Power Analysis of a Large-Scale Solar-Powered Urban Sensor Network

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ABSTRACT

Solar power is often touted as a reliable renewable energy source for low-cost sensor networks in various environments. However, there have not been extensive real-world studies to examine how well solar-powered sensor networks perform in urban settings over long periods. In this work we analyze the performance of a large-scale solar-powered sensor network over one year in Chicago, Illinois. We find that over 35% of the devices experienced charging issues between the months of October and March, resulting in over 33,000 hours of data loss. Surprisingly the devices that had issues charging were not all located near tall buildings and were often found in majority Black and Latine neighborhoods. These findings highlight the need for continued research in alternative power sources and energy harvesting techniques, and increased real-world deployments to identify additional barriers in using sensor networks for real-time monitoring in cities.

CCS CONCEPTS

• **Computer systems organization → Sensor networks**.

KEYWORDS

Sensor Networks, Urban Sensing, Environmental Sensing, Solar Power

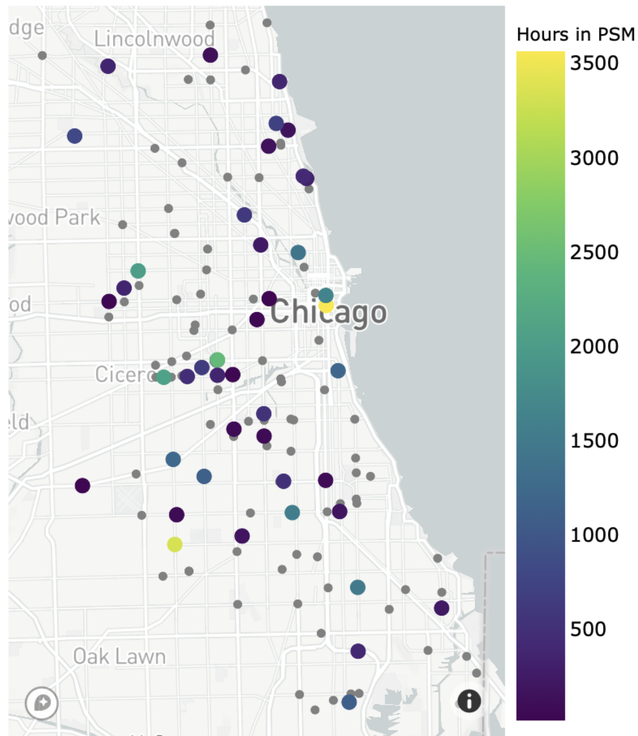

Figure 1: This map shows the locations of all sensor nodes in the network. The small gray dots represent nodes that did not enter power saving mode. The larger colored dots represent the nodes that entered power saving mode, and are color-coded by the number of hours that they were in power saving mode. One of the nodes with the highest number of hours in power saving mode is in downtown Chicago close to several tall buildings, but another node with nearly the same number of hours is in the western part of the city. Thus it is clear that simply considering areas based on the number or density of tall buildings is not enough to determine whether or not they will experience solar charging issues in winter months.

1 INTRODUCTION

One of the many challenges in working with low-cost sensor networks is maintaining power for long periods of time. Solar power is perhaps the most ubiquitous form of energy used for low-cost sensor networks because it is cost-effective and renewable [18]. Solar panels are relatively inexpensive and easy to deploy, and they provide a reliable power source to continuously operate sensors in locations that are remote, hard to reach, or simply difficult or expensive to run electrical wires or replace batteries. Because solar power eliminates the need for frequent maintenance and battery replacements, it helps reduce the cost of the sensor network while also reducing the carbon footprint associated with operating the network. Thus it is no surprise that numerous sensor networks rely on solar power as their primary power source.

Due to the vast quantity of previously deployed solar powered sensor networks and the numerous papers published about these networks, it seems guaranteed that solar power is reliable for most sensor network deployments. However, there have been very few studies looking into the reliability of solar power in urban settings. As more and more cities push to adopt sensing technologies for urban monitoring and smart city integration, it is necessary to understand how well solar energy will power these sensor networks.

In this work we examine the power performance of a large-scale solar-powered sensor network in Chicago, Illinois. We analyze data from 115 nodes deployed around the city of Chicago from July 1, 2021 to June 30, 2022. We find that 44 devices have issues charging during winter months, resulting in the loss of nearly 400,000 sensor readings. Devices with charging issues could not be predicted using open crowdsourced building data, and neighborhoods that are majority Black and Latine were disproportionately affected by charging issues, despite the lack of very tall buildings.

