Inferring network infrastructural behaviour during disasters

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***Abstract*—An unexpected increase in natural disasters has prompted a large interest in governments and organisations to utilise ICT for many different purposes such as preparation, impact mitigation, loss reduction and relief efforts. This paper presents initial work on studying disaster scenarios from device level perspective to characterise network infrastructural behaviour during extraordinary situations. We find connectivity challenges during disasters and observe sharp decline of quality metrics and loss of station quantity between ordinary and extraordinary time periods. We also make distinctions between usual and unusual behaviour seen during ordinary and extraordinary situations.**

I. Introduction

An unexpected sudden increase in natural disasters and emergencies in the past decade or so has prompted large interest among governments and private organisations [1] alike to utilise information and communication technology to the full. This includes - but is not limited to - managing risk, mitigating impact, reducing losses, preparing and warning populace, and facilitating relief and rescue efforts [2], [3], [4].

White papers by various organisations on disaster situations highlight the utility of information and communication technology during the aftermath. For instance, GSMA's 2005 report [5] on the role of mobile phones during disasters and other emergencies reflects the need for governments and mobile operators to work together in facilitating recovery from disaster situations. One of the key findings suggest the ubiquity of cellular network and the turn-around time for reinstalling mobile infrastructure to provide baseline communication services.

Network behaviour during natural disasters and emergencies is somewhat reminiscent to usage surges observed during the New Year Eves, for example [5]. Operators should prioritise calls at such times and manage other demand on their network or may be even allocating a larger part of the spectrum for emergency service use. The report also highlights the role of mobile phones as a low-cost but important supplementary information dissemination medium. This is especially true in developing countries where other infrastructure is vulnerable and widely affected in the aftermath of a disaster. The most important recommendation for the public are to 'text not talk' during emergencies as text messages are more likely to get through as they use less network capacity or can be held in a queue until there is free capacity to send.

Similarly, during the Great East Japan Earthquake of 2011, NTT suffered heavy losses [6] to its infrastructure. After the earthquake, NTT [7] committed to securing reliability in network design, monitoring and control technologies, and quake resistance enhancements for physical network equipment. Moreover, NTT started construction of large-zone scheme base stations at approximately 100 different locations across Japan to secure communications over densely populated areas in the event of widespread disaster or power outage. NTT also proposed developing a service that carries voice messages by transmitting voice files over packet network as voice calls are difficult to connect over circuit-switched networks due to congestion in the event of a disaster.

Studying affects of extraordinary situations can help in strengthening reliability and resilience in communication networks. In this paper we study data collected from an Android mobile phone application to understand how the network responds during disasters. In particular we study two disaster scenarios from device level measurements perspective to characterise network infrastructural behaviour. We find connectivity challenges during disasters and emergencies and make two important inferences from the dataset: (1) ordinary and extraordinary time periods are characteristic of usual and unusual behaviour of the quality metrics, respectively; (2) rapid and prolonged decrease of quality metrics and network performance distinguish extraordinary situations from ordinary ones.

The rest of the paper is organised as follows. Section II covers the state of the art. Section III describes the datasets and our methodology. We present our analysis in Section IV and conclude in Section V.

II. Related work

The need to design methods for creating disaster resilient and robust communication infrastructure has only been studied sporadically. In [8] method for spatial design of physical network is discussed to create robustness against earthquakes. The paper discusses theoretical method for evaluating probability of disconnection in a bounded area. The paper further discusses physical design rules for robustness, and evaluates the validity of the method and rules using earthquake intensity maps.

Some work has also focused on redefining existing network standards and their implementations, such as the GSM-network [9]. The paper proposes adjustment and implementation of a reimagined GSM-network necessary to enable mobile device geo-localisation in disaster situations. Typically, in cellular networks a mobile device transmits a signal only sporadically without request, e.g. when changing a sector or a cellular base station, making a call, sending an SMS or performing a handover. The mobile device needs to be enforced to send a signal without request to be successfully localised. The paper envisions an auxiliary GSM-network that allows the usage of a special handover procedure with frequency hopping that increases the accuracy of applied localisation techniques.

Another work [3] focuses on deploying a wireless sensor network protocol for disaster management to overcome communication deficiencies during disasters. The authors use wide area sensor node deployment and ad-hoc relay stations to send data from collapsed base stations to functioning base stations. Other works include [10], [11].

Research has also focused on using social media for real-time event detection. For example in [12] an algorithm is devised to monitor *Twitter* for particular tweets to detect a target event. The algorithm classifies tweets and produces a probabilistic model across space and time for the target event that can locate the centre and trajectory of the event location. Using Twitter dataset from Japan, the algorithm is argued to detect an earthquake with 96% probability of Japan Meteorological Agency (JMA). The system claims to deliver earthquake notification e-mails much faster than those broadcasted by the JMA. Similar work includes [13].

