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Data Descriptor

Home Comfort Dataset: Acquired from SGH

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Abstract: In this work, we share the dataset collected during the Smart Green Homes (SGH) project. The project's goal was to develop integrated products and technology solutions for households, as well as to improve the standards of comfort and user satisfaction. This was to be achieved while improving household energy efficiency and reducing the usage of gaseous pollutants, in response to the planet's sustainability issues. One of the tasks executed within the project was the collection of data from volunteers' homes, including environmental information and the level of comfort as perceived by the volunteers themselves. While used in the original project, the resulting dataset contains valuable information that could not be explored at the time. We now share this dataset with the community, which can be used for various scenarios. These may include heating appliance optimisation, presence detection and environmental prediction.

Dataset: https://doi.org/10.48527/RXSATI.

Dataset License: CC0 1.0.

Keywords: dataset; IoT; home comfort temperature

check for updates

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1. Summary

Some of the major environmental policy concerns are related to energy production and consumption, which is often linked to the emission of polluting gases that contribute to increasing the greenhouse effect [1]. An estimated 40% of global energy consumption is related to buildings, three-quarters of which are residential. One of the largest responsible actors of domestic energy consumption is climate control, which is a factor that most house occupants do not want to abdicate, despite the increase in environmental awareness. To tackle this problem, a few solutions to reduce energy consumption in home heating scenarios are being explored [2]. A general solution for this problem has not yet been widely deployed since there are a high number of different scenarios and variables: buildings have different dynamics, the occupants have different routines and the climate varies across the world [3].

This problem was the motivation for the Smart Green Homes (SGH) project [4]. The project's main focus was to develop integrated products and technological solutions for households. These solutions would raise standards of comfort and user satisfaction to a new level through the use of several technical advancements. At the same time, it would respond to the planet's sustainability problems, by increasing energy efficiency and reducing the emission of gaseous pollutants and the consumption of water. This study did not aim to reduce energy consumption directly but instead focused on creating an efficient and correct method to collect data about a family house's thermal comfort. This dataset can then be used to develop new strategies to solve the mentioned environmental problems. It is important to mention that the anonymity and confidentiality of each of the participant's data were major concerns, since this study involves sensitive data.

The dataset presented in this document has been used within the project SGH and also within a different study focused on developing methods to address the issue of missing data [5]. Given the nature of the scenario where this dataset was gathered, there are some missing values, which mainly occurred when the battery or WiFi connection failed. It was for this reason that this dataset was selected for the missing value evaluation.

To the best of our knowledge, there are not many home comfort datasets that could be used for our specific task. Nevertheless, there are some studies related to ours. For example, the following datasets [6,7] capture the effect of thermal comfort for the elderly. Our dataset is not limited to the elderly, with the volunteers being mainly young adults. Another dataset [8] correlates the effects of home occupancy with the usage of air conditioning in Italy. Our dataset was gathered in Portugal and is not limited to air conditioning appliances, since the volunteers could use whichever appliance they wished to control the temperature. Another important difference is that we also captured the outside temperature and humidity because the thermal sensation of comfort is rather hard to classify.

Furthermore, there are several works [9–11] that explore the usage of thermal comfort to optimise the usage of heating appliances. Most of these studies rely on empirical models designed to model a person's comfort level. The objective of our study was to acquire these data and use them to train models that could be adjusted for each person.

The remaining document is organised as follows. In Section 2, we summarise the procedure to acquire the dataset. Section 3 presents the description of the dataset fields and their respective meaning. In Section 4, we present a statistical validation that is useful to validate the quality of the presented dataset. The example code, which can be used to generate the plots presented in the previously mentioned section, is described in Section 5. Finally, Section 6 provides concluding remarks.

2. Methods

The goal of this work was to conduct an indoor thermal comfort study based on Portuguese families' lifestyles and the Mediterranean climate. The main factors influencing thermal comfort are metabolic rate, clothing insulation, air temperature, mean radiant temperature, airspeed and relative humidity [12]. Due to the fact that this study consists of a thermal comfort study, the collected data focus on measuring these parameters. Other features were also collected: outdoor measurements and information about the presence of people in the house. We would have liked to measure the energy consumption of the heating appliances; however, all the methods to measure this are either expensive, intrusive or may even present some harm to the volunteers.

The acquisition solution was based on an Internet of Things (IoT) platform [13,14] and several environmental sensors. IoT platforms allow for the monitoring of the devices that collect data, and the data collection process itself so that faults can be detected whenever a component is not functioning correctly.

With regard to sensing devices, technological advances in recent decades have made sensors small, inexpensive and easy to install, promoting their integration into non-industrial environments. Furthermore, they measure the environment with precision and provide reliable data readings, which makes them a good approach for monitoring domestic buildings.

