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# Understanding Seasonal Indoor Radon Variability from Data Collected with a LoRa-Enabled IoT Edge Device

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**Abstract:** The long-term assessment of radon (Rn) is a critical factor in evaluating the exposure risk faced by building occupants, and it plays a significant role in determining the implementation of Rn remediation strategies aimed at enhancing indoor air quality (IAQ). Meteorological parameters, such as temperature, relative humidity, and atmospheric pressure, as well as geological factors, such as soil properties, uranium content, rock formations, parent rock weathering, and water content, can significantly impact the assessment of Rn exposure risk and the selection of appropriate mitigation measures. A continuous monitoring campaign of a National Architectural Heritage building serving as a museum open to the public for a period of 546 consecutive days was conducted. The results of the in situ investigation revealed a broad range of seasonality in indoor Rn emission, with a negative correlation observed between Rn concentration and air temperature. The data indicated that indoor Rn concentration increases in the winter months as a result of reduced indoor air temperature and decreased air exchange, while it decreases in the summer months due to increased air temperature and enhanced natural ventilation. However, the implementation of high ventilation rates to improve IAQ may result in significant heat losses, thereby affecting the thermal comfort of building occupants during the winter months. Therefore, it is imperative to achieve a balance between ventilation practices and energy efficiency requirements to ensure both IAQ and thermal comfort for building occupants.

**Keywords:** indoor Rn concentration; LoRa-enabled IoT edge device; seasonality; continuous monitoring; exposure risk assessment; exposure risk mitigation



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## 1. Introduction

Radon ($^{222}Rn$) is a naturally occurring radioactive element, which is part of the progeny of Uranium ($^{238}U$) [1]. Since it is the only element of this progeny that occurs in the gaseous state, Rn emission is particularly important given the risk of inhalation in indoor environments, completing its decay process inside the lungs. Given the Rn half-life of 3.8 days, the continuous release of alpha particles may reach the alveolar epithelium lung cells, which can cause damage and injuries from continuous exposure [2–7]. Hence, Rn exposure may lead to oncological problems according to the World Health Organization (WHO) classification, which ranks Rn as the second cause of lung cancer after tobacco smoking and the first cause among non-smokers [8–11]. In order to evaluate indoor Rn exposure, it is not only important to assess indoor Rn concentration but also to evaluate the mechanisms that contribute to its increase along with the variation over time, together with possible relationships with other factors, such as meteorological factors (temperature, relative humidity, and atmospheric pressure) or factors associated with geology (soil properties, such as permeability, uranium content in soils and rocks, fracture in the land formed by rocky massifs, state of alteration, and water content, among others). The analysis of the problem as a whole, including all variables that may contribute to indoor Rn exposure evaluation, assumes a fundamental role in the future implementation of remediation measures [12–16].

The adoption of remediation measures should help not only to reduce indoor Rn exposure but also to keep indoor Rn concentration levels below a value considered safe, according to the European regulation of 300 Bq·m$^{-3}$. Although, there are studies that point to an increased risk from concentrations of 50 Bq·m$^{-3}$ onwards. It is widely reported that rooms with low indoor Rn concentrations may allow for the safe and secure use of a building by ensuring that users are not exposed to high-risk levels [8,17,18]. However, the concerns of building managers nowadays are not only focused on issues related to a room's Indoor Air Quality (IAQ) since the adoption of sufficiently high ventilation rates in indoor rooms seems to be enough, for most cases, to solve problems related to a high concentration of the most polluting agents, in which Rn is included [19]. More recently, issues related to energy efficiency play a decisive role in building management, and the use of high air renovation rates to tackle IAQ problems may lead to significant heat losses that notably affect the users' thermal comfort in the winter season. Therefore, the balance between ventilation habits and the energy efficiency requirements to promote users' thermal comfort is of utmost importance [20,21].

Given these conditions, the present study aims to analyze the variation in indoor Rn concentration over an extended period to determine the presence of a broad-spectrum seasonal fluctuation potentially related to meteorological factors. By utilizing a LoRa-enabled IoT edge device to collect data, the continuous acquisition of indoor Rn concentration as well as indoor air temperature, relative humidity, and atmospheric pressure allows us to assess the seasonality potential of Rn emission and its correlation with meteorological factors. This analysis fosters the development of more precise procedures for indoor radon mitigation, taking into account not only the seasonality in Rn emission but also the building's energy efficiency and its impact on the thermal comfort of the building occupants. This approach can be extended to other scenarios involving indoor gas emissions, as seasonal patterns should exhibit tendencies related to the propagation of other air pollutants.

