Towards Indoor Radon Analytics: An OLAP-based Multidimensional Approach

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Abstract: Indoor radon represents a known hazard to public health, namely, its relationship with lung cancer. The adoption of data analytics tools for indoor radon human exposure risk assessment is crucial for building management decision-making and is a fundamental requirement for the implementation of remediation measures. This work presents the implementation of a data warehouse and an OLAP cube as components of a more comprehensive IoT-based system, which has been developed for continuous indoor radon gas management in public buildings. The proposed data warehouse consists of a three-tier data storage structure to store historical measurements. Although the adopted approach has been tested with a small number of IoT sensors, the operation of the data warehouse and OLAP server assures that the system is viable and highly scalable. The increase in the number of active IoT sensors deployed in new buildings, cities, and districts will increase the richness of the data, which will help to foster even better models.

1 INTRODUCTION

Radon is a naturally occurring and chemically inert radioactive gas that is produced from the natural decay of uranium (^{238}U) which can be found in rocks and soil. Radon has no color, smell, or taste. It accumulates in enclosed spaces as it easily escapes from the ground into the indoor air. When the most stable isotope of radon (^{222}Rn) decays, it emits alpha particles, beta particles, and gamma rays (Darby et al., 2005). Due to its radioactive nature, it represents the second cause of lung cancer after smoking worldwide (WHO, 2017). Radon enters the body mainly through inhalation and it is in the lungs that its decay can cause damage in lung tissues. Radon and its decay products have been classified as carcinogenic since 1988 by the International Agency for Research on Cancer (IARC) (Gaskin et al., 2018). A study has shown that the risk of contracting lung cancer increases by 16% for every increase of 100 Bq.m^{-3} in radon concentration (Darby et al., 2005). Worldwide, inhalation of radon contributes to more than 40% of the annual dose of all ionizing radiation (APA, 2010). Since Radon is a hazardous air pollutant, when high concentrations are reached inside buildings, European Commission issued in 1990 the recommendation 90/142/Euratom to propose concentration limit values of 400 Bq.m^{-3} for old dwellings and 200 Bq.m^{-3} for new dwellings (The Commission of the European Communities, 2001). The Directive 2013/59/EURATOM, issued in 2013, forcing all member states to prepare a plan to limit

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exposition to radon gas and sets a concentration limit of 300 $Bq.m^{-3}$ (European Commission, 2014). Portugal transposed this directive into national law effectively since April 3, 2019, through Decree-Law No. 108/2018 (Curado et al., 2019).

Given the existing risk and the legislation in force, it is important to develop methodologies to evaluate and quantify the effective accumulated dose for the occupants of a building during a given period to implement remediation measures if necessary. Radon assessment campaigns can also be used to understand which factors, (internal and external), may impact indoor radon concentration. This has been the case in several studies conducted in the northern region of Portugal, which is a high-risk area (Curado et al., 2017). In the study, the authors used handheld meters to analyze the indoor radon concentration in three houses during two distinct year seasons. The results showed that human occupation along with passive ventilation strategies directly affected radon concentration. Similar results were also found in another study conducted in nine public buildings in the Alto Minho region (Curado & Lopes, 2016). However, while measurement campaigns are useful to assess the problem, they cannot implement real-time mitigation measures. To implement real-time mitigation is necessary to have systems that are continuously measuring radon concentration inside buildings. Since society is also increasingly concerned with energy-saving and energy efficiency, these systems can integrate other indoor air quality parameters and information on building occupancy to dynamically adapt remediation measures that will keep the balance between radon concentration and thermal comfort. When a building is occupied, radon levels should be at an acceptable level keeping atmospheric conditions within a comfortable range, but outside occupancy intervals energy savings can be maximized without adversely affecting radon levels in periods of occupancy.

