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Published in:
16th Scandinavian International Conference on Fluid Power, SICFP 2019

Published: 22/05/2019

Document Version
Publisher's PDF, also known as Version of record

Please cite the original version:
Jokinen, A., Calonius, O., Gorle, J., & Pietola, M. (2019). Data correlation model for hydraulic fluid filter condition monitoring. In K. Huhtala (Ed.), *16th Scandinavian International Conference on Fluid Power, SICFP 2019* (pp. 212-220). Tampereen yliopisto.

DATA CORRELATION MODEL FOR HYDRAULIC FLUID FILTER CONDITION MONITORING

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ABSTRACT

In fluid power systems, one of the most common causes of failure is contamination of the hydraulic fluid. Without filtering the fluid gets contaminated with harmful particles over time, which will cause excessive wear of components or even block motion of parts in flow control valves. In order to avoid machine downtime, it is important to monitor that adequate technical performance level of the fluid is maintained at all times.

This study contributes to condition-based maintenance of hydraulic fluid filter units by establishing a correlation equation, based on comprehensive laboratory tests and incorporated in a simulation model, relating the pressure drop over the filter unit with the main variables describing the operating conditions of the fluid system as well as with filter operating time.

The paper describes how the correlation equation and the simulation model was constructed. The results indicate that good correlation was obtained (R-square value 0.98) with the constructed equation between the physical variables and the temporal development of the pressure drop over the filter. The model can be used as a building block for a smart filter unit that can predict its lifetime.

KEYWORDS: hydraulic fluid filter, correlation model, condition monitoring

1. INTRODUCTION

In fluid power systems, one of the most common causes of failure is contamination of the hydraulic fluid [1]. In addition to its main function, i.e., to transfer energy, the fluid acts as a lubricant between moving parts in the components, enabling control of friction, wear and operating temperature.

In order to avoid machine downtime and loss of production, it is important to maintain adequate technical performance level of the fluid at all times. This is done by filtering, without which the fluid gets contaminated with harmful particles over time. Excessive concentration of particles in the fluid will cause excessive wear of components or can even block motion of parts in flow control valves. Wear can also cause insufficient efficiency in pumps, or their failure. Jammed parts in control valves can cause unreliable and erratic motion in actuators. These potential detrimental effects stress the importance of maintenance of fluid filter units.

Filter elements are usually replaced according to pre-defined time-schedules, but this is inefficient as the maintenance actions are not based on the actual time-history of the filter unit and the fluid system. Time-based maintenance can either lead to premature replacement of filters, or lead to excessive contamination levels in the fluid due to unforeseen sudden increase of particle load during the presumed service period. Condition-based maintenance of filter elements can be made possible by continuously measuring the pressure drop over the filter element and using the measured value in a filter model to predict the remaining lifetime of the element.

Filtering can also play an important role in assessing ship machinery condition (e.g., the thruster gear run condition), as wear particle concentration rate is also influenced by the removal rate of wear particles from the lubrication system. [2, 3]

Modelling the pressure drop associated with fluid flow through fibrous or porous media have been presented by several researchers over the years. However, the studies can be restricted to estimating pressure drop due to flow though clean fibrous filters [4, 5], or flow of air through porous material [6, 7]. This stresses the importance of filter testing and modelling involving contaminated fluid and gradual pressure build-up over the cartridge due to contamination retention. While the research on contamination retention in hydraulic filtration is not as extensive as in, say, industrial air filtration, in [8] a study was conducted for predicting the service life of a hydraulic filter based on the operating conditions. In the mentioned study, a model was developed for monitoring the condition of a hydraulic return line filter in a hydraulic servo system of a hot strip mill. The study presented a methodology for taking into account the influence of flow rate on the pressure difference over the filter by using down-stream pressure measurement instead of utilizing expensive flow meters. However, temperature measurement was not implemented, and thus the study did not take the influence of viscosity on the pressure difference over the filter into account.