Taking into account the project scenario, the data acquisition task had a well-defined set of requirements:

- Scalability: the platform should be able to support the increase in the number of connected devices, the increase in the associated data flow, and the increase in the amount of data to store.
- Interoperability: the platform should be able to support multiple communication standards between the platform and the sensors. If this is not possible, it should at least allow for the implementation of new communication protocols without the need to restructure the entire architecture.

- Flexibility: the flexibility of the platform is also related to the easiness of implementing different technologies and modules in the platform to perform certain tasks.
- Security and Privacy: since the platform works with sensitive data, it must ensure the integrity and confidentiality of the information. The platform must prevent any kind of unauthorised disclosure of the user data, as well as protect them from being lost, destroyed, corrupted, modified or stolen.
- Availability: it is important to ensure that the platform works properly most of the time because failures decrease the quality of the collected data.
- Robustness: the system should automatically recover from failures when possible because it is faster than handling the problem manually, which would increase the downtime of the platform.

Having the requirements clearly defined, a data acquisition platform was developed within the SGH project. The main component of the acquisition mechanism was the IoT platform, named Smart Cloud of Things (SCoT) (see Figure 1), developed specifically for the scenarios explored within the SGH project. It was able to not only receive data from several sensors or gateways and store all the information in the appropriate databases, but also to offer visualisation and pre-processing services to guarantee the quality of the acquired data. Given the focus of this document, we will not cover all the details of the acquisition platform. For more information, please check [13,14].

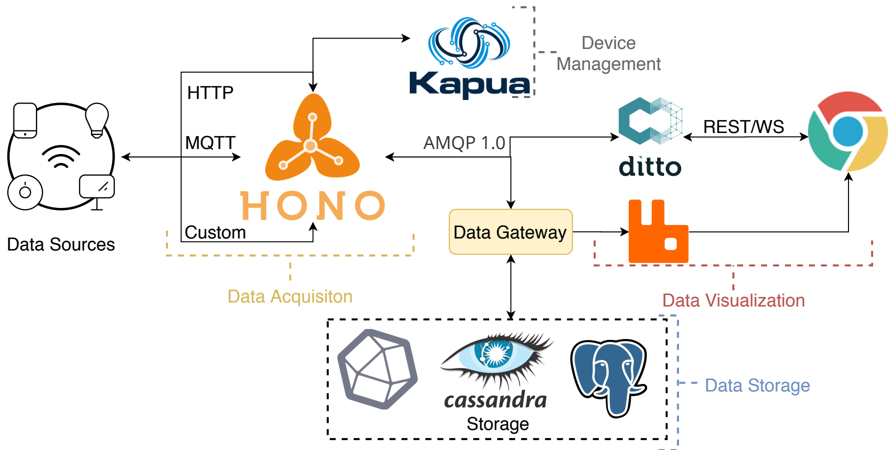


Figure 1. SCoT's architecture used for data acquisition.

The following paragraphs describe the main features of this platform, which was designed to meet the presented requirements.

The platform is based on three key services from the Eclipse Stack: Hono, Ditto and Kapua. It was further extended with custom services. These components were chosen because they cover most of the initial requirements while providing a high level of integration between them. Moreover, they are part of the Eclipse IoT (https://iot.eclipse.org/, accessed on 24 February 2023) initiative, which is well known and heavily used in this area. This approach makes updating the system an easier task, while maintaining essential performance functions under the control of the platform owners.

It is also important to mention that both the broker (Hono) and the digital twin service (Ditto) have user credentials and access policies. Each sensor/gateway has its own access credentials. It is also possible to control which users have access to them through the use of different policies. There are two types of connections that must be developed to the physical device: an incoming connection, to have access to the data; and an outgoing connection, to be able to send commands. For more detail on the automatic mapping used on our deployment, please consult [14].

Finally, IoT scenarios are inherently complex due to the data heterogeneity [15]. It becomes rather difficult to have a single database model to store the data and provide a meaningful structure. This was the reason why we developed a *Data Gateway* component.

It uses a smart parser to transform the collected information and save it correctly in three different databases, replicating it: Apache Cassandra, a NoSQL database; PostgreSQL, a relational database; and InfluxDB, a time-series database. For more details on this component, please consult [14].

The IoT platform communicated to several gateways with the use of the MQTT protocol. Each gateway communicated to several sensors through ZigBee.

The gateway acts as an intermediary between the sensors and the platform. Most sensors do not have enough computational power to directly communicate with the data acquisition platform, due to the communication protocol or the required security mechanism. In these cases, a gateway can translate all the messages from the sensors and forward them to the platform, or vice versa. This improves the security of the communications and the stability of the acquisition platform. It also promotes the heterogeneity of the system, as it allows for the usage of a higher variety of sensors. Finally, the gateway can be custom-configured to meet the requirements of the sensors in use, as long as it respects the connectivity and security policies established by the platform.