This work makes a number of contributions. We present the analysis of a large-scale solar-powered sensor network in an urban setting, showing that solar power is not as reliable as often presented. We highlight the difficulty in predicting locations with charging issues with the use of crowdsourced data and open source tools. In addition, we describe the potential social implications of charging issues in urban sensor networks, especially in cities that are segregated by race, income, or social status. Our work points to future research directions to address the shortcomings of solar power for large-scale urban networks, helping to make these networks more reliable in future deployments.

2 RELATED WORK

Although there have been prior evaluations of real-world sensor network deployments in urban settings, they have often been small-scale and short-term. A small number of researchers have shared the lessons and challenges learned from urban sensor network deployments, but many of these are focused on specific data such as noise [12] and water quality [19]. Furthermore, many of these studies rely on the power grid for data transfer and high computation tasks [2, 19].

Dehwah et al. [6] evaluate the performance of a traffic monitoring sensor network in a desert city, and describe the effect of dust storms and building shadows on solar charging. However, they do not do a deep analysis into the locations that were most affected by shadows to determine how the issue may be prevented in future deployments and the potential social implications. Thus to our knowledge, this is the first in-depth analysis of charging issues for a large-scale solar-powered urban sensor network.

3 CHICAGO AS A CASE STUDY

3.1 Building Height

According to the Council on Tall Buildings and Urban Habitat [14], amongst cities around the world, Chicago has the 10th most buildings 150 meters and higher, 11th most buildings 200 meters and higher, and 5th most buildings 300 meters and higher. However, its place on those lists is expected to fall within the coming years—Chicago has only three buildings 150 meters and higher under construction and twelve proposed for construction. By comparison, Wuhan, Shenyang, and Bangkok—cities just below Chicago on the list of most 150+ meter buildings—have 49, 14, and 17, buildings under construction respectively, and dozens more proposed in both Wuhan and Shenyang. In addition, development in other cities such as Mumbai, Nanning, and Nanjing, which all have several 150+ meter buildings under construction and proposed for construction will propel them past Chicago in the list in the coming decades.

3.2 Latitude and Sunlight Hours

Chicago has a latitude of 41.88 degrees, lying at nearly the 42nd parallel north. At this latitude, the sun is visible for 15 hours, 15 minutes during the summer solstice and 9 hours, 6 minutes during the winter solstice. According to data from the World Economic Forum [16], the top five most populous latitudes are between the 22nd and 27th parallel north, which are all much closer to the equator and thus have more sunlight on the winter solstice, with an average of 10 hours 35 minutes.

Nevertheless, a number of highly populated cities reside at or above the 42nd parallel north, including London, Moscow, Harbin, and Toronto, as well as much of Western Europe. Cities such as New York and Beijing are also located at nearly the same latitude, falling at the 41st parallel north, which receives 9 hours 13 minutes sunlight on the winter solstice. Furthermore, as the effects of climate change disproportionately affect populations who live closer to the equator, mass internal and international migration to more northern latitudes is expected [8]. Thus, understanding the performance of solar-powered sensor networks at northern latitudes is essential for future urban environmental sensing.

3.3 Racial and Economic Segregation and Inequality

Based on 2020 United States Census Data, Chicago is the fourth most racially segregated large city (population at least 200,000) in the United States [7]. Fig. 2 highlights Chicago's racial segregation, showing where the white, Black, and Latine populations live relative to each other. There is limited data comparing racial segregation in global cities, likely because many countries are more racially homogeneous than the United States.

However, segregation based on income or social status exists in many global cities, with the highest levels of inequality and segregation often found in cities of lower income countries [21]. According to Gini Index data from the 2019 American Community Survey [1], Chicago has the 10th greatest income inequality amongst US cities, with a Gini index of 0.53 (where a 0 indicates perfect equality and 1 indicates perfect inequality). Compared to cities such as London and Johannesburg, which have the highest global Gini index values—both over 0.7—Chicago has a relatively medium-high level of income inequality [3]. As seen in Fig. 3, the areas of Chicago that are considered most socioeconomically disadvantaged based on factors such as unemployment and poverty level also overlap with many of the areas shown in Fig. 2 that have a majority Black or Latine population. Thus, we believe that Chicago provides a useful case study by which to examine the potential social and equity implications that sensing technologies can introduce in cities around the globe.

