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Real-world large-scale IoT systems for community eldercare: A comparative study on system dependability

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Real-World Large-Scale IoT Systems for Community Eldercare

A Comparative Study on System Dependability

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***Abstract* — The paradigm of aging-in-place – where the elderly live and age in their own homes, independently and safely, with care provided by the community – is compelling, especially in societies that face both shortages in institutionalized eldercare resources, and rapidly-aging populations. Internet-of-Things (IoT) technologies, particularly in-home monitoring solutions, are commercially available, and can be a fundamental enabler of smart community eldercare, if they are dependable. In this paper, we present our findings on system performance of solutions from two vendors, which we have deployed at scale for technology-enabled community care. In particular, we highlight the importance of quantifying actual system performance, which may differ from perceived performance.**

Keywords—In-home monitoring, eldercare, system performance

I. Introduction

Many cities globally are experiencing shortage in institutionalized resources, such as healthcare and eldercare facilities and manpower, to adequately care for the rapidly increasing elderly (aged 65 and above) population. In Singapore, it is estimated that by 2030, one in every five persons – or roughly 900,000 persons – will be elderly [1]. Equally worrisome is an upward trend in the number of elderly who are staying alone, projected to reach 83,000 by 2030. This points to the need to rely on timely response by community caregivers and volunteers to meet the day-to-day safety needs of these elderly. Fortunately, the maturing of sensing and communication technologies, as well as data science, is enabling sensor-enabled homes that can inform community eldercare through (i) continuous monitoring of day-to-day activities of the elderly in real-time and (ii) intelligent detection of anomalous events.

SHINESeniors [2] is an inter-disciplinary research effort that studies the use of sensor-enabled homes and personalized home care technology to enable elderly Singaporeans who live alone to age-in-place through community eldercare. It represents a holistic study that builds on existing work to address (i) the immediate and personal safety needs of the elderly; (ii) the long term health and social needs of the elderly and (iii) the technology-centric and care-centric challenges for sustainable technology-enabled community eldercare.

Figure 1 illustrates the key components of our data-driven community eldercare platform, as well as the complete ecosystem of key stakeholders. The typical characteristics of each sensor-enabled home, illustrated for a typical 2-room flat (one-bedroom) in Figure 2, are as follows:

i. Each elderly is given a help button attached to a lanyard which can be activated in times of stress.
ii. There are 4 motion sensors in living room, kitchen, bedroom and bathroom.
iii. There is a door sensor to detect the open/close status of the main door.
iv. All sensors are running on Alkaline AA battery, which has average life of 1 year.
v. All 4 motion sensors, the door sensor and the help button connect to a mains-powered data collection unit (DCU) in the living room wirelessly.
vi. The DCU aggregates all sensor data and uploads them to a central server via the internet.

Each motion sensor generates records periodically, while the door sensor is event-driven. These data form the fundamental raw information of the entire platform, from which activities / events of the elderly can be derived. Generally, two types of community care can be provided by this platform: **Reactive** and **preventive care**.

- **Reactive care** refers to care in response to detection of an event which requires urgent help, e.g., activation of push button or prolonged dwell time or inactivity at home, the latter of which could signify a fall or faint. For either event, an alert is sent to community helpers and volunteers to provide necessary care. In [3], we proposed Dwell-Time-enhanced Dynamic Threshold, a scheme for computing adaptive alert thresholds that exploit region-specific dwell time to reduce the detection latency. We were able to show that the proposed scheme resulted in faster detection of prolonged dwelling in the bathroom and kitchen while maintaining reasonable false alarm rates.

- **Preventive care** refers to care in response to detection of sensor features derived from longitudinal analysis that correlate with deterioration in physical, mental or social wellbeing of the elderly. Examples of such sensor features include going out duration and frequency, duration in each part of the flat etc. In [4], we demonstrated that our system can be used to detect elderly at risk of social isolation.