The gateway was implemented on top of the Yocto project [16] and deployed on a NanoPi NEO2 [17]. The Yocto Project is an open-source collaboration project that helps developers create custom embedded Linux distributions. It is built around the concept of layers, recipes and a reference-embedded OS named Poky. A recipe is a list of instructions for building packages that are then used to build the binary image. It describes where to get the source code, dependencies for libraries or other recipes, as well as configuration and compilation options. They are stored in layers. Layers are repositories containing related sets of settings and instructions which tell the build system what to do. An image can and should be created with the use of multiple layers. Putting an entire build into one layer limits and complicates future customisation and reuse. However, distributing information into different layers simplifies future customisations and allows for the reuse of work. In addition, users can collaborate, share and reuse layers.

NanoPi-NEO2 is an ARM board released by FriendlyElec that is widely used in IoT projects. It uses an Allwinner's 64-bit H5 quad-core SoC (ARM Cortex-A53) and 512 MB of DDR3 Random Access Memory (RAM). It has a 10/100/1000 M Ethernet jack, a USB type A host, a MicroSD Slot for system boot and storage up to 128 GB and MicroUSB entry for power input (5V/2A).

The gateway was connected to a ZigBee USB stick designated CC2531. It allowed for the gateway to connect to each sensor. Through the Zigbee2mqtt bridge, the gateway forwarded all the sensors' communication through MQTT to the platform.

Three different sensors were selected for the data acquisition process: Xiaomi Aqara sensor, Xiaomi Aqara door sensor and Xiaomi Aqara temperature and humidity sensor. As seen in Figure 2. All of the sensors communicate with the gateway through ZigBee.

(a) (b) (c)

Figure 2. The sensors used for the data acquisition process. (**a**) Motion sensor. (**b**) Door sensor. (**c**) Temperature and humidity sensor.

The Aqara Motion Sensor (RTCGQ11LM) can detect motion at a 170° angle and a maximum of 7 m. It consists of an infrared sensor used to detect human motion through the moving heat source, being able to detect once every minute by default and going to sleep mode after it is triggered to save battery.

The Aqara Door and Window Sensor (MCCGQ11LM) detects the current status of doors or windows through the distance between the sensor unit and a magnet.

The temperature and humidity sensor (WSDCGQ11LM) monitors temperature, humidity and atmospheric pressure in real time. It adopts a Sensirion industrial-grade sensor which has the humidity detection accuracy of ±3% and temperature detection accuracy of ±0.3 °C. If the temperature variation exceeds 0.5 °C, the humidity variation exceeds 6% or the atmospheric pressure is no less than 25 Pa, data will be reported instantly. Otherwise, data will only be reported once per hour, approximately.

Finally, the outdoor conditions were acquired through a virtual sensor that gathered the data from the Portuguese weather service [18] based on the location of the gateway. None of the available sensors were capable of operating outdoors, and there were no guarantees that the WiFi signal was going to be available.

The described framework was installed in 13 houses, with varying types of heating and cooling systems, and across two cities (distanced by around 65 km). The data collection occurred from the 1st of March 2019 to the 23rd of November 2020 (corresponding to a period of 21 months). However, the study start and end dates varied between tenants. Each of the 13 houses represents one volunteer that was contacted through the SGH project. Each one of them needed to sign a consent form as required by the General Data Protection Regulation (RGPD in Portugal [19]). As already mentioned, the anonymity and confidentiality of the volunteers were a requirement from the start. The acquisition platform used an anonymised UUID to identify each gateway, ensuring that it would not have access to any personal information regarding the volunteers. The only information it received was the environmental data described in this document. Such details are depicted in Table 1.

Table 1. Period of the logs for each tenant, including the first and last log dates, and the rate of hours for which there was at least a log (concerning months of activity for each tenant).

Tenant	City	Start Date	End Date	Rate of Hours with at Least One Log
020102d29c86	Aveiro	10-07-2019	02-01-2020	41%
020114a6a800	Aveiro	02-04-2019	02-04-2020	69%
020125bce03a	Lamego	01-03-2019	28-02-2020	87%
020149c615c5	Aveiro	04-03-2019	23-11-2020	62%
02015d5c61cc	Aveiro	01-03-2019	13-12-2019	78%
020177a7a91d	Aveiro	01-03-2019	22-10-2020	74%
02018fe9be2c	Lamego	03-03-2019	23-11-2020	79%
02019d93db3f	Aveiro	02-03-2019	14-03-2020	67%
0201a17a7a16	Lamego	02-04-2019	02-10-2019	33%
0201a8c87da4	Aveiro	01-03-2019	23-11-2020	81%
0201b9b7d045	Aveiro	10-07-2019	23-11-2020	70%
0201e9248493	Aveiro	01-03-2019	23-06-2020	72%
0201f6cb55ed	Aveiro	02-04-2019	23-11-2020	80%

