot.

To account for periods of inactivity, we introduce an artificial `OUT` state represents network disconnection. This is assigned when the time gap between two consecutive connection events exceeds 15 minutes, under the assumption that the user is disconnected from the network during this interval. Figure 1

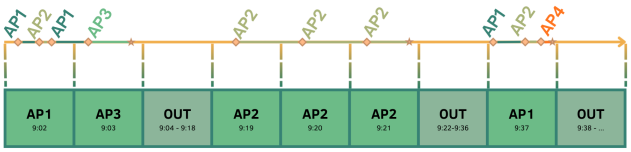

Fig. 1. Discretization of irregular connection events into one-minute intervals. The original AP connection timeline (top) and the resulting discretized sequence (bottom) are shown.

provides an illustrative example, where the absence of activity between 9:04 and 9:18 is mapped to the `OUT` state.

D. AP taxonomy

Each building is covered by a dense Wi-Fi deployment composed of multiple APs distributed across buildings, floors, and common areas. Although the number of APs varies by building. For our analysis, we classified the differents APs of all the campus into three categories: *interior, exterior, and cafeteria*. This classification allows us to distinguish the location and context of users connections within the campus.

- **Cafeteria APs**: These are APs physically installed in cafeteria spaces. Their identification was performed manually by comparing the APs locations with the campus map. Although some cafeteria APs may partially cover exterior areas, they are classified as cafeteria APs for consistency. A total of 5 APs were assigned to this category.
- **Exterior APs**: APs providing coverage mainly to outdoor areas were identified using wardriving techniques, which involve recording Wi-Fi coverage while moving through outdoor campus areas. A total of 43 APs were classified as exterior.
- **Interior APs**: All others APs were considered interior. They provide coverage inside campus buildings but without cafeteria APs. A total of 262 APs fall into this category.

IV. USER OCCUPATION AND MOBILITY

A. Identifying users' mobile

In our dataset users often appear through multiple devices with heterogeneous spatial behaviors. While some devices remain largely static, others closely follow the users physical movement across the campus. Treating all devices equally can result in duplicated user counts and fragmented mobility traces, which complicates both accurate user aggregation and the characterization of physical mobility patterns. Therefore, it is necessary to identify, for each user, the device that best captures their spatial behavior. In this subsection, we describe the methodology used to select a single representative mobile device per user.

This analysis is performed using the raw RADIUS logs covering the full observation period, from September 1st, 2024, until the blackout day (inclusive). Using the complete historical dataset allows us to robustly characterize long term mobility behavior. Thus, the algorithm to assign one device to each user follows these steps:

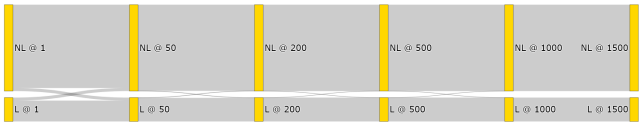

Fig. 2. State transition flow of device leadership across epochs, where devices are labeled as L (leader) or NL (non-leader) based on their mobility score.

1) Step 1: Mobility Feature Extraction: First of all, we compute a set of mobility features for each device of every user, those are: amount of AP that they see throughout the study period, the entropy of the AP distribution and the number of days they were present on campus. Entropy is a general measure of dispersion that quantifies how evenly a device's connections are distributed across different APs [10]. A low entropy value indicates that most of the device's connection time is concentrated on a single or a few dominant access points, even if several APs are observed overall. Conversely, high entropy values indicate that connection time is more evenly distributed across multiple access points, a behavior associated with higher spatial mobility. These metrics therefore, provides a compact summary of the spatial movement of every device.

2) Step 2: Device Filtering: Before ranking devices, we delete those that connect to fewer than two distinct APs over the entire dataset. Such devices do not exhibit mobility and are therefore unlikely to represent the physical movement of users.