However, to the best of our knowledge this is the first preliminary work that focuses on characterising network behavioural aspects from the mobile device perspective.

III. Data and Methodology

CrisisSignal[1] is an Android smartphone application developed by OpenSignal team to collect data on cellular and WiFi coverage in emergency situations. The application is free to download and install. It comes with two modes[2]: foreground and background. In the foreground mode the application sends a message (called a ping) containing all the measurement data to the central server once every 2 (intensive) or 5 (power saver) seconds. In the background mode the application sends the same ping once every 5 (intensive) or 30 (power saver) minutes.

We had access to a novel CrisisSignal dataset containing over 5.9 million data-points from all over the globe from mid Dec 2014 to mid Feb 2015. We aggregated values of the metrics described in Table I and grouped them on a per-day basis. Data-points were bounded by relevant geo-coordinate and timestamp ranges. Each metric was normalised to a common scale for the purposes of comparison. Please note that the accuracy of CrisisSignal measurements depends on the device and its hardware and software platform (which varies greatly). This is acceptable as the study is focused on understanding the device level perspective of the network during extraordinary situations.

[1]CrisisSignal - `http://tinyurl.com/nam34np`

[2]How to use CrisisSignal - `http://tinyurl.com/prs78a5`

TABLE II. T-TESTS FOR NUMBER OF DEVICES DURING AND AFTER DISASTER

Technology	t-value	p-value	mean (during disaster, after disaster)
Cell (floods)	-3.055	0.008868	16.44444, 127.85714
WiFi (floods)	2.7583	0.009526	167.55556, 72.94118
Cell (typhoon)	-0.3825	0.7075	88.66667, 111.81818
WiFi (typhoon)	-1.4141	0.1837	249.1667, 371.0909

IV. Analysis

We characterise two disasters for the purposes of this study: (a) simultaneous floods of Dec 2014 in Malaysia and Indonesia; and (b) Typhoon Jangmi in Philippines, also in Dec 2014. The reason for studying two very different disasters is to characterise differences in network behaviour during and after disaster periods. We use PSQL and R to analyse the data. Data has been smoothed using cubic function. The horizontal axis on each plot represents days and the vertical axis represents normalised values. We apply Welch's t-test to calculate t-statistics for the null hypothesis i.e. the difference of two sets is due to chance or activity spike ($\mu_1 = \mu_2$), or the alternative hypothesis i.e. it is due to the damage caused by the disaster ($\mu_1 \neq \mu_2$). Whenever the p-value falls below 0.05 we reject the null hypothesis in favour of the alternative hypothesis.

Malaysia/Indonesia Floods: Figures 1 and 2 show time series plots for floods in Malaysia and Indonesia. The vertical dotted lines enclose the time period when the disaster struck (2014-12-14 to 2015-01-02). Fig. 1 shows time series for cellular coverage from 2014-12-14 to 2015-02-13. The first notable trend is how the CDMA EC/IO compares to the number of cellular base stations. CDMA EC/IO is the ratio of signal energy and broadband interference. As the traffic load in the sector increases (shown by falling number of base stations), the EC/IO worsens. There could be a number of reasons for which the towers could go down including service failures, power cuts, or shutdown evoked for hardware damage control and mitigation. Another interesting trend is the number of devices during and after the disaster period. The upward trend during the disaster might be due to rising app popularity. Table II shows t-value, p-value and the means. It confirms that the floods cause the drop in the number of devices on the network during the disaster.

BER is the number of received bits of a data stream that have been altered due to factors affecting communications. Since this is the receiver side BER, it may be affected by transmission channel noise, interference, distortion, bit synchronisation problems, attenuation, wireless multipath fading, etc. Some of these factors become commonplace once devices (or load) on the network increases, especially in situations when the number of active serving cellular base stations have decreased. The arbitrary strength unit (ASU) also points towards the infrastructural behaviour during and after the disaster. ASU is an integer value that is proportional to received signal strength measured by the mobile phone. In certain situations BER may be attempted for improvement by choosing a strong signal strength, i.e. increasing the ASU of remaining active and serving cellular base stations. However, this can also cause cross-talk and more bit errors, as shown by ASU and BER trend-lines.

