Condition Monitoring for Air Filters in HVAC Systems with Variable Volume Flow

Oliver Gnepper[a] and Olaf Enge-Rosenblatt[b]

Fraunhofer Institute for Integrated Circuits IIS, Division Engineering of Adaptive Systems EAS, Zeunerstraße 38, 01069, Dresden, Germany

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Abstract: State of the art condition monitoring systems for air filters in HVAC systems require that the HVAC system is operated at nominal volume flow. For HVAC systems with variable volume flow this assumption is only fulfilled in one operating point. Outside this operating point existing condition monitoring systems assess the air filter condition in a too optimistic manner. Therefore, polluted air filters remain undetected until their regular check, leading to unneeded energy consumption. If the true condition of an air filter is known, it could be changed before it is clogged. So, a condition monitoring systems is needed which is also reliable in case of HVAC systems with variable volume flow. This work presents a model-based approach for such a condition monitoring system. Therefore, a dataset from a building is used to assess an optimal model. Furthermore, the condition monitoring systems is evaluated on that dataset.

1 INTRODUCTION

Air filters in HVAC systems are used for precipitating of dust particles from the intake air. Additionally, they protect succeeding components of an HVAC system from pollution and damage due to abrasion. Furthermore, particles which are harmful to human's respiratory system should be removed from the supply air as well. Therefore, it is necessary that air filters are in a good condition at any time. This is ensured by a professional service on a regular basis. In (Verein Deutscher Ingenieure, 2018) a quarterly visual inspection is demanded and a semestral check of the differential pressure of air filters in HVAC systems. For HVAC systems with a nominal volume flow of more than $1000\,\mathrm{m}^3/\mathrm{h}$, sensors which display the current value of the differential pressure must be installed (Verein Deutscher Ingenieure, 2018). Usually the measured differential pressure is compared with a fixed limit to determine if an air filter is clogged and must be changed. In principle, the differential pressure measured at an air filter depends on the volume flow which passes through the air filter. So, in case of HVAC systems with variable volume flow a comparison of the differential pressure with a fixed limit results in an erroneous estimation of the air filter condition.

The following section contains a review of the air filter condition monitoring state of the art. It is shown that several approaches to monitor the air filter condition exist, but these approaches are either restricted to be used in combination with a dedicated HVAC system or high effort is necessary to retrofit these approaches in existing HVAC systems. Furthermore, it is shown that several models of air filters exist which could be used to estimate the air filter condition. These models are described in Section 3. For each model the quality of fit is evaluated on a dataset from a building in Germany. This dataset is described in Section 4. The model selection method and the corresponding results are shown in Section 5. In Section 6 it is shown how the selected model is used to monitor the condition of air filters. This work is finished with a conclusion in Section 7.

2 STATE OF THE ART

Detecting if air filters in HVAC systems with variable volume flow are clogged, is a problem which is addressed in different ways. A pneumatic air filter condition indicator for HVAC systems which displays the air filter condition for two different fan speeds is de-

[a] https://orcid.org/0000-0001-6430-620X
[b] https://orcid.org/0000-0002-6069-7423

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scribed in (Ladusaw, 1966). The air filter condition is indicated by a device which floats in the air that bypasses an air filter. The floating height is also influenced by the fan speed. So, there is an indication area for the low and the high fan speed. In (Fraden and Rutstein, 2007) a method is described which uses a heated wire to measure the volume flow. If the latter drops below a predefined limit, the air filter is declared to be clogged. A similar method is claimed in (Kang et al., 2006). Herein, the temperature gradient due to a fan speed change is measured. The air filter condition is determined by comparing the temperature gradient with a predefined limit. All these approaches have in common that they detect air filter clogging, but they are not able to predict the remaining useful life of air filters. In addition to that these methods must be tuned for different types of air filters.

An air filter model which utilizes measurements that are already collected in HVAC system provides a better scalability of the desired solution. In (Kang et al., 2007) it is claimed that deviations of the total pressure difference of fans are mainly induced by air filters. Therefore, the condition of an air filter is assessed by comparing the measured total pressure difference with the one which is estimated from the characteristic fan curve. The total pressure difference is truly affected by the condition of air filters, but this is not the only influence. Therefore, this approach is a good measure for anomalies in HVAC systems. This method is designed for a particular system and does not generalize well. Therefore, it is necessary to use a model of air filters which represents the resistance of air filters to the air flow.