For this study, comprehensive laboratory tests have been made in order to produce filtration performance data relating the effect of flow rate, contaminant particle concentration, and fluid temperature to the pressure drop measured over the filter element. [9]

In this paper, the laboratory test results will be analysed and mathematical correlation expressions will be derived from the experimental data giving estimates for the pressure drop over the filter as a function of the operating conditions and service time. While these mathematical correlation expressions represent the near-term goal, the aim of the future research is to develop Internet-of-things (IoT) enabled, smart filtering connected to the overall computerized condition monitoring solution in the machine system, e.g., in a ship. The purpose is to be able to compare filter performance data that have been recorded in the machine system with the estimate given by the mathematical expressions, in order to detect the operating state of the filter cartridge and to predict its remaining lifetime by producing an estimate (trend) of how the pressure drop will evolve over time.

2. METHODS

The study to create a correlation model for the pressure drop across a filter element was twofold: perform laboratory tests at different fluid conditions, and develop a model based on said laboratory tests that could predict the pressure drop based on the different conditions. Section 2.1. examines the laboratory tests that were carried out, followed by the explanation of the succeeded modelling procedure in Section 2.2.

2.1. Experimental

The experimental part consisted of measuring the filter pressure drop at different oil conditions. For this purpose, a test bench with multiple sensors monitoring the different conditions was utilized. The filter type used in the experiments was a 5 µm rated commercial filter with glass fibre media that has an effective surface area of 0.154 m^2 through 57 pleats. The oil that was used was the standard ISO VG 32 hydraulic oil. [9]

The different oil conditions considered for this study were the oil flow rate, temperature, and gravimetric contamination level. For adjusting the gravimetric contamination level, the fluid was subjected to ISO medium test dust (ISO12103-1-A3) at different rates resulting in four different contamination levels at 2 mg/l, 5 mg/l, 8 mg/l and 10 mg/l. The flow rates were set to 40 l/min, 80 l/min and 120 l/min, and the fluid temperatures were adjusted to 30 °C, 40 °C, 50 °C, and 60 °C, [9]. Figure 1 illustrates the types of effect that the different oil conditions have on the pressure drop development over time. The different experiments were carried out until a pressure drop of 5 bar had been reached, and the sampling period used for the measurements during each experiment was two seconds. As a summary, the tests included four different contamination levels, three different flow rates, and four different fluid temperatures, resulting in 48 experiments in total. The experimental set-up was described in more detail in [9].