4 METHODS AND MATERIALS

For this work, we examined data from Microsoft Research's Eclipse network [5]. The nodes and network were designed and deployed to monitor air quality in Chicago, and are further described in [5].

4.1 Sensor Network Design

The sensor network comprised of 115 unique sensor node locations, broken down as follows:

- 80 devices placed based on locations chosen through stratified random sampling, as described in NYCCAS [9]
- 20 devices allocated to local environmental justice groups for placement according to their priorities
- 9 devices at three EPA stations, 3 devices at each station, for collocation to perform calibration

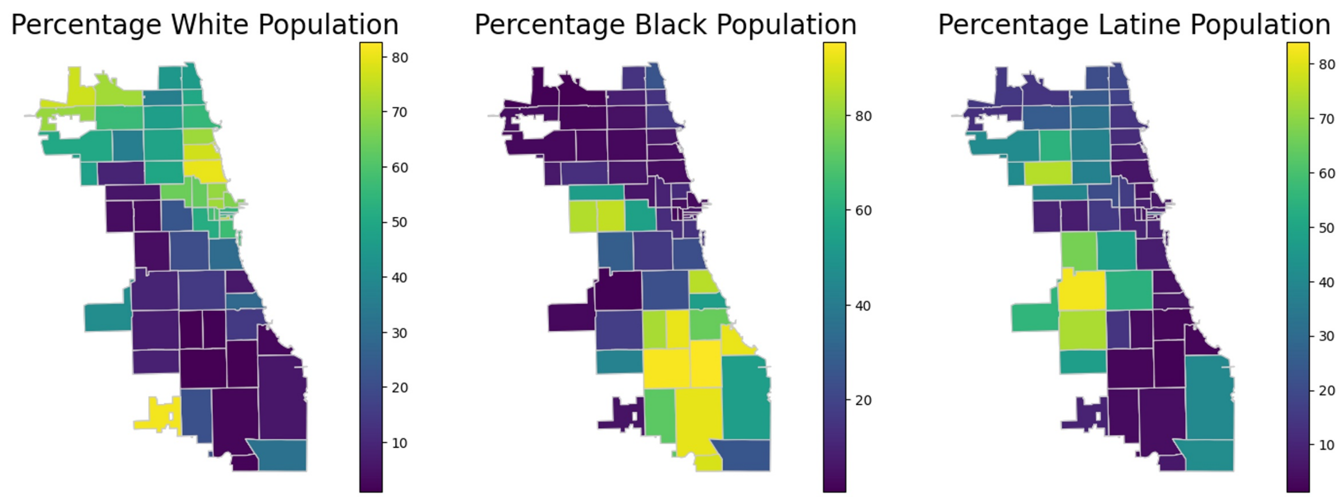

Figure 2: These maps show the city of Chicago with an outline of each zip code area. The zip codes are color coded by the percentage of each major race identified—White, Black, and Latine. The maps show that each of the races is concentrated in different areas of the city, highlighting how segregated Chicago is.

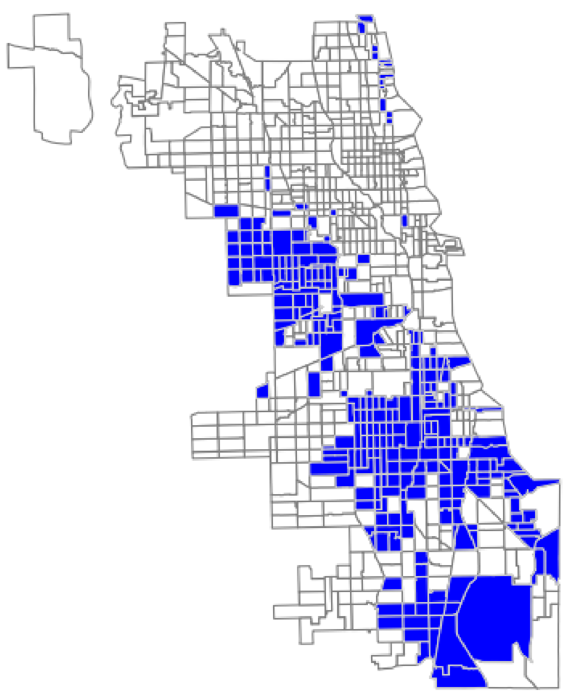

Figure 3: This map shows the city of Chicago broken down by census tracts, with the tracts deemed socioeconomically disadvantaged filled in blue. These areas were selected based on household income, poverty rate, and unemployment rate for the purpose of promoting equitable hiring [11]. Many of these areas overlap with the zip codes that are majority Black or Latine, as shown in Fig. 2, highlighting the numerous forms of inequality and segregation present in Chicago.

