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Sensor-Based Moisture Prediction for Flat Roofs[1]

Giacomo DA COL [a], Eva EGGELING [a,b], Marco HUDELIST [a], Christoph SCHINKO [a,b], Christof SURTMANN [c], Erich TEPPAN [a,d]
[a] *Fraunhofer Austria Research GmbH, KI4LIFE*
[b] *Graz University of Technology, Austria*
[c] *RPM Gebäudemonitoring GmbH, Austria*
[d] *University of Klagenfurt, Austria*

Abstract. Flat roofs have become popular also in central and northern Europe during the last decades. One advantage when compared to pitched roofs is that flat roofs are typically significantly cheaper. Furthermore, the roof space can be used also as a garden, a terrace or simply to quite easily install photo-voltaic systems on it. However, flat roofs are known to be prone to drainage and leakage issues. Roof utilization as a garden or the shadowing of installed photo-voltaic systems magnify this problem. For these reasons, installing moisture sensors inside the roof in order to monitor the moisture levels is one possibility to detect roof damages early and keep repairing costs low. In this paper we report on first results of an industrial project that aims to go one step further. Based on past sensor values the goal is to predict how moisture levels will progress in the near future and thus be able to identify problems before they become critical.

Keywords. machine learning, internet of things, predictive maintenance, real world problem, experimental evaluation, time series analysis

1. Introduction

Flat roofs, in contrast to sloped roofs, possess a very low pitch that is typically less than 10° (see Figure 1). Out of this, the main advantage of a flat roof apart from the building costs is that the roof area can be used as additional living space. Originating in zones with dry climates, flat roofs have found their way also to climate zones with more challenging climatic characteristics (e.g. icy weather, precipitation excesses evaporation, etc.). Under such climatic conditions waterproofing and isolation aspects become even more critical. In contrast to roof coverings that channel off rainfall by their constructive inclination, waterproofing of most flat roofs is achieved by a synthetic foil. Figure 1 shows a typical set up for a flat roof: On top of the base course (e.g. concrete) a vapor barrier (e.g. tar-bitumen) prevents that humidity from the interior or the base itself gets into the isolation. On top of the isolation (e.g. polystyrene) a waterproof foil (e.g. polyethylene) prevents precipitation to get inside the roof. The foil itself is often protected by a fleece on top of which there can be found gravel or some type of plates for making the roof walkable.

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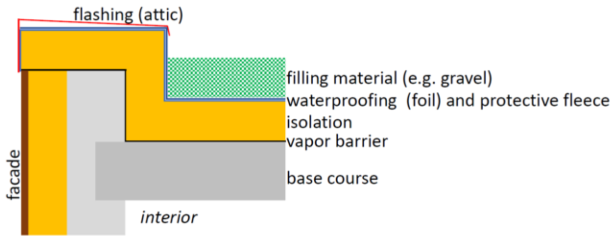

Figure 1. A typical construction set up for a flat roof.

In comparison to other roof types, flat roofs tend to be quite error prone. There are several sources of problems that come along with the foil, that is responsible for waterproofness. On the one hand there are always parts of the roof penetrating that layer, like for example the drainage parts that are responsible to let water flow off the roof. The roof parts, where the drains are plugged, have a high probability of failure. On the other hand also the foil itself can be damaged or have not been welded properly already at construction time. What makes the issue even more tricky is that problems are harder to detect compared to pitched roofs that can be checked from the inside. As there is normally a vapour barrier on top of the concrete, a leaking roof can stay undetected for a long time (or even forever). The problem with this is that a wet isolation layer looses its isolating qualities. As a consequence a lot of energy is wasted and non properly isolated roofs increase the chance of mold problems in the rooms underneath the roof, which might not be attributed to the roof leakage. Also some construction materials are very sensitive to moisture, and a constructive total loss could happen only within months. Out of these reasons roof building companies, like our project partners, have begun to install moisture sensors into the flat roofs, in particular in the isolation layer, in order to be able to detect problems as early as possible. Having a number of moisture sensors in the roof allows to detect, when there is too much water in the roof and possibly also to localize the damaged roof area.

However, what would be desirable in addition is the possibility to predict a roof's moisture level for the near future. During construction (or repair) a lot of humidity/water might have gotten into the roof and such that only taking into account the absolute moisture levels is not sufficient. The challenge is rather to estimate whether the roof gets dryer or not. If a roof gets dryer over time, this means that the construction is well functioning and a preceding damage was repaired correctly. As also some materials only allow a very short time for reaction before a constructive total loss can happen, a commercially usable moisture level prediction must perform on data of not more than a few months. As during three months not all seasonal effects are included in the data, a sound prediction must also rely on external data. Hence, conventional time series analysis is not sufficient [1].

In order to investigate whether supervised machine learning methods [2] can, in principle, be applied to predict the moisture levels inside a flat-roof equipped with a moisture sensor, an experimental evaluation was carried out in cooperation with our roof building industrial partners. In particular, a set of test roofs were equipped with moisture sensors and data was measured between the years 2012 and 2019.