The successful provision of reactive care to meet the safety needs of the elderly is conditioned on the dependability of the in-home sensor system. As events such as a push button activation, faint or fall can happen anytime and over very short intervals, all sensors as well as the DCU must be up and running at all times, so that these events can be detected. As the sensor systems are provided by commercial vendors, system dependability translates to the following requirements: (i) The uptime of each component of the sensor system must be maximized; (ii) When failure occurs, it must be detected and rectified by the vendor as quickly as possible.

To date, more than 80 elderly residential homes have been instrumented with in-home sensor-systems across multiple housing estates in Singapore, in partnership with four caregiving organizations. This includes the deployment of vendor A's system in 44 homes in Marine Parade (Nov 2014 to Mar 2017), and vendor B's system in 16 homes in Bedok (Sep 2016 to Mar 2017). Figure 3 shows the typical sensor deployment in Bedok.

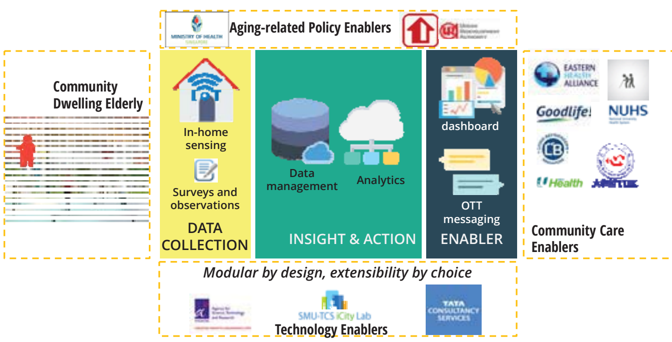

Figure 1 Design for Sensor Enabled Care

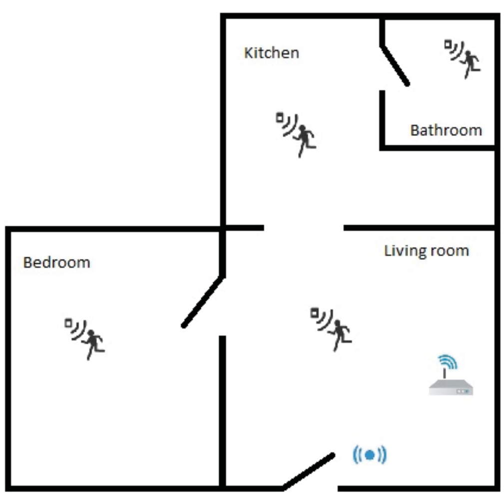

Figure 2 Sensor deployment in Marine Parade in a 2-room flat

Figure 3 Sensor deployment in Bedok in a 2-room flat

II. EVALUATION OF SYSTEM DEPENDABILITY

In this paper, we perform a quantitative study to evaluate the dependability of both vendors' systems. For a fair and consistent comparison, we only consider data collected from August 2016 onwards as data collection for vendor B only started in August 2016. For vendor A, we consider the data obtained from 10 elderly residents during the period of September 2016 to March 2017, as there are a major system issue during the months of July and August 2016, and the data collected was terminated after March 2017. For vendor B, we consider the data obtained from 5 residents in September 2016, 10 residents from Oct 2016 to Feb 2017, and 13 residents in March 2017.

A. Description of raw sensor data

1) Vendor A data format

Motion sensor data is generated every 10 seconds. A sensor will produce more than 8000 records per day and 259,000 records a month. As such a massive data is not easy to analyze, it is decided to aggregate the records per hour and analyze the sensor behavior on hourly basis throughout each month.

Since the data is collected by DCU every 10 seconds, the length of sensor non-responding (Not OK or NOK) time is measured by number of NOK. If 360 NOK are received from a sensor within an hour, the sensor is down for the entire hour ($360 \times 10s = 3600s = 1$ hour). If only 180 NOK are received within an hour, the sensor is down for half an hour.