Fig. 2 shows time series for WiFi connectivity from 2014-12-01 to 2015-02-14. During the floods the number of devices

TABLE I. METRICS MEASURED BY CRISISSIGNAL

Metric	Technology	Description
Number of devices	Cellular, WiFi	The number of devices seen on the network, calculated on a daily basis.
Bit error rate (BER)	Cellular	In digital communication systems, it is the number of received bits of a data stream over a communication channel that have been altered due to factors such as noise, interference, distortion or bit synchronisation errors.
Arbitrary strength unit (ASU)	Cellular	ASU is an integer value that is proportional to the received signal strength as measured by the mobile device. This is measured in dBm or Watts.
CDMA EC/IO	Cellular	The CDMA EC/IO is the ratio between signal energy (EC) and interference in the broadband channel (IO) for the Code Division Multiple Access (CDMA) channel access method.
Signal strength (RSSI)	WiFi	RSSI measures the power present in a received radio signal in dBm or Watts.
Number of cellular base stations	Cellular	Number of cellular base stations as seen by the mobile device.
Number of WiFi access points	WiFi	Number of WiFi access points as seen by the mobile device.

trying to find connectivity increases as cellular coverage is getting widely disrupted (Table II confirms that the trend is due to the flood). This might be driven by opportunistic search for connectivity. However, the number of active WiFi access points (APs) decrease. The received signal strength indication (RSSI) depicts a drop due to floods (p-value of 0.01455 confirms this finding). In IEEE 802.11 networks, RSSI is the relative signal strength in arbitrary units. It is an indication of power level being received by the antenna. Therefore, the higher the number, the stronger the signal.

Typhoon Jangmi: Figures 3 and 4 show plots for Typhoon Jangmi. The vertical dotted lines enclose the time period when the disaster struck (2014-12-27 to 2015-01-01). Fig. 3 shows time series for cellular coverage from 2014-12-21 to 2015-01-06. Contrary to the floods, CDMA EC/IO drops sharply before, during and after the typhoon. Multiple reasons could contribute to such a trend: emergency rollback of equipment to avoid damage, population migration, and damage caused during typhoon. The number of devices on the network decrease consistently during and after the typhoon. The t-test in Table II proves the validity of the null hypothesis in this case. We can find similarities of network behaviour during rapid events such as a typhoon and a flash crowd.

There are two other very interesting trends. Firstly, the number of cellular base stations increase consistently, regardless of the typhoon. Secondly, the signal strength (ASU) decreases consistently even though cellular base stations resume service. Two factors could contribute to such trends: (1) cellular base stations resume basic services with partial damage to hardware, or (2) temporary low capacity mobile cellular base stations are erected after the disaster to provide essential services, such as in [7] and [1].

Fig. 4 shows time series for WiFi connectivity from 2014-12-21 to 2015-01-06. The decline in number of devices is reminiscent of the trend in Fig. 3. The p-value in Table II corroborates our statement earlier for Fig. 3 about possible similarities of network behaviour during rapid events, such as a typhoon and a flash crowd. This is further confirmed by p-value (0.3513) derived for RSSI before, during and after the typhoon. However, similarities with flood disaster also exist: number of active WiFi APs decrease sharply, similar to what we witnessed in Figures 1 and 2.

V. CONCLUSION

Reliable and resilient communication networks become vital during extraordinary situations for early warning, dissemination of critical information, mitigating losses, facilitating

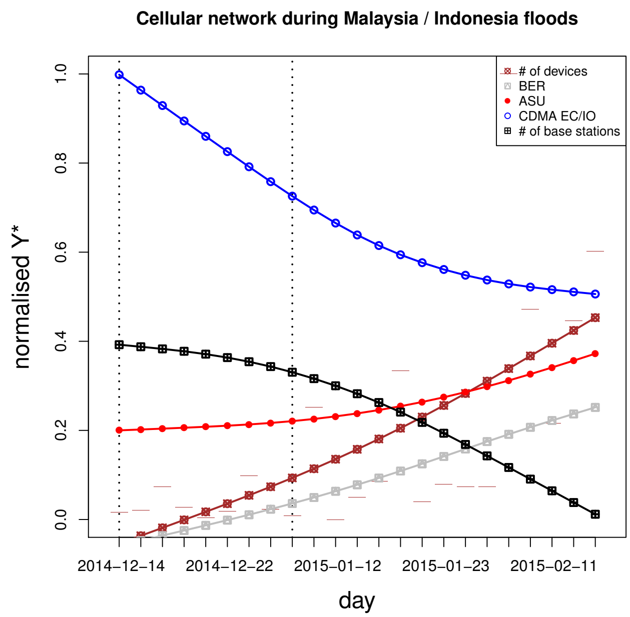

Fig. 1. Cellular connectivity during Malaysia/Indonesia Floods

relief and rescue efforts and saving lives. In this paper we have studied data collected from an Android mobile phone application to understand how the network responds during disasters. In particular we study two disaster scenarios from device level measurements perspective to characterise network infrastructural behaviour. We find connectivity challenges during disasters and emergencies and make two important inferences. Firstly, certain distinctions segregate extraordinary time period from ordinary time period. Secondly, repeated region-wide failures such as loss of station quantity, rapid and prolonged decrease of quality metrics as well as counter-intuitive or unusual behaviour of signal strength (ASU, RSSI) and error rate (BER), point towards extraordinary situations.