3. Data Records

The dataset is comprised 13 Comma-Separated Values (CSV) files, each one containing the logs associated with each tenant. The name of each file contains the respective tenant identification. Each file is divided into two columns: the date and the information. The first line has the purpose of naming each of them `name` and `info`, respectively, for processing purposes. Each one of the remaining lines on the files corresponds to an entry, which always contains both a timestamp and a JSON structure with the details provided by one of the sensors or gateway. The only way to identify the originating device of the entry is to look at the fields on the message itself. There are a total of 7 different structures, each one from a distinct source. These can be:

- Information regarding the state of the system.
  The message contains two fields: `device` and `state`. `device` can contain one of the following three: the ID of the corresponding tenant—in which case, the `state` will be either ‘‘`online`’’ or ‘‘`offline`’’; the string ‘‘`feedback`’’—which is always accompanied by ‘‘`not home`’’ in `device`; or the string ‘‘`status`’’—in which case `device` will be either ‘‘`online`’’, ‘‘`offline`’’ or ‘‘`Dongle has to reset`’’.
  The three possibilities described here are summarised in the following representations.

```
{‘‘device’’: <tenant_id>, ‘‘state’’: ‘‘online’’|‘‘offline’’}
{‘‘device’’: ‘‘feedback’’, ‘‘state’’: ‘‘not home’’}
{‘‘device’’: ‘‘status’’, ‘‘state’’: ‘‘online’’|‘‘offline’’|‘‘Dongle has to reset’’}
```

- Readings from the sensor of temperature, humidity and pressure.
  The `temperature` field is always filled up with real numbers ranging from 11.22 to 35.51. Similarly, the `linkquality` field always has a value—an integer, from 0 to 123. Both the `humidity` and `pressure` fields can have real numbers or not be included. `humidity` ranges from 26.78 to 96.1 while `pressure` ranges from 922.0 to 1032.8.
  A representation of this message is as follows.

```
{‘‘temperature’’: <float>, ‘‘linkquality’’: <int>,
‘‘humidity’’: <float>|None, ‘‘pressure’’: <float>|None}
```

- Readings from the sensors measuring the status of the doors or windows.
  In this message, two fields are always present: `contact`—which is either `true` or `false`; and `linkquality`—which is an integer between 0 and 115. Furthermore, some have a `battery` field, containing an integer between 31 and 100, and also a `voltage` field, with another integer between 2955 and 3125.
  A representation of the format for this message is as follows.

```
{‘‘contact’’: <bool>, ‘‘linkquality’’: <int>, ‘‘battery’’: <int>|None,
‘‘voltage’’: <int>|None}
```

- Readings from the motion detectors.
  Similarly to the previous one, this structure has two fields that are always present: `illuminance`, which is an integer number between 0 and 1000; `linkquality`, an integer value between 0 and 134. There can be information on `occupancy`, which is a Boolean value; on `battery`, which can have an integer between 42 and 100; and `voltage`, which can also have an integer between 2975 ad 3065. A representation of the format for this message is as follows.

```
{‘‘illuminance’’: <int>, ‘‘linkquality’’: <int>, ‘‘occupancy’’: <bool>|None,
‘‘battery’’: <int>|None, ‘‘voltage’’: <int>|None}
```

- Information about meteorologic conditions.
  This entry always contains a `description` field consisting of a string with the name of a place and followed by a date and hour. Even though this field is present in all entries, some have the word `null` in place of the local. Furthermore, always present are the fields `windspeed`—a real number between 0 and 52.9; `humidity`—an integer value comprised between −99 and 100; and `temperature`—another real number between −99 and 36.2. This entry may have a `winddirection` field, which contains a string naming one of the eight cardinal and ordinal points in Portuguese. Additionally, a `pressure` field may be present, with real numbers ranging from 996.2 to 1036.7. It can also contain a field `precipitation` with real numbers between 0 and 13.8.
  A representation of the format for this message is as follows.

```
{‘‘pressure’’: <float>|None, ‘‘windspeed’’: <float>,
‘‘description’’: ‘‘<local>|null @ <time>’’, ‘‘precipitation’’: <float>|None,
‘‘winddirection’’: ‘‘<cardinal/ordinal point>|None’’, ‘‘humidity’’: <int>,
‘‘temperature’’: <float>}
```

- Feedback from the tenant.
  In this message, the field `device` always has the string ‘‘`feedback`’’, while the required field `feedback` can be either ‘‘`comfortable`’’, ‘‘`uncomfortable`’’ or ‘‘`not home`’’.
  A representation of the format for this message is as follows.

```
{‘‘feedback’’: ‘‘comfortable’’|‘‘uncomfortable’’|‘‘not home’’,
‘‘device’’: ‘‘feedback’’}
```

Even though some files may have information dating prior to the 1st of March 2019, these entries should be ignored, since they were collected using a beta version of the software. We kept all the records since we did not want to change the data records. The files can be found at https://doi.org/10.48527/RXSATI (accessed on 24 February 2023). It is important to mention that the dataset is licensed under “Creative Commons Attribution 4.0 International”.