2. Proof of Concept Evaluation

Scenario. Our industrial partners are especially interested in being able to predict the moisture levels of a flat roof based on sensor data that is not older than three months. The reason for that is that some materials are very vulnerable to moisture such that problems and damages must be detected early. In particular, this refers to the two cases where our partners build a new roof from scratch or have repaired a damage on an existing roof. In either of the two cases some humidity/water gets into the roof because of precipitation during construction or due to the damage before repair respectively. Thus, from such a time point starting with possibly high moisture levels, the main question to be answered is whether the roof gets dryer in the long run, or at least if the situation does not get worse. Note that, this does not simply mean that the moisture level never rises. In fact, the inside condition of the roof is affected by the external weather conditions. Typically, the moisture levels go up during summer and go down during winter. Hence, accurate predictions must take into account the seasonal effects. However, in our scenario we are only allowed to use sensor data of the past three months such that seasonal effects are not fully incorporated. This makes it inevitable to not only use the data of a given roof but also use external data sources like weather data and data from other comparable roofs.
Dataset. Our industrial partners supplied us with daily moisture data of 10 sensors from 8 roofs (i.e. 2 roofs were equipped with 2 sensors). Additionally, we used historic weather data for the corresponding geographic areas and time periods. In particular, we used the outside relative humidity, the outside temperature and precipitation. For our evaluation, we created our prediction problem instances based on the subset of 7 sensors (on 6 roofs) that possesses a most recent and common overlapping time period of one and a half year (July 2016 - December 2017). For each of these selected sensors we extracted 4 different time periods of 9 consecutive months with a shifting window of 3 months. The first 3 months are used as training data in order to predict the next 6 months. Hence, we use a prediction window of twice the size compared to the observation period of the sensor in question. We have 7 (sensors) $\times$ 4 (periods) = 28 test cases. Additionally to the 3 months training data of a particular sensor for a particular period we also use a year of past data of the remaining 9 sensors and the corresponding weather data. The raw data was preprocessed to weekly averaged data.
Experimental Setup. We use the gradient-boosted decision trees provided by XGBoost to train our predictor [3]. Given the nature of our data, we model it in a tabular fashion. For this kind of data, XGBoost seems to be a good choice to create a lightweight and portable prediction solution. Our model is supplied with weekly sensor as well as weather input data and outputs the expected roof moisture for the calendar week in question. Before training, we conducted a single hyperparameter tuning with a 5-fold cross validation and a randomized parameter search with data from the first time period of the first sensor and use the same parameters[2] for all experiments.
Results and Conclusions. Figure 2 shows the predictions of our model compared to the actual measurements during the four time periods (called Q1...Q4) for each of the seven sensors (R01...R08). The sensors are located in different roofs with different construction setups (except R03_1 and R03_2 that are integrated in different parts of the same roof). Generally, the proof-of-concept is clearly given since even our quite simple model

[2]Hyperparameters: n_estimators: 173, learning_rate: 0.0481, subsample: 0.339, max_depth: 4, colsample_bytree: 0.947, min_child_weight: 6; Scikit-Learn Wrapper: XGBRegressor

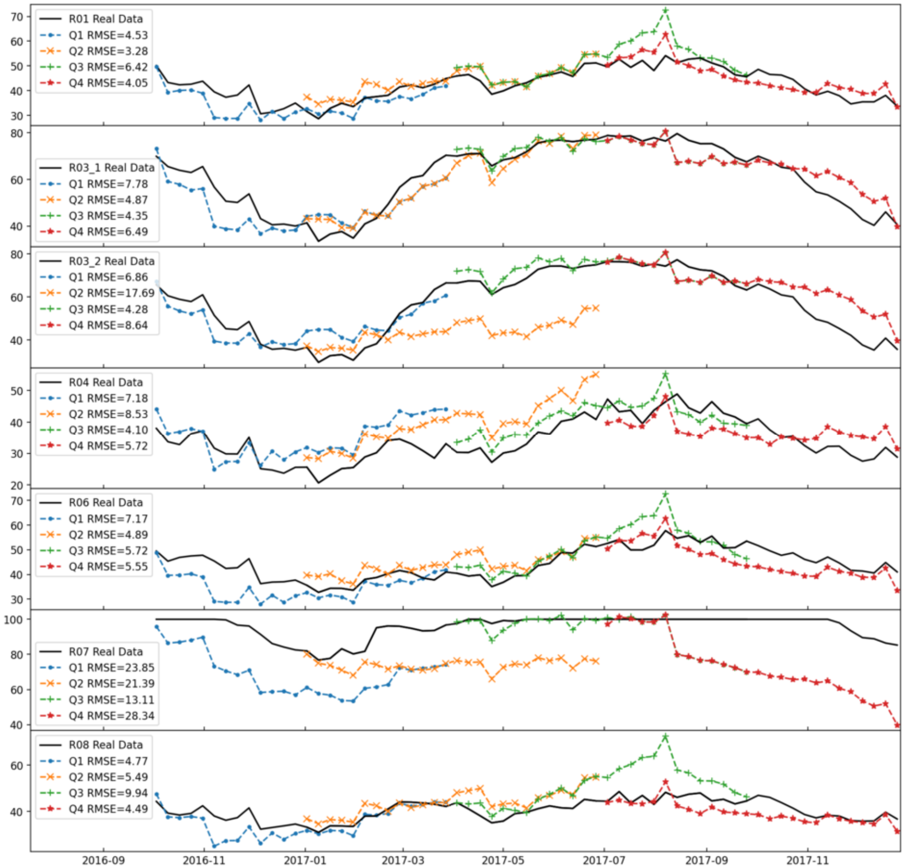

Figure 2. Real measurements compared to predicted values of our XGBoost model for all 4 time periods (called Q1...Q4) for each of the 7 sensors (R01...R08). Root Mean Squared Errors are given in the legend.

produces predictions that are accurate enough for practical purposes. These promising results open up a wide range of follow-up research activities treated in future work. In particular, we will carry out a thorough investigation comparing different machine learning algorithms.

Summarizing, we want to emphasize that the presented research contributes to the goals of the European Green Deal initiative aiming at decarbonization and waste reduction, like increasing the operating life expectancy of buildings by predictive maintenance.

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