ISTRAŽIVANJE UTICAJA RELATIVNE VLAŽNOSTI I TEMPERATURE NA IOT REŠENJE ZASNOVANO NA JEFTINIM SENZORIMA ZA PRAĆENJE KVALITETA VAZDUHA

INVESTIGATION OF THE INFLUENCE OF RELATIVE HUMIDITY AND TEMPERATURE ON THE IOT SOLUTION WITH LOW COST AIR QUALITY MONITORING SENSORS

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Usled porasta zagađenosti vazduha u gusto naseljenim oblastima, potreba za pouzdanim i pristupačnim sistema za praćenje kvaliteta vazduha je u porastu. Jeftini komercijalni senzori predstavljaju dobru početnu tačku sa praćenje kvaliteta vazduha s obzirom na njihovu dostupnost na tržištu i nisku cenu ali zaostaju u smislu tačnosti i pouzdanosti izmerenih podataka u odnosu na javne merne stanice. U ovom radu, ispitan je uticaj relativne vlažnosti i temperature vazduha na tačnost merenja ovih senzora. Različiti tipovi statističkih modela su korišćeni kako bi modelovali grešku merenja senzora prouzrokovanu relativnom vlažnošću i temperaturom vazduha. Dobijeni rezultati pokazuju da se tačnost senzora može poboljšati adekvatnom kompenzacijom greške merenja i time povećati preciznost i pouzdanost ovakvog sistema za praćenje kvaliteta vazduha.

Ključne reči: *IoT; senzori; kvalitet vazduha; monitoring; neuralne mreže*

Due to the rising air pollution in densely populated areas, the need for reliable and cost-effective air monitoring systems is on the rise. Low-cost off-the-shelf air quality sensors available on the market provide a good starting point as they are readily available and inexpensive but fall short when it comes to accuracy and reliability. In this paper, the influence of relative humidity and temperature on the accuracy of these sensors is analyzed. Different types of statistical models are used in order to model the measuring error of the sensors caused by relative humidity and temperature. Obtained results show that the accuracy of the off-the-shelf system can be improved by adequate compensation and a more reliable, yet inexpensive air monitoring systems could be implemented.

Key words: *IoT; sensors; air quality; monitoring; neural networks*

1 Introduction

The estimation of the World Health Organization (WHO) is that by the year 2050, 70% of people in the world will live in cities [1]. This trend is unavoidable but overpopulation in urban areas can significantly affect the quality of life of the citizens. Their health can be put at great risk due to the rising air pollution trends [2]. Air quality guidelines were issued by the WHO with a goal to direct activities in polluted areas [3]. In order to recognize what actions should be taken, there is a need for air monitoring IoT systems that can track the air pollution in urban areas. The number of air monitoring stations, however, is low due to the high cost per station as well as the annual calibration cost. The potential solution to this problem is using low-cost off-the-shelf sensors to monitor the air quality. These sensors unfortunately tend to have low accuracy and calibration issues. The reason for this is that the accuracy of the measurements is highly influenced by temperature and relative humidity. In this paper, two methods for calibrating off-the-shelf air quality sensors are proposed. One uses the Least Squares Method to fit the data and the other uses a neural network which further improves the calibration by using the relative humidity and temperature data [4,5]. Both methods were

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implemented so that they can be used in real-time and provide a basis for a low-cost air monitoring IOT solution. In section 2. system architecture is presented and calibration methods are explained. Section 3. provides results and discussion, while Section 4. concludes the paper and gives directions for future work.

2 System architecture and calibration methods

Device with a Plantower PMS 7003 PM low cost sensor [6] is collocated with the public monitoring station, whose measurements are used as reference measurements for the calibration. Measurements from the PM sensor are collected every minute and sent to the cloud where raw data is stored and available for further processing. Data available from public monitoring station is averaged hourly values.

Two calibration methods were implemented in this paper. The first consisted of linear calibration and the second included a simple neural network (Figure 1).

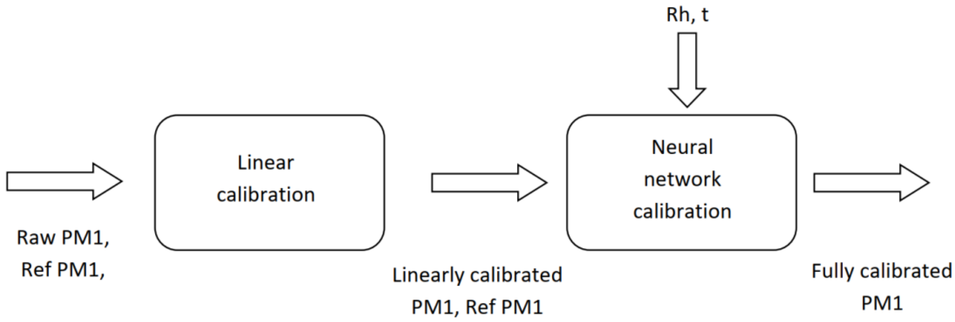

Figure 1. Calibration algorithm.

