

Machine learning for filter pollution control

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ABSTRACT

Modern buildings usually have an air-tight envelope. Therefore mechanical ventilation is very often necessary. A crucial part of the system is the filter, which allows creating an atmosphere that is free of dust, aerosols, and pollen. As organic material accumulates on the filter surface, the risk of micro-organism growth rises. This may yield health issues especially for the occupants of buildings.

For this purpose a machine-learning algorithm was developed utilizing different parameters as air temperatures, relative humidity, pressure drop coefficient and filter humidity.

The method was implemented in both a test rig and the HVAC system supplying different laboratories with fresh air in order to aggregate data for different abnormal and normal operation conditions. Subsequent considerations focuses on the test-rig measurements. The machine learning algorithm was trained successfully to detect anomalies of the filter behavior.

Finally, the change intervals of the filter may be adapted to the real degree of pollution without the requirement for visual observation in order to provide best air conditions. This algorithm is part of a general strategy for machine-learning processes for HVAC systems.

Keywords: filter, pollution, machine learning, hvac, hygiene, energy efficiency

INTRODUCTION

The Paris Agreement forces the signing states to reduce their carbon dioxide emissions [1]. For this purpose, the consumption of fossil fuels has to be reduced dramatically. That can be achieved by increasing both the renewable share of the energy supply and the energy efficiency [2]. One measure is to improve the insulation of building that leads, however, to practically air-tight building envelopes. Therefore, mechanical ventilation systems are required in order to assure a healthy ventilation rate. An important task of a mechanical ventilation system is to prevent pollutants from outside entering the building, for which purpose filters are employed. These filters are prone to fouling and, if the conditions are humid enough, to micro-organism growth, yielding severe health issues. Thus, filters are usually changed on a regular basis. This procedure is, however, most likely too often or too seldom and always combined with a manually observation according to VDI 6022, e.g.

Methods of machine learning might help solving this optimisation problem. They are widely used for internet-based services such as search engines, news

feeds, image classification, etc. They became also quite popular in conjunction with the so-called internet of things, where devices are connected over internet in order to provide some benefit to the user [3]. First academic studies investigate the utilisation of machine learning for HVAC systems [4–11].

In particular, algorithms for anomaly detection gained recently some interest. There are some publications with the intention to detect malfunctions in HVAC systems, such as Ref. [12-17].

Based on this earlier work, the objective of this contribution is to provide a set-up and machine learning algorithm to assess the micro-organism growth risk of filters. The paper is organised as follows: Section 2 presents the experimental set-up with the HVAC and measurement systems as well as the measurement series. Moreover, the machine learning algorithm with the model and the workflow is presented. Section 3 provides the results and discussion.

EXPERIMENTAL INVESTIGATION

HVAC system

The experimental investigation is carried out in one of two parallel operable HVAC systems of the “room air-flow laboratory” of the institute (see Fig. 1 for an illustration) [18]. It consists of the following major components: air intake (A), flap (B), intake filter (C), recirculation air flap (D), cooler (E), heater (F), supply fan (G), humidification (H), silencer (I), air exhaust (J), flow-rate control (K), fire protection flap (L), air emission (M) into the room air-flow laboratory and the air extraction (N) from there.

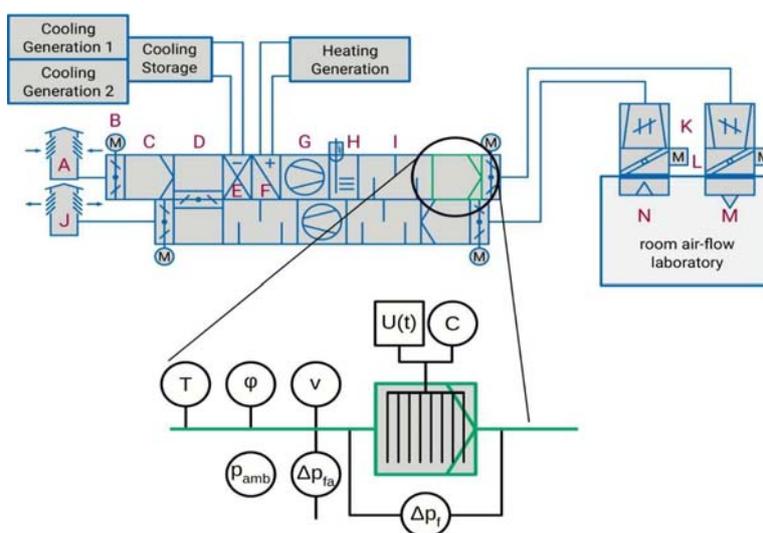


Figure 1. Schematic drawing of the experimental set-up: HVAC system of the “room air-flow laboratory” (top) and detail of the test section (bottom) with the measurement devices for temperature (T), relative humidity (φ), velocity (v), pressure drop (Δp), electrical capacity C , and the function generator for the voltage $U(t)$