In (Saarela et al., 2014) a model which combines different influences on the differential pressure development of air filters for nuclear power plants is introduced. Each influence is modelled separately. Hereby the relationship between volume flow $\dot{V}$ and differential pressure Δp of an air filter is described by a model of the form which is shown in Equation 1. This equation also includes the parameters a and n. Hereinafter this model is called type I.

$$\Delta p = a \cdot \dot{V}^n \tag{1}$$

In (Liu et al., 2003) such a model is also used to estimate the reduction of empty spaces between fibres of air filters. The same model structure is also described in (DIN Deutsches Institut für Normung e.V., 2013). Whereas, (Eckhardt, 2018) uses the following approach to model the relationship between volume flow and differential pressure of an air filter which is subsequently denoted as type II.

$$\Delta p = a \cdot \dot{V}^2 \tag{2}$$

This modelling approach is also used in (Kruger, 2013) and in (Verein Deutscher Ingenieure, 2004). The latter cites (Löffler, 1988) which extends the second order term with a linear term and the associated parameter b. This yields Equation 3. The corresponding model is consecutively called type III and is also proposed in (Kanaoka and Hiragi, 1990), (Rivers and Murphy, 2000) and (Albers, 2017).

$$\Delta p = a \cdot \dot{V}^2 + b \cdot \dot{V} \tag{3}$$

As shown, in the literature there is no standard model for air filters. In addition, there is no comparison with other models in any of the publications. Furthermore, there is no agreement in the literature on the consideration of further influences on the differential pressure, such as air density or dynamic viscosity of air as well as filter-specific parameters such as fibre thickness. While the models in (Verein Deutscher Ingenieure, 2004), (Löffler, 1988), (Kanaoka and Hiragi, 1990) and (Rivers and Murphy, 2000) cover any of these influences in detail, the model in (DIN Deutsches Institut für Normung e.V., 2013) takes only the influences of air density and dynamic viscosity of air into account. On the other hand the models in (Saarela et al., 2014), (Liu et al., 2003), (Eckhardt, 2018), (Kruger, 2013) and (Albers, 2017) neglect all influences. Therefore, for a comparison of these models, it is necessary to unify the level of detail of the models and to adapt all models in such a way that it is possible to quantify the benefit of further measured variables and derived influences, such as air density and dynamic viscosity of air.

3 FILTER MODELS

During the model unification, it must be ensured that the resulting models can be retrofitted in existing HVAC systems with as little effort as possible. In existing HVAC systems, the filter-specific parameters are usually unknown. Therefore, the level of detail of the models is reduced to such an extent that they do not contain any filter-specific parameters. Furthermore, it must be ensured that all used models can represent the influences of air density and dynamic viscosity of air. The following chapters describe the model unification procedure and the resulting models.

3.1 Exponential Model

In (DIN Deutsches Institut für Normung e.V., 2013) a model is described which takes dynamic viscosity of air and air density into account and has the same structure as model type I. Equation 4 shows the corresponding mathematical statement.

$$\Delta p = c \cdot \mu^{2-n} \cdot \rho^{n-1} \cdot \dot{V}^n \tag{4}$$

This equation includes a resistance coefficient c, dynamic viscosity of air μ, air density ρ and an exponent n. The latter is not restricted to a specific value and changes over time as the dust load increases. In (DIN Deutsches Institut für Normung e.V., 2013) Equation 5 is used to calculate the dynamic viscosity of air where T is measured in °C and μ in Pa s.

$$\mu = \frac{1.455 \cdot 10^{-6} \cdot (T + 273.15)^{0.5}}{1 + \dfrac{110.4}{T + 273.15}} \tag{5}$$

The Equations 6 to 10 can be used to estimate the air density which include the ambient pressure p, the water vapour partial pressure p_w and the relative air humidity φ (DIN Deutsches Institut für Normung e.V., 2013).

