

## Humidity monitoring in concrete using Bluetooth Low Energy sensors

Filipe Jorge Santos Ferreira Adao<sup>1</sup>, Rosemarie Helmerich<sup>1</sup>, Gerrit Voigt<sup>1</sup>, Laura Moldenhauer<sup>1</sup> and Patrick P. Neumann<sup>1</sup>

<sup>1</sup> Federal Institute for Materials Research and Testing

### ABSTRACT:

The vulnerability of low quality concrete to changing weather conditions is well known. The constant exposure to temperature changes, biological activity, and humidity ends up in damage to buildings and structures which contain this material. It is therefore necessary to take preventive measures to control the extent of the damage done by weathering and possible penetration of adverse chemicals into structures which need public safety.

The Federal Institute for Materials Research and Testing (BAM), in cooperation with the small enterprise LinTech GmbH, is working on a project to monitor humidity changes in concrete by analyzing the changes in signal strength (RSSI) from Bluetooth Low Energy sensors. In this paper, we show results which demonstrate the influence of changing water content in concrete on the received RSSI. We observed that as water content in concrete decreases, the received RSSI improves. However, the damping effect is not linearly proportional to water content, rather exponentially proportional. This suggests that changes in the received signal strength are more easily observed when water content in concrete is higher. Finally, we reconstructed a RSSI distribution map using computed tomography.

Keywords: Bluetooth Low Energy; RSSI; Concrete; Water; Monitoring; Computed Tomography.

## 1 INTRODUCTION

The continued exposure of concrete to varying humidity takes a toll on its structural integrity. This is a serious issue to public safety in constructions such as bridges, dams or buildings, where usually this material is used. It is, therefore, recommendable to take preventive measures to control the extent of this problem.

As portable and wireless technology develops and establishes itself on the market, its sustainable use in the construction of smart networks for monitoring physical quantities is an increasing reality. The Federal Institute for Materials Research and Testing (BAM), in cooperation with the small enterprise LinTech GmbH (<http://www.lintech.de>), carries out a research project where Bluetooth Low-Energy (BLE) intercommunicating sensors are developed with the purpose of monitoring water in concrete. The reason for the use of BLE is due to its low energy consumption which allows long term monitoring without having to do battery maintenance. Furthermore, it is known that the propagation of electromagnetic waves is influenced by media and, therefore, such influences can serve as indicators of the presence of a specific physical quantity in a given location. Our ideas are to setup the sensors (1) in a surface to surface communication network and (2) in a concrete-embedded network in a way which would allow content estimation and volumetric distribution of water in concrete. For more details consult Voigt et al. (2017). Furthermore, we use the Received Signal Strength Indicator (RSSI - in negative dBm) which indicates how strong the received BLE signal is for a given sensor at a certain point in space, while the transmitted signal strength remains constant.

In this paper, we present our study of the influence of varying water content in concrete on RSSI using LinTech's BLE sensors. Additionally, we show first results of our effort in estimating water content and its spatial distribution using computed tomography images.

## 2 EXPERIMENTAL PROCEDURES

### 2.1 *Studying humidity's influence on RSSI*

In our measurements, we used three BLE sensors and a BLE sniffer provided by our project partner. The sensors and the sniffer contain the BLE chip BTM-800 from Rayson (<http://bluetooth-rayson.gmc.globalmarket.com>) which has a ceramic monopole antenna (**Figure 1**). The first sensor (Sensor 1) was delivered to us by chance with a lower transmission power in relation to the second (Sensor 2) and third (Sensor 3) sensor which have similar transmission power. This results in lower RSSI readings by Sensor 1 in relation to Sensor 2 and 3.