Measurement system

The subject under consideration is the filter highlighted in Figure 1 that is prepared with electrodes made of stainless steel oriented perpendicularly to the flow direction. The electrodes are connected to a function generator providing sinusoidal voltage signals. As a measure for the humidity of the filter, the electrical capacitance exhibits the best signal-to-noise ratio compared to resistance, inductance, and impedance, as obtained from preliminary tests (see

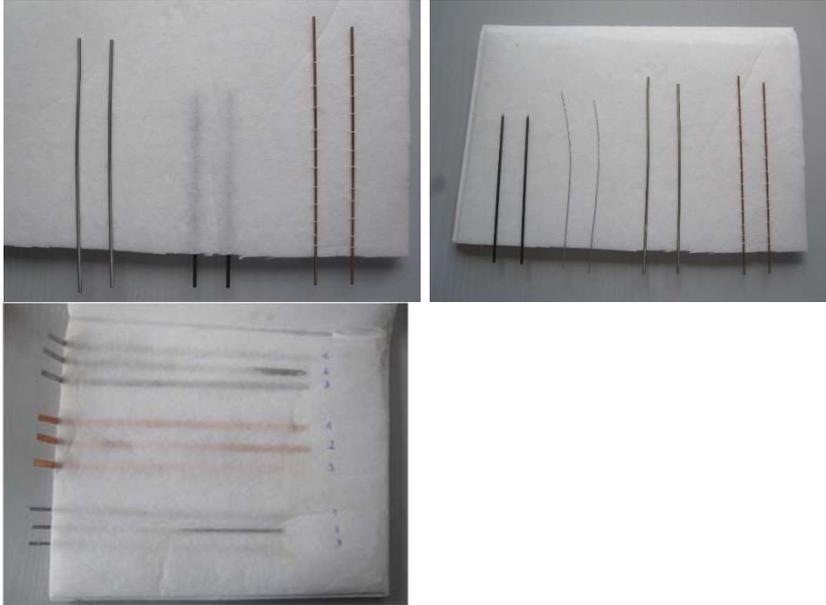


Figure 2 for the test samples).

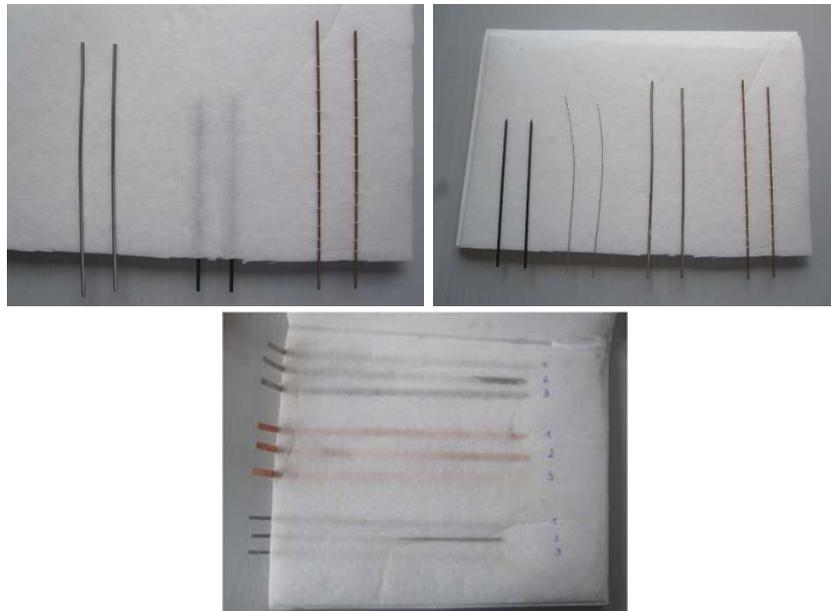


Figure 2. Test samples for the detection of the moisture (upper left: different shapes of the electrodes; upper right: different materials; lower: different mounting