## 2. Literature Review

The integration of Internet of Things (IoT) technology into the field of radon monitoring and management has seen a gradual rise, and it holds the potential to transform the way individuals view the associated risks of radon exposure [22]. This change is driven by the deployment of IoT devices for continuous monitoring, as well as the utilization of visual analytics to enhance risk perception, and by the creation of risk management tools suited for the IoT era, such as the Indoor Radon Risk Exposure Indicator (IRREI) proposed by Lopes et al. [23,24]. The advancement of IoT-based system architectures for online radon monitoring and real-time risk management is crucial for improving indoor air quality and building energy efficiency as it enables the integration of sensors, computing, and communication capabilities into cost-effective, small-scale devices [25].

Sensors are placed in buildings to gather data, which is then analyzed, processed, and stored on a central server for continuous monitoring and real-time remediation or preventative measures [26]. There are two main types of radon detection devices: passive and active [27]. Passive devices measure radon gas over a long period, while active devices provide real-time measurements [28]. Blanco-Novoa et al. [29] proposed a cost-effective IoT system for remote radon monitoring. Pereira et al. [30] presented the RnProbe, an IoT Edge Device for collecting and transmitting indoor air quality data to the cloud. Alvarellos et al. [31] developed a secure, low-cost system for monitoring and alerting radon levels, with the ability to predict radon levels and take action before reaching the risk level. They later added the capability to control airflow systems based on radon concentration [32]. Terray et al. [33] studied the feasibility of outdoor radon sensors for monitoring volcanic environments. Amato et al. [34] created a cyber–physical system to monitor and control human exposure to ionizing radiation. Medina-Pérez et al. [35] built an IoT system for real-time radon monitoring, and Forsström et al. developed a user-friendly and secure IoT platform for SMEs. Ferreira designed an IoT system to reduce radon levels in enclosed environments. The study by Alvarellos et al. [32] goes beyond the standard procedures for monitoring radon and provides a more extensive IoT system that can respond to risk mitigation without human intervention, featuring a predictive model to take action before reaching the risk level.

The greatest potential of IoT technology lies in the creation of smart and intelligent buildings, where human activity in indoor environments can be managed, leading to new opportunities for savings and improving the occupant experience [36]. IoT devices can be used to enhance a building's energy efficiency, thermal comfort, and IAQ by monitoring a variety of parameters and physically interacting with spaces [37]. For example, these devices can be used to: (i) gather data on which devices or operations consume the most energy, (ii) determine when energy usage is at its highest, (iii) understand how indoor and outdoor activities impact IAQ, and (iv) assess the impact on occupant productivity and health. Some IoT devices can even switch equipment on and off autonomously, such as when detecting inactivity, incorrect temperatures, or high levels of atmospheric pollutants [38]. By extending this resource management to larger areas, such as entire buildings, using programmable and interconnected IoT switches, it becomes possible to optimize and balance resource distribution [39].

The collection and transmission of data from IoT devices to the cloud enable the prediction of trends and patterns in energy consumption IAQ [40]. This technology provides a unique approach to forecasting indoor pollution levels before they reach hazardous levels, allowing for preventative measures to be taken. Furthermore, integrating autonomous airflow control systems and prediction models or algorithms with other variables such as energy efficiency, thermal comfort, and noise pollution can enhance the overall performance of the system. The integration of machine learning and artificial intelligence can also contribute to decision-making and preventative strategies.

The development of dashboard control and alert applications for smartphones or tablets makes resource management more accessible and convenient [41]. These applications provide mobility in the administration of resources, enabling remote management [42]. IoT-based systems are versatile and can be adapted to meet the needs of any type of building or business activity, regardless of size, and offer scalability and improved security when implemented correctly [43]. The systems can also ensure that tasks, such as turning off lights and equipment or opening windows for ventilation, are performed and provide timely notifications for preventative and corrective actions, thus avoiding downtime in the management of smart building resources [44].

## 3. Materials and Methods

### *3.1. Location and Framework of the Study Area*

For the purposes of this study, a tower building designated as a National Monument since 1926 located in the Braga district (northern Portugal) was selected. The building boasts a massive and austere medieval facade constructed of solid granite blocks, including a granite gateway arch supported with columns. This building has survived to the present day and underwent a retrofit process that began in 2010. Currently, the building serves as a museum open to the public on nearly a daily basis. The predominance of granitic rocks in the region presents itself as an indicator for a greater probability of the occurrence of high indoor Rn concentrations, as mentioned in previous works, namely those presented by Curado et al. [45], Azeredo et al. [46], and Curado et al. [47].