While sensor data is collected every 10 seconds, there is no DCU data collected by vendor A. DCU down time can only be measured by the amount of missing data in one hour. Accordingly, if 360 records from all sensors are missing in an hour, the DCU is down for the entire hour.

2) Vendor B data format

Data from vendor B has a different structure. Firstly, sensor data is not generated every 10 seconds but every hour most of the time. There are also ad-hoc records produced when motions are detected. Secondly, there are DCU data collected.

B. Data cleaning

There are two types of issues found during the data cleaning: they are incomplete files and inconsistent formatting.

1) Incomplete Files From Bedok

Although deployment of vendor B's systems started in Aug 2016, they were carried out incrementally from 5 homes to 16 homes. Thus, some files do not contain a full month's data due to the incomplete installation. As the analysis requires data of an entire month, incomplete files were removed from study.

2) Data Format Inconsistency From Marine Parade

Whereas the date format in vendor A's sensor data has been always in the format of 2016-10-13 04:37:48, there is a file having date format as 13/10/2016 4:37. Such an inconsistency was identified during the analysis, and the file removed.

In another similar case, it is found that one of a sensor's location, 'Bedroom' had been renamed as 'Bed Area' in the middle of Nov 2016, although both refer to the same sensor. Such an inconsistency has been rectified.

C. Visualization of System Performance

1) Vendor A (Marine Parade)

Each sensor's non-responding (NOK) time is plotted together with DCU downtime, as illustrated in Figure 4 for resident 8 on October 2016. The length of sensor NOK and DCU downtime is plotted per hour and per day across the entire month. The horizontal axis represents different hours of a day and the vertical axis represents days of a month. To highlight the downtime more accurately, the length of sensor non-responding time within each hour is represented in gray scale of 10 levels: the darker the gray scale, the longer the downtime. White color indicates no NOK is received during that hour and black color indicates sensor is not responding for the entire hour. This also applies to DCU downtime.

Figure 4 shows that sensors installed in the bathroom are unreliable, with more than 100 hours' downtime in Oct 2016. In contrast, the sensors from the other 3 rooms performed reliably, with a maximum downtime of 1 hour across the entire month. The DCU performs well with only one hour's downtime in the entire month.

In contrast, Figure 5 shows another example for the same resident where the DCU has been down for more than 80 hours in Dec 2016. The sensor in the bed room performs well with only 7 hours' downtime during the same period.

2) Vendor B (Bedok)

To align with the analysis done for vendor A, the data from Vendor B is also plotted on a per hour basis across the entire month. Figure 6 shows a corresponding plot of living room sensor's performance together with the DCU.

Since the data from vendor B is less granular than that of vendor A, the downtime at each hour is simply shown as the entire hour, indicated by dark color, as opposed to the white color for no downtime in that hour.

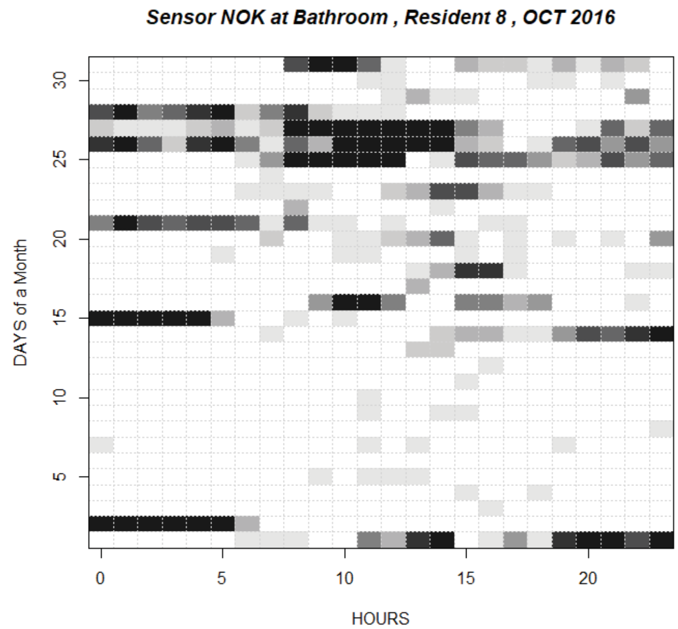

Figure 4 Sensor's performance on Oct 2016, Marine Parade, Resident 8

D. Comparison of System Performance

Figure 7 and Figure 8 compare the reliability of vendor A and vendor B's systems in January and March 2017 respectively. We make the following three observations:

- The bathroom sensors from both vendors perform poorly in terms of reliability. Specifically, we recorded more than 30 hours' of downtime. In March 2017, the downtimes are 97 and 46 hours in vendor A and vendor B's systems respectively, equivalent to uptime of 87% and 94%.

- The performance of sensors in the other rooms differ significantly between both. In Marine Parade, the average downtime across the kitchen, bedroom and living room is 0 and 4 hours in Jan and March 2017, corresponding to 99.5% uptime. However, in Bedok, the corresponding downtimes are 48 and 36 hours respectively, equivalent to uptime of 94% and 95%.
- Vendor B's DCU performs much better than vendor A's. In January, while the downtime is less than 1 hour for the former, it is close to 8 hours in the latter in Jan 2017. In March, vendor A's DCU downtime (89 hours) is almost 5 times that of vendor B's (19 hours). The figures in March 2017 translate to an uptime of 88% and 97.5% respectively for vendor A and B's DCU.

1) Discussion on DCU performance

The DCU is the most important component in the in-home sensor system, as it is the single aggregation point of all the sensors, and can thus be the single point of failure. Prior to this study, vendor B's system was perceived to perform better than vendor A's system. This perception arose due to the following: (i) vendor B's engineering team is always more open to suggestions and modifications; (ii) upon detection of system issues, vendor B's engineering team is more responsive, and more open about their diagnostics. This perception was validated by the quantitative performance.

In Figure 9, we compare the distribution of DCU downtimes across all the residents for both vendors. It is clear that the downtimes for vendor B are mainly clustered within a few hours, while vendor A's downtimes have a much larger spread, concurring with our observations above. Quantitatively, the (90^{th}, 95^{th}) percentile downtime for vendor A and B are (22, 40) hours and (20, 28) hours respectively.

2) Sensor performance (except bathroom sensor)

The collated results on the sensors' performance, when first presented to the research team, was unconvincing at first as vendor B's system was perceived to perform better than vendor A's system, as explained above. However, in this case, this perception does not translate to actual system performance where vendor A's sensors performed better than vendor B's, thus justifying the need for quantitative evaluation.

The difference in the performance could be becauase vendor B integrated commercially-available motion sensors that communicates wirelessly over z-wave (866 MHz while vendor A developed their sensors in-house that communicates wirelessly using a proprietary standard (2.4 GHz).

3) Bathroom sensor performance

The poor performance of the bathroom sensor from both vendors is another interesting finding from this study. After further investigations and survey, this poor performance can be attributed to the following reasons: (i) the relative higher humidity level in the bathroom as well as the kitchen may have given rise to signal attenuation, resulting in data loss and (ii), the longer distance between the bathroom and the DCU (compared to the other sensors) results in more significant signal attenuation, also resulting in data loss. The consistently poor performance of the bathroom sensor signifies an urgent need for action, as the bathroom is a common region where falls or fainting takes place.