- 6 devices for partner organizations to address their priorities

All devices that were not at EPA stations were installed at bus shelters throughout the city, as shown in Fig 7. These nodes were placed at the same height, about 2.5 meters above ground. Nodes at EPA stations were located on the rooftops near the EPA monitors, several meters above ground and at different heights based on the height of the building or structure housing the EPA monitor. Most of the devices were installed at their respective locations in July and August 2021, with 98 nodes (over 83%) placed by July 3rd, 2021.

4.2 Solar Power and Power Saving Mode

Each sensing node was outfitted with a rechargeable 2000 mAh lithium polymer battery, which was charged using a 10×13 cm Voltaic Systems P126 6W solar panel. The solar panel was attached horizontally, in a flat position, to the top of the node's respective bus shelter to maximize solar absorption, maintain security of the panel, and provide ease of installation.

To optimize for low-power optimization, the microcontroller operated in a duty cycled mode, consuming as little as 40 μA between measurements. The device's four electrochemical gas sensors consume microwatts of power, while the particulate matter (PM) sensor consumes up to 80 mA power as it relies on an internal fan to circulate air. Thus to optimize the overall power usage, we sampled the gases every 60 seconds and sampled the PM and transmitted data every 5 minutes. On average, the device draws 4mA current over a 24 hour period, allowing the battery to power the sensing node for approximately 15 days at the aforementioned sampling rate.

In October 2021, we noticed that one of the devices was no longer charging. After sending the local maintenance team to investigate, we determined that the sun was no longer reaching the solar panel due to the change in the sun's position and the node's location surrounded by skyscrapers. Thus, we implemented a power-saving mode to put devices into a deep sleep to avoid depleting the batteries

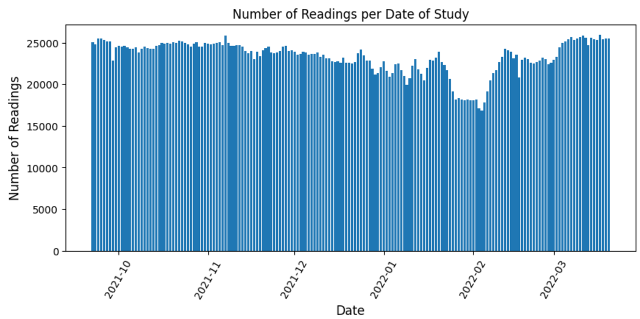

Figure 4: This plot shows the daily number of sensor readings between the autumn and spring equinox. There is a clear drop off in the number of daily readings during many of the winter days, especially in January and February.

in low- or no-light conditions. Power-saving mode was initiated when a battery's power level fell to 15% or less of its total capacity then turned off when the battery's power level had recharged to at least 40%.

4.3 Data Analysis

The battery level was logged with each device reading and stored in an Azure server. To identify devices that were in power saving mode, we wrote a function based on the logic to put devices in and out of power saving mode. We used OSM (Open Street Maps) Buildings [15] to gather data about buildings surrounding the nodes and the Shadow Accrual Maps tool [10] to calculate the amount of shadow hours at each node location. Socioeconomic data were pulled from the City of Chicago Open Data Portal [11].

5 RESULTS

5.1 Data Loss due to Power Saving Mode

Between the autumn and spring equinox of the year long study period, 44 devices (38.26%) went into power saving mode. Seven of these devices were at community selected sites, representing about 16% of the devices in power saving mode, indicating the community selected sites were not disproportionately affected.

Most devices experienced data loss to power saving mode between the month of January and March 2022, as shown in Fig. 4. In total, Devices in the networks spent 19,450,915 seconds — over 33,180 hours or 1382.5 days—in power saving mode, resulting in about 398,000 potential sensor readings that were not captured.

As shown in Fig. 5, most devices entered power saving mode numerous times, with several entering power saving mode more than five times during the study period. Thus, in many locations there may have been adequate sunlight to keep the devices charged throughout the winter months if a larger solar panel had been used or the devices had better energy harvesting to extend the battery life with the limited charge they received.