$$\rho = \frac{0.378 \cdot p \cdot p_w}{287.06 \cdot (T + 273.15)} \tag{6}$$

$$p_w = \frac{\varphi}{100} \cdot \exp(c_1 - \frac{c_2}{T + 273.15} - c_3 \cdot \ln(T + 273.15)) \tag{7}$$

$$c_1 = 59.484085 \tag{8}$$

$$c_2 = 6790.4985 \tag{9}$$

$$c_3 = 5.02802 \tag{10}$$

The building in which the data is collected which is used for the validation has two HVAC systems with humidification and one HVAC system without humidification (see Section 4). The ambient pressure is measured in none of these HVAC systems. Additionally, the relative air humidity is only measured in the two HVAC systems with humidification. In order to include the influence of the air density, it is calculated in two ways. In case of the HVAC systems with humidification the Equations 6 to 10 are used, but it is assumed that the ambient pressure is constant at $p = 101325\,\mathrm{Pa}$. Additionally, for all three HVAC systems Equation 11 is used to estimate the air density (Albers, 2017). It is analysed which of the two approaches provides more accurate results and thus represents the preferred variant for similar cases (see Section 5).

$$\rho = 1.275 \cdot \frac{273.15}{T + 273.15} \tag{11}$$

3.2 Second Order Models

The model which is described in (Verein Deutscher Ingenieure, 2004) bases on the model in (Löffler, 1988) and is shown in Equation 12.

$$\Delta p = \frac{2 \cdot c_D \cdot u^2 \cdot \rho \cdot \alpha \cdot z}{\pi \cdot d_F} \tag{12}$$

This equation includes the resistance coefficient c_D, the flow velocity u, the fibre layer thickness z, the packing density α and the fibre diameter d_F. The last three parameters are constant. Only the pressure coefficient, the differential pressure Δp, the air density ρ and the flow velocity vary over time. The flow velocity is not measured in the analysed dataset (see Section 4), but is replaceable by the following expression which introduces the volume flow $\dot{V}$ and the filter area A. The latter decreases over time as the dust load increases.

$$u = \frac{\dot{V}}{A} \tag{13}$$

As described above, Equation 13 is inserted in Equation 12 which yields Equation 14. The filter-specific parameters and the pressure coefficient are substituted by the parameter c.

$$\Delta p = c \cdot \dot{V}^2 \cdot \rho \tag{14}$$

In (Löffler, 1988) this model is extended by an additional linear term. This yields Equation 15. The parameters c_4 and c_5 in Equation 15 replace the filter-specific constants and any immeasurable coefficient (e.g. filter area) which correspond to the dust load of an air filter.

$$\Delta p = c_4 \cdot \mu \cdot \dot{V} + c_5 \cdot \rho \cdot \dot{V}^2 \tag{15}$$

The models in Equation 4, 14 and 15 have in common, that they describe the relationship between differential pressure and volume flow of an air filter, but they differ in their structure. All three models take the influence of the air condition (dynamic viscosity and density) into account. The dynamic viscosity of air is calculated as described in Equation 5. In the case of air density, it depends on whether the relative air humidity is measured. If this is the case, then Equations 6 to 10 are applied. If this is not the case, then Equation 11 is used. The different models in combination with the different approaches to consider the air density and the dynamic viscosity of air as well as the value of exponent n in model type I give rise to the following questions:

1. Which of the described models is most suitable to represent the relationship between differential pressure and volume flow of an air filter?
2. Does the consideration of the dynamic viscosity of air and air density increase a models accuracy?
3. Is it necessary to estimate the air density via the air temperature and the relative air humidity or is the air temperature sufficient?

4. How does the exponent of model type I changes as the dust load increases?

These questions will be answered by a model comparison on a real world dataset.

4 DATASET

The dataset was collected from a building in Germany. This building has three HVAC systems where an air filter is installed in every supply air duct and every return air duct. Every year during March, the air filters are changed. For each of these air filters differential pressure, volume flow and air temperature are measured. The relative air humidity is only measured for the air filters of two HVAC systems, because the third HVAC system does not include a humidification. For the air filters of the third HVAC system the influence of the relative air humidity on the model performance is not analysed.