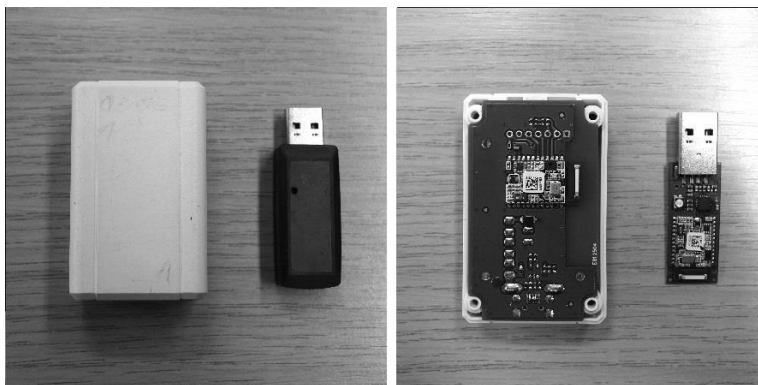


Figure 1 – BLE sensor and sniffer provided by LinTech GmbH.

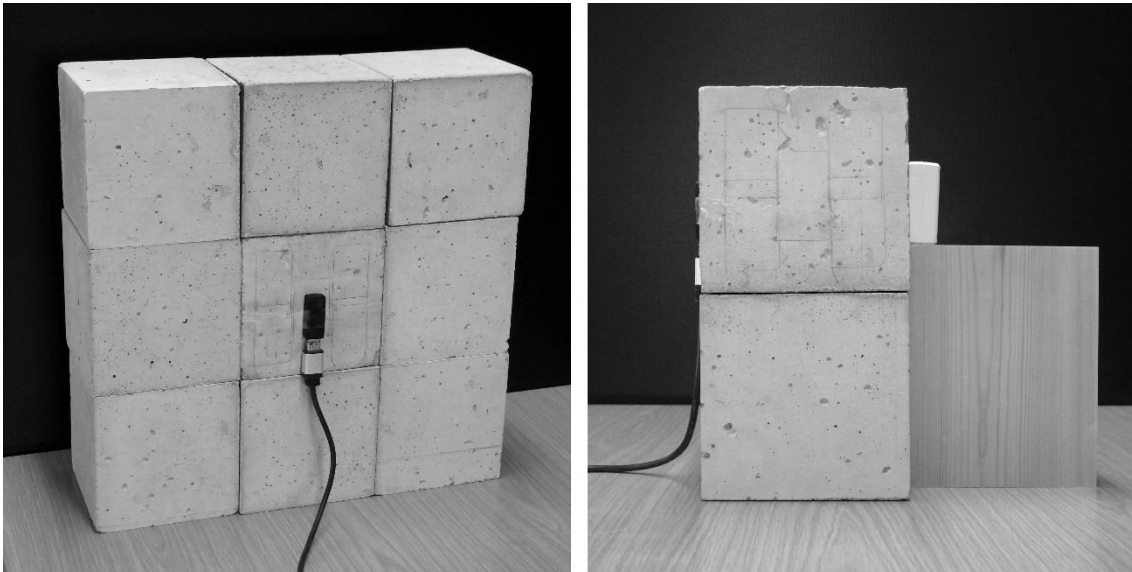


Figure 2 – a) Concrete wall consisting of nine  $45 \text{ cm}^3$  cubes with the BLE sniffer placed in the center. Central cube was made water saturated. b) Profile picture of the wall with BLE sensor placed on a wooden level on the right side and the BLE sniffer taped to the wall on the left. Here the wall was made smaller for viewing purposes.

Before studying the effect of changing humidity content in concrete on RSSI, we investigated the dependence of RSSI on the BLE sensor's antenna orientation. To do so, we put the BLE sensors in various angles ( $0^\circ$ ,  $90^\circ$ ,  $180^\circ$  and  $270^\circ$ ) in relation to the BLE sniffer. It should be noted that these measurements were done while the center cube was dry.