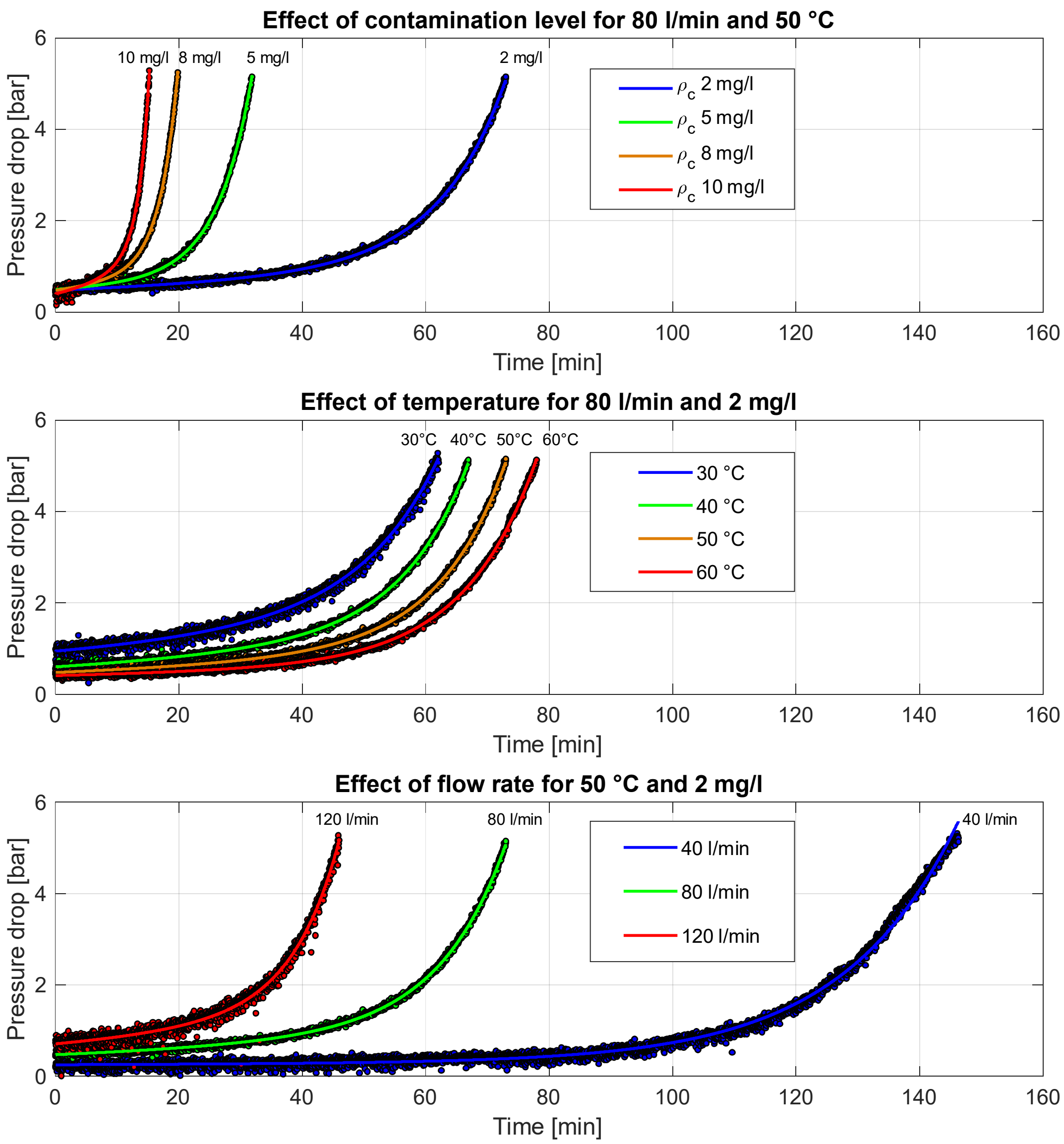

Figure 1. Examples of how the pressure drop developed when operation conditions were changed.

2.2. Model description

The main goal of this study was to establish a single model that will describe the development of the pressure drop across the filter element throughout its entire service life. Based on the experimental data, the model will consist of an equation of physical variables:

$$\Delta. = f(t, q_V, T, \rho_c), \tag{1}$$

where t is time, q_V is volumetric flow rate, T is temperature, and ρ_c is mass concentration of the contaminant i.e. the gravimetric contamination level. The approach used for constructing the model was regression analysis.

2.2.1. Equation for Δp

The first objective in the regression analysis was to find a general form for the equation (1) through curve fitting. The curve fitting was performed in the MATLAB environment for all the different 48 experiments, with the pressure drop Δp as the output and time t as the only initial input. Different models were experimented with, but the best fitting was discovered to be with an exponential function that has two exponential terms. The method utilized for finding the exponential fitting was the nonlinear least squares method, which is characterized by

$$\min_{\beta} \sum_{i=1}^{n} r_i(x)^2 = r_1(x)^2 + r_2(x)^2 + \ldots + r_n(x)^2, \qquad (2)$$

where the function $r_i(x)$ is

$$r_i(x) = y_i - f(x_i, \beta), \qquad (3)$$

where y_i is the sample, which is Δp in our case, and $f(x_i, \beta)$ is the corresponding fitting function value for the value x_i of the independent variable with a parametrization vector β. The intention was to minimize (2) by applying the Trust-Region search algorithm, which is especially suited for solving nonlinear problems. [10,11]

As the best fitting was found to be with an exponential function that has two exponential terms, the equation for Δp could now be expressed as

$$\Delta p(t) = ae^{bt} + ce^{dt}, \qquad (4)$$

where a, b, c and d are coefficients that vary at different flow rates, temperatures and contamination levels. This exponential fitting for Δp resulted in an R^2 value of over 0.99 for all but one of the original 48 experimental results.