### *3.2. Indoor Rn Concentration Assessment*

To implement the monitoring campaign, an Rn probe developed in the RnMonitor project [30] was used for in situ investigation, which was in line with approaches presented in previous works [48–54]. This probe works in continuous mode as a data collection unit. It consists of an IoT edge device with an architecture divided into three main blocks:

sensing, processing, and communication. The probe is equipped with different sensors, which allow for the acquisition of information on various parameters, as shown in Figure 1.

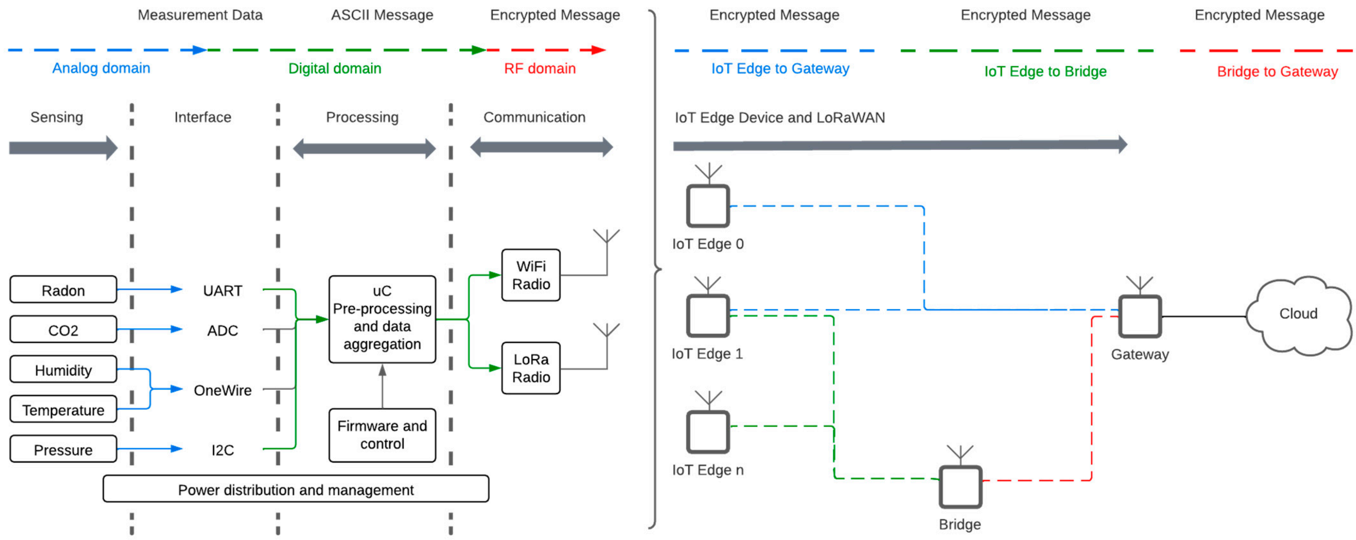


**Figure 1.** RnProbe IoT edge building blocks and LoRaWAN operation modes (adapted from [30]).

According to Pereira et al. [30], for radon measurements, the RD200M sensor from Radon FTLab was selected for its accuracy of ±10% and measurement range of up to 3700 Bq·m$^{-3}$. This sensor utilizes a Universal Asynchronous Receiver/Transmitter (UART) for receiving commands and transmitting data, which facilitates communication with the microcontroller. The measurement of relative humidity and the temperature was performed using the DHT11 from Aosong. This low-cost sensor uses a single-wire, bi-directional communication with 16 bits to communicate with the microcontroller and boasts a repeatability of 1% for relative humidity and 2 °C for temperature measurements. The MPL3115A2 from NXP was chosen to provide data on pressure levels. The sensor operates within a range of 20 kPa to 110 kPa and uses an I2C digital output interface to transmit its measurements to the microcontroller. To facilitate LoRa communication, the RN2483 from Microchip was used. This radio transceiver offers a transmission power of 14 dBm and boasts a receiver sensitivity of −146 dBm. The device communicates with the microcontroller using the Universal Asynchronous Receiver/Transmitter (UART) protocol. In terms of the processing unit, a microcontroller with various communication modes was selected to receive data from the multiple sensors, featuring options for low power consumption and, for the sake of simplicity, an integrated Wi-Fi radio. The ESP8266 from Espressif was deemed the appropriate device for this purpose.

The monitoring campaign of the indoor Rn concentration and the remaining parameters took place in continuous mode from 18.09.2020 to 16.03.2022, totaling 546 days. Data were collected with a sampling rate of 10 min and later converted into daily averages. The probe was placed in the server room, approximately 1.5 m from the ground, with the power source connected.