4. Technical Validation

The sensors were selected for the data acquisition based on their accuracy and quality (as described in Section 2). Each one of them exceeded the required sensitivity level for the proposed scenario. Furthermore, each kit was manually calibrated in the laboratory before being delivered to a volunteer.

The volunteers followed a setup guide that guaranteed the correct installation and communication with the acquisition platform. This platform kept track of the communication flow with each kit, allowing us to discover any issues with the acquisition process. There were no major issues encountered, with the most common one being the low battery on the sensors.

The dataset has some missing values, justified by the low battery and the occasional WiFi connection issues. It was used within the work presented in [5] to evaluate matrix factorisation methods as a technique to predict these gaps in the data with high accuracy. The selection of this dataset comes from the fact that, even though some data are missing, it still provided enough information to accomplish the task.

We performed a simple statistical validation on the dataset. This was achieved by measuring the correlation between the values, averaged by day, gathered from all the tenants. In particular, the temperature, the relative humidity and the atmospheric pressure were the analysed fields. The results of this analysis can be found in Figures 3–5. The charts show that the correlation between the data of the multiple tenants are high, which is expected since the data represent environmental information. Therefore, even though the absolute values are different, the underlying pattern should be similar to a certain degree.

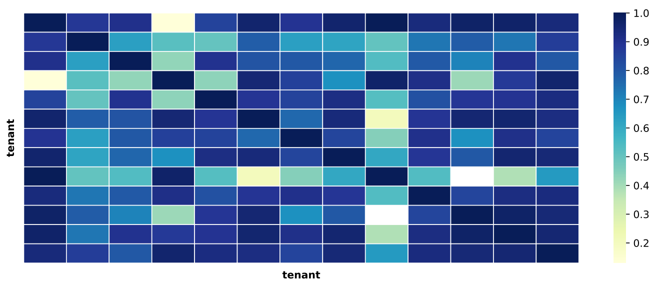


Figure 3. Correlation between the temperature, averaged by day, from all the tenants.

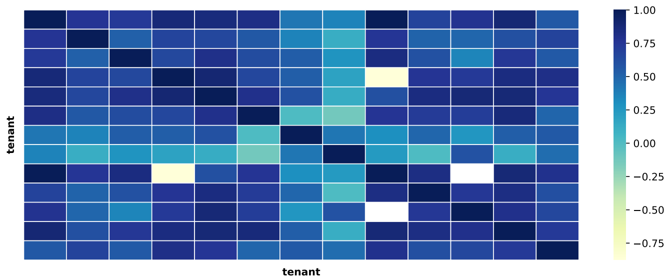


Figure 4. Correlation between the humidity, averaged by day, from all the tenants.

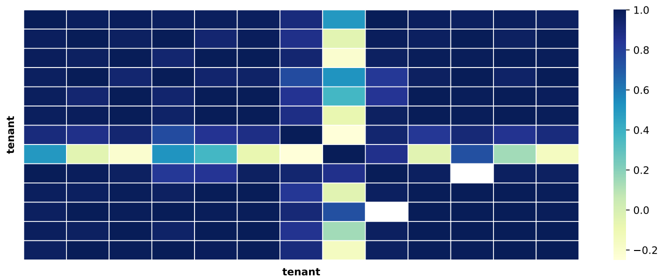


Figure 5. Correlation between the pressure, averaged by day, from all the tenants.

Moreover, we also analysed the dataset values to assess the quality of the data. In Section 4.1, we discuss the dataset distribution throughout the duration of the project. We analyse the distribution and variation of indoor temperature and humidity in Section 4.2. The occupancy analysis is given in Section 4.3. Finally, a combined evaluation of temperature and occupancy is presented in Section 4.4.

4.1. Data Distribution

When assessing the quality of the collected data, one important aspect to consider is how the data are distributed throughout the collection time span. The chart on Figure 6 was created with this goal in mind; it depicts the relative amount of missing data per month in the dataset. To create this chart, the number of entries per day for each month was averaged, and then divided by the maximum value obtained. Then, these results were subtracted from the value 1 so that they represent the relative amount of missing data.