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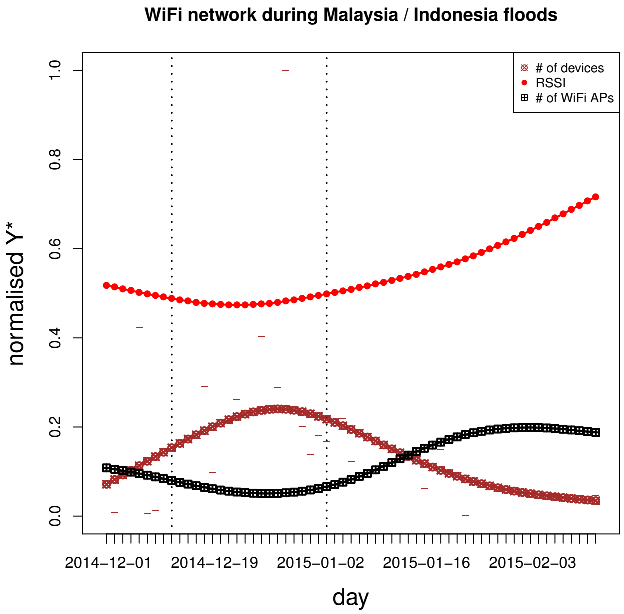

Fig. 2. WiFi connectivity during Malaysia/Indonesia Floods

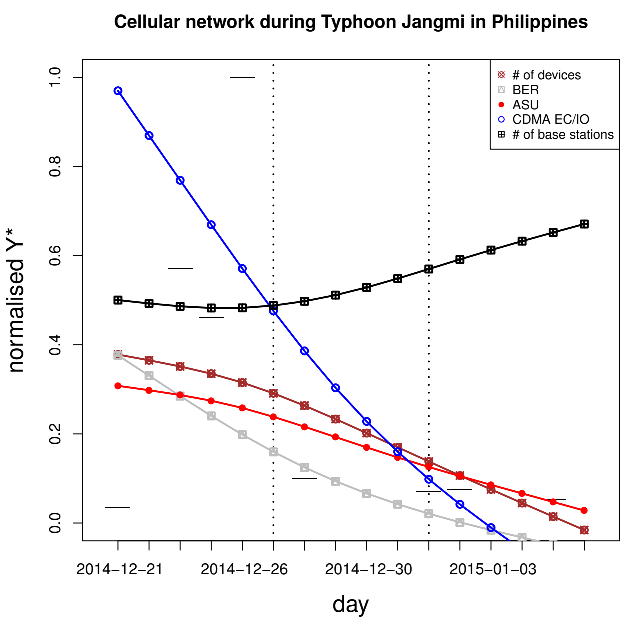

Fig. 3. Cellular connectivity during Typhoon Jangmi in Philippines

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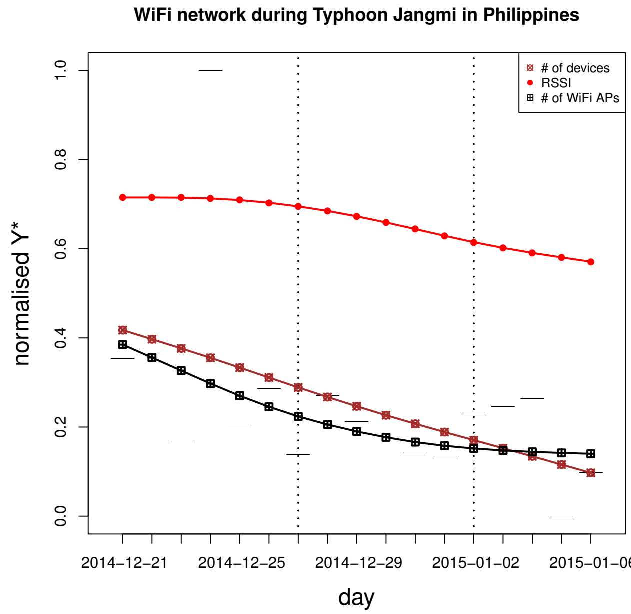

Fig. 4. WiFi connectivity during Typhoon Jangmi in Philippines

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