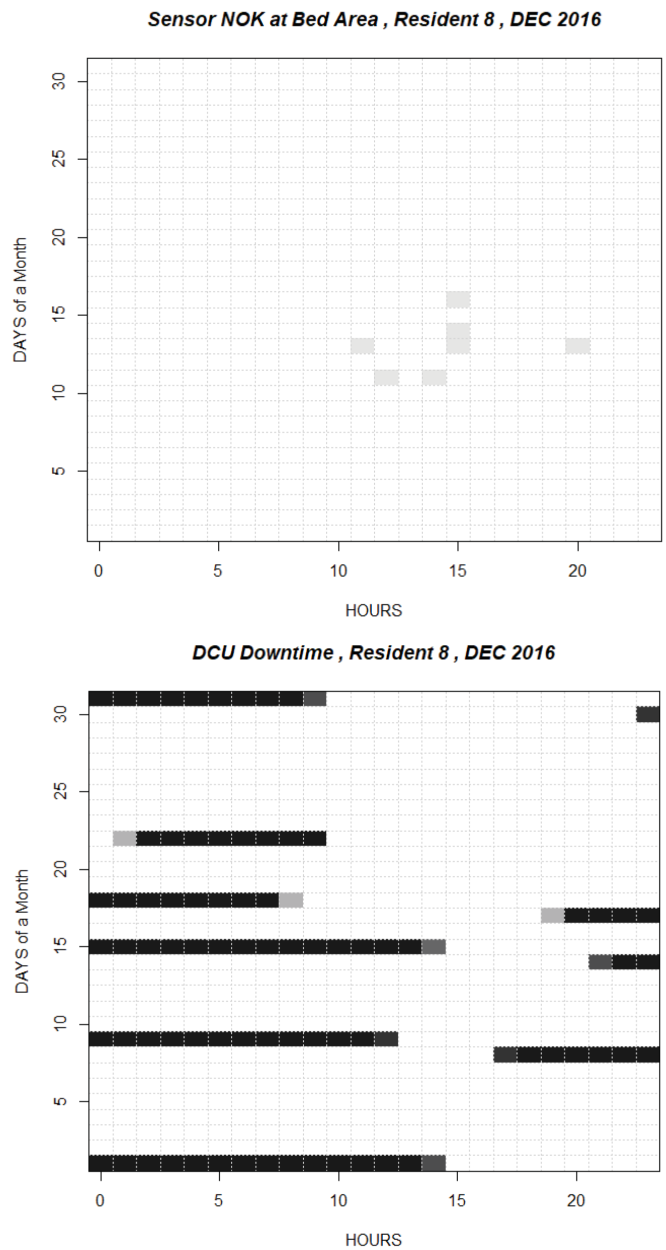

Figure 5 Sensor's performance on Dec 2016, Marine Parade, Resident 8

III. CONCLUSION & FUTURE WORK

In this paper, we present an ongoing large-scale project, where the apartments of more than 80 elderly living alone have been instrumented with unobtrusive sensor systems, so that data-driven community care can be provided to meet their safety and wellbeing needs. Each sensor system comprises a push button, door contact, motion sensors deployed in each zone (bathroom, living room, kitchen and bedroom) and a data-collection unit (DCU) that aggregates all the sensor data wirelessly and sends them to the central server for processing to inform community care.

We performed a quantitative study to evaluate the reliability of solutions provided by two different vendors in two different estates in Singapore. Data collected from 10 homes in each estate, spanning 6-months, reveal differences in system reliability. In particular, while the perceived system performance matches the actual performance in the case of the DCU, it differs in the case of the sensors' performance. Moreover, the bathroom sensor performs poorly in both cases, highlighting the need for rectification. Ongoing research seeks to develop a system monitoring and response tool to further minimize system downtime.