The data was collected during the period of 01 August 2017 until 31 March 2020. To reduce the data volume and velocity the data is logged on change with a minimal distance between two samples of one minute. Additionally, this dataset contains several inconsistencies. In some cases the measured physical quantity did not match with the one which is declared in the building management system. These incorrect matches were identified and corrected. Furthermore, the following data preprocessing steps were carried out:

1. Resample the data to a fixed frequency of one minute and apply a forward fill to close gaps which are induced by the log on change.
2. Remove samples which are marked as bad quality samples by the building management system.
3. Remove parts of a time series where the wrong physical quantity was measured.
4. Remove samples where the value jumped to 0 and instantly back to approximately its previous value.
5. Remove samples where the value was at least twice as high as the nominal maximal value.
6. Remove samples where the value was lower than the nominal minimal value.
7. Set samples to 0 when the HVAC system is turned off and the values do not reach 0 exactly.

This procedure ensures that only valid samples remain for the following analysis.

5 MODEL SELECTION

In order to answer the questions which are raised at the end of Section 3, the different model variants are compared with each other. This process is described in the following section. The obtained results are discussed in Section 5.2.

5.1 Method

Equations 4, 14 and 15 form the basis for the model comparison. According to the explanations in Section 3, the influence of the dynamic viscosity of air can be represented by means of Equation 5 and the influence of the air density either by means of Equations 6 to 10 or Equation 11. With regard to the representation of the influence of the air density, it is decisive whether the relative air humidity is recorded for the analysed HVAC system or not. If the relative air humidity is recorded, Equation 5 and Equations 6 to 10 are added to the model equations. This set of influence equations is referred to as set A in the following. If the relative air humidity is not recorded, Equation 5 can still be used, but Equation 11 is used instead of Equations 6 to 10. In the following, this set of influence equations is referred to as set B. In addition, the hypothetical case that the air temperature is not measured is also considered for comparison purposes. This is realised by assuming the influences of the air density and the dynamic viscosity of air in Equations 4, 14 and 15 to be constant at the value 1. So, set C contains the value 1 for the air density and the dynamic viscosity of air. For each combination of model type and set of influence equations the following steps are applied.

1. Start at the beginning of the time series.
2. Define a window of the duration m days which selects a data segment.
3. Estimate the variables c, c_4, c_5 and n for the selected data segment by conducting a least squares fit.
4. Use the air filter model, the determined variables as well as the measured volume flow, air temperature and relative air humidity values to estimate the differential pressure for each sample of the last day of the selected data segment.
5. Move the window one day further.
6. Repeat the steps 2 to 5 until the time series end.

This process considers changing air filter conditions as well as different usage patterns of a building during a week. The latter is considered by setting the window size to a value which is a whole-number multiple of 7 days where the whole number-multiple is in the range of 1 to 5. This variation is necessary to identify a sweet spot at which the least number of samples is used to achieve an optimal quality of fit and is the foundation for the further analysis.

As described in step 4 the model is used to calculate the estimated differential pressure $\widehat{\Delta p}$ for each sample. These values are necessary to determine the reconstruction error of the model. As a measure for the reconstruction error the root mean squared error (RMSE) is used. Equation 16 shows the used definition of RMSE where N is the number of samples.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{\Delta p_i} - \Delta p_i\right)^2} \tag{16}$$

The RMSE values are then used to answer the questions in Section 3. First, however, the length of the sliding window at which the reconstruction error becomes minimal is determined. Therefore, for each combination of model type and set the weighted mean of the RMSE values $\overline{RMSE}$ is calculated for each length of the sliding window according to Equation 17. Here M is the number of air filters for which an RMSE value was calculated, w_i is the amount of samples which was used to calculate the RMSE value and $RMSE_i$ is the RMSE value for each air filter.

$$\overline{RMSE} = \frac{\sum_{i=1}^{M}(w_i \cdot RMSE_i)}{\sum_{i=1}^{M} w_i} \tag{17}$$

The RMSE values that result from using the optimal sliding window length are used for the further analyses. Based on these RMSE values, it is first determined which combination of model type and set yield the smallest RMSE value. This answers question 1 from Section 3. Furthermore, it is investigated whether the use of a certain set has a systematic influence on the RMSE values of all model types. This analysis provides the answers to questions 2 and 3. Based on these analyses, the combination of model type I and the set is selected which provides the lowest reconstruction error. Then, for this combination, the development of the exponents is analysed for each air filter. These values are aggregated on monthly basis, since the air filters are always changed in March but never on the same day and never in the same calendar week. This analysis answers question 4.