## 4. Results and Discussion

Figure 2 shows the results obtained from the indoor Rn concentration between 18 September 2020 and 16 March 2022. This sequence, which evaluated 546 consecutive days, shows an average value for the indoor Rn concentration of 485.8 ± 237.4 Bq·m$^{-3}$, contributing to a scenario of potential high-risk exposure for the occupants who occupy the room daily. The evolution of the concentration over time also shows high variability in the measured data, with values oscillating between a minimum of 43.7 Bq·m$^{-3}$ and a maximum of 1446.7 Bq·m$^{-3}$.

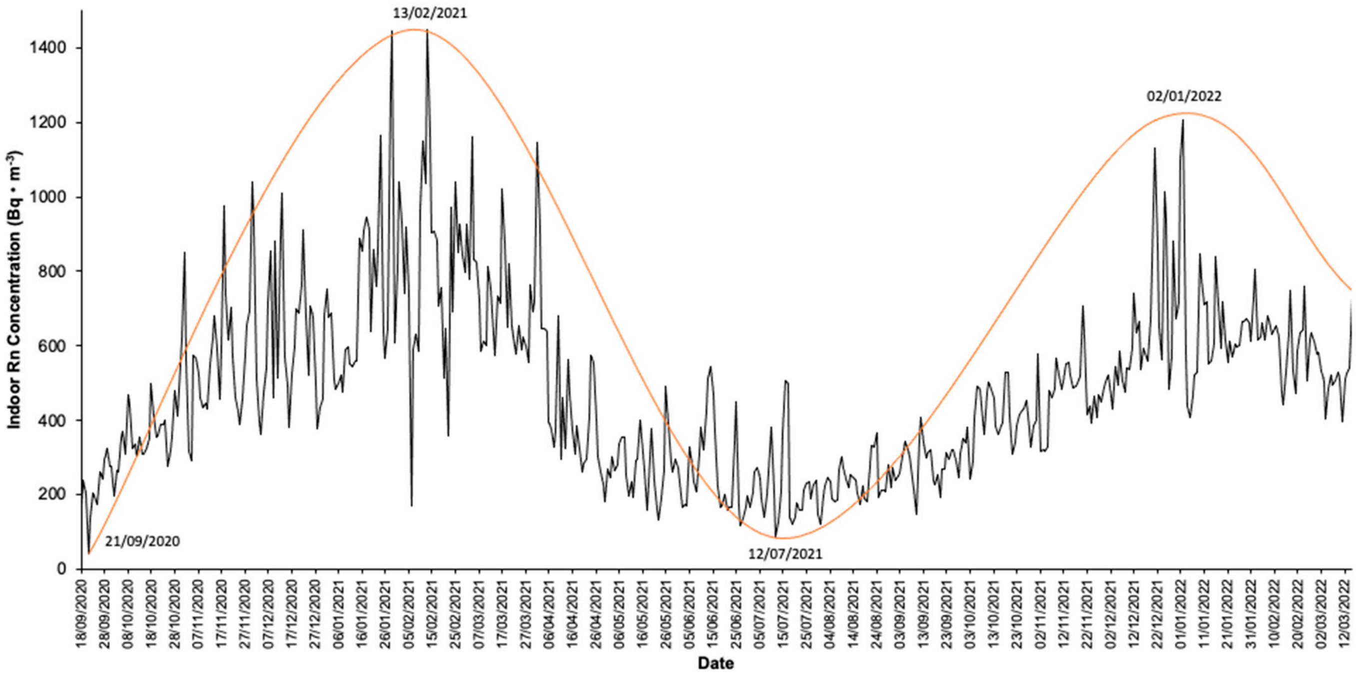


**Figure 2.** Evolution of the indoor Rn concentration over the period under review. The black line represents the indoor Rn concentration, and the orange line represents the oscillation over time, determined using the recorded peaks (maximum and minimum) and the respective occurrence dates.

According to Figure 2, the results can be represented using a sinusoid curve, which reflects a periodic, harmonic type of behavior for indoor Rn variation over time, following therefore a repetitive trend, as shown with the orange line superimposed on the black line representing the indoor Rn concentration. The layout of the results seems to point to a cycle that reaches maximum values in the winter and minimum values in the summer, among which it can be highlighted that the highest values occurred on 13 February 2021 and 2 January 2022, and the lowest values on 21 September 2020 and 12 July 2021, respectively, in winter and summer. The values recorded around the minimum value, which occurred between maximum peaks (13 February 2021 and 2 January 2022), seem to correspond to a transition zone between cycles, which adjusts to a probable correlation with other parameters, such as temperature, atmospheric pressure, or relative humidity.