To study the effect of changing water content in concrete on RSSI, we set up a concrete wall consisting of nine cubes with the center cube being saturated with water (**Figure 2**). On one side of the wall we attached a sensor at the middle point of the center cube. On the exact opposite side, we simultaneously attached the sniffer (**Figure 2b**). Afterwards, we measured the RSSI during twenty days whilst the center cube became drier under room conditions. In each day, we measured the RSSI for 1 minute with a sampling rate of 6,7 Hz, from which we calculated the mean RSSI values and corresponding standard deviations. The measurements were first done through what we defined as path one and then rotated the center cube  $90^\circ$  counterclockwise and repeated the previous process for the perpendicular path which we defined as path two. The reason for this cube rotation was to get a simple idea of how dependent from the path the results can be.

To estimate the water content in the center cube of our wall, we weighed it daily during the experiment. On day 20, we put the cube in an oven at  $60^\circ\text{C}$  temperature over the weekend. After this, we weighed the dried-up cube and measured the RSSI again.

## 2.2 Computed Tomography

To calculate tomographic distribution images of the RSSI, we have used the maximum likelihood expectation maximization (MLEM) algorithm (Neumann et al., 2016; Neumann & Bartholmai, 2015; Todd & Ramachandran, 1993). With MLEM we define a grid of cells representative of the study area where we do our RSSI measurements. The measurements are considered as rays which travel between two points (transmitter and receiver) within the study area. Using this data, cell values from which the reconstructed ray sums can be calculated from are estimated iteratively using the following formula:

$$C_i^{q+1} = \frac{C_i^q}{\sum_j A_{ij}} \sum_j \frac{A_{ij} \phi_j}{p_j^q} \quad \text{with} \quad p_j^q = \sum_i A_{ij} C_i^q \quad (1)$$

In formula (1)  $q$  is the total number of iterations,  $i$  is the current iteration,  $\phi_j$  is the array of measured data,  $A_{ij}$  is the fractional area of the  $i$ th grid cell intercepted by the  $j$ th measured ray sum (in our case this is simply the fractional path length of the  $i$ th grid cell intercepted by the  $j$ th measured ray sum), and  $p_j^q$  is the so-called ray sum which equals the path-integrated RSSI value.

Here, we built up a larger concrete cube setup made of 27 smaller cubes (**Figure 3a**) with a water saturated center cube. The RSSI measurements were done along the middle section of the cube and through six different paths which intercepted all cubes in the study area (**Figure 3b**).