5.2 Results

Table 1 shows the weighted mean RMSE values for each sliding window. These results indicate that model type I and model type III perform similar on the analysed dataset. Overall, model type II performs worse than the other model types even though in some cases the weighted mean RMSE values of model type II are similar as the ones of the other model types. This indicates that model type II is underfitting the data and consequently its complexity is not high enough. In Table 1 is also visible that the weighted mean RMSE values of each combination of model type and set rise with an increasing sliding window length. Even raising the sliding window length from one week to two weeks results in higher weighted mean RMSE values. This indicates that the condition of the analysed air filters cannot be assumed to be constant within a period of two or more weeks. Therefore, a sliding window of one week is used for the further studies. Furthermore, the weighted mean RMSE values show that the most complex models (set A) always perform worse than the other models (set B and C). This could be caused by the missing ambient pressure measurements or the data quality of the relative air humidity measurements. Additionally, models which are extended by set A could be too complex and therefore overfit the data. The latter assumption is supported by the fact that in case of model type I and type III the weighted mean RMSE values of set A increase not as fast as the ones of set B and set C when a larger sliding window length is used to increase the amount of samples.

As shown in Table 1 a sliding window with a length one week yields the best results. The corresponding RMSE values for each air filter as well as the weighted mean RMSE values are shown in Table 2. Every air filter in the analysed building is identified by a number from 1 to 6. Uneven numbers are assigned to air filters in the supply air duct. Whereas, even numbers are assigned to air filters in the return air duct. In Table 2 the RMSE values of air filters with an uneven number are always higher than the RMSE values of air filters with an even number. In case of model type I and III the RMSE values of air filters with an uneven number are almost equal for each set. Whereas, the RMSE values of air filters with an even number rise when set A is used. This also counts for model type II for every air filter. So, in these cases the usage of set A leads to overfitting models. Whereas, in case of the model types I and III for air filters with an uneven number the models lack a major influence. Due to the nearly constant RMSE values for every set the air condition is not that influence. In addition to these findings the weighted mean RMSE values show that model type I in combination with set B leads to the best results. Even though model type I in combination with set C as well as model type III in combination with set B and C lead to comparable results.

As supported by the results in Table 2 set B is used to analyse the dust load dependency of the exponent

Table 1: Weighted mean RMSE values for each sliding window length.

window length in weeks	model type I			model type II			model type III		
	set A	set B	set C	set A	set B	set C	set A	set B	set C
1	5.3303	3.7005	3.7522	9.7823	6.4420	6.3621	5.3288	3.7683	3.7671
2	5.4144	3.8586	3.8769	10.2949	6.5965	6.5028	5.4120	3.9045	3.8830
3	5.4781	3.9986	3.9719	10.5604	6.6956	6.6005	5.4728	4.0093	3.9683
4	5.5352	4.0842	4.0445	10.8248	6.8014	6.7014	5.5310	4.0902	4.0392
5	5.5903	4.1695	4.1236	11.1156	6.9083	6.8011	5.5865	4.1721	4.1163

Table 2: RMSE values for a sliding window of one week.

air filter	model type I			model type II			model type III		
	set A	set B	set C	set A	set B	set C	set A	set B	set C
1	6.9818	6.9788	6.9725	10.2139	9.2112	9.2019	7.0094	6.9775	6.9714
2	3.4586	2.9847	2.9725	3.7586	3.0807	3.0660	3.4542	3.0026	2.9900
3	5.5745	5.5556	5.5369	15.6732	13.7007	13.6616	5.5551	5.5554	5.5368
4	3.9553	3.3635	3.3426	4.0731	3.4121	3.4142	3.9408	3.4023	3.4003
5	-	2.3839	2.5264	-	4.8358	4.6676	-	2.5210	2.5311
6	-	2.3471	2.3207	-	2.7927	2.7995	-	2.3959	2.3932
weighted mean	5.3303	3.7005	3.7522	9.7823	6.4420	6.3621	5.3288	3.7683	3.7671