The temperature recorded inside the compartment with the RnProbe also presents a sinusoidal behavior, as shown in Figure 3, where a very likely negative correlation seems to be more than evident. The determination of Pearson's correlation coefficient between the sets of indoor Rn concentration and temperature results shows a value of −0.7, justifying, as observed in Figure 3, that there is an inversely proportional correlation between temperature and the concentration of Rn. A prior investigation carried out by Baltrénas et al. [55] obtained results that closely align with the findings of this study. The authors discovered that in two settings where the dominant ventilation mechanism was through unintentional air leakage points during the winter, positive correlations between radon concentration and outdoor temperature were observed, with values reaching 0.94 and 0.92, respectively. Conversely, in settings with improved airtightness, negative correlations (R = −0.96 and R = −0.62) were found between the radon concentration and outdoor temperature. The cause of this correlation between temperature and indoor Rn concentration is still without a causal explanation, and to justify this finding, it needs to be further studied and related to other parameters, such as atmospheric pressure and relative humidity. As Porstendorfer [56] found, the processes involved in the transport of Rn by atmospheric aerosols strongly influence the fluxes and concentration of indoor Rn and depend on the physical properties of the free atoms and the activity size distributions of the atmospheric aerosol.

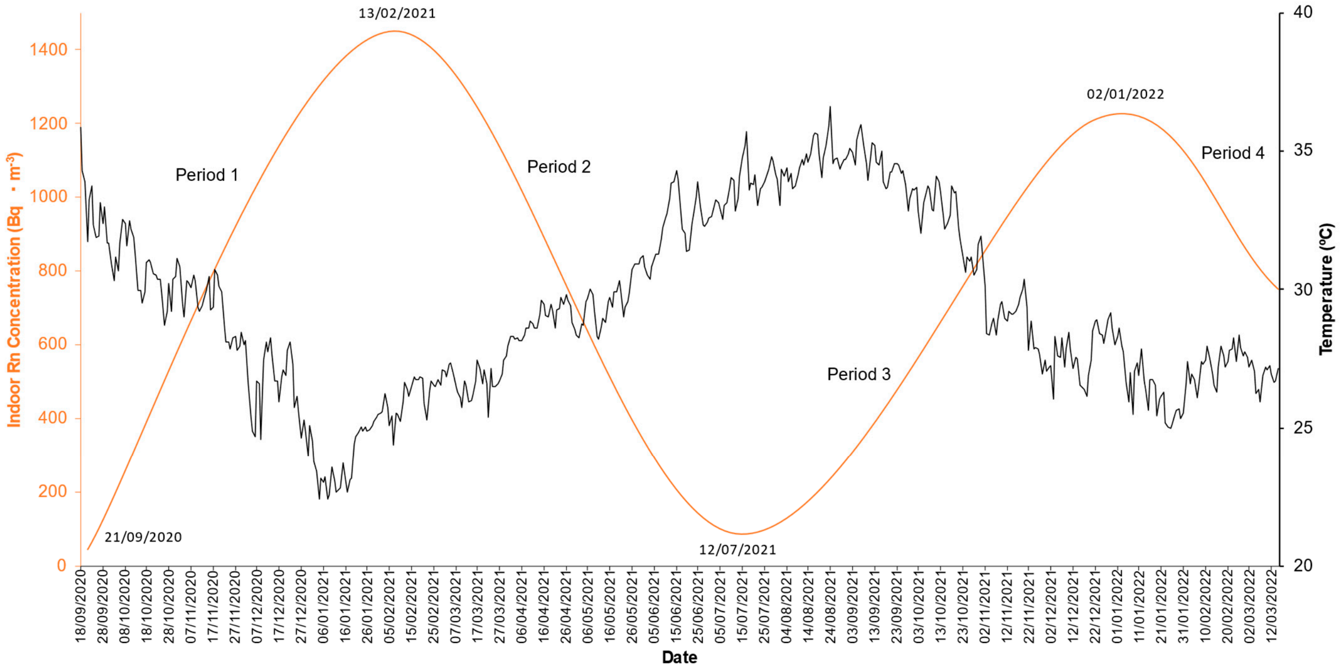


**Figure 3.** Superimposition showing the evolution of the temperature recorded in the compartment under analysis in this study (black line) and the sinusoidal representative for the evolution of the indoor Rn concentration (orange line) during the period in which the monitoring took place.