The fitted curve includes certain observable trends that are typical for exponential functions. The curve is characterized by a low and steady increase in Δp at the beginning along the time-axis, which can also be seen from Figure 1 that showcases the measurement data. After the initial steady increase, the rate of change for Δp increases markedly towards the end of the experiment, Figure 1. However, the region of increased rate of change for Δp is not as apparent at lower temperatures, i.e. at higher fluid viscosities.

The next modelling objective was to present the coefficients a, b, c and d in (4) with the help of the physical variables q_V, T and ρ_c. This was initially approached by the means of manual search, e.g. keeping some physical variables constant, such as flow rate and temperature, and varying a single variable, such as contamination level, and determining whether it had any effect on the coefficients a, b, c or d. The coefficients a and c were found to be mainly influenced by the fluid flow rate and temperature, as their sum represents the pressure drop at time instant zero. Therefore, the coefficients a and c can be expressed as

$$a + c = \Delta p(0) = \Delta p_0, \qquad (5)$$

where the initial pressure drop across the filter element at time instant zero is denoted as Δp_0. This initial pressure drop occurs when the filter is still "clean" and has not been subjected to a stream of particles. This is also depicted in the uppermost graph in Figure 1, where the initial pressure drops are similar despite the differences in the gravimetric contamination level.

The initial pressure drop could be expressed with the help of the Ergun equation (1952), which is an extension of the Darcy's law (1856) for a pressure drop for a fluid flowing through a packed bed. The Ergun equation for a pressure drop is given as [12]

$$\Delta p = \frac{150\mu(1-\epsilon)^2 v_s L}{d_p^2 \epsilon^3} + \frac{1.75(1-\epsilon)\rho v_s^2 L}{d_p \epsilon^3}, \qquad (6)$$

where μ is the dynamic viscosity, ϵ is the porosity of the bed, v_s is the superficial velocity of the fluid, L is the length of the bed, and d_p is the particle diameter. According to the Ergun equation, the effect of fluid viscosity is linear, and the effect of fluid velocity is quadratic for the pressure drop across a packed bed. For our modelling purposes, the initial pressure drop Δp_0 for different cases was obtained by linear interpolation from the measurement data, as a function of flow rate and temperature.

Despite the initial pressure drop being independent of the fluid contamination level, the coefficient c was perceived to have a decreasing trend versus higher contamination levels, though no such trend was observed with the coefficient a. An example of this is demonstrated in Figure 2, where the contamination level is varied but the flow rate and temperature are kept constant at 120 l/min and 50 °C, respectively. This trend was observed at almost all different sets of a fixed flow rate and temperature.

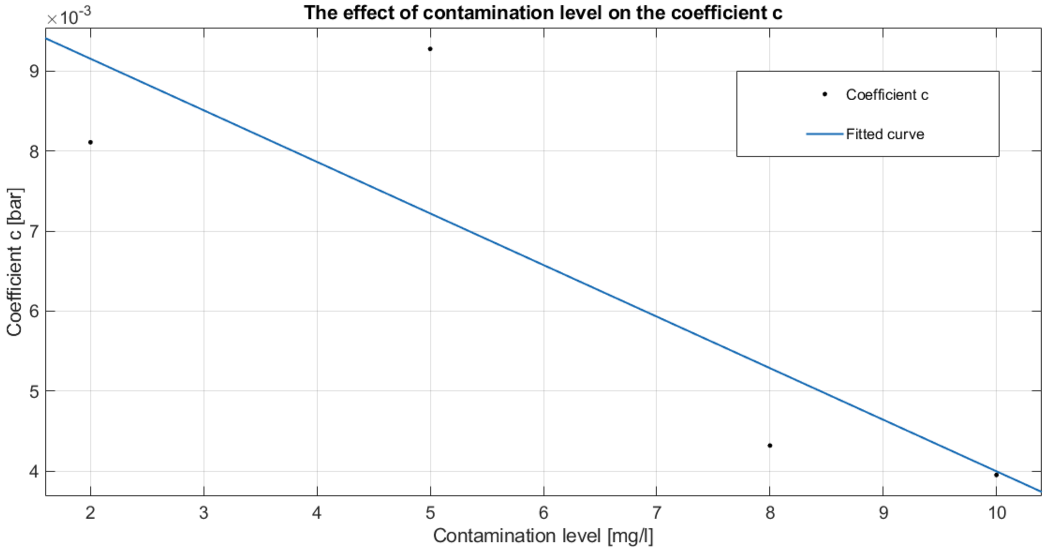

Figure 2. The coefficient c at different contamination levels, while the flow rate and temperature are kept constant (at 120 l/min, 50 °C)