Thus, the RnMonitor project (Online Monitoring Infrastructure and Active Mitigation Strategies for Indoor Radon Gas in Public Buildings in Nothern Region of Portugal) developed a system capable of online monitoring and actively mitigate radon concentration (Martins et al., 2020). The methodology described by Martins et al. corresponds to one of the RnMonitor platform modules that aggregates and displays the data collected in a set of critical buildings selected after an assessment campaign, during the first stage of the RnMonitor project execution. As there was no commercially available sensor to support the project requirements, an IoT-based multi-parameter sensor was developed for online monitoring of radon gas and other indoor air quality parameters. The measurements taken inside each compartment are transmitted hourly via radio communications to a local server. The proposed architecture uses a time-series InfluxDB database that records short-term measurements. Furthermore, it was implemented a data warehouse capable of storing long-term measurements and providing advanced analysis capabilities was yet to be implemented.

This paper presents the development and implementation of a multidimensional data warehouse that enables the RnMonitor platform not only to store long-term measurements but also to offer the possibility of using OLAP cubes to explore the data in a multidimensional way. Moreover, this work also presents the modelling and implementation of the ETL process for the creation of a data warehouse. It was coupled an OLAP server that will make use of the data warehouse. This document is structured as follows: Section 2 presents continuous monitoring systems for radon or air quality; section 3 presents the methodology to develop de data warehouse; results are presented and discussed in section 4; and, in section 5, conclusions are summarized.

2 RELATED WORKS

Over the years, several techniques have been developed for the measurement of radon concentration in air. Some of the best known are activated charcoal detectors, alpha-track detectors, and continuous radon detectors. Many campaigns are done with activated carbon detectors because they are easy to use and do not require electrical power during a collection campaign that lasts from two days to about a week. During the sampling period, the radon gas is absorbed by the activated charcoal following Van Der Wall's basic principle. The radon concentration is later determined in the laboratory by counting the gamma-ray emissions of lead (^{214}Pb) and bismuth (^{214}Bi), which are decay products of radon. Andreas C. George (1984) describes the use of this type of detector for the measurement of radon concentration.

Martín Sánchez et al. (2012) used an activated charcoal canister to identify 130 workplaces to perform a long-term study in Extremadura (Spain). The authors used this type of device since the exposure time required was only two days. Although these detectors are affordable and easy to install, they can only determine the average concentration. When it is necessary to measure the radon evolution over time, the use of portable electronic sensors is an advantage. In addition to being able to collect data over longer periods, some devices allow one to download the measurements for analysis. Using 13 portable radon monitor Airthings Corentium Plus in 13 rooms of a school in Viana do Castelo, Azevedo et al. (2020) & (2021), analyzed the evolution of radon concentration in the rooms over 41 days.

These equipment do not allow for active mitigation as the measurements are not processed in real-time by the device or sent to a cloud server for viewing, alerting, or activating a mitigation system. Zheng et al. (2016) developed a system for air quality monitoring using IoT techniques and Low Power Wide-Area (LPWA) wireless technology to transmit the data to the cloud where it is processed. Although this air quality monitoring system does not include radon measurement, the data transmission technology is interesting because it can cover a wide area. It was with this aim that a system that combines the use of IoT technologies and Low Power Wide-Area (LPWA) network communications has been developed (Sérgio I. Lopes et al., 2019). This continuous monitoring system, which the authors have called RnMonitor, makes use of IoT technologies and uses a license-free sub-gigahertz bidirectional LoRa communication to send the measurements. In a test using three LoRaWAN Gateways, the authors successfully covered the center of Viana do Castelo city with signal always below -100 dB while LoRa has an input sensibility of -148 dB (Sergio I. Lopes et al., 2019). The reader should notice that the development of the data warehouse presented in this paper is part of the RnMonitor platform. On the client-side, RnMonitor offers a front-end application that allows you to view the measurement sites with cartography-based navigation and a dashboard that makes use of Grafana to visualize the measurements over the last 24 hours, 1 week or 3 months. Additionally, Pereira et al. (2020) developed the RnProbe which is an IoT Edge device capable of measuring radon concentration, temperature, relative humidity, atmospheric pressure, and CO_2.

In the literature review, we did not find any online radon monitoring work combining the use of a data warehouse and OLAP. García-Tobar (2020) used an assessment campaign of two dwellings of a residential building in Madrid to build two OLAP cubes from the data. In other research domains, it is possible to find online monitoring systems that implement data warehouses. Soares et al. (2018) developed a data warehouse to store the water consumption of the municipality of Esposende in Nothern Portugal and thus monitor and analyze the water consumption to reduce water losses and improve water consumption management. Tshering et al. (2021) has created an IoT-based platform, using Apache Hadoop and Apache Kylin analytics engine, for continuous air quality monitoring to measure air pollution using a $PM_{2.5}$ particulate sensor.