5.2 Location of Solar Charging Issues

As expected, the node locations in downtown Chicago entered power saving mode for a long duration of the winter due to the high number of very tall buildings in the neighborhood. However, several node locations in neighborhoods outside of downtown Chicago, that lack a high density of tall buildings, also experienced solar charging issues. In fact, the node location with the second highest amount of time spent in power saving mode was not in a location near tall buildings, and 8 of the 12 node locations that had the most power saving hours were outside of the downtown area, as shown in Fig. 8. As the figure also shows, an examination of the socioeconomic factors around these nodes revealed that they mostly fall in neighborhoods with a majority Black or Latine population. As seen in Fig. 7, shadows from trees could be a potential cause for charging issues in some areas. In addition, snow or ice build up on solar panels may cause charging issues, but this is difficult to diagnose without visiting every node location while it is in power saving mode. Thus, further analysis is required to determine why these node locations experience charging issues despite the lack of tall buildings in the vicinity.

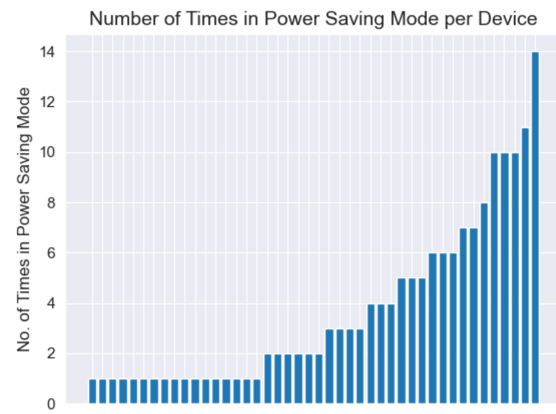

Figure 5: This bar plot shows the number of times that each device entered power saving mode. Many devices entered power saving mode numerous times, indicating that they were able to recharge, even throughout the winter months. Thus one potential solution to address this issue is to have larger solar panels or better energy harvesting for sensor nodes to continue reporting data throughout the winter months.

5.3 Predicting Solar Charging Issues

We used the OSM Buildings data [15] and Shadow Accrual Maps tool [10] to determine how well we would be able to predict a sensor location having power saving issues. With the OSM Buildings data, we examined the distance to the closest building, height of the closest building, and mean and median height of buildings within 100, 250, and 500 meters of each node location. For shadows, we used the tool to calculate the amount of time each node location was in shadow on the winter equinox, which is the shortest day (in terms of sunlight) of the year. Using both a logistic regression model for the binary case of power saving or not and a linear regression

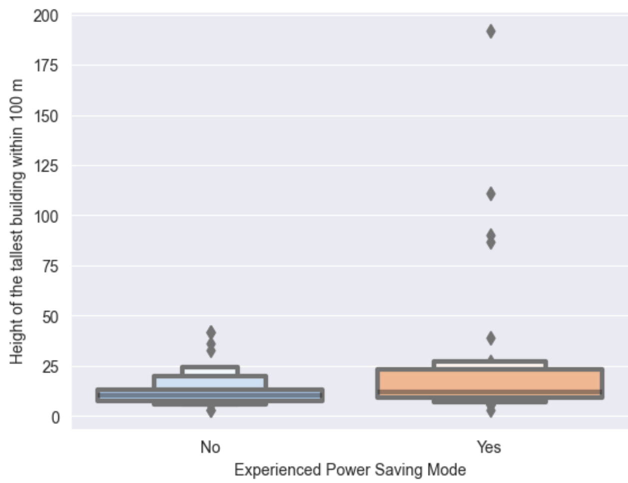

Figure 6: This boxplot shows a comparison of the height of the tallest building within 100 meters for node locations that experienced power saving mode to those that did not. Excluding the four buildings taller than 75 meters, the distribution of building heights is virtually the same for nodes that did and did not experience power saving mode, showing that access to building height is not always adequate to predicting solar charging issues.

Figure 7: This bus shelter, with the sensor shown in the red circle, is at a location that experienced power saving issues despite having no shadows recorded in the Shadow Accrual Maps [10]. It is likely that the large tree blocked the path between the sun and solar panel for several days in the winter. This highlights a challenge in having information about all of the physical objects that may block solar charging sensors in urban areas.

model for the amount of time spent in power saving mode, we found no statistical significance for either the amount of time spent in shadow, or any data related to buildings around the node locations, as highlighted for one data point in Fig. 6.