The flow rate and temperature were varied separately as well, to determine how much they affected the coefficient c. After doing this inspection manually, a general form for the coefficient c was approximated as:

$$c = \left(x_1 q_v \rho_c + x_2 q_v^{x_3}\right)\nu + x_4 q_v^{x_5} \rho_c + x_6 q_v, \quad (7)$$

where x_1 through x_6 are constants and ν is the fluid kinematic viscosity. Note that this equation uses fluid viscosity as one of its variables rather than temperature. The relationship between fluid viscosity and temperature for the ISO VG 32 oil kinematic viscosity (in cSt) was given in [9] as:

$$\nu = 300.98T^{-0.585}, \quad (8)$$

where the temperature T is expressed in °C. Now that a general form for c had been acquired, the coefficient a could be expressed with the help of (5):

$$a = \Delta p_0 - c = \Delta p_0 - \left(\left(x_1 q_v \rho_c + x_2 q_v^{x_3}\right)\nu + x_4 q_v^{x_5} \rho_c + x_6 q_v\right), \quad (9)$$

A similar approach was taken for the coefficients b and d in (4), to approximate how the different physical variables affected them. The effect of contamination level was found to be very linear for both of the coefficients. The temperature was perceived to have little to no effect, however the effect of flow rate was noticeably linear and similar across different contamination levels. Figure 3 depicts an example of the effect of contamination level and flow rate on the coefficient b.