3 SYSTEM IMPLEMENTATION

The proposed system allows the record of measurements in a multidimensional data warehouse and the use of OLAP cubes to explore the data using MDX queries. The data warehouse thus created allows keeping the historical data and pre-calculated measurements beyond the 2 years limit of the InfluxDB time series database.

3.1 RnMonitor Data Source

The data warehouse has two data sources provided by the RnMonitor platform: the application database (AppDB) and the time series database (TSDB). The data contained in these two databases can be accessed through a RESTful API providing several endpoints. The endpoints are protected using JSON Web Tokens (JWT) that must be sent in the header of each request made by the user.

The AppDB database is an open-source document-oriented NoSQL database MongoDB. Unlike relational databases, that store information in columns and rows, this type of database stores separate documents within a collection. The TSDB database is also an open-source database widely used in real-time monitoring applications, designed to be able to handle a high volume of queries and writes per second. Figure 1 shows the data model of the two databases of the RnMonitor platform.

The raw measurement data generated by the sensors are stored in the TSDB database in the ***"Measurements"*** table. There are ten attributes ***"fieldn"*** which correspond to the various air quality parameters measured where ***"n"*** corresponds to the ***"field_id"*** of the table ***"Field",*** a table that contains information about each of the parameters. Currently, the parameters analyzed are radon, temperature, CO_2, atmospheric pressure, and relative humidity.

In the AppDB database, one of the main tables is the table ***"Polygon"***, which can have four different types: compartment, building, county, and district. This table contains a parent-child relationship through an attribute indicating the parent polygon. Note that a compartment has always a building as a parent, a building has always a county as a parent and

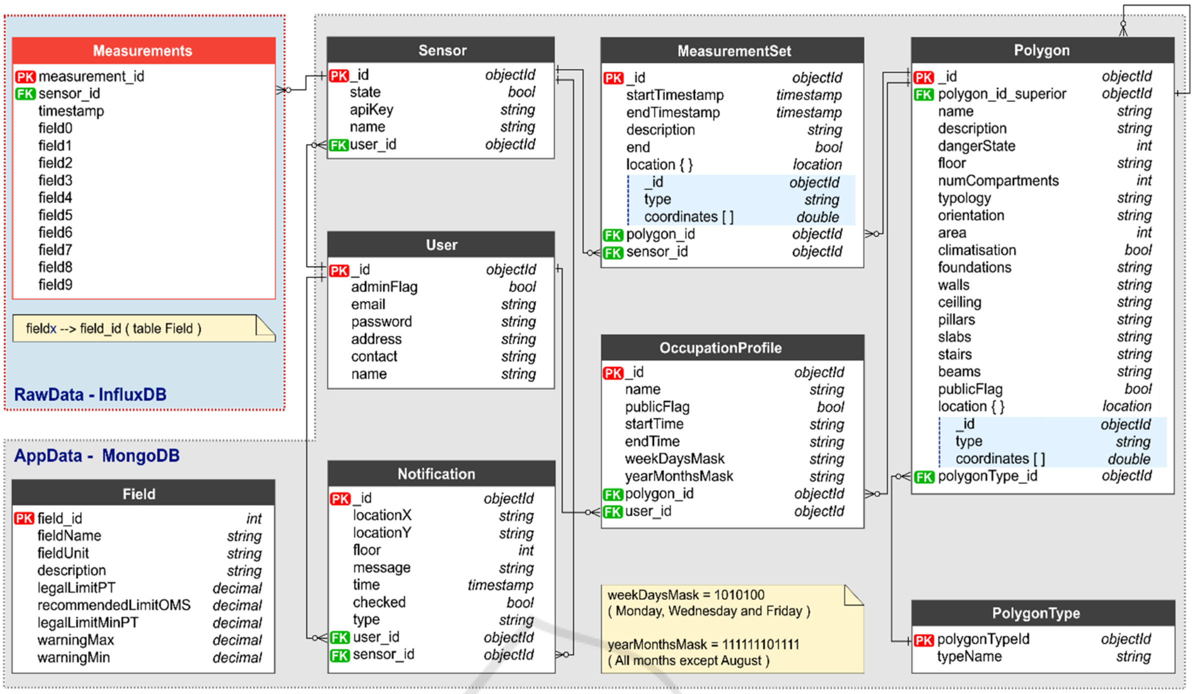

Figure 1: RnMonitor Databases model.