3) Step 3: Construction of the Mobility Score: All features are first standardized and normalized to ensure comparability across metrics. Then, they are combined into a weighted mobility score. This score is finally used to select, for each user, the leading device exhibiting the highest overall mobility. This score is defined as a weighted linear combination of the normalized mobility features.

4) Step 4: Weight Learning Using Gradient Based Methods: The weights of the score are learned under a set of constraints: they are required to be non-negative and to sum to one. The objective is to find the set of weights that maximizes the separation between different (user, device) pairs in the feature space.

The learning objective is:

$$\max_{\omega \in \Delta^3} \sum_{k=1}^{K} \left(\max_i s_{ki}(\omega) - \frac{1}{N_k} \sum_{j=1}^{N_k - 1} \max_{j \neq \arg\max_i s_{ki}} s_{kj}(\omega) \right)$$

Where K is the number of users, N_k is the number of device of the user k, $s_{ki}(\omega)$ is the score function for user k and device i that depends of the weights ω and $\Delta^3 = \left\{ \omega \in \mathbb{R}^3 \;\middle|\; \omega \geq 0,\ \mathbf{1}^\top \omega = 1 \right\}$.

Since the original optimization objective is not smooth, we apply a smooth maximum function (log-sum-exp) [11] to the function that creates the mobility score for each pair. This smooth formulation makes the objective differentiable, allowing the optimization to be performed using gradient based methods and enabling the identification of the optimal set of weights that maximizes the objective.

The effectiveness of the optimization process is validated by the stability of the leader device selection across training epochs. From the first epoch, devices are separated into leader and non-leader groups for each user, where the leader corresponds to the device with the highest score. Devices that remain leaders form continuous flows, while transitions indicate changes in the selected leader. Figure 2 shows that, after an initial adjustment phase, the leader device for each user converges rapidly and remains unchanged for the remainder of the optimization. This behavior indicates that the learned weights induce a stable scoring across epochs, resulting in a well-separated and interpretable ranking of devices.

The optimization procedure found the following set of weights as ideal outcome: $\omega^3 = [\omega_1, \omega_2, \omega_3] = [0.1765, 0.8201, 0.00015]$. Since the weight of the last coordinate is insignificant, indicating that the number of active days of the device is not an important feature, it was removed.

5) Step 5: Selection of the Representative Mobile Device: Finally, for each user, we select the device with the highest mobility score as the representative mobile device used in the remainder of the analysis. For the following analyzes, we decided to keep each user's chosen device.

B. Overall occupancy

When the power outage occurred, communication networks stopped working across the country. At the university, however, electrical power was partially maintained through emergency backup generators, allowing the campus Wi-Fi network to remain operational despite the widespread disruption.

In this context, occupancy becomes a key global variable for characterizing user behavior, as it directly reflects whether users are connected to the network at any given time. Occupancy patterns therefore provide an interpretable proxy for real-world presence and movement on campus, allowing network connectivity data to be used as a meaningful abstraction of physical behavior. Analyzing these patterns during the blackout enables us to identify deviations from normal activity and evaluate the effects of the outage.

In this way, in Figure 3 we provide the temporal evolution of user occupancy on the blackout day (orange line) compared to the most similar Monday up to 12:33 (green line), which closely matches the morning pattern of the blackout day.

Regarding the selection of the reference day, Monday, March 17, was identified as the most similar Monday by analyzing the occupancy patterns of all regular working Mondays up to 12:33, the time at which the power outage occurred. The reference Monday was chosen as the one minimizing the mean squared error with respect to the occupancy observed on the blackout day. This choice allows us to distinguish changes caused by the blackout itself from normal daily variability.