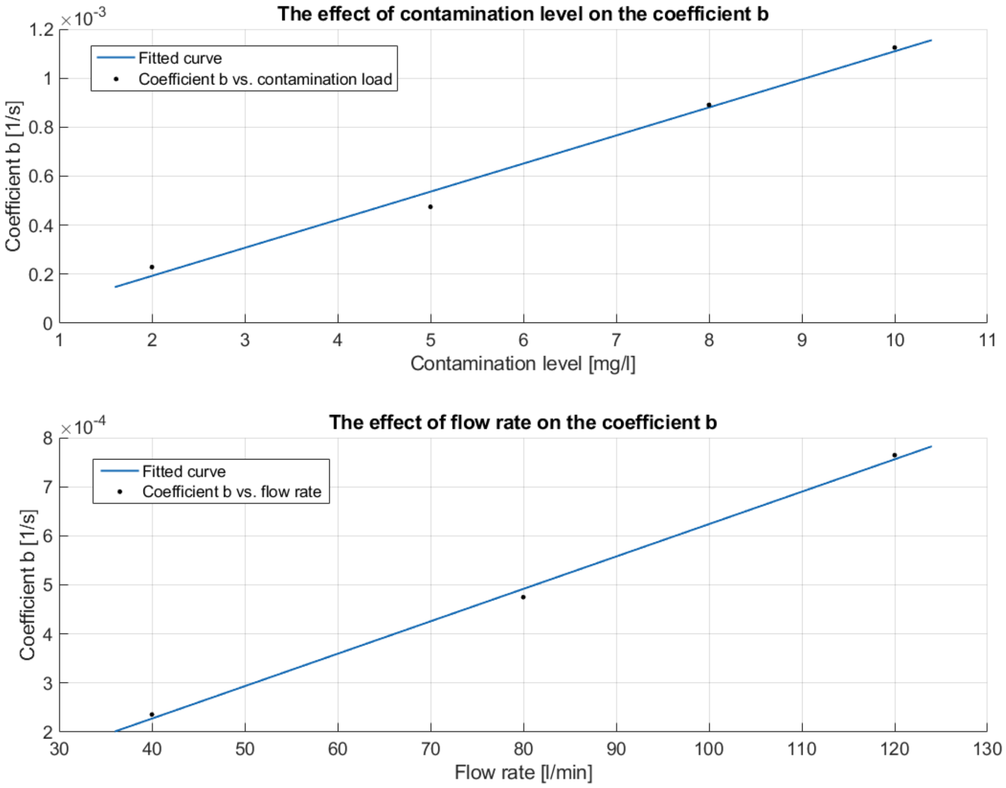

Figure 3. The effect of contamination level on b (at 80 l/min, 40 °C), and the effect of flow rate on b (at 5 mg/l, 40 °C)

As both of the coefficients b and d were discovered to vary very linearly based on the contamination level and flow rate, the two coefficients could be expressed as:

$$b = x_7 q_v \rho_c, \tag{10}$$

and

$$d = x_8 q_v \rho_c, \tag{11}$$

where x_7 and x_8 are constants. Combining the resulting functions for a, b, c and d into (4) provides us a general form for the pressure drop equation:

$$\Delta p = \left(\Delta p_0 - \left(\left(x_1 q_v \rho_c + x_2 q_v^{x_3}\right)\nu + x_4 q_v^{x_5} \rho_c + x_6 q_v\right)\right) e^{x_7 q_v \rho_c t} + \left(\left(x_1 q_v \rho_c + x_2 q_v^{x_3}\right)\nu + x_4 q_v^{x_5} \rho_c + x_6 q_v\right) e^{x_8 q_v \rho_c t} \tag{12}$$

The constants x_1—x_8 were initially obtained manually while deriving this equation. However, for better accuracy, the coefficients were later refined using parameter optimization, which is discussed in the following sub-section.

2.2.2. Parameter optimization

After deriving the mathematical model (12) for the pressure drop across the filter element, the next task was to optimize the parameters x_1—x_8 in order to improve the accuracy of the model. The experimental results for Δp were resampled into equally long lists, to avoid excessive importance of the longer experiments, mainly those that occurred at lower flow rates and contamination levels. Some of the measurements were excluded for this stage as they were inconsistent with the majority. The excluded measurements contained all the experiments done at flow rate of 40 l/min at temperatures 50 and 60 °C, therefore eight experiments in total from the original 48 experiments were excluded. The included measurements were combined into a single output list, and an input matrix that included the corresponding time, flow rate, viscosity and contamination level, was created. The problem was approached similarly as in (2), where it was treated as a cost function to be minimized. For this case, the function to minimize was:

$$\min_{x} \frac{1}{2n} \sum_{i=1}^{n} (\Delta p_i - \Delta \hat{p}_i)^2, \tag{13}$$

where Δp_i is the measured pressure drop obtained from the output list, and $\Delta \hat{p}_i$ is the estimated pressure drop calculated with (12) using the values from the input matrix. x is a vector to optimize, containing the parameters x_1—x_8, i.e., the constants of (12) that are to be determined. The amount of sample points n is 14683, which is the length of the list that contains the measured Δp values. The search algorithm used was the Nelder-Mead simplex algorithm [10], and the values that had previously been obtained manually for x_1—x_8 were used as an initial guess for the algorithm. The accuracy of the optimized, final function will be examined in the Results section.

2.2.3. Simulink model

The final step in the model establishment procedure was to simulate the response of equation (12) at different cases of flow rate, temperature and contamination level. For this purpose, a model in the Simulink environment was constructed. The model uses constant values for x_1—x_8 that were acquired through the parameter optimization, and as inputs the aforementioned physical variables: fluid flow rate, temperature and contamination level, as well as time. The fluid kinematic viscosity is calculated in the simulation using equation (8), and an initial pressure drop across the filter element is interpolated from the flow rate and temperature. The simulation has been programmed to end once a pressure drop of 5 bar has been reached. The simulation results were validated by comparisons with the experimental data, which shall be discussed in more detail in the following section.