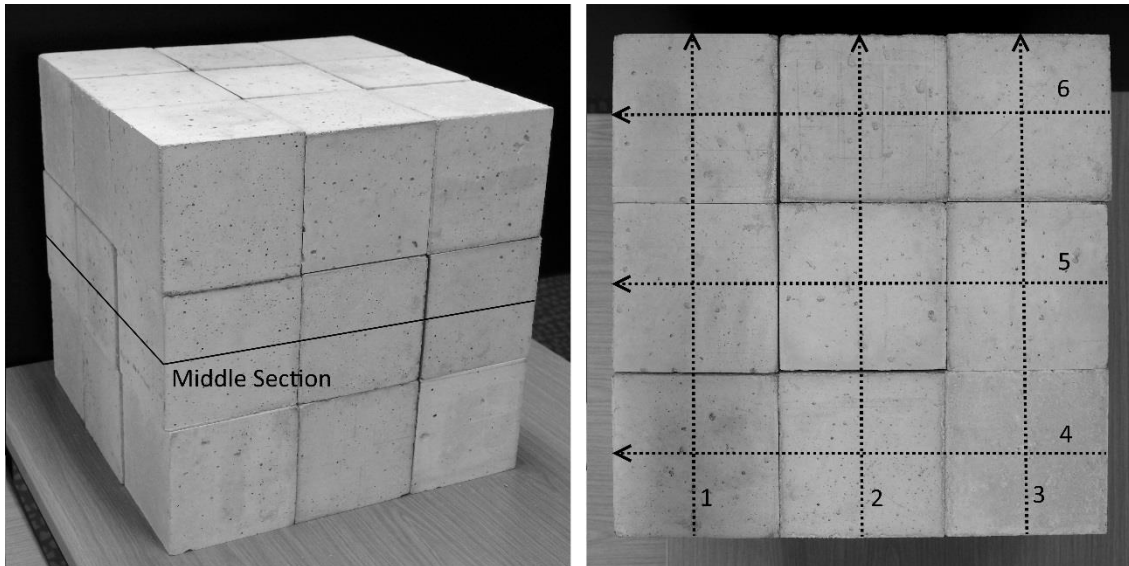


Figure 3 – a) Concrete cube consisting of twenty-seven 45 cm<sup>3</sup> cubes used for CT reconstruction. RSSI measurements were done along the middle section. b) Illustration of the chosen measurements paths.

### 3 RESULTS AND DISCUSSION

#### 3.1 Humidity's influence on RSSI

Results have shown that RSSI values are lower when the antennas from both the sensors and the sniffer are perpendicular to each other (**Figure 4**). The difference is low when the distance is of 15 cm but it becomes noticeable as the concrete thickness between sensors and sniffer increases to 45 cm. This result shows that when using monopole antennas, it is recommendable to have them parallel to each other and with similar orientation to obtain optimal RSSI readings.

After asserting the best position for the BLE sensors and sniffer antenna, we proceeded to study the influence of water content in concrete on the RSSI. **Figure 5** shows the results of our RSSI readings. We observed that during the timespan of our experiment, the mean RSSI values rise for both paths and for all sensors.

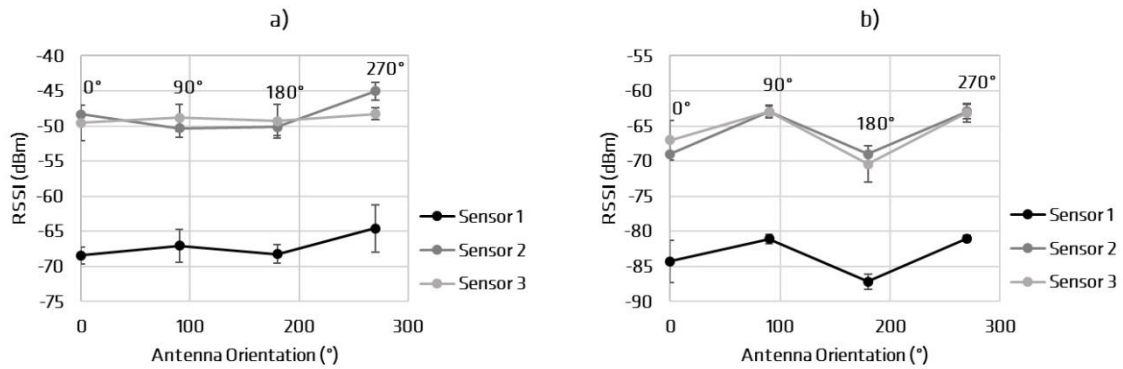


Figure 4 – Mean RSSI values obtained for different BLE sensor orientations. RSSI measured through concrete walls of a) 15 cm and b) 45 cm. Black bars represent the standard deviations.