Linear calibration was performed using the Least Squares Method [7] curve fitting. Under the assumption that the data is linearly dependent, the least Squares Method can be applied to fit the raw data to the reference data.

After linear calibration a neural network model was trained in order to further improve the accuracy of the measurements. The model consisted of two hidden layers containing 1000 and 200 neurons, respectively. The Relu activation functions were used in the neural network, the inputs to the network were relative humidity, temperature and linearly calibrated data and the desired output was the reference data. The model was trained with a 9:1 split of the training data into training and validation sets.

3 Results and performance evaluation

The data used in this paper was acquired during the months of June and July of 2020. The reference system made hourly measurements while the low-cost sensors made measurements every minute. In order to compare the values from these two systems, the measurements from the low-cost sensors were averaged for each hour and furthermore synchronized with reference system measurements. The input data for the calibration process consists of PM1 measurements from the low-cost sensors and the relative humidity and temperature from the reference sensors. The parameters for the calibration process were fit based on the first group of data and tested on the second group. The input parameters for the calibration process of the test data are shown in Figure 2.

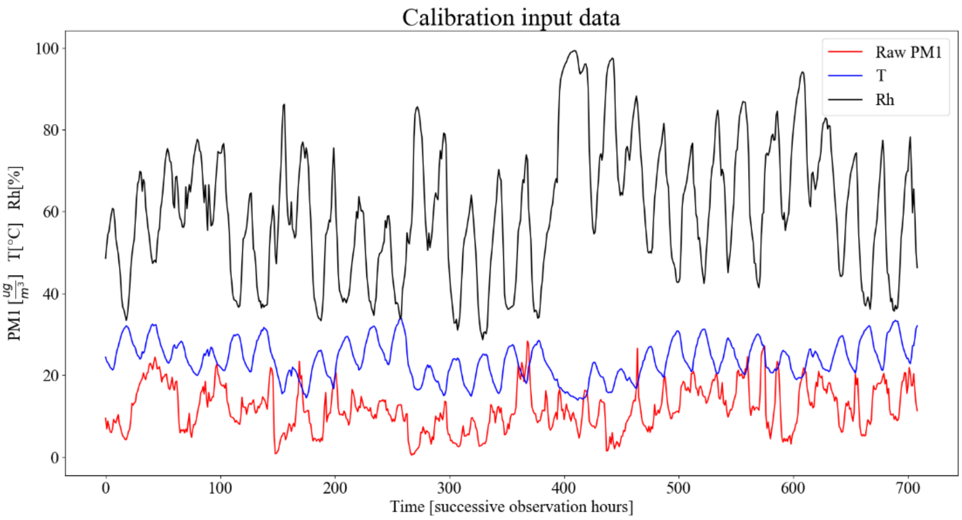

Figure 2. Calibration input data, Raw PM1 measurements (red), temperature (black) and relative humidity (blue).

After applying the linear calibration to the test data, a RMSE of 1.15 $\frac{ug}{m^3}$ was obtained. The reference data and the linearly calibrated data are shown in Figure 3.

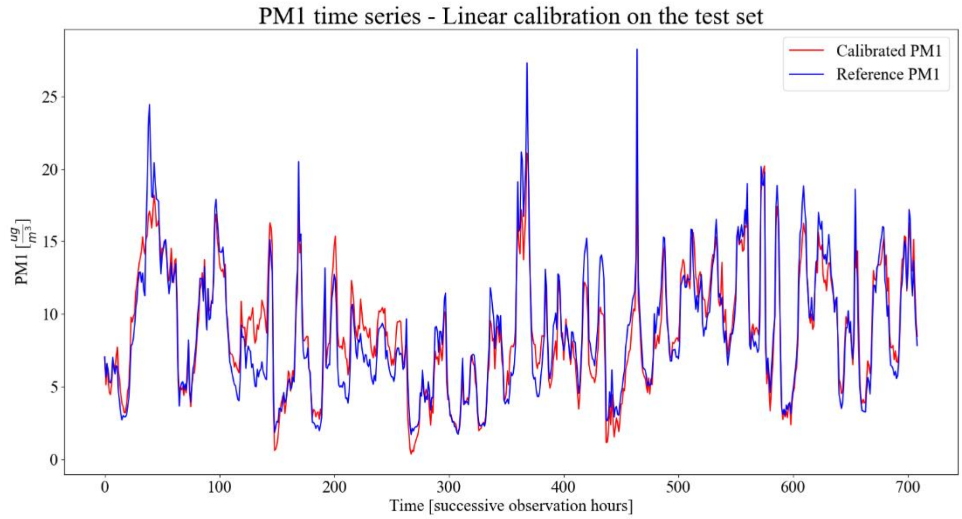

Figure 3. PM1 time series. PM1 concentration after linear calibration (red) and reference PM1 concentration (blue).