3. RESULTS

This section examines the modelling results. The Simulink model that utilizes equation (12) was experimented with at different flow rates, temperatures and contamination levels. The simulation outcomes were compared against the experimental data. Some of the comparisons are demonstrated in Figure 4 to illustrate the accuracy of the developed model. The simulation results for the early phase in the pressure drop development are largely accurate, though for some cases, clear deviation between the simulated and measured results can be observed at the end.

Table 1 assesses the goodness of equation (12), when compared against all the measured data that was included for the optimization process, i.e. the list of 14683 different Δp measurements.

Table 1. Validation of function (12) when compared against the measured data.

Goodness of fit	Value
SSE	303
R^2	0.985
RMSE	0.144

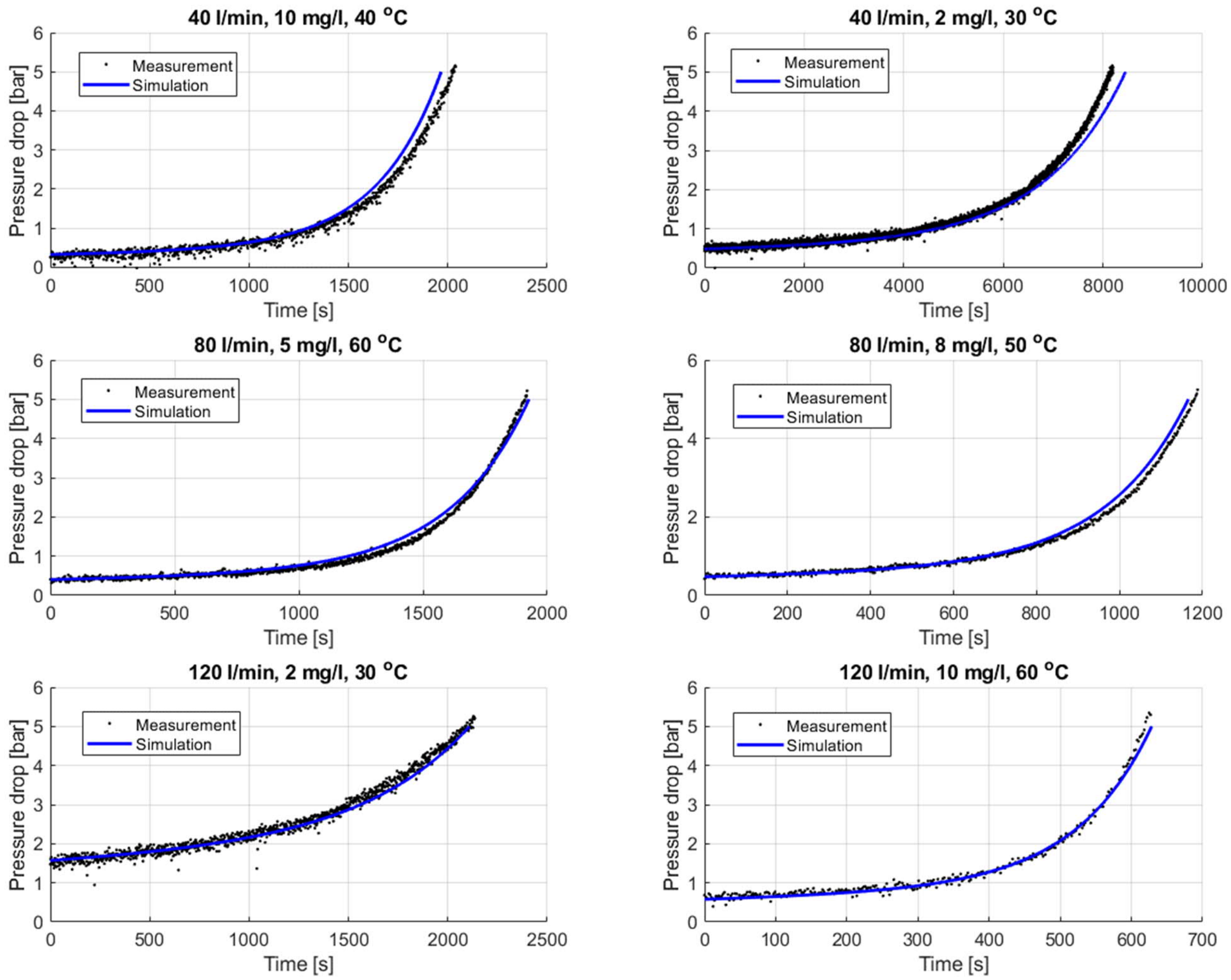

Figure 4. Comparing simulated and measured pressure drops.