The interrelation between electrical capacitance and the humidity of the filter via the permittivity ε is provided by [19]:

$$C = \frac{\pi \varepsilon L}{\operatorname{arcosh}\left(\frac{S}{D}\right)}. \quad (1)$$

Herein, L , D , and S are the length, diameter and distances of the electrodes, respectively. In this study, the electrical capacitance is actually measured and depends upon the humidity of the filter via the permittivity ε . Moreover, the pressure difference between the ambient and the inlet of the filter Δp_{fa} , the pressure drop over the filter Δp_f , the ambient pressure p_{amb} , the temperature T , relative humidity φ , and velocity of air v at the inlet of the filter are measured (see Figure 1 for details).

The measurement uncertainty of the used measurement devices and the procedure for the calculation of the dimensionless pressure drop is in accordance with [20].

The filter mounted in the HVAC channel was employed in the normal operation of the room air-flow laboratory for two periods of several months. During these periods, a lot of data points were recorded. Moreover, distinguished experiments were carried out in which the filter has been humidified manually by sprays of water droplets.

Measurement results

To analyse the measurement results a machine-learning algorithm were used [20].

Figure 3 presents a short section of the total measurement data. The objective was to find abnormal sets of parameters. Therefore the parameters have been ordered by their risk of micro-organism growth according to eq. (2),

$$P(x_i, \mu_i, \sigma_i^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}\right] \quad (2)$$

with x as the actual value, μ as the mean value, σ^2 as the standard deviation of the parameters i to n . Herein P represents the possibility a set of parameters is abnormal. Mean values and standard deviation as well as the threshold value for P are a result of the training of the machine-learning algorithm with the measured data.

Figure 4 shows an example of a two dimensional distribution of parameter sets estimated by a machine learn algorithm based on synthetic results.

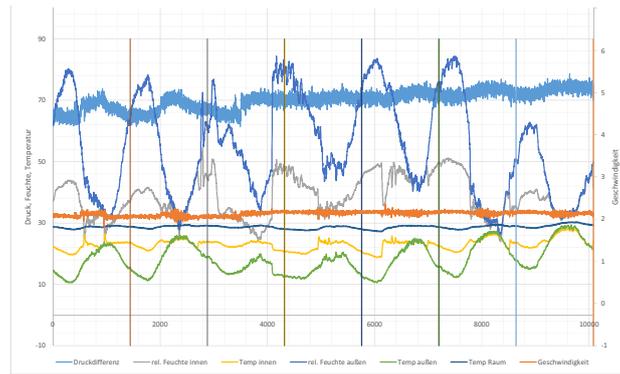


Figure 3. Measurement results containing one week

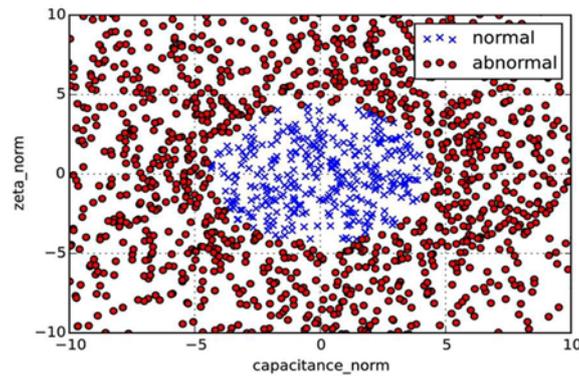


Figure 4. Distribution of normal and abnormal sets of parameters

RESULTS AND DISCUSSION

One objective of the investigations is to gain a criterion for the micro-organism growth risk in a filter. This is essential for the development of a risk management to improve a save HVAC operation and to prevent severe health issues. The most important parameters for the risk management are water, temperature, pressure drop and moisture.

Figure 5 shows schematically the influence of these parameters on micro-organism growth risk on a filter. In the first step of analysing the measurement results, no time history was taken into account.