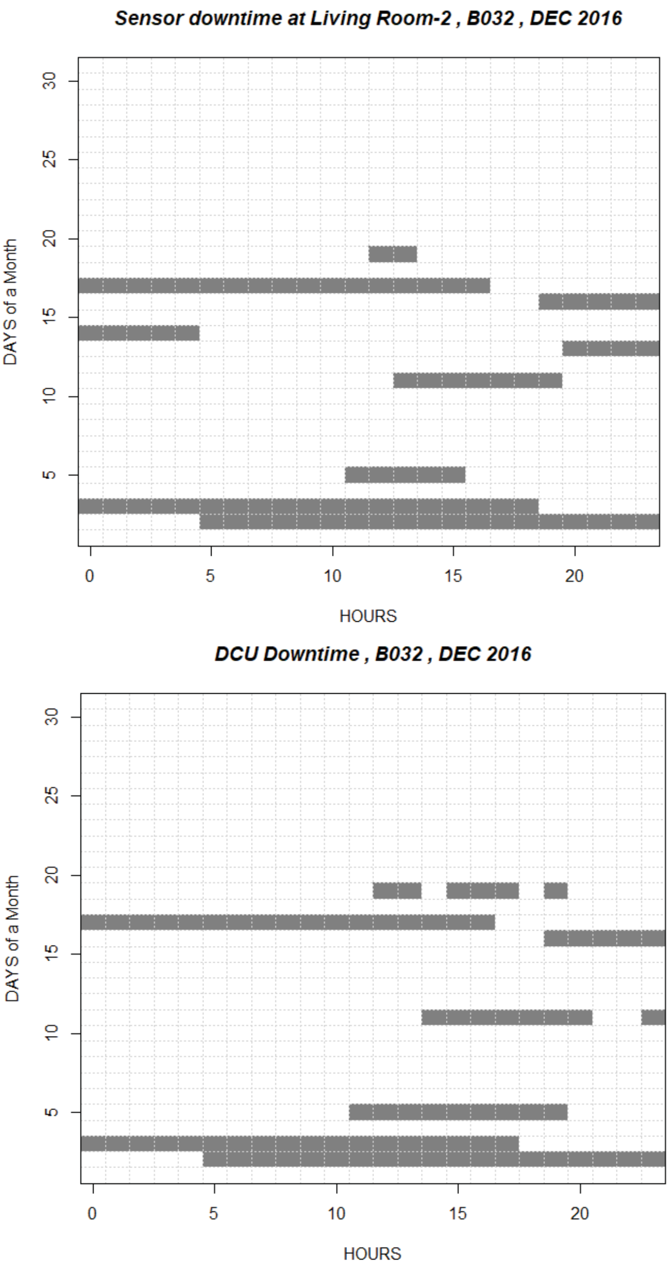

Figure 6 Sensor's performance on Dec 2016, Bedok, Resident B032

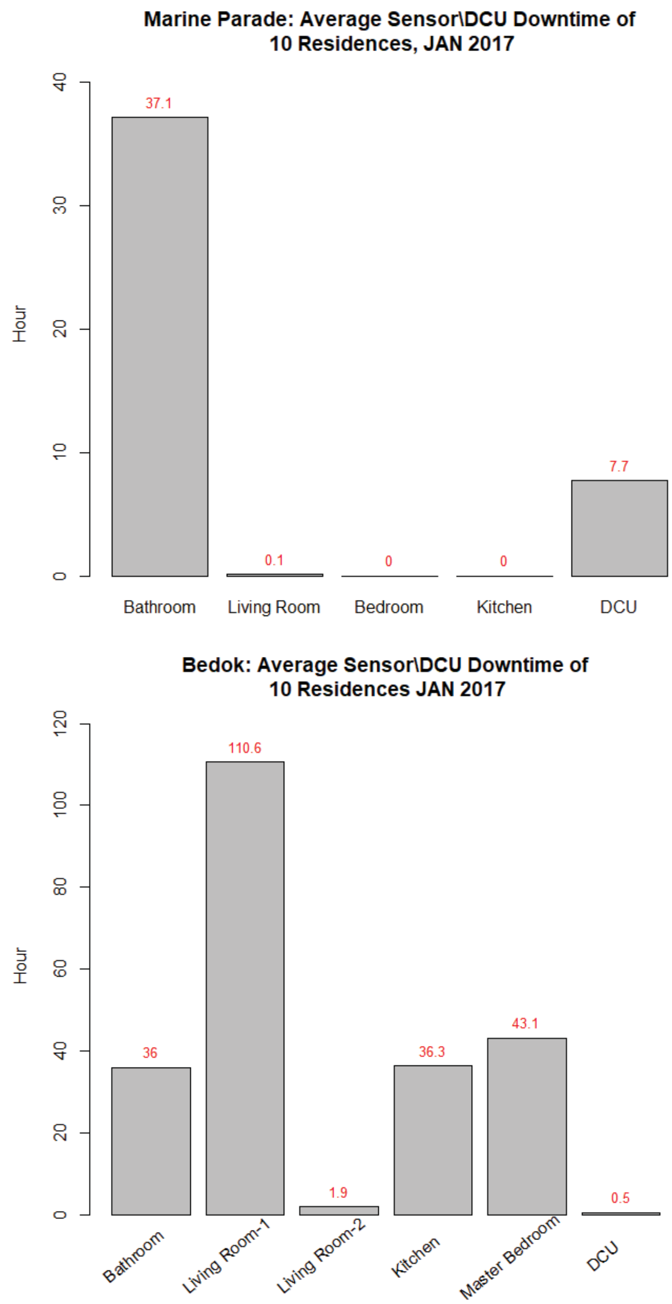