a county has always a district as a parent. The only polygon that has no parent is the so-called district because it is the highest order polygon. The ***"MeasurementSet"*** table is used to record the location of each of the sensors, as the same sensor may be used to take measurements in one room inside a building and later be removed to take measurements in a room inside another building in a different county. The sensor has no GPS locator, so its current location is only possible by looking at the ***"MeasurementSet"*** table.

The table ***"OccupationProfile"*** allows the creation of different occupation profiles for the same room or building for different users. This can be used to calculate the accumulated radon exposure dose for different workers depending on the time they spend in the compartment. The ***"Notification"*** and **"User"** tables, although implemented, do not contain useful information for the implementation of the data warehouse.

3.2 Data Warehouse

The data warehouse was implemented considering the AppDB and TSBD data models and the data analysis goals. The data warehouse model uses a star schema for easier understanding and faster queries. The model shown in Figure 2 is composed of three-dimensional tables and a fact table and two support tables. The ***"Dim_Polygon"*** dimension is the most important dimensional table. This table contains a parent-child relationship, where each polygon references its parent polygon through a foreign key that corresponds to the id of the parent polygon.

The fact table **"fact_measurement"** contains three calculated measures: ***"radon_kpi_pt"*** which corresponds to the value of radon/300 being 300 Bq.m^{-3} the radon limit in the Portuguese legislation; ***"radon_kpi_oms/100"*** being 100 Bq.m^{-3} the limit value advised by the WHO; ***"thi_value"*** which corresponds to the Temperature-Humidity Index (THI) value. This last attribute corresponds to the THI index, which represents the combination of temperature and humidity to measure the degree of thermal comfort experienced by an individual indoors. This index, developed originally by Thom (1959), combines the wet and dry bulb temperatures on a scale to mimic the thermal sensation of the human being. The Nieuwolt's (1977) modified THI correlates air temperature and relative humidity, allowing a more straightforward approach to rapidly assess indoor thermal discomfort based on the measurement of hygrothermal parameters. The Nieuwolts THI is defined by the following formula:

$$THI = 0.8 \times T + (T \times RH)/500$$

where T corresponds to indoor air temperature and RH to the indoor relative humidity.