In the Figure 3 we can see that, until 12:33, both curves follow a typical morning increase in activity. At the moment of the blackout, the backup generators were activated, and since mobile networks were no longer operational, all users

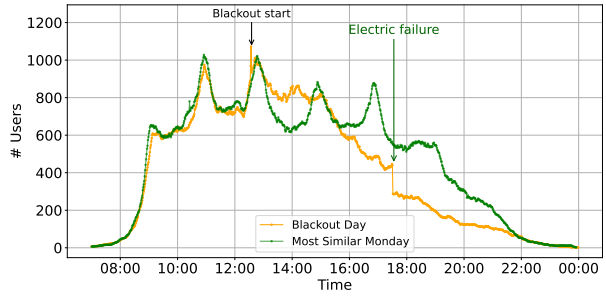

Fig. 3. Overall occupation during the blackout (orange) and the most similar Monday until 12:33 (green)

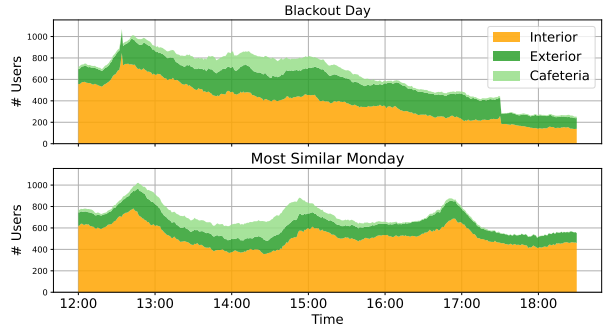

Fig. 4. Distribution of users over time during the blackout (top subplot) and the most similar Monday until 12:33 (bottom subplot)

had to connect to `eduroam`, producing the peak observed around 12:33. Between 13:00 and 15:00, occupancy remains higher than on a normal day, reflecting the continued use of Wi-Fi during the emergency.

In addition, the blackout day also exhibits a secondary abrupt drop in occupancy later in the afternoon, around 17:30. This sudden decrease is caused by a temporary failure of the DPC's UPS, which lasted for a few minutes and resulted in a widespread disconnection of users from the network.

Evacuation activities started around 15:30, producing a gradual reduction in occupancy, as seen in the orange curve. Overall occupancy continued to decrease steadily as most people eventually left the campus.

C. User distribution over time

While the previous subsection focused on overall occupancy as a global indicator of user presence on campus, this subsection shifts the analysis to a finer spatial scale. To understand how the blackout affected occupancy across different zones, we analyze the temporal evolution of user presence throughout the campus. This visualization allows us to observe reactions to the incident, identify abrupt changes in occupancy, and compare post blackout dynamics with those of a typical day.

Figure 4 shows the distribution of users between 12:00 and 18:30, with an unusual spike in occupancy occurring at 12:33 on the blackout day, corresponding to the immediate reaction of the network after the outage, followed by a continuous and monotonic decline. In contrast, the baseline Monday exhibits a cyclic pattern with clear recovery peaks around 15:00 and 17:00, reflecting the typical waves of class activity.

Examining the zones separately highlights clear differences in user behavior. Under normal conditions, the "Interior" (orange) zone maintains a dominant and relatively stable share of users. During the blackout, however, occupancy in the "Interior" zone decreases significantly faster than in the "Exterior"(green) zone, whose thicker area indicates a comparatively higher and more persistent presence. This suggests that a larger proportion of users shifted toward outdoor areas as the incident happened.

As previously shown in the earlier figure, the abrupt drop in occupancy caused by the electrical failure is again evident here. Although brief, this event is clearly reflected in the occupancy curves, producing a sharp and simultaneous decline across all zones, followed by a partial recovery. This episode further illustrates how network level and real life disruptions are immediately reflected in user presence and occupancy measurements.

The "Cafeteria" zone (light green) exhibits a distinctive occupancy pattern. Unlike offices and study areas, which experienced rapid evacuation, it maintained a relatively steady number of users during the first two hours of the blackout, likely functioning as a communal gathering point. After 15:00, occupancy drops sharply, and very few users remain in the cafeteria for the rest of the observation period.

D. New users and new devices

The identification of new users and devices during the blackout provides insight into how the extreme event affected network participation. In particular, first-time connections and newly configured devices associated with existing users may reflect adaptive responses of the campus population to the disruption.