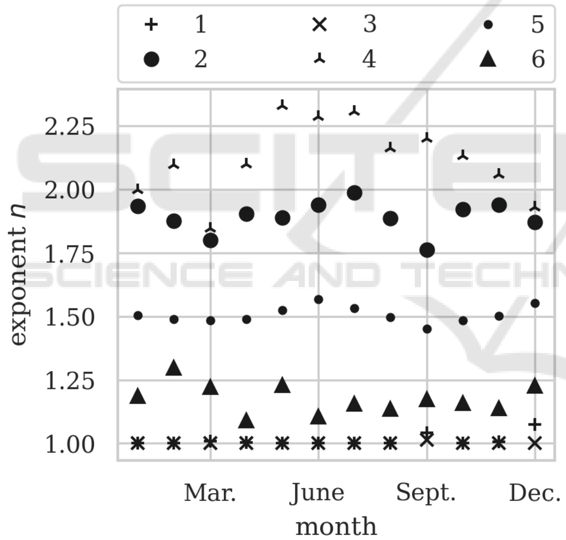

Figure 1: Development of the exponents of model type I.

of model type I. Figure 1 shows that the exponents of model type I varies around the value of 2 in case of the return air filters number 2 and number 4. In contrast, the exponents of the corresponding supply air filters nearly always have the value 1. Whereas, the exponents of the supply air filter number 5 are higher than the exponents of the return air filter number 6. As shown in Table 2 the quality of fit of the supply air filters 1 and 3 is worse than the quality of fit of the corresponding return air filters 2 and 4. This is also indicated by the values of their exponents. It was defined that the exponents cannot be lower than 1. So, the fact that the exponents of air filter 1 and 3 mostly have the value 1 also illustrates that a major influence is lacking in the model for these air filters. In addition to the differences between the exponents of each air filter Figure 1 also shows the influence of the air condition as well as the influence of the building usage. The analysed building is not that populated during March, August and September. Therefore, the HVAC system operates only at partial load or is turned off during this period. Hence, the amount of samples decreases and the quality of fit decreases as well. The influence of the air condition is indicated by a local maxima during the summer in case of the air filters 2, 4 and 5. In the end this analysis clarifies why the model type II does not perform as good as the other models. For this model it is assumed that the exponent has the value 2 which is not the case for each air filter. The models type I and III offer the possibility to choose other exponents, in case of model type I and a mixture of different exponents in case of model type III. Furthermore, this analysis also illustrates that the air condition as well as the usage of the building affect the results of the fit.

6 CONDITION MONITORING

Model type I in combination with set B yields the best quality of fit. So, the resulting model is used hereinafter to estimate the condition of air filters. At first the used condition monitoring method is described and Section 6.2 contains the results for the dataset which is described in Section 4.

6.1 Method

The model which was selected in Section 5 is used to estimate the differential pressure at nominal volume flow $\widehat{\Delta p_n}$. For existing HVAC systems, the differential pressure limit is specified for the nominal volume flow. Thus, the estimated differential pressure at nominal volume flow can be compared with the already defined differential pressure limit. The estimated differential pressure at nominal volume flow is determined as follows:

1. Start at the beginning of the time series.
2. Define a window of the duration 7 days which selects a data segment.
3. Estimate the variables c and n for the selected data segment by conducting a least squares fit.
4. Use the air filter model, the determined variables as well as the measured volume flow and air temperature values to estimate the differential pressure at nominal volume flow for the samples during the last day of the selected data segment.
5. Move the window one day further.
6. Repeat the steps 2 to 5 until the time series end.