The chart shows a non-uniform distribution of entries throughout the months. Its analysis shows that October 2020 was the month with the least amount of data, while September 2019 was the month during which the most data was collected.

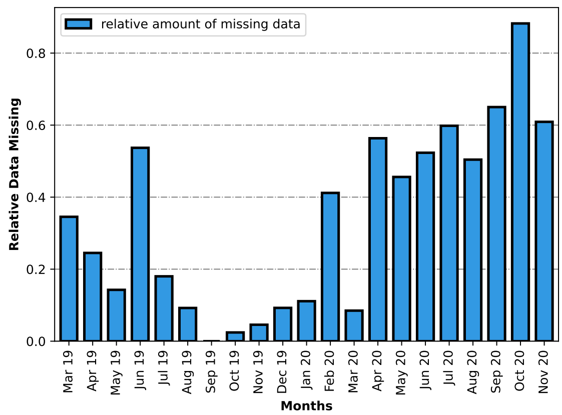


Figure 6. Relative amount of data missing.

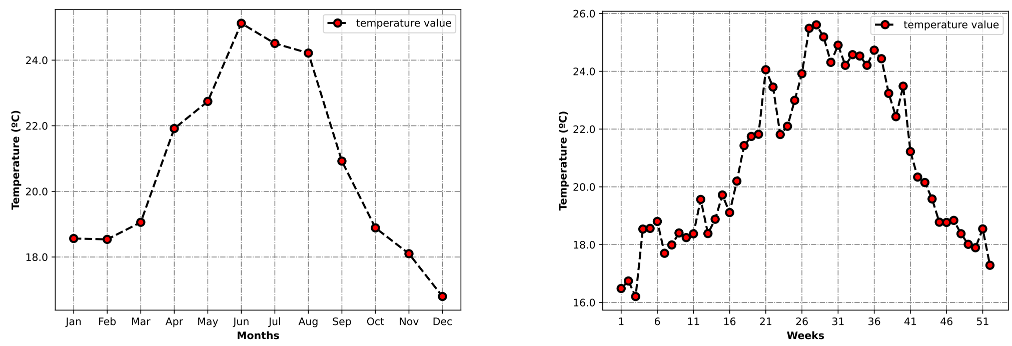
4.2. Temperature and Humidity Analysis

With the aim to analyse temperature and humidity data in the dataset, a few plots were designed. These are explored in the following subsections.

4.2.1. Average Temperature by Month and Week

Figure 7a shows the average temperature for each month of the year. As expected, the months with higher average temperatures were those in the Summer, with June being the warmest of all. The represented colder months also reflect reality, with December having the lower average of the collected temperature data.

The other figure, Figure 7b, displays similar information, having the temperature averaged for each week in a year. The conclusions drawn from analysing the previous chart are also applicable to this one. The general outline of the curve is similar, but it is possible to see some differences due to the increase in detail. In fact, the week that registered the lowest temperatures was January, instead of December.



(**a**) Averaged by month (**b**) Averaged by week

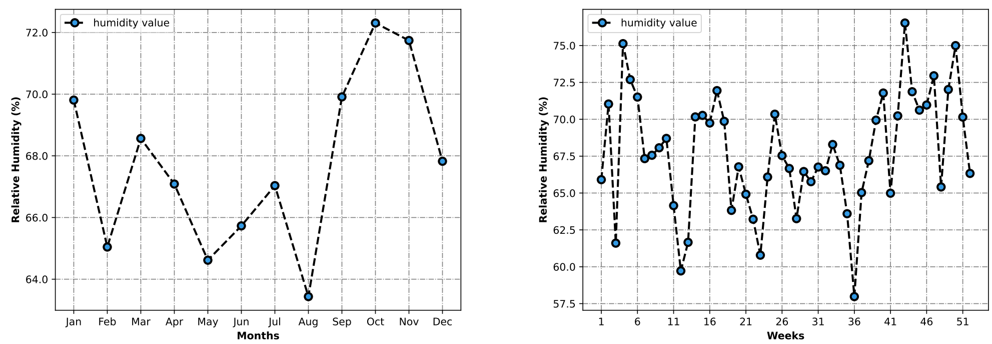
Figure 7. Charts depicting the average temperature by month (**a**) and by week **(b**).

4.2.2. Average Humidity by Month and Week

In a similar fashion to the previous charts, Figure 8 presents the humidity data averaged by months and also by weeks.

However, the results are not so typical. The chart in Figure 8a, depicting the average relative humidity by month, shows a tendency for lower relative humidity in the warmer months, but there are also outliers. One example is February, which is marked as having a lower relative humidity than both June and July, which is different from what was expected.

The curve in Figure 8b, describing the average humidity by week, portrays the same tendency. Even though the Summer weeks show an overall lower relative humidity, this value varies greatly from week to week, and from month to month.