Despite this apparent correlation between temperature and indoor Rn concentration, it is necessary to analyze this finding with some care since the RnProbe probe was placed in a compartment on the ground floor of the building, where several computer racks with servers are located. Therefore, the temperature suffers a significant increase, which should be around 5 to 15 °C, compared to the average compartment temperature throughout the year, thus influencing the calculation of relative humidity. In any case, despite being positively impacted by the presence of computer equipment in the room, it can be assumed that the temperature follows a pattern equivalent to the natural one, although with the addition of the cumulative effect of the presence of the artificial thermal source. As demonstrated in the work presented by Akbari et al. [57], the air change rate, indoor temperature, and moisture significantly affected the indoor Rn concentration, with the authors confirming the tendency for the indoor Rn concentration to be minimal for higher temperatures. Because of this situation, the questions must be asked whether temperature can be used as a mitigation measure and whether indoor Rn concentration can be controlled, not only by renewing the air (ventilation) but also by ensuring that this air is within a specific range of temperature and of relative humidity. For example, Akbari et al. suggest ranges for temperature and relative humidity of 20–22 °C and 50–60%, respectively. However, further and deeper analyses are required to be able to validate this possibility. Still, it seems that right now, justifying the use of active probes for the continuous monitoring of indoor environments, with the capacity to simultaneously record multiparameter information, such as temperature, atmospheric pressure, and relative humidity, requires the ability to analyze the parallel evolution of the different parameters and to establish correlations (or not) between them.

The lowest value for the indoor Rn concentration recorded during the monitoring period was 43.7 Bq·m$^{-3}$ on 21.09.2020. Suppose one analyzes the daily positive increments based on this reference value for the indoor Rn concentration that occurred in the periods (Figure 3) in which there is a rise or fall in that concentration. In that case, the results shown in Table 1 are obtained. As can be seen in the results obtained, the occurrences of an increase in the indoor Rn concentration are mostly associated with periods in which the temperature drops, also confirming in these periods that the rate of growth in the concentration of the indoor Rn is higher.

**Table 1.** The hourly average value of the increments recorded in the periods when the indoor Rn concentration rises or falls.

| **Time Interval** | **Positive Increments (n)** | **Minimum Registered Value ($Bq{\cdot}m^{-3}{\cdot}h^{-1}$)** | **Maximum Registered Value ($Bq{\cdot}m^{-3}{\cdot}h^{-1}$)** | **Average ($Bq{\cdot}m^{-3}{\cdot}h^{-1}$)** |
|---|---|---|---|---|
| 1 | 78 | 0.1 | 26.1 | 5.41 |
| 2 | 73 | 0.1 | 25.5 | 3.95 |
| 3 | 92 | 0.2 | 18.7 | 2.82 |
| 4 | 30 | 0.1 | 13.2 | 1.86 |
| Total | 273 | | | 3.9 |

In this case, the expected relationship between the indoor temperature and relative humidity does not show a correlation, with a Pearson coefficient practically equal to zero. This apparent disconnection between temperature and relative humidity must be associated with the influence that artificial thermal sources have on the behavior of temperature, so this parameter does not, in this situation under study, contribute to the understanding of the processes that lead to the evolution of the concentration of the indoor Rn in a particular trend. The relative humidity registered with the RnProbe in the period under analysis presented an average value of 32.6 $\pm$ 5.4% and a variation between 17.0% and 44.2%. This observation is because relative humidity is a measure dependent on the temperature of the air, so the higher the air temperature, the greater its ability to absorb moisture. In this way, evaluating the impact that the relative humidity may have on the evolution of the indoor Rn concentration in this specific situation is not possible.

Using FFT to analyze the evolution of indoor Rn concentration allows for examining the seasonal periodicity in the Rn concentration in the frequency domain, which can be influenced by factors such as alterations in ventilation procedures of the area, modifications in occupancy patterns (resulting in changes in ventilation patterns and thermal comfort, among other things), or broader changes in a seasonal nature related to meteorological parameters (temperature, atmospheric pressure, and relative humidity), as well as geogenic factors such as the water table level and soil porosity. In this way, by applying FFT to the time series of Rn concentration, it is possible to identify the frequency components that contribute to its seasonal periodicity. For example, there may be a daily frequency component due to changes in the ventilation of the environment, or a seasonal frequency component due to changes in temperature. To apply the FFT, the stationarity in the time series was verified by checking if the mean and variance of the time series are constant over time. In the case presented, the analysis of stationarity in the time series was achieved using visual inspection, as projecting the data showed consistency in the evolution of the results, indicating that the mean and variance appear to be constant (or approximately constant) over time. The analysis of the mean and variance of the series in consecutive time intervals (in this case, with the analysis of the periods indicated in Figure 3) also confirmed that they are constant over time. Finally, the augmented Dickey–Fuller (ADF) test was used, which tests the null hypothesis that the series is non-stationary. As $p < 0.05$ in this case, the null hypothesis was rejected, and the series is considered stationary. For this determination, an R routine with the RStudio software (Version 2022.12.0 + 353) was used. As there are no missing data in the time series, there is no need to apply an imputation or data cleaning technique.