Table II summarizes the classification of users and devices observed during the blackout. Users are categorized as either new users or existing users, and devices are classified according to whether they had been previously observed in the historical dataset.

Users classified as new correspond to individuals who had not previously connected any device to the `eduroam` network and therefore appear for the first time in the logs during the blackout. In contrast, existing users are those already observed in the historical records.Among these existing users, a subset connected one or more additional devices that had not been previously observed in the dataset. The number of such users is reported in parentheses in Table II.

The limited number of new users reported in Table II, together with the appearance of new devices associated with existing users, suggests that the blackout did not significantly increase network participation, but instead altered occupancy and access patterns, consistently with the changes observed in the previous figures. This highlights the ability of the campus population to adapt and sustain connectivity during the disruption.

	Users	New Devices
Existing users	2,802 (156)	179
New users	17	19

TABLE II
CLASSIFICATION OF USERS AND DEVICES OBSERVED DURING THE BLACKOUT BASED ON HISTORICAL NETWORK ACTIVITY

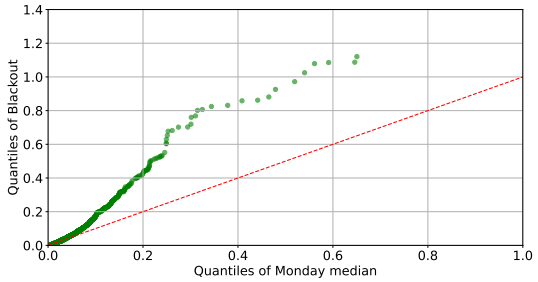

Fig. 5. Distributional comparison of usage intensity: Blackout day quantiles vs. historical Monday median quantiles

V. NETWORK TRAFFIC

After analyzing user distribution and spatial mobility during the blackout, we now examine how these behaviors translated into network activity, highlighting changes in connectivity during the event. To this end, we analyze the daily usage intensity per user to assess how users adapted their network behavior under extreme conditions. Given that mobile networks were unavailable, while University Wi-Fi systems remained operational thanks to backup generators, this rare scenario provides a unique opportunity to observe changes in network traffic during the disruption, offering insights not obtainable under normal operating conditions.

The analysis is restricted to devices observed during the blackout, and the same set of users is used to construct the baseline Mondays, ensuring a fair comparison.

With this in mind, to capture a global perspective of individual user behavior, we first characterize typical network usage using all Mondays in the observation period. For each day, we compute the daily usage intensity per user, defined as the total network traffic transmitted (input plus output, in gigabytes (GB)) divided by the total connection time in hours. Typical behavior is summarized for each user by taking the median usage intensity across Mondays. The same metric is then computed for the blackout day to enable direct comparison.

To evaluate the impact of disruption globally, Figure 5 compares the quantiles of usage intensity during blackout day versus the quantiles of each user's median rate across all historical Mondays. The blackout distribution lies systematically above the identity line ($y > x$) across nearly the entire range of quantiles, providing clear evidence of a generalized increase in per-hour data transmission during the event. These findings provide a global perspective on network traffic, demonstrating how users adapted their connectivity under extreme conditions and maintained high levels of engagement despite the disruption.

VI. SUMMARY AND FUTURE WORK

This work examined the impact of a large-scale power outage on user presence, mobility, and network activity within a university campus using Wi-Fi RADIUS logs. The blackout created a unique setting in which campus Wi-Fi remained operational while mobile networks failed, enabling the observation of behavioral adaptations under disruption.

The results show an immediate increase in Wi-Fi occupancy after the outage, followed by a gradual decline as evacuation progressed, together with clear spatial redistribution and increased network usage. Overall, the study demonstrates the potential of Wi-Fi sensing data to capture collective responses to extreme events.

As future work, network connectivity and traffic patterns could be further explored as passive proxies for presence and occupancy in academic environments, particularly for inferring attendance when traditional data sources are unavailable.

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