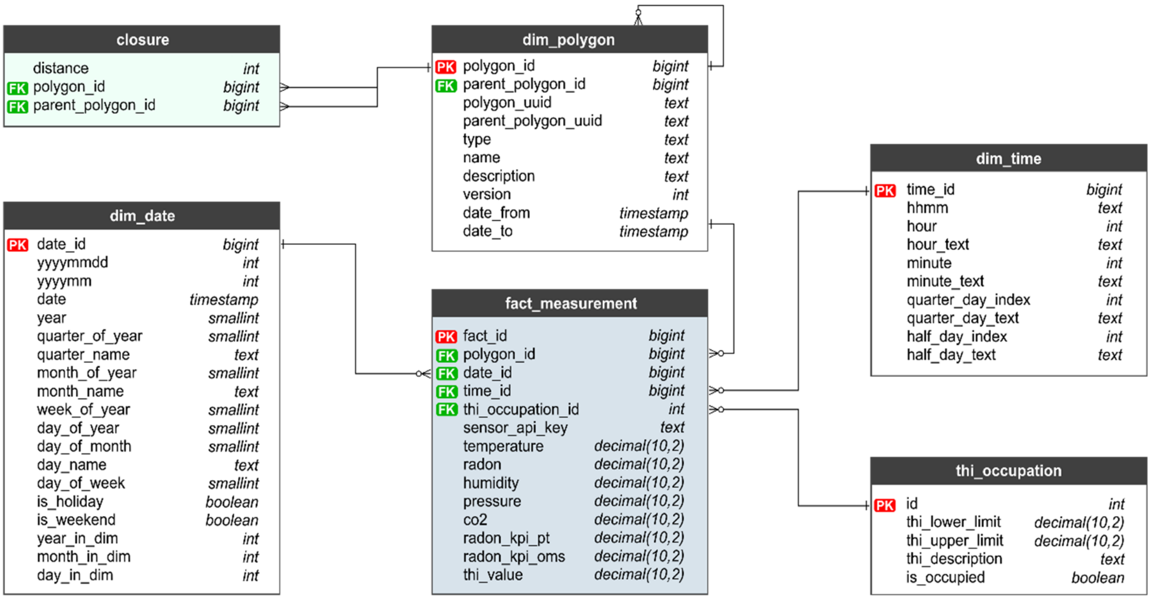

Figure 2: Data Warehouse Model.

The "Closure" table allows keeping the transitive closures of the parent-child relationships of ***"Dim_polygon"***. The hierarchy between parent and child is kept by the distance attribute that determines the distance between parent and child tuples. This table is necessary to the hierarchy definition in OLAP cube schemas when implemented on Mondrian OLAP Server. The table ***"thi_occupation"*** is used to normalize the non-quantitative attributes by removing them from the fact table and creating a table to register the different combinations. The combinations of the thi_occupation are defined in Table 1.

Table 1: Thi_occupation table content.

_id	thi_description	thi_lower	thi_uppert	Is_occupied
1	Too cold	0	8	false
2	Too cold	0	8	true
3	Need for heating	8	21	false
4	Need for heating	8	21	true
5	Comfortable	21	24	false
6	Comfortable	21	24	true
7	Need for ventilation	24	26	false
8	Need for ventilation	24	26	true
9	Too hot	26	99	false
10	Too hot	26	99	true
11	No THI data	0	0	false
12	No THI data	0	0	true

The range values for THI are defined by ***"thi_lower"*** and ***"thi_upper."*** For each ***"thi_description"*** that corresponds to a different THI interval, we have two possibilities for the compartment occupation represented by the ***"is_occupied"*** column.

3.3 ETL Process

The ETL process allows the creation of the data warehouse by extracting data from the two databases of the RnMonitor platform, manipulating and transforming the data, before loading it into the respective dimensional and fact tables of the data warehouse. The ETL process is executed once a day, thus loading the measurements performed in the previous 24 hours. The use of a data warehouse will allow a better understanding of radon behavior and discover patterns through advanced analysis techniques. That is why a daily update of the measurements is sufficient since mitigation actions can be triggered by the RnMonitor platform based on the online radon readings loaded in the TSDB database.

The ETL process was developed using Pentaho Data Integration (PDI) through the Spoon graphical interface. The transformations download data from both RnMonitor databases through several RESTful API endpoints. The ETL process is triggered by a single job that has the function of cascading several transformations. The execution of a transformation always depends on the conclusion of the previous one. There are two different ETL process execution flows. The first flow represented in the Figure 3 corresponds to the initial process. It is executed only once and serves to create the data

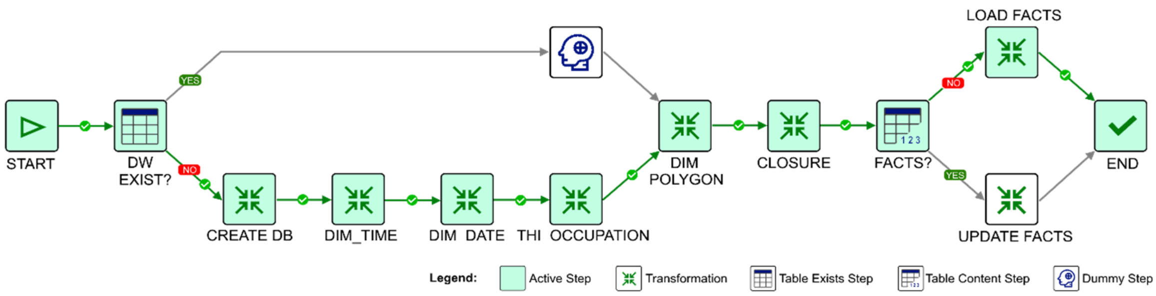

Figure 3: Initial ETL execution flow.