(**a**) Averaged by month (**b**) Averaged by week

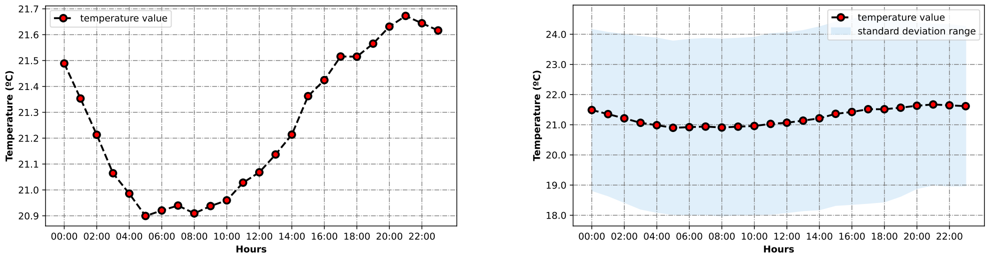
Figure 8. Charts depicting the average humidity by month (**a**) and by week (**b**).

4.2.3. Average Temperature by Hour

To further explore the temperature data, the two charts on Figure 9 were created.

The curves on both of the charts are exactly the same. They represent the average temperature for each hour of the day. On Figure 9a, the value variation throughout the day is more clear. Through its analysis, it is possible to determine that the lowest temperature is usually around 05:00 and 08:00, while the highest is around 21:00, which reflects normal values.

Figure 9b shows the same data as the previous plot, as well as a blue area which represents the standard deviation range for each value. Indeed, the standard deviation range is significant. Due to the fact that it represents an average of all the temperature data on the dataset, it contains many different ranges of values.



(**a**) Without standard deviation range (**b**) With standard deviation range

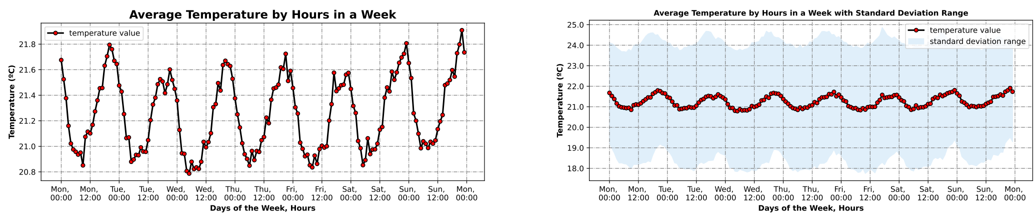
Figure 9. Charts depicting the average temperature by hour without (**a**) or with (**b**) standard deviation range.

4.2.4. Average Temperature by Hours in a Week

Aiming to analyse how the different weekdays impact temperature, the following two charts were drawn. Similar to the pair of images above (Figure 9), the curves on both of the charts on Figure 10 are exactly the same. For each hour on each day of the week, the values were averaged and put together in this chart.

In the first figure, Figure 10a, the repetition of the pattern on Figure 9a for each day of the week is clearly depicted. Upon further inspection, some differences can be seen. For example, it is possible to see that, on average, Sundays are the days with higher temperatures, when compared to the other days of the week. This is expected and reflects reality.

The other one, Figure 10b, comprises the same curve as the previous chart, and also a blue area covering the standard deviation range, using the same concept as in Figure 9b.



(**a**) Without standard deviation range (**b**) With standard deviation range

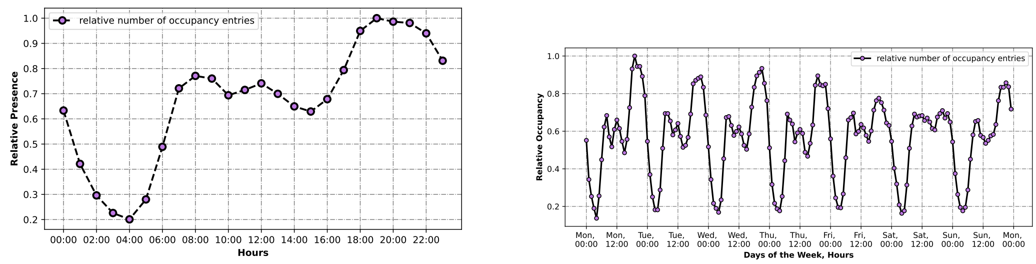
Figure 10. Charts depicting the average temperature by hours in a week without (**a**) or with (**b**) standard deviation range.

4.3. Occupancy Analysis

The following charts on Figure 11 delve into the occupancy data, which are present in the dataset in the form of multiple entries stating that movement was detected.

The first one, Figure 11a, came to be by counting all the hours when movement was detected per tenant. These values were summed by the hour and then divided by the maximum resulting value. Analysing the graph indicates that 19:00 was the hour when most tenants indicated movement, whereas 04:00 was the lowest. These values are expected.