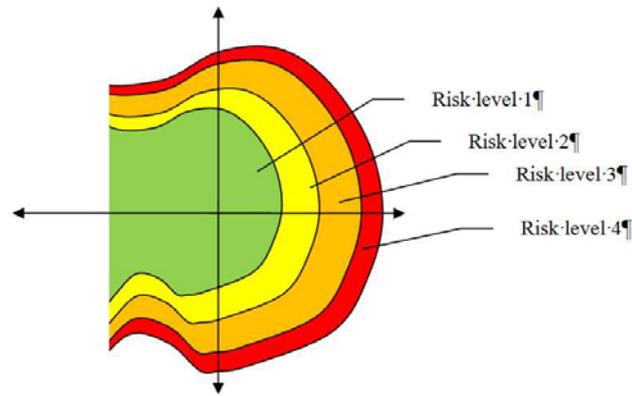


Figure 5. Influences of ambient conditions on micro-organism growth risk on filters (schematically)

It is obvious that the time history has also an influence on the micro-organism growth risk. Therefore a cumulative risk level was calculated. An example is shown in

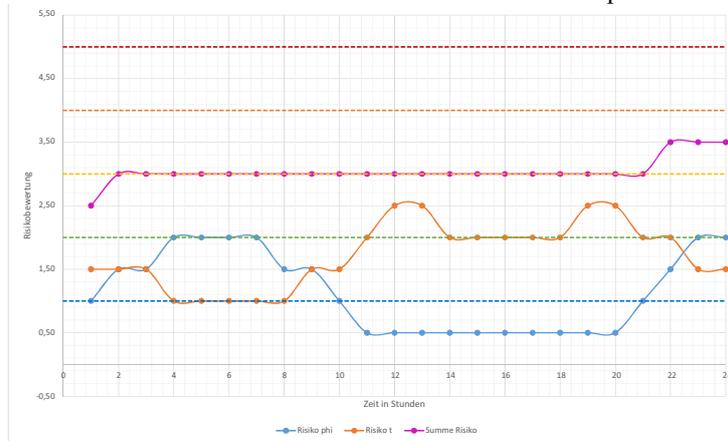


Figure 6. The overall risk level is defined as the maximum level over the last period. This requires a manual reset of the risk level after filter replacement.

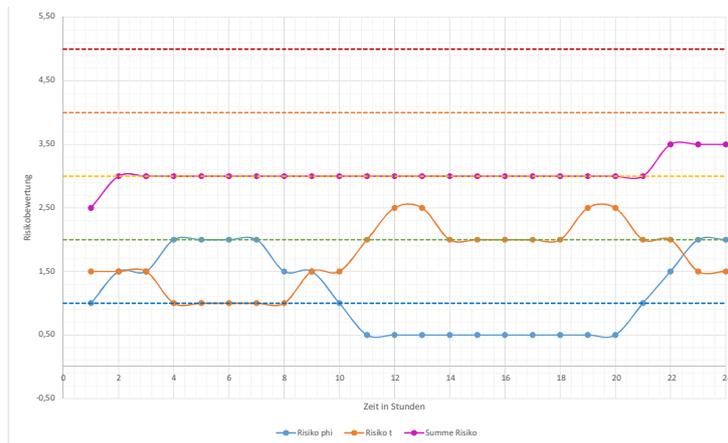


Figure 6. Influences of micro-organism growth risk on filters consideration

CONCLUSION

Since modern buildings have practically air-tight envelopes, mechanical ventilation becomes more and more important. Filters are required in this context in order to prevent pollutants from outside to enter the system. However, filters are prone to fouling, especially in humid environments, and, therefore, have to be changed on a regular basis.

In order to substitute this process by a data-driven approach, a test set-up in the HVAC system of the room air-flow laboratory of the institute was designed and an air filter was equipped with electrodes made of stainless steel. The pressure drop over the filter and the electrical capacitance were measured and employed as indicators for the level of pollution and the micro-organism growth risk.

With the present results the measurement method has been improved. That concerns the application of electrodes in the filter material to get a correlation between the moisture content and the electrical capacity. The data analysis with a machine-learning algorithm provides a risk management comprising different risk levels.

In further steps the machine learning algorithm has to be improved with data for mould growth depending upon the parameters present in this article.

ACKNOWLEDGEMENTS

This work has been supported by the Federal Ministry for Economic Affairs and Energy of the Federal Republic of Germany under Contracts no. MF 140105, no. MF 170011 and no. MF 180093.

Supported by:



on the basis of a decision
by the German Bundestag

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