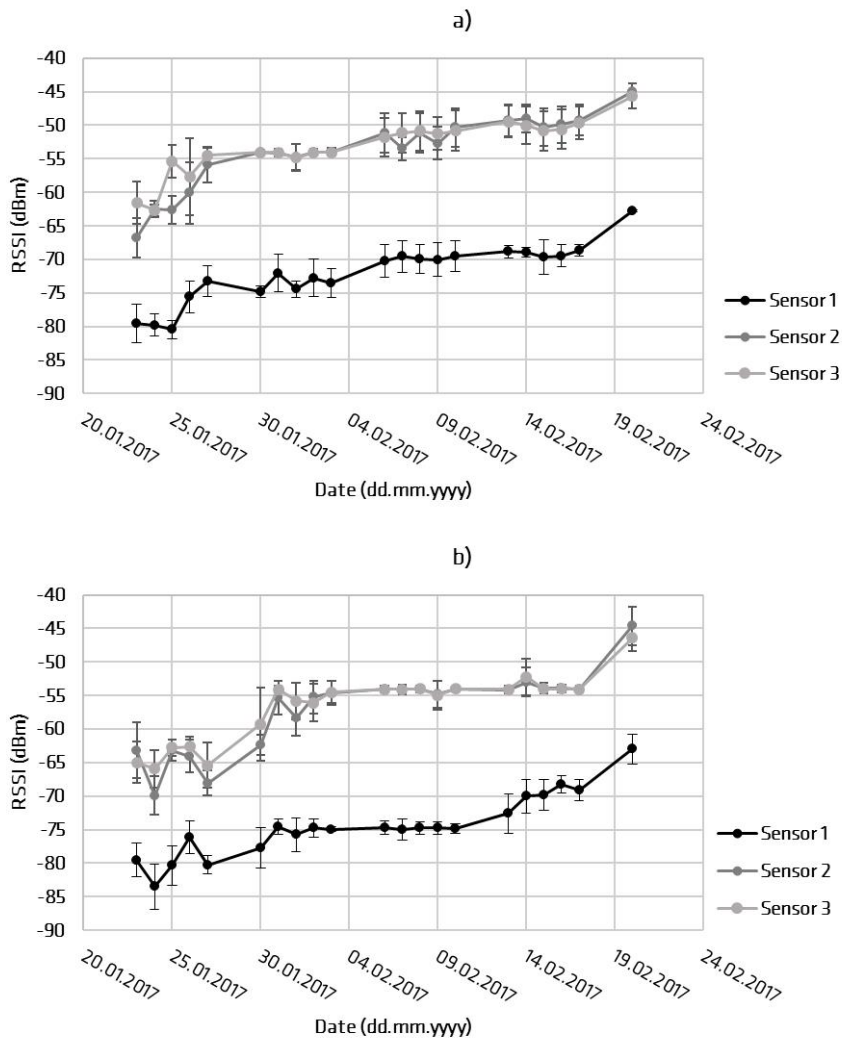


Figure 5 – Mean RSSI values obtained through a) path one and b) path two of the center cube of the concrete wall. Larger data gaps correspond to the weekend hiatuses when RSSI was not measured. Black bars represent the standard deviations.

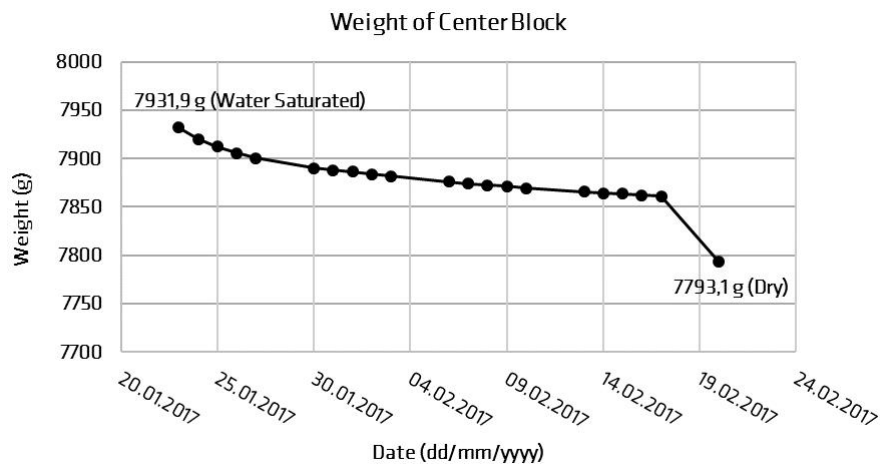


Figure 6 – Weight devolution of central concrete cube during our experiment.