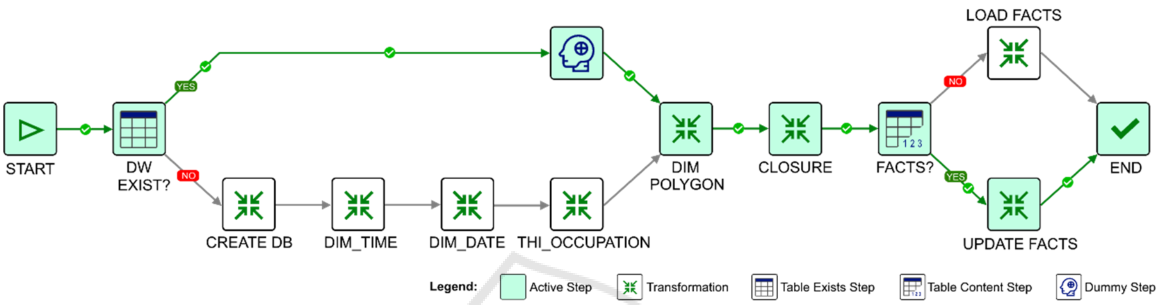

Figure 4: Update ETL execution flow.

warehouse and the various tables that compose it. It is during this phase that all the dimensional tables are populated and all the measurements that can be obtained from the TSDB are loaded. The second flow represented in Figure 4 corresponds to the update process. This process flow is the one executed daily. In case of any change in the polygons data, the ***"dim_polygon"*** dimension is updated using a Kimball slowly changing dimension of type 2. The closure table is recreated whenever the ***"dim_polygon"*** dimension has new polygons. During this execution flow the fact table ***"fact_measurements***" is loaded with the new measurements since the last update even if the system was down for several days.

3.4 OLAP

Online Analytical Processing (OLAP) is a technology that is part of many Businesses Intelligence (BI) applications and allows for complex analytical calculations. Aggregations, merging, and grouping in a relational database are not efficient. These operations are faster using OLAP since the data can be pre-calculated and pre-aggregated. Our solution provides an OLAP server to explore the cubes using MDX queries, and for that, we have used Mondrian as our OLAP Server. The data cube granularity is determined by combining the levels corresponding to each cube axis. We can change the level of granularity to a finer one or coarser one, producing a different cube measure value.

We can map members of the lower hierarchy to members of the higher hierarchy. With the members existing in our dimensional tables, the hierarchies of Figure 5 can be implemented on the cube.

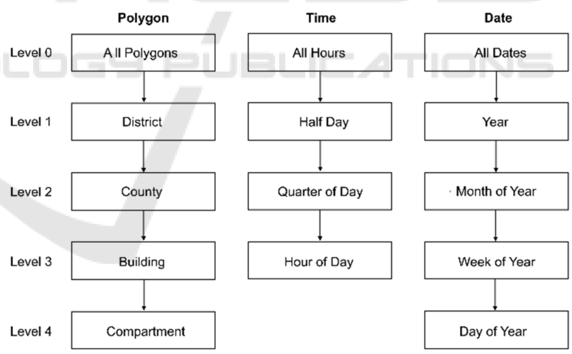

Figure 5: Dimension Hierarchies.

For the Mondrian OLAP server to use the data warehouse created, it must use a cube schema file. This XML file contains the definition of one or more OLAP cubes.

We can see the graphical representation of the cube schema in Figure 6. In this definition, we find the three dimensions with their respective hierarchies and levels. The dimensions, Time, and Date are defined outside the cube to be used in several cubes. The cube makes use of these dimensions through dimension usage. In **"Dim_Polygon"** dimension, only one hierarchical level is defined. since the relation between the polygons is defined by using a ***"closure"*** table, as the schema shows.