Figure 7 Average of Sensor and DCU downtime (Jan 2017)

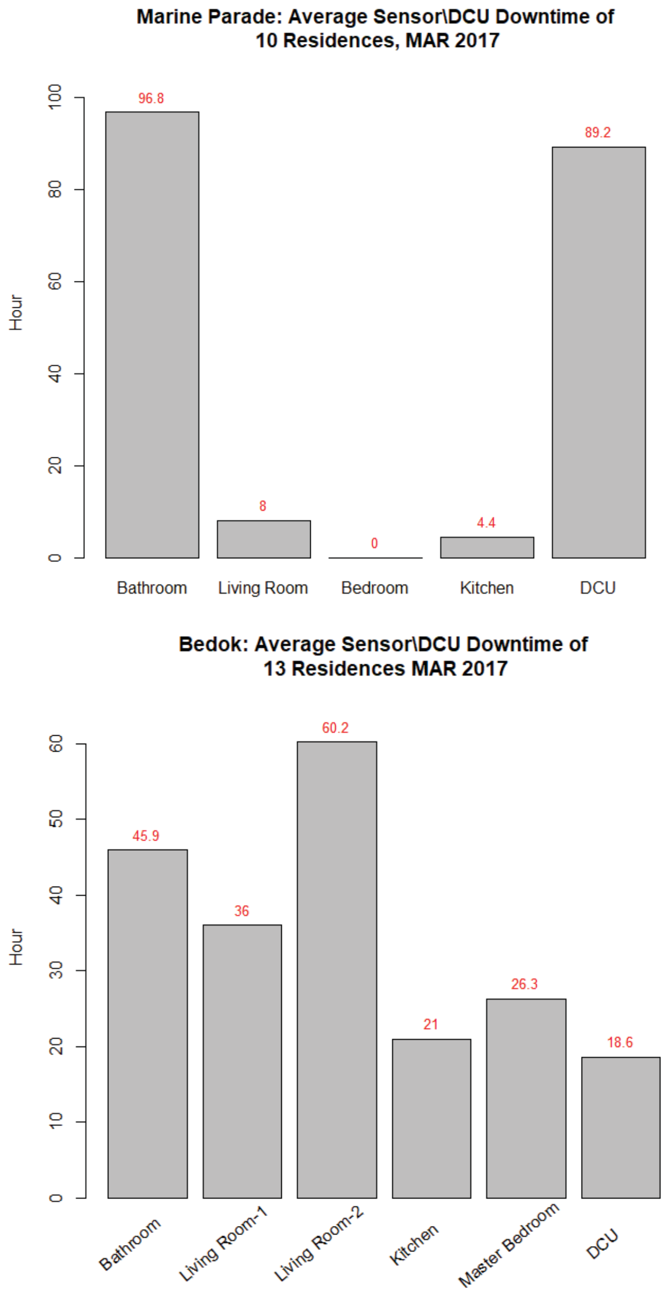

Figure 8 Average component downtime (March 2017)