4. DISCUSSION

The model developed in this study can predict the development of $\Delta\bar{A}$ up to 5 bar with a high degree of accuracy. Eight of the original 48 experiments were excluded from this inspection due to their inconsistent results. All of the excluded cases were 40 l/min cases, which might account for more noticeable discrepancies between the simulated and measured results for the 40 l/min comparisons in Figure 4. However, when considering that the model was assessed against 40 experiments that each had three independently varied physical variables, an R^2 value of 0.985 can be deemed high enough to showcase a clear correlation between the different physical variables and the development of $\Delta\bar{A}$. The greatest variance between the simulated and measured results can typically be observed at the end of the simulation, though the greatest inconsistencies in the experimental results also occurred at the end, making the end of the $\Delta\bar{A}$ curve the greatest area of uncertainty.

The equation (12) that was derived in this study is an equation of the filtration time that works only if the different oil parameters are assumed to be constants. To have the equation work better with variable parameters, the equation should be written without time as one of its variables. One possibility would be to rewrite the equation as a function of filtered mass instead of time, where the filtered mass would be defined as the cumulative integral of mass that has entered the filter, calculated from the oil contamination level and flow rate. Another possibility could be to examine the derivatives of different $\Delta\bar{A}$ curves to investigate whether a clear point where the $\Delta\bar{A}$ starts to climb excessively could be identified. As the fitting function is exponential in nature, differentiating it would be simple.

Another aspect is that the model developed in this research could be entirely media specific, and there is no guarantee that it would work with other filter types. The coefficients that were considered constants in this study would most likely vary based on the filter media. In addition, as laboratory tests that were performed at careful conditions were the basis of this research, further confirmation of the accuracy of the developed model would require additional field-testing.

5. CONCLUSIONS

The objective in this study was to develop a correlation model for the pressure drop across a filter element that is subjected to a stream of contaminated oil at different oil contamination levels, flow rates and temperatures. The study resulted in exponential equation (12) that could be used to calculate the developing pressure drop based on the aforementioned oil parameters. The model was validated against experimental data, and was found to match the empirical results with a high degree of accuracy with a coefficient of determination R^2 of over 0.98. This demonstrated a clear correlation between the oil parameters and the pressure drop development over the filter element, which is typically used for determining the remaining service life of the filter.

This study has been done as part of an initial research in order to investigate correlations between oil conditions and filter service time. The ultimate goal of the research is to develop an intelligent oil filter that can predict its remaining lifetime. This information would be used in predictive maintenance that would eliminate unnecessary filter replacements, and prevent downtime due to a filter failure. As the research is still in its early phase, more work needs to be done to develop the correlation models. Possible future prospects include a correlation model based on filtered mass, and an investigation of the rate of change of the pressure drop data, in order to more accurately detect the beginning of the actual blocking phase of the filter lifetime.

ACKNOWLEDGMENTS

This work was made as a part of a Finnish research consortium - INTENS, hosted by VTT Oy, and funded by Business Finland (project # 7733/31/2017).

NOMENCLATURE

ν	Kinematic viscosity	[mm^2/s]
ρ_c	Mass concentration of contaminant, i.e., the gravimetric contamination level	[mg/l]
a, b, c, d	Coefficients for pressure drop	[-]
Δp	Pressure drop	[bar]
Δp_0	Initial pressure drop over a filter	[bar]
q_V	Volumetric flow rate	[l/min]
t	Time	[s]
T	Temperature	[°C]
x_1—x_8	Constants for pressure drop	[-]
SSE	Sum of squares due to error (summed square of residuals)	[-]
R^2	R-square (coefficient of determination)	[-]
RMSE	Root Mean Squared Error (standard error of the regression)	[-]

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