In this case, Microsoft Excel's Data Analysis package (Version 16.68) was used, which includes Fourier Analysis. The Fast Fourier Transform (FFT) in Excel does not impose a specific order. However, to achieve the most accurate and efficient results, it is advisable to ensure that the number of data points is a power of 2. The reason for this is that the

FFT algorithm continuously divides the data into smaller pairs until each pair contains only one data point. If the number of data points is not a power of 2, the FFT will not be able to evenly divide the data. To overcome this issue, it may be necessary to pad the data with additional zeros to achieve the appropriate number of data points. However, since there is a sufficient number of data points, we opted to compute the FFT with an order of 512 samples. Figure 4 schematizes the overlap in the data obtained from the indoor Rn concentration monitoring campaign (orange line) and the results obtained from the FFT (black line).

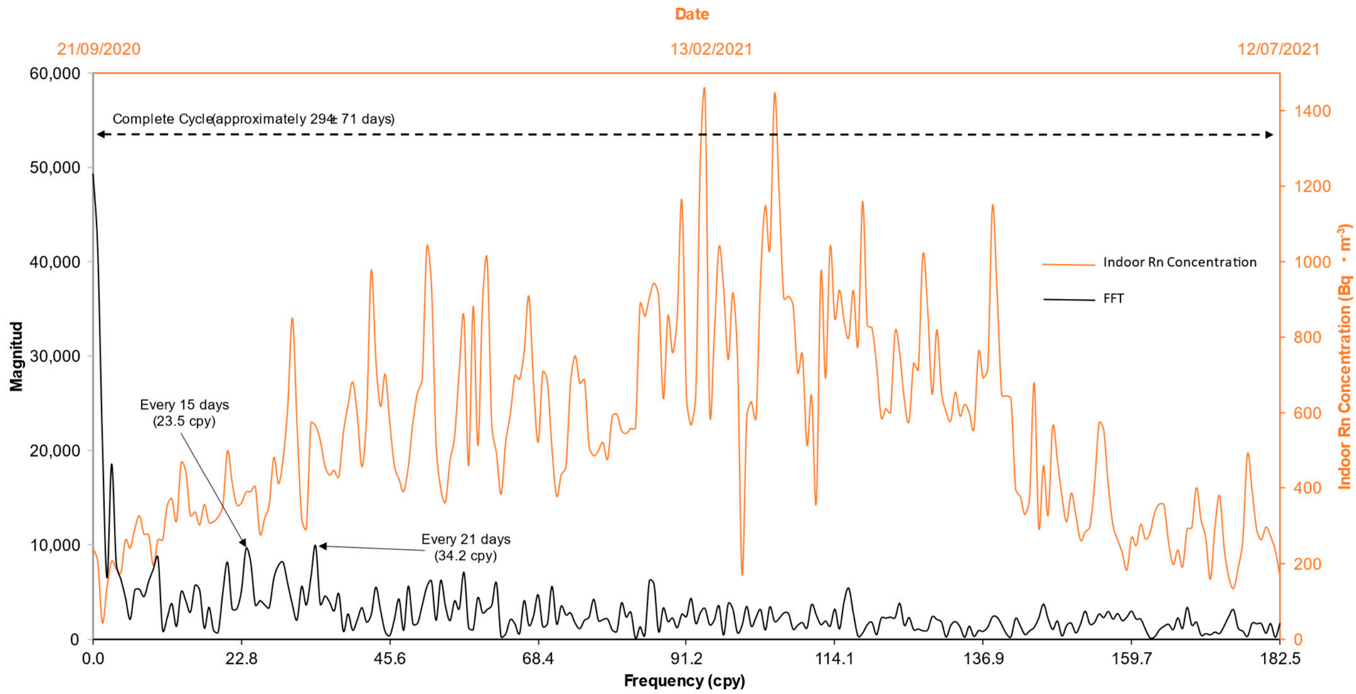


**Figure 4.** Schematic representation of the Fast Fourier Transform (FFT) application to the indoor Rn concentration measurements over the period under analysis (black line) with the superimposition of the indoor Rn concentration data (orange line).

The layout of the symmetrical line makes it possible to identify the seasonal cycle, which extends from July to June of the following year, with the lowest indoor Rn concentrations recorded precisely in the summer and the lowest indoor Rn concentrations highly likely to peak in winter, as schematically presented in Figure 5.

The seasonal variation, as determined from the daily average of the 144 measurements taken at a 10 min sampling rate, is in reality the result of a set of cyclic sinusoidal trends, which reflect variations in the indoor Rn concentration on both a daily and seasonal scale and are influenced by both natural factors (meteorological and geogenic parameters) and other variations associated with anthropogenic factors, such as forced ventilation, artificial regulation of temperature and humidity, and occupancy of spaces. Gaining a comprehensive understanding of the indoor Rn concentration variation over time and its relationship with meteorological parameters (temperature, relative humidity, pressure) and human presence parameters in spaces is essential for enhancing the effectiveness and efficiency of mitigation actions.