After the linear calibration, neural network calibration was performed. The RMSE of 0.87 $\frac{ug}{m^3}$ was achieved using the neural network which shows an improvement from the RMSE parameter calculated after using only the linear calibration. The time series for the reference data and for the data after the neural network calibration is shown in Figure 4.

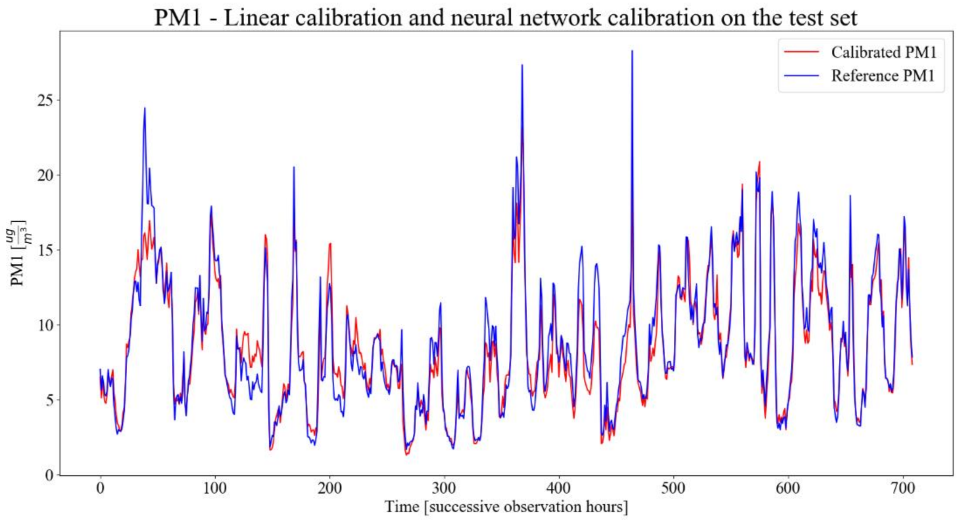

Figure 4. PM1 time series. PM1 concentration after linear and neural network calibration (red) and reference PM1 concentration (blue).

Regarding the R2 measure, a value of 0.88 was obtained using only linear calibration and a value of 0.92 was obtained after using the neural network. The calibration plot for both methods is shown in Figure 5.

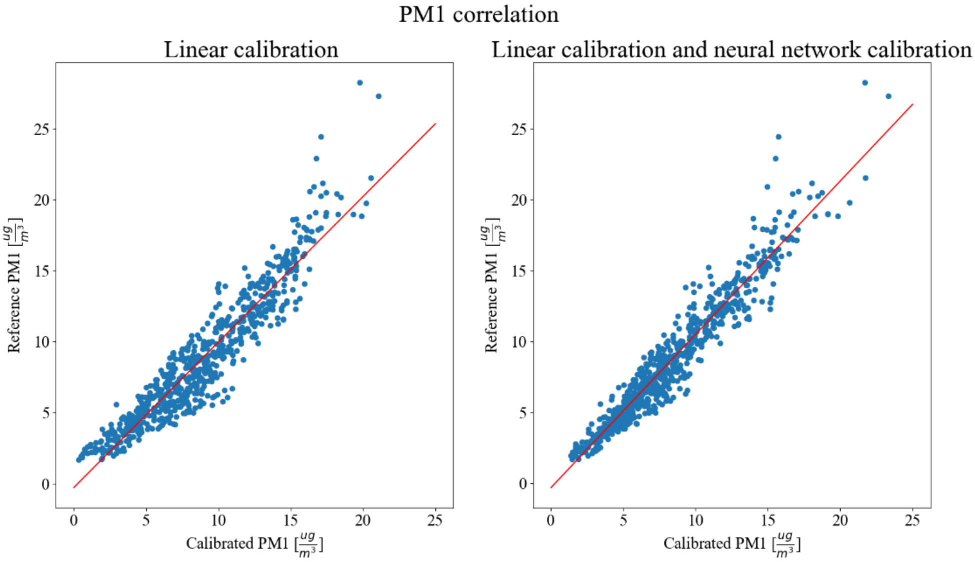

Figure 5. PM1 correlation scatter plot. Only linear calibration (left) and linear calibration with neural network calibration (right).

From the figures shown, it can be deducted that the use of a low-cost PM sensor shows quite a good correlation with the measurements of the public monitoring station, and that the usage of neural networks could further improve the correlation and increase the R2 value.

4 Conclusion

In this paper, we have presented a novel method for increasing the accuracy of a calibration by using a combination of a linear calibration with a neural network. It is shown that the used PM sensor has quite a good correlation with the reference measurements and the correlation coefficient is further improved by using a neural network. It is obvious that the temperature and relative humidity have an influence on the measurements and that they should be taken into account in order to increase the accuracy of the measurements. The measurements were conducted during June and July. The temperature was high and relative humidity was low during this period, and in future work we will implement the calibration during autumn and winter in order to see the influence of these parameters during that part of the year. Furthermore, we will do a calibration of PM2.5, PM10 and other low-cost gas sensors, like CO and NO_2.

5 Acknowledgment

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