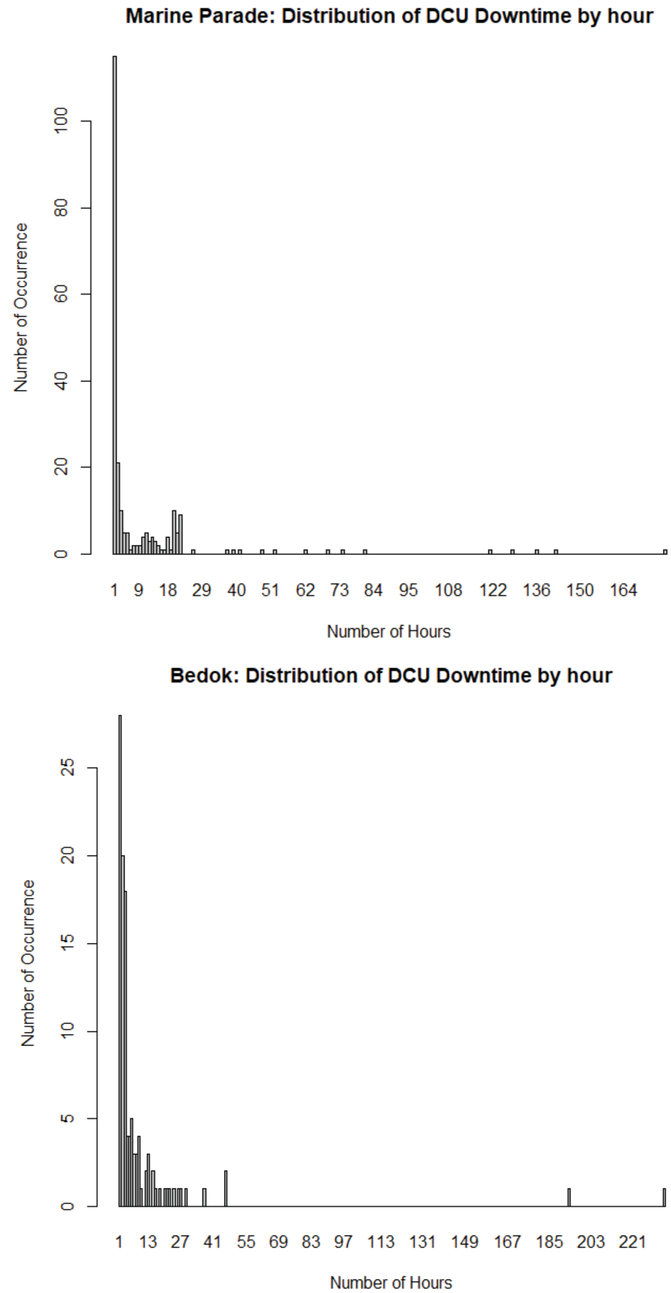

Figure 9 Distribution of DCU downtime in Marine Parade and Bedok

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REFERENCES

[1] BAI Liming, et al., (2015), SHINESeniors: Personalized Services for Active Ageing-in-Place, Proceedings of the IEEE Smart Cities Conference,Guadalajara, Mexico. Oct, 2015.

[2] K. Y. Gan. Ageing in Singapore in the next 50 years, Mar. 2015. Speech by Mr Gan Kim Yong, Minister for Health, at the SG50 Scientific Conference on Ageing, on 19 March 2015.

[3] A. C. Valera, H. P. Tan and L. Bai, "Improving the sensitivity of unobtrusive inactivity detection in sensor-enabled homes for the elderly" Proceedings of the PASTA (IEEE PerCom Workshops), March 2016.

[4] N. Goonawardene, X. P. Toh, and H. P. Tan "Sensor-Driven Detection of Social Isolation in Community Dwelling Elderly", HCI International, July 2017.