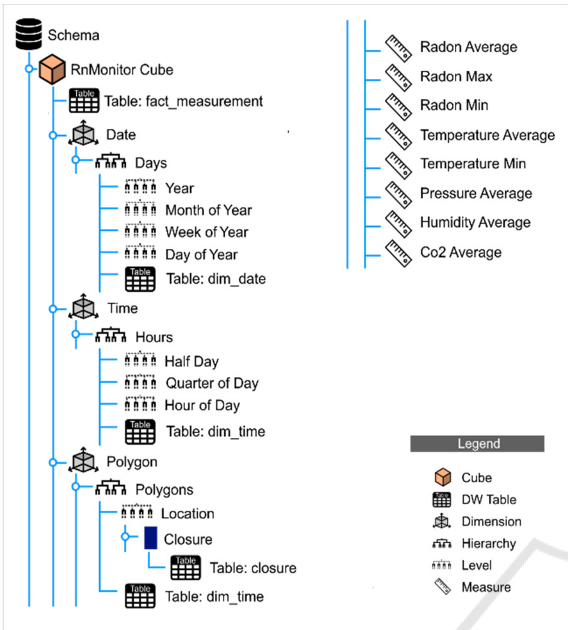

Figure 6: RnMonitor cube.

4 DISCUSSION

The data warehouse was validated by checking that the contents of the data warehouse and the data available in the two databases of the RnMonitor platform, RawData and AppData. The data warehouse content is structured according to the multidimensional schema. It contains all the records of the measurements gathered by the sensors since the beginning of the sensors' measurements. By 12 March 2022, the database contains more than 121,000 radon measurement records. The first measurement took place on 15 May 2015, and after more than 33 months the data warehouse has been updated daily proving that it supports long-term data recording (over 24 months).

Table 2: Data Warehouse content.

Total number of measurements	121 735
Data collection starting date	2019/05/15
Districts	3
Counties	10
Buildings	18
Compartments	22

The data warehouse will be used to create tools and develop strategies for radon mitigation. Table 2 show that the available measurements took place in 22 compartments of 18 different buildings located in 10 different counties which correspond to 3 different districts.

Table 3 shows the number of records per sensor in more detail. Currently, seven active sensors are gathering hourly measurements for the RnMonitor platform. More details about the implementation of the active sensors can be found in Pereira et al. (2020).

Table 3: Measurements by active sensor.

Sensor	Measurements	Start Date
D001	9554	2019-05-15T15:00:00
D003	22811	2019-05-15T15:00:00
D004	9545	2019-05-21T21:00:00
D007	8432	2019-07-05T00:00:00
D009	18246	2019-05-28T20:00:00
D0011	10273	2019-11-09T00:00:00
D0012	16457	2019-11-12T22:00:00

The validation of the OLAP server aimed to verify that the cube schema was functional and to make sure that MDX queries returned the expected results. As the Mondrian instance provides a graphical interface to test MDX queries, this functionality was tested using queries that correspond to simple OLAP operations. Since we installed the instance on a remote server, we ran the test through the browser of the Windows operating system computer and accessed the URL serving the GUI web page. Although the number of sensors that are carrying out the measurements is small, the perspective is to increase the number of sensors once the validation of the operation of the data warehouse and OLAP server confirms that the system is viable and has room to grow. The increase in the number of active sensors and the planned extension to other buildings, cities, and even districts will greatly enhance the richness of the data. A larger and more diversified data set will allow producing better models.

5 CONCLUSIONS

The assessment of indoor radon concentration and the mitigation of the associated exposure risks in public buildings becomes mandatory because European directives force member states to act to reduce the indoor exposure risk. The exposure to high radon concentrations increases the risk of developing lung cancer. This risk increases in areas with a specific geological constitution and poorly ventilated buildings. These two factors are prevalent in public buildings in the center and northern Portugal. In this context, the RnMonitor platform was created to perform continuous indoor radon monitoring in several public buildings in the North of Portugal. This paper presents the development of a data warehouse capable of storing all the measurements' history and some derived measures, which has been integrated as an additional module with the RnMonitor platform. The data are loaded to the data warehouse through the execution of an ETL process created for this purpose. An OLAP server has been coupled to the data warehouse to support OLAP cubes and business intelligence tools.

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