When analyzing the weight of the center cube, we observed that it decreased during the experiment (**Figure 6**). This decrease was exponential-like up until day 20. After the cube was made dry, we observed a steep weight loss corresponding approximately to an equal weight loss observed up until day 20. The total weight loss was of 138,8 g which we associate to the total water content that the concrete cube can contain.

The previous results bring us to the conclusion that the RSSI is indeed influenced by water content in concrete. Similar results have been obtained by Moldenhauer et al. (2016). In this study, the RSSI was measured through wet sand. They observed that as the sand got drier, the RSSI became higher. In our experiment, this is observable specially in the first five days of our experiment, where a steep water loss corresponded to a steep RSSI change, but also when comparing RSSI and water loss before and after the center cube was dehydrated. A loss of 48 g corresponded to a rise of at least -5 dBm.

An important aspect we could observe in these results is that approximately three thirds (~ -15 dBm) of the total rise in RSSI during the experiment, occurred until the center cube had lost nearly half of its total weight loss. The subsequent rise in RSSI (~ -5 dBm) occurred when the remaining half was gone. This means that variations of RSSI which we could associate with water content change are more easily observed when the total water content that the cube can contain is over 50%. Under that level, it seems to be a harder task, considering how high RSSI standard deviation can be.

### 3.2 Computed Tomography

The mean RSSI values we obtained along the middle section of our concrete cube show that the center part of the study area exhibits lower RSSI (**Table 1**). This is in line with our previous results that showed how water content in concrete can influence RSSI readings.

We used the data in **Table 1** as input data for the MLEM algorithm. A three by three grid was used. The code successfully converged into a solution within 10 iterations. **Figure 7** shows the result. The RMS value is considerably low and the reconstructed ray sums values are nearly identical to the actual RSSI measurements, meaning the data fit of the model is good. Due to the measurement setup, a cross-like pattern is noticeable because each cell value is calculated from one horizontal and vertical measurement. Furthermore, because the center cube is wet, its damping contribution is expected to be higher than that of the surrounding cubes. For that

reason, the respective cell value has the lowest value. As for the neighboring cells, because the measurements done through paths 2 and 6 are influenced by the wet center cube, the calculation of their cell values ends up being overestimated.

Table 1. MLEM Input data

	Start x (cm)	Start y (cm)	End x (cm)	End y (cm)	RSSI (dBm)
Path 1	7,5	0	7,5	45	-69,7
Path 2	22	0	22	45	-78,5
Path 3	37,5	0	37,5	45	-75
Path 4	0	7,5	45	7,5	-74,9
Path 5	0	22	45	22	-76,8
Path 6	0	37,5	45	37,5	-69,0

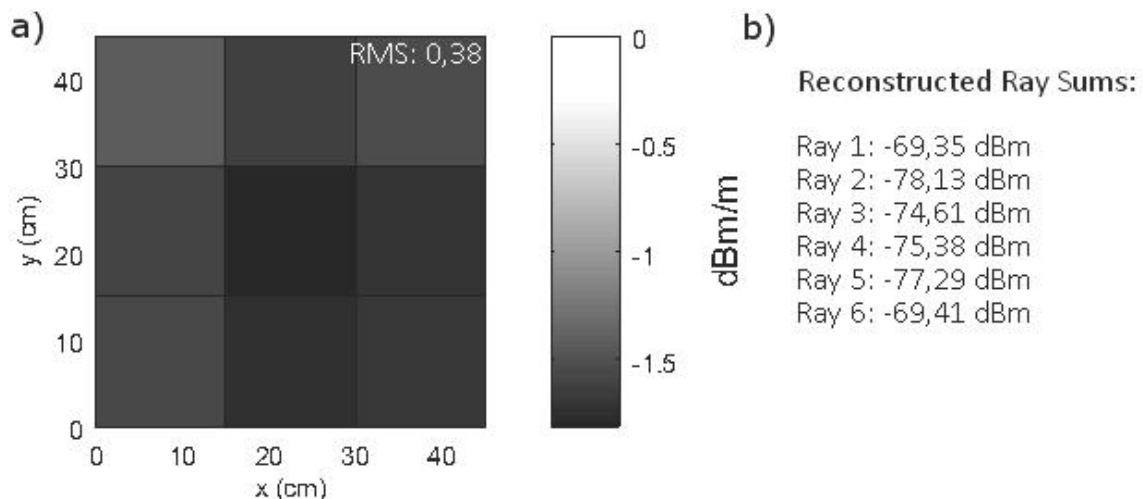
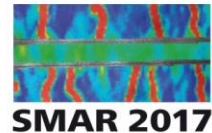