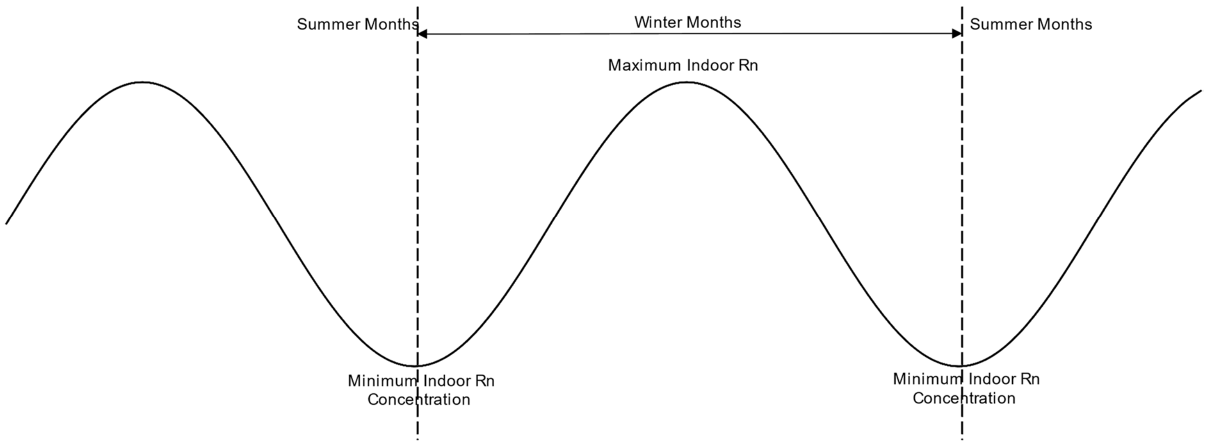


**Figure 5.** Schematic representation showing the evolution of the indoor Rn concentration within the twelve-month cycle.

Indoor air quality and energy efficiency are two crucial factors that have a significant impact on the health and well-being of building occupants. The quality of the air inside a building can be influenced by several factors, such as ventilation systems, pollutants from outdoor sources, and building materials. In contrast, energy efficiency refers to the amount of energy consumed by a building to maintain a comfortable indoor environment. In recent years, the interconnection and complementarity of these two aspects have become more apparent. Poor indoor air quality can negatively affect energy efficiency by forcing occupants to open windows or doors to improve ventilation, resulting in increased energy consumption for heating or cooling. On the other hand, energy-efficient buildings with airtight envelopes can experience indoor air quality issues due to a lack of fresh air exchange.

To better understand the relationship between indoor air quality and energy efficiency, continuously active, multi-parameter indoor air quality monitoring probes have become valuable tools for data collection. These probes measure various parameters such as temperature, humidity, carbon dioxide levels, and radon concentration, among others. The data obtained can be used to gain deeper insights into the evolution of indoor radon concentrations and other relevant parameters that require analysis. The use of these probes can assist building owners and managers in making informed decisions about improving indoor air quality while maintaining energy efficiency.

## 5. Conclusions

The World Health Organization (WHO) recognizes indoor radon (Rn) gas as the second leading cause of lung cancer, following tobacco smoking, and the primary cause of respiratory disorders among non-smokers. The long-term assessment of indoor Rn concentration plays a critical role in evaluating the exposure risk faced by building occupants and in determining the implementation of Rn remediation measures to improve IAQ and reduce exposure risk. This study has shown that indoor Rn concentration exhibits a periodic, seasonal behavior, which is likely influenced by meteorological factors as well as anthropogenic factors, such as room ventilation, the artificial alteration of air temperature and humidity using air conditioning devices, and even the pattern of room occupancy depending on the schedules of building occupants. A continuous monitoring campaign of 546 consecutive days was conducted with the recording of indoor Rn concentration, indoor air temperature, relative humidity, and atmospheric pressure. The results of the investigation revealed a broad range of seasonality, with a negative correlation observed between the indoor Rn concentration and indoor air temperature. As the indoor air temperature rises, the Rn concentration tends to decrease, leading to a reduction in indoor exposure. The relationship between the indoor Rn concentration and relative humidity was not conclusively established, as indoor relative humidity is strongly related to air temperature variation. Similarly, the influence of atmospheric pressure on the evolution of indoor Rn concentration could not be interpreted due to the lack of information on the occupancy rate of the museum room and the occurrence of ventilation actions taken by building occupants. Further analyses would require more data than the daily average values used in this study.

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