The other one, Figure 11b, was created using the same principle, but the data were aggregated by hours in a week, instead of by hours in a day, similar to the graphs in Figure 10. By analysing the chart, it is possible to see that on Saturday there was not much movement data when compared to the other weekdays.



(**a**) By hour (**b**) By hours in a week

Figure 11. Relative occupancy by the hour (**a**) and by hours in a week (**b**).

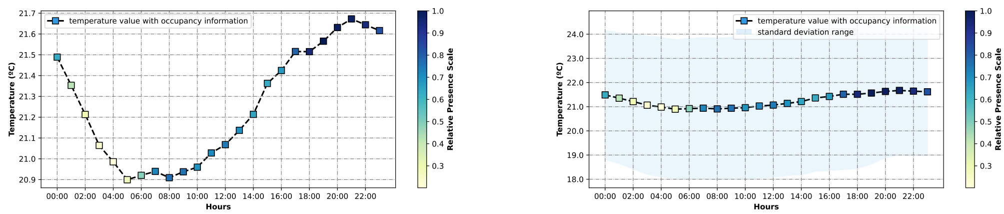
4.4. *Temperature with Occupancy Analysis*

The following subsections delve into the possible relationship between occupancy and temperature.

4.4.1. Average Temperature by Hour with Occupancy Information

The curves on the graphs on Figure 12 are in every way equal to those on Figure 9. The difference between the charts lies in the markers: the colour of these conveys information on the level of relative occupancy, taking advantage of the information described in Section 4.3. The darker the colour is, the higher the value of the relative occupancy, indicating a higher number of times the place was occupied.

As expected, when the occupancy had a higher value, the temperature also seemed to be higher. In fact, the maximum temperature value, 21:00, also corresponds to one of the maximum values of relative occupancy.



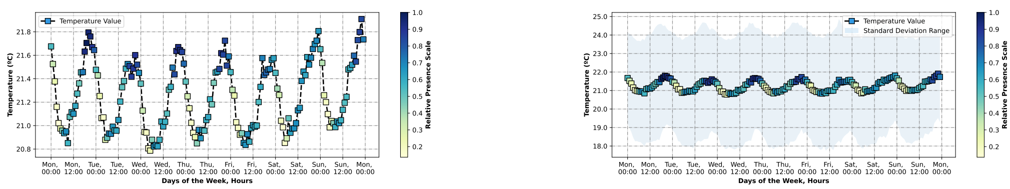
(**a**) Without standard deviation range (**b**) With standard deviation range

Figure 12. Temperature by the hour with occupancy information without (**a**) or with standard deviation range (**b**).

4.4.2. Average Temperature by Hours in a Week with Occupancy Information

Similarly to the previous pair of diagrams, on Figure 12, these next ones on Figure 13 also follow the same colour code. Furthermore, the curve depicted is the exact same as the one in Figure 10.

Analysing the data, it is possible to see the trends that have also been demonstrated by other charts; for example, the fact that Saturday afternoon has a lower occupancy when compared to the other afternoons.



(**a**) Without standard deviation range (**b**) With standard deviation range

Figure 13. Temperature by hours in a week with occupancy information without (**a**) or with standard deviation range (**b**).

5. Code Availability

In Section 4, we presented a detailed analysis of the dataset to assess the quality of the data acquisition process. The code used to conduct the analysis is publicly available and serves as a baseline for anyone that wants to process the data records. The code can be found on GitHub through the following link: https://github.com/immarianaas/home-comfort-dataset (accessed on 24 February 2023).

It is important to mention that the code provided is not used to generate the dataset or pre-process it in any manner. It serves only as a starting point for anyone that wants examples of how to process the dataset efficiently. As stated in Section 3, we did not make any alteration to the raw data acquired from the sensors and intend to share the dataset as acquired.

6. Conclusions

This document describes a dataset for home comfort temperature acquired during the execution of the SGH project. The dataset was used within the project for the analysis of thermal comfort and for training a Machine Learning (ML) model to predict the comfort temperature for each individual. Moreover, it was used as a validation dataset for a method that fills in missing values based on matrix factorisation [5].

Given the nature and the dimension of the dataset, it contains valuable information that could not be explored during the execution of the project.

There are several exploratory tasks that could take advantage of a dataset such as this one. For example, to predict the ideal temperature for a household, to optimise the usage of heating appliances, to develop models for occupancy prediction or even to test missing data replacement strategies.

Another possible use for the dataset is to simulate a large-scale deployment of an IoT scenario by replaying it. We are using this dataset to measure the overhead of multiple IoT communication protocols for continuous learning and deployment. This work will be presented in a future publication.

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