Upon further examination, we discovered that one of the issues around using crowdsourced data and open source resources is that they are not consistently updated. For example, one sensor node that was indicated to have shadow issues but did not enter power saving mode likely had a building present when the data were uploaded, but no longer has a building there as discovered on Google Maps. Likewise, as seen in Fig. 7, a node location with no building nearby that entered power saving mode was likely affected by the presence of a tree near the bus shelter, which was not captured in the tools we used, which are focused on buildings. This points to an additional shortcoming of the data available, which generally focuses on buildings and does not account for foliage, hyperlocal snowfall, and other physical phenomena that may impede the charging ability of solar panels.

6 DISCUSSION

6.1 Implications of Solar Power Issues

Despite the ubiquity of solar panels as the power source for wireless sensor networks, we found that they are not a reliable power source for urban sensor networks for cities at more northern or southern latitudes that have limited sunlight and thus will experience power issues in winter months. In addition, urban areas at latitudes closer to the equator will also experience solar charging issues during winter months if they have numerous tall buildings blocking the path of the sun. Thus, we need to continue research in alternative charging options, energy harvesting techniques, and battery-less sensors to ensure reliable power of sensor networks in urban settings.

In our study, we also found that solar charging issues are not all localized to areas with tall buildings and may be spread inequitably around a city. Thus, urban sensor network deployments have the potential to exacerbate existing societal inequalities by allowing for sensors to be more easily supported in some neighborhoods than others. In turn, this can increase the level of mistrust between residents and governments [13] and drive residents to make assumptions about the distribution of resources and harms in the city based on the physical presence of sensors [17].

6.2 Challenges around Data Access

Due to the lack of official up-to-date building information, we relied on open crowdsourced data from OSM Buildings to determine the location and height of buildings in the city. As with many open crowdsourced datasets, our data source was not completely accurate or up-to-date [20]. This was especially clear when discovering issues in shadow prediction using the Shadow Accrual Maps [10], which also relies on OSM data for building heights. Thus, relying on crowdsourced data makes it difficult to predict locations with solar charging issues or other difficulties that may arise due to building height, such as wireless connectivity [4].

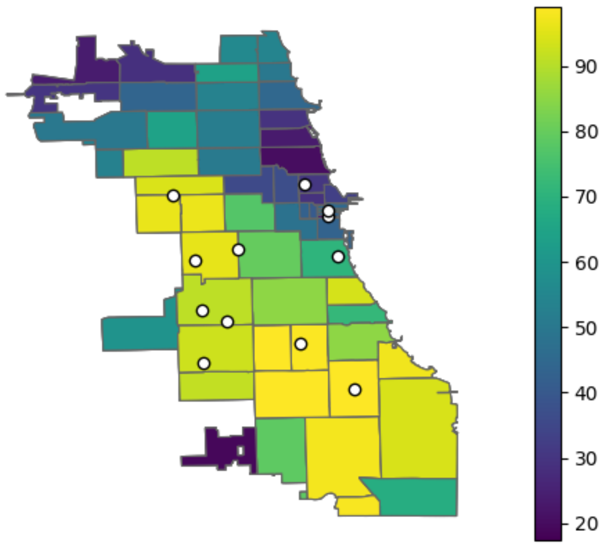

Figure 8: This map shows the sensor locations that spent the most amount of time in power saving mode, all with over 1100 hours of data loss. The map is color-coded by ZIP Code based on the percentage of non-white population, showing that the issue was more prominent in areas that had a higher non-white population.

The difficulty in working with crowdsourced data points to a need for new methods to obtain up-to-date building data. For example, researchers can help develop ways to obtain building height from satellite imagery or Google Maps. We may also look to develop easier ways for cities to create their own building databases that are kept up-to-date or develop better community science incentives to keep crowdsourced data sources such as OSM Buildings up-to-date.

7 CONCLUSION

In this work we present the power analysis of a large-scale, solar-powered sensor network across the city of Chicago. We find that a significant number of devices experience issues charging during the winter months and that it is difficult to predict which devices will have charging issues due to the limitations of open crowdsourced data. Furthermore, we discover that many of the devices with the most data loss from limited charging are located in areas that are a majority Black or Latine, pointing to the potential for sensing technologies to further the digital divide. This work presents essential findings for real-world urban sensor network design and deployment, and highlights a number of future research directions to improve urban sensor network reliability.

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