The estimated differential pressure at nominal volume flow can be used in two ways. On the one hand, it can be compared with the specified differential pressure limit and an error message can be returned in the building management system if the limit is exceeded. Alternatively, the estimated differential pressure at nominal volume flow can be scaled in such a way that the resulting value of the filter clogging C has the value $0\,\%$ at the initial differential pressure of the air filter[1] and reaches $100\,\%$ when the differential pressure limit is reached (see Equation 18). In the analysed building, several air filters from different manufacturers are operated in parallel, which is why the initial differential pressure at the respective filter stage is unknown. Therefore, in this case the minimum differential pressure after the filter change is used as the lower limit.

$$C = \frac{\widehat{\Delta p_n} - \Delta p_{min}}{\Delta p_{max} - \Delta p_{min}} \cdot 100\,\% \qquad (18)$$

6.2 Results

The process to determine the air filter condition which is described in the previous section is applied for each air filter in the dataset which is described in Section 4. In Figure 2 the results for two air filters are shown

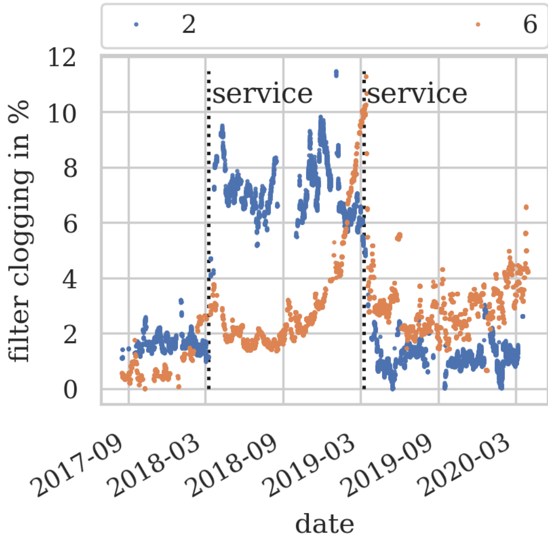

Figure 2: Filter clogging development for two air filters.

which are representative for all six analysed air filters. Furthermore, the dates at which the air filters were changed are marked by the dotted lines[2].

Figure 2 shows various effects that occur for all air filters, whereby the strength of the effect varies from filter to filter. In the case of air filter 6, the reduction of filter clogging after a filter change is clearly visible. Whereas in the case of air filter 2, the filter clogging increases after the first service and reduces as expected after the second service. This effect is a consequence of the use of different air filter brands. Each air filter brand and type has a different initial differential pressure, which is why the measured differential pressure increases after a service and thus also the calculated filter clogging. This effect can be countered by operating the HVAC system at different volume flow levels including the nominal volume flow after a service and using the measured differential pressure at nominal volume flow as a new lower limit if the initial differential pressure of the filter brand is not known. Furthermore, this initial test can be used to determine the exponent n and keep it fixed until the next service. This reduces the degrees of freedom of the model and thus reduces the overfitting potential.

Furthermore, in Figure 2 can be seen that the air filter clogging for air filter 2 is approximately constant between each service. This means that the accumulated loading of the air filter with particles between services has not led to any measurable increase of the differential pressure at a comparable volume flow. In addition, the time series shows gaps, as can be seen for air filter 2 in September 2018 and 2019. These are

[1] The initial differential pressure is usually specified by the air filter manufacturer.

[2] Due to the COVID-19 pandemic and the lockdown in Germany no filter change was carried out in March 2020.

caused by the low utilisation of the analysed building and the associated shutdown of the HVAC system during this period.

7 CONCLUSIONS

In this work, the approaches for modelling air filters which are identified in Section 2 are unified in Section 3 in such a way that they could be compared with each other and are also available in different levels of detail, which are suitable for a retrofit. The model comparison is carried out on the dataset of a building in Germany described in Section 4. The comparison described in Section 5 shows that the models derived from (DIN Deutsches Institut für Normung e.V., 2013) and (Löffler, 1988) deliver comparable results. The former achieves the best results overall. In Section 6 is described how this model can be used for condition monitoring of air filters in HVAC systems with variable volume flow. In addition, it is shown that this approach can be retrofitted to an existing building and provides plausible results.

Nevertheless, following questions with focus on condition monitoring of air filters in HVAC systems with variable volume flow are still open for further research.

- Is it possible to truly increase the quality of the air filter condition estimation by determining the exponent of model type I after a filter change and keeping it fixed for the rest of the air filter life?
- If data with better quality and a higher frequency resolution in combination with usage of relative air humidity would be available, how does that affect the performance of the analysed model types?
- Are the results independent from the analysed building and potential systematic errors in the data acquisition?

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