Figure 7 – a) RSSI distribution map calculated with the MLEM algorithm. b) Reconstructed ray sum values.

#### 4 CONCLUSIONS

Our study of the influence of water content in concrete on the RSSI, obtained with BLE sensors, showed that high water content yields significantly lower the RSSI values in comparison to those obtained when concrete is dry. This is a good indication that it is feasible to use BLE sensors for water content monitoring. However, the observed change in water content is not directly proportional to the change in RSSI. The change in the RSSI was stronger when water content was changing above 50% of its initial total weight. Under this level, the change in the RSSI was lower. This means that humidity monitoring with BLE sensors becomes increasingly challenging as water content lowers in concrete.

The next step in the study of the influence of humidity on the RSSI will be to work towards validation of the method and calibrating the obtained data to estimate directly the moisture level in concrete without the aid of other physical quantities. An important part of the calibration will involve a higher knowledge of the influence of antennas in the RSSI. In this effort, further



measurements, under different conditions, will be done to obtain a large RSSI data set to achieve accurate calibration.

In our computed tomography work, first results show that the MLEM approach can successfully calculate the RSSI distribution images using a simple grid configuration and a small number of measurements. This is a good result, although preliminary, which motivates us to work in visualizing water content distribution in concrete using the MLEM algorithm. The next step will be to increase the number of measurements, along with the cell number, to increase the resolution of our RSSI distribution images. Ultimately, our goal will be to do a time-lapse of already calibrated distribution images, which can help us monitor humidity. To do this we will need data time series that are long enough to observe humidity variation in concrete.

## 5 ACKNOWLEDGEMENTS

We would like to thank LinTech GmbH for providing us the BLE equipment necessary for our work. Many thanks to Detlev Rättsch for providing us wooden levels to place our sensors and Dipl. -Ing (FH) Frank Haamkens for providing the concrete cubes.

Our project was funded in the ZIM-KOOP program of the German Federal Minister for Economic Affairs and Energy under the contract number 16KN050827. We kindly acknowledge the national support of our project idea.

## 6 REFERENCES

- Moldenhauer, L., Köppe, E., Haamkens, F., and Helmerich, R., 2016. *Feuchtemessungen in Bauteilen und anderen Strukturen mit Bluetooth Low Energy*, in *Bautechnik*, 93, 10, 747-751, DOI: 10.1002/bate.201600074.
- Neumann, P. P., Lazik, D., and Bartholmai, M., 2016. *Tomographic Reconstruction of Soil Gas Distribution From Multiple Gas Sources Based on Sparse Sampling*. In *IEEE Sensors Journal*, 16(11), 4501–4508.
- Neumann, P. P., Lazik, D., and Bartholmai, M., 2015. *Near Real-Time Reconstruction of 2D Soil Gas Distribution from a Regular Network of Linear Gas Sensors*. In *IEEE Sensors 2015*, Busan, South Korea, 1–4.
- Todd, L. A., and Ramachandran, G., 1993. *Evaluation of optical source-detector configurations for tomographic reconstruction of concentration in indoor air*, in *Am. Ind. Hyg. Assoc. J.*, 30, 1133.
- Voigt, G., Helmerich, R., Rückschloss, M., Adao, F. (2017). *Determining Moisture in Materials and IoT*. Accepted paper SMAR 2017.